Multivariate Caughron

```r
library(vegan)
```

```
## Warning: package 'vegan' was built under R version 3.5.1
```

```
## Loading required package: permute
```

```
## Warning: package 'permute' was built under R version 3.5.1
```

```
## Loading required package: lattice
```

```
## This is vegan 2.5-2
```

```r
data(dune)
data(dune.env)
library(dummies)
```

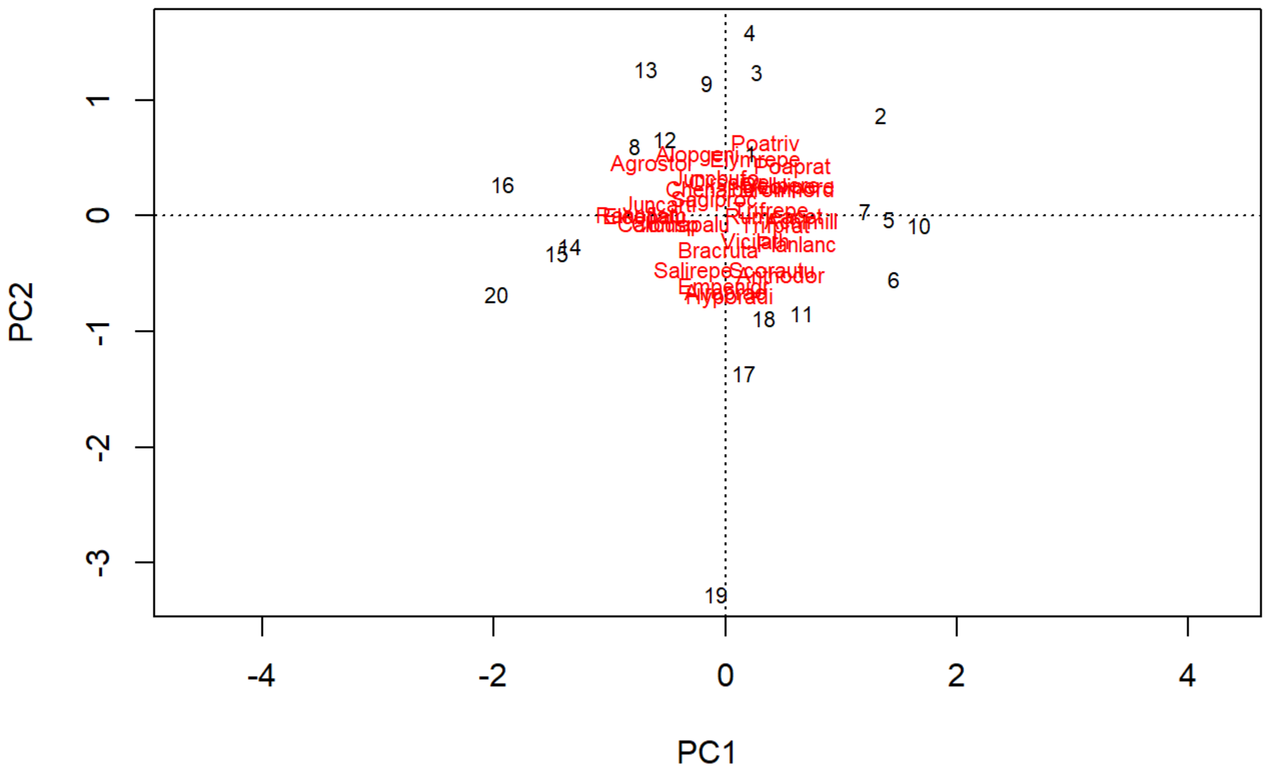
```
## Warning: package 'dummies' was built under R version 3.5.2
```

```
## dummies-1.5.6 provided by Decision Patterns
```

