Results Lathyrus paper 1

Contents

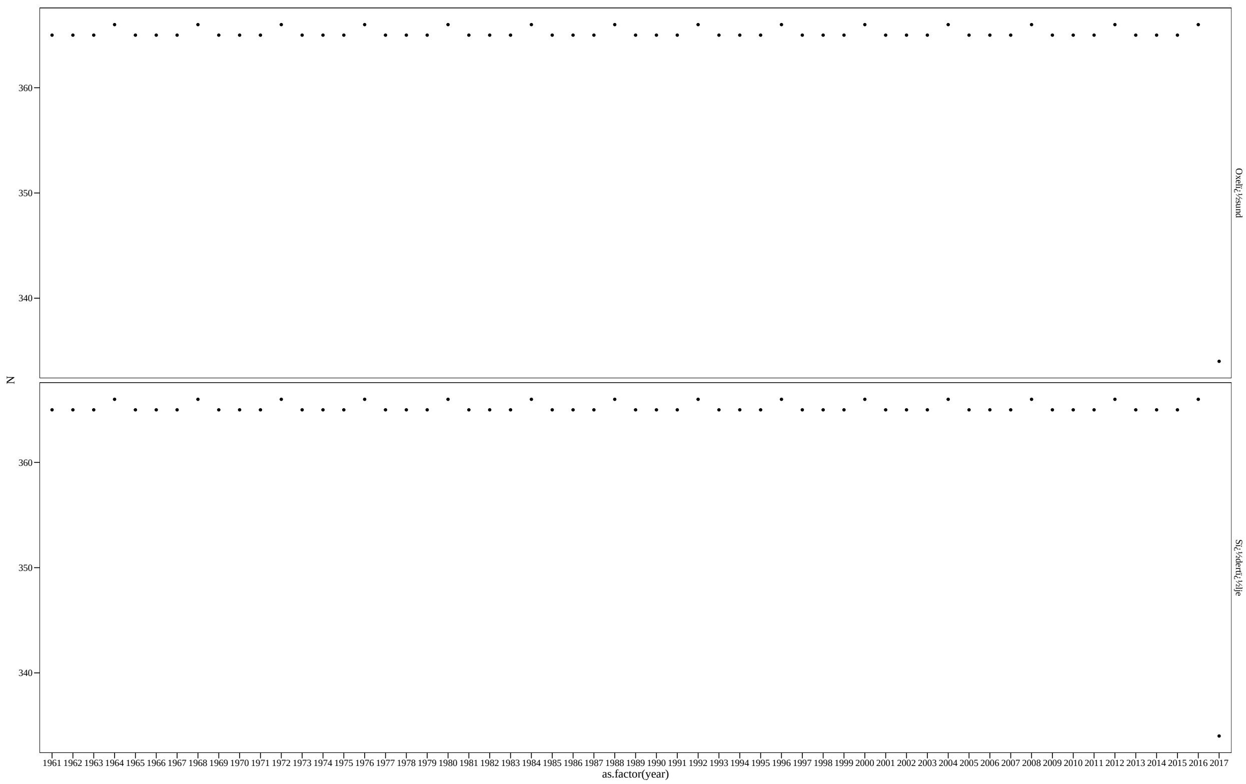
Temperature and precipitation data manipulation

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

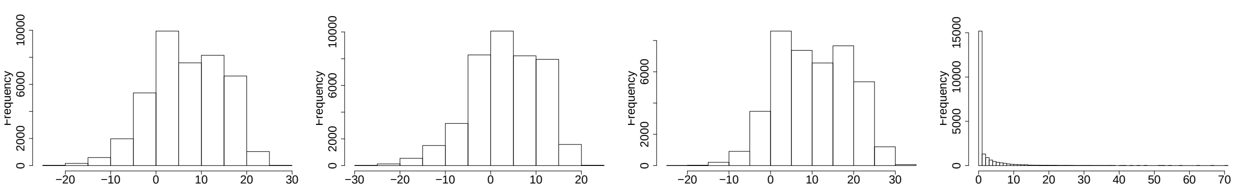
date	year	month	day	station	mean	quality_mean	min	quality__.min	max	quality_max
1961-01-01	1961	1	1	Oxelï¿½sund	-0.2	Y	-1.5	G	2.2	G
1961-01-01	1961	1	1	Sï¿½dertï¿½lje	0.0	Y	-0.5	G	1.0	G
1961-01-02	1961	1	2	Sï¿½dertï¿½lje	0.3	Y	0.8	G	2.6	G
1961-01-02	1961	1	2	Oxelï¿½sund	0.7	Y	0.7	G	3.1	G
1961-01-03	1961	1	3	Sï¿½dertï¿½lje	1.9	Y	-1.2	G	3.0	G
1961-01-03	1961	1	3	Oxelï¿½sund	2.0	Y	0.6	G	3.7	G

date	year	month	day	station	mean	quality_mean	min	quality_.min	max	quality_max

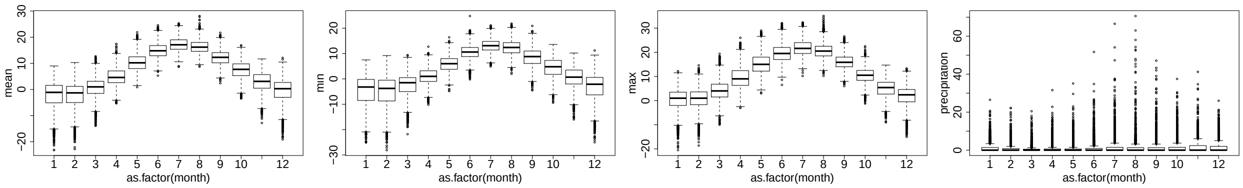
date	year	month	day	station	precipitation	quality
1961-01-01	1961	1	1	?da	0.0	Y
1961-01-02	1961	1	2	?da	0.6	Y
1961-01-03	1961	1	3	?da	5.6	Y
1961-01-04	1961	1	4	?da	10.0	Y
1961-01-05	1961	1	5	?da	0.0	Y
1961-01-06	1961	1	6	?da	0.0	Y



Distributions



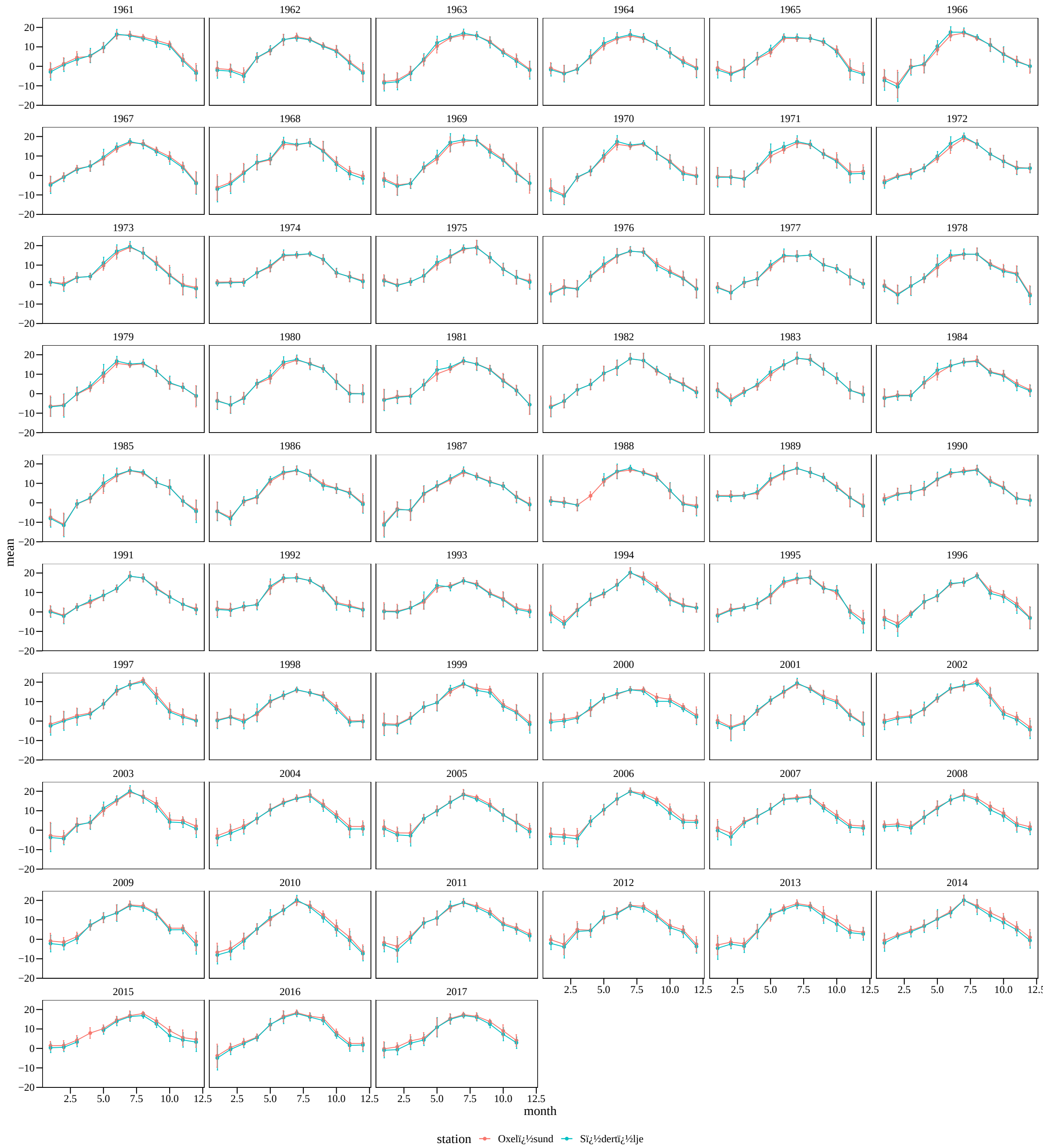
Boxplots per month



Comparisons of mean temperatures for each year for both stations

```
## Warning: Removed 2 rows containing missing values (geom_point).
```

```
## Warning: Removed 2 rows containing missing values (geom_errorbar).
```



Complete precipitation data

```r
nrow(subset(precipitation,is.na(precipitation))) #245 dates with missing precipitation
```

```
## [1] 245
```

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

```
##        year month
```

```
## 6453  1978     9
## 9893  1988     2
## 11109 1991     6
## 11354 1992     2
## 11597 1992    10
## 14031 1999     6
## 14061 1999     7
## 20753 2017    10
## 20759 2017    11
```

```
# September 1978,February 1988, June 1991, February & October 1992,June & July 1999
# October-November 2017 = missing, but ignore

# Remove NA values
precipitation<-subset(precipitation,!is.na(precipitation))

#Substitute with data from Sjögärde station
precipitation_extra<-merge(dates,precipitation_extra,all.x=T,all.y=T)
precipitation<-rbind(precipitation,
                     subset(precipitation_extra,year==1978&month==9),
                     subset(precipitation_extra,year==1988&month==2),
                     subset(precipitation_extra,year==1991&month==6),
                     subset(precipitation_extra,year==1992&month==2),
                     subset(precipitation_extra,year==1992&month==10),
                     subset(precipitation_extra,year==1999&month==6),
                     subset(precipitation_extra,year==1999&month==7))
precipitation<-precipitation[order(precipitation$date),]
```

Complete temperature data

```
temperature_wide<-gather(temperature[c(1:6,8,10)], variable, value,mean,min,max) %>%
  unite(var, variable, station) %>%
  spread(var, value) #Convert to wide format with station variables
names(temperature_wide)<-c("date","year","month","day","max_O","max_S","mean_O","mean_S","min_O","min_S

# Check for NAs
nrow(subset(temperature_wide,is.na(min_O)|is.na(min_S)))
```

```
## [1] 128
```

```
nrow(subset(temperature_wide,is.na(mean_O)|is.na(mean_S)))
```

```
## [1] 134
```

```
nrow(subset(temperature_wide,is.na(max_O)|is.na(max_S)))
```

```
## [1] 148
```

```
# Models mean_S vs mean_O for each month
models_mean<-gather(
  as.data.frame(temperature_wide %>% group_by(month) %>%
                              do(models_mean=lm(mean_S ~ mean_O, data = .))%>%
                              tidy(models_mean))[1:3],
  variable,value,estimate)%>%
  unite(var,variable,term)%>%
```

```r
  spread(var,value)
names(models_mean)<-c("month","intercept","estimate")
models_mean
```

```
##    month   intercept  estimate
## 1      1 -0.76903286 1.0147646
## 2      2 -0.68429649 1.0188784
## 3      3 -0.46892126 1.0063184
## 4      4  0.12659385 1.0179272
## 5      5  0.73423000 0.9929153
## 6      6  0.38400590 1.0002843
## 7      7  0.50460309 0.9775242
## 8      8  0.46191939 0.9515081
## 9      9  0.03051138 0.9417406
## 10    10 -0.55452420 0.9789705
## 11    11 -0.62378486 0.9779958
## 12    12 -0.69994513 0.9693166
```

```r
# Models min_S vs mi_O for each month
models_min<-gather(
  as.data.frame(temperature_wide %>% group_by(month) %>%
                           do(models_min=lm(min_S ~ min_O, data = .))%>%
                           tidy(models_min))[1:3],
  variable,value,estimate)%>%
  unite(var,variable,term)%>%
  spread(var,value)
names(models_min)<-c("month","intercept","estimate")
models_min
```

```
##    month  intercept  estimate
## 1      1 -1.0439080 0.9792638
## 2      2 -1.0526482 0.9840165
## 3      3 -0.9473471 1.0133144
## 4      4 -0.8297367 0.9256269
## 5      5 -0.2410005 0.8900552
## 6      6  1.5112718 0.7655757
## 7      7  2.9144379 0.7130278
## 8      8  2.4024397 0.7155876
## 9      9  0.7613480 0.7825174
## 10    10 -0.3834367 0.8573757
## 11    11 -0.8121493 0.9355892
## 12    12 -0.9551004 0.9547948
```

```r
# Models max_S vs max_O for each month
models_max<-gather(
  as.data.frame(temperature_wide %>% group_by(month) %>%
                           do(models_max=lm(max_S ~ max_O, data = .))%>%
                           tidy(models_max))[1:3],
  variable,value,estimate)%>%
  unite(var,variable,term)%>%
  spread(var,value)
names(models_max)<-c("month","intercept","estimate")
models_max
```

```
##    month  intercept  estimate
```

```
## 1      1 -0.6750701 1.0164750
## 2      2 -0.4737566 1.0135386
## 3      3  0.3755773 0.9386778
## 4      4  1.4684186 0.9671679
## 5      5  3.1886593 0.9168415
## 6      6  3.2349314 0.9005842
## 7      7  1.8284812 0.9615537
## 8      8  0.8358612 0.9834605
## 9      9  0.4105918 0.9713423
## 10    10 -0.1214316 0.9726466
## 11    11 -0.4194127 0.9636203
## 12    12 -0.5840180 0.9657833
```

```r
# See in which months each var is missing
unique(subset(temperature_wide,is.na(mean_S))$month) # mean_S
```

```
## [1]  4 10 11  6  3
```

```r
unique(subset(temperature_wide,is.na(mean_O))$month) # mean_O
```

```
## [1] 6 7
```

```r
unique(subset(temperature_wide,is.na(min_S))$month) # min_S
```

```
## [1]  4 10 11  6  3
```

```r
unique(subset(temperature_wide,is.na(min_O))$month) # min_O
```

```
## [1] 6 7
```

```r
unique(subset(temperature_wide,is.na(max_S))$month) # max_S
```

```
## [1]  4 10 11  6  3
```

```r
unique(subset(temperature_wide,is.na(max_O))$month) # max_O
```

```
## [1]  6  7 10
```

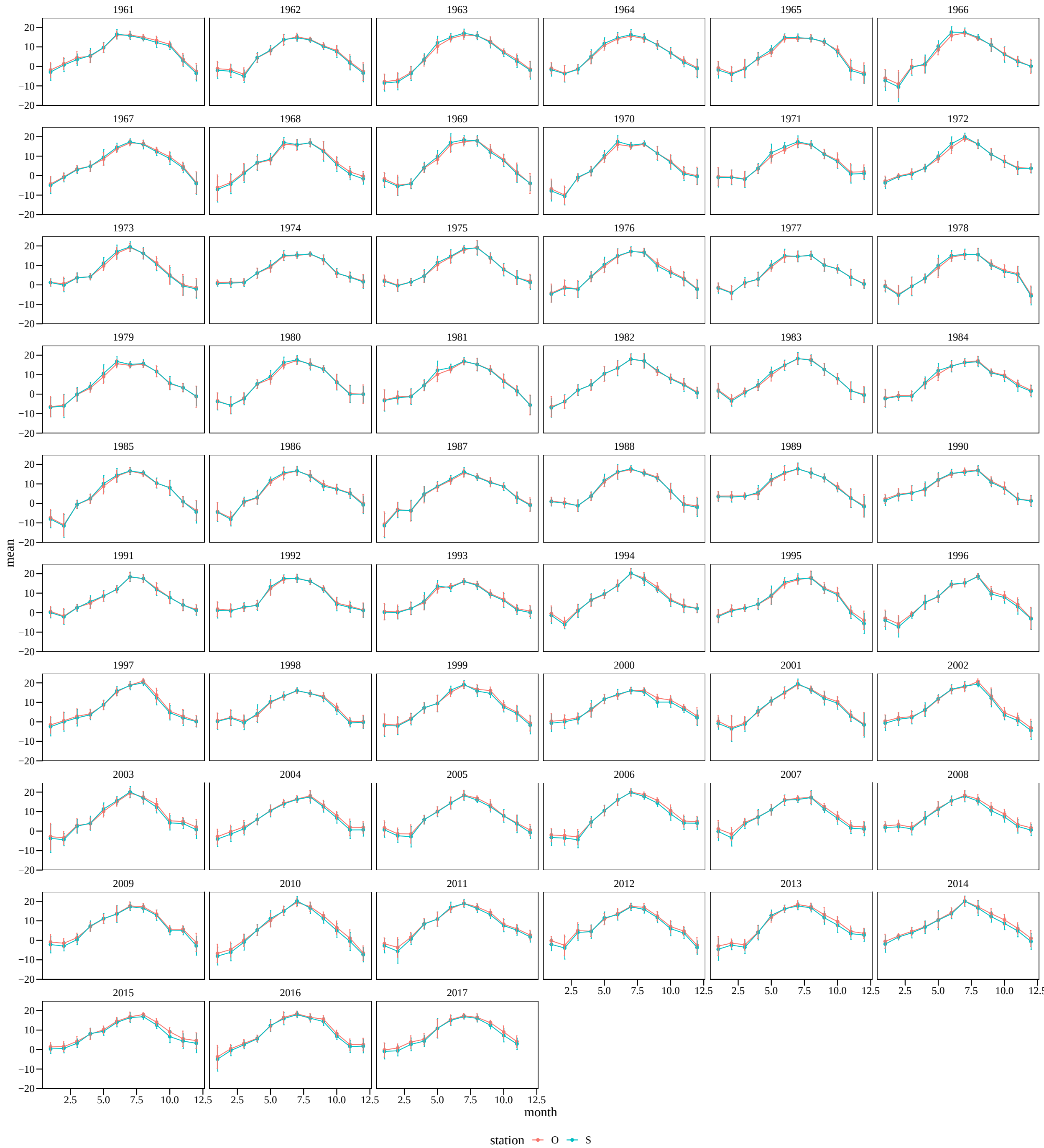
```r
# Replace missing values by imputed values

# mean_S=estimate*mean_O+intercept
# mean_O=(mean_S-intercept)/estimate  ... (same for min and max)

# mean_S
temperature_wide[is.na(temperature_wide$mean_S)&temperature_wide$month==4,8]<-
subset(models_mean,month==4)$intercept+
  subset(models_mean,month==4)$estimate*subset(temperature_wide,is.na(mean_S)&month==4)$mean_O

temperature_wide[is.na(temperature_wide$mean_S)&temperature_wide$month==10,8]<-
subset(models_mean,month==10)$intercept+
  subset(models_mean,month==10)$estimate*subset(temperature_wide,is.na(mean_S)&month==10)$mean_O

temperature_wide[is.na(temperature_wide$mean_S)&temperature_wide$month==11,8]<-
subset(models_mean,month==11)$intercept+
  subset(models_mean,month==11)$estimate*subset(temperature_wide,is.na(mean_S)&month==11)$mean_O

temperature_wide[is.na(temperature_wide$mean_S)&temperature_wide$month==6,8]<-
subset(models_mean,month==6)$intercept+
  subset(models_mean,month==6)$estimate*subset(temperature_wide,is.na(mean_S)&month==6)$mean_O
```

```r
temperature_wide[is.na(temperature_wide$mean_S)&temperature_wide$month==3,8]<-
subset(models_mean,month==3)$intercept+
  subset(models_mean,month==3)$estimate*subset(temperature_wide,is.na(mean_S)&month==3)$mean_O

# mean_O
temperature_wide[is.na(temperature_wide$mean_O)&temperature_wide$month==6,7]<-
  (subset(temperature_wide,is.na(mean_O)&month==6)$mean_S-subset(models_mean,month==6)$intercept)/
  subset(models_mean,month==6)$estimate

temperature_wide[is.na(temperature_wide$mean_O)&temperature_wide$month==7,7]<-
  (subset(temperature_wide,is.na(mean_O)&month==7)$mean_S-subset(models_mean,month==7)$intercept)/
  subset(models_mean,month==7)$estimate

# min_S
temperature_wide[is.na(temperature_wide$min_S)&temperature_wide$month==4,10]<-
subset(models_min,month==4)$intercept+
  subset(models_min,month==4)$estimate*subset(temperature_wide,is.na(min_S)&month==4)$min_O

temperature_wide[is.na(temperature_wide$min_S)&temperature_wide$month==10,10]<-
subset(models_min,month==10)$intercept+
  subset(models_min,month==10)$estimate*subset(temperature_wide,is.na(min_S)&month==10)$min_O

temperature_wide[is.na(temperature_wide$min_S)&temperature_wide$month==11,10]<-
subset(models_min,month==11)$intercept+
  subset(models_min,month==11)$estimate*subset(temperature_wide,is.na(min_S)&month==11)$min_O

temperature_wide[is.na(temperature_wide$min_S)&temperature_wide$month==6,10]<-
subset(models_min,month==6)$intercept+
  subset(models_min,month==6)$estimate*subset(temperature_wide,is.na(min_S)&month==6)$min_O

temperature_wide[is.na(temperature_wide$min_S)&temperature_wide$month==3,10]<-
subset(models_min,month==3)$intercept+
  subset(models_min,month==3)$estimate*subset(temperature_wide,is.na(min_S)&month==3)$min_O

# min_O
temperature_wide[is.na(temperature_wide$min_O)&temperature_wide$month==6,9]<-
  (subset(temperature_wide,is.na(min_O)&month==6)$min_S-subset(models_min,month==6)$intercept)/
  subset(models_min,month==6)$estimate

temperature_wide[is.na(temperature_wide$min_O)&temperature_wide$month==7,9]<-
  (subset(temperature_wide,is.na(min_O)&month==7)$min_S-subset(models_min,month==7)$intercept)/
  subset(models_min,month==7)$estimate

# max_S
temperature_wide[is.na(temperature_wide$max_S)&temperature_wide$month==4,6]<-
subset(models_max,month==4)$intercept+
  subset(models_max,month==4)$estimate*subset(temperature_wide,is.na(max_S)&month==4)$max_O

temperature_wide[is.na(temperature_wide$max_S)&temperature_wide$month==10,6]<-
subset(models_max,month==10)$intercept+
  subset(models_max,month==10)$estimate*subset(temperature_wide,is.na(max_S)&month==10)$max_O

temperature_wide[is.na(temperature_wide$max_S)&temperature_wide$month==11,6]<-
```

```r
subset(models_max,month==11)$intercept+
  subset(models_max,month==11)$estimate*subset(temperature_wide,is.na(max_S)&month==11)$max_O

temperature_wide[is.na(temperature_wide$max_S)&temperature_wide$month==6,6]<-
subset(models_max,month==6)$intercept+
  subset(models_max,month==6)$estimate*subset(temperature_wide,is.na(max_S)&month==6)$max_O

temperature_wide[is.na(temperature_wide$max_S)&temperature_wide$month==3,6]<-
subset(models_max,month==3)$intercept+
  subset(models_max,month==3)$estimate*subset(temperature_wide,is.na(max_S)&month==3)$max_O

# max_O
temperature_wide[is.na(temperature_wide$max_O)&temperature_wide$month==6,5]<-
  (subset(temperature_wide,is.na(max_O)&month==6)$max_S-subset(models_max,month==6)$intercept)/
  subset(models_max,month==6)$estimate

temperature_wide[is.na(temperature_wide$max_O)&temperature_wide$month==7,5]<-
  (subset(temperature_wide,is.na(max_O)&month==7)$max_S-subset(models_max,month==7)$intercept)/
  subset(models_max,month==7)$estimate

temperature_wide[is.na(temperature_wide$max_O)&temperature_wide$month==10,5]<-
  (subset(temperature_wide,is.na(max_O)&month==10)$max_S-subset(models_max,month==10)$intercept)/
  subset(models_max,month==10)$estimate

# Check for NAs
subset(temperature_wide,is.na(max_O)|is.na(max_S)|is.na(mean_O)|is.na(mean_S)|is.na(max_O)|is.na(max_S))
```

```
##  [1] date   year   month  day    max_O  max_S  mean_O mean_S min_O  min_S 
## <0 rows> (or 0-length row.names)
```

```r
# No NAs

temperature_compl<-gather(temperature_wide, variable, value,max_O,max_S,mean_O,mean_S,min_O,min_S) %>%
  separate(variable,c("var", "station"),sep="_",remove=T,convert=F)%>%
  spread(var, value)
```



