Maladaptive plastic responses of flowering time to geothermal heating (Cerastium 2)

Repeat and extend analyses done by Johan

Alicia Valdés

Contents

Read data from loggers

Data preparation

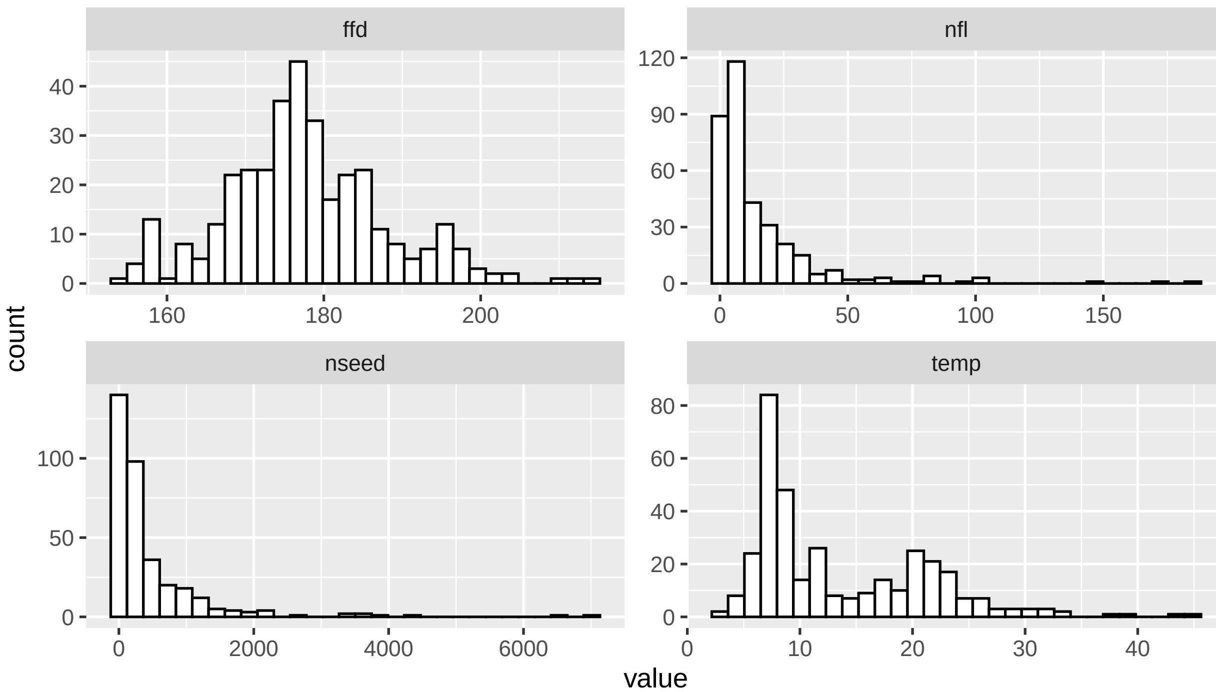
Load data, keep variables needed and merge

```
##        id id_original temp   ffd nfl    nseed year    ffd_std     nfl_std
## 1 2017_01          H1 19.4 172.0   6 269.3333 2017 -0.4912772 -0.34533654
## 4 2017_04          H5 31.0 163.5   4 106.0000 2017 -1.5514686 -0.71175481
## 6 2017_06          H7 29.4 170.0   4 105.0000 2017 -0.7407340 -0.71175481
## 7 2017_07          H8 29.0 170.0   9 150.0000 2017 -0.7407340  0.02108173
## 8 2017_08         H12 21.7 170.0   4 141.0000 2017 -0.7407340 -0.71175481
```

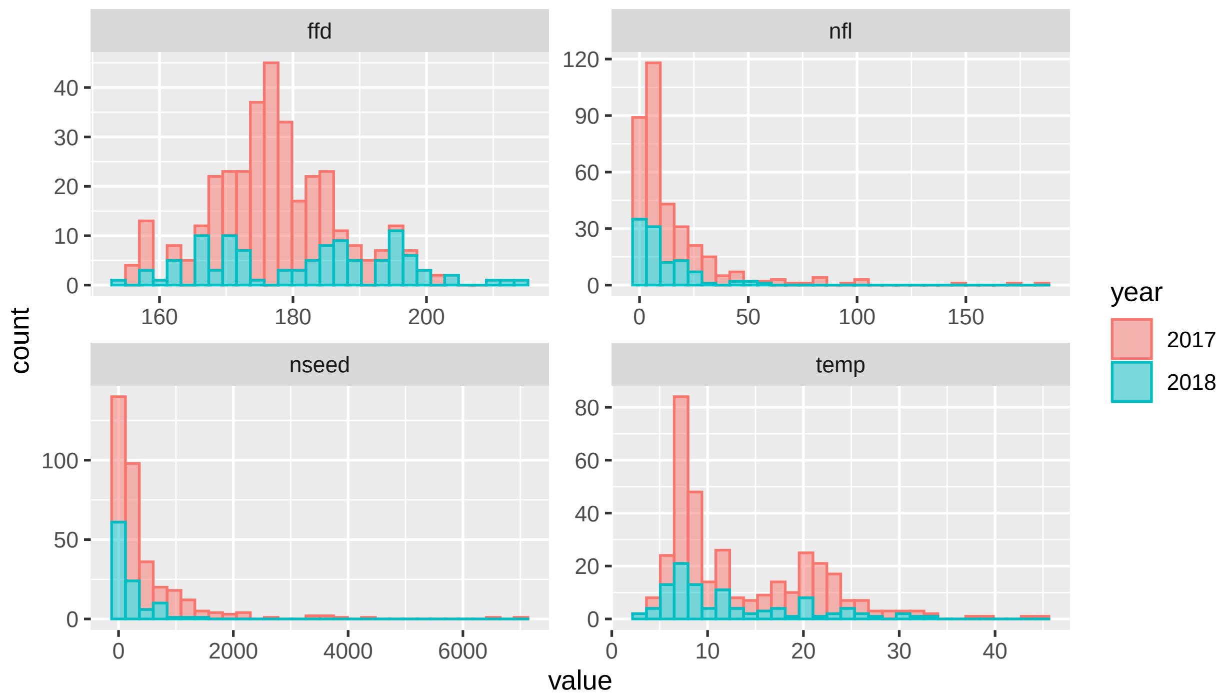
```
## 9 2017_09         H13 22.6 170.0   4 126.0000 2017 -0.7407340 -0.71175481
##   nseed_rel
## 1 0.4769565
## 4 0.1877131
## 6 0.1859422
## 7 0.2656317
## 8 0.2496938
## 9 0.2231307
```

Distributions

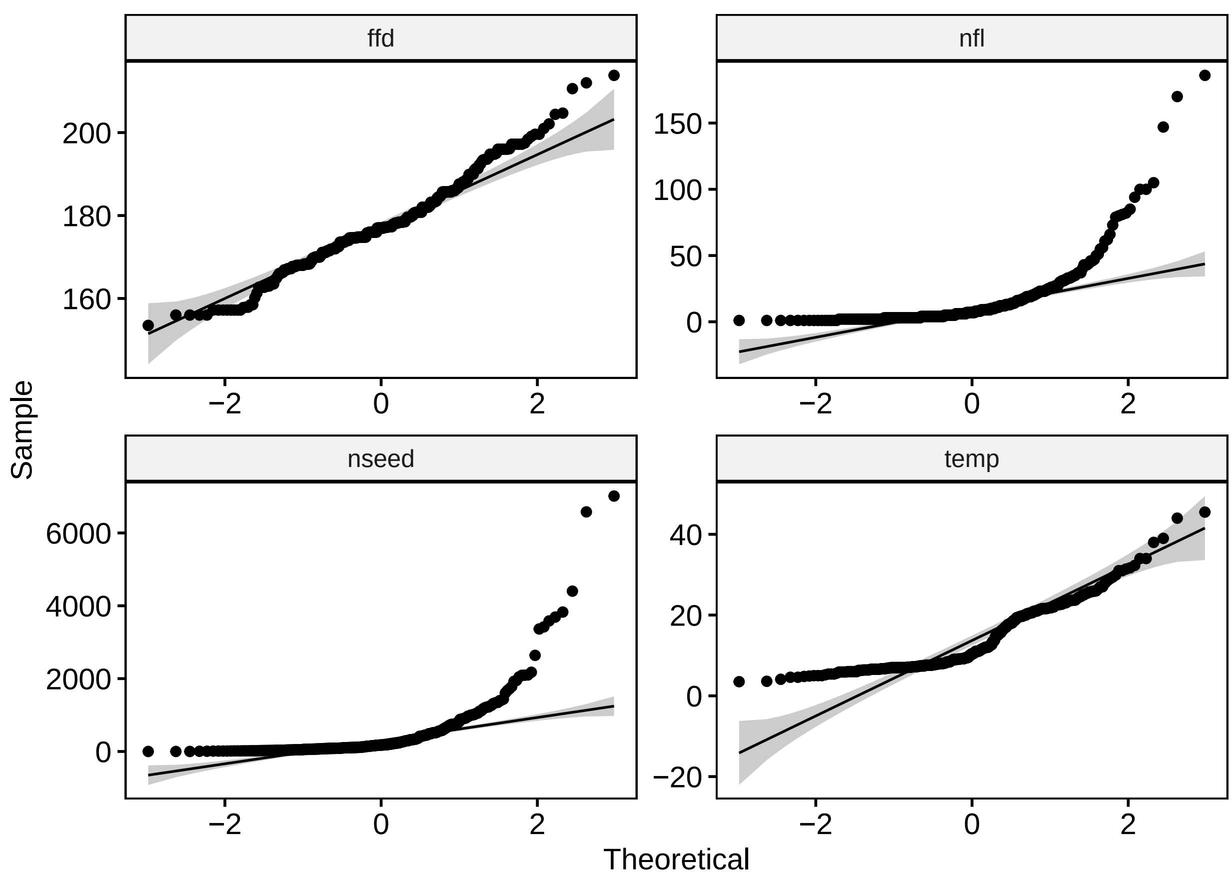
Histograms



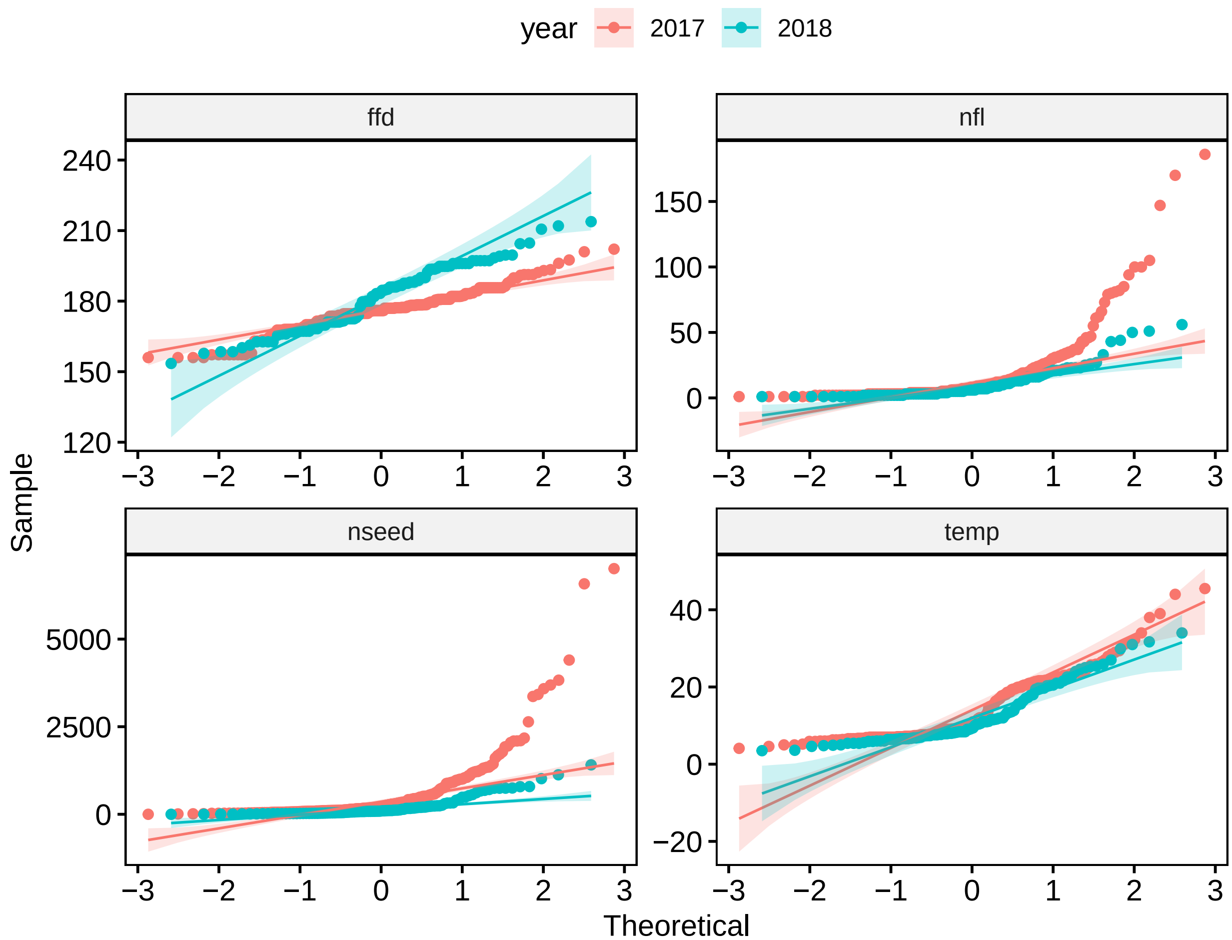
Histograms by year



QQplots



QQplots by year



1. Effect of temperature on FFD

Not including number of flowers as covariate, including quadratic effects of ffd.

```
FFD_2017_1<-lm(ffd~temp+I(temp^2),subset(mydata,year==2017))
summ(FFD_2017_1,vif=T,scale=T) # scale=T reports standardized coefs
```

Observations	245
Dependent variable	ffd
Type	OLS linear regression

F(2,242)	17.016
R^2	0.123
Adj. R^2	0.116

```
FFD_2018_1<-lm(ffd~temp+I(temp^2),subset(mydata,year==2018))
summ(FFD_2018_1,vif=T,scale=T) # scale=T reports standardized coefs
```

	Est.	S.E.	t val.	p	VIF
(Intercept)	175.939	0.482	365.338	0.000	NA
temp	-6.146	1.721	-3.572	0.000	12.715
‘I(temp^2)‘	3.673	1.721	2.135	0.034	12.715

Standard errors: OLS; Continuous predictors are mean-centered and scaled by 1 s.d.

