Appendix

for

'Examining Fouquieria splendens in an environmental and ecological context: Effect of topography and interspecific neighbors on ocotillo morphology and distribution';

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Contents

1 Details of the Analyses

This document was generated by R Markdown on 2022-12-11 using R version 4.2.1 (2022-06-23). The document provides the step-by-step analytical methods used in the manuscript by Anastasia Bernat (AVB), Acacia Tsz So Tang (ATST), Allegra Steenson (AS), Eric Larsen (EL), and Emma Greig (EG). Draft scripts were written by AVB and ATST between 2019-06-01 and 2021-01-01 until being distilled and complied by AVB at the University of Chicago into this comprehensive script. All draft scripts can be viewed in the GitHub repository, ocotillo-research (https://github.com/avbernat/ocotillo-research).

All code and output from the statistical analyses are shown. Code for data cleaning and the generation of plots is not displayed, but can be viewed in the **appendix.Rmd** file and its accompanying sourced scripts. To repeat analyses and the generation of plots, all data files and sourced scripts should follow the directory structure presented in the ocotillo-research repository.

1.1 Description of the Data

Ocotillos, *Fouquieria splendens*, were measured in Summer 2019 in the Sonoran Desert at Organ Pipe Cactus National Monument

1.2 Abbreviations Used in the Data and Code

1.3 Data Transformations

- `_b` - a column name that ends in `_b` is a column that has been recodified into binary data (0's and 1's). Example columns:
- `_c` - a column name that ends in `_c` is a column that has been centered. Example columns:
- `_s` - a column name that ends in `_s` is a column that has been standardized. Example columns:
- `log` - a column name that starts with `log` is a column that has been log transformed. Example columns:
- `_baj` - a dataset that ends in `_baj` is a dataset that only contains ocotillo measurements from ocotillos across a bajada. Example datasets: ocos_baj, segs_baj

1.4 Read in Libraries

```
library(dplyr)
library(outliers) # dixon.test
require(FactoMineR) # PCA function
library(factoextra) # get_eigenvalue function
library(corrplot) # cor.mtest
library(gridExtra)
# library(ggplot2)
# library(olsrr)
# library(lme4)
#
# library(tidyverse)
# library(ggpubr)
# library(rstatix)
```

1.5 Read Source Scripts

```
source("src/cleaning_data.R")      # clean_ocos_data(), clean_segs_data()
source("src/regression_output.R") # tidy_regression()
source("src/diagnostics.R")        # plot_diagnostic()
source("src/pretty_reg.R")         # rename_regformula() and rename_regformulaME()
```

```
source("src/pca.R")                 # PCA_graphs()
source("src/model_metrics.R")       # calculate_lk_weights()
```

1.6 Read the Data

```
ocotillo_data = read.csv("data/General_Oco_Data3.csv",
                            fileEncoding="UTF-8-BOM",  stringsAsFactors=TRUE)
branch_data = read.csv("data/branch_lengths_long.csv")
segment_data = read.csv("data/Terminal_5Segs.csv")

branches = branch_data  %>%
            group_by(Tree) %>%
            summarize(Mean_BranchLength = mean(BranchLength, na.rm=TRUE),
                      Median_BranchLength = median(BranchLength, na.rm=TRUE),
                      Max_BranchLength = max(BranchLength, na.rm=TRUE),
                      Min_BranchLength = min(BranchLength, na.rm=TRUE),
                      BranchLength_IQR = IQR(BranchLength, na.rm=TRUE))
segments = segment_data %>%
            group_by(Tree) %>%
            summarize(Mean_Terminal_SegmentLength = mean(Length, na.rm=TRUE),
                      Median_Terminal_SegmentLength = median(Length, na.rm=TRUE),
                      Max_Terminal_SegmentLength = max(Length, na.rm=TRUE),
                      Min_Terminal_SegmentLength = min(Length, na.rm=TRUE),
                      IQR_Terminal_SegmentLength = IQR(Length, na.rm=TRUE))


ocotillo_data$Median_BranchLength = branches$Median_BranchLength # other typos
ocotillo_data$BranchLength_IQR = branches$BranchLength_IQR # other typos
ocotillo_data$Median_TerminalSeg = segments$Median_Terminal_SegmentLength
ocotillo_data$Terminal_SegIQR = segments$IQR_Terminal_SegmentLength

ocos = clean_ocos_data(ocotillo_data)              # all ocotillos
ocos_baj = ocos[1:20,]                             # only ocotillos across the bajada
segs = clean_segs_data(segment_data, ocotillo_data) # all ocotillos
segs_baj = segs[1:1000,]                           # only ocotillos across the bajada
```

1.7 Normality

All measurements followed log-normal distributions except for circumference, median branch length, number of nodes, and distance to the nearest arroyo, which were normally distributed. Ocotillo data were log-transformed before analyses to meet assumptions of normality, linear regressions, and homogeneity for parametric analyses.

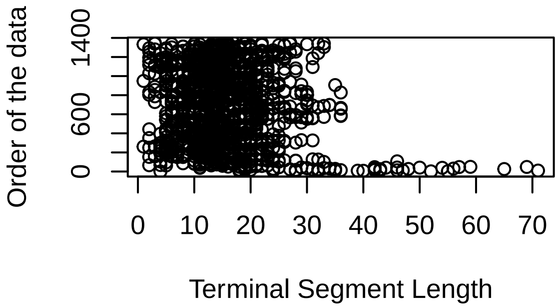
1.8 Outliers

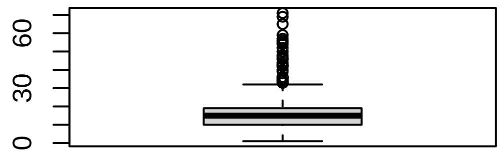
Terminal segment length IQR has an outlier - Ocotillo 1 (see graphs.Rmd). In turn, the outlier was removed and logHeight is predicted with a smaller dataset containing all ocotillos except Ocotillo 1.

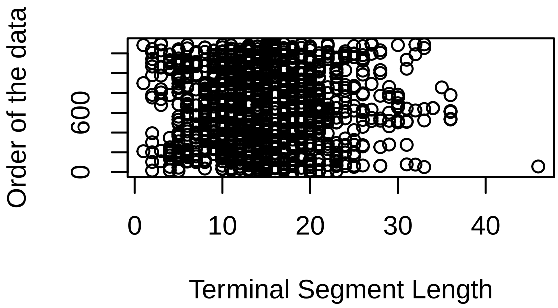
```
# Cleveland Dotplot & Boxplot
par(mfrow=c(2,2))
x = segs$Length
y = seq(1, length(x),)
plot(x,y, ylab="Order of the data", xlab="Terminal Segment Length")
boxplot(segs$Length)
```

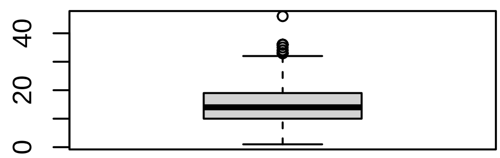
```
segs = segs[segs$Tree != 1,] # remove Plant 1 outlier

x = segs$Length
y = seq(1, length(x),)
plot(x,y, ylab="Order of the data", xlab="Terminal Segment Length")
boxplot(segs$Length)
```










```
dixon.test(ocos$Terminal_SegIQR)
```

```
##
##  Dixon test for outliers
##
## data:  ocos$Terminal_SegIQR
## Q = 0.67857, p-value < 2.2e-16
## alternative hypothesis: highest value 19 is an outlier
```

```
ocos_data = ocotillo_data[ocotillo_data$Tree != 1,]
segs_data = segment_data[segment_data$Tree != 1,]

segs_data = segs_data[complete.cases(segs_data$Length),] # also need to remove rows with NA Le

# rerun data cleaning to generate newly transformed columns
ocos = clean_ocos_data(ocos_data)
ocos_baj = ocos[1:20,]
segs = clean_segs_data(segs_data, ocos_data)
segs_baj = segs[1:1000,]
```

2 Ocotillo Morphology

Analyses below are multiple variate models of Fouquieria splendens morphology for ocotillos located on both a bajada and a plain in Organ Pipe National Monument, Arizona. All models were grouped by their response variable and ordered by their ascending AIC values. Dataset "ocos" indicates all individuals measured on the bajada and plain while "ocos_baj" indicates only the individuals measured on the bajada. Ocotillos located on the bajada were encoded with site = 0 while ocotillos on the plain were encoded with site = 1. Interspecific neighbor group is split between two types – shrub and cactus – where cactus = 0 and shrub = 1.

