analysis

2023-03-29

- Importing data
- Building MEMs and testing for spatial autocorrelation in species composition
- making pRDA model

```
library(readr)
library(vegan)
library(tidyverse)
library(usdm)
library(adespatial)
library(adegraphics)
```

Importing data

```
data <- read_csv("peerj-79676-Naas_T-data.csv",
                                      col_types = cols(`Wetland type` =
                                                                  col_factor(le
vels = c("Temp vlei",

"Large dam", "Small dam", "River edge",

"Fynbos pool")), temporary = col_factor(levels = c("temp",

"perm")), Fish = col_factor(levels = c("no-fish",

"fish"))))

data #wetland type, hydroperiod, and fish treated as factors
```

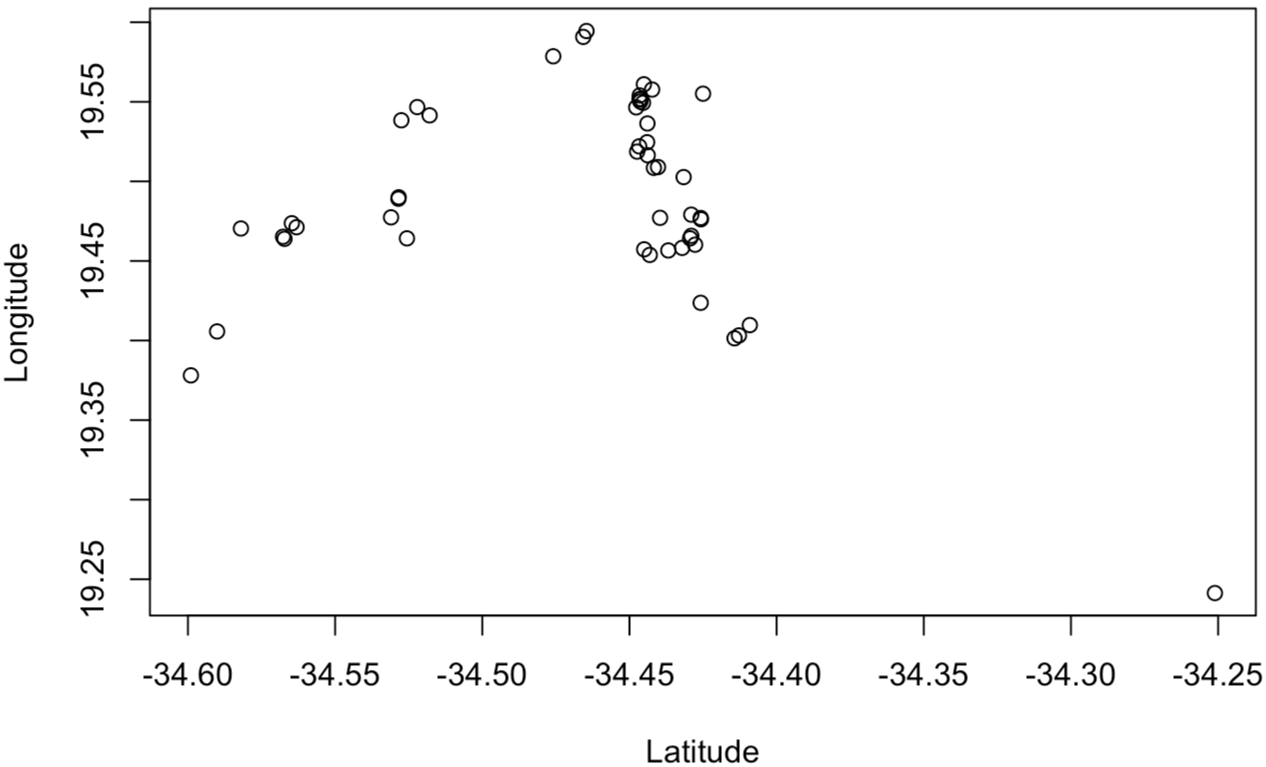
```
## # A tibble: 50 × 29
##    Site    Site …¹ Date …² Latit…³ Longi…⁴ Wetla…⁵ tempo…⁶ catch…⁷  area perim…⁸
##    <chr>   <chr>     <dbl>   <dbl>   <dbl> <fct>   <fct>   <chr>   <dbl>   <dbl>
##  1 Site_01 Zilver…  170803   -34.3    19.2 Temp v… temp    G40L     6169     445
##  2 Site_02 Zilver…  170617   -34.4    19.4 Temp v… temp    G40L     6450     324
##  3 Site_03 Zilver…  170612   -34.4    19.4 Large … perm    G40L     2785     668
##  4 Site_04 Anton …  170801   -34.4    19.4 Small … temp    G40L      296      65
##  5 Site_05 Steenk…  170801   -34.4    19.4 Temp v… temp    G40L      684     151
##  6 Site_06 Arum L…  170617   -34.4    19.5 Small … perm    G40L       60      30
##  7 Site_07 Jan Ma…  170801   -34.4    19.5 Large … perm    G40L     2296     204
##  8 Site_08 Jan Ma…  170801   -34.4    19.5 Small … perm    G40L     1305     133
##  9 Site_09 Chris …  170905   -34.4    19.5 Large … perm    G40L     2767     197
## 10 Site_10 Chris …  170905   -34.4    19.5 Small … perm    G40L     1027     123
## # … with 40 more rows, 19 more variables: pH <dbl>, Conductivity <dbl>,
## #   `Lm  Bass` <dbl>, `Tilapia M` <dbl>, Fish <fct>, Terapin <chr>, Crab <chr>,
## #   Frog <dbl>, Xl <dbl>, Af <dbl>, Sg <dbl>, Td <dbl>, Ca <dbl>, Sw <dbl>,
## #   Av <dbl>, Sp <dbl>, Sc <dbl>, Sb <dbl>, Hh <dbl>, and abbreviated variable
## #   names ¹`Site name`, ²`Date visited`, ³Latitude, ⁴Longitude,
## #   ⁵`Wetland type`, ⁶temporary, ⁷catchment, ⁸perimeter
```

```
coords <- data[,4:5]

sp_compos <- data %>%
    dplyr::select(Xl:Hh)

env <- data %>%
    dplyr::select(c(`Wetland type`, temporary,  area, perimeter, pH, Conductivity,Fis
h ))
env
```

```
## # A tibble: 50 × 7
##    `Wetland type` temporary  area perimeter    pH Conductivity Fish
##    <fct>          <fct>     <dbl>     <dbl> <dbl>        <dbl> <fct>
##  1 Temp vlei      temp       6169       445   7.5           95 no-fish
##  2 Temp vlei      temp       6450       324   7.5          300 no-fish
##  3 Large dam      perm       2785       668   7.3          210 no-fish
##  4 Small dam      temp        296        65   8.4         1450 no-fish
##  5 Temp vlei      temp        684       151   7.5          400 no-fish
##  6 Small dam      perm         60        30   7.4           94 no-fish
##  7 Large dam      perm       2296       204   7.3         1200 fish
##  8 Small dam      perm       1305       133   7.4          700 no-fish
##  9 Large dam      perm       2767       197   7.3          700 no-fish
## 10 Small dam      perm       1027       123   7.7         1000 no-fish
## # … with 40 more rows
```

