

Response of *Pinguicula vulgaris* to geothermal heating

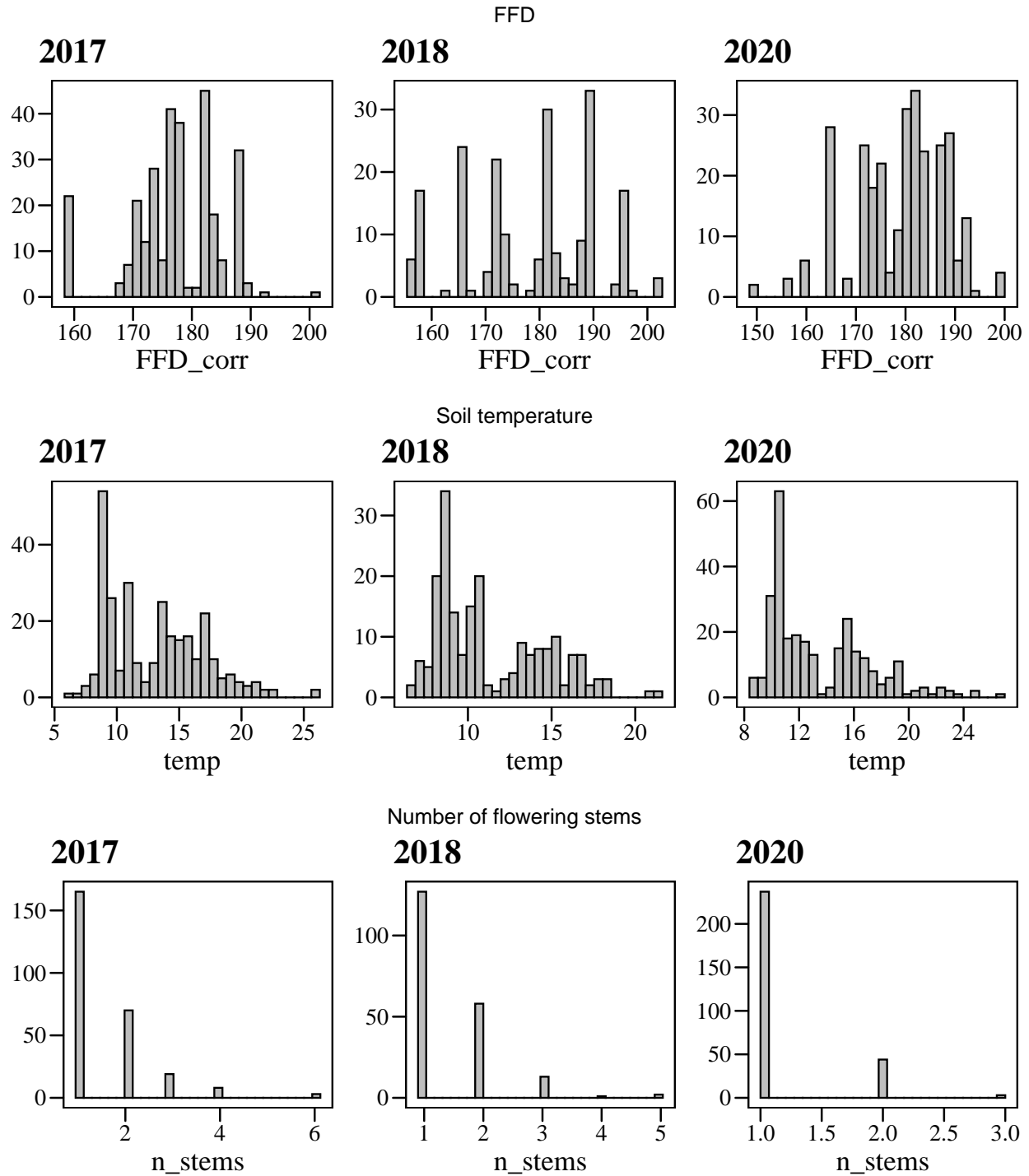
Analyses

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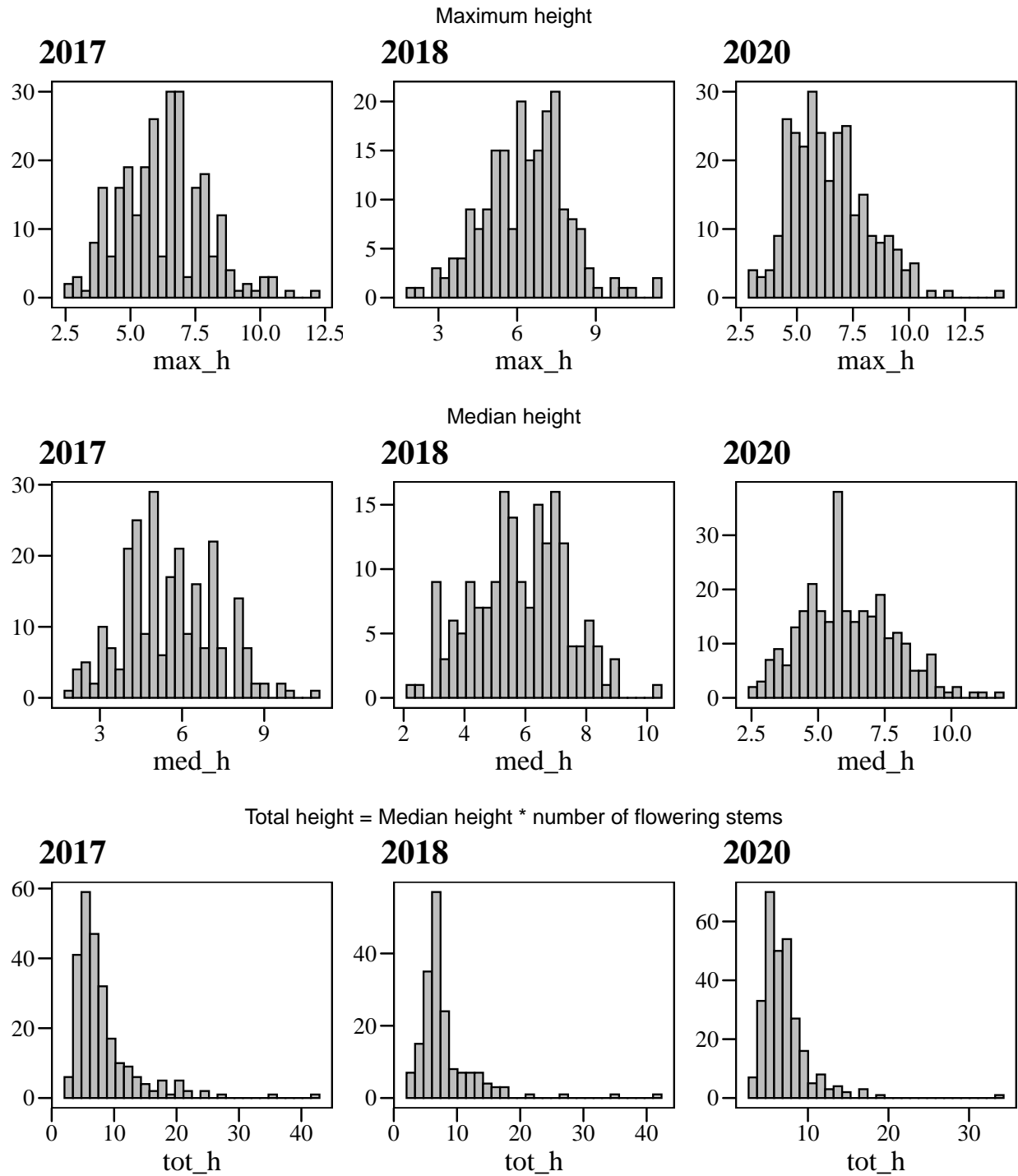
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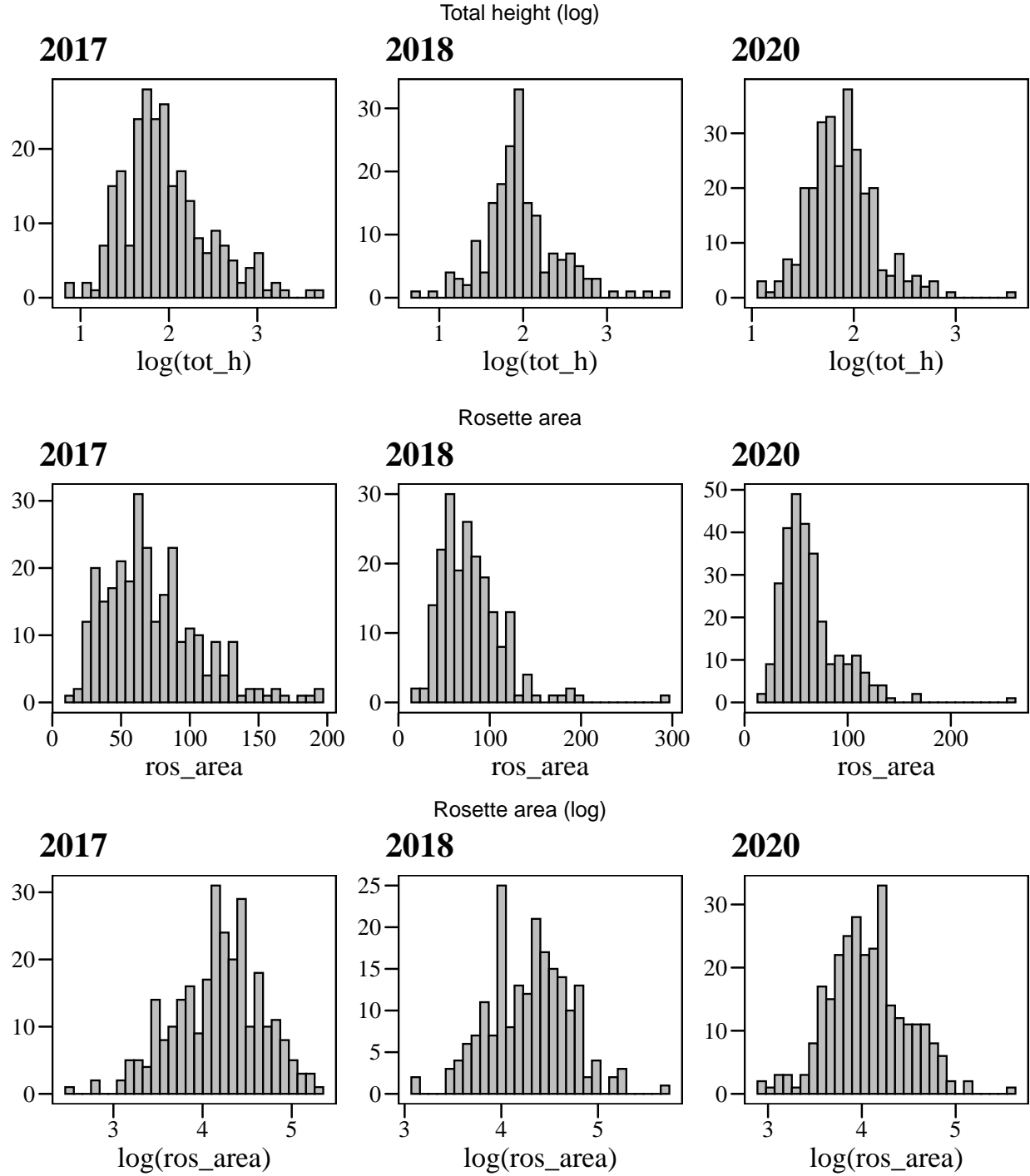
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Variable distributions



Most of them have 1 flowering stem, and the variation is not so large. Probably use another condition variable.