Average mean, min and max temperature of the two stations for further use

```
temperature_av<-as.data.frame(temperature_compl %>%
                          group_by(date,year,month,day) %>%
                          summarize(mean=mean(mean),
                                    min=mean(min),
                                    max=mean(max)))
kable(head(temperature_av))
```

date	year	month	day	mean	min	max
1961-01-01	1961	1	1	-0.10	-1.00	1.60
1961-01-02	1961	1	2	0.50	0.75	2.85
1961-01-03	1961	1	3	1.95	-0.30	3.35
1961-01-04	1961	1	4	1.60	0.00	2.30
1961-01-05	1961	1	5	0.40	-0.30	1.65
1961-01-06	1961	1	6	0.25	-0.70	1.80

```r
nrow(subset(temperature_av,is.na(mean))) # No rows with NA values for mean
```

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

```r
nrow(subset(temperature_av,is.na(min))) # No rows with NA values for min
```

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

```r
nrow(subset(temperature_av,is.na(max))) # No rows with NA values for max
```

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

Merge temperature and precipitation data

```r
weather<-merge(temperature_av,precipitation[c(1:4,6)],all.x=T,all.y=T)
kable(head(weather))
```

date	year	month	day	mean	min	max	precipitation
1961-01-01	1961	1	1	-0.10	-1.00	1.60	0.0
1961-01-02	1961	1	2	0.50	0.75	2.85	0.6
1961-01-03	1961	1	3	1.95	-0.30	3.35	5.6
1961-01-04	1961	1	4	1.60	0.00	2.30	10.0
1961-01-05	1961	1	5	0.40	-0.30	1.65	0.0
1961-01-06	1961	1	6	0.25	-0.70	1.80	0.0

```r
nrow(subset(weather,is.na(mean))) #No missing values
```

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

```r
nrow(subset(weather,is.na(min))) #No missing values
```

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

```r
nrow(subset(weather,is.na(max))) #No missing values
```

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

```r
nrow(subset(weather,is.na(precipitation)))
```

```
## [1] 35
```

```
#35 dates with missing precipitation in October-November-December 2017 --> OK
```

Calculation of GDD and GDH

Bases considered: 3/5/7/10 ºC

GDD:

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

GDH:

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

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

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

```
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	mean	min	max	precipitation	GDD3	GDD5
1961-01-01	1961	1	1	-0.1	-1	1.6	0	0	0
1961-01-02	1961	1	2	0.5	0.75	2.85	0.6	0	0
1961-01-03	1961	1	3	1.95	-0.3	3.35	5.6	0	0
1961-01-04	1961	1	4	1.6	0	2.3	10	0	0
1961-01-05	1961	1	5	0.4	-0.3	1.65	0	0	0
1961-01-06	1961	1	6	0.25	-0.7	1.8	0	0	0

GDD7	GDD10	GDH3	GDH5	GDH7	GDH10
0	0	0	0	0	0
0	0	0	0	0	0
0	0	0.4027	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_study<-merge(weather,unique(alldata[c(1,8)]))
#Keeps only data from 1987-1996 and 2006-2017
#Add column with date of vernal equinox
weather_study$vernal_time<-as.POSIXct(weather_study$vernal,format="%Y-%m-%d %H:%M:%S")
weather_study$vernal<-as.Date(substring(weather_study$vernal,1,10),format="%Y-%m-%d")
weather_study$date_julian<-as.numeric(with(weather_study,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_study,FUN=mean), #Monthly means of mean daily temperature
    aggregate(min~year+month,data=weather_study,FUN=mean), #Monthly means of min daily temperature
    aggregate(max~year+month,data=weather_study,FUN=mean), #Monthly means of max daily temperature
    aggregate(precipitation~year+month,data=weather_study,FUN=sum),#Monthly sums of precipitation
    aggregate(GDD3~year+month,data=weather_study,FUN=sum),          #Monthly sums of GDD3
    aggregate(GDD5~year+month,data=weather_study,FUN=sum),          #Monthly sums of GDD5
    aggregate(GDD7~year+month,data=weather_study,FUN=sum),          #Monthly sums of GDD7
    aggregate(GDD10~year+month,data=weather_study,FUN=sum),         #Monthly sums of GDD10
    aggregate(GDH3~year+month,data=weather_study,FUN=sum),          #Monthly sums of GDH3
    aggregate(GDH5~year+month,data=weather_study,FUN=sum),          #Monthly sums of GDH5
    aggregate(GDH7~year+month,data=weather_study,FUN=sum),          #Monthly sums of GDH7
    aggregate(GDH10~year+month,data=weather_study,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_study<-as.data.frame(weather_study %>%
                                dplyr::group_by(year) %>%
                                dplyr::arrange (date) %>%
                                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_study$FFD<-weather_study$date_julian
alldata_weather<-merge(alldata, weather_study[c(1,5:16,20:28)],all.x=T,all.y=F)
```

```
subset(alldata_weather,is.na(mean)&!is.na(FFD))[1:2] #Merge by FFD worked in all?
```

```
##      year      FFD
## 3815  1992 65.66944
## 3816  1992 65.66944
## 3817  1992 65.66944
## 3818  1992 65.66944
## 3819  1992 65.66944
## 3820  1992 65.66944
## 3821  1992 65.66944
## 3822  1992 65.66944
```

```
## 3823  1992 65.66944
## 3824  1992 65.66944
## 3825  1992 65.66944
## 3826  1992 65.66944
## 3827  1992 65.66944
## 3828  1992 65.66944
## 3829  1992 65.66944
## 10082 2006 51.85435
## 10097 2006 55.92861
## 10098 2006 55.92861
## 10099 2006 55.92861
## 10100 2006 55.92861
## 10101 2006 55.92861
## 10102 2006 55.92861
## 10103 2006 55.92861
## 10152 2006 60.00286
## 10340 2007 43.31051
## 10356 2007 47.55617
## 10357 2007 47.55617
## 10361 2007 48.22368
## 10373 2007 51.29442
## 10374 2007 51.80184
## 10375 2007 51.80184
## 10390 2007 53.13686
## 10391 2007 53.13686
## 10404 2007 56.20760
## 10405 2007 56.71502
## 10416 2007 59.89248
## 10417 2007 59.89248
## 10419 2007 60.45326
## 10422 2007 61.62819
## 10423 2007 62.34907
## 10861 2009 54.83046
## 11113 2010 56.61438
## 11351 2011 48.45552
## 11364 2011 50.77860
## 11398 2011 54.52957
## 11419 2011 61.27031
## 11617 2012 52.47132
## 11618 2012 52.47132
## 11619 2012 52.47132
## 11620 2012 52.47132
## 11632 2012 53.33785
## 11652 2012 56.02295
## 11696 2012 63.57498
## 12110 2014 49.85663
## 12128 2014 55.72972
## 12129 2014 55.72972
## 12130 2014 55.90511
## 12131 2014 55.90511
## 12132 2014 55.90511
## 12356 2015 42.09247
## 12357 2015 42.09247
## 12358 2015 42.09247
```

```
## 12363 2015 47.22255
## 12369 2015 52.35262
## 12370 2015 52.35262
## 12371 2015 52.35262
## 12372 2015 52.35262
## 12382 2015 59.89089
## 12383 2015 59.89089
## 12384 2015 59.89089
## 12387 2015 62.29909
## 12906 2017 64.60694
## 12907 2017 65.60694
## 12908 2017 65.60694
## 12909 2017 65.60694
## 12910 2017 65.60694
## 12911 2017 65.60694
## 12912 2017 66.60694
## 12913 2017 67.60694
## 12914 2017 67.60694
```

```r
tomerge<-rbind(
  subset(weather_study,FFD>65&FFD<66&year==1992)[c(1,5:16,20:28)],
  subset(weather_study,FFD>51&FFD<52&year==2006)[c(1,5:16,20:28)],
  subset(weather_study,FFD>55&FFD<56&year==2006)[c(1,5:16,20:28)],
  subset(weather_study,FFD>60&FFD<61&year==2006)[c(1,5:16,20:28)],
  subset(weather_study,FFD>43&FFD<44&year==2007)[c(1,5:16,20:28)],
  subset(weather_study,FFD>47&FFD<48&year==2007)[c(1,5:16,20:28)],
  subset(weather_study,FFD>48&FFD<49&year==2007)[c(1,5:16,20:28)],
  subset(weather_study,FFD>51&FFD<51.3&year==2007)[c(1,5:16,20:28)],
  subset(weather_study,FFD>51.3&FFD<53&year==2007)[c(1,5:16,20:28)],
  subset(weather_study,FFD>53&FFD<54&year==2007)[c(1,5:16,20:28)],
  subset(weather_study,FFD>56&FFD<56.3&year==2007)[c(1,5:16,20:28)],
  subset(weather_study,FFD>56.3&FFD<58&year==2007)[c(1,5:16,20:28)],
  subset(weather_study,FFD>59&FFD<60&year==2007)[c(1,5:16,20:28)],
  subset(weather_study,FFD>60&FFD<61&year==2007)[c(1,5:16,20:28)],
  subset(weather_study,FFD>61&FFD<62&year==2007)[c(1,5:16,20:28)],
  subset(weather_study,FFD>62&FFD<63&year==2007)[c(1,5:16,20:28)],
  subset(weather_study,FFD>54&FFD<55&year==2009)[c(1,5:16,20:28)],
  subset(weather_study,FFD>56&FFD<57&year==2010)[c(1,5:16,20:28)],
  subset(weather_study,FFD>48&FFD<49&year==2011)[c(1,5:16,20:28)],
  subset(weather_study,FFD>50&FFD<51&year==2011)[c(1,5:16,20:28)],
  subset(weather_study,FFD>54&FFD<55&year==2011)[c(1,5:16,20:28)],
  subset(weather_study,FFD>61&FFD<62&year==2011)[c(1,5:16,20:28)],
  subset(weather_study,FFD>52&FFD<53&year==2012)[c(1,5:16,20:28)],
  subset(weather_study,FFD>53&FFD<54&year==2012)[c(1,5:16,20:28)],
  subset(weather_study,FFD>56&FFD<57&year==2012)[c(1,5:16,20:28)],
  subset(weather_study,FFD>63&FFD<64&year==2012)[c(1,5:16,20:28)],
  subset(weather_study,FFD>49&FFD<50&year==2014)[c(1,5:16,20:28)],
  subset(weather_study,FFD>55&FFD<55.8&year==2014)[c(1,5:16,20:28)],
  subset(weather_study,FFD>55.8&FFD<57&year==2014)[c(1,5:16,20:28)],
  subset(weather_study,FFD>42&FFD<43&year==2015)[c(1,5:16,20:28)],
  subset(weather_study,FFD>47&FFD<48&year==2015)[c(1,5:16,20:28)],
  subset(weather_study,FFD>52&FFD<53&year==2015)[c(1,5:16,20:28)],
  subset(weather_study,FFD>59&FFD<60&year==2015)[c(1,5:16,20:28)],
  subset(weather_study,FFD>62&FFD<63&year==2015)[c(1,5:16,20:28)],
```

```r
  subset(weather_study,FFD>64&FFD<65&year==2017)[c(1,5:16,20:28)],
  subset(weather_study,FFD>65&FFD<66&year==2017)[c(1,5:16,20:28)],
  subset(weather_study,FFD>66&FFD<67&year==2017)[c(1,5:16,20:28)],
  subset(weather_study,FFD>67&FFD<68&year==2017)[c(1,5:16,20:28)])

tomerge$FFD_r<-round(tomerge$FFD,2)
alldata_weather$FFD_r<-round(alldata_weather$FFD,2)

head(tomerge)
```

```
##      year  mean  min   max precipitation   GDD3  GDD5  GDD7 GDD10     GDH3
## 1972 1992 13.95 10.9 17.55           0.1 11.225 9.225 7.225 4.225 269.4000
## 3784 2006 10.95  6.8 17.05           0.0  8.925 6.925 4.925 1.925 214.2000
## 3788 2006  8.05  2.7 14.05           0.0  5.375 3.375 1.375 0.000 129.0952
## 3793 2006  9.95  6.6 14.75           1.5  7.675 5.675 3.675 0.675 184.2000
## 4141 2007  8.05  2.4 13.60           0.0  5.000 3.000 1.000 0.000 120.3857
## 4145 2007 10.20  5.6 14.65           2.3  7.125 5.125 3.125 0.125 171.0000
##           GDH5      GDH7     GDH10 cumGDD3 cumGDD5 cumGDD7 cumGDD10
## 1972 221.40000 173.40000 101.40000 344.650  210.10 133.750   64.025
## 3784 166.20000 118.24683  58.18829 171.425  103.80  58.175   25.925
## 3788  86.59295  52.54890  17.34185 205.675  130.05  76.425   34.125
## 3793 136.20000  88.43558  33.22086 232.625  147.00  84.225   34.800
## 4141  79.24286  46.67143  13.88571 231.700  128.80  60.225   13.550
## 4145 123.00000  77.59890  28.67072 257.200  146.30  70.075   14.400
##       cumGDH3  cumGDH5  cumGDH7   cumGDH10      FFD FFD_r
## 1972 8795.121 5522.046 3511.847 1758.8064 65.66944 65.67
## 3784 4393.800 2829.954 1750.854  823.6810 51.27431 51.27
## 3788 5215.895 3465.550 2214.059 1074.3050 55.27431 55.27
## 3793 5869.318 3902.696 2456.810 1134.8377 60.27431 60.27
## 4141 6072.216 3742.352 2154.843  793.8558 43.03194 43.03
## 4145 6685.623 4174.228 2418.728  878.8309 47.03194 47.03
```

```r
head(subset(alldata_weather,is.na(mean)&!is.na(FFD)))
```

```
##      year      FFD period      id ruta genet data status
## 3815 1992 65.66944    old old_274    5    32    1     ok
## 3816 1992 65.66944    old old_753    3     1    1     ok
## 3817 1992 65.66944    old old_325    5    31    1     ok
## 3818 1992 65.66944    old old_825          1    1     ok
## 3819 1992 65.66944    old old_615         20    1     ok
## 3820 1992 65.66944    old old_426    1    10    1     ok
##                   vernal    FFD_corr FFD_imputed n_fl n_fl_imputed
## 3815 1992-03-20 08:56:00 1992-05-25           0    3            0
## 3816 1992-03-20 08:56:00 1992-05-25           0    2            0
## 3817 1992-03-20 08:56:00 1992-05-25           0    2            0
## 3818 1992-03-20 08:56:00 1992-05-25           0    3            0
## 3819 1992-03-20 08:56:00 1992-05-25           0    2            0
## 3820 1992-03-20 08:56:00 1992-05-25           0    1            0
##      shoot_vol grazing n_fr n_ovules n_seeds n_intact_seeds mean min max
## 3815  636.1750       0    1       11       4              4   NA  NA  NA
## 3816 2061.6782       0    2       25      10              0   NA  NA  NA
## 3817  589.9236       0    0        0       0              0   NA  NA  NA
## 3818 1216.7174       0    0        0       0              0   NA  NA  NA
## 3819  265.2911       0    0        0       0              0   NA  NA  NA
```

```
## 3820  628.3210       0    0        0       0              0   NA  NA  NA
##      precipitation GDD3 GDD5 GDD7 GDD10 GDH3 GDH5 GDH7 GDH10 cumGDD3
## 3815            NA   NA   NA   NA    NA   NA   NA   NA    NA      NA
## 3816            NA   NA   NA   NA    NA   NA   NA   NA    NA      NA
## 3817            NA   NA   NA   NA    NA   NA   NA   NA    NA      NA
## 3818            NA   NA   NA   NA    NA   NA   NA   NA    NA      NA
## 3819            NA   NA   NA   NA    NA   NA   NA   NA    NA      NA
## 3820            NA   NA   NA   NA    NA   NA   NA   NA    NA      NA
##      cumGDD5 cumGDD7 cumGDD10 cumGDH3 cumGDH5 cumGDH7 cumGDH10 FFD_r
## 3815      NA      NA       NA      NA      NA      NA       NA 65.67
## 3816      NA      NA       NA      NA      NA      NA       NA 65.67
## 3817      NA      NA       NA      NA      NA      NA       NA 65.67
## 3818      NA      NA       NA      NA      NA      NA       NA 65.67
## 3819      NA      NA       NA      NA      NA      NA       NA 65.67
## 3820      NA      NA       NA      NA      NA      NA       NA 65.67
```

```
#Substitute by hand in OpenOffice Calc NA values in weather columns of alldata_weather by values in #to
write.table(alldata_weather,
            file="C:/Users/User/Dropbox/SU/Projects/lathyrus/lathyrus_ms1/data/clean/alldata_weather.c
            sep="\t",dec=",",col.names=T,row.names=F)
write.table(tomerge,
            file="C:/Users/User/Dropbox/SU/Projects/lathyrus/lathyrus_ms1/data/clean/tomerge.csv",
            sep="\t",dec=",",col.names=T,row.names=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/lathyrus_ms1/data/clean/al
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
```

```
## [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
```

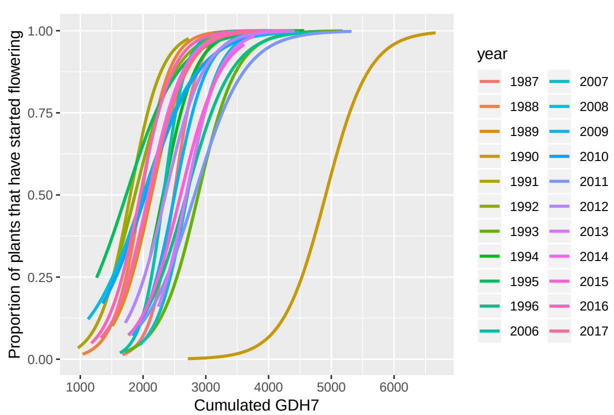
Models of proportion of plants that have started flowering against cumulated GDD/GDH

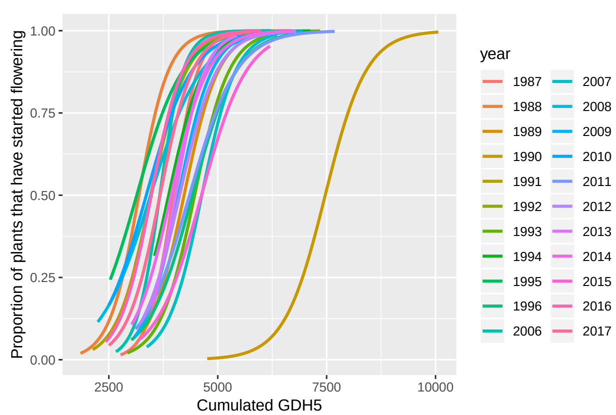
```
#Fit univariate binomial GLMs of prop_fl against each predictor
models1<-lapply(names(alldata_agg)[2:9],
         function(x) {glm(substitute(prop_fl ~ scale(i), list(i = as.name(x))),
                      family=binomial, data = alldata_agg)})

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)))
```

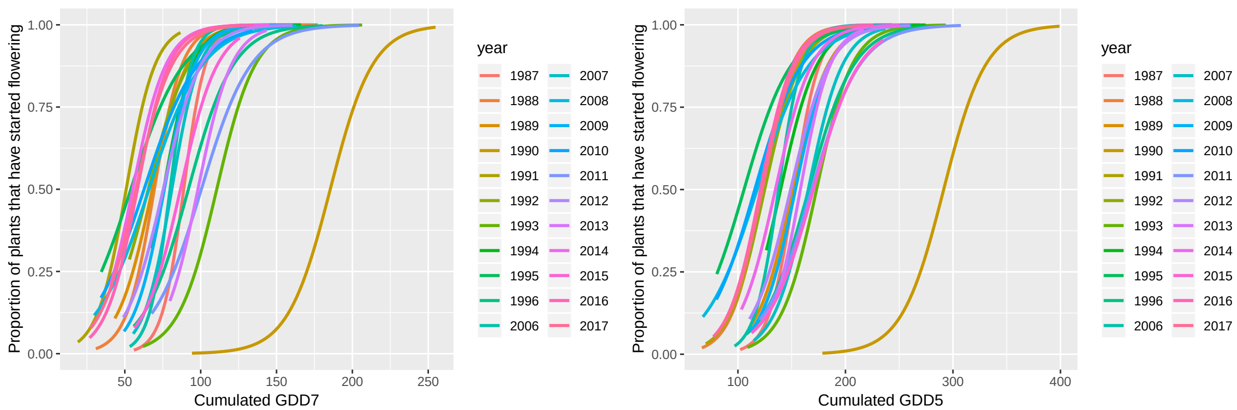
variable	Estimate	P	sig	Rsquare
scale(cumGDH7)	2.000259	<0.001	***	0.7379712
scale(cumGDH5)	1.947486	<0.001	***	0.7338785
scale(cumGDD5)	1.943972	<0.001	***	0.7315655
scale(cumGDD7)	1.919048	<0.001	***	0.7039400
scale(cumGDD3)	1.777306	<0.001	***	0.6779045
scale(cumGDH3)	1.715991	<0.001	***	0.6558200
scale(cumGDH10)	1.852057	<0.001	***	0.6544539
scale(cumGDD10)	1.574297	<0.001	***	0.5479936

