Maladaptive plastic responses of flowering time to geothermal heating

Code for analyses in the paper (revised)

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Contents

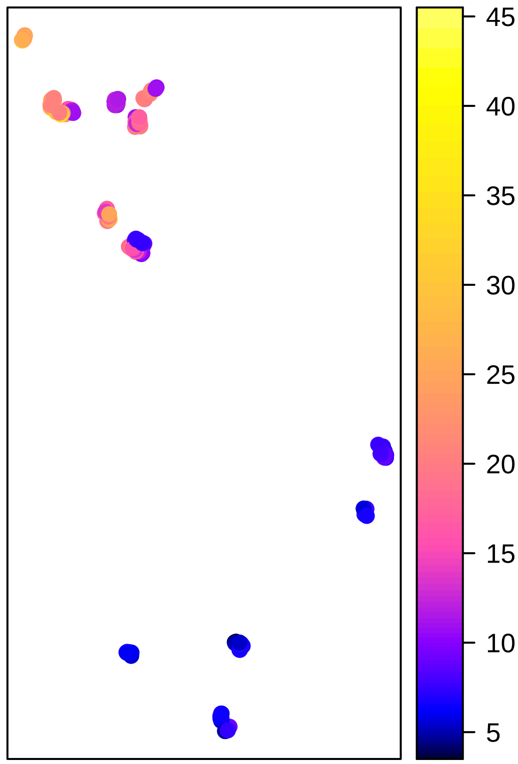
```
load(file="output/BCIs_selection_1.RData")
load(file="output/BCIs_selectionabs_1.RData")
```

Read data

The location of these files would need to be changed.

```
data_plants<-read_csv("data/clean/data_plants.csv")
coords_pls_2017<-read.dbf("gis/coords_pls_2017.dbf")
coords_pls_2018<-read.dbf("gis/coords_pls_2018.dbf")
coords_pls_2017$year<-2017
coords_pls_2018$year<-2018
coords_pls_2017$id_original<-coords_pls_2017$pl_id
coords_pls_2017$pl_id<-NULL
coords_pls_2018$id_original<-coords_pls_2018$pl_id
coords_pls_2018$pl_id<-NULL
coords_pls_2017$Id<-NULL
coords_pls_2018$Id<-NULL
data_plants<-data_plants%>%left_join(rbind(coords_pls_2017,coords_pls_2018))
logger_data<-read_csv("data/clean/logger_data.csv")
logger_data_pairs<-read_csv("data/clean/logger_data_pairs.csv")
```

```r
#Defining coordinates and coordinate system####
coordinates(data_plants) <- c("x", "y")
project1<-"+proj=utm +zone=27 +ellps=WGS84 +datum=WGS84 +units=m +no_defs"
proj4string(data_plants) = CRS(project1) #assign CRS with projected coordinates

#Some plots
spplot(data_plants, "temp", do.log=T, colorkey = TRUE)
```




```r
euclidDist <- sp::spDists(data_plants[c(1:4),],longlat = FALSE)
```

Correlation between instant measures of soil temperature and mean soil temperature during the period April 1st – June 5th recorded by loggers

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):

```r
with(logger_data%>%
       mutate(month = month(datetime)) %>%
       filter(month==4|month==5|month==6)%>%
       filter(above_below=="B")%>%
       mutate(date=date(datetime))%>%
```

```
      filter(!is.na(date))%>% # remove records with no info on date
      filter(datetime<"2018-06-06")%>% # keep only data until June 5
      group_by(logger_nr) %>%
      summarize(mean_logger=mean(temp),temp_term=mean(temp_term)),
    cor.test(mean_logger,temp_term))
```

```
##
##  Pearson's product-moment correlation
##
## data:  mean_logger and temp_term
## t = 21.901, df = 139, p-value < 2.2e-16
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  0.8370572 0.9129479
## sample estimates:
##       cor
## 0.8805259
```

Is soil temperature more weakly correlated with air temperature in warmer soils?

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 May or April-May-June. Finally, regress these correlation coefficients on mean soil temperature (from the belowground logger) for the same period (April-May-June).

May

```
data_corr<-(logger_data_pairs%>%
     mutate(month = month(datetime),date=date(datetime))%>%
              # new variables "month" and "date"
     filter(month==5)%>% # keep data from may
     group_by(date,pair,above_below)%>%
     summarise(mean=mean(temp,na.rm=T),max=max(temp),min=min(temp))%>%
   #calculate mean, max and min of air and soil temperature
     pivot_wider(names_from="above_below",values_from=c("mean","max","min"))%>%
     group_by(pair)%>%
     summarise(corr_airsoil_mean=cor(mean_A,mean_B,use="pairwise.complete.obs"),
               corr_airsoil_max=cor(max_A,max_B,use="pairwise.complete.obs"),
               corr_airsoil_min=cor(min_A,min_B,use="pairwise.complete.obs"))%>%
   # Calculate correlations air-soil temperatures
     pivot_longer(cols=corr_airsoil_mean:corr_airsoil_min,
                  names_to="measure",values_to="corr")%>%
  left_join(logger_data_pairs%>%
                 mutate(month = month(datetime))%>%
                 filter(month==5)%>%
                 filter(above_below=="B")%>%
                 group_by(pair)%>%
```

```
              summarise(meansoiltemp=mean(temp))))
  # calculate mean soil temperature for may
```

```
model_mean<-lm(corr~meansoiltemp,
               data = subset(data_corr,measure=="corr_airsoil_mean"))
model_max<-lm(corr~meansoiltemp,
               data = subset(data_corr,measure=="corr_airsoil_max"))
model_min<-lm(corr~meansoiltemp,
               data = subset(data_corr,measure=="corr_airsoil_min"))
```

Predictions of correlations for minimum and maximum temperatures:

```
ggpredict(model_mean,terms="meansoiltemp[minmax]")
```

```
## # Predicted values of corr
##
## meansoiltemp | Predicted |       95% CI
## ---------------------------------------
##         6.14 |      0.83 | [0.80, 0.86]
##        30.55 |      0.61 | [0.55, 0.68]
```

```
ggpredict(model_max,terms="meansoiltemp[minmax]")
```

```
## # Predicted values of corr
##
## meansoiltemp | Predicted |       95% CI
## ---------------------------------------
##         6.14 |      0.74 | [0.69, 0.79]
##        30.55 |      0.37 | [0.26, 0.48]
```

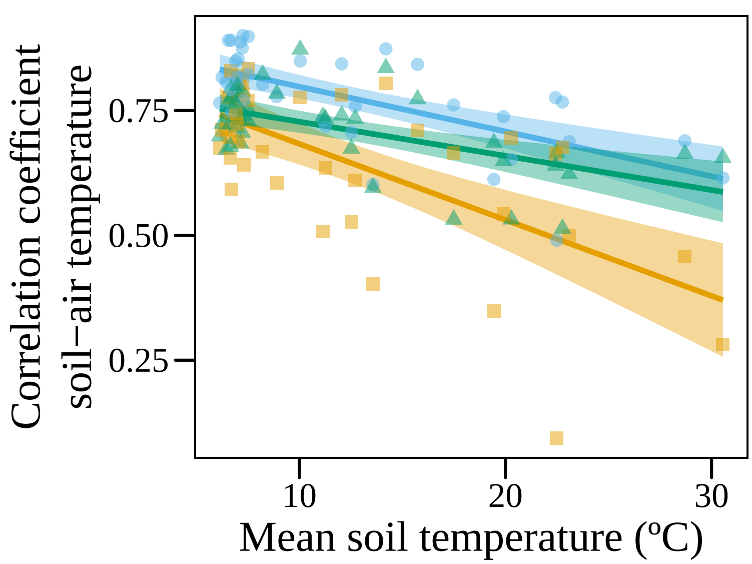
```
ggpredict(model_min,terms="meansoiltemp[minmax]")
```

```
## # Predicted values of corr
##
## meansoiltemp | Predicted |       95% CI
## ---------------------------------------
##         6.14 |      0.75 | [0.73, 0.78]
##        30.55 |      0.59 | [0.53, 0.65]
```

Figure 2: Correlations soil-air temperature vs soil temperature

```
cbPalette <- c("#E69F00", "#56B4E9", "#009E73", "#F0E442", "#0072B2",
               "#D55E00", "#CC79A7")
fig2<-(logger_data_pairs%>%
          mutate(month = month(datetime),date=date(datetime))%>%
         # new variables "month" and "date"
          filter(month==5)%>% # keep data from may
          group_by(date,pair,above_below)%>%
          summarise(mean=mean(temp,na.rm=T),max=max(temp),min=min(temp))%>%
```

```
          #calculate mean, max and min of air and soil temperature
          pivot_wider(names_from="above_below",
                      values_from=c("mean","max","min"))%>%
          group_by(pair)%>%
          summarise(corr_airsoil_mean=cor(mean_A,mean_B,
                                          use="pairwise.complete.obs"),
                    corr_airsoil_max=cor(max_A,max_B,
                                         use="pairwise.complete.obs"),
                    corr_airsoil_min=cor(min_A,min_B,
                                         use="pairwise.complete.obs"))%>%
          # Calculate correlations air-soil temperatures
          pivot_longer(cols=corr_airsoil_mean:corr_airsoil_min,
                       names_to="measure",values_to="corr")%>%
          left_join(logger_data_pairs%>%
                      mutate(month = month(datetime))%>%
                      filter(month==5)%>%
                      filter(above_below=="B")%>%
                      group_by(pair)%>%
                      summarise(meansoiltemp=mean(temp))))%>%
  # calculate mean soil temperature for may
  ggplot(.,aes(x=meansoiltemp,y=corr,color=measure,fill=measure,shape=measure))+
  geom_smooth(method="lm",size=1)+geom_point(size=2,alpha=0.5)+
  xlab("Mean soil temperature (ºC)")+
  ylab("Correlation coefficient\nsoil-air temperature")+
  my_theme()+scale_fill_manual(values=cbPalette)+
  scale_colour_manual(values=cbPalette)+
  scale_shape_manual(values=c(15,16,17)) +
  geom_text_repel(data=. %>% filter(corr<0),aes(label=pair))
fig2
```




```
ggsave(filename="output/figures/fig2.tiff",plot=fig2,
       width=12,height=10,units="cm",dpi=300)
```

Appendix S3 (part 1)

Linear models testing the effect of soil temperature on correlations between soil and air temperature (part of table in Appendix S3):

```
(logger_data_pairs%>%
     mutate(month = month(datetime),date=date(datetime))%>%
         # new variables "month" and "date"
     filter(month==5)%>% # keep data from may
     group_by(date,pair,above_below)%>%
     summarise(mean=mean(temp,na.rm=T),max=max(temp),min=min(temp))%>%
   #calculate mean, max and min of air and soil temperature
     pivot_wider(names_from="above_below",values_from=c("mean","max","min"))%>%
     group_by(pair)%>%
     summarise(corr_airsoil_mean=cor(mean_A,mean_B,use="pairwise.complete.obs"),
               corr_airsoil_max=cor(max_A,max_B,use="pairwise.complete.obs"),
               corr_airsoil_min=cor(min_A,min_B,use="pairwise.complete.obs"))%>%
   # Calculate correlations air-soil temperatures
     pivot_longer(cols=corr_airsoil_mean:corr_airsoil_min,
                  names_to="measure",values_to="corr")%>%
  left_join(logger_data_pairs%>%
                 mutate(month = month(datetime))%>%
                 filter(month==5)%>%
                 filter(above_below=="B")%>%
                 group_by(pair)%>%
              summarise(meansoiltemp=mean(temp))))%>%
  # calculate mean soil temperature for may
  group_by(measure)%>%
  do(fitcorr = tidy(lm(corr~meansoiltemp, data = .))) %>%
  unnest(fitcorr)%>%
  kable(digits=5)
```

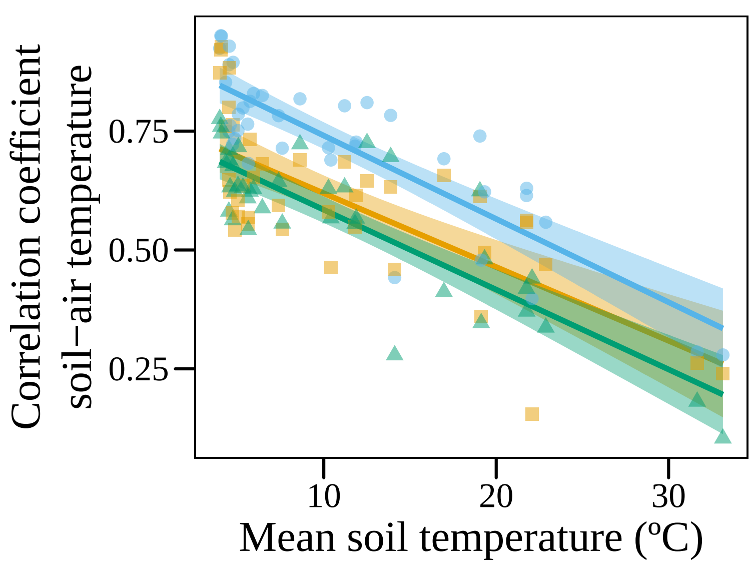
measure	term	estimate	std.error	statistic	p.value
corr_airsoil_max	(Intercept)	0.83528	0.04012	20.81870	0e+00
corr_airsoil_max	meansoiltemp	-0.01521	0.00287	-5.29894	1e-05
corr_airsoil_mean	(Intercept)	0.88734	0.02275	39.00495	0e+00
corr_airsoil_mean	meansoiltemp	-0.00897	0.00163	-5.50910	0e+00
corr_airsoil_min	(Intercept)	0.79583	0.02147	37.06454	0e+00
corr_airsoil_min	meansoiltemp	-0.00684	0.00154	-4.44851	7e-05

April-May_june

Appendix S1: Correlations soil-air temperature vs soil temperature (April-June)

```
AppS1<-(logger_data_pairs%>%
          mutate(month = month(datetime),date=date(datetime))%>%
          # new variables "month" and "date"
          filter(month==4|month==5|month==6)%>% # keep data from april-june
          group_by(date,pair,above_below)%>%
          summarise(mean=mean(temp,na.rm=T),max=max(temp),min=min(temp))%>%
          #calculate mean, max and min of air and soil temperature
          pivot_wider(names_from="above_below",
```

```
                 values_from=c("mean","max","min"))%>%
        group_by(pair)%>%
        summarise(corr_airsoil_mean=cor(mean_A,mean_B,
                                        use="pairwise.complete.obs"),
                  corr_airsoil_max=cor(max_A,max_B,
                                       use="pairwise.complete.obs"),
                  corr_airsoil_min=cor(min_A,min_B,
                                       use="pairwise.complete.obs"))%>%
        # Calculate correlations air-soil temperatures
        pivot_longer(cols=corr_airsoil_mean:corr_airsoil_min,
                     names_to="measure",values_to="corr")%>%
        left_join(logger_data_pairs%>%
                    mutate(month = month(datetime))%>%
                    filter(month==4|month==5|month==6)%>%
                    filter(above_below=="B")%>%
                    group_by(pair)%>%
                    summarise(meansoiltemp=mean(temp))))%>%
  # calculate mean soil temperature for april-june
  ggplot(.,aes(x=meansoiltemp,y=corr,color=measure,fill=measure,shape=measure))+
  geom_smooth(method="lm",size=1)+geom_point(size=2,alpha=0.5)+
  xlab("Mean soil temperature (ºC)")+
  ylab("Correlation coefficient\nsoil-air temperature")+
  my_theme()+scale_fill_manual(values=cbPalette)+
  scale_colour_manual(values=cbPalette)+
  scale_shape_manual(values=c(15,16,17)) +
  geom_text_repel(data=. %>% filter(corr<0),aes(label=pair))
AppS1
```




```
ggsave(filename="output/figures/AppS1.tiff",plot=AppS1,
       width=12,height=10,units="cm",dpi=300)
```

Appendix S2 (part 2)

Linear models testing the effect of soil temperature on correlations between soil and air temperature (part of table in Appendix S3):

```
(logger_data_pairs%>%
     mutate(month = month(datetime),date=date(datetime))%>%
          # new variables "month" and "date"
     filter(month==4|month==5|month==6)%>% # keep data from april-june
     group_by(date,pair,above_below)%>%
     summarise(mean=mean(temp,na.rm=T),max=max(temp),min=min(temp))%>%
   #calculate mean, max and min of air and soil temperature
     pivot_wider(names_from="above_below",values_from=c("mean","max","min"))%>%
     group_by(pair)%>%
     summarise(corr_airsoil_mean=cor(mean_A,mean_B,use="pairwise.complete.obs"),
               corr_airsoil_max=cor(max_A,max_B,use="pairwise.complete.obs"),
               corr_airsoil_min=cor(min_A,min_B,use="pairwise.complete.obs"))%>%
   # Calculate correlations air-soil temperatures
     pivot_longer(cols=corr_airsoil_mean:corr_airsoil_min,
                  names_to="measure",values_to="corr")%>%
  left_join(logger_data_pairs%>%
                 mutate(month = month(datetime))%>%
                 filter(month==4|month==5|month==6)%>%
                 filter(above_below=="B")%>%
                 group_by(pair)%>%
              summarise(meansoiltemp=mean(temp))))%>%
  # calculate mean soil temperature for april-june
  group_by(measure)%>%
  do(fitcorr = tidy(lm(corr~meansoiltemp, data = .))) %>%
  unnest(fitcorr)%>%
  kable(digits=5)
```

measure	term	estimate	std.error	statistic	p.value
corr_airsoil_max	(Intercept)	0.77449	0.03184	24.32387	0
corr_airsoil_max	meansoiltemp	-0.01552	0.00236	-6.57111	0
corr_airsoil_mean	(Intercept)	0.91574	0.02391	38.29900	0
corr_airsoil_mean	meansoiltemp	-0.01752	0.00177	-9.88060	0
corr_airsoil_min	(Intercept)	0.75246	0.02361	31.87482	0
corr_airsoil_min	meansoiltemp	-0.01679	0.00175	-9.59056	0

Hypothesis 1: Effect of temperature on FFD

Models including quadratic effects of ffd.

```
data_plants$year_fct<-as.factor(data_plants$year)
FFD_1<-lm(ffd~(temp+I(temp^2))*year_fct,data_plants)
summ(FFD_1,vif=T)
```

Quadratic terms of ffd not significant. Refit models without quadratic terms of ffd.