Relationships between fitness and condition variables

Chose between maximum height, median height, rosette area (log) and total height (log) as condition variables.

Used first Poisson models, but they showed significant overdispersion and zero-inflation. Best fitting models were zero-inflated negative binomial GLMs, so I used those

Maximum height

```
cond1_17<-glmmTMB(n_seeds~max_h,ziformula=~1,family="nbinom2",ping_17_data)
cond1_18<-glmmTMB(n_seeds~max_h,ziformula=~1,family="nbinom2",ping_18_data)
cond1_20<-glmmTMB(n_seeds~max_h,ziformula=~1,family="nbinom2",ping_20_data)
```

```
summary(cond1_17)
```

```
## Family: nbinom2 ( log )
## Formula:          n_seeds ~ max_h
## Zero inflation:    ~1
## Data: ping_17_data
##
##      AIC      BIC   logLik deviance df.resid
##  2081.7   2095.9  -1036.8   2073.7     255
##
##
## Overdispersion parameter for nbinom2 family (): 2.7
##
## Conditional model:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  5.15492    0.22372  23.041  <2e-16 ***
## max_h        0.05572    0.03405   1.636    0.102
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Zero-inflation model:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -0.1005     0.1244  -0.807    0.419
```

```
summary(cond1_18)
```

```
## Family: nbinom2 ( log )
## Formula:          n_seeds ~ max_h
## Zero inflation:    ~1
## Data: ping_18_data
##
##      AIC      BIC   logLik deviance df.resid
##  1202.4   1215.5  -597.2   1194.4     194
##
##
## Overdispersion parameter for nbinom2 family (): 2.91
##
## Conditional model:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  4.50062    0.27313  16.478  < 2e-16 ***
## max_h        0.11903    0.04096   2.906  0.00366 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Zero-inflation model:
```

```
##           Estimate Std. Error z value Pr(>|z|)
## (Intercept)  0.4520      0.1458    3.1 0.00193 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
summary(cond1_20)
```

```
## Family: nbinom2 ( log )
## Formula:          n_seeds ~ max_h
## Zero inflation:    ~1
## Data: ping_20_data
##
##      AIC      BIC   logLik deviance df.resid
##  1923.2   1937.7   -957.6   1915.2     270
##
##
## Overdispersion parameter for nbinom2 family (): 6.29
##
## Conditional model:
##           Estimate Std. Error z value Pr(>|z|)
## (Intercept)  5.02433    0.14697   34.19 < 2e-16 ***
## max_h         0.06723    0.02252    2.99  0.00283 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Zero-inflation model:
##           Estimate Std. Error z value Pr(>|z|)
## (Intercept)  0.1023      0.1210    0.845  0.398
```

Median height

```
cond2_17<-glmmTMB(n_seeds~med_h,ziformula=~1,family="nbinom2",ping_17_data)
cond2_18<-glmmTMB(n_seeds~med_h,ziformula=~1,family="nbinom2",ping_18_data)
cond2_20<-glmmTMB(n_seeds~med_h,ziformula=~1,family="nbinom2",ping_20_data)
```

```
summary(cond2_17)
```

```
## Family: nbinom2 ( log )
## Formula:          n_seeds ~ med_h
## Zero inflation:    ~1
## Data: ping_17_data
##
##      AIC      BIC   logLik deviance df.resid
##  1930.1   1944.1   -961.1   1922.1     241
##
##
## Overdispersion parameter for nbinom2 family (): 2.74
##
## Conditional model:
##           Estimate Std. Error z value Pr(>|z|)
```

```
## (Intercept)  5.64057    0.17938   31.44   <2e-16 ***
## med_h        -0.02697    0.03066   -0.88    0.379
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Zero-inflation model:
##           Estimate Std. Error z value Pr(>|z|)
## (Intercept) -0.05717    0.12783  -0.447   0.655
```

```
summary(cond2_18)
```

```
## Family: nbinom2 ( log )
## Formula:          n_seeds ~ med_h
## Zero inflation:    ~1
## Data: ping_18_data
##
##      AIC      BIC   logLik deviance df.resid
##  1085.5   1098.3   -538.8   1077.5     175
##
##
## Overdispersion parameter for nbinom2 family (): 2.63
##
## Conditional model:
##           Estimate Std. Error z value Pr(>|z|)
## (Intercept)  5.44661    0.28597  19.046   <2e-16 ***
## med_h        -0.02995    0.04849   -0.618    0.537
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Zero-inflation model:
##           Estimate Std. Error z value Pr(>|z|)
## (Intercept)   0.4664    0.1536   3.037  0.00239 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
summary(cond2_20)
```

```
## Family: nbinom2 ( log )
## Formula:          n_seeds ~ med_h
## Zero inflation:    ~1
## Data: ping_20_data
##
##      AIC      BIC   logLik deviance df.resid
##  1930.7   1945.2   -961.4   1922.7     270
##
##
## Overdispersion parameter for nbinom2 family (): 5.94
##
## Conditional model:
##           Estimate Std. Error z value Pr(>|z|)
## (Intercept)  5.60256    0.13281  42.18   <2e-16 ***
## med_h        -0.02478    0.02141   -1.16    0.247
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Zero-inflation model:
##           Estimate Std. Error z value Pr(>|z|)
## (Intercept)  0.1023      0.1210   0.845   0.398
```

Rosette area (log)

```
cond3_17<-glmmTMB(n_seeds~log(ros_area),ziformula=~1,family="nbinom2",
  ping_17_data)
cond3_18<-glmmTMB(n_seeds~log(ros_area),ziformula=~1,family="nbinom2",
  ping_18_data)
cond3_20<-glmmTMB(n_seeds~log(ros_area),ziformula=~1,family="nbinom2",
  ping_20_data)
```

```
summary(cond3_17)
```

```
## Family: nbinom2 ( log )
## Formula:          n_seeds ~ log(ros_area)
## Zero inflation:    ~1
## Data: ping_17_data
##
##      AIC      BIC   logLik deviance df.resid
##  2076.4   2090.7  -1034.2   2068.4      262
##
##
## Overdispersion parameter for nbinom2 family ():    3
##
## Conditional model:
##           Estimate Std. Error z value Pr(>|z|)
## (Intercept)    3.4967     0.4501   7.768 7.97e-15 ***
## log(ros_area)    0.4780     0.1072   4.458 8.28e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Zero-inflation model:
##           Estimate Std. Error z value Pr(>|z|)
## (Intercept) -0.04513     0.12266  -0.368   0.713
```

```
summary(cond3_18)
```

```
## Family: nbinom2 ( log )
## Formula:          n_seeds ~ log(ros_area)
## Zero inflation:    ~1
## Data: ping_18_data
##
##      AIC      BIC   logLik deviance df.resid
##  1195.5   1208.6   -593.7   1187.5      194
##
##
```



```
## Overdispersion parameter for nbinom2 family (): 3.16
##
## Conditional model:
##           Estimate Std. Error z value Pr(>|z|)
## (Intercept)    2.7849    0.6127   4.545 5.49e-06 ***
## log(ros_area)    0.5757    0.1420   4.055 5.01e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Zero-inflation model:
##           Estimate Std. Error z value Pr(>|z|)
## (Intercept)    0.4520    0.1458    3.1 0.00193 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
summary(cond3_20)
```

```
## Family: nbinom2 ( log )
## Formula:          n_seeds ~ log(ros_area)
## Zero inflation:    ~1
## Data: ping_20_data
##
##      AIC      BIC   logLik deviance df.resid
## 1914.7   1929.1  -953.3   1906.7      270
##
##
## Overdispersion parameter for nbinom2 family (): 6.71
##
## Conditional model:
##           Estimate Std. Error z value Pr(>|z|)
## (Intercept)    3.86037    0.37036  10.423 < 2e-16 ***
## log(ros_area)    0.39389    0.09164   4.298 1.72e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Zero-inflation model:
##           Estimate Std. Error z value Pr(>|z|)
## (Intercept)    0.1023    0.1210   0.845   0.398
```

Total height (log)

```
cond4_17<-glmmTMB(n_seeds~log(tot_h),ziformula=~1,family="nbinom2",
  ping_17_data)
cond4_18<-glmmTMB(n_seeds~log(tot_h),ziformula=~1,family="nbinom2",
  ping_18_data)
cond4_20<-glmmTMB(n_seeds~log(tot_h),ziformula=~1,family="nbinom2",
  ping_20_data)
```

```
summary(cond4_17)
```

```
## Family: nbinom2 ( log )
```

```
## Formula:          n_seeds ~ log(tot_h)
## Zero inflation:    ~1
## Data: ping_17_data
##
##      AIC      BIC   logLik deviance df.resid
##  1917.9   1931.9   -955.0   1909.9     241
##
##
## Overdispersion parameter for nbinom2 family (): 3
##
## Conditional model:
##           Estimate Std. Error z value Pr(>|z|)
## (Intercept)  4.6430     0.2337  19.863 < 2e-16 ***
## log(tot_h)    0.4100     0.1125   3.643 0.000269 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Zero-inflation model:
##           Estimate Std. Error z value Pr(>|z|)
## (Intercept) -0.05716     0.12783  -0.447   0.655
```

```
summary(cond4_18)
```

```
## Family: nbinom2 ( log )
## Formula:          n_seeds ~ log(tot_h)
## Zero inflation:    ~1
## Data: ping_18_data
##
##      AIC      BIC   logLik deviance df.resid
##  1066.2   1079.0   -529.1   1058.2     175
##
##
## Overdispersion parameter for nbinom2 family (): 3.42
##
## Conditional model:
##           Estimate Std. Error z value Pr(>|z|)
## (Intercept)  3.8697     0.3106  12.458 < 2e-16 ***
## log(tot_h)    0.6615     0.1476   4.481 7.44e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Zero-inflation model:
##           Estimate Std. Error z value Pr(>|z|)
## (Intercept)  0.4664     0.1536   3.037 0.00239 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
summary(cond4_20)
```

```
## Family: nbinom2 ( log )
## Formula:          n_seeds ~ log(tot_h)
## Zero inflation:    ~1
## Data: ping_20_data
```

```
##
##      AIC      BIC   logLik deviance df.resid
##  1893.4   1907.8   -942.7   1885.4      270
##
##
## Overdispersion parameter for nbinom2 family (): 7.9
##
## Conditional model:
##           Estimate Std. Error z value Pr(>|z|)
## (Intercept)  4.19879    0.18918  22.194 < 2e-16 ***
## log(tot_h)   0.65456    0.09879   6.626 3.45e-11 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Zero-inflation model:
##           Estimate Std. Error z value Pr(>|z|)
## (Intercept)   0.1023     0.1210   0.845   0.398
```

Rosette area and total height have significant effects on fitness on the 3 years. Total height has larger effect sizes than rosette area in 2 out of 3 years (checked with models with scaled predictors, not shown). Now using rosette area as condition variable.

