## Analyses & results

## GCFR vs SWAFR manuscript

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```
# General programming
library(tidyverse)
library(here) # for more reliable file paths
library(glue) # better than paste()
library(magrittr) # for %<>% & %$%
# GIS
library(raster)
library(rgdal)
# Analyses
library(canprot) # for CLES
library(broom) # to tidy model outputs
# Figures
library(cowplot) # for panelling
library(ggfortify) # for autoplot() of PCAs
# Environmental variable names in nice order
var_names <- c(</pre>
  "Elevation",
  "MAP",
  "PDQ",
  "Surface T",
  "NDVI",
  "CEC",
  "Clay",
  "Soil C",
  "Hq"
# Preserve clean plotting environment
op <- par()
# Global ggplot2 theme settings
theme_set(theme_bw() + theme(
  strip.background = element_blank(),
  panel.grid = element_blank()
))
```

## 1. Comparing environmental heterogeneity

```
data_dir <- here("data/derived-data/May-2019")
GCFR_file_names <- glue("{data_dir}/GCFR_{var_names}_masked2.tif")
SWAFR_file_names <- glue("{data_dir}/SWAFR_{var_names}_masked2.tif")
GCFR_variables <- stack(GCFR_file_names)
SWAFR_variables <- stack(SWAFR_file_names)
names(GCFR_variables) <- str_replace_all(var_names, " ", "_")</pre>
```

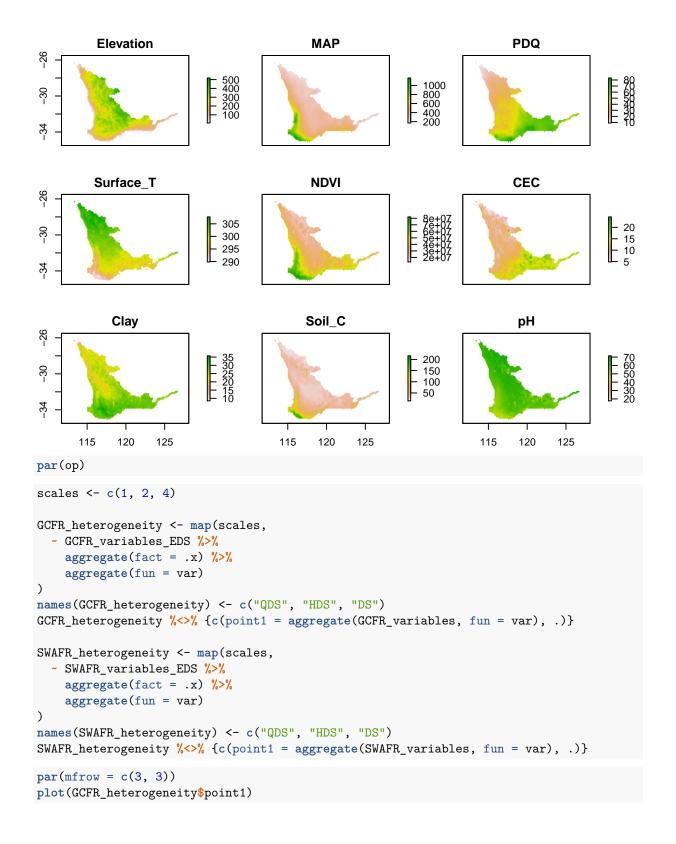
```
names(SWAFR_variables) <- str_replace_all(var_names, " ", "_")</pre>
GCFR_variables
               : RasterStack
## class
## dimensions: 140, 220, 30800, 9 (nrow, ncol, ncell, nlayers)
## resolution : 0.05, 0.05 (x, y)
## extent
              : 16.45, 27.45, -35.15, -28.15 (xmin, xmax, ymin, ymax)
               : +proj=longlat +datum=WGS84 +no_defs +ellps=WGS84 +towgs84=0,0,0
## crs
                                                       PDQ,
                                                                Surface_T,
## names
                    Elevation,
                                         MAP,
## min values: 6.366550e+00, 4.490771e+01, 3.845532e+00, 2.913266e+02, 6.709096e+06, 2.699161e+00,
## max values : 1.693627e+03, 9.445777e+02, 2.042740e+02, 3.123608e+02, 8.453450e+07, 2.350940e+01,
SWAFR variables
## class
               : RasterStack
## dimensions : 200, 280, 56000, 9 (nrow, ncol, ncell, nlayers)
## resolution : 0.05, 0.05 (x, y)
              : 112.9, 126.9, -35.5, -25.5 (xmin, xmax, ymin, ymax)
## extent
## crs
              : +proj=longlat +datum=WGS84 +no_defs +ellps=WGS84 +towgs84=0,0,0
                                                                     Surface_T,
## names
                     Elevation,
                                           MAP,
                                                           PDQ,
                                                                                          NDVI,
              :
## min values : 4.407049e-01, 1.677904e+02, 8.773942e+00, 2.892730e+02, -1.272565e+06,
                                                                                                 4.344898
## max values : 5.276772e+02, 1.212685e+03, 9.061172e+01,
                                                                 3.082984e+02, 8.391765e+07,
                                                                                                 3.031978
par(mfrow = c(3, 3))
plot(GCFR_variables)
         Elevation
                                         MAP
                                                                        PDQ
-29
                           1500
                                                        - 800
- 600
- 400
- 200
                                                                                       - 150
- 100
- 50
                          - 1000
- 500
                           1000
-32
-35
                                         NDVI
                                                                        CEC
        Surface_T
-29
                                                          8e+07
                           310
