Vignette ecospat package

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& 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)

Loading required package: ade4

```
## Loading required package: ape
## Loading required package: gbm
## Loading required package: survival
## Loading required package: lattice
## Loading required package: splines
## Loading required package: parallel
## Loaded gbm 2.1.3
## Loading required package: sp
citation("ecospat")
## To cite package 'ecospat' in publications use:
##
##
     Olivier Broennimann, Valeria Di Cola and Antoine Guisan (2018).
     ecospat: Spatial Ecology Miscellaneous Methods. R package
##
##
     version 2.2.1.
##
     http://www.unil.ch/ecospat/home/menuguid/ecospat-resources/tools.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 = {2018},
##
       note = {R package version 2.2.1},
##
##
       url = {http://www.unil.ch/ecospat/home/menuguid/ecospat-resources/tools.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_anisophyllon"
## [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"
                                         "Leontodon autumnalis"
## [35] "Hypochaeris_radicata"
## [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"
                                         "Veronica_aphylla"
## [51] "Veronica_alpina"
## [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"
                                         "Ranunculus_acris_sl"
## [65] "Prunella_vulgaris"
## [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"
## [87] "glm_Campanula_scheuchzeri"
                                         "glm_Festuca_pratensis_sl"
## [89] "glm_Bromus_erectus_sstr"
                                         "glm_Saxifraga_oppositifolia"
## [91] "glm_Daucus_carota"
                                         "glm_Pritzelago_alpina_sstr"
## [93] "gbm_Bromus_erectus_sstr"
                                         "gbm_Saxifraga_oppositifolia"
## [95] "gbm_Daucus_carota"
                                         "gbm_Pritzelago_alpina_sstr"
```

1.0.2 Test data for the Niche Overlap Analysis

ecospat.testNiche.inv()

```
data(ecospat.testNiche.inv)
names(ecospat.testNiche.inv)
    [1] "x"
                                                                     "p"
##
                                       "aetpet"
                                                      "gdd"
    [6] "pet"
                        "stdp"
                                       "tmax"
                                                      "tmin"
                                                                     "tmp"
## [11] "species_occ" "predictions"
ecospat.testNiche.nat()
data(ecospat.testNiche.nat)
names(ecospat.testNiche.nat)
                                                                     "p"
                        "y"
                                       "aetpet"
##
   [1] "x"
                                                      "gdd"
                       "stdp"
                                       "tmax"
   [6] "pet"
                                                      "tmin"
                                                                     "tmp"
## [11] "species_occ" "predictions"
```

1.0.3 Test tree for Phylogenetic Diversity Analysis

ecospat.testTree()

```
fpath <- system.file("extdata", "ecospat.testTree.tre", package="ecospat")
fpath</pre>
```

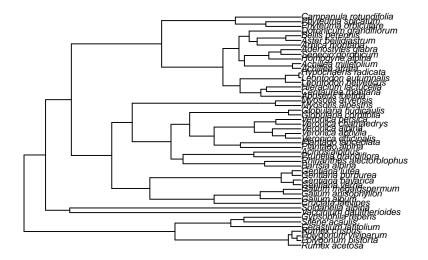
[1] "C:/Users/obroenni/Documents/R/win-library/3.5/ecospat/extdata/ecospat.testTree.tre"

```
tree<-read.tree(fpath)
tree$tip.label</pre>
```

```
##
    [1] "Rumex_acetosa"
                                     "Polygonum_bistorta"
## [3] "Polygonum_viviparum"
                                     "Rumex_crispus"
## [5] "Cerastium latifolium"
                                     "Silene acaulis"
## [7] "Gypsophila_repens"
                                     "Vaccinium_gaultherioides"
## [9] "Soldanella alpina"
                                     "Cruciata laevipes"
## [11] "Galium album"
                                     "Galium anisophyllon"
## [13] "Galium_megalospermum"
                                     "Gentiana verna"
## [15] "Gentiana_bavarica"
                                     "Gentiana_purpurea"
## [17] "Gentiana_lutea"
                                     "Bartsia_alpina"
## [19] "Rhinanthus alectorolophus"
                                     "Prunella grandiflora"
## [21] "Acinos_alpinus"
                                     "Plantago alpina"
## [23] "Plantago_lanceolata"
                                     "Veronica_officinalis"
## [25] "Veronica_aphylla"
                                     "Veronica_alpina"
## [27] "Veronica_chamaedrys"
                                     "Veronica_persica"
## [29] "Globularia_cordifolia"
                                     "Globularia_nudicaulis"
## [31] "Myosotis_alpestris"
                                     "Myosotis_arvensis"
## [33] "Aposeris_foetida"
                                     "Centaurea_montana"
## [35] "Hieracium lactucella"
                                     "Leontodon helveticus"
## [37] "Leontodon_autumnalis"
                                     "Hypochaeris_radicata"
## [39] "Achillea_atrata"
                                     "Achillea_millefolium"
## [41] "Homogyne_alpina"
                                     "Senecio_doronicum"
## [43] "Adenostyles_glabra"
                                     "Arnica_montana"
## [45] "Aster_bellidiastrum"
                                     "Bellis_perennis"
## [47] "Doronicum_grandiflorum"
                                     "Phyteuma_orbiculare"
                                     "Campanula_rotundifolia"
## [49] "Phyteuma_spicatum"
```

Plot tree

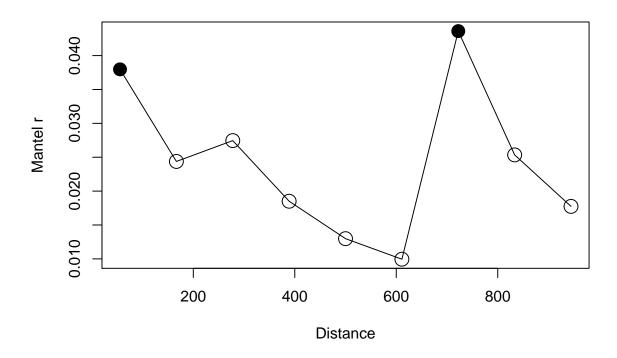
```
plot(tree, cex=0.6)
```



2 Pre-Modelling Analysis

2.1 Spatial Auto-correlation

 ${\bf 2.1.1} \quad {\bf Mantel~Correlogram~with~\it ecospat.mantel.correlogram()}$



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)</pre>
```

[1] 4

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

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

[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</pre>
```

```
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
## [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
```

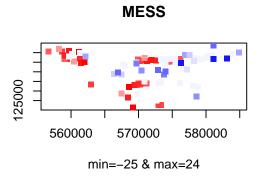
2.3.2 Extrapolation detection, creating a MESS object with ecospat.mess()

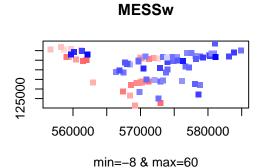
```
x <- ecospat.testData[c(2,3,4:8)]
proj<- x[1:90,] #A projection dataset.
cal<- x[91:300,] #A calibration dataset</pre>
```

```
mess.object<-ecospat.mess (proj, cal, w="default")</pre>
```

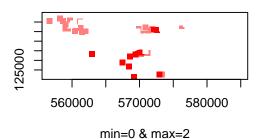
2.3.2.1 Plot MESS with ecospat.plot.mess()

```
ecospat.plot.mess (mess.object, cex=1, pch=15)
```





#MESSneg



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 MESSw plot, same as previous plot but with weighted by the number of predictors. Finally, the MESSneg plot shows at each site how many predictors have values outside of their calibration range.

