

Tutorial for Bioregionalization R package

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`virtual_sp` is a dataset simulated that comes with the package. This dataset relies on the response curve of virtual species to a virtual raster. The virtual raster contains 10000 cells and was simulated using `gstat` R package. See here for details.

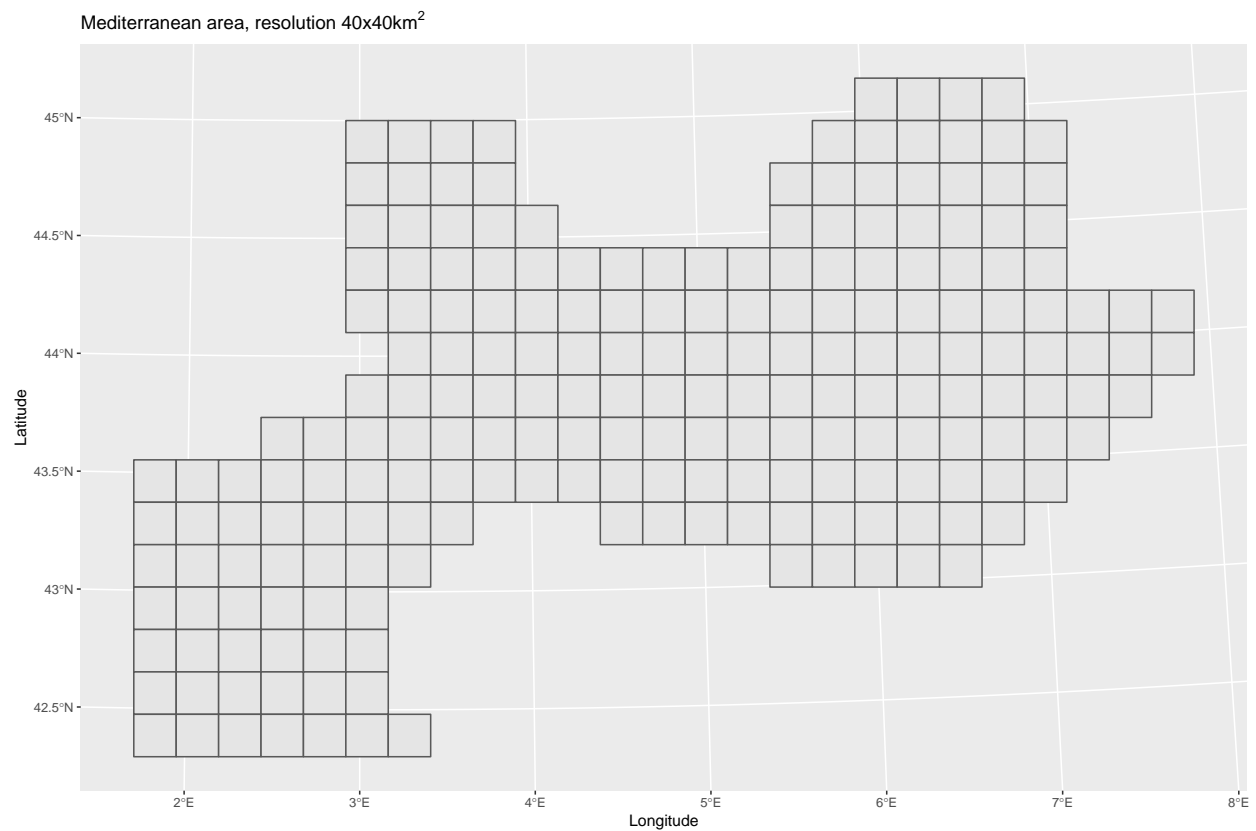
Based on this layer, the `virtualspecies` R package (Leroy et al. 2015) was used to simulate the response curve of 100 virtual species. A Gaussian curve was used. The mean and standard deviation of the response function was varying among species, such as some of them are more or less generalists/specialists.

