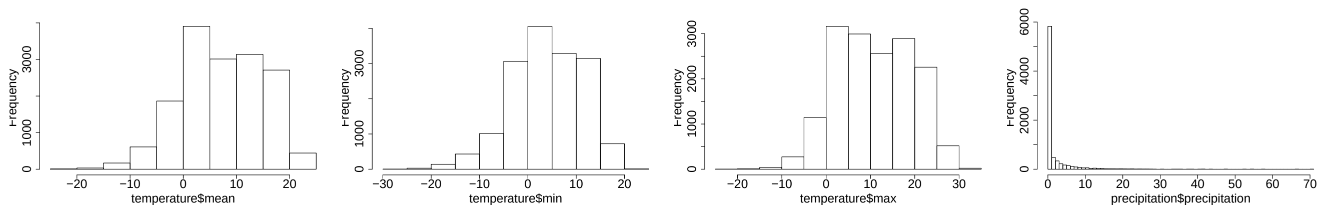
# Lathyrus - Weather

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

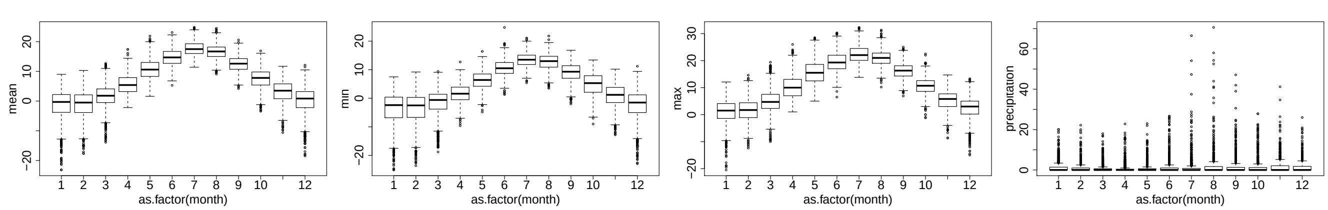
| station | date | year | month | day | mean | quality_mean | min | quality_.min | max | quality_max |
|---|---|---|---|---|---|---|---|---|---|---|
| Oxelösund | 1987-01-01 | 1987 | 1 | 1 | -11.6 | Y | -14.5 | G | -9.0 | G |
| Oxelösund | 1987-01-02 | 1987 | 1 | 2 | -10.4 | Y | -16.5 | G | -7.8 | G |
| 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 |

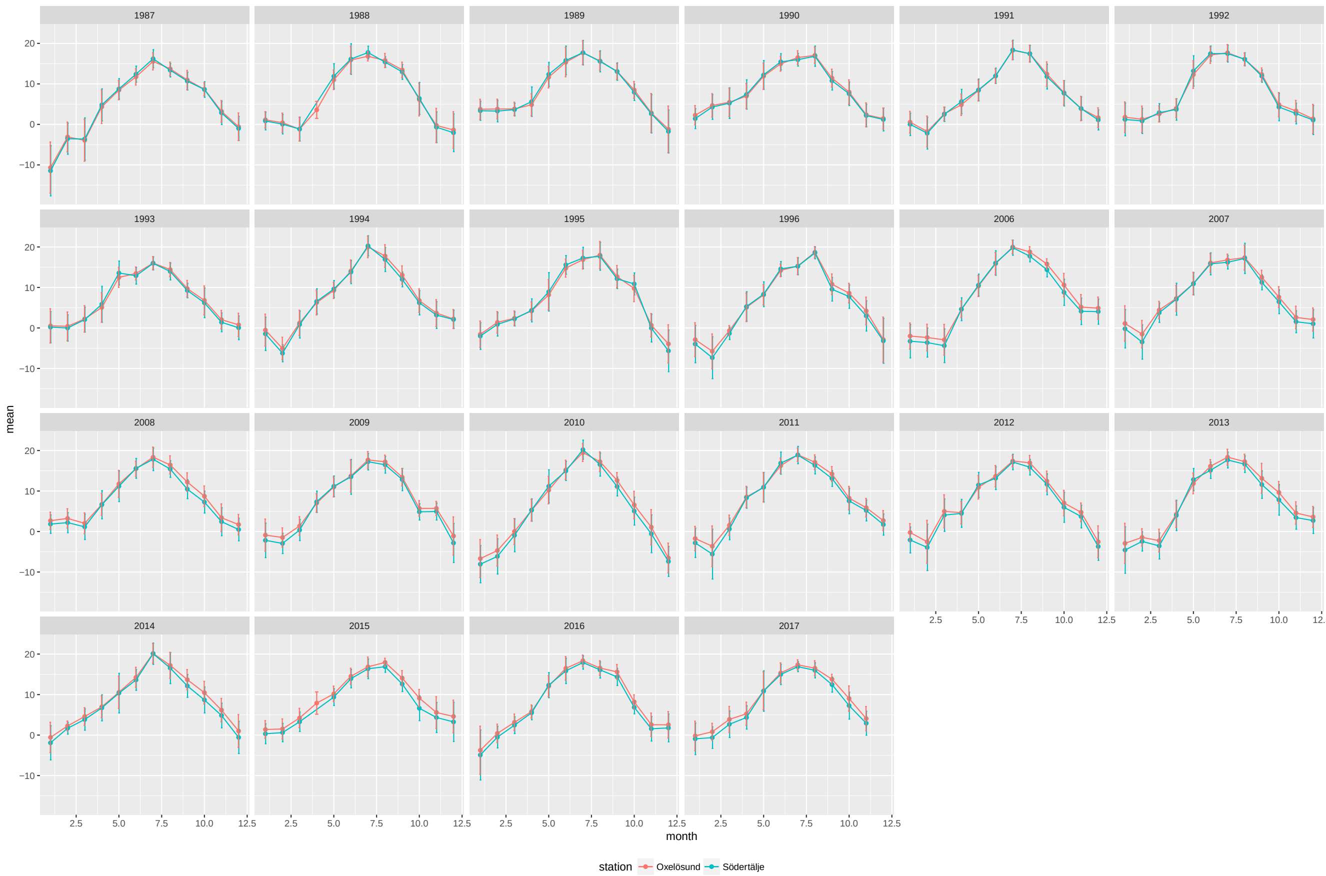
Distributions




Boxplots per month



Comparisons of mean temperatures for each year for both stations: they look quite similar




Temperature: average mean, min and max of the two stations for further use + join with precipitation data

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

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

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

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

```
##      year month
## 397  1988     2
## 1613 1991     6
## 1858 1992     2
## 2101 1992    10
## 7970 2017    10
## 7976 2017    11
```

```
#February 1988, June 1991, February 1992, October 1992 all missing
#Substitute with mean of all years for each specific date
weather$precipitation[is.na(weather$precipitation)&weather$year==1988&weather$month==2]<-
```

```
  with(subset(aggregate(precipitation ~ year+month+day, data= weather, FUN=sum),month==2),
  aggregate(precipitation~day,FUN=mean)$precipitation)
weather$precipitation[is.na(weather$precipitation)&weather$year==1991&weather$month==6]<-
  with(subset(aggregate(precipitation ~ year+month+day, data= weather, FUN=sum),month==6),
  aggregate(precipitation~day,FUN=mean)$precipitation)
weather$precipitation[is.na(weather$precipitation)&weather$year==1992&weather$month==2]<-
  with(subset(aggregate(precipitation ~ year+month+day, data= weather, FUN=sum),month==2),
  aggregate(precipitation~day,FUN=mean)$precipitation)
weather$precipitation[is.na(weather$precipitation)&weather$year==1992&weather$month==10]<-
  with(subset(aggregate(precipitation ~ year+month+day, data= weather, FUN=sum),month==10),
  aggregate(precipitation~day,FUN=mean)$precipitation)
#October-November 2017 leave as NAs, will be available later
```

Calculation of GDD and GDH (base =3/5/7/10 ºC)
GDD:

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

GDH:

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

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

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

```
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 | date_ok | mean | min | max | precipitation |
|---|---|---|---|---|---|---|---|---|
| 1987-01-01 | 1987 | 1 | 1 | 01/01/1987 | -11.25 | -14.15 | -8.5 | 0 |

| date | year | month | day | date_ok | mean | min | max | precipitation |
|---|---|---|---|---|---|---|---|---|
| 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 |

Define 3 periods:
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)

```
weather<-merge(weather,unique(alldata[c(1,8)])) #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 monthly means of temperature and montly sums of precipitation, GDD and GDH

```
mean_weather1<-join_all(list(
    aggregate(mean ~ year+month, data=weather, FUN=mean), #Monthly means of mean daily temperature
    aggregate(min ~ year+month, data=weather, FUN=mean), #Monthly means of min daily temperature
    aggregate(max ~ year+month, data=weather, FUN=mean), #Monthly means of max daily temperature
    aggregate(precipitation ~ year+month, data= weather, FUN=sum),#Monthly sums of precipitation
    aggregate(GDD3 ~ year+month,data= weather, FUN=sum),          #Monthly sums of GDD3
    aggregate(GDD5 ~ year+month,data= weather, FUN=sum),          #Monthly sums of GDD5
    aggregate(GDD7 ~ year+month,data= weather, FUN=sum),          #Monthly sums of GDD7
    aggregate(GDD10 ~ year+month,data= weather, FUN=sum),         #Monthly sums of GDD10
    aggregate(GDH3 ~ year+month,data= weather, FUN=sum),          #Monthly sums of GDH3
    aggregate(GDH5 ~ year+month,data= weather, FUN=sum),          #Monthly sums of GDH5
    aggregate(GDH7 ~ year+month,data= weather, FUN=sum),          #Monthly sums of GDH7
    aggregate(GDH10 ~ year+month,data= weather, FUN=sum)),        #Monthly sums of GDH10
    by = NULL, type = "left", match = "all")
```

```
## Joining by: year, month
## Joining by: year, month
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## Joining by: year, month
## Joining by: year, month
## Joining by: year, month
## Joining by: year, month
## Joining by: year, month
## Joining by: year, month
```

```r
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 |

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)
```

```r
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)
```