1. Models for FFD

1.1. Effect of temperature on FFD

Using linear models, including quadratic effects of temp (included first but removed in 2017 because they were not significant).

```
FFD_2017_1<-lm(FFD_corr~temp,ping_17_data)
summary(FFD_2017_1)
```

```
##
## Call:
## lm(formula = FFD_corr ~ temp, data = ping_17_data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -14.2025  -2.6261  -0.2459   2.9045  23.4895
##
## Coefficients:
##           Estimate Std. Error t value Pr(>|t|)
## (Intercept) 196.20860    1.10402  177.72 <2e-16 ***
## temp        -1.44386    0.08105  -17.81 <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 5.342 on 290 degrees of freedom
## Multiple R-squared:  0.5225, Adjusted R-squared:  0.5209
## F-statistic: 317.4 on 1 and 290 DF, p-value: < 2.2e-16
```

```
FFD_2018_1<-lm(FFD_corr~temp+I(temp^2),ping_18_data)
summary(FFD_2018_1)
```

```
##
## Call:
## lm(formula = FFD_corr ~ temp + I(temp^2), data = ping_18_data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -12.4932  -4.3128   0.0669   3.0298  16.1994
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  235.5409     5.7042  41.293 < 2e-16 ***
## temp        -6.7120     0.9608  -6.986 4.21e-11 ***
## I(temp^2)     0.1369     0.0380   3.604 0.000397 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 5.604 on 198 degrees of freedom
## Multiple R-squared:  0.7895, Adjusted R-squared:  0.7874
## F-statistic: 371.3 on 2 and 198 DF,  p-value: < 2.2e-16
```

```
FFD_2020_1<-lm(FFD_corr~temp+I(temp^2),ping_20_data)
summary(FFD_2020_1)
```

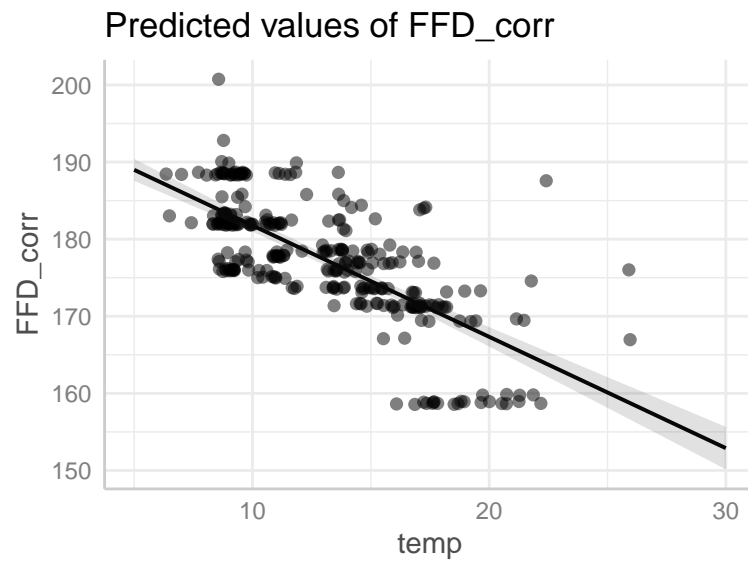
```
##
## Call:
## lm(formula = FFD_corr ~ temp + I(temp^2), data = ping_20_data)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -12.3407  -2.5589   0.2415   2.8193  14.0155
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  216.81764     3.78519  57.281 < 2e-16 ***
## temp        -3.37575     0.51862  -6.509 3.41e-10 ***
## I(temp^2)     0.03967     0.01681   2.360  0.0189 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4.435 on 284 degrees of freedom
## Multiple R-squared:  0.7598, Adjusted R-squared:  0.7581
## F-statistic: 449.2 on 2 and 284 DF,  p-value: < 2.2e-16
```

Model diagnostics (not shown) indicated that linear models are OK.

2017:

```
plot(ggpredict(FFD_2017_1),add.data=T)
```

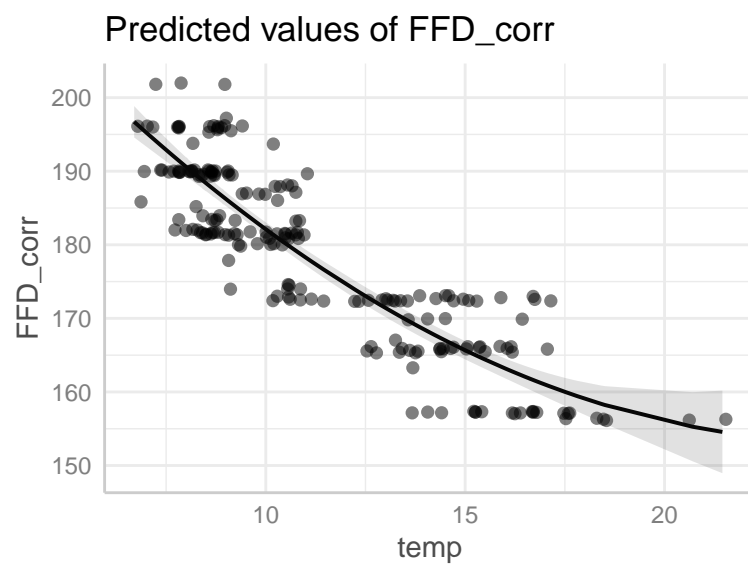
```
## $temp
```



2018:

```
plot(ggpredict(FFD_2018_1),add.data=T)
```

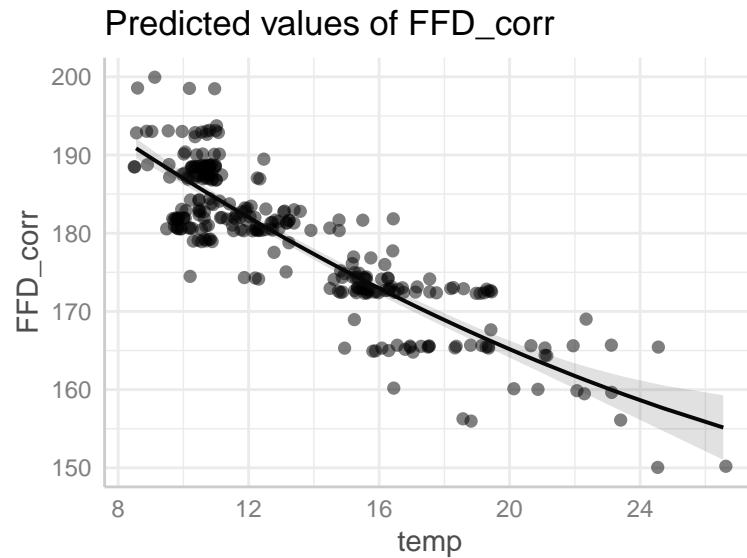
```
## $temp
```



2020:

```
plot(ggpredict(FFD_2020_1),add.data=T)
```

```
## $temp
```



The effects look almost linear in 2018 and 2020.

Predictions of FFD_corr for minimum and maximum temperatures:

```
ggpredict(FFD_2017_1, terms="temp[minmax]")
```

```
## # Predicted values of FFD_corr
## # x = temp
##
##      x | Predicted |           95% CI
## -----
##  6.20 |    187.26 | [186.01, 188.51]
## 26.00 |    158.67 | [156.52, 160.81]
```

187.26-158.67=28.59 days earlier on warmer soils

```
ggpredict(FFD_2018_1, terms="temp[minmax]")
```

```
## # Predicted values of FFD_corr
## # x = temp
##
##      x | Predicted |           95% CI
## -----
##  6.70 |    196.72 | [194.59, 198.85]
## 21.45 |    154.57 | [148.95, 160.18]
```

196.72-154.57=42.15 days earlier on warmer soils

```
ggpredict(FFD_2020_1, terms="temp[minmax]")
```

```
## # Predicted values of FFD_corr
## # x = temp
##
##      x | Predicted |           95% CI
## -----
##  8.55 |    190.85 | [189.57, 192.14]
## 26.55 |    155.16 | [151.03, 159.28]
```

```
# 190.85-155.16=35.69 days earlier on warmer soils
```

2. Models for fitness

2.1 Effect of temperature on fitness

Fitness as number of seeds

Including rosette area (log) as condition variable. Quadratic effects of temperature significant in 2017 and 2018, but not on 2020, where I removed the quadratic term. I used only plants from control treatment in 2020. Using negative binomial GLMs with zero inflation (best fitting models).

```
fitness_2017_1<-glmmTMB(n_seeds~temp+I(temp^2)+log(ros_area),ziformula=~1,
  ping_17_data,family="nbinom2")
fitness_2018_1<-glmmTMB(n_seeds~temp+I(temp^2)+log(ros_area),ziformula=~1,
  ping_18_data,family="nbinom2")
fitness_2020_1<-glmmTMB(n_seeds~temp+log(ros_area),ziformula=~1,
  subset(ping_20_data,treatment=="C"),family="nbinom2")
```

```
summary(fitness_2017_1)
```

```
## Family: nbinom2 ( log )
## Formula:          n_seeds ~ temp + I(temp^2) + log(ros_area)
## Zero inflation:      ~1
## Data: ping_17_data
##
##      AIC      BIC   logLik deviance df.resid
##  2069.8   2091.3  -1028.9   2057.8      260
##
##
## Overdispersion parameter for nbinom2 family (): 3.23
##
## Conditional model:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)   1.288022   0.827613   1.556  0.11963
## temp          0.265971   0.099391   2.676  0.00745 **
## I(temp^2)     -0.008355   0.003462  -2.413  0.01581 *
## log(ros_area)  0.544520   0.103771   5.247 1.54e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Zero-inflation model:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -0.04512    0.12266  -0.368   0.713
```

```
summary(fitness_2018_1)
```

```
## Family: nbinom2 ( log )
## Formula:          n_seeds ~ temp + I(temp^2) + log(ros_area)
## Zero inflation:      ~1
```

```
## Data: ping_18_data
##
##      AIC      BIC   logLik deviance df.resid
##   1187.2   1207.0   -587.6   1175.2     192
##
##
## Overdispersion parameter for nbinom2 family (): 3.67
##
## Conditional model:
##           Estimate Std. Error z value Pr(>|z|)
## (Intercept)  1.743223   1.116646   1.561 0.118494
## temp         0.290840   0.138840   2.095 0.036190 *
## I(temp^2)    -0.013855   0.005432  -2.551 0.010750 *
## log(ros_area) 0.497321   0.140055   3.551 0.000384 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Zero-inflation model:
##           Estimate Std. Error z value Pr(>|z|)
## (Intercept)  0.4520     0.1458     3.1 0.00193 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

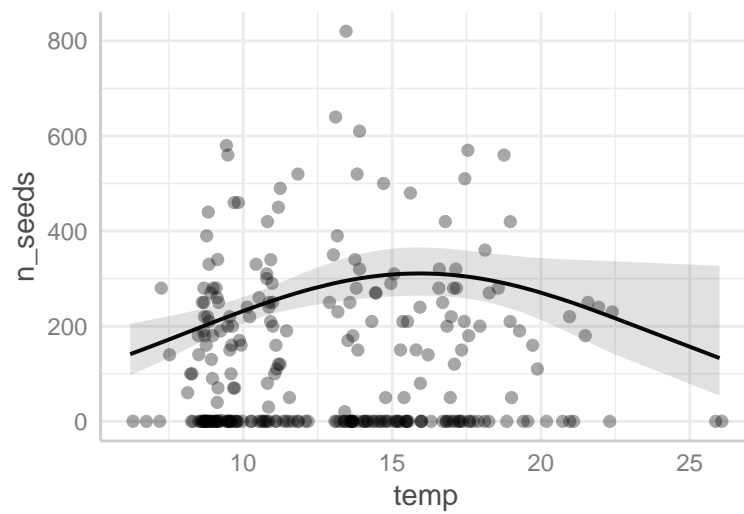
```
summary(fitness_2020_1)
```