Observations	104
Dependent variable	ffd
Type	OLS linear regression

F(2,101)	25.765
R^2	0.338
Adj. R^2	0.325

	Est.	S.E.	t val.	p	VIF
(Intercept)	181.876	1.100	165.267	0.000	NA
temp	-15.623	4.972	-3.142	0.002	20.214
‘I(temp^2)‘	8.094	4.972	1.628	0.107	20.214

Standard errors: OLS; Continuous predictors are mean-centered and scaled by 1 s.d.

Quadratic term of ffd significant in 2017 but not in 2018. Refit model for 2018 withouth quadratic term of ffd.

```
FFD_2018_2<-lm(ffd~temp,subset(mydata,year==2018))
summ(FFD_2018_2,scale=T)
```

Observations	104
Dependent variable	ffd
Type	OLS linear regression

F(1,102)	48.102
R^2	0.320
Adj. R^2	0.314

	Est.	S.E.	t val.	p
(Intercept)	181.876	1.109	163.946	0.000
temp	-7.731	1.115	-6.936	0.000

Standard errors: OLS; Continuous predictors are mean-centered and scaled by 1 s.d.

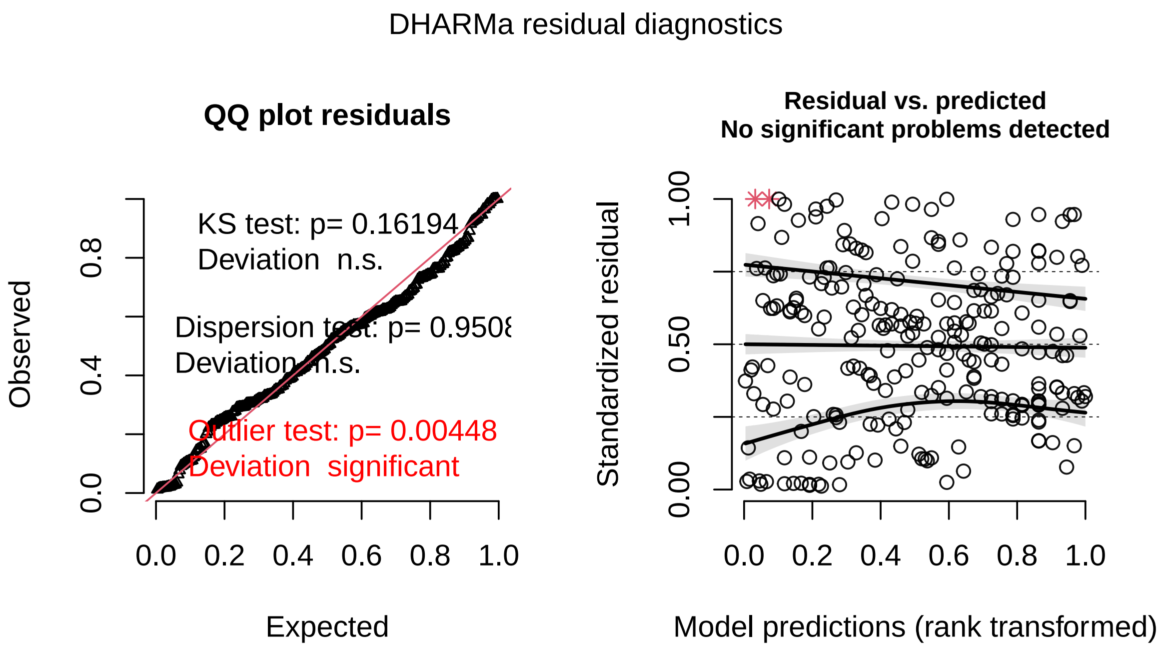
Predictions of ffd for minimum and maximum temperatures:

```
## # Predicted values of ffd
## # x = temp
```

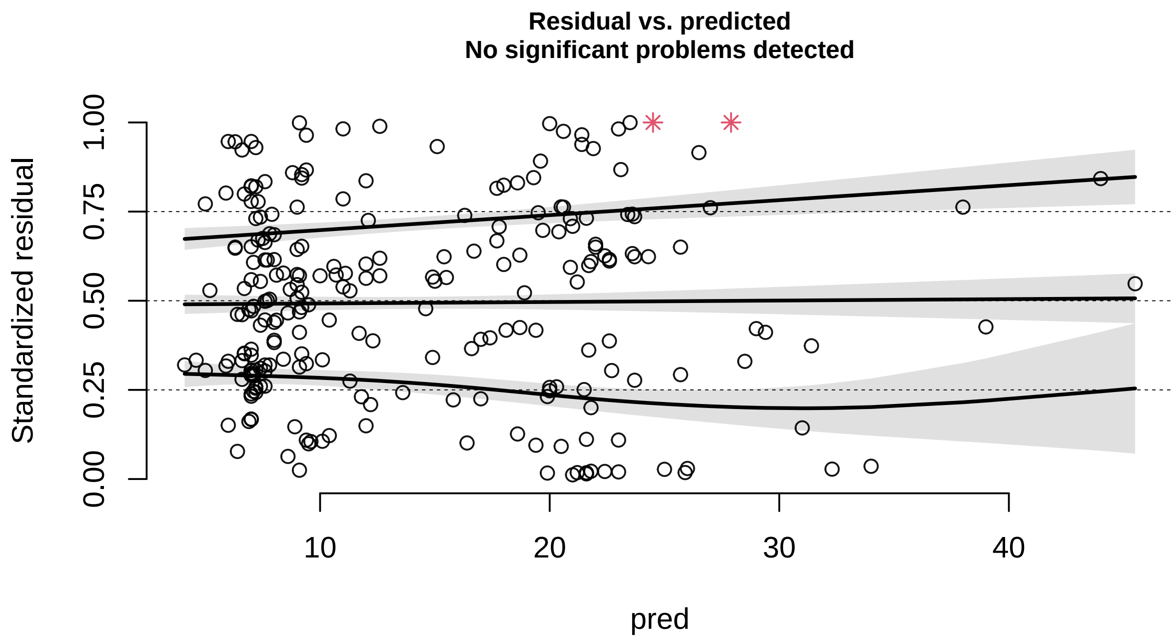
```
##
##      x | Predicted |           95% CI
## ------------------------------------
##   4.10 |    180.75 | [178.70, 182.80]
## 45.50 |     173.63 | [165.24, 182.02]

## # Predicted values of ffd
## # x = temp
##
##      x | Predicted |           95% CI
## ------------------------------------
##   3.50 |    191.36 | [187.91, 194.81]
## 34.00 |     158.74 | [151.85, 165.63]
```

Model diagnostics

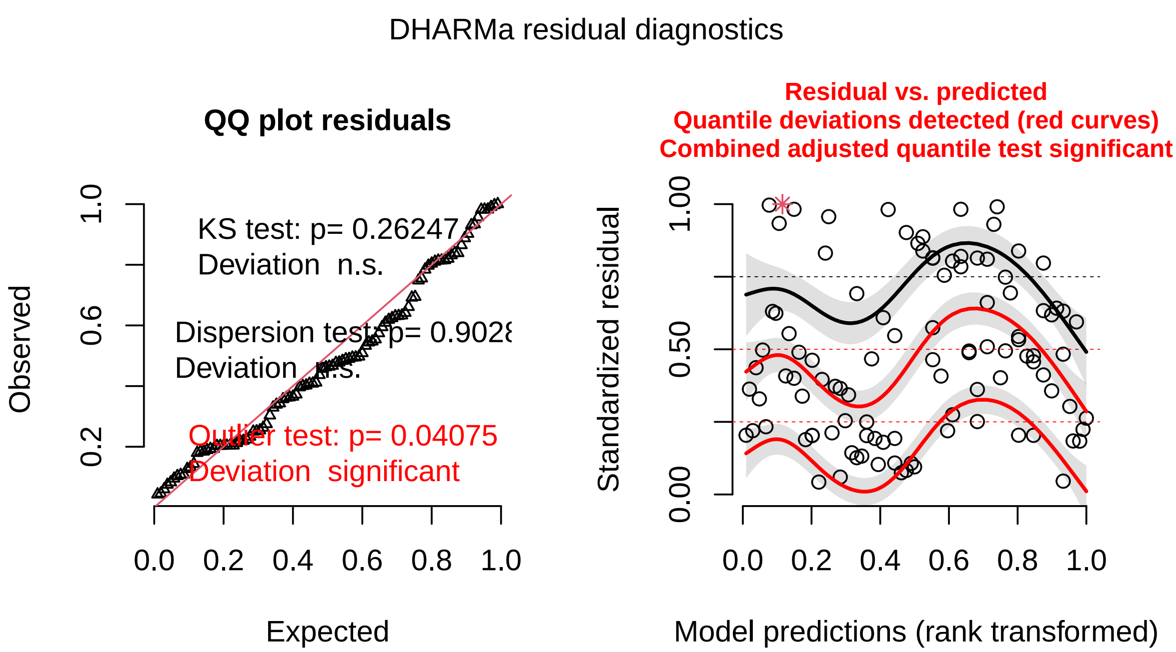
FFD_2017_1



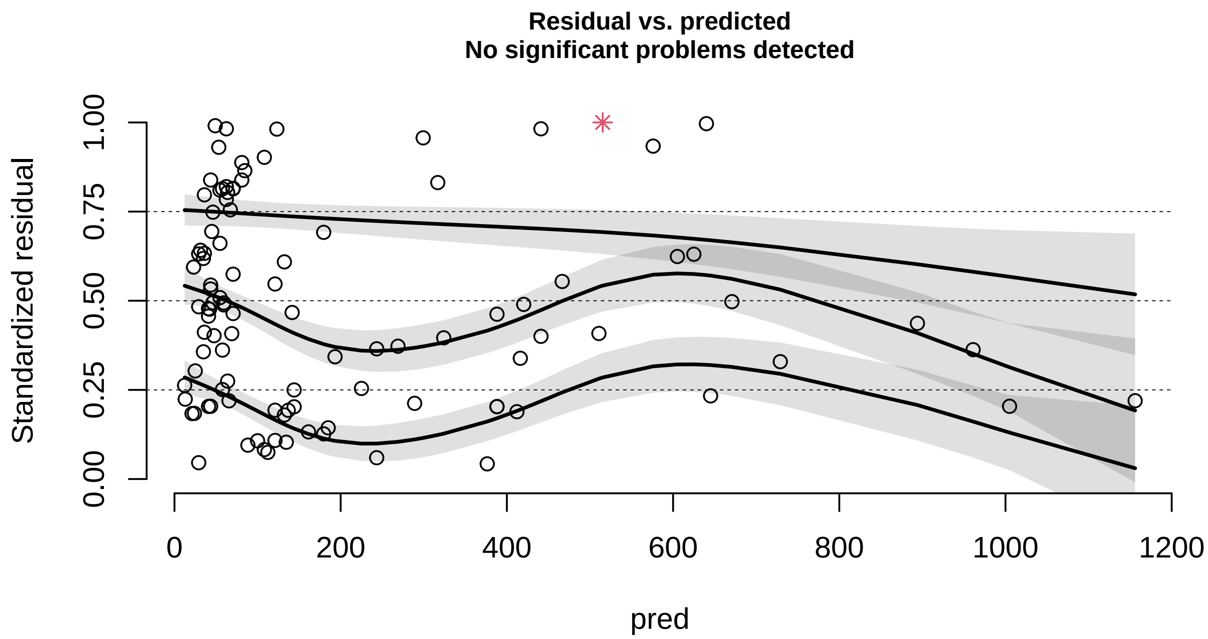
Residuals against temp



2018:



Residuals against temp



Models should be OK.

Piecewise regresssion (not shown).

```
FFD_2017_segm<-segmented(lm(ffd~temp,subset(mydata,year==2017)),
                         seg.Z=~temp,psi=20)
slope(FFD_2017_segm)
```

```
## $temp
##             Est.  St.Err.  t value CI(95%).l CI(95%).u
## slope1 -0.41168 0.068323 -6.02550  -0.54626  -0.27709
## slope2  0.96590 1.177400  0.82034  -1.35350   3.28530
```

```
AIC(FFD_2017_1,FFD_2017_segm)
```

```
##               df      AIC
## FFD_2017_1     4 1690.033
## FFD_2017_segm  5 1689.235
```

CIs for the slope of the second segment include zero (means it is not significantly different from zero?). Very little difference in AIC (<2), so the piecewise regression is not better.

```
FFD_2018_segm<-segmented(lm(ffd~temp,subset(mydata,year==2018)),
                         seg.Z=~temp,psi=15)
slope(FFD_2018_segm)
```

```
## $temp
##             Est. St.Err.  t value CI(95%).l CI(95%).u
## slope1 -2.18310 0.53289 -4.09680   -3.2404  -1.12590
## slope2 -0.36933 0.38814 -0.95153   -1.1394   0.40073
```

```
AIC(FFD_2018_1,FFD_2018_segm)
```

```
##                df      AIC
## FFD_2018_1      4 803.0307
## FFD_2018_segm  5 800.0710
```

CIs for the slope of the second segment include zero (means it is not significantly different from zero?). Difference in AIC >2 so the piecewise regression seems to be better.