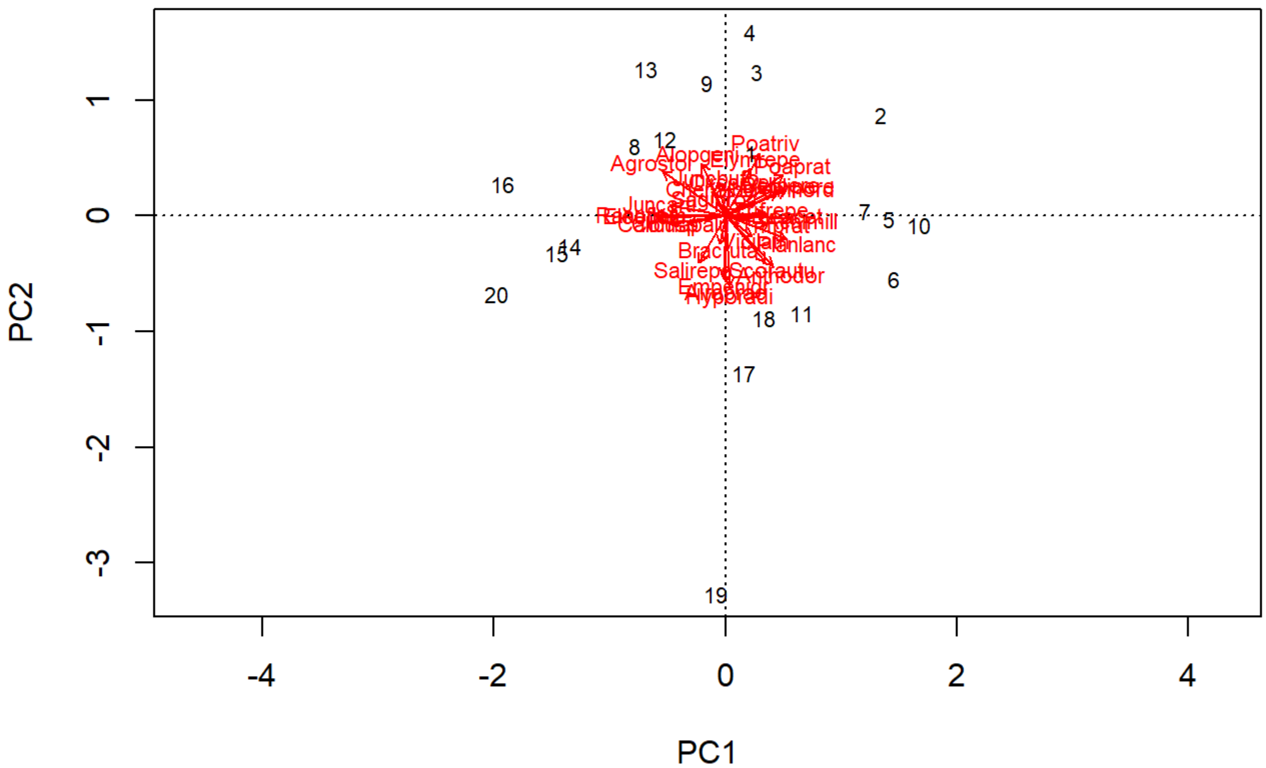
```r
dune_pca<-rda(dune, scale = TRUE)
dune_pca
```

```
## Call: rda(X = dune, scale = TRUE)
##
##               Inertia Rank
## Total              30
## Unconstrained      30   19
## Inertia is correlations
##
## Eigenvalues for unconstrained axes:
##   PC1   PC2   PC3   PC4   PC5   PC6   PC7   PC8
## 7.032 4.997 3.555 2.644 2.139 1.758 1.478 1.316
## (Showed only 8 of all 19 unconstrained eigenvalues)
```

```r
plot(dune_pca)
```