                                                                                       - 20
- 15
- 10
- 5
                                                          6e+07
-32
                                                          4e+07
                                                         2e+07
35
                                         Soil_C
           Clay
                                                                         pН
                         -32
      18 20 22 24 26
                                    18 20 22 24 26
                                                                   18 20 22 24 26
par(op)
par(mfrow = c(3, 3))
```

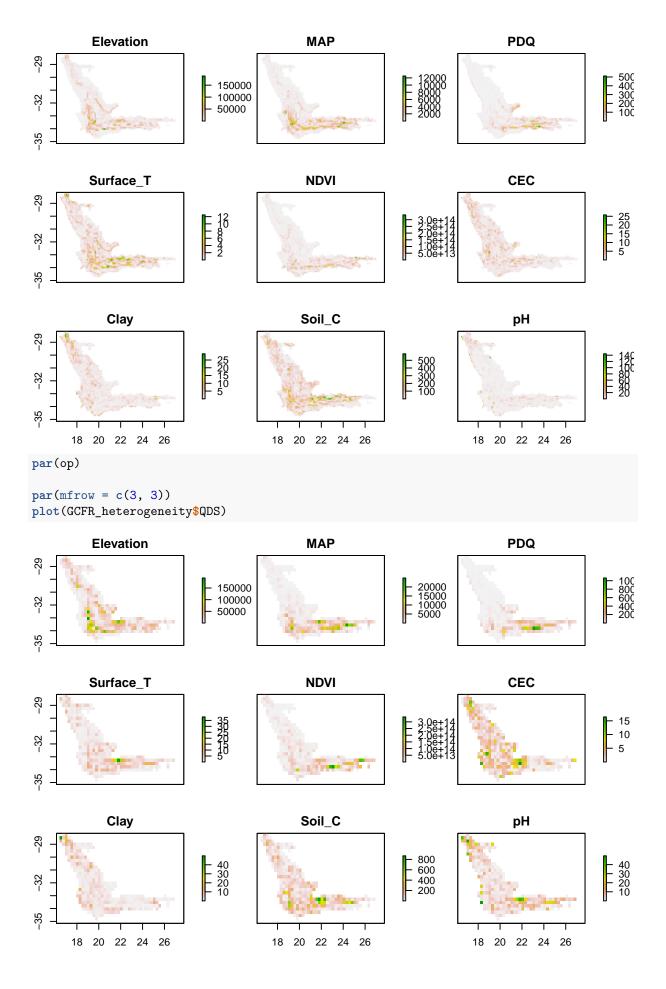
plot(SWAFR\_variables)

```
Elevation
                                          MAP
                                                                         PDQ
                                                                                        - 80
- 60
- 40
- 20
-30
-34
         Surface_T
                                          NDVI
                                                                          CEC
-26
                                                           8e+07
                            305
                          - 300
- 295
- 290
                                                           6e+07
-30
                                                           4e+07
                                                           2e+07
0e+00
-34
           Clay
                                         Soil_C
                                                                          pН
-26
                                                           200
150
100
50
-30
₹
            120
                  125
                                           120
                                                 125
      115
                                     115
                                                                    115
                                                                          120
                                                                                125
par(op)
EDS_template_raster <- GCFR_variables$Elevation %>%
  aggregate(fact = 5) %>% # aggregate up to QDS
  disaggregate(fact = 2) # disaggregate down to EDS
GCFR_variables_EDS <- resample(</pre>
  GCFR_variables, EDS_template_raster,
  method = "bilinear"
)
GCFR_variables_EDS
## class
               : RasterBrick
## dimensions : 56, 88, 4928, 9 (nrow, ncol, ncell, nlayers)
## resolution : 0.125, 0.125 (x, y)
              : 16.45, 27.45, -35.15, -28.15 (xmin, xmax, ymin, ymax)
## extent
## crs
               : +proj=longlat +datum=WGS84 +no_defs +ellps=WGS84 +towgs84=0,0,0
## source
               : memory
                                         MAP,
                                                         PDQ,
                                                                  Surface_T,
                                                                                      NDVI,
                                                                                                      CEC,
## names
                    Elevation,
## min values: 7.740328e+00, 6.333686e+01, 5.568253e+00, 2.926559e+02, 7.119721e+06, 3.109218e+00,
## max values: 1.611345e+03, 9.199011e+02, 1.921860e+02, 3.109162e+02, 8.301637e+07, 2.076085e+01,
EDS_template_raster <- SWAFR_variables$Elevation %>%
  aggregate(fact = 5) %>%
  disaggregate(fact = 2)
SWAFR_variables_EDS <- resample(</pre>
  SWAFR_variables, EDS_template_raster,
  method = "bilinear"
SWAFR_variables_EDS
## class
               : RasterBrick
## dimensions : 80, 112, 8960, 9 (nrow, ncol, ncell, nlayers)
## resolution : 0.125, 0.125 (x, y)
```

```
: 112.9, 126.9, -35.5, -25.5 (xmin, xmax, ymin, ymax)
## extent
## crs
                : +proj=longlat +datum=WGS84 +no_defs +ellps=WGS84 +towgs84=0,0,0
                : memory