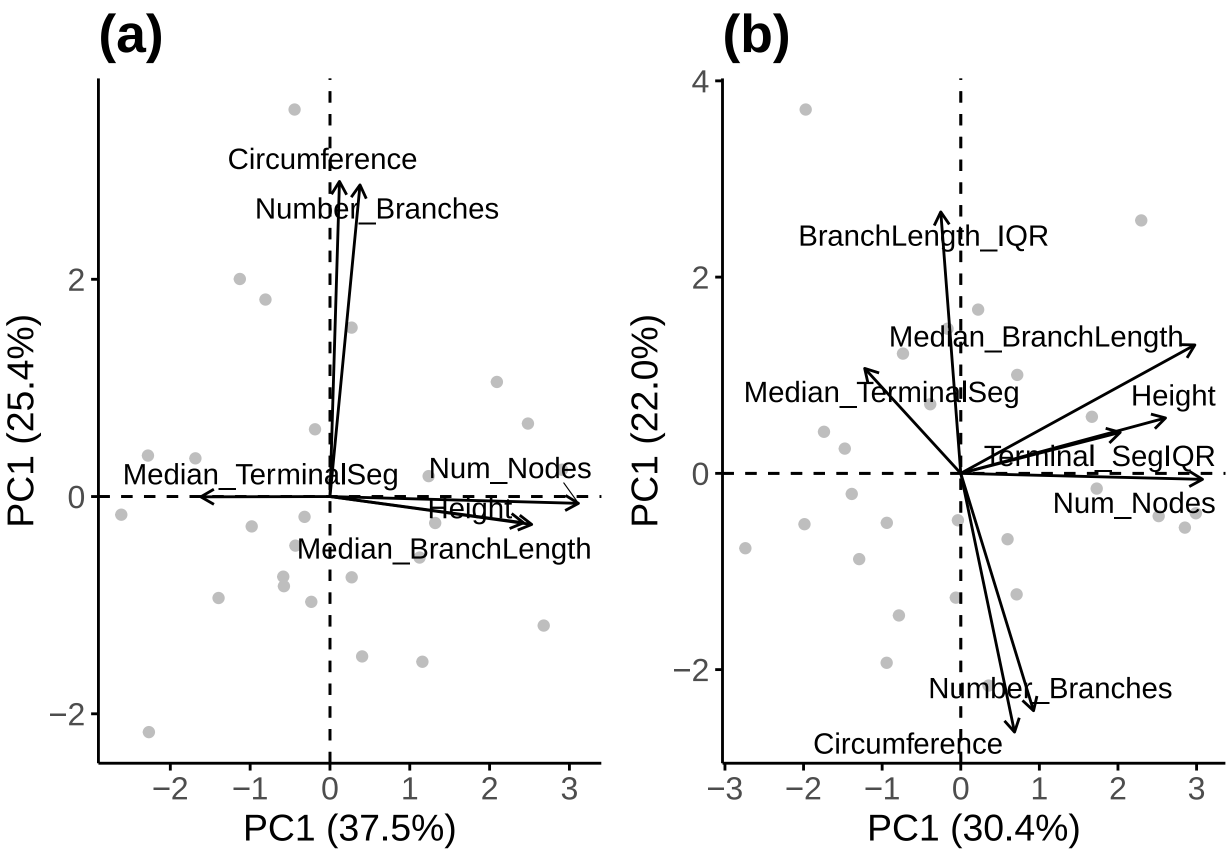
2.1 Principal Component Analysis

2.1.1 Without and With IQR Variables:

```
# Without IQR Vars:
d = ocos[, c("Height", "Circumference",
             "Number_Branches", "Median_BranchLength",
             "Num_Nodes", "Median_TerminalSeg")]
abbreviations = c("Height", "Circ", "NB", "M TSL", "M BL", "Nodes")
pca = PCA_graphs(d, "(a) ", abbreviations)

# With IQR Vars:
d = ocos[, c("Height", "Circumference",
             "Number_Branches", "Median_BranchLength",
             "Num_Nodes", "Median_TerminalSeg",
             "BranchLength_IQR",
             "Terminal_SegIQR")]
abbreviations = c("Height", "Circ", "NB", "M TSL", "TSL IQR", "BL IQR", "M BL", "Nodes")
pca_IQR = PCA_graphs(d, "(b)", abbreviations)

grid.arrange(pca, pca_IQR, nrow=1)
```



This PCA suggests that there is a lot of variation around range, so much so that it apparently drives the PCA when you add it in.

2.2 Addressing Multicollinearity

Elevation and site were highly correlated (R = -0.86), which led to multicollinearity. In turn, we removed any interactions between elevation and site in the model comparison process in order to minimize relationships that were spurious.

```
cor(ocos$Site, ocos$Elevation_c)
```

```
## [1] -0.8576868
```

2.3 Multiple Variate Modeling

2.3.1 Height

2.3.1.1 Plain and Bajada

Model Comparisons

```
data<-data.frame(R=ocos$logHeight,
                 A=ocos$Site,
                 B=ocos$NumNodes_c,
                 C=ocos$Median_BL_c)

source("src/compare_models.R")
model_comparisonsAIC("src/generic models-gaussian lm 3-FF.R")
```

```
## Loading required package: Matrix
```

```
##        [,1]      [,2]      [,3]      [,4]       [,5]       [,6]
## AICs   -19.56829 -17.66286 -17.37006 -16.71477  -16.29006  -15.90138
## models 9         12        5         1          4          14
## probs  0.3343988 0.1289745 0.1114103 0.08028396 0.06492396 0.05345691
##        [,7]
## AICs   -15.85385
## models 16
## probs  0.05220147
##
## m9   lm(formula = R ~ A * C, data = data)
## m12  lm(formula = R ~ A * C + B, data = data)
## m5   lm(formula = R ~ A + C, data = data)
## m1   lm(formula = R ~ A, data = data)
## m4   lm(formula = R ~ A + B, data = data)
## m14  lm(formula = R ~ A * B + A * C, data = data)
## m16  lm(formula = R ~ A * C + B * C, data = data)
```

```
anova(m12, m9, test="Chisq") # Adding B does not improve fit
anova(m9, m5, test="Chisq") # Adding A*C improves fit
# anova(m3, m0, test="Chisq") # Adding C improves fit
# anova(m1, m0, test="Chisq") # Adding A improves fit
```

```
## Analysis of Variance Table
##
## Model 1: R ~ A * C + B
## Model 2: R ~ A * C
##   Res.Df     RSS Df  Sum of Sq Pr(>Chi)
## 1     21 0.48643
## 2     22 0.48820 -1 -0.0017724   0.7821
```

```
## Analysis of Variance Table
##
## Model 1: R ~ A * C
## Model 2: R ~ A + C
##   Res.Df     RSS Df Sum of Sq Pr(>Chi)
## 1     22 0.48820
## 2     23 0.57376 -1 -0.085552  0.04959 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Best Fit

```
M1 = lm(logHeight ~ Site * Median_BL_c, data=ocos) # our best fit model before was just Site +
summary(M1)
```

```
##
## Call:
## lm(formula = logHeight ~ Site * Median_BL_c, data = ocos)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.32196 -0.09643  0.00036  0.09695  0.22765
##
## Coefficients:
##                    Estimate Std. Error t value Pr(>|t|)
## (Intercept)       1.0172203  0.0353968  28.738  < 2e-16 ***
## Site              0.3607716  0.0727430   4.960 5.81e-05 ***
## Median_BL_c       0.0022331  0.0008785   2.542   0.0186 *
## Site:Median_BL_c -0.0026652  0.0013574  -1.963   0.0624 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.149 on 22 degrees of freedom
## Multiple R-squared:  0.6365, Adjusted R-squared:  0.5869
## F-statistic: 12.84 on 3 and 22 DF,  p-value: 4.628e-05
```

Likelihood and Weights

```
summary_tableH = calculate_lk_weights(model_list=list(m0, m1, m3, m5, m9), best_fit=m9,
                                      R="logHeight", A="Site", B="Elevation_c", C="Median_BL_c

summary_tableH
```

```
##                         Equation       AIC     dAIC Likelihood  Weight
## 1                  logHeight ~ 1   0.74084 20.30913    0.00004 0.00002
## 2               logHeight ~ Site -16.71477  2.85353    0.24008 0.15257
## 3        logHeight ~ Median_BL_c  -3.64494 15.92335    0.00035 0.00022
## 4 logHeight ~ Site + Median_BL_c -17.37006  2.19823    0.33317 0.21172
## 5 logHeight ~ Site * Median_BL_c -19.56829  0.00000    1.00000 0.63547
```

T-Test (Height vs. Site)

```r
# significant difference exists even if Plant 1 is removed
t.test(ocos$Height~ocos$Site)
t.test(ocos$logHeight~ocos$Site)
```

```
##
##  Welch Two Sample t-test
##
## data:  ocos$Height by ocos$Site
## t = -4.4794, df = 7.7329, p-value = 0.002239
## alternative hypothesis: true difference in means between group 0 and group 1 is not equal t
## 95 percent confidence interval:
##  -1.8803879 -0.5972061
## sample estimates:
## mean in group 0 mean in group 1
##        2.732632        3.971429
##
##
##  Welch Two Sample t-test
##
## data:  ocos$logHeight by ocos$Site
## t = -4.8408, df = 9.5826, p-value = 0.000769
## alternative hypothesis: true difference in means between group 0 and group 1 is not equal t
## 95 percent confidence interval:
##  -0.5440943 -0.1997020
## sample estimates:
## mean in group 0 mean in group 1
##       0.9937884       1.3656866
```

2.3.1.2 Bajada Only Model Comparisons

```r
data<-data.frame(R=ocos_baj$logHeight,
                 A=ocos_baj$NumNodes_c,
                 B=ocos_baj$Elevation_c,
                 C=ocos_baj$Median_BL_c)

source("src/compare_models.R")
model_comparisonsAIC("src/generic models-gaussian lm 3-FF.R")
```

```
##        [,1]      [,2]      [,3]       [,4]       [,5]       [,6]
## AICs   -20.32776 -19.31201 -18.37805  -18.1727   -18.12138  -17.31229
## models 3         6         5          10         16         7
## probs  0.2602793 0.1566293 0.09818969 0.08860851 0.08636389 0.05762884
##
## m3   lm(formula = R ~ C, data = data)
## m6   lm(formula = R ~ B + C, data = data)
## m5   lm(formula = R ~ A + C, data = data)
## m10  lm(formula = R ~ B * C, data = data)
## m16  lm(formula = R ~ A * C + B * C, data = data)
## m7   lm(formula = R ~ A + B + C, data = data)
```

```r
anova(m3, m6, test="Chisq") # Adding B does not improve fit
anova(m3, m5, test="Chisq") # Adding A does not improve fit
anova(m3, m0, test="Chisq") # Adding C improves fit
```

```
## Analysis of Variance Table
##
## Model 1: R ~ C
## Model 2: R ~ B + C
##   Res.Df     RSS Df Sum of Sq Pr(>Chi)
## 1     18 0.31395
## 2     17 0.29887  1  0.015076   0.3544
## Analysis of Variance Table
##
## Model 1: R ~ C
## Model 2: R ~ A + C
##   Res.Df     RSS Df  Sum of Sq Pr(>Chi)
## 1     18 0.31395
## 2     17 0.31316  1 0.00078845   0.8361
## Analysis of Variance Table
##
## Model 1: R ~ C
## Model 2: R ~ 1
##   Res.Df     RSS Df Sum of Sq  Pr(>Chi)
## 1     18 0.31395
## 2     19 0.58261 -1  -0.26866 8.683e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Best Fit

```
M2 = lm(logHeight ~ Median_BL_c, data=ocos_baj)
summary(M2)
```

```
##
## Call:
## lm(formula = logHeight ~ Median_BL_c, data = ocos_baj)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.281344 -0.091491 -0.009278  0.104050  0.230972
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 1.026680   0.029735  34.528  < 2e-16 ***
## Median_BL_c 0.002614   0.000666   3.925 0.000993 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1321 on 18 degrees of freedom
## Multiple R-squared:  0.4611, Adjusted R-squared:  0.4312
## F-statistic:  15.4 on 1 and 18 DF,  p-value: 0.0009932
```