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

```
mean_weather1_b<-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")
```

```
## Joining by: year
## Joining by: year
## Joining by: year
## Joining by: year
## Joining by: year
## Joining by: year
## Joining by: year
## Joining by: year
## Joining by: year
## Joining by: year
## Joining by: year
```

```
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 = "_")

mean_weather3<-merge(merge(mean_weather2,mean_weather2_b),
               aggregate(FFD ~ year, data= alldata, FUN=mean)) #Merge with previous data & mean FFD per ye
pander(head(mean_weather3), split.table = 100, style = 'rmarkdown')
```

| year | GDD10_1 | GDD10_10 | GDD10_11 | GDD10_12 | GDD10_2 | GDD10_3 | GDD10_4 | GDD10_5 |
|---|---|---|---|---|---|---|---|---|
| 1987 | 0 | 5.15 | 0 | 0 | 0 | 0 | 11.48 | 22.18 |
| 1988 | 0 | 2.5 | 0 | 0 | 0 | 0 | 0 | 53.9 |
| 1989 | 0 | 6.3 | 0 | 0 | 0 | 0 | 1.45 | 71 |
| 1990 | 0 | 7.825 | 0 | 0 | 0.7 | 5.75 | 8.75 | 87.92 |
| 1991 | 0 | 9.65 | 0 | 0 | 0 | 0 | 1.825 | 20.6 |
| 1992 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 100.6 |

| GDD10_6 | GDD10_7 | GDD10_8 | GDD10_9 | GDD3_1 | GDD3_10 | GDD3_11 | GDD3_12 | GDD3_2 |
|---|---|---|---|---|---|---|---|---|
| 74.4 | 183.4 | 121.1 | 49.88 | 0 | 174.2 | 35.23 | 2.925 | 0 |

| GDD10_6 | GDD10_7 | GDD10_8 | GDD10_9 | GDD3_1 | GDD3_10 | GDD3_11 | GDD3_12 | GDD3_2 |
|---|---|---|---|---|---|---|---|---|
| 190.7 | 241.1 | 183.2 | 99.97 | 5.175 | 144.9 | 4.025 | 4.625 | 0.975 |
| 169.8 | 245 | 177.4 | 97.45 | 36.58 | 163.4 | 54.35 | 2.425 | 35.95 |
| 164 | 206.1 | 220.1 | 47.62 | 11.5 | 150.6 | 23.62 | 7.975 | 56.7 |
| 69.25 | 263 | 242.2 | 79.82 | 1.025 | 149.1 | 48.98 | 10.03 | 6.55 |
| 220.2 | 240.8 | 197 | 73.5 | 25.68 | 72.6 | 26.38 | 19.32 | 15.82 |

| GDD3_3 | GDD3_4 | GDD3_5 | GDD3_6 | GDD3_7 | GDD3_8 | GDD3_9 | GDD5_1 | GDD5_10 |
|---|---|---|---|---|---|---|---|---|
| 2.35 | 71.9 | 189.9 | 283.7 | 400.4 | 338.1 | 242.9 | 0 | 112.2 |
| 0.3 | 46.15 | 261.4 | 400.6 | 458.1 | 400.2 | 309.9 | 0.125 | 93.95 |
| 41.12 | 87.9 | 280.7 | 379.8 | 462 | 394.4 | 302.8 | 12.25 | 102 |
| 92.08 | 135.3 | 294 | 373.9 | 423.1 | 437.1 | 245.6 | 0 | 97.8 |
| 16.38 | 97.08 | 177.2 | 275.3 | 480 | 459.1 | 283.1 | 0 | 95.17 |
| 28.65 | 48.6 | 304.5 | 430.2 | 457.8 | 413.9 | 280.6 | 6.475 | 32.42 |

| GDD5_11 | GDD5_12 | GDD5_2 | GDD5_3 | GDD5_4 | GDD5_5 | GDD5_6 | GDD5_7 | GDD5_8 |
|---|---|---|---|---|---|---|---|---|
| 8 | 0 | 0 | 0 | 45.05 | 128.8 | 223.7 | 338.4 | 276.1 |
| 0 | 0.55 | 0 | 0 | 18.7 | 199.4 | 340.6 | 396.1 | 338.2 |
| 25.43 | 0 | 13.32 | 11.05 | 44.95 | 218.7 | 319.8 | 400 | 332.4 |
| 5.9 | 1.175 | 28.48 | 55.15 | 83.55 | 232 | 313.9 | 361.1 | 375.1 |
| 14.93 | 1.3 | 1.475 | 0.2 | 51.05 | 115.5 | 215.3 | 418 | 397.1 |
| 5.125 | 6.625 | 2.65 | 4.925 | 20.15 | 242.5 | 370.2 | 395.8 | 351.9 |

| GDD5_9 | GDD7_1 | GDD7_10 | GDD7_11 | GDD7_12 | GDD7_2 | GDD7_3 | GDD7_4 | GDD7_5 |
|---|---|---|---|---|---|---|---|---|
| 182.9 | 0 | 54.52 | 0.525 | 0 | 0 | 0 | 28 | 72.12 |
| 249.8 | 0 | 48.55 | 0 | 0 | 0 | 0 | 3.45 | 137.4 |
| 242.8 | 1.525 | 47.3 | 5 | 0 | 3.225 | 1.25 | 18.4 | 156.7 |
| 185.6 | 0 | 52.45 | 0.25 | 0 | 12.28 | 29.77 | 42.83 | 170 |
| 223.2 | 0 | 51.7 | 1.25 | 0 | 0 | 0 | 15.25 | 63.23 |
| 220.6 | 1.925 | 12.13 | 0.475 | 0 | 0 | 0 | 5.8 | 180.6 |

| GDD7_6 | GDD7_7 | GDD7_8 | GDD7_9 | GDH10_1 | GDH10_10 | GDH10_11 | GDH10_12 | GDH10_2 |
|---|---|---|---|---|---|---|---|---|
| 163.7 | 276.4 | 214.1 | 123.2 | 0 | 272.7 | 0.1071 | 0 | 0 |
| 280.6 | 334.1 | 276.2 | 189.8 | 0 | 209.2 | 0 | 0 | 0 |
| 259.8 | 338 | 270.4 | 182.8 | 0.2146 | 271.8 | 5.733 | 0 | 4.731 |
| 254 | 299.1 | 313.1 | 126 | 0 | 302.4 | 0 | 0 | 73.29 |
| 155.3 | 356 | 335.1 | 163.2 | 0 | 329.6 | 0 | 0 | 0 |
| 310.2 | 333.8 | 289.9 | 160.6 | 0.9524 | 82.06 | 0 | 0 | 0.1572 |

| GDH10_3 | GDH10_4 | GDH10_5 | GDH10_6 | GDH10_7 | GDH10_8 | GDH10_9 | GDH3_1 | GDH3_10 |
|---|---|---|---|---|---|---|---|---|
| 0 | 396.3 | 788.1 | 1912 | 4418 | 2957 | 1365 | 1.581 | 4186 |
| 0 | 42.65 | 1724 | 4630 | 5787 | 4402 | 2539 | 155.5 | 3531 |
| 11.85 | 145.7 | 2085 | 4153 | 5886 | 4321 | 2461 | 1044 | 3935 |
| 283 | 490 | 2368 | 3969 | 4947 | 5292 | 1294 | 394.8 | 3695 |
| 2.702 | 153.1 | 687.4 | 1782 | 6313 | 5812 | 2139 | 120.8 | 3625 |
| 1.584 | 37.61 | 2601 | 5288 | 5785 | 4727 | 1868 | 751.9 | 1837 |

| GDH3_11 | GDH3_12 | GDH3_2 | GDH3_3 | GDH3_4 | GDH3_5 | GDH3_6 | GDH3_7 | GDH3_8 |
|---|---|---|---|---|---|---|---|---|
| 905.9 | 110.3 | 12.81 | 116.9 | 1981 | 4572 | 6809 | 9609 | 8114 |
| 176.9 | 166.5 | 48.84 | 41 | 1300 | 6274 | 9613 | 10995 | 9605 |
| 1338 | 131.8 | 985.6 | 1167 | 2211 | 6737 | 9115 | 11089 | 9466 |
| 675.4 | 266.1 | 1441 | 2380 | 3358 | 7055 | 8975 | 10155 | 10491 |
| 1233 | 324.3 | 171.5 | 546.1 | 2431 | 4276 | 6607 | 11521 | 11020 |
| 737.9 | 535.7 | 466.2 | 818.2 | 1337 | 7308 | 10326 | 10987 | 9935 |

| GDH3_9 | GDH5_1 | GDH5_10 | GDH5_11 | GDH5_12 | GDH5_2 | GDH5_3 | GDH5_4 | GDH5_5 |
|---|---|---|---|---|---|---|---|---|
| 5835 | 0 | 2761 | 287.3 | 19.73 | 0 | 40.97 | 1287 | 3177 |
| 7436 | 18.19 | 2314 | 20.98 | 50.17 | 0 | 0.953 | 622.2 | 4794 |
| 7268 | 391.9 | 2519 | 674.5 | 9.541 | 404.9 | 476.9 | 1277 | 5263 |
| 5898 | 57.66 | 2441 | 234.7 | 56.51 | 750.1 | 1483 | 2195 | 5580 |
| 6796 | 2.691 | 2362 | 435.6 | 85.53 | 55.24 | 156.9 | 1435 | 2880 |
| 6733 | 279.9 | 975.5 | 217 | 186.5 | 144.7 | 241.8 | 611.4 | 5842 |

| GDH5_6 | GDH5_7 | GDH5_8 | GDH5_9 | GDH7_1 | GDH7_10 | GDH7_11 | GDH7_12 | GDH7_2 |
|---|---|---|---|---|---|---|---|---|
| 5369 | 8121 | 6626 | 4425 | 0 | 1473 | 52.38 | 0.05882 | 0 |
| 8173 | 9507 | 8117 | 5997 | 0 | 1227 | 0 | 5.685 | 0 |
| 7675 | 9601 | 7978 | 5830 | 91.17 | 1307 | 211.4 | 0 | 149 |
| 7535 | 8667 | 9003 | 4471 | 0.8285 | 1359 | 43.62 | 6.003 | 363.9 |
| 5169 | 10033 | 9532 | 5362 | 0 | 1328 | 61.8 | 15.42 | 10.9 |
| 8886 | 9499 | 8447 | 5297 | 66.25 | 432.1 | 34.62 | 24.36 | 31.32 |

| GDH7_3 | GDH7_4 | GDH7_5 | GDH7_6 | GDH7_7 | GDH7_8 | GDH7_9 | max_1 | max_10 | max_11 |
|---|---|---|---|---|---|---|---|---|---|
| 10.77 | 824.4 | 1984 | 3930 | 6633 | 5139 | 3064 | -7.285 | 11.1 | 5.132 |
| 0 | 269 | 3388 | 6733 | 8019 | 6629 | 4566 | 2.397 | 9.655 | 2.557 |
| 140.6 | 640.5 | 3854 | 6237 | 8113 | 6493 | 4425 | 6.076 | 10.98 | 5.175 |
| 830.1 | 1293 | 4173 | 6095 | 7179 | 7515 | 3079 | 3.89 | 10.51 | 4.687 |
| 35.04 | 700.7 | 1762 | 3751 | 8545 | 8044 | 3972 | 2.829 | 10.17 | 5.768 |
| 50.12 | 227.3 | 4447 | 7446 | 8011 | 6959 | 3875 | 4.556 | 7.882 | 5.093 |

| max_12 | max_2 | max_3 | max_4 | max_5 | max_6 | max_7 | max_8 | max_9 | mean_1 |
|---|---|---|---|---|---|---|---|---|---|
| 1.971 | 0.2143 | -0.1855 | 9.142 | 13.35 | 15.88 | 20.29 | 17.38 | 14.63 | -11.06 |
| 1.639 | 1.928 | 1.576 | 7.467 | 16.28 | 21.12 | 21.66 | 19.77 | 17.41 | 0.9823 |
| 1.198 | 6.259 | 6.944 | 9.075 | 17.31 | 20 | 22.62 | 19.72 | 16.84 | 3.556 |
| 3.345 | 6.946 | 9.221 | 11.9 | 17.45 | 19.73 | 20.74 | 21.49 | 14.12 | 1.848 |
| 4.05 | 0.3339 | 4.895 | 9.76 | 12.35 | 15.42 | 23.01 | 21.7 | 16.32 | 0.2839 |
| 3.582 | 3.747 | 5.831 | 7.013 | 17.88 | 22 | 22.17 | 20 | 15.4 | 1.502 |

| mean_10 | mean_11 | mean_12 | mean_2 | mean_3 | mean_4 | mean_5 | mean_6 | mean_7 |
|---|---|---|---|---|---|---|---|---|
| 8.644 | 3.035 | -0.7887 | -3.32 | -3.774 | 4.578 | 8.615 | 12.08 | 15.89 |
| 6.266 | -0.4783 | -1.719 | 0.2379 | -1.165 | 3.59 | 11.44 | 16.03 | 17.56 |
| 8.216 | 2.73 | -1.474 | 3.539 | 3.735 | 5.237 | 12 | 15.57 | 17.7 |
| 7.773 | 2.28 | 1.327 | 4.482 | 5.356 | 7.195 | 12.06 | 15.21 | 16.23 |
| 7.753 | 3.907 | 1.384 | -1.966 | 2.552 | 5.245 | 8.461 | 11.96 | 18.34 |
| 4.587 | 3 | 1.213 | 1.06 | 2.744 | 3.828 | 12.75 | 17.31 | 17.58 |