Observations	349
Dependent variable	ffd
Type	OLS linear regression

F(5,343)	28.500
R^2	0.294
Adj. R^2	0.283

	Est.	S.E.	t val.	p	VIF
(Intercept)	183.736	2.052	89.536	0.000	NA
temp	-0.779	0.254	-3.065	0.002	17.405
I(temp^2)	0.012	0.007	1.832	0.068	16.329
year_fct2018	18.016	4.167	4.323	0.000	16.426
temp:year_fct2018	-1.383	0.595	-2.322	0.021	76.002
I(temp^2):year_fct2018	0.021	0.017	1.219	0.224	35.733

Standard errors: OLS

```
FFD_1<-lm(ffd~temp*year_fct,data_plants)
summ(FFD_1,vif=T)
```

Observations	349
Dependent variable	ffd
Type	OLS linear regression

F(3,345)	44.212
R^2	0.278
Adj. R^2	0.271

	Est.	S.E.	t val.	p	VIF
(Intercept)	180.626	1.162	155.505	0.000	NA
temp	-0.332	0.072	-4.620	0.000	1.369
year_fct2018	14.478	2.082	6.955	0.000	4.033
temp:year_fct2018	-0.738	0.140	-5.250	0.000	4.164

Standard errors: OLS

Predictions of ffd for minimum and maximum temperatures:

```
range(subset(data_plants,year==2017)$temp)
```

```
## [1]  4.1 45.5
```

```
range(subset(data_plants,year==2018)$temp)
```

```
## [1]  3.5 34.0
```

```r
ggpredict(FFD_1,terms=c("temp[4.1,45.5]","year_fct[2017]"))
```

```
## # Predicted values of ffd
##
##  temp | Predicted |           95% CI
## ------------------------------------
##  4.10 |    179.26 | [177.47, 181.06]
## 45.50 |    165.52 | [160.97, 170.08]
```

```r
# 179.26-165.52=14 days earlier on warmer soils
ggpredict(FFD_1,terms=c("temp[3.5,34.0]","year_fct[2018]"))
```

```
## # Predicted values of ffd
##
##  temp | Predicted |           95% CI
## ------------------------------------
##  3.50 |    191.36 | [188.66, 194.06]
## 34.00 |    158.74 | [153.35, 164.13]
```

```r
# 191.36-158.74=45 days earlier on warmer soils
```

Hypothesis 2: Effect of temperature on fitness

```r
fitness_1<-glm.nb(n_seed_round~(temp+I(temp^2))*year_fct+log(nfl),
                      data_plants) # Quadratic term significant, keep
summ(fitness_1,vif=T)
```

Observations	349
Dependent variable	n_seed_round
Type	Generalized linear model
Family	Negative Binomial(2.0752)
Link	log

$\chi^2()$	0.747	0.097	4472.025	4502.865
Pseudo-R^2 (Cragg-Uhler)	0.747	0.097	4472.025	4502.865
Pseudo-R^2 (McFadden)	0.747	0.097	4472.025	4502.865
AIC	0.747	0.097	4472.025	4502.865
BIC	0.747	0.097	4472.025	4502.865

Predictions of fitness for minimum and maximum temperatures:

```r
range(subset(data_plants,year==2017)$temp)
```

```
## [1]  4.1 45.5
```

	Est.	S.E.	z val.	p	VIF
(Intercept)	4.227	0.168	25.104	0.000	NA
temp	-0.051	0.021	-2.498	0.012	17.929
I(temp^2)	0.001	0.001	1.064	0.287	16.480
year_fct2018	-1.158	0.334	-3.464	0.001	16.560
log(nfl)	0.983	0.036	27.345	0.000	1.102
temp:year_fct2018	0.088	0.048	1.829	0.067	76.148
I(temp^2):year_fct2018	-0.003	0.001	-2.142	0.032	35.522

Standard errors: MLE

```
range(subset(data_plants,year==2018)$temp)
```

```
## [1]  3.5 34.0
```

```
ggpredict(fitness_1,terms=c("temp[4.1,45.5]","year_fct[2017]"))
```

```
## # Predicted counts of n_seed_round
##
##  temp | Predicted |           95% CI
## ------------------------------------
##  4.10 |    810.91 | [659.59, 996.93]
## 45.50 |    311.40 | [142.72, 679.46]
##
## Adjusted for:
## * nfl = 15.17
```

```
ggpredict(fitness_1,terms=c("temp[3.5,34.0]","year_fct[2018]"))
```

```
## # Predicted counts of n_seed_round
##
##  temp | Predicted |           95% CI
## ------------------------------------
##  3.50 |    343.18 | [246.14, 478.48]
## 34.00 |     63.33 | [ 29.27, 137.00]
##
## Adjusted for:
## * nfl = 15.17
```

Figure 3: Effects of temperature on ffd and fitness

Model prediction ffd : based on model FFD_1 (without quadratic term of ffd)

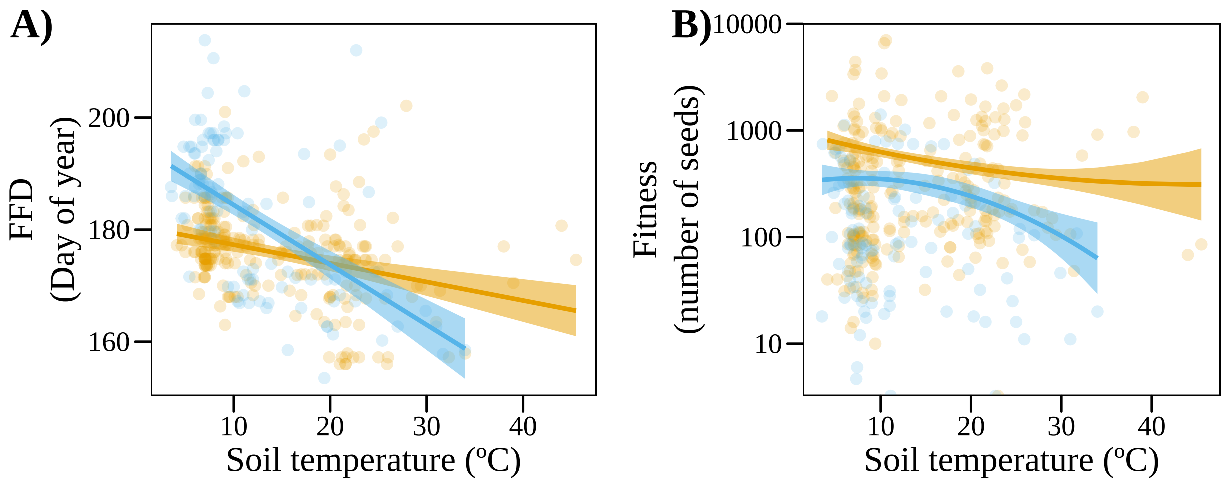
```
predict_FFD<-ggpredict(FFD_1,terms=c("temp [all]","year_fct"))
```

Model prediction fitness : based on model fitness_1

```r
predict_fitness<-ggpredict(fitness_1,terms=c("temp [all]","year_fct"))
```

```r
fig3<-
  grid.arrange(
    # ffd
    ggplot(data.frame(data_plants),aes(x=temp,y=ffd))+
  xlab("Soil temperature (ºC)")+ylab("FFD\n(Day of year)")+my_theme()+
  geom_point(aes(color=year_fct),size=2,alpha=0.2)+
  geom_ribbon(data=subset(predict_FFD,group==2017&
                            x>=min(subset(data_plants,year==2017)$temp)&
                            x<=max(subset(data_plants,year==2017)$temp)),
              aes(x=x,y=predicted,ymin=conf.low,ymax=conf.high,fill=group),
              alpha=0.5)+
  geom_line(data=subset(predict_FFD,group==2017&
                            x>=min(subset(data_plants,year==2017)$temp)&
                            x<=max(subset(data_plants,year==2017)$temp)),
            aes(x=x,y=predicted,color=group),size=1)+
  geom_ribbon(data=subset(predict_FFD,group==2018&
                             x>=min(subset(data_plants,year==2018)$temp)&
                             x<=max(subset(data_plants,year==2018)$temp)),
              aes(x=x,y=predicted,ymin=conf.low,ymax=conf.high,fill=group),
              alpha=0.5)+
  geom_line(data=subset(predict_FFD,group==2018&
                            x>=min(subset(data_plants,year==2018)$temp)&
                            x<=max(subset(data_plants,year==2018)$temp)),
            aes(x=x,y=predicted,color=group),size=1)+
  ggtitle("A)")+theme(plot.title=element_text(hjust=-0.35,vjust=-3))+
  theme(plot.margin = unit(c(-0.6,0.3,0,0.3), "cm"))+
  scale_fill_manual(values=cbPalette)+scale_color_manual(values=cbPalette),
    # fitness
    ggplot(data.frame(data_plants),aes(x=temp,y=nseed))+
      xlab("Soil temperature (ºC)")+ylab("Fitness\n(number of seeds)")+
      my_theme()+
      geom_point(aes(color=year_fct),size=2,alpha=0.2)+
      geom_ribbon(data=subset(predict_fitness,group==2017&
                            x>=min(subset(data_plants,year==2017)$temp)&
                            x<=max(subset(data_plants,year==2017)$temp)),
                aes(x=x,y=predicted,ymin=conf.low,ymax=conf.high,fill=group),
                alpha=0.5)+
      geom_line(data=subset(predict_fitness,group==2017&
                            x>=min(subset(data_plants,year==2017)$temp)&
                            x<=max(subset(data_plants,year==2017)$temp)),
              aes(x=x,y=predicted,color=group),size=1)+
    geom_ribbon(data=subset(predict_fitness,group==2018&
                            x>=min(subset(data_plants,year==2018)$temp)&
                            x<=max(subset(data_plants,year==2018)$temp)),
                aes(x=x,y=predicted,ymin=conf.low,ymax=conf.high,fill=group),
                alpha=0.5)+
      geom_line(data=subset(predict_fitness,group==2018&
                            x>=min(subset(data_plants,year==2018)$temp)&
                            x<=max(subset(data_plants,year==2018)$temp)),
              aes(x=x,y=predicted,color=group),size=1)+
      ggtitle("B)")+theme(plot.title=element_text(hjust=-0.35,vjust=-3))+
```

```
    theme(plot.margin = unit(c(-0.6,0.3,0,0.3), "cm"))+
    scale_fill_manual(values=cbPalette)+scale_color_manual(values=cbPalette)+
    scale_y_continuous(trans='log10'),
  ncol=2)
```




```
ggsave(filename="output/figures/fig3.tiff",plot=fig3,
       width=22,height=8,units="cm",dpi=300)
```

Hypothesis 3: Effect of temperature on selection on FFD

Models including quadratic effects of temp.

```
selection_1<-lm(nseed_rel~ffd_std*(temp+I(temp^2))*year_fct+nfl_std,
                    data_plants)
summ(selection_1,vif=T)
```

Observations	349
Dependent variable	nseed_rel
Type	OLS linear regression

F(12,336)	26.559
R^2	0.487
Adj. R^2	0.468

Quadratic terms of temp not significant. Refit models without quadratic terms of temp

```
selection_1<-lm(nseed_rel~ffd_std*temp*year_fct+nfl_std,
                    data_plants)
summ(selection_1,vif=T)
```

	Est.	S.E.	t val.	p	VIF
(Intercept)	1.612	0.277	5.812	0.000	NA
ffd_std	0.430	0.359	1.200	0.231	36.292
temp	-0.062	0.033	-1.845	0.066	18.854
I(temp^2)	0.001	0.001	1.040	0.299	17.109
year_fct2018	-0.227	0.716	-0.317	0.751	30.420
nfl_std	1.155	0.071	16.333	0.000	1.411
ffd_std:temp	-0.030	0.042	-0.718	0.473	174.924
ffd_std:I(temp^2)	0.001	0.001	0.581	0.562	76.286
ffd_std:year_fct2018	-0.851	0.738	-1.153	0.250	45.614
temp:year_fct2018	0.037	0.111	0.336	0.737	165.435
I(temp^2):year_fct2018	-0.001	0.004	-0.180	0.857	96.685
ffd_std:temp:year_fct2018	0.090	0.101	0.890	0.374	248.539
ffd_std:I(temp^2):year_fct2018	-0.002	0.003	-0.503	0.615	132.433

Standard errors: OLS

Observations	349
Dependent variable	nseed_rel
Type	OLS linear regression

F(8,340)	39.925
R^2	0.484
Adj. R^2	0.472

	Est.	S.E.	t val.	p	VIF
(Intercept)	1.392	0.154	9.043	0.000	NA
ffd_std	0.285	0.189	1.510	0.132	10.148
temp	-0.029	0.010	-3.045	0.003	1.563
year_fct2018	-0.116	0.299	-0.388	0.699	5.357
nfl_std	1.146	0.070	16.436	0.000	1.382
ffd_std:temp	-0.008	0.009	-0.819	0.414	8.727
ffd_std:year_fct2018	-0.466	0.312	-1.496	0.136	8.189
temp:year_fct2018	0.016	0.022	0.721	0.472	6.547
ffd_std:temp:year_fct2018	0.035	0.018	1.909	0.057	8.373

Standard errors: OLS

BCa intervals

Used for assessing significance.

```
BCIs_selection_1
```

```
##                    lower        upper
## ffd          -0.008584666  0.684259512
## temp         -0.052020609 -0.012808410
## year         -0.797945338  0.438874288
## nfl           0.910796373  1.512663133
## ffd:temp     -0.023623329  0.006147101
## ffd:year     -1.046057968  0.086767603
```

```
## temp:year     -0.016084941  0.058141968
## ffd:temp:year  0.005119411  0.064779651
```

Figure 4: Effects of temperature on selection

```
quantile(subset(data_plants,year==2017)$temp,probs=c(0.05,0.95))
```

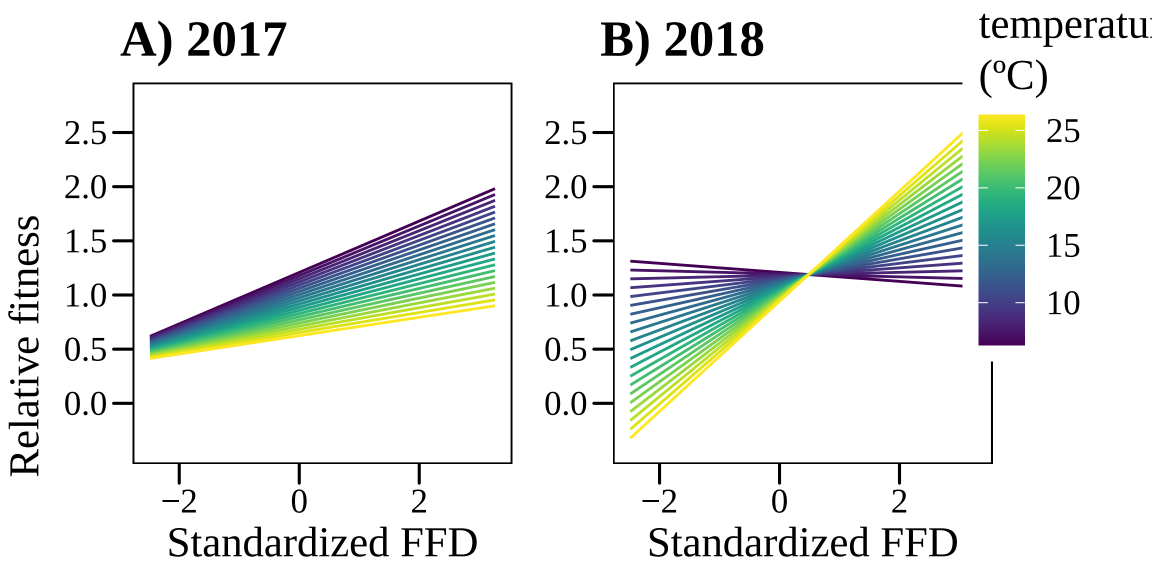
```
##    5%   95%
##  6.32 26.90
```

```
quantile(subset(data_plants,year==2018)$temp,probs=c(0.05,0.95))
```

```
##     5%    95%
##  5.060 25.825
```

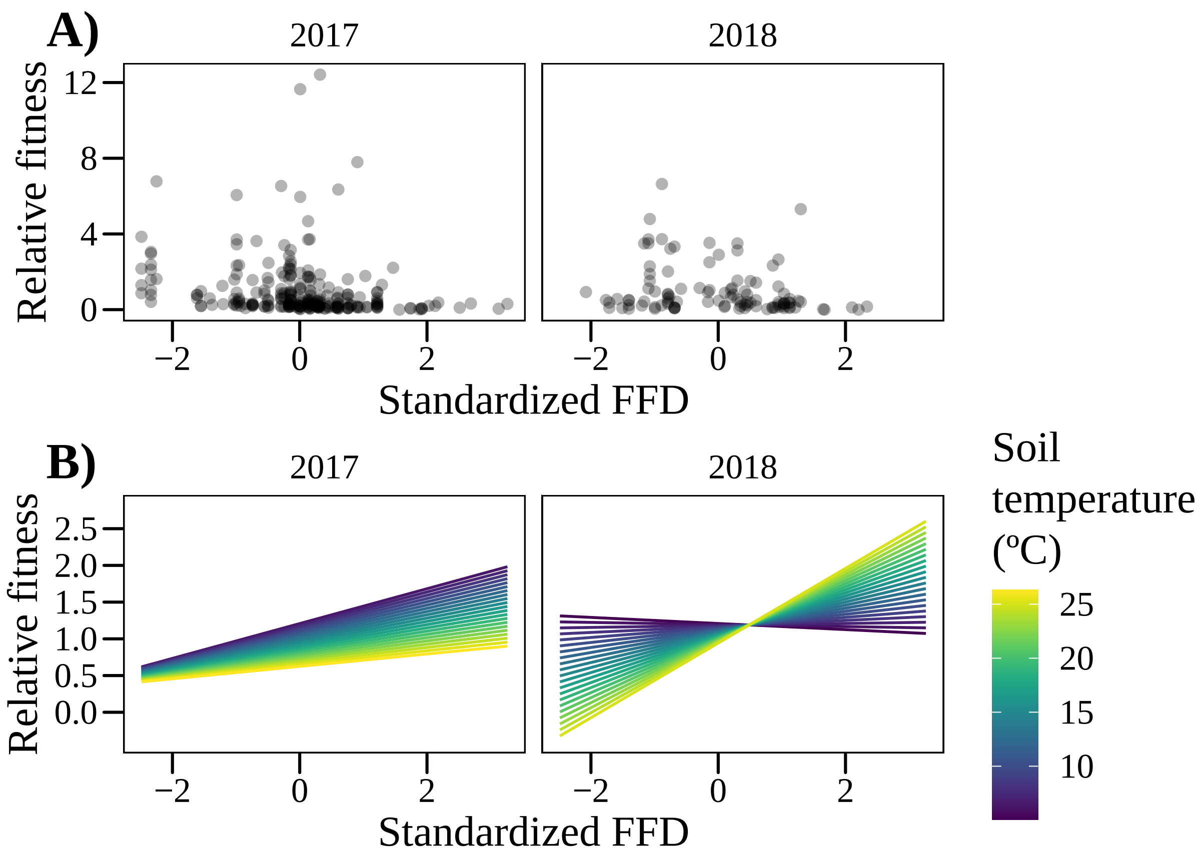
```
pred_fitness_17<-ggpredict(selection_1,
                           terms = c("ffd_std[all]","temp[6.32:26.90]",
                                     "year_fct[2017]"))
pred_fitness_18<-ggpredict(selection_1,
                           terms = c("ffd_std[all]","temp[5.060:25.825]",
                                     "year_fct[2018]"))
```

```
legend <- as_ggplot(get_legend(ggplot(pred_fitness_17,
                          aes(x,predicted,colour=group,fill=group))+
  geom_line(aes(color=as.numeric(as.character(group))),size=0.5)+my_theme()+
  scale_color_viridis()+
  theme(legend.position=c(0.5,0.75))+labs(colour="Soil\ntemperature\n(ºC)")+
  xlab("Standardized FFD")+ylab(NULL)+ggtitle("A) 2017")))
fig4old<-grid.arrange(
  ggplot(pred_fitness_17,aes(x,predicted,colour=group,fill=group))+
    geom_line(aes(color=as.numeric(as.character(group))),size=0.5)+my_theme()+
    scale_color_viridis()+labs(colour="Soil temperature (ºC)")+
    xlab("Standardized FFD")+ylab(NULL)+ggtitle("A) 2017")+
    scale_y_continuous(limits=c(-0.4,2.8),breaks=c(0,0.5,1,1.5,2,2.5)),
  ggplot(pred_fitness_18,aes(x,predicted,colour=group,fill=group))+
    geom_line(aes(color=as.numeric(as.character(group))),size=0.5)+my_theme()+
    scale_color_viridis()+labs(colour="Soil temperature (ºC)")+
    xlab("Standardized FFD")+ylab(NULL)+ggtitle("B) 2018")+
    scale_y_continuous(limits=c(-0.4,2.8),breaks=c(0,0.5,1,1.5,2,2.5)),
  legend,
  ncol=3,left=textGrob("Relative fitness",rot=90,just=0.7,
                      gp=gpar(fontsize=16,fontfamily="serif")),
  widths=c(1,1,0.3))
```




```
ggsave(filename="output/figures/fig4old.tiff",plot=fig4old,
       width=25,height=12,units="cm",dpi=300)
```

```
fig4<-cowplot::plot_grid(ggplot(data.frame(data_plants),
                                aes(x=ffd_std,y=nseed_rel))+
                           facet_grid(~year,scales="fixed")+
                           geom_point(size=1.5,alpha=0.3)+
                           my_theme()+ggtitle("A)")+
                           xlab("Standardized FFD")+ylab("Relative fitness")+
                           theme(plot.title=element_text(hjust=-0.1,vjust=-5))+
                           theme(plot.margin = unit(c(-0.6,0.3,0,0.3), "cm")),
                         ggplot(rbind(data.frame(pred_fitness_17),
                                      data.frame(pred_fitness_18)),
                                aes(x,predicted,colour=group,fill=group))+
                           facet_grid(~facet,scales="free")+
                           geom_line(aes(color=as.numeric(as.character(group))),
                                     size=0.5)+
                           my_theme_legend()+
                           theme(legend.position="right")+ggtitle("B)")+
                           scale_color_viridis()+
                           labs(colour="Soil\ntemperature\n(ºC)")+
                           xlab("Standardized FFD")+ylab("Relative fitness")+
                           theme(plot.title=element_text(hjust=-0.1,vjust=-5))+
                           theme(plot.margin = unit(c(-0.6,0.3,0,0.3), "cm"))+
                           scale_y_continuous(limits=c(-0.4,2.8),
                                              breaks=c(0,0.5,1,1.5,2,2.5)),
                         ncol=1,align="v",axis="lr")
fig4
```




```
ggsave(filename="output/figures/fig4.tiff",plot=fig4,
       width=18,height=16,units="cm",dpi=300)
```

