

Vignette ecospat package

Contents

1	Load data	1
2	Pre-Modelling Analysis	4
2.1	Spatial Auto-correlation	4
2.2	Predictor Variable Selection	4
2.3	Climate Analogy Tools	4
2.4	Phylogenetic Diversity Measures	6
2.5	Niche Quantification and Comparison with Ordination techniques	6
2.6	Biotic Interactions	13
2.7	Data Preparation	15
3	Core Niche Modelling	18
3.1	Model Evaluation	18
3.2	Spatial Predictions and Projections	19
3.3	Spatial prediction of communities	24
3.4	SESAM framework with <i>ecospat.SESAM.prr()</i>	25
4	Post-Modelling	25
4.1	Spatial Predictions of species assamblages	25

=====
Valeria Di Cola, Olivier Broennimann, Blaise Petitpierre, Manuela D’Amen, Frank Breiner & Antoine Guisan ##### 08 November, 2017

Miscellaneous methods and utilities for spatial ecology analysis, written by current and former members and collaborators of the *ecospat* group of Antoine Guisan, Department of Ecology and Evolution (DEE) & Institute of Earth Surface Dynamics (IDYST), University of Lausanne, Switzerland.

ecospat offers the possibility to perform Pre-modelling Analysis, such as Spatial autocorrelation analysis, MESS (Multivariate Environmental Similarity Surfaces) analyses, Phylogenetic diversity Measures, Biotic Interactions. It also provides functions to complement *biomod2* in preparing the data, calibrating and evaluating (e.g. boyce index) and projecting the models. Complementary analysis based on model predictions (e.g. co-occurrences analyses) are also provided.

In addition, the *ecospat* package includes Niche Quantification and Overlap functions that were used in Broennimann et al. 2012 and Petitpierre et al. 2012 to quantify climatic niche shifts between the native and invaded ranges of invasive species.

1 Load data

```
library(ecospat)
citation("ecospat")

## To cite package 'ecospat' in publications use:
##
##   Broennimann O, Di Cola V, Guisan A (2026). _ecospat: Spatial Ecology
##   Miscellaneous Methods_. R package version 4.1.3,
##   <https://www.unil.ch/ecospat/home/menuguid/ecospat-resources.html>.
##
## A BibTeX entry for LaTeX users is
```

```
##
## @Manual{,
##   title = {ecospat: Spatial Ecology Miscellaneous Methods},
##   author = {Olivier Broennimann and Valeria {Di Cola} and Antoine Guisan},
##   year = {2026},
##   note = {R package version 4.1.3},
##   url = {https://www.unil.ch/ecospat/home/menuguid/ecospat-resources.html},
## }

```

1.0.1 Test data for the ecospat library

ecospat.testData()

```
data(ecospat.testData)
names(ecospat.testData)
```

```
## [1] "numplots"           "long"
## [3] "lat"                "ddeg"
## [5] "mind"               "srad"
## [7] "slp"                "topo"
## [9] "Achillea_atrata"    "Achillea_millefolium"
## [11] "Acinos_alpinus"     "Adenostyles_glabra"
## [13] "Aposeris_foetida"   "Arnica_montana"
## [15] "Aster_bellidiastrum" "Bartsia_alpina"
## [17] "Bellis_perennis"    "Campanula_rotundifolia"
## [19] "Centaurea_montana"  "Cerastium_latifolium"
## [21] "Cruciata_laevipes"  "Doronicum_grandiflorum"
## [23] "Galium_album"       "Galium_anisophyllum"
## [25] "Galium_megalospermum" "Gentiana_bavarica"
## [27] "Gentiana_lutea"     "Gentiana_purpurea"
## [29] "Gentiana_verna"     "Globularia_cordifolia"
## [31] "Globularia_nudicaulis" "Gypsophila_repens"
## [33] "Hieracium_lactucella" "Homogyne_alpina"
## [35] "Hypochaeris_radicata" "Leontodon_autumnalis"
## [37] "Leontodon_helveticus" "Myosotis_alpestris"
## [39] "Myosotis_arvensis"  "Phyteuma_orbiculare"
## [41] "Phyteuma_spicatum"  "Plantago_alpina"
## [43] "Plantago_lanceolata" "Polygonum_bistorta"
## [45] "Polygonum_viviparum" "Prunella_grandiflora"
## [47] "Rhinanthus_alectorolophus" "Rumex_acetosa"
## [49] "Rumex_crispus"      "Vaccinium_gaultherioides"
## [51] "Veronica_alpina"    "Veronica_aphylla"
## [53] "Agrostis_capillaris" "Bromus_erectus_sstr"
## [55] "Campanula_scheuchzeri" "Carex sempervirens"
## [57] "Cynosurus_cristatus" "Dactylis_glomerata"
## [59] "Daucus_carota"      "Festuca_pratensis_sl"
## [61] "Geranium_sylvaticum" "Leontodon_hispidus_sl"
## [63] "Potentilla_erecta"  "Pritzelago_alpina_sstr"
## [65] "Prunella_vulgaris"  "Ranunculus_acris_sl"
## [67] "Saxifraga_oppositifolia" "Soldanella_alpina"
## [69] "Taraxacum_officinale_aggr" "Trifolium_repens_sstr"
## [71] "Veronica_chamaedrys" "Parnassia_palustris"
## [73] "glm_Agrostis_capillaris" "glm_Leontodon_hispidus_sl"
## [75] "glm_Dactylis_glomerata" "glm_Trifolium_repens_sstr"
## [77] "glm_Geranium_sylvaticum" "glm_Ranunculus_acris_sl"
## [79] "glm_Prunella_vulgaris" "glm_Veronica_chamaedrys"
## [81] "glm_Taraxacum_officinale_aggr" "glm_Plantago_lanceolata"
## [83] "glm_Potentilla_erecta" "glm_Carex sempervirens"
## [85] "glm_Soldanella_alpina" "glm_Cynosurus_cristatus"

```

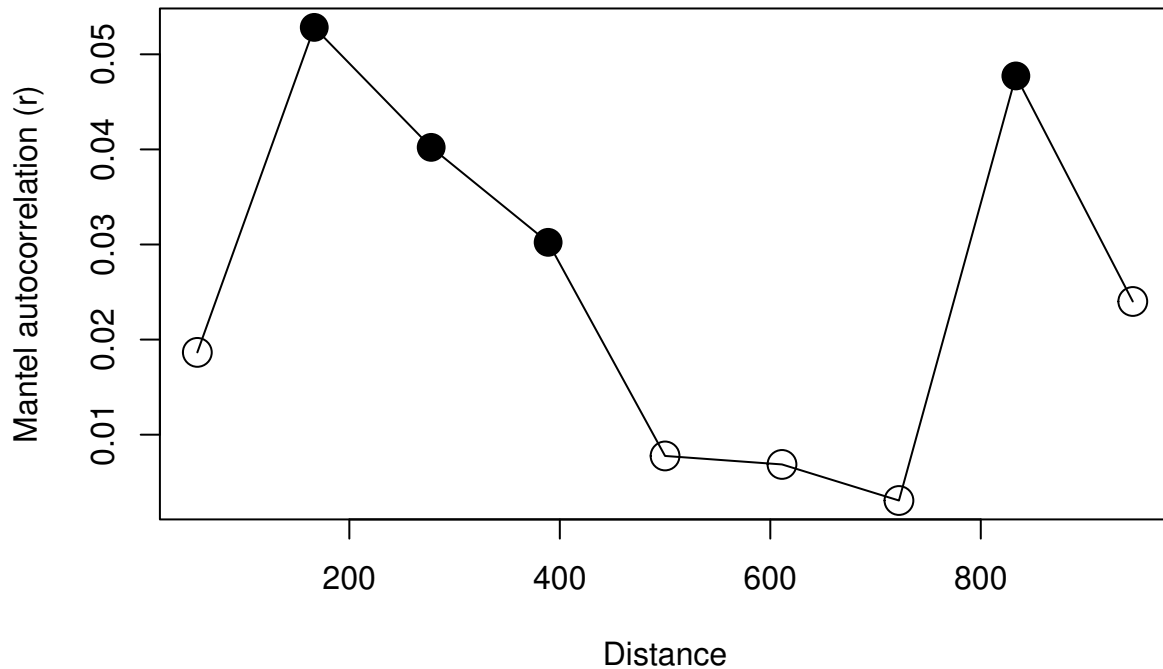

2 Pre-Modelling Analysis

2.1 Spatial Auto-correlation

2.1.1 Mantel Correlogram with *ecospat.mantel.correlogram()*

```
ecospat.mantel.correlogram(dfvar=ecospat.testData[c(2:16)],colxy=1:2, n=100,  
                           colvar=3:7, max=1000, nclass=10, nperm=100)
```

```
## Registered S3 method overwritten by 'ecodist':  
## method from  
## dim.dist proxy
```



The graph indicates that spatial autocorrelation (SA) is minimal at a distance of 180 meters. Note however that SA is not significantly different than zero for several distances (open circles).

