Lathyrus - Weather

Contents

Temperature and precipitation data manipulation **2**
Distributions . . . 2
Boxplots per month . . . 2
Comparisons of mean temperatures for each year for both stations . . . 3
Average mean, min and max temperature of the two stations for further use + join with precipitation data 3
Calculation of GDD and GDH . . . 4
Definition of 3 periods with respect to vernal equinox . . . 5
Calculate julian date as day with respect to vernal equinox . . . 5
Calculations weather by month . . . 5
Calculations weather by period . . . 6
Calculations weather for period "b" . . . 8

Calculations FFD stats **8**

Models of FFD against weather variables **10**
With mean of FFD . . . 10
With variance of FFD . . . 12
With range of FFD (duration* of flowering) . . . 13
With skewness of FFD . . . 14
With kurtosis of FFD . . . 14
Plots of the best models . . . 15
Models of FFD against temperature AND precipitation . . . 16

Calculations cumulated GDD/GDH **17**

Calculations proportion of plants that have started flowering at each FFD **18**

Models of proportion of plants that have started flowering against cumulated GDD/GDH **18**
Plots of the best models . . . 19

Plots for year 1990 **20**

Chilling temperatures in winter **24**

Models FFD against winter variables **24**
With mean of FFD . . . 24
With variance of FFD . . . 25
With range of FFD . . . 25
With skewness of FFD . . . 25
With kurtosis of FFD . . . 26

Influence of winter temperature / precipitation in response to spring temperature **26**
Models with effects of mean temperature April and May, measures of chilling and their interaction on mean FFD . . . 27

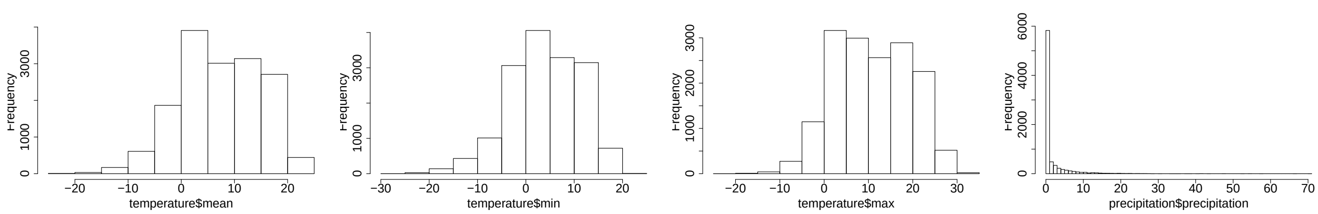
Temperature and precipitation data manipulation

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

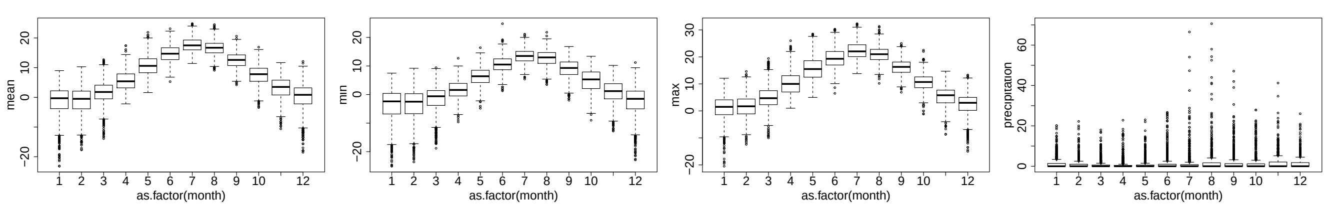
station	date	year	month	day	mean	quality_mean	min	quality_.min	max	quality_max
Oxelösund	1987-01-01	1987	1	1	-11.6	Y	-14.5	G	-9.0	G
Oxelösund	1987-01-02	1987	1	2	-10.4	Y	-16.5	G	-7.8	G
Oxelösund	1987-01-03	1987	1	3	-9.9	Y	-11.8	G	-8.3	G
Oxelösund	1987-01-04	1987	1	4	-14.1	Y	-17.0	G	-10.4	G
Oxelösund	1987-01-05	1987	1	5	-4.6	Y	-17.0	G	-1.5	G
Oxelösund	1987-01-06	1987	1	6	-10.7	Y	-14.5	G	-3.0	G

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

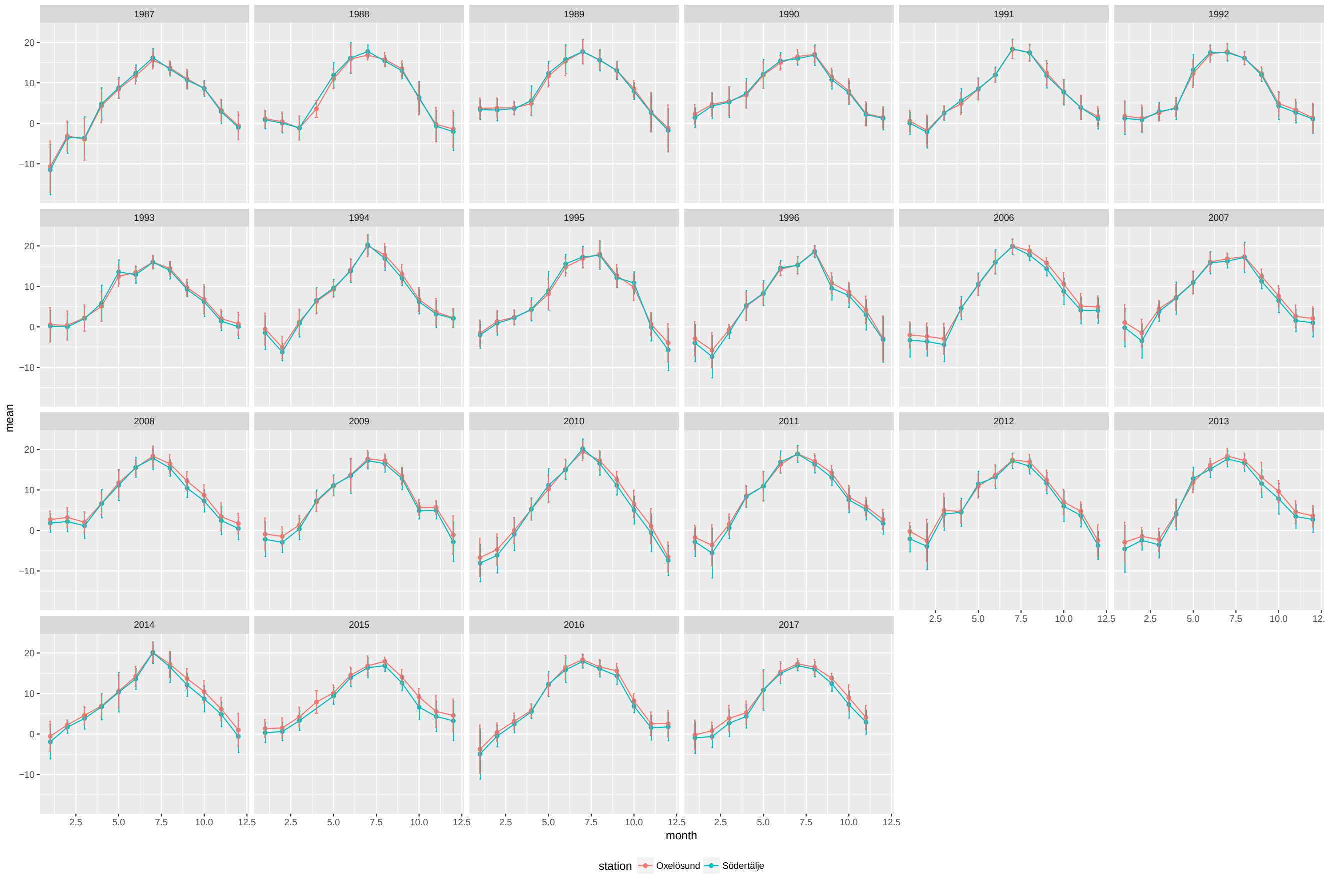
Distributions



Boxplots per month



Comparisons of mean temperatures for each year for both stations



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

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

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

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

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

```
##      year month
## 397  1988     2
## 1613 1991     6
## 1858 1992     2
## 2101 1992    10
## 7970 2017    10
```

```
## 7976 2017     11
```

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

Calculation of GDD and GDH

Bases considered: 3/5/7/10 ºC

GDD:

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

GDH:

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

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

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

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

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

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

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

Definition of 3 periods with respect to vernal equinox

a) Before vernal equinox (March 20-21 depending on the year)

b) From vernal equinox to 60 days after

c) 61+ days after vernal equinox (May 20-21 depending on the year)

```r
weather<-merge(weather,unique(alldata[c(1,6)])) #Add column with date of vernal equinox
weather$vernal_time<-as.POSIXct(weather$vernal,format="%d/%m/%y %H:%M")
weather$vernal<-as.Date(substring(weather$vernal,1,10),format="%Y-%m-%d")
weather$period<-with(weather,ifelse(date<vernal,"a",
                                ifelse(date>=vernal&date<=vernal+60,"b","c")))
```

Calculate julian date as day with respect to vernal equinox

```r
weather$date_julian<-as.numeric(with(weather,as.POSIXct(date)-vernal_time)/60/24)
```