Likelihood and Weights

```
summary_tableH2 = calculate_lk_weights(model_list=list(m0, m3, m5, m6), best_fit=m3,
                                       R="logHeight", A="NumNodes_c", B="Elevation_c", C="Media
```

```
summary_tableH2
```

```
##                                 Equation       AIC     dAIC Likelihood  Weight
## 1                          logHeight ~ 1  -9.96201 10.36574    0.00561 0.00283
## 2                logHeight ~ Median_BL_c -20.32776  0.00000    1.00000 0.50387
## 3  logHeight ~ NumNodes_c + Median_BL_c -18.37805  1.94971    0.37725 0.19008
## 4 logHeight ~ Elevation_c + Median_BL_c -19.31201  1.01575    0.60177 0.30322
```

2.3.1.3 Summary: Site And Median Branch Length Affect Height Before proceeding, re-reading the full dataset. No outliers for the remaining model comparisons.

```
ocos_data = ocotillo_data
segs_data = segment_data

# rerun data cleaning to generate newly transformed columns
ocos = clean_ocos_data(ocos_data)
ocos_baj = ocos[1:20,]
# segs = clean_segs_data(segs_data, ocos_data)
# segs_baj = segs[1:1000,]
```

2.3.2 Number of Nodes

2.3.2.1 Plain and Bajada

Model Comparisons

```
data<-data.frame(R=ocos$logNodes,
                 A=ocos$Site,
                 B=ocos$Median_BL_c,
                 C=ocos$Elevation_c)

source("src/compare_models.R")
model_comparisonsAIC("src/generic models-gaussian lm 3-FF.R")
```

```
##        [,1]      [,2]      [,3]      [,4]       [,5]       [,6]
## AICs   -5.929535 -4.047644 -3.936627 -3.884457  -3.156741  -2.783342
## models 6         7         10        4          12         1
## probs  0.2771221 0.1081493 0.1023097 0.09967544 0.06927343 0.05747568
##
## m6   lm(formula = R ~ B + C, data = data)
## m7   lm(formula = R ~ A + B + C, data = data)
## m10  lm(formula = R ~ B * C, data = data)
## m4   lm(formula = R ~ A + B, data = data)
## m12  lm(formula = R ~ A * C + B, data = data)
## m1   lm(formula = R ~ A, data = data)
```

```
anova(m10, m6, test="Chisq") # Adding B*C does not improve fit
anova(m7, m6, test="Chisq") # Adding A does not improve fit
anova(m6, m2, test="Chisq") # Adding C improves fit
anova(m6, m3, test="Chisq") # Adding B improves fit
```

```
## Analysis of Variance Table
##
## Model 1: R ~ B * C
```

```
## Model 2: R ~ B + C
##   Res.Df     RSS Df   Sum of Sq Pr(>Chi)
## 1     23 0.94345
## 2     24 0.94370 -1 -0.00024785    0.938
## Analysis of Variance Table
##
## Model 1: R ~ A + B + C
## Model 2: R ~ B + C
##   Res.Df     RSS Df  Sum of Sq Pr(>Chi)
## 1     23 0.93958
## 2     24 0.94370 -1 -0.0041191   0.7508
## Analysis of Variance Table
##
## Model 1: R ~ B + C
## Model 2: R ~ B
##   Res.Df    RSS Df Sum of Sq Pr(>Chi)
## 1     24 0.9437
## 2     25 1.3685 -1  -0.42478 0.001013 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## Analysis of Variance Table
##
## Model 1: R ~ B + C
## Model 2: R ~ C
##   Res.Df    RSS Df Sum of Sq Pr(>Chi)
## 1     24 0.9437
## 2     25 1.1742 -1   -0.2305  0.01547 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Best Fit

```
M7 = lm(logNodes ~ Median_BL_c + Elevation_c, data=ocos)
summary(M7)
```

```
##
## Call:
## lm(formula = logNodes ~ Median_BL_c + Elevation_c, data = ocos)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.48291 -0.08337 -0.02124  0.10650  0.31194
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  5.1362817  0.0381618 134.592  < 2e-16 ***
## Median_BL_c  0.0019862  0.0008204   2.421  0.02340 *
## Elevation_c -0.0047692  0.0014510  -3.287  0.00311 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1983 on 24 degrees of freedom
## Multiple R-squared:  0.4478, Adjusted R-squared:  0.4018
```

```
## F-statistic: 9.732 on 2 and 24 DF,  p-value: 0.0008034
```

Likelihood and Weights

```
summary_tableNN = calculate_lk_weights(model_list=list(m0, m1, m2, m4, m6, m7, m10), best_fit=
                                       R="logNodes", A="Site", B="Median_BL_c", C="Elevation_c

summary_tableNN
```

```
##                                      Equation      AIC     dAIC Likelihood
## 1                               logNodes ~ 1  6.10545 12.03499    0.00244
## 2                            logNodes ~ Site -2.78334  3.14619    0.20740
## 3                     logNodes ~ Median_BL_c  2.10488  8.03441    0.01800
## 4              logNodes ~ Site + Median_BL_c -3.88446  2.04508    0.35968
## 5       logNodes ~ Median_BL_c + Elevation_c -5.92953  0.00000    1.00000
## 6 logNodes ~ Site + Median_BL_c + Elevation_c -4.04764  1.88189    0.39026
## 7       logNodes ~ Median_BL_c * Elevation_c -3.93663  1.99291    0.36919
##    Weight
## 1 0.00104
## 2 0.08837
## 3 0.00767
## 4 0.15325
## 5 0.42608
## 6 0.16628
## 7 0.15730
```

2.3.2.2 Bajada Only

Model Comparisons

```
data<-data.frame(R=ocos_baj$logNodes,
                 A=ocos_baj$Median_BL_c,
                 B=ocos_baj$TSegIQR_c,
                 C=ocos_baj$BL_IQR_c)

source("src/compare_models.R")
model_comparisonsAIC("src/generic models-gaussian lm 3-FF.R")
```

```
##        [,1]      [,2]      [,3]       [,4]       [,5]       [,6]
## AICs   -14.10619 -12.52402 -12.18164  -12.12459  -11.89457  -11.81931
## models 7         11        13         12         4          5
## probs  0.2456309 0.1113573 0.09383668 0.09119758 0.08128955 0.07828748
##        [,7]       [,8]      [,9]
## AICs   -11.58637  -11.18583 -11.17536
## models 14         9         16
## probs  0.06968019 0.057034  0.05673633
##
## m7   lm(formula = R ~ A + B + C, data = data)
## m11  lm(formula = R ~ A * B + C, data = data)
## m13  lm(formula = R ~ B * C + A, data = data)
## m12  lm(formula = R ~ A * C + B, data = data)
## m4   lm(formula = R ~ A + B, data = data)
## m5   lm(formula = R ~ A + C, data = data)
## m14  lm(formula = R ~ A * B + A * C, data = data)
```

```
## m9   lm(formula = R ~ A * C, data = data)
## m16  lm(formula = R ~ A * C + B * C, data = data)
```

```
anova(m7, m5, test="Chisq") # Adding B marginally improves fit
anova(m7, m4, test="Chisq") # Adding C marginally improves fit
anova(m4, m2, test="Chisq") # Adding B improves fit
anova(m4, m1, test="Chisq") # Adding A improves fit
```

```
## Analysis of Variance Table
##
## Model 1: R ~ A + B + C
## Model 2: R ~ A + C
##   Res.Df     RSS Df Sum of Sq Pr(>Chi)
## 1     16 0.35083
## 2     17 0.43470 -1 -0.083866   0.0505 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## Analysis of Variance Table
##
## Model 1: R ~ A + B + C
## Model 2: R ~ A + B
##   Res.Df     RSS Df Sum of Sq Pr(>Chi)
## 1     16 0.35083
## 2     17 0.43306 -1 -0.082233   0.0528 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## Analysis of Variance Table
##
## Model 1: R ~ A + B
## Model 2: R ~ B
##   Res.Df     RSS Df Sum of Sq  Pr(>Chi)
## 1     17 0.43306
## 2     18 0.80123 -1  -0.36816 0.0001437 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## Analysis of Variance Table
##
## Model 1: R ~ A + B
## Model 2: R ~ A
##   Res.Df     RSS Df Sum of Sq  Pr(>Chi)
## 1     17 0.43306
## 2     18 0.92085 -1  -0.48779 1.209e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Best Fit

```
M8 = lm(logNodes ~ Median_BL_c + TSegIQR_c, data=ocos_baj)
summary(M8)
```

```
##
## Call:
## lm(formula = logNodes ~ Median_BL_c + TSegIQR_c, data = ocos_baj)
##
```

```
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.297256 -0.059501  0.006539  0.129383  0.223915
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  5.086866   0.037027 137.384  < 2e-16 ***
## Median_BL_c  0.004148   0.001091   3.802 0.001426 **
## TSegIQR_c   -0.060672   0.013865  -4.376 0.000412 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1596 on 17 degrees of freedom
## Multiple R-squared:  0.5588, Adjusted R-squared:  0.5069
## F-statistic: 10.77 on 2 and 17 DF,  p-value: 0.0009532
```

Likelihood and Weights

```
summary_tableNN2 = calculate_lk_weights(model_list=list(m0, m1, m2, m4, m5, m7), best_fit=m4,
                                       R="logNodes", A="Median_BL_c", B="TSegIQR_c", C="")

summary_tableNN2
```

```
##                               Equation       AIC     dAIC Likelihood  Weight
## 1                         logNodes ~ 1   0.47171 12.36627    0.00206 0.00090
## 2                logNodes ~ Median_BL_c   1.19380 13.08837    0.00144 0.00062
## 3                  logNodes ~ TSegIQR_c  -1.58932 10.30525    0.00578 0.00251
## 4    logNodes ~ Median_BL_c + TSegIQR_c -11.89457  0.00000    1.00000 0.43416
## 5              logNodes ~ Median_BL_c + -11.81931  0.07526    0.96307 0.41813
## 6 logNodes ~ Median_BL_c + TSegIQR_c + -14.10619  2.21163    0.33094 0.14368
```