| mean_10 | mean_11 | mean_12 | mean_2 | mean_3 | mean_4 | mean_5 | mean_6 | mean_7 |
|---|---|---|---|---|---|---|---|---|

| mean_8 | mean_9 | min_1 | min_10 | min_11 | min_12 | min_2 | min_3 | min_4 | min_5 |
|---|---|---|---|---|---|---|---|---|---|
| 13.54 | 10.83 | -14.89 | 6.134 | 1.145 | -3.689 | -6.427 | -7.032 | 0.48 | 4.902 |
| 15.58 | 13.2 | -0.2194 | 4.935 | -3.492 | -5.461 | -1.328 | -3.773 | 0.6933 | 6.584 |
| 15.62 | 13.06 | 0.8468 | 5.565 | 0.02833 | -4.735 | 1.179 | 1.079 | 1.965 | 6.794 |
| 16.95 | 11.1 | -0.379 | 5.04 | 0.09167 | -1.339 | 2.211 | 1.86 | 2.878 | 7.521 |
| 17.46 | 12.11 | -2.135 | 5.216 | 1.635 | -1.239 | -4.146 | 0.3242 | 1.927 | 5.077 |
| 16.08 | 12.12 | -1.344 | 1.439 | 0.8933 | -1.324 | -1.528 | 0.2306 | 1.168 | 7.766 |

| min_6 | min_7 | min_8 | min_9 | precipitation_1 | precipitation_10 | precipitation_11 |
|---|---|---|---|---|---|---|
| 9.033 | 11.55 | 10.43 | 7.568 | 9.3 | 55.4 | 80.6 |
| 11.59 | 13.9 | 12.05 | 9.247 | 78 | 42 | 21.1 |
| 11.32 | 13.19 | 11.73 | 9.353 | 3.9 | 40.3 | 46.2 |
| 11.2 | 12.55 | 12.71 | 8.245 | 63.4 | 72.6 | 42.4 |
| 8.928 | 13.96 | 13.93 | 8.553 | 50 | 23.6 | 48.4 |
| 12.68 | 13.37 | 12.71 | 9.302 | 33 | 57.34 | 112.3 |

| precipitation_12 | precipitation_2 | precipitation_3 | precipitation_4 | precipitation_5 |
|---|---|---|---|---|
| 41.2 | 14.5 | 25.4 | 5.7 | 52.6 |
| 46.3 | 35.96 | 15.8 | 26.4 | 19.5 |
| 41.3 | 38.8 | 51.3 | 19 | 27.9 |
| 31.1 | 74.1 | 22.6 | 9.3 | 16.8 |
| 34.6 | 26.3 | 28.7 | 9.3 | 54.5 |
| 12.3 | 35.96 | 29.9 | 79.8 | 5.2 |

| precipitation_6 | precipitation_7 | precipitation_8 | precipitation_9 | prec456 | prec45 |
|---|---|---|---|---|---|
| 47.9 | 58.8 | 93.4 | 82.6 | 106.2 | 58.3 |
| 51.4 | 141.7 | 39 | 31.3 | 97.3 | 45.9 |
| 40.4 | 62.2 | 42.8 | 18.2 | 87.3 | 46.9 |
| 33.4 | 71.4 | 33 | 154.7 | 59.5 | 26.1 |
| 54.22 | 29.4 | 79.7 | 60 | 118 | 63.8 |
| 35.9 | 63.5 | 44.3 | 27.8 | 120.9 | 85 |

| prec123456 | prec123 | prec34 | mean456 | mean45 | mean123456 | mean123 | mean34 | max456 |
|---|---|---|---|---|---|---|---|---|
| 155.4 | 49.2 | 31.1 | 25.27 | 13.19 | 7.116 | -18.16 | 0.8041 | 38.38 |
| 227.1 | 129.8 | 42.2 | 31.06 | 15.03 | 31.12 | 0.05567 | 2.425 | 44.86 |
| 181.3 | 94 | 70.3 | 32.81 | 17.24 | 43.64 | 10.83 | 8.972 | 46.39 |
| 219.6 | 160.1 | 31.9 | 34.47 | 19.26 | 46.16 | 11.69 | 12.55 | 49.08 |
| 223 | 105 | 38 | 25.67 | 13.71 | 26.54 | 0.8694 | 7.797 | 37.54 |
| 219.8 | 98.87 | 109.7 | 33.89 | 16.58 | 39.2 | 5.306 | 6.572 | 46.9 |

| max45 | max123456 | max123 | max34 | min456 | min45 | min123456 | min123 | min34 |
|---|---|---|---|---|---|---|---|---|
| 22.49 | 31.12 | -7.257 | 8.956 | 14.41 | 5.382 | -13.93 | -28.35 | -6.552 |
| 23.75 | 50.76 | 5.9 | 9.042 | 18.86 | 7.277 | 13.54 | -5.32 | -3.079 |

| max45 | max123456 | max123 | max34 | min456 | min45 | min123456 | min123 | min34 |
|---|---|---|---|---|---|---|---|---|
| 26.39 | 65.66 | 19.28 | 16.02 | 20.08 | 8.759 | 23.18 | 3.104 | 3.044 |
| 29.35 | 69.13 | 20.06 | 21.12 | 21.6 | 10.4 | 25.29 | 3.691 | 4.738 |
| 22.11 | 45.59 | 8.058 | 14.66 | 15.93 | 7.004 | 9.975 | -5.958 | 2.251 |
| 24.89 | 61.03 | 14.13 | 12.84 | 21.61 | 8.934 | 18.97 | -2.64 | 1.399 |

| GDD3_456 | GDD3_45 | GDD3_123456 | GDD3_123 | GDD3_34 | GDD5_456 | GDD5_45 | GDD5_123456 |
|---|---|---|---|---|---|---|---|
| 545.6 | 261.9 | 547.9 | 2.35 | 74.25 | 397.5 | 173.8 | 397.5 |
| 708.1 | 307.5 | 714.5 | 6.45 | 46.45 | 558.7 | 218.1 | 558.8 |
| 748.3 | 368.6 | 862 | 113.7 | 129 | 583.4 | 263.6 | 620 |
| 803.3 | 429.3 | 963.5 | 160.3 | 227.4 | 629.5 | 315.5 | 713.1 |
| 549.5 | 274.2 | 573.5 | 23.95 | 113.5 | 381.8 | 166.6 | 383.5 |
| 783.3 | 353.1 | 853.5 | 70.15 | 77.25 | 632.9 | 262.6 | 646.9 |

| GDD5_123 | GDD5_34 | GDD7_456 | GDD7_45 | GDD7_123456 | GDD7_123 | GDD7_34 | GDD10_456 |
|---|---|---|---|---|---|---|---|
| 0 | 45.05 | 263.9 | 100.1 | 263.9 | 0 | 28 | 108.1 |
| 0.125 | 18.7 | 421.4 | 140.8 | 421.4 | 0 | 3.45 | 244.6 |
| 36.62 | 56 | 434.8 | 175.1 | 440.8 | 6 | 19.65 | 242.2 |
| 83.62 | 138.7 | 466.8 | 212.8 | 508.8 | 42.05 | 72.6 | 260.6 |
| 1.675 | 51.25 | 233.8 | 78.47 | 233.8 | 0 | 15.25 | 91.67 |
| 14.05 | 25.08 | 496.6 | 186.4 | 498.6 | 1.925 | 5.8 | 320.9 |

| GDD10_45 | GDD10_123456 | GDD10_123 | GDD10_34 | GDH3_456 | GDH3_45 | GDH3_123456 |
|---|---|---|---|---|---|---|
| 33.65 | 108.1 | 0 | 11.48 | 13363 | 6553 | 13494 |
| 53.9 | 244.6 | 0 | 0 | 17187 | 7574 | 17432 |
| 72.45 | 242.2 | 0 | 1.45 | 18063 | 8948 | 21259 |
| 96.67 | 267.1 | 6.45 | 14.5 | 19388 | 10413 | 23604 |
| 22.43 | 91.67 | 0 | 1.825 | 13313 | 6706 | 14151 |
| 100.6 | 320.9 | 0 | 0 | 18971 | 8645 | 21007 |

| GDH3_123 | GDH3_34 | GDH5_456 | GDH5_45 | GDH5_123456 | GDH5_123 | GDH5_34 | GDH7_456 |
|---|---|---|---|---|---|---|---|
| 131.3 | 2098 | 9834 | 4465 | 9875 | 40.97 | 1328 | 6738 |
| 245.3 | 1341 | 13589 | 5416 | 13608 | 19.14 | 623.1 | 10390 |
| 3196 | 3378 | 14215 | 6540 | 15489 | 1274 | 1754 | 10731 |
| 4215 | 5738 | 15310 | 7775 | 17601 | 2291 | 3678 | 11561 |
| 838.3 | 2977 | 9483 | 4314 | 9698 | 214.8 | 1592 | 6214 |
| 2036 | 2155 | 15339 | 6453 | 16006 | 666.4 | 853.2 | 12120 |

| GDH7_45 | GDH7_123456 | GDH7_123 | GDH7_34 | GDH10_456 | GDH10_45 | GDH10_123456 |
|---|---|---|---|---|---|---|
| 2808 | 6749 | 10.77 | 835.2 | 3096 | 1184 | 3096 |
| 3657 | 10390 | 0 | 269 | 6397 | 1767 | 6397 |
| 4494 | 11112 | 380.8 | 781.1 | 6384 | 2231 | 6401 |
| 5466 | 12756 | 1195 | 2124 | 6827 | 2858 | 7183 |
| 2463 | 6260 | 45.94 | 735.7 | 2622 | 840.5 | 2625 |
| 4674 | 12268 | 147.7 | 277.4 | 7926 | 2638 | 7929 |

| GDH10_123 | GDH10_34 | GDD10_b | GDD3_b | GDD5_b | GDD7_b | GDH10_b | GDH3_b | GDH5_b |
|---|---|---|---|---|---|---|---|---|
| 0 | 396.3 | 20.05 | 185.5 | 117.1 | 64.97 | 746.9 | 4780 | 3129 |
| 0 | 42.65 | 18.25 | 192.2 | 126.5 | 73.25 | 818.6 | 4840 | 3219 |
| 16.79 | 157.5 | 29.17 | 269.5 | 170 | 97.05 | 1077 | 6616 | 4386 |
| 356.3 | 773 | 85.72 | 387.4 | 277.6 | 184.4 | 2532 | 9479 | 6945 |
| 2.702 | 155.8 | 8.375 | 203.1 | 106.7 | 40.6 | 425.2 | 5112 | 2996 |
| 2.694 | 39.2 | 31.1 | 205.8 | 133.1 | 80.9 | 965.9 | 5136 | 3361 |

| GDH7_b | max_b | mean_b | min_b | precipitation_b | FFD |
|---|---|---|---|---|---|
| 1892 | 9.311 | 5.066 | 1.459 | 60.8 | 66.26 |
| 2023 | 9.239 | 5.348 | 2.011 | 38.9 | 59.91 |
| 2677 | 11.07 | 6.96 | 3.329 | 60 | 53.86 |
| 4806 | 13.95 | 8.953 | 4.628 | 21.3 | 54.46 |
| 1527 | 9.773 | 5.672 | 2.386 | 67.5 | 65 |
| 2142 | 9.229 | 5.594 | 2.466 | 93.4 | 59.85 |