Appendix S3

```
quantile(subset(data_plants,year==2017)$temp)
```

```
##   0%  25%  50%  75% 100%
##  4.1  7.4 10.7 20.6 45.5
```

```
mean(subset(data_plants,year==2017&temp<=7.4)$temp)
```

```
## [1] 6.714286
```

```
# Mean cat 1 = 6.714286
mean(subset(data_plants,year==2017&temp>7.4&temp<=10.7)$temp)
```

```
## [1] 8.748333
```

```r
# Mean cat 2 = 8.748333
mean(subset(data_plants,year==2017&temp>10.7&temp<=20.6)$temp)
```

```
## [1] 16.2129
```

```r
# Mean cat 3 = 16.2129
mean(subset(data_plants,year==2017&temp>20.6)$temp)
```

```
## [1] 25.10667
```

```r
# Mean cat 4 = 25.10667

quantile(subset(data_plants,year==2018)$temp)
```

```
##     0%    25%    50%    75%   100%
##  3.500  6.875  9.300 17.075 34.000
```

```r
mean(subset(data_plants,year==2018&temp<=6.875)$temp)
```

```
## [1] 5.784615
```

```r
# Mean cat 1 = 5.784615
mean(subset(data_plants,year==2018&temp>6.875&temp<=9.300)$temp)
```

```
## [1] 7.95
```

```r
# Mean cat 2 = 7.95
mean(subset(data_plants,year==2018&temp>9.300&temp<=17.075)$temp)
```

```
## [1] 12.45
```

```r
# Mean cat 3 = 12.45
mean(subset(data_plants,year==2018&temp>17.075)$temp)
```

```
## [1] 23.28846
```

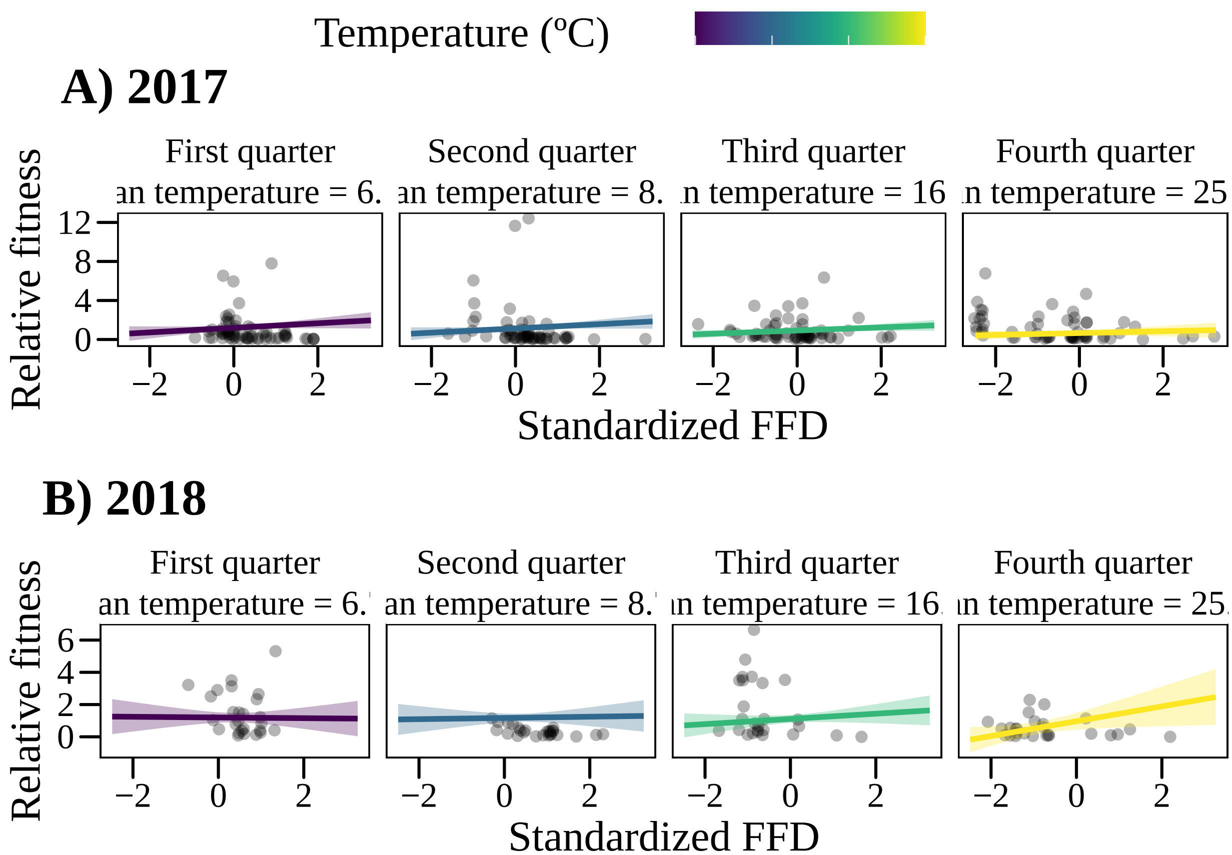
```r
# Mean cat 4 = 23.28846

pred_fitness_17_cats<-rbind(
  (data.frame(ggpredict(selection_1,
                          terms = c("ffd_std[all]","temp[6.714286]",
                                    "year_fct[2017]")))%>%
     mutate(temp_cat=1)%>%
     dplyr::rename(FFD_std=x, fitness=predicted,temp=group)),
  (data.frame(ggpredict(selection_1,
                       terms = c("ffd_std[all]","temp[8.748333]",
                                    "year_fct[2017]")))%>%
     mutate(temp_cat=2)%>%
```

```
    dplyr::rename(FFD_std=x, fitness=predicted,temp=group)),
  (data.frame(ggpredict(selection_1,
                        terms = c("ffd_std[all]","temp[16.2129]",
                                  "year_fct[2017]")))%>%
    mutate(temp_cat=3)%>%
    dplyr::rename(FFD_std=x, fitness=predicted,temp=group)),
  (data.frame(ggpredict(selection_1,
                        terms = c("ffd_std[all]","temp[25.10667]",
                                  "year_fct[2017]")))%>%
    mutate(temp_cat=4)%>%
    dplyr::rename(FFD_std=x, fitness=predicted,temp=group)))

pred_fitness_18_cats<-rbind(
  (data.frame(ggpredict(selection_1,
                          terms = c("ffd_std[all]","temp[5.784615]",
                                  "year_fct[2018]")))%>%
    mutate(temp_cat=1)%>%
    dplyr::rename(FFD_std=x, fitness=predicted,temp=group)),
  (data.frame(ggpredict(selection_1,
                        terms = c("ffd_std[all]","temp[7.95]",
                                  "year_fct[2018]")))%>%
    mutate(temp_cat=2)%>%
    dplyr::rename(FFD_std=x, fitness=predicted,temp=group)),
  (data.frame(ggpredict(selection_1,
                        terms = c("ffd_std[all]","temp[12.45]",
                                  "year_fct[2018]")))%>%
    mutate(temp_cat=3)%>%
    dplyr::rename(FFD_std=x, fitness=predicted,temp=group)),
  (data.frame(ggpredict(selection_1,
                        terms = c("ffd_std[all]","temp[23.28846]",
                                  "year_fct[2018]")))%>%
    mutate(temp_cat=4)%>%
    dplyr::rename(FFD_std=x, fitness=predicted,temp=group)))


label_names1 <- list(
  '1'="First quarter\nMean temperature = 6.7ºC",
  '2'="Second quarter\nMean temperature = 8.7ºC",
  '3'="Third quarter\nMean temperature = 16.2ºC",
  '4'="Fourth quarter\nMean temperature = 25.1ºC"
)

labeller_function1 <- function(variable,value){
  return(label_names1[value])
}
```

```
leg <- as_ggplot(get_legend(ggplot(subset(data.frame(data_plants),
                                          year==2017)%>%
         # Define 4 temp categories based on quartiles
         mutate(temp_cat=as.factor(
           ifelse(temp<=7.4,1,
                  ifelse(temp>7.4&temp<=10.7,2,
                         ifelse(temp>10.7&temp<=20.6,3,4))))),
```

```
      aes(x=ffd_std,y=nseed_rel))+
  facet_grid(~temp_cat,scales="free",
             labeller=labeller(temp_cat=labeller_function1))+
  geom_jitter(size=1.5,alpha=0.3,width=0.05)+
  geom_line(data=pred_fitness_17_cats,
            aes(x=FFD_std,y=fitness,color=temp_cat),size=1)+
  geom_ribbon(data=pred_fitness_17_cats,aes(x=FFD_std,y=fitness,
                                     ymin=conf.low,ymax=conf.high,
                                     fill=temp_cat),alpha=0.3)+
  my_theme()+scale_color_viridis(labels=NULL)+scale_fill_viridis(labels=NULL)+
  theme(legend.position="top")+labs(colour="Temperature (ºC)      ")+
  xlab("Standardized FFD")+
  ylab("Relative fitness")+
  #scale_x_continuous(breaks=c(-4,-2,0,2,4,6,8))+
  theme(strip.text.x=element_text(margin=margin(2,0,2,0)))+
  guides(fill=FALSE)+ggtitle("A) 2017")))

AppS3<-grid.arrange(leg,
             ggplot(subset(data.frame(data_plants),year==2017)%>%
         # Define 4 temp categories based on quartiles
         mutate(temp_cat=as.factor(
           ifelse(temp<=7.4,1,
                  ifelse(temp>7.4&temp<=10.7,2,
                         ifelse(temp>10.7&temp<=20.6,3,4))))),
      aes(x=ffd_std,y=nseed_rel))+
  facet_grid(~temp_cat,scales="free",
             labeller=labeller(temp_cat=labeller_function1))+
  geom_jitter(size=1.5,alpha=0.3,width=0.05)+
  geom_line(data=pred_fitness_17_cats,
            aes(x=FFD_std,y=fitness,color=temp_cat),size=1)+
  geom_ribbon(data=pred_fitness_17_cats,aes(x=FFD_std,y=fitness,
                                     ymin=conf.low,ymax=conf.high,
                                     fill=temp_cat),alpha=0.3)+
  my_theme()+scale_color_viridis(labels=NULL)+scale_fill_viridis(labels=NULL)+
  labs(colour="Temperature (ºC)      ")+
  xlab("Standardized FFD")+
  ylab("Relative fitness")+
  #scale_x_continuous(breaks=c(-4,-2,0,2,4,6,8))+
  theme(strip.text.x=element_text(margin=margin(2,0,2,0)))+
  guides(fill=FALSE)+ggtitle("A) 2017"),
  ggplot(subset(data.frame(data_plants),year==2018)%>%
         # Define 4 temp categories based on quartiles
         mutate(temp_cat=as.factor(
           ifelse(temp<=6.875,1,
                  ifelse(temp>6.875&temp<=9.300,2,
                         ifelse(temp>9.300&temp<=17.075,3,4))))),
      aes(x=ffd_std,y=nseed_rel))+
  facet_grid(~temp_cat,scales="free",
             labeller=labeller(temp_cat=labeller_function1))+
  geom_jitter(size=1.5,alpha=0.3,width=0.05)+
  geom_line(data=pred_fitness_18_cats,
            aes(x=FFD_std,y=fitness,color=temp_cat),size=1)+
  geom_ribbon(data=pred_fitness_18_cats,aes(x=FFD_std,y=fitness,
```

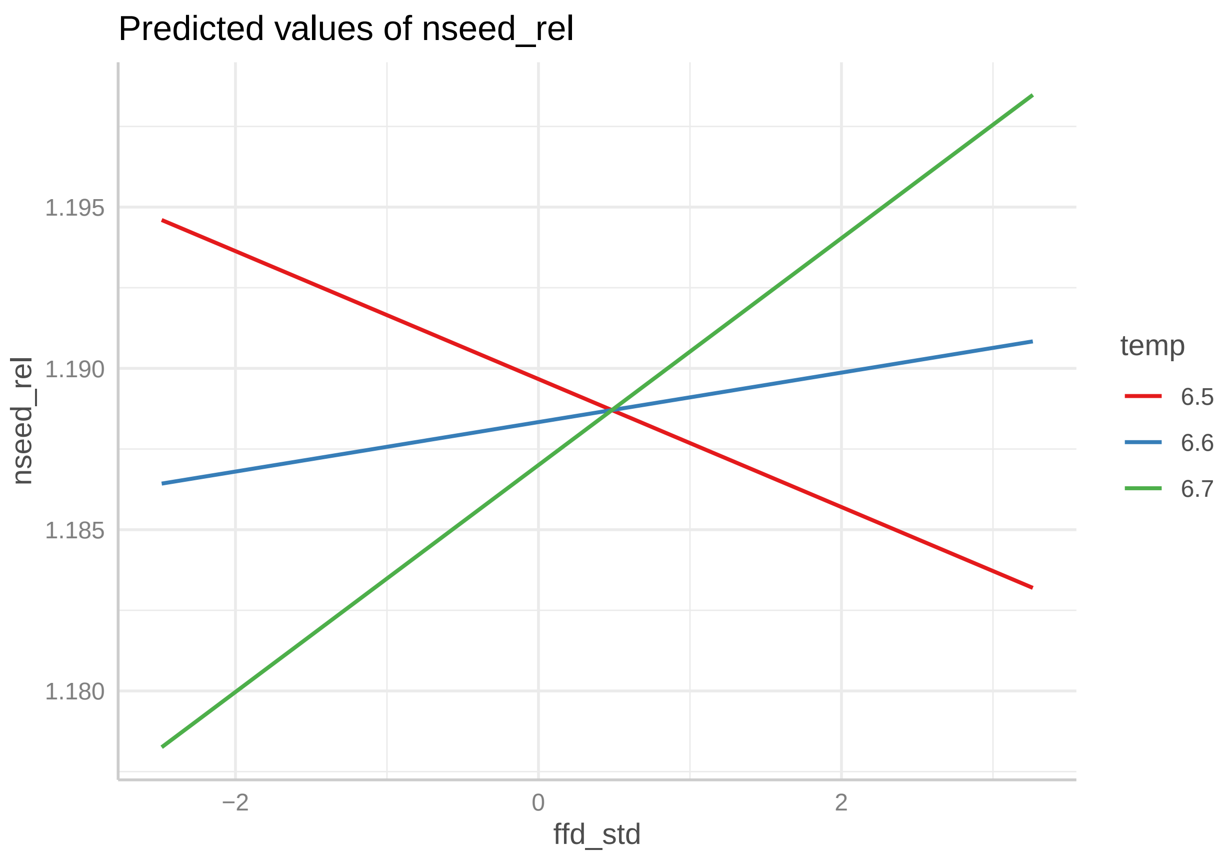
```
                                        ymin=conf.low,ymax=conf.high,
                                        fill=temp_cat),alpha=0.3)+
  my_theme()+scale_color_viridis(labels=NULL)+scale_fill_viridis(labels=NULL)+
  labs(colour="Temperature (ºC)       ")+
  xlab("Standardized FFD")+
  ylab("Relative fitness")+
  #scale_x_continuous(breaks=c(-4,-2,0,2,4,6,8))+
  theme(strip.text.x=element_text(margin=margin(2,0,2,0)))+
  guides(fill=FALSE)+ggtitle("B) 2018"),
                         ncol=1,heights=c(0.1,1,1))
```




```
ggsave(filename="output/figures/AppS3.tiff",plot=AppS3,
       width=26,height=20,units="cm",dpi=300)
```

Predictions of fitness:

```
plot(ggpredict(selection_1,
               terms=c("ffd_std[all]","temp[6.5:6.7 by=0.1]","year_fct[2018]")),
     ci=F)
```



In 2018, the model predicted that selection favoured earlier flowering at soil temperatures up to 6.5 ºC, while later flowering was favoured at higher soil temperatures.

Effect of temperature on the relationship absolute fitness-FFD

Models including quadratic effects of temp.

```
selectionabs_1<-lm(nseed~ffd*(temp+I(temp^2))*year_fct+log(nfl),
                    data_plants)
summ(selectionabs_1,vif=T)
```

Observations	349
Dependent variable	nseed
Type	OLS linear regression

F(12,336)	22.428
R^2	0.445
Adj. R^2	0.425

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

	Est.	S.E.	t val.	p	VIF
(Intercept)	-3702.327	4319.099	-0.857	0.392	NA
ffd	19.653	24.277	0.810	0.419	61.046
temp	222.177	498.972	0.445	0.656	14320.683
I(temp^2)	-4.978	13.387	-0.372	0.710	14002.892
year_fct2018	3144.184	6321.543	0.497	0.619	8065.191
log(nfl)	515.262	35.200	14.638	0.000	1.436
ffd:temp	-1.437	2.833	-0.507	0.612	13179.891
ffd:I(temp^2)	0.031	0.076	0.404	0.687	13350.712
ffd:year_fct2018	-22.143	35.261	-0.628	0.530	8366.639
temp:year_fct2018	-688.831	808.454	-0.852	0.395	29903.418
I(temp^2):year_fct2018	17.705	23.116	0.766	0.444	13413.326
ffd:temp:year_fct2018	4.243	4.613	0.920	0.358	29190.766
ffd:I(temp^2):year_fct2018	-0.107	0.134	-0.799	0.425	12886.949

Standard errors: OLS

```
selectionabs_1<-lm(nseed~ffd*temp*year_fct+log(nfl),
                   data_plants)
summ(selectionabs_1,vif=T)
```

Observations	349
Dependent variable	nseed
Type	OLS linear regression

F(8,340)	33.702
R^2	0.442
Adj. R^2	0.429

	Est.	S.E.	t val.	p	VIF
(Intercept)	-2643.509	2290.279	-1.154	0.249	NA
ffd	13.084	12.794	1.023	0.307	17.081
temp	54.818	110.909	0.494	0.621	712.772
year_fct2018	-226.645	2888.248	-0.078	0.937	1696.073
log(nfl)	509.726	34.707	14.686	0.000	1.407
ffd:temp	-0.396	0.630	-0.628	0.530	657.537
ffd:year_fct2018	-1.890	15.990	-0.118	0.906	1733.237
temp:year_fct2018	-125.856	157.307	-0.800	0.424	1140.545
ffd:temp:year_fct2018	0.845	0.891	0.948	0.344	1097.854

Standard errors: OLS

BCa intervals

Used for assessing significance.

```r
BCIs_selectionabs_1
```

```
##                      lower        upper
## ffd              -7.183279   40.9875411
## temp           -110.875215  246.8754244
## year          -4437.256576 4207.5829387
## nfl             387.139500  711.7212794
## ffd:temp         -1.508089    0.5633312
## ffd:year        -27.527025   21.3947202
## temp:year      -362.614782   92.6495408
## ffd:temp:year    -0.417493    2.2024819
```

Keep separate models for both years here?

Tests of residual spatial autocorrelation

I think it makes no sense to test for spatial autocorrelation in the residuals of models with year as a factor, because we are mixing plants for different years.

By now, I will run separate models for each year and test for residual spatial autocorrelation in those.