For every species in every cell, we could derive a suitability index. Species with suitability index inferior to 0.15 were arbitrarily set absent.

```
# Import Mediterranean dataset
data("medit")
# Import virtual dataset
# data("virtual_sp")

# Plot of environmental values
# sp_df %>%
#   distinct(site, .keep_all = TRUE) %>%
#   ggplot(aes(x, y)) +
#   geom_tile(aes(fill = env, color = env),
#             alpha = 0.8, width = 1, height = 1) +
#   scale_color_distiller("Value", palette = "OrRd") +
#   scale_fill_distiller("Value", palette = "OrRd") +
#   coord_equal() +
#   labs(title = "Environmental variable") +
#   theme(panel.background = element_rect(fill = "transparent", colour = NA))

# Plot of Mediterranean area
medit[[2]] %>%
  ggplot() +
  geom_sf() +
  labs(title = expression("Mediterranean area, resolution 40x40km"^2),
       x = "Longitude", y = "Latitude")
```



```
sp_df <- medit[[1]] %>%
  rename(site = id) %>%
  mutate(site = as.character(site),
         sp = as.character(sp))

colnames(medit[[2]]) <- c("site", "geometry")
medit[[2]]$site <- as.character(medit[[2]]$site)
colnames(medit[[2]]) <- c("site", "geometry")
```

The first step is to convert the data.frame into a contingency table.

```
#sp_mat <- contingency(sp_df, "site", "sp", "pa", binary = TRUE)
sp_mat <- contingency(sp_df, "site", "sp", ab = NULL, binary = TRUE)
knitr::kable(sp_mat[1:5, 1:5])
```