Models of FFD against temperature, precipitation and GDD/GDH

```r
#List of variables to test as predictors of FFD
varlist<-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)]

#Fit univariate linear models of FFD against each predictor
models<-lapply(varlist, function(x) {
  summary(lm(substitute(FFD ~ scale(i), list(i = as.name(x))), data = mean_weather3, na.action=na.exclude)
})

#Build a table with estimate, p and r square for all fitted models
models<-cbind(varlist,
             ldply(models, function(x) coef(x)[2]),
             ldply(models, function(x) coef(x)[8]),
             ldply(models, function(x) x$adj.r.squared)
      )
names(models)<-c("variable","estimate","p","adj.rsquare")
models$sig<-ifelse(models$p<0.05,"*","") # *=p<0.05

#Order models by R square
kable(arrange(models,desc(adj.rsquare)))
```

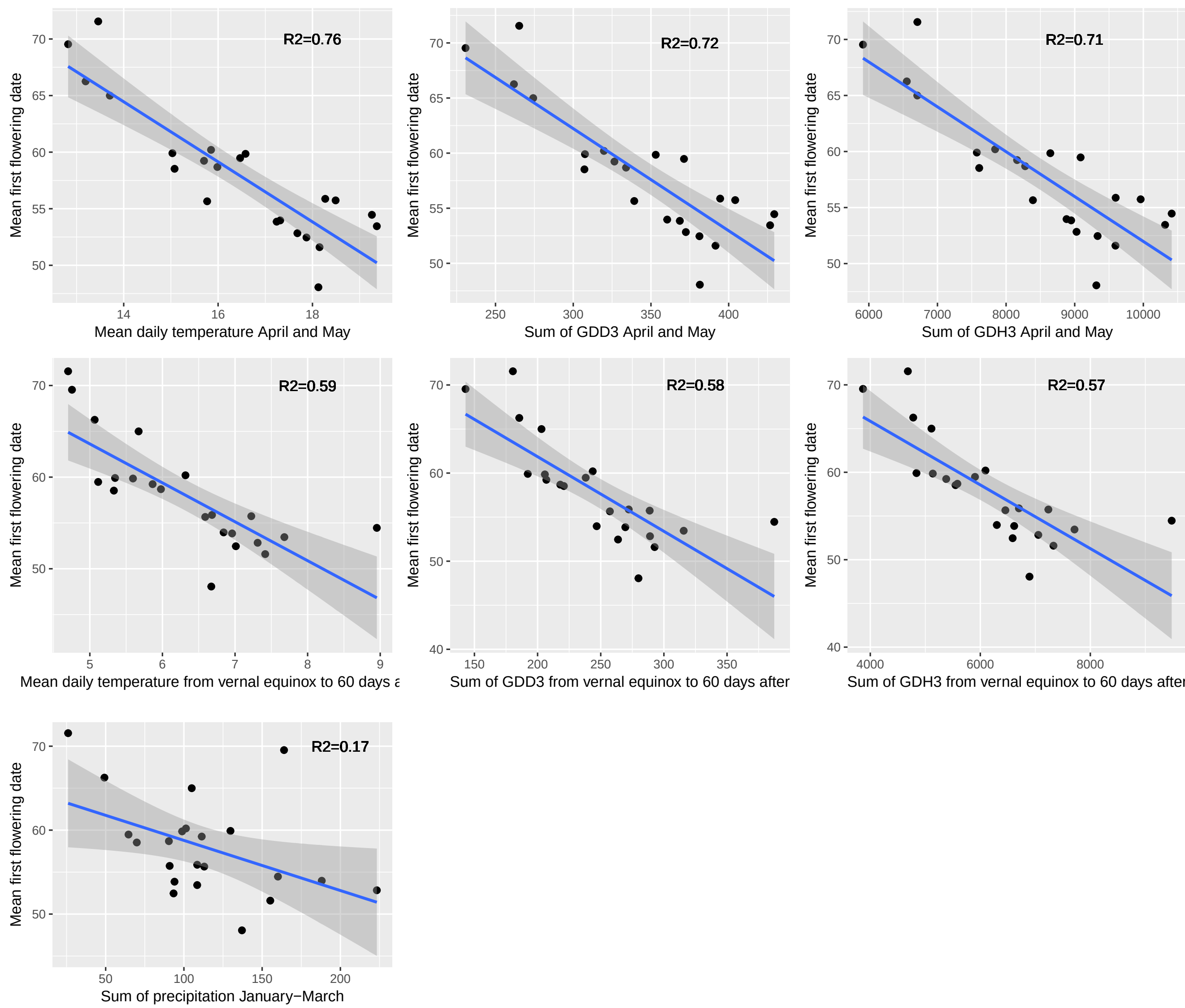
| variable | estimate | p | adj.rsquare | sig |
|---|---|---|---|---|
| mean45 | -5.1849896 | 0.0000001 | 0.7630498 | * |
| GDD3_45 | -5.0441786 | 0.0000004 | 0.7194888 | * |
| GDH3_45 | -5.0178764 | 0.0000005 | 0.7114849 | * |
| max45 | -4.9528736 | 0.0000010 | 0.6918838 | * |
| GDH5_45 | -4.8801515 | 0.0000019 | 0.6702579 | * |
| min45 | -4.8686906 | 0.0000022 | 0.6668788 | * |
| GDD5_45 | -4.8126881 | 0.0000035 | 0.6504817 | * |
| GDD3_123456 | -4.6353692 | 0.0000141 | 0.5998155 | * |
| max456 | -4.6246422 | 0.0000152 | 0.5968114 | * |
| mean_b | -4.5952544 | 0.0000187 | 0.5886171 | * |
| GDH3_123456 | -4.5870688 | 0.0000198 | 0.5863439 | * |
| mean456 | -4.5859233 | 0.0000200 | 0.5860261 | * |
| GDH7_45 | -4.5828322 | 0.0000204 | 0.5851690 | * |

| variable | estimate | p | adj.rsquare | sig |
|---|---|---|---|---|
| GDD3_b | -4.5799452 | 0.0000208 | 0.5843690 | * |
| GDH3_b | -4.5457539 | 0.0000262 | 0.5749327 | * |
| max_b | -4.5031575 | 0.0000347 | 0.5632756 | * |
| GDH5_b | -4.4117654 | 0.0000611 | 0.5386352 | * |
| GDD3_456 | -4.4082191 | 0.0000624 | 0.5376892 | * |
| GDD7_45 | -4.3824648 | 0.0000726 | 0.5308423 | * |
| GDH5_123456 | -4.3576458 | 0.0000838 | 0.5242821 | * |
| GDH3_456 | -4.3475396 | 0.0000888 | 0.5216214 | * |
| GDD5_b | -4.2894433 | 0.0001228 | 0.5064463 | * |
| GDD5_123456 | -4.2643975 | 0.0001406 | 0.4999672 | * |
| max123456 | -4.1957447 | 0.0002013 | 0.4824018 | * |
| GDH7_b | -4.1236790 | 0.0002883 | 0.4642699 | * |
| GDD5_456 | -4.1059995 | 0.0003140 | 0.4598697 | * |
| GDH5_456 | -4.0999520 | 0.0003233 | 0.4583689 | * |
| GDH10_45 | -3.9257444 | 0.0007109 | 0.4160853 | * |
| GDH7_123456 | -3.9069637 | 0.0007701 | 0.4116365 | * |
| mean_5 | -3.9001012 | 0.0007927 | 0.4100162 | * |
| min456 | -3.8994131 | 0.0007950 | 0.4098539 | * |
| max_5 | -3.8567727 | 0.0009491 | 0.3998518 | * |
| GDD3_5 | -3.8507067 | 0.0009730 | 0.3984379 | * |
| mean123456 | -3.8273777 | 0.0010696 | 0.3930207 | * |
| GDH3_5 | -3.8260771 | 0.0010753 | 0.3927197 | * |
| GDD5_5 | -3.8162815 | 0.0011184 | 0.3904556 | * |
| GDH5_5 | -3.7598963 | 0.0013965 | 0.3775364 | * |
| GDD3_34 | -3.7598828 | 0.0013965 | 0.3775333 | * |
| GDD7_b | -3.7570601 | 0.0014119 | 0.3768917 | * |
| GDH7_456 | -3.7208404 | 0.0016217 | 0.3687005 | * |
| GDD7_123456 | -3.6978632 | 0.0017681 | 0.3635453 | * |
| GDH3_34 | -3.6687642 | 0.0019694 | 0.3570624 | * |
| min_b | -3.6628696 | 0.0020125 | 0.3557554 | * |
| GDD7_5 | -3.6273016 | 0.0022895 | 0.3479135 | * |
| GDD7_456 | -3.6159711 | 0.0023842 | 0.3454315 | * |
| GDH7_5 | -3.6071686 | 0.0024601 | 0.3435086 | * |
| min_5 | -3.5628548 | 0.0028736 | 0.3338996 | * |
| max34 | -3.5578811 | 0.0029234 | 0.3328285 | * |
| GDH5_34 | -3.4082101 | 0.0048028 | 0.3012967 | * |
| GDH10_b | -3.3730280 | 0.0053669 | 0.2940815 | * |
| mean34 | -3.3727538 | 0.0053715 | 0.2940255 | * |
| min_4 | -3.3509468 | 0.0057482 | 0.2895912 | * |
| mean_4 | -3.3460457 | 0.0058359 | 0.2885986 | * |
| min123456 | -3.3259438 | 0.0062070 | 0.2845424 | * |
| GDD10_45 | -3.2817989 | 0.0070909 | 0.2757207 | * |
| GDH10_5 | -3.2644627 | 0.0074654 | 0.2722885 | * |
| GDD5_34 | -3.2608922 | 0.0075446 | 0.2715839 | * |
| GDD3_4 | -3.1796787 | 0.0095402 | 0.2557651 | * |
| GDH10_123456 | -3.1776533 | 0.0095950 | 0.2553757 | * |
| GDD3_123 | -3.1303685 | 0.0109503 | 0.2463550 | * |
| GDH3_123 | -3.1174784 | 0.0113458 | 0.2439194 | * |
| GDH10_456 | -3.1036246 | 0.0117838 | 0.2413129 | * |
| GDH7_34 | -3.1014542 | 0.0118537 | 0.2409056 | * |
| GDH3_4 | -3.0737322 | 0.0127761 | 0.2357284 | * |
| max123 | -3.0568329 | 0.0133665 | 0.2325952 | * |
| max_3 | -2.9802826 | 0.0163260 | 0.2186187 | * |
| mean123 | -2.9539687 | 0.0174580 | 0.2138962 | * |
| GDD10_5 | -2.9462525 | 0.0178017 | 0.2125193 | * |