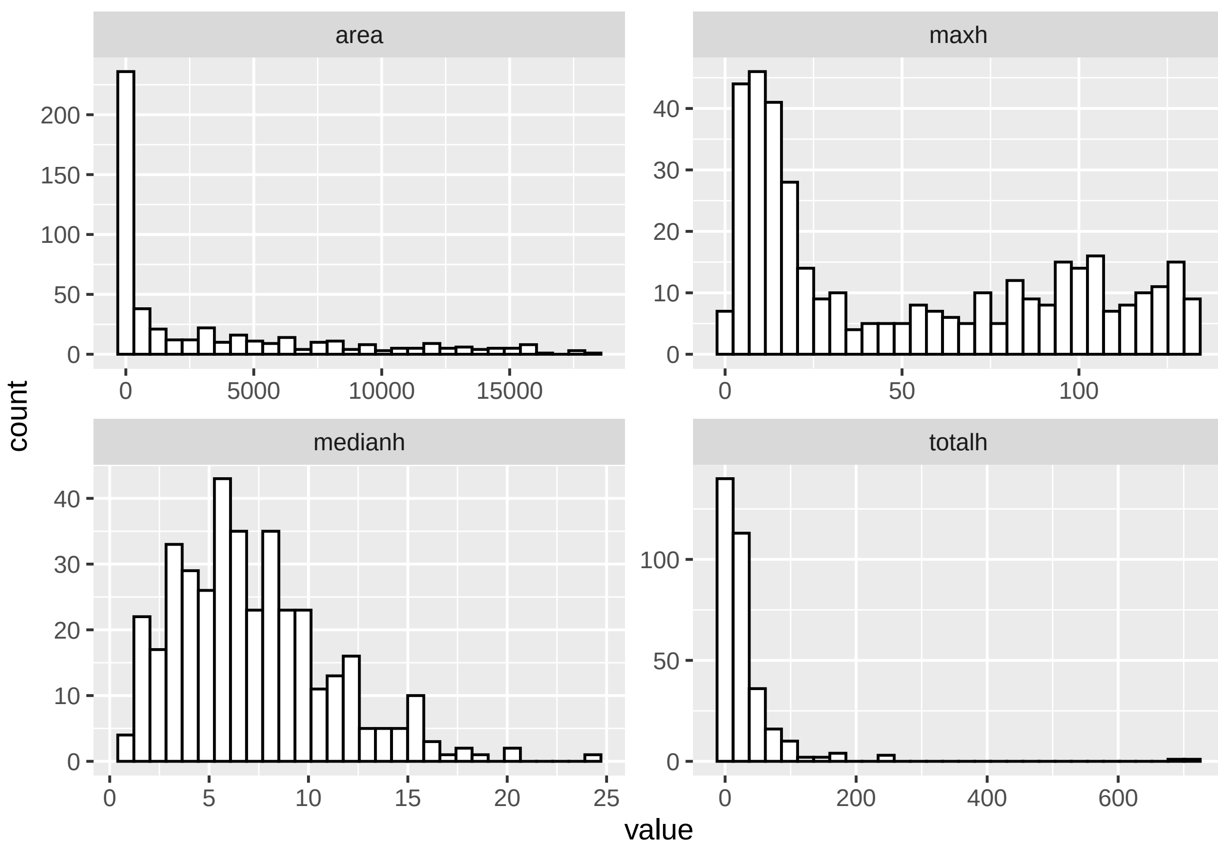
Plot 2018 (not used)

Keep the linear model, as the piecewise one does not seem to fit much better (the reduction in AIC was also small).

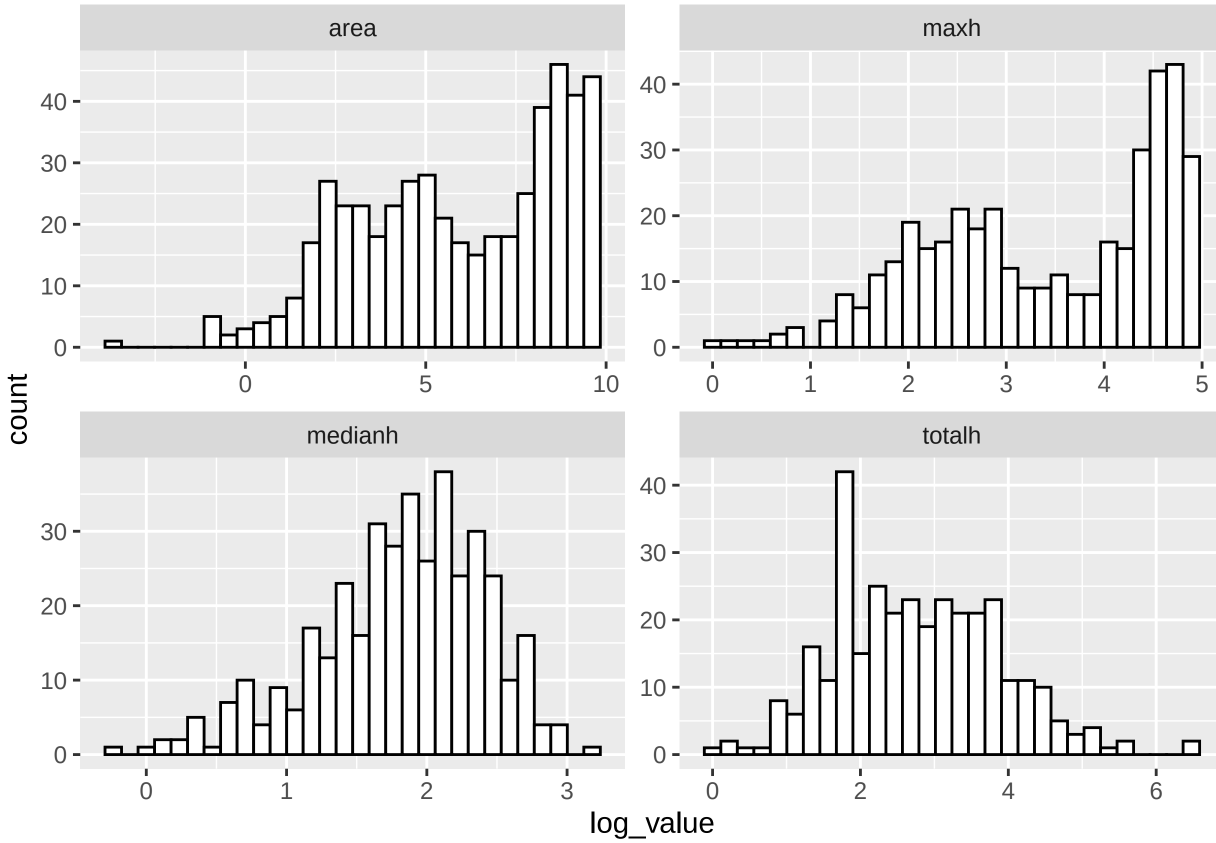
2. Effect of temperature on plant size

For 2017, get data on rosette diameter, maximum and median height from previous ms.

Distributions



Distributions (log)



Models of area, maximum height, median height and total height vs soil temperature

2018

Observations	247
Dependent variable	area
Type	OLS linear regression

F(1,245)	0.135
R^2	0.001
Adj. R^2	-0.004

	Est.	S.E.	t val.	p
(Intercept)	146.745	34.654	4.235	0.000
temp1	-0.851	2.312	-0.368	0.713

Standard errors: OLS

Significant negative effect of temperature on median height.

Observations	138 (109 missing obs. deleted)
Dependent variable	maxh
Type	OLS linear regression

F(1,136)	3.196
R^2	0.023
Adj. R^2	0.016

	Est.	S.E.	t val.	p
(Intercept)	11.518	0.881	13.079	0.000
temp1	-0.106	0.059	-1.788	0.076

Standard errors: OLS

Observations	133 (114 missing obs. deleted)
Dependent variable	medianh
Type	OLS linear regression

F(1,131)	5.726
R^2	0.042
Adj. R^2	0.035

	Est.	S.E.	t val.	p
(Intercept)	9.994	0.724	13.810	0.000
temp1	-0.117	0.049	-2.393	0.018

Standard errors: OLS

Observations	133 (114 missing obs. deleted)
Dependent variable	totalh
Type	OLS linear regression

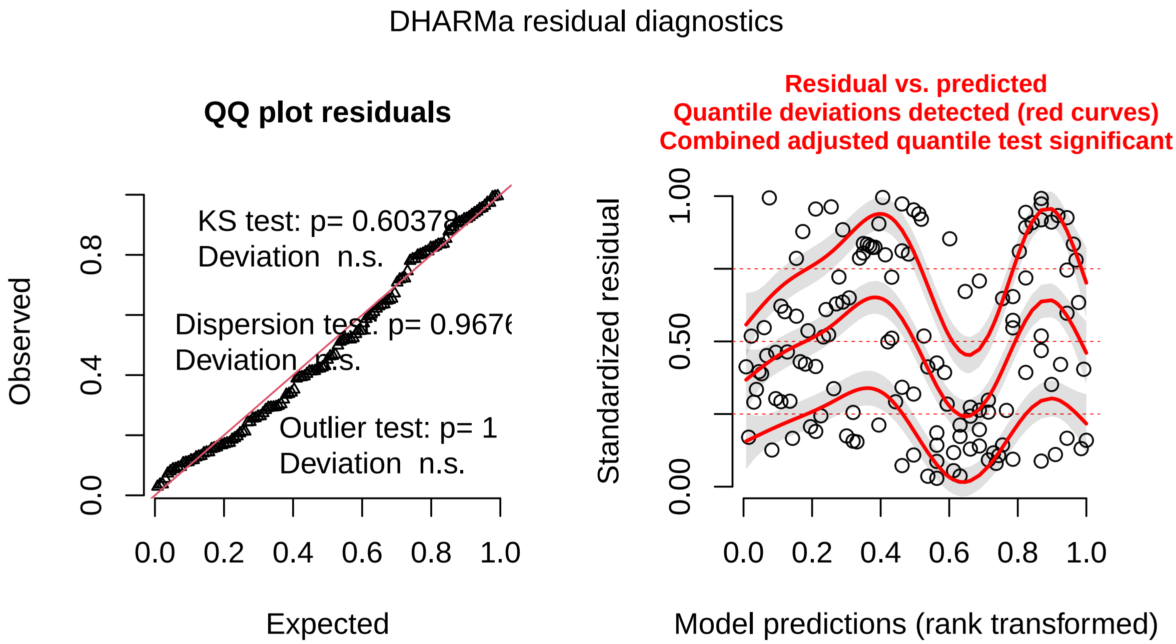
F(1,131)	0.190
R^2	0.001
Adj. R^2	-0.006

	Est.	S.E.	t val.	p
(Intercept)	40.514	12.047	3.363	0.001
temp1	-0.354	0.813	-0.436	0.664

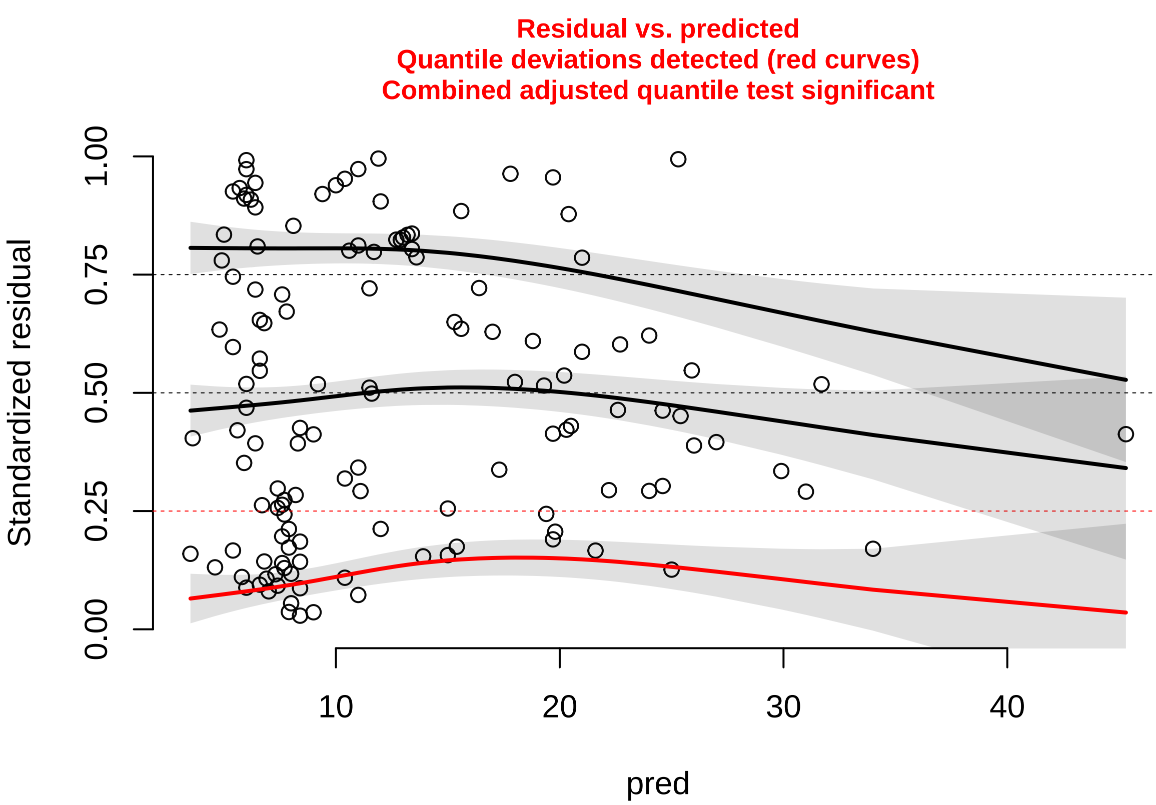
Standard errors: OLS

Model diagnostics

qq-plot and plot of residuals vs. predicted:



Residuals against temperature



Predictions of fitness for minimum and maximum temperatures:

```
## # Predicted values of medianh
## # x = temp1
##
##     x | Predicted |        95% CI
## ---------------------------------
##  3.50 |      9.59 | [8.44, 10.73]
## 45.30 |      4.70 | [1.50,  7.90]
```

2017

Observations	251 (166 missing obs. deleted)
Dependent variable	area
Type	OLS linear regression

F(1,249)	2.913
R^2	0.012
Adj. R^2	0.008

	Est.	S.E.	t val.	p
(Intercept)	5301.212	617.179	8.589	0.000
temp1	73.075	42.818	1.707	0.089

Standard errors: OLS

Observations	255 (162 missing obs. deleted)
Dependent variable	maxh
Type	OLS linear regression

F(1,253)	3.814
R^2	0.015
Adj. R^2	0.011

	Est.	S.E.	t val.	p
(Intercept)	66.023	4.965	13.298	0.000
temp1	0.676	0.346	1.953	0.052

Standard errors: OLS

Observations	255 (162 missing obs. deleted)
Dependent variable	medianh
Type	OLS linear regression

F(1,253)	3.521
R^2	0.014
Adj. R^2	0.010

Marginally significant (p=0.06) negative effect of temperature on median height. Significant positive effect of temperature on total height, but I am not sure this variable is OK to use.