Hypothesis 1

```r
FFD_2017<-lm(ffd~temp,subset(data_plants,year==2017))
FFD_2018<-lm(ffd~temp,subset(data_plants,year==2018))
summ(FFD_2017)
```

Observations	245
Dependent variable	ffd
Type	OLS linear regression

F(1,243)	29.049
R^2	0.107
Adj. R^2	0.103

	Est.	S.E.	t val.	p
(Intercept)	180.626	0.996	181.397	0.000
temp	-0.332	0.062	-5.390	0.000

Standard errors: OLS

```r
summ(FFD_2018)
```

Spatial correlograms

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)	195.104	2.206	88.424	0.000
temp	-1.070	0.154	-6.936	0.000

Standard errors: OLS

```
res_FFD_2017<-residuals(FFD_2017)
res_FFD_2018<-residuals(FFD_2018)
```

```
correlog_FFD_2017 <- correlog(x=subset(data_plants,year==2017)$x,
                              y=subset(data_plants,year==2017)$y,
                              res_FFD_2017,increment=1, resamp=100,quiet=F)
```

```
## 10  of  100 20  of  100 30  of  100 40  of  100 50  of  100 60  of  100 70  of  100 80  of  100 90  o
```

```
correlog_FFD_2018 <- correlog(x=subset(data_plants,year==2018)$x,
                              y=subset(data_plants,year==2018)$y,
                              res_FFD_2018,increment=1, resamp=100,quiet=F)
```

```
## 10  of  100 20  of  100 30  of  100 40  of  100 50  of  100 60  of  100 70  of  100 80  of  100 90  o
```

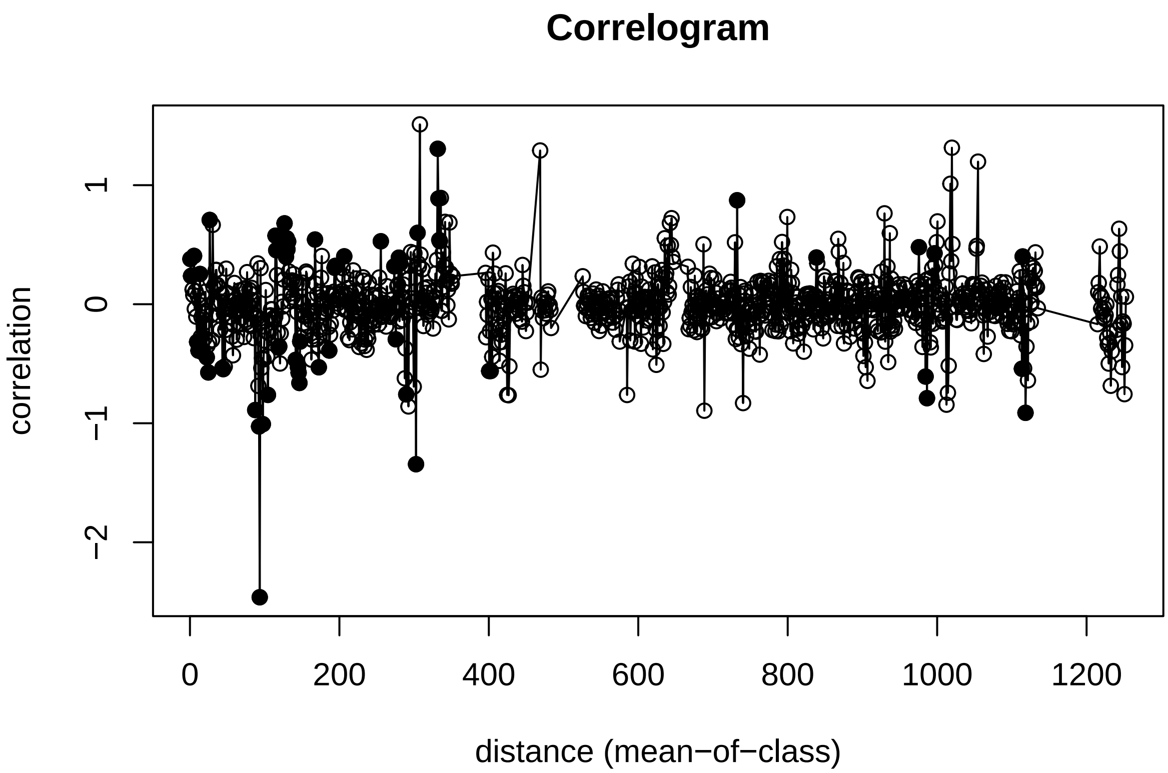
```
spline.correlog_FFD_2017 <- spline.correlog(x=subset(data_plants,year==2017)$x,
                              y=subset(data_plants,year==2017)$y,
                              res_FFD_2017,resamp=100,quiet=F,type="boot")
```

```
## 10  of  100 20  of  100 30  of  100 40  of  100 50  of  100 60  of  100 70  of  100 80  of  100 90  o
```

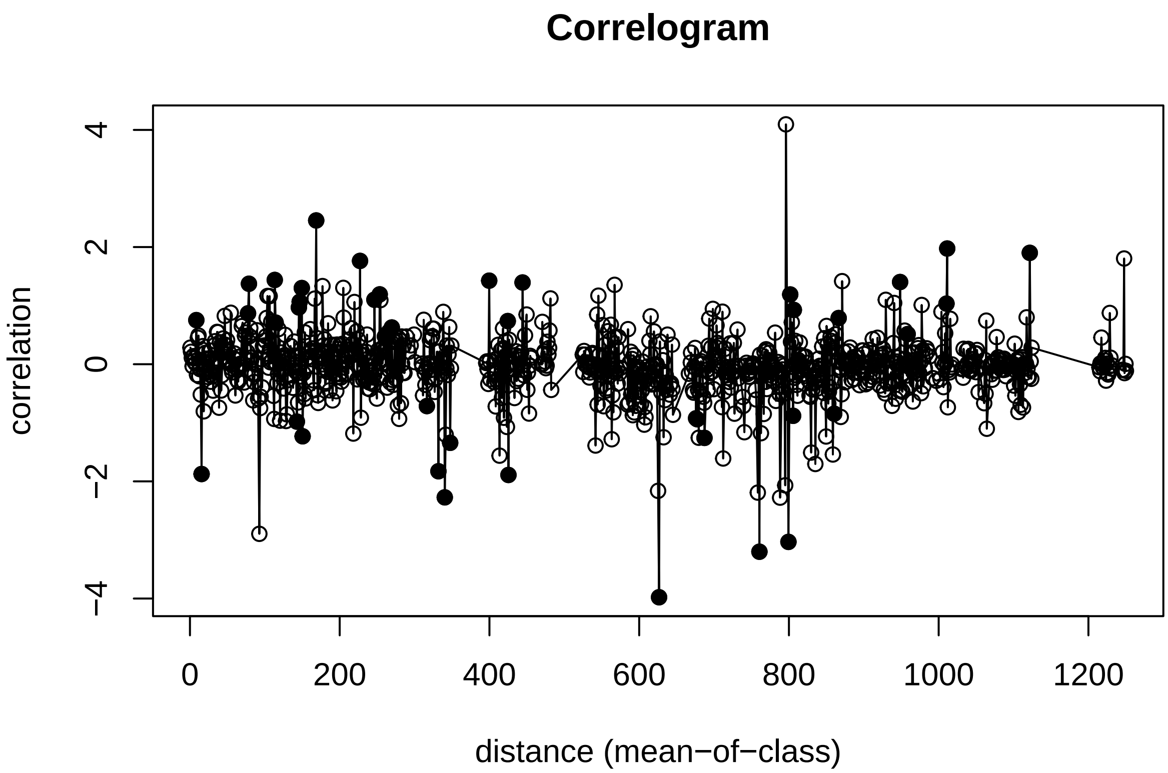
```
spline.correlog_FFD_2018 <- spline.correlog(x=subset(data_plants,year==2018)$x,
                              y=subset(data_plants,year==2018)$y,
                              res_FFD_2018,resamp=100,quiet=F,type="boot")
```

```
## 10  of  100 20  of  100 30  of  100 40  of  100 50  of  100 60  of  100 70  of  100 80  of  100 90  o
```

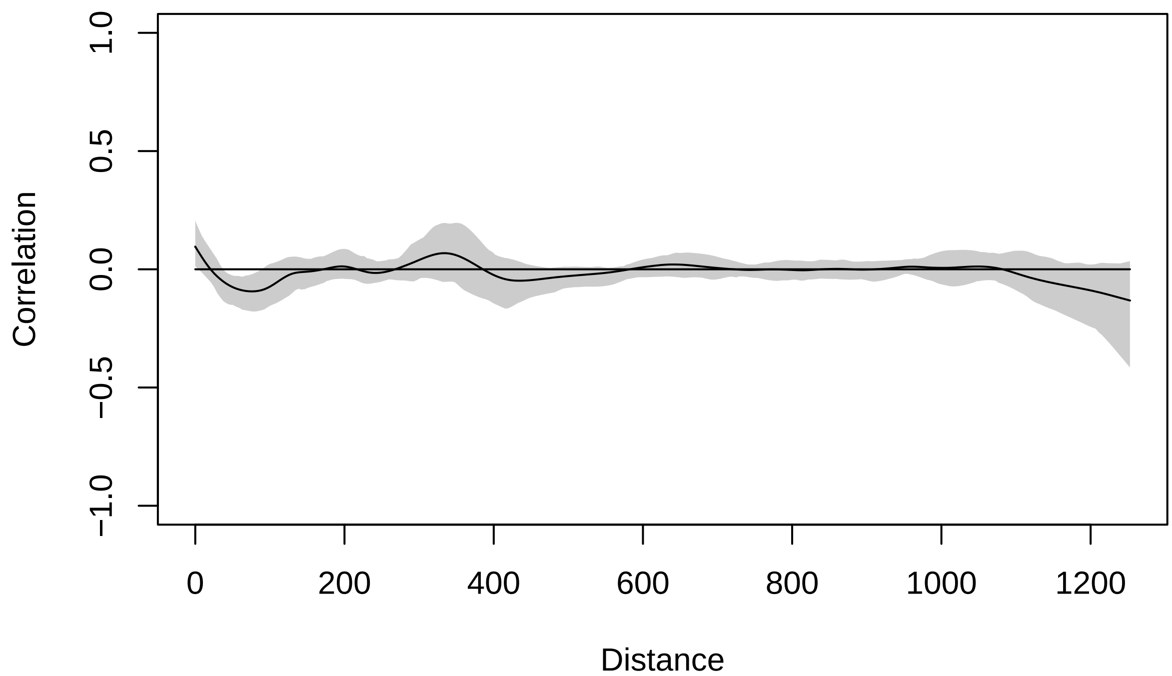
```
plot(correlog_FFD_2017)
```



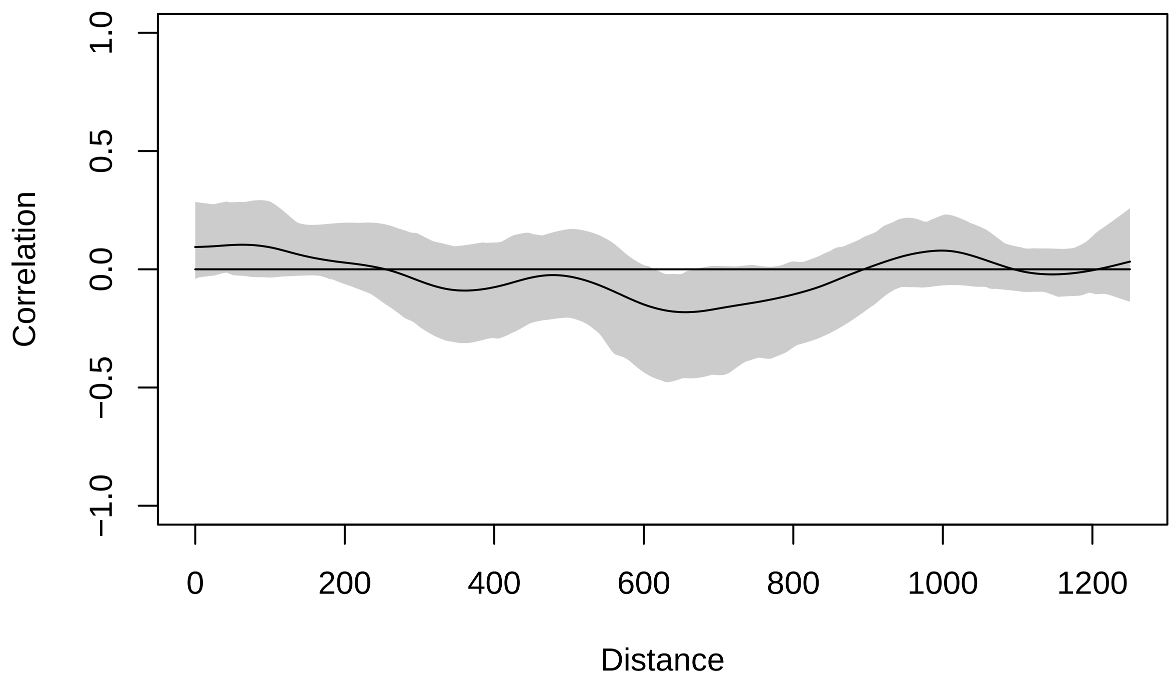

```
plot(correlog_FFD_2018)
```




```
plot(spline.correlog_FFD_2017)
```




```
plot(spline.correlog_FFD_2018)
```



Moran's I

Calculation of global Moran's I with a permutation test (1000 random permutations), based on a connectivity matrix of pairwise Euclidean distances among the plants up to a distance of 30 m.

```
# Create neighbours matrix (30 m)
data_plants.listw_2017 <- nb2listw(dnearneigh(subset(data_plants,year==2017),
                                              0,30))
data_plants.listw_2018 <- nb2listw(dnearneigh(subset(data_plants,year==2018),
                                              0,30))
moran_FFD_2017<- moran.mc(res_FFD_2017, listw=data_plants.listw_2017,nsim=999)
moran_FFD_2018<- moran.mc(res_FFD_2018, listw=data_plants.listw_2018,nsim=999)
```

```
moran_FFD_2017 # Significant autocorrelation in the residuals
```

```
##
##  Monte-Carlo simulation of Moran I
##
## data:  res_FFD_2017
## weights: data_plants.listw_2017
## number of simulations + 1: 1000
##
## statistic = 0.04303, observed rank = 980, p-value = 0.02
## alternative hypothesis: greater
```

```
moran_FFD_2018 # Significant autocorrelation in the residuals
```

```
##
##  Monte-Carlo simulation of Moran I
##
## data:  res_FFD_2018
## weights: data_plants.listw_2018
## number of simulations + 1: 1000
##
## statistic = 0.082696, observed rank = 962, p-value = 0.038
## alternative hypothesis: greater
```

Moran's eigenvector mapping

```
ME.FFD_2017 <-ME(FFD_2017,listw=data_plants.listw_2017,
               data=subset(data_plants,year==2017),
               alpha=0.1,verbose=T)
```

```
## eV[,11], I: 0.01463088 ZI: NA, pr(ZI): 0.16
```

```
ME.FFD_2018 <-ME(FFD_2018,listw=data_plants.listw_2018,
               data=subset(data_plants,year==2018),
               alpha=0.1,verbose=T)
```

```
## eV[,4], I: 0.02947613 ZI: NA, pr(ZI): 0.19
```

```
vector1_2017_FFD<-ME.FFD_2017$vectors[,1]
vector1_2018_FFD<-ME.FFD_2018$vectors[,1]

FFD_2017_ME<-lm(ffd~temp+vector1_2017_FFD,
                subset(data_plants,year==2017))
FFD_2018_ME<-lm(ffd~temp+vector1_2018_FFD,subset(data_plants,year==2018))
summ(FFD_2017_ME)
```

Observations	245
Dependent variable	ffd
Type	OLS linear regression

F(2,242)	18.245
R^2	0.131
Adj. R^2	0.124

```
summ(FFD_2018_ME)
```

Tests of residual spatial autocorrelation

	Est.	S.E.	t val.	p
(Intercept)	180.866	0.988	182.973	0.000
temp	-0.349	0.061	-5.700	0.000
vector1_2017_FFD	19.614	7.548	2.599	0.010

Standard errors: OLS

Observations	104
Dependent variable	ffd
Type	OLS linear regression

F(2,101)	28.531
R^2	0.361
Adj. R^2	0.348

	Est.	S.E.	t val.	p
(Intercept)	193.920	2.200	88.129	0.000
temp	-0.974	0.155	-6.284	0.000
vector1_2018_FFD	28.781	11.368	2.532	0.013

Standard errors: OLS

```
res_FFD_2017_ME<-residuals(FFD_2017_ME)
res_FFD_2018_ME<-residuals(FFD_2018_ME)
```

```
correlog_FFD_2017_ME <- correlog(x=subset(data_plants,year==2017)$x,
                                 y=subset(data_plants,year==2017)$y,
                                 res_FFD_2017_ME,increment=1, resamp=100,quiet=F)
```

Spatial correlograms

```
## 10   of   100 20   of   100 30   of   100 40   of   100 50   of   100 60   of   100 70   of   100 80   of   100 90   o
```

```
correlog_FFD_2018_ME <- correlog(x=subset(data_plants,year==2018)$x,
                                 y=subset(data_plants,year==2018)$y,
                                 res_FFD_2018_ME,increment=1, resamp=100,quiet=F)
```

```
## 10   of   100 20   of   100 30   of   100 40   of   100 50   of   100 60   of   100 70   of   100 80   of   100 90   o
```

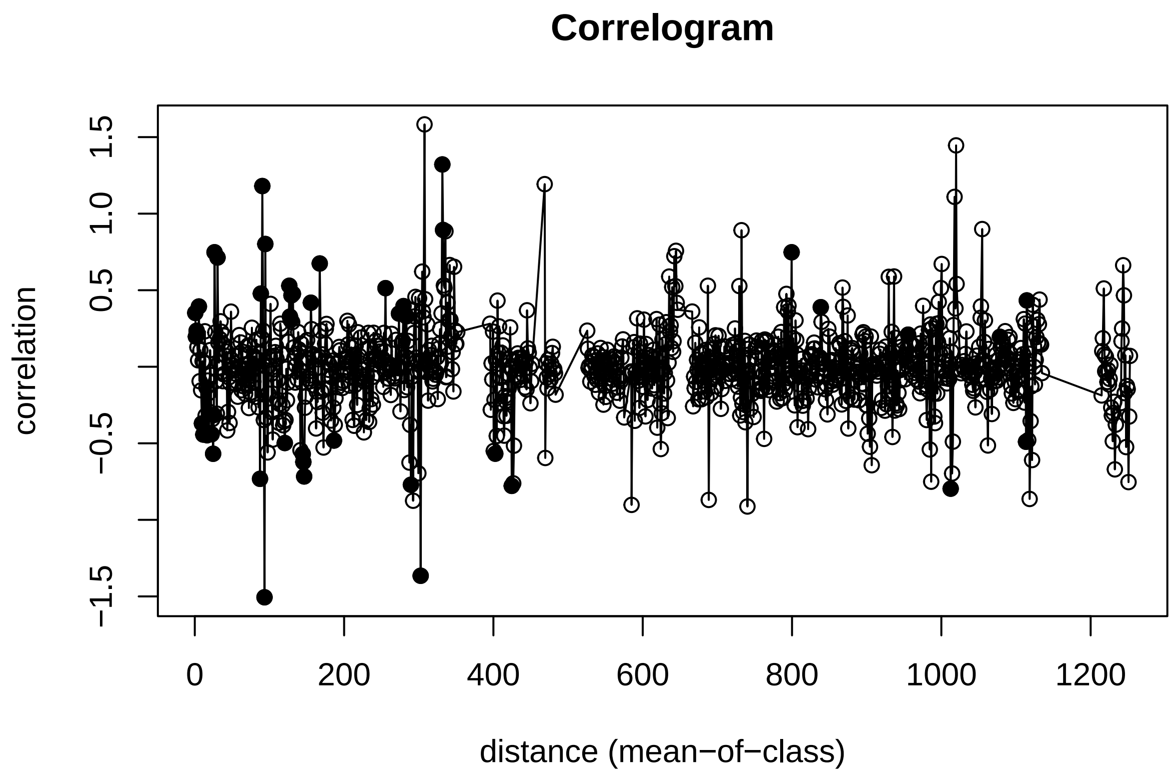
```
spline.correlog_FFD_2017_ME <- spline.correlog(x=subset(data_plants,year==2017)$x,
                                 y=subset(data_plants,year==2017)$y,
                                 res_FFD_2017_ME,resamp=100,quiet=F,type="boot")
```

```
## 10   of   100 20   of   100 30   of   100 40   of   100 50   of   100 60   of   100 70   of   100 80   of   100 90   o
```