| variable | estimate | p | adj.rsquare | sig |
|---|---|---|---|---|
| GDD3_3 | -2.9212621 | 0.0189525 | 0.2080848 | * |
| GDH3_3 | -2.9152068 | 0.0192402 | 0.2070160 | * |
| GDH5_4 | -2.9007501 | 0.0199413 | 0.2044732 | * |
| GDD5_4 | -2.8767286 | 0.0211516 | 0.2002760 | * |
| max_4 | -2.8577282 | 0.0221501 | 0.1969808 | * |
| GDH5_123 | -2.8328665 | 0.0235133 | 0.1927021 | * |
| min34 | -2.8260397 | 0.0238991 | 0.1915338 | * |
| min123 | -2.7979266 | 0.0255416 | 0.1867522 | * |
| GDD10_123456 | -2.7390295 | 0.0292745 | 0.1768897 | * |
| GDD10_456 | -2.7212542 | 0.0304822 | 0.1739544 | * |
| prec123 | -2.7123125 | 0.0311045 | 0.1724851 | * |
| GDH7_4 | -2.7039931 | 0.0316924 | 0.1711223 | * |
| GDD7_34 | -2.6903421 | 0.0326762 | 0.1688953 | * |
| mean_3 | -2.6574360 | 0.0351467 | 0.1635733 | * |
| GDH5_3 | -2.6566170 | 0.0352100 | 0.1634417 | * |
| GDH10_34 | -2.5036997 | 0.0486963 | 0.1395771 | * |
| GDD5_123 | -2.4826176 | 0.0508323 | 0.1363979 | |
| GDD10_b | -2.4817078 | 0.0509261 | 0.1362613 | |
| GDD7_4 | -2.4802228 | 0.0510795 | 0.1360385 | |
| GDD5_3 | -2.3732046 | 0.0631022 | 0.1203302 | |
| GDH7_123 | -2.3394551 | 0.0673087 | 0.1155201 | |
| GDH7_3 | -2.2865138 | 0.0743315 | 0.1081135 | |
| min_3 | -2.2461990 | 0.0800393 | 0.1025871 | |
| GDH10_4 | -2.2180662 | 0.0842127 | 0.0987888 | |
| GDD10_34 | -1.9764426 | 0.1269923 | 0.0681381 | |
| GDD10_4 | -1.8171680 | 0.1625972 | 0.0498646 | |
| GDH10_3 | -1.7154241 | 0.1886765 | 0.0389948 | |
| GDD7_3 | -1.6907937 | 0.1953942 | 0.0364575 | |
| GDD7_123 | -1.6630099 | 0.2031640 | 0.0336394 | |
| GDH10_123 | -1.6538966 | 0.2057571 | 0.0327253 | |
| prec123456 | -1.6395445 | 0.2098857 | 0.0312957 | |
| precipitation_5 | 1.6008654 | 0.2212863 | 0.0275052 | |
| prec45 | 1.4765924 | 0.2606477 | 0.0159390 | |
| precipitation_3 | -1.3294572 | 0.3126848 | 0.0034528 | |
| precipitation_b | 1.1138316 | 0.3994975 | -0.0124802 | |
| GDD10_3 | -1.0898747 | 0.4098978 | -0.0140768 | |
| GDD10_123 | -1.0662355 | 0.4203040 | -0.0156183 | |
| prec34 | -0.7285344 | 0.5835604 | -0.0339483 | |
| prec456 | 0.1933505 | 0.8847374 | -0.0488694 | |
| precipitation_4 | 0.1802574 | 0.8924973 | -0.0490173 | |

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.

Some plots of the best models




Models of FFD against temperatureGDD/GDH AND precipitation

Precipitation is significant in some cases but R2 does not increase much from the previous best model (with mean45 = mean temperature April and May, R2=0.76)

```
summary(lm(FFD~mean45*prec123,mean_weather3))  #Interaction NS, precipitation NS
```

```
##
## Call:
## lm(formula = FFD ~ mean45 * prec123, data = mean_weather3)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -5.2827 -1.3653 -0.2629  2.3127  4.2203
##
## Coefficients:
##                  Estimate Std. Error t value Pr(>|t|)
## (Intercept)    104.024422  13.433618   7.744 3.89e-07 ***
## mean45          -2.670367   0.853957  -3.127  0.00582 **
## prec123         -0.047380   0.112524  -0.421  0.67869
```

```
## mean45:prec123   0.001697   0.006939   0.245  0.80953
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.877 on 18 degrees of freedom
## Multiple R-squared:  0.7957, Adjusted R-squared:  0.7616
## F-statistic: 23.37 on 3 and 18 DF,  p-value: 1.975e-06
```

```
summary(lm(FFD~mean45+prec123,mean_weather3))  #No interaction, precipitation NS
```

```
##
## Call:
## lm(formula = FFD ~ 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~GDD3_45*prec123,mean_weather3)) #Interaction NS, precipitation NS
```

```
##
## Call:
## lm(formula = FFD ~ GDD3_45 * prec123, data = mean_weather3)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -6.1774 -1.2511 -0.3619  2.2143  4.7947
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)      9.330e+01  1.058e+01   8.819 5.96e-08 ***
## GDD3_45         -9.278e-02  3.222e-02  -2.879  0.00998 **
## prec123         -5.107e-02  8.716e-02  -0.586  0.56519
## GDD3_45:prec123  6.366e-05  2.581e-04   0.247  0.80799
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.971 on 18 degrees of freedom
## Multiple R-squared:  0.7821, Adjusted R-squared:  0.7458
## F-statistic: 21.54 on 3 and 18 DF,  p-value: 3.494e-06
```

```
summary(lm(FFD~GDD3_45+prec123,mean_weather3)) #No interaction, precipitation NS (p=0.054)
```

```
##
## Call:
## lm(formula = FFD ~ GDD3_45 + prec123, data = mean_weather3)
##
```

```
## Residuals:
##     Min      1Q  Median      3Q     Max
## -6.1510 -1.1496 -0.3974  2.0844  5.0295
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 90.90620    4.08299  22.265 4.49e-15 ***
## GDD3_45     -0.08545    0.01215  -7.035 1.07e-06 ***
## prec123     -0.02989    0.01455  -2.054    0.054 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.896 on 19 degrees of freedom
## Multiple R-squared:  0.7814, Adjusted R-squared:  0.7584
## F-statistic: 33.96 on 2 and 19 DF,  p-value: 5.331e-07
```

```
summary(lm(FFD~GDH3_45*prec123,mean_weather3)) #Interaction NS, precipitation NS
```

```
##
## Call:
## lm(formula = FFD ~ GDH3_45 * prec123, data = mean_weather3)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -6.1924 -1.1064 -0.1906  2.0673  4.8168
##
## Coefficients:
##                   Estimate Std. Error t value Pr(>|t|)
## (Intercept)      9.454e+01  1.161e+01   8.140 1.91e-07 ***
## GDH3_45         -3.904e-03  1.435e-03  -2.721    0.014 *
## prec123         -4.641e-02  9.616e-02  -0.483    0.635
## GDH3_45:prec123  1.912e-06  1.158e-05   0.165    0.871
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.005 on 18 degrees of freedom
## Multiple R-squared:  0.7771, Adjusted R-squared:  0.7399
## F-statistic: 20.92 on 3 and 18 DF,  p-value: 4.283e-06
```

```
summary(lm(FFD~GDH3_45+prec123,mean_weather3)) #No interaction, precipitation *
```

```
##
## Call:
## lm(formula = FFD ~ GDH3_45 + prec123, data = mean_weather3)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -6.1729 -1.0301 -0.1711  2.0169  4.9810
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) 92.7718222  4.3868514  21.148 1.15e-14 ***
## GDH3_45     -0.0036847  0.0005314  -6.933 1.31e-06 ***
## prec123     -0.0307299  0.0146758  -2.094   0.0499 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.927 on 19 degrees of freedom
```

```
## Multiple R-squared:  0.7767, Adjusted R-squared:  0.7532
## F-statistic: 33.05 on 2 and 19 DF,  p-value: 6.511e-07
```

```r
summary(lm(FFD~max45+prec123,mean_weather3))   #Precipitation*
```

```
##
## Call:
## lm(formula = FFD ~ max45 + prec123, data = mean_weather3)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -4.5949 -1.7013 -0.4401  1.4154  5.6183
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 111.15538    7.21690  15.402 3.45e-12 ***
## max45        -1.90038    0.28661  -6.630 2.42e-06 ***
## prec123      -0.03186    0.01511  -2.108   0.0485 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.021 on 19 degrees of freedom
## Multiple R-squared:  0.7622, Adjusted R-squared:  0.7371
## F-statistic: 30.45 on 2 and 19 DF,  p-value: 1.187e-06
```

```r
summary(lm(FFD~min45+prec123,mean_weather3))   #Precipitation NS
```

```
##
## Call:
## lm(formula = FFD ~ min45 + prec123, data = mean_weather3)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -8.2857 -1.9317 -0.2012  2.0414  4.8252
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 83.66159    3.96216  21.115 1.19e-14 ***
## min45       -3.00722    0.54510  -5.517 2.54e-05 ***
## prec123     -0.01719    0.01811  -0.949    0.355
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.409 on 19 degrees of freedom
## Multiple R-squared:  0.6971, Adjusted R-squared:  0.6652
## F-statistic: 21.86 on 2 and 19 DF,  p-value: 1.181e-05
```

```r
summary(lm(FFD~GDH5_45+prec123,mean_weather3)) #Precipitation*
```

```
##
## Call:
## lm(formula = FFD ~ GDH5_45 + prec123, data = mean_weather3)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -6.3781 -1.2420 -0.3821  2.3479  4.7472
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
```

```
## (Intercept) 86.5446865  3.7816034  22.886 2.71e-15 ***
## GDH5_45     -0.0040018  0.0006127  -6.531 2.96e-06 ***
## prec123     -0.0356953  0.0151261  -2.360   0.0291 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.053 on 19 degrees of freedom
## Multiple R-squared:  0.7571, Adjusted R-squared:  0.7316
## F-statistic: 29.62 on 2 and 19 DF,  p-value: 1.448e-06
```

```r
summary(lm(FFD~GDD5_45+prec123,mean_weather3)) #Precipitation*
```

```
##
## Call:
## lm(formula = FFD ~ GDD5_45 + prec123, data = mean_weather3)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -6.8301 -1.5019 -0.0224  2.4347  4.7790
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 83.94212    3.57850  23.457 1.72e-15 ***
## GDD5_45     -0.09004    0.01442  -6.246 5.35e-06 ***
## prec123     -0.03653    0.01557  -2.346     0.03 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.147 on 19 degrees of freedom
## Multiple R-squared:  0.7419, Adjusted R-squared:  0.7147
## F-statistic:  27.3 on 2 and 19 DF,  p-value: 2.584e-06
```

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)
```

Calculate 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

```r
#From the start of the year
weather<-as.data.frame(weather %>%
         group_by(year) %>%
         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") %>%
                group_by(year) %>%
                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) %>%
```

```
                group_by(year) %>%
                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)

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

```
##  [1] year           FFD            period         id
##  [5] ruta           genet          data           status
##  [9] vernal         FFD_corr       FFD_imputed    n_fl
## [13] n_fl_imputed   shoot_vol      grazing        n_fr
## [17] n_ovules       n_seeds        n_intact_seeds mean
## [21] min            max            precipitation  GDD3
## [25] GDD5           GDD7           GDD10          GDH3
## [29] GDH5           GDH7           GDH10          cumGDD3
## [33] cumGDD5        cumGDD7        cumGDD10       cumGDH3
## [37] cumGDH5        cumGDH7        cumGDH10       cumGDD3v
## [41] cumGDD5v       cumGDD7v       cumGDD10v      cumGDH3v
## [45] cumGDH5v       cumGDH7v       cumGDH10v      cumGDD3a
## [49] cumGDD5a       cumGDD7a       cumGDD10a      cumGDH3a
## [53] cumGDH5a       cumGDH7a       cumGDH10a      FFD_r
## <0 rows> (or 0-length row.names)
```