	Est.	S.E.	t val.	p
(Intercept)	7.222	0.439	16.450	0.000
temp1	-0.057	0.031	-1.876	0.062

Standard errors: OLS

Observations	195 (222 missing obs. deleted)
Dependent variable	totalh
Type	OLS linear regression

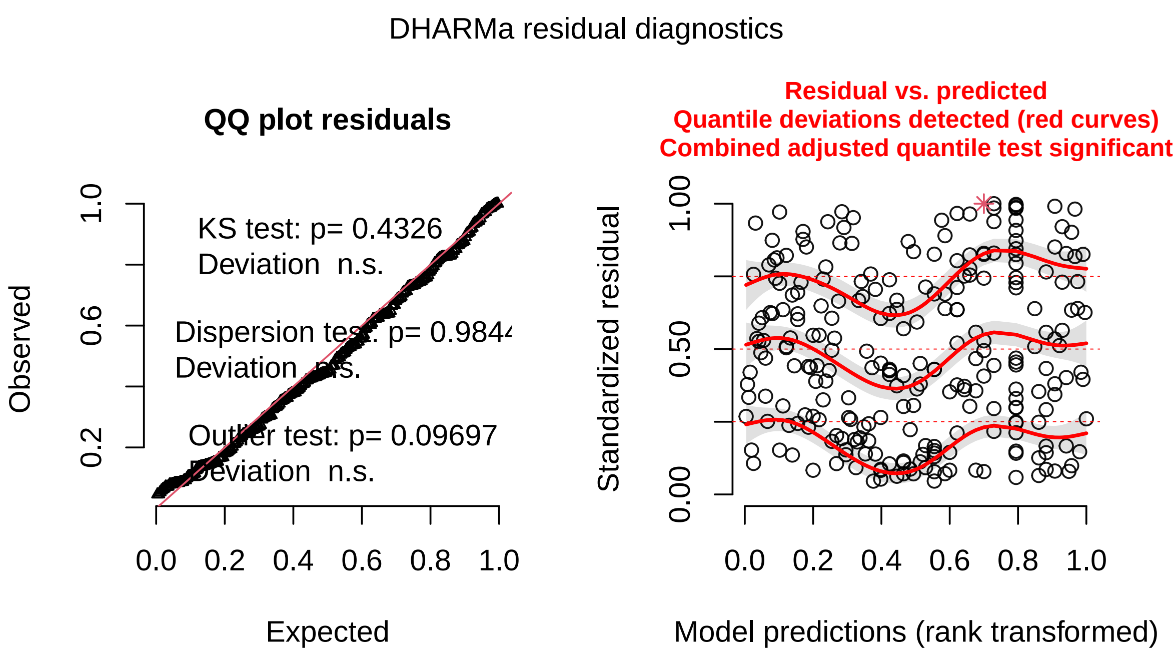
F(1,193)	6.284
R^2	0.032
Adj. R^2	0.027

	Est.	S.E.	t val.	p
(Intercept)	11.721	8.123	1.443	0.151
temp1	1.404	0.560	2.507	0.013

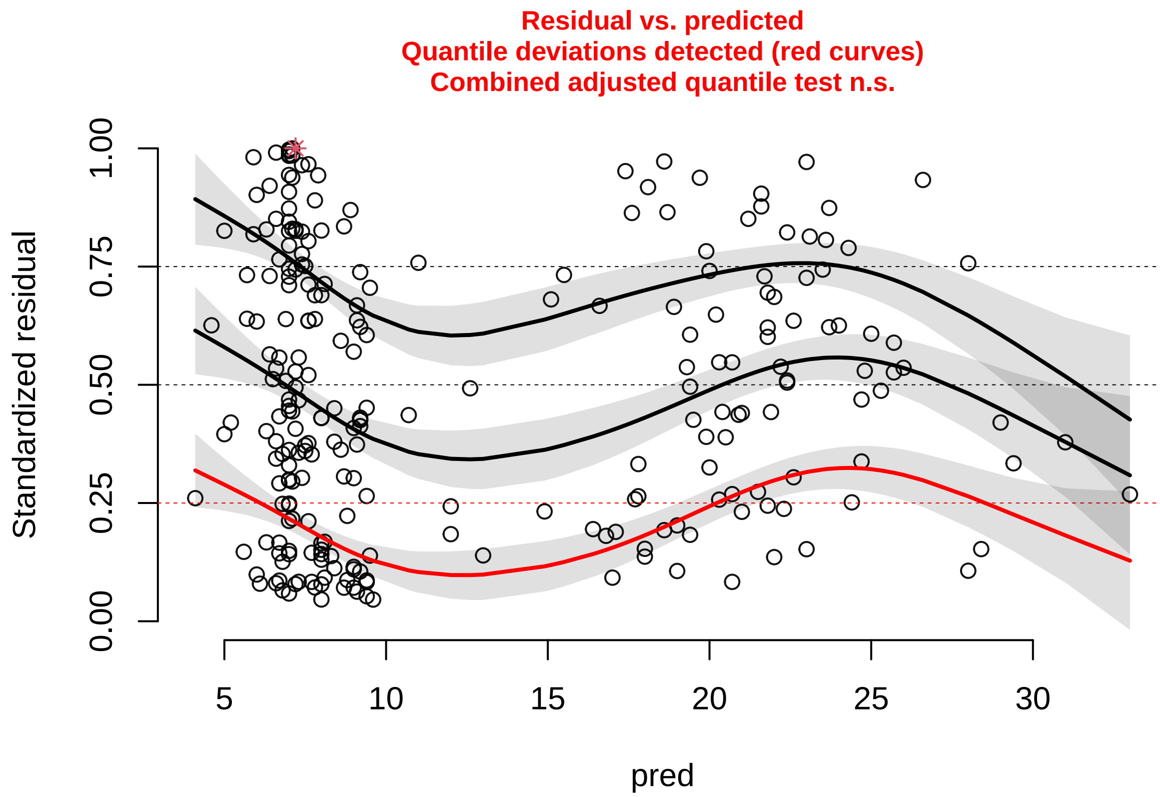
Standard errors: OLS

Model diagnostics

qq-plot and plot of residuals vs. predicted:



Residuals against temperature



Both years

Observations	498 (166 missing obs. deleted)
Dependent variable	area
Type	OLS linear regression

F(1,496)	0.818
R^2	0.002
Adj. R^2	-0.000

	Est.	S.E.	t val.	p
(Intercept)	2883.168	407.701	7.072	0.000
temp1	25.085	27.728	0.905	0.366

Standard errors: OLS

Observations	393 (271 missing obs. deleted)
Dependent variable	maxh
Type	OLS linear regression

Significant negative effect of temperature on median height.

F(1,391)	0.949
R^2	0.002
Adj. R^2	-0.000

	Est.	S.E.	t val.	p
(Intercept)	48.118	4.466	10.775	0.000
temp1	0.299	0.307	0.974	0.331

Standard errors: OLS

Observations	388 (276 missing obs. deleted)
Dependent variable	medianh
Type	OLS linear regression

F(1,386)	8.274
R^2	0.021
Adj. R^2	0.018

	Est.	S.E.	t val.	p
(Intercept)	8.172	0.393	20.770	0.000
temp1	-0.078	0.027	-2.876	0.004

Standard errors: OLS

Observations	328 (336 missing obs. deleted)
Dependent variable	totalh
Type	OLS linear regression

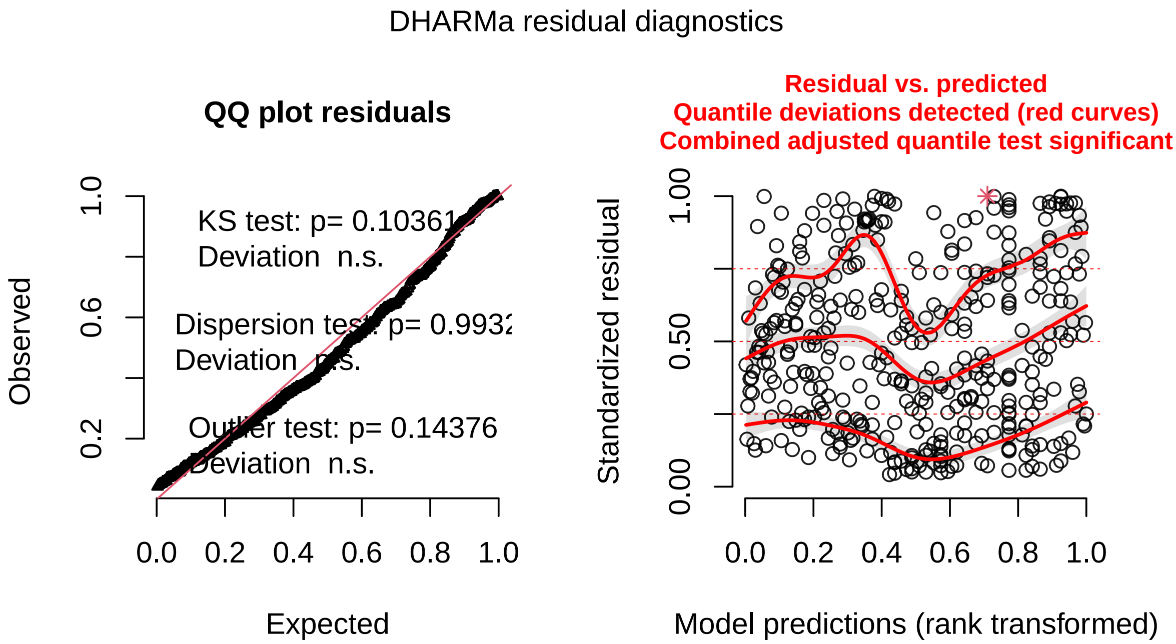
F(1,326)	1.941
R^2	0.006
Adj. R^2	0.003

	Est.	S.E.	t val.	p
(Intercept)	23.748	6.905	3.439	0.001
temp1	0.658	0.472	1.393	0.165

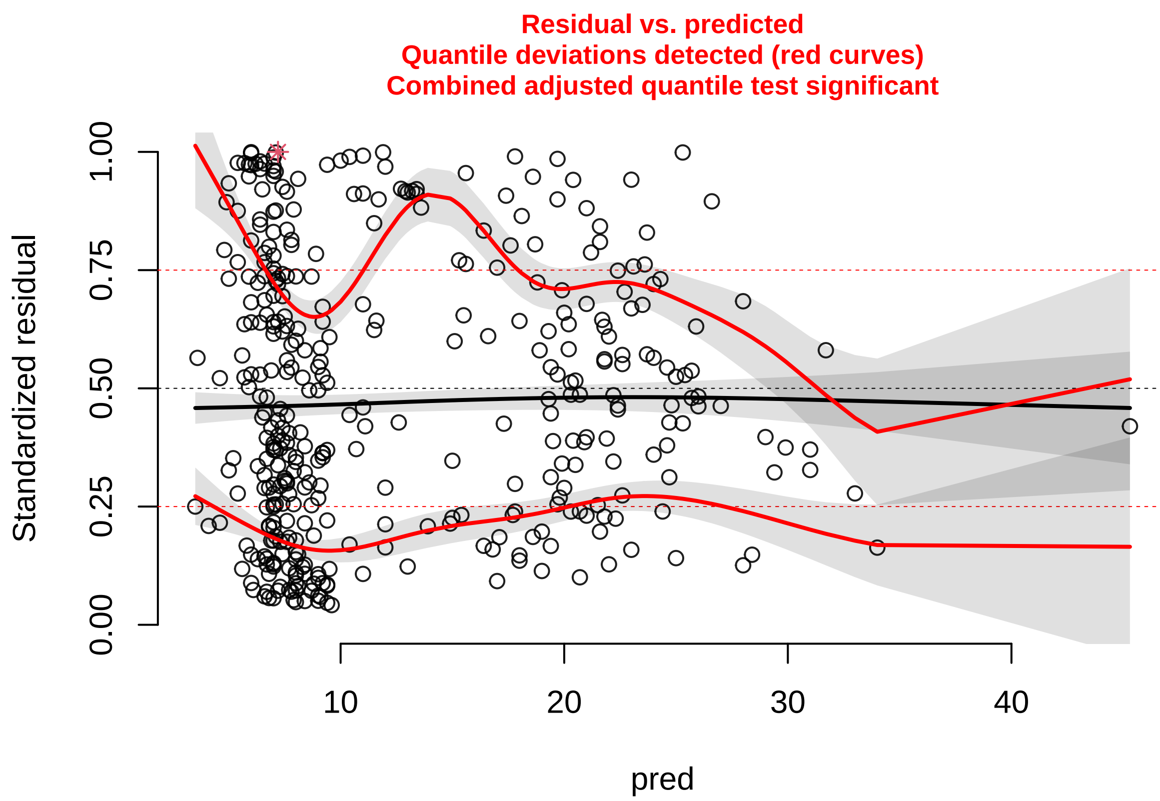
Standard errors: OLS

Model diagnostics

qq-plot and plot of residuals vs. predicted:



Residuals against temperature



3. Effect of temperature on fitness

```
fitness_2017_1<-lm(nseed~temp+I(temp^2)+log(nfl),subset(mydata,year==2017))
summ(fitness_2017_1,vif=T,scale=T) # scale=T reports standardized coefs
```

Observations	245
Dependent variable	nseed
Type	OLS linear regression

F(3,241)	67.240
R^2	0.456
Adj. R^2	0.449

	Est.	S.E.	t val.	p	VIF
(Intercept)	564.692	43.167	13.082	0.000	NA
temp	-344.358	158.067	-2.179	0.030	13.354
‘I(temp^2)‘	195.214	155.818	1.253	0.211	12.977
‘log(nfl)‘	647.075	45.688	14.163	0.000	1.116

Standard errors: OLS; Continuous predictors are mean-centered and scaled by 1 s.d.

```
fitness_2018_1<-lm(nseed~temp+I(temp^2)+log(nfl),subset(mydata,year==2018))
summ(fitness_2018_1,vif=T,scale=T) # scale=T reports standardized coefs
```

Observations	104
Dependent variable	nseed
Type	OLS linear regression

F(3,100)	42.951
R^2	0.563
Adj. R^2	0.550

	Est.	S.E.	t val.	p	VIF
(Intercept)	212.442	18.026	11.785	0.000	NA
temp	0.861	81.497	0.011	0.992	20.244
‘I(temp^2)‘	-60.226	81.470	-0.739	0.461	20.231
‘log(nfl)‘	199.191	18.141	10.980	0.000	1.003

Standard errors: OLS; Continuous predictors are mean-centered and scaled by 1 s.d.

