Supporting Analyses for Lilaeopsis Drought Ecology

Jacob Malcom, Anna Malcom, and William Radke

Overview

This document captures analyses and observations that are not central to the results of the paper, *Water (or the Lack Thereof), Management, and Conservation of an Endangered Desert Wetland Obligate,* Lilaeopsis schaffneriana subsp. recurva. That is, during data processing we made observations that are informative but which may be distracting if included in the primary code.

All of the data was read from Excel files using readxl and prepped for analysis in `prep_data.R`. Code for replicating the results (and tables and figures) of the main paper is found in `main_analyses.R`.

```
library(dplyr)
library(FactoMineR)
library(ggplot2)
library(ggthemes)
library(pscl)

load("../data/field_dat.Rdata")
load("../data/crit_dat.Rdata")
load("../data/resil_dat.Rdata")

knitr::opts_chunk$set(dpi = 300)
knitr::opts_chunk$set(fig.height = 3)
```

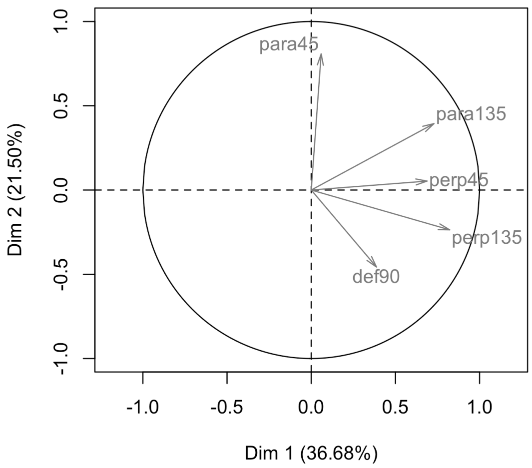
Lilaeopsis presence, absence, and abundance

Forest canopy PCA

We measured forest canopy openness in five places above or around each sample location along Leslie Creek. We performed a PCA to evaluate the extent to which forest canopy variance was shared.

	eigenvalue	percentage of variance	cumulative percentage of variance
comp 1	1.8339529	36.679057	36.67906
comp 2	1.0750538	21.501075	58.18013
comp 3	1.0095273	20.190546	78.37068

comp 4	0.7089513	14.179027	92.54971
comp 5	0.3725147	7.450295	100.00000



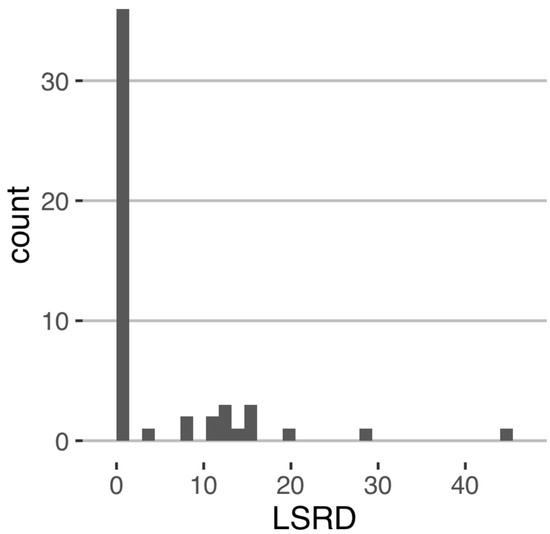
Biplot of the five riparian canopy measurements. *We used PCs 1 and 2 in some models because they account for 58% of the variance.*

The loadings on the first 1-2 PCs are not very strong, but they are sufficient for removing three of five variables. In fact, a basic model using just the original canopy measurements is substantially less parsimonius than one using the first two PCs:

```
mod6 <- zeroinfl(LSRD ~ perp45 + perp135 + para45 + para135 + def90,
                 data = field_dat, dist = "negbin", EM = TRUE)
# summary(mod6)
AICc(mod6)

## [1] 206.4245

mod7 <- zeroinfl(LSRD ~ canopy_PC1 + canopy_PC2,
                 data = field_dat, dist = "negbin", EM = TRUE)
# summary(mod7)
AICc(mod7)

## [1] 195.1703
```

Distribution of Lilaeopsis densities

We need to see the distribution of densities to choose the best way to model the relationship to the predictor variables.