Plots of the best models

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

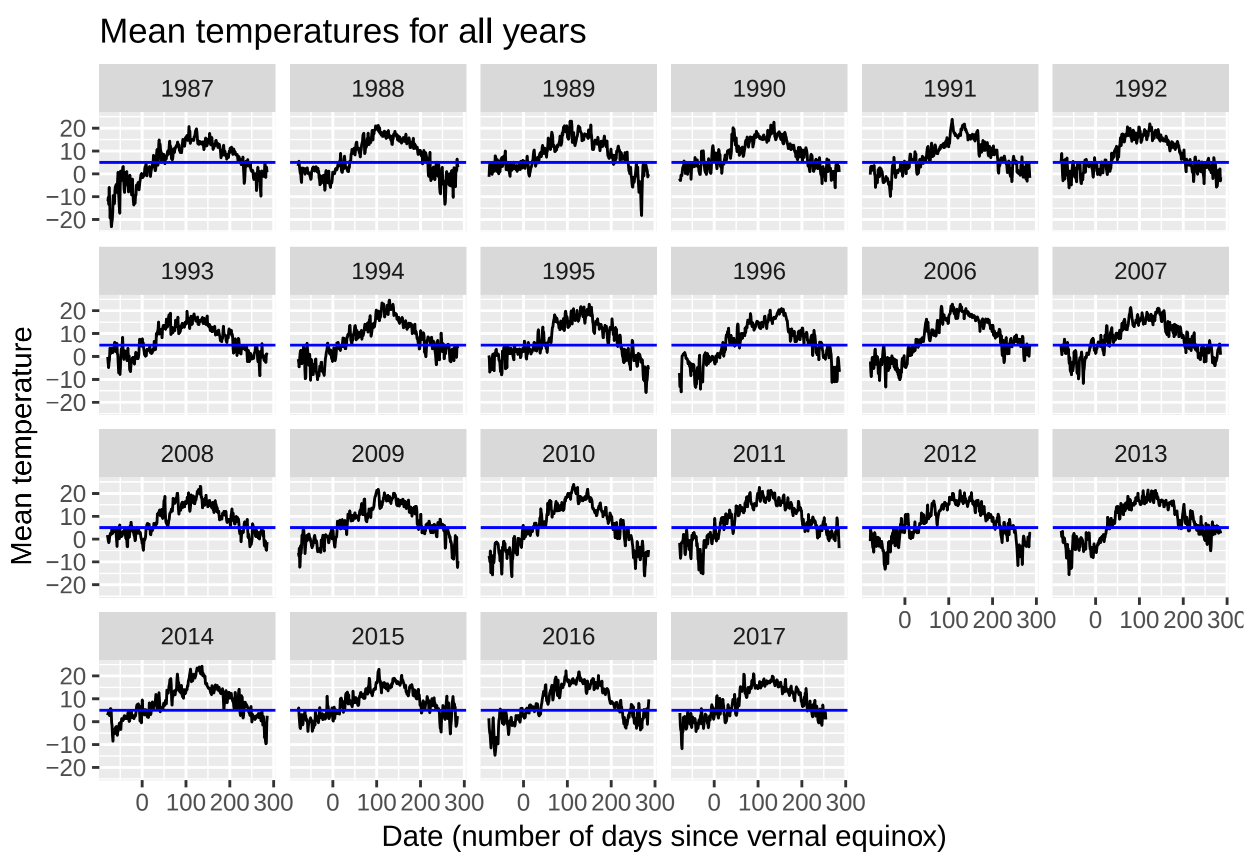


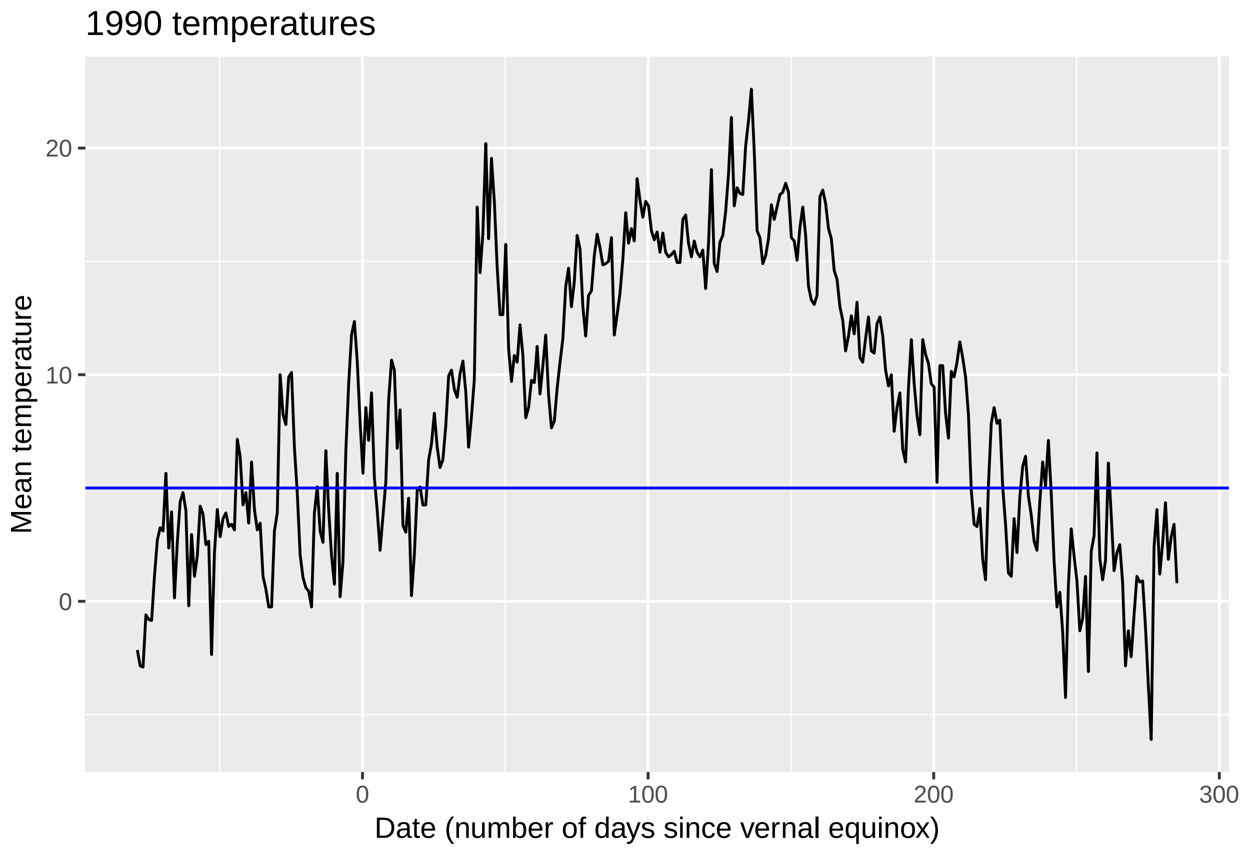


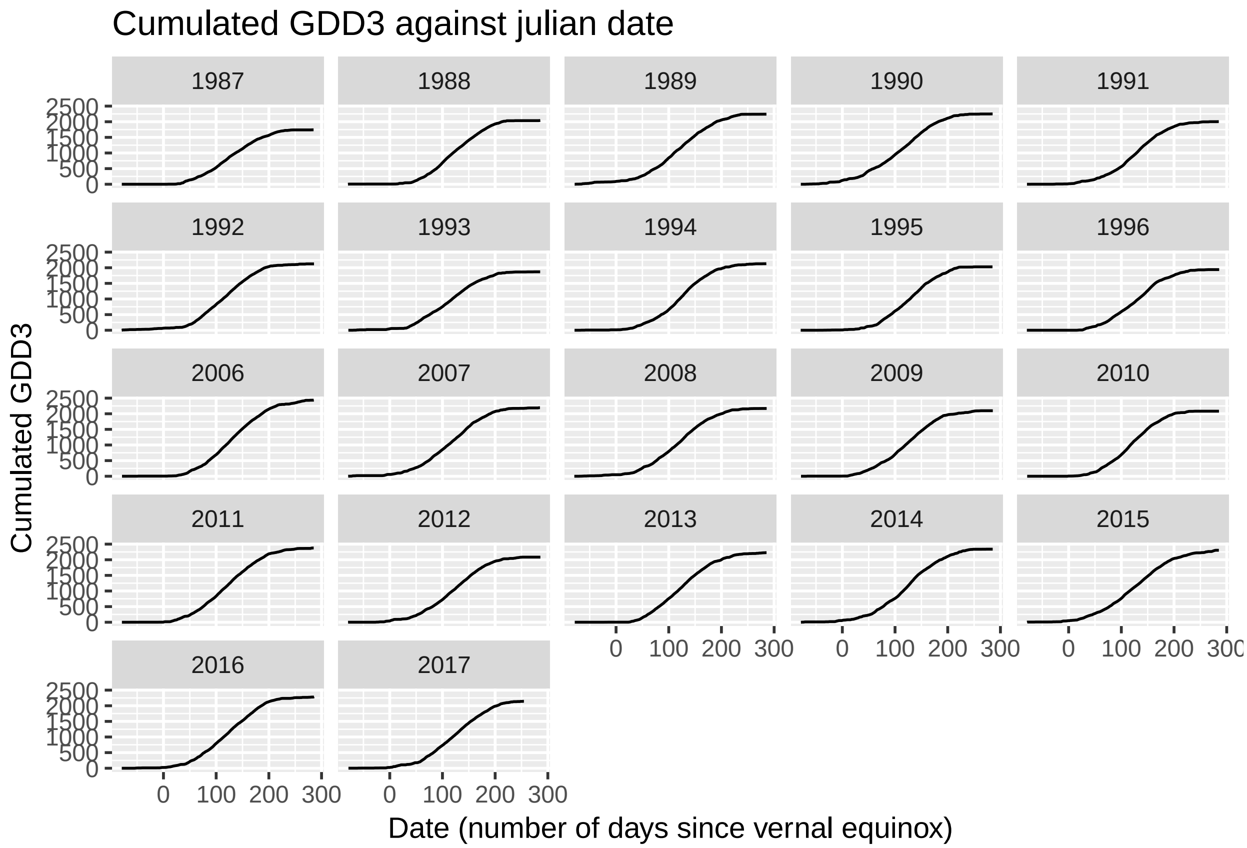


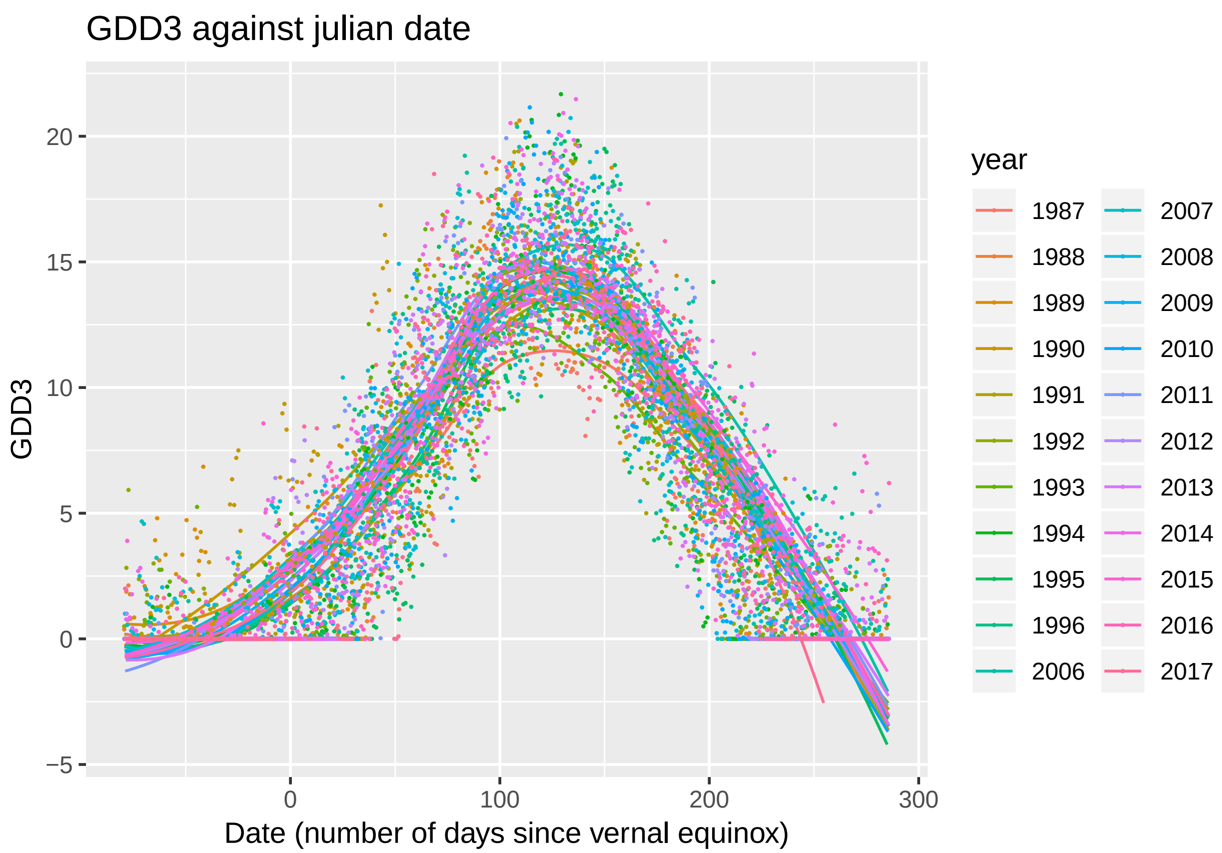
Plots for year 1990

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

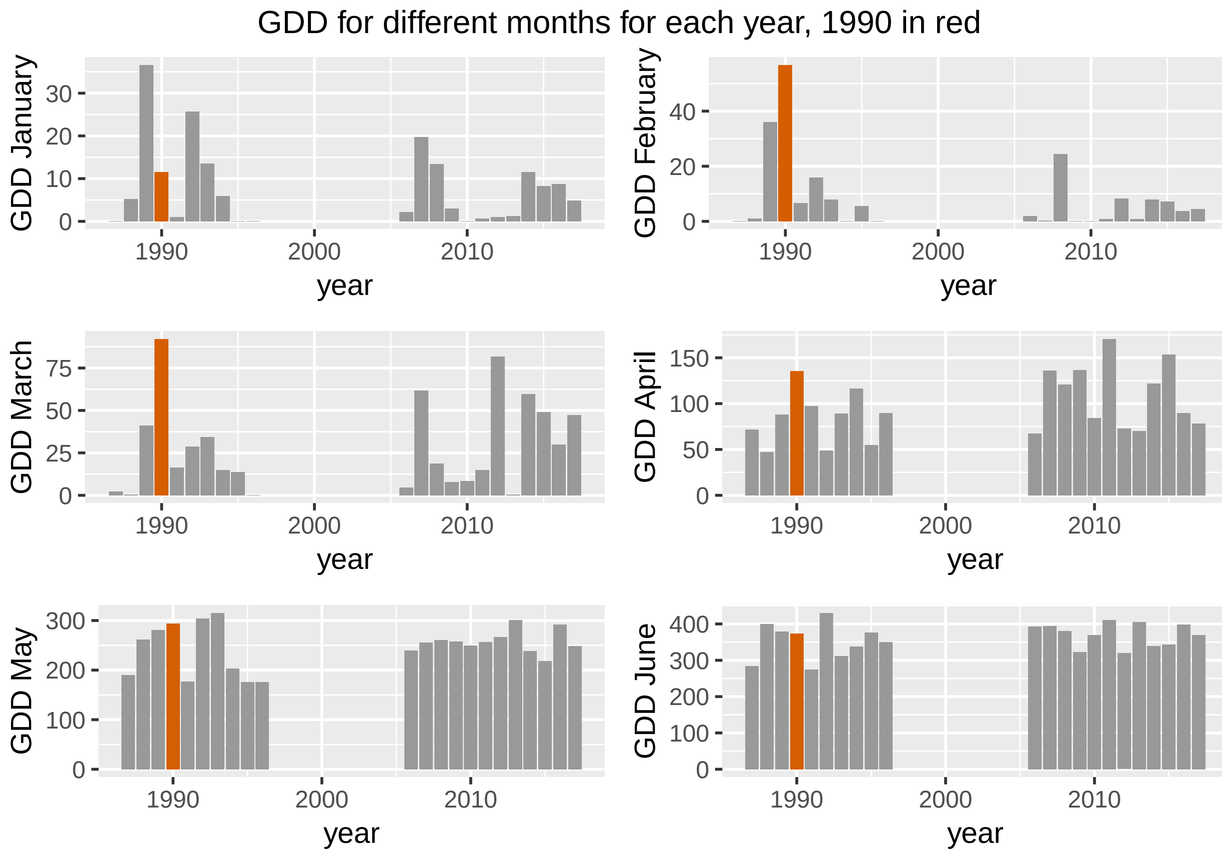



1990 temperatures
Mean temperature
20
10
0
0
100
200
300
Date (number of days since vernal equinox)


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



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



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

Select data for analyses paper

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

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

Calculation of relative fitness and standardized traits

Relativization and standardization was done within each year.

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

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

Calculation of position and duration of flowering season

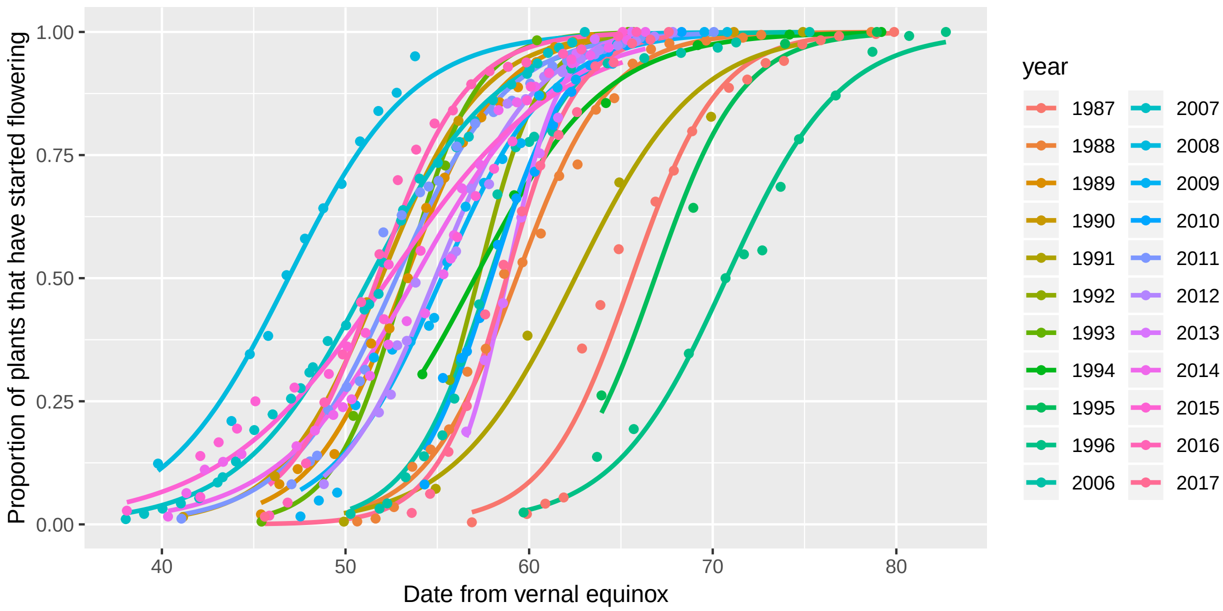
Calculate proportion of plants flowering per year at each date

```r
propfl<-as.data.frame(aggregate(id~FFD+year,data=alldata_weather_subs[c(1:3)],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

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

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



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

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

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

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

Calculate other metrics of the flowering season and merge

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

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

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

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

Selection differentials for each year

FFD, linear

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

```
##    year nobs
## 1  1987  238
## 2  1988  171
## 3  1989   98
## 4  1990  131
## 5  1991  165
## 6  1992  116
## 7  1993  171
## 8  1994  166
## 9  1995   35
## 10 1996  124
## 11 2006   87
## 12 2007   93
## 13 2008   80
## 14 2009   59
## 15 2010   74
## 16 2011   85
## 17 2012  110
## 18 2013   69
## 19 2014   63
## 20 2015   36
## 21 2016  111
## 22 2017  129
```

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

	year	term	estimate	std.error	statistic	p.value	sig
2	1987	FFD_std	-0.372	0.092	-4.052	0.000	*

	year	term	estimate	std.error	statistic	p.value	sig
4	1988	FFD_std	-0.302	0.106	-2.840	0.005	*
6	1989	FFD_std	-0.609	0.128	-4.767	0.000	*
8	1990	FFD_std	-0.504	0.161	-3.129	0.002	*
10	1991	FFD_std	-0.600	0.078	-7.646	0.000	*
12	1992	FFD_std	-0.438	0.183	-2.391	0.018	*
14	1993	FFD_std	-0.448	0.131	-3.410	0.001	*
16	1994	FFD_std	-0.558	0.176	-3.177	0.002	*
18	1995	FFD_std	-0.487	0.218	-2.236	0.032	*
20	1996	FFD_std	-0.373	0.106	-3.512	0.001	*
22	2006	FFD_std	-0.423	0.133	-3.177	0.002	*
24	2007	FFD_std	-0.411	0.111	-3.712	0.000	*
26	2008	FFD_std	-0.500	0.120	-4.149	0.000	*
28	2009	FFD_std	-0.213	0.276	-0.772	0.444	
30	2010	FFD_std	-0.492	0.164	-3.008	0.004	*
32	2011	FFD_std	-0.696	0.196	-3.545	0.001	*
34	2012	FFD_std	-1.035	0.187	-5.532	0.000	*
36	2013	FFD_std	-0.425	0.322	-1.319	0.192	
38	2014	FFD_std	-0.668	0.173	-3.854	0.000	*
40	2015	FFD_std	0.048	0.231	0.208	0.837	
42	2016	FFD_std	-0.351	0.096	-3.664	0.000	*
44	2017	FFD_std	0.282	0.497	0.567	0.572	

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

FFD, quadratic

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

	year	term	estimate	std.error	statistic	p.value	sig
3	1987	I(FFD_std^2)	-0.053	0.153	-0.348	0.728	
6	1988	I(FFD_std^2)	-0.060	0.134	-0.444	0.658	
9	1989	I(FFD_std^2)	0.133	0.198	0.673	0.502	
12	1990	I(FFD_std^2)	0.233	0.212	1.099	0.274	
15	1991	I(FFD_std^2)	0.132	0.140	0.945	0.346	
18	1992	I(FFD_std^2)	0.029	0.311	0.092	0.927	
21	1993	I(FFD_std^2)	0.040	0.217	0.184	0.854	
24	1994	I(FFD_std^2)	0.287	0.285	1.009	0.315	
27	1995	I(FFD_std^2)	0.307	0.357	0.860	0.396	
30	1996	I(FFD_std^2)	-0.178	0.179	-0.997	0.321	
33	2006	I(FFD_std^2)	0.169	0.147	1.151	0.253	
36	2007	I(FFD_std^2)	0.190	0.192	0.991	0.324	

	year	term	estimate	std.error	statistic	p.value	sig
39	2008	I(FFD_std^2)	0.321	0.126	2.549	0.013	*
42	2009	I(FFD_std^2)	-0.438	0.495	-0.884	0.381	
45	2010	I(FFD_std^2)	0.283	0.284	0.994	0.324	
48	2011	I(FFD_std^2)	0.370	0.262	1.416	0.161	
51	2012	I(FFD_std^2)	1.119	0.275	4.063	0.000	*
54	2013	I(FFD_std^2)	0.006	0.605	0.011	0.992	
57	2014	I(FFD_std^2)	0.355	0.286	1.241	0.219	
60	2015	I(FFD_std^2)	-0.846	0.475	-1.783	0.084	
63	2016	I(FFD_std^2)	0.015	0.136	0.112	0.911	
66	2017	I(FFD_std^2)	-0.249	0.501	-0.497	0.620	

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

Number of flowers, linear

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

	year	term	estimate	std.error	statistic	p.value	sig
2	1987	n_fl_std	0.766	0.081	9.478	0.000	*
4	1988	n_fl_std	0.541	0.101	5.376	0.000	*
6	1989	n_fl_std	0.846	0.113	7.504	0.000	*
8	1990	n_fl_std	0.678	0.156	4.346	0.000	*
10	1991	n_fl_std	0.667	0.075	8.877	0.000	*
12	1992	n_fl_std	0.114	0.187	0.606	0.546	
14	1993	n_fl_std	0.435	0.132	3.307	0.001	*
16	1994	n_fl_std	0.487	0.177	2.751	0.007	*
18	1995	n_fl_std	0.420	0.222	1.892	0.067	
20	1996	n_fl_std	0.642	0.095	6.750	0.000	*
22	2006	n_fl_std	0.776	0.113	6.866	0.000	*
24	2007	n_fl_std	0.275	0.115	2.387	0.019	*
26	2008	n_fl_std	0.760	0.102	7.479	0.000	*
28	2009	n_fl_std	0.319	0.274	1.165	0.249	
30	2010	n_fl_std	0.280	0.170	1.644	0.104	
32	2011	n_fl_std	0.914	0.185	4.933	0.000	*
34	2012	n_fl_std	1.054	0.186	5.666	0.000	*
36	2013	n_fl_std	0.083	0.326	0.255	0.800	
38	2014	n_fl_std	0.252	0.191	1.324	0.190	
40	2015	n_fl_std	-0.003	0.231	-0.012	0.990	
42	2016	n_fl_std	0.606	0.083	7.267	0.000	*
44	2017	n_fl_std	-0.541	0.496	-1.091	0.277	

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

Number of flowers, quadratic