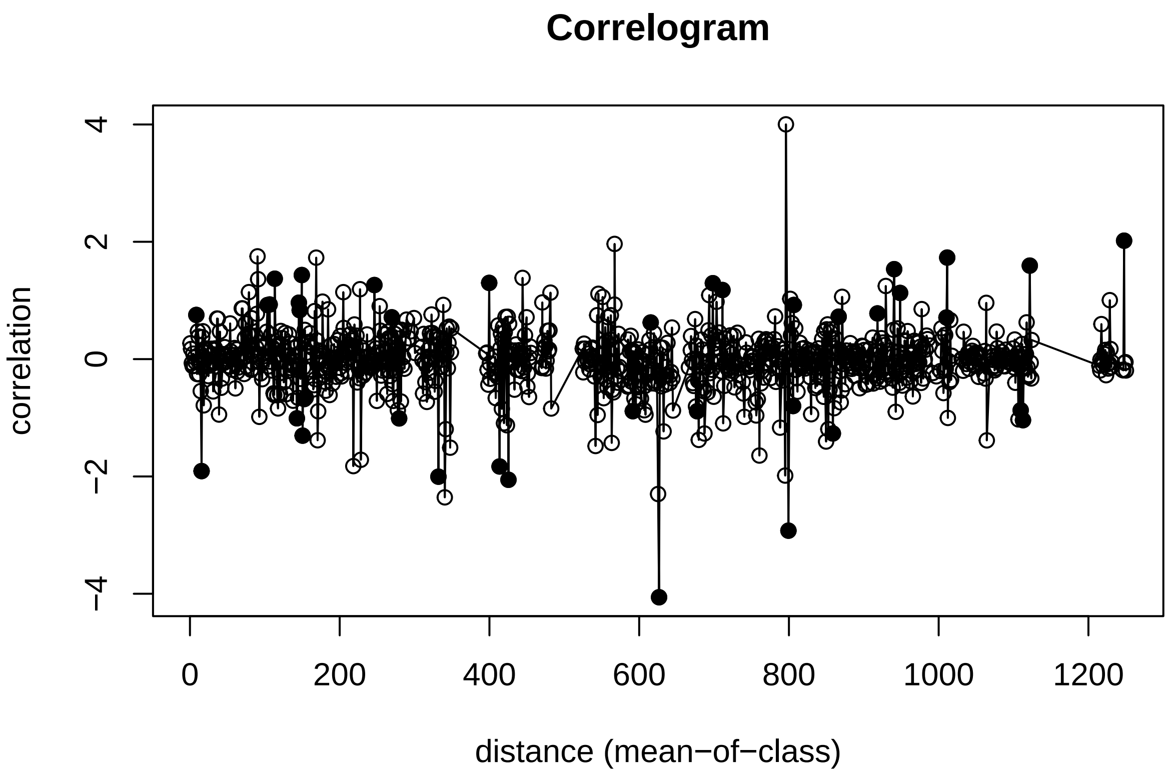
```r
spline.correlog_FFD_2018_ME <- spline.correlog(x=subset(data_plants,year==2018)$x,
                              y=subset(data_plants,year==2018)$y,
                              res_FFD_2018_ME,resamp=100,quiet=F,type="boot")
```

```
## 10  of  100 20  of  100 30  of  100 40  of  100 50  of  100 60  of  100 70  of  100 80  of  100 90  o
```

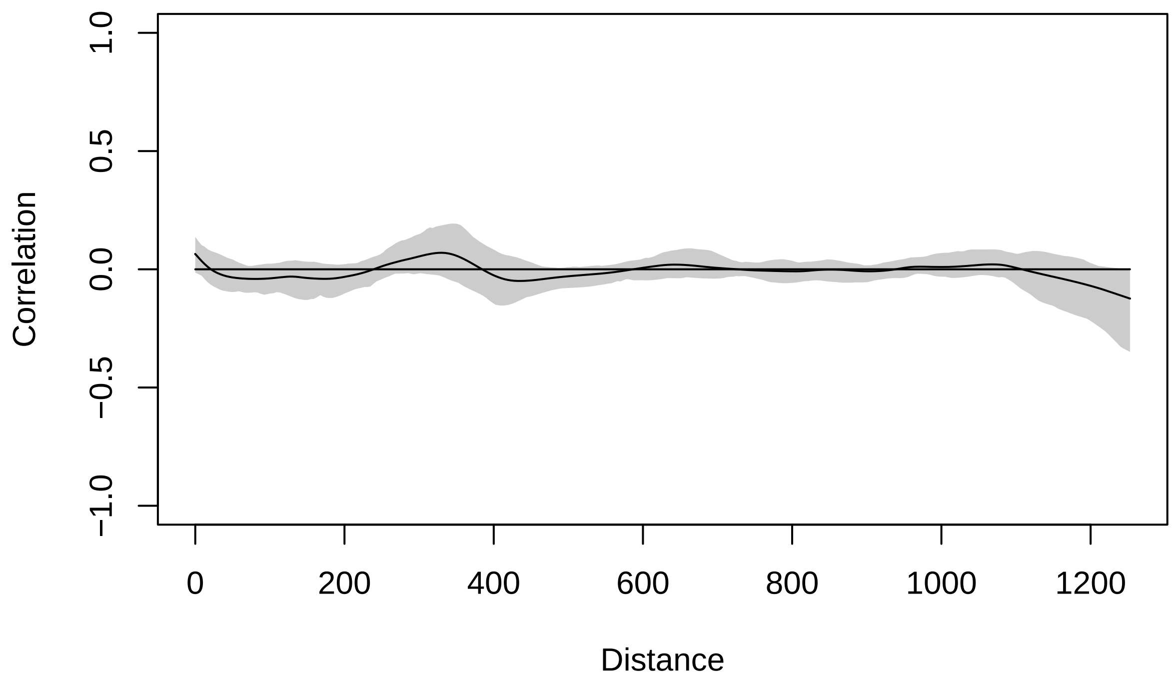
```r
plot(correlog_FFD_2017_ME)
```



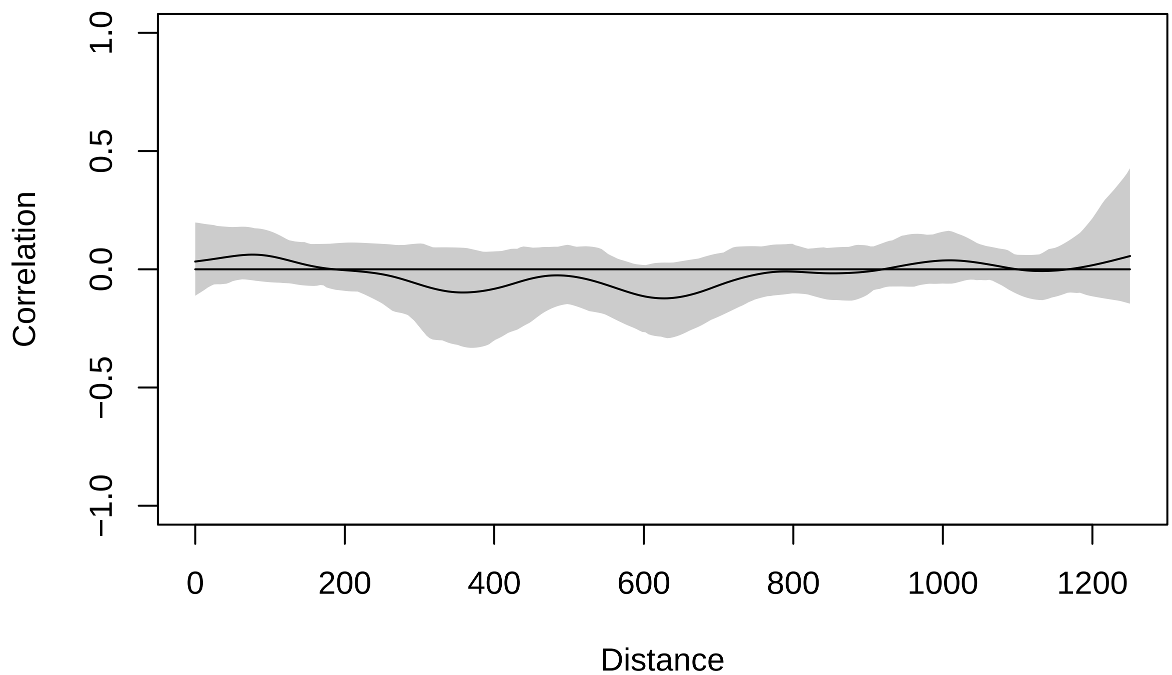

```r
plot(correlog_FFD_2018_ME)
```




```
plot(spline.correlog_FFD_2017_ME)
```




```
plot(spline.correlog_FFD_2018_ME)
```



Moran's I Calculation of global Moran's I with a permutation test (1000 random permutations), based on a connectivity matrix of pairwise Euclidean distances among the plants up to a distance of 30 m.

```
res_FFD_2017_ME<-residuals(FFD_2017_ME)
res_FFD_2018_ME<-residuals(FFD_2018_ME)
moran_FFD_2017_ME<- moran.mc(res_FFD_2017_ME, listw=data_plants.listw_2017,
                             nsim=999)
moran_FFD_2018_ME<- moran.mc(res_FFD_2018_ME, listw=data_plants.listw_2018,
                             nsim=999)
```

```
moran_FFD_2017_ME # No significant autocorrelation in the residuals
```

```
##
##  Monte-Carlo simulation of Moran I
##
## data:  res_FFD_2017_ME
## weights: data_plants.listw_2017
## number of simulations + 1: 1000
##
## statistic = 0.014631, observed rank = 846, p-value = 0.154
## alternative hypothesis: greater
```

```
moran_FFD_2018_ME # No significant autocorrelation in the residuals
```

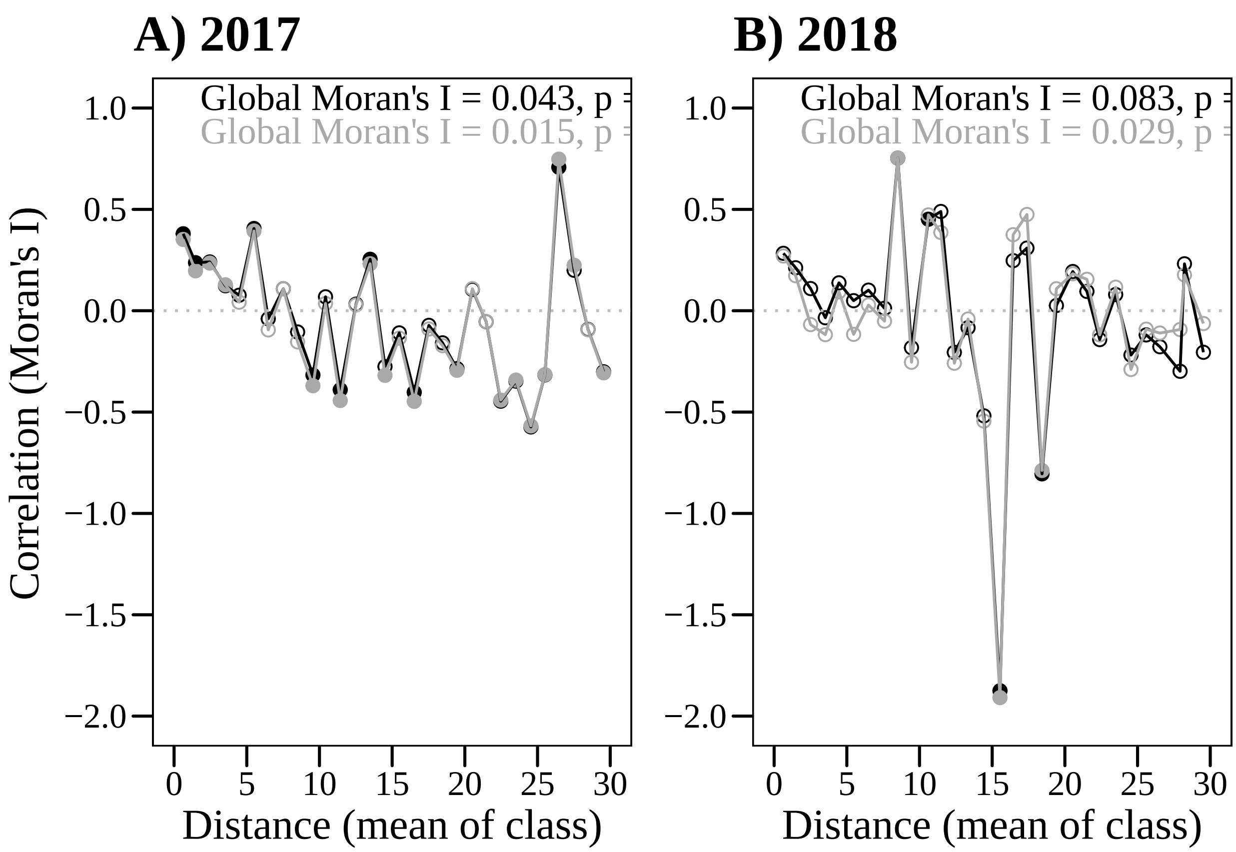
```
##
##  Monte-Carlo simulation of Moran I
##
## data:  res_FFD_2018_ME
## weights: data_plants.listw_2018
## number of simulations + 1: 1000
##
## statistic = 0.029476, observed rank = 818, p-value = 0.182
## alternative hypothesis: greater
```

Plots SI

```
# FFD_2017
corr_FFD_2017<-data.frame(cbind(distance=
                                as.vector(correlog_FFD_2017$mean.of.class[1:31]),
                      correlation=as.vector(correlog_FFD_2017$correlation[1:31]),
                      p=as.vector(correlog_FFD_2017$p[1:31])))
corr_FFD_2017_ME<-data.frame(cbind(distance=
                                   as.vector(
                                     correlog_FFD_2017_ME$mean.of.class[1:31]),
                                 correlation=
                                   as.vector(correlog_FFD_2017_ME$correlation[1:31]),
                                  p=as.vector(correlog_FFD_2017_ME$p[1:31])))
corr_FFD_2017$type<-"FFD_2017"
corr_FFD_2017_ME$type<-"FFD_2017_ME"
corr_FFD_2017<-rbind(corr_FFD_2017,corr_FFD_2017_ME)
corr_FFD_2017$sig<-as.factor(ifelse(corr_FFD_2017$p<0.05,1,0))

# FFD_2018
corr_FFD_2018<-data.frame(cbind(distance=
                                as.vector(correlog_FFD_2018$mean.of.class[1:31]),
                      correlation=as.vector(correlog_FFD_2018$correlation[1:31]),
                      p=as.vector(correlog_FFD_2018$p[1:31])))
corr_FFD_2018_ME<-data.frame(cbind(distance=
                                   as.vector(
                                     correlog_FFD_2018_ME$mean.of.class[1:31]),
                                 correlation=
                                   as.vector(correlog_FFD_2018_ME$correlation[1:31]),
                                  p=as.vector(correlog_FFD_2018_ME$p[1:31])))
corr_FFD_2018$type<-"FFD_2018"
corr_FFD_2018_ME$type<-"FFD_2018_ME"
corr_FFD_2018<-rbind(corr_FFD_2018,corr_FFD_2018_ME)
corr_FFD_2018$sig<-as.factor(ifelse(corr_FFD_2018$p<0.05,1,0))
```

```
# CHANGE MORAN'S I VALUES
App_FFD<-grid.arrange(
  ggplot(corr_FFD_2017,aes(x=distance, y=correlation)) +
    geom_point(aes(colour=type,shape=sig),size=2) +
    geom_line(aes(colour=type)) + ylab(NULL)+
    scale_x_continuous("Distance (mean of class)",limits=c(0,30),
                       breaks=c(0,5,10,15,20,25,30)) +
    scale_y_continuous(limits=c(-2,1),
```

```
                   breaks = seq(-2,1,0.5))+
  scale_shape_manual(values=c(1,19))+
  scale_color_manual(values=c("black","darkgrey"))+
  geom_hline(aes(yintercept=0), colour="grey",linetype=3)+
  my_theme()+ggtitle("A) 2017")+
  annotation_custom(grobTree(textGrob("Global Moran's I = 0.043, p = 0.027",
                                      x=0.1,y=0.97,hjust=0,
                                      gp=gpar(col="black",fontsize=14,
                                              fontfamily="serif"))))+
  annotation_custom(grobTree(textGrob("Global Moran's I = 0.015, p = 0.174",
                                      x=0.1,y=0.92,hjust=0,
                                      gp=gpar(col="darkgrey",fontsize=14,
                                              fontfamily="serif")))),
ggplot(corr_FFD_2018,aes(x=distance, y=correlation)) +
  geom_point(aes(colour=type,shape=sig),size=2) +
  geom_line(aes(colour=type)) + ylab(NULL)+
  scale_x_continuous("Distance (mean of class)",limits=c(0,30),
                   breaks=c(0,5,10,15,20,25,30)) +
  scale_y_continuous(limits=c(-2,1),
                   breaks = seq(-2,1,0.5))+
  scale_shape_manual(values=c(1,19))+
  scale_color_manual(values=c("black","darkgrey"))+
  geom_hline(aes(yintercept=0), colour="grey",linetype=3)+
  my_theme()+ggtitle("B) 2018")+
  annotation_custom(grobTree(textGrob("Global Moran's I = 0.083, p = 0.035",
                                      x=0.1,y=0.97,hjust=0,
                                      gp=gpar(col="black",fontsize=14,
                                              fontfamily="serif"))))+
  annotation_custom(grobTree(textGrob("Global Moran's I = 0.029, p = 0.209",
                                      x=0.1,y=0.92,hjust=0,
                                      gp=gpar(col="darkgrey",fontsize=14,
                                              fontfamily="serif")))),
ncol=2,left=textGrob("Correlation (Moran's I)",just="center",
                    hjust=0.42,
                    gp=gpar(fontsize=16,fontfamily="serif"),
                    rot = 90))
```




```
ggsave(filename="output/figures/App_FFD.tiff",
       plot=App_FFD,device="tiff",width=28,height=12,units="cm",dpi=300,
       compression="lzw")
```

Hypothesis 2

```
fitness_2017<-glm.nb(n_seed_round~temp+log(nfl),
                     subset(data_plants,year==2017))
fitness_2018<-glm.nb(n_seed_round~temp+log(nfl),
                     subset(data_plants,year==2018))
# No quadratic terms of temperature because they were
# non-significant in both models
summ(fitness_2017,vif=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-R^2 (Cragg-Uhler)	0.722	0.088	3273.106	3287.112
Pseudo-R^2 (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)	4.079	0.113	36.029	0.000	NA
temp	-0.030	0.006	-5.117	0.000	1.094
log(nfl)	0.982	0.042	23.377	0.000	1.094

Standard errors: MLE

```
summ(fitness_2018,vif=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-R^2 (Cragg-Uhler)	0.684	0.091	1203.369	1213.947
Pseudo-R^2 (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)	3.543	0.188	18.878	0.000	NA
temp	-0.042	0.010	-4.166	0.000	1.003
log(nfl)	0.981	0.069	14.202	0.000	1.003

Standard errors: MLE

Spatial correlograms

```
res_fitness_2017<-residuals(fitness_2017)
res_fitness_2018<-residuals(fitness_2018)
```

```
correlog_fitness_2017 <- correlog(x=subset(data_plants,year==2017)$x,
                          y=subset(data_plants,year==2017)$y,
                          res_fitness_2017,increment=1, resamp=100,quiet=F)
```

```
## 10  of  100 20  of  100 30  of  100 40  of  100 50  of  100 60  of  100 70  of  100 80  of  100 90  o
```

```r
correlog_fitness_2018 <- correlog(x=subset(data_plants,year==2018)$x,
                                  y=subset(data_plants,year==2018)$y,
                                  res_fitness_2018,increment=1, resamp=100,quiet=F)
```

```
## 10  of  100 20  of  100 30  of  100 40  of  100 50  of  100 60  of  100 70  of  100 80  of  100 90  o
```

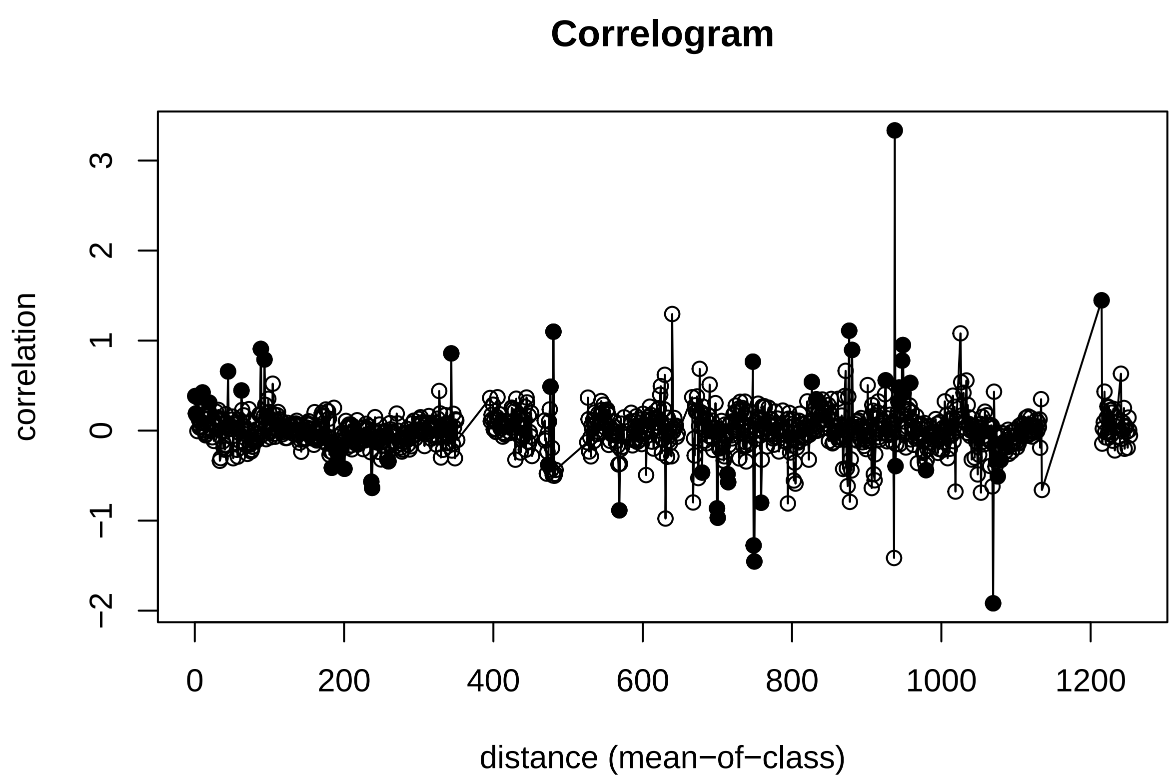
```r
spline.correlog_fitness_2017 <- spline.correlog(x=subset(data_plants,year==2017)$x,
                                  y=subset(data_plants,year==2017)$y,
                                  res_fitness_2017,resamp=100,quiet=F,type="boot")
```

```
## 10  of  100 20  of  100 30  of  100 40  of  100 50  of  100 60  of  100 70  of  100 80  of  100 90  o
```