2.2 Predictor Variable Selection

2.2.1 Number of Predictors with Pearson Correlation *ecospat.npred()*

```
colvar <- ecospat.testData[c(4:8)]  
x <- cor(colvar, method="pearson")  
ecospat.npred(x, th=0.75)
```

```
## [1] 4
```

2.2.2 Number of Predictors with Spearman Correlation *ecospat.npred()*

```
x <- cor(colvar, method="spearman")  
ecospat.npred(x, th=0.75)
```

```
## [1] 4
```

2.3 Climate Analogy Tools

2.3.1 Climate Analogy with *ecospat.climan()*

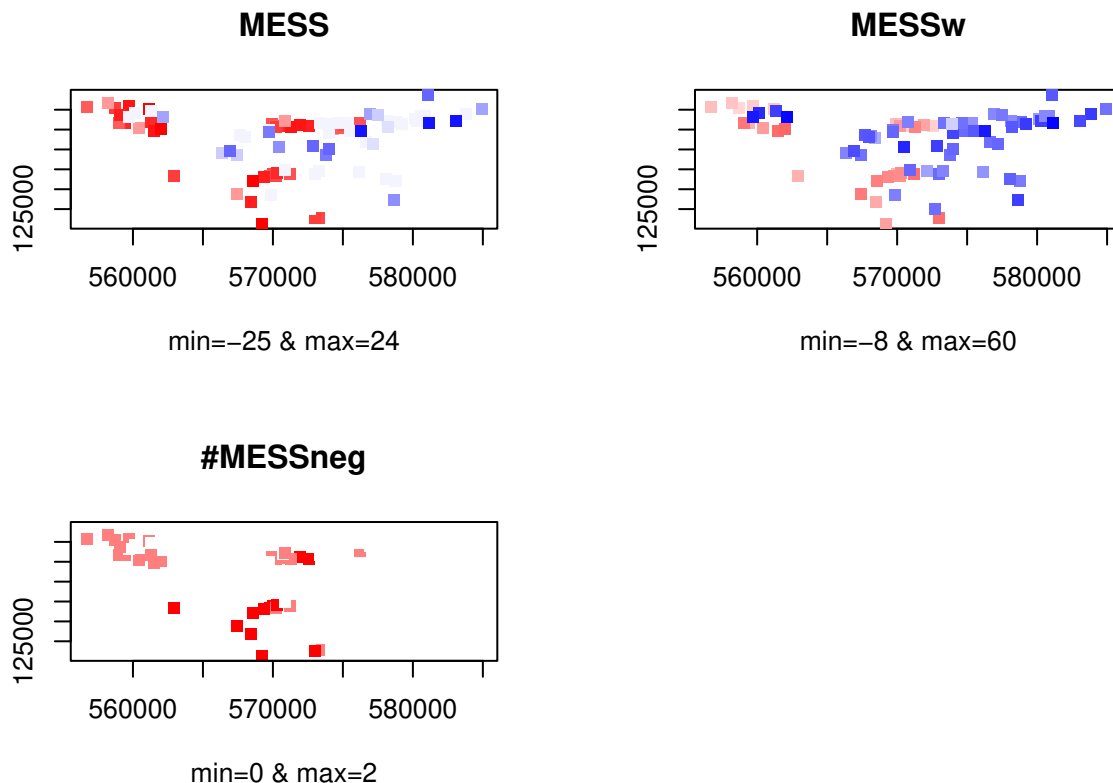
```
x <- ecospat.testData[c(4:8)]
p<- x[1:90,] #A projection dataset.
ref<- x[91:300,] # A reference dataset
```

```
ecospat.climan(ref,p)
```

```
## [1] 0.185415746 -0.028290993 -0.032909931 -0.009237875 -0.034642032
## [6] -0.209006928 -0.084295612 -0.103622863 0.355220600 -0.136258661
## [11] -0.087182448 -0.209006928 -0.143187067 -0.124711316 -0.114844720
## [16] -0.230596451 0.276046242 0.249093277 -0.125288684 -0.101226337
## [21] -0.113883908 -0.204653076 -0.001154734 -0.132217090 -0.100461894
## [26] 0.464738681 -0.416578541 -0.044457275 -0.018475751 -0.122225532
## [31] -0.137611720 -0.050808314 0.254605027 -0.062012319 0.238294633
## [36] -0.159141330 -0.147806005 0.277670365 -0.071593533 -0.019053118
## [41] 0.390781314 0.175132571 0.401892929 0.843703731 0.286155800
## [46] 0.321142114 0.668511130 0.252253209 0.440050672 0.177247206
## [51] 0.831525456 0.303710525 0.197182304 0.219273698 0.196637663
## [56] 0.195300816 0.142395786 0.176988160 -0.051991905 0.265163111
## [61] -0.020785219 -0.017898383 0.553965995 0.409635110 0.323633285
## [66] 0.468693064 0.124983005 -0.032909931 0.165642783 0.147046687
## [71] 0.202895471 0.341992334 0.225508458 0.133254065 0.485295264
## [76] -0.047344111 -0.012282931 0.165429659 0.134199992 0.216655251
## [81] 0.139419127 0.121254775 0.098782992 0.591393741 0.110866239
## [86] 0.146010655 0.095562156 0.093353356 0.081712342 0.160531262
```

2.3.2 Extrapolation detection, creating a MESS object with *ecospat.mess()*

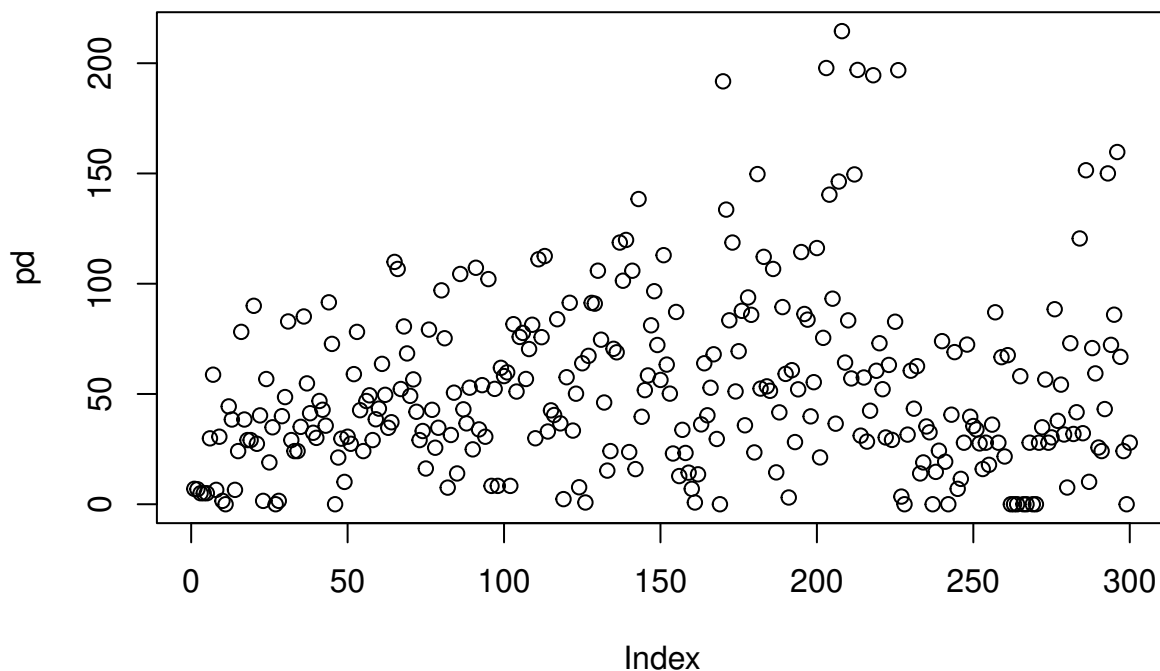
```
x <- ecospat.testData[c(2,3,4:8)]
proj<- x[1:90,] #A projection dataset.
cal<- x[91:300,] #A calibration dataset
mess.object<-ecospat.mess (proj, cal, w="default")
ecospat.plot.mess (mess.object, cex=1, pch=15)
```



In the MESS plot pixels in red indicate sites where at least one environmental predictor has values outside of the range of that predictor in the calibration dataset. In the MESS_w plot, same as previous plot but with weighted by the number of predictors. Finally, the MESS_{neg} plot shows at each site how many predictors have values outside of their calibration range.

2.4 Phylogenetic Diversity Measures

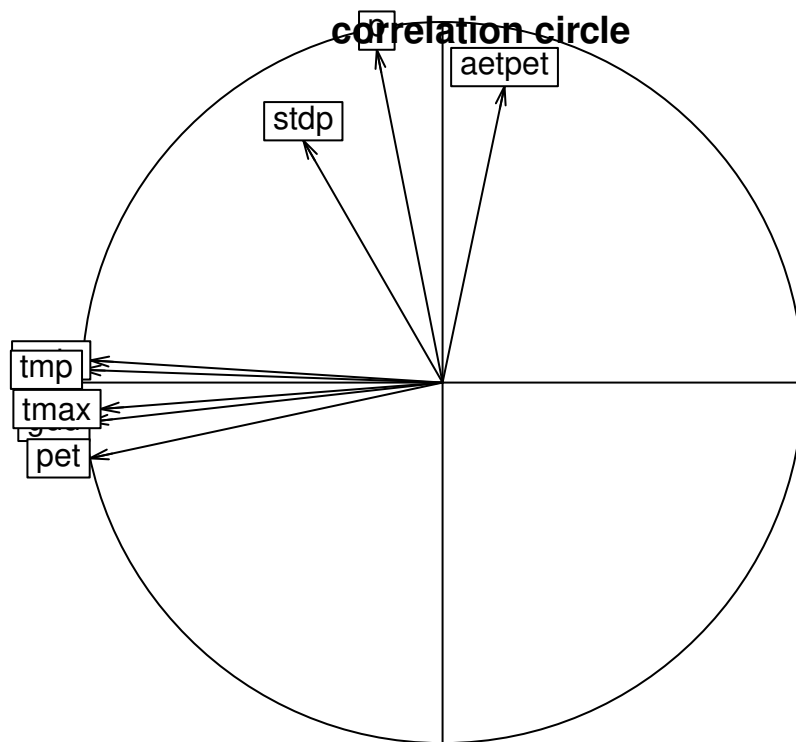
```
if(requireNamespace("ape")){
  fpath <- system.file("extdata", "ecospat.testTree.tre", package="ecospat")
  tree <- ape::read.tree(fpath)
  data <- ecospat.testData[9:52]
  pd<- ecospat.calculate.pd(tree, data, method = "spanning", type = "species", root = TRUE, average
  plot(pd)
}
```



2.5 Niche Quantification and Comparison with Ordination techniques

First we load the test data for the niche dynamics analysis in invaded and native range. A PCA is calibrated on all the sites of the study area, including both native and invaded ranges (same as PCA_{env} in Broenniman et al. 2012). Finally, we plot the variables Contributions

```
library(ade4)
inv <- ecospat.testNiche.inv
nat <- ecospat.testNiche.nat
pca.env <- ade4::dudi.pca(rbind(nat,inv)[,3:10],scannf=F,nf=2)
ecospat.plot.contrib(contrib=pca.env$co, eigen=pca.env$eig)
```



axis1 = 61.14 % axis2 = 25.09 %

The correlation circle indicate the

contribution of original predictors to the PCA axes.