```
## Family: nbinom2 ( log )
## Formula:      n_seeds ~ temp + log(ros_area)
## Zero inflation: ~1
## Data: subset(ping_20_data, treatment == "C")
##
##      AIC      BIC   logLik deviance df.resid
##   558.3   569.7   -274.1   548.3     68
##
##
## Overdispersion parameter for nbinom2 family (): 5.59
##
## Conditional model:
##           Estimate Std. Error z value Pr(>|z|)
## (Intercept)  4.852175   1.074719   4.515 6.34e-06 ***
## temp        -0.004944   0.025800  -0.192   0.848
## log(ros_area) 0.144982   0.229599   0.631   0.528
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Zero-inflation model:
##           Estimate Std. Error z value Pr(>|z|)
## (Intercept) -0.08224    0.23428  -0.351   0.726
```

Significant effects in 2017 and 2018.

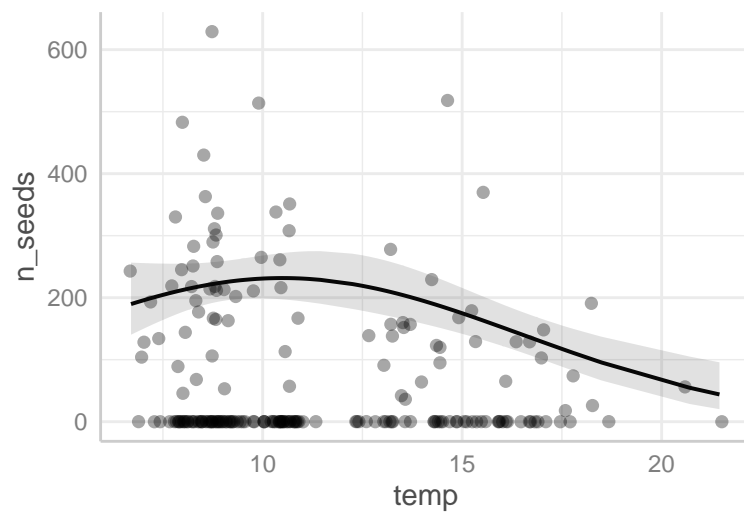
```
plot(ggeffect(fitness_2017_1,type="zero_inflated",terms="temp[all]"),
     add.data=T) # * positive effect of temp
```


Predicted counts of n_seeds



```
plot(ggeffect(fitness_2018_1,type="zero_inflated",terms="temp[all]"),
     add.data=T) # * negative effect of temp
```

Predicted counts of n_seeds



Fitness as 0/1

Proportion of plants in each year that produced 0 seeds:

```
nrow(subset(ping_17_data,n_seeds==0))/nrow(ping_17_data)
```

```
## [1] 0.4623288
```

```
nrow(subset(ping_18_data,n_seeds==0))/nrow(ping_18_data)
```

```
## [1] 0.6069652
```

```
nrow(subset(ping_20_data,n_seeds==0))/nrow(ping_20_data)
```

```
## [1] 0.5052265
```

Around half of the plants in each year produced no seeds.

Therefore, I tried also fitting logistic regressions (binomial GLMs) with fitness as a 0/1 variable (0 = no seeds produced, 1 = at least 1 seed produced).

Create 0/1 variable for fitness:

```
ping_17_data$fitness_01<-with(ping_17_data,ifelse(n_seeds==0,0,
                                                    ifelse(n_seeds>0,1,NA)))
ping_18_data$fitness_01<-with(ping_18_data,ifelse(n_seeds==0,0,
                                                    ifelse(n_seeds>0,1,NA)))
ping_20_data$fitness_01<-with(ping_20_data,ifelse(n_seeds==0,0,
                                                    ifelse(n_seeds>0,1,NA)))
```

Including rosette area (log) as condition variable. I first included quadratic effects of temperature, but then removed them because they were never significant. I used only plants from control treatment in 2020.

```
fitness_01_2017_1<-glm(fitness_01~temp+log(ros_area),ping_17_data,
                        family="binomial")
fitness_01_2018_1<-glm(fitness_01~temp+log(ros_area),ping_18_data,
                        family="binomial")
fitness_01_2020_1<-glm(fitness_01~temp+log(ros_area),
                        subset(ping_20_data,treatment=="C"),family="binomial")
```

```
summary(fitness_01_2017_1)
```

```
##
## Call:
## glm(formula = fitness_01 ~ temp + log(ros_area), family = "binomial",
##      data = ping_17_data)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -1.246  -1.197   1.124   1.156   1.213
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)    0.39707    1.22288   0.325   0.745
## temp          -0.01218    0.03229  -0.377   0.706
## log(ros_area) -0.04655    0.25539  -0.182   0.855
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 368.62  on 265  degrees of freedom
## Residual deviance: 368.46  on 263  degrees of freedom
## (26 observations deleted due to missingness)
## AIC: 374.46
##
## Number of Fisher Scoring iterations: 3
```

```
summary(fitness_01_2018_1)
```

```
##
## Call:
## glm(formula = fitness_01 ~ temp + log(ros_area), family = "binomial",
##      data = ping_18_data)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -1.0074  -0.9974  -0.9815   1.3658   1.4047
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -0.444958   1.729915  -0.257   0.797
## temp          -0.007492   0.045896  -0.163   0.870
## log(ros_area)  0.018144   0.358033   0.051   0.960
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 264.63  on 197  degrees of freedom
## Residual deviance: 264.59  on 195  degrees of freedom
## (3 observations deleted due to missingness)
## AIC: 270.59
##
## Number of Fisher Scoring iterations: 4
```

```
summary(fitness_01_2020_1)
```

```
##
## Call:
## glm(formula = fitness_01 ~ temp + log(ros_area), family = "binomial",
##      data = subset(ping_20_data, treatment == "C"))
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -1.469  -1.204   0.974   1.125   1.366
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)   2.97166   3.18921   0.932   0.351
## temp          -0.07502   0.06792  -1.105   0.269
## log(ros_area) -0.45641   0.66657  -0.685   0.494
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 101.076  on 72  degrees of freedom
## Residual deviance:  99.729  on 70  degrees of freedom
## (6 observations deleted due to missingness)
## AIC: 105.73
##
## Number of Fisher Scoring iterations: 4
```

No significant effects.

2.2. Effect of treatment on fitness (2020)

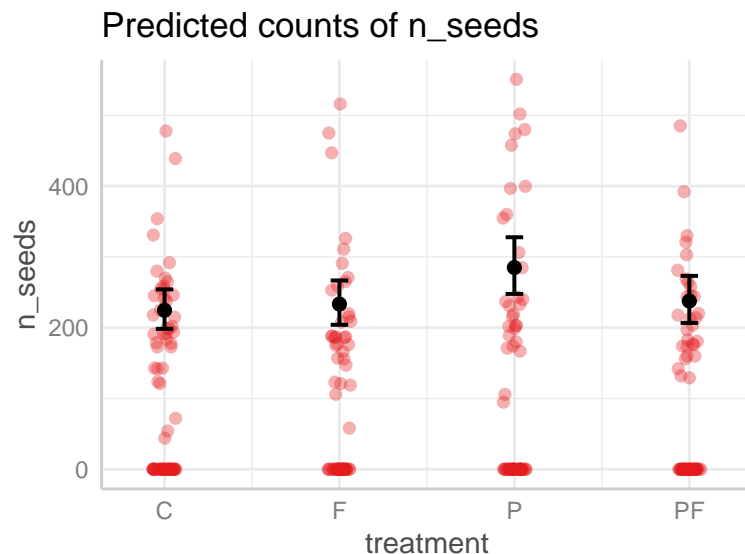
Fitness as number of seeds

Using a negative binomial GLM with zero inflation. Including total height (log) as condition variable.

```
fitness_2020_treat<-glmmTMB(n_seeds~treatment+log(ros_area),ziformula=~1,  
                             ping_20_data,family="nbinom2")  
summary(fitness_2020_treat)
```

```
## Family: nbinom2 ( log )  
## Formula:      n_seeds ~ treatment + log(ros_area)  
## Zero inflation:      ~1  
## Data: ping_20_data  
##  
##      AIC      BIC    logLik deviance df.resid  
##  1913.5   1938.8   -949.8   1899.5      267  
##  
##  
## Overdispersion parameter for nbinom2 family (): 7.09  
##  
## Conditional model:  
##              Estimate Std. Error z value Pr(>|z|)  
## (Intercept)    3.82956    0.36805  10.405 < 2e-16 ***  
## treatmentF     0.03837    0.09092   0.422  0.6730  
## treatmentP     0.23815    0.09402   2.533  0.0113 *  
## treatmentPF    0.05676    0.09325   0.609  0.5427  
## log(ros_area)  0.38164    0.09000   4.240 2.23e-05 ***  
## ---  
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1  
##  
## Zero-inflation model:  
##              Estimate Std. Error z value Pr(>|z|)  
## (Intercept)    0.1023    0.1210   0.845  0.398
```

```
plot(ggeffect(fitness_2020_treat,term="treatment"),add.data=T)
```



Fitness significantly larger in pollination treatment than in control.

Fitness as 0/1

Logistic regression (binomial GLM) with fitness as a 0/1 variable (0 = no seeds produced, 1 = at least 1 seed produced).

```
fitness_01_2020_treat<-glm(fitness_01~treatment+log(ros_area),ping_20_data,
                           family="binomial")
summary(fitness_01_2020_treat)
```

```
##
## Call:
## glm(formula = fitness_01 ~ treatment + log(ros_area), family = "binomial",
##      data = ping_20_data)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -1.4094  -1.1304  -0.9658   1.1965   1.4398
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)    1.9525     1.2321   1.585   0.113
## treatmentF    -0.1235     0.3398  -0.363   0.716
## treatmentP    -0.2678     0.3445  -0.777   0.437
## treatmentPF   -0.3704     0.3394  -1.091   0.275
## log(ros_area) -0.4601     0.2975  -1.547   0.122
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 379.13  on 273  degrees of freedom
## Residual deviance: 375.35  on 269  degrees of freedom
## (13 observations deleted due to missingness)
## AIC: 385.35
```

```
##
## Number of Fisher Scoring iterations: 4
```

No significant effects.

2.3. Effect of temperature AND treatment on fitness (2020)

Fitness as number of seeds

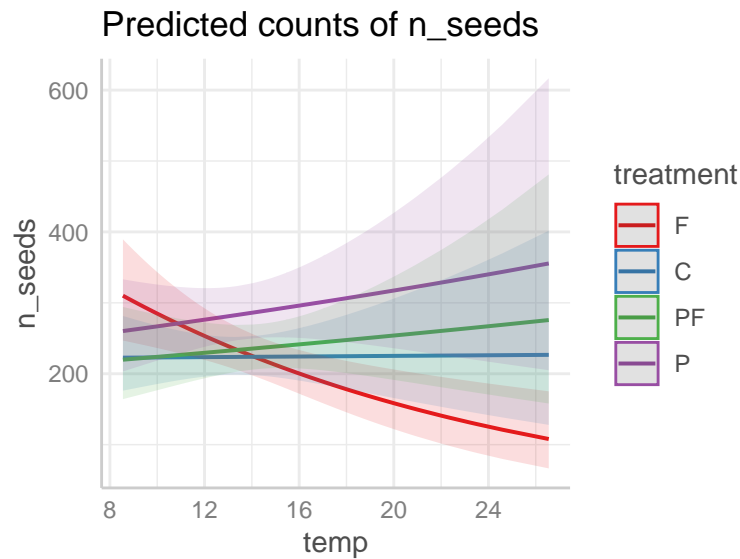
Using a negative binomial GLM with zero inflation. Including rosette area (log) as condition variable. Including temperature and treatment as predictors both in the “count” part of the model and in the “zero-inflation” part of the model.