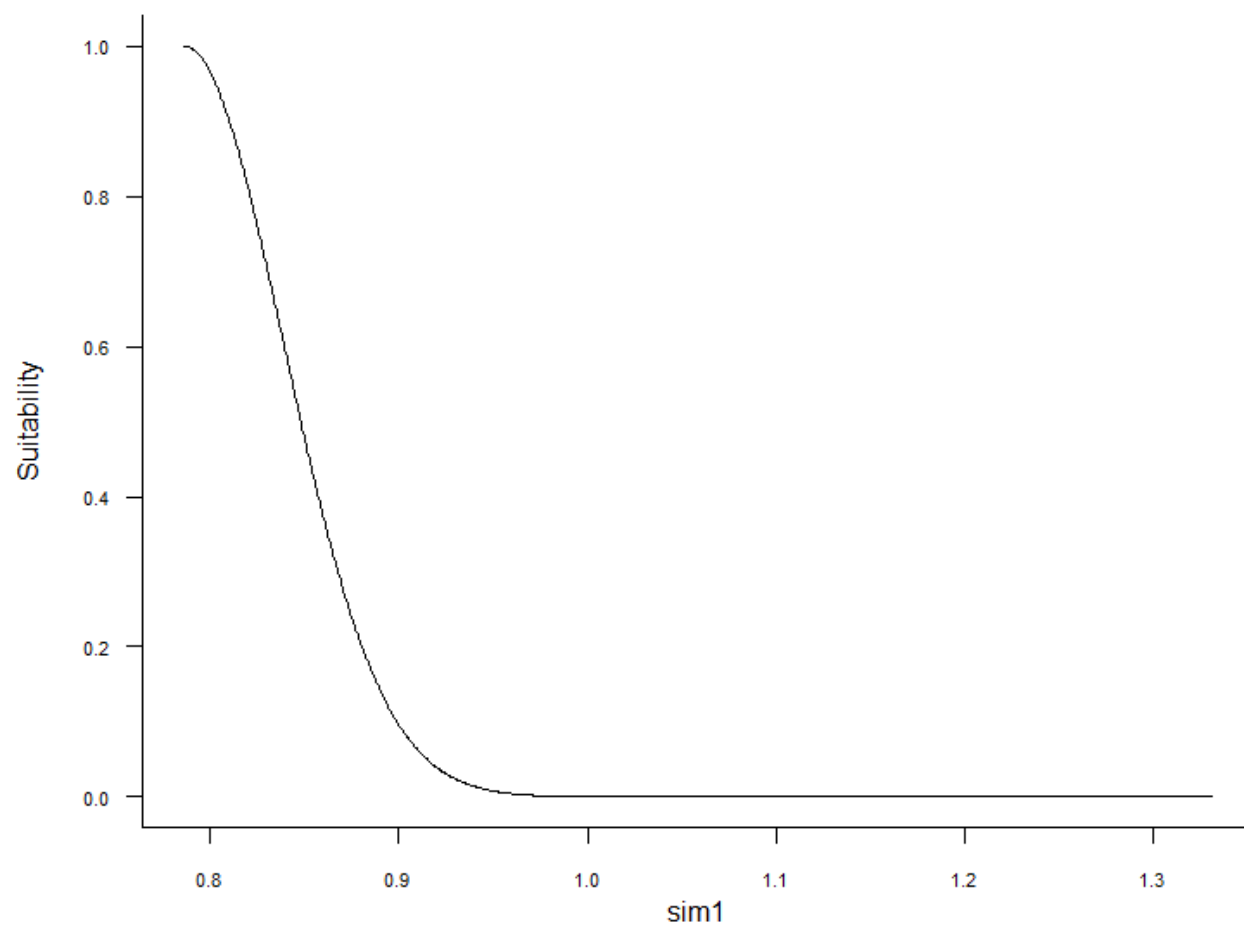


Figure 1: Example of response curve for one virtual species.

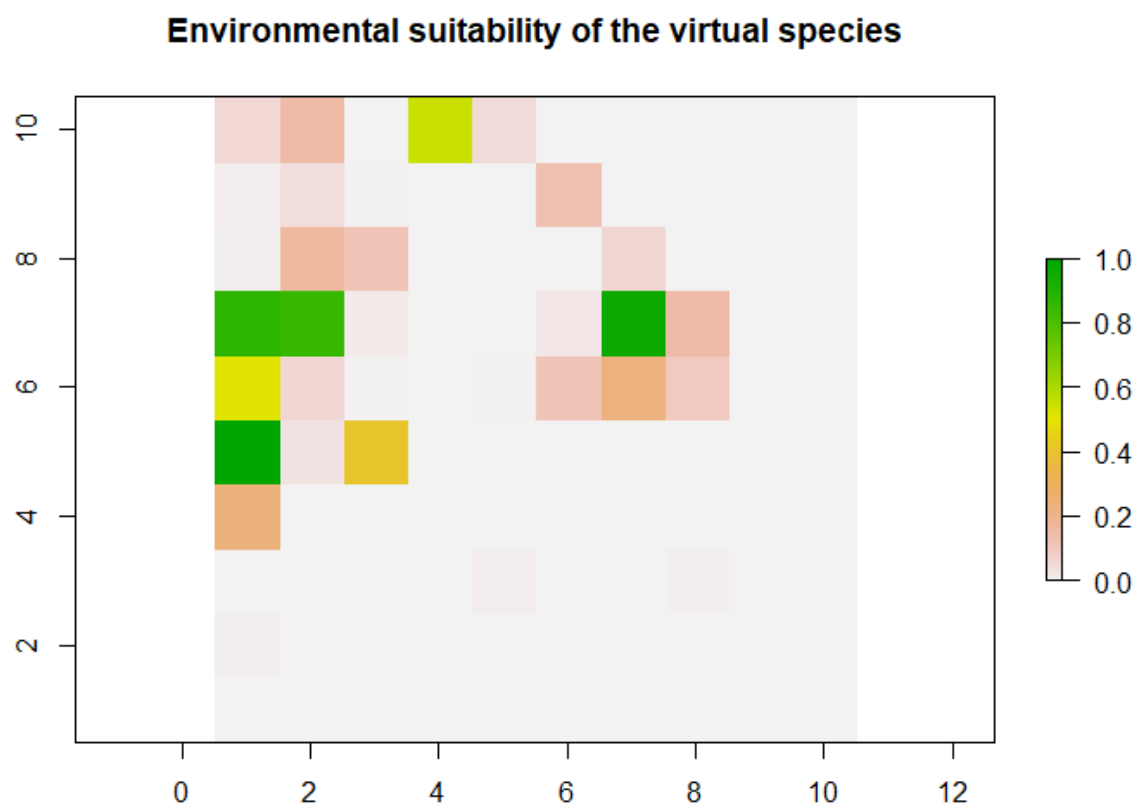


Figure 2: Example of suitability map for one virtual species.