Building MEMs and testing for spatial autocorrelation in species composition

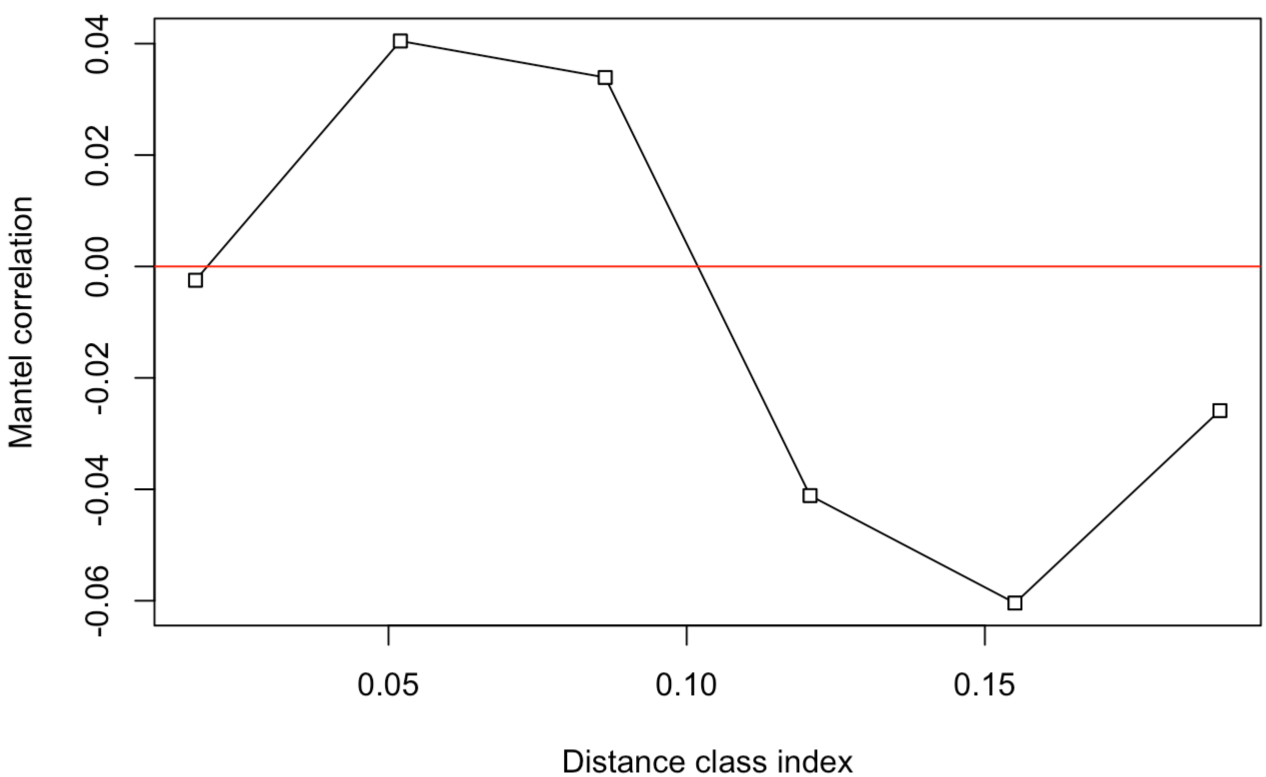
```
dec <- decostand(sp_compos, "hell")#transforming species composition

plot(data[,4:5])
```




```
mantel.correlog(vegdist(sp_compos), XY = coords)#no  spatial autocorrelation
```

```
##
## Mantel Correlogram Analysis
##
## Call:
##
## mantel.correlog(D.eco = vegdist(sp_compos), XY = coords)
##
##          class.index      n.dist  Mantel.cor Pr(Mantel) Pr(corrected)
## D.cl.1    0.0176250 378.0000000 -0.0024746      0.518         0.518
## D.cl.2    0.0519805 422.0000000  0.0404736      0.119         0.238
## D.cl.3    0.0863360 608.0000000  0.0339321      0.192         0.384
## D.cl.4    0.1206916 428.0000000 -0.0411226      0.133         0.476
## D.cl.5    0.1550471 344.0000000 -0.0604176      0.109         0.545
## D.cl.6    0.1894026 