Calculations weather by month

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

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

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

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

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

Calculations weather by period

Calculate temperature, precipitation and GDD/GDH for different periods considered to be important:
- April-June
- April-May
- January-June
- January-March
- March-April

```r
#Precipitation
mean_weather2$prec456<-with(mean_weather2,precipitation_4+precipitation_5+precipitation_6)
mean_weather2$prec45<-with(mean_weather2,precipitation_4+precipitation_5)
mean_weather2$prec123456<-with(mean_weather2,precipitation_1+precipitation_2+precipitation_3+
                    precipitation_4+precipitation_5+precipitation_6)
mean_weather2$prec123<-with(mean_weather2,precipitation_1+precipitation_2+precipitation_3)
mean_weather2$prec34<-with(mean_weather2,precipitation_3+precipitation_4)

#Mean temperature
mean_weather2$mean456<-with(mean_weather2,mean_4+mean_5+mean_6)
mean_weather2$mean45<-with(mean_weather2,mean_4+mean_5)
mean_weather2$mean123456<-with(mean_weather2,mean_1+mean_2+mean_3+mean_4+mean_5+mean_6)
mean_weather2$mean123<-with(mean_weather2,mean_1+mean_2+mean_3)
mean_weather2$mean34<-with(mean_weather2,mean_3+mean_4)
```

```
#Max temperature
mean_weather2$max456<-with(mean_weather2,max_4+max_5+max_6)
mean_weather2$max45<-with(mean_weather2,max_4+max_5)
mean_weather2$max123456<-with(mean_weather2,max_1+max_2+max_3+max_4+max_5+max_6)
mean_weather2$max123<-with(mean_weather2,max_1+max_2+max_3)
mean_weather2$max34<-with(mean_weather2,max_3+max_4)

#Min temperature
mean_weather2$min456<-with(mean_weather2,min_4+min_5+min_6)
mean_weather2$min45<-with(mean_weather2,min_4+min_5)
mean_weather2$min123456<-with(mean_weather2,min_1+min_2+min_3+min_4+min_5+min_6)
mean_weather2$min123<-with(mean_weather2,min_1+min_2+min_3)
mean_weather2$min34<-with(mean_weather2,min_3+min_4)

#GDD3
mean_weather2$GDD3_456<-with(mean_weather2,GDD3_4+GDD3_5+GDD3_6)
mean_weather2$GDD3_45<-with(mean_weather2,GDD3_4+GDD3_5)
mean_weather2$GDD3_123456<-with(mean_weather2,GDD3_1+GDD3_2+GDD3_3+GDD3_4+GDD3_5+GDD3_6)
mean_weather2$GDD3_123<-with(mean_weather2,GDD3_1+GDD3_2+GDD3_3)
mean_weather2$GDD3_34<-with(mean_weather2,GDD3_3+GDD3_4)

#GDD5
mean_weather2$GDD5_456<-with(mean_weather2,GDD5_4+GDD5_5+GDD5_6)
mean_weather2$GDD5_45<-with(mean_weather2,GDD5_4+GDD5_5)
mean_weather2$GDD5_123456<-with(mean_weather2,GDD5_1+GDD5_2+GDD5_3+GDD5_4+GDD5_5+GDD5_6)
mean_weather2$GDD5_123<-with(mean_weather2,GDD5_1+GDD5_2+GDD5_3)
mean_weather2$GDD5_34<-with(mean_weather2,GDD5_3+GDD5_4)

#GDD7
mean_weather2$GDD7_456<-with(mean_weather2,GDD7_4+GDD7_5+GDD7_6)
mean_weather2$GDD7_45<-with(mean_weather2,GDD7_4+GDD7_5)
mean_weather2$GDD7_123456<-with(mean_weather2,GDD7_1+GDD7_2+GDD7_3+GDD7_4+GDD7_5+GDD7_6)
mean_weather2$GDD7_123<-with(mean_weather2,GDD7_1+GDD7_2+GDD7_3)
mean_weather2$GDD7_34<-with(mean_weather2,GDD7_3+GDD7_4)

#GDD10
mean_weather2$GDD10_456<-with(mean_weather2,GDD10_4+GDD10_5+GDD10_6)
mean_weather2$GDD10_45<-with(mean_weather2,GDD10_4+GDD10_5)
mean_weather2$GDD10_123456<-with(mean_weather2,GDD10_1+GDD10_2+GDD10_3+GDD10_4+GDD10_5+GDD10_6)
mean_weather2$GDD10_123<-with(mean_weather2,GDD10_1+GDD10_2+GDD10_3)
mean_weather2$GDD10_34<-with(mean_weather2,GDD10_3+GDD10_4)

#GDH3
mean_weather2$GDH3_456<-with(mean_weather2,GDH3_4+GDH3_5+GDH3_6)
mean_weather2$GDH3_45<-with(mean_weather2,GDH3_4+GDH3_5)
mean_weather2$GDH3_123456<-with(mean_weather2,GDH3_1+GDH3_2+GDH3_3+GDH3_4+GDH3_5+GDH3_6)
mean_weather2$GDH3_123<-with(mean_weather2,GDH3_1+GDH3_2+GDH3_3)
mean_weather2$GDH3_34<-with(mean_weather2,GDH3_3+GDH3_4)

#GDH5
mean_weather2$GDH5_456<-with(mean_weather2,GDH5_4+GDH5_5+GDH5_6)
mean_weather2$GDH5_45<-with(mean_weather2,GDH5_4+GDH5_5)
mean_weather2$GDH5_123456<-with(mean_weather2,GDH5_1+GDH5_2+GDH5_3+GDH5_4+GDH5_5+GDH5_6)
mean_weather2$GDH5_123<-with(mean_weather2,GDH5_1+GDH5_2+GDH5_3)
mean_weather2$GDH5_34<-with(mean_weather2,GDH5_3+GDH5_4)
```

```
#GDH7
mean_weather2$GDH7_456<-with(mean_weather2,GDH7_4+GDH7_5+GDH7_6)
mean_weather2$GDH7_45<-with(mean_weather2,GDH7_4+GDH7_5)
mean_weather2$GDH7_123456<-with(mean_weather2,GDH7_1+GDH7_2+GDH7_3+GDH7_4+GDH7_5+GDH7_6)
mean_weather2$GDH7_123<-with(mean_weather2,GDH7_1+GDH7_2+GDH7_3)
mean_weather2$GDH7_34<-with(mean_weather2,GDH7_3+GDH7_4)

#GDH10
mean_weather2$GDH10_456<-with(mean_weather2,GDH10_4+GDH10_5+GDH10_6)
mean_weather2$GDH10_45<-with(mean_weather2,GDH10_4+GDH10_5)
mean_weather2$GDH10_123456<-with(mean_weather2,GDH10_1+GDH10_2+GDH10_3+GDH10_4+GDH10_5+GDH10_6)
mean_weather2$GDH10_123<-with(mean_weather2,GDH10_1+GDH10_2+GDH10_3)
mean_weather2$GDH10_34<-with(mean_weather2,GDH10_3+GDH10_4)
```

Calculations weather for period "b"

Calculate temperature, precipitation and GDD/GDH for period "b" (from vernal equinox to 60 days after) and merge with previous data

```
mean_weather1_b<-plyr::join_all(list(
    aggregate(mean ~ year, data=subset(weather,period=="b"), FUN=mean), #Mean of mean daily temperature
    aggregate(min ~ year, data=subset(weather,period=="b"), FUN=mean), #Mean of min daily temperature
    aggregate(max ~ year, data=subset(weather,period=="b"), FUN=mean), #Mean of max daily temperature
    aggregate(precipitation ~ year, data= subset(weather,period=="b"), FUN=sum),#Sum of precipitation
    aggregate(GDD3 ~ year,data= subset(weather,period=="b"), FUN=sum),          #Sum of GDD3
    aggregate(GDD5 ~ year,data= subset(weather,period=="b"), FUN=sum),          #Sum of GDD5
    aggregate(GDD7 ~ year,data= subset(weather,period=="b"), FUN=sum),          #Sum of GDD7
    aggregate(GDD10 ~ year,data= subset(weather,period=="b"), FUN=sum),         #Sum of GDD10
    aggregate(GDH3 ~ year,data= subset(weather,period=="b"), FUN=sum),          #Sum of GDH3
    aggregate(GDH5 ~ year,data= subset(weather,period=="b"), FUN=sum),          #Sum of GDH5
    aggregate(GDH7 ~ year,data= subset(weather,period=="b"), FUN=sum),          #Sum of GDH7
    aggregate(GDH10 ~ year,data= subset(weather,period=="b"), FUN=sum)),        #Sum of GDH10
    by = NULL, type = "left", match = "all")

mean_weather2_b<-gather(mean_weather1_b, variable, value,mean,min,max,precipitation,
               GDD3,GDD5,GDD7,GDD10,GDH3,GDH5,GDH7,GDH10) %>%
               unite(var, variable) %>%
               spread(var, value) #Convert to wide format with variables for period "b"
colnames(mean_weather2_b)[2:13]<-paste(colnames(mean_weather2_b)[2:13],"b", sep = "_")
```

Calculations FFD stats

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

```
mean_weather3<-merge(merge(mean_weather2,mean_weather2_b),
               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"   "prec456"           "prec45"
## [148] "prec123456"        "prec123"           "prec34"
## [151] "mean456"           "mean45"            "mean123456"
## [154] "mean123"           "mean34"            "max456"
## [157] "max45"             "max123456"         "max123"
## [160] "max34"             "min456"            "min45"
## [163] "min123456"         "min123"            "min34"
## [166] "GDD3_456"          "GDD3_45"           "GDD3_123456"
```

```
## [169] "GDD3_123"         "GDD3_34"          "GDD5_456"
## [172] "GDD5_45"          "GDD5_123456"      "GDD5_123"
## [175] "GDD5_34"          "GDD7_456"         "GDD7_45"
## [178] "GDD7_123456"      "GDD7_123"         "GDD7_34"
## [181] "GDD10_456"        "GDD10_45"         "GDD10_123456"
## [184] "GDD10_123"        "GDD10_34"         "GDH3_456"
## [187] "GDH3_45"          "GDH3_123456"      "GDH3_123"
## [190] "GDH3_34"          "GDH5_456"         "GDH5_45"
## [193] "GDH5_123456"      "GDH5_123"         "GDH5_34"
## [196] "GDH7_456"         "GDH7_45"          "GDH7_123456"
## [199] "GDH7_123"         "GDH7_34"          "GDH10_456"
## [202] "GDH10_45"         "GDH10_123456"     "GDH10_123"
## [205] "GDH10_34"         "GDD10_b"          "GDD3_b"
## [208] "GDD5_b"           "GDD7_b"           "GDH10_b"
## [211] "GDH3_b"           "GDH5_b"           "GDH7_b"
## [214] "max_b"            "mean_b"           "min_b"
## [217] "precipitation_b"  "FFD_mean"         "FFD_var"
## [220] "FFD_dur"          "FFD_skew"         "FFD_kurt"
```

Models of FFD against weather variables

With mean of FFD

```r
models<-lapply(names(mean_weather3)[c(7:9,19:21,31:33,43:45,
        55:57,67:69,79:81,91:93,103:105,115:117,127:129,139:141,146:217)],
         function(x) {lm(substitute(FFD_mean ~ scale(i), list(i = as.name(x))),
                          data = mean_weather3)})
models_summary<-lapply(X = models, FUN = summary)%>% lapply(prettify) %>% bind_rows()
models_summary<-models_summary[c(1:2,5,6)]
names(models_summary)<-c("variable","Estimate","P","sig")
models_summary<-subset(models_summary,!variable=="(Intercept)")
models_summary<-cbind(models_summary,sapply(lapply(X = models, FUN = summary), "[[", 9))
names(models_summary)[5]<-"Rsquare"
kable(arrange(subset(models_summary,P<0.05),desc(Rsquare)))
```

variable	Estimate	P	sig	Rsquare
scale(mean45)	-5.184990	<0.001	***	0.7630498
scale(GDD3_45)	-5.044179	<0.001	***	0.7194888
scale(GDH3_45)	-5.017876	<0.001	***	0.7114849
scale(max45)	-4.952874	<0.001	***	0.6918838
scale(GDH5_45)	-4.880152	<0.001	***	0.6702579
scale(min45)	-4.868691	<0.001	***	0.6668788
scale(GDD5_45)	-4.812688	<0.001	***	0.6504817
scale(GDD3_123456)	-4.635369	<0.001	***	0.5998155
scale(max456)	-4.624642	<0.001	***	0.5968114
scale(mean_b)	-4.595254	<0.001	***	0.5886171
scale(GDH3_123456)	-4.587069	<0.001	***	0.5863439
scale(mean456)	-4.585923	<0.001	***	0.5860261
scale(GDH7_45)	-4.582832	<0.001	***	0.5851690
scale(GDD3_b)	-4.579945	<0.001	***	0.5843690
scale(GDH3_b)	-4.545754	<0.001	***	0.5749327
scale(max_b)	-4.503158	<0.001	***	0.5632756
scale(GDH5_b)	-4.411765	<0.001	***	0.5386352
scale(GDD3_456)	-4.408219	<0.001	***	0.5376892

