Preamble

Packages

```
library(arm) # standardize()
library(MuMIn) # r.squared.GLMM()
library(dplyr) # filter()
library(ggplot2) # ggplot()
library(usdm) # vif()
library(qpcR) # akaike.weights()
library(lme4) # lmer(), glmer(), glmer.nb()
```

Loading data

```
#Set working directory
setwd("~/Dropbox/University Work/Year 4 Sem 2/Dissertation/Write Up/Data/R")
#Load raw data
RAW <- read.csv("R_seedlings.csv", header=TRUE, sep=",")
#Remove NA values from columns of interest
Seedlings <- RAW %>%
  filter(Comp.Y.N. == "Y") %>%
  filter(!is.na(LAI.4.ring)) %>%
  filter(!is.na(Comp.seed.total)) %>%
  filter(!is.na(Comp.adult.log.metric)) %>%
  filter(!is.na(Elevation)) %>%
  filter(!is.na(Species))
```

Single fixed effect models

Determination of random effects structure

The procedure below is conducted for all combinations of singular plant traits (response) and competition variables/elevation (fixed effect), resulting in 24 random intercept models and 24 random slope models, each with a unique response-fixed effect combination.

For each response-fixed effect combination, ΔAIC_{rsri} (daic_rsri) values are assessed to determine whether a random intercept or random slope model is of better quality.

```
daic_rsri <- AIC(stdz.mod_fvfm_elev_rs) - AIC(stdz.mod_fvfm_elev_ri)</pre>
```

Reporting the best single fixed effect models

The Δ AIC_r (daic1), R_M^2 (rm1), R_C^2 (rc1), slope (slope1) and standard error of the slope estimate (se1) was calculated for the best models (random slope or random intercept) to assess model quality. Δ AIC_r is calculated as the AIC difference between a random effects model and the model in question

Multiple fixed effect models

Variance inflation factors

Model comparison

Model comparison was conducted for each plant trait. Models with different fixed effect combinations were compared using AIC and R_C^2 (Appendix IV).

```
# All fixed effects
stdz.mod_fvfm_full <- standardize(lmer(D.FvFm ~ LAI.4.ring +</pre>
    Comp.seed.total + Comp.adult.log.metric + Elevation + (1 |
    Species) + (1 | Site), data = Seedlings, REML = F), standardize.y = T)
stdz.mod_fvfm_lai_seed_isi <- standardize(lmer(D.FvFm ~ LAI.4.ring +</pre>
    Comp.seed.total + Comp.adult.log.metric + (1 | Species) +
    (1 | Site), data = Seedlings, REML = F), standardize.y = T)
# -ISI
stdz.mod fvfm lai seed elev <- standardize(lmer(D.FvFm ~ LAI.4.ring +
    Comp.seed.total + Elevation + (1 | Species) + (1 | Site),
    data = Seedlings, REML = F), standardize.y = T)
# -Herbaceous plant abundance
stdz.mod_fvfm_lai_isi_elev <- standardize(lmer(D.FvFm ~ LAI.4.ring +
    Comp.adult.log.metric + Elevation + (1 | Species) + (1 |
    Site), data = Seedlings, REML = F), standardize.y = T)
# -LAI
stdz.mod_fvfm_seed_isi_elev <- standardize(lmer(D.FvFm ~ Comp.seed.total +
    Comp.adult.log.metric + Elevation + (1 | Species) + (1 |
    Site), data = Seedlings, REML = F), standardize.y = T)
```

```
# Elevation + random effects
stdz.mod fvfm elev ri <- standardize(lmer(D.FvFm ~ Elevation +
    (1 | Species) + (1 | Site), data = Seedlings, REML = F),
    standardize.y = T)
# LAI + random effects
stdz.mod_fvfm_lai_ri <- standardize(lmer(D.FvFm ~ LAI.4.ring +</pre>
    (1 | Species) + (1 | Site), data = Seedlings, REML = F),
    standardize.y = T)
# ISI + random effects
stdz.mod_fvfm_isi_ri <- standardize(lmer(D.FvFm ~ Comp.adult.log.metric +
    (1 | Species) + (1 | Site), data = Seedlings, REML = F),
    standardize.y = T)
# Herbaceous plant abundance + random effects
stdz.mod_fvfm_seed_ri <- standardize(lmer(D.FvFm ~ Comp.seed.total +
    (1 | Species) + (1 | Site), data = Seedlings, REML = F),
    standardize.y = T)
# Random effects + random effects
stdz.mod_fvfm_rand <- standardize(lmer(D.FvFm ~ (1 | Species) +</pre>
    (1 | Site), data = Seedlings, REML = F), standardize.y = T)
# Example of model using random slope terms for some fixed
# effects
stdz.mod_area_int <- standardize(lmer(Leaf.area ~ LAI.4.ring +
    Comp.seed.total + Comp.adult.log.metric + Elevation + (1 +
   LAI.4.ring + Comp.seed.total + Elevation | Species) + (1 |
   Site), data = R_seedlings_D.FvFm, REML = F), standardize.y = T)
```