124.0000000 -0.0258708      0.340         0.680
## D.cl.7    0.2237582  48.0000000         NA         NA            NA
## D.cl.8    0.2581137   8.0000000         NA         NA            NA
## D.cl.9    0.2924692  22.0000000         NA         NA            NA
## D.cl.10   0.3268247  14.0000000         NA         NA            NA
## D.cl.11   0.3611803  32.0000000         NA         NA            NA
## D.cl.12   0.3955358  22.0000000         NA         NA            NA
```

```
plot(mantel.correlog(vegdist(sp_compos), XY = coords))
```



```
mems <- dbmem(data[,4:5], MEM.autocor = "positive")#building MEMs and only taking eig
envectors with positive Moran's I
s.value(coords, mems[,1:2], include.origin = FALSE)
```

```
## Warning: Unused parameters: include

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```
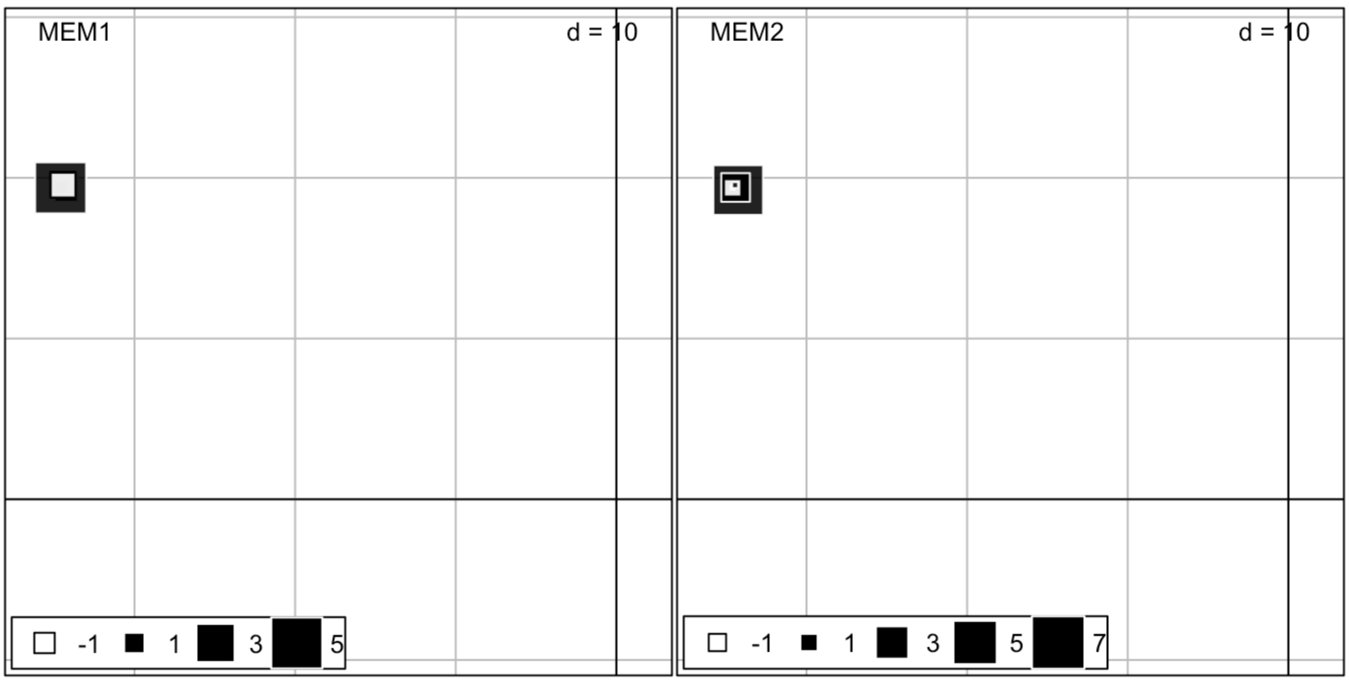




