Analyses of species distributions in peatlands

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21 October, 2024

Contents

Load the R packages that you will use

If you do not have the R packages installed, you need to install them.

```
library(tidyverse)
library(readxl)
library(knitr)
library(ggeffects)
library(car)
library(glmmTMB)
library(ggplot2)
library(vegan)
library(rdacca.hp)
library(gridExtra)
library(ggthemes)
library(egg)
library(cowplot)
library(BiodiversityR)
library(ggrepel)
library(performance)
library(sjPlot)
library(DHARMa)
library(extrafont)
library(caret)
```

Data preparation

Read data from Excel file

Note that you need to change the path to the folder where you have the Excel file

```r
data_peat<-read_excel("data/edited/Modelling_SDM_species_data.xlsx",
                      sheet="SDM Data")
```

Have a look at the data

This shows the first rows of your data file in "tibble" format. You can also see the variable type for each variable (double or character).

```r
data_peat
```

```
## # A tibble: 115 x 29
##    n_samples depth depth_corrected fen   tot_Sphagnum  Erio Carex Erica
##        <dbl> <chr>           <dbl> <chr>        <dbl> <dbl> <dbl> <dbl>
##  1         1 0                   0 N              100     0     0     0
##  2         2 14-15              14 N               87     3     2     8
##  3         3 20-21              20 N               74     6     6    14
##  4         4 30-31              30 N               87     5     4     4
##  5         5 40-41              40 N               90     2     3     5
##  6         6 50-51              50 N               41    46     9     4
##  7         7 55-56              55 N               74    19     6     1
##  8         8 60-61              60 N               94     4     1     1
##  9         9 65-66              65 N               95     3     1     1
## 10        10 70-71              70 N               90     3     4     3
##    other_veg Balticum Medium Cuspidata Austinii Fuscum Rubellum Acutifolia
##        <dbl>    <dbl>  <dbl>     <dbl>    <dbl>  <dbl>    <dbl>      <dbl>
##  1         0     32    68         0           0      0      0          0
##  2         0     72.4  25.3       2.30        0      0      0          0
##  3         0     32.4  64.9       0           0      0      0          2.70
##  4         0     26.4  27.6       0           0      0     36.8        9.20
##  5         0     18.9   5.56      3.33        0      0      0         72.2
##  6         0     17.1  41.5      22.0         0      0     19.5        0
##  7         0     56.8  21.6      21.6         0      0      0          0
##  8         0     48.9  38.3      12.8         0      0      0          0
##  9         0     58.9  26.3      14.7         0      0      0          0
## 10         0     54.4  11.1      34.4         0      0      0          0
##    `Diseased Acutifolia` Angustifolium Tenellum Papillosum Fallax Stems   age
##                    <dbl>         <dbl>    <dbl>      <dbl>  <dbl> <dbl> <dbl>
##  1                     0             0        0          0      0     0     0
##  2                     0             0        0          0      0     0    75
##  3                     0             0        0          0      0     0   136
##  4                     0             0        0          0      0     0   244
##  5                     0             0        0          0      0     0   352
##  6                     0             0        0          0      0     0   452
##  7                     0             0        0          0      0     0   505
##  8                     0             0        0          0      0     0   555
##  9                     0             0        0          0      0     0   606
## 10                     0             0        0          0      0     0   643
##     temp imp_temp moist nutrient  fire   dry
##    <dbl>    <dbl> <chr>    <dbl> <dbl> <dbl>
##  1  6.35        0 NA           0     0     0
##  2  6.92        1 NA           0     0     0
##  3  7.39        1 NA           0     0     0
```

```
## 4  8.21        0 NA          0     0     0
## 5  8.00        1 -0.38       1     0     0
## 6  7.81        1 -0.3        1     0     0
## 7  7.71        1 0.01        1     0     0
## 8  7.62        1 -0.26       1     0     0
## 9  7.52        1 0.22        1     0     0
## 10 7.45        1 -0.25       1     0     0
## # i 105 more rows
```

Convert some variables to factors

It is better to convert some variables (those that are Y/N or 0/1) to factors.

```
data_peat<-data_peat%>%
  mutate(fen=as.factor(fen),imp_temp=as.factor(imp_temp),
         nutrient=as.factor(nutrient),fire=as.factor(fire),dry=as.factor(dry))
# with mutate you create new variables that are equal to the old variables
# but are coded as factors
```

Convert moist to numeric

For some reason, moist appears as a character variable. It should be numeric, so we convert it.

```
data_peat<-data_peat%>%
  mutate(moist=as.numeric(moist))
```

Ordinations (vegan package)

Suggested reading: https://www.davidzeleny.net/anadat-r/doku.php/en:ordination

(lots of info on this webpage!)

Chapter 10 in this pdf: https://apps.worldagroforestry.org/downloads/Publications/PDFS/b13695.pdf

Using the vegan package.

Constrained ordination, specifically a Distance-based redundancy analysis (db-RDA) with Bray-Curtis distance. You can read about all types in the webpage above if you feel like it.

Conditioned or partial ordination: we can set age as a conditioning term that is "partialled out" from the analysis before constraints, i.e. the effect of age is partialled out before analysing the effects of the other variables (temp, moist, nutrient, fire and dry). Thus, this is now a partial db-RDA analysis conditioned on age.

Data for ordination:

```
data_ordi2<-data_peat %>%
  filter_at(vars(Balticum:Fallax),
            all_vars(!is.na(.)))%>% # Remove rows with all NAs
  filter_at(vars(Balticum:Fallax),
            any_vars(.>0))%>% # Remove rows with all zeros - WHY?
  filter(!is.na(age)&!is.na(temp)&!is.na(moist)&!is.na(nutrient)&!is.na(fire)&
           !is.na(dry))%>% # Remove rows with NA in predictors
  rename(Deformed_Acutifolia=`Diseased Acutifolia`) #Rename to avoid problems
```

Partial distance-based redundancy analysis (db-RDA) with Bray-Curtis distance.

See https://www.davidzeleny.net/anadat-r/doku.php/en:similarity for info on distances.

Wtih age as condition

Calculate ordination:

```
ordination<-capscale(data_ordi2[10:21]~ # species data matrix
                       temp+moist+nutrient+fire+dry+ # Environmental variables
                       Condition(age), # Age is "partialled out" before constraints
                     data = data_ordi2, distance="bray") # Bray-Curtis distance
```

Result of the ordination:

```
ordination
```

```
## Call: capscale(formula = data_ordi2[10:21] ~ temp + moist + nutrient +
## fire + dry + Condition(age), data = data_ordi2, distance = "bray")
##
##               Inertia Proportion Rank
## Total         31.0247
## RealTotal     34.7843     1.0000
## Conditional    3.6259     0.1042    1
## Constrained    4.7631     0.1369    5
## Unconstrained 26.3953     0.7588   34
## Imaginary     -3.7596
## Inertia is squared Bray distance
## Species scores projected from '[' 'data_ordi2' '10:21'
##
## Eigenvalues for constrained axes:
##  CAP1  CAP2  CAP3  CAP4  CAP5
## 3.393 0.780 0.337 0.162 0.091
##
## Eigenvalues for unconstrained axes:
##  MDS1  MDS2  MDS3  MDS4  MDS5  MDS6  MDS7  MDS8
## 7.438 4.231 3.327 2.484 2.345 2.009 1.231 0.598
## (Showing 8 of 34 unconstrained eigenvalues)
```

"Intertia" is the total variance - your environmental variables explain 0.1369 of this variance ("constrained" part).

Proportion explained by each ordination axis. CAP1-CAP5 are the "constrained" axes, explained by your environmental variables. MDS1-MDS34 are the "unconstrained" axes.

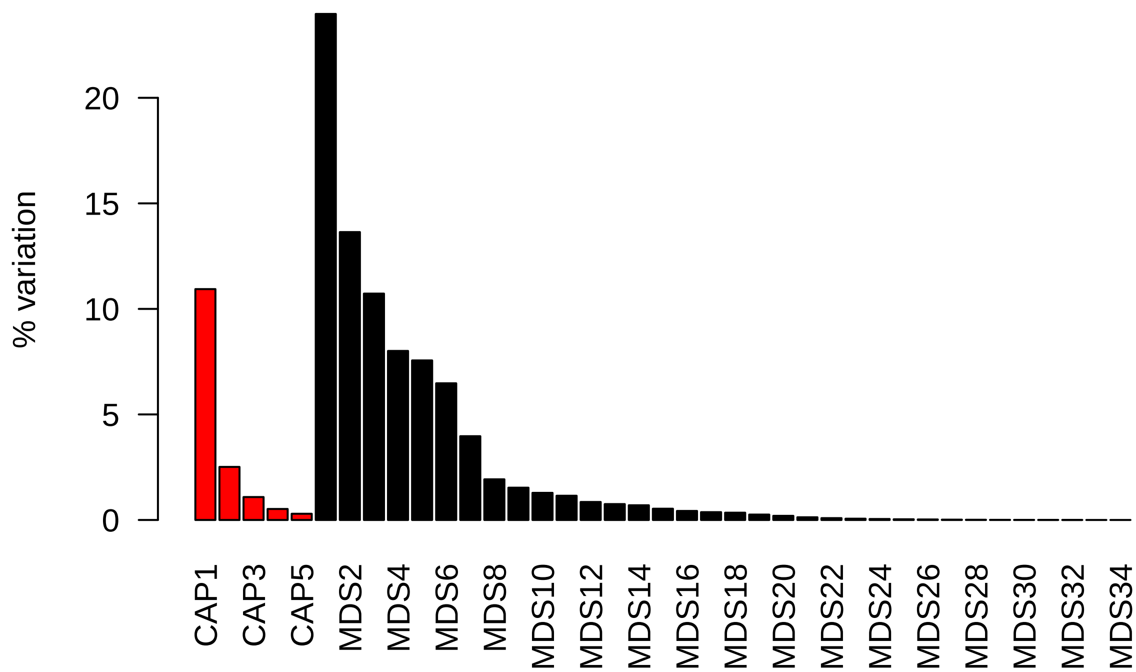
```
eigenvals(ordination) %>%
  summary()
```

```
## Importance of components:
##                         CAP1    CAP2    CAP3     CAP4     CAP5   MDS1   MDS2
## Eigenvalue            3.3933 0.77980 0.33695 0.161578 0.091465 7.4376 4.2314
## Proportion Explained  0.1089 0.02503 0.01081 0.005186 0.002935 0.2387 0.1358
```

```
## Cumulative Proportion 0.1089 0.13393 0.14475 0.149932 0.152868 0.3916 0.5274
##                          MDS3    MDS4    MDS5    MDS6    MDS7    MDS8    MDS9
## Eigenvalue             3.3274 2.48429 2.34529 2.00858 1.23102 0.59753 0.47441
## Proportion Explained  0.1068 0.07973 0.07527 0.06446 0.03951 0.01918 0.01523
## Cumulative Proportion 0.6342 0.71390 0.78917 0.85363 0.89314 0.91232 0.92754
##                          MDS10   MDS11    MDS12    MDS13    MDS14    MDS15
## Eigenvalue             0.39839 0.35604 0.264432 0.233304 0.216297 0.165550
## Proportion Explained  0.01279 0.01143 0.008487 0.007488 0.006942 0.005313
## Cumulative Proportion 0.94033 0.95175 0.960241 0.967728 0.974670 0.979983
##                          MDS16    MDS17    MDS18    MDS19    MDS20    MDS21
## Eigenvalue             0.13273 0.114764 0.107089 0.079177 0.060863 0.039731
## Proportion Explained  0.00426 0.003683 0.003437 0.002541 0.001953 0.001275
## Cumulative Proportion 0.98424 0.987927 0.991364 0.993905 0.995858 0.997133
##                            MDS22     MDS23     MDS24     MDS25    MDS26
## Eigenvalue             0.0271939 0.0187321 0.0140133 0.0100910 0.007259
## Proportion Explained  0.0008728 0.0006012 0.0004497 0.0003239 0.000233
## Cumulative Proportion 0.9980060 0.9986072 0.9990569 0.9993808 0.999614
##                            MDS27     MDS28     MDS29     MDS30     MDS31
## Eigenvalue             0.0045627 3.097e-03 0.0018197 1.307e-03 7.537e-04
## Proportion Explained  0.0001464 9.941e-05 0.0000584 4.194e-05 2.419e-05
## Cumulative Proportion 0.9997602 9.999e-01 0.9999180 1.000e+00 1.000e+00
##                            MDS32     MDS33     MDS34
## Eigenvalue             4.030e-04 9.125e-05 9.071e-07
## Proportion Explained  1.293e-05 2.929e-06 2.911e-08
## Cumulative Proportion 1.000e+00 1.000e+00 1.000e+00
```

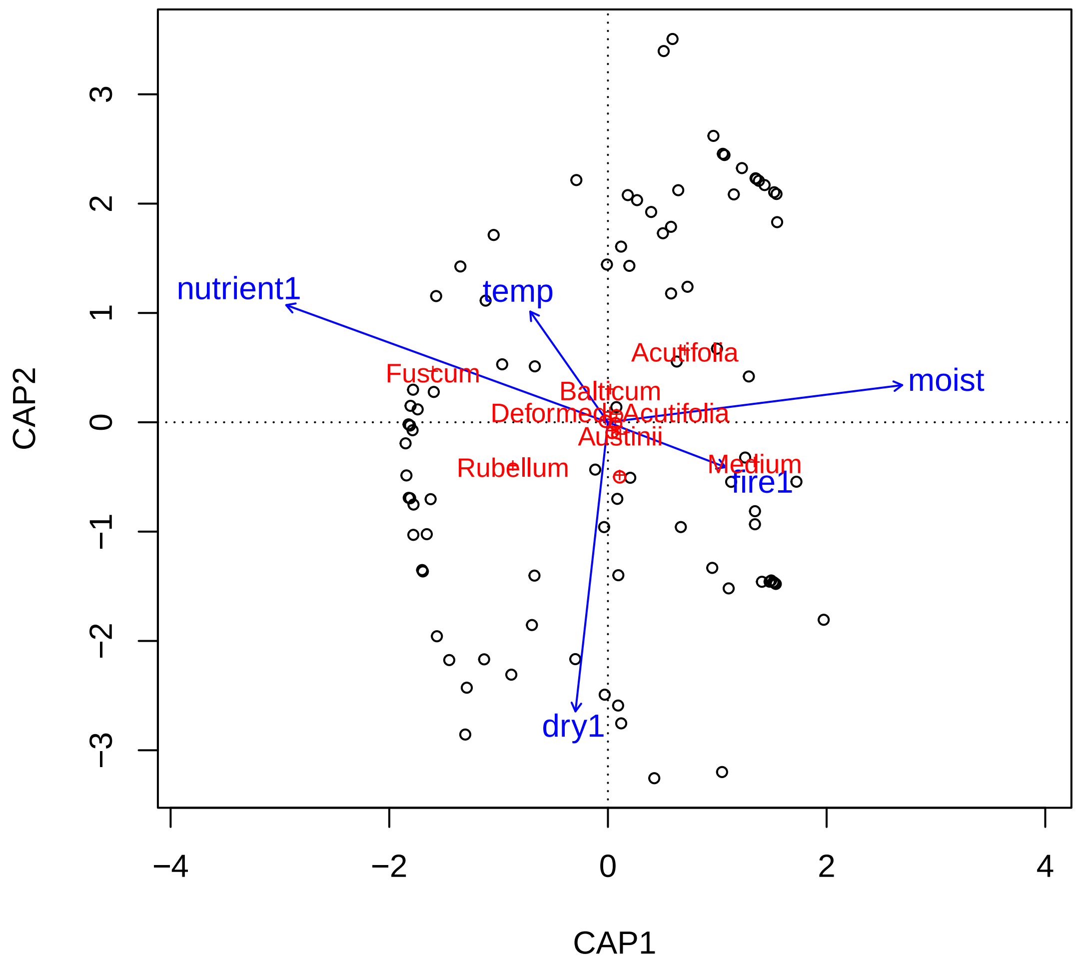
Barplot of percentage variance explained by individual axes

```
expl_var_ordination <- c(ordination$CCA$eig/ordination$tot.chi*100,
                         ordination$CA$eig/ordination$tot.chi*100)
barplot (expl_var_ordination,
         col = c(rep ('red',
                      length (ordination$CCA$eig/ordination$tot.chi*100)),
                 rep ('black',
                      length (ordination$CA$eig/ordination$tot.chi*100))),
         las = 2, ylab = '% variation')
```



Plot of the ordination (species in red and sites-samples in black):

```
vegan::ordiplot(ordination,display = c('species', 'sites', 'bp'))
orditorp(ordination,display="species",cex=0.8,col="red")
```



This shows the two first constrained axes of the ordination. You can see how the sites and species distribute along these axes.

Test significance of the ordination with Monte Carlo permutation test.

For the whole model:

```
anova (ordination, permutations = 999)
```

```
## Permutation test for capscale under reduced model
## Permutation: free
## Number of permutations: 999
##
## Model: capscale(formula = data_ordi2[10:21] ~ temp + moist + nutrient + fire + dry + Condition(age),
##          Df SumOfSqs      F Pr(>F)
## Model     5   4.7631 2.8872  0.001 ***
## Residual 80  26.3953
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

The model is significant.

For each explanatory variable (with all the others used as covariables, independently from their order in the model):

```r
anova (ordination, by = 'margin', permutations = 999)
```

```
## Permutation test for capscale under reduced model
## Marginal effects of terms
## Permutation: free
## Number of permutations: 999
##
## Model: capscale(formula = data_ordi2[10:21] ~ temp + moist + nutrient + fire + dry + Condition(age),
##          Df SumOfSqs      F Pr(>F)
## temp      1   0.3226 0.9778  0.429
## moist     1   0.8303 2.5164  0.017 *
## nutrient  1   1.1292 3.4225  0.003 **
## fire      1   0.1145 0.3471  0.958
## dry       1   0.8159 2.4728  0.020 *
## Residual 80  26.3953
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Moist, nutrient and dry show significant effects.

For each axis:

```r
anova (ordination, by = 'axis', permutations = 999)
```

```
## Permutation test for capscale under reduced model
## Forward tests for axes
## Permutation: free
## Number of permutations: 999
##
## Model: capscale(formula = data_ordi2[10:21] ~ temp + moist + nutrient + fire + dry + Condition(age),
##          Df SumOfSqs       F Pr(>F)
## CAP1      1   3.3933 10.2846  0.001 ***
## CAP2      1   0.7798  2.3635  0.260
## CAP3      1   0.3369  1.0212  0.901
## CAP4      1   0.1616  0.4897  0.985
## CAP5      1   0.0915  0.2772  0.989
## Residual 80  26.3953
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Only axis 1 is significant.

Ordination plot with ggplot2.

Install ggord package (you only need to do this once):

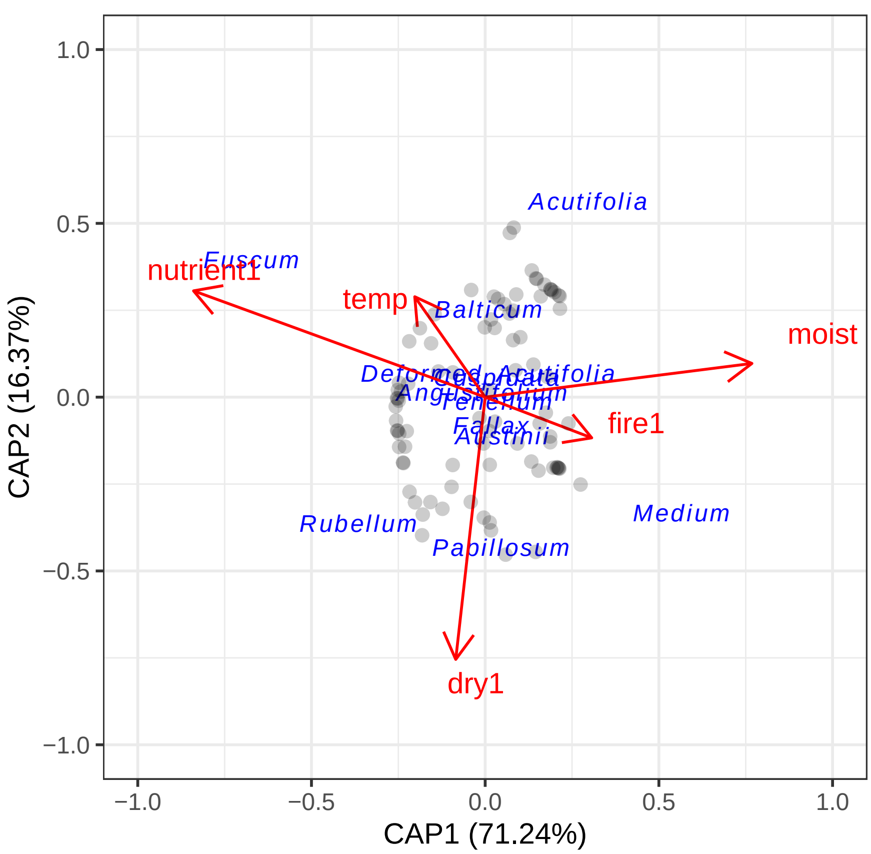
```
# Enable the r-universe repo
options(repos = c(
    fawda123 = 'https://fawda123.r-universe.dev',
    CRAN = 'https://cloud.r-project.org'))

# Install ggord
install.packages('ggord')
```

```
## package 'ggord' successfully unpacked and MD5 sums checked
##
## The downloaded binary packages are in
##   C:\Users\alici\AppData\Local\Temp\RtmpOcgiTa\downloaded_packages
```

Load ggord package:

```
library(ggord)
```

```
ggord(ordination,ptslab=T,repel=T,labcol="red",veccol="red",size=NA,addsize=3,
      xlims=c(-1.1,1.1),ylims=c(-1.1,1.1))+
  geom_point(size=3,shape=20,color="black",alpha=0.2)
```



Abundance models (zero-inflated beta regressions)

Without interactions

Check how many rows with each species absent:

```r
nrow(data_peat%>%filter(tot_Sphagnum==0))
```

```
## [1] 22
```

```r
nrow(data_peat%>%filter(Erio==0)) # 1 row
```

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

```r
nrow(data_peat%>%filter(Carex==0)) # 2 rows
```

```
## [1] 2
```

```r
nrow(data_peat%>%filter(Erica==0)) # 5 rows
```

```
## [1] 5
```

```r
nrow(data_peat%>%filter(Balticum==0))
```

```
## [1] 65
```

```r
nrow(data_peat%>%filter(Medium==0))
```

```
## [1] 49
```

```r
nrow(data_peat%>%filter(Cuspidata==0))
```

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

```r
nrow(data_peat%>%filter(Austinii==0))
```

```
## [1] 82
```

```r
nrow(data_peat%>%filter(Fuscum==0))
```

```
## [1] 56
```

```r
nrow(data_peat%>%filter(Rubellum==0))
```

```
## [1] 61
```

More species?

Erio, Erica and Carex have too few rows with absences. Presence/absence models will not work for these species. Fit models only for the abundance of those species.

Abundance of Medium and Fuscum includes 0 and 100 - change 100 to 99.

```
data_peat$Medium<-ifelse(data_peat$Medium>99,99,data_peat$Medium)
data_peat$Fuscum<-ifelse(data_peat$Fuscum>99,99,data_peat$Fuscum)
```

Convert variables to proportions (from 0 to 1) instead of percentages:

```
data_peat<-data_peat%>%
  mutate(tot_Sphagnum_prop=tot_Sphagnum/100,
         Erio_prop=Erio/100,
         Erica_prop=Erica/100,
         Carex_prop=Carex/100,
         Medium_prop=Medium/100,
         Fuscum_prop=Fuscum/100,
         Rubellum_prop=Rubellum/100,
         Balticum_prop=Balticum/100,
         Cuspidata_prop=Cuspidata/100)
```

Check combinations of the three factors and the fen-bog factor:

```
with(data_peat,table(fen,nutrient))
```

```
##    nutrient
## fen  0  1
##   N 33 50
##   Y 32  0
```

```
with(data_peat,table(fen,fire))
```

```
##    fire
## fen  0  1
##   N 71 12
##   Y 26  6
```

```
with(data_peat,table(fen,dry))
```

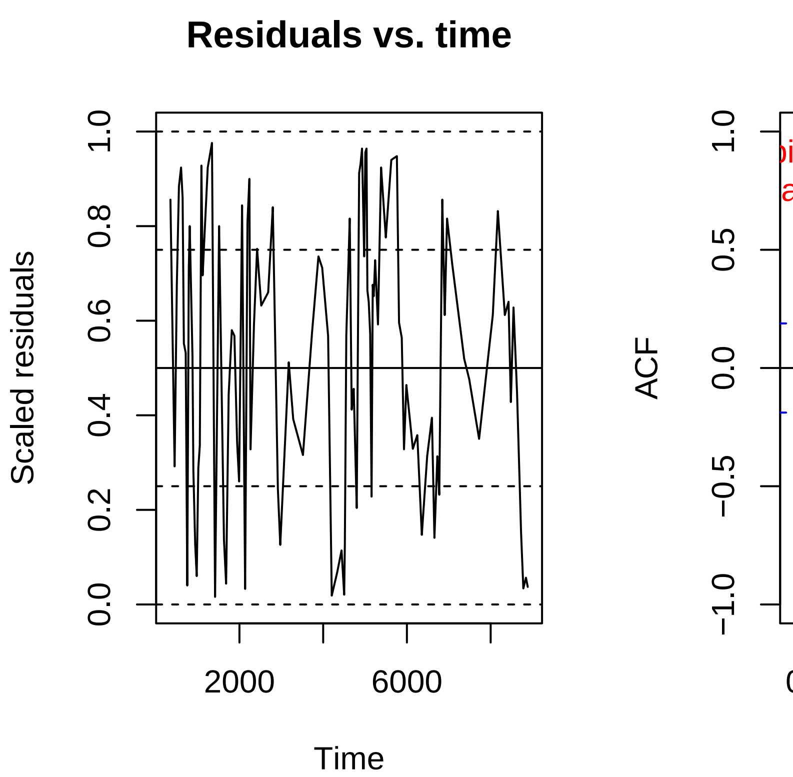
```
##    dry
## fen  0  1
##   N 52 31
##   Y 18 14
```

There are 0 cases where fen=Y and nutrient=1 so we will not be able to test the fen*nutrient interactions. We can include all interactions but this one in the models.

Plant groups

```r
mod_abund_tot_Sphagnum_temp<-glmmTMB(tot_Sphagnum_prop~temp+moist+nutrient+
                                  fire+dry,family="beta_family",
                                ziformula=~.,data=data_peat)
mod_abund_Erio_nozi_temp<-glmmTMB(Erio_prop~temp+moist+nutrient+
                                  fire+dry,family="beta_family",
                                ziformula=~0,data=subset(data_peat,Erio_prop>0))
mod_abund_Erica_nozi_temp<-glmmTMB(Erica_prop~temp+moist+nutrient+
                                  fire+dry,family="beta_family",
                                  ziformula=~0, data_erica<-subset(data_peat,Erica>0))
mod_abund_Carex_nozi_temp<-glmmTMB(Carex_prop~temp+moist+nutrient+
                                  fire+dry,family="beta_family",
                                ziformula=~0,data=subset(data_peat,Carex_prop>0))
```

```r
testTemporalAutocorrelation(simulateResiduals(mod_abund_tot_Sphagnum_temp),
                            subset(data_peat,
                                   !is.na(tot_Sphagnum_prop)&!is.na(temp)&
                                     !is.na(moist)&!is.na(nutrient)&
                                     !is.na(fire)&!is.na(dry))$age, plot = T)
```

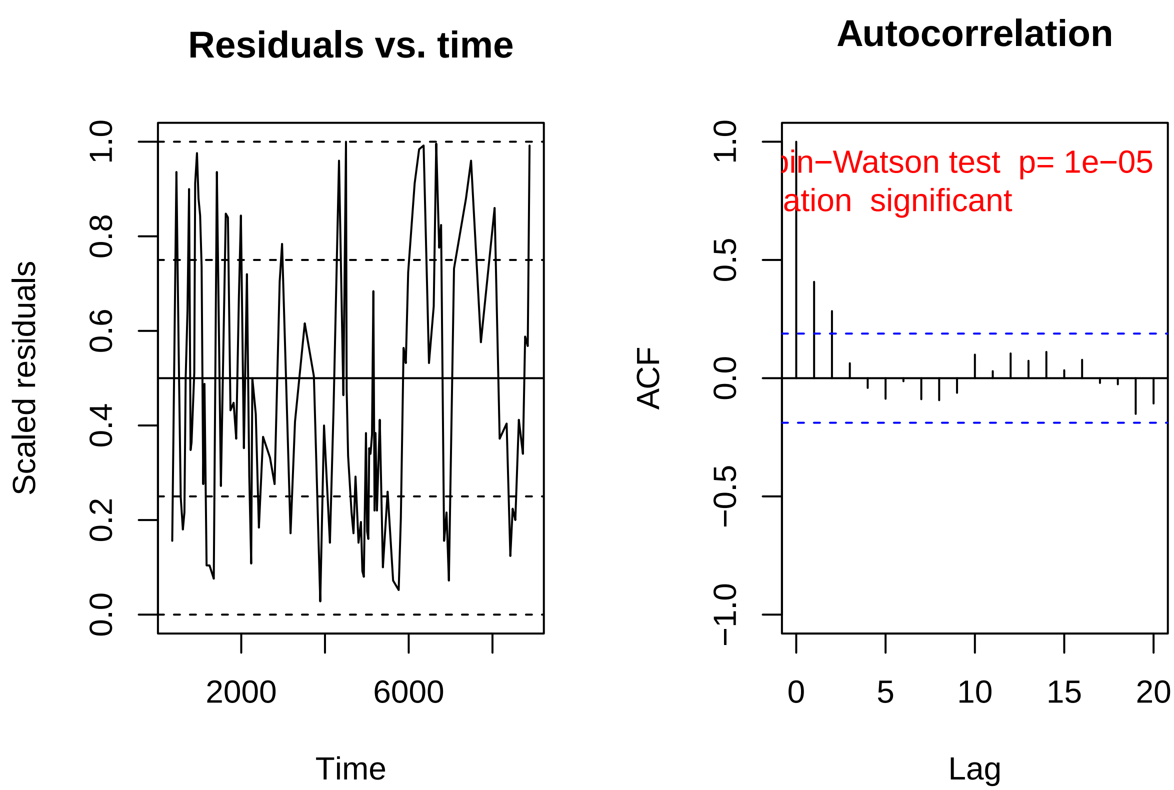


Check for temporal autocorrelation in residuals