Quadratic terms of ffd not significant. Refit models withouth quadratic terms of ffd.

```r
fitness_2017_2<-lm(nseed~temp+log(nfl),subset(mydata,year==2017))
summ(fitness_2017_2,vif=T,scale=T) # scale=T reports standardized coefs
```

Observations	245
Dependent variable	nseed
Type	OLS linear regression

F(2,242)	99.840
R^2	0.452
Adj. R^2	0.448

	Est.	S.E.	t val.	p	VIF
(Intercept)	564.692	43.218	13.066	0.000	NA
temp	-154.606	45.279	-3.415	0.001	1.093
‘log(nfl)‘	638.951	45.279	14.112	0.000	1.093

Standard errors: OLS; Continuous predictors are mean-centered and scaled by 1 s.d.

```r
fitness_2018_2<-lm(nseed~temp+log(nfl),subset(mydata,year==2018))
summ(fitness_2018_2,vif=T,scale=T) # scale=T reports standardized coefs
```

Observations	104
Dependent variable	nseed
Type	OLS linear regression

F(2,101)	64.443
R^2	0.561
Adj. R^2	0.552

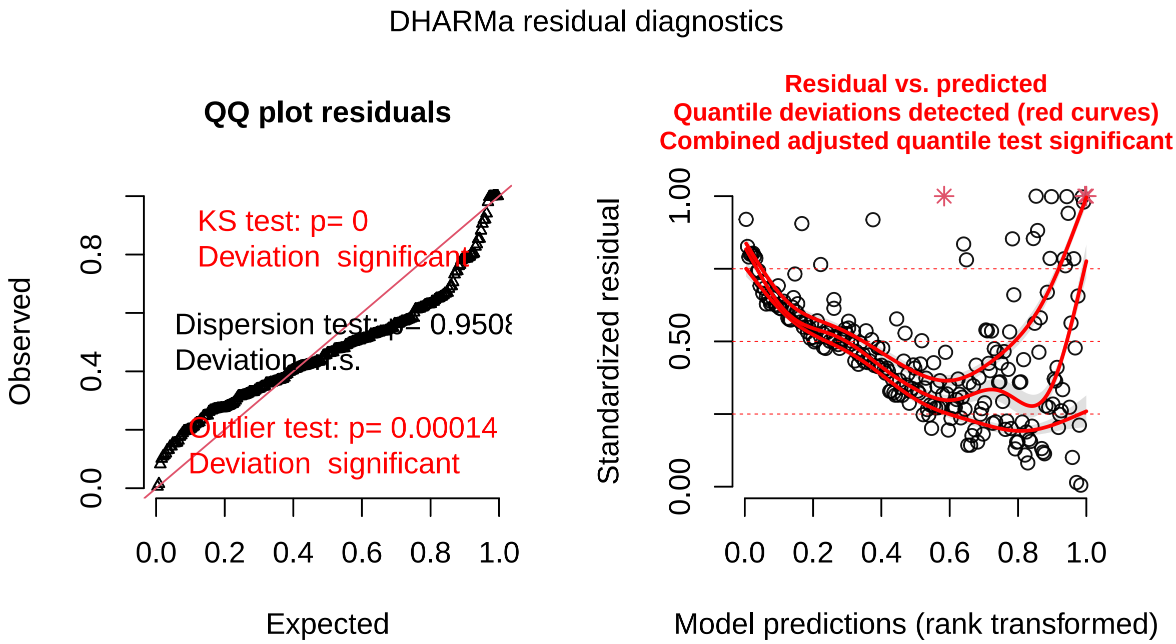
	Est.	S.E.	t val.	p	VIF
(Intercept)	212.442	17.985	11.812	0.000	NA
temp	-57.875	18.092	-3.199	0.002	1.002
‘log(nfl)‘	199.581	18.092	11.031	0.000	1.002

Standard errors: OLS; Continuous predictors are mean-centered and scaled by 1 s.d.

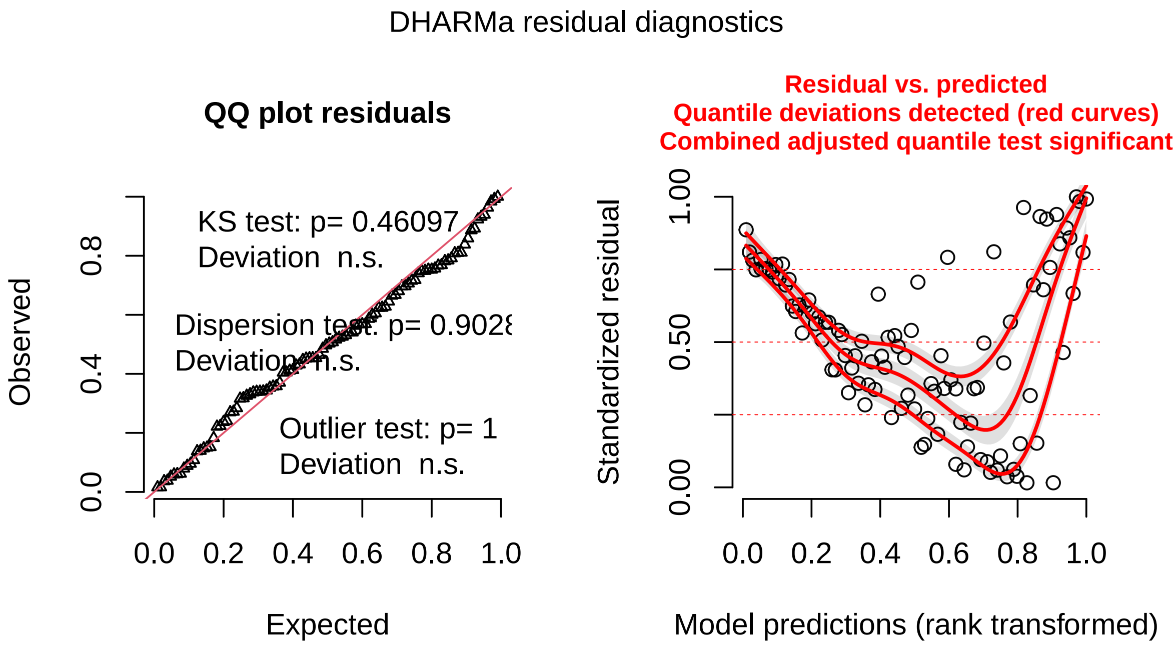
Model diagnostics

qq-plot and plot of residuals vs. predicted:

2017:



2018:



Quite bad looking! We should try another distribution.

GLMs with poisson distribution

```
mydata$n_seed_round<-with(mydata,round(nseed))
fitness_2017_3<-glm(n_seed_round~temp+I(temp^2)+log(nfl),
                    subset(mydata,year==2017),family="poisson")
summ(fitness_2017_3,vif=T,scale=T)
```

Observations	245
Dependent variable	n_seed_round
Type	Generalized linear model
Family	poisson
Link	log

$\chi^2(3)$	149330.384
Pseudo-R² (Cragg-Uhler)	1.000
Pseudo-R² (McFadden)	0.714
AIC	59784.973
BIC	59798.978

	Est.	S.E.	z val.	p	VIF
(Intercept)	5.815	0.004	1506.414	0.000	NA
temp	-0.595	0.011	-55.431	0.000	15.530
‘I(temp^2)‘	0.347	0.011	32.117	0.000	15.107
‘log(nfl)‘	1.033	0.003	381.797	0.000	1.113

Standard errors: MLE; Continuous predictors are mean-centered and scaled by 1 s.d.

```
fitness_2018_3<-glm(n_seed_round~temp+I(temp^2)+log(nfl),
                    subset(mydata,year==2018),family="poisson")
summ(fitness_2018_3,vif=T,scale=T)
```

Observations	104
Dependent variable	n_seed_round
Type	Generalized linear model
Family	poisson
Link	log

$\chi^2(3)$	21316.452
Pseudo-R² (Cragg-Uhler)	1.000
Pseudo-R² (McFadden)	0.744
AIC	7359.145
BIC	7369.723

```
overdisp_fun(fitness_2017_3)
```

```
##      chisq      ratio        rdf          p
## 90313.0502   374.7429   241.0000     0.0000
```

	Est.	S.E.	z val.	p	VIF
(Intercept)	4.826	0.010	479.086	0.000	NA
temp	0.234	0.034	6.935	0.000	15.061
‘I(temp^2)‘	-0.588	0.038	-15.296	0.000	15.078
‘log(nfl)‘	1.009	0.008	128.832	0.000	1.008

Standard errors: MLE; Continuous predictors are mean-centered and scaled by 1 s.d.

```
overdisp_fun(fitness_2018_3)
```

```
##       chisq      ratio        rdf          p
## 5744.43831   57.44438  100.00000    0.00000
```

There is significant overdispersion.

GLMs with negative binomial distribution

```
fitness_2017_4<-glm.nb(n_seed_round~temp+I(temp^2)+log(nfl),
                       subset(mydata,year==2017))
summ(fitness_2017_4,vif=T,scale=T) # scale=T reports standardized coefs
```

Observations	245
Dependent variable	n_seed_round
Type	Generalized linear model
Family	Negative Binomial(2.1088)
Link	log

$\chi^2()$	0.723	0.088	3273.867	3291.374
Pseudo-R² (Cragg-Uhler)	0.723	0.088	3273.867	3291.374
Pseudo-R² (McFadden)	0.723	0.088	3273.867	3291.374
AIC	0.723	0.088	3273.867	3291.374
BIC	0.723	0.088	3273.867	3291.374

	Est.	S.E.	z val.	p	VIF
(Intercept)	5.787	0.044	130.869	0.000	NA
temp	-0.408	0.162	-2.515	0.012	13.378
‘I(temp^2)‘	0.173	0.160	1.078	0.281	13.002
‘log(nfl)‘	1.092	0.047	23.320	0.000	1.116

Standard errors: MLE; Continuous predictors are mean-centered and scaled by 1 s.d.

```
fitness_2018_4<-glm.nb(n_seed_round~temp+I(temp^2)+log(nfl),
                       subset(mydata,year==2018))
summ(fitness_2018_4,vif=T,scale=T) # scale=T reports standardized coefs
```

Observations	104
Dependent variable	n_seed_round
Type	Generalized linear model
Family	Negative Binomial(1.9935)
Link	log

$\chi^2()$	0.694	0.094	1202.008	1215.230
Pseudo-R² (Cragg-Uhler)	0.694	0.094	1202.008	1215.230
Pseudo-R² (McFadden)	0.694	0.094	1202.008	1215.230
AIC	0.694	0.094	1202.008	1215.230
BIC	0.694	0.094	1202.008	1215.230

	Est.	S.E.	z val.	p	VIF
(Intercept)	4.828	0.070	68.612	0.000	NA
temp	0.264	0.320	0.825	0.409	20.150
‘I(temp^2)‘	-0.593	0.321	-1.846	0.065	20.136
‘log(nfl)‘	1.018	0.071	14.304	0.000	1.003

Standard errors: MLE; Continuous predictors are mean-centered and scaled by 1 s.d.

Quadratic terms of ffd not significant. Refit models withouth quadratic terms of ffd.

```
fitness_2017_5<-glm.nb(n_seed_round~temp+log(nfl),subset(mydata,year==2017))
summ(fitness_2017_5,vif=T,scale=T)
```

Observations	245
Dependent variable	n_seed_round
Type	Generalized linear model
Family	Negative Binomial(2.0993)
Link	log

$\chi^2()$	0.722	0.088	3273.106	3287.112
Pseudo-R² (Cragg-Uhler)	0.722	0.088	3273.106	3287.112
Pseudo-R² (McFadden)	0.722	0.088	3273.106	3287.112
AIC	0.722	0.088	3273.106	3287.112
BIC	0.722	0.088	3273.106	3287.112

	Est.	S.E.	z val.	p	VIF
(Intercept)	5.788	0.044	130.603	0.000	NA
temp	-0.238	0.047	-5.117	0.000	1.094
‘log(nfl)‘	1.087	0.046	23.377	0.000	1.094

Standard errors: MLE; Continuous predictors are mean-centered and scaled by 1 s.d.

```
fitness_2018_5<-glm.nb(n_seed_round~temp+log(nfl),subset(mydata,year==2018))
summ(fitness_2018_5,vif=T,scale=T)
```

Observations	104
Dependent variable	n_seed_round
Type	Generalized linear model
Family	Negative Binomial(1.9313)
Link	log

$\chi^2()$	0.684	0.091	1203.369	1213.947
Pseudo-R² (Cragg-Uhler)	0.684	0.091	1203.369	1213.947
Pseudo-R² (McFadden)	0.684	0.091	1203.369	1213.947
AIC	0.684	0.091	1203.369	1213.947
BIC	0.684	0.091	1203.369	1213.947

	Est.	S.E.	z val.	p	VIF
(Intercept)	4.837	0.071	67.703	0.000	NA
temp	-0.301	0.072	-4.166	0.000	1.003
‘log(nfl)‘	1.026	0.072	14.202	0.000	1.003

Standard errors: MLE; Continuous predictors are mean-centered and scaled by 1 s.d.

Predictions of fitness for minimum and maximum temperatures:

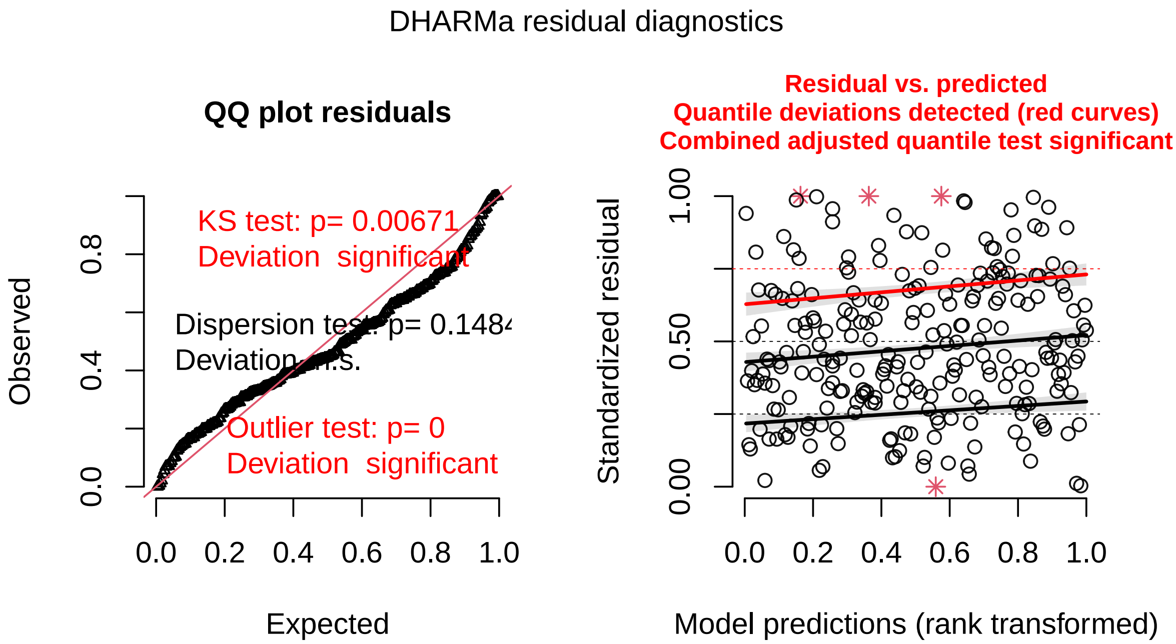
```
## # Predicted counts of n_seed_round
## # x = temp
##
##     x | Predicted |           95% CI
## --------------------------------------
##  4.10 |    849.90 | [719.89, 1003.40]
## 45.50 |    243.83 | [169.94,  349.84]
##
## Adjusted for:
## * nfl = 17.13
```

```
## # Predicted counts of n_seed_round
## # x = temp
##
##     x | Predicted |          95% CI
## -------------------------------------
##  3.50 |    301.27 | [238.31, 380.87]
## 34.00 |     84.77 | [ 54.15, 132.71]
##
## Adjusted for:
## * nfl = 10.54
```