```
MEMs <- cbind(MEM1=mems$MEM1, MEM2=mems$MEM2)
```

making pRDA model

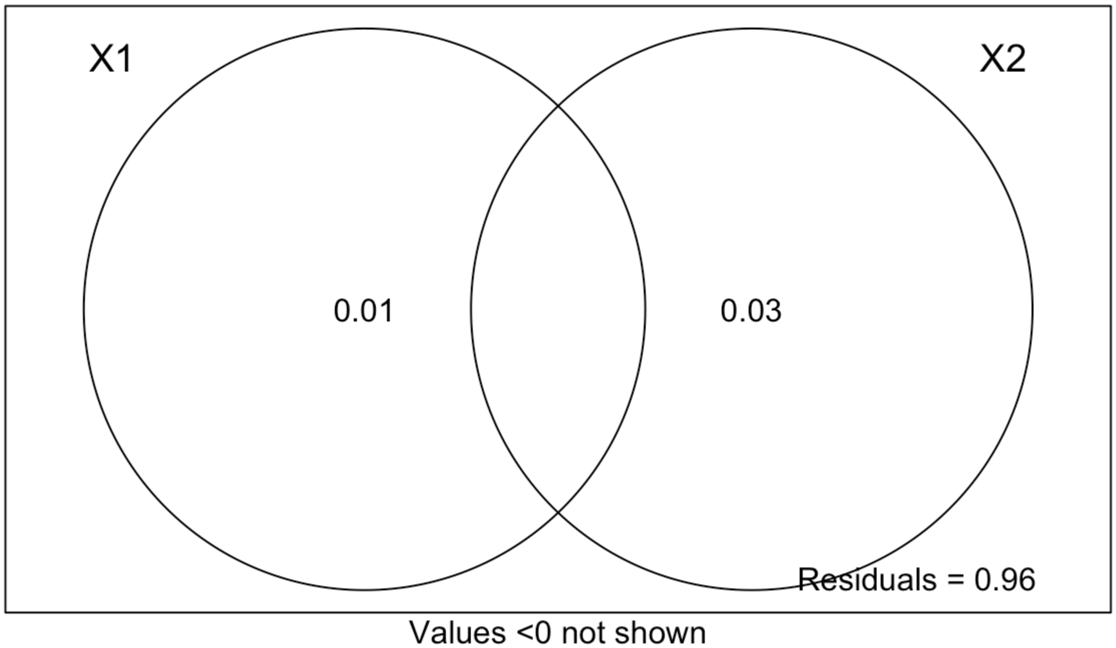
```
gm <- rda(dec~`Wetland type`+ temporary+  area+ perimeter+ pH+ Conductivity+Fish + Co
ndition(MEMs), data=env)
gm
```