	100787	101188	103246	103316	103375
1030.23076923077	0	0	0	0	0
1113	0	0	0	0	0
1117	0	0	0	0	0
1119.5	0	0	0	0	0
1119.85714285714	0	0	0	0	0

We then need to project the network.

```
sp_proj <- project_network(sp_mat, similarity = "simpson")
sp_proj <- sp_proj[, c("id1", "id2", "simpson")]
knitr::kable(head(sp_proj))
```

id1	id2	simpson
2	3	1
2	4	1
3	4	1
7	8	1
12	13	1
14	18	1

Running OSLOM.

```
run_oslom(sp_proj, n_runs = 5, t_param = 0.1, cp_param = 0.5,
          saving_directory = "D:/PIERRE_DENELLE/CarHab/Bioregionalization_extra/")
```

Converting the OSLOM .tp file into a list.

```
#res <- readLines("../OSLOM2/vignette.txt_oslo_files/tp")
res <- readRDS("../Bioregionalization_extra/tp.rds")
oslom_vignette <- oslom_output(res, sp_mat)

print(paste0("Number of bioregions detected = ",
             length(unique(oslom_vignette$bioregion))))
```

```
## [1] "Number of bioregions detected = 24"
```

Step 3 of Figure 1 (see Lenormand et al. (2019))

$$\rho_{ij} = \frac{n_{ij} - \frac{n_i n_j}{n}}{\sqrt{(\frac{n-n_j}{n-1})(1 - \frac{n_j}{n})\frac{n_j n_i}{n}}}$$