Now we can predict the scores on the axes

```
# PCA scores for the whole study area
scores.globclim <- pca.env$li

# PCA scores for the species native distribution
scores.sp.nat <- ade4::suprow(pca.env,nat[which(nat[,11]==1),3:10])$li

# PCA scores for the species invasive distribution
scores.sp.inv <- ade4::suprow(pca.env,inv[which(inv[,11]==1),3:10])$li

# PCA scores for the whole native study area
scores.clim.nat <- ade4::suprow(pca.env,nat[,3:10])$li

# PCA scores for the whole invaded study area
scores.clim.inv <- ade4::suprow(pca.env,inv[,3:10])$li
```

2.5.1 Calculate the Occurrence Densities Grid with *ecospat.grid.clim.dyn()*

For a species in the native range (North America)

```
# gridding the native niche
grid.clim.nat <- ecospat.grid.clim.dyn(glob=scores.globclim,
                                     glob1=scores.clim.nat,
                                     sp=scores.sp.nat, R=100,
                                     th.sp=0)
```

```
## Registered S3 methods overwritten by 'adehabitatMA':
##   method          from
##   print.SpatialPixelsDataFrame sp
##   print.SpatialPixels          sp
```

For a species in the invaded range (Australia)

```
# gridding the invasive niche
grid.clim.inv <- ecospat.grid.clim.dyn(glob=scores.globclim,
                                     glob1=scores.clim.inv,
                                     sp=scores.sp.inv, R=100,
                                     th.sp=0)
```

2.5.2 Calculate Niche Overlap with *ecospat.niche.overlap()*

```
# Compute Schoener's D, index of niche overlap
D.overlap <- ecospat.niche.overlap (grid.clim.nat, grid.clim.inv, cor = TRUE)$D
D.overlap
```

```
## [1] 0.224586
```

The niche overlap between the native and the invaded range is 22%.

2.5.3 Perform the Niche Equivalency Test with *ecospat.niche.equivalency.test()* according to Warren et al. (2008)

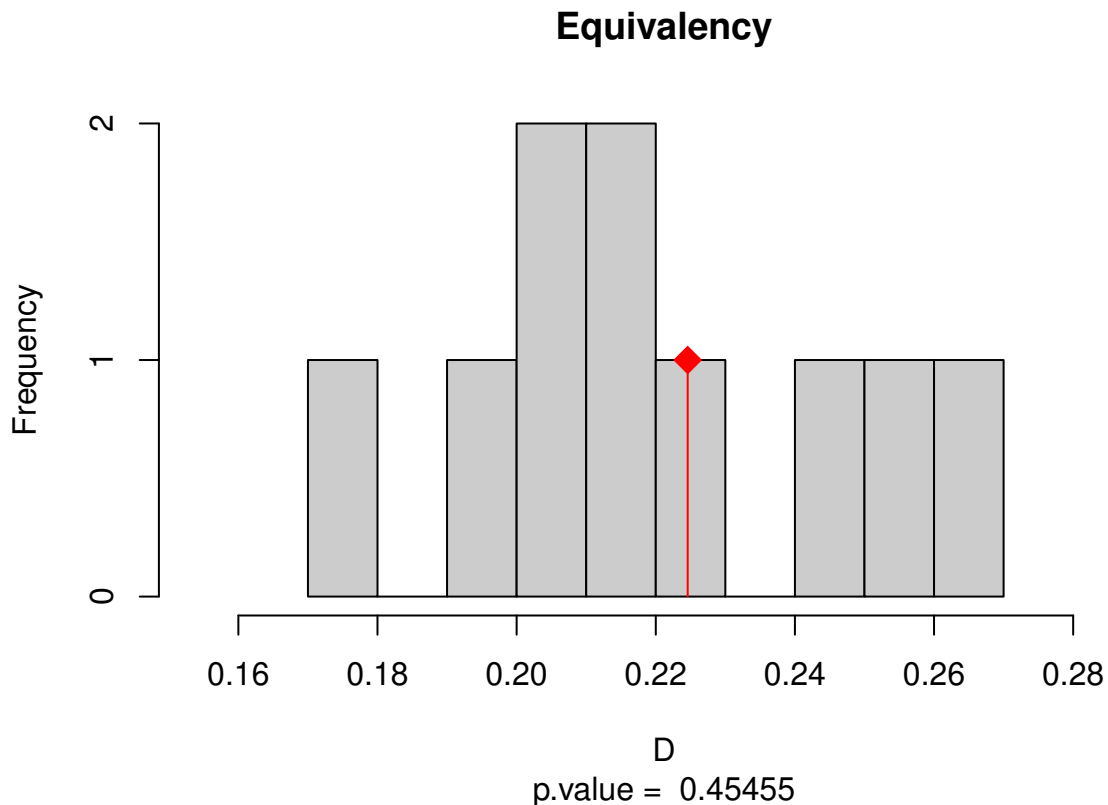
It is recommended to use at least 1000 replications for the equivalency test. As an example we used `rep = 10`, to reduce the computational time.

```
eq.test <- ecospat.niche.equivalency.test(grid.clim.nat, grid.clim.inv,rep=10,
                                         intersection = 0.1,
                                         overlap.alternative = "higher",
                                         expansion.alternative = "lower",
                                         stability.alternative = "higher",
                                         unfilling.alternative = "lower")
```

Niche equivalency test H1: the observed overlap between the native and invaded niche is higher than if the two niches are randomized, the niche expansion of the invaded niche is lower, the niche stability is higher and the niche unfilling is lower than if the two niches are randomized.

Plot Equivalency test

```
ecospat.plot.overlap.test(eq.test, "D", "Equivalency")
```

2.5.4 Perform the Niche Similarity Test with `ecospat.niche.similarity.test()`

Shifts randomly on niche (here the invasive niche) in the study area. It is recommended to use at least 1000 replications for the similarity test. As an example we used `rep = 10`, to reduce the computational time.

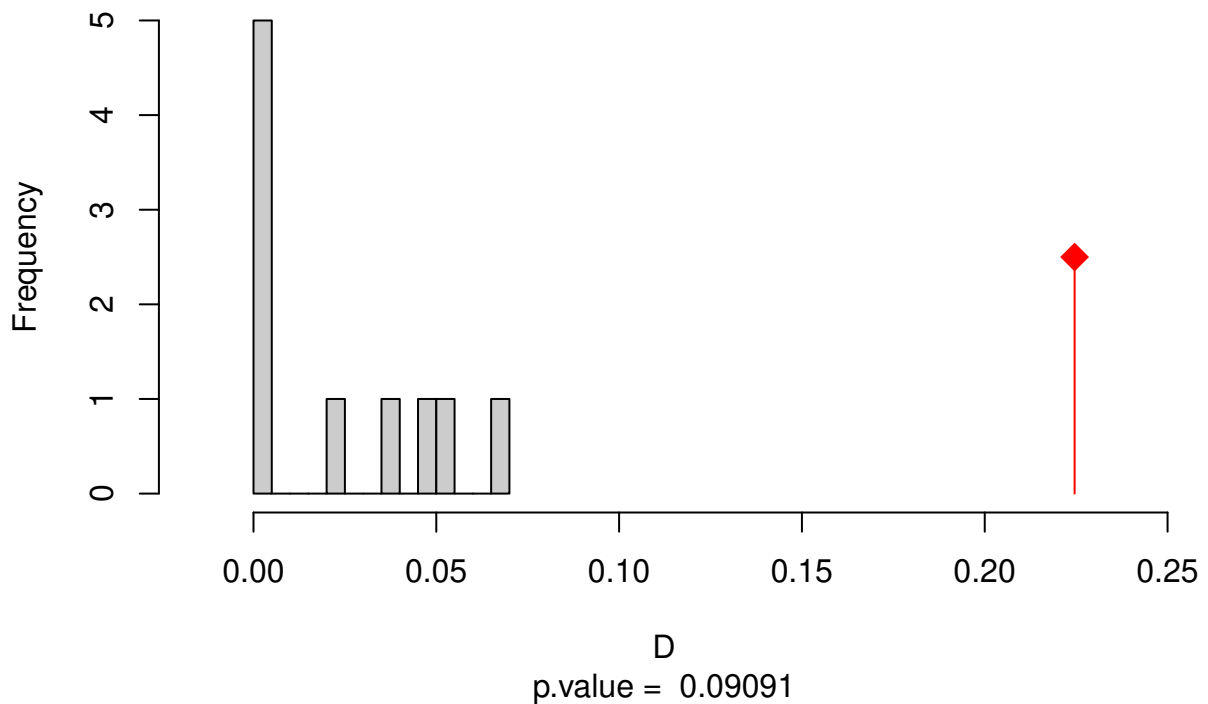
```
sim.test <- ecospat.niche.similarity.test(grid.clim.nat, grid.clim.inv, rep=10,
                                         overlap.alternative = "higher",
                                         expansion.alternative = "lower",
                                         stability.alternative = "higher",
                                         unfilling.alternative = "lower",
                                         intersection = 0.1,
                                         rand.type=1)
```

Niche similarity test H1: the observed overlap between the native and invaded is higher than randomly shifted invasive niches in the invaded study area, the niche expansion of the invaded niche is lower, the niche stability is higher and the niche unfilling is lower than if the two niches are randomized.