Reporting the best multiple fixed effect models

The Δ AlC_r (daic2), Akaike weight (W_i), R_C^2 (rc2), R_M^2 (rm2), slope of each fixed effect (slope2) and standard error (se2) of each slope estimate was calculated to assess model quality.

```
# Random effects model
stdz.mod_fvfm_null <- standardize(lmer(D.FvFm ~ (1 | Species) +</pre>
    (1 | Site), data = Seedlings), standardize.y = T)
# Delta AIC
daic2 <- AIC(stdz.mod fvfm null) - AIC(stdz.mod fvfm lai isi elev)
# Dataframe of model iterations with AIC values for Akaike
stdz.mod_fvfm_aic <- c(AIC(stdz.mod_fvfm_full), AIC(stdz.mod_fvfm_lai_seed_isi),
    AIC(stdz.mod_fvfm_lai_seed_elev), AIC(stdz.mod_fvfm_lai_isi_elev),
    AIC(stdz.mod_fvfm_seed_isi_elev), AIC(stdz.mod_fvfm_rand),
    AIC(stdz.mod_fvfm_elev_ri), AIC(stdz.mod_fvfm_lai_ri), AIC(stdz.mod_fvfm_isi_ri),
    AIC(stdz.mod_fvfm_seed_ri))
stdz.mod_fvfm_model_name <- c("stdz.mod_fvfm_full", "stdz.mod_fvfm_lai_seed_isi",
    "stdz.mod_fvfm_lai_seed_elev", "stdz.mod_fvfm_lai_isi_elev",
    "stdz.mod_fvfm_seed_isi_elev", "stdz.mod_fvfm_rand", "stdz.mod_fvfm_elev_ri",
    "stdz.mod_fvfm_lai_ri", "stdz.mod_fvfm_isi_ri", "stdz.mod_fvfm_seed_ri")
stdz.mod_fvfm_aic <- data.frame(stdz.mod_fvfm_model_name, stdz.mod_fvfm_aic)
# Akaike weights
stdz.mod_fvfm_wi <- akaike.weights(stdz.mod_fvfm_aic$stdz.mod_fvfm_aic)
# pseudo-r-squared
r2 <- unname(r.squaredGLMM(stdz.mod_fvfm_lai_isi_elev))</pre>
# Variance explained by fixed effects
rm2 <- r2[1]
# Variance explained by whole model
```