variable	Estimate	P	sig	Rsquare
scale(GDD7_45)	-4.382465	<0.001	***	0.5308423
scale(GDH5_123456)	-4.357646	<0.001	***	0.5242821
scale(GDH3_456)	-4.347540	<0.001	***	0.5216214
scale(GDD5_b)	-4.289443	<0.001	***	0.5064463
scale(GDD5_123456)	-4.264398	<0.001	***	0.4999672
scale(max123456)	-4.195745	<0.001	***	0.4824018
scale(GDH7_b)	-4.123679	<0.001	***	0.4642699
scale(GDD5_456)	-4.106000	<0.001	***	0.4598697
scale(GDH5_456)	-4.099952	<0.001	***	0.4583689
scale(GDH10_45)	-3.925744	0.001	***	0.4160853
scale(GDH7_123456)	-3.906964	0.001	***	0.4116365
scale(mean_5)	-3.900101	0.001	***	0.4100162
scale(min456)	-3.899413	0.001	***	0.4098539
scale(max_5)	-3.856773	0.001	***	0.3998518
scale(GDD3_5)	-3.850707	0.001	***	0.3984379
scale(mean123456)	-3.827378	0.001	**	0.3930207
scale(GDH3_5)	-3.826077	0.001	**	0.3927197
scale(GDD5_5)	-3.816282	0.001	**	0.3904556
scale(GDH5_5)	-3.759896	0.001	**	0.3775364
scale(GDD3_34)	-3.759883	0.001	**	0.3775333
scale(GDD7_b)	-3.757060	0.001	**	0.3768917
scale(GDH7_456)	-3.720840	0.002	**	0.3687005
scale(GDD7_123456)	-3.697863	0.002	**	0.3635453
scale(GDH3_34)	-3.668764	0.002	**	0.3570624
scale(min_b)	-3.662870	0.002	**	0.3557554
scale(GDD7_5)	-3.627302	0.002	**	0.3479135
scale(GDD7_456)	-3.615971	0.002	**	0.3454315
scale(GDH7_5)	-3.607169	0.002	**	0.3435086
scale(min_5)	-3.562855	0.003	**	0.3338996
scale(max34)	-3.557881	0.003	**	0.3328285
scale(GDH5_34)	-3.408210	0.005	**	0.3012967
scale(GDH10_b)	-3.373028	0.005	**	0.2940815
scale(mean34)	-3.372754	0.005	**	0.2940255
scale(min_4)	-3.350947	0.006	**	0.2895912
scale(mean_4)	-3.346046	0.006	**	0.2885986
scale(min123456)	-3.325944	0.006	**	0.2845424
scale(GDD10_45)	-3.281799	0.007	**	0.2757207
scale(GDH10_5)	-3.264463	0.007	**	0.2722885
scale(GDD5_34)	-3.260892	0.008	**	0.2715839
scale(GDD3_4)	-3.179679	0.01	**	0.2557651
scale(GDH10_123456)	-3.177653	0.01	**	0.2553757
scale(GDD3_123)	-3.130368	0.011	*	0.2463550
scale(GDH3_123)	-3.117478	0.011	*	0.2439194
scale(GDH10_456)	-3.103625	0.012	*	0.2413129
scale(GDH7_34)	-3.101454	0.012	*	0.2409056
scale(GDH3_4)	-3.073732	0.013	*	0.2357284
scale(max123)	-3.056833	0.013	*	0.2325952
scale(max_3)	-2.980283	0.016	*	0.2186187
scale(mean123)	-2.953969	0.017	*	0.2138962
scale(GDD10_5)	-2.946252	0.018	*	0.2125193
scale(GDD3_3)	-2.921262	0.019	*	0.2080848
scale(GDH3_3)	-2.915207	0.019	*	0.2070160
scale(GDH5_4)	-2.900750	0.02	*	0.2044732
scale(GDD5_4)	-2.876729	0.021	*	0.2002760
scale(max_4)	-2.857728	0.022	*	0.1969808

variable	Estimate	P	sig	Rsquare
scale(GDH5_123)	-2.832867	0.024	*	0.1927021
scale(min34)	-2.826040	0.024	*	0.1915338
scale(min123)	-2.797927	0.026	*	0.1867522
scale(GDD10_123456)	-2.739030	0.029	*	0.1768897
scale(GDD10_456)	-2.721254	0.03	*	0.1739544
scale(prec123)	-2.712312	0.031	*	0.1724851
scale(GDH7_4)	-2.703993	0.032	*	0.1711223
scale(GDD7_34)	-2.690342	0.033	*	0.1688953
scale(mean_3)	-2.657436	0.035	*	0.1635733
scale(GDH5_3)	-2.656617	0.035	*	0.1634417
scale(GDH10_34)	-2.503700	0.049	*	0.1395771

The model explaining the most variance is still the one with mean daily temperature for April and May, followed by GDD3 and GDH3 for April and May.
April and May seems to be the most important period.

With variance of FFD

```
models1<-lapply(names(mean_weather3)[c(7:9,19:21,31:33,43:45,
        55:57,67:69,79:81,91:93,103:105,115:117,127:129,139:141,146:217)],
         function(x) {lm(substitute(FFD_var ~ scale(i), list(i = as.name(x))),
                          data = mean_weather3)})
models1_summary<-lapply(X = models1, FUN = summary)%>% lapply(prettify) %>% bind_rows()
models1_summary<-models1_summary[c(1:2,5,6)]
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 = summary), "[[", 9))
names(models1_summary)[5]<-"Rsquare"
kable(arrange(subset(models1_summary,P<0.05),desc(Rsquare)))
```

variable	Estimate	P	sig	Rsquare
scale(min_4)	8.151468	<0.001	***	0.4743879
scale(mean_4)	8.038161	<0.001	***	0.4599109
scale(GDH3_4)	8.037441	<0.001	***	0.4598196
scale(GDD3_4)	8.032277	<0.001	***	0.4591648
scale(GDH5_4)	7.853654	<0.001	***	0.4367707
scale(GDD5_4)	7.813938	0.001	***	0.4318600
scale(prec123)	7.488779	0.001	**	0.3925914
scale(max_4)	7.421222	0.001	**	0.3846421
scale(GDH7_4)	7.322167	0.002	**	0.3731168
scale(GDD3_34)	7.306501	0.002	**	0.3713081
scale(GDH3_34)	7.253307	0.002	**	0.3651959
scale(GDH5_34)	7.246428	0.002	**	0.3644088
scale(GDD5_34)	6.996616	0.003	**	0.3363287
scale(GDH7_34)	6.937819	0.003	**	0.3298629
scale(GDD7_4)	6.843835	0.004	**	0.3196409
scale(max34)	6.627601	0.005	**	0.2966520
scale(mean34)	6.619558	0.005	**	0.2958112
scale(precipitation_3)	6.538071	0.006	**	0.2873496
scale(GDD7_34)	6.340653	0.008	**	0.2672846
scale(min34)	6.145390	0.011	*	0.2480437
scale(GDH10_4)	5.956967	0.014	*	0.2300473

variable	Estimate	P	sig	Rsquare
scale(GDD10__5)	-5.883035	0.015	*	0.2231391
scale(GDH10__34)	5.811609	0.017	*	0.2165470
scale(GDH10__5)	-5.773252	0.018	*	0.2130402
scale(GDH7__5)	-5.329271	0.03	*	0.1741386
scale(prec123456)	5.273856	0.032	*	0.1695015
scale(GDD7__5)	-5.175003	0.036	*	0.1613499
scale(GDD10__45)	-5.125389	0.038	*	0.1573169
scale(max__5)	-5.008008	0.043	*	0.1479297
scale(GDH5__5)	-4.986880	0.044	*	0.1462632

The models explaining the most variance are those with temperatures in April. Also precipitation January-March explains quite a lot. Variance in phenology increases when April is warm and January-March are rainy.

With range of FFD (duration* of flowering)

*Not including the time that last flowers are open

```
models2<-lapply(names(mean_weather3)[c(7:9,19:21,31:33,43:45,
        55:57,67:69,79:81,91:93,103:105,115:117,127:129,139:141,146:217)],
         function(x) {lm(substitute(FFD_dur ~ scale(i), list(i = as.name(x))),
                         data = mean_weather3)})
models2_summary<-lapply(X = models2, FUN = summary)%>% lapply(prettify) %>% bind_rows()
models2_summary<-models2_summary[c(1:2,5,6)]
names(models2_summary)<-c("variable","Estimate","P","sig")
models2_summary<-subset(models2_summary,!variable=="(Intercept)")
models2_summary<-cbind(models2_summary,sapply(lapply(X = models2, FUN = summary), "[[", 9))
names(models2_summary)[5]<-"Rsquare"
kable(arrange(subset(models2_summary,P<0.05),desc(Rsquare)))
```

variable	Estimate	P	sig	Rsquare
scale(mean__4)	3.621201	0.003	**	0.3328336
scale(GDH3__4)	3.614649	0.003	**	0.3314496
scale(GDD3__4)	3.609215	0.003	**	0.3303035
scale(GDH5__4)	3.604250	0.003	**	0.3292578
scale(GDD5__4)	3.562413	0.004	**	0.3205044
scale(min__4)	3.548473	0.004	**	0.3176104
scale(GDH7__4)	3.528323	0.004	**	0.3134472
scale(max__4)	3.462665	0.005	**	0.3000465
scale(GDH7__34)	3.450340	0.005	**	0.2975590
scale(GDD5__34)	3.359466	0.007	**	0.2794923
scale(GDD7__34)	3.331894	0.007	**	0.2741060
scale(GDH5__34)	3.319082	0.008	**	0.2716183
scale(GDH10__34)	3.317050	0.008	**	0.2712246
scale(GDD7__4)	3.269501	0.009	**	0.2620814
scale(GDH10__4)	3.185110	0.011	*	0.2461786
scale(GDD3__34)	3.161853	0.012	*	0.2418691
scale(precipitation__4)	-3.127918	0.013	*	0.2356377
scale(GDD10__34)	3.046065	0.016	*	0.2208839
scale(GDH3__34)	3.038279	0.016	*	0.2195009
scale(prec45)	-2.910855	0.022	*	0.1973694
scale(max__b)	2.812926	0.028	*	0.1810050
scale(mean__b)	2.784634	0.029	*	0.1763815
scale(GDD10__4)	2.764382	0.031	*	0.1731008

variable	Estimate	P	sig	Rsquare
scale(GDH3_b)	2.600170	0.044	*	0.1473823
scale(GDD3_b)	2.599882	0.044	*	0.1473386

The models explaining the most variance are those with temperatures in April. Duration of flowering increases when April is warm. Also precipitation in April explains quite a lot, with duration decreasing when April is rainy.