```
fitness_2020_temp_treat_2<-glmmTMB(n_seeds~temp*treatment+log(ros_area),
                                   ziformula=~.,ping_20_data,family="nbinom2")
summary(fitness_2020_temp_treat_2)
```

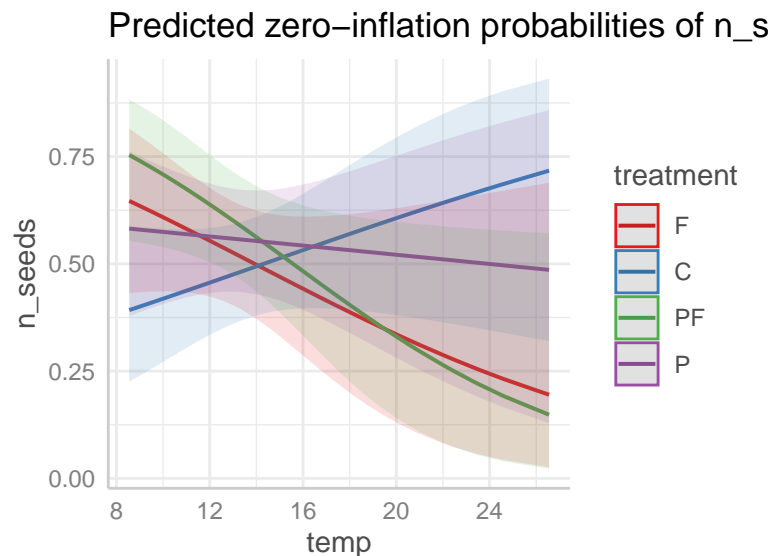
```
## Family: nbinom2 ( log )
## Formula:          n_seeds ~ temp * treatment + log(ros_area)
## Zero inflation:    ~.
## Data: ping_20_data
##
##      AIC      BIC   logLik deviance df.resid
##  1915.6   1984.2   -938.8   1877.6      255
##
##
## Overdispersion parameter for nbinom2 family (): 7.65
##
## Conditional model:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)    3.9460783  0.4872894   8.098 5.59e-16 ***
## temp           0.0009796  0.0216021   0.045  0.9638
## treatmentF     0.8409260  0.3941930   2.133  0.0329 *
## treatmentP     0.0158910  0.4178332   0.038  0.9697
## treatmentPF    -0.1123631  0.4455066  -0.252  0.8009
## log(ros_area)  0.3494890  0.0879891   3.972 7.13e-05 ***
## temp:treatmentF -0.0596171  0.0283388  -2.104  0.0354 *
## temp:treatmentP  0.0163604  0.0303279   0.539  0.5896
## temp:treatmentPF 0.0116164  0.0313609   0.370  0.7111
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Zero-inflation model:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)   -3.09367    1.67981  -1.842  0.0655 .
## temp          0.07603    0.06414   1.185  0.2359
## treatmentF     2.65354    1.41908   1.870  0.0615 .
## treatmentP     1.60274    1.32982   1.205  0.2281
## treatmentPF     3.56759    1.41344   2.524  0.0116 *
## log(ros_area)  0.48299    0.30896   1.563  0.1180
## temp:treatmentF -0.18844    0.10290  -1.831  0.0671 .
## temp:treatmentP -0.09752    0.09470  -1.030  0.3031
```

```
## temp:treatmentPF -0.23529    0.10047  -2.342    0.0192 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
plot(ggpredict(fitness_2020_temp_treat_2,terms=c("temp[all]","treatment"),
  type="fixed"))
```



```
plot(ggpredict(fitness_2020_temp_treat_2,terms=c("temp[all]","treatment"),
  type="zi_prob"))
```



First plot: fitness decreases with temperature only for plants in F treatment. This seems contrary to what I would expect - see how can we explain this! Second plot: the probability of zero inflation is represented; values of 1 in the Y-axis indicate a 100% probability of zero inflation (i.e. of producing 0 seeds), so it is like an “inversed” logistic model. The probability of zero inflation decreases with temperature for plants in the PF treatment (and almost in the F treatment, $p=0.07$). In other words, the probability of producing

seeds increases with temperature in those treatments. This agrees with my expectations, as pollination and prey supplementation might partly compensate for the maladaptive nature of plasticity on heated soils, “restoring” interactions that might be lost in these areas because of different sensitivities to warming between plants and interacting animals.

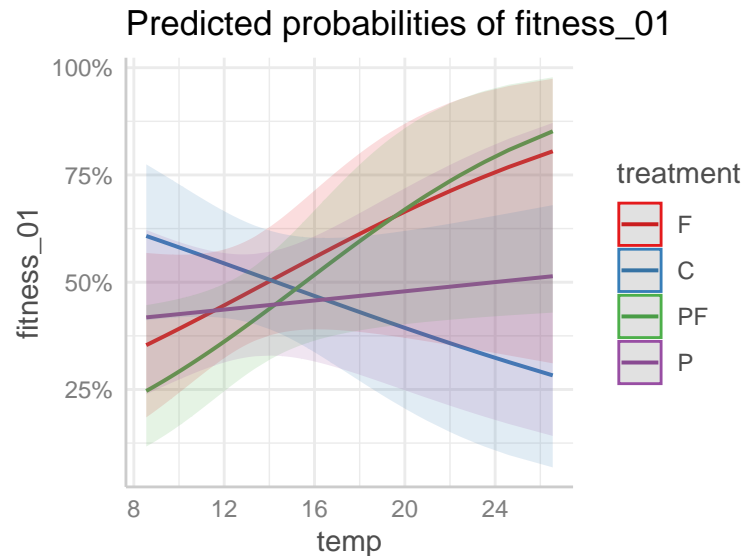
Fitness as 0/1

Logistic regression (binomial GLM) with fitness as a 0/1 variable (0 = no seeds produced, 1 = at least 1 seed produced).

```
fitness_01_2020_temp_treat<-glm(fitness_01~temp*treatment+log(ros_area),
                                ping_20_data,family="binomial")
summary(fitness_01_2020_temp_treat)
```

```
##
## Call:
## glm(formula = fitness_01 ~ temp * treatment + log(ros_area),
##      family = "binomial", data = ping_20_data)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -1.5994  -1.1043  -0.8436   1.1696   1.6781
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)    3.09365    1.67980   1.842  0.0655 .
## temp          -0.07603    0.06414  -1.185  0.2359
## treatmentF     -2.65355    1.41907  -1.870  0.0615 .
## treatmentP     -1.60275    1.32979  -1.205  0.2281
## treatmentPF    -3.56759    1.41342  -2.524  0.0116 *
## log(ros_area)  -0.48299    0.30896  -1.563  0.1180
## temp:treatmentF  0.18844    0.10290   1.831  0.0671 .
## temp:treatmentP  0.09752    0.09470   1.030  0.3031
## temp:treatmentPF 0.23529    0.10046   2.342  0.0192 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 379.13  on 273  degrees of freedom
## Residual deviance: 367.26  on 265  degrees of freedom
##      (13 observations deleted due to missingness)
## AIC: 385.26
##
## Number of Fisher Scoring iterations: 4
```

```
plot(ggpredict(fitness_01_2020_temp_treat,terms=c("temp[all]","treatment")))
```

The probability of producing seeds increases with temperature for plants in the PF treatment (and almost in the F treatment, $p=0.07$). This agrees with the results of the previous zero-inflated model and with my expectations.

Relationship among fitness_01 and temp for the different treatments:

```
summary(glm(fitness_01~temp+log(ros_area),subset(ping_20_data,treatment=="C"),
            family="binomial"))
```

```
##
## Call:
## glm(formula = fitness_01 ~ temp + log(ros_area), family = "binomial",
##      data = subset(ping_20_data, treatment == "C"))
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -1.469  -1.204   0.974   1.125   1.366
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)   2.97166    3.18921   0.932   0.351
## temp         -0.07502    0.06792  -1.105   0.269
## log(ros_area) -0.45641    0.66657  -0.685   0.494
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 101.076  on 72  degrees of freedom
## Residual deviance:  99.729  on 70  degrees of freedom
## (6 observations deleted due to missingness)
## AIC: 105.73
##
## Number of Fisher Scoring iterations: 4
```

```
summary(glm(fitness_01~temp+log(ros_area),subset(ping_20_data,treatment=="P"),
            family="binomial"))
```

```
##
## Call:
## glm(formula = fitness_01 ~ temp + log(ros_area), family = "binomial",
##      data = subset(ping_20_data, treatment == "P"))
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -1.4777  -1.0747  -0.8701   1.2341   1.5696
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)    2.71572    2.40295   1.130   0.258
## temp           0.02208    0.07044   0.313   0.754
## log(ros_area) -0.78215    0.53825  -1.453   0.146
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 89.354  on 64  degrees of freedom
## Residual deviance: 87.020  on 62  degrees of freedom
## (3 observations deleted due to missingness)
## AIC: 93.02
##
## Number of Fisher Scoring iterations: 4
```

```
summary(glm(fitness_01~temp+log(ros_area),subset(ping_20_data,treatment=="F"),
            family="binomial"))
```

```
##
## Call:
## glm(formula = fitness_01 ~ temp + log(ros_area), family = "binomial",
##      data = subset(ping_20_data, treatment == "F"))
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -1.5185  -1.0893  -0.8647   1.1335   1.5292
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)    1.24345    3.60428   0.345   0.730
## temp           0.10710    0.08433   1.270   0.204
## log(ros_area) -0.66462    0.77774  -0.855   0.393
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 92.867  on 66  degrees of freedom
## Residual deviance: 89.542  on 64  degrees of freedom
## (2 observations deleted due to missingness)
## AIC: 95.542
##
## Number of Fisher Scoring iterations: 4
```

```
summary(glm(fitness_01~temp+log(ros_area),subset(ping_20_data,treatment=="PF"),
            family="binomial")) # **
```

```
##
## Call:
## glm(formula = fitness_01 ~ temp + log(ros_area), family = "binomial",
##      data = subset(ping_20_data, treatment == "PF"))
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -1.6574  -0.9435  -0.8573   1.1494   1.6291
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -2.27192    2.58212  -0.880   0.3789
## temp           0.15866    0.07731   2.052   0.0401 *
## log(ros_area) -0.03190    0.58285  -0.055   0.9564
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 94.477  on 68  degrees of freedom
## Residual deviance: 90.000  on 66  degrees of freedom
## (2 observations deleted due to missingness)
## AIC: 96
##
## Number of Fisher Scoring iterations: 4
```

Effect of temperature only significant in the PF treatment.

3. Selection models

3.1. Effect of temperature on selection on FFD

Standardize traits and relativize fitness:

```
# Standardize FFD
ping_17_data$FFD_corr_std<-as.numeric(scale(ping_17_data$FFD_corr))
ping_18_data$FFD_corr_std<-as.numeric(scale(ping_18_data$FFD_corr))
ping_20_data$FFD_corr_std<-as.numeric(scale(ping_20_data$FFD_corr))
# Standardize rosette area (first log, then scale)
ping_17_data$ros_area_std<-as.numeric(scale(log(ping_17_data$ros_area)))
ping_18_data$ros_area_std<-as.numeric(scale(log(ping_18_data$ros_area)))
ping_20_data$ros_area_std<-as.numeric(scale(log(ping_20_data$ros_area)))
# Relativize fitness
ping_17_data$n_seeds_rel<-with(ping_17_data,n_seeds/mean(n_seeds,na.rm=T))
ping_18_data$n_seeds_rel<-with(ping_18_data,n_seeds/mean(n_seeds,na.rm=T))
ping_20_data$n_seeds_rel<-with(ping_20_data,n_seeds/mean(n_seeds,na.rm=T))
# ping_20_data, treatment C
ping_20_data_C<-subset(ping_20_data,treatment=="C")%>%
  mutate(FFD_corr_std=as.numeric(scale(FFD_corr)),
         ros_area_std=as.numeric(scale(log(ros_area))),
         n_seeds_rel=n_seeds/mean(n_seeds,na.rm=T))
```

Using linear models. I first included quadratic effects of temperature, but then removed them because they were never significant. I used only plants from control treatment in 2020.

```
selection_2017_1<-lm(n_seeds_rel~FFD_corr_std*temp+ros_area_std,
                    subset(ping_17_data,
                          !is.na(n_seeds_rel)&!is.na(ros_area_std)))
selection_2018_1<-lm(n_seeds_rel~FFD_corr_std*temp+ros_area_std,
                    subset(ping_18_data,
                          !is.na(n_seeds_rel)&!is.na(ros_area_std)))
selection_2020_C_1<-lm(n_seeds_rel~FFD_corr_std*temp+ros_area_std,
                    subset(ping_20_data_C,
                          !is.na(n_seeds_rel)&!is.na(ros_area_std)))
```

Model diagnostics (not shown) looked bad, model residuals did not meet the assumption of normality, so using 95% bias-corrected and accelerated (BCa) bootstrap intervals for the model estimates to determine significance. Same for all selection models below.

```
summary(selection_2017_1)
```

```
##
## Call:
## lm(formula = n_seeds_rel ~ FFD_corr_std * temp + ros_area_std,
##     data = subset(ping_17_data, !is.na(n_seeds_rel) & !is.na(ros_area_std)))
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.4817 -1.0159 -0.5127  0.8582  5.2239
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    1.143966   0.391887   2.919  0.00382 **
## FFD_corr_std   -0.499080   0.310116  -1.609  0.10875
## temp           -0.005024   0.029311  -0.171  0.86405
## ros_area_std    0.226390   0.080472   2.813  0.00528 **
## FFD_corr_std:temp 0.024816   0.019853   1.250  0.21242
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.263 on 261 degrees of freedom
## Multiple R-squared:  0.03777,    Adjusted R-squared:  0.02302
## F-statistic: 2.561 on 4 and 261 DF,  p-value: 0.03899
```

```
BCIs_selection_2017_1
```

```
##              lower      upper
## FFD_corr_std  -1.039085631  0.01563183
## temp          -0.055230702  0.04905280
## ros_area_std   0.084908942  0.38036201
## FFD_corr_std_temp -0.009755021  0.06044988
```

```
summary(selection_2018_1)
```

```
##
## Call:
## lm(formula = n_seeds_rel ~ FFD_corr_std * temp + ros_area_std,
##     data = subset(ping_18_data, !is.na(n_seeds_rel) & !is.na(ros_area_std)))
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.7911 -1.1189 -0.6131  1.0257  6.5540
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    4.04607    0.87400   4.629 6.72e-06 ***
## FFD_corr_std   -0.17690    0.48494  -0.365  0.71568
## temp          -0.28030    0.08097  -3.462  0.00066 ***
## ros_area_std    0.28395    0.11284   2.516  0.01267 *
## FFD_corr_std:temp -0.04880    0.04264  -1.144  0.25386
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.542 on 193 degrees of freedom
## Multiple R-squared:  0.09422,    Adjusted R-squared:  0.07545
## F-statistic: 5.019 on 4 and 193 DF,  p-value: 0.0007189
```

```
BCIs_selection_2018_1
```

```
##              lower      upper
## FFD_corr_std   -0.95511284  0.50911004
## temp          -0.43366537 -0.13816882
## ros_area_std    0.06627545  0.54524510
## FFD_corr_std_temp -0.10959951  0.01048242
```

```
summary(selection_2020_C_1)
```

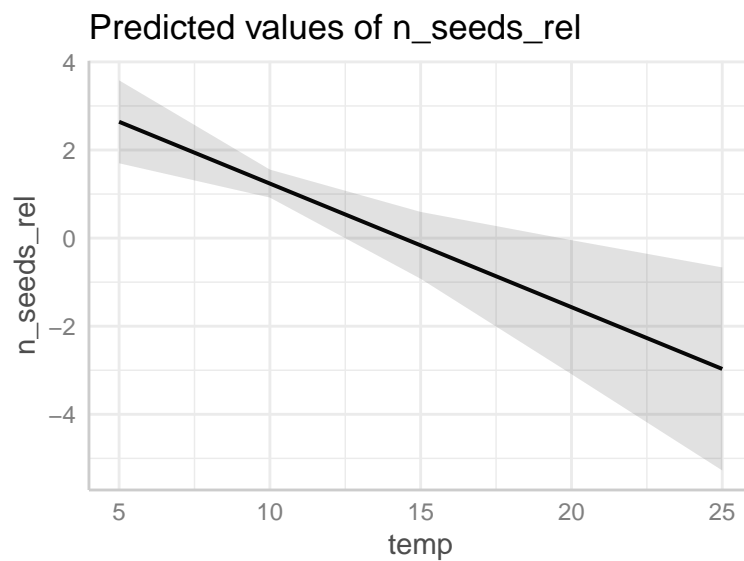
```
##
## Call:
## lm(formula = n_seeds_rel ~ FFD_corr_std * temp + ros_area_std,
##     data = subset(ping_20_data_C, !is.na(n_seeds_rel) & !is.na(ros_area_std)))
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.4168 -0.8890 -0.1020  0.7287  3.1506
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    2.15578    1.17824   1.830  0.0717 .
## FFD_corr_std   -1.21101    0.52138  -2.323  0.0232 *
## temp          -0.07076    0.08680  -0.815  0.4178
## ros_area_std    0.04574    0.14557   0.314  0.7543
## FFD_corr_std:temp 0.05570    0.02688   2.072  0.0421 *
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.101 on 68 degrees of freedom
## Multiple R-squared:  0.08945,    Adjusted R-squared:  0.03589
## F-statistic:  1.67 on 4 and 68 DF,  p-value: 0.1671
```

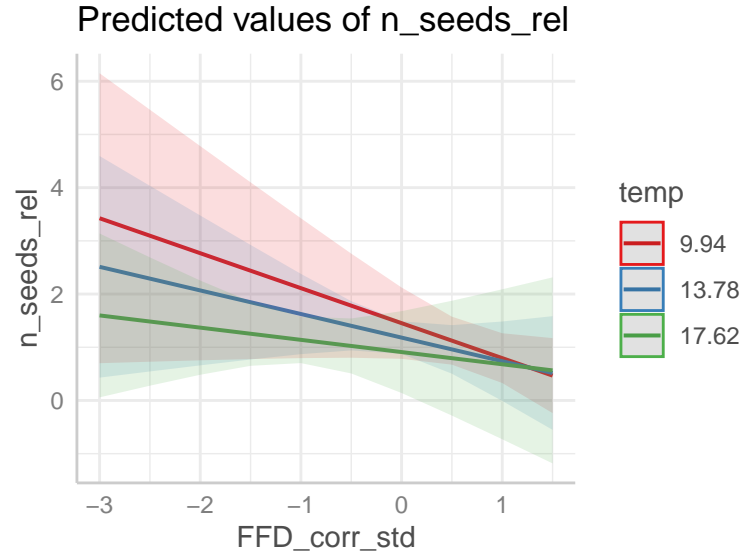
```
BCIs_selection_2020_C_1
```

```
##               lower      upper
## FFD_corr_std  -2.24909831 -0.1706967
## temp          -0.22355165  0.1048648
## ros_area_std  -0.20645779  0.3233816
## FFD_corr_std_temp 0.01123784  0.1056189
```

```
plot(ggpredict(selection_2018_1,terms=c("temp")))
```



```
plot(ggpredict(selection_2020_C_1,
               terms=c("FFD_corr_std","temp")))
```



2018: higher fitness in colder soils. 2020: early flowering relatively more favoured in colder soils (similar to result for *Cerastium* but it seems that there is no selection on FFD in warmer soils here - if we look only at plants in the C treatment).

3.2. Effect of treatment on selection on FFD (2020)

Using a linear model.

```
selection_2020_2<-lm(n_seeds_rel~FFD_corr_std*treatment+ros_area_std,
                     subset(ping_20_data,!is.na(n_seeds_rel)&!is.na(ros_area_std)))
summary(selection_2020_2)
```

```
##
## Call:
## lm(formula = n_seeds_rel ~ FFD_corr_std * treatment + ros_area_std,
##     data = subset(ping_20_data, !is.na(n_seeds_rel) & !is.na(ros_area_std)))
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.3236 -1.0199 -0.7033  0.8322  3.7932
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)      1.01841    0.14584   6.983 2.33e-11 ***
## FFD_corr_std       0.03204    0.14545   0.220   0.826
## treatmentF      -0.01674    0.21138  -0.079   0.937
## treatmentP       0.09227    0.21262   0.434   0.665
## treatmentPF     -0.11554    0.20915  -0.552   0.581
## ros_area_std      0.03915    0.07849   0.499   0.618
## FFD_corr_std:treatmentF -0.17303    0.23003  -0.752   0.453
## FFD_corr_std:treatmentP -0.10864    0.20761  -0.523   0.601
## FFD_corr_std:treatmentPF -0.20857    0.20920  -0.997   0.320
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## Residual standard error: 1.241 on 265 degrees of freedom
## Multiple R-squared:  0.01302,    Adjusted R-squared:  -0.01678
## F-statistic: 0.437 on 8 and 265 DF,  p-value: 0.8982
```

BCIs_selection_2020_2

```
##               lower      upper
## FFD_corr_std  -0.2439157 0.2521828
## treatmentF    -0.3954734 0.3794365
## treatmentP    -0.3308150 0.5546696
## treatmentPF   -0.4783482 0.2751327
## ros_area      -0.1003675 0.1899238
## FFD_corr_std:treatmentF -0.5021839 0.2346059
## FFD_corr_std:treatmentP -0.5124433 0.2845641
## FFD_corr_std:treatmentPF -0.5468687 0.1659684
```

No significant effects.

3.3. Effects of temperature AND treatment on selection on FFD (2020)

Using a linear model.