```
seldiffs_nfl_q<-data.frame(data_sel %>% group_by(year) %>%
  do(model = lm(n_intact_seeds_rel ~ n_fl_std+I(n_fl_std^2), data = .)) %>% tidy(model))
seldiffs_nfl_q$sig<-ifelse(seldiffs_nfl_q$p.value<0.05,"*","")
seldiffs_nfl_q$estimate<-ifelse(seldiffs_nfl_q$term=="I(nfl_std^2)",2*(seldiffs_nfl_q$estimate),
                                seldiffs_nfl_q$estimate)
seldiffs_nfl_q$std.error<-ifelse(seldiffs_nfl_q$term=="I(nflD_std^2)",2*(seldiffs_nfl_q$std.error),
                                seldiffs_nfl_q$std.error)
#Double Quadratic regression coefficients and standard errors
kable(subset(seldiffs_nfl_q,term=="I(n_fl_std^2)"),digits=3)  #Quadratic selection differentials for nf
```

	year	term	estimate	std.error	statistic	p.value	sig
3	1987	I(n_fl_std^2)	-0.006	0.043	-0.135	0.892	
6	1988	I(n_fl_std^2)	0.001	0.066	0.009	0.993	
9	1989	I(n_fl_std^2)	0.027	0.099	0.274	0.785	
12	1990	I(n_fl_std^2)	-0.229	0.070	-3.292	0.001	*
15	1991	I(n_fl_std^2)	-0.013	0.060	-0.210	0.834	
18	1992	I(n_fl_std^2)	-0.261	0.106	-2.455	0.016	*
21	1993	I(n_fl_std^2)	-0.132	0.086	-1.532	0.127	
24	1994	I(n_fl_std^2)	-0.166	0.094	-1.769	0.079	
27	1995	I(n_fl_std^2)	-0.191	0.115	-1.664	0.106	
30	1996	I(n_fl_std^2)	-0.078	0.070	-1.121	0.264	
33	2006	I(n_fl_std^2)	-0.095	0.042	-2.260	0.026	*
36	2007	I(n_fl_std^2)	-0.132	0.053	-2.489	0.015	*
39	2008	I(n_fl_std^2)	-0.101	0.057	-1.760	0.082	
42	2009	I(n_fl_std^2)	-0.258	0.125	-2.058	0.044	*
45	2010	I(n_fl_std^2)	-0.300	0.109	-2.740	0.008	*
48	2011	I(n_fl_std^2)	0.036	0.131	0.276	0.783	
51	2012	I(n_fl_std^2)	-0.179	0.110	-1.621	0.108	
54	2013	I(n_fl_std^2)	-0.185	0.322	-0.574	0.568	
57	2014	I(n_fl_std^2)	-0.222	0.091	-2.428	0.018	*
60	2015	I(n_fl_std^2)	-0.272	0.161	-1.694	0.100	
63	2016	I(n_fl_std^2)	-0.062	0.066	-0.944	0.347	
66	2017	I(n_fl_std^2)	0.156	0.350	0.447	0.656	

```
#I(n_fl_std^2) * (stabilizing selection - decreases variance) in 1990,1992,2006,2007,2009,2010,2014
```

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
```

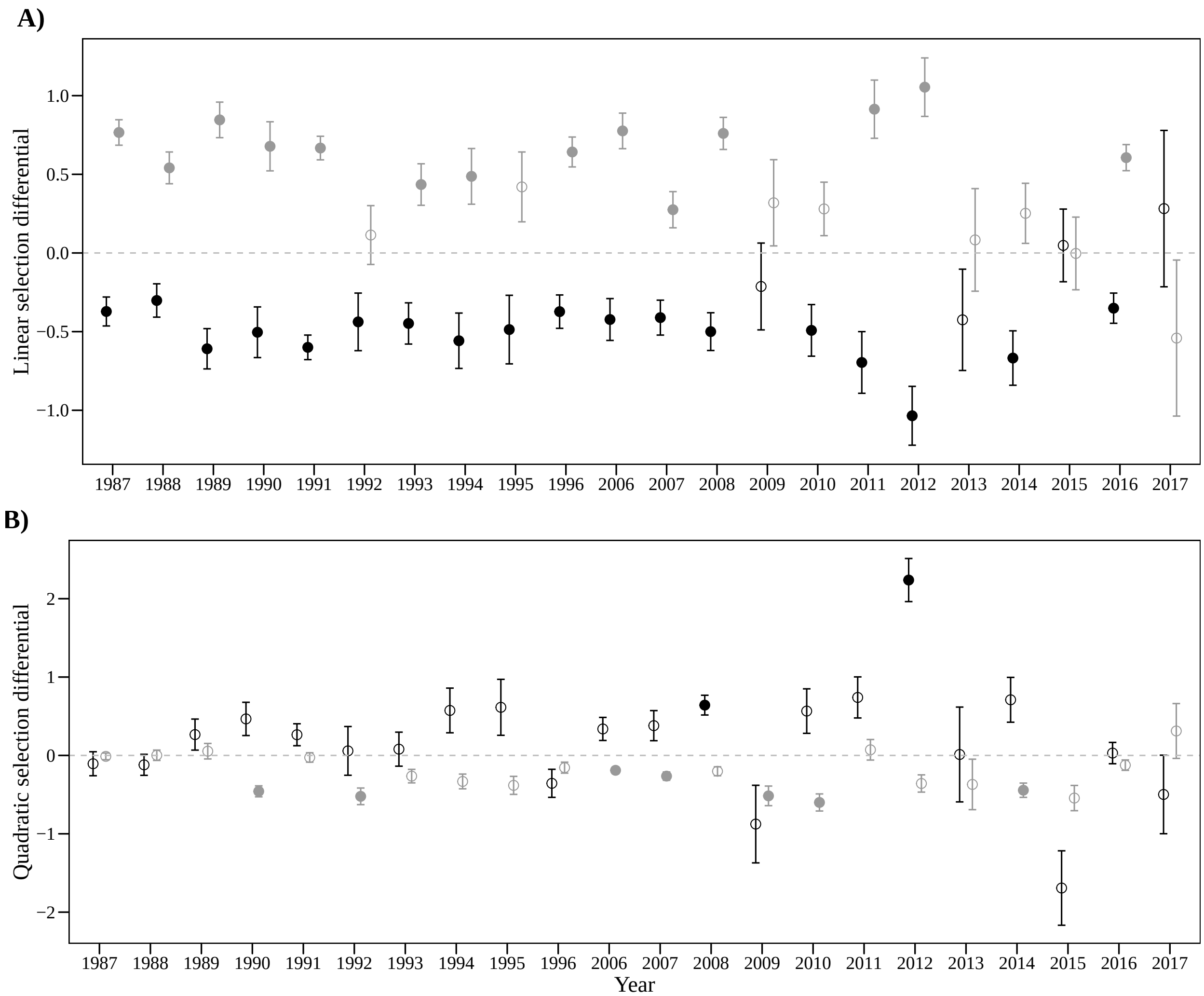
	year	term	estimate	std.error	sig
2	1987	FFD_std	-0.372	0.092	*
4	1988	FFD_std	-0.302	0.106	*
6	1989	FFD_std	-0.609	0.128	*

	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	*

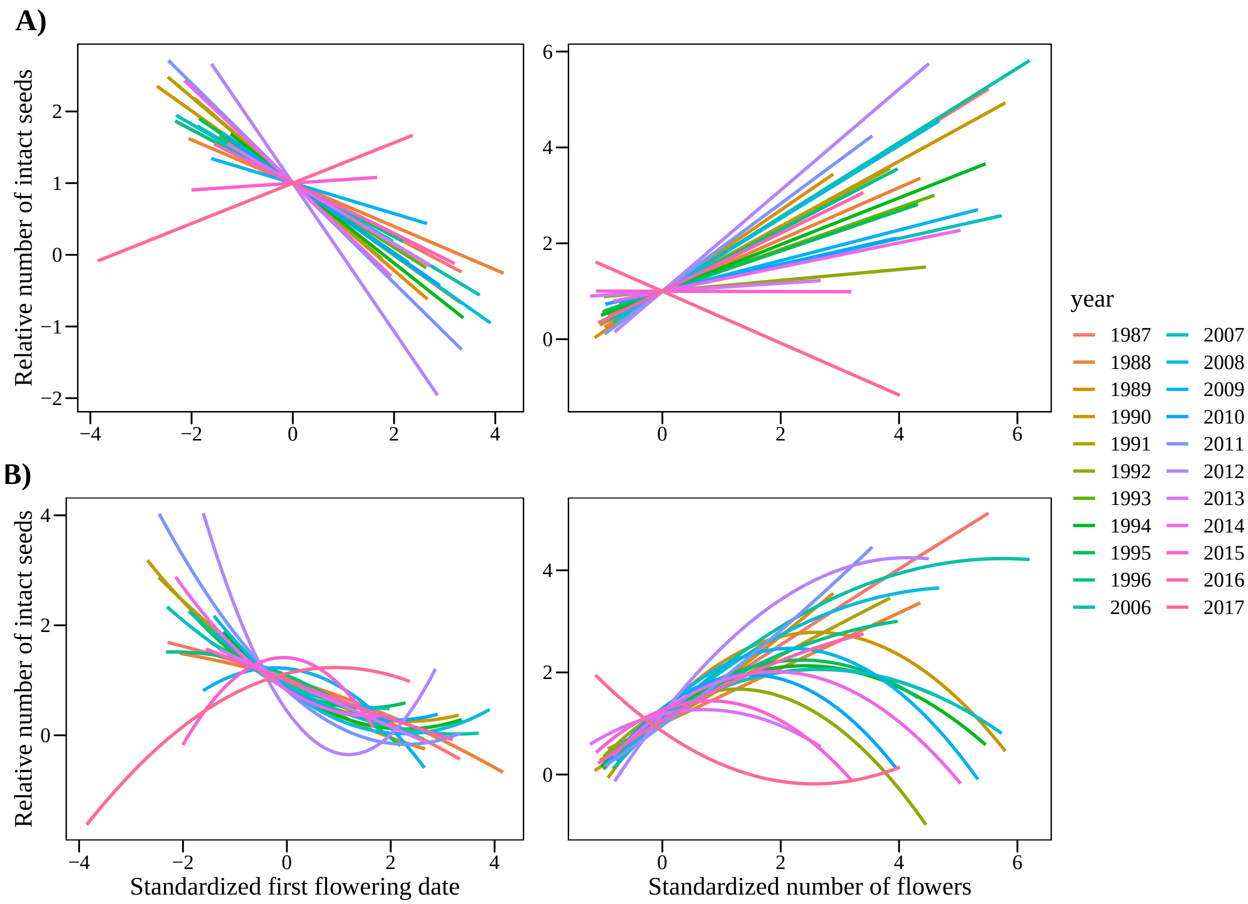
	year	term	estimate	std.error	sig
242	2007	n_fl_std	0.275	0.115	*
261	2008	n_fl_std	0.760	0.102	*
281	2009	n_fl_std	0.319	0.274	
302	2010	n_fl_std	0.280	0.170	
321	2011	n_fl_std	0.914	0.185	*
341	2012	n_fl_std	1.054	0.186	*
362	2013	n_fl_std	0.083	0.326	
381	2014	n_fl_std	0.252	0.191	
401	2015	n_fl_std	-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	

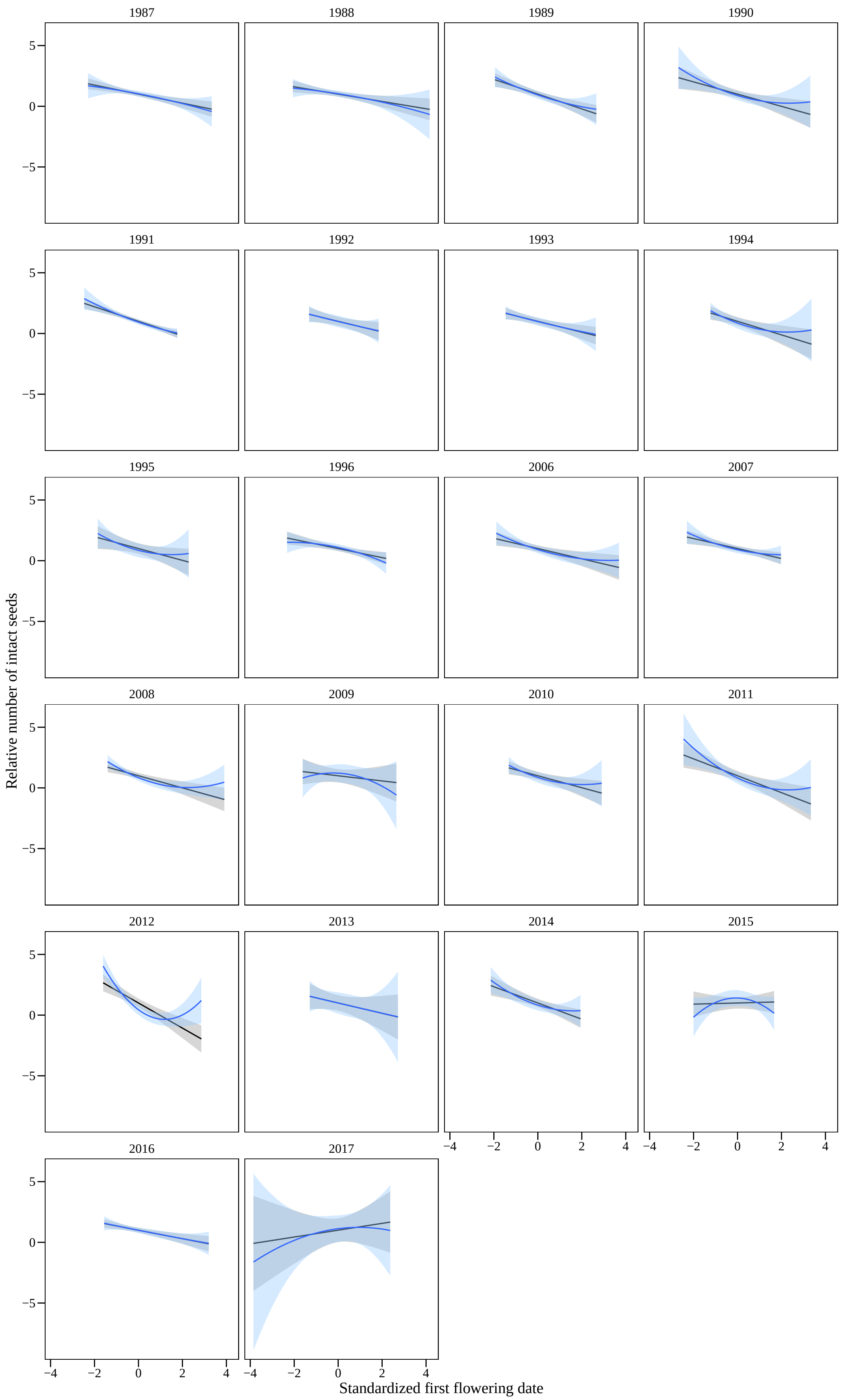
```r
write.table(seldiffs,file="seldiffs.txt",sep="\t")
```

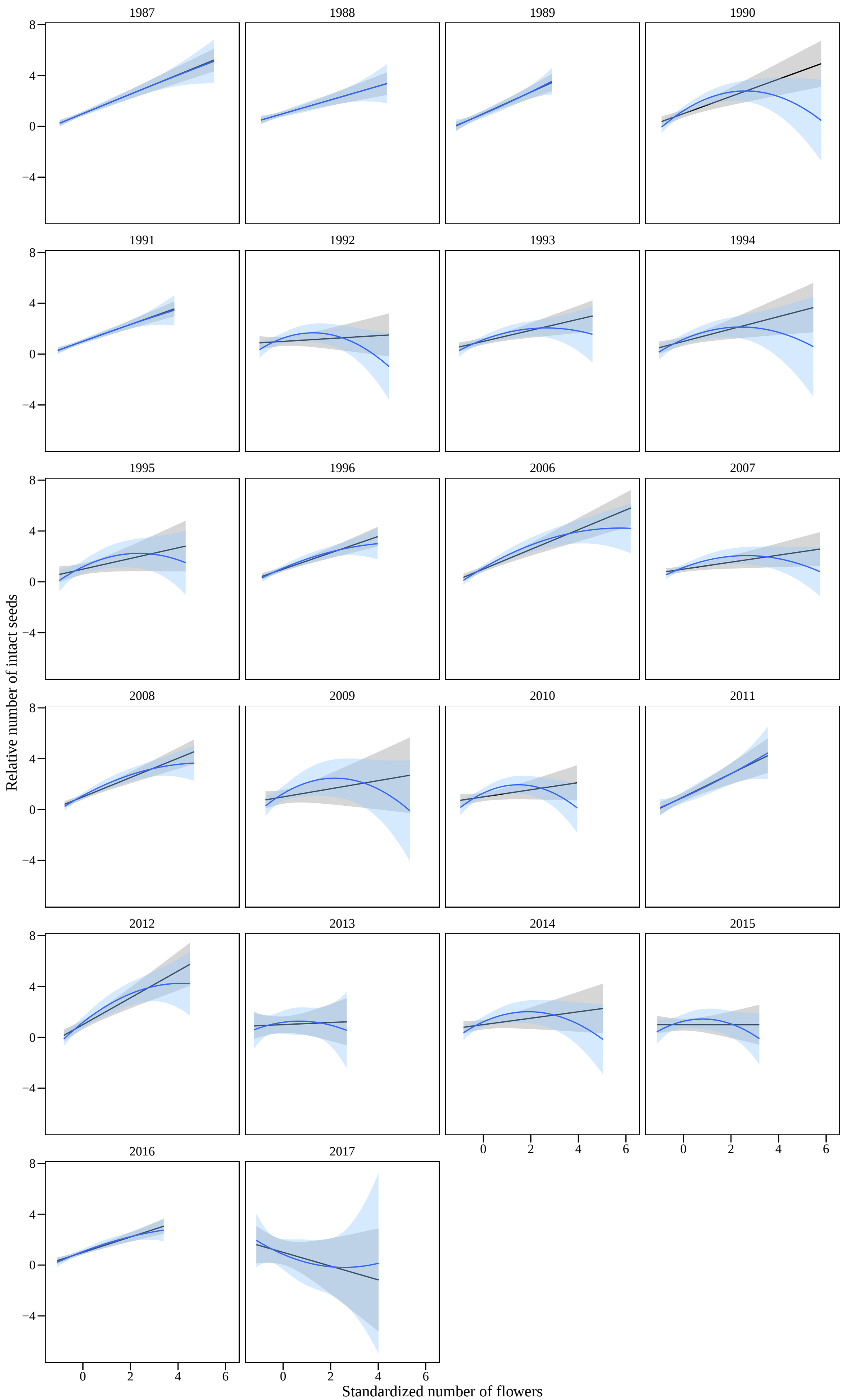
Plots



A)
Linear selection differential
1.0
0.5
0.0
−0.5
−1.0
1987 1988 1989 1990 1991 1992 1993 1994 1995 1996 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017
B)
Quadratic selection differential
2
1
0
−1
−2
1987 1988 1989 1990 1991 1992 1993 1994 1995 1996 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017
Year


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


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


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

Selection gradients for each year

FFD, linear

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

	year	term	estimate	std.error	statistic	p.value	sig
2	1987	FFD_std	-0.078	0.088	-0.883	0.378	
5	1988	FFD_std	-0.088	0.111	-0.789	0.431	
8	1989	FFD_std	-0.144	0.143	-1.010	0.315	
11	1990	FFD_std	-0.276	0.169	-1.631	0.105	
14	1991	FFD_std	-0.321	0.089	-3.597	0.000	*
17	1992	FFD_std	-0.463	0.199	-2.323	0.022	*
20	1993	FFD_std	-0.321	0.144	-2.236	0.027	*
23	1994	FFD_std	-0.439	0.188	-2.340	0.020	*
26	1995	FFD_std	-0.371	0.248	-1.497	0.144	
29	1996	FFD_std	-0.170	0.101	-1.684	0.095	
32	2006	FFD_std	-0.210	0.117	-1.796	0.076	
35	2007	FFD_std	-0.368	0.131	-2.816	0.006	*
38	2008	FFD_std	-0.201	0.112	-1.796	0.076	
41	2009	FFD_std	-0.052	0.332	-0.158	0.875	
44	2010	FFD_std	-0.478	0.195	-2.459	0.016	*
47	2011	FFD_std	-0.292	0.218	-1.338	0.185	
50	2012	FFD_std	-0.665	0.210	-3.174	0.002	*
53	2013	FFD_std	-0.426	0.331	-1.284	0.204	
56	2014	FFD_std	-0.777	0.211	-3.676	0.001	*
59	2015	FFD_std	0.083	0.315	0.264	0.794	
62	2016	FFD_std	-0.055	0.097	-0.563	0.575	
65	2017	FFD_std	-0.020	0.595	-0.034	0.973	

```
#FFD * (selection for early flowering) in 1991,1992,1993,1994,2007,2010,2012,2014
```