Calculate 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+
                        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
library(dplyr) #problems with plyr and dplyr

alldata_agg<-as.data.frame(alldata_agg %>%
                group_by(year) %>%
                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
```

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

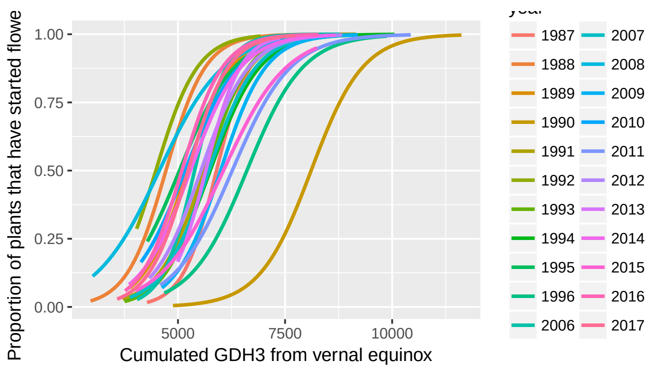
Models of proportion of plants that have started flowering against cumulated GDD/GDH

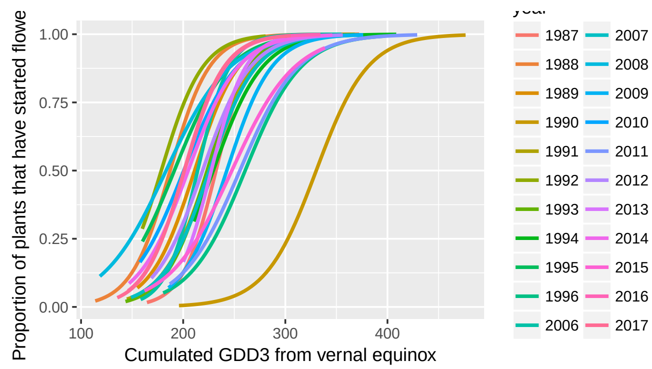
```r
#Fit univariate binomial GLMs of prop_fl against each predictor
models1<-lapply(names(alldata_agg)[2:25],
                function(x) {glm(substitute(prop_fl ~ scale(i), list(i = as.name(x))), family=binomial, da

models1_summary<-lapply(X = models1, FUN = summary)
models1_R2<-lapply(X = models1, FUN = NagelkerkeR2)

#Build a table with estimate, p and r square for all fitted models
models1_table<-cbind(names(alldata_agg)[2:25],
              ldply(models1_summary, function(x) coef(x)[2]),
              ldply(models1_summary, function(x) coef(x)[8]),
              ldply(models1_R2, function(x) x$R2)
      )
names(models1_table)<-c("variable","estimate","p","rsquare")
models1_table$sig<-ifelse(models1_table$p<0.05,"*","") # *=p<0.05