2.3.2.3 Summary: Branch Length and Elevation Affect Number of Nodes

2.3.3 Median Branch Length

2.3.3.1 Plain and Bajada

Model Comparisons

```
data<-data.frame(R=ocos$logMedian_BL,
                 A=ocos$Site,
                 B=ocos$Height_c,
                 C=ocos$TSegIQR_c,
                 D=ocos$NumNodes_c)

source("src/compare_models.R")
model_comparisonsAIC("src/generic models-gaussian lm 4-FF.R")
```

```
##        [,1]
## AICs   -34.74984
## models 10
## probs  0.04987695
##
## m10  lm(formula = R ~ C + D, data = data)
```

```r
anova(m10, m4, test="Chisq") # Adding C improves fit
anova(m10, m3, test="Chisq") # Adding D improves fit
```

```
## Analysis of Variance Table
##
## Model 1: R ~ C + D
## Model 2: R ~ D
##   Res.Df     RSS Df Sum of Sq  Pr(>Chi)
## 1     24 0.32453
## 2     25 0.66399 -1  -0.33945 5.434e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## Analysis of Variance Table
##
## Model 1: R ~ C + D
## Model 2: R ~ C
##   Res.Df     RSS Df Sum of Sq  Pr(>Chi)
## 1     24 0.32453
## 2     25 0.65709 -1  -0.33256 7.079e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Best Fit

```r
M9 = lm(logMedian_BL ~ TSegIQR_c + NumNodes_c, data=ocos)
summary(M9)
```

```
##
## Call:
## lm(formula = logMedian_BL ~ TSegIQR_c + NumNodes_c, data = ocos)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.290021 -0.067142  0.004931  0.067450  0.193219
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 5.5690819  0.0223791 248.852  < 2e-16 ***
## TSegIQR_c   0.0402168  0.0080268   5.010 4.05e-05 ***
## NumNodes_c  0.0026843  0.0005413   4.959 4.61e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1163 on 24 degrees of freedom
## Multiple R-squared:  0.6289, Adjusted R-squared:  0.598
## F-statistic: 20.34 on 2 and 24 DF,  p-value: 6.823e-06
```

Likelihood and Weights

```r
summary_tableBL = calculate_lk_weights(model_list=list(m0, m3, m4, m10), best_fit=m10,
                                       R="logMedian_BL", A="Site", B="Height_c", C="TSegIQR_c"
```

```r
summary_tableBL
```

```
##                                  Equation       AIC     dAIC Likelihood  Weight
## 1                        logMedian_BL ~ 1 -11.98561 22.76423    0.00001 0.00001
## 2                logMedian_BL ~ TSegIQR_c -17.70300 17.04684    0.00020 0.00020
## 3               logMedian_BL ~ NumNodes_c -17.42121 17.32863    0.00017 0.00017
## 4 logMedian_BL ~ TSegIQR_c + NumNodes_c -34.74984  0.00000    1.00000 0.99962
```

2.3.3.2 Bajada Only

Model Comparisons

```r
data<-data.frame(R=ocos_baj$logMedian_BL,
                 A=ocos_baj$Height_c,
                 B=ocos_baj$TSegIQR_c,
                 C=ocos_baj$NumNodes_c)

source("src/compare_models.R")
model_comparisonsAIC("src/generic models-gaussian lm 3-FF.R")
```

```
##        [,1]      [,2]      [,3]      [,4]      [,5]       [,6]       [,7]
## AICs   -29.64027 -29.39345 -29.15553 -28.63111 -28.43322  -28.40369  -27.88314
## models 11        16        14        17        6          13         7
## probs  0.1755253 0.1551473 0.1377463 0.1059751 0.09599139 0.09458438 0.07290932
##        [,8]
## AICs   -27.6411
## models 15
## probs  0.06459897
##
## m11  lm(formula = R ~ A * B + C, data = data)
## m16  lm(formula = R ~ A * C + B * C, data = data)
## m14  lm(formula = R ~ A * B + A * C, data = data)
## m17  lm(formula = R ~ A * B + A * C + B * C, data = data)
## m6   lm(formula = R ~ B + C, data = data)
## m13  lm(formula = R ~ B * C + A, data = data)
## m7   lm(formula = R ~ A + B + C, data = data)
## m15  lm(formula = R ~ A * B + B * C, data = data)
```

```r
anova(m11, m7, test="Chisq") # Adding A*B marginally improves fit
anova(m7, m5, test="Chisq") # Adding B improves fit
anova(m7, m4, test="Chisq") # Adding C improves fit
anova(m7, m6, test="Chisq") # Adding A does not improve fit
anova(m6, m3, test="Chisq") # Adding C improves fit
anova(m6, m2, test="Chisq") # Adding B improves fit
```

```
## Analysis of Variance Table
##
## Model 1: R ~ A * B + C
## Model 2: R ~ A + B + C
##   Res.Df     RSS Df Sum of Sq Pr(>Chi)
## 1     15 0.14600
## 2     16 0.17617 -1 -0.030172   0.0783 .
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## Analysis of Variance Table
##
## Model 1: R ~ A + B + C
## Model 2: R ~ A + C
##   Res.Df     RSS Df Sum of Sq Pr(>Chi)
## 1     16 0.17617
## 2     17 0.23791 -1 -0.061743  0.01788 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## Analysis of Variance Table
##
## Model 1: R ~ A + B + C
## Model 2: R ~ A + B
##   Res.Df     RSS Df Sum of Sq  Pr(>Chi)
## 1     16 0.17617
## 2     17 0.30923 -1  -0.13306 0.0005085 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## Analysis of Variance Table
##
## Model 1: R ~ A + B + C
## Model 2: R ~ B + C
##   Res.Df     RSS Df Sum of Sq Pr(>Chi)
## 1     16 0.17617
## 2     17 0.18942 -1 -0.013246   0.2727
## Analysis of Variance Table
##
## Model 1: R ~ B + C
## Model 2: R ~ C
##   Res.Df     RSS Df Sum of Sq  Pr(>Chi)
## 1     17 0.18942
## 2     18 0.44864 -1  -0.25922 1.412e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## Analysis of Variance Table
##
## Model 1: R ~ B + C
## Model 2: R ~ B
##   Res.Df     RSS Df Sum of Sq  Pr(>Chi)
## 1     17 0.18942
## 2     18 0.34038 -1  -0.15096 0.0002325 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Best Fit

```
M10 = lm(logMedian_BL ~ TSegIQR_c + NumNodes_c, data=ocos_baj)
summary(M10)
```

```
##
## Call:
## lm(formula = logMedian_BL ~ TSegIQR_c + NumNodes_c, data = ocos_baj)
```

```
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.163881 -0.061722  0.000693  0.058162  0.180000
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 5.5809824  0.0263172 212.066  < 2e-16 ***
## TSegIQR_c   0.0383766  0.0079564   4.823 0.000159 ***
## NumNodes_c  0.0027351  0.0007431   3.681 0.001853 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1056 on 17 degrees of freedom
## Multiple R-squared:  0.6207, Adjusted R-squared:  0.5761
## F-statistic: 13.91 on 2 and 17 DF,  p-value: 0.0002636
```

Likelihood and Weights

```
summary_tableBL2 = calculate_lk_weights(model_list=list(m0, m2, m3, m6), best_fit=m6,
                                       R="logMedian_BL", A="Height_c", B="TSegIQR_c", C="NumNo

summary_tableBL2
```

```
##                                Equation       AIC     dAIC Likelihood  Weight
## 1                      logMedian_BL ~ 1 -13.04270 15.39052    0.00045 0.00045
## 2              logMedian_BL ~ TSegIQR_c -18.71110  9.72212    0.00774 0.00768
## 3             logMedian_BL ~ NumNodes_c -13.18795 15.24527    0.00049 0.00049
## 4 logMedian_BL ~ TSegIQR_c + NumNodes_c -28.43322  0.00000    1.00000 0.99139
```

2.3.3.3 Summary: Height, Number of Nodes, and Terminal Segment Length IQR Affect Median Branch Length

2.3.4 Circumference

2.3.4.1 Plain and Bajada

Model Comparisons

```
data<-data.frame(R=ocos$logCirc,
                 A=ocos$NBranch_c,
                 B=ocos$Site)

source("src/compare_models.R")
model_comparisonsAIC("src/generic models-gaussian lm 2-FF.R")
```

```
##        [,1]      [,2]      [,3]
## AICs   5.042321  6.585812  7.217476
## models 1         3         4
## probs  0.5326555 0.2461964 0.179522
##
## m1   lm(formula = R ~ A, data = data)
## m3   lm(formula = R ~ A + B, data = data)
## m4   lm(formula = R ~ A * B, data = data)
```

```r
anova(m4, m3, test='Chisq') # Adding A*B does not improve fit
anova(m3, m1, test='Chisq') # Adding B does not improve fit
anova(m1, m0, test='Chisq') # Adding A does improve fit
```

```
## Analysis of Variance Table
##
## Model 1: R ~ A * B
## Model 2: R ~ A + B
##   Res.Df    RSS Df Sum of Sq Pr(>Chi)
## 1     23 1.4260
## 2     24 1.5002 -1 -0.074133   0.2742
## Analysis of Variance Table
##
## Model 1: R ~ A + B
## Model 2: R ~ A
##   Res.Df    RSS Df Sum of Sq Pr(>Chi)
## 1     24 1.5002
## 2     25 1.5258 -1  -0.02558   0.5224
## Analysis of Variance Table
##
## Model 1: R ~ A
## Model 2: R ~ 1
##   Res.Df    RSS Df Sum of Sq Pr(>Chi)
## 1     25 1.5258
## 2     26 2.0327 -1  -0.50696  0.00395 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Best Fit

```r
M3 = lm(logCirc ~ NBranch_c, data=ocos)
summary(M3)
```

```
##
## Call:
## lm(formula = logCirc ~ NBranch_c, data = ocos)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.51395 -0.07211  0.05566  0.12737  0.52349
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 1.586649   0.047543  33.373   <2e-16 ***
## NBranch_c   0.015306   0.005311   2.882    0.008 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.247 on 25 degrees of freedom
## Multiple R-squared:  0.2494, Adjusted R-squared:  0.2194
## F-statistic: 8.307 on 1 and 25 DF,  p-value: 0.008
```

Likelihood and Weights

```
summary_tableC = calculate_lk_weights(model_list=list(m0, m1, m3, m4), best_fit=m2,
                                      R="logCirc", A="NBranch_c", B="Site", C=" ")

summary_tableC
```

```
##                       Equation      AIC    dAIC Likelihood  Weight
## 1                  logCirc ~ 1 10.78820 1.92275    0.38237 0.74262
## 2          logCirc ~ NBranch_c  5.04232 7.66863    0.02162 0.04198
## 3 logCirc ~ NBranch_c + Site  6.58581 6.12514    0.04677 0.09083
## 4 logCirc ~ NBranch_c * Site  7.21748 5.49348    0.06414 0.12456
```

2.3.4.2 Bajada Only

Model Comparisons