## source
                      Elevation,
                                             MAP,
                                                             PDQ,
                                                                      Surface_T,
                                                                                            NDVI,
## min values : 7.149977e+00, 1.708365e+02, 9.094913e+00, 2.898587e+02, 1.308367e+07, 4.849654e+00,
## max values : 5.180779e+02, 1.163782e+03, 8.326768e+01, 3.077511e+02, 8.209903e+07, 2.458403e+01,
par(mfrow = c(3, 3))
plot(GCFR_variables_EDS)
          Elevation
                                             MAP
                                                                               PDQ
                              1500
                                                               800
600
                                                                                              - 150
- 100
- 50
                                                             - 600
- 400
- 200
                              1000
-32
                            - 500
-35
                                             NDVI
                                                                               CEC
         Surface_T
                              310
                                                                                              - 15
- 10
- 5
                            - 305
- 300
- 295
-32
-35
            Clay
                                            Soil_C
                                                                               рΗ
-29
                           35250
                                                             = 128
= 80
= 40
= 20
-32
-35
      18 20 22 24 26
                                       18 20 22 24 26
                                                                         18 20 22 24 26
par(op)
par(mfrow = c(3, 3))
plot(SWAFR_variables_EDS)
```

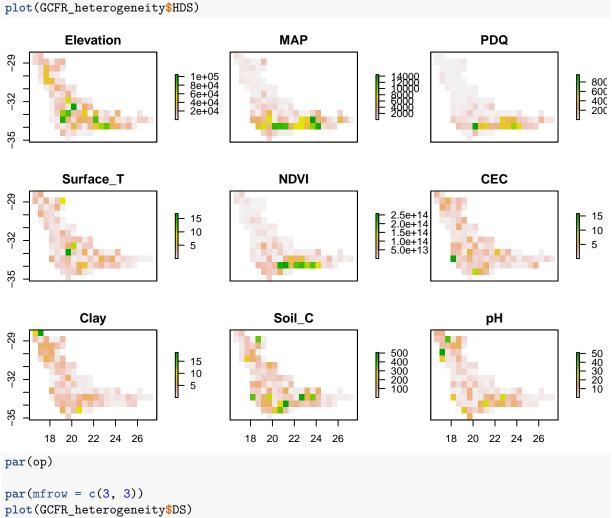
CEC,

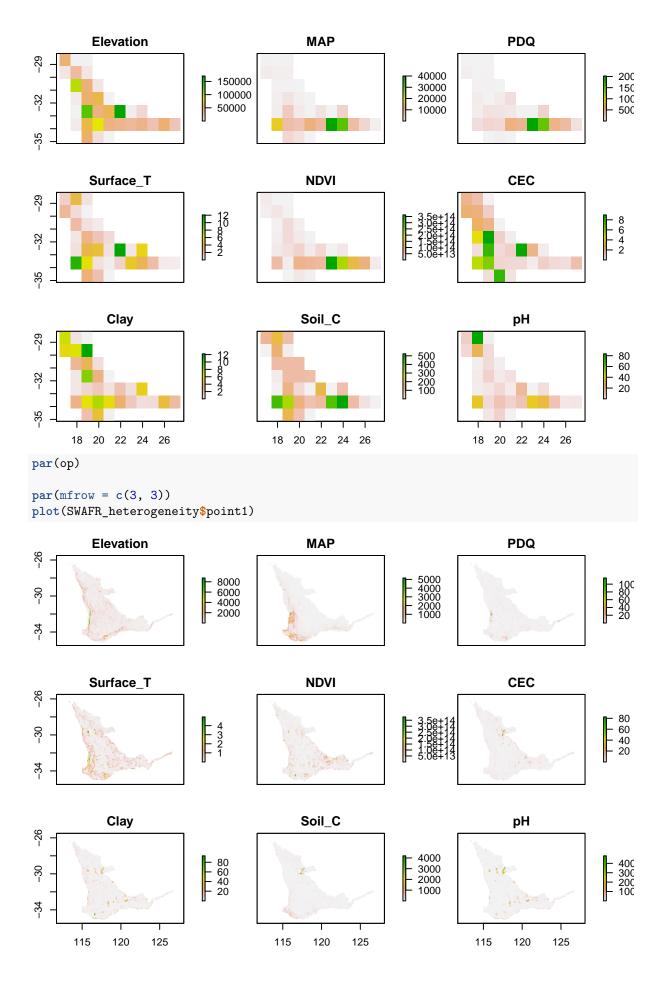




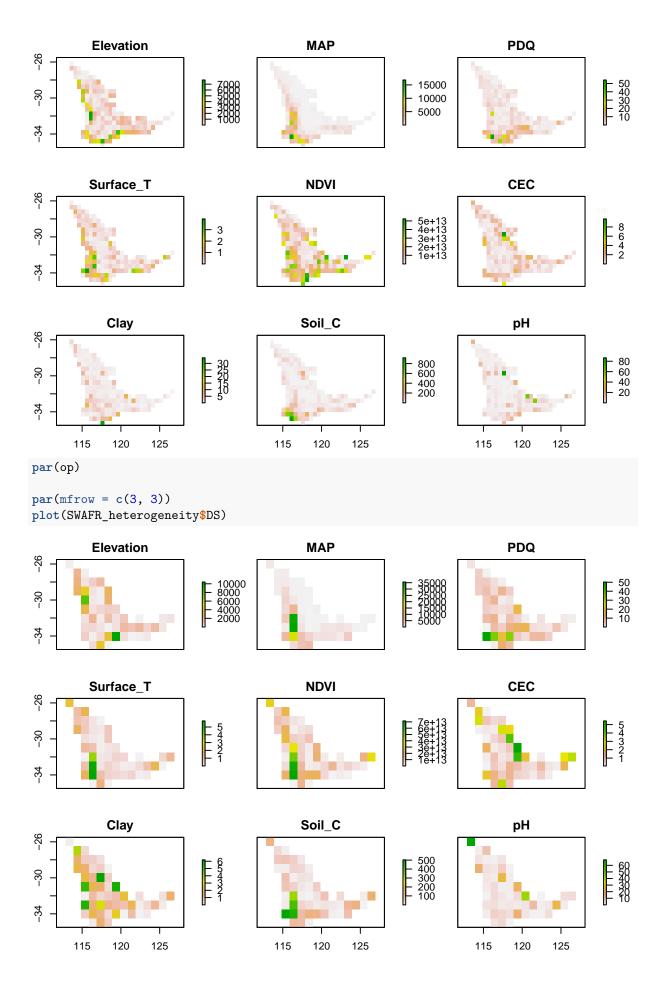
```
par(op)

par(mfrow = c(3, 3))
plot(GCFR_heterogeneity$HDS)
```





```
par(op)
par(mfrow = c(3, 3))
plot(SWAFR_heterogeneity$QDS)
                                                                                                                             PDQ
                Elevation
                                                                        MAP
-26
                                            - 20000
- 15000
- 10000
- 5000
                                                                                                 - 8000
- 6000
- 4000
- 2000
                                                                                                                                                     - 60
- 40
- 40
- 10
-30
-34
               Surface_T
                                                                        NDVI
                                                                                                                             CEC
-26
                                                                                                - 2.5e+14
- 2.0e+14
- 1.5e+14
- 1.0e+14
- 5.0e+13
                                            - 10
- 8
- 6
- 4
- 2
                                                                                                                                                      - 30
- 20
- 10
-30
-34
                   Clay
                                                                      Soil_C
                                                                                                                              рΗ
-26
                                                                                                    2000
1500
1000
                                            - 80
- 60
- 40
- 20
                                                                                                 - 2000