With skewness of FFD

```
models3<-lapply(names(mean_weather3)[c(7:9,19:21,31:33,43:45,
        55:57,67:69,79:81,91:93,103:105,115:117,127:129,139:141,146:217)],
         function(x) {lm(substitute(FFD_skew ~ scale(i), list(i = as.name(x))),
                          data = mean_weather3)})
models3_summary<-lapply(X = models3, FUN = summary)%>% lapply(prettify) %>% bind_rows()
models3_summary<-models3_summary[c(1:2,5,6)]
names(models3_summary)<-c("variable","Estimate","P","sig")
models3_summary<-subset(models3_summary,!variable=="(Intercept)")
models3_summary<-cbind(models3_summary,sapply(lapply(X = models3, FUN = summary), "[[", 9))
names(models3_summary)[5]<-"Rsquare"
kable(arrange(subset(models3_summary,P<0.05),desc(Rsquare)))
```

variable	Estimate	P	sig	Rsquare
scale(max_3)	-0.2778038	0.016	*	0.2195825
scale(mean_3)	-0.2723942	0.019	*	0.2091858
scale(min_3)	-0.2630691	0.024	*	0.1917437
scale(GDH3_3)	-0.2346696	0.047	*	0.1423664

The models explaining the most variance are those with temperatures in March. The positive skewness of the FFD curve increases when March is cold. This could mean that when March is cold, there is a faster response to warming temperatures, and more plants start flowering in the beginning of the season?

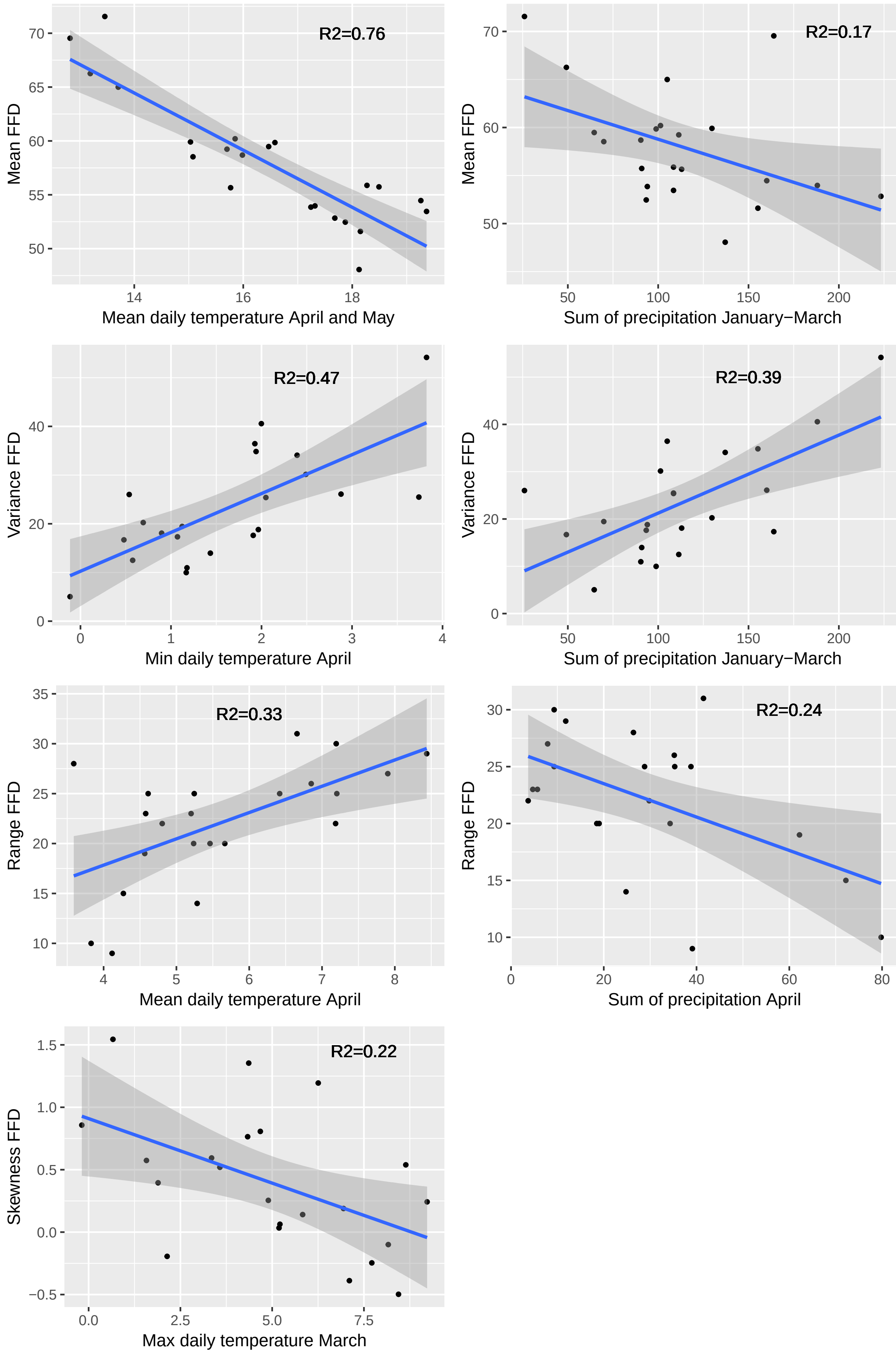
With kurtosis of FFD

```
models4<-lapply(names(mean_weather3)[c(7:9,19:21,31:33,43:45,
        55:57,67:69,79:81,91:93,103:105,115:117,127:129,139:141,146:217)],
         function(x) {lm(substitute(FFD_kurt ~ scale(i), list(i = as.name(x))),
                          data = mean_weather3)})
models4_summary<-lapply(X = models4, FUN = summary)%>% lapply(prettify) %>% bind_rows()
models4_summary<-models4_summary[c(1:2,5,6)]
names(models4_summary)<-c("variable","Estimate","P","sig")
models4_summary<-subset(models4_summary,!variable=="(Intercept)")
models4_summary<-cbind(models4_summary,sapply(lapply(X = models4, FUN = summary), "[[", 9))
names(models4_summary)[5]<-"Rsquare"
kable(arrange(subset(models4_summary,P<0.05),desc(Rsquare)))
```

variable Estimate P sig Rsquare ——— ——— — —- ———

No sigificant relationships for FFD_kurt.

Plots of the best models



Models of FFD against temperature AND precipitation

Adding precipitation does not increase much the R2

```
summary(lm(FFD_mean~mean45+prec123,mean_weather3)) #Increase from 0.76 to 0.77
```

```
##
## Call:
## lm(formula = FFD_mean ~ mean45 + prec123, data = mean_weather3)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -5.2507 -1.2709 -0.1221  2.2449  4.4405
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 101.00818    5.19573  19.441 5.33e-14 ***
## mean45       -2.47939    0.33725  -7.352 5.74e-07 ***
## prec123      -0.02010    0.01452  -1.384    0.182
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.805 on 19 degrees of freedom
## Multiple R-squared:  0.795,  Adjusted R-squared:  0.7734
## F-statistic: 36.84 on 2 and 19 DF,  p-value: 2.894e-07
```

```
summary(lm(FFD_var~min_4+prec123,mean_weather3))  #Increase from 0.47 to 0.54
```

```
##
## Call:
## lm(formula = FFD_var ~ min_4 + prec123, data = mean_weather3)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -9.4595 -6.0517 -0.4775  5.2824 16.6785
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  3.97186    4.58187   0.867   0.3968
## min_4        5.60130    2.08084   2.692   0.0144 *
## prec123      0.09022    0.04683   1.927   0.0691 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7.847 on 19 degrees of freedom
## Multiple R-squared:  0.5812, Adjusted R-squared:  0.5371
## F-statistic: 13.19 on 2 and 19 DF,  p-value: 0.0002563
```

```
summary(lm(FFD_dur~mean_4+precipitation_4,mean_weather3))  #Increase from 0.33 to 0.37
```

```
##
## Call:
## lm(formula = FFD_dur ~ mean_4 + precipitation_4, data = mean_weather3)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -9.2605 -2.0883 -0.2592  1.9054  9.7233
##
## Coefficients:
```

```
##                 Estimate Std. Error t value Pr(>|t|)
## (Intercept)     13.31611    5.90498   2.255   0.0361 *
## mean_4           2.00158    0.86087   2.325   0.0313 *
## precipitation_4 -0.08428    0.05554  -1.517   0.1456
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.746 on 19 degrees of freedom
## Multiple R-squared:  0.4333, Adjusted R-squared:  0.3736
## F-statistic: 7.263 on 2 and 19 DF,  p-value: 0.004539
```

Calculations cumulated GDD/GDH

Sum of GDD/GDH until each date, with 3 different starting dates:
- from the start of the year
- from the vernal equinox
- from April 15 (or 16) - vernal equinox + 26 days

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

#From vernal equinox
weather_vernal<-as.data.frame(subset(weather,period=="b"|period=="c") %>%
                dplyr::group_by(year) %>%
                dplyr::mutate(cumGDD3v=cumsum(x = GDD3),cumGDD5v=cumsum(x = GDD5),
                       cumGDD7v=cumsum(x = GDD7),cumGDD10v=cumsum(x = GDD10),
                       cumGDH3v=cumsum(x = GDH3),cumGDH5v=cumsum(x = GDH5),
                       cumGDH7v=cumsum(x = GDH7),cumGDH10v=cumsum(x = GDH10)))

#From April 15 (or 16) - vernal equinox + 26 days
weather_apr15<-as.data.frame(subset(weather,date>=vernal+26) %>%
                dplyr::group_by(year) %>%
                dplyr::mutate(cumGDD3a=cumsum(x = GDD3),cumGDD5a=cumsum(x = GDD5),
                       cumGDD7a=cumsum(x = GDD7),cumGDD10a=cumsum(x = GDD10),
                       cumGDH3a=cumsum(x = GDH3),cumGDH5a=cumsum(x = GDH5),
                       cumGDH7a=cumsum(x = GDH7),cumGDH10a=cumsum(x = GDH10)))
```

Merge with previous data

```
weather$FFD<-weather$date_julian
weather_vernal$FFD<-weather_vernal$date_julian
weather_apr15$FFD<-weather_apr15$date_julian

alldata_weather<-merge(alldata, weather[c(1,6:17,22:30)], all.x=T,all.y=F)
alldata_weather<-merge(alldata_weather,weather_vernal[c(1,30:38)], all.x=T,all.y=F)
alldata_weather<-merge(alldata_weather,weather_apr15[c(1,30:38)], all.x=T,all.y=F)
```

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

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

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

```r
nrow(subset(alldata_weather_subs,n_fr>n_fl)) #4 cases where n_fruits>n_flowers --> fix again
```