```
data<-data.frame(R=ocos_baj$logCirc,
                 A=ocos_baj$NBranch_c,
                 B=ocos_baj$X1m_Num4)

source("src/compare_models.R")
model_comparisonsAIC("src/generic models-gaussian lm 2-FF.R")
```

```
##        [,1]      [,2]      [,3]
## AICs   -1.746312 -1.746312 2.41489
## models 3         4         1
## probs  0.4675952 0.4675952 0.05838165
##
## m3   lm(formula = R ~ A + B, data = data)
## m4   lm(formula = R ~ A * B, data = data)
## m1   lm(formula = R ~ A, data = data)
```

```
anova(m4, m3, test='Chisq') # Adding A*B does not improve fit
anova(m3, m1, test='Chisq') # Adding B does improve fit
anova(m3, m2, test="Chisq") # Adding A does improve fit
```

```
## Analysis of Variance Table
##
## Model 1: R ~ A * B
## Model 2: R ~ A + B
##   Res.Df     RSS Df Sum of Sq Pr(>Chi)
## 1     17 0.71931
## 2     17 0.71931  0         0
## Analysis of Variance Table
##
## Model 1: R ~ A + B
## Model 2: R ~ A
##   Res.Df     RSS Df Sum of Sq Pr(>Chi)
## 1     17 0.71931
## 2     18 0.97883 -1  -0.25951  0.01327 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
## Analysis of Variance Table
##
## Model 1: R ~ A + B
## Model 2: R ~ B
##   Res.Df     RSS Df Sum of Sq  Pr(>Chi)
## 1     17 0.71931
## 2     18 1.25149 -1  -0.53218 0.0003904 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Best Fit

```
M4 = lm(logCirc ~ NBranch_c + X1m_Num4, data=ocos_baj) # ??? Test PCA with other variables
summary(M4)
```

```
##
## Call:
## lm(formula = logCirc ~ NBranch_c + X1m_Num4, data = ocos_baj)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.41812 -0.02303  0.04341  0.09768  0.27088
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 1.580213   0.047350  33.373  < 2e-16 ***
## NBranch_c   0.018031   0.005084   3.546  0.00248 **
## X1m_Num4    0.523976   0.211575   2.477  0.02407 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2057 on 17 degrees of freedom
## Multiple R-squared:  0.5412, Adjusted R-squared:  0.4873
## F-statistic: 10.03 on 2 and 17 DF,  p-value: 0.001329
```

Likelihood and Weights

```
summary_tableC2 = calculate_lk_weights(model_list=list(m0, m1, m3, m4), best_fit=m3,
                                      R="logCirc", A="NBranch_c", B="X1m_Num4", C=" ")

summary_tableC2
```

```
##                          Equation      AIC     dAIC Likelihood  Weight
## 1                     logCirc ~ 1  9.83772 11.58403    0.00305 0.00143
## 2             logCirc ~ NBranch_c  2.41489  4.16120    0.12486 0.05868
## 3 logCirc ~ NBranch_c + X1m_Num4 -1.74631  0.00000    1.00000 0.46995
## 4 logCirc ~ NBranch_c * X1m_Num4 -1.74631  0.00000    1.00000 0.46995
```

2.3.4.3 Summary: Number of Branches Affects Circumference

2.3.5 Number of Branches

2.3.5.1 Plain and Bajada

Model Comparisons

```
data<-data.frame(R=ocos$logNB,
                 A=ocos$Circ_c,
                 B=ocos$Inter_plant_b,
                 C=ocos$Inter_Dis_c,
                 D=ocos$Arroyo_c)

source("src/compare_models.R")
model_comparisonsAIC("src/generic models-gaussian lm 4-FF.R")
```

```
##        [,1]       [,2]       [,3]
## AICs   4.213291   5.164004   5.362141
## models 13         32         15
## probs  0.09786685 0.06084023 0.05510183
##
## m13  lm(formula = R ~ A + C + D, data = data)
## m32  lm(formula = R ~ C * D + A, data = data)
## m15  lm(formula = R ~ A + B + C + D, data = data)
```

```
anova(m32, m13, test='Chisq') # Adding C*D does not improve fit
anova(m15, m13, test='Chisq') # Adding B does not improve fit
anova(m13, m7, test='Chisq')  # Adding C marginally improves fit
anova(m13, m10, test='Chisq') # Adding A improves fit
anova(m10, m3, test='Chisq')  # Adding D improves fit
```

```
## Analysis of Variance Table
##
## Model 1: R ~ C * D + A
## Model 2: R ~ A + C + D
##   Res.Df    RSS Df Sum of Sq Pr(>Chi)
## 1     22 1.2272
## 2     23 1.2759 -1 -0.048633   0.3505
## Analysis of Variance Table
##
## Model 1: R ~ A + B + C + D
## Model 2: R ~ A + C + D
##   Res.Df    RSS Df Sum of Sq Pr(>Chi)
## 1     22 1.2363
## 2     23 1.2759 -1 -0.039594   0.4013
## Analysis of Variance Table
##
## Model 1: R ~ A + C + D
## Model 2: R ~ A + D
##   Res.Df    RSS Df Sum of Sq Pr(>Chi)
## 1     23 1.2759
## 2     24 1.4635 -1  -0.18762   0.0659 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## Analysis of Variance Table
##
## Model 1: R ~ A + C + D
## Model 2: R ~ C + D
```

```
##   Res.Df    RSS Df Sum of Sq  Pr(>Chi)
## 1     23 1.2759
## 2     24 2.2366 -1  -0.96072 3.161e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## Analysis of Variance Table
##
## Model 1: R ~ C + D
## Model 2: R ~ C
##   Res.Df    RSS Df Sum of Sq Pr(>Chi)
## 1     24 2.2366
## 2     25 2.8558 -1  -0.61915  0.00995 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Best Fit

```
M5 = lm(logNB ~ Circ_c + Inter_Dis_c + Arroyo_c, data=ocos)
summary(M5)
```

```
##
## Call:
## lm(formula = logNB ~ Circ_c + Inter_Dis_c + Arroyo_c, data = ocos)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.41496 -0.15450 -0.01115  0.13114  0.53858
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  3.1079521  0.0453272  68.567  < 2e-16 ***
## Circ_c       0.1439291  0.0345854   4.162 0.000376 ***
## Inter_Dis_c  0.0666066  0.0362173   1.839 0.078849 .
## Arroyo_c    -0.0016415  0.0006386  -2.570 0.017102 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2355 on 23 degrees of freedom
## Multiple R-squared:  0.6109, Adjusted R-squared:  0.5602
## F-statistic: 12.04 on 3 and 23 DF,  p-value: 6.104e-05
```

Likelihood and Weights

```
data<-data.frame(R=ocos$logNB,
                 A=ocos$Circ_c,
                 B=ocos$Inter_plant_b,
                 C=ocos$Inter_Dis_c,
                 D=ocos$Arroyo_c)
```

```
summary_tableNB = calculate_lk_weights(model_list=list(m0, m3, m4, m10, m13), best_fit=m13,
                              R="logNB", A="Circ_c", B="Inter_plant_b", C="Inter_Dis_c", D="Ar

summary_tableNB
```

```
##                                  Equation      AIC     dAIC Likelihood  Weight
## 1                              logNB ~ 1 23.70105 19.48776    0.00006 0.00006
## 2                    logNB ~ Inter_Dis_c 21.96707 17.75378    0.00014 0.00014
## 3                       logNB ~ Arroyo_c 15.92543 11.71214    0.00286 0.00285
## 4          logNB ~ Inter_Dis_c + Arroyo_c 17.36890 13.15561    0.00139 0.00138
## 5 logNB ~ Circ_c + Inter_Dis_c + Arroyo_c  4.21329  0.00000    1.00000 0.99557
```

T-Test (Number of Branches vs. Interspecific Plant Group)

```
t.test(ocos$logNB~ocos$Inter_Plant_Group)
```

```
##
##  Welch Two Sample t-test
##
## data:  ocos$logNB by ocos$Inter_Plant_Group
## t = 2.467, df = 19.119, p-value = 0.02324
## alternative hypothesis: true difference in means between group cactus and group shrub is no
## 95 percent confidence interval:
##  0.04894531 0.59528703
## sample estimates:
## mean in group cactus  mean in group shrub
##             3.298836             2.976720
```

2.3.5.2 Bajada Only

Model Comparisons

```
data<-data.frame(R=ocos_baj$logNB,
                 A=ocos_baj$Inter_plant_b,
                 B=ocos_baj$Circ_c,
                 C=ocos_baj$Intra_Dis_c)

source("src/compare_models.R")
model_comparisonsAIC("src/generic models-gaussian lm 3-FF.R")
```

```
##        [,1]      [,2]
## AICs   -5.315751 -3.320744
## models 15        17
## probs  0.6511801 0.2401546
##
## m15  lm(formula = R ~ A * B + B * C, data = data)
## m17  lm(formula = R ~ A * B + A * C + B * C, data = data)
```

```
anova(m17, m15, test="Chisq") # Adding A*C does not improve fit
anova(m15, m13, test="Chisq") # Adding A*B improves fit
anova(m13, m10, test="Chisq") # Adding A marginally improves fit
anova(m10, m6, test="Chisq") # Adding B*C improves fit
```

```
## Analysis of Variance Table
##
## Model 1: R ~ A * B + A * C + B * C
## Model 2: R ~ A * B + B * C
##   Res.Df     RSS Df   Sum of Sq Pr(>Chi)
## 1     13 0.44567
## 2     14 0.44578 -1 -0.00011127   0.9546
```

```
## Analysis of Variance Table
##
## Model 1: R ~ A * B + B * C
## Model 2: R ~ B * C + A
##   Res.Df     RSS Df Sum of Sq Pr(>Chi)
## 1     14 0.44578
## 2     15 0.65063 -1  -0.20486   0.0112 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## Analysis of Variance Table
##
## Model 1: R ~ B * C + A
## Model 2: R ~ B * C
##   Res.Df     RSS Df Sum of Sq Pr(>Chi)
## 1     15 0.65063
## 2     16 0.77666 -1  -0.12603  0.08827 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## Analysis of Variance Table
##
## Model 1: R ~ B * C
## Model 2: R ~ B + C
##   Res.Df     RSS Df Sum of Sq Pr(>Chi)
## 1     16 0.77666
## 2     17 0.99549 -1  -0.21883  0.03374 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Best Fit

```
M6 = lm(logNB ~ Inter_plant_b*Circ_c +Circ_c*Intra_Dis_c, data=ocos_baj)
summary(M6)
```

```
##
## Call:
## lm(formula = logNB ~ Inter_plant_b * Circ_c + Circ_c * Intra_Dis_c,
##     data = ocos_baj)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.29534 -0.10917  0.01188  0.10091  0.26039
##
## Coefficients:
##                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)           3.300898   0.077335  42.683 3.15e-16 ***
## Inter_plant_b        -0.180378   0.103000  -1.751 0.101773
## Circ_c                0.247218   0.059201   4.176 0.000933 ***
## Intra_Dis_c           0.030922   0.015610   1.981 0.067595 .
## Inter_plant_b:Circ_c -0.191679   0.075570  -2.536 0.023732 *
## Circ_c:Intra_Dis_c   -0.035565   0.009896  -3.594 0.002935 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