- 1500
- 1000
- 500
                                                                                                                                                     = 300
= 200
= 150
= 150
-30
-34
           115
                                                               115
                     120
                               125
                                                                         120
                                                                                    125
                                                                                                                    115
                                                                                                                              120
                                                                                                                                        125
par(op)
par(mfrow = c(3, 3))
plot(SWAFR_heterogeneity$HDS)
```



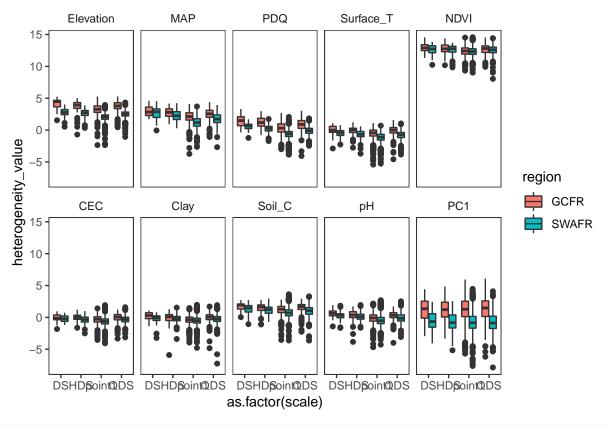
```
par(op)
# Join regions' datasets
heterogeneity <- map2(GCFR_heterogeneity, SWAFR_heterogeneity,
  ~ na.exclude(rbind(
    cbind(region = "GCFR", as.data.frame(log10(.x))),
    cbind(region = "SWAFR", as.data.frame(log10(.y)))
 ))
)
heterogeneity_PCAs <- map(heterogeneity,
 ~ prcomp(
    x[, -1],
    center = TRUE,
    scale. = TRUE
  )
)
map(heterogeneity_PCAs, summary)
## $point1
## Importance of components:
                             PC1
                                    PC2
                                            PC3
                                                     PC4
                                                             PC5
                                                                    PC6
## Standard deviation
                          1.8539 1.2243 0.89661 0.86925 0.75606 0.7470
## Proportion of Variance 0.3819 0.1665 0.08932 0.08396 0.06351 0.0620
## Cumulative Proportion 0.3819 0.5484 0.63775 0.72171 0.78522 0.8472
                              PC7
                                      PC8
## Standard deviation
                          0.73289 0.66832 0.62552
## Proportion of Variance 0.05968 0.04963 0.04347
## Cumulative Proportion 0.90690 0.95653 1.00000
##
## $QDS
## Importance of components:
##
                             PC1
                                    PC2
                                             PC3
                                                     PC4
                                                             PC5
                                                                     PC6
                          1.9543 1.1147 0.90436 0.88177 0.80313 0.71216
## Standard deviation
## Proportion of Variance 0.4244 0.1381 0.09087 0.08639 0.07167 0.05635
## Cumulative Proportion 0.4244 0.5624 0.65327 0.73966 0.81133 0.86768
##
                              PC7
                                      PC8
                                              PC9
## Standard deviation
                          0.66146 0.62594 0.60128
## Proportion of Variance 0.04861 0.04353 0.04017
## Cumulative Proportion 0.91630 0.95983 1.00000
##
## $HDS
## Importance of components:
                                    PC2
                                           PC3
                                                    PC4
                                                            PC5
##
                             PC1
                                                                    PC6
                                                                           PC7
## Standard deviation
                          1.8740 1.0746 0.9850 0.90862 0.82854 0.76507 0.7099
## Proportion of Variance 0.3902 0.1283 0.1078 0.09173 0.07628 0.06504 0.0560
## Cumulative Proportion 0.3902 0.5185 0.6263 0.71808 0.79435 0.85939 0.9154
##
                              PC8