```
##
##  Durbin-Watson test
```

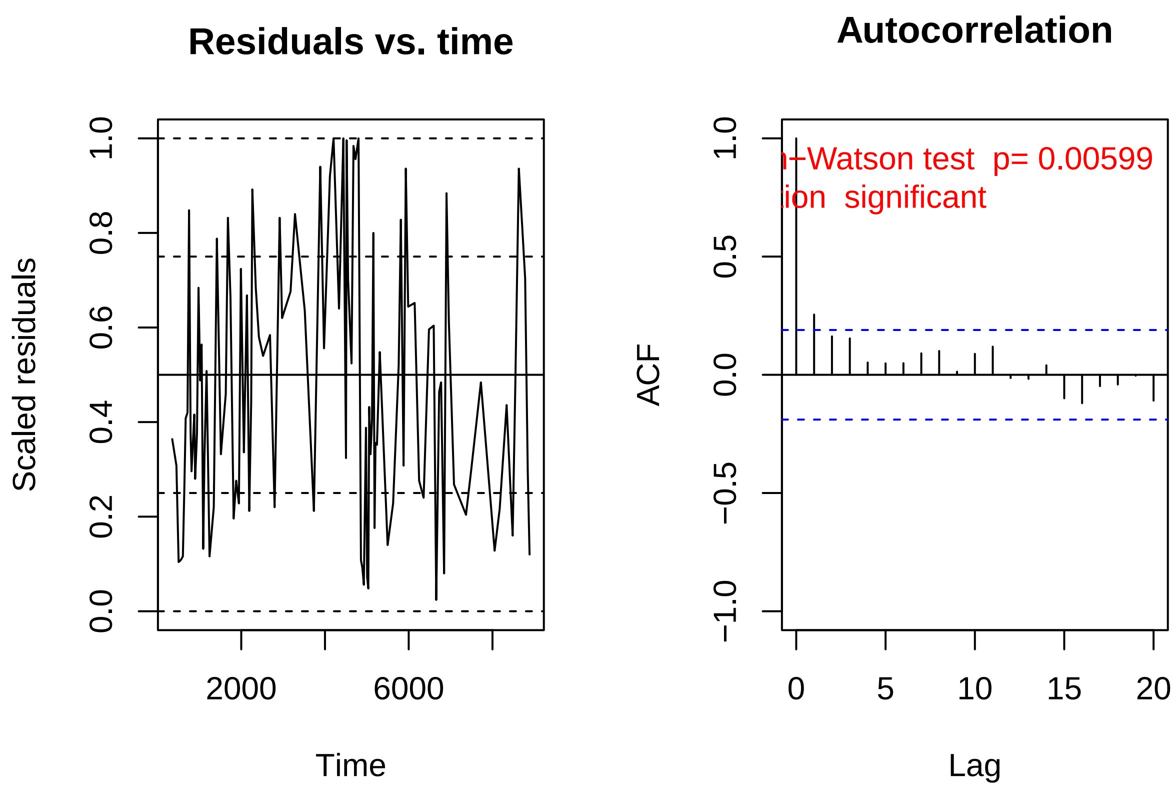
```
##
## data:  simulationOutput$scaledResiduals ~ 1
## DW = 1.1524, p-value = 8.779e-06
## alternative hypothesis: true autocorrelation is not 0
```

```
testTemporalAutocorrelation(simulateResiduals(mod_abund_Erio_nozi_temp),
                            subset(data_peat,
                                   Erio_prop>0&!is.na(temp)&
                                     !is.na(moist)&!is.na(nutrient)&
                                     !is.na(fire)&!is.na(dry))$age, plot = T)
```



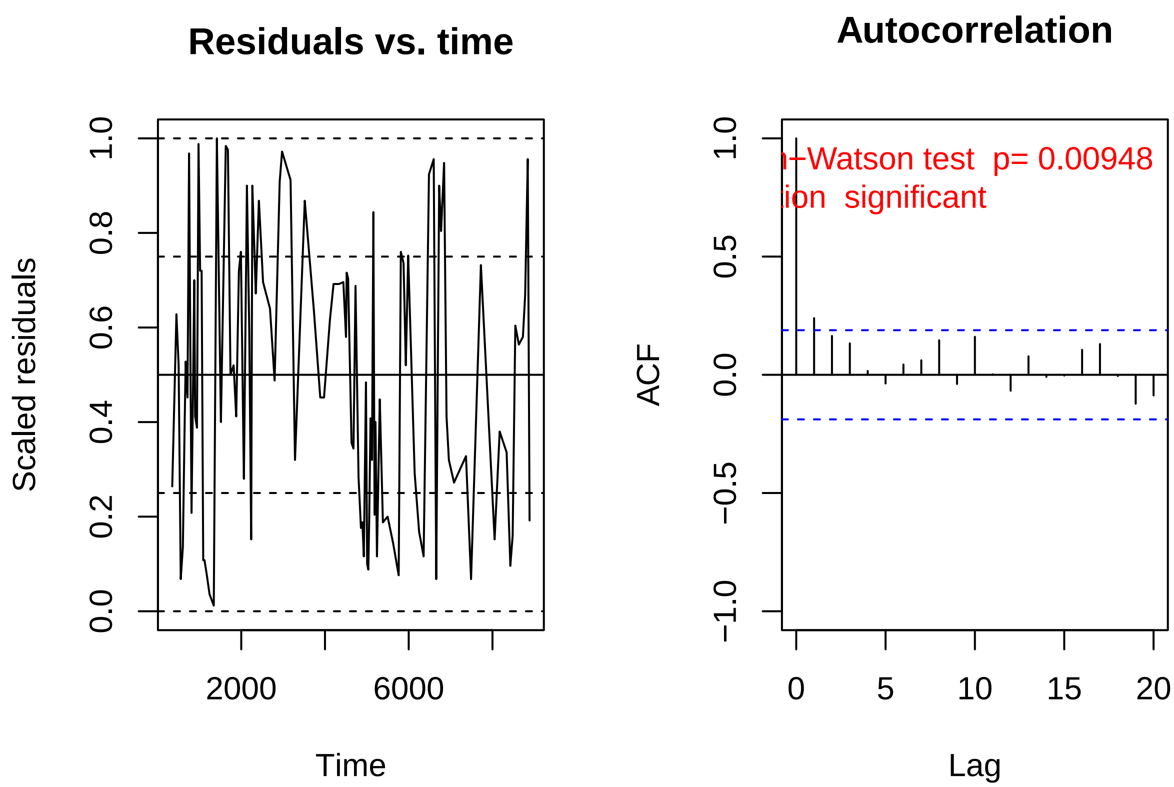

```
##
##  Durbin-Watson test
##
## data:  simulationOutput$scaledResiduals ~ 1
## DW = 1.1429, p-value = 6.953e-06
## alternative hypothesis: true autocorrelation is not 0
```

```
testTemporalAutocorrelation(simulateResiduals(mod_abund_Erica_nozi_temp),
                            subset(data_peat,
                                   Erica_prop>0&!is.na(temp)&
                                     !is.na(moist)&!is.na(nutrient)&
                                     !is.na(fire)&!is.na(dry))$age, plot = T)
```




```
##
##  Durbin-Watson test
##
## data:  simulationOutput$scaledResiduals ~ 1
## DW = 1.4736, p-value = 0.005989
## alternative hypothesis: true autocorrelation is not 0
```

```
testTemporalAutocorrelation(simulateResiduals(mod_abund_Carex_nozi_temp),
                            subset(data_peat,
                                   Carex_prop>0&!is.na(temp)&
                                     !is.na(moist)&!is.na(nutrient)&
                                     !is.na(fire)&!is.na(dry))$age, plot = T)
```




```
##
##  Durbin-Watson test
##
## data:  simulationOutput$scaledResiduals ~ 1
## DW = 1.5054, p-value = 0.00948
## alternative hypothesis: true autocorrelation is not 0
```

Significant autocorrelation in all models.

AR models Models including an autoregressive covariance structure (AR(1)), see: https://cran.r-project.org/web/packages/glmmTMB/vignettes/covstruct.html https://www.flutterbys.com.au/stats/tut/tut8.3a.html

Create data with no NAs and times and group variables:

```
data_peat_noNapredictors<-subset(data_peat,!is.na(temp)&!is.na(moist)&
                                    !is.na(nutrient)&!is.na(fire)&!is.na(dry))
times <- factor(data_peat_noNapredictors$age)
group <- factor(rep(1,108))

dat0 <- data.frame(tot_Sphagnum_prop=data_peat_noNapredictors$tot_Sphagnum_prop,
                   Erio_prop=data_peat_noNapredictors$Erio_prop,
                   Erica_prop=data_peat_noNapredictors$Erica_prop,
                   Carex_prop=data_peat_noNapredictors$Carex_prop,
                   temp=data_peat_noNapredictors$temp,
```

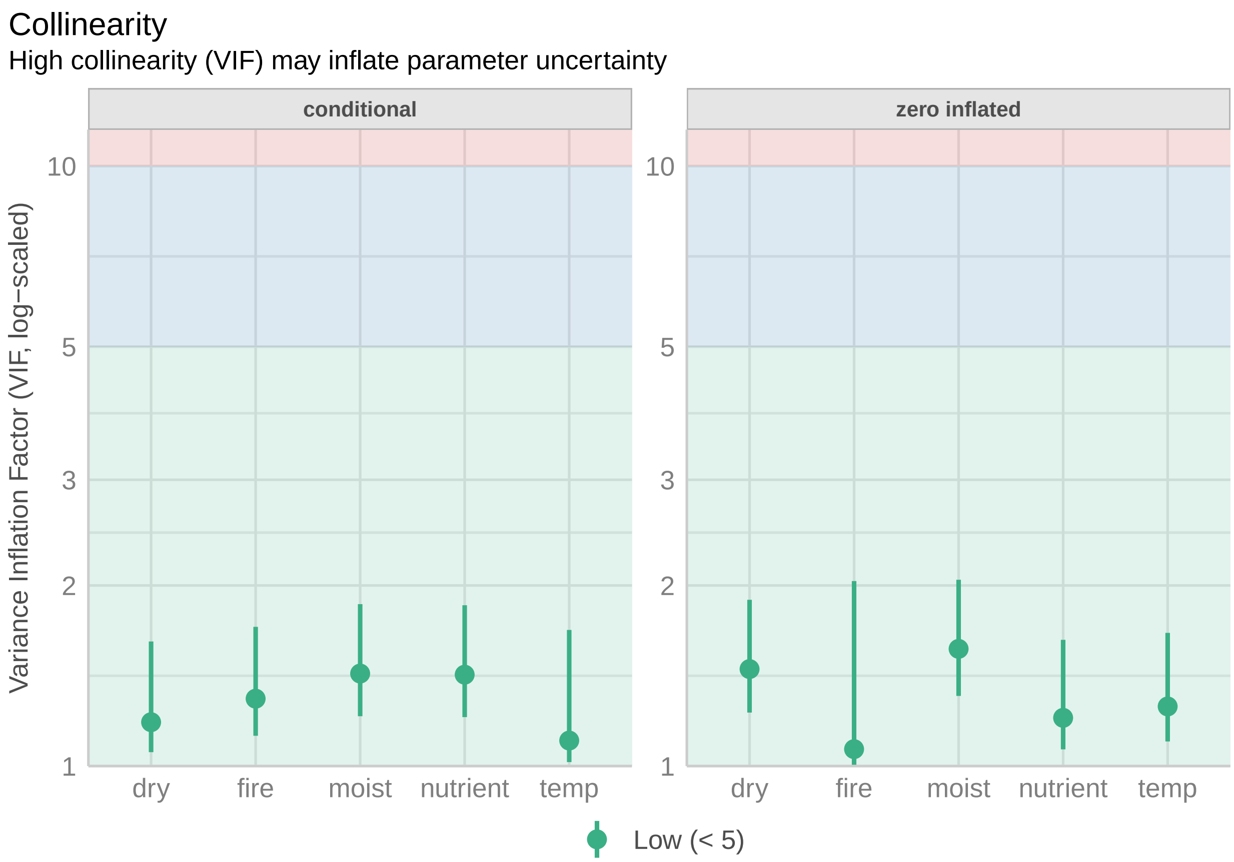
```r
                    age=data_peat_noNapredictors$age,
                    moist=data_peat_noNapredictors$moist,
                    nutrient=data_peat_noNapredictors$nutrient,
                    fire=data_peat_noNapredictors$fire,
                    dry=data_peat_noNapredictors$dry,
                    fen=data_peat_noNapredictors$fen,
                    times, group)

data_peat_noNapredictors_Erica<-subset(data_peat_noNapredictors,Erica_prop>0)
times_Erica <- factor(data_peat_noNapredictors_Erica$age)
group_Erica <- factor(rep(1,107))

dat0_Erica <- data.frame(tot_Sphagnum_prop=subset(data_peat_noNapredictors,
                                                  Erica_prop>0)$tot_Sphagnum_prop,
                    Erio_prop=subset(data_peat_noNapredictors,
                                     Erica_prop>0)$Erio_prop,
                    Erica_prop=subset(data_peat_noNapredictors,
                                      Erica_prop>0)$Erica_prop,
                    Carex_prop=subset(data_peat_noNapredictors,
                                      Erica_prop>0)$Carex_prop,
                    temp=subset(data_peat_noNapredictors,
                                Erica_prop>0)$temp,
                    age=subset(data_peat_noNapredictors,
                               Erica_prop>0)$age,
                    moist=subset(data_peat_noNapredictors,
                                 Erica_prop>0)$moist,
                    nutrient=subset(data_peat_noNapredictors,
                                    Erica_prop>0)$nutrient,
                    fire=subset(data_peat_noNapredictors,
                                Erica_prop>0)$fire,
                    dry=subset(data_peat_noNapredictors,
                               Erica_prop>0)$dry,
                    fen=subset(data_peat_noNapredictors,
                               Erica_prop>0)$fen,
                    times_Erica, group_Erica)
```

Fit AR models:

```r
mod_abund_tot_Sphagnum_temp_AR<-glmmTMB(tot_Sphagnum_prop~temp+moist+nutrient+
                                          fire+dry+ar1(times+0|group),
                                        family="beta_family",ziformula=~.,
                                        data=dat0)
mod_abund_Erio_nozi_temp_AR<-glmmTMB(Erio_prop~temp+moist+nutrient+
                                       fire+dry+ar1(times+0|group),
                                     family="beta_family",ziformula=~0,
                                     data=dat0)
mod_abund_Erica_nozi_temp_AR<-glmmTMB(Erica_prop~temp+moist+nutrient+
                                        fire+dry+ar1(times_Erica+0|group_Erica),
                                      family="beta_family",ziformula=~0,
                                      data=dat0_Erica)
mod_abund_Carex_nozi_temp_AR<-glmmTMB(Carex_prop~temp+moist+nutrient+
                                        fire+dry+ar1(times+0|group),
                                      family="beta_family",ziformula=~0,
```

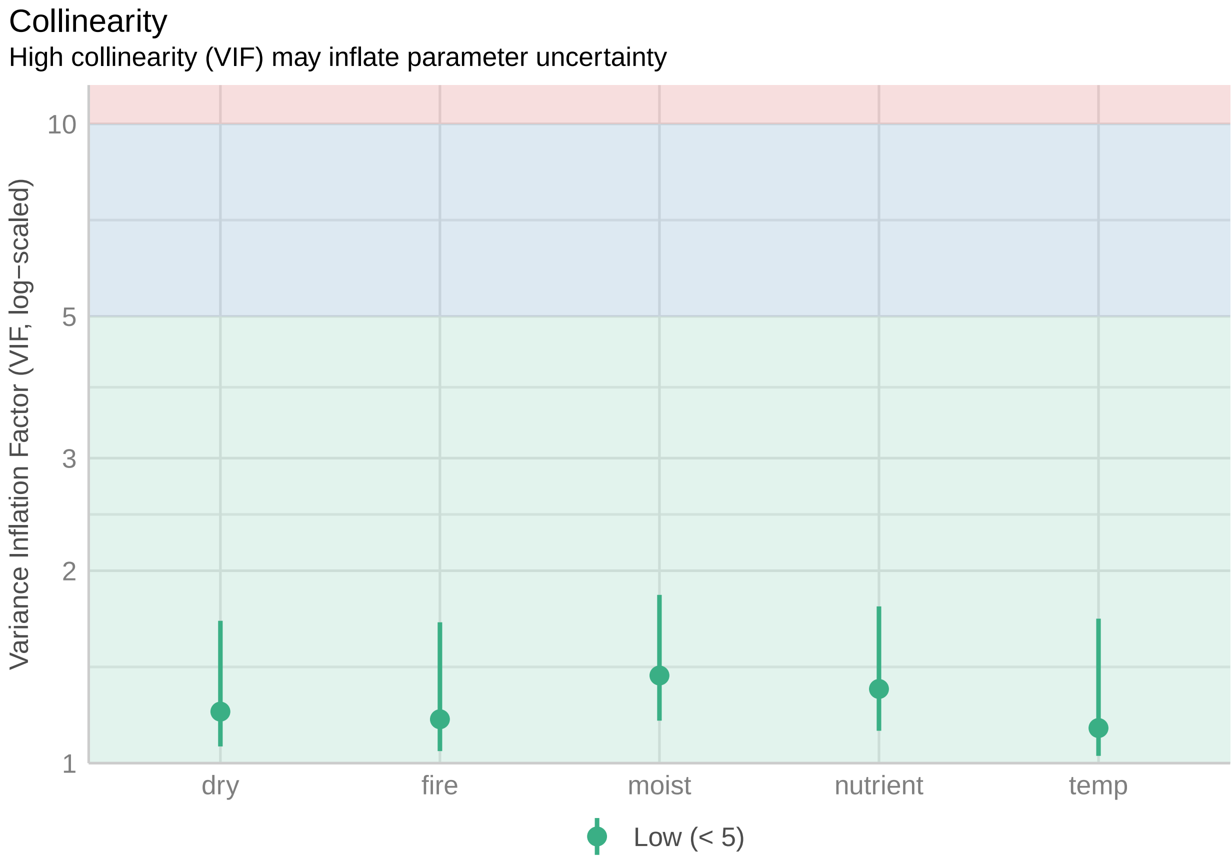
```r
                                                    data=dat0)
```

```r
plot(check_collinearity(mod_abund_tot_Sphagnum_temp))
```

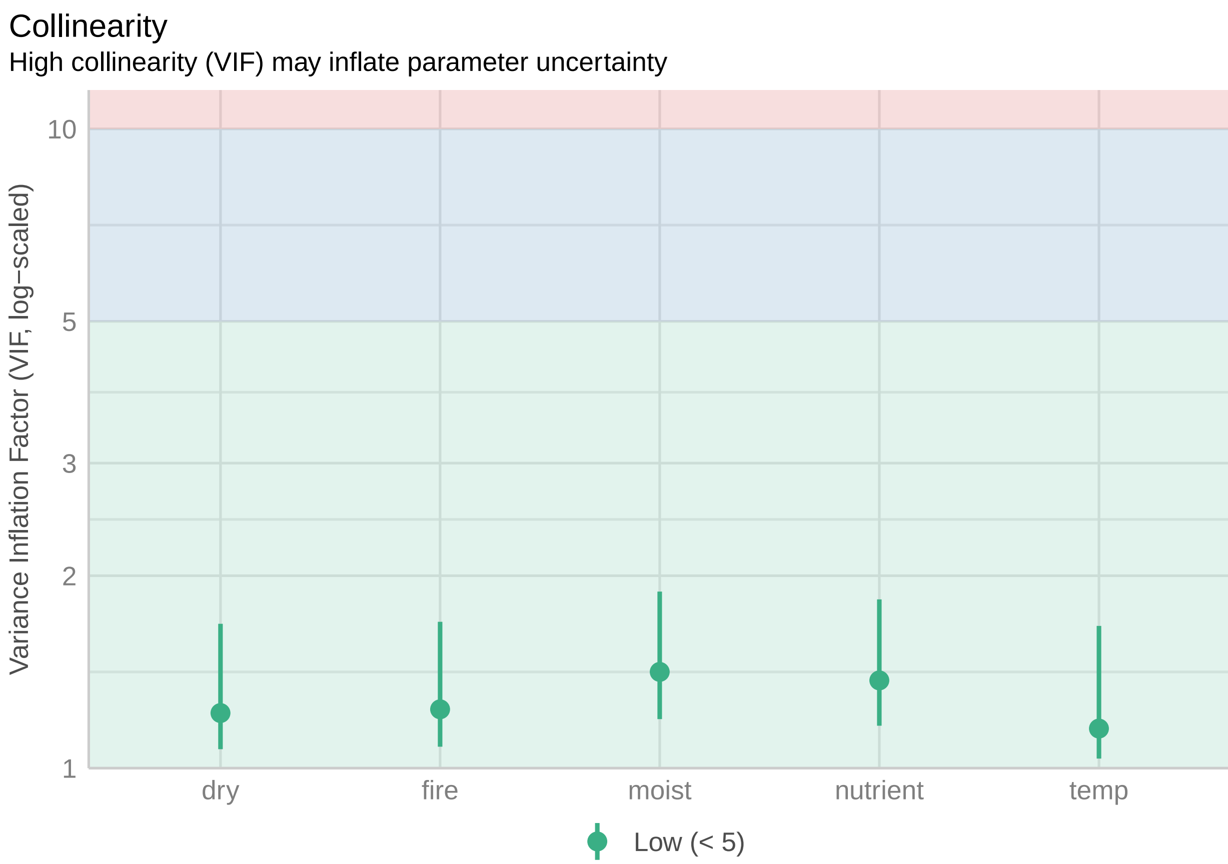


Check VIFs

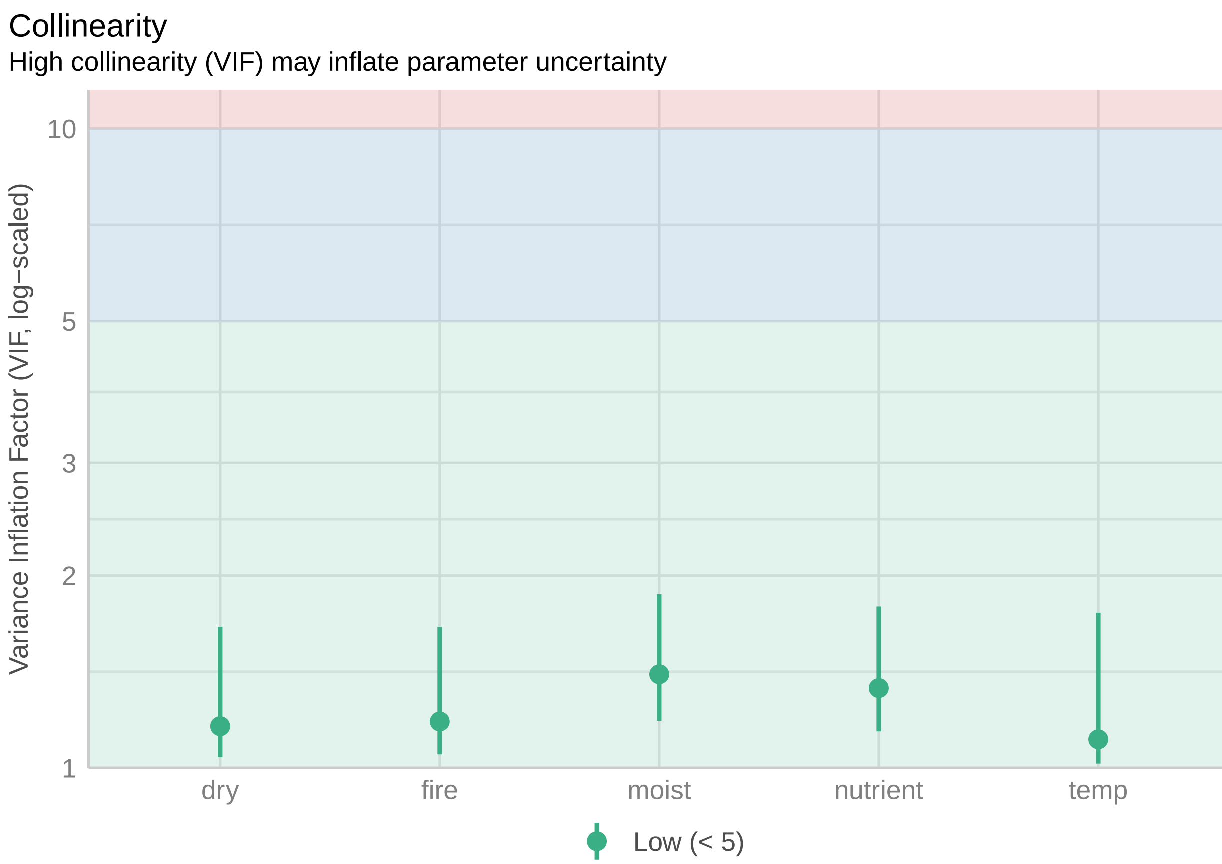
```r
plot(check_collinearity(mod_abund_Erio_nozi_temp))
```




```
plot(check_collinearity(mod_abund_Erica_nozi_temp))
```




```r
plot(check_collinearity(mod_abund_Carex_nozi_temp))
```



VIFs are all under 2.