2.4 Phylogenetic Diversity Measures

[26]

##

34.8871800

0.0000000

```
fpath <- system.file("extdata", "ecospat.testTree.tre", package="ecospat")
tree <- read.tree(fpath)
data <- ecospat.testData[9:52]</pre>
```

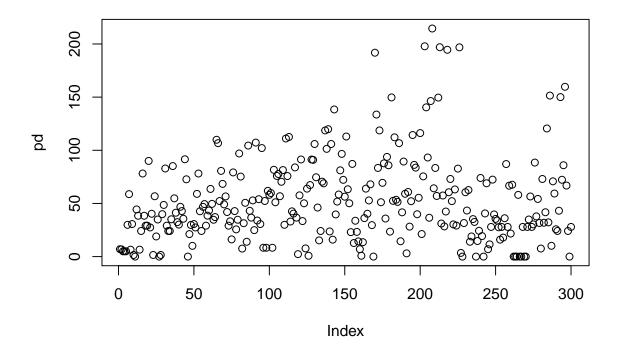
2.4.1 Calculate Phylogenetic Diversity Measures ecospat.calculate.pd

```
pd<- ecospat.calculate.pd(tree, data, method = "spanning", type = "species", root = TRUE, average =
## Progress (. = 100 pixels calculated):
## ... [300]
## All 300 pixels done.
pd
##
     [1]
           6.9782188
                       6.7981743
                                   4.9964700
                                               4.9964700
                                                           4.9964700
##
     [6]
          29.8820547
                      58.7451752
                                   6.5223035
                                              30.6152478
                                                           1.5258335
##
           0.0000000 44.3661803
                                  38.4155607
                                               6.5223035 24.0929443
    [11]
                                  29.0894143 29.0894143 89.9839758
##
    [16]
         78.1607950 38.4155607
    [21]
          27.4135569
                     40.2827035
                                   1.5258335
                                              56.7686202
                                                          18.9535475
```

1.5258335 39.9291325 48.5997861

```
##
    [31]
          82.8763723
                     29.0894143
                                  24.0929443
                                               24.0929443
                                                           35.0949481
                                                           30.0984781
##
    [36]
          85.1406422
                     54.7974724
                                  41.2817284
                                               32.4100269
##
    [41]
          46.8247511
                      42.8358475
                                  35.6223697
                                               91.5539224
                                                           72.7022527
##
    [46]
           0.0000000
                      21.1862293
                                  29.7320308
                                               10.1187868
                                                           30.6152478
##
    [51]
          27.4135569
                      59.0015345
                                  78.1536692
                                               42.6423378
                                                           24.0929443
##
    [56]
          46.8050070
                      49.3924266
                                  29.0894143
                                               38.5290848
                                                           43.3611373
##
    [61]
          63.6397674
                      49.6097169
                                  34.6522309
                                               37.1871282 109.8813371
    [66] 106.6971561
                      52.2512132
                                  80.6221671
                                               68.3867818
                                                           49.1362998
##
##
    [71]
          56.6138690
                      41.9283257
                                  29.0894143
                                               33.2026673
                                                           16.1897593
##
    [76]
          79.1938213
                      42.8115427
                                  25.6187778
                                               34.6805724
                                                           96.9902366
##
    [81]
          75.2672695
                       7.5313673
                                  31.4078882
                                               50.5865673
                                                           13.9570775
##
    [86] 104.4121025
                      43.0464918
                                  36.6693230
                                               52.8590823
                                                           24.8855847
##
    [91] 107.2302322
                      33.9358604
                                  54.0048319
                                               30.6152478 102.0983385
                      52.3071062
##
    [96]
           8.3170826
                                   8.3170826
                                               61.8562896
                                                           58.1179346
## [101]
          59.7939424
                       8.3170826
                                  81.6495398
                                               51.1054635
                                                           75.8701970
## [106]
          77.6947419
                      56.7929250
                                  70.3693202
                                               81.3965205
                                                           29.9118877
## [111] 111.0790432
                      75.7518798 112.5482496
                                               32.9763735
                                                           42.5644761
                     83.8955419
                                  36.6693230
## [116]
          40.4507005
                                                2.3184739
                                                           57.5978451
## [121]
          91.3453370
                      33.3983912
                                  50.1351419
                                                7.7084002
                                                           63.9227817
                      67.2813325
                                               90.9578739 105.9024741
## [126]
           0.7926404
                                  91.2965996
## [131]
          74.6128871
                      46.1321553
                                  15.2479619
                                               24.0929443
                                                           70.4802708
## [136]
                                                           23.6602184
          68.8949899 118.6657550 101.3545260 119.8539056
## [141] 105.8968281
                      15.9336325 138.4059855
                                               39.6674173
                                                           51.7391372
## [146]
          58.4119283
                      81.1388699
                                  96.6048825
                                               72.2156025
                                                           56.3601992
## [151] 112.9489963
                      63.3258805
                                  50.1594468
                                               23.0021994
                                                           87.1886965
## [156]
          12.7714946
                      33.7421666
                                  23.2537702
                                               14.3226164
                                                            6.9752071
## [161]
           0.7926404
                      13.5641350
                                  36.2007616
                                               63.9227817
                                                           40.3310946
## [166]
          52.8264129
                      67.9956878
                                  29.5843437
                                                0.0000000 191.7818606
## [171] 133.6077875
                      83.3977825 118.6711630
                                               51.1512871
                                                           69.3838811
## [176]
          87.7066616
                      35.8005270
                                  93.7797077
                                               85.8984840
                                                           23.4933413
## [181] 149.7094684
                      52.4451847 112.1873673
                                               53.4479612
                                                           51.4341108
## [186] 106.6959500
                      14.4361405
                                  41.6547546
                                               89.4018733
                                                           59.1068292
## [191]
           3.0516670
                     60.7852739
                                  28.1850877
                                               52.1002690 114.3651475
          86.2640717
                      83.7092232
                                  39.8499777
## [196]
                                               55.3514065 116.1795597
## [201]
          21.2346203
                      75.4593878 197.8157358 140.3806968
                                                           93.2192350
## [206]
          36.5337815 146.3370747 214.5450205
                                               64.2439145
                                                           83.3740177
## [211]
          57.0440643 149.5697614 196.9415036
                                               31.0984631
                                                           57.4769230
## [216]
          28.4014469
                      42.3978747 194.5384819
                                               60.5204195
                                                           73.0060715
          52.1628582
                      30.2801165
## [221]
                                  63.1752097
                                               29.1789484
                                                           82.7662787
## [226] 196.8309769
                       3.4666557
                                   0.0000000
                                               31.5688084
                                                           60.5650008
## [231]
                     62.5952411
                                  13.9570775
          43.3334929
                                               18.9495667
                                                           35.2646601
## [236]
          32.6155790
                       0.0000000
                                  14.6693623
                                               24.2745827
                                                           73.9480832
                       0.0000000
                                  40.6115985
## [241]
          19.2825866
                                               68.9862341
                                                            6.9782188
                      27.9105497
                                  72.4020225
## [246]
          11.5030881
                                               39.6781995
                                                           35.4596364
## [251]
          33.9160835
                      27.5735165
                                  15.9619740
                                               27.9105497
                                                           17.8628493
## [256]
          36.0936777
                      87.0440848
                                  27.9105497
                                               66.6907987
                                                           21.6475811
## [261]
          67.5969904
                       0.0000000
                                   0.0000000
                                                0.0000000
                                                           58.0542370
## [266]
           0.0000000
                       0.0000000 27.9105497
                                                0.0000000
                                                            0.0000000
          27.9105497
                      34.8887684 56.5556633
                                               27.9105497
                                                           30.3097595
## [271]
## [276]
          88.4296666
                      37.8150727
                                  54.2397810
                                               31.6243116
                                                            7.5799087
## [281]
          73.0136833
                      31.8638035
                                  41.7172212 120.5228857
                                                           32.2001243
## [286] 151.4545228
                      10.1544492
                                  70.8133537
                                               59.3255687
                                                           25.7211220
                      43.1500941 150.0299191
## [291]
          24.1115267
                                               72.2758570
                                                           85.9498096
## [296] 159.7242106 66.8328159 24.0929443
                                                0.0000000
                                                           27.9105497
```