                                     PC9
## Standard deviation
                          0.65867 0.5724
## Proportion of Variance 0.04821 0.0364
## Cumulative Proportion 0.96360 1.0000
##
## $DS
## Importance of components:
                             PC1
                                           PC3
                                                    PC4
                                                            PC5
                                                                           PC7
##
                                    PC2
                                                                    PC6
## Standard deviation
                          1.9271 1.0859 0.9999 0.91028 0.79126 0.73452 0.6469
## Proportion of Variance 0.4126 0.1310 0.1111 0.09207 0.06957 0.05995 0.0465
## Cumulative Proportion 0.4126 0.5437 0.6547 0.74681 0.81637 0.87632 0.9228
```

```
##
                                 PC8
                                         PC9
## Standard deviation
                            0.62256 0.55410
## Proportion of Variance 0.04306 0.03411
## Cumulative Proportion 0.96589 1.00000
# Force PC1 scores to be positive if all vars rotations are negative
heterogeneity_PCAs %<>% map(function(PCA) {
  if (all(PCA$rotation[, 1] <= 0)) {</pre>
    message("Multiplying this one by -1")
    PCA$rotation[, 1] %<>% multiply_by(-1)
                        %<>% multiply_by(-1)
    PCA$x[, 1]
  }
  PCA
})
plot_grid(plotlist = map2(
  .x = heterogeneity_PCAs,
  .y = heterogeneity,
  .f =
    ~ autoplot(.x, data = .y, colour = "region",
      alpha = 0.25,
                       = TRUE, loadings.colour
      loadings
      loadings.label = TRUE, loadings.label.colour = "black",
      loadings.label.hjust = -0.25
    ggtitle(unique(.y$scale)) +
    geom_hline(yintercept = 0, linetype = "dashed", alpha = 0.5) +
    geom_vline(xintercept = 0, linetype = "dashed", alpha = 0.5)
))
     0.050
                                                    0.1
     0.025
                                                PC2 (13.81%)
PC2 (16.65%)
                                  region
                                                                                 region
     0.000
                                      GCFR
                                                                                      GCFR
                                                    0.0
    -0.025
                                                                                      SWAFR
                                      SWAFR
    -0.050
                                                   -0.1
         -0.0500.0250.0000.025
                                                         -0.10-0.050.00 0.05 0.10
             PC1 (38.19%)
                                                            PC1 (42.43%)
     0.2
                                                    0.2
                                                                      CEC
PC2 (12.83%)
     0.1
                                                PC2 (13.1%)
                                                    0.1
                                  region
                                                                                 region
     0.0
                                      GCFR
                                                                                      GCFR
                                                    0.0
                                      SWAFR
                                                                                      SWAFR
    -0.1
                                                   -0.1
                                                   -0.2
    -0.2
                  0.0
                         0.1
                                                        -0.2 -0.1 0.0 0.1 0.2
            -0.1
            PC1 (39.02%)
                                                            PC1 (41.26%)