Distribution of Lilaeopsis densities. *Many sampled points have no Lilaeopsis.*

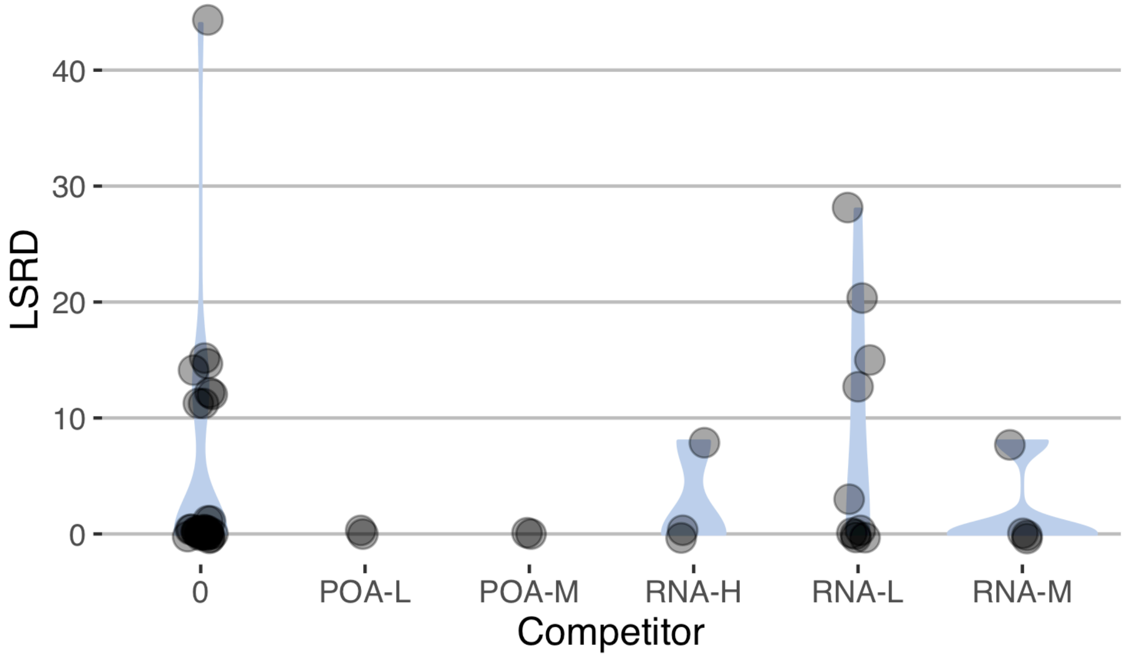
Given this distribution we could either (a) model the presence/absence separately, e.g., using a binomial model and a count [neg. binomial or Poisson] model; or (b) model as a zero-inflated count mixture model. We chose the latter option, with a caveat.

Lilaeopsis density and potential herbaceous competitors

The zero-inflated model caveat is that keeping the plant competitors in the zero-inflated model did not work:

```
model <- zeroinfl(LSRD ~ Competitor, data = field_dat, dist = "negbin",
EM = TRUE)

## Error in solve.default(as.matrix(fit$hessian)): system is computatio
nally singular: reciprocal condition number = 1.50489e-26
```

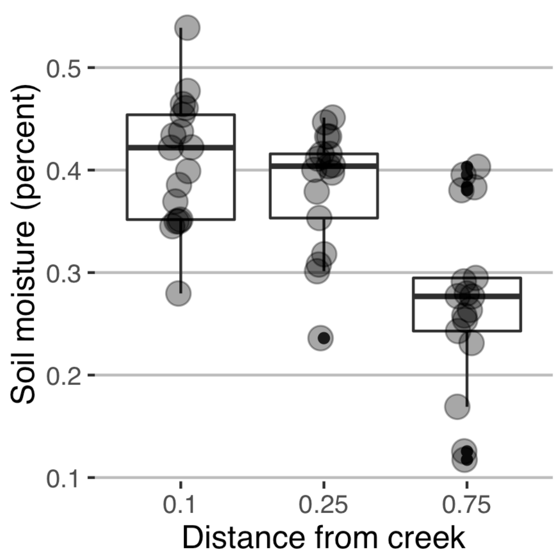
We next checked if *Lilaeopsis* density covaried with competitors; if not, then we can safely drop competitor from the models.



The distribution of Lilaeopsis densities did not covary strongly with any of the competitor species. *'POA' = grasses (Poaceae), 'RNA' = Rorippa nasturtium-aquaticum; H = high, M = medium, L = low competitor density.*

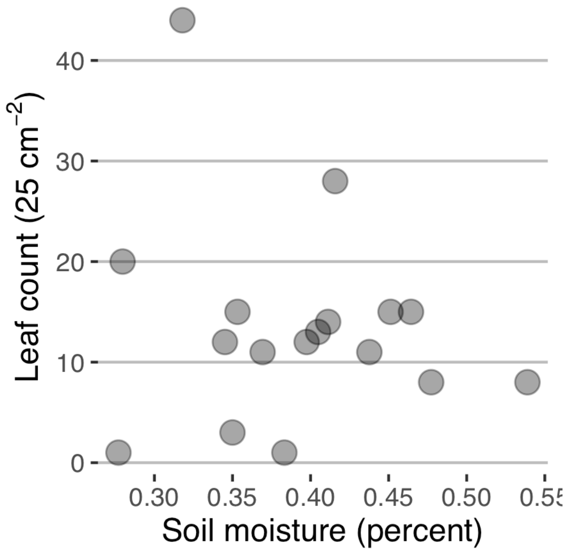
Soil moisture as a function of distance from the creek...