#Order models by R square
kable(arrange(models1_table,desc(rsquare)))
```

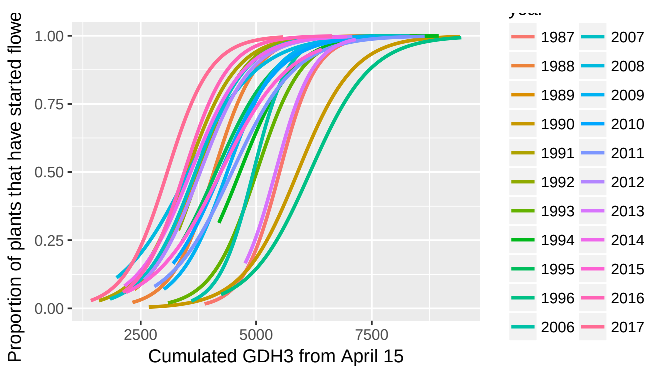
| variable | estimate | p | rsquare | sig |
|---|---|---|---|---|
| cumGDH3v | 2.082269 | 0 | 0.8247790 | * |
| cumGDD3v | 2.057905 | 0 | 0.8164516 | * |
| cumGDH5v | 2.056648 | 0 | 0.8040185 | * |
| cumGDD5v | 2.001531 | 0 | 0.7844822 | * |
| cumGDH7v | 2.008885 | 0 | 0.7681064 | * |
| cumGDH3a | 1.838762 | 0 | 0.7538278 | * |
| cumGDH5a | 1.851639 | 0 | 0.7502433 | * |
| cumGDD3a | 1.812851 | 0 | 0.7439834 | * |
| cumGDH7 | 1.997160 | 0 | 0.7368036 | * |
| cumGDD5a | 1.818132 | 0 | 0.7362666 | * |
| cumGDD7v | 1.929839 | 0 | 0.7316111 | * |
| cumGDH5 | 1.936327 | 0 | 0.7303357 | * |
| cumGDD5 | 1.936957 | 0 | 0.7296362 | * |
| cumGDH7a | 1.839629 | 0 | 0.7284625 | * |
| cumGDD7a | 1.820732 | 0 | 0.7108344 | * |
| cumGDD7 | 1.912560 | 0 | 0.7024659 | * |
| cumGDD3 | 1.767286 | 0 | 0.6746137 | * |
| cumGDH10v | 1.822322 | 0 | 0.6631881 | * |
| cumGDH10 | 1.843080 | 0 | 0.6521309 | * |
| cumGDH3 | 1.700881 | 0 | 0.6504500 | * |
| cumGDH10a | 1.697304 | 0 | 0.6366075 | * |
| cumGDD10v | 1.573997 | 0 | 0.5572632 | * |
| cumGDD10a | 1.549451 | 0 | 0.5511551 | * |
| cumGDD10 | 1.578339 | 0 | 0.5489817 | * |

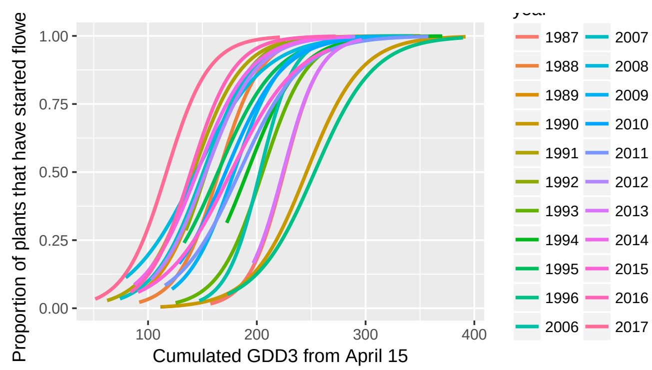
The cumulated number of GDH3 and GDD3 (computed from the vernal equinox) are the variables explaining more variation in the proportion of plants that have started flowering

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

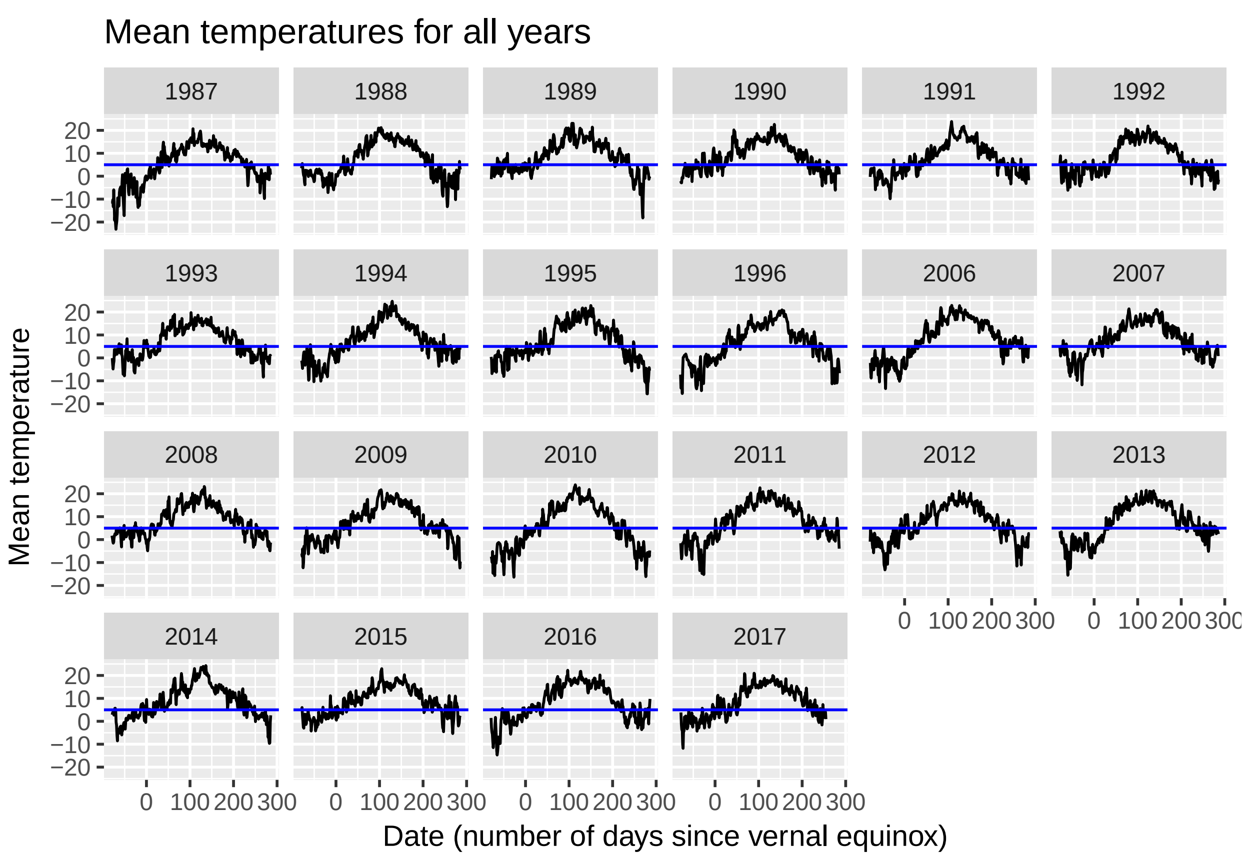


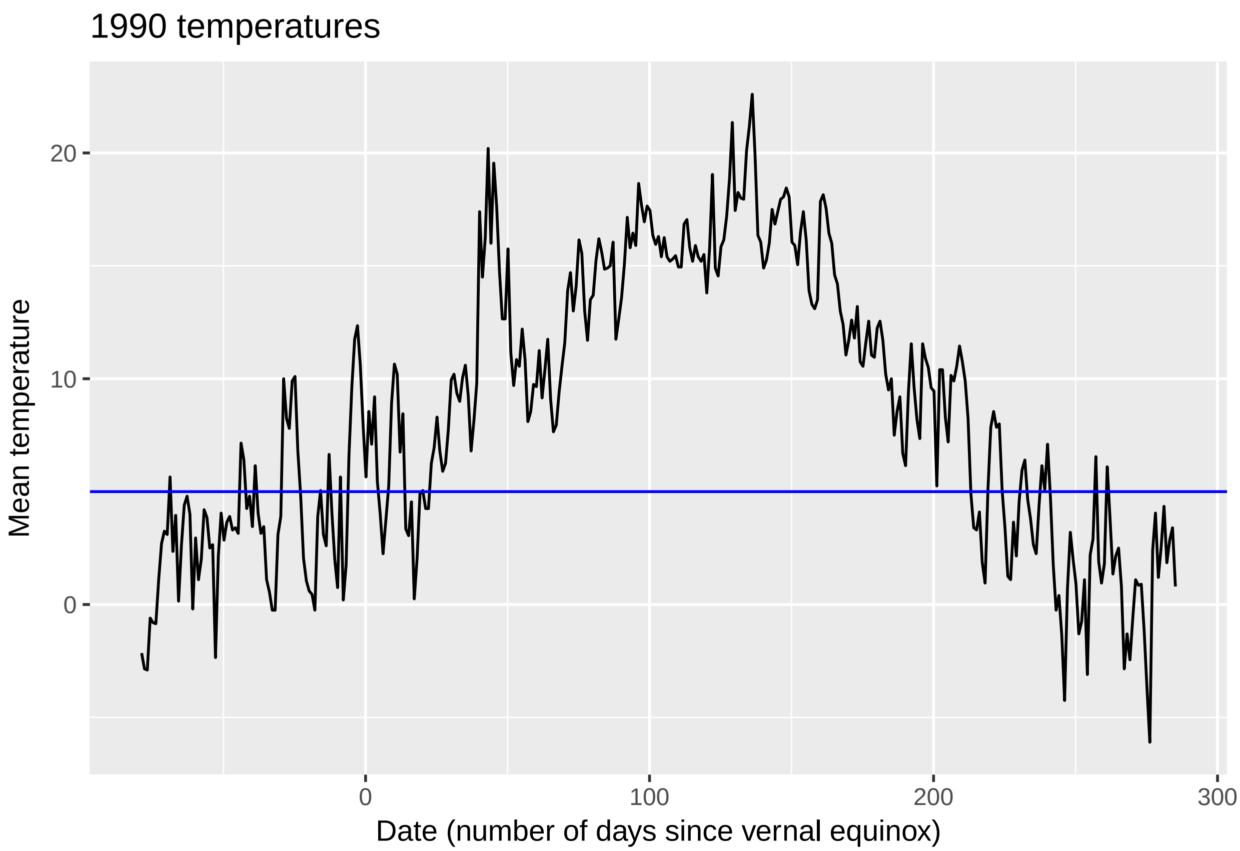



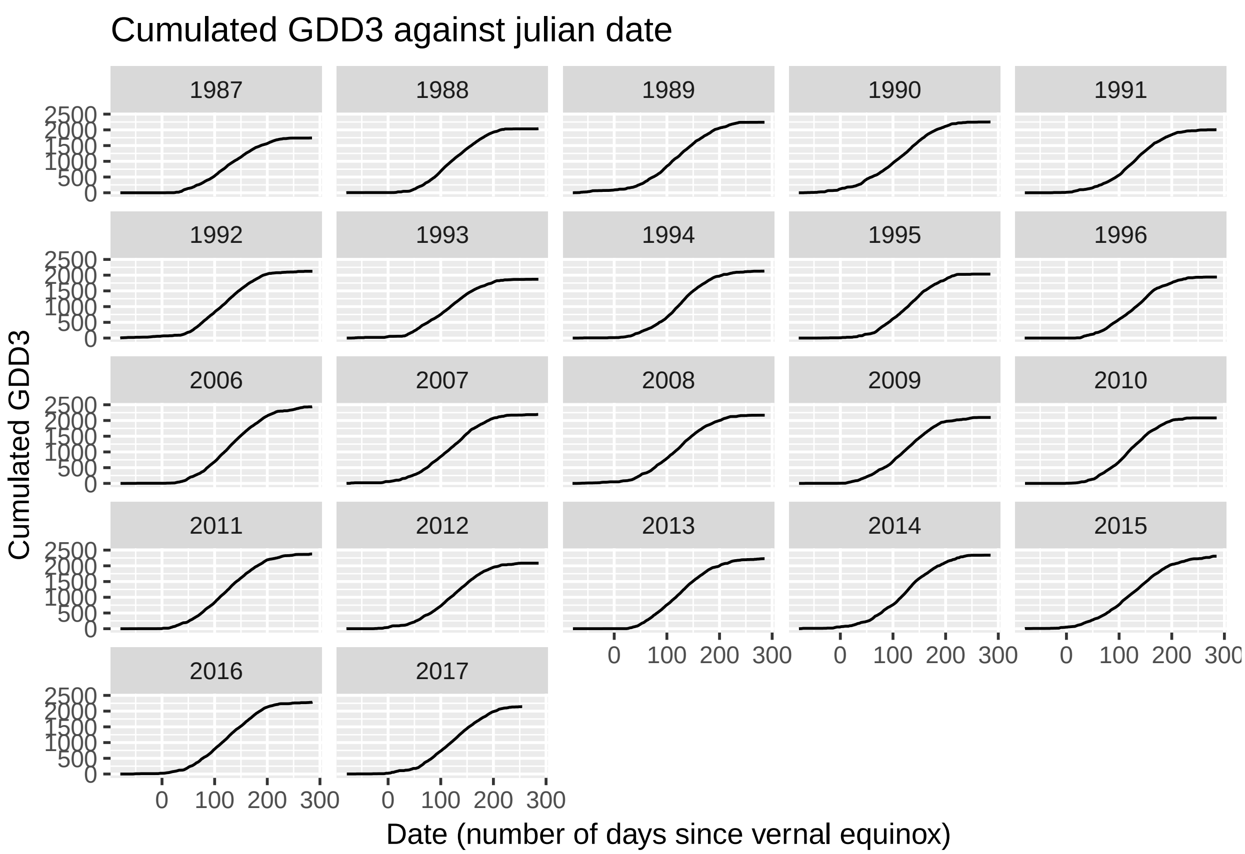



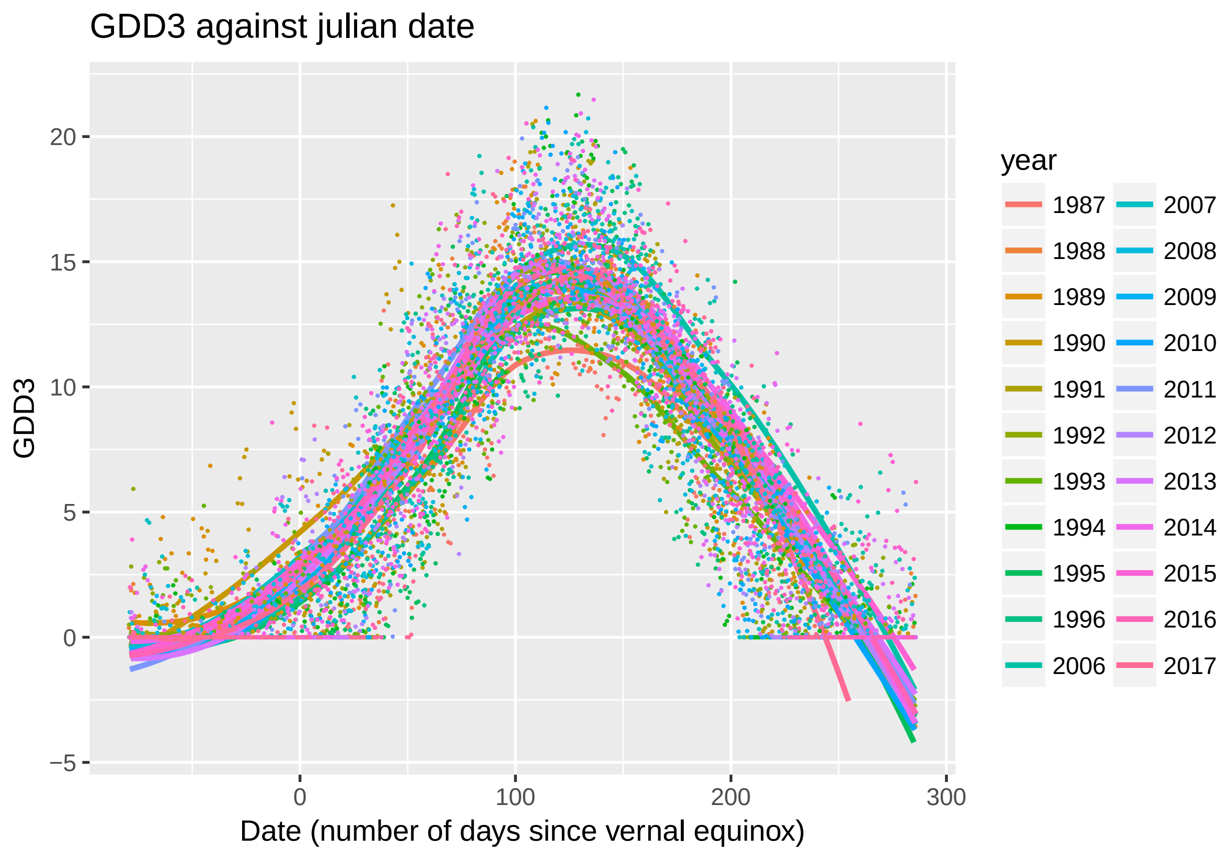



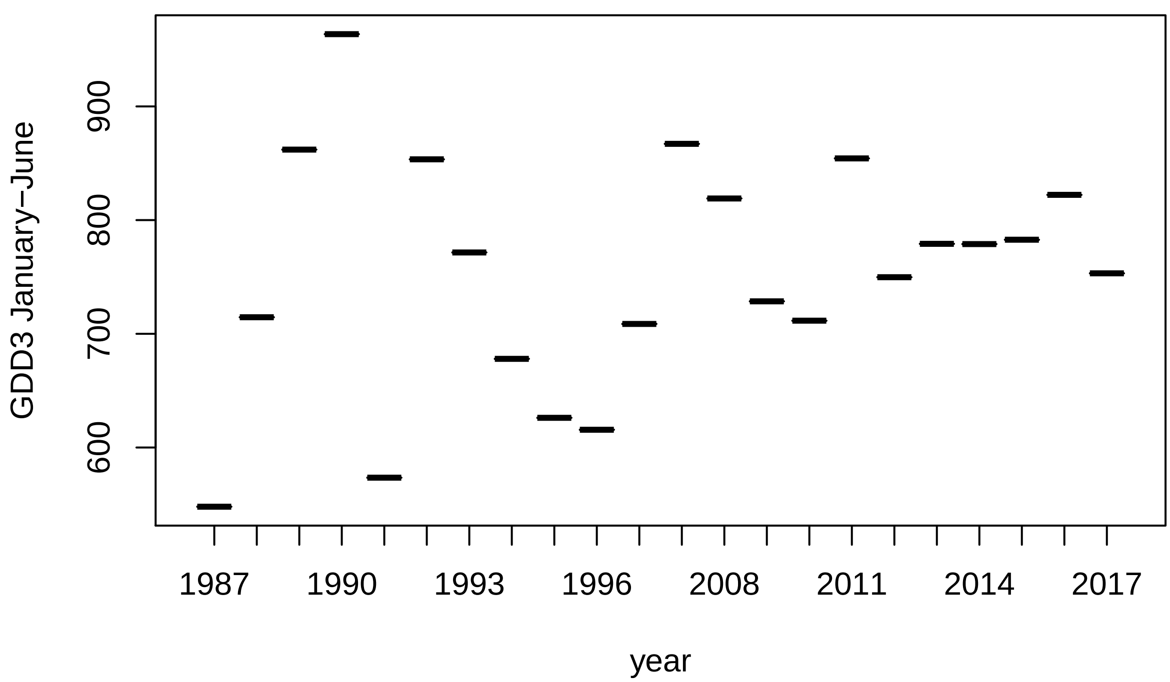

Year 1990 shows high values of GDD/GDH
Some plots to look at these high values

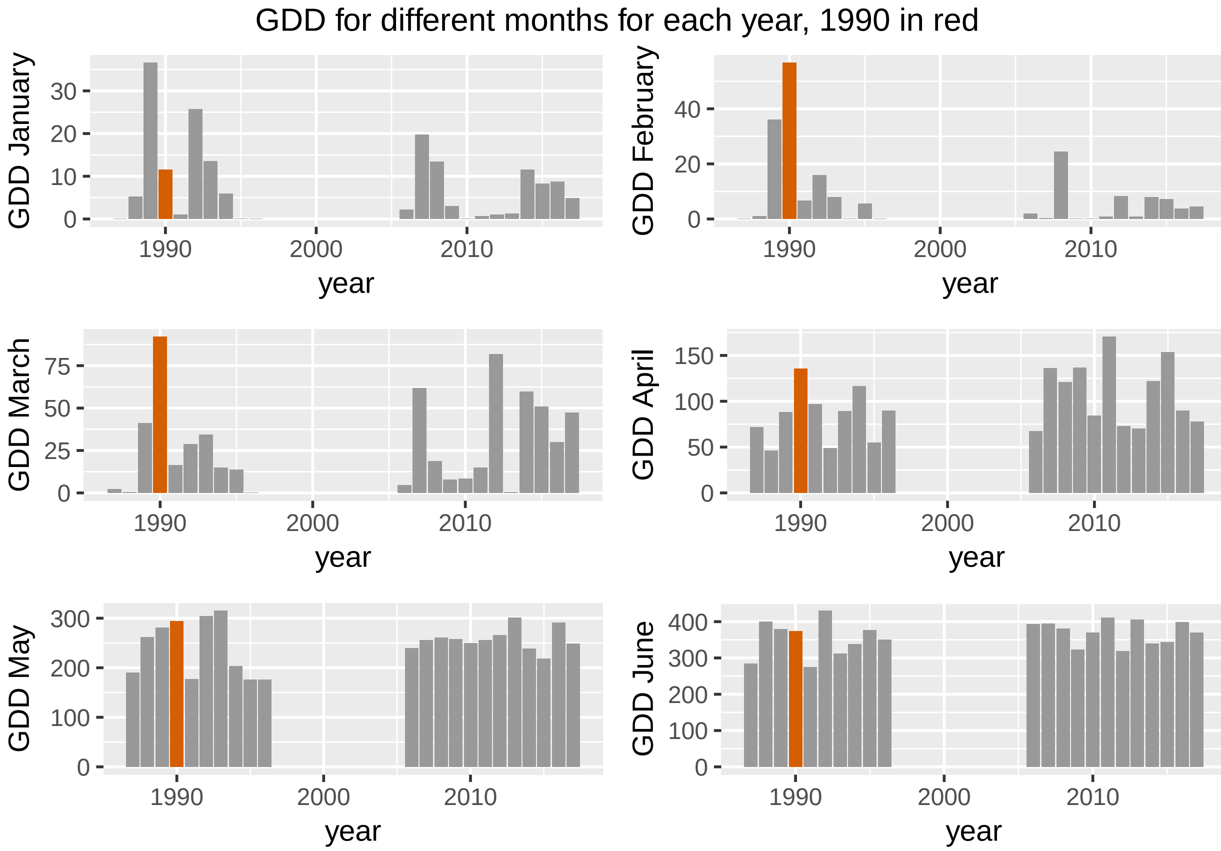


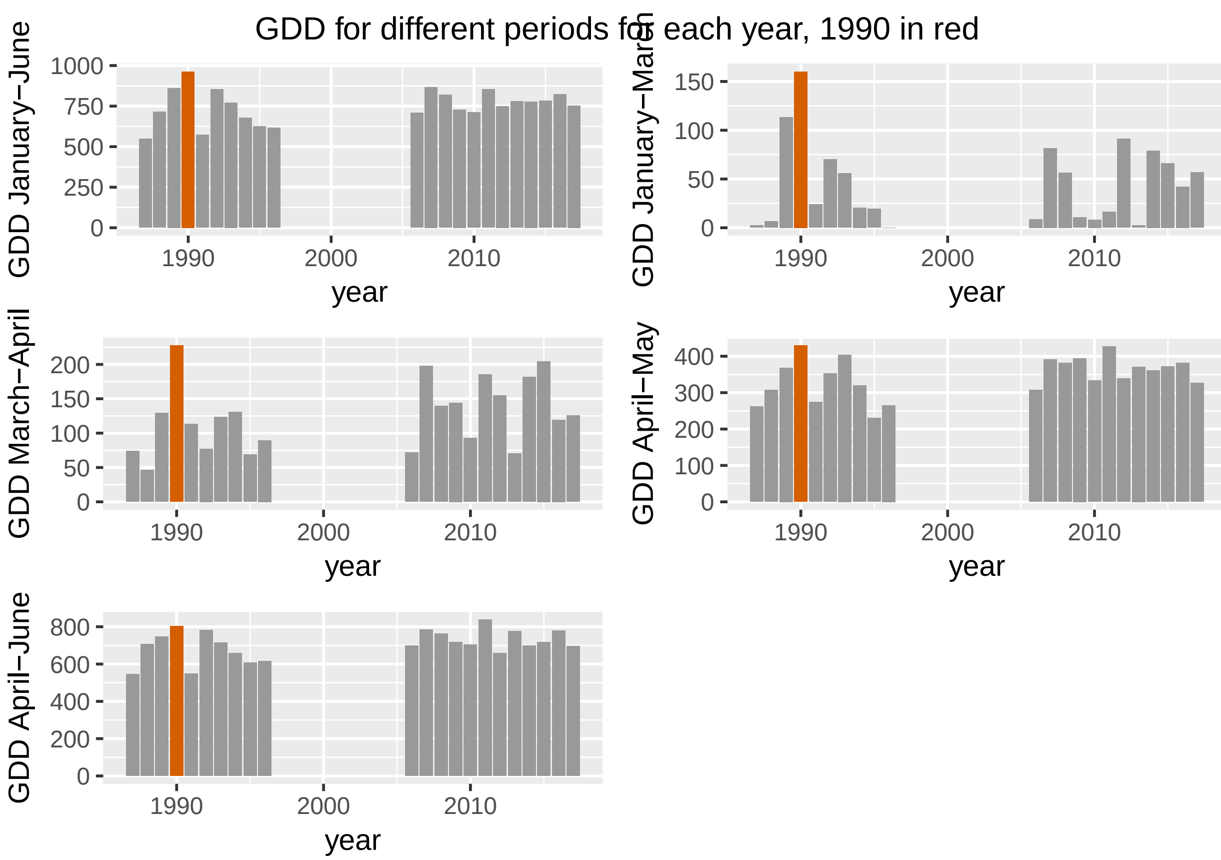

1990 temperatures
Mean temperature
20
10
0
0
100
200
300
Date (number of days since vernal equinox)


Cumulated GDD3 against julian date
Cumulated GDD3
1987
1988
1989
1990
1991
1992
1993
1994
1995
1996
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
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)
-5
0
5
10
15
20
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
600
700
800
900
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<-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")
```

```
## Joining by: year
## Joining by: year
## Joining by: year
## Joining by: year
## Joining by: year
## Joining by: year
## Joining by: year
## Joining by: year
## Joining by: year
```

```
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