Plot Similarity test

```
ecospat.plot.overlap.test(sim.test, "D", "Similarity")
```

Similarity



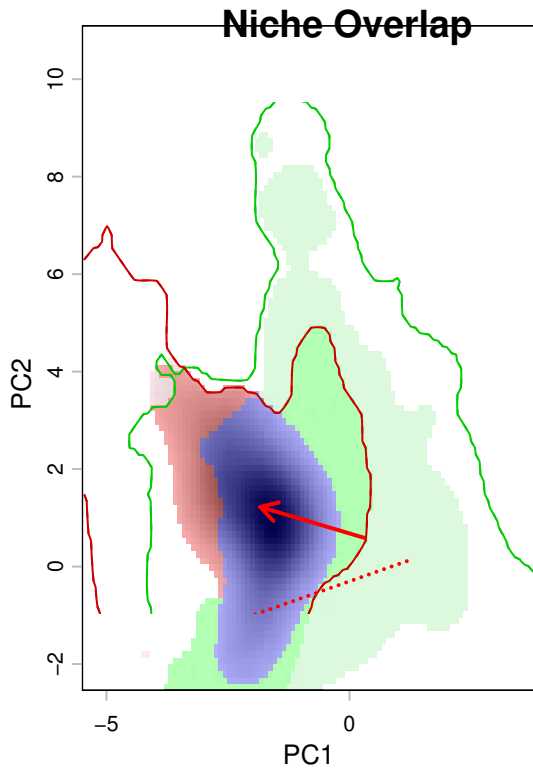
2.5.5 Delimiting niche categories and quantifying niche dynamics in analogue climates with *ecospat.niche.dyn.index()*

```
niche.dyn <- ecospat.niche.dyn.index (grid.clim.nat, grid.clim.inv)
```

2.5.5.1 Visualizing niche categories, niche dynamics and climate analogy between ranges with *ecospat.plot.niche.dyn()* Plot niche overlap

```
ecospat.plot.niche.dyn(grid.clim.nat, grid.clim.inv, quant=0.25, interest=2,  
  title= "Niche Overlap", name.axis1="PC1",  
  name.axis2="PC2")
```

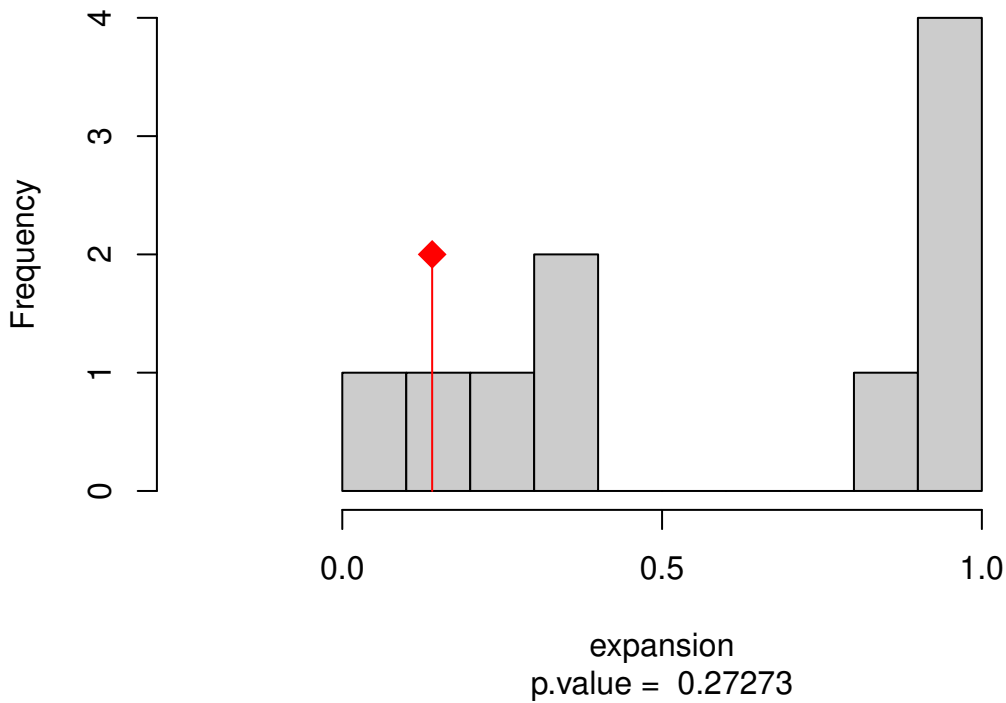
```
ecospat.shift.centroids(scores.sp.nat, scores.sp.inv, scores.clim.nat, scores.clim.inv)
```



Plot Similarity test for niche expansion, stability and unfilling

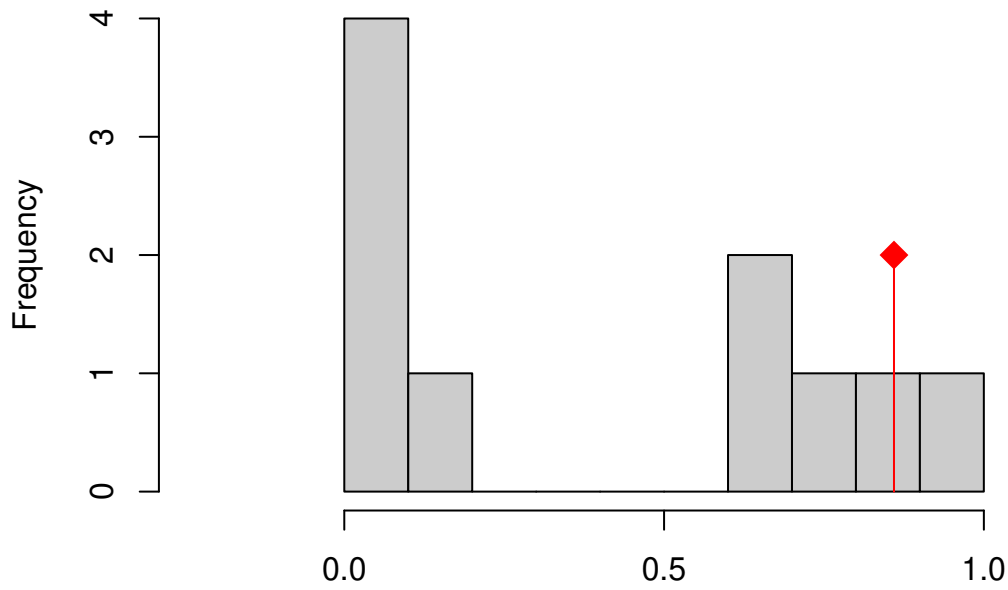
```
ecospat.plot.overlap.test(sim.test, "expansion", "Similarity")
```

Similarity



```
ecospat.plot.overlap.test(sim.test, "stability", "Similarity")
```

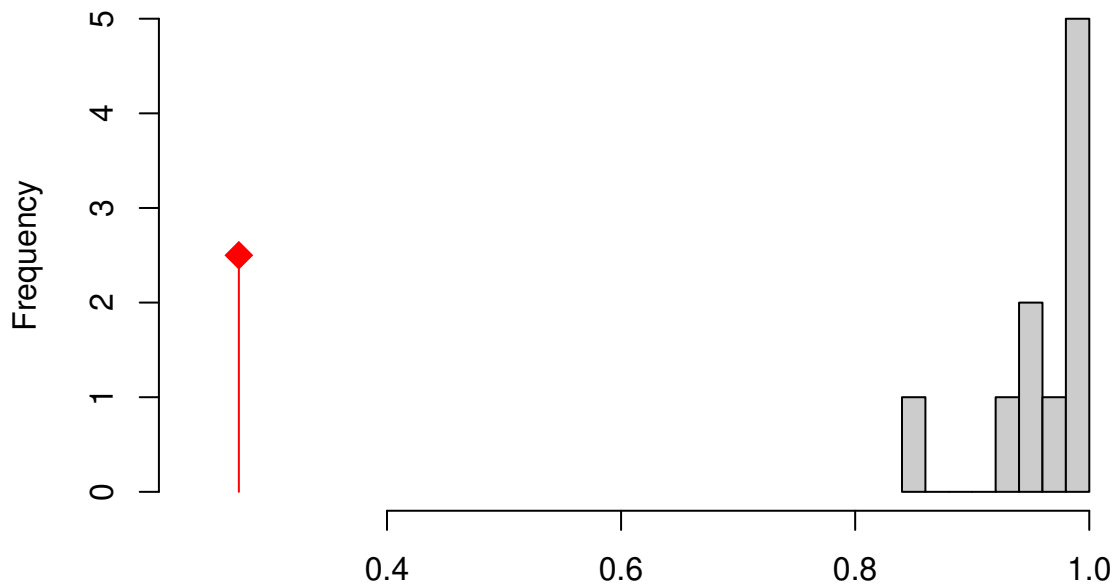
Similarity



stability
p.value = 0.27273

```
ecospat.plot.overlap.test(sim.test, "unfilling", "Similarity")
```