PC1s <- map(heterogeneity_PCAs, ~tibble(PC1 = .x$x[, 1]))
heterogeneity %<>% map2(PC1s, ~cbind(.x, .y))
```

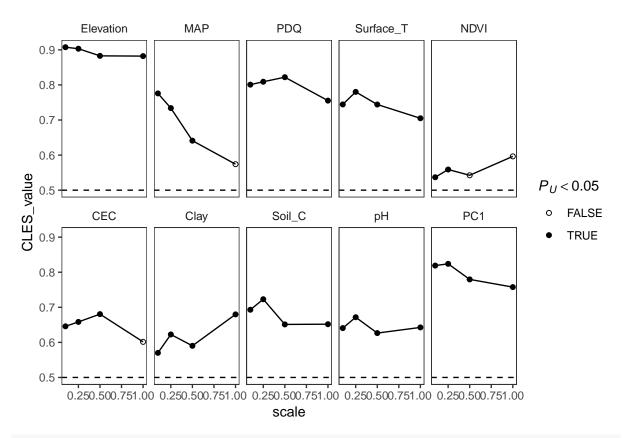
```
CLES_results <- map2_dfr(
  .x = heterogeneity %>%
   map(filter, region == "GCFR") %>%
   map(dplyr::select, -region),
  .y = heterogeneity %>%
   map(filter, region == "SWAFR") %>%
   map(dplyr::select, -region),
  .id = "scale", # for every spatial scale,
  ~ map2_df(
   .x = .x,
   y = y
    .id = "variable", # for every variable in each region,
    ~ tibble(
     CLES value = CLES(.y, .x), # calculate the CLES,
     U_test = wilcox.test(.x, .y, conf.int = TRUE) %>% # & Mann-Whitney U-test
       tidy() %>%
       list()
 )
)
CLES_results %<>% mutate(
 variable = factor(variable, levels = var_names %>%
   str_replace_all(" ", "_") %>%
   c("PC1")
 ),
 scale = case when(
   scale == "point1" ~ 0.10,
   scale == "QDS" ~ 0.25,
   scale == "HDS"
                  ~ 0.50,
   scale == "DS"
                   ~ 1.00
 ),
 diff = map_dbl(U_test, "estimate"),
 P_U = map_dbl(U_test, "p.value"),
 U_low = map_dbl(U_test, "conf.low"),
 U_upp = map_dbl(U_test, "conf.high")
CLES_results
## # A tibble: 40 x 8
     scale variable CLES_value U_test
                                               diff
                                                          P_U U_low U_upp
                                                        <dbl> <dbl> <dbl>
##
     <dbl> <fct>
                         <dbl> <list>
                                               <dbl>
                         0.908 <tibble [1 \times 7^{-} 1.24 0.
## 1
     0.1 Elevation
                                                              1.20
                                                                    1.27
                         0.776 <tibble [1 x 7~ 0.927    1.57e-249 0.879    0.976
## 2
      O.1 MAP
## 3
      0.1 PDQ
                        0.801 <tibble [1 x 7~ 0.937 2.97e-296 0.891 0.983
## 4
      ## 5
       O.1 NDVI
                       0.537 <tibble [1 x 7~ 0.0919 6.81e- 6 0.0520 0.132
## 6
      0.1 CEC
                        0.646 <tibble [1 x 7~ 0.322 4.31e- 71 0.288 0.356
## 7
       0.1 Clay
                        0.570 <tibble [1 x 7~ 0.151 1.02e- 17 0.117 0.185
## 8
       0.1 Soil_C
                       0.693 <tibble [1 x 7~ 0.514 3.24e-123 0.475 0.554
                         0.641 <tibble [1 x 7~ 0.386 2.39e- 66 0.344 0.428
## 9
       0.1 pH
## 10
                         0.819 <tibble [1 x 7~ 2.09
      0.1 PC1
                                                    0.
## # ... with 30 more rows
CLES models <- CLES results %>%
 split(.$variable) %>%
 map(~lm(CLES_value ~ scale, .x))
CLES_models$Elevation
```

##

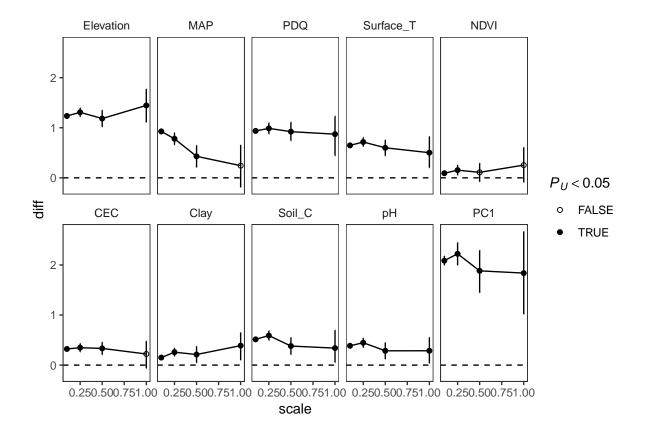
```
## Call:
## lm(formula = CLES_value ~ scale, data = .x)
## Coefficients:
## (Intercept)
                     scale
##
      0.90749
                  -0.02919
# Summarise those models
CLES_model_summaries <- CLES_models %>%
 map_df(.id = "variable", tidy) %>%
 filter(term != "(Intercept)") %>%
 mutate(sig = case_when(
   p.value <= 0.05 ~ "*",
   p.value <= 0.10 ~ ".",
   TRUE
 )) %>%
 mutate(variable = factor(variable, levels = var_names %>%
     str_replace_all(" ", "_") %>%
     c("PC1")
 )) %>%
 mutate_if(is.numeric, round, digits = 3) %>%
 dplyr::select(variable, estimate, p.value, sig)
CLES_model_summaries
## # A tibble: 10 x 4
##
     variable estimate p.value sig
                 <dbl> <dbl> <chr>
## 1 Elevation -0.029 0.135 " "
## 2 MAP
                 -0.224 0.028 *
## 3 PDQ
                 -0.055 0.26 " "
                         0.207 " "
## 4 Surface_T -0.062
                 0.059 0.134 " "
## 5 NDVI
                 -0.054 0.361 " "
## 6 CEC
## 7 Clay
                 0.104 0.143 " "
                 -0.065 0.27 " "
## 8 Soil_C
## 9 pH
                 -0.013 0.729 " "
## 10 PC1
                 -0.076
                         0.059 .