2.4.1.1 Plot the results (correlation of phylogenetic diversity with species richness)



2.5 Niche Quantification and Comparison with Ordination techniques

Loading test data for the niche dynamics analysis in the invaded range

```
inv <- ecospat.testNiche.inv</pre>
```

Loading test data for the niche dynamics analysis in the native range

nat <- ecospat.testNiche.nat</pre>

2.5.1 PCA-ENVIRONMENT

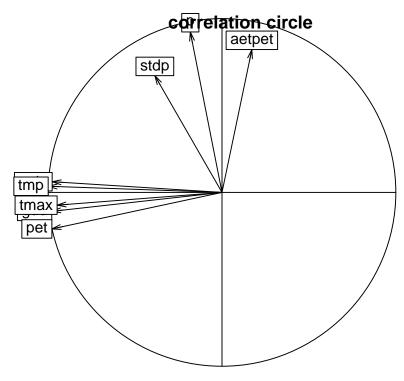
2.5.1.1 The PCA is calibrated on all the sites of the study area

Calibrating the PCA in the whole studay area, including both native and invaded ranges (same as PCAenv in Broenniman et al. 2012)

```
pca.env <- dudi.pca(rbind(nat,inv)[,3:10],scannf=F,nf=2)</pre>
```

2.5.1.2 Plot Variables Contribution with ecospat.plot.contrib()

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.

2.5.1.3 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 <- suprow(pca.env,nat[which(nat[,11]==1),3:10])$li

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

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

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

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

For a species in the native range (North America)

For a species in the invaded range (Australia)

2.5.3 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=T)$D
D.overlap</pre>
```

[1] 0.224586

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

2.5.4 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.

Niche equivalency test H1: Is the overlap between the native and invaded niche higher than two random niches?

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

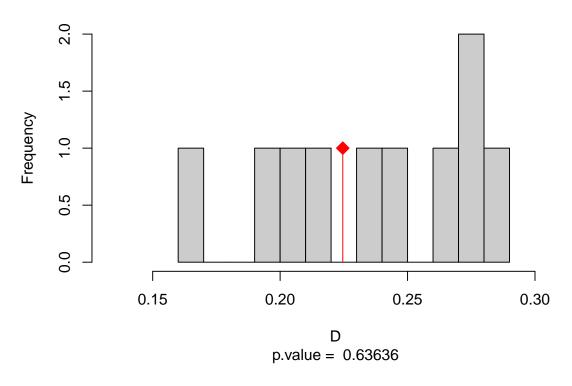
Shifting randomly the invasive niche in the invaded study area It is recomended to use at least 1000 replications for the similarity test. As an example we used rep = 10, to reduce the computational time.

Niche similarity test H1: Is the overlap between the native and invaded higher than when the invasive niche is randomly introduced in the invaded study area?

2.5.5.1 Plot Equivalency test

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

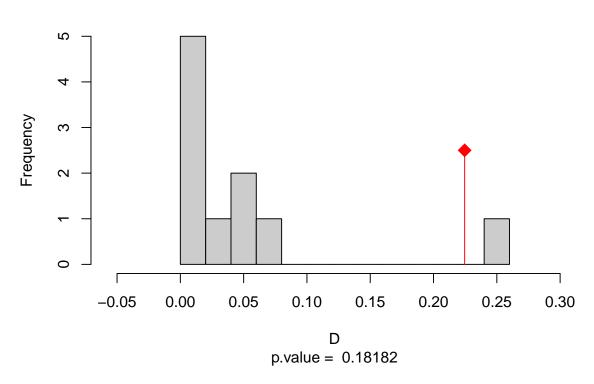




2.5.5.2 Plot Similarity test

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

Similarity



We see that the niche overlap D is 22% and this value is compared to the random distribution of the niche equivalency and niche similarity tests.

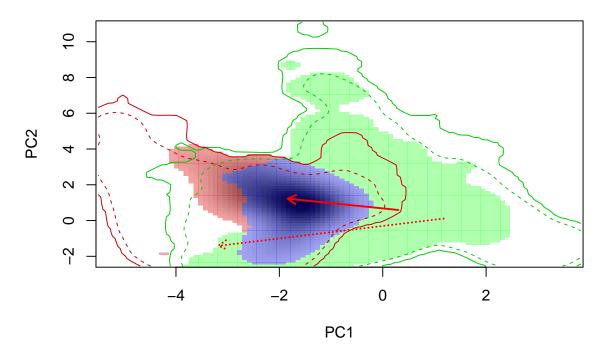
2.5.6 Delimiting niche categories and quantifying niche dynamics in analogue climates with ecospat.niche.dyn.index()