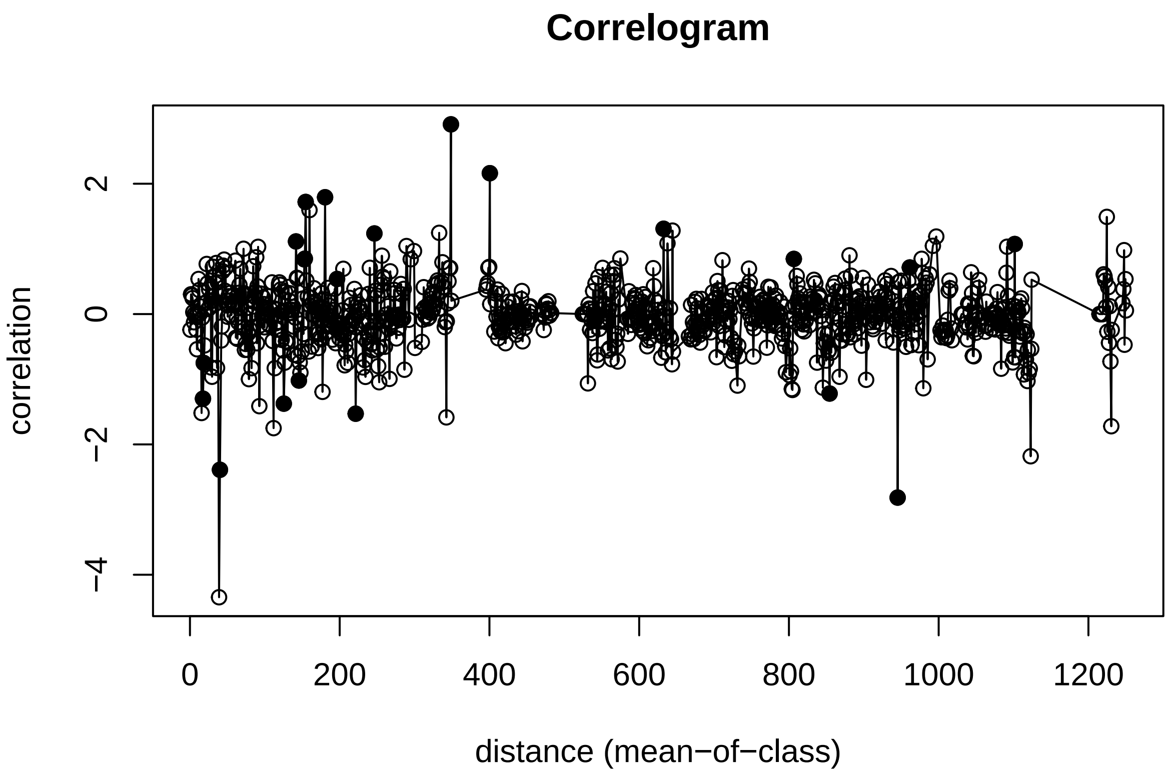
```r
spline.correlog_fitness_2018 <- spline.correlog(x=subset(data_plants,year==2018)$x,
                                  y=subset(data_plants,year==2018)$y,
                                  res_fitness_2018,resamp=100,quiet=F,type="boot")
```

```
## 10  of  100 20  of  100 30  of  100 40  of  100 50  of  100 60  of  100 70  of  100 80  of  100 90  o
```

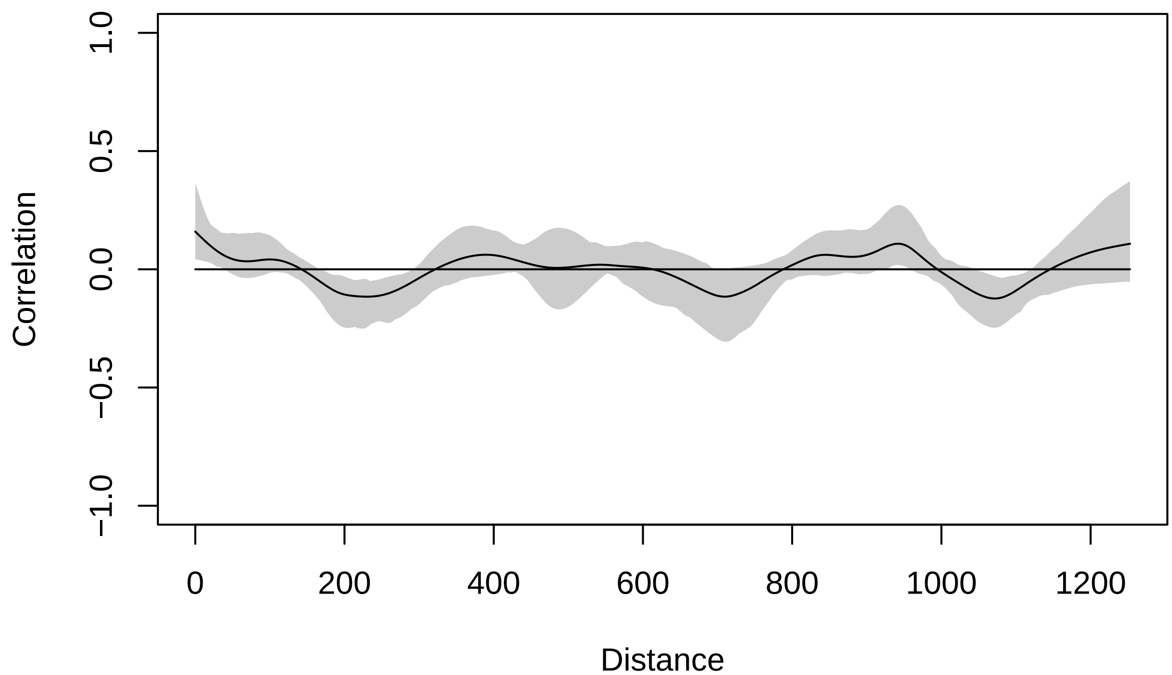
```r
plot(correlog_fitness_2017)
```



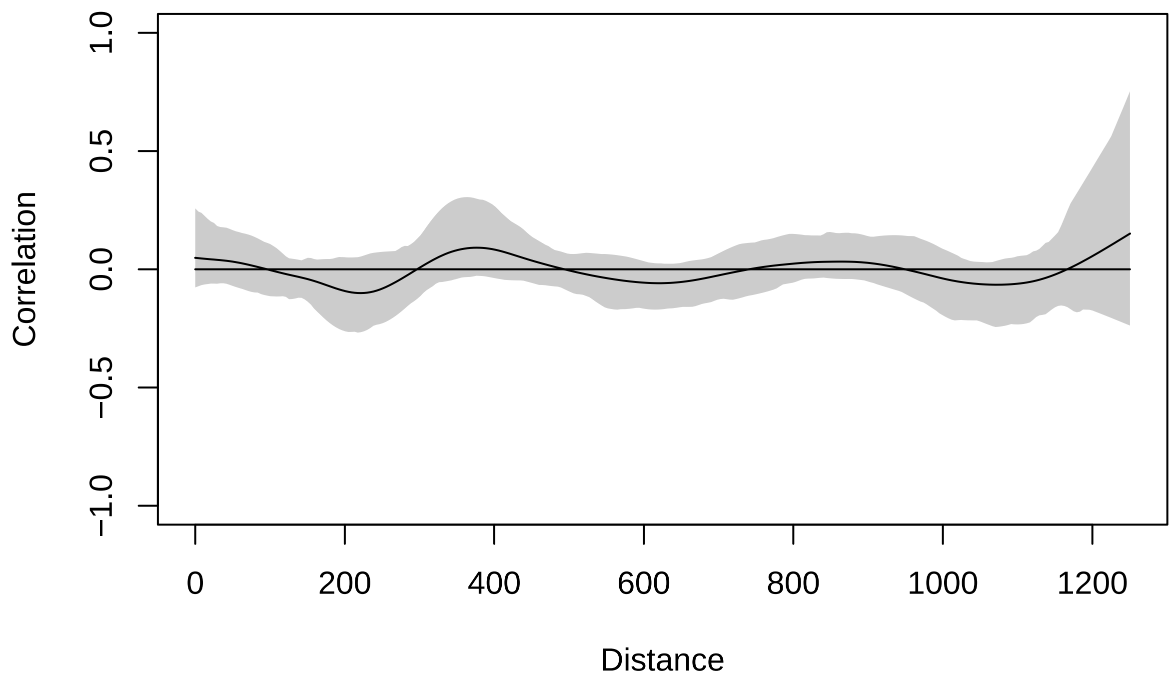

```r
plot(correlog_fitness_2018)
```




```
plot(spline.correlog_fitness_2017)
```




```
plot(spline.correlog_fitness_2018)
```



Moran's I

Calculation of global Moran's I with a permutation test (1000 random permutations), based on a connectivity matrix of pairwise Euclidean distances among the plants up to a distance of 30 m.

```
moran_fitness_2017<- moran.mc(res_fitness_2017,
                              listw=data_plants.listw_2017,nsim=999)
moran_fitness_2018<- moran.mc(res_fitness_2018,
                              listw=data_plants.listw_2018,nsim=999)
```

```
moran_fitness_2017 # Significant autocorrelation in the residuals
```

```
##
##  Monte-Carlo simulation of Moran I
##
## data:  res_fitness_2017
## weights: data_plants.listw_2017
## number of simulations + 1: 1000
##
## statistic = 0.12186, observed rank = 1000, p-value = 0.001
## alternative hypothesis: greater
```

```
moran_fitness_2018 # No significant autocorrelation in the residuals
```

```
##
##  Monte-Carlo simulation of Moran I
##
## data:  res_fitness_2018
## weights: data_plants.listw_2018
## number of simulations + 1: 1000
##
## statistic = 0.054454, observed rank = 891, p-value = 0.109
## alternative hypothesis: greater
```

Moran's eigenvector mapping

```
ME.fitness_2017 <-ME(fitness_2017,listw=data_plants.listw_2017,
               data=subset(data_plants,year==2017),
               alpha=0.1,verbose=T)
```

```
## eV[,3], I: 0.03874708 ZI: NA, pr(ZI): 0.06
## eV[,11], I: 0.01278019 ZI: NA, pr(ZI): 0.13
```

```
vector1_2017_fitness<-ME.fitness_2017$vectors[,1]
vector2_2017_fitness<-ME.fitness_2017$vectors[,2]

fitness_2017_ME<-glm.nb(n_seed_round~temp+log(nfl)+
                          vector1_2017_fitness+vector2_2017_fitness,
                        subset(data_plants,year==2017))
summ(fitness_2017_ME)
```

Observations	245
Dependent variable	n_seed_round
Type	Generalized linear model
Family	Negative Binomial(2.2191)
Link	log

$\chi^2()$	0.739	0.092	3261.922	3282.929
Pseudo-R² (Cragg-Uhler)	0.739	0.092	3261.922	3282.929
Pseudo-R² (McFadden)	0.739	0.092	3261.922	3282.929
AIC	0.739	0.092	3261.922	3282.929
BIC	0.739	0.092	3261.922	3282.929

Tests of residual spatial autocorrelation

```
res_fitness_2017_ME<-residuals(fitness_2017_ME)
```

	Est.	S.E.	z val.	p
(Intercept)	4.102	0.112	36.788	0.000
temp	-0.029	0.006	-5.027	0.000
log(nfl)	0.960	0.042	22.870	0.000
vector1__2017__fitness	-2.297	0.684	-3.360	0.001
vector2__2017__fitness	-1.418	0.693	-2.046	0.041

Standard errors: MLE

```
correlog_fitness_2017_ME <- correlog(x=subset(data_plants,year==2017)$x,
                            y=subset(data_plants,year==2017)$y,
                            res_fitness_2017_ME,increment=1, resamp=100,quiet=F)
```

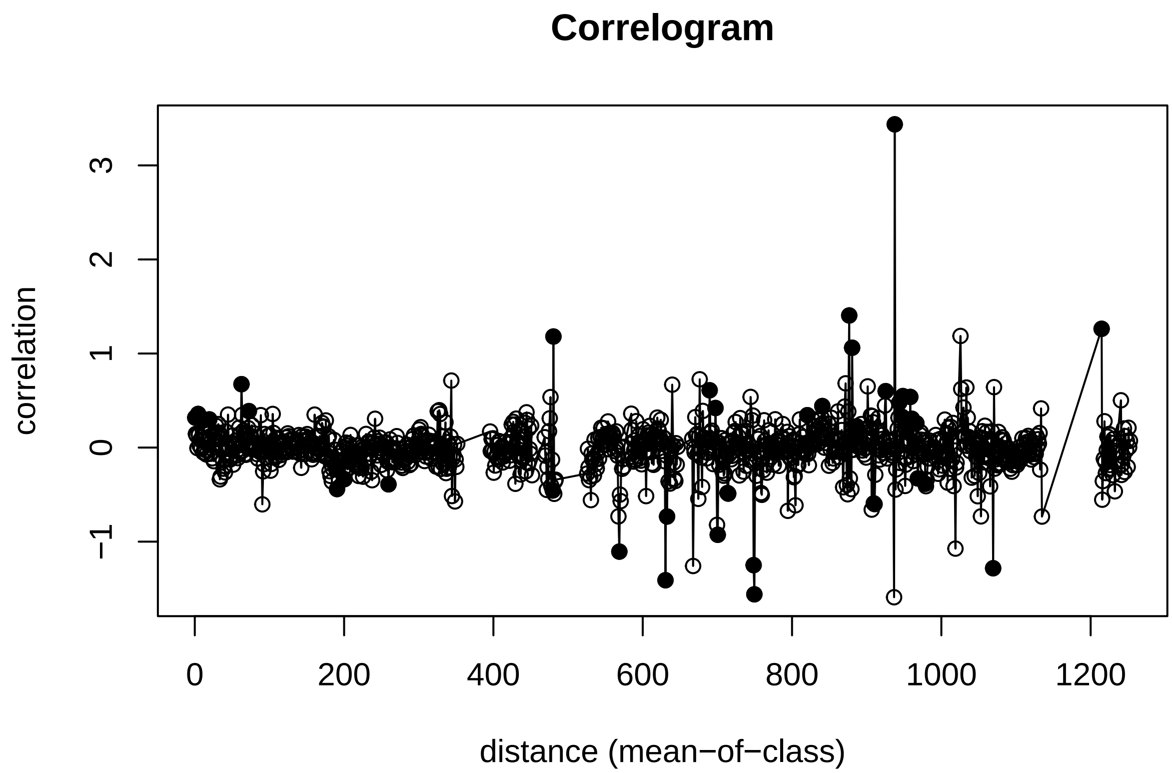
Spatial correlograms

```
## 10  of  100 20  of  100 30  of  100 40  of  100 50  of  100 60  of  100 70  of  100 80  of  100 90  o
```

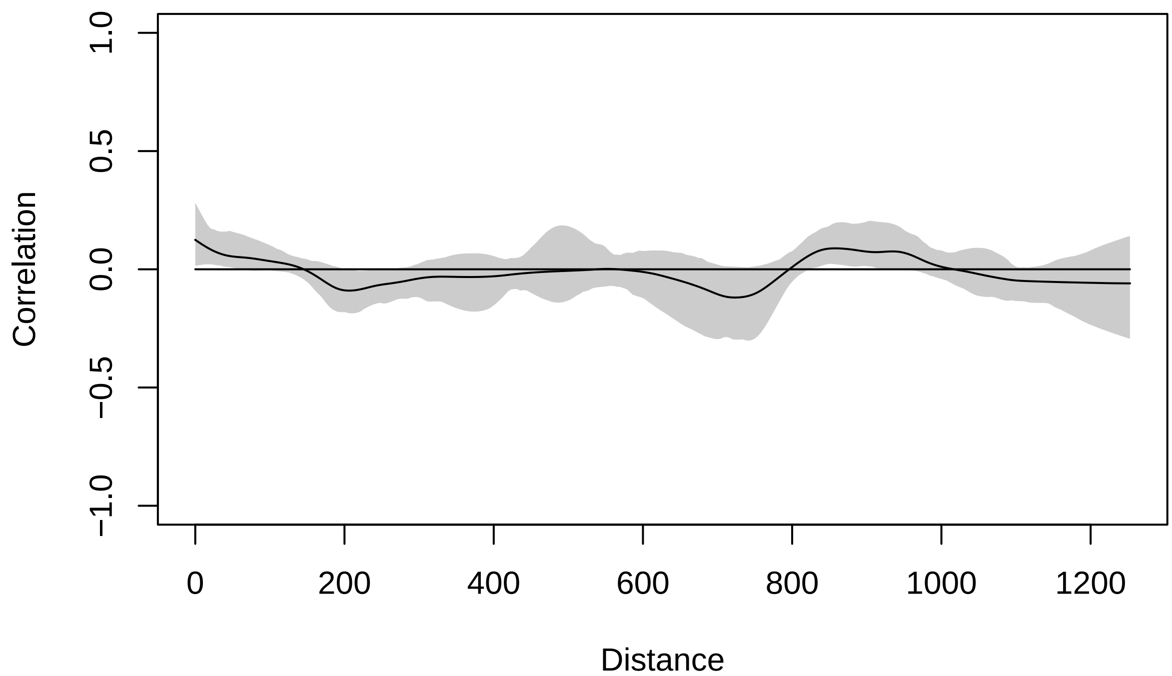
```
spline.correlog_fitness_2017_ME <- spline.correlog(x=subset(data_plants,year==2017)$x,
                            y=subset(data_plants,year==2017)$y,
                            res_fitness_2017_ME,resamp=100,quiet=F,type="boot")
```

```
## 10  of  100 20  of  100 30  of  100 40  of  100 50  of  100 60  of  100 70  of  100 80  of  100 90  o
```

```
plot(correlog_fitness_2017_ME)
```




```
plot(spline.correlog_fitness_2017_ME)
```



Moran's I Calculation of global Moran's I with a permutation test (1000 random permutations), based on a connectivity matrix of pairwise Euclidean distances among the plants up to a distance of 30 m.

```
moran_fitness_2017_ME<- moran.mc(res_fitness_2017_ME,
                                 listw=data_plants.listw_2017,nsim=999)
```

```
moran_fitness_2017_ME # STILL significant autocorrelation in the residuals
```

```
##
##  Monte-Carlo simulation of Moran I
##
## data:  res_fitness_2017_ME
## weights: data_plants.listw_2017
## number of simulations + 1: 1000
##
## statistic = 0.098683, observed rank = 1000, p-value = 0.001
## alternative hypothesis: greater
```