heterogeneity %>% #heterogeneity_df %>%
 bind_rows(.id = "scale") %>%
 gather(
   variable, heterogeneity_value,
   -region, -scale#, -lon, -lat
 mutate(variable = factor(variable, levels = var_names %>%
    str_replace_all(" ", "_") %>%
    c("PC1")
 )) %>%
  ggplot(aes(as.factor(scale), heterogeneity_value, fill = region)) +
   geom_boxplot() +
   facet_wrap(~variable, nrow = 2)
```



```
ggplot(CLES_results) +
  aes(scale, CLES_value, group = variable) +
  geom_hline(yintercept = 0.5, lty = "dashed") +
  geom_line() +
  geom_point(aes(shape = P_U < 0.05)) +
  scale_shape_manual(name = bquote(italic("P"["U"]) < 0.05), values = c(1, 19)) +
  facet_wrap(~variable, nrow = 2)</pre>
```



```
ggplot(CLES_results) +
  aes(scale, diff, group = variable) +
  geom_hline(yintercept = 0.0, lty = "dashed") +
  geom_line() +
  geom_errorbar(aes(ymin = U_low, ymax = U_upp), width = 0) +
  geom_point(aes(shape = P_U < 0.05)) +
  scale_shape_manual(name = bquote(italic("P"["U"]) < 0.05), values = c(1, 19)) +
  facet_wrap(~variable, nrow = 2)</pre>
```



## 2. Comparing & decomposing regions' species richness

```
# Assign a variable to the global environment,
# not simply the parent environment (as with <<-),
# with the same name
assign_global <- function(x) {</pre>
  assign(
          = deparse(substitute(x)),
    value = x,
    envir = .GlobalEnv
  )
}
# Read in and assign all polygon objects to global environment
import_region_polygons <- function(borders_dir =</pre>
                                      here("data/derived-data/borders")) {
  # GCFR ---
                        <- readOGR(glue("{borders_dir}/GCFR_border"))
  GCFR border
  GCFR_border_buffered <- readOGR(glue("{borders_dir}/GCFR_border_buffered"))</pre>
                        <- readOGR(glue("{borders_dir}/GCFR_box"))
  GCFR_box
                        <- readOGR(glue("{borders_dir}/GCFR_QDS"))
  GCFR_QDS
  assign_global(GCFR_border)
  assign_global(GCFR_border_buffered)
  assign_global(GCFR_box)
  assign_global(GCFR_QDS)
```

```
SWAFR_border
                        <- readOGR(glue("{borders_dir}/SWBP_Mike-Cramer"))
  SWAFR_border_buffered <- readOGR(glue("{borders_dir}/SWAFR_border_buffered"))
                        <- readOGR(glue("{borders_dir}/SWAFR_box"))</pre>
  SWAFR_box
                        <- readOGR(glue("{borders_dir}/SWAFR_QDS"))</pre>
  SWAFR_QDS
  assign_global(SWAFR_border)
  assign_global(SWAFR_border_buffered)
  assign_global(SWAFR_box)
  assign_global(SWAFR_QDS)
  # FIXME: Why are these shapefile imports throwing non-fatal errors/warnings?
  # TODO: Add GIS-std-checkers here too
}
# Include lon/lat when converting from Raster* to data.frame
raster2df <- function(r) {</pre>
  lon_lat <- xyFromCell(r, 1:ncell(r))</pre>
  colnames(lon_lat) <- c("lon", "lat")</pre>
  df <- as.data.frame(log10(r))</pre>
  df <- cbind(lon_lat, df)</pre>
  df
}
import_region_polygons()
## OGR data source with driver: ESRI Shapefile
## Source: "C:\Users\user\Desktop\Cape-vs-SWA\data\derived-data\borders\GCFR_border", layer: "LA_CUR
## with 2 features
## It has 1 fields
## OGR data source with driver: ESRI Shapefile
## Source: "C:\Users\user\Desktop\Cape-vs-SWA\data\derived-data\borders\GCFR_border_buffered", layer
## with 1 features
## It has 1 fields
## OGR data source with driver: ESRI Shapefile
## Source: "C:\Users\user\Desktop\Cape-vs-SWA\data\derived-data\borders\GCFR_box", layer: "value"
## with 1 features
## It has 1 fields
## OGR data source