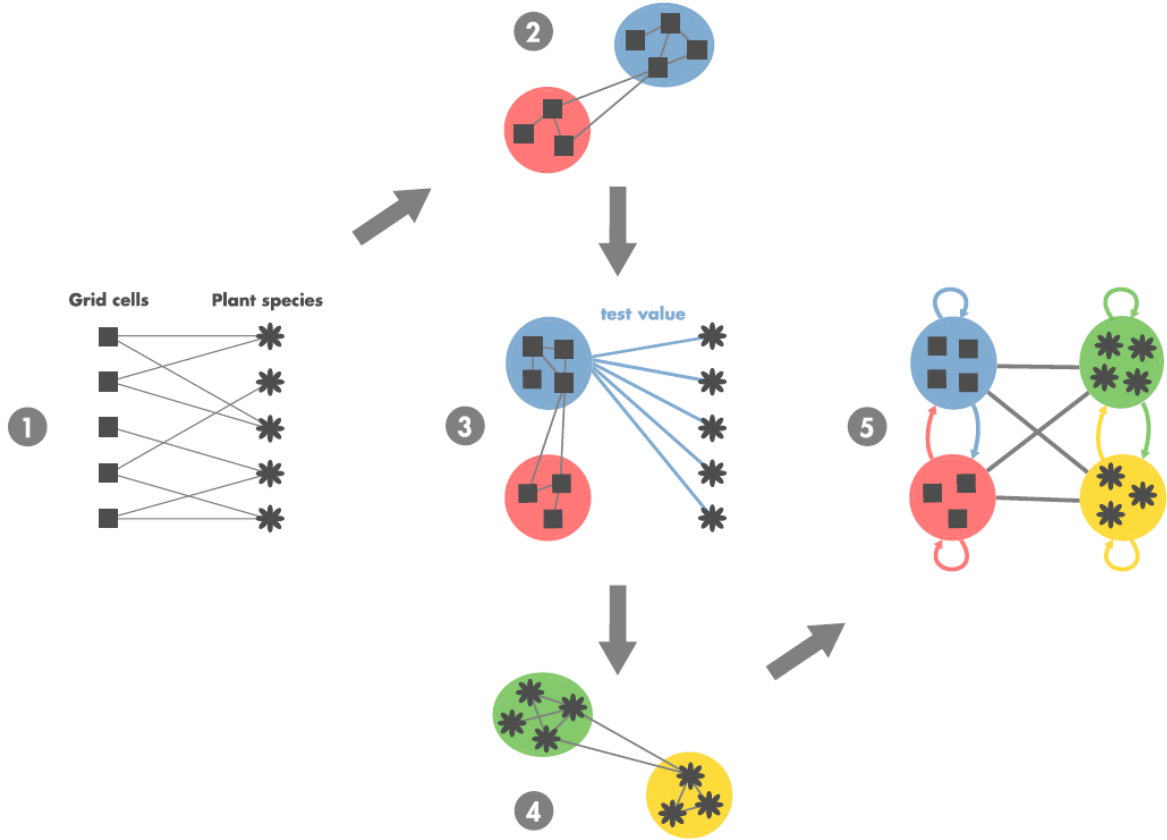


Figure 3: Steps of the biogeographical network analysis. 1. Biogeographical bipartite network where grid cells and species are linked by the presence of a species (or a group of species) in a given grid cell during a certain time window. Note that there is no link between nodes belonging to the same set. 2. The bipartite network is then spatially projected by using a similarity measure of species composition between grid cells. Bioregions are then identified with a network community detection algorithm. 3. The test value matrix based on the contribution of species to bioregions is computed. 4. Then, a network of similarity between species is built, based on the test value matrix. Groups of species sharing similar spatial features are identified using a community detection algorithm. 5. Finally, a coarse-grained biogeographical network unveiling the biogeographical structure of the studied area and the relationship between bioregions is obtained.