Similarity



unfilling
p.value = 0.09091

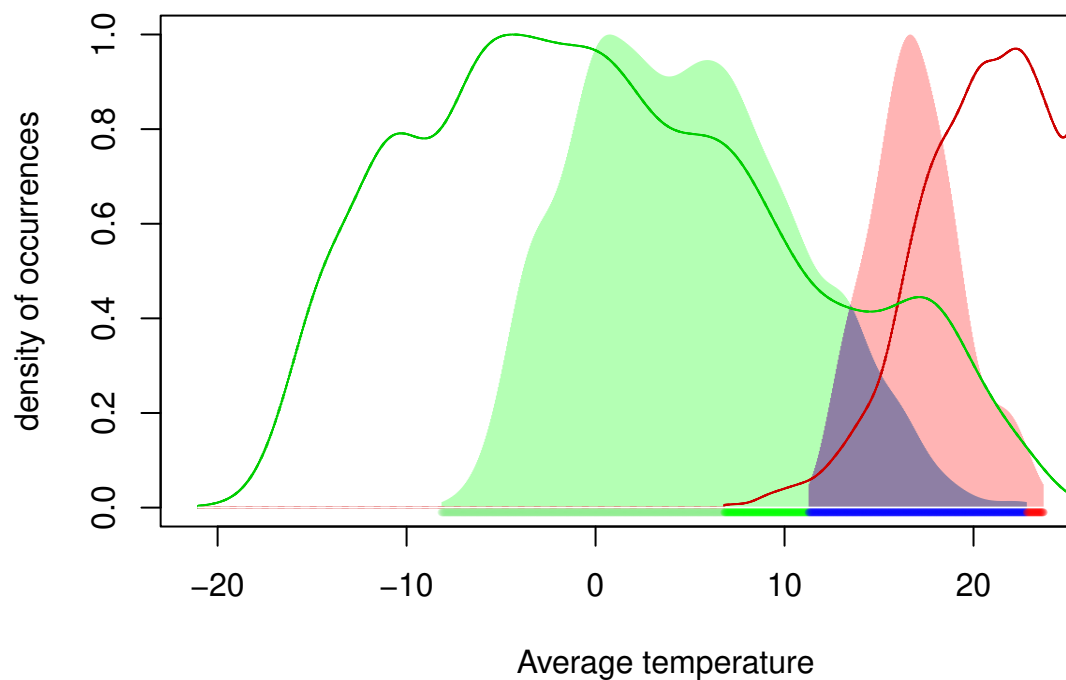
```
# gridding the native niche  
grid.clim.t.nat <- ecospat.grid.clim.dyn(glob=as.data.frame(rbind(nat,inv)[,10]),  
                                         glob1=as.data.frame(nat[,10]),
```

```

sp=as.data.frame(nat[which(nat[,11]==1),10]),
R=1000, th.sp=0)
# gridding the invaded niche
grid.clim.t.inv <- ecospat.grid.clim.dyn(glob=as.data.frame(rbind(nat,inv)[,10]),
glob1=as.data.frame(inv[,10]),
sp=as.data.frame(inv[which(inv[,11]==1),10]),
R=1000, th.sp=0)
t.dyn<-ecospat.niche.dyn.index (grid.clim.t.nat, grid.clim.t.inv)
ecospat.plot.niche.dyn(grid.clim.t.nat, grid.clim.t.inv, quant=0,
interest=2, title= "Niche Overlap",
name.axis1="Average temperature")

```

2.5.5.2 Plot the niche dynamics along one gradient (here temperature) with **Niche Overlap**



ecospat.plot.niche.dyn()

2.6 Biotic Interactions

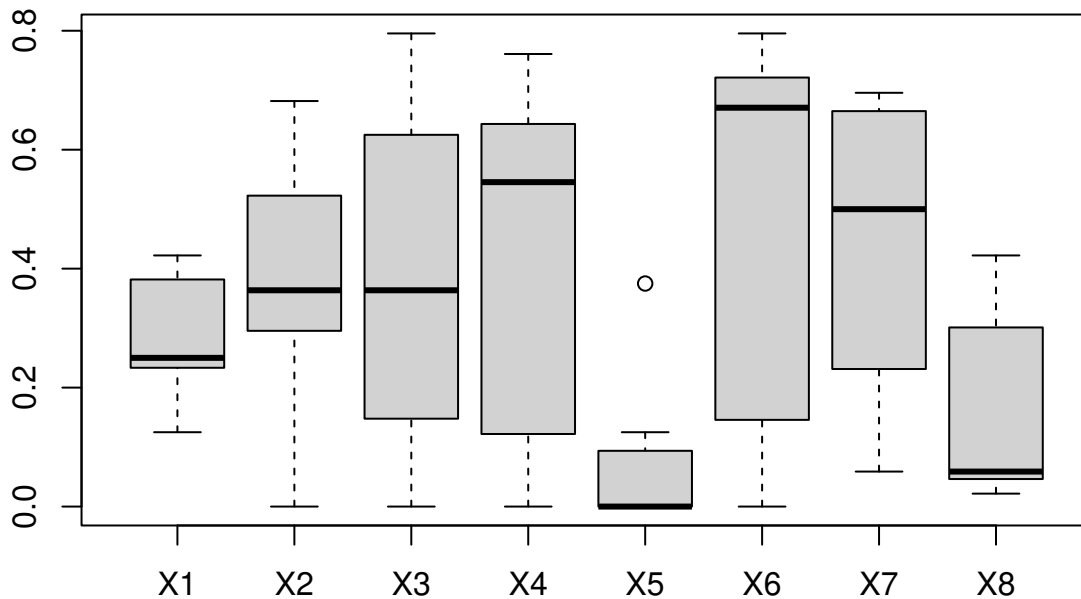
2.6.1 Species Co-occurrences Analysis with a Presence-absence matrix using the function *ecospat.co_occurrences()*

```
data <- ecospat.testData[c(9:16,54:57)]
```

For each pair of species (sp1, sp2), the number (N) of plots where both species were present is divided by the number of plots where the rarest of the two species is present. This index ranges from 0 (no co-occurrence) to 1 (always in co-occurrence) as given in eq. 1.

where $N(S1 \text{ intersects } S2)$ is the number of times species S1 and S2 co-occur, while $\text{Min}(NS1, NS2)$ is the number of times species S1 and S2 co-occur, while is the occurrence frequency of the rarest of the two species.

```
ecospat.co_occurrences (data)
```



```
##                               Aposeris_foetida  Arnica_montana  Aster_bellidiastrum
## Aposeris_foetida                1.0000000      0.3636364      0.2500000
## Arnica_montana                   0.3636364      1.0000000      0.36363636
## Aster_bellidiastrum              0.2500000      0.3636364      1.0000000
## Bartsia_alpina                   0.2222222      0.5454545      0.59090909
## Bromus_erectus_sstr              0.1250000      0.0000000      0.0000000
## Campanula_scheuchzeri            0.2444444      0.6818182      0.79545455
## Carex sempervirens               0.4000000      0.5000000      0.65909091
## Cynosurus_cristatus              0.4222222      0.2272727      0.04545455
##
##                               Bartsia_alpina  Bromus_erectus_sstr  Campanula_scheuchzeri
## Aposeris_foetida                0.22222222      0.1250      0.24444444
## Arnica_montana                   0.54545455      0.0000      0.68181818
## Aster_bellidiastrum              0.59090909      0.0000      0.79545455
## Bartsia_alpina                   1.00000000      0.0000      0.76086957
## Bromus_erectus_sstr              0.00000000      1.0000      0.00000000
## Campanula_scheuchzeri            0.76086957      0.0000      1.00000000
## Carex sempervirens               0.69565217      0.0625      0.67058824
## Cynosurus_cristatus              0.02173913      0.3750      0.04705882
##
##                               Carex sempervirens  Cynosurus_cristatus
## Aposeris_foetida                0.40000000      0.42222222
## Arnica_montana                   0.50000000      0.22727273
## Aster_bellidiastrum              0.65909091      0.04545455
## Bartsia_alpina                   0.69565217      0.02173913
## Bromus_erectus_sstr              0.06250000      0.37500000
## Campanula_scheuchzeri            0.67058824      0.04705882
## Carex sempervirens               1.00000000      0.05882353
## Cynosurus_cristatus              0.05882353      1.00000000
```

2.6.2 Pairwise co-occurrence Analysis with calculation of the C-score index using the function *ecospat.Cscore()*

This function allows to apply a pairwise null model analysis to a presence-absence community matrix to determine which species associations are significant across the study area. The strength of associations is quantified by the C-score index and a ‘fixed-equiprobable’ null model algorithm is applied.

It is recommended to use at least 10000 permutations for the test. As an example we used `nperm = 100`, to reduce the computational time.

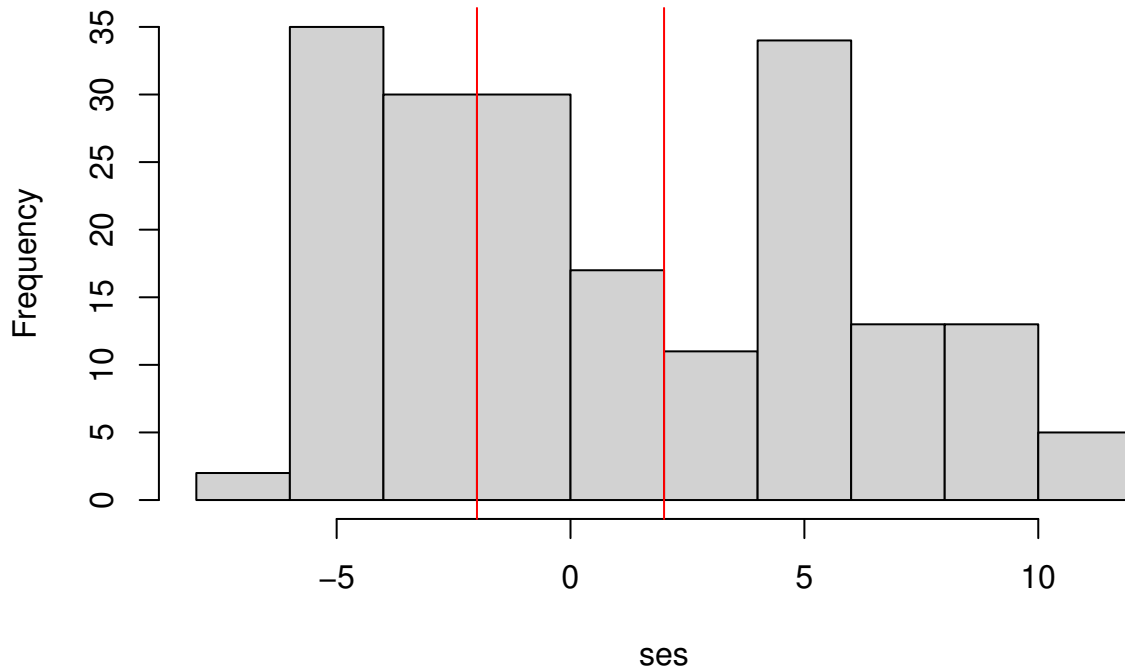
```
data <- ecospat.testData[c(53,62,58,70,61,66,65,71,69,43,63,56,68,57,55,60,54,67,59,64)]
nperm <- 100
```

```

outpath <- getwd()
ecospat.Cscore(data, nperm, outpath)