FFD, quadratic and correlational

```
selgrads_FFD_q<-data.frame(data_sel %>% group_by(year) %>%
  do(model = lm(n_intact_seeds_rel ~ FFD_std+I(FFD_std^2)+n_fl_std+I(n_fl_std^2)+FFD_std:n_fl_std, data
selgrads_FFD_q$sig<-ifelse(selgrads_FFD_q$p.value<0.05,"*","")
kable(subset(selgrads_FFD_q,term=="I(FFD_std^2)"),digits=3)
```

	year	term	estimate	std.error	statistic	p.value	sig
3	1987	I(FFD_std^2)	-0.071	0.085	-0.836	0.404	
9	1988	I(FFD_std^2)	0.091	0.075	1.208	0.229	
15	1989	I(FFD_std^2)	0.035	0.134	0.259	0.796	
21	1990	I(FFD_std^2)	-0.009	0.129	-0.072	0.942	
27	1991	I(FFD_std^2)	0.056	0.087	0.646	0.519	
33	1992	I(FFD_std^2)	0.096	0.184	0.525	0.600	

	year	term	estimate	std.error	statistic	p.value	sig
39	1993	I(FFD_std^2)	0.105	0.127	0.827	0.410	
45	1994	I(FFD_std^2)	0.099	0.160	0.617	0.538	
51	1995	I(FFD_std^2)	0.100	0.280	0.358	0.723	
57	1996	I(FFD_std^2)	-0.049	0.093	-0.529	0.598	
63	2006	I(FFD_std^2)	0.131	0.085	1.549	0.125	
69	2007	I(FFD_std^2)	0.248	0.147	1.681	0.096	
75	2008	I(FFD_std^2)	0.070	0.066	1.049	0.297	
81	2009	I(FFD_std^2)	0.031	0.301	0.102	0.919	
87	2010	I(FFD_std^2)	0.196	0.165	1.183	0.241	
93	2011	I(FFD_std^2)	0.050	0.168	0.300	0.765	
99	2012	I(FFD_std^2)	0.370	0.187	1.976	0.051	
105	2013	I(FFD_std^2)	0.178	0.362	0.491	0.625	
111	2014	I(FFD_std^2)	0.340	0.207	1.645	0.105	
117	2015	I(FFD_std^2)	-0.975	0.364	-2.679	0.012	*
123	2016	I(FFD_std^2)	0.005	0.076	0.062	0.951	
129	2017	I(FFD_std^2)	-0.206	0.406	-0.507	0.613	

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

	year	term	estimate	std.error	statistic	p.value	sig
6	1987	FFD_std:n_fl_std	0.010	0.180	0.058	0.954	
12	1988	FFD_std:n_fl_std	0.578	0.179	3.236	0.001	*
18	1989	FFD_std:n_fl_std	0.061	0.225	0.271	0.787	
24	1990	FFD_std:n_fl_std	-0.285	0.287	-0.996	0.321	
30	1991	FFD_std:n_fl_std	0.183	0.172	1.063	0.289	
36	1992	FFD_std:n_fl_std	0.172	0.252	0.681	0.497	
42	1993	FFD_std:n_fl_std	0.222	0.196	1.132	0.259	
48	1994	FFD_std:n_fl_std	-0.084	0.225	-0.374	0.709	
54	1995	FFD_std:n_fl_std	-0.070	0.496	-0.141	0.889	
60	1996	FFD_std:n_fl_std	-0.006	0.139	-0.041	0.967	
66	2006	FFD_std:n_fl_std	0.340	0.255	1.333	0.186	
72	2007	FFD_std:n_fl_std	0.394	0.263	1.498	0.138	
78	2008	FFD_std:n_fl_std	-0.096	0.245	-0.391	0.697	
84	2009	FFD_std:n_fl_std	2.395	0.883	2.713	0.009	*
90	2010	FFD_std:n_fl_std	0.379	0.358	1.061	0.293	
96	2011	FFD_std:n_fl_std	-0.313	0.503	-0.623	0.535	
102	2012	FFD_std:n_fl_std	-0.335	0.430	-0.778	0.438	
108	2013	FFD_std:n_fl_std	0.455	0.449	1.013	0.315	
114	2014	FFD_std:n_fl_std	0.315	0.351	0.896	0.374	
120	2015	FFD_std:n_fl_std	-1.041	0.555	-1.875	0.071	
126	2016	FFD_std:n_fl_std	0.500	0.189	2.640	0.010	*
132	2017	FFD_std:n_fl_std	-0.006	0.759	-0.008	0.994	

```
#Correlational selection gradients
#FFD_std:n_fl_std* (correlational selection) in 1988,2009 and 2016
```

All selection gradients

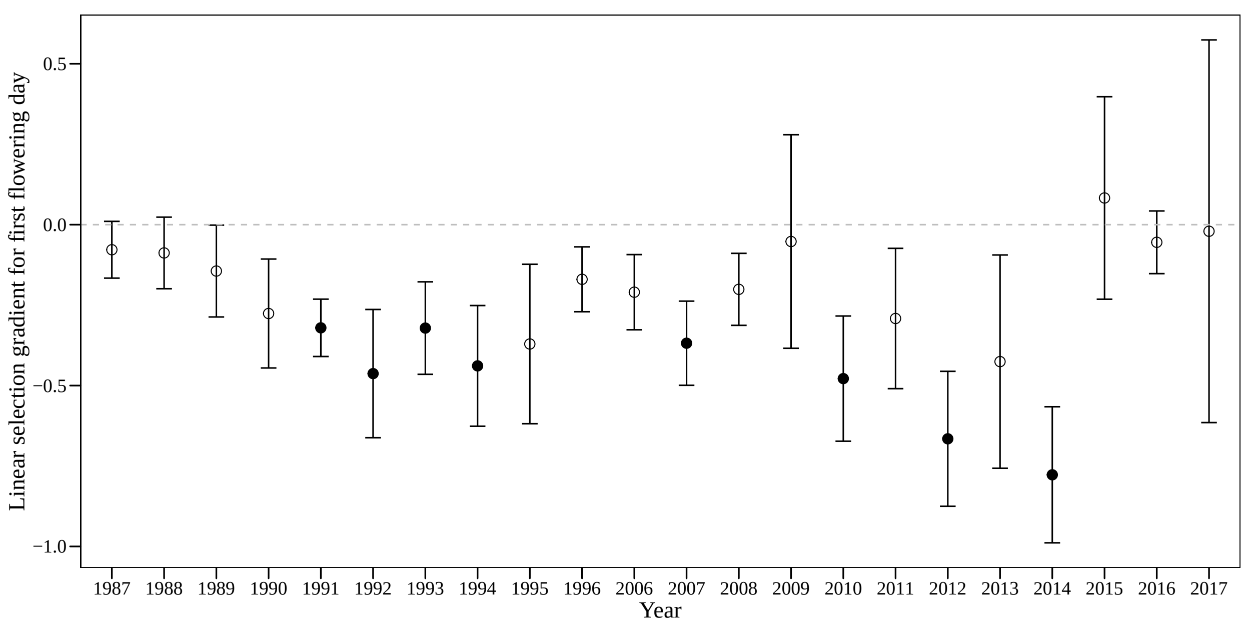
```r
selgrads<-rbind(subset(selgrads_FFD,term=="FFD_std")[c(1:4,7)],
                subset(selgrads_FFD_q,term=="I(FFD_std^2)")[c(1:4,7)],
                subset(selgrads_FFD_q,term=="FFD_std:n_fl_std")[c(1:4,7)])
selgrads$estimate<-round(selgrads$estimate,3)
selgrads$std.error<-round(selgrads$std.error,3)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

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

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

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

Plots



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

Merge data

```
selgrads_FFD_values<-subset(selgrads_FFD,term=="FFD_std")[c(1,3)]
selgrads_FFD_values$selgradFFD<-selgrads_FFD_values$estimate
selgrads_FFD_values$estimate<-NULL
data_sel_agg<-merge(mean_weather4,selgrads_FFD_values)
data_sel_agg$year<-as.factor(data_sel_agg$year)
data_sel<-merge(data_sel,data_sel_agg[c(1:145,156)],by="year")
data_sel$precipitation_13<-data_sel$precipitation_1+
  data_sel$precipitation_2+data_sel$precipitation_3
```

Results 1: Among-year variation and trends

Trends

Trends in climate 22 years

```
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)         9.15      0.753     12.2  1.09e-10
## 2 as.integer(year)    0.104     0.0573     1.82 8.36e- 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)        0.577      1.18      0.489   0.630
## 2 as.integer(year)   0.0807     0.0898    0.899   0.379
```

```
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)        4.89      0.592       8.26 0.0000000703
## 2 as.integer(year)   0.0670    0.0451      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)       -2.07      1.28      -1.63    0.120
## 2 as.integer(year)   0.0455    0.0972     0.468   0.645
```

```
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)        1.37      0.446      3.06  0.00614
## 2 as.integer(year)   0.0201    0.0340     0.593 0.560
```

```
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_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
```

Trends in climate all years available

```
## Calculations weather by month

## Monthly means of temperature and montly GDD and GDH
mean_temp<-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(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_temp<-gather(mean_temp, variable, value,mean,min,max,
               GDD3,GDD5,GDD7,GDD10,GDH3,GDH5,GDH7,GDH10) %>%
               unite(var, variable, month) %>%
               spread(var, value) #Convert to wide format with monthly variables

## Monthly sums of precipitation
mean_prec<-aggregate(precipitation~year+month,data=weather,FUN=sum) #Monthly sums of precipitation
mean_prec<-gather(mean_prec, variable, value,precipitation) %>%
               unite(var, variable, month) %>%
               spread(var, value) #Convert to wide format with monthly variables

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

```
## # A tibble: 2 x 5
##   term             estimate std.error statistic p.value
##   <chr>               <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept)      -91.6      36.7        -2.49  0.0156
## 2 as.integer(year)   0.0482    0.0185      2.61  0.0116
```

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

```
## # A tibble: 2 x 5
##   term              estimate std.error statistic   p.value
##   <chr>                <dbl>     <dbl>     <dbl>     <dbl>
## 1 (Intercept)      -104.       26.6        -3.91 0.000257
## 2 as.integer(year)    0.0570    0.0134      4.26 0.0000798
```

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

```
## # A tibble: 2 x 5
##   term             estimate std.error statistic p.value
##   <chr>               <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept)      -48.3      21.9        -2.21 0.0312
## 2 as.integer(year)   0.0320    0.0110      2.91 0.00520
```

```
with(summarySE(mean_temp, 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)      -96.2      36.9         -2.61  0.0118
## 2 as.integer(year)   0.0487    0.0186       2.62  0.0112
```

```r
with(summarySE(mean_temp, 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)      -84.8      20.4         -4.16 0.000112
## 2 as.integer(year)   0.0451    0.0102       4.40 0.0000498
```

```r
with(summarySE(mean_temp, 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)      -49.9     18.5          -2.70 0.00909
## 2 as.integer(year)   0.0303   0.00928       3.26 0.00191
```

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

```
## # A tibble: 2 x 5
##   term              estimate std.error statistic p.value
##   <chr>                <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept)      -109.        41.6         -2.62  0.0112
## 2 as.integer(year)    0.0536     0.0209       2.56  0.0131
```

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

```
## # A tibble: 2 x 5
##   term             estimate std.error statistic  p.value
##   <chr>               <dbl>     <dbl>     <dbl>    <dbl>
## 1 (Intercept)      -58.9     16.0          -3.67 0.000544
## 2 as.integer(year)   0.0301   0.00806       3.74 0.000442
```

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

```
## # A tibble: 2 x 5
##   term             estimate std.error statistic p.value
##   <chr>               <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept)      -44.8     15.9          -2.82 0.00668
## 2 as.integer(year)   0.0255   0.00799       3.19 0.00235
```

```r
with(summarySE(mean_prec, 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)      -427.      272.         -1.57  0.122
## 2 as.integer(year)    0.229     0.137       1.68  0.0992
```

```r
with(summarySE(mean_prec, 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)       89.9      305.          0.295  0.769
```

```
## 2 as.integer(year)  -0.0293     0.153    -0.191   0.849
```

```
with(summarySE(mean_prec, 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)      -73.5      350.       -0.210   0.834
## 2 as.integer(year)   0.0549     0.176     0.312   0.756
```

Trends in climate 1987-2017

```
with(subset(summarySE(mean_temp, measurevar="max_3", groupvars=c("year")),
     year>1986),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)      -121.       96.5         -1.25   0.220
## 2 as.integer(year)    0.0630    0.0482       1.31   0.202
```

```
with(subset(summarySE(mean_temp, measurevar="max_4", groupvars=c("year")),
     year>1986),tidy(lm(max_4~as.integer(year)))) #*
```

```
## # A tibble: 2 x 5
##   term              estimate std.error statistic p.value
##   <chr>                <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept)      -142.       64.0         -2.22  0.0344
## 2 as.integer(year)    0.0761    0.0320       2.38  0.0241
```

```
with(subset(summarySE(mean_temp, measurevar="max_5", groupvars=c("year")),
     year>1986),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)      -48.0      62.2       -0.772   0.446
## 2 as.integer(year)   0.0318    0.0310     1.02    0.314
```

```
with(subset(summarySE(mean_temp, measurevar="mean_3", groupvars=c("year")),
     year>1986),tidy(lm(mean_3~as.integer(year)))) #NS
```

```
## # A tibble: 2 x 5
##   term             estimate std.error statistic p.value
##   <chr>               <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept)      -58.9      97.5       -0.605   0.550
## 2 as.integer(year)   0.0301    0.0487     0.619   0.541
```

```
with(subset(summarySE(mean_temp, measurevar="mean_4", groupvars=c("year")),
     year>1986),tidy(lm(mean_4~as.integer(year)))) #NS
```

```
## # A tibble: 2 x 5
##   term             estimate std.error statistic p.value
##   <chr>               <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept)      -90.7      51.1        -1.77  0.0865
## 2 as.integer(year)   0.0481    0.0255      1.88  0.0697
```

```r
with(subset(summarySE(mean_temp, measurevar="mean_5", groupvars=c("year")),
     year>1986),tidy(lm(mean_5~as.integer(year)))) #NS
```

```
## # A tibble: 2 x 5
##   term             estimate std.error statistic p.value
##   <chr>               <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept)      -41.1      52.2       -0.787   0.438
## 2 as.integer(year)   0.0259    0.0261     0.991   0.330
```

```r
with(subset(summarySE(mean_temp, measurevar="min_3", groupvars=c("year")),
     year>1986),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)      -11.2      107.       -0.105    0.917
## 2 as.integer(year)   0.00471    0.0536    0.0879   0.931
```

```r
with(subset(summarySE(mean_temp, measurevar="min_4", groupvars=c("year")),
     year>1986),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)      -23.0      43.1       -0.534   0.597
## 2 as.integer(year)   0.0123    0.0215     0.570   0.573
```

```r
with(subset(summarySE(mean_temp, measurevar="min_5", groupvars=c("year")),
     year>1986),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)      -41.2      42.8       -0.963   0.343
## 2 as.integer(year)   0.0237    0.0214     1.11    0.277
```

```r
with(subset(summarySE(mean_prec, measurevar="precipitation_3",groupvars=c("year")),
            year>1986),tidy(lm(precipitation_3~as.integer(year)))) #NS
```

```
## # A tibble: 2 x 5
##   term             estimate std.error statistic p.value
##   <chr>               <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept)      -356.      668.       -0.533   0.598
## 2 as.integer(year)    0.193     0.334     0.578   0.568
```

```r
with(subset(summarySE(mean_prec, measurevar="precipitation_4", groupvars=c("year")),
            year>1986),tidy(lm(precipitation_4~as.integer(year)))) #NS
```

```
## # A tibble: 2 x 5
##   term              estimate std.error statistic p.value
##   <chr>                <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept)      -147.        859.     -0.171    0.865
## 2 as.integer(year)    0.0886      0.429   0.207    0.838
```

```r
with(subset(summarySE(mean_prec, measurevar="precipitation_5", groupvars=c("year")),
            year>1986),tidy(lm(precipitation_5~as.integer(year)))) #NS
```

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

```
##   term              estimate std.error statistic p.value
##   <chr>                <dbl>     <dbl>     <dbl>   <dbl>
## 1 (Intercept)      -794.      859.        -0.925   0.363
## 2 as.integer(year)    0.415     0.429      0.967   0.341
```

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
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

```r
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 - Old approach, not used in paper

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

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

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

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

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

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

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

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

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

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

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

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

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

Ranges and means

Mean daily temperature March

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

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

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

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

Mean daily temperature April

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

```
## [1] 3.7 8.4
```

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

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

Mean daily temperature May

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

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

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

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

Mean FFD

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

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

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

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

Mean fitness

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

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

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

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

Selection gradients for FFD