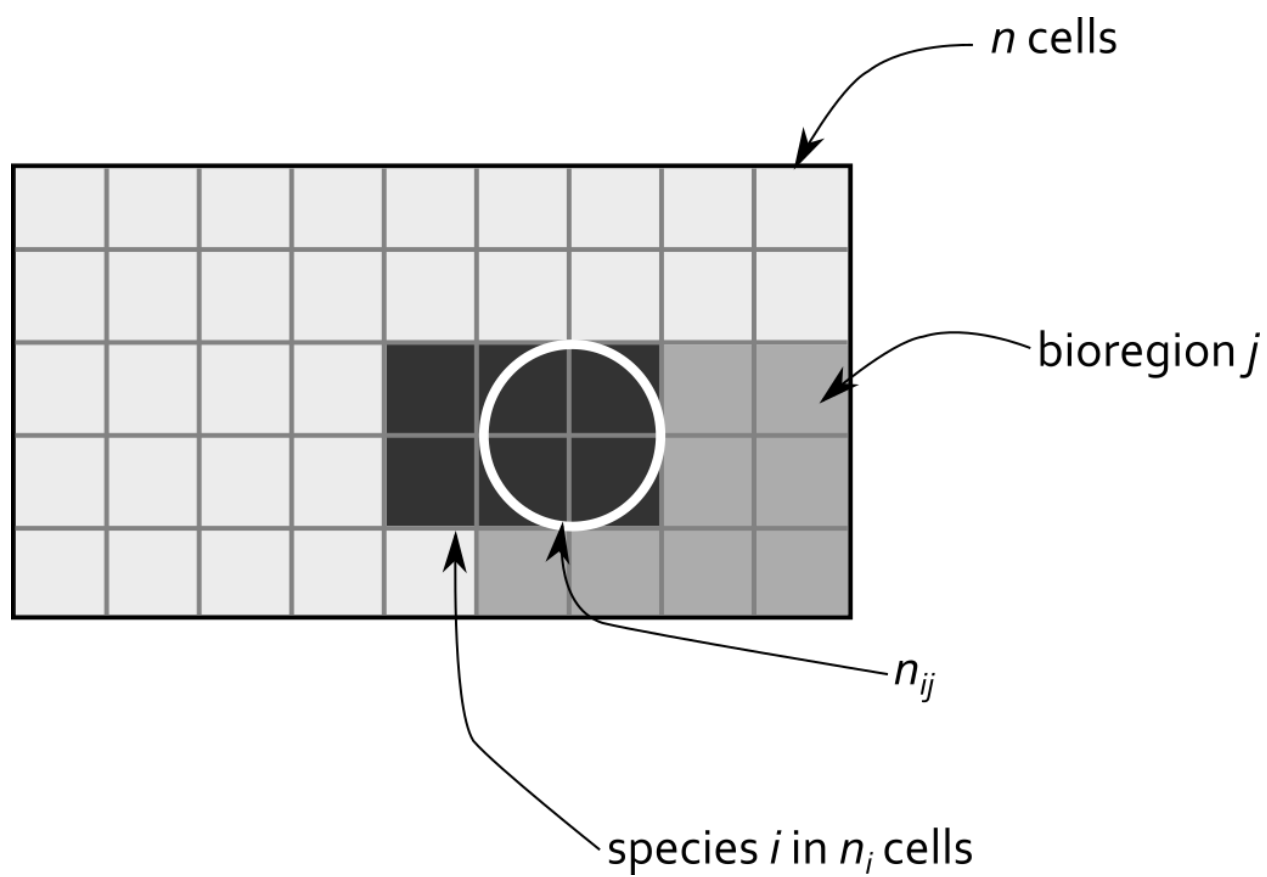


Figure 4: Principle of the zscore calculation.

```

# tmp <- left_join(sp_df, oslom_vignette, by = "site")
tmp <- left_join(sp_df, oslom_vignette, by = "site")
z_scores <- zscore(tmp, sp_col = "sp", site_col = "site",
                  bioregion_col = "bioregion")

top10 <- z_scores %>%
  group_by(bioregion) %>%
  top_n(n = 10, zscore) %>% # extract top 10
  mutate(rank = rank(-zscore, # ranking zscore in an ascending order
                    ties.method = "first")) %>% # if tie zscore, first species
  dplyr::select(sp, bioregion, zscore, rank) %>%
  mutate(zscore = round(zscore, 1)) %>% # rounding zscore to 1 digit
  as.data.frame()

knitr::kable(top10[which(top10$bioregion == "2"), ])