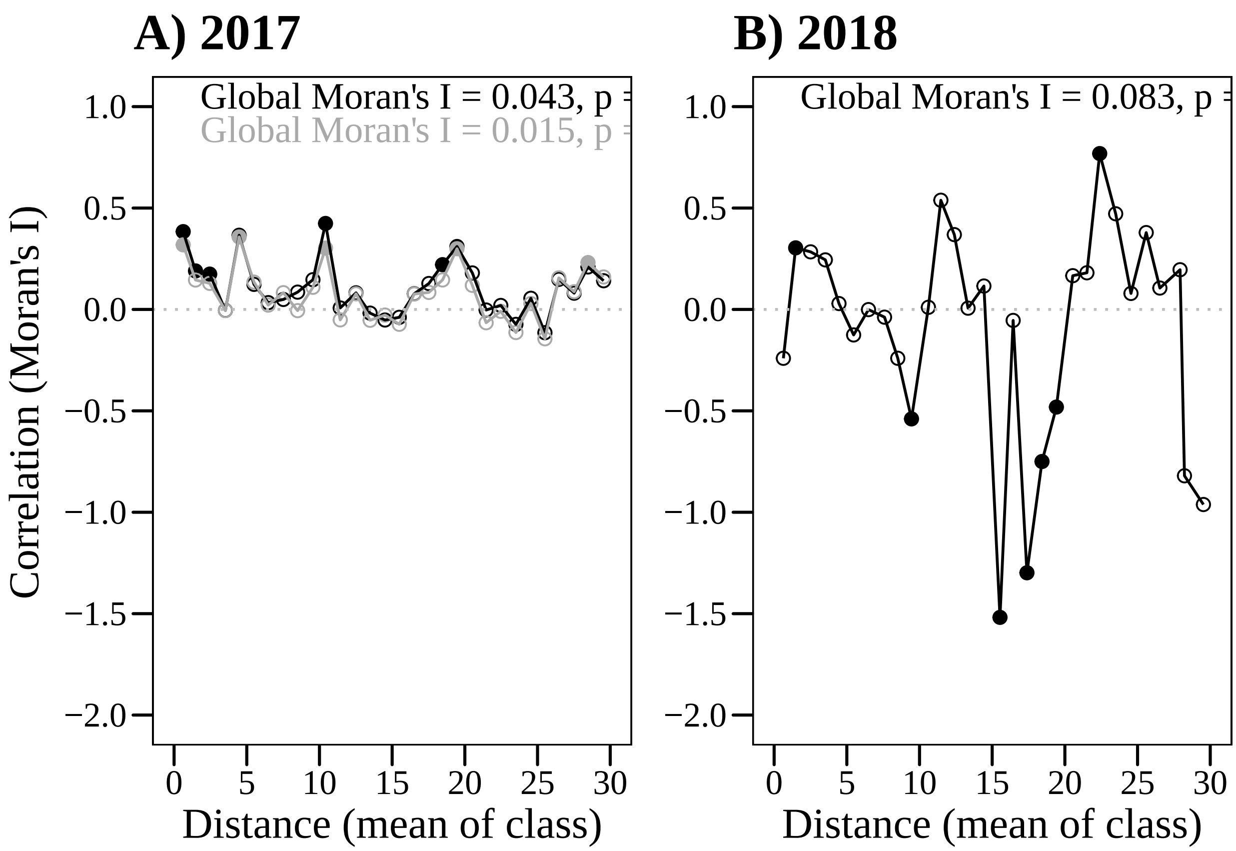
Plots SI

```
# fitness_2017
corr_fitness_2017<-data.frame(cbind(distance=
```

```
                                as.vector(correlog_fitness_2017$mean.of.class[1:31]),
                      correlation=as.vector(correlog_fitness_2017$correlation[1:31]),
                      p=as.vector(correlog_fitness_2017$p[1:31])))
corr_fitness_2017_ME<-data.frame(cbind(distance=
                                   as.vector(
                                     correlog_fitness_2017_ME$mean.of.class[1:31]),
                                 correlation=
                                   as.vector(correlog_fitness_2017_ME$correlation[1:31]),
                                  p=as.vector(correlog_fitness_2017_ME$p[1:31])))
corr_fitness_2017$type<-"fitness_2017"
corr_fitness_2017_ME$type<-"fitness_2017_ME"
corr_fitness_2017<-rbind(corr_fitness_2017,corr_fitness_2017_ME)
corr_fitness_2017$sig<-as.factor(ifelse(corr_fitness_2017$p<0.05,1,0))

# fitness_2018
corr_fitness_2018<-data.frame(cbind(distance=
                                as.vector(correlog_fitness_2018$mean.of.class[1:31]),
                      correlation=as.vector(correlog_fitness_2018$correlation[1:31]),
                      p=as.vector(correlog_fitness_2018$p[1:31])))
corr_fitness_2018$sig<-as.factor(ifelse(corr_fitness_2018$p<0.05,1,0))
```

```
# CHANGE MORAN'S I VALUES
App_fitness<-grid.arrange(
  ggplot(corr_fitness_2017,aes(x=distance, y=correlation)) +
    geom_point(aes(colour=type,shape=sig),size=2) +
    geom_line(aes(colour=type)) + ylab(NULL)+
    scale_x_continuous("Distance (mean of class)",limits=c(0,30),
                       breaks=c(0,5,10,15,20,25,30)) +
    scale_y_continuous(limits=c(-2,1),
                       breaks = seq(-2,1,0.5))+
    scale_shape_manual(values=c(1,19))+
    scale_color_manual(values=c("black","darkgrey"))+
    geom_hline(aes(yintercept=0), colour="grey",linetype=3)+
    my_theme()+ggtitle("A) 2017")+
    annotation_custom(grobTree(textGrob("Global Moran's I = 0.043, p = 0.027",
                                        x=0.1,y=0.97,hjust=0,
                                        gp=gpar(col="black",fontsize=14,
                                                fontfamily="serif"))))+
    annotation_custom(grobTree(textGrob("Global Moran's I = 0.015, p = 0.174",
                                        x=0.1,y=0.92,hjust=0,
                                        gp=gpar(col="darkgrey",fontsize=14,
                                                fontfamily="serif")))),
  ggplot(corr_fitness_2018,aes(x=distance, y=correlation)) +
    geom_point(aes(shape=sig),size=2,color="black") +
    geom_line(color="black") + ylab(NULL)+
    scale_x_continuous("Distance (mean of class)",limits=c(0,30),
                       breaks=c(0,5,10,15,20,25,30)) +
    scale_y_continuous(limits=c(-2,1),
                       breaks = seq(-2,1,0.5))+
    scale_shape_manual(values=c(1,19))+
    geom_hline(aes(yintercept=0), colour="grey",linetype=3)+
    my_theme()+ggtitle("B) 2018")+
    annotation_custom(grobTree(textGrob("Global Moran's I = 0.083, p = 0.035",
```

```r
                                                   x=0.1,y=0.97,hjust=0,
                                                   gp=gpar(col="black",fontsize=14,
                                                           fontfamily="serif")))),
  ncol=2,left=textGrob("Correlation (Moran's I)",just="center",
                       hjust=0.42,
                       gp=gpar(fontsize=16,fontfamily="serif"),
                       rot = 90))
```




```r
ggsave(filename="output/figures/App_fitness.tiff",
       plot=App_fitness,device="tiff",width=28,height=12,units="cm",dpi=300,
       compression="lzw")
```

Hypothesis 3

```r
selection_2017<-lm(nseed_rel~ffd_std*temp+nfl_std,
                   subset(data_plants,year==2017))
selection_2018<-lm(nseed_rel~ffd_std*temp+nfl_std,
                   subset(data_plants,year==2018))
summ(selection_2017,vif=T)
```

Observations	245
Dependent variable	nseed_rel
Type	OLS linear regression

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

	Est.	S.E.	t val.	p	VIF
(Intercept)	1.408	0.166	8.460	0.000	NA
ffd_std	0.331	0.206	1.602	0.110	7.311
temp	-0.030	0.010	-2.937	0.004	1.151
nfl_std	1.213	0.089	13.663	0.000	1.354
ffd_std:temp	-0.009	0.010	-0.848	0.397	6.682

Standard errors: OLS

```
summ(selection_2018,vif=T)
```

Observations	104
Dependent variable	nseed_rel
Type	OLS linear regression

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

	Est.	S.E.	t val.	p	VIF
(Intercept)	1.374	0.201	6.825	0.000	NA
ffd_std	-0.293	0.205	-1.431	0.156	5.999
temp	-0.021	0.016	-1.368	0.174	1.805
nfl_std	0.976	0.101	9.679	0.000	1.453
ffd_std:temp	0.027	0.012	2.241	0.027	5.976

Standard errors: OLS

Spatial correlograms

```
res_selection_2017<-residuals(selection_2017)
res_selection_2018<-residuals(selection_2018)
```

```
correlog_selection_2017 <- correlog(x=subset(data_plants,year==2017)$x,
                              y=subset(data_plants,year==2017)$y,
                              res_selection_2017,increment=1, resamp=100,quiet=F)
```

```
## 10  of  100 20  of  100 30  of  100 40  of  100 50  of  100 60  of  100 70  of  100 80  of  100 90  o
```

```
correlog_selection_2018 <- correlog(x=subset(data_plants,year==2018)$x,
                                   y=subset(data_plants,year==2018)$y,
                                   res_selection_2018,increment=1, resamp=100,quiet=F)
```

```
## 10   of   100 20   of   100 30   of   100 40   of   100 50   of   100 60   of   100 70   of   100 80   of   100 90
```

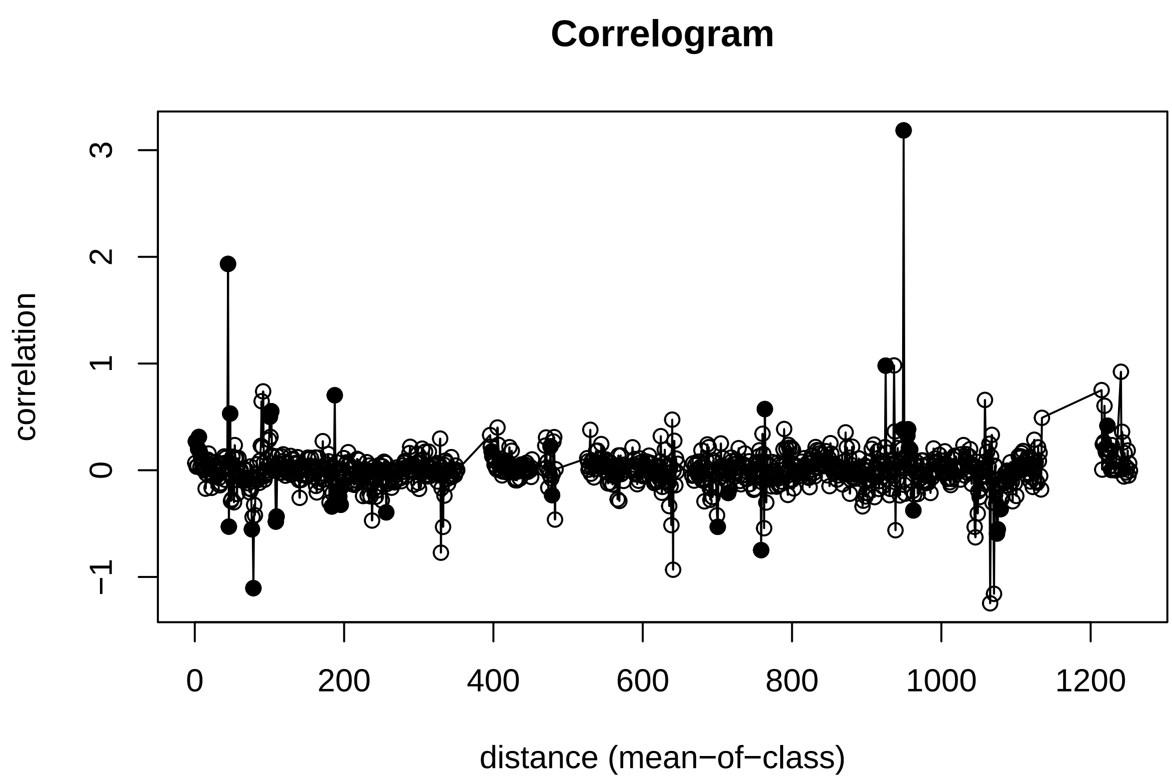
```
spline.correlog_selection_2017 <- spline.correlog(x=subset(data_plants,year==2017)$x,
                                   y=subset(data_plants,year==2017)$y,
                                   res_selection_2017,resamp=100,quiet=F,type="boot")
```

```
## 10   of   100 20   of   100 30   of   100 40   of   100 50   of   100 60   of   100 70   of   100 80   of   100 90
```

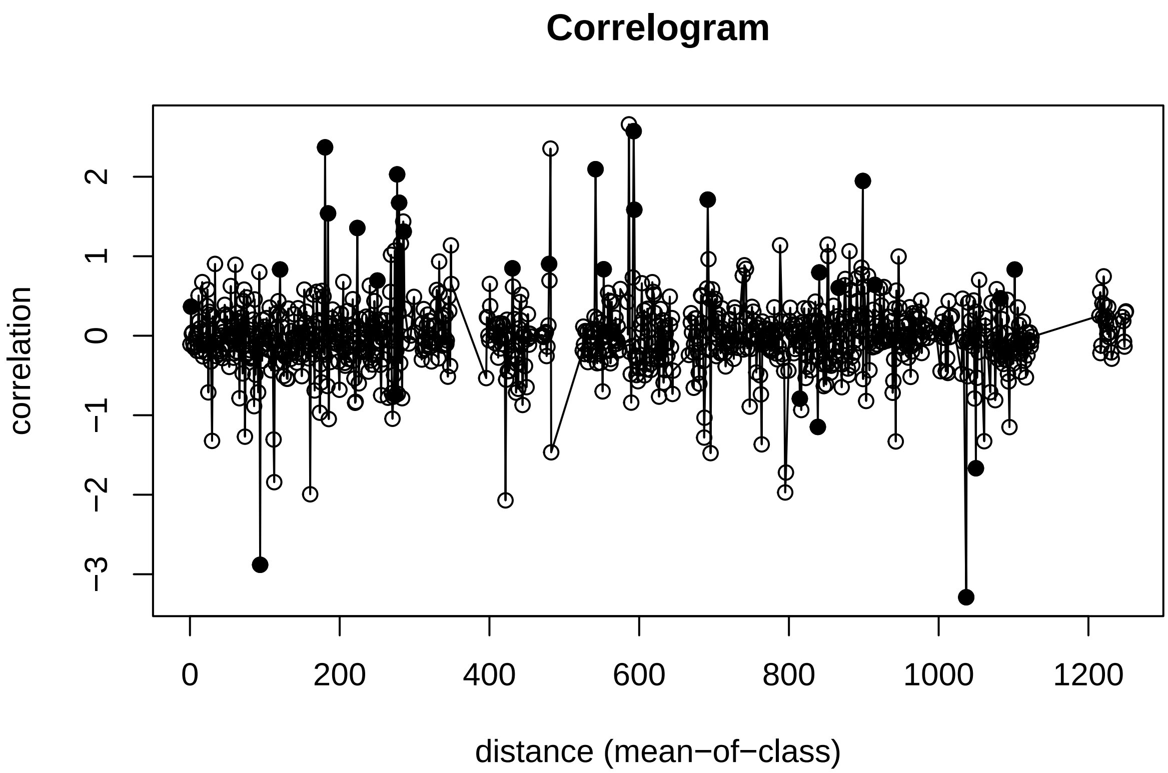
```
spline.correlog_selection_2018 <- spline.correlog(x=subset(data_plants,year==2018)$x,
                                   y=subset(data_plants,year==2018)$y,
                                   res_selection_2018,resamp=100,quiet=F,type="boot")
```

```
## 10   of   100 20   of   100 30   of   100 40   of   100 50   of   100 60   of   100 70   of   100 80   of   100 90
```

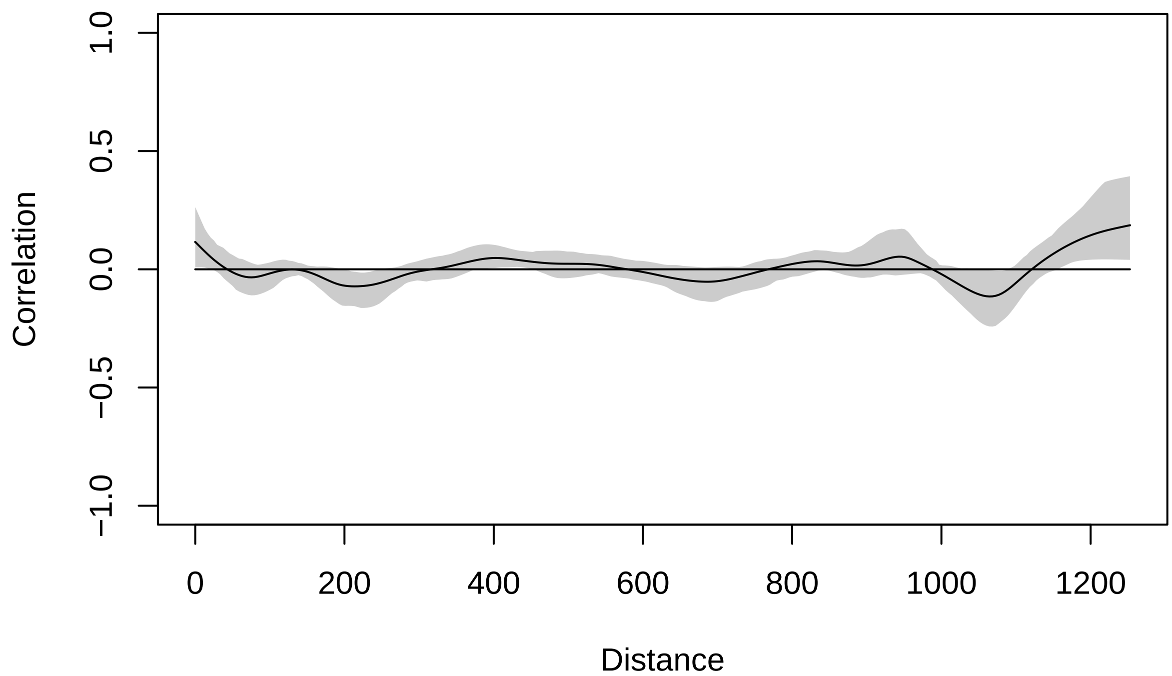
```
plot(correlog_selection_2017)
```



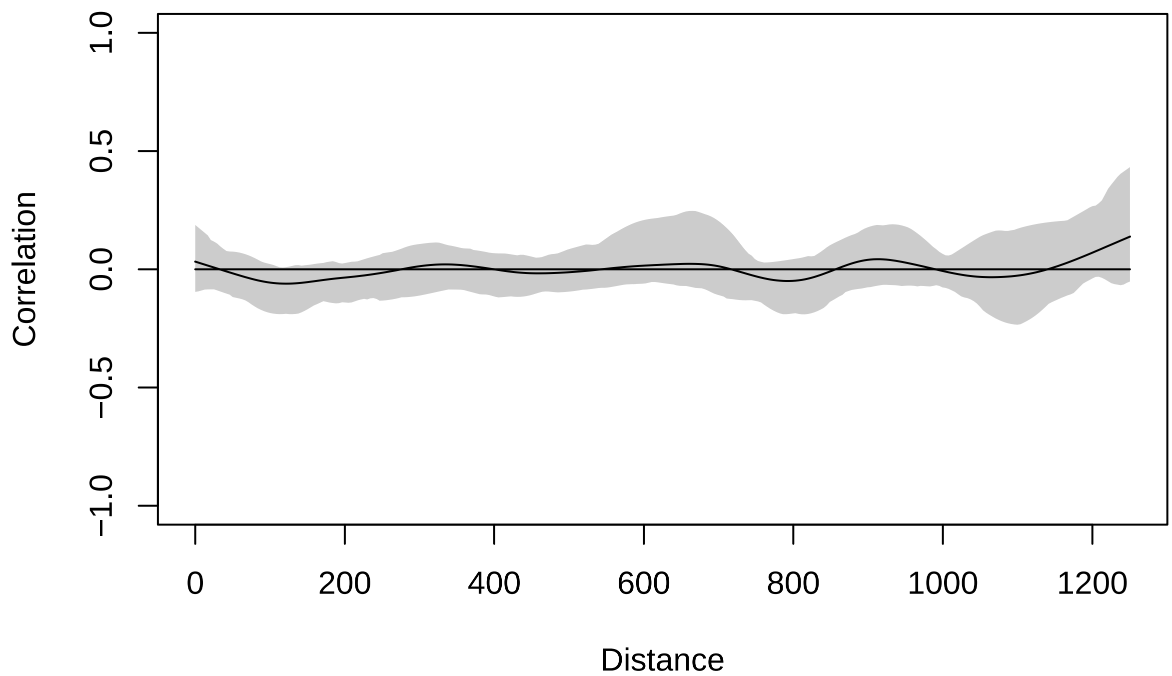

```
plot(correlog_selection_2018)
```




```
plot(spline.correlog_selection_2017)
```




```
plot(spline.correlog_selection_2018)
```



Moran's I

Calculation of global Moran's I with a permutation test (1000 random permutations), based on a connectivity matrix of pairwise Euclidean distances among the plants up to a distance of 30 m.

```
moran_selection_2017<- moran.mc(res_selection_2017,
                              listw=data_plants.listw_2017,nsim=999)
moran_selection_2018<- moran.mc(res_selection_2018,
                              listw=data_plants.listw_2018,nsim=999)
```

```
moran_selection_2017 # Significant autocorrelation in the residuals
```

```
##
##  Monte-Carlo simulation of Moran I
##
## data:  res_selection_2017
## weights: data_plants.listw_2017
## number of simulations + 1: 1000
##
## statistic = 0.097925, observed rank = 1000, p-value = 0.001
## alternative hypothesis: greater
```

```r
moran_selection_2018 # No significant autocorrelation in the residuals
```

```
##
##  Monte-Carlo simulation of Moran I
##
## data:  res_selection_2018
## weights: data_plants.listw_2018
## number of simulations + 1: 1000
##
## statistic = 0.025308, observed rank = 772, p-value = 0.228
## alternative hypothesis: greater
```