```
## [1] 4
```

```r
#Equal n_fl to n_fr
alldata_weather_subs$n_fl<-with(alldata_weather_subs,ifelse(n_fr>n_fl,n_fr,n_fl))
```

Calculations proportion of plants that have started flowering at each FFD

```r
#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+
                          cumGDD3v+cumGDD5v+cumGDD7v+cumGDD10v+cumGDH3v+cumGDH5v+cumGDH7v+cumGDH10v+
                          cumGDD3a+cumGDD5a+cumGDD7a+cumGDD10a+cumGDH3a+cumGDH5a+cumGDH7a+cumGDH10a+year,
                          data=alldata_weather_subs[c(1:2,4,32:55)],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

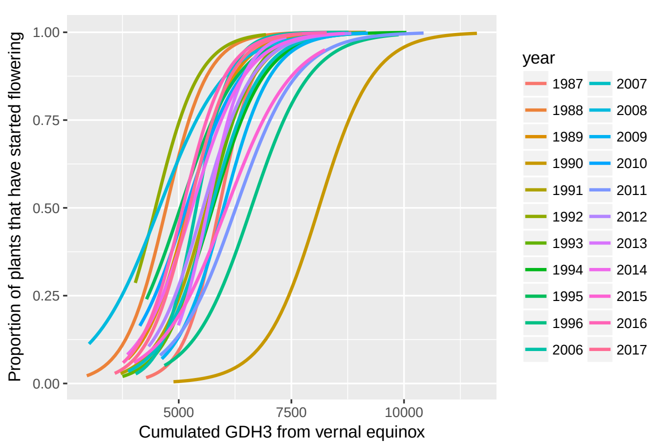
```r
#Fit univariate binomial GLMs of prop_fl against each predictor
models5<-lapply(names(alldata_agg)[2:25],
         function(x) {glm(substitute(prop_fl ~ scale(i), list(i = as.name(x))),
                          family=binomial, data = alldata_agg)})

models5_summary<-lapply(X = models5, FUN = summary)%>% lapply(prettify) %>% bind_rows()
models5_summary<-models5_summary[c(1:2,5,7)]
names(models5_summary)<-c("variable","Estimate","P","sig")
models5_summary<-subset(models5_summary,!variable=="(Intercept)")
models5_summary<-cbind(models5_summary,sapply(lapply(X = models5, FUN = NagelkerkeR2), "[[", 2))
names(models5_summary)[5]<-"Rsquare"
kable(arrange(subset(models5_summary,P<0.05),desc(Rsquare)))
```

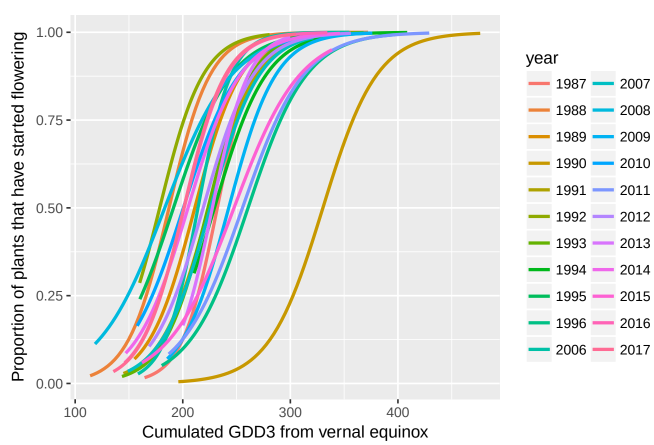
variable	Estimate	P	sig	Rsquare
scale(cumGDH3v)	2.082269	<0.001	***	0.8247790
scale(cumGDD3v)	2.057905	<0.001	***	0.8164516
scale(cumGDH5v)	2.056648	<0.001	***	0.8040185
scale(cumGDD5v)	2.001531	<0.001	***	0.7844822
scale(cumGDH7v)	2.008885	<0.001	***	0.7681064
scale(cumGDH3a)	1.838762	<0.001	***	0.7538278
scale(cumGDH5a)	1.851639	<0.001	***	0.7502433
scale(cumGDD3a)	1.812851	<0.001	***	0.7439834
scale(cumGDH7)	1.997160	<0.001	***	0.7368036
scale(cumGDD5a)	1.818132	<0.001	***	0.7362666
scale(cumGDD7v)	1.929839	<0.001	***	0.7316111
scale(cumGDH5)	1.936327	<0.001	***	0.7303357
scale(cumGDD5)	1.936957	<0.001	***	0.7296362
scale(cumGDH7a)	1.839629	<0.001	***	0.7284625
scale(cumGDD7a)	1.820732	<0.001	***	0.7108344
scale(cumGDD7)	1.912560	<0.001	***	0.7024659
scale(cumGDD3)	1.767286	<0.001	***	0.6746137
scale(cumGDH10v)	1.822322	<0.001	***	0.6631881
scale(cumGDH10)	1.843080	<0.001	***	0.6521309
scale(cumGDH3)	1.700881	<0.001	***	0.6504500
scale(cumGDH10a)	1.697304	<0.001	***	0.6366075
scale(cumGDD10v)	1.573997	<0.001	***	0.5572632
scale(cumGDD10a)	1.549451	<0.001	***	0.5511551
scale(cumGDD10)	1.578339	<0.001	***	0.5489817

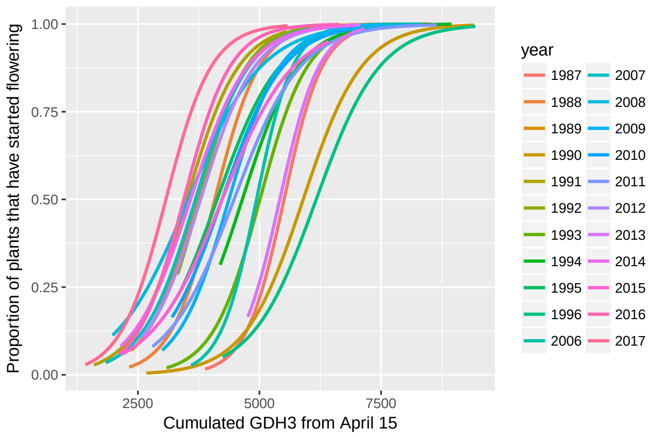
The cumulated number of GDH3 and GDD3 (computed from the vernal equinox) are the variables explaining more variation in the proportion of plants that have started flowering