```

Histogram of standardized effect size



```

## $ObsCscoreTot
## [1] 2675.468
##
## $SimCscoreTot
## [1] 2465.931
##
## $PVal.less
## [1] 1
##
## $PVal.greater
## [1] 0.00990099
##
## $SES.Tot
## [1] 54.55579

```

The function returns the C-score index for the observed community (ObsCscoreTot), p.value (PValTot) and standardized effect size (SES.Tot). It saves also a table in the working directory where the same metrics are calculated for each species pair (only the table with species pairs with significant p-values is saved in this version)

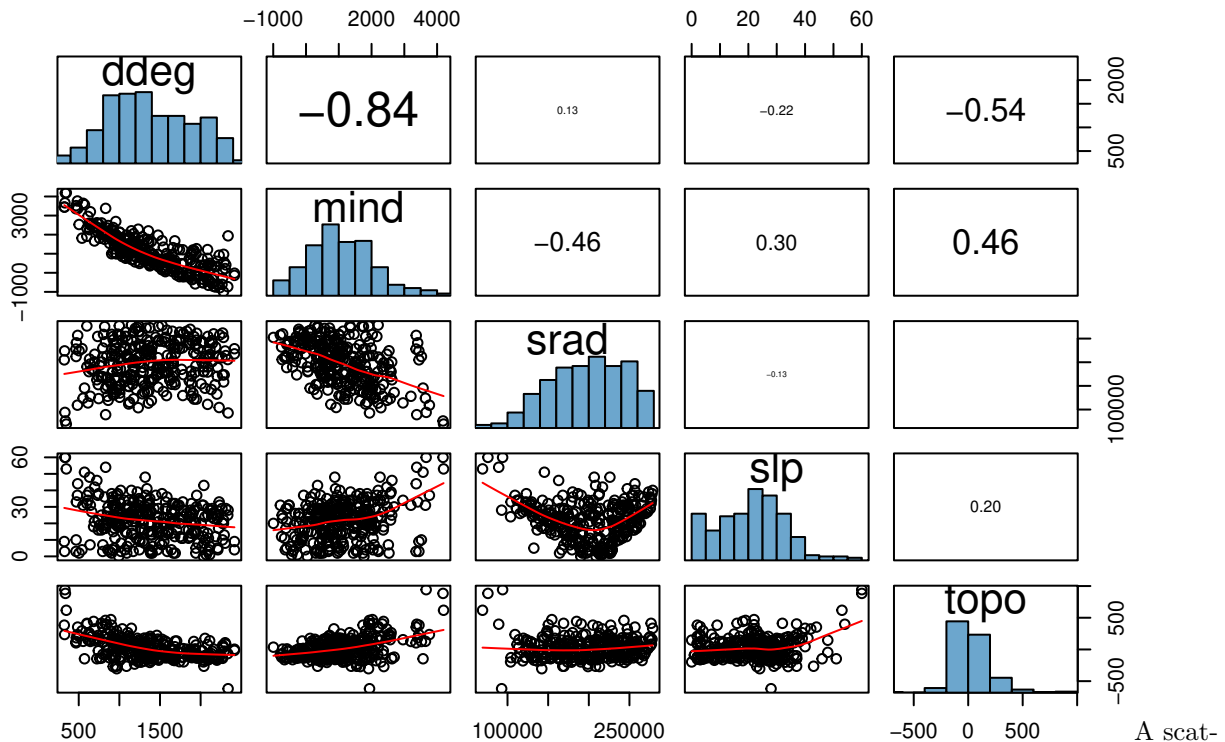
2.7 Data Preparation

2.7.1 Correlation Plot of Variables with *ecospat.cor.plot()*

```

data <- ecospat.testData[,4:8]
ecospat.cor.plot(data)

```



A scatter plot of matrices, with bivariate scatter plots below the diagonal, histograms on the diagonal, and the Pearson correlation above the diagonal. Useful for descriptive statistics of small data sets (better with less than 10 variables).

2.7.2 Calibration And Evaluation Dataset

```
data <- ecospat.testData
caleval <- ecospat.caleval (data = ecospat.testData[53], xy = data[2:3],
  row.num = 1:nrow(data), nrep = 2, ratio = 0.7,
  disaggregate = 0.2, pseudoabs = 100, npres = 10,
  replace = FALSE)
head(caleval)
```

```
## $eval
##   yeval yeval
## 1     92   NA
## 2    160   NA
## 3    119   NA
## 4    152  254
## 5    238  239
## 6    220  260
## 7    235  211
## 8    242   57
## 9    121   84
## 10   296   34
## 11   113  184
## 12   214  300
## 13   204  133
## 14   116  253
## 15   189  198
## 16    85  120
## 17   283  272
## 18    67  292
## 19   155  243
## 20   229  212
```



```

## 21  203  225
## 22  225  248
## 23  295  275
## 24  293  156
## 25  273  189
## 26  206  231
## 27  250  281
## 28  217  258
## 29  248  145
## 30  134  262
## 31   30  278
## 32  246  266
## 33  114  249
##
## $cal
##   ycal ycal
## 1    99  NA
## 2    NA  NA
## 3    90  NA
## 4    NA  NA
## 5    NA  NA
## 6    54  NA
## 7     9 103
## 8   224  53
## 9    56 200
## 10  251 188
## 11  266  79
## 12   55  85
## 13  166  31
## 14  228  17
## 15  244 139
## 16  180 274
## 17  291  95
## 18   37  15
## 19   14 240
## 20  145 100
## 21  232 154
## 22    3 233
## 23  147  18
## 24   27 106
## 25  276   8
## 26  212 178
## 27   23  36
## 28    2 265
## 29  271  51
## 30  110   3
## 31  278  67
## 32   24  21
## 33  258 181
## 34  261 171
## 35  297  43
## 36  123 115
## 37   33 222
## 38  279 270
## 39  223 293
## 40    4  33
## 41  264 289
## 42  290  49

```

```
## 43 275 204
## 44 289 273
## 45 186 221
## 46 294 259
## 47 249 44
## 48 267 245
## 49 219 290
## 50 230 252
## 51 11 168
## 52 45 16
## 53 262 255
## 54 263 203
## 55 247 269
## 56 185 236
## 57 193 182
## 58 20 256
## 59 268 205
## 60 231 169
## 61 94 246
## 62 16 201
## 63 237 45
## 64 243 5
## 65 281 291
## 66 177 24
## 67 240 234
## 68 192 196
## 69 140 224
## 70 210 230
## 71 288 206
## 72 286 199
## 73 150 299
## 74 75 71
## 75 53 22
## 76 157 283
## 77 156 241
```

We obtained an evaluation and calibration dataset with a desired ratio of disaggregation.

3 Core Niche Modelling

3.1 Model Evaluation

3.1.1 Presence-only Evaluation Indices- Boyce Index

The argument `fit` is a vector containing the predicted suitability values

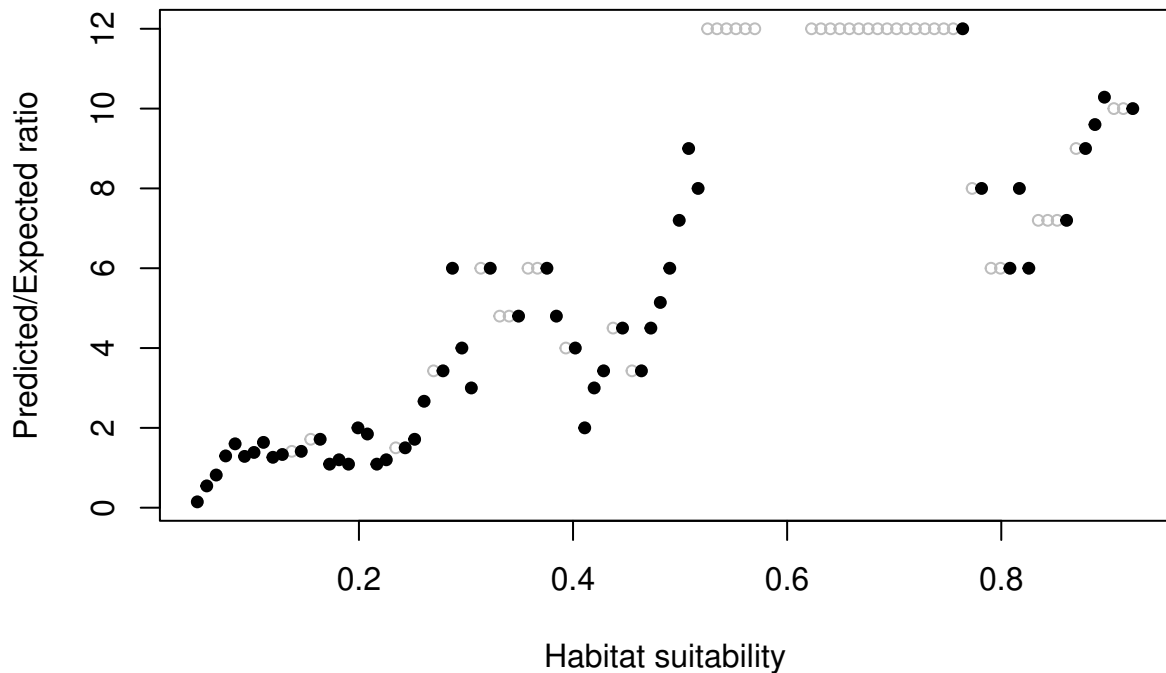
```
fit <- ecospat.testData$glm_Saxifraga_oppositifolia
```

The argument `obs` is a vector containing the predicted suitability values of the validation points (presence records)

```
obs<-ecospat.testData$glm_Saxifraga_oppositifolia[which(ecospat.testData$Saxifraga_oppositifolia==1)
```

Calculate and plot Boyce Index with `ecospat.boyce`

```
ecospat.boyce (fit, obs, nclass = 0, window.w = "default", res = 100,
              PPlot = TRUE)$cor
```



```
## [1] 0.91
```

Here the boyce index is 0.91. If the rank of predicted expected ratio would be completely ordered along habitat suitability axis then boyce index would be 1.