```r
summary(mod_abund_tot_Sphagnum_temp_AR)
```

Model summaries (Appendix S4, Table S1)

```
##  Family: beta  ( logit )
## Formula:
## tot_Sphagnum_prop ~ temp + moist + nutrient + fire + dry + ar1(times +
##     0 | group)
## Zero inflation:                     ~.
## Data: dat0
##
##      AIC      BIC   logLik deviance df.resid
##     55.6    101.2    -10.8     21.6       91
##
## Random effects:
##
## Conditional model:
##  Groups Name     Variance Std.Dev. Corr
##  group  times352 0.3525   0.5937   0.74 (ar1)
## Number of obs: 108, groups:  group, 1
##
```

```
## Zero-inflation model:
##  Groups Name      Variance Std.Dev. Corr
##  group  times352  1549     39.35
##         times452  1549     39.35    0.20
##         times505  1549     39.35    0.04 0.20
##         times555  1549     39.35    0.01 0.04 0.20
##         times606  1549     39.35    0.00 0.01 0.04 0.20
##         times643  1549     39.35    0.00 0.00 0.01 0.04 0.20
##         times673  1549     39.35    0.00 0.00 0.00 0.01 0.04 0.20
##         times717  1549     39.35    0.00 0.00 0.00 0.00 0.01 0.04 0.20
##         times754  1549     39.35    0.00 0.00 0.00 0.00 0.00 0.01 0.04 0.20
##         times791  1549     39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.01 0.04
##         times813  1549     39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.01
##         times879  1549     39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##         times900  1549     39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##         times943  1549     39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##         times980  1549     39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##         times1018 1549     39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##         times1054 1549     39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##         times1092 1549     39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##         times1122 1549     39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##         times1172 1549     39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##         times1243 1549     39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##         times1344 1549     39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##         times1418 1549     39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##         times1514 1549     39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##         times1631 1549     39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##         times1682 1549     39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##         times1743 1549     39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##         times1818 1549     39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##         times1880 1549     39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##         times1944 1549     39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##         times1992 1549     39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##         times2063 1549     39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##         times2136 1549     39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##         times2192 1549     39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##         times2238 1549     39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##         times2265 1549     39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##         times2347 1549     39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##         times2422 1549     39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##         times2521 1549     39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##         times2687 1549     39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##         times2797 1549     39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##         times2918 1549     39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##         times2975 1549     39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##         times3178 1549     39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##         times3284 1549     39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##         times3517 1549     39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##         times3735 1549     39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##         times3887 1549     39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##         times3977 1549     39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##         times4118 1549     39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##         times4205 1549     39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##         times4335 1549     39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
```

```
##          times4439 1549      39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times4502 1549      39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times4518 1549      39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times4552 1549      39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times4634 1549      39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times4681 1549      39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times4729 1549      39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times4801 1549      39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times4859 1549      39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times4893 1549      39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times4928 1549      39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times4979 1549      39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times5007 1549      39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times5035 1549      39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times5056 1549      39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times5088 1549      39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times5123 1549      39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times5156 1549      39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times5184 1549      39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times5207 1549      39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times5241 1549      39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times5309 1549      39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times5383 1549      39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times5496 1549      39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times5627 1549      39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times5760 1549      39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times5812 1549      39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times5877 1549      39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times5930 1549      39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times5987 1549      39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times6142 1549      39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times6248 1549      39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times6356 1549      39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times6484 1549      39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times6597 1549      39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times6657 1549      39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times6727 1549      39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times6773 1549      39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times6845 1549      39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times6903 1549      39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times6959 1549      39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times7082 1549      39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times7368 1549      39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times7489 1549      39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times7724 1549      39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times8051 1549      39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times8172 1549      39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times8338 1549      39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times8427 1549      39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times8482 1549      39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times8546 1549      39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times8630 1549      39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times8727 1549      39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times8780 1549      39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
```

```
##         times8843 1549      39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##         times8886 1549      39.35    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##
##
##
##
##
##
##
##
##
##
##   0.20
##   0.04 0.20
##   0.01 0.04 0.20
##   0.00 0.01 0.04 0.20
##   0.00 0.00 0.01 0.04 0.20
##   0.00 0.00 0.00 0.01 0.04 0.20
##   0.00 0.00 0.00 0.00 0.01 0.04 0.20
##   0.00 0.00 0.00 0.00 0.00 0.01 0.04 0.20
##   0.00 0.00 0.00 0.00 0.00 0.00 0.01 0.04 0.20
##   0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.01 0.04 0.20
##   0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.01 0.04 0.20
##   0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.01 0.04 0.20
##   0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.01 0.04 0.20
##   0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.01 0.04 0.20
##   0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.01 0.04 0.20
##   0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.01 0.04
##   0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.01
##   0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##   0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
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##   0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##   0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##   0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
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##   0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##   0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##   0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##   0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##   0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##   0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
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##   0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
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##   0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##   0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##   0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
```

```
##  0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##  0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##  0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##  0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##  0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##  0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##  0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
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##  0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##  0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##  0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##  0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##  0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##  0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##  0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
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## Number of obs: 108, groups:  group, 1
##
## Dispersion parameter for beta family (): 3.44
##
## Conditional model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  2.10007    1.63543   1.284   0.1991
## temp        -0.34931    0.19228  -1.817   0.0693 .
## moist       -0.33661    0.31292  -1.076   0.2821
## nutrient1    0.93646    0.43094   2.173   0.0298 *
## fire1       -0.00962    0.38750  -0.025   0.9802
## dry1         0.77269    0.33494   2.307   0.0211 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Zero-inflation model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept) -22.2407    22.1631  -1.004    0.316
## temp          1.0338     2.2753   0.454    0.650
## moist        -2.0543     4.9777  -0.413    0.680
## nutrient1    -1.8913     4.6790  -0.404    0.686
## fire1         0.7909     4.3447   0.182    0.856
## dry1          1.6162     4.0908   0.395    0.693
```

```r
summary(mod_abund_Erio_nozi_temp_AR)
```

```
##  Family: beta  ( logit )
## Formula:
## Erio_prop ~ temp + moist + nutrient + fire + dry + ar1(times +      0 | group)
## Data: dat0
##
##      AIC      BIC   logLik deviance df.resid
##   -131.9   -107.8     75.0   -149.9       99
##
## Random effects:
##
## Conditional model:
##  Groups Name     Variance Std.Dev. Corr
##  group  times352 1.774    1.332    0.40 (ar1)
## Number of obs: 108, groups:  group, 1
##
## Dispersion parameter for beta family (): 2.44e+09
##
## Conditional model:
##             Estimate Std. Error z value Pr(>|z|)
```

```
## (Intercept) -2.49962    1.55869  -1.604  0.10879
## temp         0.20835    0.18698   1.114  0.26516
## moist        0.46845    0.32084   1.460  0.14428
## nutrient1   -1.06209    0.38822  -2.736  0.00622 **
## fire1       -0.03764    0.30454  -0.124  0.90163
## dry1        -0.73115    0.34943  -2.092  0.03640 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
summary(mod_abund_Erica_nozi_temp_AR)
```

```
##  Family: beta  ( logit )
## Formula:
## Erica_prop ~ temp + moist + nutrient + fire + dry + ar1(times_Erica +
##     0 | group_Erica)
## Data: dat0_Erica
##
##      AIC      BIC   logLik deviance df.resid
##   -203.0   -178.9    110.5   -221.0       98
##
## Random effects:
##
## Conditional model:
##  Groups      Name           Variance Std.Dev. Corr
##  group_Erica times_Erica352 0.2012   0.4485   0.86 (ar1)
## Number of obs: 107, groups:  group_Erica, 1
##
## Dispersion parameter for beta family (): 9.52
##
## Conditional model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -3.9887     1.1921  -3.346  0.00082 ***
## temp          0.2613     0.1427   1.831  0.06706 .
## moist         0.1136     0.2088   0.544  0.58637
## nutrient1    -0.1462     0.2644  -0.553  0.58018
## fire1         0.3012     0.2295   1.312  0.18937
## dry1         -0.1264     0.2460  -0.514  0.60729
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
summary(mod_abund_Carex_nozi_temp_AR)
```

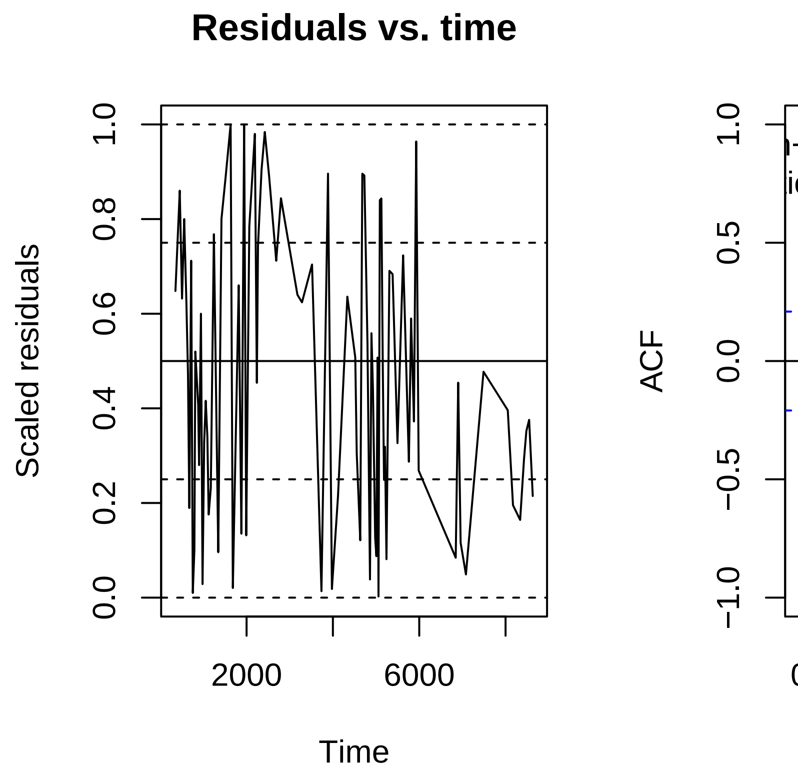
```
##  Family: beta  ( logit )
## Formula:
## Carex_prop ~ temp + moist + nutrient + fire + dry + ar1(times +      0 | group)
## Data: dat0
##
##      AIC      BIC   logLik deviance df.resid
##   -238.6   -214.4    128.3   -256.6       99
##
## Random effects:
##
## Conditional model:
```

```
##  Groups Name     Variance Std.Dev. Corr
##  group  times352 0.1134   0.3367   0.88 (ar1)
## Number of obs: 108, groups:  group, 1
##
## Dispersion parameter for beta family (): 13.7
##
## Conditional model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -2.8667     1.1471  -2.499  0.01245 *
## temp          0.1743     0.1341   1.300  0.19378
## moist        -0.1457     0.1774  -0.821  0.41149
## nutrient1    -0.8390     0.2655  -3.161  0.00157 **
## fire1         0.1887     0.2024   0.932  0.35113
## dry1         -0.3596     0.1992  -1.805  0.07110 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Selected Sphagnum species

```
mod_abund_Medium_temp<-glmmTMB(Medium_prop~temp+moist+
                            nutrient+fire+dry,family="beta_family",
                          ziformula=~.,data=data_peat)
mod_abund_Fuscum_temp<-glmmTMB(Fuscum_prop~temp+moist+
                            nutrient+fire+dry,family="beta_family",
                          ziformula=~.,data=data_peat)
mod_abund_Rubellum_temp<-glmmTMB(Rubellum_prop~temp+moist+
                              nutrient+fire+dry,family="beta_family",
                            ziformula=~.,data=data_peat)
mod_abund_Balticum_temp<-glmmTMB(Balticum_prop~temp+moist+
                              nutrient+fire+dry,family="beta_family",
                            ziformula=~.,data=data_peat)
mod_abund_Cuspidata_temp<-glmmTMB(Cuspidata_prop~temp+moist+
                               nutrient+fire+dry,family="beta_family",
                             ziformula=~.,data=data_peat)
```

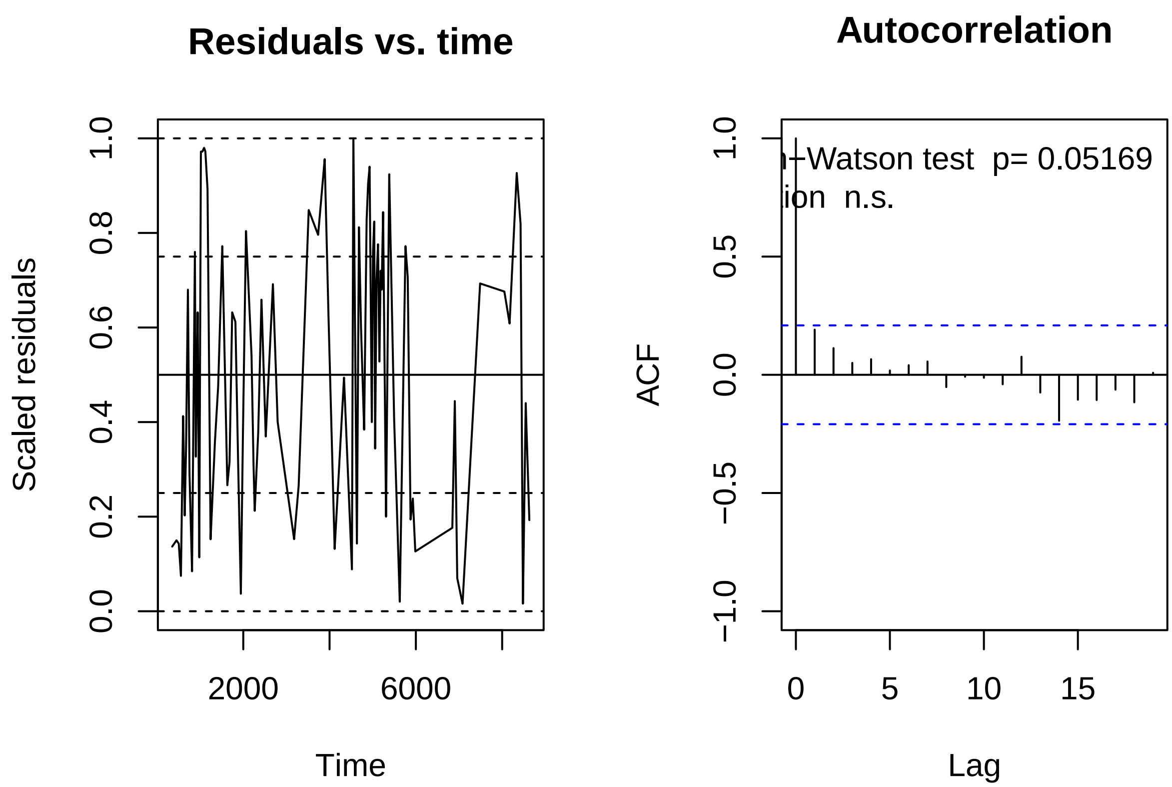
```
testTemporalAutocorrelation(simulateResiduals(mod_abund_Medium_temp),
                            subset(data_peat,
                                   !is.na(Medium_prop)&!is.na(temp)&
                                     !is.na(moist)&!is.na(nutrient)&
                                     !is.na(fire)&!is.na(dry))$age, plot = T)
```



Check for temporal autocorrelation in residuals

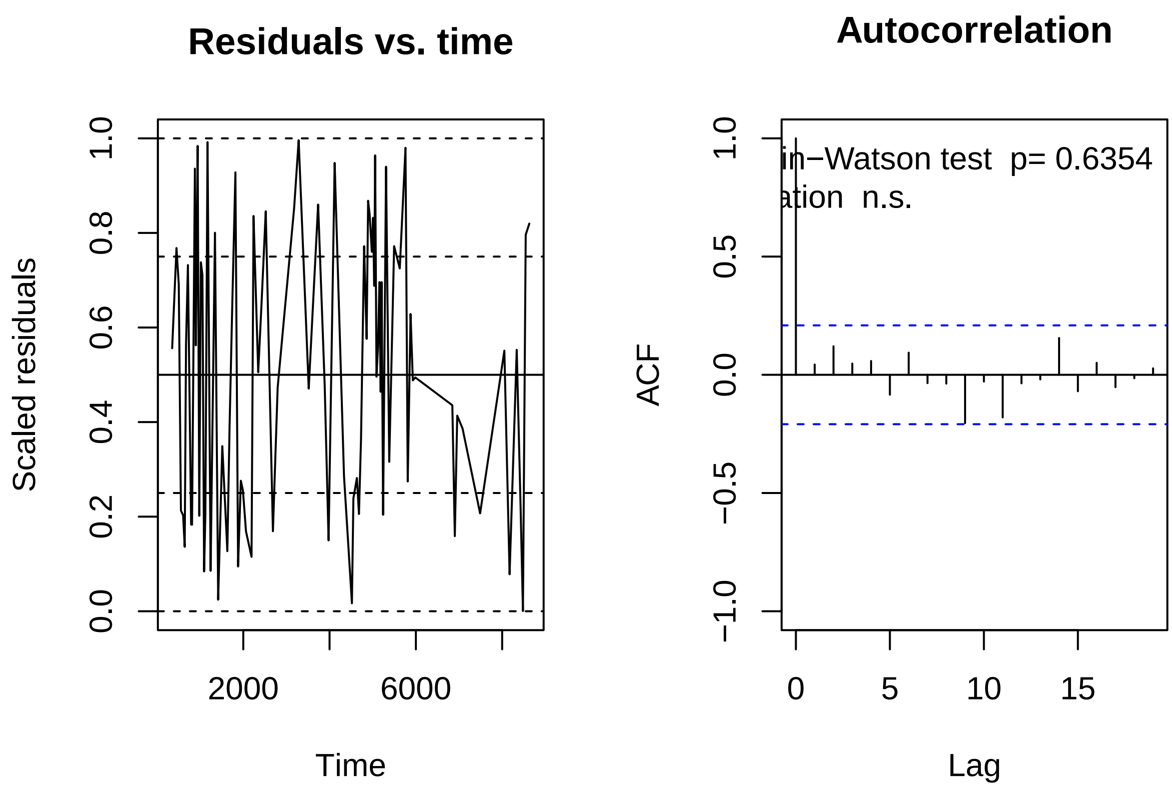
```
##
##  Durbin-Watson test
##
## data:  simulationOutput$scaledResiduals ~ 1
## DW = 1.8376, p-value = 0.444
## alternative hypothesis: true autocorrelation is not 0
```

```
testTemporalAutocorrelation(simulateResiduals(mod_abund_Fuscum_temp),
                            subset(data_peat,
                                   !is.na(Fuscum_prop)&!is.na(temp)&
                                     !is.na(moist)&!is.na(nutrient)&
                                     !is.na(fire)&!is.na(dry))$age, plot = T)
```



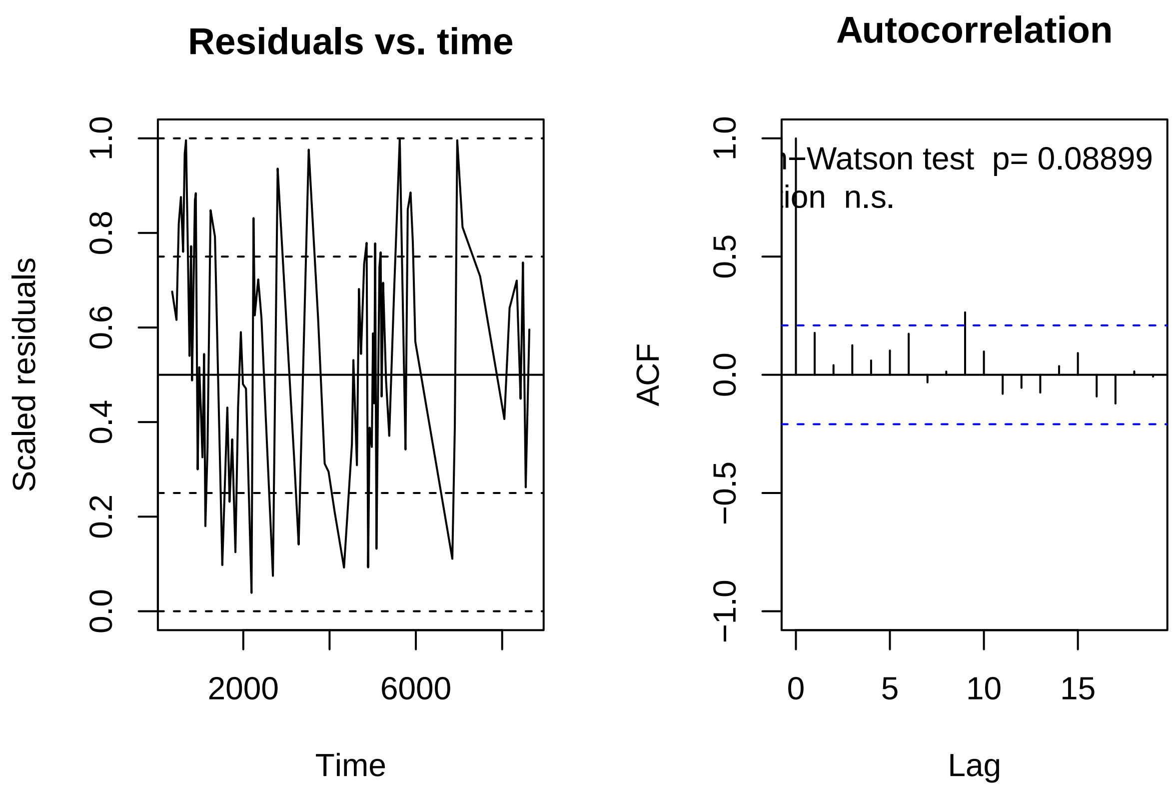

```
##
##  Durbin-Watson test
##
## data:  simulationOutput$scaledResiduals ~ 1
## DW = 1.5908, p-value = 0.05169
## alternative hypothesis: true autocorrelation is not 0
```

```
testTemporalAutocorrelation(simulateResiduals(mod_abund_Rubellum_temp),
                            subset(data_peat,
                                   !is.na(Rubellum_prop)&!is.na(temp)&
                                     !is.na(moist)&!is.na(nutrient)&
                                     !is.na(fire)&!is.na(dry))$age, plot = T)
```



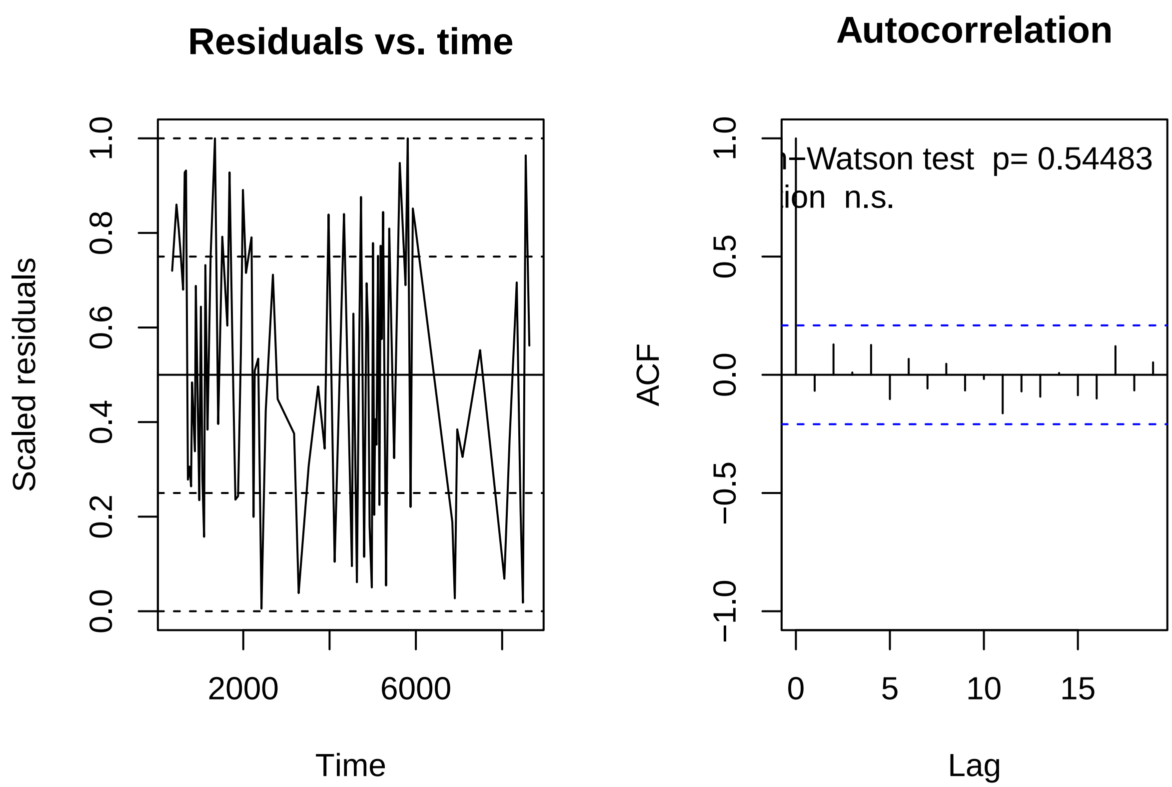

```
##
##  Durbin-Watson test
##
## data:  simulationOutput$scaledResiduals ~ 1
## DW = 1.8993, p-value = 0.6354
## alternative hypothesis: true autocorrelation is not 0
```

```
testTemporalAutocorrelation(simulateResiduals(mod_abund_Balticum_temp),
                            subset(data_peat,
                                   !is.na(Balticum_prop)&!is.na(temp)&
                                     !is.na(moist)&!is.na(nutrient)&
                                     !is.na(fire)&!is.na(dry))$age, plot = T)
```




```
##
##  Durbin-Watson test
##
## data:  simulationOutput$scaledResiduals ~ 1
## DW = 1.6414, p-value = 0.08899
## alternative hypothesis: true autocorrelation is not 0
```

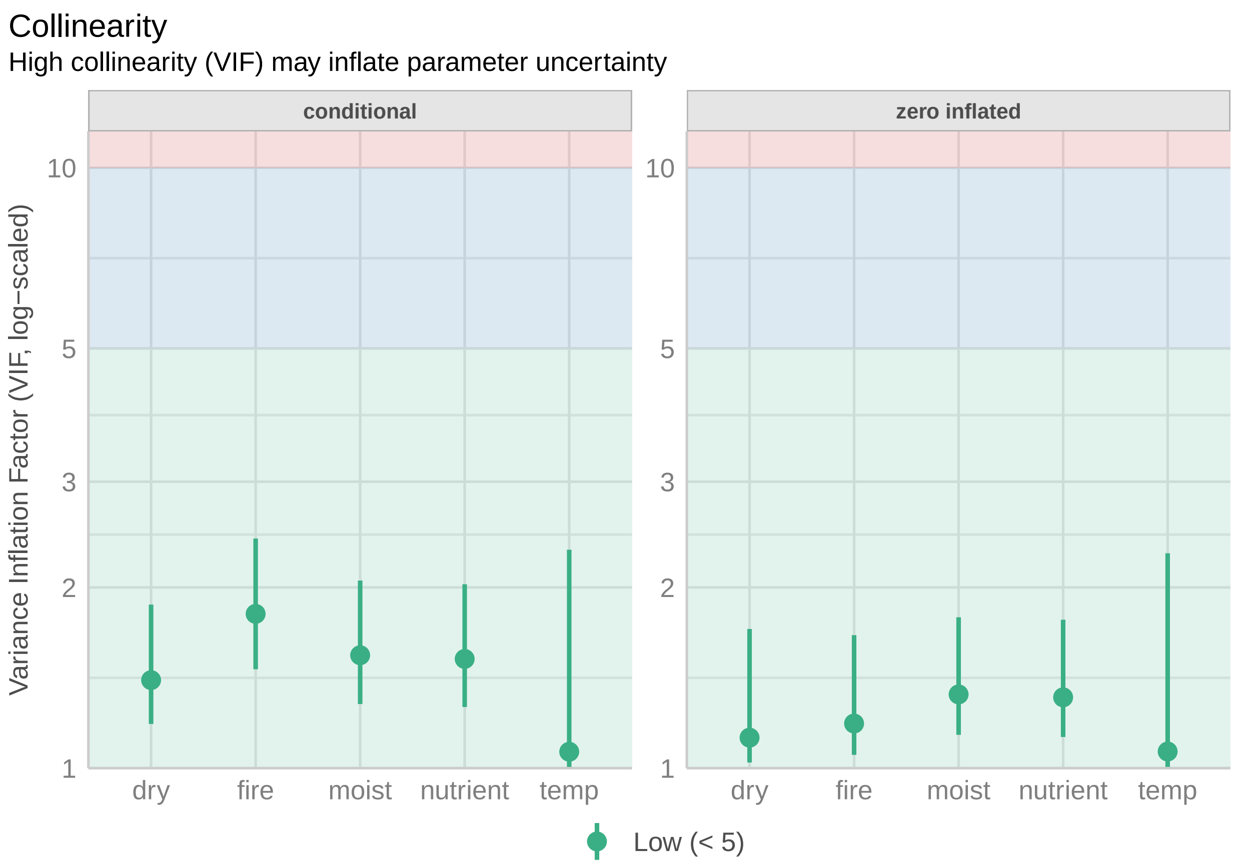
```
testTemporalAutocorrelation(simulateResiduals(mod_abund_Cuspidata_temp),
                            subset(data_peat,
                                   !is.na(Cuspidata_prop)&!is.na(temp)&
                                     !is.na(moist)&!is.na(nutrient)&
                                     !is.na(fire)&!is.na(dry))$age, plot = T)
```




```
##
##  Durbin-Watson test
##
## data:  simulationOutput$scaledResiduals ~ 1
## DW = 2.1286, p-value = 0.5448
## alternative hypothesis: true autocorrelation is not 0
```

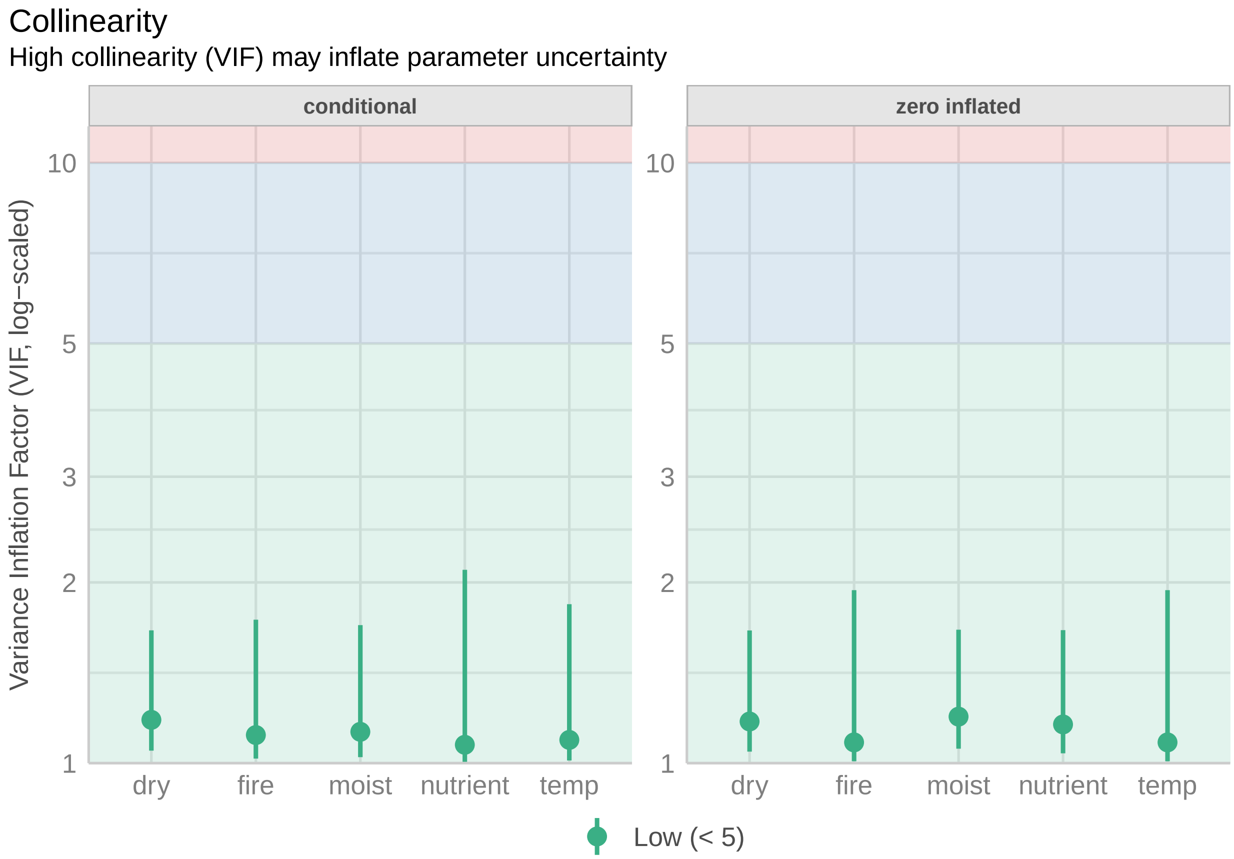
No significant autocorrelation in any of the models.

```r
plot(check_collinearity(mod_abund_Medium_temp))
```