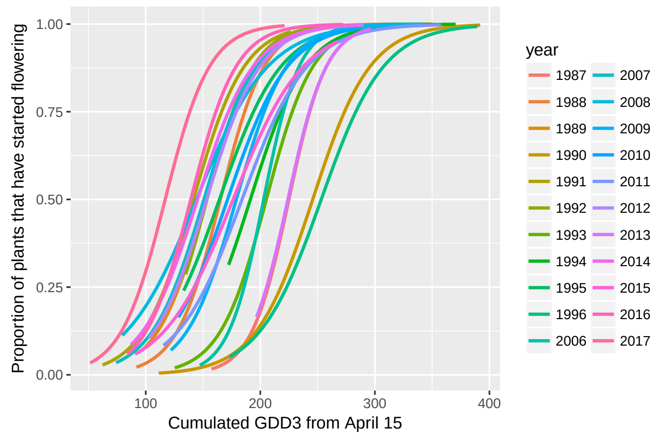
Plots of the best models

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



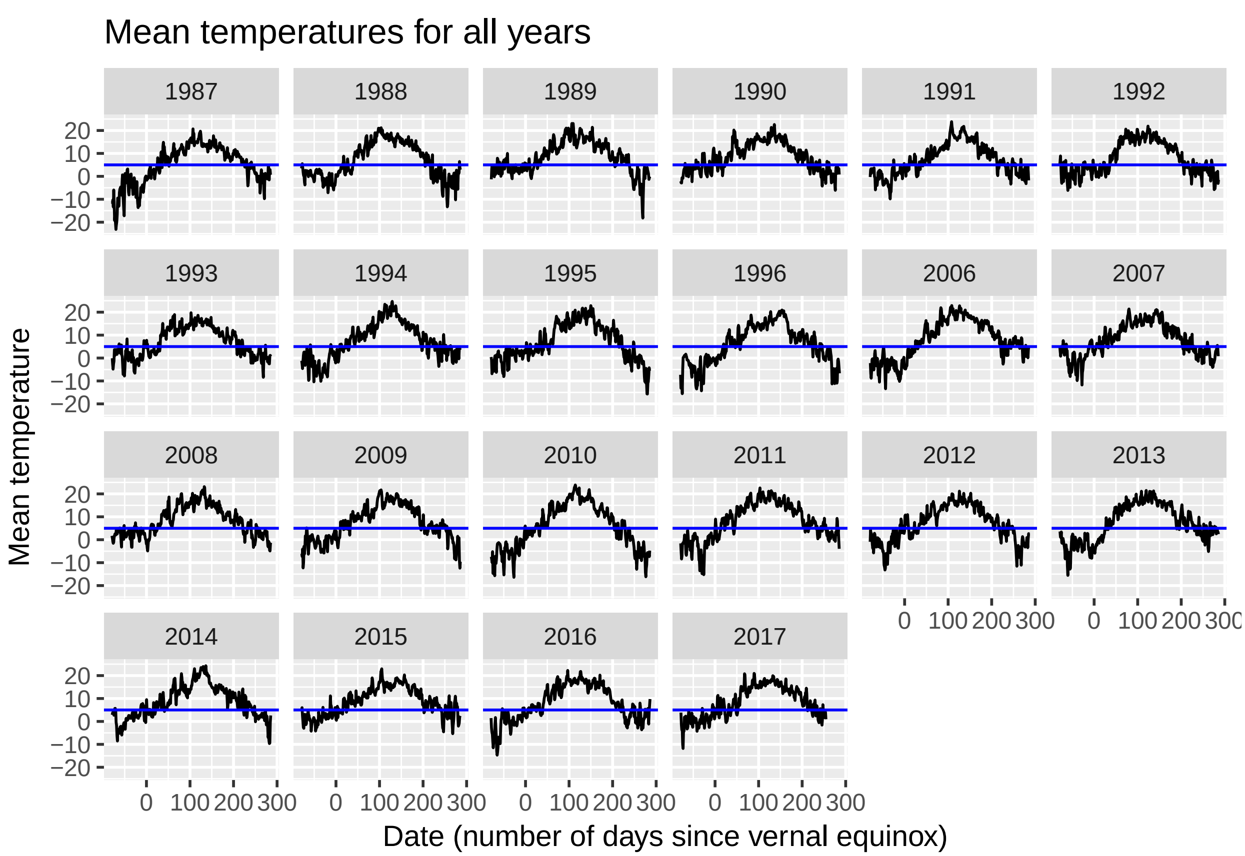


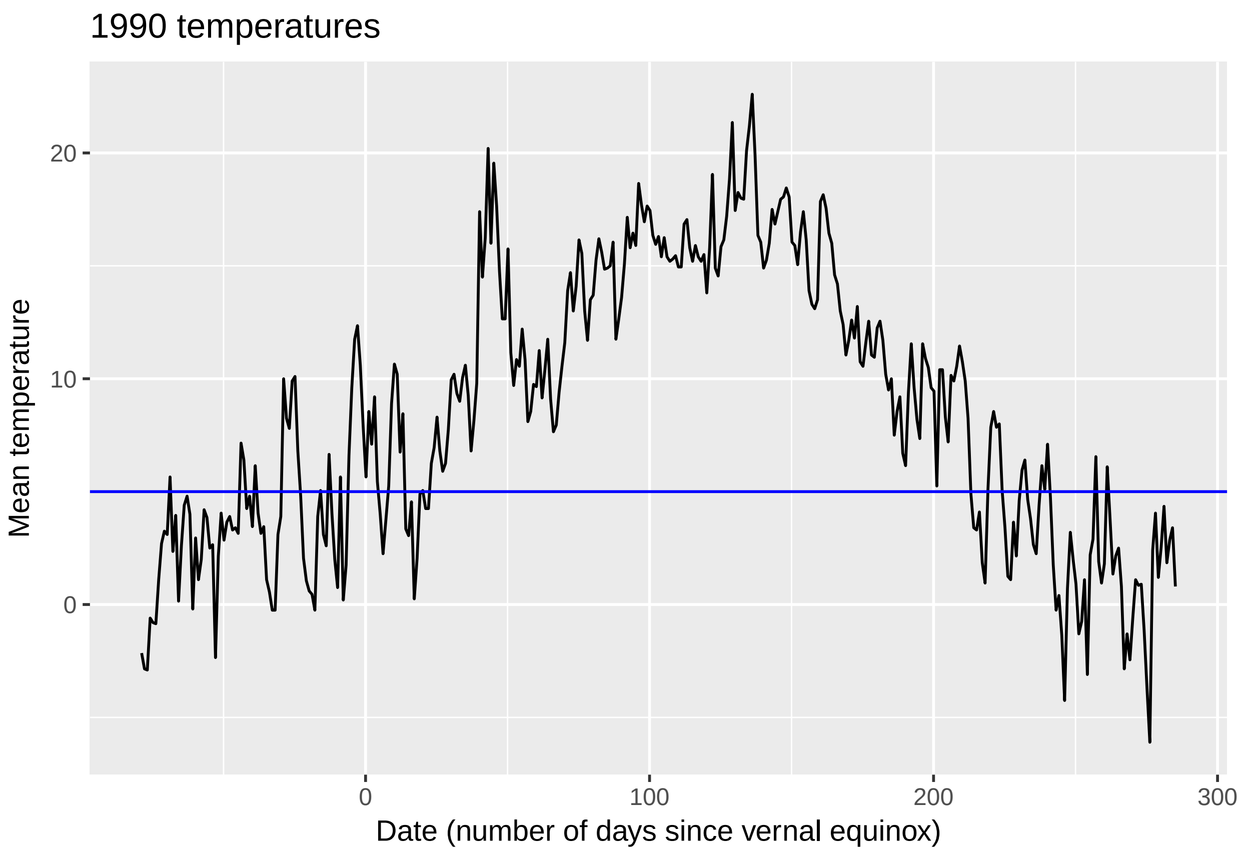


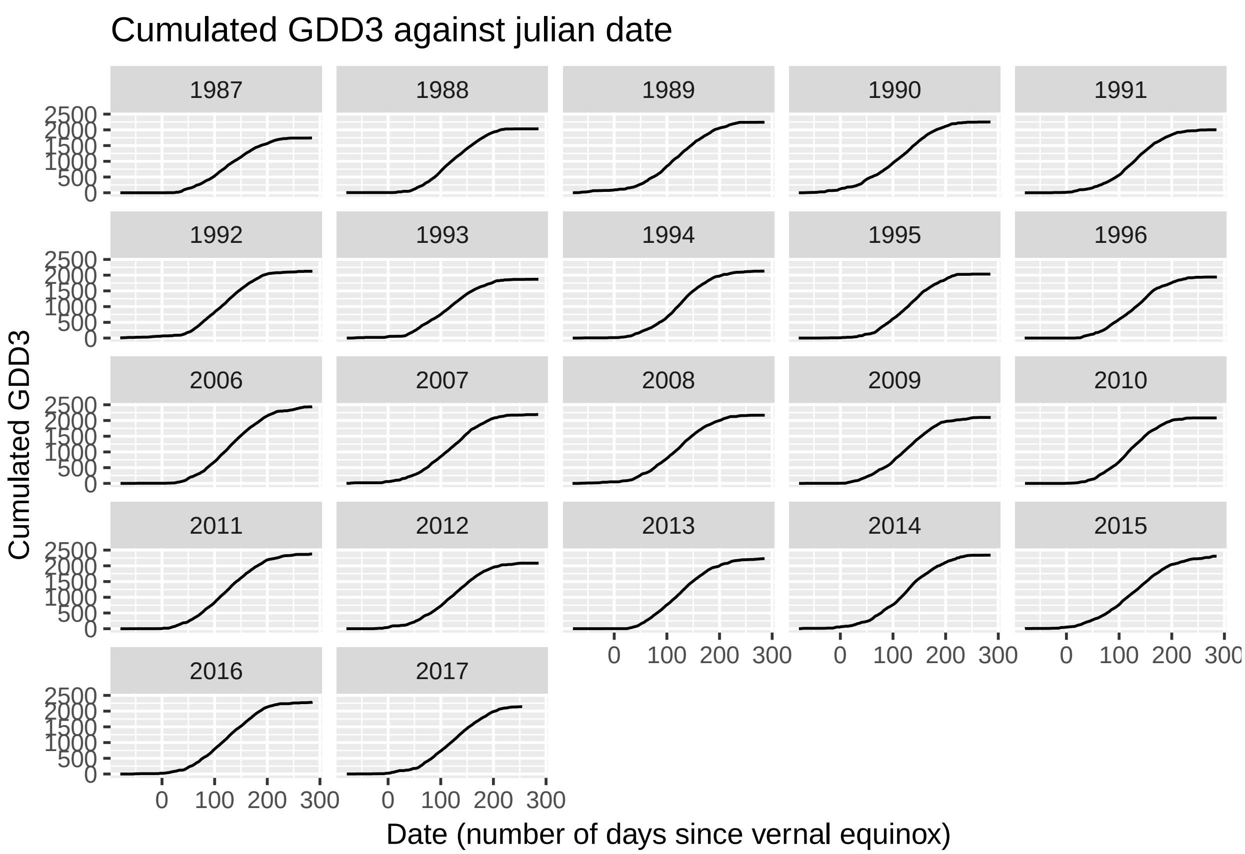


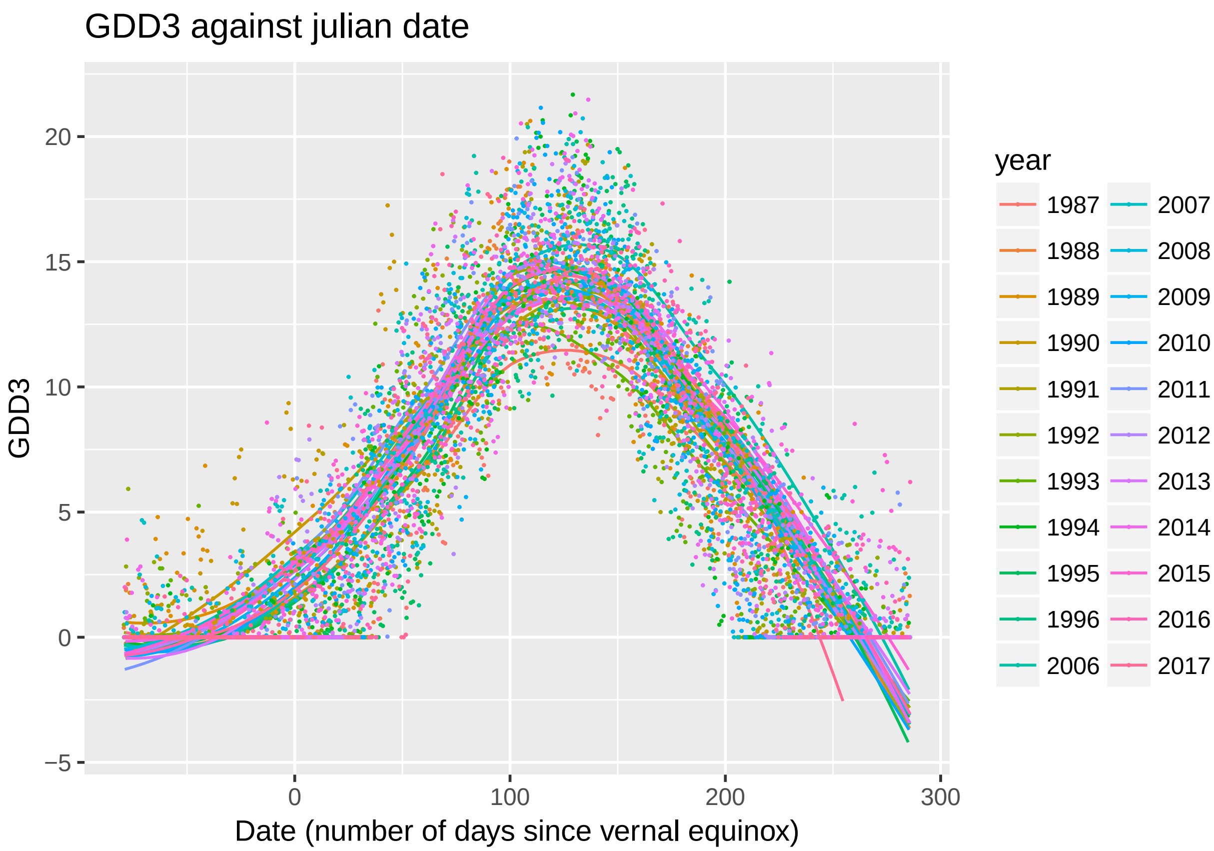
Plots for year 1990

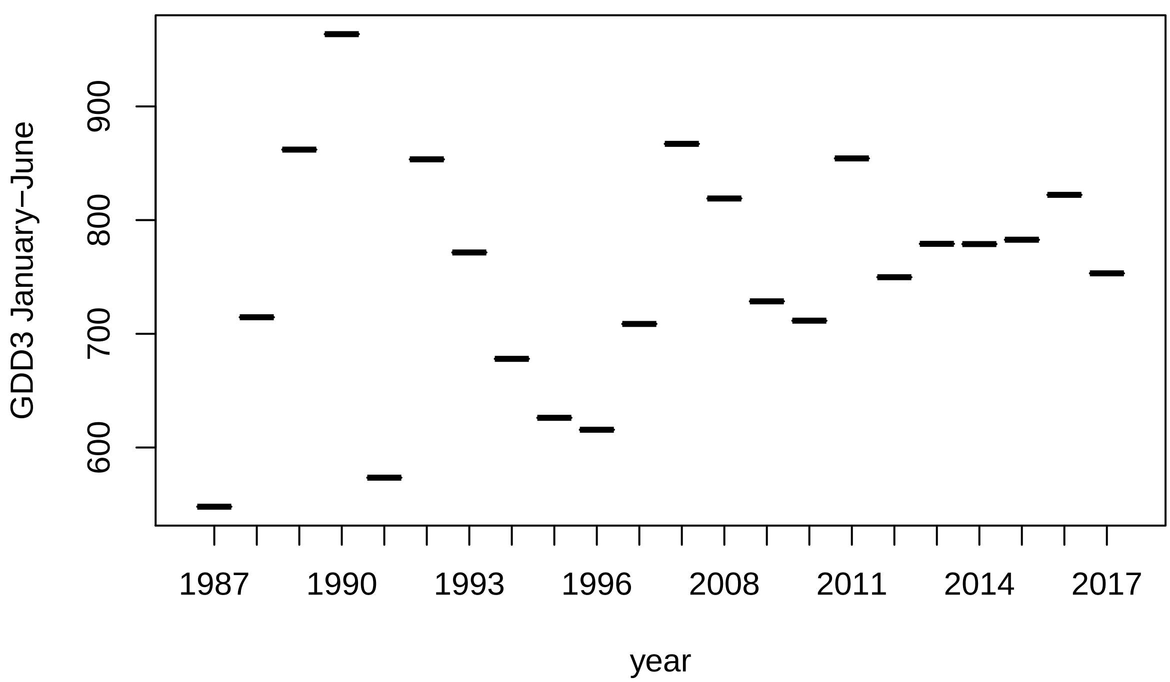
Year 1990 shows high values of GDD/GDH
Some plots to look at these high values