3.1.2 Accuracy of Community Prediction

Indices of accuracy of community predictions `ecospat.CommunityEval()`

```
eval<-ecospat.testData[c(53,62,58,70,61,66,65,71,69,43,63,56,68,57,55,60,54,67,59,64)]
pred<-ecospat.testData[c(73:92)]
```

```
CommunityEval<-ecospat.CommunityEval (eval, pred, proba = TRUE, ntir=5,verbose = T)
```

```
## trial 1 on 5
## trial 2 on 5
## trial 3 on 5
## trial 4 on 5
## trial 5 on 5
```

3.2 Spatial Predictions and Projections

3.2.1 ESM Ensemble of Small Models

```
library(biomod2)
```

```
## biomod2 4.3-4-3 loaded.
## /!\ Welcome to augmented biomod2 with abundance modeling available! (*o*)
## Take a look at the HOME and NEWS section on the website to see all the features!
## Loading required package: nnet
## Loading required package: rpart
## Loading required package: cito
## Warning in library(package, lib.loc = lib.loc, character.only = TRUE,
## logical.return = TRUE, : there is no package called 'cito'
## Loading required package: mda
```

```

## Warning in library(package, lib.loc = lib.loc, character.only = TRUE,
## logical.return = TRUE, : there is no package called 'mda'
## Loading required package: gam
## Warning in library(package, lib.loc = lib.loc, character.only = TRUE,
## logical.return = TRUE, : there is no package called 'gam'
## Loading required package: mgcv
## Loading required package: nlme
## This is mgcv 1.9-3. For overview type 'help("mgcv-package")'.
##
## Attaching package: 'mgcv'
## The following object is masked from 'package:nnet':
##
##      multinom
## Loading required package: gbm
## Loaded gbm 2.2.2
## This version of gbm is no longer under development. Consider transitioning to gbm3, https://github.com
## Loading required package: earth
## Loading required package: Formula
## Loading required package: plotmo
## Loading required package: plotrix
## Loading required package: maxnet
## Loading required package: randomForest
## randomForest 4.7-1.2
## Type rfNews() to see new features/changes/bug fixes.
## Loading required package: xgboost
# species
# occurrences
xy <- inv[,1:2]
head(xy)

##           x           y
## 1 142.25 -10.25
## 2 142.25 -10.75
## 3 131.25 -11.25
## 4 132.25 -11.25
## 5 142.25 -11.25
## 6 142.75 -11.25
sp_occ <- inv[11]

# env
current <- inv[3:7]
head(current)

##      aetpet      gdd      p      pet      stdp
## 1 0.3180346 7965.1 1595.7 1950.320 137.8134
## 2 0.2807616 7888.9 1693.7 1991.475 156.3950
## 3 0.2638533 8165.3 1595.0 2179.968 127.0621
## 4 0.2790938 8195.6 1346.0 1919.897 114.7686

```

```

## 5 0.3030646 7858.1 1711.1 1795.255 158.3286
## 6 0.3217786 7888.5 1711.1 1788.220 151.8030
## BIOMOD
t1 <- Sys.time()
sp<-1

### Formating the data with the BIOMOD_FormatingData() function form the package biomod2

myBiomodData <- biomod2::BIOMOD_FormatingData( resp.var = as.numeric(sp_occ[,sp]),
                                             expl.var = current,
                                             resp.xy = xy,
                                             resp.name = colnames(sp_occ)[sp])

##
## ----- species_occ Data Formating -----
##
##      ! Response variable name was converted into species.occ
## ----- Done -----

### Calibration of simple bivariate models

# remove invisible(capture.output)) to print output in the console
# this is just to keep the vignette short
invisible(capture.output(my.ESM <- ecospat.ESM.Modeling( data=myBiomodData,
                                                         models=c('GLM'),
                                                         NbRunEval=2,
                                                         DataSplit=70,
                                                         weighting.score=c("AUC"),
                                                         parallel=F)
           )
)

## Warning in .BIOMOD_Modeling.check.args(bm.format = bm.format, modeling.id =
## modeling.id, : The metric 'ROC' will be switch to 'AUCroc'.

## Warning: executing %dopar% sequentially: no parallel backend registered

## Warning in coords.roc(roc1, "best", ret = c("threshold", "sens", "spec"), :
## 'transpose=TRUE' is deprecated. Only 'transpose=FALSE' will be allowed in a
## future version.
## Warning in coords.roc(roc1, "best", ret = c("threshold", "sens", "spec"), :
## 'transpose=TRUE' is deprecated. Only 'transpose=FALSE' will be allowed in a
## future version.
## Warning in coords.roc(roc1, "best", ret = c("threshold", "sens", "spec"), :
## 'transpose=TRUE' is deprecated. Only 'transpose=FALSE' will be allowed in a
## future version.
## Warning in coords.roc(roc1, "best", ret = c("threshold", "sens", "spec"), :
## 'transpose=TRUE' is deprecated. Only 'transpose=FALSE' will be allowed in a
## future version.
## Warning in coords.roc(roc1, "best", ret = c("threshold", "sens", "spec"), :
## 'transpose=TRUE' is deprecated. Only 'transpose=FALSE' will be allowed in a
## future version.

## Warning in .BIOMOD_Modeling.check.args(bm.format = bm.format, modeling.id =
## modeling.id, : The metric 'ROC' will be switch to 'AUCroc'.

## Warning in coords.roc(roc1, "best", ret = c("threshold", "sens", "spec"), :
## 'transpose=TRUE' is deprecated. Only 'transpose=FALSE' will be allowed in a
## future version.
## Warning in coords.roc(roc1, "best", ret = c("threshold", "sens", "spec"), :
## 'transpose=TRUE' is deprecated. Only 'transpose=FALSE' will be allowed in a

```



```
## Warning in coords.roc(roc1, "best", ret = c("threshold", "sens", "spec"), :
## 'transpose=TRUE' is deprecated. Only 'transpose=FALSE' will be allowed in a
## future version.
## Warning in coords.roc(roc1, "best", ret = c("threshold", "sens", "spec"), :
## 'transpose=TRUE' is deprecated. Only 'transpose=FALSE' will be allowed in a
## future version.

## Warning in .BIOMOD_Modeling.check.args(bm.format = bm.format, modeling.id =
## modeling.id, : The metric 'ROC' will be switch to 'AUCroc'.

## Warning in coords.roc(roc1, "best", ret = c("threshold", "sens", "spec"), :
## 'transpose=TRUE' is deprecated. Only 'transpose=FALSE' will be allowed in a
## future version.
## Warning in coords.roc(roc1, "best", ret = c("threshold", "sens", "spec"), :
## 'transpose=TRUE' is deprecated. Only 'transpose=FALSE' will be allowed in a
## future version.
## Warning in coords.roc(roc1, "best", ret = c("threshold", "sens", "spec"), :
## 'transpose=TRUE' is deprecated. Only 'transpose=FALSE' will be allowed in a
## future version.
## Warning in coords.roc(roc1, "best", ret = c("threshold", "sens", "spec"), :
## 'transpose=TRUE' is deprecated. Only 'transpose=FALSE' will be allowed in a
## future version.
## Warning in coords.roc(roc1, "best", ret = c("threshold", "sens", "spec"), :
## 'transpose=TRUE' is deprecated. Only 'transpose=FALSE' will be allowed in a
## future version.
## Warning in coords.roc(roc1, "best", ret = c("threshold", "sens", "spec"), :
## 'transpose=TRUE' is deprecated. Only 'transpose=FALSE' will be allowed in a
## future version.

## Warning in .BIOMOD_Modeling.check.args(bm.format = bm.format, modeling.id =
## modeling.id, : The metric 'ROC' will be switch to 'AUCroc'.

## Warning in coords.roc(roc1, "best", ret = c("threshold", "sens", "spec"), :
## 'transpose=TRUE' is deprecated. Only 'transpose=FALSE' will be allowed in a
## future version.
## Warning in coords.roc(roc1, "best", ret = c("threshold", "sens", "spec"), :
## 'transpose=TRUE' is deprecated. Only 'transpose=FALSE' will be allowed in a
## future version.
## Warning in coords.roc(roc1, "best", ret = c("threshold", "sens", "spec"), :
## 'transpose=TRUE' is deprecated. Only 'transpose=FALSE' will be allowed in a
## future version.
## Warning in coords.roc(roc1, "best", ret = c("threshold", "sens", "spec"), :
## 'transpose=TRUE' is deprecated. Only 'transpose=FALSE' will be allowed in a
## future version.
## Warning in coords.roc(roc1, "best", ret = c("threshold", "sens", "spec"), :
## 'transpose=TRUE' is deprecated. Only 'transpose=FALSE' will be allowed in a
## future version.
## Warning in coords.roc(roc1, "best", ret = c("threshold", "sens", "spec"), :
## 'transpose=TRUE' is deprecated. Only 'transpose=FALSE' will be allowed in a
## future version.
## Warning in coords.roc(roc1, "best", ret = c("threshold", "sens", "spec"), :
## 'transpose=TRUE' is deprecated. Only 'transpose=FALSE' will be allowed in a
## future version.
## Warning in coords.roc(roc1, "best", ret = c("threshold", "sens", "spec"), :
```

```

## 'transpose=TRUE' is deprecated. Only 'transpose=FALSE' will be allowed in a
## future version.

## Warning in .BIOMOD_Modeling.check.args(bm.format = bm.format, modeling.id =
## modeling.id, : The metric 'ROC' will be switch to 'AUCroc'.

## Warning in coords.roc(roc1, "best", ret = c("threshold", "sens", "spec"), :
## 'transpose=TRUE' is deprecated. Only 'transpose=FALSE' will be allowed in a
## future version.
## Warning in coords.roc(roc1, "best", ret = c("threshold", "sens", "spec"), :
## 'transpose=TRUE' is deprecated. Only 'transpose=FALSE' will be allowed in a
## future version.
## Warning in coords.roc(roc1, "best", ret = c("threshold", "sens", "spec"), :
## 'transpose=TRUE' is deprecated. Only 'transpose=FALSE' will be allowed in a
## future version.
## Warning in coords.roc(roc1, "best", ret = c("threshold", "sens", "spec"), :
## 'transpose=TRUE' is deprecated. Only 'transpose=FALSE' will be allowed in a
## future version.
## Warning in coords.roc(roc1, "best", ret = c("threshold", "sens", "spec"), :
## 'transpose=TRUE' is deprecated. Only 'transpose=FALSE' will be allowed in a
## future version.
## Warning in coords.roc(roc1, "best", ret = c("threshold", "sens", "spec"), :
## 'transpose=TRUE' is deprecated. Only 'transpose=FALSE' will be allowed in a
## future version.
## Warning in coords.roc(roc1, "best", ret = c("threshold", "sens", "spec"), :
## 'transpose=TRUE' is deprecated. Only 'transpose=FALSE' will be allowed in a
## future version.
## Warning in coords.roc(roc1, "best", ret = c("threshold", "sens", "spec"), :
## 'transpose=TRUE' is deprecated. Only 'transpose=FALSE' will be allowed in a
## future version.
## Warning in coords.roc(roc1, "best", ret = c("threshold", "sens", "spec"), :
## 'transpose=TRUE' is deprecated. Only 'transpose=FALSE' will be allowed in a
## future version.
## Warning in coords.roc(roc1, "best", ret = c("threshold", "sens", "spec"), :
## 'transpose=TRUE' is deprecated. Only 'transpose=FALSE' will be allowed in a
## future version.

### Evaluation and average of simple bivariate models to ESMs
my.ESM_EF <- ecospat.ESM.EnsembleModeling(my.ESM,weighting.score=c("SomersD"),threshold=0)

### Projection of simple bivariate models into new space
my.ESM_proj_current <- ecospat.ESM.Projection(ESM.modeling.output=my.ESM,
                                             new.env=current)

### Projection of calibrated ESMs into new space
my.ESM_EFproj_current <- ecospat.ESM.EnsembleProjection(ESM.prediction.output=my.ESM_proj_current,
                                                       ESM.EnsembleModeling.output=my.ESM_EF)