```
## Residual standard error: 0.1784 on 14 degrees of freedom
## Multiple R-squared:  0.8077, Adjusted R-squared:  0.739
## F-statistic: 11.76 on 5 and 14 DF,  p-value: 0.0001314
```

Likelihood and Weights

```
summary_tableNB2 = calculate_lk_weights(model_list=list(m0, m2, m3, m6, m10, m13, m15), best_f
                                        R="logNB", A="Inter_plant_b", B="Circ_c", C="Intra_Dis_

summary_tableNB2
```

```
##                                                  Equation      AIC     dAIC
## 1                                               logNB ~ 1 17.65763 22.97339
## 2                                          logNB ~ Circ_c  7.35392 12.66967
## 3                                     logNB ~ Intra_Dis_c 11.42258 16.73833
## 4                            logNB ~ Circ_c + Intra_Dis_c  4.75253 10.06828
## 5                            logNB ~ Circ_c * Intra_Dis_c  1.78796  7.10371
## 6            logNB ~ Circ_c * Intra_Dis_c + Inter_plant_b  0.24673  5.56248
## 7 logNB ~ Inter_plant_b * Circ_c + Circ_c * Intra_Dis_c -5.31575  0.00000
##   Likelihood  Weight
## 1    0.00001 0.00001
## 2    0.00177 0.00161
## 3    0.00023 0.00021
## 4    0.00651 0.00592
## 5    0.02867 0.02608
## 6    0.06196 0.05637
## 7    1.00000 0.90979
```

2.3.5.3 Summary: Circumference, Major Interspecific Group, and Arroyo Distance Affect Number of Branches

2.4 Mixed Effect, Multiple Variate Modeling

2.4.1 Terminal Segment Lengths

2.4.1.1 Plain and Bajada

Model Comparisons

```
data<-data.frame(R=segs$Length_c,
                 A=segs$T1m_NumCacti,
                 B=segs$Num_Nodes_c,
                 C=segs$BranchLength_IQR_c,
                 X=segs$Tree,
                 Y=segs$seg_num)

source("src/compare_models.R")
model_comparisonsAIC("src/generic models-gaussian lmer 2-RF + 3-FF REMLF.R")
```

```
## Warning: Some predictor variables are on very different scales: consider
## rescaling

## Warning: Some predictor variables are on very different scales: consider
## rescaling
```

```
## Warning: Some predictor variables are on very different scales: consider
## rescaling

## Warning: Some predictor variables are on very different scales: consider
## rescaling

## Warning: Some predictor variables are on very different scales: consider
## rescaling

##        [,1]      [,2]      [,3]      [,4]      [,5]
## AICs   8257.873  8259.752  8259.872  8259.967  8261.751
## models 11        14        15        8         17
## probs  0.4110724 0.1605991 0.1512525 0.1442369 0.0591095
##
## m11  R ~ A * B + C + (1 | X) + (1 | Y)
## m14  R ~ A * B + A * C + (1 | X) + (1 | Y)
## m15  R ~ A * B + B * C + (1 | X) + (1 | Y)
## m8   R ~ A * B + (1 | X) + (1 | Y)
## m17  R ~ A * B + A * C + B * C + (1 | X) + (1 | Y)
```

```
anova(m17, m15, test="Chisq") # Adding A*C does not improve fit
anova(m15, m13, test="Chisq") # Adding A*B improves fit
anova(m15, m11, test="Chisq") # Adding B*C does not improve fit
# anova(m15, m11, test="Chisq") # Adding B*C improves fit
anova(m11, m7, test="Chisq") # Adding A*B does improve fit
anova(m11, m4, test="Chisq") # Adding C improves fit
```

```
## Data: data
## Models:
## m15: R ~ A * B + B * C + (1 | X) + (1 | Y)
## m17: R ~ A * B + A * C + B * C + (1 | X) + (1 | Y)
##     npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
## m15    9 8259.9 8306.4 -4120.9   8241.9
## m17   10 8261.8 8313.5 -4120.9   8241.8 0.1209  1     0.7281
## Data: data
## Models:
## m13: R ~ B * C + A + (1 | X) + (1 | Y)
## m15: R ~ A * B + B * C + (1 | X) + (1 | Y)
##     npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
## m13    8 8265.8 8307.2 -4124.9   8249.8
## m15    9 8259.9 8306.4 -4120.9   8241.9 7.9518  1   0.004804 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## Data: data
## Models:
## m11: R ~ A * B + C + (1 | X) + (1 | Y)
## m15: R ~ A * B + B * C + (1 | X) + (1 | Y)
##     npar    AIC    BIC  logLik deviance Chisq Df Pr(>Chisq)
## m11    8 8257.9 8299.2 -4120.9   8241.9
## m15    9 8259.9 8306.4 -4120.9   8241.9 4e-04  1     0.9848
## Data: data
## Models:
## m7: R ~ A + B + C + (1 | X) + (1 | Y)
```

```
## m11: R ~ A * B + C + (1 | X) + (1 | Y)
##     npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
## m7     7 8266.0 8302.2 -4126.0   8252.0
## m11    8 8257.9 8299.2 -4120.9   8241.9 10.174  1   0.001424 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## Data: data
## Models:
## m4: R ~ A + B + (1 | X) + (1 | Y)
## m11: R ~ A * B + C + (1 | X) + (1 | Y)
##     npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
## m4     6 8265.8 8296.9 -4126.9   8253.8
## m11    8 8257.9 8299.2 -4120.9   8241.9 11.969  2   0.002518 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Best Fit

```
# M11 = lmer(Length_c ~ T1m_NumCacti * Num_Nodes_c + Num_Nodes_c * BranchLength_IQR_c +
#                                                  (1 | Tree) + (1 | seg_num), data=segs)
# summary(M11)
M11 = lmer(Length_c ~ T1m_NumCacti * Num_Nodes_c + Num_Nodes_c + BranchLength_IQR_c +
                                               (1 | Tree) + (1 | seg_num), data=segs)
summary(M11)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula:
## Length_c ~ T1m_NumCacti * Num_Nodes_c + Num_Nodes_c + BranchLength_IQR_c +
##     (1 | Tree) + (1 | seg_num)
##    Data: segs
##
## REML criterion at convergence: 8261.2
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.0056 -0.6311 -0.0657  0.5834  4.7451
##
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  Tree     (Intercept)  4.8741  2.2077
##  seg_num  (Intercept)  0.5249  0.7245
##  Residual             31.7408  5.6339
## Number of obs: 1300, groups:  Tree, 26; seg_num, 5
##
## Fixed effects:
##                          Estimate Std. Error t value
## (Intercept)              -0.11455    0.62093  -0.184
## T1m_NumCacti             -0.90637    0.55288  -1.639
## Num_Nodes_c              -0.06100    0.01423  -4.286
## BranchLength_IQR_c        0.03217    0.01688   1.906
## T1m_NumCacti:Num_Nodes_c  0.04746    0.01486   3.194
##
## Correlation of Fixed Effects:
```

```
##              (Intr) T1m_NC Nm_Nd_ BL_IQR
## T1m_NumCact -0.334
## Num_Nodes_c  0.170 -0.069
## BrnchL_IQR_ -0.098  0.153  0.030
## T1m_NC:N_N_ -0.152 -0.285 -0.528  0.131
```

Likelihood and Weights

```
# summary_tableSL = calculate_lk_weights(model_list=list(m0, m1, m2, m3, m4, m5, m6, m7, m11,
#                                        best_fit=m15,
#                                        R="Length_c", A="T1m_NumCacti", B="Num_Nodes_c", C="Br
#                                        X="Tree", Y="seg_num", is_lm=FALSE)
summary_tableSL = calculate_lk_weights(model_list=list(m0, m4, m7, m11),
                                     best_fit=m11,
                                     R="Length_c", A="T1m_NumCacti", B="Num_Nodes_c", C="Bran
                                     X="Tree", Y="seg_num", is_lm=FALSE)

summary_tableSL$Equation = gsub("T1m_NumBranchLength_IQLength_c_cacti", "T1m_NumCacti",
                                summary_tableSL$Equation )
summary_tableSL$Equation = gsub("BranchLength_IQLength_c_c", "BranchLength_IQR_c",
                                summary_tableSL$Equation)

summary_tableSL
```

```
##                                                                                  Equation
## 1                                                    Length_c ~ (1 | Tree) + (1 | seg_num)
## 2                      Length_c ~ T1m_NumCacti + Num_Nodes_c + (1 | Tree) + (1 | seg_num)
## 3 Length_c ~ T1m_NumCacti + Num_Nodes_c + BranchLength_IQR_c + (1 | Tree) + (1 | seg_num)
## 4 Length_c ~ T1m_NumCacti * Num_Nodes_c + BranchLength_IQR_c + (1 | Tree) + (1 | seg_num)
##        AIC     dAIC Likelihood  Weight
## 1 8271.553 13.68091    0.00107 0.00103
## 2 8265.841  7.96895    0.01860 0.01795
## 3 8266.047  8.17404    0.01679 0.01620
## 4 8257.873  0.00000    1.00000 0.96482
```