```
niche.dyn <- ecospat.niche.dyn.index (grid.clim.nat, grid.clim.inv, intersection = 0.1)</pre>
```

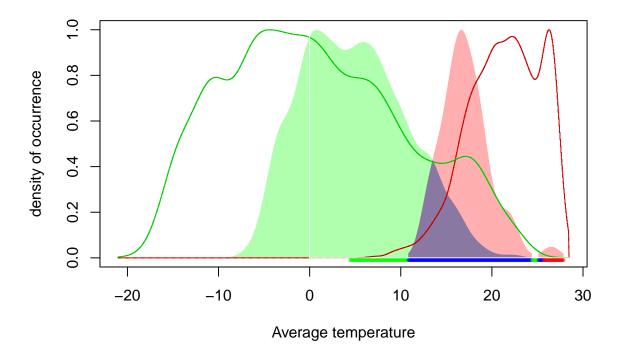
2.5.6.1 Visualizing niche categories, niche dynamics and climate analogy between ranges with ecospat.plot.niche.dyn()

Plot niche overlap

Niche Overlap



2.5.6.2 Plot the niche dynamics along one gradient (here temperature) with ecospat.plot.niche.dyn()



2.6 Biotic Interactions

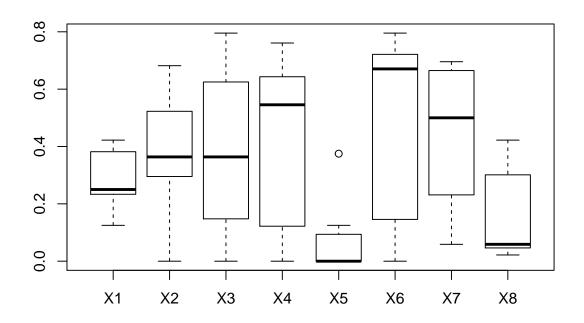
2.6.1 Species Co-occurrences Analysis with a Presence-absence matrix using the function ecospat.co occurrences()

```
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 intersects S2) is the number of times species S1 and S2 co-occur, while 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 Arr	nica_montana	Aster_bellidiastrum	
##	Aposeris_foetida	1.0000000	0.3636364	0.25000000	
##	Arnica_montana	0.3636364	1.0000000	0.36363636	
##	Aster_bellidiastrum	0.2500000	0.3636364	1.00000000	
##	Bartsia_alpina	0.222222	0.5454545	0.59090909	
##	Bromus_erectus_sstr	0.1250000	0.0000000	0.00000000	
##	${\tt Campanula_scheuchzeri}$	0.244444	0.6818182	0.79545455	
##	Carex_sempervirens	0.400000	0.5000000	0.65909091	
##	Cynosurus_cristatus	0.422222	0.2272727	0.04545455	
##		Bartsia_alpina Bromu	us_erectus_ss	tr	
##	Aposeris_foetida	0.2222222	0.12	50	
##	Arnica_montana	0.54545455	0.00	00	
##	Aster_bellidiastrum	0.59090909	0.00	00	
##	Bartsia_alpina	1.00000000	0.00	00	
##	Bromus_erectus_sstr	0.00000000	1.000	00	
##	${\tt Campanula_scheuchzeri}$	0.76086957	0.00	00	
##	Carex_sempervirens	0.69565217	0.06	25	
##	Cynosurus_cristatus	0.02173913	0.37	50	
##		Campanula_scheuchzer	ri Carex_semp	ervirens	
##	Aposeris_foetida	0.244444	44 0.4	4000000	
##	Arnica_montana	0.6818181	18 0.	0.5000000	
##	Aster_bellidiastrum	0.7954545	55 0.0	65909091	
##	Bartsia_alpina	0.7608695	57 0.0	69565217	
##	Bromus_erectus_sstr	0.0000000	0.0	06250000	
##	${\tt Campanula_scheuchzeri}$	1.0000000	0.0	67058824	
##	Carex_sempervirens	0.6705882	24 1.0	0000000	
##	Cynosurus_cristatus	0.0470588	32 0.0	05882353	
##		${\tt Cynosurus_cristatus}$			
##	Aposeris_foetida	0.4222222			
##	Arnica_montana	0.22727273			
##	Aster_bellidiastrum	0.04545455			

```
## Bartsia_alpina 0.02173913
## Bromus_erectus_sstr 0.37500000
## Campanula_scheuchzeri 0.04705882
## Carex_sempervirens 0.05882353
## Cynosurus_cristatus 1.00000000
```

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

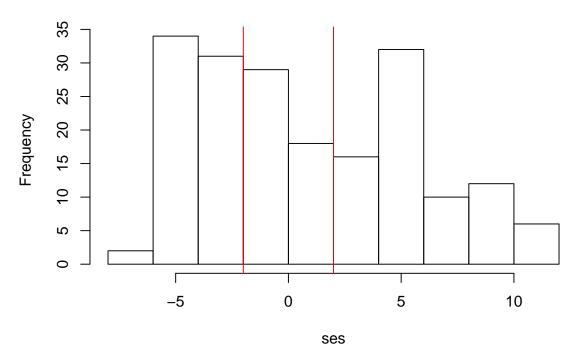
This function allows to apply a pairwise null model analysis to a presence-absence community matrix to determine which species associations are significant across the study area. The strength of associations is quantified by the C-score index and a 'fixed-equiprobable' null model algorithm is applied.

It is recomended 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)</pre>
```

```
## Computing observed co-occurence matrix
## .........
## ......
## .....
## Computing permutations
## .....
## 100 permutations to go
## .........
## 50 permutations to go
## ..........
## Computing P-values
## ......
## Exporting dataset
## ..........
## ......
## ......
```

Histogram of standardized effect size



```
## $ObsCscoreTot
## [1] 2675.468
##

## $SimCscoreTot
## [1] 2467.251
##

## $PVal.less
## [1] 1
##

## $PVal.greater
## [1] 0.00990099
##

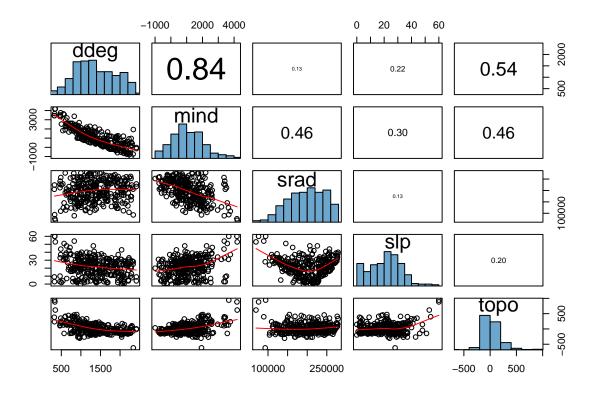
## $SES.Tot
## [1] 61.75911
```

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)</pre>
```



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

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

3 Core Niche Modelling

3.1 Model Evaluation

${\bf 3.1.1} \quad {\bf Presence-only \ Evaluation \ Indices- \ Boyce \ Index}$

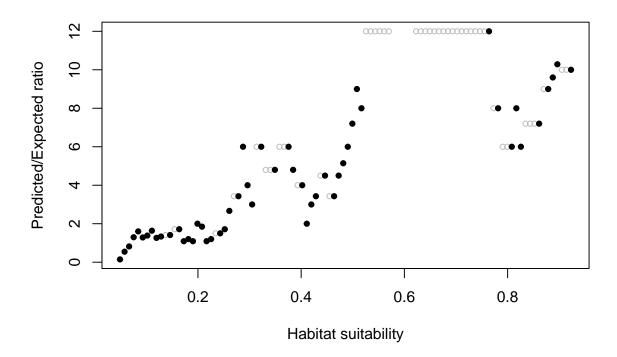
The argument fit is a vector containing the predicted suitability values