```

	sp	bioregion	zscore	rank
67	84264	2	41.8	1
68	84472	2	14.5	2

Interaction plots.

```

ex_lambda <- lambda(dat = z_scores, sp_col = "sp", zscore_col = "zscore",
                  bioregion_col = "bioregion",
                  criterion = "top10", plot = TRUE)

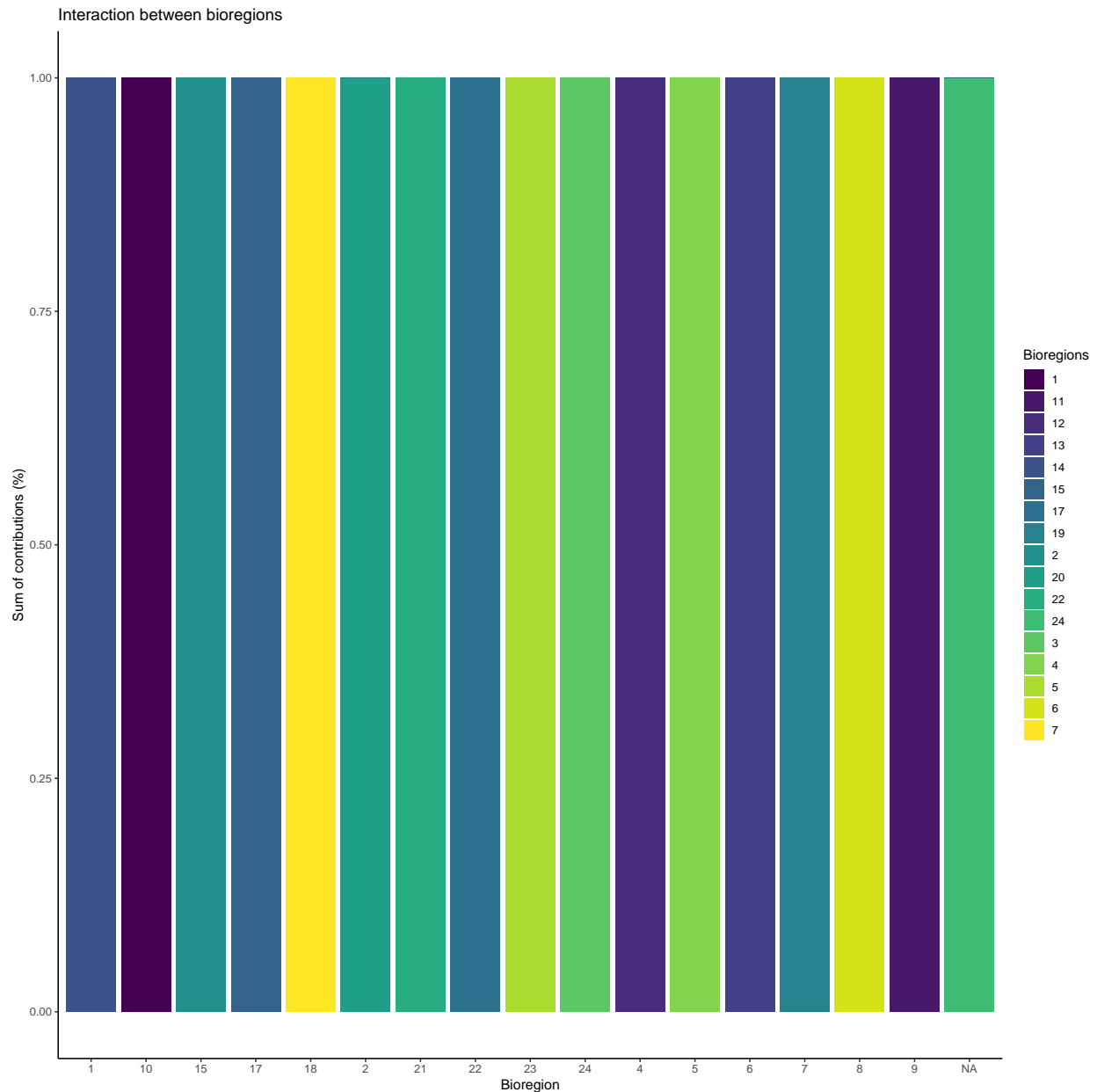
ex_lambda

```

```

## [[1]]
##   focal_bioregion bioregion sum_rho
## 1             21         22      1
## 2             22         17      1
## 3             23          5      1
## 4             17         15      1
## 5             <NA>        17      0
## 6             <NA>        24      1
## 7              5          4      1
## 8             18          7      1
## 9              8          6      1
## 10            15          2      1
## 11            10          1      1
## 12            24          3      1
## 13             9         11      1
## 14             4         12      1
## 15             7         19      1
## 16             6         13      1
## 17             2         20      1
## 18             2         19      0
## 19             1         14      1
##
## [[2]]

```

Example with Ward analysis and k-means clustering.

```
# CA_res <- CA_cluster(sp_mat)
ward_res <- ward_cluster(sp_mat)
```

Bipartite algorithms applied on example dataset.

```
# With fastgreedy
bip <- algo_bipartite(dat = sp_mat, algo = "greedy", weight = FALSE)

# With Beckett algorithm
bip2 <- algo_bipartite(dat = sp_mat, algo = "LPAwb", weight = FALSE)

# Only sites
```

```

bip_site <- bip %>%
  filter(cat == "site") %>%
  rename(site = node) %>%
  dplyr::select(site, module)

bip_site2 <- bip2 %>%
  filter(cat == "site") %>%
  rename(site = node) %>%
  dplyr::select(site, module)