```

3.3 Spatial prediction of communities

Input data for the first argument (proba) as data frame of rough probabilities from SDMs for all species in columns in the considered sites in rows.

```
proba <- ecospat.testData[,73:92]
```

Input data for the second argument (sr) as data frame with richness value in the first column and sites.


```
sr <- as.data.frame(rowSums(proba))
```

3.4 SESAM framework with *ecospat.SESAM.prr()*

```
prr<-ecospat.SESAM.prr(proba, sr)
head(prr)[,1:4]
```

```
##   glm_Agrostis_capillaris glm_Leontodon_hispidus_sl glm_Dactylis_glomerata
## 1                      0                      1                      1
## 2                      1                      0                      1
## 3                      1                      0                      1
## 4                      1                      0                      1
## 5                      1                      0                      1
## 6                      1                      0                      1
##   glm_Trifolium_repens_sstr
## 1                      0
## 2                      1
## 3                      1
## 4                      1
## 5                      1
## 6                      1
```

4 Post-Modelling

4.1 Spatial Predictions of species assemblages

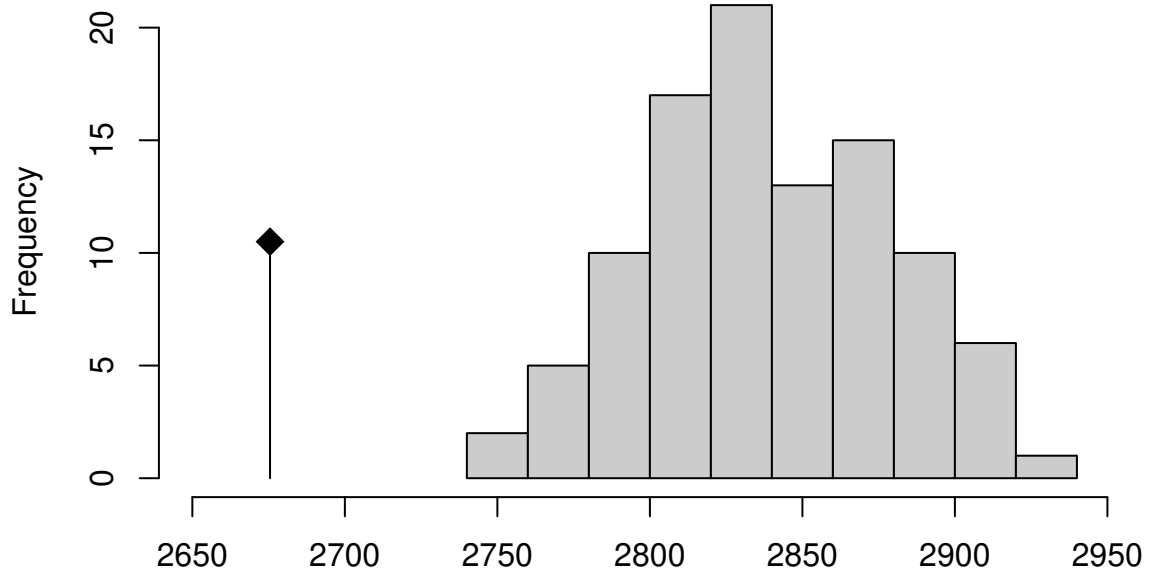
4.1.1 Co-occurrence analysis & Environmentally Constrained Null Models

Input data as a matrix of plots (rows) x species (columns). Input matrices should have column names (species names) and row names (sampling plots).

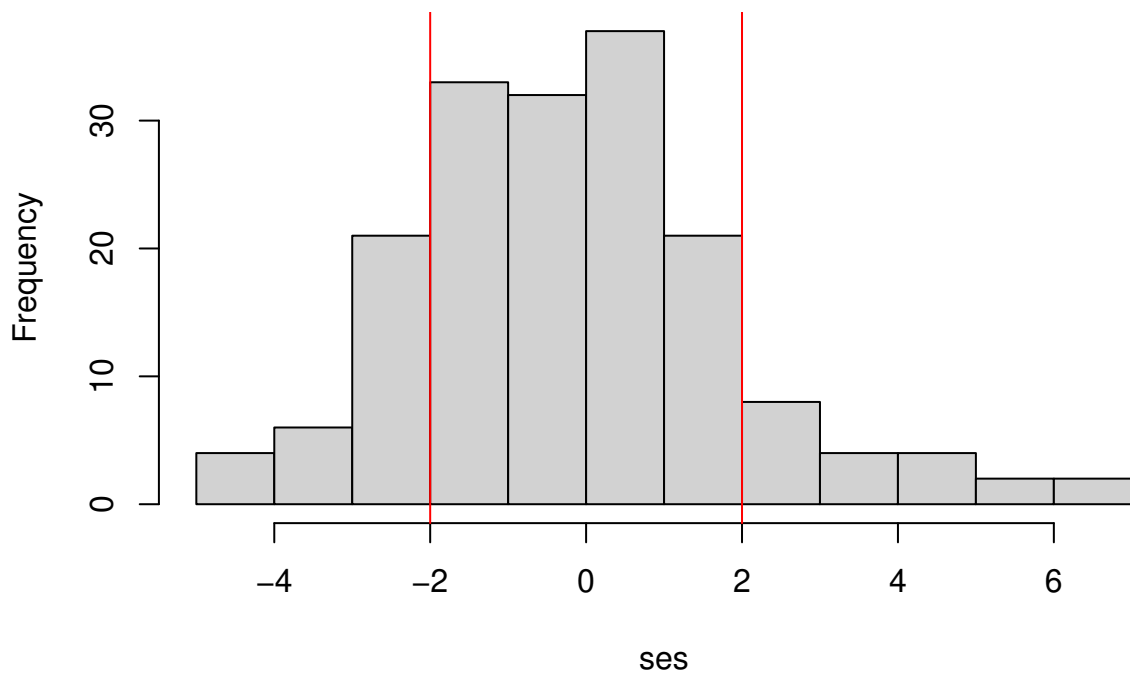
```
presence<-ecospat.testData[c(53,62,58,70,61,66,65,71,69,43,63,56,68,57,55,60,54,67,59,64)]
pred<-ecospat.testData[c(73:92)]
```

Define the number of permutations. It is recommended to use at least 10000 permutations for the test. As an example we used `nperm = 100`, to reduce the computational time. Then Define the `outpath`. Then we can run Run the function `ecospat.cons_Cscore`. The function tests for non-random patterns of species co-occurrence in a presence-absence matrix. It calculates the C-score index for the whole community and for each species pair. An environmental constraint is applied during the generation of the null communities.

```
nbpermut <- 100
outpath <- getwd()
ecospat.cons_Cscore(presence, pred, nbpermut, outpath)
```



Simulated C-scores
Histogram of standardized effect size



```
## $ObsCscoreTot
## [1] 2675.468
##
## $SimCscoreTot
## [1] 2839.598
##
## $PVal.less
## [1] 0.00990099
##
## $PVal.greater
## [1] 1
##
## $SES.Tot
```

```
## [1] -4.064741
```

The function returns - the C-score index for the observed community (ObsCscoreTot), - the mean of C-score for the simulated communities (SimCscoreTot), - the p.values (PVal.less and PVal.greater) to evaluate the significance of the difference between the former two indices. - the standardized effect size for the whole community (SES.Tot). A SES that is greater than 2 or less than -2 is statistically significant with a tail probability of less than 0.05 (Gotelli & McCabe 2002 - Ecology). If a community is structured by competition, we would expect the C-score to be large relative to a randomly assembled community (positive SES). In this case the observed C-score is significantly lower than expected by chance, this meaning that the community is dominated by positive interactions (aggregated pattern).

A table is saved in the path specified where the same metrics are calculated for each species pair (only the table with species pairs with significant p.values is saved).