2.4.1.2 Bajada Only

Model Comparisons

```
data<-data.frame(R=segs_baj$Length_c,
                 A=segs_baj$T1m_NumCacti,
                 B=segs_baj$Num_Nodes_c,
                 C=segs_baj$BranchLength_IQR_c,
                 X=segs_baj$Tree,
                 Y=segs_baj$seg_num)

source("src/compare_models.R")
model_comparisonsAIC("src/generic models-gaussian lmer 2-RF + 3-FF REMLF.R")
```

```
## Warning: Some predictor variables are on very different scales: consider
## rescaling

## Warning: Some predictor variables are on very different scales: consider
## rescaling
```

```
## Warning: Some predictor variables are on very different scales: consider
## rescaling

## Warning: Some predictor variables are on very different scales: consider
## rescaling

## Warning: Some predictor variables are on very different scales: consider
## rescaling

##        [,1]      [,2]      [,3]       [,4]       [,5]       [,6]
## AICs   6306.037  6306.425  6307.794   6307.886   6308.032   6308.255
## models 7         11        13         6          12         4
## probs  0.2104824 0.1734001 0.08743109 0.08351391 0.07761663 0.06945919
##        [,7]       [,8]
## AICs   6308.273   6308.339
## models 14         15
## probs  0.06883631 0.06658537
##
## m7   R ~ A + B + C + (1 | X) + (1 | Y)
## m11  R ~ A * B + C + (1 | X) + (1 | Y)
## m13  R ~ B * C + A + (1 | X) + (1 | Y)
## m6   R ~ B + C + (1 | X) + (1 | Y)
## m12  R ~ A * C + B + (1 | X) + (1 | Y)
## m4   R ~ A + B + (1 | X) + (1 | Y)
## m14  R ~ A * B + A * C + (1 | X) + (1 | Y)
## m15  R ~ A * B + B * C + (1 | X) + (1 | Y)
```

```
# anova(m15, m13, test="Chisq") # Adding A*B does not improve fit
# anova(m13, m10, test="Chisq") # Adding A marginally improves fit
# anova(m10, m6, test="Chisq") # Adding B*C improves fit
```

```
anova(m11, m7, test="Chisq") # Adding A*B does not improve fit
anova(m12, m7, test="Chisq") # Adding A*C does not improve fit
anova(m13, m7, test="Chisq") # Adding B*C does not improve fit
anova(m7, m6, test="Chisq") # Adding A improves fit
anova(m7, m5, test="Chisq") # Adding B improves fit
anova(m7, m4, test="Chisq") # Adding C improves fit
```

```
## Data: data
## Models:
## m7: R ~ A + B + C + (1 | X) + (1 | Y)
## m11: R ~ A * B + C + (1 | X) + (1 | Y)
##     npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
## m7     7 6306.0 6340.4 -3146.0   6292.0
## m11    8 6306.4 6345.7 -3145.2   6290.4 1.6124  1     0.2042
## Data: data
## Models:
## m7: R ~ A + B + C + (1 | X) + (1 | Y)
## m12: R ~ A * C + B + (1 | X) + (1 | Y)
##     npar  AIC    BIC logLik deviance  Chisq Df Pr(>Chisq)
## m7     7 6306 6340.4  -3146     6292
## m12    8 6308 6347.3  -3146     6292 0.0048  1      0.945
```

```
## Data: data
## Models:
## m7: R ~ A + B + C + (1 | X) + (1 | Y)
## m13: R ~ B * C + A + (1 | X) + (1 | Y)
##     npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
## m7     7 6306.0 6340.4 -3146.0   6292.0
## m13    8 6307.8 6347.1 -3145.9   6291.8 0.2429  1     0.6221
## Data: data
## Models:
## m6: R ~ B + C + (1 | X) + (1 | Y)
## m7: R ~ A + B + C + (1 | X) + (1 | Y)
##    npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
## m6    6 6307.9 6337.3 -3147.9   6295.9
## m7    7 6306.0 6340.4 -3146.0   6292.0 3.8488  1    0.04978 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## Data: data
## Models:
## m5: R ~ A + C + (1 | X) + (1 | Y)
## m7: R ~ A + B + C + (1 | X) + (1 | Y)
##    npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
## m5    6 6317.3 6346.7 -3152.7   6305.3
## m7    7 6306.0 6340.4 -3146.0   6292.0 13.255  1  0.0002718 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## Data: data
## Models:
## m4: R ~ A + B + (1 | X) + (1 | Y)
## m7: R ~ A + B + C + (1 | X) + (1 | Y)
##    npar    AIC    BIC  logLik deviance  Chisq Df Pr(>Chisq)
## m4    6 6308.3 6337.7 -3148.1   6296.3
## m7    7 6306.0 6340.4 -3146.0   6292.0 4.2173  1    0.04001 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Best Fit

```
# M12 = lmer(Length_c ~ Num_Nodes_c * BranchLength_IQR_c + (1 | Tree) + (1 | seg_num), data=se
# summary(M12)
M12 = lmer(Length_c ~ T1m_NumCacti + Num_Nodes_c + BranchLength_IQR_c + (1 | Tree) + (1 | seg_
summary(M12)
```

```
## Linear mixed model fit by REML ['lmerMod']
## Formula: Length_c ~ T1m_NumCacti + Num_Nodes_c + BranchLength_IQR_c +
##     (1 | Tree) + (1 | seg_num)
##    Data: segs_baj
##
## REML criterion at convergence: 6303.7
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.0267 -0.6410 -0.0702  0.6018  4.8337
##
```

```
## Random effects:
##  Groups   Name        Variance Std.Dev.
##  Tree     (Intercept)  4.7156  2.1715
##  seg_num  (Intercept)  0.5403  0.7351
##  Residual             30.2246  5.4977
## Number of obs: 1000, groups:  Tree, 20; seg_num, 5
##
## Fixed effects:
##                     Estimate Std. Error t value
## (Intercept)         -0.38354    0.68256  -0.562
## T1m_NumCacti        -1.07047    0.57634  -1.857
## Num_Nodes_c         -0.05820    0.01488  -3.912
## BranchLength_IQR_c   0.03532    0.01808   1.954
##
## Correlation of Fixed Effects:
##             (Intr) T1m_NC Nm_Nd_
## T1m_NumCact -0.336
## Num_Nodes_c  0.271 -0.061
## BrnchL_IQR_ -0.205  0.171 -0.027
```

Likelihood and Weights

```
# summary_tableSL2 = calculate_lk_weights(model_list=list(m0, m2, m3, m6, m10), best_fit=m10,
#                                         R="Length_c", A="T1m_NumCacti", B="Num_Nodes_c", C="B
#                                         X="Tree", Y="seg_num", is_lm=FALSE)

summary_tableSL2 = calculate_lk_weights(model_list=list(m0, m1, m2, m3, m4, m5, m7), best_fit=
                                        R="Length_c", A="T1m_NumCacti", B="Num_Nodes_c", C="Bra
                                        X="Tree", Y="seg_num", is_lm=FALSE)

summary_tableSL2$Equation = gsub("BranchLength_IQLength_c_c", "BranchLength_IQR_c",
                                 summary_tableSL2$Equation)
summary_tableSL2
```

```
##
## 1                                                                    Length_c ~ (1 | Tree)
## 2                                                     Length_c ~ T1m_NumCacti + (1 | Tree)
## 3                                                      Length_c ~ Num_Nodes_c + (1 | Tree)
## 4                                               Length_c ~ BranchLength_IQR_c + (1 | Tree)
## 5                                       Length_c ~ T1m_NumCacti + Num_Nodes_c + (1 | Tree)
## 6               Length_c ~ T1m_NumBranchLength_IQR_cacti + BranchLength_IQR_c + (1 | Tree)
## 7 Length_c ~ T1m_NumBranchLength_IQR_cacti + Num_Nodes_c + BranchLength_IQR_c + (1 | Tree)
##        AIC     dAIC Likelihood  Weight
## 1 6318.499 12.46216    0.00197 0.00137
## 2 6317.343 11.30610    0.00351 0.00243
## 3 6310.653  4.61565    0.09948 0.06902
## 4 6317.902 11.86483    0.00265 0.00184
## 5 6308.255  2.21733    0.33000 0.22898
## 6 6317.292 11.25512    0.00360 0.00250
## 7 6306.037  0.00000    1.00000 0.69387
```

2.4.1.3 Summary: Number of Nodes, Branch Length IQR, and Number of Cacti Affect Terminal Segment Lengths

3 Ocotillo Neighbors and Site Geography

3.1 Multiple Variate Modeling

3.1.1 Nearest Ocotillo Distance

3.1.1.1 Plain and Bajada

Model Comparisons

```
data<-data.frame(R=ocos$logIntraD,
                 A=ocos$Height_c,
                 B=ocos$Elevation_c,
                 C=ocos$Circ_c)

source("src/compare_models.R")
model_comparisonsAIC("src/generic models-gaussian lm 3-FF.R")
```

```
##        [,1]      [,2]      [,3]      [,4]
## AICs   49.29513  50.88404  52.11031  52.89587
## models 16        17        12        6
## probs  0.4342005 0.1961843 0.1062632 0.0717463
##
## m16  lm(formula = R ~ A * C + B * C, data = data)
## m17  lm(formula = R ~ A * B + A * C + B * C, data = data)
## m12  lm(formula = R ~ A * C + B, data = data)
## m6   lm(formula = R ~ B + C, data = data)
```

```
anova(m17, m16, test='Chisq') # Adding A*B does not improve fit
anova(m16, m12, test='Chisq') # Adding B*C improves fit
anova(m16, m13, test='Chisq') # Adding A*C improves fit
```

```
## Analysis of Variance Table
##
## Model 1: R ~ A * B + A * C + B * C
## Model 2: R ~ A * C + B * C
##   Res.Df    RSS Df Sum of Sq Pr(>Chi)
## 1     20 5.7544
## 2     21 5.8427 -1 -0.088285   0.5796
## Analysis of Variance Table
##
## Model 1: R ~ A * C + B * C
## Model 2: R ~ A * C + B
##   Res.Df    RSS Df Sum of Sq Pr(>Chi)
## 1     21 5.8427
## 2     22 6.9833 -1   -1.1407  0.04289 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## Analysis of Variance Table
##
## Model 1: R ~ A * C + B * C
## Model 2: R ~ B * C + A
##   Res.Df    RSS Df Sum of Sq Pr(>Chi)
## 1     21 5.8427
## 2     22 8.3353 -1   -2.4926 0.002761 **
```

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

Best Fit

```
M13 = lm(logIntraD ~ Height_c * Circ_c + Elevation_c * Circ_c, data=ocos)
summary(M13)
```