```r
round(with(subset(selgrads_FFD,term=="FFD_std"),range(estimate)),2)
```

```
## [1] -0.78  0.08
```

```r
round(with(subset(selgrads_FFD,term=="FFD_std"),mean(estimate)),2)
```

```
## [1] -0.28
```

Fig. 1

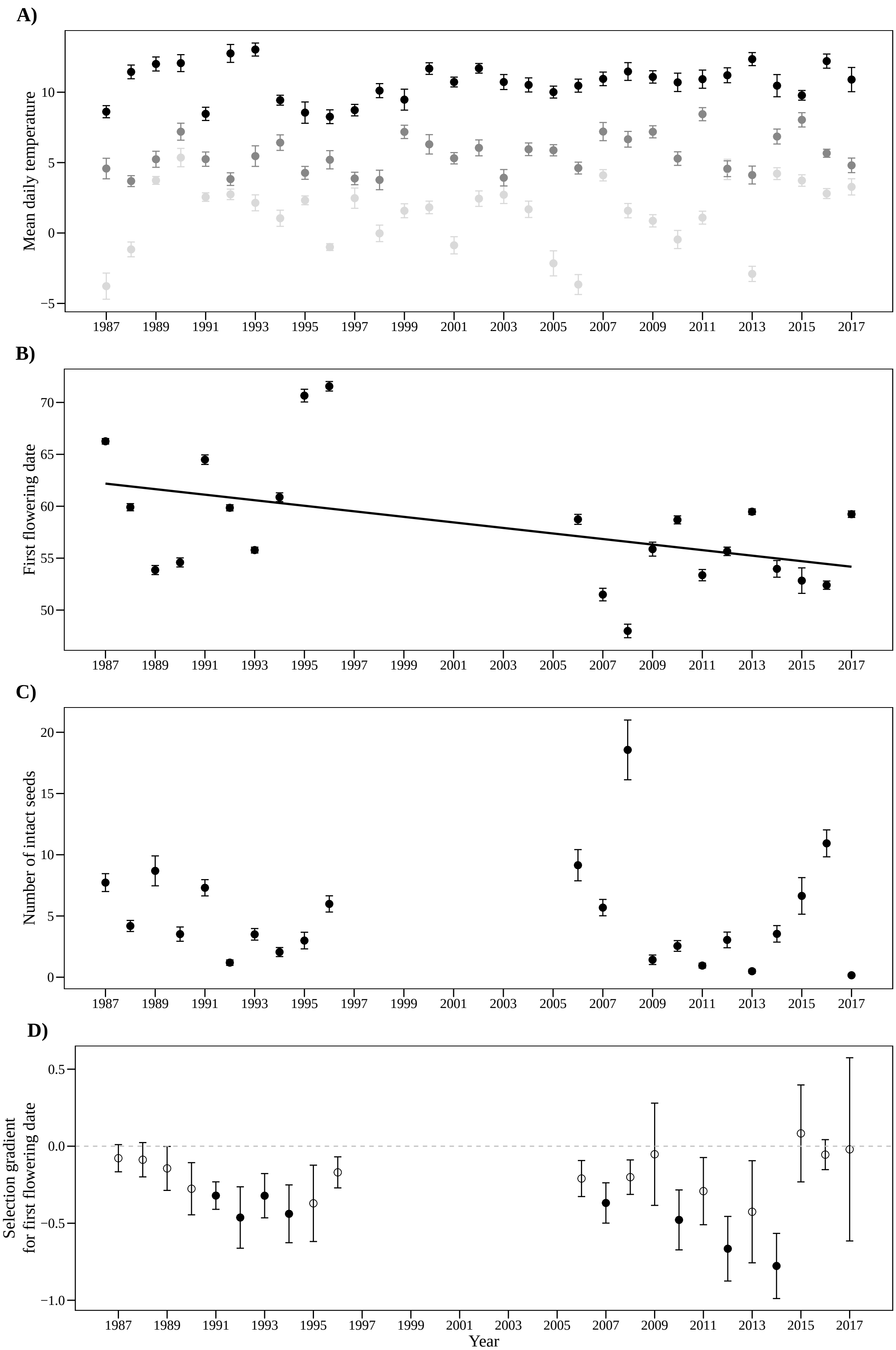

A)
Mean daily temperature
−5
0
5
10
1987
1989
1991
1993
1995
1997
1999
2001
2003
2005
2007
2009
2011
2013
2015
2017
B)
First flowering date
50
55
60
65
70
C)
Number of intact seeds
0
5
10
15
20
D)
Selection gradient
for first flowering date
−1.0
−0.5
0.0
0.5
Year

Fig. S1

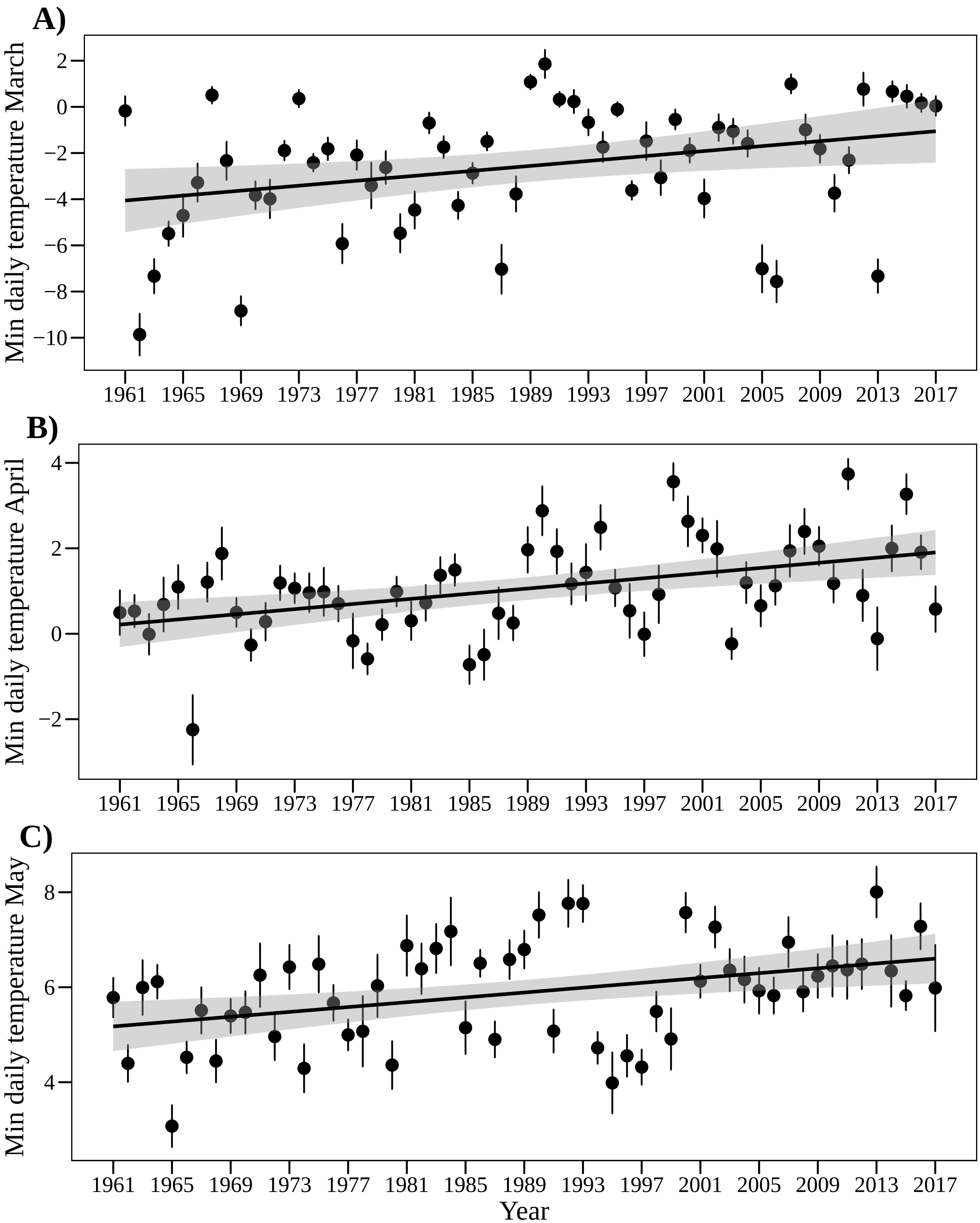

A)
Min daily temperature March
2
0
−2
−4
−6
−8
−10
1961 1965 1969 1973 1977 1981 1985 1989 1993 1997 2001 2005 2009 2013 2017
B)
Min daily temperature April
4
2
0
−2
1961 1965 1969 1973 1977 1981 1985 1989 1993 1997 2001 2005 2009 2013 2017
C)
Min daily temperature May
8
6
4
1961 1965 1969 1973 1977 1981 1985 1989 1993 1997 2001 2005 2009 2013 2017
Year

Fig. S2

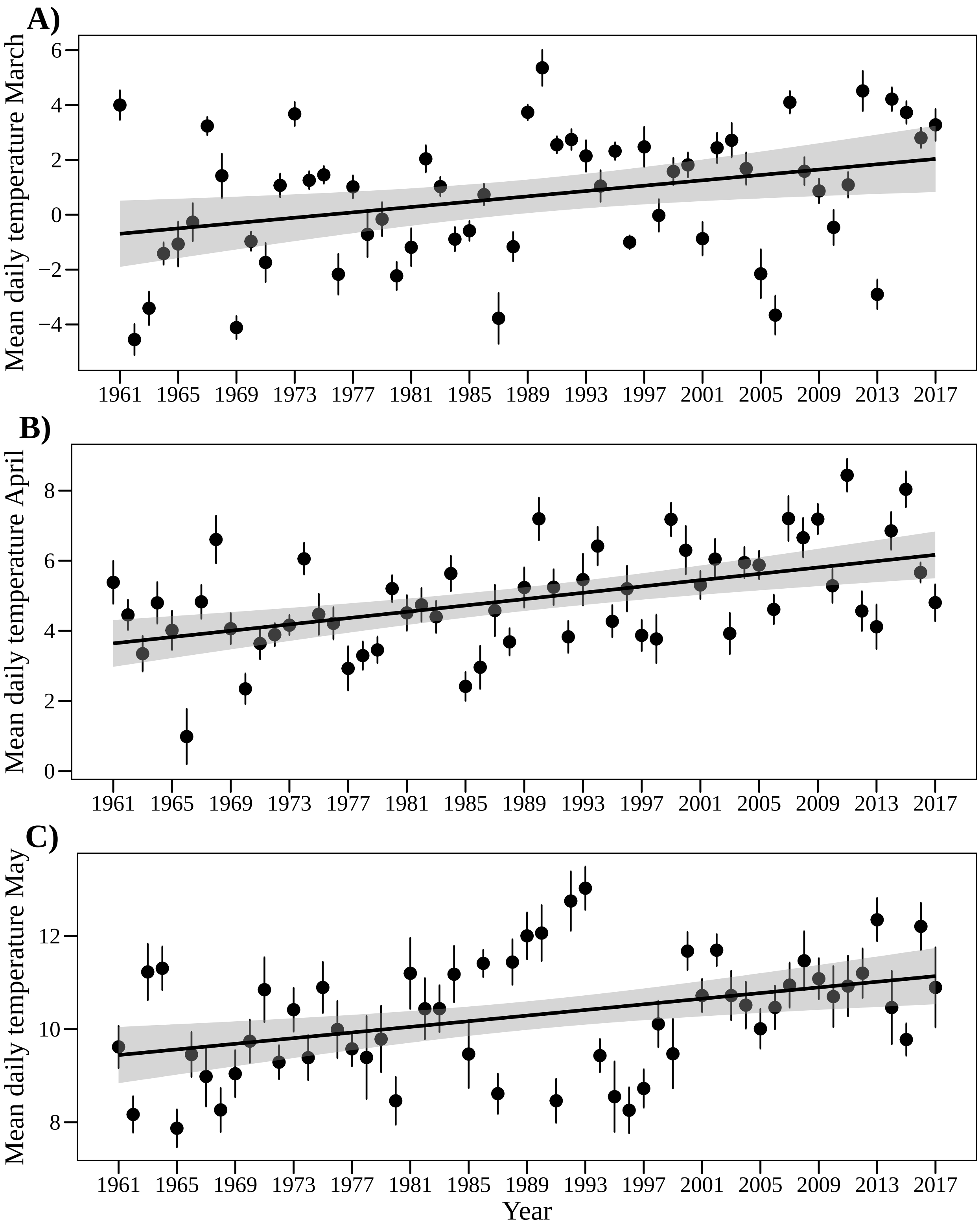

A)
Mean daily temperature March
6
4
2
0
−2
−4
1961
1965
1969
1973
1977
1981
1985
1989
1993
1997
2001
2005
2009
2013
2017
B)
Mean daily temperature April
8
6
4
2
0
C)
Mean daily temperature May
12
10
8
Year

Fig. S3

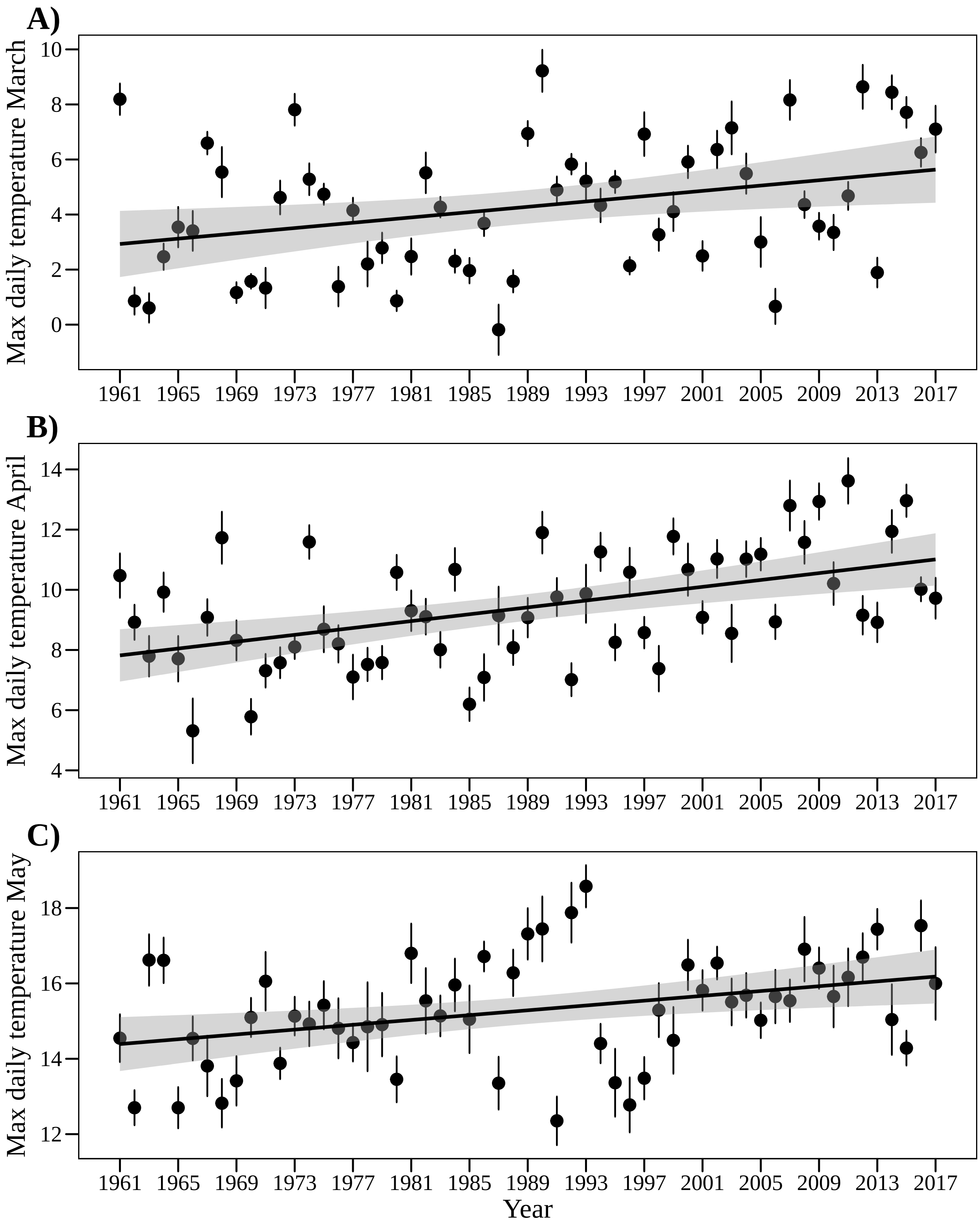
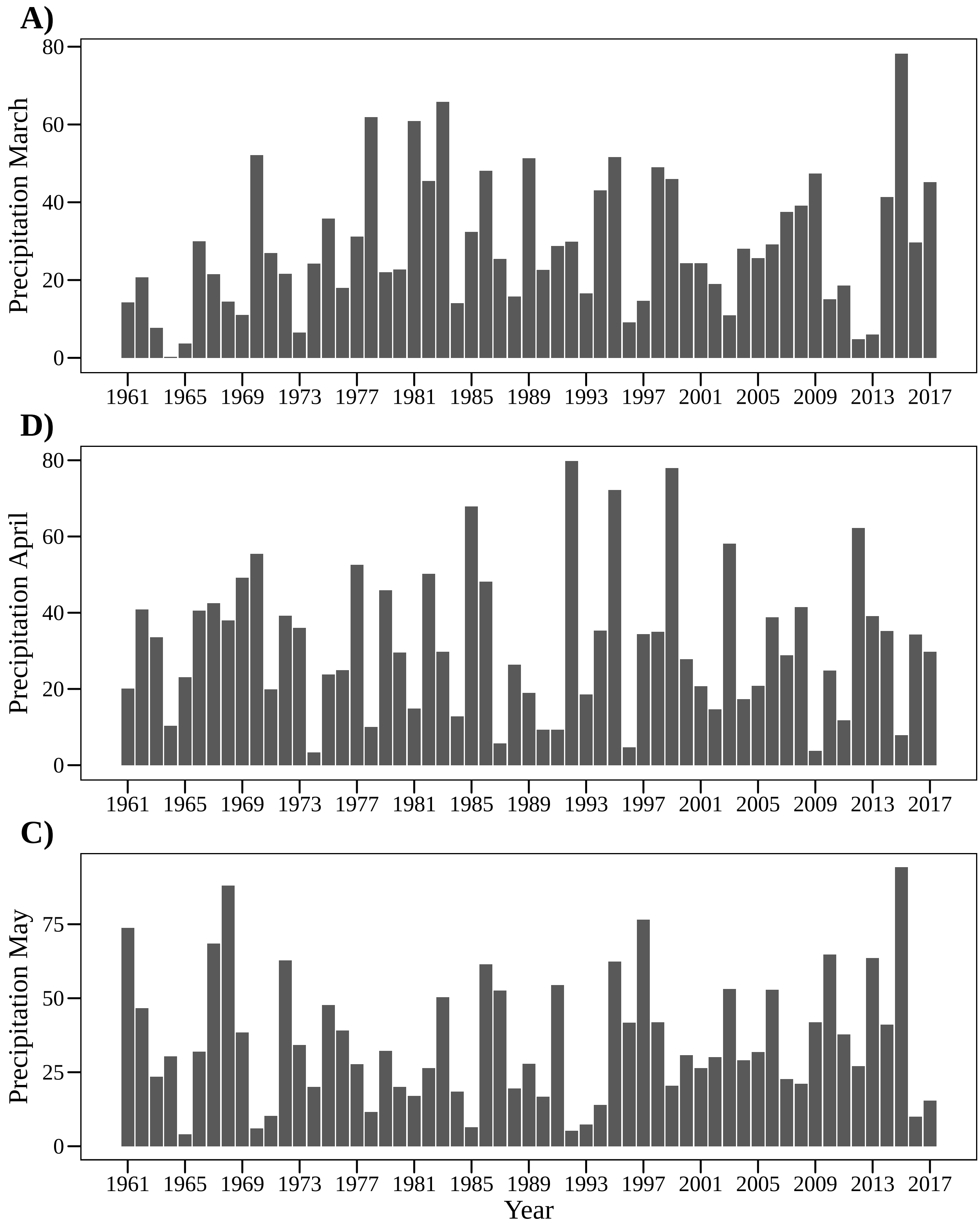

A)
Max daily temperature March
10
8
6
4
2
0
1961 1965 1969 1973 1977 1981 1985 1989 1993 1997 2001 2005 2009 2013 2017
B)
Max daily temperature April
14
12
10
8
6
4
1961 1965 1969 1973 1977 1981 1985 1989 1993 1997 2001 2005 2009 2013 2017
C)
Max daily temperature May
18
16
14
12
1961 1965 1969 1973 1977 1981 1985 1989 1993 1997 2001 2005 2009 2013 2017
Year

Fig. S4


A)
Precipitation March
80
60
40
20
0
1961
1965
1969
1973
1977
1981
1985
1989
1993
1997
2001
2005
2009
2013
2017
D)
Precipitation April
80
60
40
20
0
1961
1965
1969
1973
1977
1981
1985
1989
1993
1997
2001
2005
2009
2013
2017
C)
Precipitation May
75
50
25
0
1961
1965
1969
1973
1977
1981
1985
1989
1993
1997
2001
2005
2009
2013
2017
Year

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(2,3,42,158:160,170:172,182:184,194:196)]
subset1[,3:15]<-scale(subset1[,3:15])
globmod_FFD<-lmer(FFD ~ max_3+max_4+max_5+mean_3+mean_4+mean_5+min_3+min_4+min_5+
                    precipitation_3+precipitation_4+precipitation_5+n_fl+(1|id),
                  data = subset1,REML=FALSE,na.action="na.fail")

# Excluding collinear variables with r > 0.5
smat1 <- abs(cor(subset1[, -c(1,2,3)])) <= .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,fixed=c("n_fl"),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 ~ <2 unique rhs>, data = subset1, REML = FALSE,
##      na.action = na.fail)
##
## Component models:
##        df   logLik     AICc delta weight
## 134567  9 -7135.47 14289.02  0.00   0.72
## 234567  9 -7136.42 14290.91  1.89   0.28
##
## Term codes:
##          max_3          mean_3          mean_4          mean_5
##              1               2               3               4
```

```
##            n_fl precipitation_3 precipitation_4
##               5               6               7
##
## Model-averaged coefficients:
## (full average)
##                 Estimate Std. Error Adjusted SE z value Pr(>|z|)
## (Intercept)     58.93579    0.11385     0.11391 517.402  < 2e-16 ***
## max_3           -0.23642    0.18487     0.18490   1.279  0.20104
## mean_4          -2.18826    0.13431     0.13437  16.285  < 2e-16 ***
## mean_5          -3.75437    0.11313     0.11319  33.169  < 2e-16 ***
## precipitation_3 -0.71610    0.10450     0.10455   6.849  < 2e-16 ***
## precipitation_4 -0.34510    0.12449     0.12455   2.771  0.00559 **
## n_fl            -2.40748    0.10086     0.10092  23.856  < 2e-16 ***
## mean_3          -0.07392    0.13620     0.13622   0.543  0.58738
##
## (conditional average)
##                 Estimate Std. Error Adjusted SE z value Pr(>|z|)
## (Intercept)      58.9358     0.1138      0.1139 517.402  < 2e-16 ***
## max_3            -0.3282     0.1316      0.1316   2.493  0.01266 *
## mean_4           -2.1883     0.1343      0.1344  16.285  < 2e-16 ***
## mean_5           -3.7544     0.1131      0.1132  33.169  < 2e-16 ***
## precipitation_3  -0.7161     0.1045      0.1045   6.849  < 2e-16 ***
## precipitation_4  -0.3451     0.1245      0.1245   2.771  0.00559 **
## n_fl             -2.4075     0.1009      0.1009  23.856  < 2e-16 ***
## mean_3           -0.2643     0.1266      0.1266   2.087  0.03692 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Relative variable importance:
##                      mean_4 mean_5 n_fl precipitation_3 precipitation_4
## Importance:          1.00   1.00   1.00 1.00            1.00
## N containing models:    2      2      2    2               2
##                      max_3 mean_3
## Importance:          0.72  0.28
## N containing models:    1     1
```

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

```
##                      n_fl  precipitation_3 mean_5 mean_4 precipitation_4
## Importance:             1     1               1      1   0.95
## N containing models:  312   156              52     96    156
##                      max_3 mean_3 min_3 min_4 max_4 max_5 min_5
## Importance:           0.63  0.23   0.07 <0.01 <0.01 <0.01 <0.01
## N containing models:    72    72     72    24    96    52   104
##                      precipitation_5
## Importance:          <0.01
## N containing models:   104
```

```
r.squaredGLMM(get.models(modsel_FFD,subset=1)$"1585") #R square of best model
```

```
##            R2m       R2c
## [1,] 0.5767624 0.6282567
```

FFD for each plant with year (Table S2)

```
summary(lmer(FFD ~ scale(mean_4)+scale(mean_5)+
               scale(precipitation_3)+scale(precipitation_4)+scale(n_fl)+
               as.integer(as.character(year))+(1|id),data = data_sel,
             REML=FALSE,na.action="na.fail"))
```

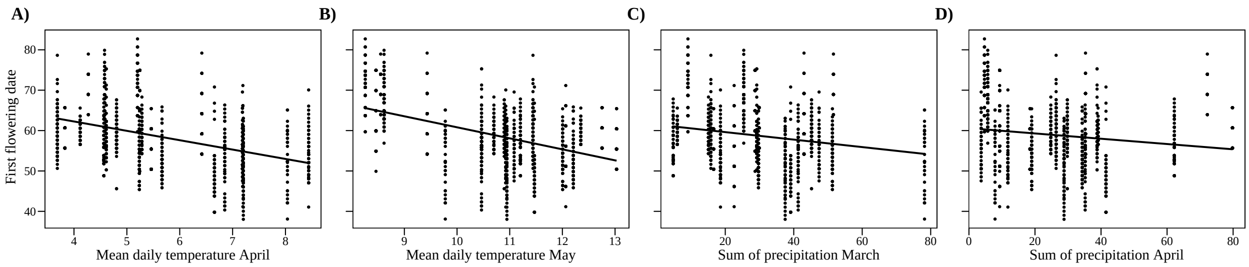
```
## Linear mixed model fit by maximum likelihood . t-tests use
##   Satterthwaite's method [lmerModLmerTest]
## Formula: FFD ~ scale(mean_4) + scale(mean_5) + scale(precipitation_3) +
##     scale(precipitation_4) + scale(n_fl) + as.integer(as.character(year)) +
##     (1 | id)
##    Data: data_sel
##
##      AIC      BIC   logLik deviance df.resid
##  14274.6  14326.7  -7128.3  14256.6     2402
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.0355 -0.6631 -0.0491  0.6069  4.9269
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  id       (Intercept)  2.131   1.460
##  Residual             19.836   4.454
## Number of obs: 2411, groups:  id, 834
##
## Fixed effects:
##                                 Estimate Std. Error         df t value
## (Intercept)                    167.02128   23.08144  939.67257   7.236
## scale(mean_4)                   -2.18039    0.12074 2263.92516 -18.058
## scale(mean_5)                   -3.83104    0.10578 2287.83738 -36.218
## scale(precipitation_3)          -0.75574    0.10337 2256.01351  -7.311
## scale(precipitation_4)          -0.26880    0.12195 2334.68749  -2.204
## scale(n_fl)                     -2.35892    0.10026 2295.68057 -23.528
## as.integer(as.character(year))  -0.05408    0.01155  936.66273  -4.683
##                                Pr(>|t|)
## (Intercept)                    9.58e-13 ***
## scale(mean_4)                   < 2e-16 ***
## scale(mean_5)                   < 2e-16 ***
## scale(precipitation_3)         3.67e-13 ***
## scale(precipitation_4)           0.0276 *
## scale(n_fl)                     < 2e-16 ***
## as.integer(as.character(year)) 3.24e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) scl(m_4) sc(_5) sc(_3) scl(p_4) scl(_)
## scale(mn_4)  0.336
## scale(mn_5)  0.054 -0.201
## scl(prcp_3) -0.002 -0.396    0.221
## scl(prcp_4)  0.333  0.516   -0.399 -0.232
## scale(n_fl)  0.070 -0.023    0.001 -0.023  0.007
```

```
## as.ntg(.()) -1.000 -0.335   -0.053  0.002 -0.333   -0.070
```

```r
r.squaredGLMM(lmer(FFD ~ scale(mean_4)+scale(mean_5)+
               scale(precipitation_3)+scale(precipitation_4)+scale(n_fl)+
               as.integer(as.character(year))+(1|id),data = data_sel,
             REML=FALSE,na.action="na.fail"))
```

```
##            R2m       R2c
## [1,] 0.5877444 0.6277298
```