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

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

```
obs <-cospat.testData \\ \$glm_Saxifraga\_oppositifolia \\ \llbracket which (ecospat.testData \\ \$Saxifraga\_oppositifolia \\ \rrbracket ==1)
```

Calculate and plot Boyce Index with ecospat.boyce



[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. Community Eval()

```
 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)]
```

```
ComEval<-ecospat.CommunityEval (eval, pred, proba=T, ntir=5)</pre>
```

```
## 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)
## Loading required package: raster
##
## Attaching package: 'raster'
## The following objects are masked from 'package:ape':
##
       rotate, zoom
## Loading required package: reshape
## Loading required package: ggplot2
## biomod2 3.3-7 loaded.
## Type browseVignettes(package='biomod2') to access directly biomod2 vignettes.
path.wd<-getwd()</pre>
# species
# occurrences
xy <- inv[,1:2]</pre>
head(xy)
##
          X
## 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]
current <- inv[3:7]</pre>
head(current)
##
        aetpet
                  gdd
                                 pet
                          р
## 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
setwd(path.wd)
t1 <- Sys.time()</pre>
sp<-1
### Formating the data with the BIOMOD_FormatingData() function form the package biomod2
myBiomodData <- BIOMOD FormatingData( resp.var = as.numeric(sp occ[,sp]),</pre>
                                  expl.var = current,
                                  resp.xy = xy,
                                  resp.name = colnames(sp_occ)[sp])
##
       ## -
## Response variable name was converted into species.occ
## > No pseudo absences selection !
      ! No data has been set aside for modeling evaluation
myBiomodOption <- Print_Default_ModelingOptions()</pre>
##
## Defaut modeling options. copy, change what you want paste it as arg to BIOMOD_ModelingOptions
##
## ----- 'BIOMOD.Model.Options' -------
##
##
## GLM = list( type = 'quadratic',
             interaction.level = 0,
##
             myFormula = NULL,
             test = 'AIC',
##
##
             family = binomial(link = 'logit'),
             mustart = 0.5,
##
             control = glm.control(epsilon = 1e-08, maxit = 50
## , trace = FALSE) ),
##
## GBM = list( distribution = 'bernoulli',
            n.trees = 2500,
##
             interaction.depth = 7,
##
             n.minobsinnode = 5,
##
             shrinkage = 0.001,
##
             bag.fraction = 0.5,
             train.fraction = 1,
##
##
             cv.folds = 3,
             keep.data = FALSE,
##
##
             verbose = FALSE,
##
             perf.method = 'cv'),
##
## GAM = list( algo = 'GAM_mgcv',
             type = 's_smoother',
##
             k = -1,
##
##
             interaction.level = 0,
##
             myFormula = NULL,
```

```
##
               family = binomial(link = 'logit'),
##
               method = 'GCV.Cp',
##
               optimizer = c('outer', 'newton'),
##
               select = FALSE,
               knots = NULL,
##
               paraPen = NULL,
##
               control = list(nthreads = 1, irls.reg = 0, epsilon = 1e-07
## , maxit = 200, trace = FALSE, mgcv.tol = 1e-07, mgcv.half = 15
## , rank.tol = 1.49011611938477e-08
## , nlm = list(ndigit=7, gradtol=1e-06, stepmax=2, steptol=1e-04, iterlim=200, check.analyticals=0)
## , optim = list(factr=1e+07)
## , newton = list(conv.tol=1e-06, maxNstep=5, maxSstep=2, maxHalf=30, use.svd=0)
## , outerPIsteps = 0, idLinksBases = TRUE, scalePenalty = TRUE
## , keepData = FALSE, scale.est = fletcher, edge.correct = FALSE) ),
##
##
## CTA = list( method = 'class',
               parms = 'default',
##
               cost = NULL,
               control = list(xval = 5, minbucket = 5, minsplit = 5
## , cp = 0.001, maxdepth = 25) ),
##
##
## ANN = list( NbCV = 5,
               size = NULL,
##
##
               decay = NULL,
##
               rang = 0.1,
               maxit = 200),
##
##
## SRE = list( quant = 0.025),
## FDA = list( method = 'mars',
               add_args = NULL),
##
##
## MARS = list( type = 'simple',
                interaction.level = 0,
##
                myFormula = NULL,
##
                nk = NULL,
##
                penalty = 2,
                thresh = 0.001,
##
##
                nprune = NULL,
##
                pmethod = 'backward'),
## RF = list( do.classif = TRUE,
              ntree = 500,
##
              mtry = 'default',
##
##
              nodesize = 5,
##
              maxnodes = NULL),
## MAXENT.Phillips = list( path_to_maxent.jar = 'W:/40_tools/Ecospat R Package/obroenni/ecospat/ecos
                  memory_allocated = 512,
                  background_data_dir = 'default',
##
                  maximumbackground = 'default',
##
##
                  maximumiterations = 200,
##
                  visible = FALSE,
##
                  linear = TRUE,
##
                  quadratic = TRUE,
##
                  product = TRUE,
```

```
##
                threshold = TRUE,
##
                hinge = TRUE,
##
                lq2lqptthreshold = 80,
##
                121qthreshold = 10,
##
                hingethreshold = 15,
##
                beta_threshold = -1,
               beta_categorical = -1,
##
##
                beta_lqp = -1,
##
                beta_hinge = -1,
##
                betamultiplier = 1,
##
                defaultprevalence = 0.5),
##
## MAXENT.Tsuruoka = list( l1_regularizer = 0,
                        12_regularizer = 0,
##
##
                        use_sgd = FALSE,
##
                        set_heldout = 0,
##
                        verbose = FALSE)
myBiomodOption@GLM$test = 'none'
myBiomodOption@GBM$interaction.depth = 2
### Calibration of simple bivariate models
my.ESM <- ecospat.ESM.Modeling( data=myBiomodData,</pre>
                            models=c('GLM','RF'),
                            models.options=myBiomodOption,
                            NbRunEval=1,
                            DataSplit=70,
                            weighting.score=c("AUC"),
                            parallel=F)
## Warning in dir.create(paste("./ESM.BIOMOD.output", data@sp.name, sep =
## "_")): '.\ESM.BIOMOD.output_species.occ' existe déjà
##
## > Automatic weights creation to rise a 0.5 prevalence
## Loading required library...
##
## Checking Models arguments...
## ! User defined data-split table was given -> NbRunEval, DataSplit and do.full.models argument wil
## Creating suitable Workdir...
##
## > Automatic weights creation to rise a 0.5 prevalence
##
##
## ----- ESM.BIOMOD.1 Modeling Summary ------
##
## 2 environmental variables ( aetpet gdd )
## Number of evaluation repetitions : 2
## Models selected : GLM RF
## Total number of model runs : 4
##
```

```
##
## -=-=- Run : ESM.BIOMOD.1_AllData
##
## -=-=- ESM.BIOMOD.1_AllData_RUN1
## Model=GLM ( quadratic with no interaction )
## No stepwise procedure
## ! You might be confronted to models convergence issues !
## selected formula : ESM.BIOMOD.1 ~ 1 + aetpet + I(aetpet^2) + gdd + I(gdd^2)
## <environment: 0x00000001b54e950>
##
## Model scaling...
## Evaluating Model stuff...
## Model=Breiman and Cutler's random forests for classification and regression
## Model scaling...
## Evaluating Model stuff...
##
## -=-=- ESM.BIOMOD.1_AllData_RUN2
## Model=GLM ( quadratic with no interaction )
## No stepwise procedure
## ! You might be confronted to models convergence issues !
## selected formula : ESM.BIOMOD.1 ~ 1 + aetpet + I(aetpet^2) + gdd + I(gdd^2)
## <environment: 0x0000000212623c0>
##
## Model scaling...
## Evaluating Model stuff...
## Model=Breiman and Cutler's random forests for classification and regression
## Model scaling...
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
##
## Evaluating Model stuff...
## ----- Done ----- Done -----
##
## Loading required library...
## Checking Models arguments...
##! User defined data-split table was given -> NbRunEval, DataSplit and do.full.models argument wil
## Creating suitable Workdir...
##
## > Automatic weights creation to rise a 0.5 prevalence
##
##
## ----- ESM.BIOMOD.2 Modeling Summary ------
## 2 environmental variables ( aetpet p )
## Number of evaluation repetitions : 2
## Models selected : GLM RF
## Total number of model runs : 4
##
```

```
##
## -=-=- Run : ESM.BIOMOD.2_AllData
##
## -=-=- ESM.BIOMOD.2_AllData_RUN1
## Model=GLM ( quadratic with no interaction )
## No stepwise procedure
## ! You might be confronted to models convergence issues !
## selected formula : ESM.BIOMOD.2 ~ 1 + aetpet + I(aetpet^2) + p + I(p^2)
## <environment: 0x000000021d89058>
##
## Model scaling...
## Evaluating Model stuff...
## Model=Breiman and Cutler's random forests for classification and regression
## Model scaling...
## Evaluating Model stuff...
##
## -=-=- ESM.BIOMOD.2_AllData_RUN2
## Model=GLM ( quadratic with no interaction )
## No stepwise procedure
## ! You might be confronted to models convergence issues !
## selected formula : ESM.BIOMOD.2 \sim 1 + aetpet + I(aetpet^2) + p + I(p^2)
## <environment: 0x000000021642388>
##
## Model scaling...
## Evaluating Model stuff...
## Model=Breiman and Cutler's random forests for classification and regression
## Model scaling...
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
##
## Evaluating Model stuff...
##
## Loading required library...
## Checking Models arguments...
##! User defined data-split table was given -> NbRunEval, DataSplit and do.full.models argument wil
## Creating suitable Workdir...
##
## > Automatic weights creation to rise a 0.5 prevalence
##
##
## ----- ESM.BIOMOD.3 Modeling Summary -------
## 2 environmental variables ( aetpet pet )
## Number of evaluation repetitions : 2
## Models selected : GLM RF
## Total number of model runs : 4
##
```

```
##
## -=-=- Run : ESM.BIOMOD.3_AllData
##
## -=-=- ESM.BIOMOD.3_AllData_RUN1
##
## Model=GLM ( quadratic with no interaction )
## No stepwise procedure
## ! You might be confronted to models convergence issues !
## selected formula : ESM.BIOMOD.3 ~ 1 + aetpet + I(aetpet^2) + pet + I(pet^2)
## <environment: 0x00000001e85b180>
##
## Model scaling...
## Evaluating Model stuff...
## Model=Breiman and Cutler's random forests for classification and regression
## Model scaling...
## Evaluating Model stuff...
##
## -=-=- ESM.BIOMOD.3_AllData_RUN2
## Model=GLM ( quadratic with no interaction )
## No stepwise procedure
## ! You might be confronted to models convergence issues !
## selected formula : ESM.BIOMOD.3 ~ 1 + aetpet + I(aetpet^2) + pet + I(pet^2)
## <environment: 0x000000021630a50>
##
## Model scaling...
## Evaluating Model stuff...
## Model=Breiman and Cutler's random forests for classification and regression
## Model scaling...
## Warning: glm.fit: algorithm did not converge
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