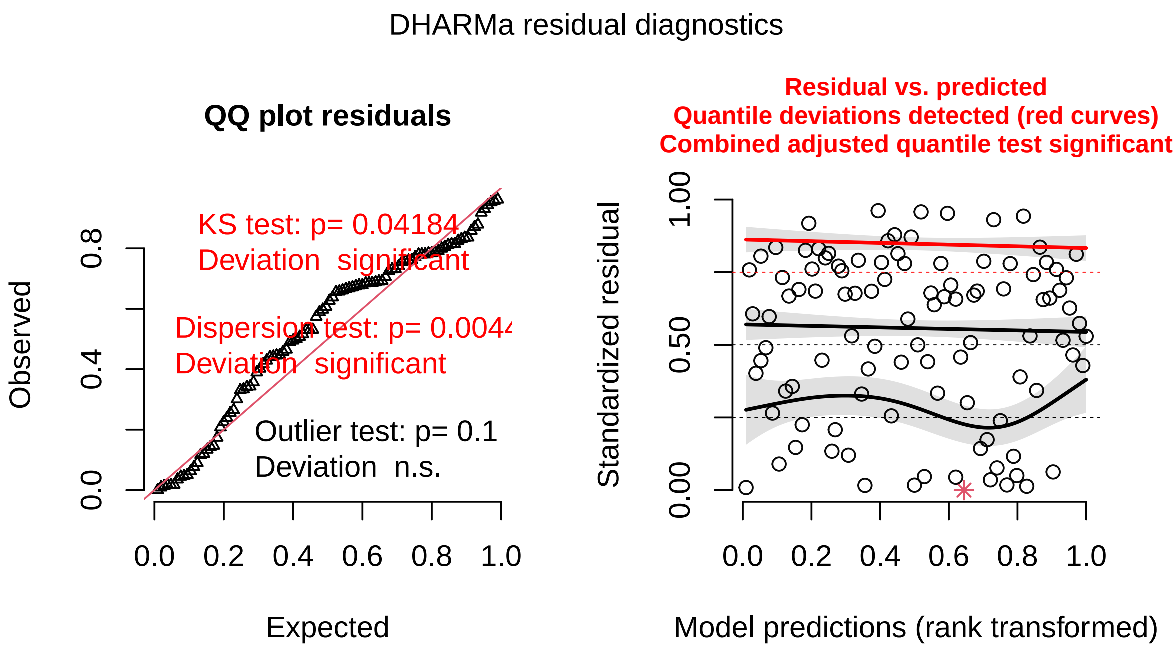
Model diagnostics

qq-plot and plot of residuals vs. predicted:

2017:



2018:



Some problems but maybe not so bad. Need to look a bit more into this later.

Figure 2: Effects of temperature on ffd, size and fitness in 2018

Model predictions ffd : based on models FFD_2017_1 (with quadratic term of ffd) and FFD_2018_2 (without quadratic term of ffd).

Model predictions size : based on models medianh1_2017 and medianh1_2018.

Model predictions fitness : based on models fitness_2017_5 and fitness_2018_5.

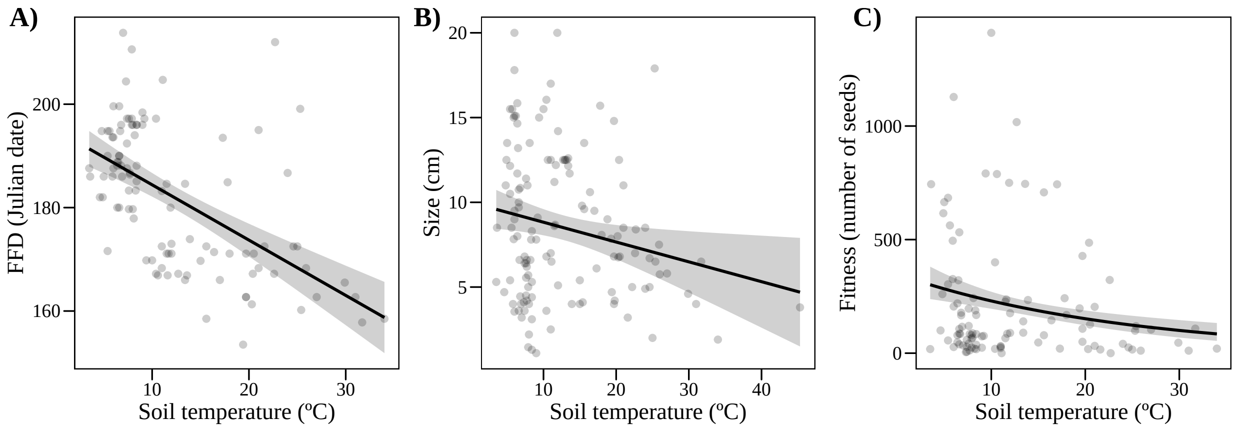
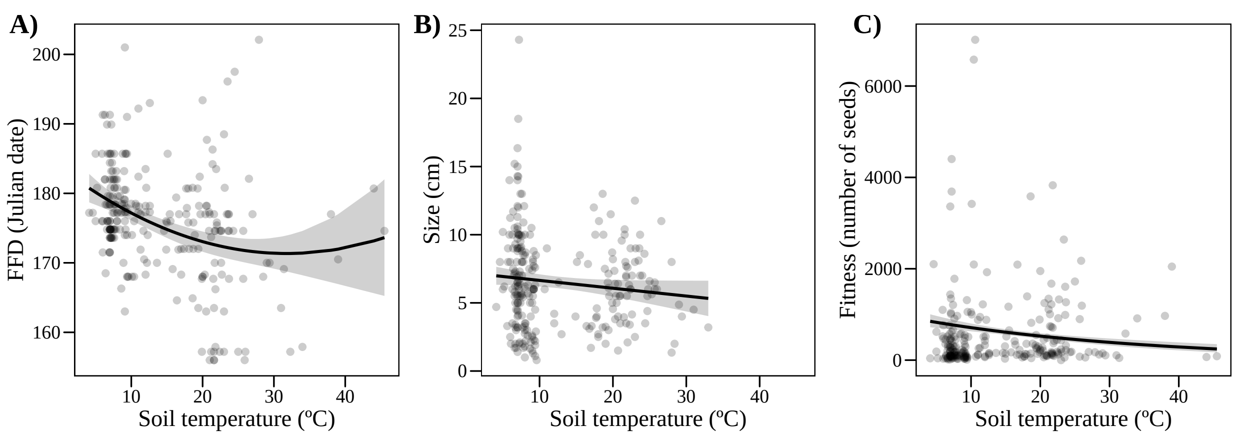


Figure S1: Effects of temperature on ffd, size and fitness in 2017



4. How useful soil temperature is as a cue for air temperature

Do correlations between soil and air temperature vary with soil temperature?

We test this using logger pairs.

After looking at plots from individual pairs of loggers, make a new variable pair_problem: - 0 = no problem - 1 = some problems (remove)

Use only logger pairs with no problems (53 pairs out of 73): pairs 1-4,9,11,13-16,21-62,70.

Most loggers end up on June 6th, so using data until June 5th.

Using pairs of loggers where above and belowground logger are at less than 2 m distance.

```
## [1] 68
```

```
## [1] 32
```

68 loggers (34 pairs), of which 32 loggers in Cerastium plants, and 36 loggers in other plants.

Period April-May-June

For each date and logger pair, calculate mean, max and min of air and soil temperature (from, respectively, the above and belowground logger). Then, calculate the correlation coefficient for air and soil temperatures over the period April-May-June. Finally, regress these correlation coefficients on mean soil temperature (from the belowground logger) **for the same period (April-May-June)**.

Linear models testing the effect of soil temperature on correlations between soil and air temperature:

measure	term	estimate	std.error	statistic	p.value
corr_airsoil_max	(Intercept)	0.70490	0.03085	22.84701	0
corr_airsoil_max	meansoiltemp	-0.01201	0.00213	-5.65264	0
corr_airsoil_mean	(Intercept)	0.88168	0.02732	32.26804	0
corr_airsoil_mean	meansoiltemp	-0.01581	0.00188	-8.39776	0
corr_airsoil_min	(Intercept)	0.73125	0.02851	25.64630	0
corr_airsoil_min	meansoiltemp	-0.01572	0.00196	-8.00263	0

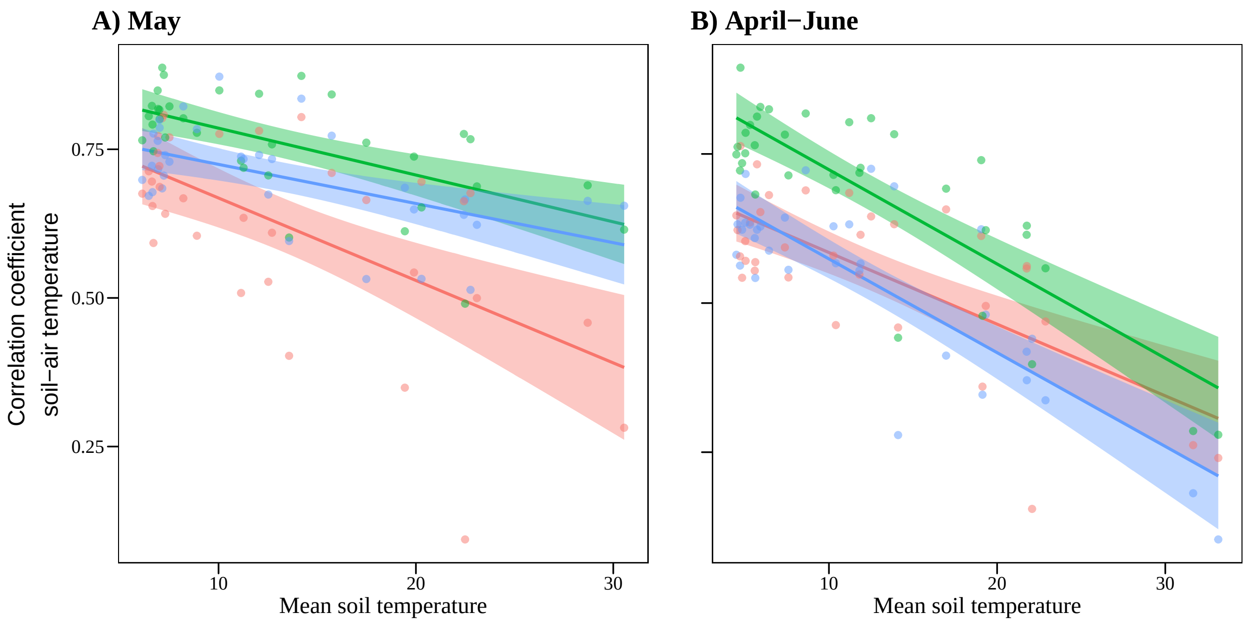
May only

For each date and logger pair, calculate mean, max and min of air and soil temperature (from, respectively, the above and belowground logger). Then, calculate the correlation coefficient for air and soil temperatures over the month of May. Finally, regress these correlation coefficients on mean soil temperature (from the belowground logger) **for the same period (May)**.

Linear models testing the effect of soil temperature on correlations between soil and air temperature:

measure	term	estimate	std.error	statistic	p.value
corr_airsoil_max	(Intercept)	0.80671	0.04746	16.99948	0.00000
corr_airsoil_max	meansoiltemp	-0.01387	0.00319	-4.34703	0.00013
corr_airsoil_mean	(Intercept)	0.86430	0.02597	33.28017	0.00000
corr_airsoil_mean	meansoiltemp	-0.00788	0.00175	-4.51305	0.00008
corr_airsoil_min	(Intercept)	0.79047	0.02599	30.41351	0.00000
corr_airsoil_min	meansoiltemp	-0.00658	0.00175	-3.76854	0.00067

Figure 3: Correlations soil-air temperature vs soil temperature

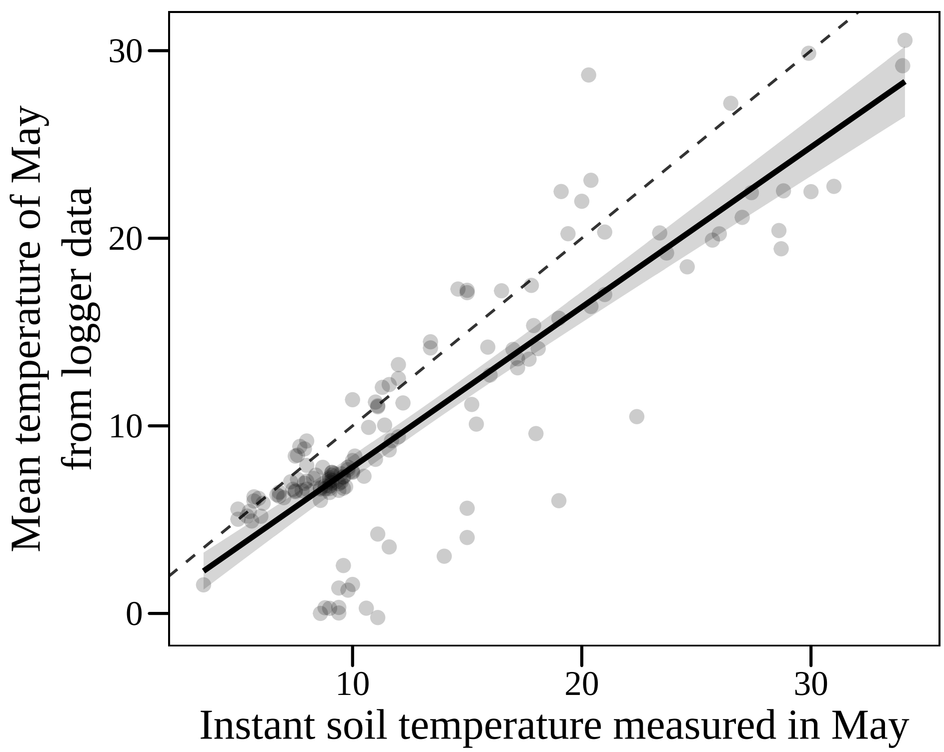


Possible Appendix: Are instantaneous measures of soil temperature representative for the conditions during the entire spring/growing season?