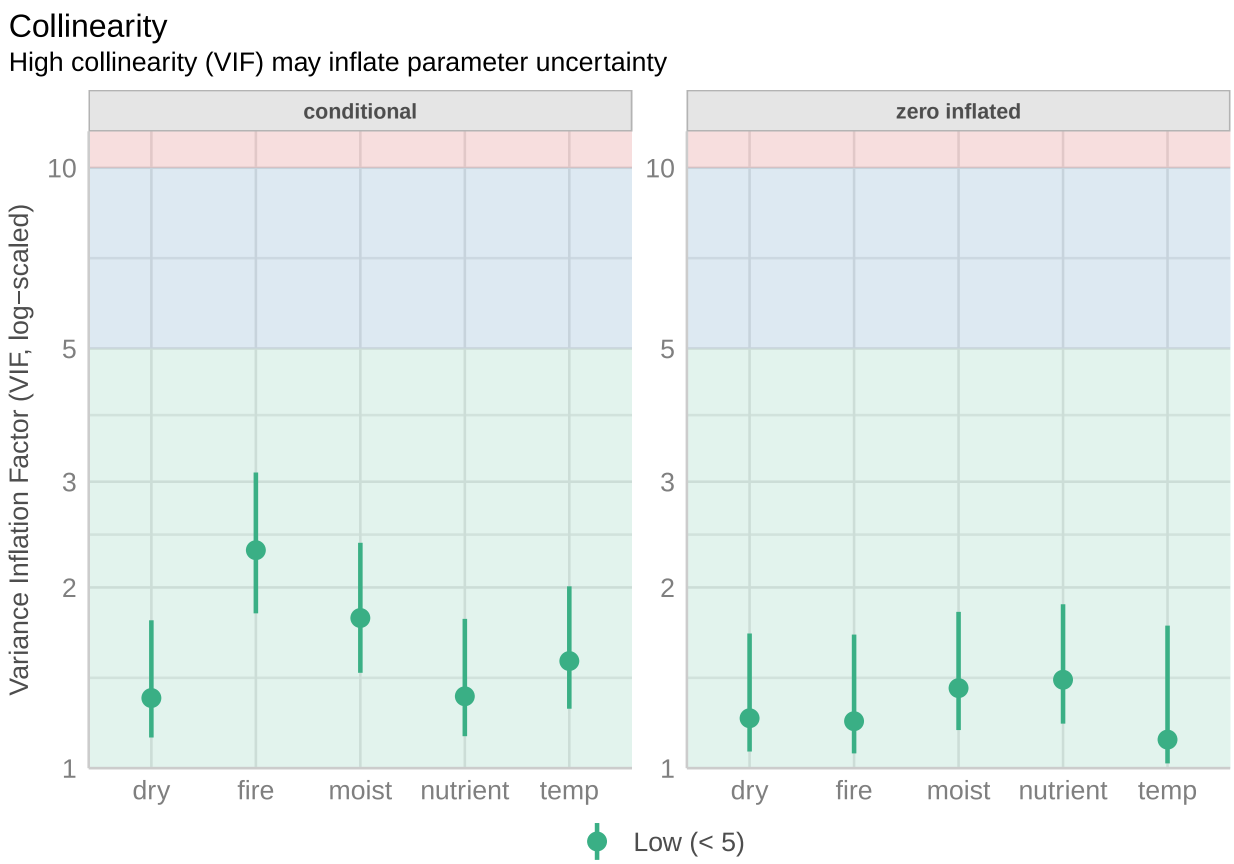


Check VIFs

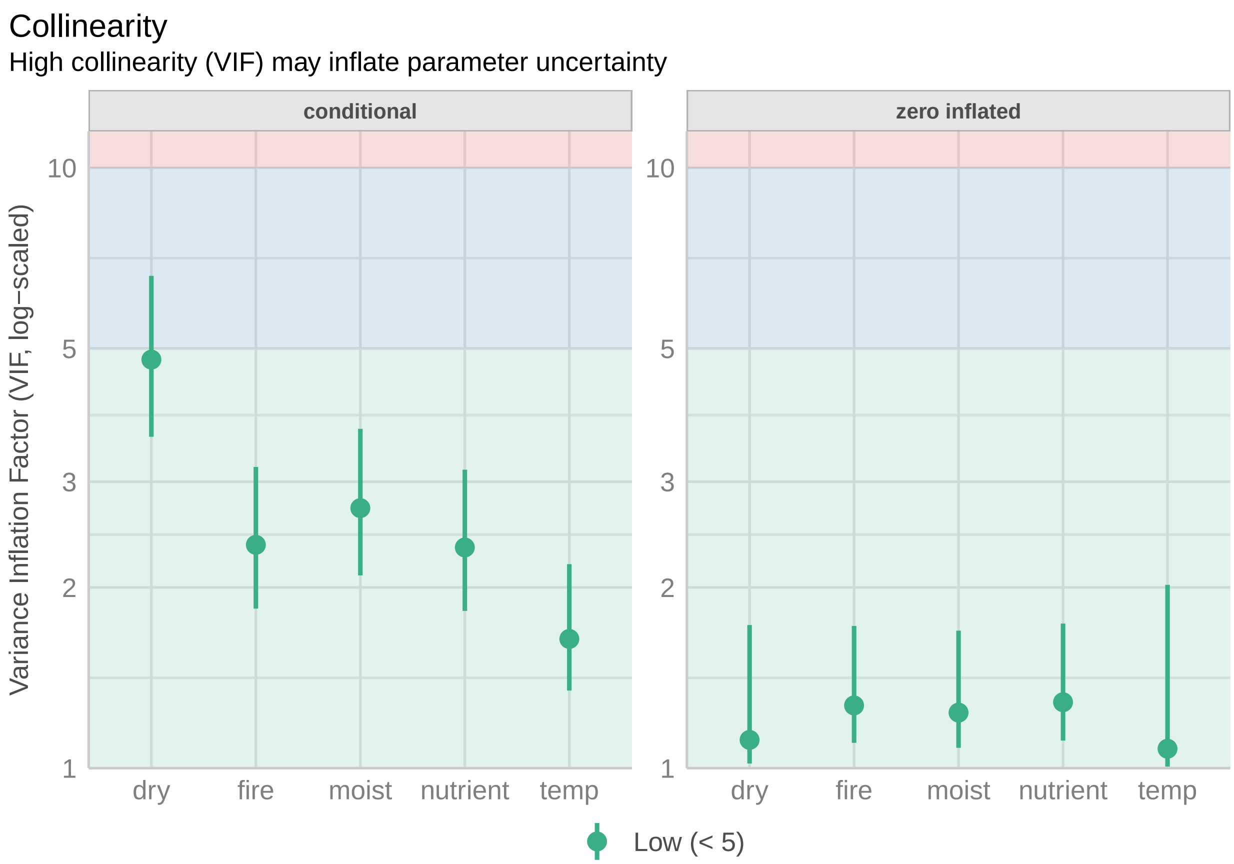
```
# All under 2
plot(check_collinearity(mod_abund_Fuscum_temp))
```



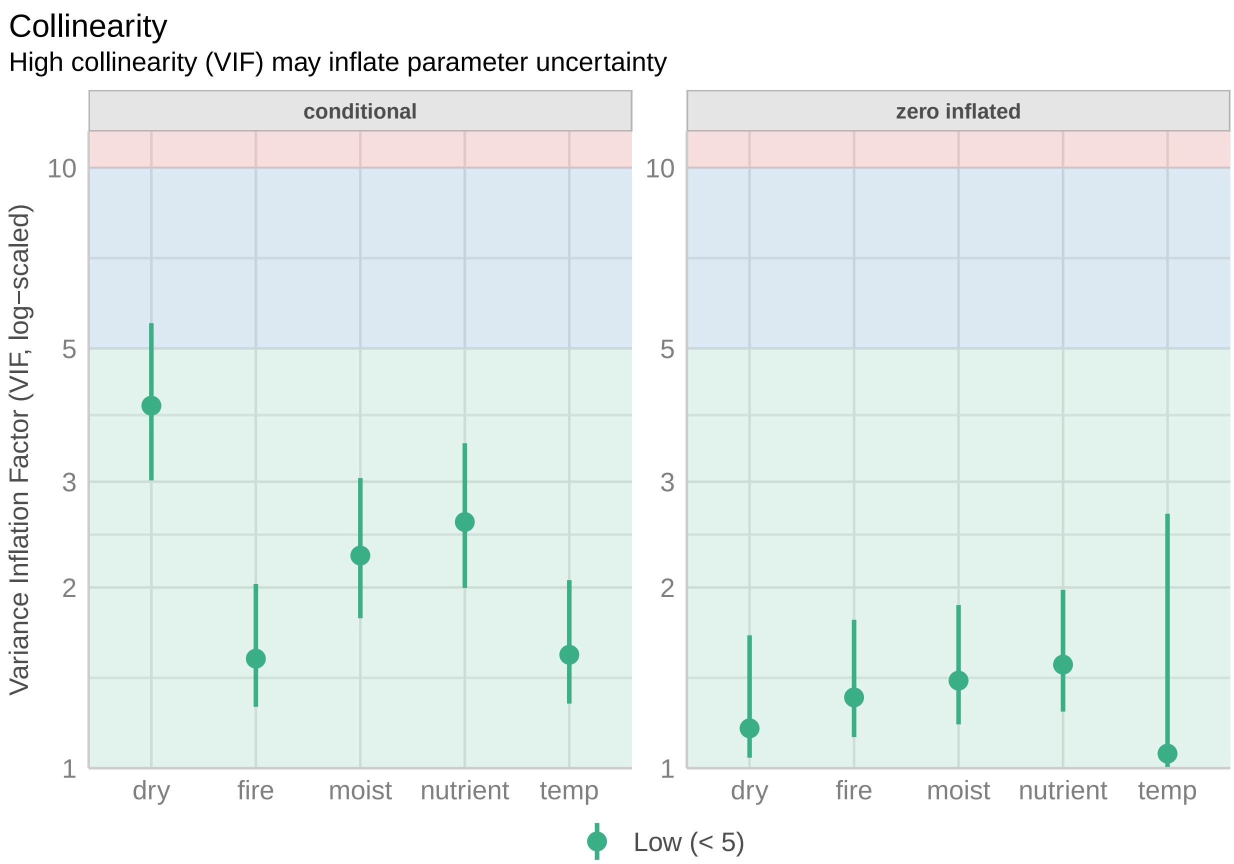

```
# All under 2
plot(check_collinearity(mod_abund_Rubellum_temp))
```




```r
# Fire just over 2 in the conditional component
plot(check_collinearity(mod_abund_Balticum_temp))
```




```r
# All but temp over 2 in the conditional component
plot(check_collinearity(mod_abund_Cuspidata_temp))
```




```
# Dry, moist and nutrient over 2 in the conditional component
```

```
mod_abund_Rubellum_temponly<-glmmTMB(Rubellum_prop~temp,family="beta_family",
                            ziformula=~.,
                            data=data_peat)
mod_abund_Balticum_temponly<-glmmTMB(Balticum_prop~temp,family="beta_family",
                            ziformula=~.,
                            data=data_peat)
mod_abund_Cuspidata_temponly<-glmmTMB(Cuspidata_prop~temp,family="beta_family",
                             ziformula=~.,
                             data=data_peat)
mod_abund_Rubellum_moistonly<-glmmTMB(Rubellum_prop~moist,family="beta_family",
                            ziformula=~.,
                            data=data_peat)
mod_abund_Balticum_moistonly<-glmmTMB(Balticum_prop~moist,family="beta_family",
                            ziformula=~.,
                            data=data_peat)
mod_abund_Cuspidata_moistonly<-glmmTMB(Cuspidata_prop~moist,family="beta_family",
                             ziformula=~.,
                             data=data_peat)
mod_abund_Rubellum_nutrientonly<-glmmTMB(Rubellum_prop~nutrient,
                                         family="beta_family",
                            ziformula=~.,
```

```
                             data=data_peat)
mod_abund_Balticum_nutrientonly<-glmmTMB(Balticum_prop~nutrient,
                                          family="beta_family",
                             ziformula=~.,
                             data=data_peat)
mod_abund_Cuspidata_nutrientonly<-glmmTMB(Cuspidata_prop~nutrient,
                                           family="beta_family",
                              ziformula=~.,
                              data=data_peat)
mod_abund_Rubellum_fireonly<-glmmTMB(Rubellum_prop~fire,family="beta_family",
                             ziformula=~.,
                             data=data_peat)
mod_abund_Balticum_fireonly<-glmmTMB(Balticum_prop~fire,family="beta_family",
                             ziformula=~.,
                             data=data_peat)
mod_abund_Cuspidata_fireonly<-glmmTMB(Cuspidata_prop~fire,family="beta_family",
                              ziformula=~.,
                              data=data_peat)
mod_abund_Rubellum_dryonly<-glmmTMB(Rubellum_prop~dry,family="beta_family",
                             ziformula=~.,
                             data=data_peat)
mod_abund_Balticum_dryonly<-glmmTMB(Balticum_prop~dry,family="beta_family",
                             ziformula=~.,
                             data=data_peat)
mod_abund_Cuspidata_dryonly<-glmmTMB(Cuspidata_prop~dry,family="beta_family",
                              ziformula=~.,
                              data=data_peat)
```

Rubellum, Balticum and Cuspidata: models with single variables in the condtiional part

Model summaries

Appendix S4, Table S2 Models including all variables:

```
summary(mod_abund_Rubellum_temp)
```

```
##  Family: beta  ( logit )
## Formula:          Rubellum_prop ~ temp + moist + nutrient + fire + dry
## Zero inflation:                  ~.
## Data: data_peat
##
##      AIC      BIC   logLik deviance df.resid
##     88.2    120.4    -31.1     62.2       75
##
##
## Dispersion parameter for beta family (): 7.22
##
## Conditional model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -3.7859     1.6364  -2.313   0.0207 *
## temp          0.3823     0.1893   2.019   0.0435 *
```

```
## moist        -0.1540     0.3386  -0.455   0.6493
## nutrient1    -0.3577     0.3667  -0.976   0.3293
## fire1         1.5528     0.6888   2.254   0.0242 *
## dry1          0.2977     0.3008   0.990   0.3223
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Zero-inflation model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)   5.9745     2.3917   2.498   0.0125 *
## temp         -0.4823     0.2773  -1.739   0.0820 .
## moist         1.4042     0.6867   2.045   0.0409 *
## nutrient1    -1.4843     0.6394  -2.321   0.0203 *
## fire1        -0.1982     0.8354  -0.237   0.8124
## dry1         -1.2438     0.5922  -2.100   0.0357 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(mod_abund_Balticum_temp)
```

```
##  Family: beta  ( logit )
## Formula:          Balticum_prop ~ temp + moist + nutrient + fire + dry
## Zero inflation:                 ~.
## Data: data_peat
##
##      AIC      BIC   logLik deviance df.resid
##     76.0    108.2    -25.0     50.0       75
##
##
## Dispersion parameter for beta family ():  8.1
##
## Conditional model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -4.2932     1.6920  -2.537  0.01117 *
## temp          0.4806     0.2055   2.338  0.01937 *
## moist         2.0557     0.6296   3.265  0.00109 **
## nutrient1     0.5598     0.4920   1.138  0.25516
## fire1         1.1379     0.7028   1.619  0.10542
## dry1         -1.9242     0.7302  -2.635  0.00841 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Zero-inflation model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -8.4660     2.5792  -3.282 0.001029 **
## temp          1.2718     0.3347   3.799 0.000145 ***
## moist        -0.2772     0.7344  -0.378 0.705788
## nutrient1    -1.2621     0.6655  -1.897 0.057892 .
## fire1         0.1217     0.9072   0.134 0.893316
## dry1          0.6320     0.6491   0.974 0.330169
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(mod_abund_Cuspidata_temp)
```

```
##  Family: beta  ( logit )
## Formula:          Cuspidata_prop ~ temp + moist + nutrient + fire + dry
## Zero inflation:                  ~.
## Data: data_peat
##
##      AIC      BIC   logLik deviance df.resid
##     75.8    108.1    -24.9     49.8       75
##
##
## Dispersion parameter for beta family (): 5.31
##
## Conditional model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept) -4.12263    2.04793  -2.013   0.0441 *
## temp         0.31880    0.21638   1.473   0.1407
## moist        0.07361    0.63200   0.116   0.9073
## nutrient1    0.25380    0.62183   0.408   0.6832
## fire1        0.22088    0.59615   0.370   0.7110
## dry1         0.41630    0.77722   0.536   0.5922
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Zero-inflation model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -5.7366     2.3596  -2.431  0.01505 *
## temp          0.9702     0.3035   3.196  0.00139 **
## moist        -1.1786     0.7321  -1.610  0.10740
## nutrient1    -1.7028     0.6946  -2.452  0.01422 *
## fire1        -0.3984     0.8549  -0.466  0.64118
## dry1          0.4072     0.6332   0.643  0.52020
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Single-variable models:

```r
summary(mod_abund_Rubellum_temponly)
```

```
##  Family: beta  ( logit )
## Formula:          Rubellum_prop ~ temp
## Zero inflation:                 ~.
## Data: data_peat
##
##      AIC      BIC   logLik deviance df.resid
##    109.3    121.9    -49.6     99.3       88
##
##
## Dispersion parameter for beta family (): 5.07
##
## Conditional model:
##             Estimate Std. Error z value Pr(>|z|)
```

```
## (Intercept)  -1.6655     1.4993  -1.111    0.267
## temp          0.1381     0.1785   0.773    0.439
##
## Zero-inflation model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)   4.0701     1.8855   2.159   0.0309 *
## temp         -0.4215     0.2286  -1.844   0.0652 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(mod_abund_Balticum_temponly)
```

```
##  Family: beta  ( logit )
## Formula:          Balticum_prop ~ temp
## Zero inflation:                 ~.
## Data: data_peat
##
##      AIC      BIC   logLik deviance df.resid
##     84.9     97.6    -37.4     74.9       88
##
##
## Dispersion parameter for beta family (): 4.73
##
## Conditional model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -1.4339     1.3585  -1.056    0.291
## temp          0.1011     0.1836   0.550    0.582
##
## Zero-inflation model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -8.9799     2.3660  -3.795 0.000147 ***
## temp          1.2527     0.3067   4.085 4.41e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(mod_abund_Cuspidata_temponly)
```

```
##  Family: beta  ( logit )
## Formula:          Cuspidata_prop ~ temp
## Zero inflation:                  ~.
## Data: data_peat
##
##      AIC      BIC   logLik deviance df.resid
##     71.1     83.7    -30.5     61.1       88
##
##
## Dispersion parameter for beta family (): 5.07
##
## Conditional model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -3.3242     1.3942  -2.384   0.0171 *
## temp          0.2539     0.1825   1.392   0.1641
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Zero-inflation model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -6.1113     2.1423  -2.853  0.00434 **
## temp          0.9043     0.2765   3.271  0.00107 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(mod_abund_Rubellum_moistonly)
```

```
##  Family: beta  ( logit )
## Formula:          Rubellum_prop ~ moist
## Zero inflation:                  ~.
## Data: data_peat
##
##      AIC      BIC   logLik deviance df.resid
##     97.1    109.5    -43.6     87.1       83
##
##
## Dispersion parameter for beta family (): 5.02
##
## Conditional model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -0.4487     0.1599  -2.805  0.00502 **
## moist         0.3130     0.2852   1.097  0.27242
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Zero-inflation model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)   0.6959     0.2444   2.847  0.00441 **
## moist         1.6599     0.5531   3.001  0.00269 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(mod_abund_Balticum_moistonly)
```

```
##  Family: beta  ( logit )
## Formula:          Balticum_prop ~ moist
## Zero inflation:                  ~.
## Data: data_peat
##
##      AIC      BIC   logLik deviance df.resid
##     95.9    108.3    -43.0     85.9       83
##
##
## Dispersion parameter for beta family (): 5.11
##
## Conditional model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -0.7264     0.1762  -4.122 3.75e-05 ***
## moist         0.6799     0.4200   1.619    0.105
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Zero-inflation model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)   0.9850     0.2404   4.097 4.19e-05 ***
## moist         0.3255     0.4997   0.651    0.515
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(mod_abund_Cuspidata_moistonly)
```

```
##  Family: beta  ( logit )
## Formula:          Cuspidata_prop ~ moist
## Zero inflation:                  ~.
## Data: data_peat
##
##      AIC      BIC   logLik deviance df.resid
##     82.8     95.2    -36.4     72.8       83
##
##
## Dispersion parameter for beta family (): 4.83
##
## Conditional model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -1.3815     0.2092  -6.603 4.04e-11 ***
## moist         0.2179     0.4312   0.505    0.613
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Zero-inflation model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)   0.9832     0.2398   4.100 4.13e-05 ***
## moist        -0.1685     0.4920  -0.343    0.732
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(mod_abund_Rubellum_nutrientonly)
```

```
##  Family: beta  ( logit )
## Formula:          Rubellum_prop ~ nutrient
## Zero inflation:                 ~.
## Data: data_peat
##
##      AIC      BIC   logLik deviance df.resid
##     99.6    112.3    -44.8     89.6       88
##
##
## Dispersion parameter for beta family (): 5.25
##
## Conditional model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -0.1886     0.2809  -0.671    0.502
```

```
## nutrient1    -0.4386     0.3270  -1.341    0.180
##
## Zero-inflation model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)   1.5581     0.3890   4.006 6.19e-05 ***
## nutrient1    -1.6007     0.4863  -3.292 0.000996 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(mod_abund_Balticum_nutrientonly)
```

```
##  Family: beta  ( logit )
## Formula:          Balticum_prop ~ nutrient
## Zero inflation:                 ~.
## Data: data_peat
##
##      AIC      BIC   logLik deviance df.resid
##    106.1    118.8    -48.1     96.1       88
##
##
## Dispersion parameter for beta family ():  4.7
##
## Conditional model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -0.7575     0.2623  -2.888  0.00388 **
## nutrient1     0.1075     0.3311   0.325  0.74544
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Zero-inflation model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)   1.1575     0.3457   3.349 0.000812 ***
## nutrient1    -0.5895     0.4600  -1.281 0.200075
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(mod_abund_Cuspidata_nutrientonly)
```

```
##  Family: beta  ( logit )
## Formula:          Cuspidata_prop ~ nutrient
## Zero inflation:                  ~.
## Data: data_peat
##
##      AIC      BIC   logLik deviance df.resid
##     81.3     94.0    -35.7     71.3       88
##
##
## Dispersion parameter for beta family (): 4.71
##
## Conditional model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept) -1.45643    0.34205  -4.258 2.06e-05 ***
## nutrient1    0.05989    0.39492   0.152    0.879
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Zero-inflation model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)   1.5581     0.3890   4.006 6.19e-05 ***
## nutrient1    -0.9902     0.4934  -2.007   0.0448 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(mod_abund_Rubellum_fireonly)
```

```
##  Family: beta  ( logit )
## Formula:          Rubellum_prop ~ fire
## Zero inflation:                 ~.
## Data: data_peat
##
##      AIC      BIC   logLik deviance df.resid
##    107.0    119.6    -48.5     97.0       88
##
##
## Dispersion parameter for beta family (): 5.94
##
## Conditional model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -0.6370     0.1468  -4.340 1.42e-05 ***
## fire1         1.1483     0.4691   2.448   0.0144 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Zero-inflation model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)   0.5645     0.2326   2.427   0.0152 *
## fire1         0.6394     0.6982   0.916   0.3597
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(mod_abund_Balticum_fireonly)
```

```
##  Family: beta  ( logit )
## Formula:          Balticum_prop ~ fire
## Zero inflation:                 ~.
## Data: data_peat
##
##      AIC      BIC   logLik deviance df.resid
##    107.5    120.2    -48.8     97.5       88
##
##
## Dispersion parameter for beta family (): 4.68
##
## Conditional model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept) -0.68766    0.17521  -3.925 8.68e-05 ***
```

```
## fire1       -0.03992    0.52363  -0.076    0.939
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Zero-inflation model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)   0.7885     0.2412   3.269  0.00108 **
## fire1         0.4155     0.7011   0.593  0.55340
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(mod_abund_Cuspidata_fireonly)
```

```
##  Family: beta  ( logit )
## Formula:          Cuspidata_prop ~ fire
## Zero inflation:                  ~.
## Data: data_peat
##
##      AIC      BIC   logLik deviance df.resid
##     85.5     98.1    -37.7     75.5       88
##
##
## Dispersion parameter for beta family ():  4.7
##
## Conditional model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept) -1.42642    0.22431  -6.359 2.03e-10 ***
## fire1        0.06722    0.49887   0.135    0.893
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Zero-inflation model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)   1.0330     0.2541   4.065  4.8e-05 ***
## fire1        -0.2221     0.6524  -0.340    0.734
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(mod_abund_Rubellum_dryonly)
```

```
##  Family: beta  ( logit )
## Formula:          Rubellum_prop ~ dry
## Zero inflation:                 ~.
## Data: data_peat
##
##      AIC      BIC   logLik deviance df.resid
##    107.1    119.8    -48.6     97.1       88
##
##
## Dispersion parameter for beta family ():  5.5
##
## Conditional model:
##             Estimate Std. Error z value Pr(>|z|)
```

```
## (Intercept)  -0.7776     0.2061  -3.773 0.000162 ***
## dry1          0.5141     0.2828   1.818 0.069076 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Zero-inflation model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)   0.9651     0.2938   3.285  0.00102 **
## dry1         -0.7932     0.4488  -1.767  0.07717 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(mod_abund_Balticum_dryonly)
```

```
##  Family: beta  ( logit )
## Formula:          Balticum_prop ~ dry
## Zero inflation:                 ~.
## Data: data_peat
##
##      AIC      BIC   logLik deviance df.resid
##    103.1    115.7    -46.5     93.1       88
##
##
## Dispersion parameter for beta family ():  4.7
##
## Conditional model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -0.6663     0.1854  -3.594 0.000326 ***
## dry1         -0.1209     0.3957  -0.305 0.759999
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Zero-inflation model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)   0.4925     0.2706   1.820   0.0688 .
## dry1          1.0831     0.5238   2.068   0.0387 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(mod_abund_Cuspidata_dryonly)
```

```
##  Family: beta  ( logit )
## Formula:          Cuspidata_prop ~ dry
## Zero inflation:                  ~.
## Data: data_peat
##
##      AIC      BIC   logLik deviance df.resid
##     84.1     96.7    -37.0     74.1       88
##
##
## Dispersion parameter for beta family (): 4.73
##
## Conditional model:
```

```
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -1.4632     0.2404  -6.086 1.15e-09 ***
## dry1          0.1653     0.4057   0.407    0.684
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Zero-inflation model:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)   0.7985     0.2838   2.813   0.0049 **
## dry1          0.5878     0.5090   1.155   0.2482
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
summary(mod_abund_Medium_temp)
```

Appendix S4, Table S3

```
##  Family: beta  ( logit )
## Formula:          Medium_prop ~ temp + moist + nutrient + fire + dry
## Zero inflation:                ~.
## Data: data_peat
##
##      AIC      BIC   logLik deviance df.resid
##     90.6    122.8    -32.3     64.6       75
##
##
## Dispersion parameter for beta family (): 2.62
##
## Conditional model:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)   2.5357     1.5412   1.645 0.099922 .
## temp         -0.2236     0.1975  -1.132 0.257495
## moist         0.4826     0.4374   1.103 0.269872
## nutrient1    -1.4385     0.4174  -3.446 0.000569 ***
## fire1        -2.0354     0.5844  -3.483 0.000496 ***
## dry1          0.8982     0.4180   2.149 0.031653 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Zero-inflation model:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -9.3866     2.4380  -3.850 0.000118 ***
## temp          1.2058     0.3015   3.999 6.36e-05 ***
## moist        -0.8121     0.6367  -1.275 0.202148
## nutrient1    -0.3181     0.5857  -0.543 0.587050
## fire1        -1.1860     0.8119  -1.461 0.144094
## dry1          0.5460     0.5709   0.956 0.338943
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(mod_abund_Fuscum_temp)
```

```
##  Family: beta  ( logit )
## Formula:          Fuscum_prop ~ temp + moist + nutrient + fire + dry
## Zero inflation:               ~.
## Data: data_peat
##
##      AIC      BIC   logLik deviance df.resid
##     86.8    119.0    -30.4     60.8       75
##
##
## Dispersion parameter for beta family (): 4.87
##
## Conditional model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept) -7.04035    1.47830  -4.762 1.91e-06 ***
## temp         0.84838    0.17391   4.878 1.07e-06 ***
## moist       -0.09151    0.35419  -0.258  0.79612
## nutrient1    0.22191    0.40164   0.553  0.58060
## fire1        0.27420    0.62292   0.440  0.65980
## dry1        -0.83406    0.30669  -2.720  0.00654 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Zero-inflation model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)   3.3062     2.2940   1.441  0.14953
## temp         -0.2370     0.2736  -0.866  0.38637
## moist         2.2433     0.7313   3.068  0.00216 **
## nutrient1    -1.2672     0.5820  -2.178  0.02944 *
## fire1         0.7600     0.9292   0.818  0.41336
## dry1         -1.0151     0.6227  -1.630  0.10310
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(mod_abund_Rubellum_temponly)
```

```
##  Family: beta  ( logit )
## Formula:          Rubellum_prop ~ temp
## Zero inflation:                 ~.
## Data: data_peat
##
##      AIC      BIC   logLik deviance df.resid
##    109.3    121.9    -49.6     99.3       88
##
##
## Dispersion parameter for beta family (): 5.07
##
## Conditional model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -1.6655     1.4993  -1.111    0.267
## temp          0.1381     0.1785   0.773    0.439
```

```
##
## Zero-inflation model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)   4.0701     1.8855   2.159   0.0309 *
## temp         -0.4215     0.2286  -1.844   0.0652 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(mod_abund_Balticum_temponly)
```

```
##  Family: beta  ( logit )
## Formula:          Balticum_prop ~ temp
## Zero inflation:                 ~.
## Data: data_peat
##
##      AIC      BIC   logLik deviance df.resid
##     84.9     97.6    -37.4     74.9       88
##
##
## Dispersion parameter for beta family (): 4.73
##
## Conditional model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -1.4339     1.3585  -1.056    0.291
## temp          0.1011     0.1836   0.550    0.582
##
## Zero-inflation model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -8.9799     2.3660  -3.795 0.000147 ***
## temp          1.2527     0.3067   4.085 4.41e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(mod_abund_Cuspidata_temponly)
```