Moran's eigenvector mapping

```r
ME.selection_2017 <-ME(selection_2017,listw=data_plants.listw_2017,
               data=subset(data_plants,year==2017),
               alpha=0.05,verbose=T)
```

```
## eV[,3], I: 0.0498509 ZI: NA, pr(ZI): 0.02
## eV[,11], I: 0.01902798 ZI: NA, pr(ZI): 0.11
```

```r
vector1_2017_selection<-ME.selection_2017$vectors[,1]
vector2_2017_selection<-ME.selection_2017$vectors[,2]

selection_2017_ME<-lm(nseed_rel~ffd_std*temp+nfl_std+
                        vector1_2017_selection+vector2_2017_selection,
                     subset(data_plants,year==2017))
summ(selection_2017_ME)
```

Observations	245
Dependent variable	nseed_rel
Type	OLS linear regression

F(6,238)	41.275
R^2	0.510
Adj. R^2	0.498

	Est.	S.E.	t val.	p
(Intercept)	1.377	0.163	8.456	0.000
ffd_std	0.422	0.200	2.113	0.036
temp	-0.029	0.010	-2.848	0.005
nfl_std	1.150	0.086	13.326	0.000
vector1_2017_selection	-4.244	1.158	-3.666	0.000
vector2_2017_selection	-3.725	1.188	-3.135	0.002
ffd_std:temp	-0.012	0.010	-1.284	0.200

Standard errors: OLS

Tests of residual spatial autocorrelation

```
res_selection_2017_ME<-residuals(selection_2017_ME)
```

```
correlog_selection_2017_ME <- correlog(x=subset(data_plants,year==2017)$x,
                              y=subset(data_plants,year==2017)$y,
                              res_selection_2017_ME,increment=1, resamp=100,quiet=F)
```

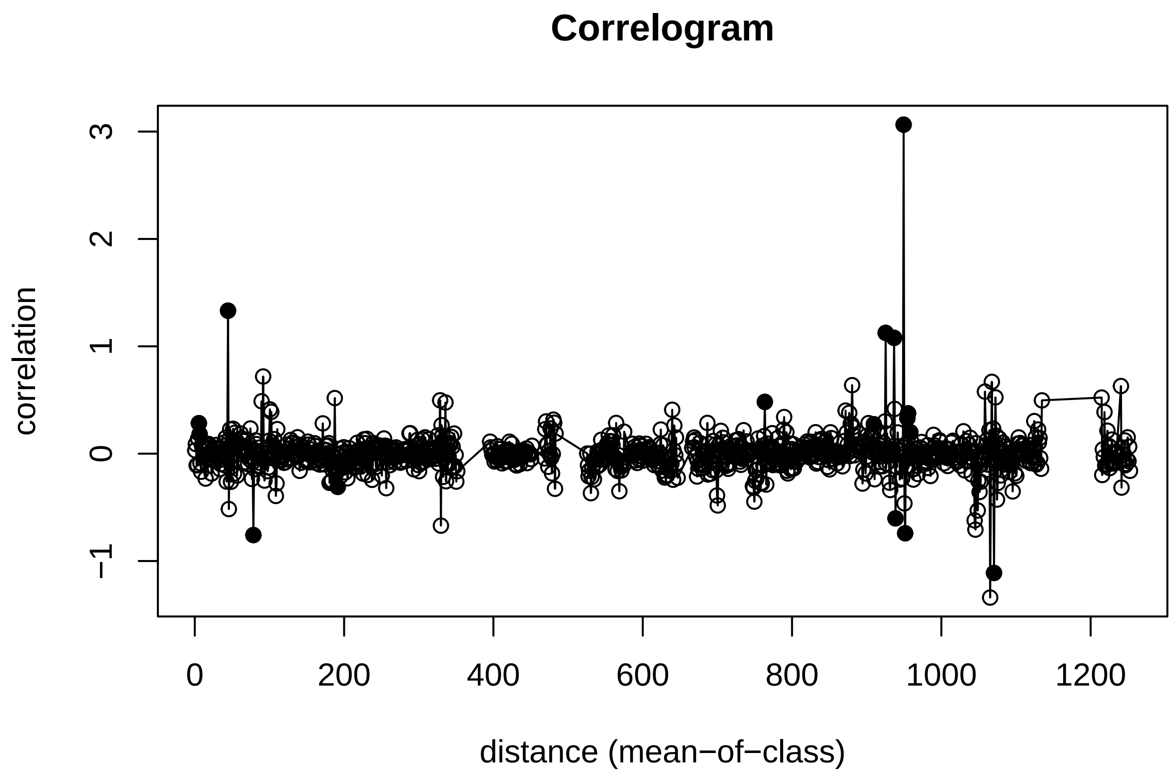
Spatial correlograms

```
## 10  of  100 20  of  100 30  of  100 40  of  100 50  of  100 60  of  100 70  of  100 80  of  100 90  o
```

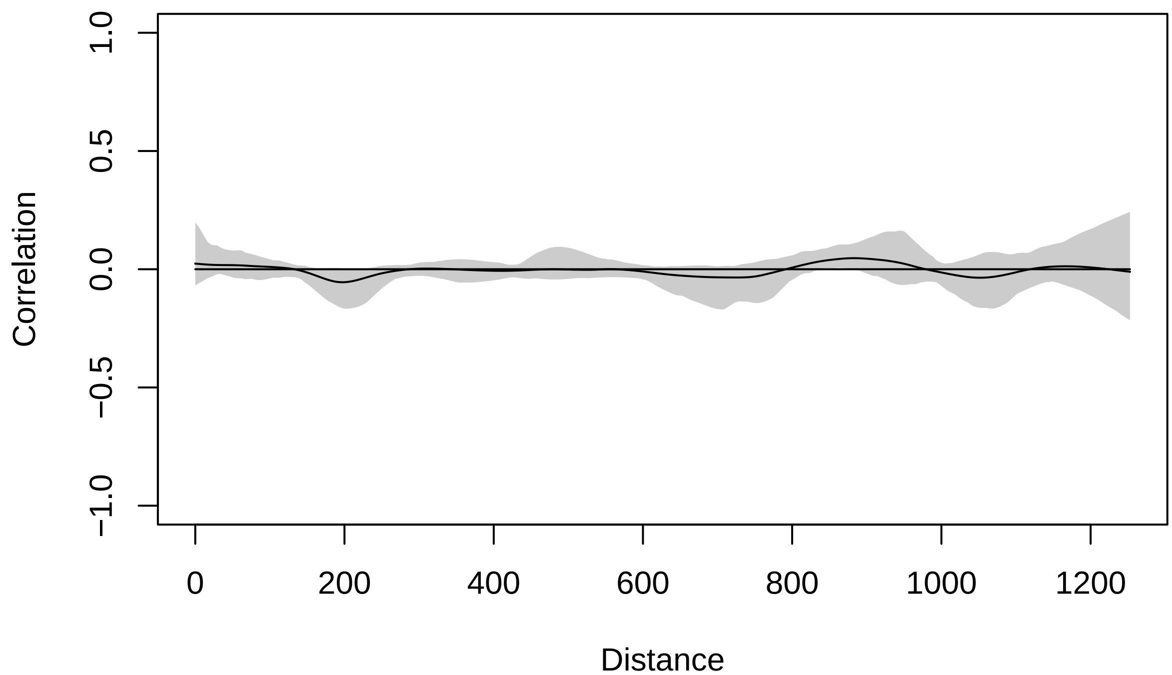
```
spline.correlog_selection_2017_ME <- spline.correlog(x=subset(data_plants,year==2017)$x,
                              y=subset(data_plants,year==2017)$y,
                              res_selection_2017_ME,resamp=100,quiet=F,type="boot")
```

```
## 10  of  100 20  of  100 30  of  100 40  of  100 50  of  100 60  of  100 70  of  100 80  of  100 90  o
```

```
plot(correlog_selection_2017_ME)
```



```r
plot(spline.correlog_selection_2017_ME)
```



Moran's I Calculation of global Moran's I with a permutation test (1000 random permutations), based on a connectivity matrix of pairwise Euclidean distances among the plants up to a distance of 30 m.

```r
res_selection_2017_ME<-residuals(selection_2017_ME)
moran_selection_2017_ME<- moran.mc(res_selection_2017_ME,
                                   listw=data_plants.listw_2017,nsim=999)
```

```r
moran_selection_2017_ME # No significant autocorrelation in the residuals
```

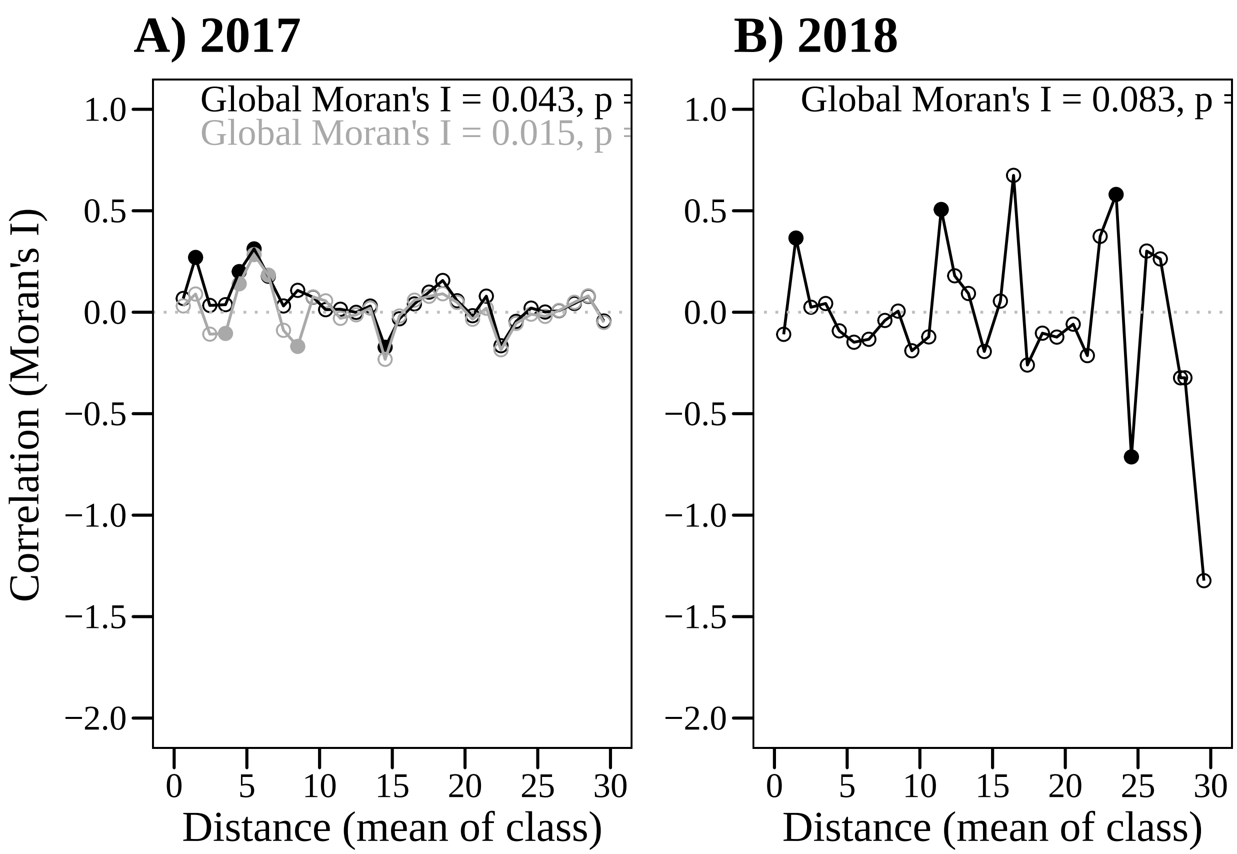
```
##
##  Monte-Carlo simulation of Moran I
##
## data:  res_selection_2017_ME
## weights: data_plants.listw_2017
## number of simulations + 1: 1000
##
## statistic = 0.019028, observed rank = 876, p-value = 0.124
## alternative hypothesis: greater
```

Plots SI

```r
# selection_2017
corr_selection_2017<-data.frame(cbind(distance=
                              as.vector(correlog_selection_2017$mean.of.class[1:31]),
                      correlation=as.vector(correlog_selection_2017$correlation[1:31]),
                      p=as.vector(correlog_selection_2017$p[1:31])))
corr_selection_2017_ME<-data.frame(cbind(distance=
                                 as.vector(
                                   correlog_selection_2017_ME$mean.of.class[1:31]),
                               correlation=
                                 as.vector(correlog_selection_2017_ME$correlation[1:31]),
                                p=as.vector(correlog_selection_2017_ME$p[1:31])))
corr_selection_2017$type<-"selection_2017"
corr_selection_2017_ME$type<-"selection_2017_ME"
corr_selection_2017<-rbind(corr_selection_2017,corr_selection_2017_ME)
corr_selection_2017$sig<-as.factor(ifelse(corr_selection_2017$p<0.05,1,0))

# selection_2018
corr_selection_2018<-data.frame(cbind(distance=
                              as.vector(correlog_selection_2018$mean.of.class[1:31]),
                      correlation=as.vector(correlog_selection_2018$correlation[1:31]),
                      p=as.vector(correlog_selection_2018$p[1:31])))
corr_selection_2018$sig<-as.factor(ifelse(corr_selection_2018$p<0.05,1,0))
```

```r
# CHANGE MORAN'S I VALUES
App_selection<-grid.arrange(
  ggplot(corr_selection_2017,aes(x=distance, y=correlation)) +
    geom_point(aes(colour=type,shape=sig),size=2) +
    geom_line(aes(colour=type)) + ylab(NULL)+
    scale_x_continuous("Distance (mean of class)",limits=c(0,30),
                       breaks=c(0,5,10,15,20,25,30)) +
    scale_y_continuous(limits=c(-2,1),
                       breaks = seq(-2,1,0.5))+
    scale_shape_manual(values=c(1,19))+
    scale_color_manual(values=c("black","darkgrey"))+
    geom_hline(aes(yintercept=0), colour="grey",linetype=3)+
    my_theme()+ggtitle("A) 2017")+
    annotation_custom(grobTree(textGrob("Global Moran's I = 0.043, p = 0.027",
                                        x=0.1,y=0.97,hjust=0,
                                        gp=gpar(col="black",fontsize=14,
                                                fontfamily="serif"))))+
    annotation_custom(grobTree(textGrob("Global Moran's I = 0.015, p = 0.174",
                                        x=0.1,y=0.92,hjust=0,
                                        gp=gpar(col="darkgrey",fontsize=14,
                                                fontfamily="serif")))),
  ggplot(corr_selection_2018,aes(x=distance, y=correlation)) +
    geom_point(aes(shape=sig),size=2,color="black") +
    geom_line(color="black") + ylab(NULL)+
    scale_x_continuous("Distance (mean of class)",limits=c(0,30),
                       breaks=c(0,5,10,15,20,25,30)) +
    scale_y_continuous(limits=c(-2,1),
                       breaks = seq(-2,1,0.5))+
```

```
    scale_shape_manual(values=c(1,19))+
    geom_hline(aes(yintercept=0), colour="grey",linetype=3)+
    my_theme()+ggtitle("B) 2018")+
    annotation_custom(grobTree(textGrob("Global Moran's I = 0.083, p = 0.035",
                                        x=0.1,y=0.97,hjust=0,
                                        gp=gpar(col="black",fontsize=14,
                                                fontfamily="serif")))),
  ncol=2,left=textGrob("Correlation (Moran's I)",just="center",
                      hjust=0.42,
                      gp=gpar(fontsize=16,fontfamily="serif"),
                      rot = 90))
```




```
ggsave(filename="output/figures/App_selection.tiff",
       plot=App_selection,device="tiff",width=28,height=12,units="cm",dpi=300,
       compression="lzw")
```

R Session Info

```
sessionInfo()
```

```
## R version 4.1.2 (2021-11-01)
## Platform: x86_64-w64-mingw32/x64 (64-bit)
```

```
## Running under: Windows 10 x64 (build 19043)
##
## Matrix products: default
##
## locale:
## [1] LC_COLLATE=English_Sweden.1252  LC_CTYPE=English_Sweden.1252
## [3] LC_MONETARY=English_Sweden.1252 LC_NUMERIC=C
## [5] LC_TIME=English_Sweden.1252
##
## attached base packages:
## [1] grid      stats     graphics  grDevices utils     datasets  methods
## [8] base
##
## other attached packages:
##  [1] spatialreg_1.2-1   Matrix_1.4-0       spdep_1.2-1        sf_1.0-5
##  [5] spData_2.0.1       ncf_1.2-9          sp_1.4-6           foreign_0.8-82
##  [9] ggrepel_0.9.1      viridis_0.6.2      viridisLite_0.4.0  car_3.0-12
## [13] lmtest_0.9-39      zoo_1.8-9          ggforce_0.3.3      lubridate_1.8.0
## [17] effects_4.2-1      carData_3.0-5      segmented_1.3-4    MASS_7.3-54
## [21] MuMIn_1.43.17      ggeffects_1.1.1    kableExtra_1.3.4   jtools_2.1.4
## [25] ggpubr_0.4.0       broom_0.7.11       RColorBrewer_1.1-2 DHARMa_0.4.5
## [29] gridExtra_2.3      knitr_1.37         ggthemes_4.2.4     forcats_0.5.1
## [33] stringr_1.4.0      dplyr_1.0.6        purrr_0.3.4        readr_2.1.1
## [37] tidyr_1.1.4        tibble_3.1.2       ggplot2_3.3.5      tidyverse_1.3.1
##
## loaded via a namespace (and not attached):
##  [1] readxl_1.3.1       backports_1.4.1    systemfonts_1.0.3  splines_4.1.2
##  [5] digest_0.6.27      htmltools_0.5.2    gdata_2.18.0       fansi_0.4.2
##  [9] magrittr_2.0.1     tzdb_0.2.0         modelr_0.1.8       gmodels_2.18.1
## [13] vroom_1.5.7        svglite_2.0.0      colorspace_2.0-1   rvest_1.0.2
## [17] mitools_2.4        haven_2.4.3        xfun_0.29          rgdal_1.5-28
## [21] crayon_1.4.2       jsonlite_1.7.3     lme4_1.1-27.1      survival_3.2-13
## [25] glue_1.4.2         polyclip_1.10-0    gtable_0.3.0       webshot_0.5.2
## [29] abind_1.4-5        scales_1.1.1       DBI_1.1.2          rstatix_0.7.0
## [33] Rcpp_1.0.8         units_0.7-2        bit_4.0.4          proxy_0.4-26
## [37] stats4_4.1.2       survey_4.1-1       httr_1.4.2         wk_0.6.0
## [41] ellipsis_0.3.2     pkgconfig_2.0.3    farver_2.1.0       nnet_7.3-17
## [45] dbplyr_2.1.1       deldir_1.0-6       utf8_1.2.1         labeling_0.4.2
## [49] tidyselect_1.1.1   rlang_0.4.10       munsell_0.5.0      cellranger_1.1.0
## [53] tools_4.1.2        cli_3.1.1          generics_0.1.1     sjlabelled_1.1.8
## [57] evaluate_0.14      fastmap_1.1.0      yaml_2.2.2         bit64_4.0.5
## [61] fs_1.5.2           pander_0.6.4       s2_1.0.7           nlme_3.1-155
## [65] xml2_1.3.3         compiler_4.1.2     rstudioapi_0.13    e1071_1.7-9
## [69] ggsignif_0.6.3     reprex_2.0.1       tweenr_1.0.2       stringi_1.7.6
## [73] highr_0.9          lattice_0.20-45    classInt_0.4-3     nloptr_1.2.2.3
## [77] vctrs_0.3.8        pillar_1.6.1       LearnBayes_2.15.1  lifecycle_1.0.1
## [81] cowplot_1.1.1      insight_0.15.0     raster_3.4-10      R6_2.5.1
## [85] KernSmooth_2.23-20 codetools_0.2-18   boot_1.3-28        gtools_3.9.2
## [89] assertthat_0.2.1   withr_2.4.3        mgcv_1.8-38        expm_0.999-6
## [93] parallel_4.1.2     hms_1.1.1          coda_0.19-4        class_7.3-20
## [97] minqa_1.2.4        rmarkdown_2.11
```