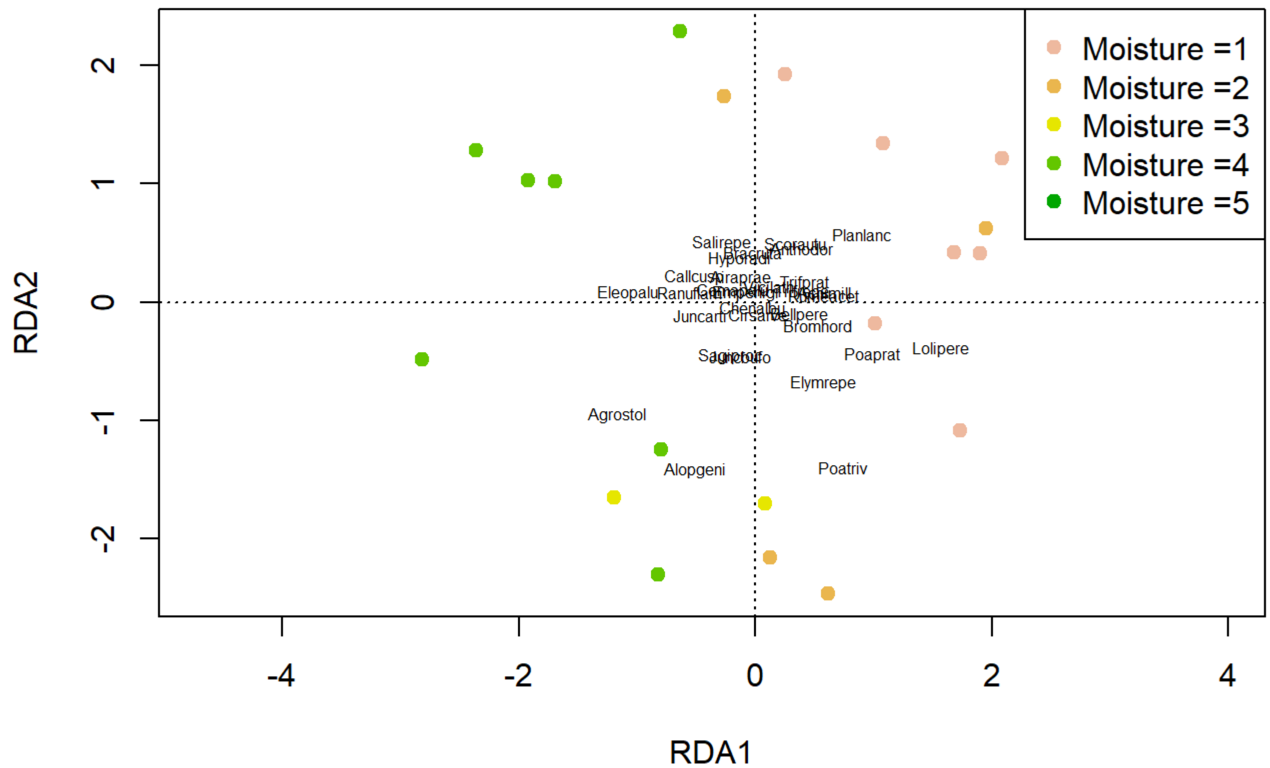

```
biplot(dune_pca)
```




```
rda_dune = rda(dune ~ dune.env$Moisture + dune.env$Management +dune.env$A1 +dune.env$Use + dune.
env$Manure)
rda_dune
```

```
## Call: rda(formula = dune ~ dune.env$Moisture + dune.env$Management
## + dune.env$A1 + dune.env$Use + dune.env$Manure)
##
##                Inertia Proportion Rank
## Total          84.1237     1.0000
## Constrained    63.2062     0.7513   12
## Unconstrained 20.9175     0.2487    7
## Inertia is variance
## Some constraints were aliased because they were collinear (redundant)
##
## Eigenvalues for constrained axes:
##   RDA1   RDA2   RDA3   RDA4   RDA5   RDA6   RDA7   RDA8   RDA9  RDA10
## 22.396 16.208  7.039  4.038  3.760  2.609  2.167  1.803  1.404  0.917
##  RDA11  RDA12
##  0.582  0.284
##
## Eigenvalues for unconstrained axes:
##   PC1   PC2   PC3   PC4   PC5   PC6   PC7
## 6.627 4.309 3.549 2.546 2.340 0.934 0.612
```

```
plot(rda_dune, type='n')
text(rda_dune, 'sp', cex=.5)
# generate vector of colors
color_vect = rev(terrain.colors(6))[-1]
points(rda_dune, 'sites', pch=19,
       col=color_vect[dune.env$Moisture])
legend('topright', paste("Moisture =", 1:5, sep=''),
       col=color_vect, pch=19)
```



What does this graphic indicate? What is the goal of creating this graphic?

Creating a graphic like this can indicate variables that may be valuable to pursue when building out models. This is a method that can illuminate basic relationships between variables. In this case we see that moisture values are clustered in different quadrants with particular species.Additionally, there is a pattern of moisture increasing from left to right. This indicates that moisture is probably a good variable to investigate later for explaining cover in the different species.