```

Cz computation on bipartite results.

```

bip_cz <- bip[, c("node", "module", "cat")]
colnames(bip_cz) <- c("node", "mod", "cat")

link_cz <- sp_df[, c("site", "sp")] %>%
  left_join(bip_cz[which(bip_cz$cat == "site"), c("node", "mod")],
    by = c("site" = "node")) %>%
  rename(mod_site = mod) %>%
  left_join(bip_cz[which(bip_cz$cat == "sp"), c("node", "mod")],
    by = c("sp" = "node")) %>%
  rename(mod_sp = mod)

cz_bip <- cz(link_dat = link_cz, dat = bip_cz, ab = NULL)

head(cz_bip[[1]])

```

```

##      node mod  cat C n_link_mod mean_link_mod sd_link_mod      z
## 1    1113  1 site 0      10      9.565217    10.2373 0.04247043
## 2    1117  1 site 0      10      9.565217    10.2373 0.04247043
## 3   1119.5  1 site 0      10      9.565217    10.2373 0.04247043
## 4    1157  1 site 0      10      9.565217    10.2373 0.04247043
## 5  1340.75  1 site 0      10      9.565217    10.2373 0.04247043
## 6  1434.75  1 site 0      10      9.565217    10.2373 0.04247043

```

Projection on a map.

```

color_vector <- c(brewer.pal(12, "Paired"), brewer.pal(12, "Set3"))
getPalette <- colorRampPalette(brewer.pal(9, "Set1"))

plot_grid(
  # Plot of Mediterreanean region
  medit[[2]] %>%
    ggplot() +
    geom_sf() +
    labs(title = expression("Mediterranean area, resolution 20x20km"^2),
      x = "Longitude", y = "Latitude"),
  # Plot of OSLOM bioregions
  sp_df %>%
    left_join(oslom_vignette, by = "site") %>%
    distinct(site, .keep_all = TRUE) %>%
    left_join(medit[[2]], by = "site") %>%

```

```

st_as_sf() %>%
group_by(bioregion) %>%
summarise() %>%
ggplot() +
geom_sf(aes(fill = as.factor(bioregion)), color = "black", alpha = 0.8) +
scale_fill_manual("Bioregions",
                  values = getPalette(length(unique(oslom_vignette$bioregion)))) +
labs(title = "OSLOM bioregions", x = "Longitude", y = "Latitude"),

# Plot of Ward bioregions
sp_df %>%
left_join(ward_res, by = "site") %>%
distinct(site, .keep_all = TRUE) %>%
left_join(medit[[2]], by = "site") %>%
st_as_sf() %>%
group_by(cluster) %>%
summarise() %>%
ggplot() +
geom_sf(aes(fill = as.factor(cluster)), color = "black", alpha = 0.8) +
scale_fill_manual("Bioregions",
                  values = getPalette(length(unique(ward_res$cluster)))) +
labs(title = "Ward bioregions", x = "Longitude", y = "Latitude"),

# Plot of fastgreedy bioregions
sp_df %>%
left_join(bip_site, by = "site") %>%
distinct(site, .keep_all = TRUE) %>%
left_join(medit[[2]], by = "site") %>%
st_as_sf() %>%
group_by(module) %>%
summarise() %>%
ggplot() +
geom_sf(aes(fill = as.factor(module)), color = "black", alpha = 0.8) +
scale_fill_manual("Bioregions",
                  values = getPalette(length(unique(bip_site$module)))) +
labs(title = "Fastgreedy bioregions", x = "Longitude", y = "Latitude"),

# Plot of LPAwb bioregions
sp_df %>%
left_join(bip_site2, by = "site") %>%
distinct(site, .keep_all = TRUE) %>%
left_join(medit[[2]], by = "site") %>%
st_as_sf() %>%
group_by(module) %>%
summarise() %>%
ggplot() +
geom_sf(aes(fill = as.factor(module)), color = "black", alpha = 0.8) +
scale_fill_manual("Bioregions",
                  values = getPalette(length(unique(bip_site2$module)))) +
labs(title = "LPAwb bioregions", x = "Longitude", y = "Latitude"),
nrow = 2)

```