Variation among species in plant trait-elevation relationship

The procedure below was conducted for each plant trait.

```
# linear mixed model
All fvfm lmer rs <- lmer(D.FvFm ~ Elevation + (Elevation | Species) +
    (1 | Site), data = Seedlings, REML = F)
# Scatter plot of trait-elevation relationship with linear
# regressions for each species
ALL_fvfm_scatter <- ggplot(Seedlings, aes(x = Elevation, y = D.FvFm)) +
    geom_smooth(aes(fill = Species, colour = Species), method = lm,
        se = T) + geom_point(aes(colour = Species), alpha = 0.5)
# Interval plot of slope estimates for trait-elevation
# relationship Slope estimate for each species
fvfm1 <- unname(coef(lm(D.FvFm ~ Elevation, data = subset(Seedlings,</pre>
    Species == "AV"))))
# Combining slope estimates into a list
fvfm_slope \leftarrow c(fvfm1[2], fvfm2[2], fvfm3[2], fvfm4[2], fvfm5[2],
    fvfm6[2], fvfm7[2], fvfm8[2], fvfm9[2])
# Slope standard error estimates for each species
fvfme1 <- unname(sqrt(diag(vcov(lm(D.FvFm ~ Elevation, data = subset(Seedlings,</pre>
    Species == "AV")))))
# Combining slope estimates into a list
fvfm_se \leftarrow c(fvfme1[2], fvfme2[2], fvfme3[2], fvfme4[2], fvfme5[2],
    fvfme6[2], fvfme7[2], fvfme8[2], fvfme9[2])
# Creating a dataframe of slope estimates of standard errors
# for all species
species <- c("AV", "CR", "CT", "DL", "HG", "ID", "MS", "SP",
    "TG")
fvfm_slope <- data.frame(species, fvfm_slope, fvfm_se)</pre>
# Interval plot of slope estimates
fvfm <- ggplot(fvfm_slope, aes(x = species)) + geom_point(aes(y = fvfm_slope,</pre>
    colour = species), size = 2) + geom_errorbar(aes(ymin = fvfm_slope -
    fvfm_se, ymax = fvfm_slope + fvfm_se, colour = species),
    width = 1) + geom_hline(aes(yintercept = 0), linetype = 5)
```

Relationship between competition/abiotic environmental variables and elevation

The procedure below was conducted for each competition/abiotic environmental variable.

```
# Linear mixed model
LAI4ring_vs_elev_lmer <- lmer(LAI.4.ring ~ Elevation + (1 | Site),
    data = Seedlings, REML = F)</pre>
```

Generalised linear mixed model forms assuming different distributions of herbaceous plant abundance data are compared.

Scatter plot of competition-elevation relationship with fixed effect regression line.

```
# Prediction grid for every combination of parameter values
LAI4ring_pred <- expand.grid(Elevation = c(seq(from = 378, to = 3224,
    by = 1)), Site = c("PA400", "PA800", "VC", "SP1500", "SP1750",
    "TRU08", "TRU07", "TRU06", "TRU04", "TRU02"), LAI.4.ring = 0)
# Model matrix
matrix_LAI4ring = model.matrix(terms(LAI4ring_vs_elev_lmer),
    data = LAI4ring pred)
head(matrix_LAI4ring)
# Calculate predictions
LAI4ring_pred$LAI.4.ring = matrix_LAI4ring %*% fixef(LAI4ring_vs_elev_lmer)
head(LAI4ring pred)
# Add variance term for each prediction
LAI4ring_var <- diag(matrix_LAI4ring %*% tcrossprod(vcov(LAI4ring_vs_elev_lmer),
    matrix_LAI4ring))
# Create combined data frame for scatter plot
LAI4ring_pred <- data.frame(LAI4ring_pred, plo = LAI4ring_pred$LAI.4.ring -
    2 * sqrt(LAI4ring_var), phi = LAI4ring_pred$LAI.4.ring +
    2 * sqrt(LAI4ring_var))
# Scatterplot
LAI4ring_elev <- ggplot(Seedlings, aes(x = Elevation, y = LAI.4.ring)) +
    geom_point(aes(colour = Site), alpha = 0.8) + layer(data = LAI4ring_pred,
    geom = "line", mapping = aes(x = Elevation, y = LAI.4.ring),
    stat = "identity", position = "identity", params = list(na.rm = F,
        alpha = 1, size = 1)) + layer(data = LAI4ring_pred, geom = "ribbon",
    mapping = aes(x = Elevation, ymin = plo, ymax = phi), stat = "identity",
    position = "identity", params = list(na.rm = F, alpha = 0.6))
```