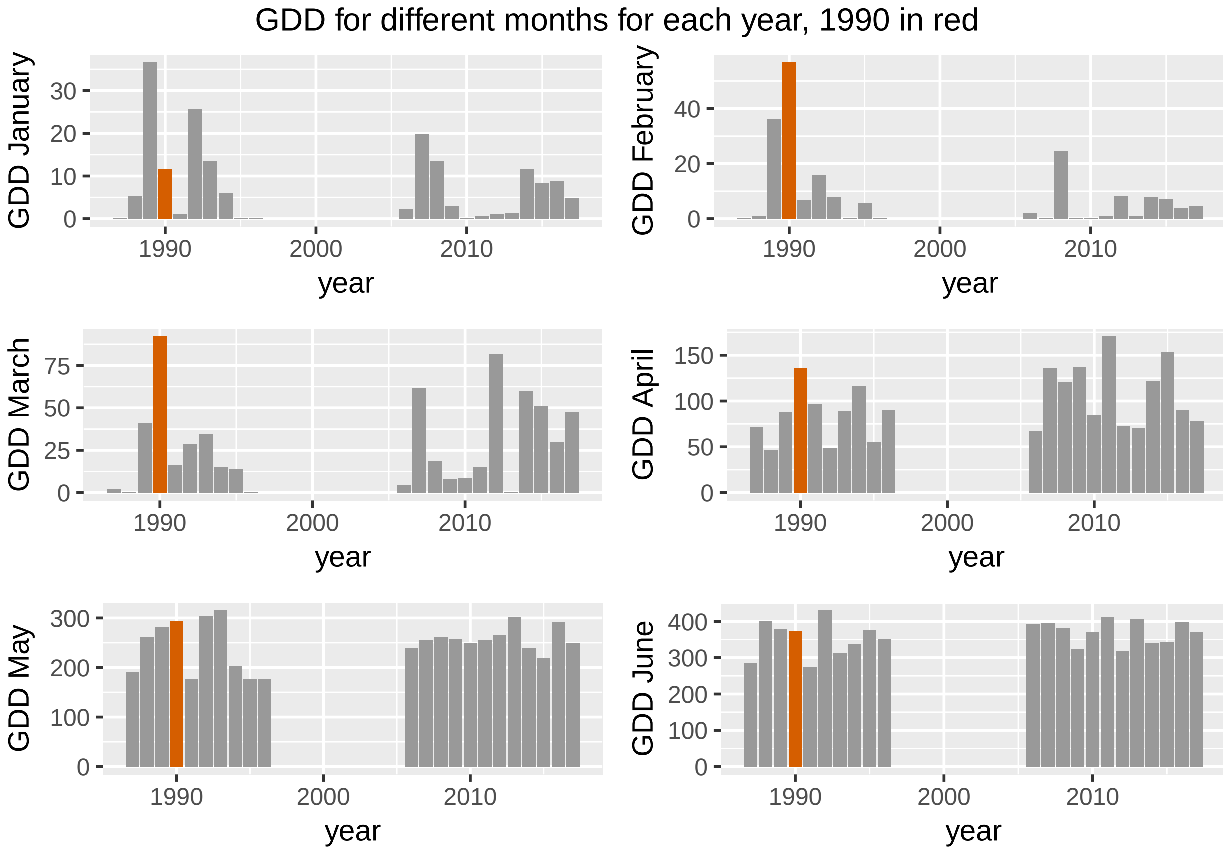


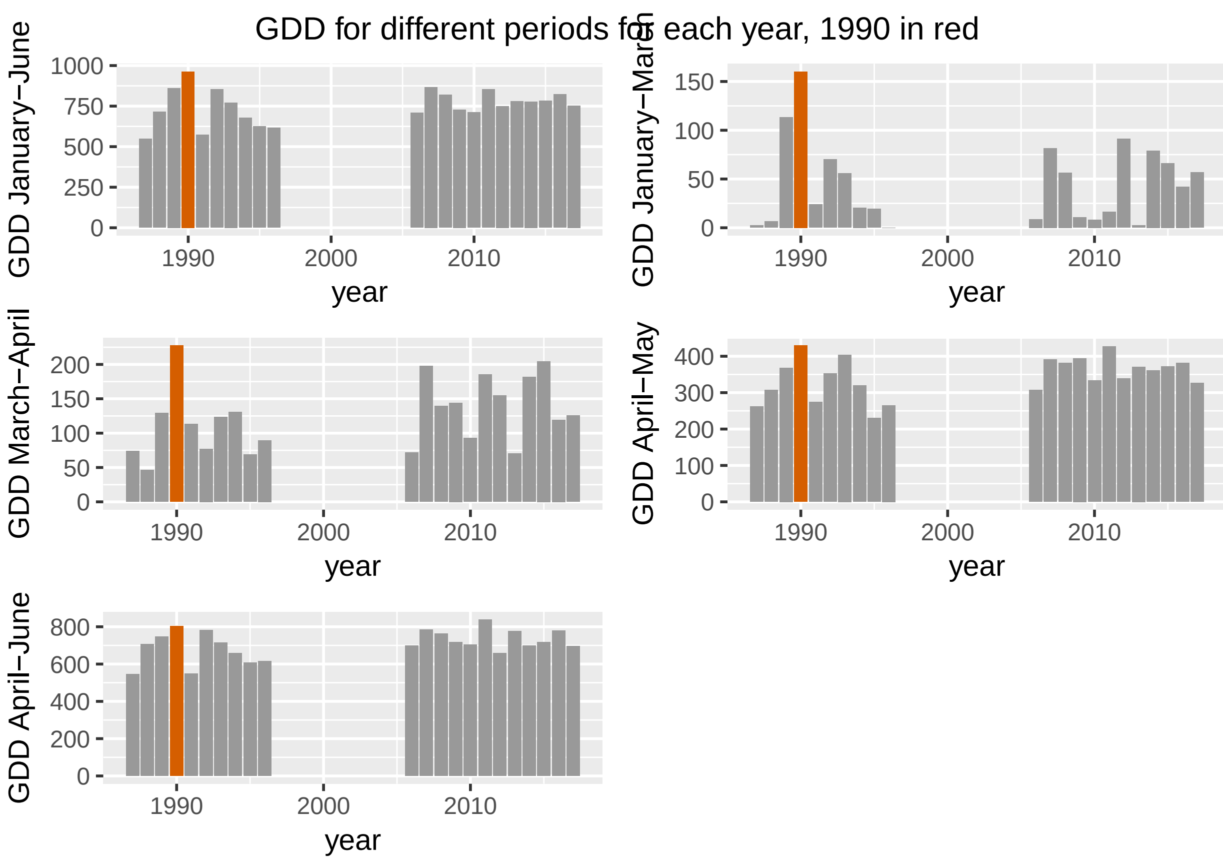

1990 temperatures
Mean temperature
20
10
0
0
100
200
300
Date (number of days since vernal equinox)


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
2500
2000
1500
1000
500
0
0
100
200
300
Date (number of days since vernal equinox)


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


GDD3 January−June
900
800
700
600
1987
1990
1993
1996
2008
2011
2014
2017
year





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

Chilling temperatures in winter

Calculate number of days with temperatures below 0 / -5 during winter (winter = 1st of December – day before vernal equinox), as well as mean temperatures and precipitation

```
weather$winter<-as.factor(with(weather,ifelse(month==12|period=="a",1,0)))
#Define winter (=December or January-March till day before vernal equinox)
```

```
weather$mean_below_0<-with(weather,ifelse(mean<0,1,0))
weather$min_below_0<-with(weather,ifelse(min<0,1,0))
weather$max_below_0<-with(weather,ifelse(max<0,1,0))
weather$mean_below_minus5<-with(weather,ifelse(mean<(-5),1,0))
weather$min_below_minus5<-with(weather,ifelse(min<(-5),1,0))
weather$max_below_minus5<-with(weather,ifelse(max<(-5),1,0))

mean_weather3_w<-plyr::join_all(list(
    aggregate(mean ~ year, data=subset(weather,winter==1), FUN=mean),   #Mean of mean daily temperature
    aggregate(min ~ year, data=subset(weather,winter==1), FUN=mean),    #Mean of min daily temperature
    aggregate(max ~ year, data=subset(weather,winter==1), FUN=mean),    #Mean of max daily temperature
    aggregate(precipitation ~ year, data= subset(weather,winter==1), FUN=sum),#Sum of precipitation
    aggregate(mean_below_0 ~ year,data= subset(weather,winter==1), FUN=sum),  #N days with mean<0
    aggregate(min_below_0 ~ year,data= subset(weather,winter==1), FUN=sum),  #N days with min<0
    aggregate(max_below_0 ~ year,data= subset(weather,winter==1), FUN=sum),  #N days with max<0
    aggregate(mean_below_minus5 ~ year,data= subset(weather,winter==1), FUN=sum), #N days with mean<-5
    aggregate(min_below_minus5 ~ year,data= subset(weather,winter==1), FUN=sum),  #N days with min<-5
    aggregate(max_below_minus5 ~ year,data= subset(weather,winter==1), FUN=sum)), #N days with max<-5
    by = NULL, type = "left", match = "all")

colnames(mean_weather3_w)[2:11]<-paste(colnames(mean_weather3_w)[2:11],"w", sep = "_")

mean_weather4<-merge(mean_weather3,mean_weather3_w) #Merge with previous data
```