##
## Evaluating Model stuff...
## ----- Done ----- Done -----
##
##
## Loading required library...
## Checking Models arguments...
##! User defined data-split table was given -> NbRunEval, DataSplit and do.full.models argument wil
## Creating suitable Workdir...
##
## > Automatic weights creation to rise a 0.5 prevalence
##
##
## ----- ESM.BIOMOD.4 Modeling Summary ------
##
## 2 environmental variables ( aetpet stdp )
## Number of evaluation repetitions : 2
## Models selected : GLM RF
## Total number of model runs : 4
##
```

```
##
##
## -=-=- Run : ESM.BIOMOD.4_AllData
##
## -=-=- ESM.BIOMOD.4 AllData RUN1
## Model=GLM ( quadratic with no interaction )
## No stepwise procedure
## ! You might be confronted to models convergence issues !
## selected formula : ESM.BIOMOD.4 ~ 1 + aetpet + I(aetpet^2) + stdp + I(stdp^2)
## <environment: 0x00000001cf34938>
##
## Model scaling...
## Evaluating Model stuff...
## Model=Breiman and Cutler's random forests for classification and regression
## Model scaling...
## Evaluating Model stuff...
## -=-=- ESM.BIOMOD.4_AllData_RUN2
##
## Model=GLM ( quadratic with no interaction )
## No stepwise procedure
## ! You might be confronted to models convergence issues !
## selected formula : ESM.BIOMOD.4 ~ 1 + aetpet + I(aetpet^2) + stdp + I(stdp^2)
## <environment: 0x000000021aa3e48>
##
## Model scaling...
## Evaluating Model stuff...
## Model=Breiman and Cutler's random forests for classification and regression
## Model scaling...
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
##
## Evaluating Model stuff...
## ----- Done ----- Done -----
##
##
## Loading required library...
## Checking Models arguments...
##! User defined data-split table was given -> NbRunEval, DataSplit and do.full.models argument wil
## Creating suitable Workdir...
##
## > Automatic weights creation to rise a 0.5 prevalence
##
##
## ----- ESM.BIOMOD.5 Modeling Summary ------
##
## 2 environmental variables ( gdd p )
## Number of evaluation repetitions : 2
## Models selected : GLM RF
## Total number of model runs : 4
```

```
##
##
## -=-=- Run : ESM.BIOMOD.5_AllData
##
## -=-=- ESM.BIOMOD.5 AllData RUN1
## Model=GLM ( quadratic with no interaction )
## No stepwise procedure
## ! You might be confronted to models convergence issues !
## selected formula : ESM.BIOMOD.5 \sim 1 + gdd + I(gdd^2) + p + I(p^2)
## <environment: 0x00000001faf0a50>
##
## Model scaling...
## Evaluating Model stuff...
## Model=Breiman and Cutler's random forests for classification and regression
## Model scaling...
## Evaluating Model stuff...
## -=-=- ESM.BIOMOD.5_AllData_RUN2
##
## Model=GLM ( quadratic with no interaction )
## No stepwise procedure
## ! You might be confronted to models convergence issues !
## selected formula : ESM.BIOMOD.5 \sim 1 + gdd + I(gdd^2) + p + I(p^2)
## <environment: 0x00000002161b8c0>
##
## Model scaling...
## Evaluating Model stuff...
## Model=Breiman and Cutler's random forests for classification and regression
## Model scaling...
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
##
## Evaluating Model stuff...
## ----- Done ----- Done -----
##
##
## Loading required library...
## Checking Models arguments...
##! User defined data-split table was given -> NbRunEval, DataSplit and do.full.models argument wil
## Creating suitable Workdir...
##
## > Automatic weights creation to rise a 0.5 prevalence
##
##
## ----- ESM.BIOMOD.6 Modeling Summary ------
##
## 2 environmental variables ( gdd pet )
## Number of evaluation repetitions : 2
## Models selected : GLM RF
## Total number of model runs : 4
```

```
##
##
## -=-=- Run : ESM.BIOMOD.6_AllData
##
## -=-=- ESM.BIOMOD.6_AllData_RUN1
## Model=GLM ( quadratic with no interaction )
## No stepwise procedure
## ! You might be confronted to models convergence issues !
## selected formula : ESM.BIOMOD.6 ~ 1 + gdd + I(gdd^2) + pet + I(pet^2)
## <environment: 0x00000001cb956d0>
##
## Model scaling...
## Evaluating Model stuff...
## Model=Breiman and Cutler's random forests for classification and regression
## Model scaling...
## Evaluating Model stuff...
## -=-=- ESM.BIOMOD.6_AllData_RUN2
##
## Model=GLM ( quadratic with no interaction )
## No stepwise procedure
## ! You might be confronted to models convergence issues !
## selected formula : ESM.BIOMOD.6 ~ 1 + gdd + I(gdd^2) + pet + I(pet^2)
## <environment: 0x00000001cf1c6e8>
##
## Model scaling...
## Evaluating Model stuff...
## Model=Breiman and Cutler's random forests for classification and regression
## Model scaling...
## Warning: glm.fit: algorithm did not converge
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
##
## Evaluating Model stuff...
##
## Loading required library...
##
## Checking Models arguments...
##! User defined data-split table was given -> NbRunEval, DataSplit and do.full.models argument wil
## Creating suitable Workdir...
##
## > Automatic weights creation to rise a 0.5 prevalence
##
## ----- ESM.BIOMOD.7 Modeling Summary ------
##
## 2 environmental variables ( gdd stdp )
## Number of evaluation repetitions : 2
## Models selected : GLM RF
```

```
## Total number of model runs : 4
##
## -=-=- Run : ESM.BIOMOD.7_AllData
## -=-=- ESM.BIOMOD.7 AllData RUN1
##
## Model=GLM ( quadratic with no interaction )
## No stepwise procedure
## ! You might be confronted to models convergence issues !
## selected formula : ESM.BIOMOD.7 ~ 1 + gdd + I(gdd^2) + stdp + I(stdp^2)
## <environment: 0x00000002156b1d8>
## Model scaling...
## Evaluating Model stuff...
## Model=Breiman and Cutler's random forests for classification and regression
## Model scaling...
## Evaluating Model stuff...
##
## -=-=- ESM.BIOMOD.7_AllData_RUN2
## Model=GLM ( quadratic with no interaction )
## No stepwise procedure
## ! You might be confronted to models convergence issues !
## selected formula : ESM.BIOMOD.7 ~ 1 + gdd + I(gdd^2) + stdp + I(stdp^2)
## <environment: 0x00000002161b2a0>
##
## Model scaling...
## Evaluating Model stuff...
## Model=Breiman and Cutler's random forests for classification and regression
## Model scaling...
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
##
## Evaluating Model stuff...
## ----- Done ----- Done
##
## Loading required library...
##
## Checking Models arguments...
##! User defined data-split table was given -> NbRunEval, DataSplit and do.full.models argument wil
## Creating suitable Workdir...
##
## > Automatic weights creation to rise a 0.5 prevalence
##
##
## ----- ESM.BIOMOD.8 Modeling Summary ------
##
## 2 environmental variables ( p pet )
## Number of evaluation repetitions : 2
## Models selected : GLM RF
```

```
## Total number of model runs : 4
##
## -=-=- Run : ESM.BIOMOD.8_AllData
## -=-=- ESM.BIOMOD.8 AllData RUN1
##
## Model=GLM ( quadratic with no interaction )
## No stepwise procedure
## ! You might be confronted to models convergence issues !
## selected formula : ESM.BIOMOD.8 ~ 1 + p + I(p^2) + pet + I(pet^2)
## <environment: 0x00000001faae810>
## Model scaling...
## Evaluating Model stuff...
## Model=Breiman and Cutler's random forests for classification and regression
## Model scaling...
## Evaluating Model stuff...
##
## -=-=- ESM.BIOMOD.8_AllData_RUN2
## Model=GLM ( quadratic with no interaction )
## No stepwise procedure
## ! You might be confronted to models convergence issues !
## selected formula : ESM.BIOMOD.8 ~ 1 + p + I(p^2) + pet + I(pet^2)
## <environment: 0x000000021631508>
##
## Model scaling...
## Evaluating Model stuff...
## Model=Breiman and Cutler's random forests for classification and regression
## Model scaling...
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
##
## Evaluating Model stuff...
## ----- Done ----- Done
##
## Loading required library...
##
## Checking Models arguments...
##! User defined data-split table was given -> NbRunEval, DataSplit and do.full.models argument wil
## Creating suitable Workdir...
##
## > Automatic weights creation to rise a 0.5 prevalence
##
##
## ----- ESM.BIOMOD.9 Modeling Summary ------ ESM.BIOMOD.9
##
## 2 environmental variables ( p stdp )
## Number of evaluation repetitions : 2
## Models selected : GLM RF
##
```

```
## Total number of model runs : 4
##
##
## -=-=- Run : ESM.BIOMOD.9_AllData
## -=-=- ESM.BIOMOD.9_AllData_RUN1
##
## Model=GLM ( quadratic with no interaction )
## No stepwise procedure
## ! You might be confronted to models convergence issues !
## selected formula : ESM.BIOMOD.9 ~ 1 + p + I(p^2) + stdp + I(stdp^2)
## <environment: 0x000000021239fd0>
## Model scaling...
## Evaluating Model stuff...
## Model=Breiman and Cutler's random forests for classification and regression
## Model scaling...
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
##
## Evaluating Model stuff...
##
## -=-=- ESM.BIOMOD.9_AllData_RUN2
## Model=GLM ( quadratic with no interaction )
## No stepwise procedure
## ! You might be confronted to models convergence issues !
## selected formula : ESM.BIOMOD.9 \sim 1 + p + I(p^2) + stdp + I(stdp^2)
## <environment: 0x000000024946608>
##
## Model scaling...
## Evaluating Model stuff...
## Model=Breiman and Cutler's random forests for classification and regression
## Model scaling...
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
##
## Evaluating Model stuff...
## ----- Done ----- Done -----
##
##
## Loading required library...
## Checking Models arguments...
##
##! User defined data-split table was given -> NbRunEval, DataSplit and do.full.models argument wil
## Creating suitable Workdir...
##
## > Automatic weights creation to rise a 0.5 prevalence
##
## ----- ESM.BIOMOD.10 Modeling Summary ------
```

```
##
## 2 environmental variables ( pet stdp )
## Number of evaluation repetitions : 2
## Models selected : GLM RF
## Total number of model runs : 4
##
##
## -=-=- Run : ESM.BIOMOD.10_AllData
##
##
## -=-=- ESM.BIOMOD.10_AllData_RUN1
##
## Model=GLM ( quadratic with no interaction )
## No stepwise procedure
## ! You might be confronted to models convergence issues !
## selected formula : ESM.BIOMOD.10 ~ 1 + pet + I(pet^2) + stdp + I(stdp^2)
## <environment: 0x00000001fab1e98>
##
## Model scaling...
## Evaluating Model stuff...
## Model=Breiman and Cutler's random forests for classification and regression
## Model scaling...
## Evaluating Model stuff...
##
## -=-=-ESM.BIOMOD.10 AllData RUN2
##
## Model=GLM ( quadratic with no interaction )
## No stepwise procedure
## ! You might be confronted to models convergence issues !
## selected formula : ESM.BIOMOD.10 ~ 1 + pet + I(pet^2) + stdp + I(stdp^2)
## <environment: 0x000000021653ef0>
## Model scaling...
## Evaluating Model stuff...
## Model=Breiman and Cutler's random forests for classification and regression
## Model scaling...
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
##
## Evaluating Model stuff...
## ----- Done ----- Done -----
### 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)
##
## -----= Do Models Projections ------
```