Correlations logger temperature - instant temperature

May

For each logger_nr, get mean temperature during May 2017 and compare with temp_term (which was measured with a thermometer at 10 cm depth on May 2017):



Observations	141
Dependent variable	meanmay_logger
Type	OLS linear regression

F(1,139)	399.799
R^2	0.742
Adj. R^2	0.740

	Est.	S.E.	t val.	p
(Intercept)	-0.727	0.625	-1.163	0.247
temp_term	0.853	0.043	19.995	0.000

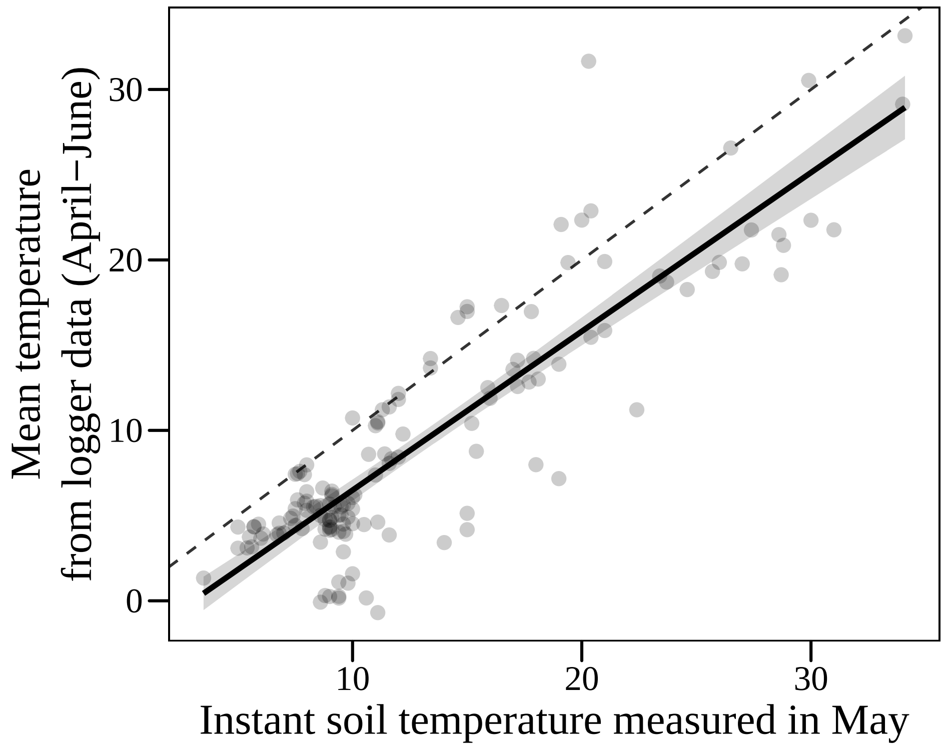
Standard errors: OLS

Correlation mean temperature of may from logger data (only belowground loggers) and soil temperature measured in may with thermometer:

```
## [1] 0.8614051
```

April-June

For each logger_nr, get mean temperature during April-June and compare with temp_term (which was measured with a thermometer at 10 cm depth on May 2017):



Observations	141
Dependent variable	mean_logger
Type	OLS linear regression

F(1,139)	479.674
R^2	0.775
Adj. R^2	0.774

	Est.	S.E.	t val.	p
(Intercept)	-2.825	0.624	-4.529	0.000
temp_term	0.932	0.043	21.901	0.000

Standard errors: OLS

Correlation mean temperature from logger data (only belowground loggers) and soil temperature measured in may with thermometer:

```
## [1] 0.8805259
```

5. Effect of temperature on selection on FFD

```
selection_2017_1<-lm(nseed_rel~ffd_std*temp+ffd_std*I(temp^2)+nfl_std,
                     subset(mydata,year==2017))
selection_2018_1<-lm(nseed_rel~ffd_std*temp+ffd_std*I(temp^2)+nfl_std,
```

```r
                        subset(mydata,year==2018))
summ(selection_2017_1,scale=T)
```

Observations	245
Dependent variable	nseed_rel
Type	OLS linear regression

F(6,238)	34.508
R^2	0.465
Adj. R^2	0.452

	Est.	S.E.	t val.	p
(Intercept)	0.974	0.082	11.947	0.000
ffd_std	0.212	0.103	2.051	0.041
temp	-0.514	0.284	-1.808	0.072
‘I(temp^2)‘	0.288	0.279	1.033	0.303
nfl_std	1.226	0.090	13.667	0.000
ffd_std:temp	-0.275	0.356	-0.770	0.442
ffd_std:‘I(temp^2)‘	0.229	0.365	0.627	0.531

Standard errors: OLS; Continuous predictors are mean-centered and scaled by 1 s.d.

```r
summ(selection_2018_1,scale=T)
```

Observations	104
Dependent variable	nseed_rel
Type	OLS linear regression

F(6,97)	22.809
R^2	0.585
Adj. R^2	0.560

	Est.	S.E.	t val.	p
(Intercept)	1.137	0.106	10.768	0.000
ffd_std	0.019	0.130	0.143	0.886
temp	-0.395	0.597	-0.662	0.510
‘I(temp^2)‘	0.244	0.661	0.369	0.713
nfl_std	0.973	0.103	9.437	0.000
ffd_std:temp	0.314	0.512	0.614	0.541
ffd_std:‘I(temp^2)‘	-0.076	0.520	-0.146	0.884

Standard errors: OLS; Continuous predictors are mean-centered and scaled by 1 s.d.

Quadratic terms of ffd not significant. Refit models withouth quadratic terms of ffd.

```r
selection_2017_2<-lm(nseed_rel~ffd_std*temp+nfl_std,
                     subset(mydata,year==2017))
selection_2018_2<-lm(nseed_rel~ffd_std*temp+nfl_std,
                     subset(mydata,year==2018))
summ(selection_2017_2,scale=T,digits=5)
```

Observations	245
Dependent variable	nseed_rel
Type	OLS linear regression

F(4,240)	51.54890
R^2	0.46212
Adj. R^2	0.45315

	Est.	S.E.	t val.	p
(Intercept)	0.97807	0.08042	12.16219	0.00000
ffd_std	0.21003	0.09939	2.11311	0.03562
temp	-0.24042	0.08186	-2.93713	0.00363
nfl_std	1.21323	0.08880	13.66288	0.00000
ffd_std:temp	-0.06739	0.07949	-0.84781	0.39739

Standard errors: OLS; Continuous predictors are mean-centered and scaled by 1 s.d.

```r
summ(selection_2018_2,scale=T,digits=5)
```

Observations	104
Dependent variable	nseed_rel
Type	OLS linear regression

F(4,99)	34.66004
R^2	0.58340
Adj. R^2	0.56657

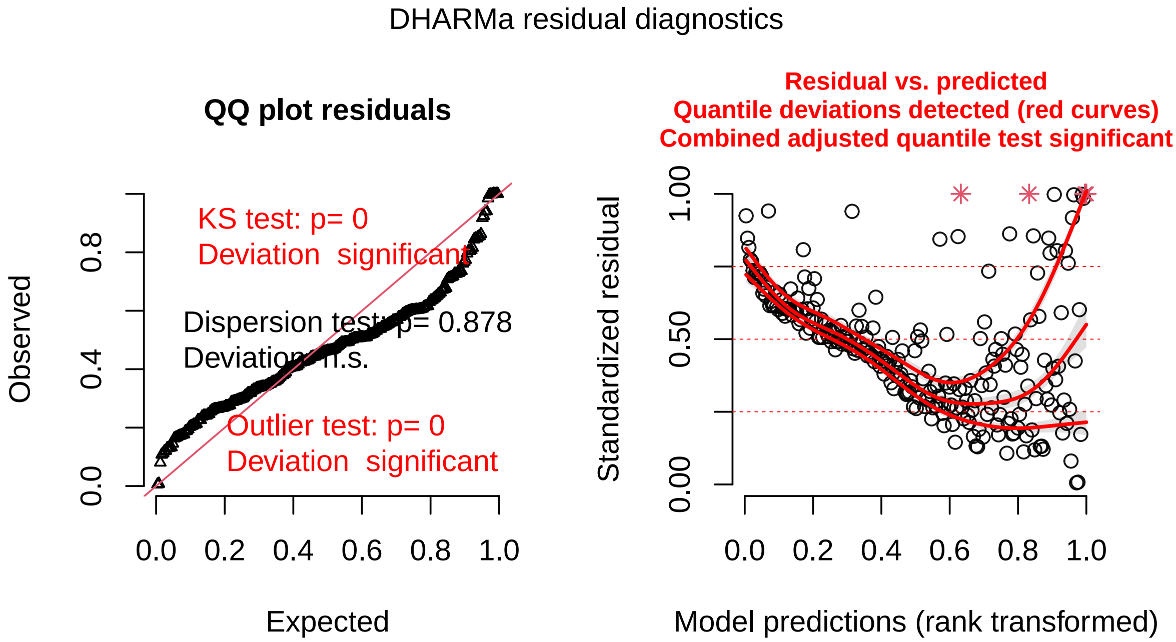
	Est.	S.E.	t val.	p
(Intercept)	1.11076	0.09682	11.47190	0.00000
ffd_std	0.04479	0.12296	0.36422	0.71647
temp	-0.15383	0.11242	-1.36836	0.17430
nfl_std	0.97607	0.10084	9.67898	0.00000
ffd_std:temp	0.19755	0.08813	2.24150	0.02723

Standard errors: OLS; Continuous predictors are mean-centered and scaled by 1 s.d.

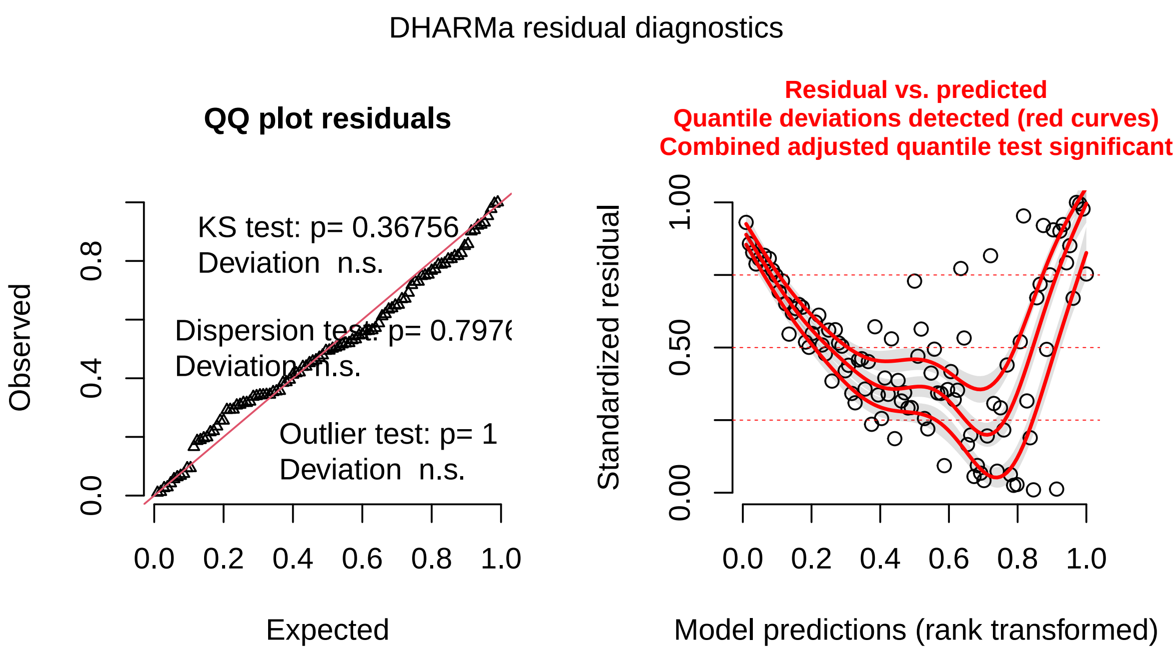
Model diagnostics

qq-plot and plot of residuals vs. predicted:

2017:



2018:



Quite bad looking! If we want to keep the linear model with normal distribution (i.e. a "classic" selection model), we can assess significances using BCa intervals.

BCa intervals

2017

```
##                lower       upper
## ffd       0.01263314  0.79840750
## temp     -0.05558642 -0.01320301
## nfl       0.91302964  1.69711242
## ffd:temp -0.02536854  0.00526291
```

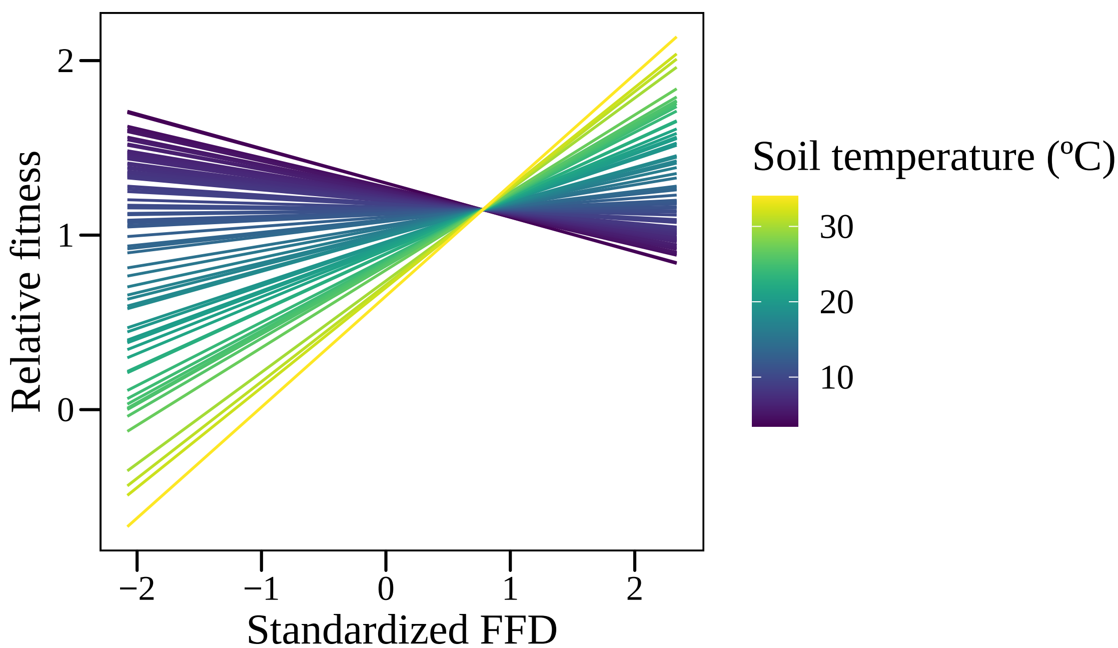
FFD significant according to BCa intervals.

2018

```
##                 lower        upper
## ffd      -0.746527205  0.210568390
## temp     -0.041058874 -0.001521278
## nfl       0.731203424  1.257755839
## ffd:temp  0.004107204  0.052202141
```

The significances according to the BCa intervals are similar to the ones given in the model summary.