```
##  Family: beta  ( logit )
## Formula:          Cuspidata_prop ~ temp
## Zero inflation:                  ~.
## Data: data_peat
##
##      AIC      BIC   logLik deviance df.resid
##     71.1     83.7    -30.5     61.1       88
##
##
## Dispersion parameter for beta family (): 5.07
##
## Conditional model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -3.3242     1.3942  -2.384   0.0171 *
## temp          0.2539     0.1825   1.392   0.1641
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

```
## Zero-inflation model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -6.1113     2.1423  -2.853  0.00434 **
## temp          0.9043     0.2765   3.271  0.00107 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(mod_abund_Rubellum_moistonly)
```

```
##  Family: beta  ( logit )
## Formula:          Rubellum_prop ~ moist
## Zero inflation:                 ~.
## Data: data_peat
##
##      AIC      BIC   logLik deviance df.resid
##     97.1    109.5    -43.6     87.1       83
##
##
## Dispersion parameter for beta family (): 5.02
##
## Conditional model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -0.4487     0.1599  -2.805  0.00502 **
## moist         0.3130     0.2852   1.097  0.27242
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Zero-inflation model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)   0.6959     0.2444   2.847  0.00441 **
## moist         1.6599     0.5531   3.001  0.00269 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(mod_abund_Balticum_moistonly)
```

```
##  Family: beta  ( logit )
## Formula:          Balticum_prop ~ moist
## Zero inflation:                 ~.
## Data: data_peat
##
##      AIC      BIC   logLik deviance df.resid
##     95.9    108.3    -43.0     85.9       83
##
##
## Dispersion parameter for beta family (): 5.11
##
## Conditional model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -0.7264     0.1762  -4.122 3.75e-05 ***
## moist         0.6799     0.4200   1.619    0.105
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## Zero-inflation model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)   0.9850     0.2404   4.097 4.19e-05 ***
## moist         0.3255     0.4997   0.651    0.515
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(mod_abund_Cuspidata_moistonly)
```

```
##  Family: beta  ( logit )
## Formula:          Cuspidata_prop ~ moist
## Zero inflation:                  ~.
## Data: data_peat
##
##      AIC      BIC   logLik deviance df.resid
##     82.8     95.2    -36.4     72.8       83
##
##
## Dispersion parameter for beta family (): 4.83
##
## Conditional model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -1.3815     0.2092  -6.603 4.04e-11 ***
## moist         0.2179     0.4312   0.505    0.613
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Zero-inflation model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)   0.9832     0.2398   4.100 4.13e-05 ***
## moist        -0.1685     0.4920  -0.343    0.732
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(mod_abund_Rubellum_nutrientonly)
```

```
##  Family: beta  ( logit )
## Formula:          Rubellum_prop ~ nutrient
## Zero inflation:                 ~.
## Data: data_peat
##
##      AIC      BIC   logLik deviance df.resid
##     99.6    112.3    -44.8     89.6       88
##
##
## Dispersion parameter for beta family (): 5.25
##
## Conditional model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -0.1886     0.2809  -0.671    0.502
## nutrient1    -0.4386     0.3270  -1.341    0.180
##
```

```
## Zero-inflation model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)   1.5581     0.3890   4.006 6.19e-05 ***
## nutrient1    -1.6007     0.4863  -3.292 0.000996 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(mod_abund_Balticum_nutrientonly)
```

```
##  Family: beta  ( logit )
## Formula:          Balticum_prop ~ nutrient
## Zero inflation:                  ~.
## Data: data_peat
##
##      AIC      BIC   logLik deviance df.resid
##    106.1    118.8    -48.1     96.1       88
##
##
## Dispersion parameter for beta family ():  4.7
##
## Conditional model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -0.7575     0.2623  -2.888  0.00388 **
## nutrient1     0.1075     0.3311   0.325  0.74544
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Zero-inflation model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)   1.1575     0.3457   3.349 0.000812 ***
## nutrient1    -0.5895     0.4600  -1.281 0.200075
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(mod_abund_Cuspidata_nutrientonly)
```

```
##  Family: beta  ( logit )
## Formula:          Cuspidata_prop ~ nutrient
## Zero inflation:                   ~.
## Data: data_peat
##
##      AIC      BIC   logLik deviance df.resid
##     81.3     94.0    -35.7     71.3       88
##
##
## Dispersion parameter for beta family (): 4.71
##
## Conditional model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept) -1.45643    0.34205  -4.258 2.06e-05 ***
## nutrient1    0.05989    0.39492   0.152    0.879
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## Zero-inflation model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)   1.5581     0.3890   4.006 6.19e-05 ***
## nutrient1    -0.9902     0.4934  -2.007   0.0448 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(mod_abund_Rubellum_fireonly)
```

```
##  Family: beta  ( logit )
## Formula:          Rubellum_prop ~ fire
## Zero inflation:                  ~.
## Data: data_peat
##
##      AIC      BIC   logLik deviance df.resid
##    107.0    119.6    -48.5     97.0       88
##
##
## Dispersion parameter for beta family (): 5.94
##
## Conditional model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -0.6370     0.1468  -4.340 1.42e-05 ***
## fire1         1.1483     0.4691   2.448   0.0144 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Zero-inflation model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)   0.5645     0.2326   2.427   0.0152 *
## fire1         0.6394     0.6982   0.916   0.3597
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(mod_abund_Balticum_fireonly)
```

```
##  Family: beta  ( logit )
## Formula:          Balticum_prop ~ fire
## Zero inflation:                  ~.
## Data: data_peat
##
##      AIC      BIC   logLik deviance df.resid
##    107.5    120.2    -48.8     97.5       88
##
##
## Dispersion parameter for beta family (): 4.68
##
## Conditional model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept) -0.68766    0.17521  -3.925 8.68e-05 ***
## fire1       -0.03992    0.52363  -0.076    0.939
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Zero-inflation model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)   0.7885     0.2412   3.269  0.00108 **
## fire1         0.4155     0.7011   0.593  0.55340
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
summary(mod_abund_Cuspidata_fireonly)
```

```
##  Family: beta  ( logit )
## Formula:          Cuspidata_prop ~ fire
## Zero inflation:                  ~.
## Data: data_peat
##
##      AIC      BIC   logLik deviance df.resid
##     85.5     98.1    -37.7     75.5       88
##
##
## Dispersion parameter for beta family ():  4.7
##
## Conditional model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept) -1.42642    0.22431  -6.359 2.03e-10 ***
## fire1        0.06722    0.49887   0.135    0.893
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Zero-inflation model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)   1.0330     0.2541   4.065  4.8e-05 ***
## fire1        -0.2221     0.6524  -0.340    0.734
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
summary(mod_abund_Rubellum_dryonly)
```

```
##  Family: beta  ( logit )
## Formula:          Rubellum_prop ~ dry
## Zero inflation:                 ~.
## Data: data_peat
##
##      AIC      BIC   logLik deviance df.resid
##    107.1    119.8    -48.6     97.1       88
##
##
## Dispersion parameter for beta family ():  5.5
##
## Conditional model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -0.7776     0.2061  -3.773 0.000162 ***
## dry1          0.5141     0.2828   1.818 0.069076 .
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Zero-inflation model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)   0.9651     0.2938   3.285  0.00102 **
## dry1         -0.7932     0.4488  -1.767  0.07717 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(mod_abund_Balticum_dryonly)
```

```
##  Family: beta  ( logit )
## Formula:          Balticum_prop ~ dry
## Zero inflation:                 ~.
## Data: data_peat
##
##      AIC      BIC   logLik deviance df.resid
##    103.1    115.7    -46.5     93.1       88
##
##
## Dispersion parameter for beta family ():  4.7
##
## Conditional model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -0.6663     0.1854  -3.594 0.000326 ***
## dry1         -0.1209     0.3957  -0.305 0.759999
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Zero-inflation model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)   0.4925     0.2706   1.820   0.0688 .
## dry1          1.0831     0.5238   2.068   0.0387 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(mod_abund_Cuspidata_dryonly)
```

```
##  Family: beta  ( logit )
## Formula:          Cuspidata_prop ~ dry
## Zero inflation:                  ~.
## Data: data_peat
##
##      AIC      BIC   logLik deviance df.resid
##     84.1     96.7    -37.0     74.1       88
##
##
## Dispersion parameter for beta family (): 4.73
##
## Conditional model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -1.4632     0.2404  -6.086 1.15e-09 ***
```

```
## dry1          0.1653     0.4057   0.407    0.684
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Zero-inflation model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)   0.7985     0.2838   2.813   0.0049 **
## dry1          0.5878     0.5090   1.155   0.2482
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

With fen-bog and interactions

Plant groups only

Step 1: Models with all interactions (except fen*nutrient) In these models I include all interactions of fen with the other variables (except for fen*nutrient which will give problems).

I use AR models from the start!

```
mod_abund_tot_Sphagnum_temp_AR_all_ints<-glmmTMB(tot_Sphagnum_prop~
                                                   (temp+moist+fire+dry)*fen+
                                                   nutrient+
                                                   ar1(times+0|group),
                                                 family="beta_family",
                                                 ziformula=~.,
                                                 data=dat0)
mod_abund_Erio_nozi_temp_AR_all_ints<-glmmTMB(Erio_prop~
                                                (temp+moist+fire+dry)*fen+
                                                nutrient+
                                                ar1(times+0|group),
                                              family="beta_family",
                                              ziformula=~0,
                                              data=dat0)
mod_abund_Erica_nozi_temp_AR_all_ints<-glmmTMB(Erica_prop~
                                                 (temp+moist+fire+dry)*fen+
                                                 nutrient+
                                                 ar1(times_Erica+0|group_Erica),
                                               family="beta_family",
                                               ziformula=~0,
                                               data=dat0_Erica)
mod_abund_Carex_nozi_temp_AR_all_ints<-glmmTMB(Carex_prop~
                                                 (temp+moist+fire+dry)*fen+
                                                 nutrient+
                                                 ar1(times+0|group),
                                               family="beta_family",
                                               ziformula=~0,
                                               data=dat0)
```

```
summary(mod_abund_tot_Sphagnum_temp_AR_all_ints)
```

```
##  Family: beta  ( logit )
```

```
## Formula:
## tot_Sphagnum_prop ~ (temp + moist + fire + dry) * fen + nutrient +
##     ar1(times + 0 | group)
## Zero inflation:                      ~.
## Data: dat0
##
##      AIC      BIC   logLik deviance df.resid
##     49.3    121.7      2.3     -4.7       81
##
## Random effects:
##
## Conditional model:
##  Groups Name     Variance Std.Dev. Corr
##  group  times352 0.277    0.5263   0.85 (ar1)
## Number of obs: 108, groups:  group, 1
##
## Zero-inflation model:
##  Groups Name      Variance Std.Dev. Corr
##  group  times352  46943    216.7
##         times452  46943    216.7    0.79
##         times505  46943    216.7    0.62 0.79
##         times555  46943    216.7    0.49 0.62 0.79
##         times606  46943    216.7    0.39 0.49 0.62 0.79
##         times643  46943    216.7    0.31 0.39 0.49 0.62 0.79
##         times673  46943    216.7    0.24 0.31 0.39 0.49 0.62 0.79
##         times717  46943    216.7    0.19 0.24 0.31 0.39 0.49 0.62 0.79
##         times754  46943    216.7    0.15 0.19 0.24 0.31 0.39 0.49 0.62 0.79
##         times791  46943    216.7    0.12 0.15 0.19 0.24 0.31 0.39 0.49 0.62
##         times813  46943    216.7    0.10 0.12 0.15 0.19 0.24 0.31 0.39 0.49
##         times879  46943    216.7    0.08 0.10 0.12 0.15 0.19 0.24 0.31 0.39
##         times900  46943    216.7    0.06 0.08 0.10 0.12 0.15 0.19 0.24 0.31
##         times943  46943    216.7    0.05 0.06 0.08 0.10 0.12 0.15 0.19 0.24
##         times980  46943    216.7    0.04 0.05 0.06 0.08 0.10 0.12 0.15 0.19
##         times1018 46943    216.7    0.03 0.04 0.05 0.06 0.08 0.10 0.12 0.15
##         times1054 46943    216.7    0.02 0.03 0.04 0.05 0.06 0.08 0.10 0.12
##         times1092 46943    216.7    0.02 0.02 0.03 0.04 0.05 0.06 0.08 0.10
##         times1122 46943    216.7    0.01 0.02 0.02 0.03 0.04 0.05 0.06 0.08
##         times1172 46943    216.7    0.01 0.01 0.02 0.02 0.03 0.04 0.05 0.06
##         times1243 46943    216.7    0.01 0.01 0.01 0.02 0.02 0.03 0.04 0.05
##         times1344 46943    216.7    0.01 0.01 0.01 0.01 0.02 0.02 0.03 0.04
##         times1418 46943    216.7    0.01 0.01 0.01 0.01 0.01 0.02 0.02 0.03
##         times1514 46943    216.7    0.00 0.01 0.01 0.01 0.01 0.01 0.02 0.02
##         times1631 46943    216.7    0.00 0.00 0.01 0.01 0.01 0.01 0.01 0.02
##         times1682 46943    216.7    0.00 0.00 0.00 0.01 0.01 0.01 0.01 0.01
##         times1743 46943    216.7    0.00 0.00 0.00 0.00 0.01 0.01 0.01 0.01
##         times1818 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.01 0.01 0.01
##         times1880 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.01 0.01
##         times1944 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.01
##         times1992 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##         times2063 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##         times2136 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##         times2192 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##         times2238 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##         times2265 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
```

```
##          times2347 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times2422 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times2521 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times2687 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times2797 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times2918 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times2975 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times3178 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times3284 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times3517 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times3735 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times3887 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times3977 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times4118 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times4205 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times4335 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times4439 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times4502 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times4518 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times4552 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times4634 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times4681 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times4729 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times4801 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times4859 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times4893 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times4928 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times4979 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times5007 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times5035 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times5056 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times5088 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times5123 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times5156 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times5184 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times5207 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times5241 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times5309 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times5383 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times5496 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times5627 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times5760 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times5812 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times5877 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times5930 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times5987 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times6142 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times6248 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times6356 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times6484 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times6597 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times6657 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times6727 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times6773 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
```

```
##          times6845 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times6903 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times6959 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times7082 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times7368 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times7489 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times7724 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times8051 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times8172 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times8338 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times8427 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times8482 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times8546 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times8630 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times8727 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times8780 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times8843 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##          times8886 46943    216.7    0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##
##
##
##
##
##
##
##
##
##
##   0.79
##   0.62 0.79
##   0.49 0.62 0.79
##   0.39 0.49 0.62 0.79
##   0.31 0.39 0.49 0.62 0.79
##   0.24 0.31 0.39 0.49 0.62 0.79
##   0.19 0.24 0.31 0.39 0.49 0.62 0.79
##   0.15 0.19 0.24 0.31 0.39 0.49 0.62 0.79
##   0.12 0.15 0.19 0.24 0.31 0.39 0.49 0.62 0.79
##   0.10 0.12 0.15 0.19 0.24 0.31 0.39 0.49 0.62 0.79
##   0.08 0.10 0.12 0.15 0.19 0.24 0.31 0.39 0.49 0.62 0.79
##   0.06 0.08 0.10 0.12 0.15 0.19 0.24 0.31 0.39 0.49 0.62 0.79
##   0.05 0.06 0.08 0.10 0.12 0.15 0.19 0.24 0.31 0.39 0.49 0.62 0.79
##   0.04 0.05 0.06 0.08 0.10 0.12 0.15 0.19 0.24 0.31 0.39 0.49 0.62 0.79
##   0.03 0.04 0.05 0.06 0.08 0.10 0.12 0.15 0.19 0.24 0.31 0.39 0.49 0.62 0.79
##   0.02 0.03 0.04 0.05 0.06 0.08 0.10 0.12 0.15 0.19 0.24 0.31 0.39 0.49 0.62
##   0.02 0.02 0.03 0.04 0.05 0.06 0.08 0.10 0.12 0.15 0.19 0.24 0.31 0.39 0.49
##   0.01 0.02 0.02 0.03 0.04 0.05 0.06 0.08 0.10 0.12 0.15 0.19 0.24 0.31 0.39
##   0.01 0.01 0.02 0.02 0.03 0.04 0.05 0.06 0.08 0.10 0.12 0.15 0.19 0.24 0.31
##   0.01 0.01 0.01 0.02 0.02 0.03 0.04 0.05 0.06 0.08 0.10 0.12 0.15 0.19 0.24
##   0.01 0.01 0.01 0.01 0.02 0.02 0.03 0.04 0.05 0.06 0.08 0.10 0.12 0.15 0.19
##   0.01 0.01 0.01 0.01 0.01 0.02 0.02 0.03 0.04 0.05 0.06 0.08 0.10 0.12 0.15
##   0.00 0.01 0.01 0.01 0.01 0.01 0.02 0.02 0.03 0.04 0.05 0.06 0.08 0.10 0.12
##   0.00 0.00 0.01 0.01 0.01 0.01 0.01 0.02 0.02 0.03 0.04 0.05 0.06 0.08 0.10
##   0.00 0.00 0.00 0.01 0.01 0.01 0.01 0.01 0.02 0.02 0.03 0.04 0.05 0.06 0.08
##   0.00 0.00 0.00 0.00 0.01 0.01 0.01 0.01 0.01 0.02 0.02 0.03 0.04 0.05 0.06
```

```
##   0.00 0.00 0.00 0.00 0.00 0.01 0.01 0.01 0.01 0.01 0.02 0.02 0.03 0.04 0.05
##   0.00 0.00 0.00 0.00 0.00 0.00 0.01 0.01 0.01 0.01 0.01 0.02 0.02 0.03 0.04
##   0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.01 0.01 0.01 0.01 0.01 0.02 0.02 0.03
##   0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.01 0.01 0.01 0.01 0.01 0.02 0.02
##   0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.01 0.01 0.01 0.01 0.01 0.02
##   0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.01 0.01 0.01 0.01 0.01
##   0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.01 0.01 0.01 0.01
##   0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.01 0.01 0.01
##   0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.01 0.01
##   0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.01
##   0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##   0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
##   0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00
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##   0.03 0.04 0.05 0.06 0.08 0.10 0.12 0.15 0.19 0.24 0.31 0.39 0.49 0.62 0.79
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##  0.12 0.15 0.19 0.24 0.31 0.39 0.49 0.62 0.79
## Number of obs: 108, groups:  group, 1
##
## Dispersion parameter for beta family (): 3.46
##
## Conditional model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  0.77494    1.84736   0.420   0.6749
## temp        -0.11320    0.22358  -0.506   0.6126
## moist       -0.33660    0.30335  -1.110   0.2672
## fire1        0.13818    0.44972   0.307   0.7586
## dry1         0.63903    0.35357   1.807   0.0707 .
## fenY         1.00612    4.56641   0.220   0.8256
## nutrient1    0.42662    0.45166   0.945   0.3449
## temp:fenY   -0.28090    0.51963  -0.541   0.5888
## moist:fenY   1.04336    1.18786   0.878   0.3798
## fire1:fenY  -0.06444    0.83388  -0.077   0.9384
## dry1:fenY   -0.55846    0.99548  -0.561   0.5748
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Zero-inflation model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -69.805    122.359  -0.571   0.5683
## temp          -6.287     12.416  -0.506   0.6126
## moist        -17.779     10.915  -1.629   0.1034
## fire1         26.678     10.745   2.483   0.0130 *
## dry1         -10.918     15.151  -0.721   0.4711
## fenY         116.692    156.657   0.745   0.4563
## nutrient1     46.007     32.176   1.430   0.1528
```

```
## temp:fenY     -1.258     15.898  -0.079   0.9369
## moist:fenY   -39.574     34.338  -1.153   0.2491
## fire1:fenY   -45.509     24.730  -1.840   0.0657 .
## dry1:fenY      5.955     24.642   0.242   0.8090
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
summary(mod_abund_Erio_nozi_temp_AR_all_ints)
```

```
##  Family: beta  ( logit )
## Formula:
## Erio_prop ~ (temp + moist + fire + dry) * fen + nutrient + ar1(times +
##     0 | group)
## Data: dat0
##
##      AIC      BIC   logLik deviance df.resid
##   -139.8   -102.2     83.9   -167.8       94
##
## Random effects:
##
## Conditional model:
##  Groups Name     Variance Std.Dev. Corr
##  group  times352 1.414    1.189    0.32 (ar1)
## Number of obs: 108, groups:  group, 1
##
## Dispersion parameter for beta family (): 6.91e+07
##
## Conditional model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)   0.7154     1.8317   0.391   0.6961
## temp         -0.2687     0.2315  -1.160   0.2459
## moist         0.1943     0.3305   0.588   0.5566
## fire1        -0.3960     0.3900  -1.016   0.3099
## dry1         -0.6043     0.3665  -1.649   0.0991 .
## fenY         -6.1007     3.9617  -1.540   0.1236
## nutrient1    -0.5681     0.3882  -1.464   0.1433
## temp:fenY     0.8595     0.4681   1.836   0.0663 .
## moist:fenY    1.4168     0.8475   1.672   0.0946 .
## fire1:fenY    0.9494     0.6118   1.552   0.1207
## dry1:fenY    -1.0238     0.9618  -1.064   0.2871
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
summary(mod_abund_Erica_nozi_temp_AR_all_ints)
```

```
##  Family: beta  ( logit )
## Formula:
## Erica_prop ~ (temp + moist + fire + dry) * fen + nutrient + ar1(times_Erica +
##     0 | group_Erica)
## Data: dat0_Erica
##
##      AIC      BIC   logLik deviance df.resid
##   -231.4   -194.0    129.7   -259.4       93
```

```
##
## Random effects:
##
## Conditional model:
##  Groups      Name           Variance Std.Dev. Corr
##  group_Erica times_Erica352 1.161    1.077    0.26 (ar1)
## Number of obs: 107, groups:  group_Erica, 1
##
## Dispersion parameter for beta family (): 1.91e+08
##
## Conditional model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -6.5057     1.3644  -4.768 1.86e-06 ***
## temp          0.5638     0.1743   3.235  0.00122 **
## moist         0.3326     0.3002   1.108  0.26787
## fire1         1.0142     0.3470   2.923  0.00346 **
## dry1         -0.4458     0.3143  -1.418  0.15611
## fenY          4.3705     3.4773   1.257  0.20880
## nutrient1    -0.5904     0.3410  -1.731  0.08339 .
## temp:fenY    -0.5556     0.4108  -1.352  0.17626
## moist:fenY   -1.3484     0.7899  -1.707  0.08783 .
## fire1:fenY   -1.8475     0.5665  -3.261  0.00111 **
## dry1:fenY     1.6238     0.8517   1.907  0.05658 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
summary(mod_abund_Carex_nozi_temp_AR_all_ints)
```

```
##  Family: beta  ( logit )
## Formula:
## Carex_prop ~ (temp + moist + fire + dry) * fen + nutrient + ar1(times +
##     0 | group)
## Data: dat0
##
##      AIC      BIC   logLik deviance df.resid
##   -231.7   -194.1    129.8   -259.7       94
##
## Random effects:
##
## Conditional model:
##  Groups Name     Variance Std.Dev. Corr
##  group  times352 0.1299   0.3604   0.92 (ar1)
## Number of obs: 108, groups:  group, 1
##
## Dispersion parameter for beta family (): 14.1
##
## Conditional model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept) -2.79618    1.49697  -1.868   0.0618 .
## temp         0.15354    0.18065   0.850   0.3954
## moist       -0.15270    0.19694  -0.775   0.4381
## fire1        0.19671    0.26604   0.739   0.4597
## dry1        -0.44931    0.22874  -1.964   0.0495 *
## fenY         0.78051    2.47848   0.315   0.7528
```

```
## nutrient1   -0.73381    0.29508  -2.487   0.0129 *
## temp:fenY   -0.08138    0.28959  -0.281   0.7787
## moist:fenY  -0.42157    0.51345  -0.821   0.4116
## fire1:fenY  -0.04639    0.40144  -0.116   0.9080
## dry1:fenY    0.82013    0.57203   1.434   0.1517
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Step 2: Models with only significant interactions In these models I include only the interactions of fen with the other variables that were significant in step 1. If one interaction was significant only in the abundance part ("conditional model") or on the presence part ("zero-inflation model") I inlcude it only on that part of the model.

```
# Total Sphagnum: no significant interactions
# Erio: no significant interactions
# Erica: significant interaction fire*fen
mod_abund_Erica_nozi_temp_AR_sig_ints<-glmmTMB(Erica_prop~
                                                  temp+moist+fire+dry+nutrient+
                                                  fen+fen:fire+
                                                  ar1(times_Erica+0|group_Erica),
                                                family="beta_family",
                                                ziformula=~0,
                                                data=dat0_Erica)
# Carex: no significant interactions
```

```
summary(mod_abund_Erica_nozi_temp_AR_sig_ints)
```

Model summaries (Appendix S4, Table S4)

```
##  Family: beta  ( logit )
## Formula:
## Erica_prop ~ temp + moist + fire + dry + nutrient + fen + fen:fire +
##     ar1(times_Erica + 0 | group_Erica)
## Data: dat0_Erica
##
##      AIC      BIC   logLik deviance df.resid
##   -232.5   -203.1    127.2   -254.5       96
##
## Random effects:
##
## Conditional model:
##  Groups      Name           Variance Std.Dev. Corr
##  group_Erica times_Erica352 1.237    1.112    0.29 (ar1)
## Number of obs: 107, groups:  group_Erica, 1
##
## Dispersion parameter for beta family (): 1.37e+10
##
## Conditional model:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -5.8718     1.2820  -4.580 4.65e-06 ***
```

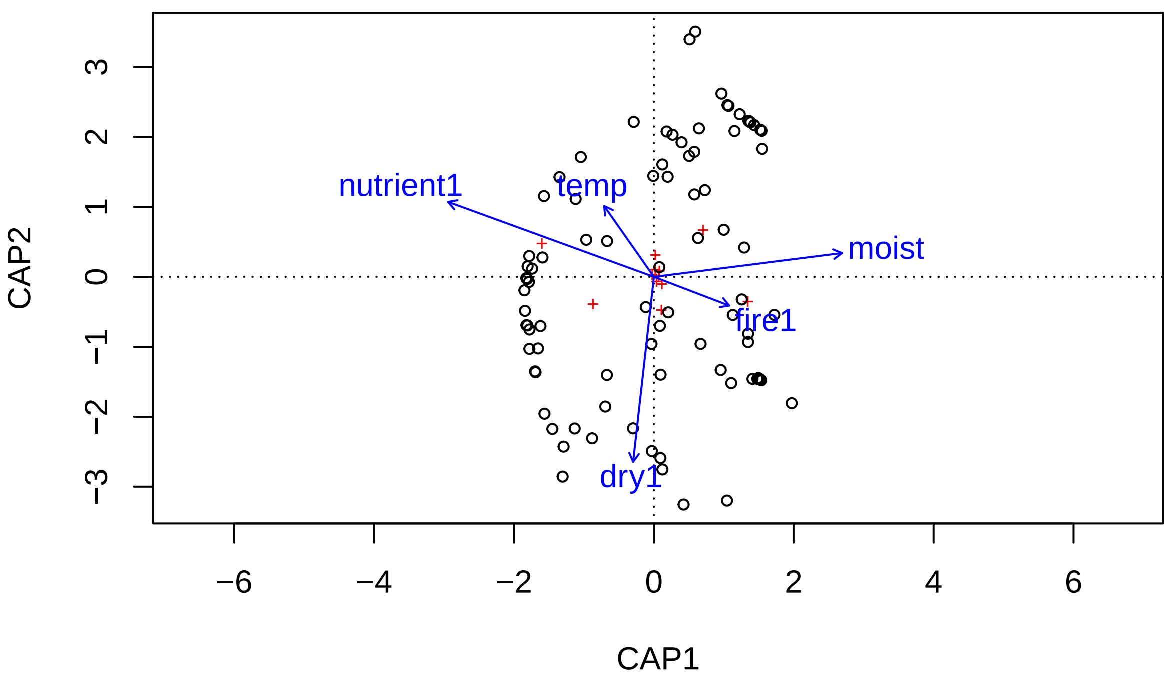
```
## temp           0.4746     0.1655   2.868  0.00413 **
## moist          0.1788     0.2766   0.646  0.51801
## fire1          0.9927     0.3494   2.841  0.00450 **
## dry1          -0.3012     0.2963  -1.016  0.30946
## nutrient1     -0.5776     0.3507  -1.647  0.09954 .
## fenY          -0.1945     0.4529  -0.429  0.66758
## fire1:fenY    -1.7018     0.5617  -3.030  0.00245 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Figures

Figure 1: Ordination

Check: https://rstudio-pubs-static.s3.amazonaws.com/694016_e2d53d65858d4a1985616fa3855d237f.html Ordination plot with vegan:

```
ordination_plot_temp<-ordiplot(ordination,display = c('species', 'sites', 'bp'))
```



Extract information on the locations of sites (circles in the ordiplot) via function sites.long. Information on characteristics of the sites is added via the argument of env.data.

Extract information on species with function species.long.