! 'do.stack' arg is always set as TRUE for data.frame/matrix dataset

```
## > Projecting ESM.BIOMOD.1_AllData_RUN2_GLM ...
## > Projecting ESM.BIOMOD.1_AllData_RUN2_RF ...
## ----- Done ----- Done -----
## ----- Do Models Projections ------
##
##
     ! 'do.stack' arg is always set as TRUE for data.frame/matrix dataset
  > Projecting ESM.BIOMOD.2 AllData RUN2 GLM ...
  > Projecting ESM.BIOMOD.2_AllData_RUN2_RF ...
## ----- Done -----
##
##
     ! 'do.stack' arg is always set as TRUE for data.frame/matrix dataset
##
## > Projecting ESM.BIOMOD.3_AllData_RUN2_GLM ...
  > Projecting ESM.BIOMOD.3_AllData_RUN2_RF ...
## ------ Done ----- Done -----
##
## ----- Do Models Projections -------
##
     ! 'do.stack' arg is always set as TRUE for data.frame/matrix dataset
## > Projecting ESM.BIOMOD.4_AllData_RUN2_GLM ...
  > Projecting ESM.BIOMOD.4_AllData_RUN2_RF ...
## ----- Done ----- Done -----
##
## ------ Do Models Projections -------
##
     ! 'do.stack' arg is always set as TRUE for data.frame/matrix dataset
  > Projecting ESM.BIOMOD.5_AllData_RUN2_GLM ...
  > Projecting ESM.BIOMOD.5_AllData_RUN2_RF ...
  ##
     ! 'do.stack' arg is always set as TRUE for data.frame/matrix dataset
## > Projecting ESM.BIOMOD.6_AllData_RUN2_GLM ...
## > Projecting ESM.BIOMOD.6_AllData_RUN2_RF ...
## ------ Done ----- Done -----
##
##
     ! 'do.stack' arg is always set as TRUE for data.frame/matrix dataset
## > Projecting ESM.BIOMOD.7_AllData_RUN2_GLM ...
  > Projecting ESM.BIOMOD.7_AllData_RUN2_RF ...
##
## ----- Do Models Projections ------
##
     ! 'do.stack' arg is always set as TRUE for data.frame/matrix dataset
 > Projecting ESM.BIOMOD.8_AllData_RUN2_GLM ...
  > Projecting ESM.BIOMOD.8_AllData_RUN2_RF ...
## ------ Done ----- Done -----
  ------ Do Models Projections ------
##
##
     ! 'do.stack' arg is always set as TRUE for data.frame/matrix dataset
## > Projecting ESM.BIOMOD.9_AllData_RUN2_GLM ...
## > Projecting ESM.BIOMOD.9_AllData_RUN2_RF ...
```