Models FFD against winter variables

With mean of FFD

```
models6<-lapply(names(mean_weather4)[c(223:232)],
         function(x) {lm(substitute(FFD_mean ~ scale(i), list(i = as.name(x))),
                         data = mean_weather4)})
models6_summary<-lapply(X = models6, FUN = summary)%>% lapply(prettify) %>% bind_rows()
models6_summary<-models6_summary[c(1:2,5,6)]
names(models6_summary)<-c("variable","Estimate","P","sig")
models6_summary<-subset(models6_summary,!variable=="(Intercept)")
models6_summary<-cbind(models6_summary,sapply(lapply(X = models6, FUN = summary), "[[", 9))
names(models6_summary)[5]<-"Rsquare"
kable(arrange(subset(models6_summary,P<0.05),desc(Rsquare)))
```

variable	Estimate	P	sig	Rsquare
scale(precipitation_w)	-3.665808	0.002	**	0.3564066
scale(mean_w)	-3.324004	0.006	**	0.2841524
scale(max_w)	-3.287951	0.007	**	0.2769429
scale(min_w)	-3.286051	0.007	**	0.2765653
scale(min_below_0_w)	3.234009	0.008	**	0.2663034
scale(mean_below_0_w)	3.100545	0.012	*	0.2407351

variable	Estimate	P	sig	Rsquare
scale(min_below_minus5_w)	2.970477	0.017	*	0.2168540
scale(max_below_minus5_w)	2.865391	0.022	*	0.1983071
scale(max_below_0_w)	2.676526	0.034	*	0.1666529
scale(mean_below_minus5_w)	2.625453	0.038	*	0.1584634

More precipitation and higher temperatures in winter are correlated with earlier flowering.
More cold days in winter is correlated with later flowering.

With variance of FFD

```
models7<-lapply(names(mean_weather4)[c(223:232)],
         function(x) {lm(substitute(FFD_var ~ scale(i), list(i = as.name(x))),
                         data = mean_weather4)})
models7_summary<-lapply(X = models7, FUN = summary)%>% lapply(prettify) %>% bind_rows()
models7_summary<-models7_summary[c(1:2,5,6)]
names(models7_summary)<-c("variable","Estimate","P","sig")
models7_summary<-subset(models7_summary,!variable=="(Intercept)")
models7_summary<-cbind(models7_summary,sapply(lapply(X = models7, FUN = summary), "[[", 9))
names(models7_summary)[5]<-"Rsquare"
kable(arrange(subset(models7_summary,P<0.05),desc(Rsquare)))
```

variable	Estimate	P	sig	Rsquare
scale(precipitation_w)	6.159057	0.01	*	0.2493708
scale(min_w)	5.093744	0.04	*	0.1547648
scale(min_below_minus5_w)	-5.050440	0.042	*	0.1512980

More precipitation and higher temperatures in winter are correlated with higher variance in FFD.
More cold days in winter is correlated with lower variance in FFD.

With range of FFD

```
models8<-lapply(names(mean_weather4)[c(223:232)],
         function(x) {lm(substitute(FFD_dur ~ scale(i), list(i = as.name(x))),
                         data = mean_weather4)})
models8_summary<-lapply(X = models8, FUN = summary)%>% lapply(prettify) %>% bind_rows()
models8_summary<-models8_summary[c(1:2,5,6)]
names(models8_summary)<-c("variable","Estimate","P","sig")
models8_summary<-subset(models8_summary,!variable=="(Intercept)")
models8_summary<-cbind(models8_summary,sapply(lapply(X = models8, FUN = summary), "[[", 9))
names(models8_summary)[5]<-"Rsquare"
kable(arrange(subset(models8_summary,P<0.05),desc(Rsquare)))
```

variable Estimate P sig Rsquare ——— ——— — —- ———

No sigificant relationships for FFD_dur.

With skewness of FFD

```
models9<-lapply(names(mean_weather4)[c(223:232)],
         function(x) {lm(substitute(FFD_skew ~ scale(i), list(i = as.name(x))),
                          data = mean_weather4)})
models9_summary<-lapply(X = models9, FUN = summary)%>% lapply(prettify) %>% bind_rows()
models9_summary<-models9_summary[c(1:2,5,6)]
names(models9_summary)<-c("variable","Estimate","P","sig")
models9_summary<-subset(models9_summary,!variable=="(Intercept)")
models9_summary<-cbind(models9_summary,sapply(lapply(X = models9, FUN = summary), "[[", 9))
names(models9_summary)[5]<-"Rsquare"
kable(arrange(subset(models9_summary,P<0.05),desc(Rsquare)))
```

variable Estimate P sig Rsquare ——— ——— — —- ———

No sigificant relationships for FFD_skew.

With kurtosis of FFD

```
models10<-lapply(names(mean_weather4)[c(223:232)],
         function(x) {lm(substitute(FFD_kurt ~ scale(i), list(i = as.name(x))),
                          data = mean_weather4)})
models10_summary<-lapply(X = models10, FUN = summary)%>% lapply(prettify) %>% bind_rows()
models10_summary<-models10_summary[c(1:2,5,6)]
names(models10_summary)<-c("variable","Estimate","P","sig")
models10_summary<-subset(models10_summary,!variable=="(Intercept)")
models10_summary<-cbind(models10_summary,sapply(lapply(X = models10, FUN = summary), "[[", 9))
names(models10_summary)[5]<-"Rsquare"
kable(arrange(subset(models10_summary,P<0.05),desc(Rsquare)))
```

variable Estimate P sig Rsquare ——— ——— — —- ———

No sigificant relationships for FFD_kurt.

Influence of winter temperature / precipitation in response to spring temperature

Does winter temperature/precipitation influence the response of plants to spring temperature?
Do fewer days with freezing temperatures/warmer temperatures in winter mean lower sensitivity to increasing spring temperatures?
Sensitivity to increasing spring temperatures for each year: calculated as the coefficients from yearly models of proportion of plants having started flowering against cumulated number of GDH3 (computed from the vernal equinox) (This was the variable explaining the most variance in the proportion of plants having started flowering)

```
#Proportion of plants having started flowering
models11<-with(alldata_agg,
            by(alldata_agg, year,
               function(x) glm(prop_fl ~ cumGDH3v, data = x,family=binomial)))
coefs_models11<-as.data.frame(sapply(models11, coef)[2,])
coefs_models11$year<-row.names(coefs_models11)
names(coefs_models11)<-c("resp_cumGDH3v","year")

mean_weather5<-merge(mean_weather4,coefs_models11)

#Fit univariate linear models of resp_cumGDH3v against each winter predictor
models12<-lapply(names(mean_weather5)[c(223:232)],
```

```
         function(x) {lm(substitute(resp_cumGDH3v ~ scale(i), list(i = as.name(x))),
                         data = mean_weather5)})
models12_summary<-lapply(X = models12, FUN = summary)%>% lapply(prettify) %>% bind_rows()
models12_summary<-models12_summary[c(1:2,5,6)]
names(models12_summary)<-c("variable","Estimate","P","sig")
models12_summary<-subset(models12_summary,!variable=="(Intercept)")
models12_summary<-cbind(models12_summary,sapply(lapply(X = models12, FUN = summary), "[[", 9))
names(models12_summary)[5]<-"Rsquare"
kable(arrange(subset(models12_summary,P<0.05),desc(Rsquare)))
```

variable	Estimate	P	sig	Rsquare
scale(precipitation_w)	-0.0001855	0.017	*	0.2171773

It seems that only winter precipitation influences the response of plants to increasing spring temperatures (with higher winter precipitation, plants are less responsive to increasing spring temperatures), and the effect is not very strong.

Models with effects of mean temperature April and May, measures of chilling and their interaction on mean FFD

Another way of testing the relation among winter conditions and response to spring temperature.

```
#Fit linear models of FFD against mean45*chilling measure
models13<-lapply(names(mean_weather5)[c(223:232)],
         function(x) {lm(substitute(FFD_mean ~ scale(mean45)*scale(i), list(i = as.name(x))),
                         data = mean_weather5)})
models13_summary<-lapply(X = models13, FUN = summary)%>% lapply(prettify) %>% bind_rows()
models13_summary<-models13_summary[c(1:2,5,6)]
names(models13_summary)<-c("variable","Estimate","P","sig")
models13_summary<-subset(models13_summary,!variable=="(Intercept)")
models13_summary<-cbind(models13_summary,sapply(lapply(X = models13, FUN = summary), "[[", 9))
names(models13_summary)[5]<-"Rsquare"
kable(models13_summary)
```

	variable	Estimate	P	sig	Rsquare
2	scale(mean45)	-4.7457820	<0.001	***	0.7532095
3	scale(mean_w)	-0.6212424	0.433		0.7505072
4	scale(mean45):scale(mean_w)	0.4149907	0.561		0.7565030
6	scale(mean45)	-4.7801955	<0.001	***	0.7836344
7	scale(min_w)	-0.6503415	0.417		0.7505538
8	scale(mean45):scale(min_w)	0.2376274	0.74		0.7593436
10	scale(mean45)	-4.7129081	<0.001	***	0.7479327
11	scale(max_w)	-0.6130020	0.43		0.7450429
12	scale(mean45):scale(max_w)	0.5797146	0.434		0.7472340
14	scale(mean45)	-4.5739840	<0.001	***	0.7540362
15	scale(precipitation_w)	-0.9389310	0.218		0.7532095
16	scale(mean45):scale(precipitation_w)	0.8633909	0.233		0.7505072
18	scale(mean45)	-4.7976312	<0.001	***	0.7565030
19	scale(mean_below_0_w)	0.6538479	0.391		0.7836344
20	scale(mean45):scale(mean_below_0_w)	-0.3261530	0.677		0.7505538
22	scale(mean45)	-4.6357497	<0.001	***	0.7593436
23	scale(min_below_0_w)	0.9374463	0.217		0.7479327
24	scale(mean45):scale(min_below_0_w)	-0.3015655	0.683		0.7450429

	variable	Estimate	P	sig	Rsquare
26	scale(mean45)	-4.9904244	<0.001	***	0.7472340
27	scale(max_below_0_w)	0.2976368	0.691		0.7540362
28	scale(mean45):scale(max_below_0_w)	-0.6363942	0.484		0.7532095
30	scale(mean45)	-4.9988855	<0.001	***	0.7505072
31	scale(mean_below_minus5_w)	0.2594075	0.75		0.7565030
32	scale(mean45):scale(mean_below_minus5_w)	-0.4067785	0.632		0.7836344
34	scale(mean45)	-4.8856369	<0.001	***	0.7505538
35	scale(min_below_minus5_w)	0.5212374	0.504		0.7593436
36	scale(mean45):scale(min_below_minus5_w)	-0.2585940	0.735		0.7479327
38	scale(mean45)	-4.9796597	<0.001	***	0.7450429
39	scale(max_below_minus5_w)	0.0768539	0.938		0.7472340
40	scale(mean45):scale(max_below_minus5_w)	-0.6100128	0.445		0.7540362

Interactions are never significant Test this within years instead of among years?