```r
sites.long1_temp <- sites.long(ordination_plot_temp, env.data=data_ordi2)
species.long2_temp <- species.long(ordination_plot_temp)
row.names(species.long2_temp)<-c("Balticum","Medium","Cuspidata","Austinii",
                                 "Fuscum","Rubellum","Acutifolia",
                                 "Deformed Acutifolia","Angustifolium",
                                 "Tenellum","Papillosum","Fallax" )
head(sites.long1_temp)
```

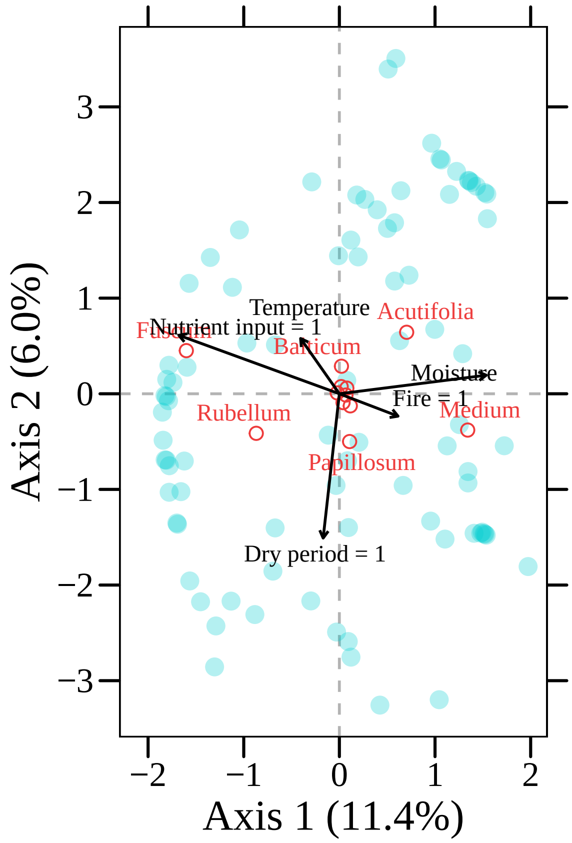
```
##   n_samples depth depth_corrected fen tot_Sphagnum Erio Carex Erica other_veg
## 1         5 40-41              40   N           90    2     3     5         0
## 2         6 50-51              50   N           41   46     9     4         0
## 3         7 55-56              55   N           74   19     6     1         0
## 4         8 60-61              60   N           94    4     1     1         0
## 5         9 65-66              65   N           95    3     1     1         0
## 6        10 70-71              70   N           90    3     4     3         0
##   Balticum    Medium Cuspidata Austinii Fuscum Rubellum Acutifolia
## 1 18.88889  5.555556  3.333333        0      0   0.0000   72.22222
## 2 17.07317 41.463415 21.951220        0      0  19.5122    0.00000
## 3 56.75676 21.621622 21.621622        0      0   0.0000    0.00000
## 4 48.93617 38.297872 12.765957        0      0   0.0000    0.00000
## 5 58.94737 26.315789 14.736842        0      0   0.0000    0.00000
## 6 54.44444 11.111111 34.444444        0      0   0.0000    0.00000
##   Deformed_Acutifolia Angustifolium Tenellum Papillosum Fallax Stems age
## 1                   0             0        0          0      0     0 352
## 2                   0             0        0          0      0     0 452
## 3                   0             0        0          0      0     0 505
## 4                   0             0        0          0      0     0 555
## 5                   0             0        0          0      0     0 606
## 6                   0             0        0          0      0     0 643
##       temp imp_temp moist nutrient fire dry      axis1    axis2 labels
## 1 8.001761        1 -0.38        1    0   0 0.59086730 3.505911      1
## 2 7.813114        1 -0.30        1    0   0 0.07727259 0.138946      2
## 3 7.713132        1  0.01        1    0   0 0.39535538 1.923636      3
## 4 7.618808        1 -0.26        1    0   0 0.72793145 1.239533      4
## 5 7.522598        1  0.22        1    0   0 0.50282379 1.729268      5
## 6 7.452799        1 -0.25        1    0   0 0.18165566 2.078032      6
```

```r
species.long2_temp
```

```
##                           axis1        axis2              labels
## Balticum             0.02150429  0.288125104            Balticum
## Medium               1.34182312 -0.379491731              Medium
## Cuspidata            0.07782837  0.059025172           Cuspidata
## Austinii             0.11412739 -0.126341595            Austinii
## Fuscum              -1.60035421  0.451093787              Fuscum
## Rubellum            -0.86907633 -0.413578832            Rubellum
## Acutifolia           0.70333758  0.642889127          Acutifolia
## Deformed Acutifolia  0.01874410  0.075148342 Deformed_Acutifolia
## Angustifolium       -0.02218882  0.008814302       Angustifolium
## Tenellum             0.06860906 -0.013454710            Tenellum
## Papillosum           0.10708721 -0.499541083          Papillosum
## Fallax               0.03825752 -0.092474147              Fallax
```

```r
vectors.long3_temp  <- data.frame(summary(ordination)$biplot[,1:2])
row.names(vectors.long3_temp)<-c("Temperature","Moisture","Nutrient input = 1",
                                 "Fire = 1","Dry period = 1")
```

```r
figure1 <- ggplot() +
  geom_vline(xintercept = c(0), color = "grey70", linetype = 2) +
  geom_hline(yintercept = c(0), color = "grey70", linetype = 2) +
  xlab("Axis 1 (11.4%)") + ylab("Axis 2 (6.0%)") +  coord_fixed()+
  scale_x_continuous(sec.axis = dup_axis(labels=NULL, name=NULL)) +
  scale_y_continuous(breaks=seq(-3,3,by=1),
                     sec.axis = dup_axis(labels=NULL, name=NULL)) +
  geom_point(data=sites.long1_temp,aes(x=axis1, y=axis2),
             size=3,alpha=0.3,shape=16,color="darkturquoise") +
  geom_point(data=species.long2_temp,aes(x=axis1, y=axis2),
             size=2,shape=1,color="brown2") +
  geom_text_repel(data=species.long2_temp,aes(x=axis1, y=axis2, label=labels),
                  colour="brown2",size=3,family="serif")+
  geom_segment(data=vectors.long3_temp, aes(x=0, y=0, xend=CAP1*2, yend=CAP2*2),
               color="black", size=0.5,arrow=arrow(length=unit(0.02,"npc"))) +
  geom_text_repel(data=vectors.long3_temp[1,],
                  aes(x=CAP1*2.16,y=CAP2*2.4,
                      label=rownames(vectors.long3_temp[1,])),
                  cex=3,direction="both",segment.size=0.25,color="black",
                  family="serif") +
  geom_text_repel(data=vectors.long3_temp[2,],
                  aes(x=CAP1*2.3,y=CAP2*2.3,
                      label=rownames(vectors.long3_temp[2,])),
                  cex=3,direction="both",segment.size=0.25,color="black",
                  family="serif") +
  geom_text_repel(data=vectors.long3_temp[3,],
                  aes(x=CAP1*2.5,y=CAP2*2.3,
                      label=rownames(vectors.long3_temp[3,])),
                  cex=3,direction="both",segment.size=0.25,color="black",
                  family="serif") +
  geom_text_repel(data=vectors.long3_temp[4,],
                  aes(x=CAP1*2.7,y=CAP2*2.2,
                      label=rownames(vectors.long3_temp[4,])),
                  cex=3,direction="both",segment.size=0.25,color="black",
                  family="serif") +
  geom_text_repel(data=vectors.long3_temp[5,],
                  aes(x=CAP1*4.5,y=CAP2*2.5,
                      label=rownames(vectors.long3_temp[5,])),
                  cex=3,direction="both",segment.size=0.25,color="black",
                  family="serif") +
  my_theme()
figure1
```




```
ggsave(filename="output/figures/figure1.tiff",plot=figure1,
       width=12,height=16.8,units="cm",dpi=300)
```

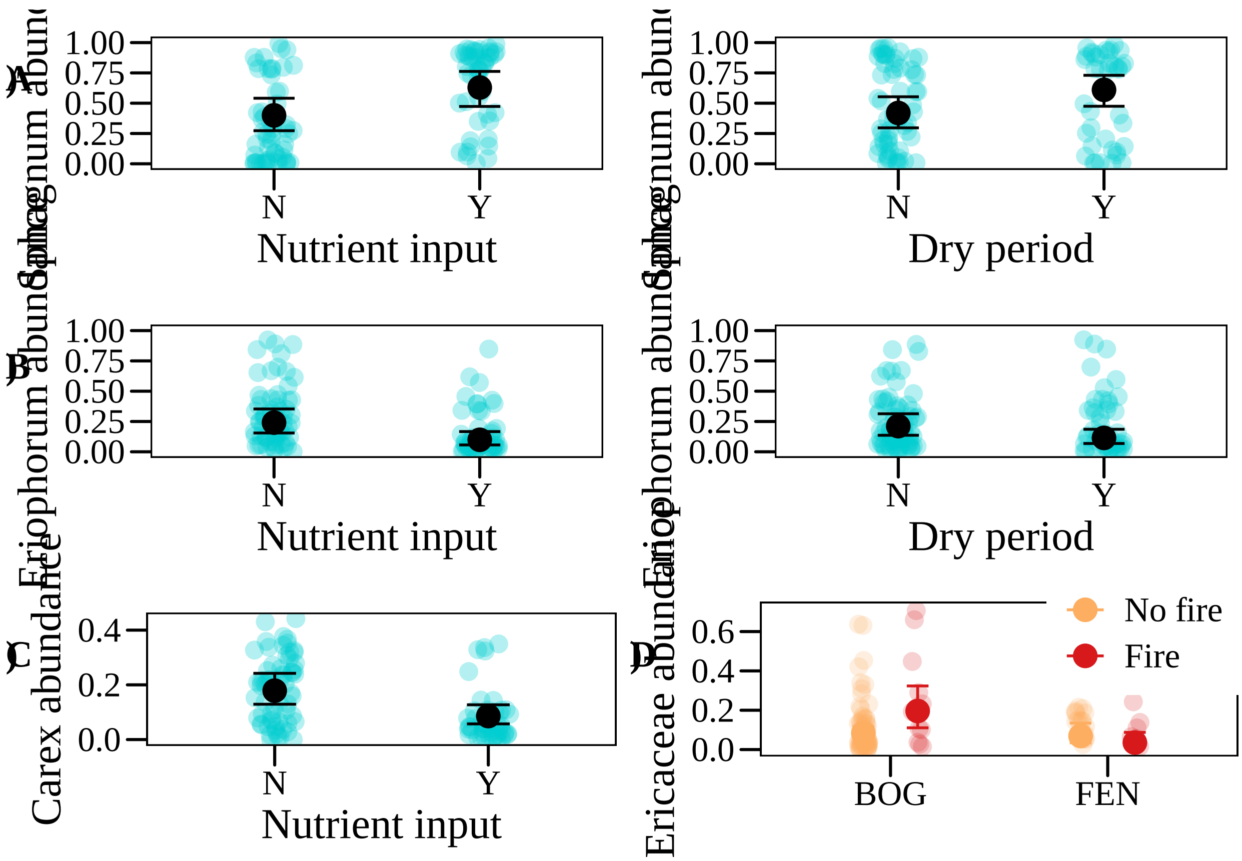
Figure 2: Plant gropus

```
figure2_a1<-
  # Total Sphagnum abundance ~ nutr
  ggplot()+
      geom_jitter(data=data_peat,aes(x=nutrient,y=tot_Sphagnum_prop),
                  position = position_jitter(0.1,0.01),
                  size=3,alpha=0.3,shape=16,color="darkturquoise")+
      geom_point(data=data.frame(ggemmeans(mod_abund_tot_Sphagnum_temp_AR,
                                           type="fixed",terms=c("nutrient"))),
                 aes(x=x,y=predicted),size=4,shape=16)+
      geom_errorbar(data=data.frame(ggemmeans(mod_abund_tot_Sphagnum_temp_AR,
                                              type="fixed",terms=c("nutrient"))),
                    aes(x=x,y=predicted,ymin=conf.low,ymax=conf.high),
                    width=0.2,size=0.5)+
  scale_y_continuous(breaks=c(0,0.2,0.4,0.6,0.8))+
      my_theme()+xlab("Nutrient input")+ylab("Sphagnum abundance")+
  scale_y_continuous(limits=c(0,1),breaks=c(0,0.25,0.5,0.75,1))+
  theme(plot.margin = margin(r = 10, l = 5,t=10,b=10))+
  scale_x_discrete(labels = c("N", "Y"))
figure2_a2<-
```

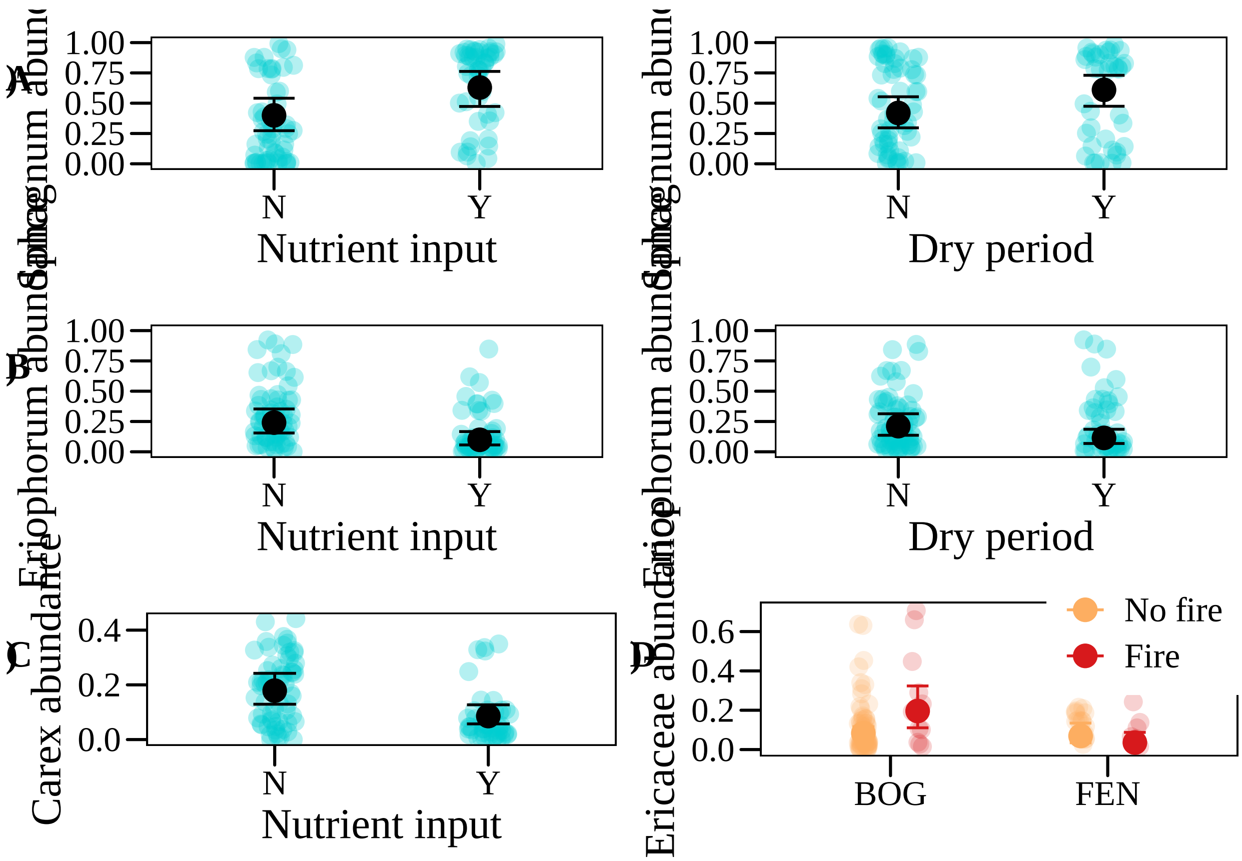
```r
  # Total Sphagnum abundance ~ dry
  ggplot()+
  geom_jitter(data=data_peat,aes(x=dry,y=tot_Sphagnum_prop),
              position = position_jitter(0.1,0.01),
              size=3,alpha=0.3,shape=16,color="darkturquoise")+
  geom_point(data=data.frame(ggemmeans(mod_abund_tot_Sphagnum_temp_AR,
                                       type="fixed",terms=c("dry"))),
             aes(x=x,y=predicted),size=4,shape=16)+
  geom_errorbar(data=data.frame(ggemmeans(mod_abund_tot_Sphagnum_temp_AR,
                                          type="fixed",terms=c("dry"))),
                aes(x=x,y=predicted,ymin=conf.low,ymax=conf.high),
                width=0.2,size=0.5)+
  scale_y_continuous(breaks=c(0,0.2,0.4,0.6,0.8,1))+
  my_theme()+xlab("Dry period")+ylab("Sphagnum abundance") +
  scale_y_continuous(limits=c(0,1),breaks=c(0,0.25,0.5,0.75,1))+
  theme(plot.margin = margin(r = 10, l = 5,t=10,b=10))+
  scale_x_discrete(labels = c("N", "Y"))
figure2_b1<-
  # Erio abundance ~ nutr
  ggplot()+
  geom_jitter(data=data_peat,aes(x=nutrient,y=Erio_prop),
              position = position_jitter(0.1,0.01),
              size=3,alpha=0.3,shape=16,color="darkturquoise")+
  geom_point(data=data.frame(ggemmeans(mod_abund_Erio_nozi_temp_AR,
                                       type="fixed",terms=c("nutrient"))),
             aes(x=x,y=predicted),size=4,shape=16)+
  geom_errorbar(data=data.frame(ggemmeans(mod_abund_Erio_nozi_temp_AR,
                                          type="fixed",terms=c("nutrient"))),
                aes(x=x,y=predicted,ymin=conf.low,ymax=conf.high),
                width=0.2,size=0.5)+
  scale_y_continuous(breaks=c(0,0.2,0.4,0.6,0.8))+
  my_theme()+xlab("Nutrient input")+ylab("Eriophorum abundance")+
  scale_y_continuous(limits=c(0,1),breaks=c(0,0.25,0.5,0.75,1))+
  theme(plot.margin = margin(r = 10, l = 5,t=10,b=10))+
  scale_x_discrete(labels = c("N", "Y"))
figure2_b2<-
  # Erio abundance ~ dry
  ggplot()+
  geom_jitter(data=data_peat,aes(x=dry,y=Erio_prop),
              position = position_jitter(0.1,0.01),
              size=3,alpha=0.3,shape=16,color="darkturquoise")+
  geom_point(data=data.frame(ggemmeans(mod_abund_Erio_nozi_temp_AR,
                                       type="fixed",terms=c("dry"))),
             aes(x=x,y=predicted),size=4,shape=16)+
  geom_errorbar(data=data.frame(ggemmeans(mod_abund_Erio_nozi_temp_AR,
                                          type="fixed",terms=c("dry"))),
                aes(x=x,y=predicted,ymin=conf.low,ymax=conf.high),
                width=0.2,size=0.5)+
  scale_y_continuous(breaks=c(0,0.2,0.4,0.6,0.8))+
  my_theme()+xlab("Dry period")+ylab("Eriophorum abundance")+
  scale_y_continuous(limits=c(0,1),breaks=c(0,0.25,0.5,0.75,1))+
  theme(plot.margin = margin(r = 10, l = 5,t=10,b=10))+
  scale_x_discrete(labels = c("N", "Y"))
```

```r
figure2_c<-
  # Carex abundance ~ nutr
   ggplot()+
  geom_jitter(data=data_peat,aes(x=nutrient,y=Carex_prop),
              position = position_jitter(0.1,0.01),
              size=3,alpha=0.3,shape=16,color="darkturquoise")+
  geom_point(data=data.frame(ggemmeans(mod_abund_Carex_nozi_temp_AR,
                                       type="fixed",terms=c("nutrient"))),
             aes(x=x,y=predicted),size=4,shape=16)+
  geom_errorbar(data=data.frame(ggemmeans(mod_abund_Carex_nozi_temp_AR,
                                          type="fixed",terms=c("nutrient"))),
                aes(x=x,y=predicted,ymin=conf.low,ymax=conf.high),
                width=0.2,size=0.5)+
  scale_y_continuous(breaks=c(0,0.2,0.4,0.6,0.8))+
  my_theme()+xlab("Nutrient input")+ylab("Carex abundance")+
  theme(plot.margin = margin(l=10,r = 5,t=10,b=10))+
  scale_x_discrete(labels = c("N", "Y"))
figure2_d<-
  # Erica abundance ~ fire:fen
  ggplot()+
  geom_jitter(data=dat0_Erica,aes(x=fen,y=Erica_prop,color=fire),
              position=position_jitterdodge(jitter.width=0.1,
                                            jitter.height=0.01,
                                            dodge.width=0.5),
              size=3,alpha=0.2,shape=16)+
  geom_point(data=data.frame(ggemmeans(mod_abund_Erica_nozi_temp_AR_sig_ints,
                                       type="fixed",terms=c("fen","fire"))),
             aes(x=x,y=predicted,color=group),
             size=4,shape=16,position=position_dodge(0.5))+
  geom_errorbar(data=data.frame(ggemmeans(mod_abund_Erica_nozi_temp_AR_sig_ints,
                                          type="fixed",terms=c("fen","fire"))),
                aes(x=x,y=predicted,ymin=conf.low,ymax=conf.high,color=group),
                width=0.2,size=0.5,position=position_dodge(0.5))+
  scale_color_manual(values=c("#fdae61","#d7191c"),
                     labels=c("No fire","Fire"))+
  my_theme_legend()+xlab("Type")+ylab("Ericaceae abundance")+
  scale_x_discrete(labels = c("BOG", "FEN"))+
  theme(axis.title.x = element_text(colour = "white"))+
  guides(color=guide_legend(title=NULL))+
  theme(legend.position=c(0.8,0.8))
```

```r
figure2_a<-cowplot::plot_grid(figure2_a1,figure2_a2,ncol=2,labels=c("A)",NULL),
                              label_fontfamily="Times New Roman")
figure2_b<-cowplot::plot_grid(figure2_b1,figure2_b2,ncol=2,labels=c("B)",NULL),
                              label_fontfamily="Times New Roman")
figure2_cd<-cowplot::plot_grid(figure2_c,figure2_d,ncol=2,labels=c("C)","D)"),
                              label_fontfamily="Times New Roman")
figure2<-grid.arrange(figure2_a,figure2_b,figure2_cd,nrow=3)
```




```r
plot(figure2)
```




```
ggsave(filename="output/figures/figure2.tiff",
       plot=figure2,width=25,height=30,units="cm",dpi=300)
```

Appendix S4: Figure S1: Selected Sphagnum species: Medium, Balticum and Cuspidata

```
# Create average line among factors=0 and factors=1
average_prediction_Medium_temp<-rbind(
  tibble(ggpredict(mod_abund_Medium_temp,type="zi_prob",terms=c("temp[all]"),
                   condition=c(nutrient=1,fire=1,dry=1)))%>%
    select(-group)%>%mutate(type="a"),
  tibble(ggpredict(mod_abund_Medium_temp,type="zi_prob",terms=c("temp[all]"),
                   condition=c(nutrient=0,fire=0,dry=0)))%>%
    select(-group)%>%mutate(type="b"),
  tibble(ggpredict(mod_abund_Medium_temp,type="zi_prob",terms=c("temp[all]"),
                   condition=c(nutrient=0,fire=1,dry=1)))%>%
    select(-group)%>%mutate(type="c"),
  tibble(ggpredict(mod_abund_Medium_temp,type="zi_prob",terms=c("temp[all]"),
                   condition=c(nutrient=1,fire=0,dry=1)))%>%
    select(-group)%>%mutate(type="d"),
  tibble(ggpredict(mod_abund_Medium_temp,type="zi_prob",terms=c("temp[all]"),
                   condition=c(nutrient=1,fire=1,dry=0)))%>%
    select(-group)%>%mutate(type="e"),
```

```
  tibble(ggpredict(mod_abund_Medium_temp,type="zi_prob",terms=c("temp[all]"),
                   condition=c(nutrient=0,fire=0,dry=1)))%>%
    select(-group)%>%mutate(type="f"),
  tibble(ggpredict(mod_abund_Medium_temp,type="zi_prob",terms=c("temp[all]"),
                   condition=c(nutrient=0,fire=1,dry=0)))%>%
    select(-group)%>%mutate(type="g"),
  tibble(ggpredict(mod_abund_Medium_temp,type="zi_prob",terms=c("temp[all]"),
                   condition=c(nutrient=1,fire=0,dry=0)))%>%
    select(-group)%>%mutate(type="h")
)%>%
  group_by(x)%>%summarise(predicted=mean(predicted),std.error=mean(std.error),
                          conf.low=mean(conf.low),conf.high=mean(conf.high))
```

```
# Create average line among factors=0 and factors=1
average_prediction_Balticum_temp<-rbind(
  tibble(ggpredict(mod_abund_Balticum_temp,type="zi_prob",terms=c("temp[all]"),
                   condition=c(nutrient=1,fire=1,dry=1)))%>%
    select(-group)%>%mutate(type="a"),
  tibble(ggpredict(mod_abund_Balticum_temp,type="zi_prob",terms=c("temp[all]"),
                   condition=c(nutrient=0,fire=0,dry=0)))%>%
    select(-group)%>%mutate(type="b"),
  tibble(ggpredict(mod_abund_Balticum_temp,type="zi_prob",terms=c("temp[all]"),
                   condition=c(nutrient=0,fire=1,dry=1)))%>%
    select(-group)%>%mutate(type="c"),
  tibble(ggpredict(mod_abund_Balticum_temp,type="zi_prob",terms=c("temp[all]"),
                   condition=c(nutrient=1,fire=0,dry=1)))%>%
    select(-group)%>%mutate(type="d"),
  tibble(ggpredict(mod_abund_Balticum_temp,type="zi_prob",terms=c("temp[all]"),
                   condition=c(nutrient=1,fire=1,dry=0)))%>%
    select(-group)%>%mutate(type="e"),
  tibble(ggpredict(mod_abund_Balticum_temp,type="zi_prob",terms=c("temp[all]"),
                   condition=c(nutrient=0,fire=0,dry=1)))%>%
    select(-group)%>%mutate(type="f"),
  tibble(ggpredict(mod_abund_Balticum_temp,type="zi_prob",terms=c("temp[all]"),
                   condition=c(nutrient=0,fire=1,dry=0)))%>%
    select(-group)%>%mutate(type="g"),
  tibble(ggpredict(mod_abund_Balticum_temp,type="zi_prob",terms=c("temp[all]"),
                   condition=c(nutrient=1,fire=0,dry=0)))%>%
    select(-group)%>%mutate(type="h")
)%>%
  group_by(x)%>%summarise(predicted=mean(predicted),std.error=mean(std.error),
                          conf.low=mean(conf.low),conf.high=mean(conf.high))
```

```
# Create average line among factors=0 and factors=1
average_prediction_Cuspidata_temp<-rbind(
  tibble(ggpredict(mod_abund_Cuspidata_temp,type="zi_prob",terms=c("temp[all]"),
                   condition=c(nutrient=1,fire=1,dry=1)))%>%
    select(-group)%>%mutate(type="a"),
  tibble(ggpredict(mod_abund_Cuspidata_temp,type="zi_prob",terms=c("temp[all]"),
                   condition=c(nutrient=0,fire=0,dry=0)))%>%
    select(-group)%>%mutate(type="b"),
  tibble(ggpredict(mod_abund_Cuspidata_temp,type="zi_prob",terms=c("temp[all]"),
                   condition=c(nutrient=0,fire=1,dry=1)))%>%
```