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



Position (Table 1B)

```r
summary(lm(FFD_mean~scale(mean_4)+scale(mean_5)+
             scale(precipitation_3)+scale(precipitation_4),data=mean_weather4))
```

```
##
## Call:
## lm(formula = FFD_mean ~ scale(mean_4) + scale(mean_5) + scale(precipitation_3) +
##     scale(precipitation_4), data = mean_weather4)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -4.795 -1.475 -0.857  2.307  4.298
##
## Coefficients:
##                        Estimate Std. Error t value Pr(>|t|)
## (Intercept)             58.0087     0.6109  94.948  < 2e-16 ***
## scale(mean_4)           -3.4288     0.8158  -4.203 0.000598 ***
## scale(mean_5)           -4.0042     0.6710  -5.967 1.53e-05 ***
## scale(precipitation_3)  -0.8033     0.7242  -1.109 0.282781
## scale(precipitation_4)  -0.6272     0.7647  -0.820 0.423499
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.866 on 17 degrees of freedom
## Multiple R-squared:  0.8085, Adjusted R-squared:  0.7635
## F-statistic: 17.95 on 4 and 17 DF,  p-value: 6.222e-06
```

```r
## Including year (Table S2)
summary(lm(FFD_mean~scale(mean_4)+scale(mean_5)+
             scale(precipitation_3)+scale(precipitation_4)+
             as.integer(as.character(year)),data=mean_weather4))
```

```
##
## Call:
## lm(formula = FFD_mean ~ scale(mean_4) + scale(mean_5) + scale(precipitation_3) +
##     scale(precipitation_4) + as.integer(as.character(year)),
##     data = mean_weather4)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -4.8706 -2.0284 -0.1892  1.8135  3.6351
##
## Coefficients:
##                                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)                    247.78141  128.30717   1.931  0.07138 .
## scale(mean_4)                   -2.89109    0.86846  -3.329  0.00425 **
## scale(mean_5)                   -3.91044    0.65185  -5.999 1.86e-05 ***
## scale(precipitation_3)          -0.85092    0.70090  -1.214  0.24235
## scale(precipitation_4)          -0.29790    0.77213  -0.386  0.70471
## as.integer(as.character(year))  -0.09477    0.06408  -1.479  0.15854
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.77 on 16 degrees of freedom
## Multiple R-squared:  0.8316, Adjusted R-squared:  0.7789
## F-statistic:  15.8 on 5 and 16 DF,  p-value: 1.074e-05
```

```
summary(lm(date_10~scale(mean_4)+scale(mean_5)+
             scale(precipitation_3)+scale(precipitation_4),data=mean_weather4))
```

```
##
## Call:
## lm(formula = date_10 ~ scale(mean_4) + scale(mean_5) + scale(precipitation_3) +
##     scale(precipitation_4), data = mean_weather4)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -5.9498 -2.0615  0.0164  2.8620  4.4201
##
## Coefficients:
##                        Estimate Std. Error t value Pr(>|t|)
## (Intercept)             51.3422     0.7494  68.510  < 2e-16 ***
## scale(mean_4)           -4.4653     1.0007  -4.462 0.000342 ***
## scale(mean_5)           -3.5314     0.8231  -4.290 0.000495 ***
## scale(precipitation_3)  -0.9934     0.8883  -1.118 0.279025
## scale(precipitation_4)  -0.3525     0.9380  -0.376 0.711728
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.515 on 17 degrees of freedom
## Multiple R-squared:  0.7722, Adjusted R-squared:  0.7186
## F-statistic: 14.41 on 4 and 17 DF,  p-value: 2.616e-05
```

```
## Including year (Table S2)
summary(lm(date_10~scale(mean_4)+scale(mean_5)+
             scale(precipitation_3)+scale(precipitation_4)+
             as.integer(as.character(year)),data=mean_weather4))
```

```
##
## Call:
## lm(formula = date_10 ~ scale(mean_4) + scale(mean_5) + scale(precipitation_3) +
##     scale(precipitation_4) + as.integer(as.character(year)),
##     data = mean_weather4)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -5.9977 -1.9844  0.1781  3.0318  4.0254
##
## Coefficients:
##                                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)                    171.01894  165.11268   1.036  0.31571
## scale(mean_4)                   -4.12621    1.11758  -3.692  0.00198 **
## scale(mean_5)                   -3.47230    0.83883  -4.139  0.00077 ***
## scale(precipitation_3)          -1.02339    0.90195  -1.135  0.27324
## scale(precipitation_4)          -0.14485    0.99361  -0.146  0.88591
## as.integer(as.character(year))  -0.05977    0.08246  -0.725  0.47903
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.565 on 16 degrees of freedom
## Multiple R-squared:  0.7795, Adjusted R-squared:  0.7105
## F-statistic: 11.31 on 5 and 16 DF,  p-value: 8.533e-05
```

```
summary(lm(date_90~scale(mean_4)+scale(mean_5)+
             scale(precipitation_3)+scale(precipitation_4),data=mean_weather4))
```

```
##
## Call:
## lm(formula = date_90 ~ scale(mean_4) + scale(mean_5) + scale(precipitation_3) +
##     scale(precipitation_4), data = mean_weather4)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.9452 -1.5702 -0.0700  0.9684  4.3423
##
## Coefficients:
##                         Estimate Std. Error t value Pr(>|t|)
## (Intercept)              62.8290     0.4630 135.700  < 2e-16 ***
## scale(mean_4)            -2.3242     0.6182  -3.759  0.00156 **
## scale(mean_5)            -4.5554     0.5085  -8.958 7.57e-08 ***
## scale(precipitation_3)  -0.4612     0.5488  -0.840  0.41241
## scale(precipitation_4)  -0.8100     0.5795  -1.398  0.18017
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.172 on 17 degrees of freedom
## Multiple R-squared:  0.8733, Adjusted R-squared:  0.8435
## F-statistic:  29.3 on 4 and 17 DF,  p-value: 1.99e-07
```

```
## Including year (Table S2)
summary(lm(date_90~scale(mean_4)+scale(mean_5)+
             scale(precipitation_3)+scale(precipitation_4)+
             as.integer(as.character(year)),data=mean_weather4))
```

```
##
## Call:
## lm(formula = date_90 ~ scale(mean_4) + scale(mean_5) + scale(precipitation_3) +
##     scale(precipitation_4) + as.integer(as.character(year)),
##     data = mean_weather4)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.9744 -1.2969  0.1108  1.2138  4.3634
##
## Coefficients:
##                                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)                    135.84263  102.05050   1.331   0.2018
## scale(mean_4)                   -2.11732    0.69074  -3.065   0.0074 **
## scale(mean_5)                   -4.51932    0.51845  -8.717 1.79e-07 ***
## scale(precipitation_3)          -0.47949    0.55747  -0.860   0.4024
## scale(precipitation_4)          -0.68335    0.61412  -1.113   0.2823
## as.integer(as.character(year))  -0.03646    0.05096  -0.715   0.4846
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.204 on 16 degrees of freedom
## Multiple R-squared:  0.8772, Adjusted R-squared:  0.8389
## F-statistic: 22.87 on 5 and 16 DF,  p-value: 9.171e-07
```

Duration (Table 1C)

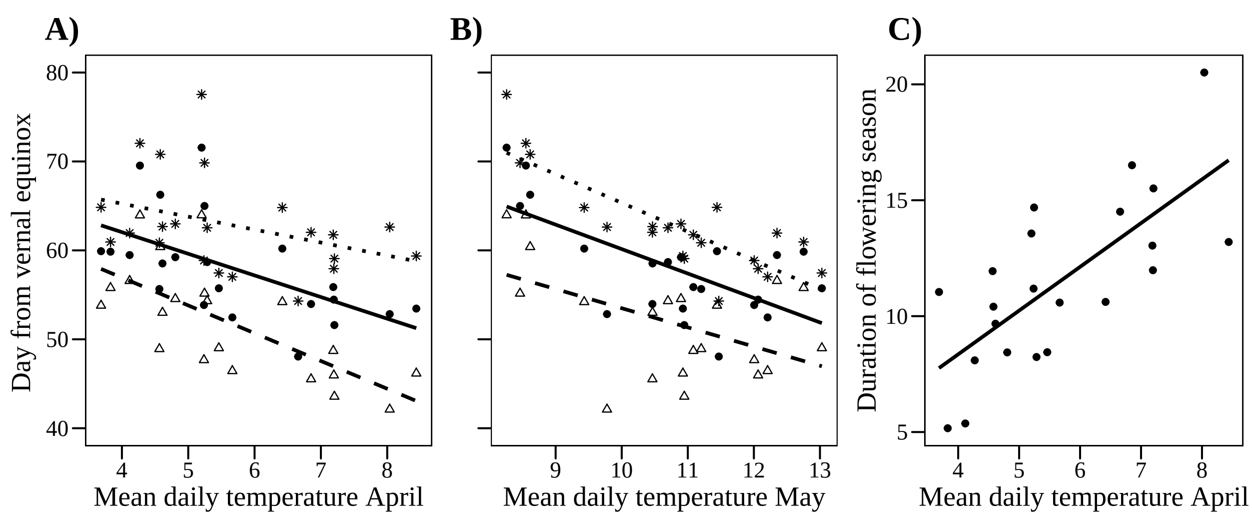
```
summary(lm(days_90_10~scale(mean_4)+scale(mean_5)+
             scale(precipitation_3)+scale(precipitation_4),data=mean_weather4))
```

```
##
## Call:
## lm(formula = days_90_10 ~ scale(mean_4) + scale(mean_5) + scale(precipitation_3) +
##     scale(precipitation_4), data = mean_weather4)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.2386 -1.6181 -0.5183  1.7595  3.9669
##
## Coefficients:
##                        Estimate Std. Error t value Pr(>|t|)
## (Intercept)             11.4868     0.5095  22.546 4.19e-14 ***
## scale(mean_4)            2.1411     0.6803   3.147  0.00588 **
## scale(mean_5)           -1.0240     0.5596  -1.830  0.08487 .
## scale(precipitation_3)   0.5322     0.6039   0.881  0.39049
## scale(precipitation_4)  -0.4575     0.6377  -0.717  0.48284
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.39 on 17 degrees of freedom
## Multiple R-squared:  0.6492, Adjusted R-squared:  0.5666
## F-statistic: 7.863 on 4 and 17 DF,  p-value: 0.0008864
```

```r
## Including year  (Table S2)
summary(lm(days_90_10~scale(mean_4)+scale(mean_5)+
             scale(precipitation_3)+scale(precipitation_4)+
             as.integer(as.character(year)),data=mean_weather4))
```

```
##
## Call:
## lm(formula = days_90_10 ~ scale(mean_4) + scale(mean_5) + scale(precipitation_3) +
##     scale(precipitation_4) + as.integer(as.character(year)),
##     data = mean_weather4)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -2.9757 -1.8779 -0.4593  1.8555  3.7887
##
## Coefficients:
##                                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)                    -35.17631  113.48046  -0.310   0.7606
## scale(mean_4)                    2.00890    0.76811   2.615   0.0187 *
## scale(mean_5)                   -1.04702    0.57652  -1.816   0.0881 .
## scale(precipitation_3)           0.54389    0.61990   0.877   0.3933
## scale(precipitation_4)          -0.53850    0.68290  -0.789   0.4419
## as.integer(as.character(year))   0.02330    0.05667   0.411   0.6864
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.45 on 16 degrees of freedom
## Multiple R-squared:  0.6528, Adjusted R-squared:  0.5443
## F-statistic: 6.017 on 5 and 16 DF,  p-value: 0.002568
```

Fig. 3: Response of position and duration to climate



Results 3: Response of fitness to climate

```
# Variables to use
subset2<-data_sel[c(3,20,42,158:160,170:172,182:184,194:196)]
subset2[,c(3:15)]<-scale(subset2[,c(3:15)])
globmod_fitness<-lmer(n_intact_seeds ~ max_3+max_4+max_5+mean_3+mean_4+mean_5+
                        min_3+min_4+min_5+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 ~ <5 unique rhs>, data = subset2,
##      REML = FALSE, na.action = na.fail)
##
## Component models:
##         df   logLik     AICc delta weight
## 24567    8 -8521.07 17058.21  0.00   0.31
## 124567   9 -8520.37 17058.82  0.62   0.23
## 234567   9 -8520.56 17059.20  0.99   0.19
## 245678   9 -8520.87 17059.82  1.61   0.14
## 1245678 10 -8519.98 17060.06  1.85   0.12
##
## Term codes:
##          max_3          max_4          min_3          min_5
##              1              2              3              4
```

```
##            n_fl precipitation_3 precipitation_4 precipitation_5
##               5               6               7               8
##
## Model-averaged coefficients:
## (full average)
##                 Estimate Std. Error Adjusted SE z value Pr(>|z|)
## (Intercept)      5.03974    0.18224     0.18233  27.640  < 2e-16 ***
## max_4           -0.93545    0.23551     0.23561   3.970 7.18e-05 ***
## min_5           -0.54457    0.21384     0.21394   2.545  0.01091 *
## precipitation_3  0.55102    0.19498     0.19507   2.825  0.00473 **
## precipitation_4 -0.91986    0.22170     0.22181   4.147 3.37e-05 ***
## n_fl             3.73133    0.17636     0.17645  21.147  < 2e-16 ***
## max_3           -0.10854    0.20801     0.20806   0.522  0.60191
## min_3            0.04192    0.12813     0.12816   0.327  0.74360
## precipitation_5 -0.04027    0.12441     0.12446   0.324  0.74628
##
## (conditional average)
##                 Estimate Std. Error Adjusted SE z value Pr(>|z|)
## (Intercept)       5.0397     0.1822      0.1823  27.640  < 2e-16 ***
## max_4            -0.9354     0.2355      0.2356   3.970 7.18e-05 ***
## min_5            -0.5446     0.2138      0.2139   2.545  0.01091 *
## precipitation_3   0.5510     0.1950      0.1951   2.825  0.00473 **
## precipitation_4  -0.9199     0.2217      0.2218   4.147 3.37e-05 ***
## n_fl              3.7313     0.1764      0.1765  21.147  < 2e-16 ***
## max_3            -0.3058     0.2482      0.2483   1.232  0.21799
## min_3             0.2193     0.2167      0.2169   1.011  0.31189
## precipitation_5  -0.1522     0.2036      0.2037   0.747  0.45504
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Relative variable importance:
##                      max_4 min_5 n_fl precipitation_3 precipitation_4
## Importance:          1.00  1.00  1.00 1.00            1.00
## N containing models:    5     5     5    5               5
##                      max_3 precipitation_5 min_3
## Importance:          0.35  0.26            0.19
## N containing models:    2     2               1
```

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

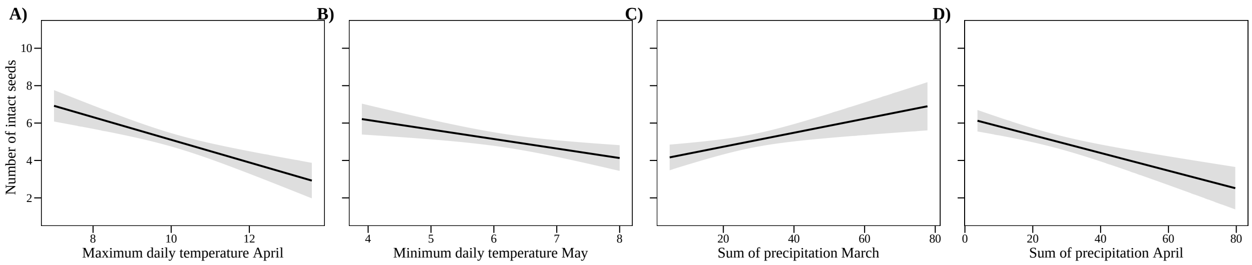
```
##                      n_fl  precipitation_4 max_4 precipitation_3 min_5
## Importance:             1     1            0.99  0.96            0.82
## N containing models:  312   156              96   156             104
##                      max_3 precipitation_5 min_3 mean_3 mean_5 max_5
## Importance:           0.35  0.28            0.2  0.13   0.06   0.04
## N containing models:    72   104              72   72     52     52
##                      mean_4 min_4
## Importance:          <0.01  <0.01
## N containing models:    96     24
```

```r
r.squaredGLMM(get.models(modsel_fitness,subset=1)$"1794") #R square of best model
```

```
##            R2m       R2c
## [1,] 0.1765938 0.2128953
```

Fig. S5: Response of fitness to climate

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



Results 4: Differences in selection among years

Total 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.

Table 2A

Total selection

```
# Variables to use
subset3<-data_sel[c(3,44:45,158:160,170:172,182:184,194:196)]
subset3[,c(4:15)]<-scale(subset3[,c(4:15)])
globmod_total_selection<-lmer(n_intact_seeds_rel ~ FFD_std+
                            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_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(1:3)])) <= .5 # TRUE: cor<=0.5,FALSE: cor>0.5
smat3[!lower.tri(smat3)] <- NA
rownames(smat3)<-paste("FFD_std:", names(smat3[1,1:12]),sep="")
colnames(smat3)<-paste("FFD_std:", names(smat3[1,1:12]),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_total_selection<-pdredge(globmod_total_selection,subset=smat3,fixed=c("FFD_std"),
                          cluster=clust1)
```

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

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

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

```
## lmer(formula = n_intact_seeds_rel ~ <6 unique rhs>, data =
##      subset3, REML = FALSE, na.action = na.fail)
##
## Component models:
##        df   logLik     AICc delta weight
## 13467   8 -5099.99 10216.04  0.00   0.22
## 12467   8 -5100.08 10216.21  0.17   0.20
## 14567   8 -5100.14 10216.34  0.29   0.19
## 1467    7 -5101.45 10216.94  0.89   0.14
## 14678   8 -5100.48 10217.01  0.97   0.14
## 145678  9 -5099.78 10217.63  1.58   0.10
##
## Term codes:
##                FFD_std           FFD_std:max_5          FFD_std:mean_5
##                      1                       2                       3
##          FFD_std:min_4           FFD_std:min_5 FFD_std:precipitation_3
##                      4                       5                       6
## FFD_std:precipitation_4 FFD_std:precipitation_5
##                      7                       8
##
## Model-averaged coefficients:
## (full average)
##                         Estimate Std. Error Adjusted SE z value Pr(>|z|)
## (Intercept)              0.98052    0.04448     0.04450  22.033  < 2e-16
## FFD_std                 -0.43589    0.04143     0.04146  10.515  < 2e-16
## FFD_std:mean_5           0.01776    0.03985     0.03985   0.446  0.65586
## FFD_std:min_4           -0.16766    0.04784     0.04786   3.503  0.00046
## FFD_std:precipitation_3  0.17676    0.04751     0.04754   3.718  0.00020
## FFD_std:precipitation_4 -0.10414    0.04663     0.04665   2.233  0.02558
## FFD_std:max_5            0.01591    0.03789     0.03790   0.420  0.67460
## FFD_std:min_5            0.02013    0.04052     0.04053   0.497  0.61938
## FFD_std:precipitation_5 -0.01284    0.03277     0.03278   0.392  0.69519
##
## (Intercept)             ***
## FFD_std                 ***
## FFD_std:mean_5
## FFD_std:min_4           ***
## FFD_std:precipitation_3 ***
## FFD_std:precipitation_4 *
## FFD_std:max_5
## FFD_std:min_5
## FFD_std:precipitation_5
##
## (conditional average)
##                         Estimate Std. Error Adjusted SE z value Pr(>|z|)
## (Intercept)              0.98052    0.04448     0.04450  22.033  < 2e-16
## FFD_std                 -0.43589    0.04143     0.04146  10.515  < 2e-16
## FFD_std:mean_5           0.07976    0.04675     0.04677   1.705 0.088163
## FFD_std:min_4           -0.16766    0.04784     0.04786   3.503 0.000460
## FFD_std:precipitation_3  0.17676    0.04751     0.04754   3.718 0.000201
## FFD_std:precipitation_4 -0.10414    0.04663     0.04665   2.233 0.025579
## FFD_std:max_5            0.07777    0.04698     0.04700   1.655 0.097986
## FFD_std:min_5            0.06866    0.04762     0.04764   1.441 0.149523
## FFD_std:precipitation_5 -0.05392    0.04789     0.04791   1.125 0.260426
```

```
##
## (Intercept)             ***
## FFD_std                 ***
## FFD_std:mean_5          .
## FFD_std:min_4           ***
## FFD_std:precipitation_3 ***
## FFD_std:precipitation_4 *
## FFD_std:max_5           .
## FFD_std:min_5
## FFD_std:precipitation_5
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Relative variable importance:
##                      FFD_std FFD_std:min_4 FFD_std:precipitation_3
## Importance:          1.00    1.00          1.00
## N containing models:    6       6             6
##                      FFD_std:precipitation_4 FFD_std:min_5
## Importance:          1.00                    0.29
## N containing models:    6                       2
##                      FFD_std:precipitation_5 FFD_std:mean_5 FFD_std:max_5
## Importance:          0.24                    0.22           0.20
## N containing models:    2                       1              1
```

```
importance(modsel_total_selection) # Variable importance
```

```
##                      FFD_std FFD_std:precipitation_3 FFD_std:min_4
## Importance:          1.00    0.99                    0.83
## N containing models:  312     156                      24
##                      FFD_std:precipitation_4 FFD_std:min_5
## Importance:          0.80                    0.28
## N containing models:  156                     104
##                      FFD_std:precipitation_5 FFD_std:mean_5 FFD_std:max_5
## Importance:          0.23                    0.21           0.19
## N containing models:  104                      52             52
##                      FFD_std:mean_4 FFD_std:min_3 FFD_std:mean_3
## Importance:          0.08           0.04          0.04
## N containing models:   96             72            72
##                      FFD_std:max_3 FFD_std:max_4
## Importance:          0.03          0.03
## N containing models:   72            96
```

```
r.squaredGLMM(get.models(modsel_total_selection,subset=1)$"1696") #R square of best model
```

```
##            R2m       R2c
## [1,] 0.0523048 0.1008011
```

```
# Anova (Table 4A) with model including variables that were significant in the averaged model
Anova(lmer(n_intact_seeds_rel ~ FFD_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                 110.440  1  < 2.2e-16 ***
```

```
## FFD_std:min_4            10.732  1  0.0010527 **
## FFD_std:precipitation_3  12.479  1  0.0004115 ***
## FFD_std:precipitation_4   3.482  1  0.0620396 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Direct selection

```
# Variables to use
subset4<-data_sel[c(3,44:46,158:160,170:172,182:184,194:196)]
subset4[,c(5:16)]<-scale(subset4[,c(5:16)])
globmod_direct_selection<-lmer(n_intact_seeds_rel ~ FFD_std+n_fl_std+
                          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_3+FFD_std:precipitation_4+
                          FFD_std:precipitation_5+(1|id),
                        data = subset4,REML=FALSE,na.action="na.fail")
# Excluding collinear variables with r > 0.5
smat4 <- abs(cor(subset4[, -c(1:4)])) <= .5 # TRUE: cor<=0.5,FALSE: cor>0.5
smat4[!lower.tri(smat4)] <- NA
rownames(smat4)<-paste("FFD_std:", names(smat4[1,1:12]),sep="")
colnames(smat4)<-paste("FFD_std:", names(smat4[1,1:12]),sep="")

clusterType <- if(length(find.package("snow", quiet = TRUE))) "SOCK" else "PSOCK"
clust1 <- try(makeCluster(getOption("cl.cores", 3), type = clusterType))
clusterExport(clust1, "subset4")
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_direct_selection<-pdredge(globmod_direct_selection,subset=smat4,
                                 fixed=c("FFD_std","n_fl_std"),cluster=clust1)
```

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

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

```
##
## Call:
## model.avg(object = modsel_direct_selection, subset = delta <
##     2)
##
## Component model call:
## lmer(formula = n_intact_seeds_rel ~ <6 unique rhs>, data =
```

```
##      subset4, REML = FALSE, na.action = na.fail)
##
## Component models:
##         df   logLik     AICc delta weight
## 124578   9 -5068.40 10154.88  0.00   0.23
## 125678   9 -5068.52 10155.11  0.24   0.20
## 123578   9 -5068.55 10155.18  0.31   0.20
## 125789   9 -5068.94 10155.96  1.08   0.13
## 12578    8 -5070.01 10156.08  1.20   0.13
## 1256789 10 -5068.13 10156.35  1.48   0.11
##
## Term codes:
##                FFD_std                n_fl_std           FFD_std:max_5
##                      1                       2                       3
##         FFD_std:mean_5           FFD_std:min_4           FFD_std:min_5
##                      4                       5                       6
## FFD_std:precipitation_3 FFD_std:precipitation_4 FFD_std:precipitation_5
##                      7                       8                       9
##
## Model-averaged coefficients:
## (full average)
##                         Estimate Std. Error Adjusted SE z value Pr(>|z|)
## (Intercept)              0.99321    0.04273     0.04275  23.232  < 2e-16
## FFD_std                 -0.26526    0.04593     0.04596   5.772  < 2e-16
## n_fl_std                 0.37709    0.04648     0.04651   8.108  < 2e-16
## FFD_std:mean_5           0.01903    0.04128     0.04129   0.461 0.644860
## FFD_std:min_4           -0.16110    0.04730     0.04733   3.404 0.000665
## FFD_std:precipitation_3  0.19049    0.04713     0.04716   4.039 5.36e-05
## FFD_std:precipitation_4 -0.10849    0.04613     0.04616   2.351 0.018745
## FFD_std:min_5            0.02277    0.04278     0.04278   0.532 0.594664
## FFD_std:max_5            0.01561    0.03764     0.03764   0.415 0.678436
## FFD_std:precipitation_5 -0.01340    0.03331     0.03332   0.402 0.687620
##
## (Intercept)             ***
## FFD_std                 ***
## n_fl_std                ***
## FFD_std:mean_5
## FFD_std:min_4           ***
## FFD_std:precipitation_3 ***
## FFD_std:precipitation_4 *
## FFD_std:min_5
## FFD_std:max_5
## FFD_std:precipitation_5
##
## (conditional average)
##                         Estimate Std. Error Adjusted SE z value Pr(>|z|)
## (Intercept)              0.99321    0.04273     0.04275  23.232  < 2e-16
## FFD_std                 -0.26526    0.04593     0.04596   5.772 1.00e-08
## n_fl_std                 0.37709    0.04648     0.04651   8.108  < 2e-16
## FFD_std:mean_5           0.08287    0.04617     0.04619   1.794 0.072799
## FFD_std:min_4           -0.16110    0.04730     0.04733   3.404 0.000664
## FFD_std:precipitation_3  0.19049    0.04713     0.04716   4.039 5.36e-05
## FFD_std:precipitation_4 -0.10849    0.04613     0.04616   2.351 0.018745
## FFD_std:min_5            0.07254    0.04712     0.04714   1.539 0.123865
```