```
##
## Call:
## lm(formula = logIntraD ~ Height_c * Circ_c + Elevation_c * Circ_c,
##     data = ocos)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1.06238 -0.27632 -0.03242  0.31913  0.79202
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)         1.909967   0.107710  17.732  4.1e-14 ***
## Height_c            0.151895   0.151130   1.005  0.32631
## Circ_c              0.345398   0.103330   3.343  0.00309 **
## Elevation_c        -0.008339   0.004714  -1.769  0.09140 .
## Height_c:Circ_c     0.560131   0.187136   2.993  0.00693 **
## Circ_c:Elevation_c  0.010944   0.005405   2.025  0.05579 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.5275 on 21 degrees of freedom
## Multiple R-squared:  0.5542, Adjusted R-squared:  0.4481
## F-statistic: 5.222 on 5 and 21 DF,  p-value: 0.002865
```

Likelihood and Weights

```
summary_tableOD = calculate_lk_weights(model_list=list(m0, m13, m16), best_fit=m16,
                                       R="logIntraD", A="Height_c", B="Elevation_c", C="Circ_c

summary_tableOD
```

```
##                                              Equation      AIC     dAIC
## 1                                       logIntraD ~ 1 61.10871 11.81358
## 2          logIntraD ~ Elevation_c * Circ_c + Height_c 56.88857  7.59343
## 3 logIntraD ~ Height_c * Circ_c + Elevation_c * Circ_c 49.29513  0.00000
##   Likelihood  Weight
## 1    0.00272 0.00265
## 2    0.02244 0.02189
## 3    1.00000 0.97545
```

3.1.1.2 Bajada Only

Model Comparisons

```
data<-data.frame(R=ocos_baj$logIntraD,
                 A=ocos_baj$Elevation_c,
```

```
                 B=ocos_baj$NBranch_c,
                 C=ocos_baj$Inter_Dis_c)

source("src/compare_models.R")
model_comparisonsAIC("src/generic models-gaussian lm 3-FF.R")
```

```
##        [,1]      [,2]      [,3]      [,4]
## AICs   26.32863  27.43601  28.15627  29.16864
## models 13        15        16        17
## probs  0.4185242 0.2405784 0.1678242 0.1011625
##
## m13  lm(formula = R ~ B * C + A, data = data)
## m15  lm(formula = R ~ A * B + B * C, data = data)
## m16  lm(formula = R ~ A * C + B * C, data = data)
## m17  lm(formula = R ~ A * B + A * C + B * C, data = data)
```

```
anova(m15, m13, test="Chisq") # Adding A*B does not improve fit
anova(m13, m10, test="Chisq") # Adding A improves fit
```

```
## Analysis of Variance Table
##
## Model 1: R ~ A * B + B * C
## Model 2: R ~ B * C + A
##   Res.Df    RSS Df Sum of Sq Pr(>Chi)
## 1     14 2.2925
## 2     15 2.3972 -1  -0.10464   0.4241
## Analysis of Variance Table
##
## Model 1: R ~ B * C + A
## Model 2: R ~ B * C
##   Res.Df    RSS Df Sum of Sq Pr(>Chi)
## 1     15 2.3972
## 2     16 3.5318 -1   -1.1346  0.00771 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Best Fit

```
M14 = lm(logIntraD ~ NBranch_c * Inter_Dis_c + Elevation_c, data=ocos_baj)
summary(M14)
```

```
##
## Call:
## lm(formula = logIntraD ~ NBranch_c * Inter_Dis_c + Elevation_c,
##     data = ocos_baj)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.94276 -0.06483  0.06156  0.17411  0.72809
##
## Coefficients:
##                           Estimate Std. Error t value Pr(>|t|)
```

```
## (Intercept)            2.008306   0.134660  14.914 2.11e-10 ***
## NBranch_c              0.005610   0.012193   0.460   0.6520    
## Inter_Dis_c           -0.128589   0.117645  -1.093   0.2916    
## Elevation_c           -0.019725   0.007403  -2.664   0.0177 *  
## NBranch_c:Inter_Dis_c -0.061525   0.018887  -3.258   0.0053 ** 
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.3998 on 15 degrees of freedom
## Multiple R-squared:  0.6568, Adjusted R-squared:  0.5652 
## F-statistic: 7.175 on 4 and 15 DF,  p-value: 0.001949
```

Likelihood and Weights

```
summary_tableOD2 = calculate_lk_weights(model_list=list(m0, m10, m13), best_fit=m13,
                                       R="logIntraD", A="Elevation_c", B="NBranch_c", C="Inter

summary_tableOD2
```

```
##                                             Equation      AIC     dAIC
## 1                                      logIntraD ~ 1 39.71503 13.38640
## 2              logIntraD ~ NBranch_c * Inter_Dis_c 32.07877  5.75014
## 3 logIntraD ~ NBranch_c * Inter_Dis_c + Elevation_c 26.32863  0.00000
##   Likelihood  Weight
## 1    0.00124 0.00117
## 2    0.05641 0.05334
## 3    1.00000 0.94549
```

3.1.1.3 Summary: Elevation and Ocotillo Size Relates to Nearest Ocotillo Distance

3.1.2 Interspecific Distance

3.1.2.1 Plain and Bajada

Model Comparisons

```
data<-data.frame(R=ocos$logInterD,
                 A=ocos$Arroyo_c,
                 B=ocos$Elevation_c)

source("src/compare_models.R")
model_comparisonsAIC("src/generic models-gaussian lm 2-FF.R")
```

```
##        [,1]      [,2]      [,3]      [,4]      [,5]      
## AICs   67.66712  69.59774  69.70135  69.74496  70.79399  
## models 1         3         2         5         4         
## probs  0.4336972 0.1651807 0.1568411 0.1534581 0.09082293
##
## m1   lm(formula = R ~ A, data = data)
## m3   lm(formula = R ~ A + B, data = data)
## m2   lm(formula = R ~ B, data = data)
## m0   lm(formula = R ~ 1, data = data)
## m4   lm(formula = R ~ A * B, data = data)
```

```r
anova(m3, m1, test="Chisq") # Adding B does not improve fit
anova(m1, m0, test="Chisq") # Adding A improves fit
anova(m2, m0, test="Chisq") # Adding B does not improve fit
```

```
## Analysis of Variance Table
##
## Model 1: R ~ A + B
## Model 2: R ~ A
##   Res.Df    RSS Df Sum of Sq Pr(>Chi)
## 1     24 15.477
## 2     25 15.517 -1 -0.039825   0.8037
## Analysis of Variance Table
##
## Model 1: R ~ A
## Model 2: R ~ 1
##   Res.Df    RSS Df Sum of Sq Pr(>Chi)
## 1     25 15.517
## 2     26 18.047 -1   -2.5298   0.0435 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## Analysis of Variance Table
##
## Model 1: R ~ B
## Model 2: R ~ 1
##   Res.Df    RSS Df Sum of Sq Pr(>Chi)
## 1     25 16.731
## 2     26 18.047 -1   -1.3155   0.1609
```

Best Fit

```r
M15 = lm(logInterD ~ Arroyo_c, data=ocos_baj)
summary(M15)
```

```
##
## Call:
## lm(formula = logInterD ~ Arroyo_c, data = ocos_baj)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -1.4781 -0.2324  0.0124  0.4395  1.2321
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.561844   0.157644   3.564  0.00222 **
## Arroyo_c    -0.005405   0.002290  -2.361  0.02972 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.6552 on 18 degrees of freedom
## Multiple R-squared:  0.2364, Adjusted R-squared:  0.194
## F-statistic: 5.573 on 1 and 18 DF,  p-value: 0.02972
```

Likelihood and Weights

```
summary_tableID = calculate_lk_weights(model_list=list(m0, m1), best_fit=m1,
                                       R="logInterD", A="Arroyo_c", B="Elevation_c", C="")

summary_tableID
```

```
##                Equation      AIC    dAIC Likelihood  Weight
## 1         logInterD ~ 1 69.74496 2.07784    0.35384 0.26136
## 2 logInterD ~ Arroyo_c 67.66712 0.00000    1.00000 0.73864
```

3.1.2.2 Bajada Only

Model Comparisons

```
data<-data.frame(R=ocos_baj$logInterD,
                 A=ocos_baj$Arroyo_c,
                 B=ocos_baj$Elevation_c)

source("src/compare_models.R")
model_comparisonsAIC("src/generic models-gaussian lm 2-FF.R")
```

```
##        [,1]      [,2]      [,3]      [,4]      [,5]
## AICs   43.73701  44.38602  44.765    45.98429  47.13157
## models 1         2         3         4         5
## probs  0.3534489 0.2555031 0.2113984 0.1149044 0.06474523
##
## m1   lm(formula = R ~ A, data = data)
## m2   lm(formula = R ~ B, data = data)
## m3   lm(formula = R ~ A + B, data = data)
## m4   lm(formula = R ~ A * B, data = data)
## m0   lm(formula = R ~ 1, data = data)
```

```
anova(m3, m1, test="Chisq") # Adding B does not improve fit
anova(m1, m0, test="Chisq") # Adding A improves fit
```

```
## Analysis of Variance Table
##
## Model 1: R ~ A + B
## Model 2: R ~ A
##   Res.Df    RSS Df Sum of Sq Pr(>Chi)
## 1     17 7.3603
## 2     18 7.7269 -1  -0.36655   0.3575
## Analysis of Variance Table
##
## Model 1: R ~ A
## Model 2: R ~ 1
##   Res.Df     RSS Df Sum of Sq Pr(>Chi)
## 1     18  7.7269
## 2     19 10.1192 -1   -2.3923  0.01824 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

Best Fit

```r
M17 = lm(logInterD ~ Arroyo_c, data=ocos_baj)
summary(M17)
```

```
##
## Call:
## lm(formula = logInterD ~ Arroyo_c, data = ocos_baj)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -1.4781 -0.2324  0.0124  0.4395  1.2321
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.561844   0.157644   3.564  0.00222 **
## Arroyo_c    -0.005405   0.002290  -2.361  0.02972 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.6552 on 18 degrees of freedom
## Multiple R-squared:  0.2364, Adjusted R-squared:  0.194
## F-statistic: 5.573 on 1 and 18 DF,  p-value: 0.02972
```

Likelihood and Weights

```r
summary_tableID2 = calculate_lk_weights(model_list=list(m0, m1), best_fit=m1,
                                       R="logInterD", A="Arroyo_c", B="Elevation_c", C="")

summary_tableID2
```

```
##                Equation      AIC    dAIC Likelihood  Weight
## 1          logInterD ~ 1 47.13157 3.39456    0.18318 0.15482
## 2 logInterD ~ Arroyo_c 43.73701 0.00000    1.00000 0.84518
```

3.1.2.3 Summary: Arroyo Distance Relates to Interspecific Distance