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]</pre>
```

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))</pre>
```

3.4 SESAM framework with ecospat.SESAM.prr()

```
#ecospat.SESAM.prr(proba, sr)
```

4 Post-Modelling

4.1 Spatial Predictions of species assamblages

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

```
nbpermut <- 100
```

Define the outpath

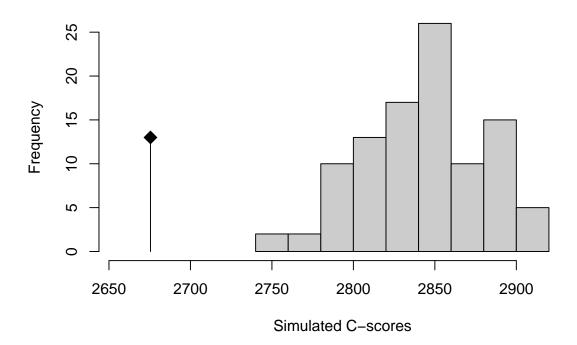
```
outpath <- getwd()</pre>
```

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.

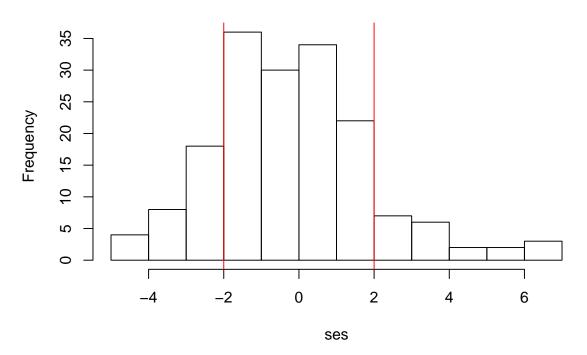
ecospat.cons_Cscore(presence, pred, nbpermut, outpath)

```
## Computing observed co-occurence matrix
## ......
## .....
## Computing permutations
## .....
## .....
## .....
```



```
## Permutations finished Wed Jun 13 15:41:01 2018
## ......
## Exporting dataset
## .....
## .....
```

Histogram of standardized effect size



```
## $0bsCscoreTot
## [1] 2675.468
##
## $SimCscoreTot
## [1] 2842.198
##
## $PVal.less
## [1] 0.00990099
##
## $PVal.greater
## [1] 1
##
## $SES.Tot
## [1] -4.609203
```

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 dominate 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).