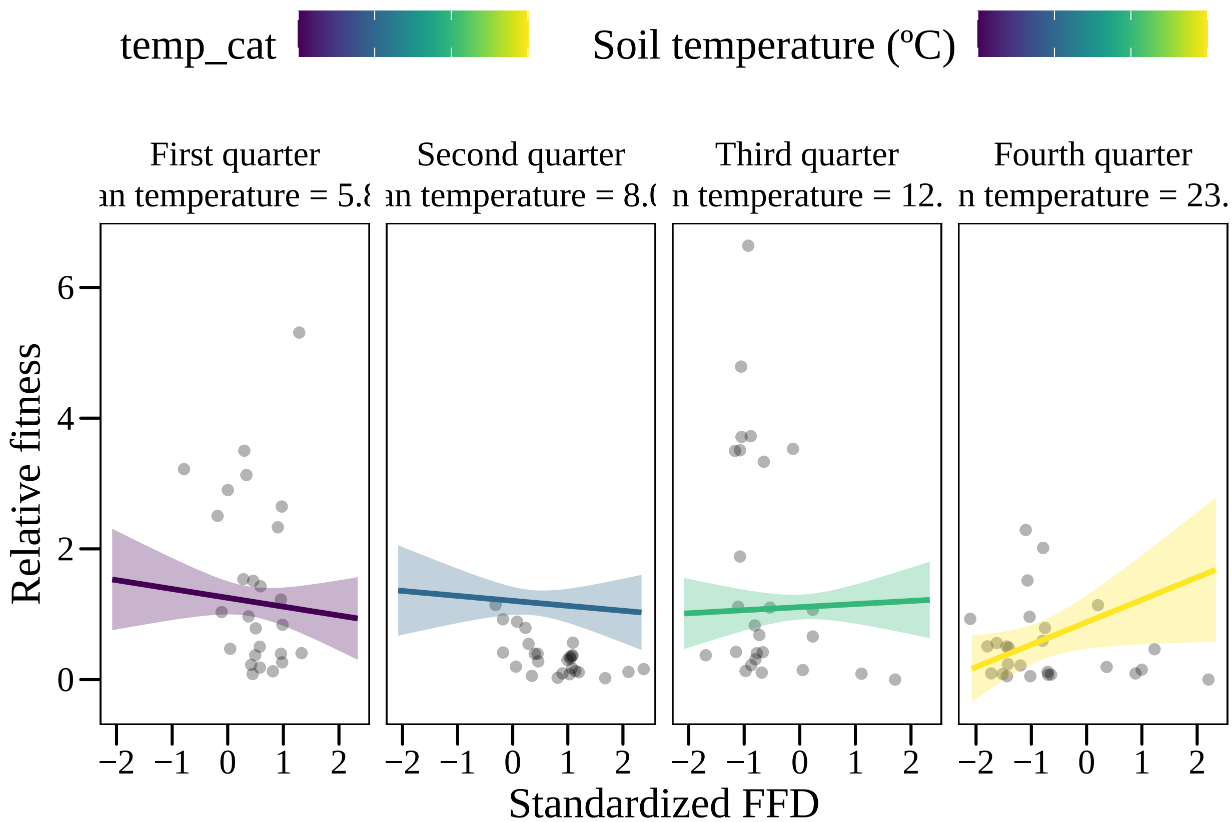
Figure 4: Effects of temperature on selection in 2018



Possble Appendix: Relationships between std FFD and relative fitness for different parts of the distribution of soil temperature

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
```

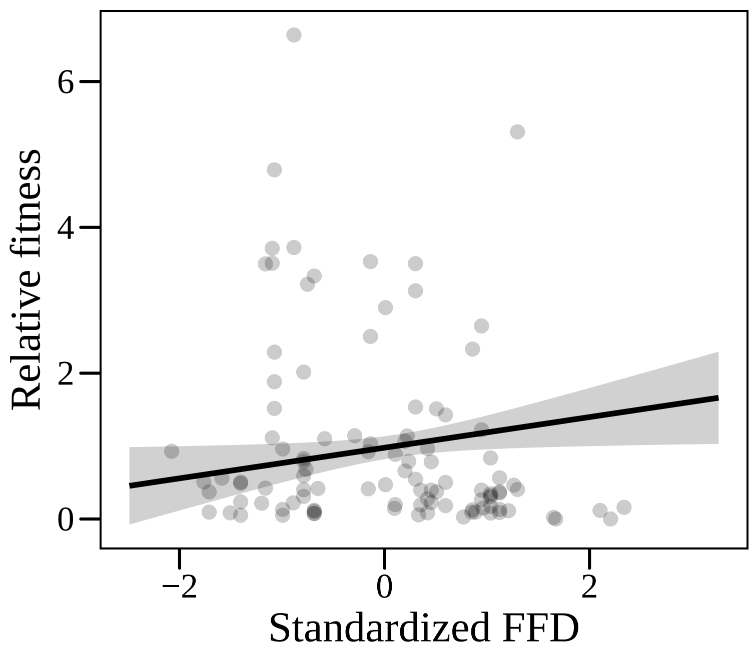
```
##   3.500   6.875   9.300  12.368  17.075  34.000

## [1] 5.784615

## [1] 7.95

## [1] 12.45

## [1] 23.28846
```




```
## List of 2
##  $ strip.text.x:List of 11
##   ..$ family       : NULL
##   ..$ face         : NULL
##   ..$ colour       : NULL
##   ..$ size         : NULL
##   ..$ hjust        : NULL
##   ..$ vjust        : NULL
##   ..$ angle        : NULL
##   ..$ lineheight   : NULL
##   ..$ margin       : 'margin' num [1:4] 2points 0points 2points 0points
##   .. ..- attr(*, "unit")= int 8
##   ..$ debug        : NULL
##   ..$ inherit.blank: logi FALSE
```

```
##   ..- attr(*, "class")= chr [1:2] "element_text" "element"
##  $ fill        : logi FALSE
##  - attr(*, "class")= chr [1:2] "theme" "gg"
##  - attr(*, "complete")= logi FALSE
##  - attr(*, "validate")= logi TRUE
```

Figure S2: Effects of ffd on relative fitness in 2018



6. Effect of temperature on the relationship absolute fitness-FFD

```
selectionabs_2017_1<-lm(nseed~ffd*temp+ffd*I(temp^2)+log(nfl),
                     subset(mydata,year==2017))
selectionabs_2018_1<-lm(nseed~ffd*temp+ffd*I(temp^2)+log(nfl),
                     subset(mydata,year==2018))
summ(selectionabs_2017_1,scale=F)
```

Observations	245
Dependent variable	nseed
Type	OLS linear regression

F(6,238)	34.508
R^2	0.465
Adj. R^2	0.452

	Est.	S.E.	t val.	p
(Intercept)	-6682.670	4879.792	-1.369	0.172
ffd	35.520	27.405	1.296	0.196
temp	394.423	560.245	0.704	0.482
I(temp^2)	-8.887	15.022	-0.592	0.555
log(nfl)	625.843	45.793	13.667	0.000
ffd:temp	-2.451	3.181	-0.770	0.442
ffd:I(temp^2)	0.054	0.086	0.627	0.531

Standard errors: OLS

```
summ(selectionabs_2018_1,scale=F)
```

Observations	104
Dependent variable	nseed
Type	OLS linear regression

F(6,97)	22.809
R^2	0.585
Adj. R^2	0.560

	Est.	S.E.	t val.	p
(Intercept)	1263.606	1411.947	0.895	0.373
ffd	-7.074	7.767	-0.911	0.365
temp	-134.639	192.293	-0.700	0.485
I(temp^2)	1.104	5.710	0.193	0.847
log(nfl)	197.641	20.943	9.437	0.000
ffd:temp	0.676	1.101	0.614	0.541
ffd:I(temp^2)	-0.005	0.033	-0.146	0.884

Standard errors: OLS

Quadratic terms of ffd not significant. Refit models withouth quadratic terms of ffd.

```
selectionabs_2017_2<-lm(nseed~ffd*temp+log(nfl),subset(mydata,year==2017))
selectionabs_2018_2<-lm(nseed~ffd*temp+log(nfl),subset(mydata,year==2018))
summ(selectionabs_2017_2,scale=F)
```

Observations	245
Dependent variable	nseed
Type	OLS linear regression

F(4,240)	51.549
R^2	0.462
Adj. R^2	0.453

	Est.	S.E.	t val.	p
(Intercept)	-4647.341	2606.895	-1.783	0.076
ffd	23.284	14.531	1.602	0.110
temp	88.601	124.771	0.710	0.478
log(nfl)	619.124	45.314	13.663	0.000
ffd:temp	-0.601	0.709	-0.848	0.397

Standard errors: OLS

```
summ(selectionabs_2018_2,scale=F)
```

Observations	104
Dependent variable	nseed
Type	OLS linear regression

F(4,99)	34.660
R^2	0.583
Adj. R^2	0.567

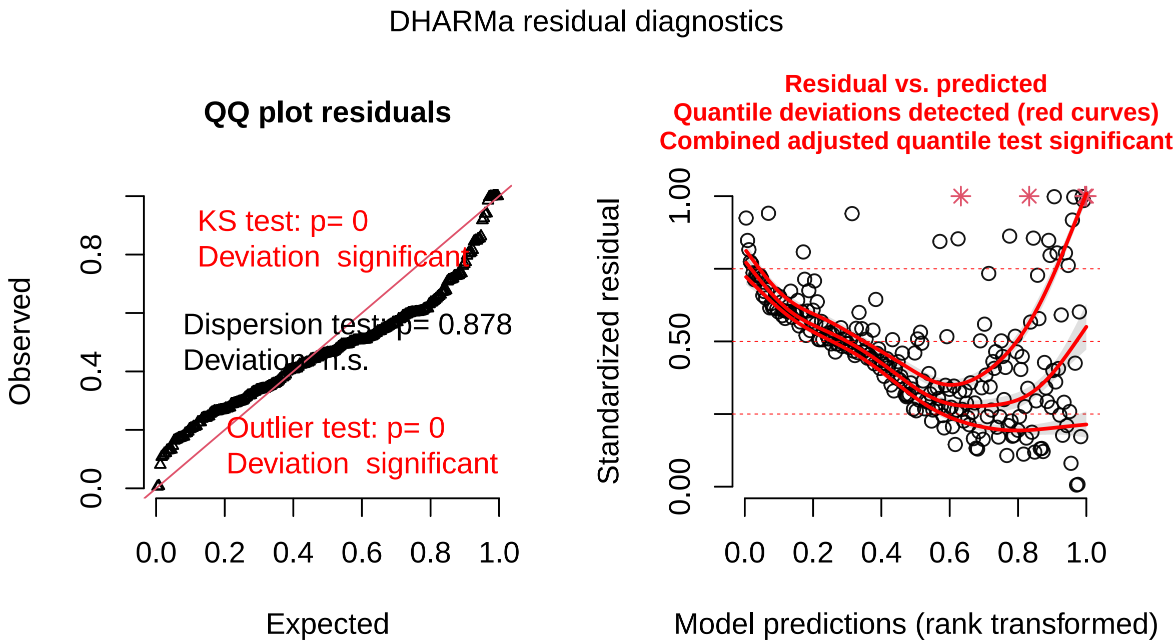
	Est.	S.E.	t val.	p
(Intercept)	755.873	607.739	1.244	0.217
ffd	-4.561	3.188	-1.431	0.156
temp	-81.835	33.624	-2.434	0.017
log(nfl)	198.339	20.492	9.679	0.000
ffd:temp	0.425	0.190	2.241	0.027

Standard errors: OLS

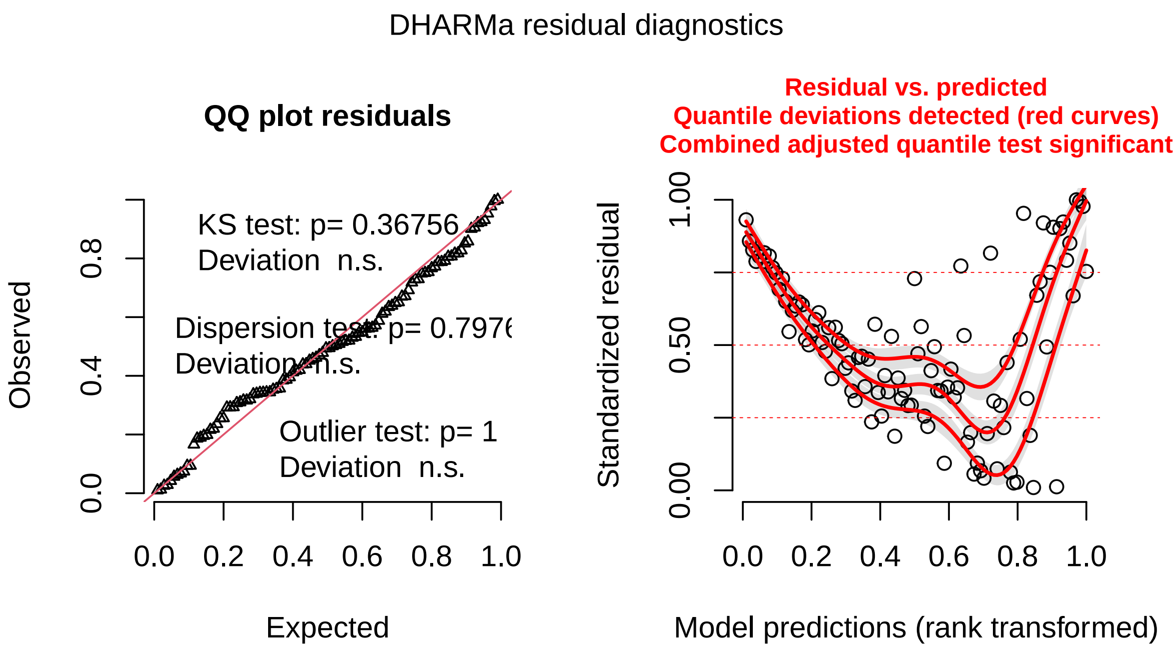
Model diagnostics

qq-plot and plot of residuals vs. predicted:

2017:



2018:



Quite bad looking! If we want to keep the linear model with normal distribution (i.e. a "classic" selection model), we can assess significances using BCa intervals.

BCa intervals

2017

```
##                lower       upper
## ffd         1.003472  55.8864223
## temp      -78.573251 302.5052709
## nfl       464.314453 862.8055575
## ffd:temp   -1.809086   0.3783896
```

FFD significant according to BCa intervals.

2018

```
##                   lower      upper
## ffd        -11.50971090   3.372549
## temp      -150.49193405 -12.073003
## nfl        148.84572035 256.836465
## ffd:temp     0.05646157   0.817838
```

The significances according to the BCa intervals are similar to the ones given in the model summary.