We expect that soil moisture will be higher closer to the edge of the creek, so the distance category and soil moisture may be redundant.



As expected, soil moisture drops as the distance from the edge of the creek increases. *However, we considered models with both soil moisture and distance class in the predictor variable set because the moisture of the near- and mid-distance classes overlaps extensively.*

...and Lilaeopsis leaf density as a function of moisture



Even though soil moisture covaries with distance from the creek, and leaf density is associated with distance, soil moisture is not well-correlated with leaf density. *This may indicate that a different limiting factor shapes leaf density once a particular moisture level is reached.*

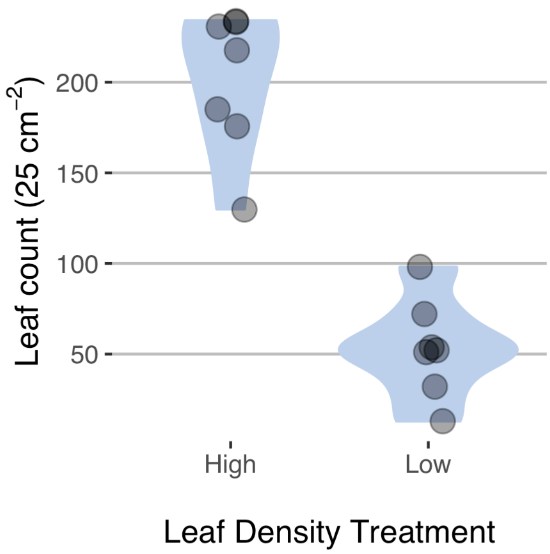
It's not clear why the density-distance-moisture relationship is not transitive, but that's what the data suggest.

Lilaeopsis drought resistance and resilience

Experimental leaf densities

We tested if the leaf density treatment of the resistance and resilience experiments was significantly different.

```
t.test(Leaf_count ~ Density, data = dens_dat)

##
##  Welch Two Sample t-test
##
## data:  Leaf_count by Density
## t = 8.1996, df = 10.685, p-value = 6.227e-06
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  108.0251 187.6892
## sample estimates:
## mean in group High  mean in group Low
##          201.00000           53.14286
```



As expected, the density of Lilaeopsis leaves was higher for the high treatment than for the the low treatment.

Resistance and resilence models

For both the resistance and the resilience experiment data we evaluated additive and interaction models, and used Akaike's Information Criterion to select the best-supported model.

```
# Days-to-critical analysis:
mod1 <- lm(Days_to_Crit ~ Treat + Density, data = crit_dat)
mod2 <- lm(Days_to_Crit ~ Treat * Density, data = crit_dat)

candidates <- list(mod1, mod2)
AICc_table <- aictab(candidates)

## Warning in aictab.AIClm(candidates):
## Model names have been supplied automatically in the table

knitr::kable(data.frame(AICc_table))
```

Modnames	K	AICc	Delta_AICc	ModelLik	AICcWt	LL	Cum.Wt
Mod1	7	84.96619	0.000000	1.0000000	0.9057526	-33.73310	0.9057526
Mod2	11	89.49188	4.525686	0.1040542	0.0942474	-29.03165	1.0000000

```
# Drought resilience analysis:
mod1 <- lm(Condition ~ Density + Treat + Day, data = resil_dat)
mod2 <- lm(Condition ~ Density * Day + Treat, data = resil_dat)
mod3 <- lm(Condition ~ Density * Day * Treat, data = resil_dat)
```

```r
candidates <- list(mod1, mod2, mod3)
AICc_table <- aictab(candidates)

## Warning in aictab.AIClm(candidates):
## Model names have been supplied automatically in the table

knitr::kable(data.frame(AICc_table))
```

	Modnames	K	AICc	Delta_AICc	ModelLik	AICcWt	LL	Cum.Wt
3	Mod3	21	1617.399	0.000000	1.0000000	0.9865197	-786.9003	0.9865197
2	Mod2	9	1626.177	8.777422	0.0124167	0.0122493	-803.9358	0.9987691
1	Mod1	8	1630.772	13.372856	0.0012477	0.0012309	-807.2642	1.0000000

Because of the overwhelming support for the interaction models for both the drought resistance and the drought resilience analyses, we simply use the parameter estimates from the interaction model rather than average the estimates.