```
#Fit univariate linear models of FFD against each predictor
models2<-lapply(names(mean_weather4)[c(219:228)], function(x) {
  summary(lm(substitute(FFD ~ scale(i), list(i = as.name(x))), data = mean_weather4, na.action=na.exclude)
})

#Build a table with estimate, p and r square for all fitted models
models2<-cbind(names(mean_weather4)[c(219:228)],
              ldply(models2, function(x) coef(x)[2]),
              ldply(models2, function(x) coef(x)[8]),
              ldply(models2, function(x) x$adj.r.square)
      )
names(models2)<-c("variable","estimate","p","adj.rsquare")
models2$sig<-ifelse(models2$p<0.05,"*","") # *=p<0.05

#Order models by R square
kable(arrange(models2,desc(adj.rsquare)))
```

| variable | estimate | p | adj.rsquare | sig |
|---|---|---|---|---|
| precipitation__w | -3.665808 | 0.0019909 | 0.3564066 | * |
| mean__w | -3.324004 | 0.0062438 | 0.2841524 | * |
| max__w | -3.287951 | 0.0069619 | 0.2769429 | * |
| min__w | -3.286051 | 0.0070015 | 0.2765653 | * |
| min__below__0__w | 3.234009 | 0.0081628 | 0.2663034 | * |
| mean__below__0__w | 3.100545 | 0.0118830 | 0.2407351 | * |
| min__below__minus5__w | 2.970477 | 0.0167406 | 0.2168540 | * |
| max__below__minus5__w | 2.865391 | 0.0217429 | 0.1983071 | * |
| max__below__0__w | 2.676526 | 0.0336962 | 0.1666529 | * |
| mean__below__minus5__w | 2.625453 | 0.0376865 | 0.1584634 | * |

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

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
models3<-with(alldata_agg,
            by(alldata_agg, year,
               function(x) glm(prop_fl ~ cumGDH3v, data = x,family=binomial)))
coefs_models3<-as.data.frame(sapply(models3, coef)[2,])
coefs_models3$year<-row.names(coefs_models3)
names(coefs_models3)<-c("resp_cumGDH3v","year")

mean_weather5<-merge(mean_weather4,coefs_models3)

#Fit univariate linear models of resp_cumGDH3v against each winter predictor
models4<-lapply(names(mean_weather5)[c(219:228)], function(x) {
  summary(lm(substitute(resp_cumGDH3v ~ scale(i), list(i = as.name(x))), data = mean_weather5, na.action=na
})

#Build a table with estimate, p and r square for all fitted models
models4<-cbind(names(mean_weather5)[c(219:228)],
              ldply(models4, function(x) coef(x)[2]),
              ldply(models4, function(x) coef(x)[8]),
              ldply(models4, function(x) x$adj.r.square)
      )
names(models4)<-c("variable","estimate","p","adj.rsquare")
models4$sig<-ifelse(models4$p<0.05,"*","") # *=p<0.05

#Order models by R square
kable(arrange(models4,desc(adj.rsquare)))
```

| variable | estimate | p | adj.rsquare | sig |
|---|---|---|---|---|
| precipitation__w | -0.0001855 | 0.0166639 | 0.2171773 | * |
| mean__below__0__w | 0.0000915 | 0.2641913 | 0.0149978 | |
| min__w | -0.0000882 | 0.2820526 | 0.0104699 | |
| min__below__minus5__w | 0.0000872 | 0.2878224 | 0.0090796 | |

| variable | estimate | p | adj.rsquare | sig |
|---|---|---|---|---|
| mean_w | -0.0000790 | 0.3366843 | -0.0014774 | |
| min_below_0_w | 0.0000698 | 0.3972606 | -0.0121292 | |
| max_w | -0.0000632 | 0.4442198 | -0.0189611 | |
| mean_below_minus5_w | 0.0000572 | 0.4895856 | -0.0246136 | |
| max_below_minus5_w | 0.0000498 | 0.5475656 | -0.0307106 | |
| max_below_0_w | 0.0000471 | 0.5700600 | -0.0327793 | |

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.
Another ways of testing this relation among winter conditions and response to spring temperature: Models with effects of mean temperature April and May, measures of chilling and their interaction on mean FFD.

```r
#Fit linear models of FFD against mean45*chilling measure
models5<-lapply(names(mean_weather5)[c(219:228)], function(x) {
  summary(lm(substitute(FFD ~ scale(mean45)*scale(i), list(i = as.name(x))),
          data = mean_weather5, na.action=na.exclude))
})

#Build a table with estimate, p and r square for all fitted models
models5<-cbind(names(mean_weather5)[c(219:228)],
              ldply(models5, function(x) coef(x)[4]),
              ldply(models5, function(x) coef(x)[16]),
              ldply(models5, function(x) x$adj.r.square)
      )
names(models5)<-c("variable","estimate","p","adj.rsquare")
models5$sig<-ifelse(models5$p<0.05,"*","") # *=p<0.05

#Order models by R square
kable(arrange(models5,desc(adj.rsquare)))
```

| variable | estimate | p | adj.rsquare | sig |
|---|---|---|---|---|
| precipitation_w | 0.8633909 | 0.2332496 | 0.7836344 | |
| min_below_0_w | -0.3015655 | 0.6826601 | 0.7593436 | |
| max_w | 0.5797146 | 0.4343327 | 0.7565030 | |
| max_below_minus5_w | -0.6100128 | 0.4447081 | 0.7540362 | |
| mean_w | 0.4149907 | 0.5612885 | 0.7532095 | |
| mean_below_0_w | -0.3261530 | 0.6774032 | 0.7505538 | |
| min_w | 0.2376274 | 0.7398845 | 0.7505072 | |
| max_below_0_w | -0.6363942 | 0.4837476 | 0.7479327 | |
| min_below_minus5_w | -0.2585940 | 0.7348488 | 0.7472340 | |
| mean_below_minus5_w | -0.4067785 | 0.6321929 | 0.7450429 | |

Test this within years instead of among years?