```
    select(-group)%>%mutate(type="c"),
  tibble(ggpredict(mod_abund_Cuspidata_temp,type="zi_prob",terms=c("temp[all]"),
                   condition=c(nutrient=1,fire=0,dry=1)))%>%
    select(-group)%>%mutate(type="d"),
  tibble(ggpredict(mod_abund_Cuspidata_temp,type="zi_prob",terms=c("temp[all]"),
                   condition=c(nutrient=1,fire=1,dry=0)))%>%
    select(-group)%>%mutate(type="e"),
  tibble(ggpredict(mod_abund_Cuspidata_temp,type="zi_prob",terms=c("temp[all]"),
                   condition=c(nutrient=0,fire=0,dry=1)))%>%
    select(-group)%>%mutate(type="f"),
  tibble(ggpredict(mod_abund_Cuspidata_temp,type="zi_prob",terms=c("temp[all]"),
                   condition=c(nutrient=0,fire=1,dry=0)))%>%
    select(-group)%>%mutate(type="g"),
  tibble(ggpredict(mod_abund_Cuspidata_temp,type="zi_prob",terms=c("temp[all]"),
                   condition=c(nutrient=1,fire=0,dry=0)))%>%
    select(-group)%>%mutate(type="h")
)%>%
  group_by(x)%>%summarise(predicted=mean(predicted),std.error=mean(std.error),
                          conf.low=mean(conf.low),conf.high=mean(conf.high))
```

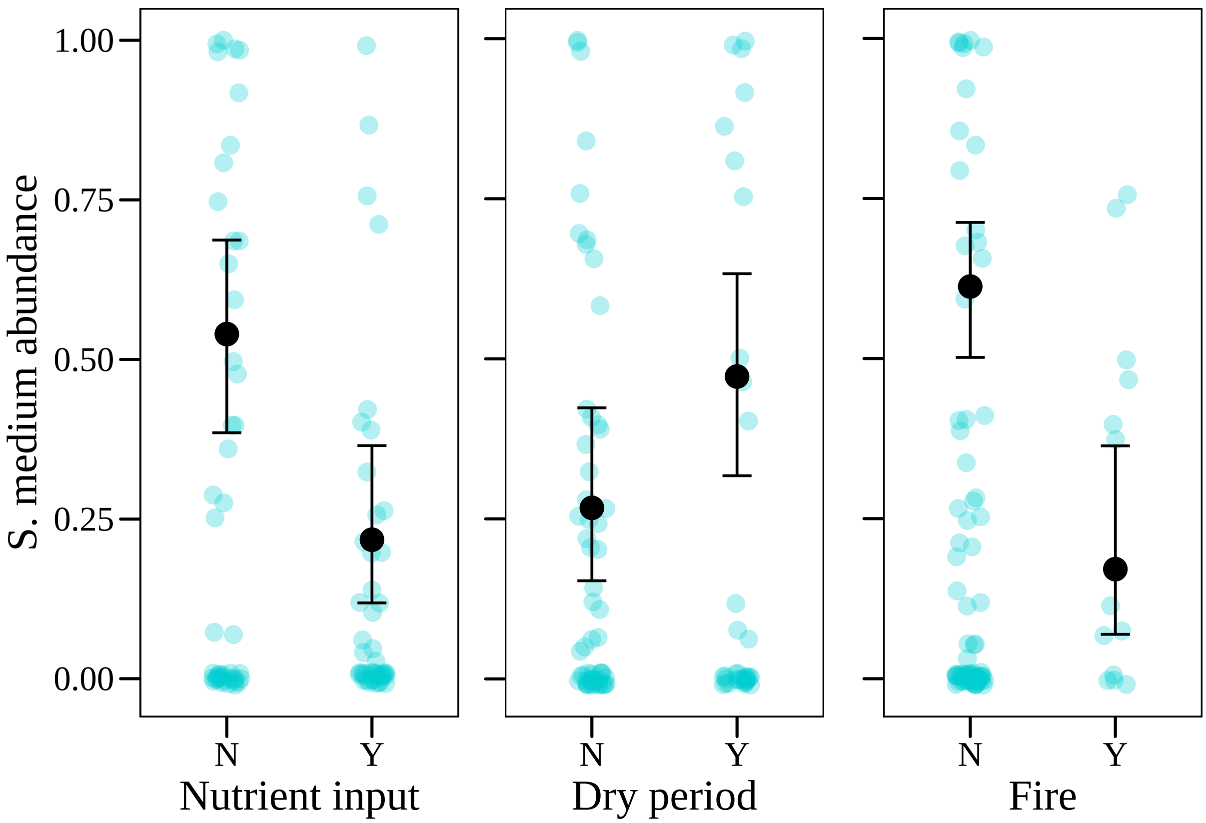
```
# Create average line among factors=0 and factors=1
average_prediction_Cuspidata_nutrient<-rbind(
  tibble(ggpredict(mod_abund_Cuspidata_temp,type="zi_prob",terms=c("nutrient"),
                   condition=c(fire=1,dry=1)))%>%
    select(-group)%>%mutate(type="a"),
  tibble(ggpredict(mod_abund_Cuspidata_temp,type="zi_prob",terms=c("nutrient"),
                   condition=c(fire=0,dry=0)))%>%
    select(-group)%>%mutate(type="b"),
  tibble(ggpredict(mod_abund_Cuspidata_temp,type="zi_prob",terms=c("nutrient"),
                   condition=c(fire=0,dry=1)))%>%
    select(-group)%>%mutate(type="c"),
  tibble(ggpredict(mod_abund_Cuspidata_temp,type="zi_prob",terms=c("nutrient"),
                   condition=c(fire=1,dry=0)))%>%
    select(-group)%>%mutate(type="d")
  )%>%
  group_by(x)%>%summarise(predicted=mean(predicted),
                          std.error=mean(std.error,na.rm=T),
                          conf.low=mean(conf.low,na.rm=T),
                          conf.high=mean(conf.high,na.rm=T))
```

```
figures1_a<-
  # Medium presence ~ temp
  ggplot()+
  geom_ribbon(data=average_prediction_Medium_temp,
              aes(x=x,y=1-predicted,ymin=1-conf.low,ymax=1-conf.high),
              alpha=0.2)+
  geom_line(data=average_prediction_Medium_temp,aes(x=x,y=1-predicted))+
  geom_point(data=data_peat,aes(x=temp,y=Medium_prop),
             size=3,alpha=0.3,shape=16,color="darkturquoise")+
  my_theme()+xlab("Temperature")+ylab("Probability of S. medium presence")+
  theme(plot.margin=margin(l = 5,t=10,b=10))
figures1_b_1<-
  # Medium abundance ~ nutr
```

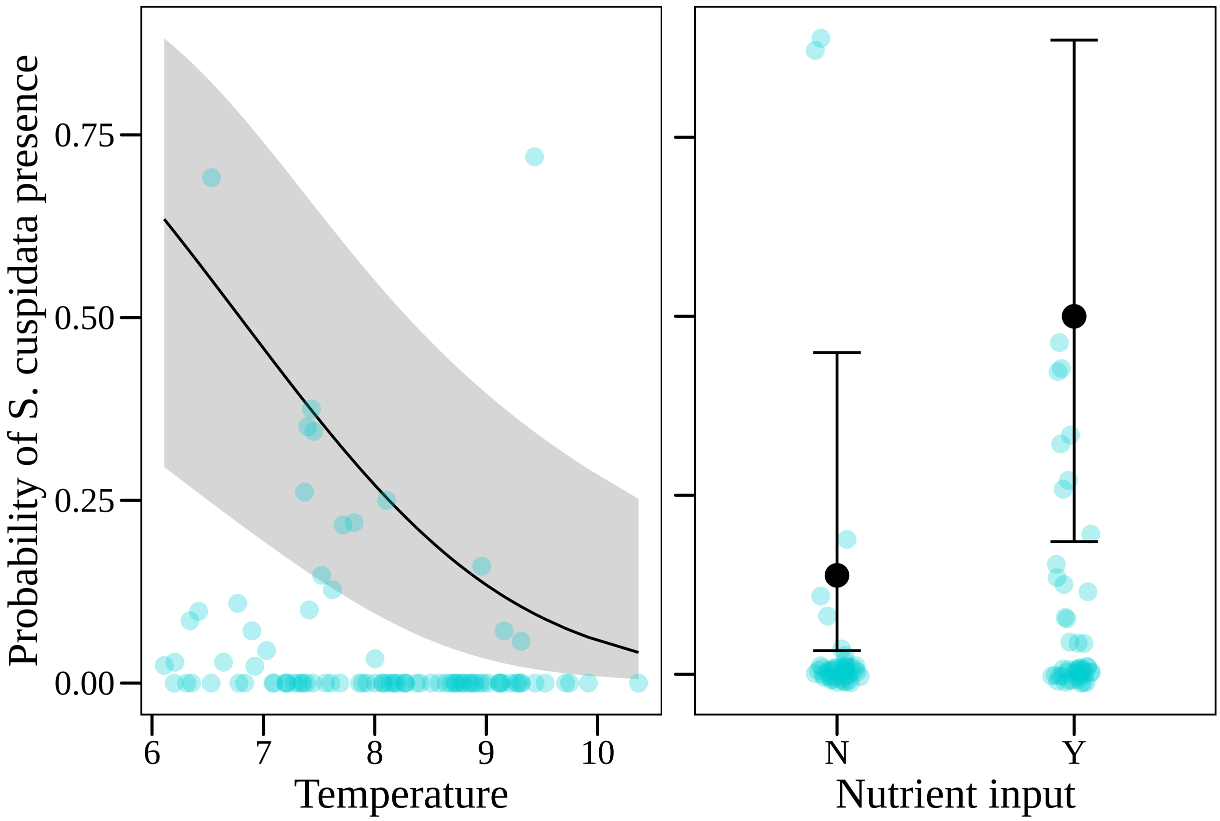
```
  ggplot()+
  geom_jitter(data=data_peat,aes(x=nutrient,y=Medium_prop),
              position = position_jitter(0.1,0.01),
              size=3,alpha=0.3,shape=16,color="darkturquoise")+
  geom_point(data=data.frame(ggemmeans(mod_abund_Medium_temp,
                                       type="fixed",terms=c("nutrient"))),
             aes(x=x,y=predicted),size=4,shape=16)+
  geom_errorbar(data=data.frame(ggemmeans(mod_abund_Medium_temp,
                                          type="fixed",terms=c("nutrient"))),
                aes(x=x,y=predicted,ymin=conf.low,ymax=conf.high),
                width=0.2,size=0.5)+
  my_theme()+xlab("Nutrient input")+ylab("S. medium abundance")+
  theme(plot.margin = margin(l=10,r = 5,t=10,b=10))+
  scale_x_discrete(labels = c("N", "Y"))
figures1_b_2<-
  # Medium abundance ~ dry
  ggplot()+
  geom_jitter(data=data_peat,aes(x=dry,y=Medium_prop),
              position = position_jitter(0.1,0.01),
              size=3,alpha=0.3,shape=16,color="darkturquoise")+
  geom_point(data=data.frame(ggemmeans(mod_abund_Medium_temp,
                                     type="fixed",terms=c("dry"))),
             aes(x=x,y=predicted),size=4,shape=16)+
  geom_errorbar(data=data.frame(ggemmeans(mod_abund_Medium_temp,
                                          type="fixed",terms=c("dry"))),
                aes(x=x,y=predicted,ymin=conf.low,ymax=conf.high),
                width=0.2,size=0.5)+
  my_theme()+xlab("Dry period")+ylab("S. medium abundance")+
  theme(axis.text.y = element_blank(),
        axis.title.y = element_blank(),
        plot.margin = margin(r = 10, l = 5,t=10,b=10))+
  scale_x_discrete(labels = c("N", "Y"))
figures1_b_3<-
  # Medium abundance ~ fire
  ggplot()+
  geom_jitter(data=data_peat,aes(x=fire,y=Medium_prop),
              position = position_jitter(0.1,0.01),
              size=3,alpha=0.3,shape=16,color="darkturquoise")+
  geom_point(data=data.frame(ggemmeans(mod_abund_Medium_temp,
                                     type="fixed",terms=c("fire"))),
             aes(x=x,y=predicted),size=4,shape=16)+
  geom_errorbar(data=data.frame(ggemmeans(mod_abund_Medium_temp,
                                          type="fixed",terms=c("fire"))),
                aes(x=x,y=predicted,ymin=conf.low,ymax=conf.high),
                width=0.2,size=0.5)+
  my_theme()+xlab("Fire")+ylab("S. medium abundance")+
  theme(axis.text.y = element_blank(),
        axis.title.y = element_blank(),
        plot.margin = margin(r = 10, l = 5,t=10,b=10))+
  scale_x_discrete(labels = c("N", "Y"))
figures1_c<-
  # Balticum presence ~ temp
  ggplot()+
```

```r
  geom_ribbon(data=average_prediction_Balticum_temp,
              aes(x=x,y=1-predicted,ymin=1-conf.low,ymax=1-conf.high),
              alpha=0.2)+
  geom_line(data=average_prediction_Balticum_temp,aes(x=x,y=1-predicted))+
  geom_point(data=data_peat,aes(x=temp,y=Balticum_prop),
             size=3,alpha=0.3,shape=16,color="darkturquoise")+
  my_theme()+xlab("Temperature")+ylab("Probability of S. balticum presence")+
  theme(plot.margin=margin(l = 5,t=10,b=10))
figures1_d_1<-
  # Cuspidata presence ~ temp
  ggplot()+
  geom_ribbon(data=average_prediction_Cuspidata_temp,
              aes(x=x,y=1-predicted,ymin=1-conf.low,ymax=1-conf.high),
              alpha=0.2)+
  geom_line(data=average_prediction_Cuspidata_temp,aes(x=x,y=1-predicted))+
  geom_point(data=data_peat,aes(x=temp,y=Cuspidata_prop),
             size=3,alpha=0.3,shape=16,color="darkturquoise")+
  my_theme()+xlab("Temperature")+ylab("Probability of S. cuspidata presence")+
  theme(plot.margin=margin(l = 5,t=10,b=10))
figures1_d_2<-
  # Cuspidata presence ~ nutr
  ggplot()+
  geom_jitter(data=data_peat,aes(x=nutrient,y=Cuspidata_prop),
              position=position_jitter(0.1,0.01),
              size=3,alpha=0.3,shape=16,color="darkturquoise")+
  geom_point(data=average_prediction_Cuspidata_nutrient,
             aes(x=x,y=1-predicted),size=4,shape=16)+
  geom_errorbar(data=average_prediction_Cuspidata_nutrient,
                aes(x=x,y=1-predicted,ymin=1-conf.low,ymax=1-conf.high),
                width=0.2,size=0.5)+
  my_theme()+xlab("Nutrient input")+ylab("Probability of S. cuspidata presence")+
  theme(plot.margin = margin(l=10,r = 5,t=10,b=10) )+
  theme(axis.text.y = element_blank(),axis.title.y = element_blank(),
        plot.margin = margin(r = 10, l = 5,t=10,b=10))+
  scale_x_discrete(labels = c("N", "Y"))
```

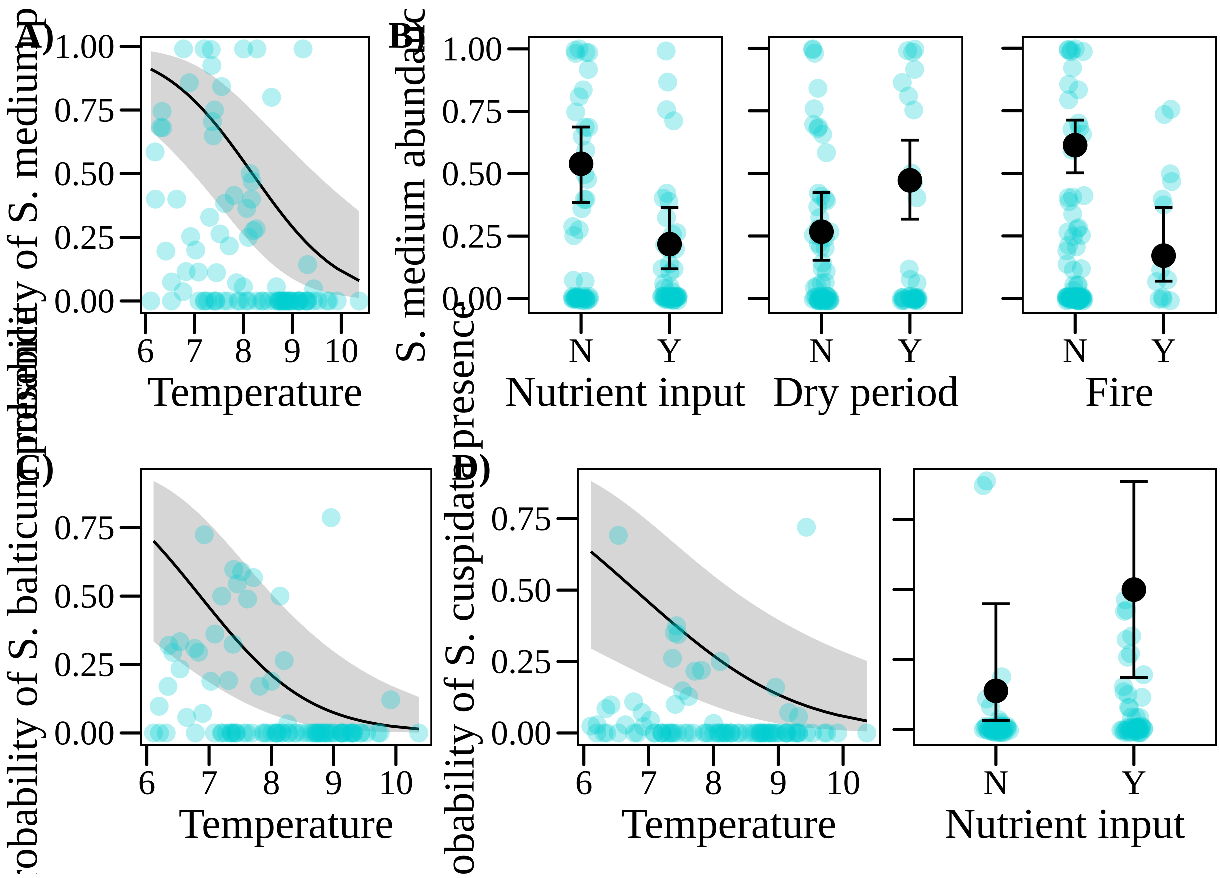
```r
figures1_b<-ggarrange(figures1_b_1,figures1_b_2,figures1_b_3,nrow=1)
```




```
figures1_d<-ggarrange(figures1_d_1,figures1_d_2,nrow=1)
```




```r
figures1<-cowplot::plot_grid(
  cowplot::plot_grid(figures1_a,figures1_b,ncol=2,labels=c("A)","B)"),
            label_fontfamily="serif",rel_widths=c(0.3,0.7))+
    theme(plot.background=element_rect(fill="white", color = NA)),
  cowplot::plot_grid(figures1_c,figures1_d,ncol=2,labels=c("C)","D)"),
            label_fontfamily="serif",rel_widths=c(0.35,0.65))+
    theme(plot.background=element_rect(fill="white", color = NA)),
  nrow=2)
figures1
```




```
ggsave(filename="output/figures/figures1.tiff",plot=figures1,
       width=28,height=21,units="cm",dpi=300)
```

Appendix S4: Figure S2: Selected Sphagnum species: Fuscum and Rubellum

Create average predictions

```
# Create average line among factors=0 and factors=1
average_prediction_Fuscum_moist<-rbind(
  tibble(ggpredict(mod_abund_Fuscum_temp,type="zi_prob",terms=c("moist[all]"),
                   condition=c(nutrient=1,fire=1,dry=1)))%>%
    select(-group)%>%mutate(type="a"),
  tibble(ggpredict(mod_abund_Fuscum_temp,type="zi_prob",terms=c("moist[all]"),
                   condition=c(nutrient=0,fire=0,dry=0)))%>%
    select(-group)%>%mutate(type="b"),
  tibble(ggpredict(mod_abund_Fuscum_temp,type="zi_prob",terms=c("moist[all]"),
                   condition=c(nutrient=0,fire=1,dry=1)))%>%
    select(-group)%>%mutate(type="c"),
  tibble(ggpredict(mod_abund_Fuscum_temp,type="zi_prob",terms=c("moist[all]"),
                   condition=c(nutrient=1,fire=0,dry=1)))%>%
    select(-group)%>%mutate(type="d"),
  tibble(ggpredict(mod_abund_Fuscum_temp,type="zi_prob",terms=c("moist[all]"),
                   condition=c(nutrient=1,fire=1,dry=0)))%>%
    select(-group)%>%mutate(type="e"),
  tibble(ggpredict(mod_abund_Fuscum_temp,type="zi_prob",terms=c("moist[all]"),
```

```r
                  condition=c(nutrient=0,fire=0,dry=1)))%>%
    select(-group)%>%mutate(type="f"),
  tibble(ggpredict(mod_abund_Fuscum_temp,type="zi_prob",terms=c("moist[all]"),
                  condition=c(nutrient=0,fire=1,dry=0)))%>%
    select(-group)%>%mutate(type="g"),
  tibble(ggpredict(mod_abund_Fuscum_temp,type="zi_prob",terms=c("moist[all]"),
                  condition=c(nutrient=1,fire=0,dry=0)))%>%  # NaNs produced
    select(-group)%>%mutate(type="h")
)%>%
  group_by(x)%>%summarise(predicted=mean(predicted),
                          std.error=mean(std.error,na.rm=T),
                          conf.low=mean(conf.low,na.rm=T),
                          conf.high=mean(conf.high,na.rm=T))
```

```r
# Create average line among factors=0 and factors=1
average_prediction_Fuscum_nutrient<-rbind(
  tibble(ggpredict(mod_abund_Fuscum_temp,type="zi_prob",terms=c("nutrient"),
                  condition=c(fire=1,dry=1)))%>%
    select(-group)%>%mutate(type="a"),
  tibble(ggpredict(mod_abund_Fuscum_temp,type="zi_prob",terms=c("nutrient"),
                  condition=c(fire=0,dry=0)))%>%
    select(-group)%>%mutate(type="b"),
  tibble(ggpredict(mod_abund_Fuscum_temp,type="zi_prob",terms=c("nutrient"),
                  condition=c(fire=0,dry=1)))%>%
    select(-group)%>%mutate(type="c"),
  tibble(ggpredict(mod_abund_Fuscum_temp,type="zi_prob",terms=c("nutrient"),
                  condition=c(fire=1,dry=0)))%>%
    select(-group)%>%mutate(type="d")
  )%>%
  group_by(x)%>%summarise(predicted=mean(predicted),
                          std.error=mean(std.error,na.rm=T),
                          conf.low=mean(conf.low,na.rm=T),
                          conf.high=mean(conf.high,na.rm=T))
```

```r
# Create average line among factors=0 and factors=1
average_prediction_Rubellum_moist<-rbind(
  tibble(ggpredict(mod_abund_Rubellum_temp,type="zi_prob",terms=c("moist[all]"),
                  condition=c(nutrient=1,fire=1,dry=1)))%>%
    select(-group)%>%mutate(type="a"),
  tibble(ggpredict(mod_abund_Rubellum_temp,type="zi_prob",terms=c("moist[all]"),
                  condition=c(nutrient=0,fire=0,dry=0)))%>%
    select(-group)%>%mutate(type="b"),
  tibble(ggpredict(mod_abund_Rubellum_temp,type="zi_prob",terms=c("moist[all]"),
                  condition=c(nutrient=0,fire=1,dry=1)))%>%
    select(-group)%>%mutate(type="c"),
  tibble(ggpredict(mod_abund_Rubellum_temp,type="zi_prob",terms=c("moist[all]"),
                  condition=c(nutrient=1,fire=0,dry=1)))%>%
    select(-group)%>%mutate(type="d"),
  tibble(ggpredict(mod_abund_Rubellum_temp,type="zi_prob",terms=c("moist[all]"),
                  condition=c(nutrient=1,fire=1,dry=0)))%>%
    select(-group)%>%mutate(type="e"),
  tibble(ggpredict(mod_abund_Rubellum_temp,type="zi_prob",terms=c("moist[all]"),
                  condition=c(nutrient=0,fire=0,dry=1)))%>%
```

```
    select(-group)%>%mutate(type="f"),
  tibble(ggpredict(mod_abund_Rubellum_temp,type="zi_prob",terms=c("moist[all]"),
                   condition=c(nutrient=0,fire=1,dry=0)))%>%
    select(-group)%>%mutate(type="g"),
  tibble(ggpredict(mod_abund_Rubellum_temp,type="zi_prob",terms=c("moist[all]"),
                   condition=c(nutrient=1,fire=0,dry=0)))%>%  # NaNs produced
    select(-group)%>%mutate(type="h")
)%>%
  group_by(x)%>%summarise(predicted=mean(predicted),
                          std.error=mean(std.error,na.rm=T),
                          conf.low=mean(conf.low,na.rm=T),
                          conf.high=mean(conf.high,na.rm=T))
```

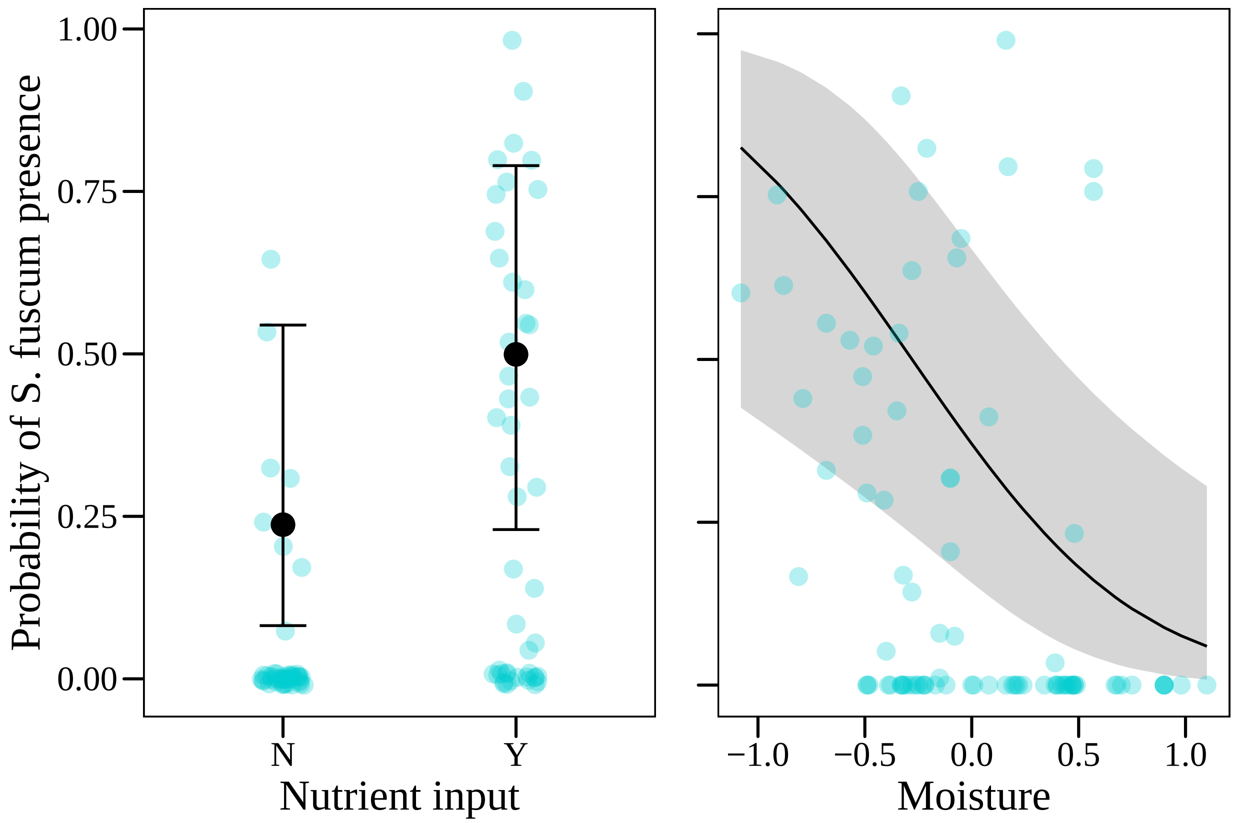
```
# Create average line among factors=0 and factors=1
average_prediction_Rubellum_nutrient<-rbind(
  tibble(ggpredict(mod_abund_Rubellum_temp,type="zi_prob",terms=c("nutrient"),
                   condition=c(fire=1,dry=1)))%>%
    select(-group)%>%mutate(type="a"),
  tibble(ggpredict(mod_abund_Rubellum_temp,type="zi_prob",terms=c("nutrient"),
                   condition=c(fire=0,dry=0)))%>%
    select(-group)%>%mutate(type="b"),
  tibble(ggpredict(mod_abund_Rubellum_temp,type="zi_prob",terms=c("nutrient"),
                   condition=c(fire=0,dry=1)))%>%
    select(-group)%>%mutate(type="c"),
  tibble(ggpredict(mod_abund_Rubellum_temp,type="zi_prob",terms=c("nutrient"),
                   condition=c(fire=1,dry=0)))%>%
    select(-group)%>%mutate(type="d")
  )%>%
  group_by(x)%>%summarise(predicted=mean(predicted),
                          std.error=mean(std.error,na.rm=T),
                          conf.low=mean(conf.low,na.rm=T),
                          conf.high=mean(conf.high,na.rm=T))
```