```
selection_2020_4<-lm(n_seeds_rel~temp*FFD_corr_std+treatment*FFD_corr_std+
  ros_area_std,
  subset(ping_20_data,
    !is.na(n_seeds_rel)&!is.na(ros_area_std)))
summary(selection_2020_4)
```

```
##
## Call:
## lm(formula = n_seeds_rel ~ temp * FFD_corr_std + treatment *
##     FFD_corr_std + ros_area_std, data = subset(ping_20_data,
##     !is.na(n_seeds_rel) & !is.na(ros_area_std)))
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.6231 -0.9907 -0.3866  0.7953  3.5552
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    0.25647    0.62498   0.410  0.681868
## temp           0.07921    0.04678   1.693  0.091607 .
## FFD_corr_std  -1.43049    0.38037  -3.761  0.000209 ***
## treatmentF    -0.11100    0.20523  -0.541  0.589061
## treatmentP     0.10302    0.20594   0.500  0.617309
## treatmentPF   -0.14088    0.20210  -0.697  0.486363
## ros_area_std   0.07138    0.07676   0.930  0.353313
## temp:FFD_corr_std  0.09609    0.02096   4.584  7.07e-06 ***
## FFD_corr_std:treatmentF  0.23431    0.23975   0.977  0.329305
## FFD_corr_std:treatmentP  0.09395    0.20599   0.456  0.648696
## FFD_corr_std:treatmentPF  0.03622    0.21021   0.172  0.863319
```

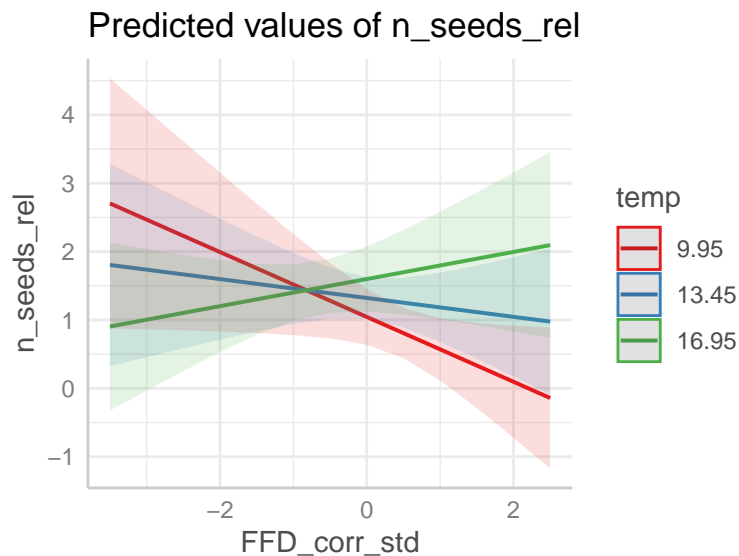


```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.199 on 263 degrees of freedom
## Multiple R-squared:  0.08603,    Adjusted R-squared:  0.05128
## F-statistic: 2.476 on 10 and 263 DF,  p-value: 0.007559
```

```
BCIs_selection_2020_4
```

```
##               lower      upper
## temp          -0.02349156  0.1747039
## FFD_corr_std  -2.19100067 -0.6485627
## treatmentF    -0.50654149  0.2758650
## treatmentP    -0.32443037  0.5253801
## treatmentPF   -0.51070004  0.2303668
## ros_area      -0.06302381  0.2148771
## temp:FFD_corr_std  0.05470308  0.1455280
## FFD_corr_std:treatmentF -0.15418183  0.6573400
## FFD_corr_std:treatmentP -0.28540735  0.4486986
## FFD_corr_std:treatmentPF -0.33160160  0.4015506
```

```
plot(ggpredict(selection_2020_4,terms=c("FFD_corr_std","temp")))
```



3.4. Effects of all 2-way interactions between temperature, treatment and FFD (2020)

Using a linear model.

```
selection_2020_5<-lm(n_seeds_rel~temp*FFD_corr_std+treatment*FFD_corr_std+
  temp*treatment+ros_area_std,
  subset(ping_20_data,
    !is.na(n_seeds_rel)&!is.na(ros_area_std)))
summary(selection_2020_5)
```

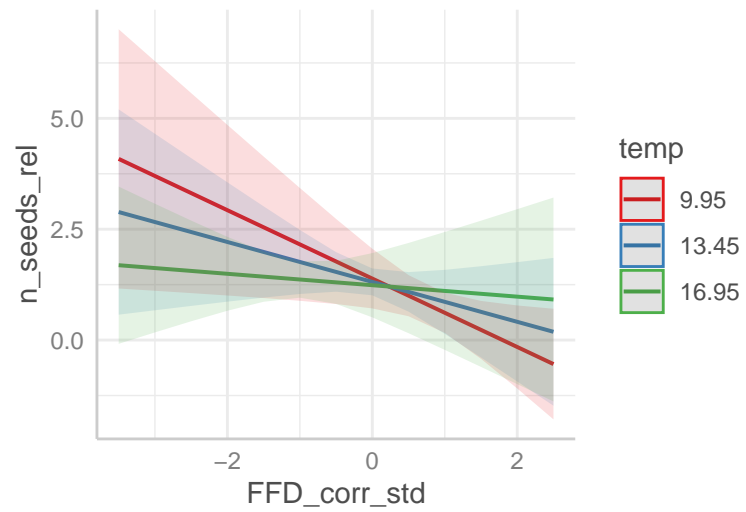
```
##
## Call:
## lm(formula = n_seeds_rel ~ temp * FFD_corr_std + treatment *
##     FFD_corr_std + temp * treatment + ros_area_std, data = subset(ping_20_data,
##     !is.na(n_seeds_rel) & !is.na(ros_area_std)))
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.7317 -0.9480 -0.3496  0.8046  3.4920
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)      1.59935      1.23177   1.298 0.195295
## temp            -0.02137      0.09195  -0.232 0.816424
## FFD_corr_std    -1.68429      0.44664  -3.771 0.000201 ***
## treatmentF       0.17886      1.63570   0.109 0.913012
## treatmentP      -2.33063      1.65891  -1.405 0.161238
## treatmentPF     -3.50625      1.70453  -2.057 0.040682 *
## ros_area_std     0.04605      0.07687   0.599 0.549654
## temp:FFD_corr_std  0.09176      0.02092   4.387 1.67e-05 ***
## FFD_corr_std:treatmentF  0.17726      0.45528   0.389 0.697350
## FFD_corr_std:treatmentP  0.67229      0.44780   1.501 0.134481
## FFD_corr_std:treatmentPF  0.79810      0.44441   1.796 0.073676 .
## temp:treatmentF    -0.02113      0.12040  -0.175 0.860827
## temp:treatmentP     0.18274      0.12351   1.480 0.140206
## temp:treatmentPF    0.24995      0.12577   1.987 0.047931 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.189 on 260 degrees of freedom
## Multiple R-squared:  0.1107, Adjusted R-squared:  0.06625
## F-statistic:  2.49 on 13 and 260 DF,  p-value: 0.003213
```

BCIs_selection_2020_5

```
##              lower      upper
## temp            -0.184626822  0.1534943
## FFD_corr_std    -2.626127440 -0.7508462
## treatmentF      -3.059487500  3.4216620
## treatmentP      -5.650687875  1.5638039
## treatmentPF     -6.408723265 -0.4510886
## ros_area        -0.085773858  0.1866892
## temp:FFD_corr_std  0.048805084  0.1419049
## FFD_corr_std:treatmentF -0.639901563  1.0233315
## FFD_corr_std:treatmentP -0.245801187  1.5145334
## FFD_corr_std:treatmentPF  0.009365014  1.6174803
## temp:treatmentF    -0.257822863  0.2104748
## temp:treatmentP    -0.110071327  0.4218805
## temp:treatmentPF    0.030029525  0.4688786
```

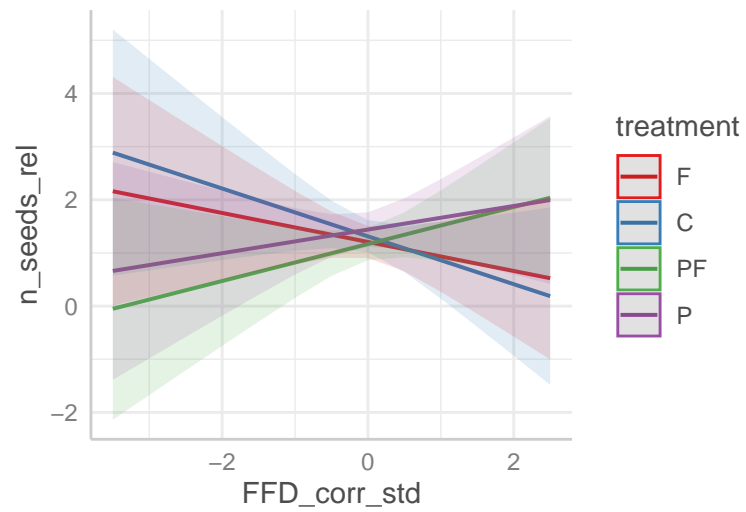
```
plot(ggpredict(selection_2020_5, terms=c("FFD_corr_std", "temp")))
```

Predicted values of n_seeds_rel

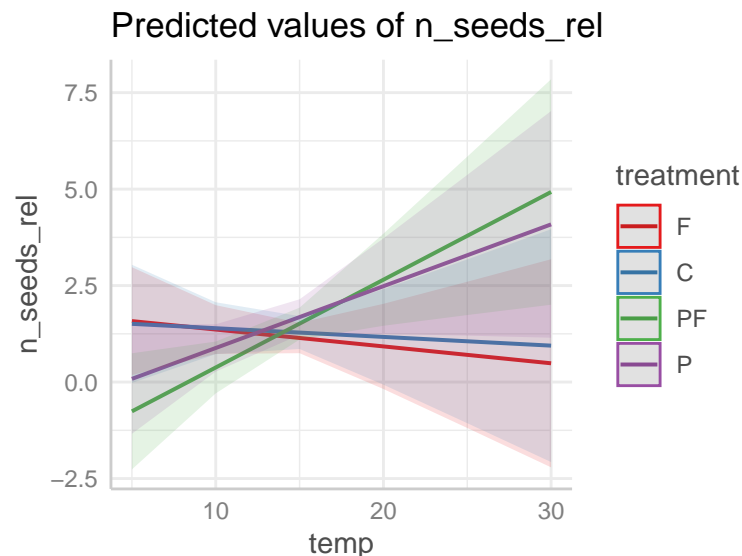


```
plot(ggpredict(selection_2020_5, terms=c("FFD_corr_std", "treatment")))
```

Predicted values of n_seeds_rel



```
plot(ggpredict(selection_2020_5, terms=c("temp", "treatment")))
```



Fitness increases with early flowering in C and F treatments, but with later flowering in P and PF treatments (only FFD_corr_std:treatmentPF significant - only PF different from C).

Similar result as in the model for fitness (section 2.3): Fitness increases with temperature in the PF treatment.

3.5. Effects of all 2-way interactions between temperature, treatment and FFD + 3-way interaction (2020)

Using a linear model.