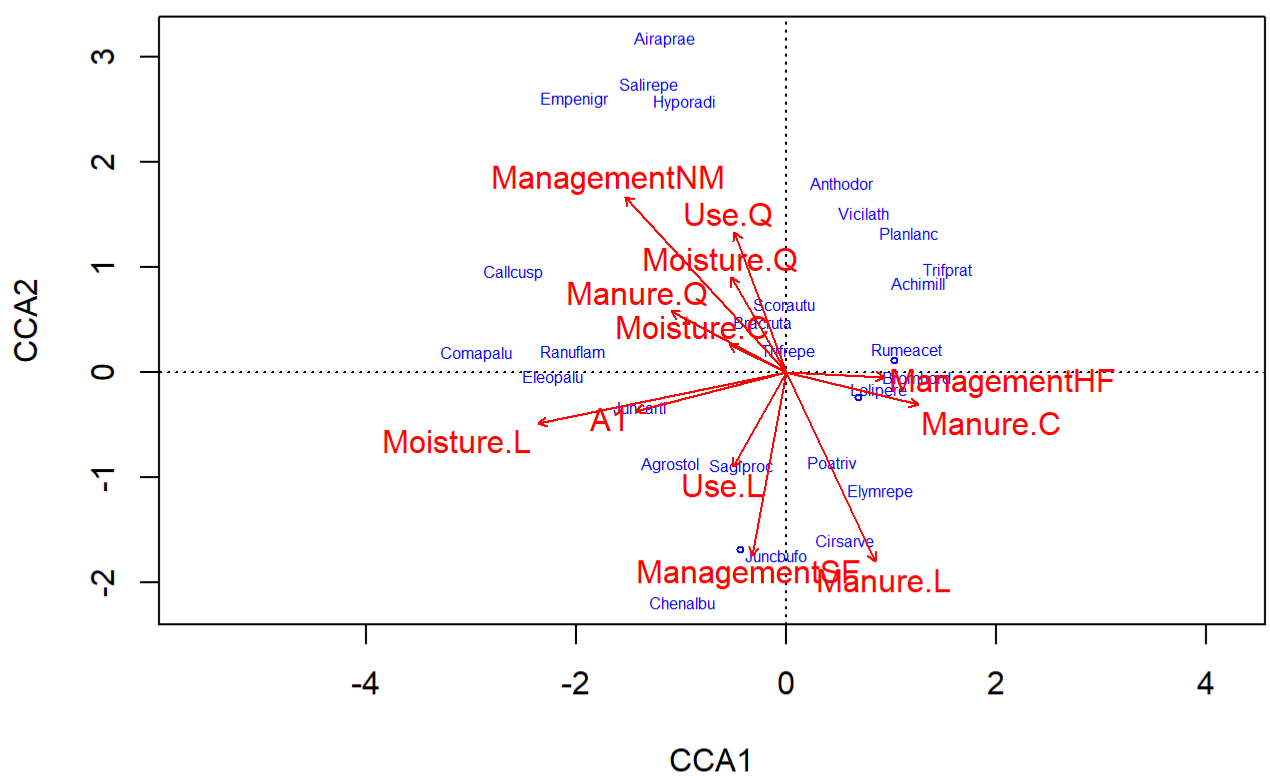
```
cca_dune = cca(dune ~ ., data=dune.env)
```

```
anova(cca_dune, by='margin', permutations = 999)
```

```
## Permutation test for cca under reduced model
## Marginal effects of terms
## Permutation: free
## Number of permutations: 999
##
## Model: cca(formula = dune ~ A1 + Moisture + Management + Use + Manure, data = dune.env)
##            Df ChiSquare      F Pr(>F)
## A1          1   0.11070 1.2660  0.241
## Moisture    3   0.31587 1.2041  0.235
## Management  2   0.15882 0.9081  0.560
## Use         2   0.13010 0.7439  0.776
## Manure      3   0.25490 0.9717  0.510
## Residual    7   0.61210
```

2.

```
plot(cca_dune, type='n', scaling=1)
orditorp(cca_dune, display='sp', cex=0.5, scaling=1, col='blue')
text(cca_dune, display='bp', col='red')
```




```
anova(rda_dune, by='margin', permutations=10)
```

```
## Permutation test for rda under reduced model
## Marginal effects of terms
## Permutation: free
## Number of permutations: 10
##
## Model: rda(formula = dune ~ dune.env$Moisture + dune.env$Management + dune.env$A1 + dune.env
$Use + dune.env$Manure)
##                     Df Variance      F Pr(>F)
## dune.env$Moisture    3  11.9409 1.3320 0.1818
## dune.env$Management  2   7.1574 1.1976 0.2727
## dune.env$A1          1   2.3704 0.7933 0.7273
## dune.env$Use         2   4.9785 0.8330 0.8182
## dune.env$Manure      3   9.6257 1.0737 0.1818
## Residual             7  20.9175
```

3. The two analyses do agree with eachother. However, although we surmised an importance of moisture there was no significance in either of the anova tests. So, even though it may graphically look like moisture is an important predictor it may not be as important as it originally looked.

I think both analyses can be useful depending on the situation. The CCA analysis is helpful for seeing the vectors but the RDA seems more useful when you have a specific variable you'd like to investigate.