```
figures2_a_1<-
  # Fusum presence ~ nutr
  ggplot()+
  geom_jitter(data=data_peat,aes(x=nutrient,y=Fuscum_prop),
              position=position_jitter(0.1,0.01),
              size=3,alpha=0.3,shape=16,color="darkturquoise")+
  geom_point(data=average_prediction_Fuscum_nutrient,
             aes(x=x,y=1-predicted),size=4,shape=16)+
  geom_errorbar(data=average_prediction_Fuscum_nutrient,
                aes(x=x,y=1-predicted,ymin=1-conf.low,ymax=1-conf.high),
                width=0.2,size=0.5)+
  my_theme()+xlab("Nutrient input")+ylab("Probability of S. fuscum presence")+
  scale_x_discrete(labels = c("N", "Y"))
figures2_a_2<-
  # Fusum presence ~ moist
  ggplot()+
  geom_ribbon(data=average_prediction_Fuscum_moist,
              aes(x=x,y=1-predicted,ymin=1-conf.low,ymax=1-conf.high),
              alpha=0.2)+
  geom_line(data=average_prediction_Fuscum_moist,aes(x=x,y=1-predicted))+
```

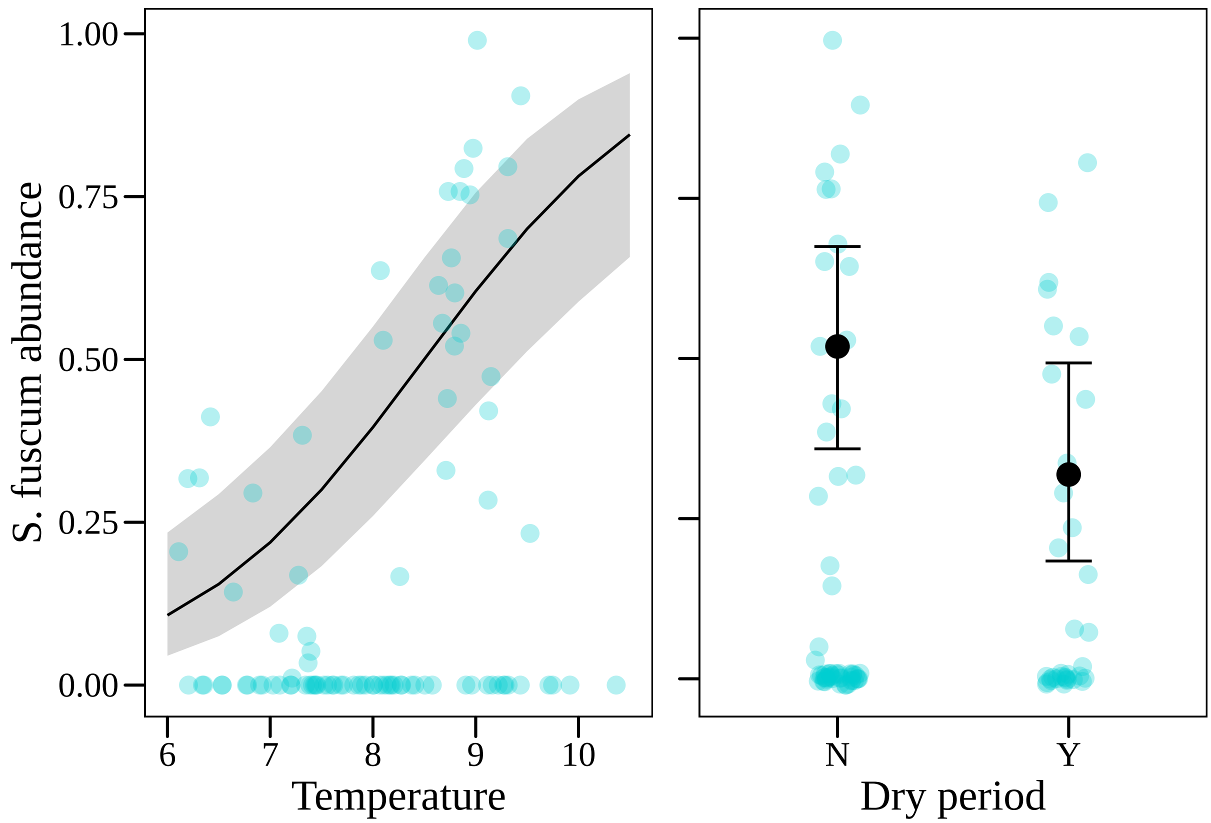
```r
  geom_point(data=data_peat,aes(x=moist,y=Fuscum_prop),
             size=3,alpha=0.3,shape=16,color="darkturquoise")+
  my_theme()+xlab("Moisture")+ylab("Probability of S. fuscum presence")+
  theme(axis.text.y = element_blank(),axis.title.y = element_blank(),
        plot.margin = margin(r = 10, l = 5,t=10,b=10))+
  theme(plot.margin = margin(l=10,r = 5,t=10,b=10) )
figures2_b_1<-
  # Fuscum abundance ~ temp
  ggplot()+
  geom_ribbon(data=data.frame(ggemmeans(mod_abund_Fuscum_temp,
                                        type="fixed",terms=c("temp"))),
              aes(x=x,y=predicted,ymin=conf.low,ymax=conf.high),alpha=0.2)+
  geom_line(data=data.frame(ggemmeans(mod_abund_Fuscum_temp,
                                      type="fixed",terms=c("temp"))),
            aes(x=x,y=predicted))+
  geom_point(data=data_peat,aes(x=temp,y=Fuscum_prop),
             size=3,alpha=0.3,shape=16,color="darkturquoise")+
  my_theme()+xlab("Temperature")+ylab("S. fuscum abundance")+
  theme(plot.margin = margin(l=10,r = 5,t=10,b=10) )
figures2_b_2<-
  # Fuscum abundance ~ dry
  ggplot()+
  geom_jitter(data=data_peat,aes(x=dry,y=Fuscum_prop),
              position = position_jitter(0.1,0.01),
              size=3,alpha=0.3,shape=16,color="darkturquoise")+
  geom_point(data=data.frame(ggemmeans(mod_abund_Fuscum_temp,
                                       type="fixed",terms=c("dry"))),
             aes(x=x,y=predicted),size=4,shape=16)+
  geom_errorbar(data=data.frame(ggemmeans(mod_abund_Fuscum_temp,
                                          type="fixed",terms=c("dry"))),
                aes(x=x,y=predicted,ymin=conf.low,ymax=conf.high),
                width=0.2,size=0.5)+
  my_theme()+xlab("Dry period")+ylab("S. fuscum abundance")+
  theme(axis.text.y = element_blank(),axis.title.y = element_blank(),
        plot.margin = margin(r = 10, l = 5,t=10,b=10))+
  scale_x_discrete(labels = c("N", "Y"))
figures2_c_1<-
  # Rubellum presence ~ nutr
  ggplot()+
  geom_jitter(data=data_peat,aes(x=nutrient,y=Rubellum_prop),
              position=position_jitter(0.1,0.01),
              size=3,alpha=0.3,shape=16,color="darkturquoise")+
  geom_point(data=average_prediction_Rubellum_nutrient,
             aes(x=x,y=1-predicted),size=4,shape=16)+
  geom_errorbar(data=average_prediction_Rubellum_nutrient,
                aes(x=x,y=1-predicted,ymin=1-conf.low,ymax=1-conf.high),
                width=0.2,size=0.5)+
  my_theme()+xlab("Nutrient input")+ylab("Probability of S. rubellum presence")+
  theme(plot.margin = margin(l=10,r = 5,t=10,b=10) )+
  scale_x_discrete(labels = c("N", "Y"))
figures2_c_2<-
  # Rubellum presence ~ moist
  ggplot()+
```

```
  geom_ribbon(data=average_prediction_Rubellum_moist,
              aes(x=x,y=1-predicted,ymin=1-conf.low,ymax=1-conf.high),
              alpha=0.2)+
  geom_line(data=average_prediction_Rubellum_moist,aes(x=x,y=1-predicted))+
  geom_point(data=data_peat,aes(x=moist,y=Rubellum_prop),
             size=3,alpha=0.3,shape=16,color="darkturquoise")+
  my_theme()+xlab("Moisture")+ylab("Probability of S. rubellum presence")+
  theme(plot.margin = margin(l=10,r = 5,t=10,b=10) )+
  theme(axis.text.y = element_blank(),axis.title.y = element_blank(),
        plot.margin = margin(r = 10, l = 5,t=10,b=10))
figures2_d<-
  # Rubellum abundance ~ fire
  ggplot()+
  geom_jitter(data=data_peat,aes(x=fire,y=Rubellum_prop),
              position = position_jitter(0.1,0.01),
              size=3,alpha=0.3,shape=16,color="darkturquoise")+
  geom_point(data=data.frame(ggemmeans(mod_abund_Rubellum_temp,
                                       type="fixed",terms=c("fire"))),
             aes(x=x,y=predicted),size=4,shape=16)+
  geom_errorbar(data=data.frame(ggemmeans(mod_abund_Rubellum_temp,
                                          type="fixed",terms=c("fire"))),
                aes(x=x,y=predicted,ymin=conf.low,ymax=conf.high),
                width=0.2,size=0.5)+
  my_theme()+xlab("Fire")+ylab("S. rubellum abundance")+
  theme(plot.margin=margin(r = 10,l = 5,t=10,b=10))+
  scale_x_discrete(labels = c("N", "Y"))
```

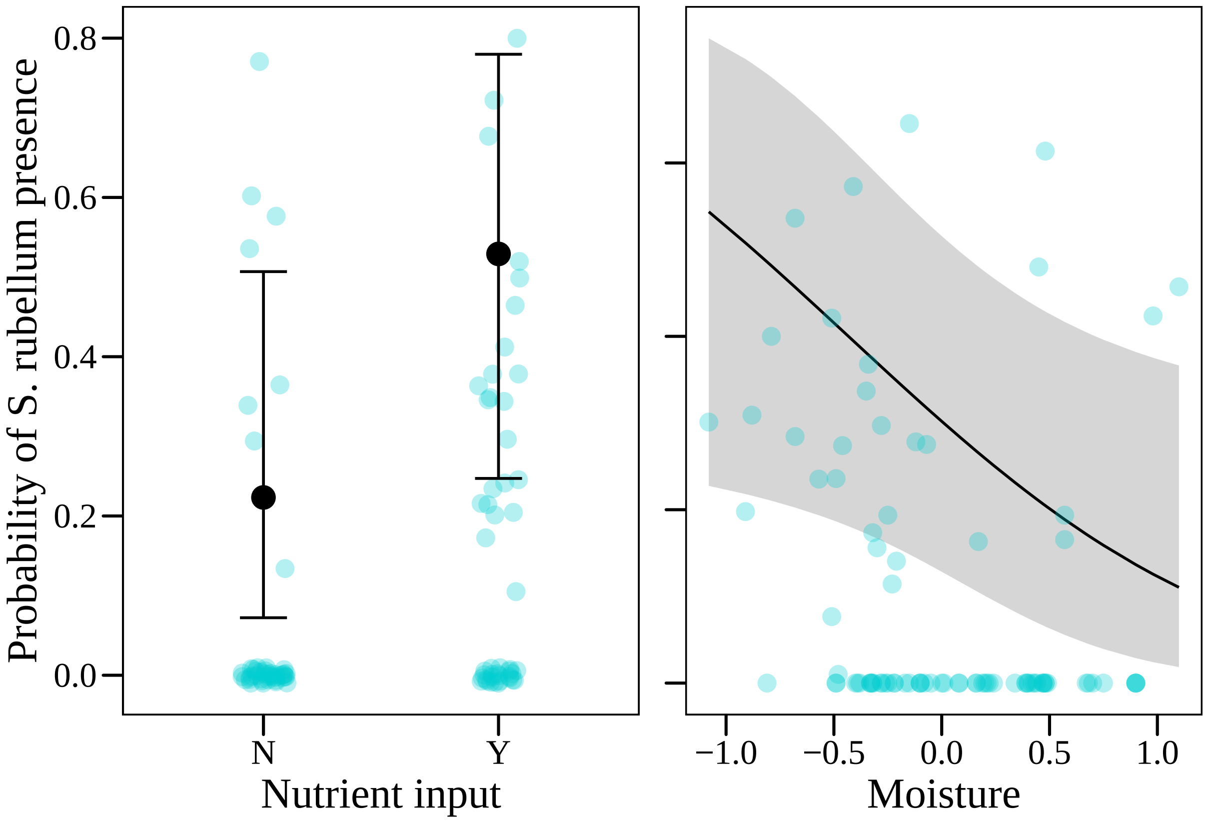
```
figures2_a<-ggarrange(figures2_a_1,figures2_a_2,nrow=1)
```



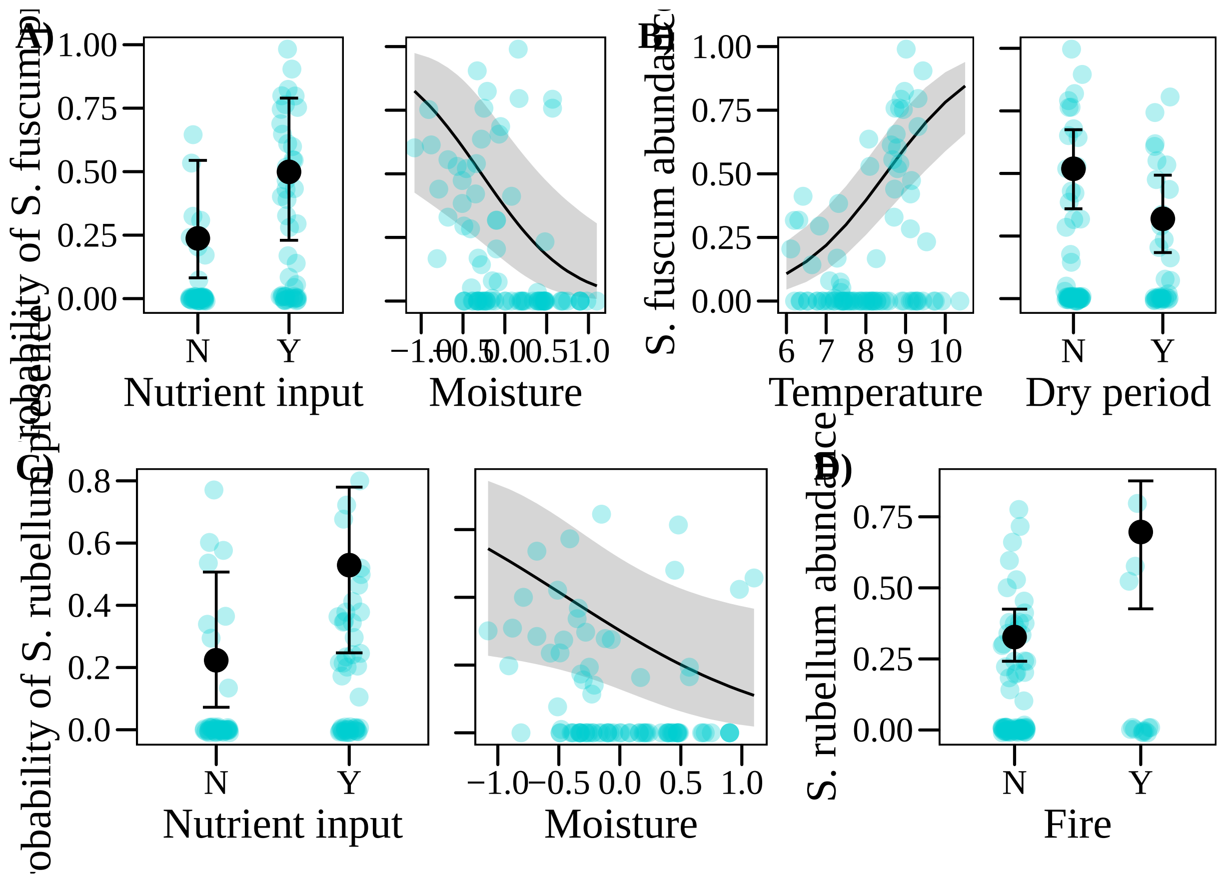

```
figures2_b<-ggarrange(figures2_b_1,figures2_b_2,nrow=1)
```




```
figures2_c<-ggarrange(figures2_c_1,figures2_c_2,nrow=1)
```




```
figures2<-cowplot::plot_grid(
  cowplot::plot_grid(figures2_a,figures2_b,ncol=2,labels=c("A)","B)"),
            label_fontfamily="serif")+
    theme(plot.background=element_rect(fill="white", color = NA)),
  cowplot::plot_grid(figures2_c,figures2_d,ncol=2,labels=c("C)","D)"),
            label_fontfamily="serif",rel_widths=c(0.64,0.36))+
    theme(plot.background=element_rect(fill="white", color = NA)),
  nrow=2)
figures2
```




```r
ggsave(filename="output/figures/figures2.tiff",plot=figures2,
       width=28,height=21,units="cm",dpi=300)
```

Model fit and predictive power

Adjusted R2 of the models

Appendix S4, Table S1.

Using Adjusted R2 for zero-inflated models for the total Sphagnum model, and Ferrari's R2 for the other models.

```r
r2_zeroinflated(mod_abund_tot_Sphagnum_temp_AR)$R2_adjusted
```

```
## adjusted R2
##   0.8323318
```

```r
r2_ferrari(mod_abund_Erio_nozi_temp_AR,correct_bounds=T)
```

```
## # R2 for Generalized Linear Regression
##   Ferrari's R2: 0.982
```

```r
r2_ferrari(mod_abund_Erica_nozi_temp_AR,correct_bounds=T)
```

```
## # R2 for Generalized Linear Regression
##   Ferrari's R2: 0.488
```

```r
r2_ferrari(mod_abund_Carex_nozi_temp_AR,correct_bounds=T)
```

```
## # R2 for Generalized Linear Regression
##   Ferrari's R2: 0.470
```

Appendix S4, Table S2.

Using Adjusted R2 for zero-inflated models for all models.

```r
r2_zeroinflated(mod_abund_Rubellum_temp)$R2_adjusted
```

```
## adjusted R2
##   0.3208883
```

```r
r2_zeroinflated(mod_abund_Balticum_temp)$R2_adjusted
```

```
## adjusted R2
##   0.2788194
```

```r
r2_zeroinflated(mod_abund_Cuspidata_temp)$R2_adjusted
```

```
## adjusted R2
## -0.02351098
```

Appendix S4, Table S3.

Using Adjusted R2 for zero-inflated models for all models.

```r
r2_zeroinflated(mod_abund_Medium_temp)$R2_adjusted
```

```
## adjusted R2
##  0.09550764
```

```r
r2_zeroinflated(mod_abund_Fuscum_temp)$R2_adjusted
```

```
## adjusted R2
##   0.4266486
```

Appendix S4, Table S4

Using Ferrari's R2.

```r
r2_ferrari(mod_abund_Erica_nozi_temp_AR_sig_ints,correct_bounds=T)
```

```
## # R2 for Generalized Linear Regression
##   Ferrari's R2: 0.960
```

RMSE and MAE

Appendix S4, Table S1.

```r
RMSE_tot_Sphagnum<-RMSE(predict(mod_abund_tot_Sphagnum_temp_AR,newdata=dat0,
                                type="response"),dat0$tot_Sphagnum_prop)
RMSE_Erio<-RMSE(predict(mod_abund_Erio_nozi_temp_AR,newdata=dat0,
                        type="response"),dat0$Erio_prop)
RMSE_Erica<-RMSE(predict(mod_abund_Erica_nozi_temp_AR,newdata=dat0_Erica,
                        type="response"),dat0_Erica$Erica_prop)
RMSE_Carex<-RMSE(predict(mod_abund_Carex_nozi_temp_AR,newdata=dat0,
                         type="response"),dat0$Carex_prop)
MAE_tot_Sphagnum<-MAE(predict(mod_abund_tot_Sphagnum_temp_AR,newdata=dat0,
                                type="response"),dat0$tot_Sphagnum_prop)
MAE_Erio<-MAE(predict(mod_abund_Erio_nozi_temp_AR,newdata=dat0,
                        type="response"),dat0$Erio_prop)
MAE_Erica<-MAE(predict(mod_abund_Erica_nozi_temp_AR,newdata=dat0_Erica,
                        type="response"),dat0_Erica$Erica_prop)
MAE_Carex<-MAE(predict(mod_abund_Carex_nozi_temp_AR,newdata=dat0,
                         type="response"),dat0$Carex_prop)
RMSE_tot_Sphagnum
```

```
## [1] 0.1859424
```

```r
RMSE_Erio
```

```
## [1] 4.716145e-10
```

```r
RMSE_Erica
```

```
## [1] 0.1140918
```

```r
RMSE_Carex
```

```
## [1] 0.08960026
```

```r
MAE_tot_Sphagnum
```

```
## [1] 0.1407095
```

```r
MAE_Erio
```

```
## [1] 3.820696e-10
```

```r
MAE_Erica
```

```
## [1] 0.08347723
```

```r
MAE_Carex
```

```
## [1] 0.06910944
```

Appendix S4, Table S2.

```r
RMSE_Rubellum<-RMSE(predict(mod_abund_Rubellum_temp,
                            newdata=subset(data_peat,!is.na(Rubellum_prop)&
                                                 !is.na(temp)&!is.na(moist)&
                                                 !is.na(nutrient)&!is.na(fire)&
                                                 !is.na(dry)),
                            type="response"),
                    subset(data_peat,!is.na(Rubellum_prop)&!is.na(temp)&
                             !is.na(moist)&!is.na(nutrient)&!is.na(fire)&
                             !is.na(dry))$Rubellum_prop)
RMSE_Balticum<-RMSE(predict(mod_abund_Balticum_temp,
                            newdata=subset(data_peat,!is.na(Balticum_prop)&
                                                 !is.na(temp)&!is.na(moist)&
                                                 !is.na(nutrient)&!is.na(fire)&
                                                 !is.na(dry)),
                            type="response"),
                    subset(data_peat,!is.na(Balticum_prop)&!is.na(temp)&
                             !is.na(moist)&!is.na(nutrient)&!is.na(fire)&
                             !is.na(dry))$Balticum_prop)
RMSE_Cuspidata<-RMSE(predict(mod_abund_Cuspidata_temp,
                            newdata=subset(data_peat,!is.na(Cuspidata_prop)&
                                                 !is.na(temp)&!is.na(moist)&
                                                 !is.na(nutrient)&!is.na(fire)&
                                                 !is.na(dry)),
                            type="response"),
                    subset(data_peat,!is.na(Cuspidata_prop)&!is.na(temp)&
                             !is.na(moist)&!is.na(nutrient)&!is.na(fire)&
                             !is.na(dry))$Cuspidata_prop)
MAE_Rubellum<-MAE(predict(mod_abund_Rubellum_temp,
                            newdata=subset(data_peat,!is.na(Rubellum_prop)&
                                                 !is.na(temp)&!is.na(moist)&
                                                 !is.na(nutrient)&!is.na(fire)&
                                                 !is.na(dry)),
                            type="response"),
                    subset(data_peat,!is.na(Rubellum_prop)&!is.na(temp)&
                             !is.na(moist)&!is.na(nutrient)&!is.na(fire)&
                             !is.na(dry))$Rubellum_prop)
```

```r
MAE_Balticum<-MAE(predict(mod_abund_Balticum_temp,
                           newdata=subset(data_peat,!is.na(Balticum_prop)&
                                            !is.na(temp)&!is.na(moist)&
                                            !is.na(nutrient)&!is.na(fire)&
                                            !is.na(dry)),
                           type="response"),
                   subset(data_peat,!is.na(Balticum_prop)&!is.na(temp)&
                            !is.na(moist)&!is.na(nutrient)&!is.na(fire)&
                            !is.na(dry))$Balticum_prop)
MAE_Cuspidata<-MAE(predict(mod_abund_Cuspidata_temp,
                           newdata=subset(data_peat,!is.na(Cuspidata_prop)&
                                            !is.na(temp)&!is.na(moist)&
                                            !is.na(nutrient)&!is.na(fire)&
                                            !is.na(dry)),
                           type="response"),
                   subset(data_peat,!is.na(Cuspidata_prop)&!is.na(temp)&
                            !is.na(moist)&!is.na(nutrient)&!is.na(fire)&
                            !is.na(dry))$Cuspidata_prop)
RMSE_Rubellum
```

```
## [1] 0.1835248
```

```r
RMSE_Balticum
```

```
## [1] 0.1639562
```

```r
RMSE_Cuspidata
```

```
## [1] 0.1263958
```

```r
MAE_Rubellum
```

```
## [1] 0.1336444
```

```r
MAE_Balticum
```

```
## [1] 0.1011828
```

```r
MAE_Cuspidata
```

```
## [1] 0.0710446
```

Appendix S4, Table S3.

```r
RMSE_Medium<-RMSE(predict(mod_abund_Medium_temp,
                           newdata=subset(data_peat,!is.na(Medium_prop)&
                                            !is.na(temp)&!is.na(moist)&
                                            !is.na(nutrient)&!is.na(fire)&
```

```
                                               !is.na(dry)),
                             type="response"),
                     subset(data_peat,!is.na(Medium_prop)&!is.na(temp)&
                              !is.na(moist)&!is.na(nutrient)&!is.na(fire)&
                              !is.na(dry))$Medium_prop)
RMSE_Fuscum<-RMSE(predict(mod_abund_Fuscum_temp,
                             newdata=subset(data_peat,!is.na(Fuscum_prop)&
                                               !is.na(temp)&!is.na(moist)&
                                               !is.na(nutrient)&!is.na(fire)&
                                               !is.na(dry)),
                             type="response"),
                     subset(data_peat,!is.na(Fuscum_prop)&!is.na(temp)&
                              !is.na(moist)&!is.na(nutrient)&!is.na(fire)&
                              !is.na(dry))$Fuscum_prop)
MAE_Medium<-MAE(predict(mod_abund_Medium_temp,
                             newdata=subset(data_peat,!is.na(Medium_prop)&
                                               !is.na(temp)&!is.na(moist)&
                                               !is.na(nutrient)&!is.na(fire)&
                                               !is.na(dry)),
                             type="response"),
                     subset(data_peat,!is.na(Medium_prop)&!is.na(temp)&
                              !is.na(moist)&!is.na(nutrient)&!is.na(fire)&
                              !is.na(dry))$Medium_prop)
MAE_Fuscum<-MAE(predict(mod_abund_Fuscum_temp,
                             newdata=subset(data_peat,!is.na(Fuscum_prop)&
                                               !is.na(temp)&!is.na(moist)&
                                               !is.na(nutrient)&!is.na(fire)&
                                               !is.na(dry)),
                             type="response"),
                     subset(data_peat,!is.na(Fuscum_prop)&!is.na(temp)&
                              !is.na(moist)&!is.na(nutrient)&!is.na(fire)&
                              !is.na(dry))$Fuscum_prop)
RMSE_Medium
```

```
## [1] 0.2801295
```

```
RMSE_Fuscum
```

```
## [1] 0.220228
```

```
MAE_Medium
```

```
## [1] 0.2036867
```

```
MAE_Fuscum
```

```
## [1] 0.1617892
```

Appendix S4, Table S4

```r
RMSE_Erica_ints<-RMSE(predict(mod_abund_Erica_nozi_temp_AR_sig_ints,
                              newdata=dat0_Erica,
                              type="response"),dat0_Erica$Erica_prop)
MAE_Erica_ints<-MAE(predict(mod_abund_Erica_nozi_temp_AR_sig_ints,
                              newdata=dat0_Erica,
                              type="response"),dat0_Erica$Erica_prop)
RMSE_Erica_ints
```

```
## [1] 8.499476e-11
```

```r
MAE_Erica_ints
```

```
## [1] 6.91838e-11
```

R session info

```r
sessionInfo()
```

```
## R version 4.4.1 (2024-06-14 ucrt)
## Platform: x86_64-w64-mingw32/x64
## Running under: Windows 11 x64 (build 22631)
##
## Matrix products: default
##
##
## locale:
## [1] LC_COLLATE=English_United States.utf8
## [2] LC_CTYPE=English_United States.utf8
## [3] LC_MONETARY=English_United States.utf8
## [4] LC_NUMERIC=C
## [5] LC_TIME=English_United States.utf8
##
## time zone: Europe/Madrid
## tzcode source: internal
##
## attached base packages:
## [1] tcltk     stats     graphics  grDevices utils     datasets  methods
## [8] base
##
## other attached packages:
##  [1] ggord_1.1.8          caret_6.0-94         extrafont_0.19
##  [4] DHARMa_0.4.6         sjPlot_2.8.16        performance_0.12.2
##  [7] ggrepel_0.9.5        BiodiversityR_2.16-1 cowplot_1.1.3
## [10] egg_0.4.5            ggthemes_5.1.0       gridExtra_2.3
## [13] rdacca.hp_1.1-1      vegan_2.6-6.1        lattice_0.22-6
## [16] permute_0.9-7        glmmTMB_1.1.9        car_3.1-2
## [19] carData_3.0-5        ggeffects_1.7.0      knitr_1.48
## [22] readxl_1.4.3         lubridate_1.9.3      forcats_1.0.0
## [25] stringr_1.5.1        dplyr_1.1.4          purrr_1.0.2
```

```
## [28] readr_2.1.5          tidyr_1.3.1          tibble_3.2.1
## [31] ggplot2_3.5.1        tidyverse_2.0.0
##
## loaded via a namespace (and not attached):
##   [1] rstudioapi_0.16.0    datawizard_0.12.2    magrittr_2.0.3
##   [4] TH.data_1.1-2        estimability_1.5.1   farver_2.1.2
##   [7] nloptr_2.1.1         rmarkdown_2.28       ragg_1.3.2
##  [10] vctrs_0.6.5          minqa_1.2.8          base64enc_0.1-3
##  [13] htmltools_0.5.8.1    haven_2.5.4          survey_4.4-2
##  [16] cellranger_1.1.0     pROC_1.18.5          Formula_1.2-5
##  [19] sjmisc_2.8.10        parallelly_1.38.0    htmlwidgets_1.6.4
##  [22] plyr_1.8.9           sandwich_3.1-0       emmeans_1.10.4
##  [25] zoo_1.8-12           TMB_1.9.14           lifecycle_1.0.4
##  [28] iterators_1.0.14     pkgconfig_2.0.3      sjlabelled_1.2.0
##  [31] Matrix_1.7-0         R6_2.5.1             fastmap_1.2.0
##  [34] snakecase_0.11.1     future_1.34.0        digest_0.6.37
##  [37] numDeriv_2016.8-1.1  colorspace_2.1-1     textshaping_0.4.0
##  [40] Hmisc_5.1-3          labeling_0.4.3       fansi_1.0.6
##  [43] effects_4.2-2        timechange_0.3.0     abind_1.4-5
##  [46] mgcv_1.9-1           compiler_4.4.1       Rcmdr_2.9-2
##  [49] proxy_0.4-27         withr_3.0.1          htmlTable_2.4.3
##  [52] backports_1.5.0      DBI_1.2.3            highr_0.11
##  [55] relimp_1.0-5         Rttf2pt1_1.3.12      lava_1.8.0
##  [58] MASS_7.3-61          sjstats_0.19.0       ModelMetrics_1.2.2.2
##  [61] tools_4.4.1          lmtest_0.9-40        foreign_0.8-87
##  [64] extrafontdb_1.0      future.apply_1.11.2  nnet_7.3-19
##  [67] glue_1.7.0           nlme_3.1-166         grid_4.4.1
##  [70] checkmate_2.3.2      reshape2_1.4.4       cluster_2.1.6
##  [73] see_0.8.5            generics_0.1.3       recipes_1.1.0
##  [76] gtable_0.3.5         nortest_1.0-4        tzdb_0.4.0
##  [79] class_7.3-22         data.table_1.15.4    hms_1.1.3
##  [82] utf8_1.2.4           foreach_1.5.2        pillar_1.9.0
##  [85] mitools_2.4          splines_4.4.1        RcmdrMisc_2.9-1
##  [88] survival_3.7-0       tidyselect_1.2.1     stats4_4.4.1
##  [91] xfun_0.47            hardhat_1.4.0        timeDate_4032.109
##  [94] stringi_1.8.4        yaml_2.3.10          boot_1.3-30
##  [97] evaluate_0.24.0      codetools_0.2-20     cli_3.6.3
## [100] rpart_4.1.23         systemfonts_1.1.0    xtable_1.8-4
## [103] munsell_0.5.1        Rcpp_1.0.13          globals_0.16.3
## [106] coda_0.19-4.1        parallel_4.4.1       gower_1.0.1
## [109] tcltk2_1.2-11        listenv_0.9.1        lme4_1.1-35.5
## [112] mvtnorm_1.2-6        ipred_0.9-15         prodlim_2024.06.25
## [115] scales_1.3.0         e1071_1.7-14         insight_0.20.3
## [118] rlang_1.1.4          multcomp_1.4-26
```