```
selection_2020_6<-lm(n_seeds_rel~temp*FFD_corr_std*treatment+ros_area_std,
                     subset(ping_20_data,
                             !is.na(n_seeds_rel)&!is.na(ros_area_std)))
summary(selection_2020_6)
```

```
##
## Call:
## lm(formula = n_seeds_rel ~ temp * FFD_corr_std * treatment +
##     ros_area_std, data = subset(ping_20_data, !is.na(n_seeds_rel) &
##     !is.na(ros_area_std)))
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2.2157 -0.9021 -0.2892  0.7957  3.4739
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    2.099921   1.239307   1.694   0.0914 .
## temp          -0.067828   0.093240  -0.727   0.4676
## FFD_corr_std  -1.144709   0.498531  -2.296   0.0225 *
## treatmentF     -0.067294   1.798968  -0.037   0.9702
## treatmentP    -3.657823   1.725980  -2.119   0.0350 *
## treatmentPF   -4.228560   1.730185  -2.444   0.0152 *
## ros_area_std    0.056727   0.076326   0.743   0.4580
```

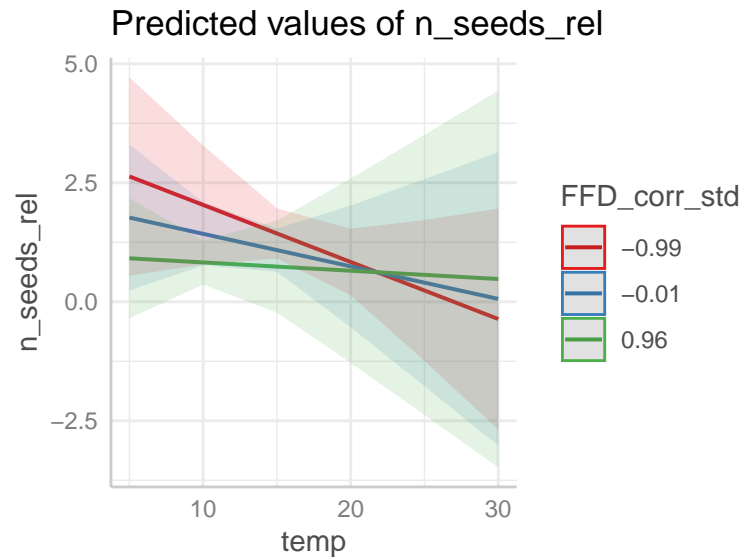
```
## temp:FFD_corr_std      0.052521  0.026558  1.978  0.0490 *
## temp:treatmentF      0.001691  0.139569  0.012  0.9903
## temp:treatmentP      0.315166  0.133229  2.366  0.0187 *
## temp:treatmentPF     0.324458  0.131012  2.477  0.0139 *
## FFD_corr_std:treatmentF -0.035968  1.068838 -0.034  0.9732
## FFD_corr_std:treatmentP -1.152131  0.854927 -1.348  0.1790
## FFD_corr_std:treatmentPF -0.474901  0.913909 -0.520  0.6038
## temp:FFD_corr_std:treatmentF 0.009271  0.086158  0.108  0.9144
## temp:FFD_corr_std:treatmentP 0.138441  0.055670  2.487  0.0135 *
## temp:FFD_corr_std:treatmentPF 0.093359  0.059175  1.578  0.1159
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.179 on 257 degrees of freedom
## Multiple R-squared:  0.1358, Adjusted R-squared:  0.08202
## F-statistic: 2.525 on 16 and 257 DF,  p-value: 0.001275
```

BCIs_selection_2020_6

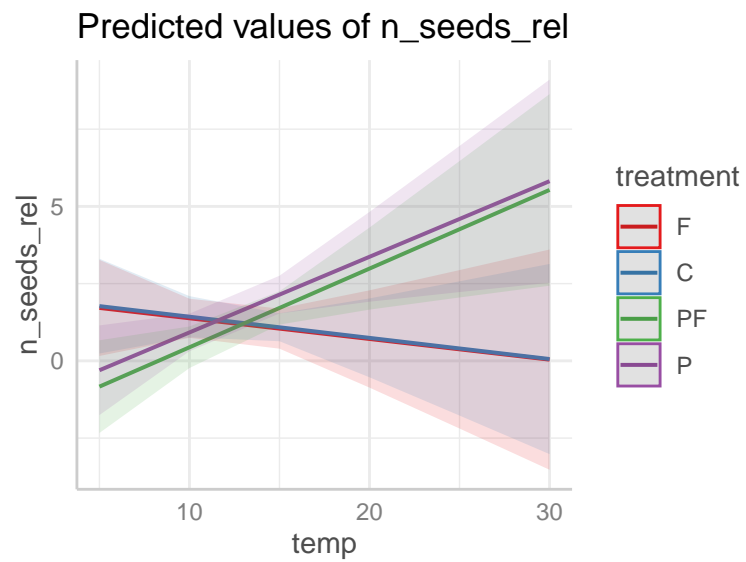
```
##               lower      upper
## temp          -0.229097318  0.10569628
## FFD_corr_std  -2.072500136 -0.22912958
## treatmentF    -3.598994878  3.37081416
## treatmentP    -7.219489689  0.35450576
## treatmentPF   -7.323376314 -0.94078818
## ros_area      -0.077634104  0.19644086
## temp:FFD_corr_std  0.009868915  0.09825223
## temp:treatmentF -0.250200767  0.26489845
## temp:treatmentP  0.011096034  0.58679132
## temp:treatmentPF  0.077803427  0.55959391
## FFD_corr_std:treatmentF -2.213633634  1.94410329
## FFD_corr_std:treatmentP -3.022549777  0.57011226
## FFD_corr_std:treatmentPF -2.295277552  1.56197945
## temp:FFD_corr_std:treatmentF -0.145687403  0.17660897
## temp:FFD_corr_std:treatmentP  0.022701983  0.26013887
## temp:FFD_corr_std:treatmentPF -0.050505533  0.23197336
```

2-way significant interactions:

```
plot(ggpredict(selection_2020_6,terms=c("temp","FFD_corr_std")))
```



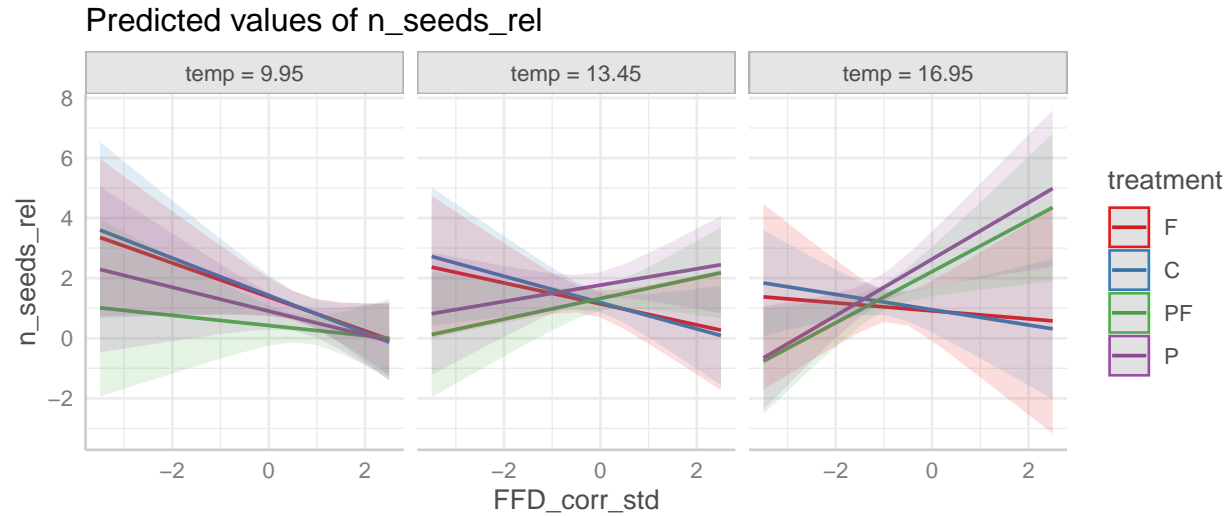
```
plot(ggpredict(selection_2020_6, terms=c("temp", "treatment")))
```



Similar results as before.

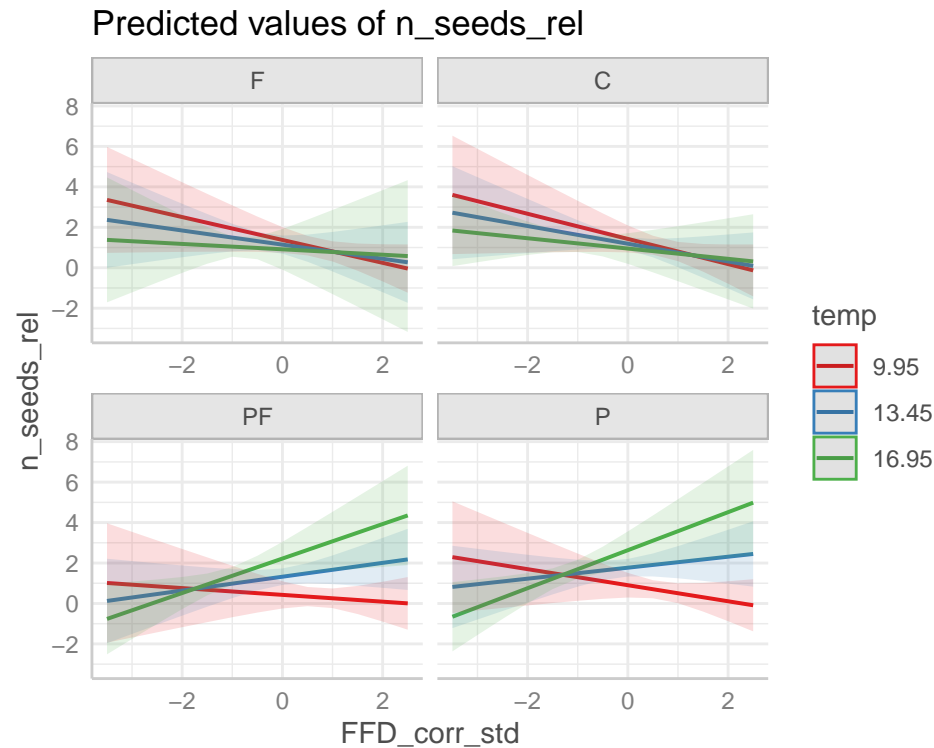
3-way interaction (two different representations):

```
plot(ggpredict(selection_2020_6, terms=c("FFD_corr_std", "treatment", "temp")))
```



At low temperatures (left panel above), it is always better to flower early. At medium and high temperatures (center and right panel above), it is better to flower early for plants in the C and F treatments, but better to flower late for plants in the P and PF treatments (only temp * FFD * treatmentP is significantly different from control).

```
plot(ggpredict(selection_2020_6, terms=c("FFD_corr_std", "temp", "treatment")))
```



In other words, for plants in C and F treatments, it is always better to flower early, irrespective of soil temperature. For plants in P and PF treatments (only in P if we look at significance), it is better to flower early at cold soil temperatures, but late at warm soil temperatures.