```
## FFD_std:max_5            0.07921    0.04639     0.04641   1.707 0.087911
## FFD_std:precipitation_5 -0.05501    0.04761     0.04763   1.155 0.248144
##
## (Intercept)             ***
## FFD_std                 ***
## n_fl_std                ***
## FFD_std:mean_5          .
## FFD_std:min_4           ***
## FFD_std:precipitation_3 ***
## FFD_std:precipitation_4 *
## FFD_std:min_5
## FFD_std:max_5           .
## 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:    6       6        6
##                      FFD_std:precipitation_3 FFD_std:precipitation_4
## Importance:          1.00                    1.00
## N containing models:    6                       6
##                      FFD_std:min_5 FFD_std:precipitation_5 FFD_std:mean_5
## Importance:          0.31          0.24                    0.23
## N containing models:    2             2                       1
##                      FFD_std:max_5
## Importance:          0.20
## N containing models:    1
```

```r
importance(modsel_direct_selection) # Variable importance
```

```
##                      FFD_std n_fl_std FFD_std:precipitation_3
## Importance:          1.00    1.00     1.00
## N containing models:  312     312      156
##                      FFD_std:precipitation_4 FFD_std:min_4 FFD_std:min_5
## Importance:          0.84                    0.83          0.30
## N containing models:  156                      24           104
##                      FFD_std:precipitation_5 FFD_std:mean_5 FFD_std:max_5
## Importance:          0.24                    0.21           0.19
## N containing models:  104                      52             52
##                      FFD_std:mean_4 FFD_std:mean_3 FFD_std:min_3
## Importance:          0.10           0.04           0.04
## N containing models:   96             72             72
##                      FFD_std:max_3 FFD_std:max_4
## Importance:          0.03          0.03
## N containing models:   72            96
```

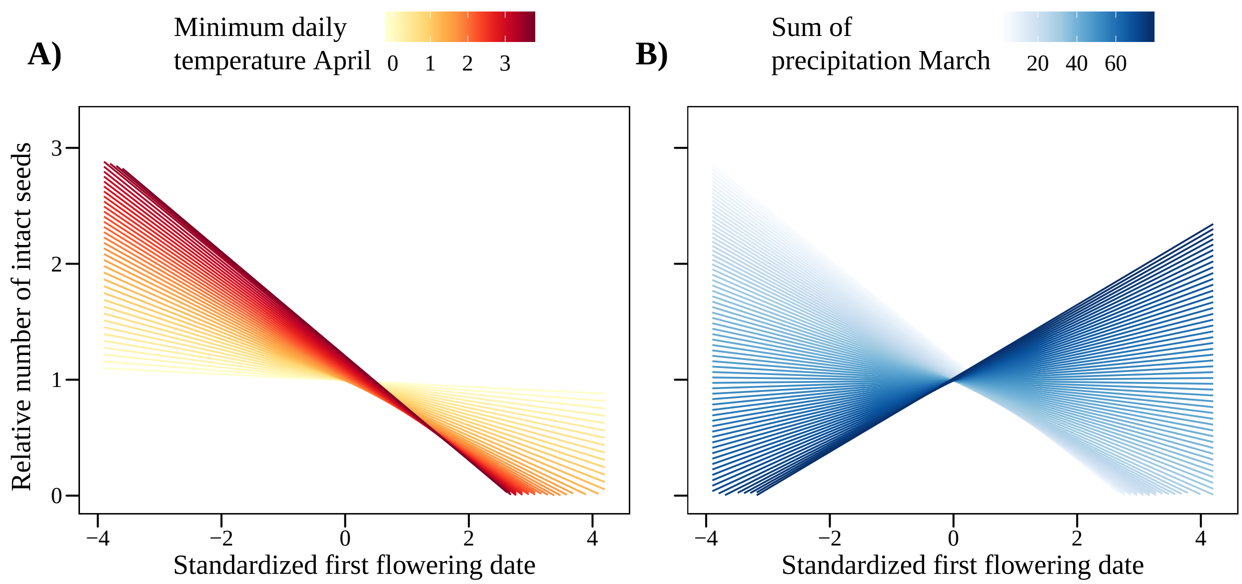
```r
r.squaredGLMM(get.models(modsel_direct_selection,subset=1)$"1696") #R square of best model
```

```
##             R2m       R2c
## [1,] 0.07869985 0.1091796
```

```r
# Anova (Table 4A) with model including variables that were significant in the averaged model
Anova(lmer(n_intact_seeds_rel ~ FFD_std+n_fl_std+FFD_std:min_4+FFD_std:precipitation_3+FFD_std:precipita
             (1|id),data = subset4,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                    33.9346  1  5.700e-09 ***
## n_fl_std                   65.5539  1  5.655e-16 ***
## FFD_std:min_4               9.8971  1  0.0016554 **
## FFD_std:precipitation_3 14.8032  1  0.0001193 ***
## FFD_std:precipitation_4  3.8258  1  0.0504682 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Fig. 4: Response of selection gradients to climate, position and duration of flowering season



Proportion of among-year variation in selection explained by climatic factors

New approach, used in paper (as in Hunter et al. 2018, code suggested by M. Morrissey)

Total selection

```
data_seldiff<-subset(seldiffs_FFD,term=="FFD_std")[c(1,3:4)]
names(data_seldiff)<-c("year","seldiff","SE_seldiff")
data_seldiff<-merge(data_seldiff,unique(data_sel[c(1,183,194:195)]))

myprior <- list(R = list(V=1, nu=0.002))
model_seldiff<-MCMCglmm(seldiff~min_4+precipitation_3+precipitation_4,
                        mev=data_seldiff$SE_seldiff^2,data=data_seldiff,family="gaussian",
                        nitt=500000,burnin=10000,thin=10,prior=myprior,verbose=F)
summary(model_seldiff)
```

```
##
##  Iterations = 10001:499991
##  Thinning interval  = 10
##  Sample size  = 49000
##
##  DIC: -45.08212
##
##  R-structure:  ~units
##
##       post.mean  l-95% CI u-95% CI eff.samp
## units  0.008614 0.0001654  0.02545    26981
##
##  Location effects: seldiff ~ min_4 + precipitation_3 + precipitation_4
##
##                  post.mean   l-95% CI   u-95% CI eff.samp    pMCMC
## (Intercept)     -0.4133329 -0.6173872 -0.2169013    44937 0.000694 ***
## min_4           -0.1016228 -0.1988787  0.0010747    49000 0.044816 *
## precipitation_3  0.0064293  0.0001542  0.0124070    45739 0.035959 *
## precipitation_4 -0.0030515 -0.0071497  0.0009109    45171 0.126857
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
head(model_seldiff$Sol)
```

```
## Markov Chain Monte Carlo (MCMC) output:
## Start = 10001
## End = 10061
## Thinning interval = 10
##      (Intercept)       min_4 precipitation_3 precipitation_4
## [1,]  -0.3998219 -0.09674928     0.006378197   -0.0041210045
## [2,]  -0.5259151 -0.06098454     0.007392883   -0.0023528603
## [3,]  -0.4648922 -0.07840509     0.004329411   -0.0005784594
## [4,]  -0.3389845 -0.07602173     0.002947726   -0.0040342880
## [5,]  -0.2988876 -0.16370341     0.008589856   -0.0055957991
## [6,]  -0.4489627 -0.18361127     0.012362785   -0.0041570949
## [7,]  -0.3362850 -0.17877344     0.008890463   -0.0024266769
```

```r
head(model_seldiff$VCV)
```

```
## Markov Chain Monte Carlo (MCMC) output:
## Start = 10001
## End = 10061
## Thinning interval = 10
##      sqrt(mev):sqrt(mev).meta       units
## [1,]                        1 0.004017486
## [2,]                        1 0.003822586
## [3,]                        1 0.003851605
## [4,]                        1 0.011562218
## [5,]                        1 0.004692417
## [6,]                        1 0.002797495
## [7,]                        1 0.010188612
```

```r
nMCMC_seldiff<-dim(model_seldiff$Sol)[1] # Sample size

# To contain posterior distribution of the variance in seldiffs associated with the environment
post.Var_seldiff<-array(dim=nMCMC_seldiff)
```

```r
# The posterior samples of the partial regression coefficients of seldiffs on the predictor
# variables relate to the variance in seldiffs associated with the multivariate environment
# according to: V(Y) = T(B) %*% V(X) %*% B
# (standard expression for a variance of a linear transformation)
# V(Y) = variance of selection differentials arising from environmental variation
# V(X) = covariance matrix of the environmental variable
# B = linear transformation of X onto Y (partial regression coefficients)

# Apply this transformation to each posterior sample to generate a posterior distribution of
# the variance in seldiffs associated with environmental variables
# This is the numerator of equation 12 in Hunter et al. 2018, for calculating
# the proportion of the total variation in selection attributed to the environmental
# component of the model. The denominator is this quantity plus the residual variance.

# Calculate the variance, over all posterior samples
Sigma_seldiff<-var(as.matrix(model_seldiff$X[,2:4])) # Covariance matrix of environmental vars
for(i in 1:nMCMC_seldiff){
  post.Var_seldiff[i]<- t(model_seldiff$Sol[i,2:4]) %*% Sigma_seldiff %*%model_seldiff$Sol[i,2:4]
  # Variance of seldiffs arising from environmental variation
}

# Two flavours of the estimate of the variance associated with the climate variables
# (Numerator of equation 12)
mean(post.Var_seldiff)
```

```
## [1] 0.01931822
```

```r
posterior.mode(as.mcmc(post.Var_seldiff))
```

```
##       var1
## 0.01166978
```

```r
# 95% credible interval of the variance
HPDinterval(as.mcmc(post.Var_seldiff))
```

```
##             lower      upper
## var1 0.0004505412 0.04333703
## attr(,"Probability")
## [1] 0.95
```

```r
# Visualise
par(mfrow=c(1,2))
plot(density(post.Var_seldiff))

# Two flavours of the estimate of the proportion of variance associated with the climate variables
# (Equation 12 in paper)
mean(post.Var_seldiff/(post.Var_seldiff+model_seldiff$VCV[,2])) # 0.6964514
```

```
## [1] 0.6988433
```

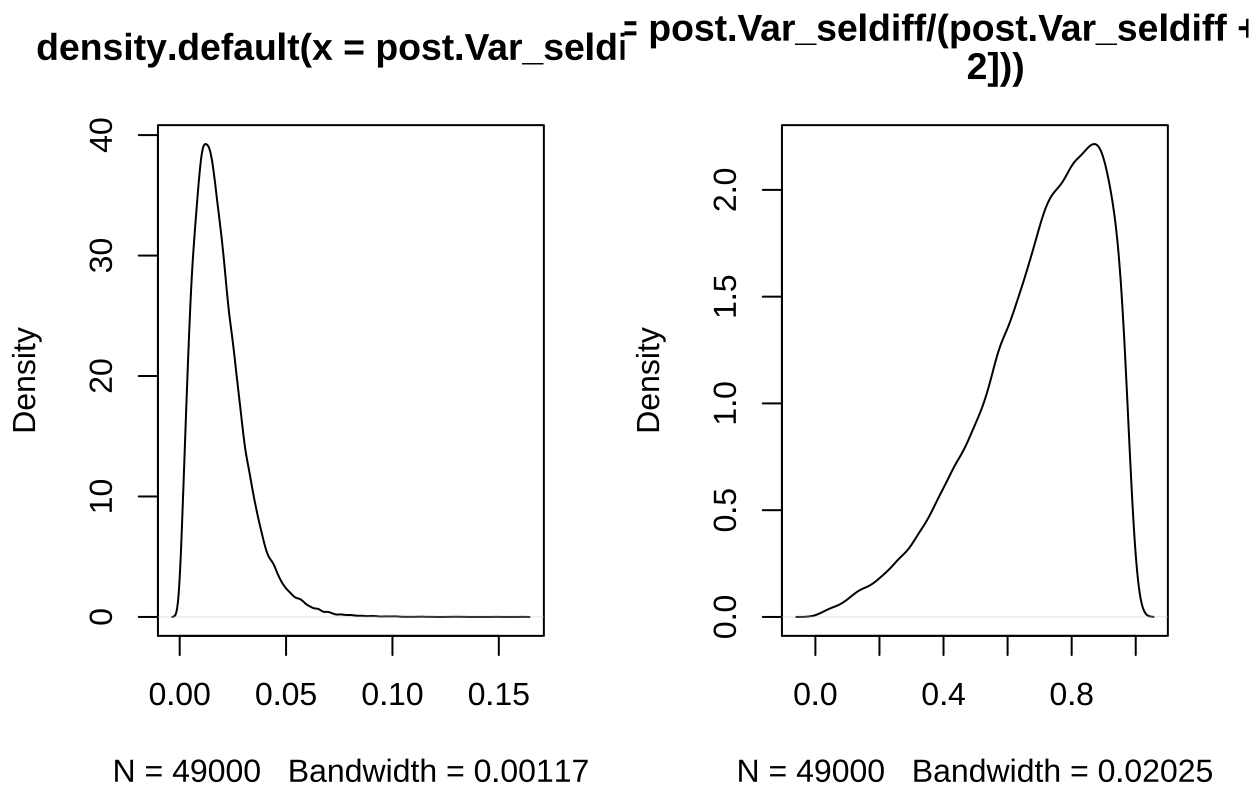
```r
posterior.mode(as.mcmc(post.Var_seldiff/(post.Var_seldiff+model_seldiff$VCV[,2]))) # 0.8768223
```

```
##      var1
## 0.8513595
```

```r
# 95% credible interval of the variance
HPDinterval(as.mcmc(post.Var_seldiff/(post.Var_seldiff+model_seldiff$VCV[,2])))
```

```
##          lower     upper
## var1 0.3169073 0.9868782
## attr(,"Probability")
## [1] 0.95
```

```r
# visualise
plot(density(post.Var_seldiff/(post.Var_seldiff+model_seldiff$VCV[,2])))
```



Direct selection

```r
data_selgrad<-subset(selgrads_FFD,term=="FFD_std")[c(1,3:4)]
names(data_selgrad)<-c("year","selgrad","SE_selgrad")
data_selgrad<-merge(data_selgrad,unique(data_sel[c(1,183,194:195)]))

myprior <- list(R = list(V=1, nu=0.002))
model_selgrad<-MCMCglmm(selgrad~min_4+precipitation_3+precipitation_4,
                        mev=data_selgrad$SE_selgrad^2,data=data_selgrad,family="gaussian",
                        nitt=500000,burnin=10000,thin=10,prior=myprior,verbose=F)
summary(model_selgrad)
```

```
##
##  Iterations = 10001:499991
##  Thinning interval  = 10
##  Sample size  = 49000
```

```
##
##  DIC: -43.31532
##
##  R-structure:  ~units
##
##       post.mean  l-95% CI u-95% CI eff.samp
## units  0.009445 0.0002167   0.0282    27862
##
##  Location effects: selgrad ~ min_4 + precipitation_3 + precipitation_4
##
##                  post.mean   l-95% CI   u-95% CI eff.samp  pMCMC
## (Intercept)     -0.1590834 -0.3679922  0.0475776    48142 0.1251
## min_4           -0.0714259 -0.1783877  0.0311843    48257 0.1720
## precipitation_3  0.0047258 -0.0019180  0.0115077    48582 0.1634
## precipitation_4 -0.0044848 -0.0088568 -0.0003264    47689 0.0354 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
head(model_selgrad$Sol)
```

```
## Markov Chain Monte Carlo (MCMC) output:
## Start = 10001
## End = 10061
## Thinning interval = 10
##        (Intercept)       min_4 precipitation_3 precipitation_4
## [1,] -0.3138949613 -0.04649852     0.005952000    -0.003629383
## [2,] -0.2269608761 -0.07127537     0.007584386    -0.005084662
## [3,] -0.3456372964 -0.08834029     0.009560066    -0.001483256
## [4,] -0.1449598042 -0.12732725     0.008422195    -0.003519351
## [5,] -0.1506481398 -0.10808140     0.005317887    -0.003202894
## [6,] -0.2951803315  0.02818424     0.002228509    -0.001856042
## [7,]  0.0005587952 -0.11019463     0.006224538    -0.010597123
```

```r
head(model_selgrad$VCV)
```

```
## Markov Chain Monte Carlo (MCMC) output:
## Start = 10001
## End = 10061
## Thinning interval = 10
##      sqrt(mev):sqrt(mev).meta        units
## [1,]                        1 0.0188259416
## [2,]                        1 0.0063999487
## [3,]                        1 0.0018760043
## [4,]                        1 0.0005359311
## [5,]                        1 0.0025661817
## [6,]                        1 0.0056761676
## [7,]                        1 0.0269613106
```

```r
nMCMC_selgrad<-dim(model_selgrad$Sol)[1] # Sample size

# To contain posterior distribution of the variance in selgrads associated with the environment
post.Var_selgrad<-array(dim=nMCMC_selgrad)

# The posterior samples of the partial regression coefficients of selgrads on the predictor
# variables relate to the variance in selgrads associated with the multivariate environment
# according to: V(Y) = T(B) %*% V(X) %*% B
```

```r
# (standard expression for a variance of a linear transformation)
# V(Y) = variance of selection graderentials arising from environmental variation
# V(X) = covariance matrix of the environmental variable
# B = linear transformation of X onto Y (partial regression coefficients)

# Apply this transformation to each posterior sample to generate a posterior distribution of
# the variance in selgrads associated with environmental variables
# This is the numerator of equation 12 in Hunter et al. 2018, for calculating
# the proportion of the total variation in selection attributed to the environmental
# component of the model. The denominator is this quantity plus the residual variance.

# Calculate the variance, over all posterior samples
Sigma_selgrad<-var(as.matrix(model_selgrad$X[,2:4])) # Covariance matrix of environmental vars
for(i in 1:nMCMC_selgrad){
  post.Var_selgrad[i]<- t(model_selgrad$Sol[i,2:4]) %*% Sigma_selgrad %*%model_selgrad$Sol[i,2:4]
  # Variance of selgrads arising from environmental variation
}

# Two flavours of the estimate of the variance associated with the climate variables
# (Numerator of equation 12)
mean(post.Var_selgrad)
```

```
## [1] 0.01920759
```

```r
posterior.mode(as.mcmc(post.Var_selgrad))
```

```
##       var1
## 0.01031349
```

```r
# 95% credible interval of the variance
HPDinterval(as.mcmc(post.Var_selgrad))
```

```
##             lower      upper
## var1 0.0003372438 0.04396499
## attr(,"Probability")
## [1] 0.95
```

```r
# Visualise
par(mfrow=c(1,2))
plot(density(post.Var_selgrad))

# Two flavours of the estimate of the proportion of variance associated with the climate variables
# (Equation 12 in paper)
mean(post.Var_selgrad/(post.Var_selgrad+model_selgrad$VCV[,2])) # 0.6756869
```

```
## [1] 0.6785572
```

```r
posterior.mode(as.mcmc(post.Var_selgrad/(post.Var_selgrad+model_selgrad$VCV[,2]))) # 0.8413189
```

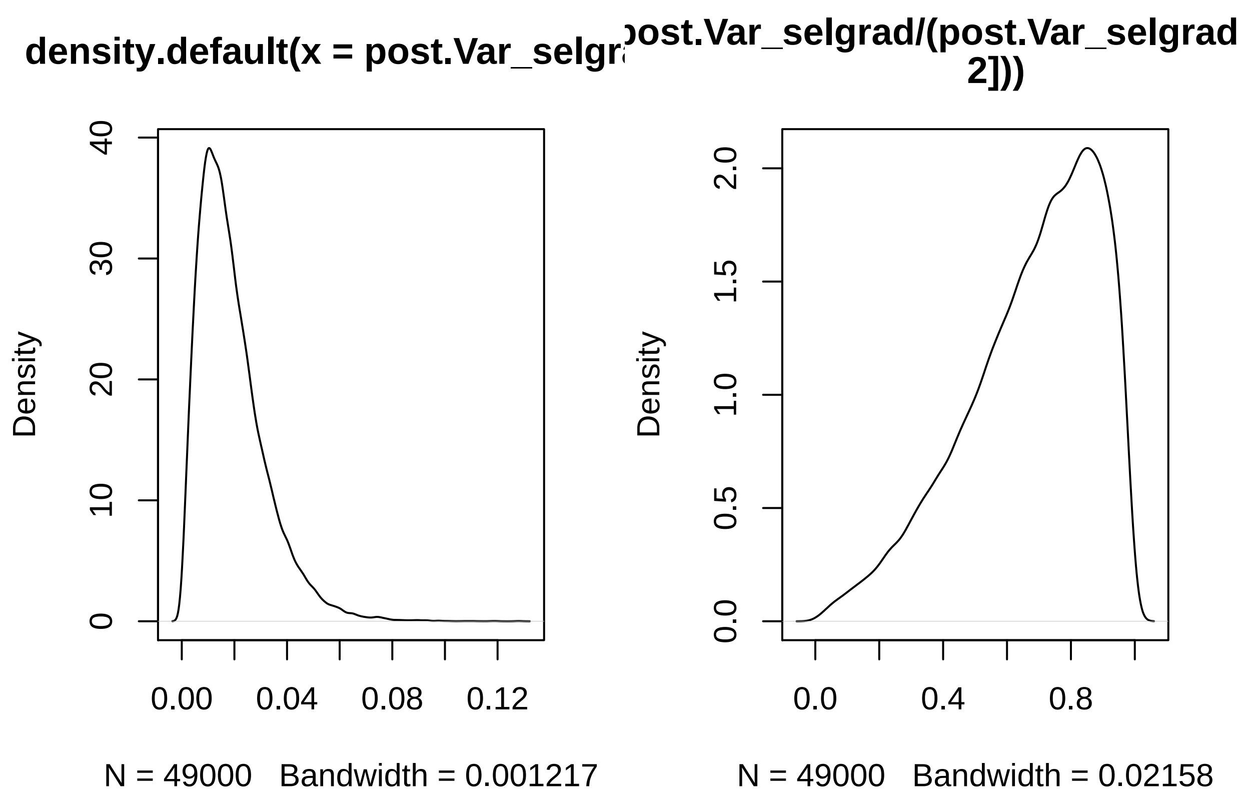
```
##      var1
## 0.8351334
```

```r
# 95% credible interval of the variance
HPDinterval(as.mcmc(post.Var_selgrad/(post.Var_selgrad+model_selgrad$VCV[,2])))
```

```
##          lower    upper
## var1 0.2734406 0.987345
```

```
## attr(,"Probability")
## [1] 0.95
```

```r
# visualise
plot(density(post.Var_selgrad/(post.Var_selgrad+model_selgrad$VCV[,2])))
```



Psterior mean vs posterior mode: This is something that Bayesians will argue about, with strong feelings and no real solution. I don't think these are differences that will massively influence your overall interpretation. The posterior mode is most directly analogous to the maximum likelihood estimate. In that sense it ought to be preferable. However, the mean is used more often, I think mostly for practical reasons (there is typically less run-to-run variation in the value of the posterior mean than mode to to MCMC error). Sorry that is not more helpful.

If you plot the posterior distributions (i.e. as a histogram or using the density() function) of your estimates of the proportions of variation explained by each variable individually, you'll find that they are very skewed. The values with the most posterior support are very small. However, the distributions will indicate very high uncertainty, with quite large values of the proportion explained being compatible with the available data, such that the mean of the posterior distribution is higher. Such are the frustrations with tackling hard and important questions that are extremely challenging analytically!