```
## Call: rda(formula = dec ~ `Wetland type` + temporary + area + perimeter
## + pH + Conductivity + Fish + Condition(MEMs), data = env)
##
##               Inertia Proportion Rank
## Total         0.63751    1.00000
## Conditional   0.01718    0.02695    2
## Constrained   0.18152    0.28474   10
## Unconstrained 0.43880    0.68830   11
## Inertia is variance
##
## Eigenvalues for constrained axes:
##    RDA1    RDA2    RDA3    RDA4    RDA5    RDA6    RDA7    RDA8    RDA9   RDA10
## 0.09671 0.03645 0.02549 0.01227 0.00469 0.00315 0.00166 0.00084 0.00020 0.00005
##
## Eigenvalues for unconstrained axes:
##     PC1     PC2     PC3     PC4     PC5     PC6     PC7     PC8     PC9    PC10
## 0.16202 0.09384 0.07409 0.04716 0.02274 0.01410 0.01213 0.00533 0.00341 0.00269
##    PC11
## 0.00129
```

```
varpart(sp_compos, env, MEMs)
```

```
##
## Partition of variance in RDA
##
## Call: varpart(Y = sp_compos, X = env, MEMs)
##
## Explanatory tables:
## X1:  env
## X2:  MEMs
##
## No. of explanatory tables: 2
## Total variation (SS): 86178202
##             Variance: 1758739
## No. of observations: 50
##
## Partition table:
##                      Df R.squared Adj.R.squared Testable
## [a+c] = X1           10   0.21141       0.00921     TRUE
## [b+c] = X2            2   0.07047       0.03092     TRUE
## [a+b+c] = X1+X2      12   0.27619       0.04144     TRUE
## Individual fractions
## [a] = X1|X2          10                 0.01052     TRUE
## [b] = X2|X1           2                 0.03224     TRUE
## [c]                   0                -0.00132    FALSE
## [d] = Residuals                         0.95856    FALSE
## ---
## Use function 'rda' to test significance of fractions of interest
```

```
plot(varpart(sp_compos, env, MEMs))
```




```
anova.cca(gm)
```

```
## Permutation test for rda under reduced model
## Permutation: free
## Number of permutations: 999
##
## Model: rda(formula = dec ~ `Wetland type` + temporary + area + perimeter + pH + Co
nductivity + Fish + Condition(MEMs), data = env)
##          Df Variance      F Pr(>F)
## Model    10  0.18152 1.5306  0.022 *
## Residual 37  0.43880
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
anova.cca(gm, by = "term")#only variable that is significant is wetland type
```

```
## Permutation test for rda under reduced model
## Terms added sequentially (first to last)
## Permutation: free
## Number of permutations: 999
##
## Model: rda(formula = dec ~ `Wetland type` + temporary + area + perimeter + pH + Co
nductivity + Fish + Condition(MEMs), data = env)
##                Df Variance      F Pr(>F)
## `Wetland type`  4  0.10443 2.2014  0.008 **
## temporary       1  0.00774 0.6525  0.697
## area            1  0.01668 1.4067  0.236
## perimeter       1  0.01118 0.9429  0.432
## pH              1  0.00693 0.5845  0.727
## Conductivity    1  0.01441 1.2155  0.324
## Fish            1  0.02014 1.6985  0.130
## Residual       37  0.43880
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
anova.cca(gm, by = "axis")
```

```
## Permutation test for rda under reduced model
## Forward tests for axes
## Permutation: free
## Number of permutations: 999
##
## Model: rda(formula = dec ~ `Wetland type` + temporary + area + perimeter + pH + Co
nductivity + Fish + Condition(MEMs), data = env)
##          Df Variance      F Pr(>F)
## RDA1      1  0.09671 8.1544  0.011 *
## RDA2      1  0.03645 3.0739  0.785
## RDA3      1  0.02549 2.1493  0.955
## RDA4      1  0.01227 1.0345  1.000
## RDA5      1  0.00469 0.3959  1.000
## RDA6      1  0.00315 0.2659  1.000
## RDA7      1  0.00166 0.1396  1.000
## RDA8      1  0.00084 0.0711  1.000
## RDA9      1  0.00020 0.0173  1.000
## RDA10     1  0.00005 0.0044  1.000
## Residual 37  0.43880
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
RsquareAdj(gm)#pretty small adjR2
```

```
## $r.squared
## [1] 0.2847405
##
## $adj.r.squared
## [1] 0.1029127
```

```
plot(gm)
```