with driver: ESRI Shapefile
## Source: "C:\Users\user\Desktop\Cape-vs-SWA\data\derived-data\borders\GCFR_QDS", layer: "areakm2"
## with 1920 features
## It has 4 fields
## OGR data source with driver: ESRI Shapefile
## Source: "C:\Users\user\Desktop\Cape-vs-SWA\data\derived-data\borders\SWBP_Mike-Cramer", layer: "S
## with 1 features
## It has 1 fields
## OGR data source with driver: ESRI Shapefile
## Source: "C:\Users\user\Desktop\Cape-vs-SWA\data\derived-data\borders\SWAFR_border_buffered", laye
## with 1 features
## It has 1 fields
## OGR data source with driver: ESRI Shapefile
## Source: "C:\Users\user\Desktop\Cape-vs-SWA\data\derived-data\borders\SWAFR_box", layer: "value"
## with 1 features
## It has 1 fields
## OGR data source with driver: ESRI Shapefile
## Source: "C:\Users\user\Desktop\Cape-vs-SWA\data\derived-data\borders\SWAFR_QDS", layer: "areakm2"
## with 2464 features
## It has 4 fields
# Import EDS polygons
ZA_EDS <- readOGR(here("data/raw-data/QDGC/qdgc_zaf"), layer = "qdgc_03_zaf")
```

```
## OGR data source with driver: ESRI Shapefile
## Source: "C:\Users\user\Desktop\Cape-vs-SWA\data\raw-data\QDGC\qdgc_zaf", layer: "qdgc_03_zaf"
## with 14144 features
## It has 4 fields
AU_EDS <- readOGR(here("data/raw-data/QDGC/qdgc_aus"), layer = "qdgc_03_aus")
## OGR data source with driver: ESRI Shapefile
## Source: "C:\Users\user\Desktop\Cape-vs-SWA\data\raw-data\QDGC\qdgc_aus", layer: "qdgc_03_aus"
## with 89216 features
## It has 4 fields
# Crop to regions
GCFR_EDS <- crop(ZA_EDS, GCFR_box)</pre>
SWAFR_EDS <- crop(AU_EDS, SWAFR_box)</pre>
Larsen_grid <- rbind(GCFR_EDS, SWAFR_EDS)</pre>
Larsen_grid$edgc <- Larsen_grid$qdgc</pre>
Larsen_grid$qdgc <- str_remove(Larsen_grid$edgc, ".$")</pre>
Larsen_grid$hdgc <- str_remove(Larsen_grid$qdgc, ".$")</pre>
Larsen_grid$dgc <- str_remove(Larsen_grid$hdgc, ".$")</pre>
heterogeneity_w_coords <- map2(GCFR_heterogeneity, SWAFR_heterogeneity,
  ~ na.exclude(rbind(
    cbind(region = "GCFR", raster2df(.x)),
    cbind(region = "SWAFR", raster2df(.y))
  ))
heterogeneity <- map2(heterogeneity, heterogeneity_w_coords, full_join)
heterogeneity$QDS$QDS <- heterogeneity$QDS %$%
  SpatialPoints(
                = data.frame(x = lon, y = lat),
    coords
    proj4string = crs(Larsen_grid)
  ) %over%
  Larsen_grid %>%
  pull(qdgc)
heterogeneity$HDS$HDS <- heterogeneity$HDS %$%
  SpatialPoints(
    coords
              = data.frame(x = lon, y = lat),
    proj4string = crs(Larsen_grid)
  ) %over%
  Larsen_grid %>%
  pull(hdgc)
heterogeneity$DS$DS <- heterogeneity$DS %$%
  SpatialPoints(
    coords = data.frame(x = lon, y = lat),
    proj4string = crs(Larsen_grid)
  ) %over%
  Larsen_grid %>%
  pull(dgc)
GCFR_species_occ <- read_rds(here(</pre>
  "data/derived-data/flora",
  "trimmed_GCFR_clean_flora_spdf_species"
))
```

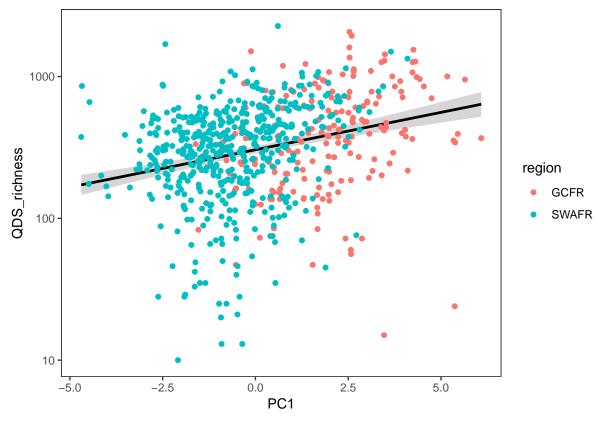
```
SWAFR_species_occ <- read_rds(here(</pre>
  "data/derived-data/flora".
  "trimmed_SWAFR_clean_flora_spdf_species"
))
GCFR_species_occ@data %>%
 group_by(species) %>%
 summarise(n_collections = n()) %>%
 arrange(desc(n_collections)) %>%
 write_csv(here("draft-02/manuscript_ver3/GCFR-species.csv"))
GCFR_bad_species <-
 read_csv(here("draft-02/manuscript_ver3/GCFR-species.csv")) %>%
 filter(n collections < 5) %>%
 pull(species)
SWAFR species occ@data %>%
 group_by(species) %>%
 summarise(n_collections = n()) %>%
 arrange(desc(n_collections)) %>%
 write_csv(here("draft-02/manuscript_ver3/SWAFR-species.csv"))
SWAFR_bad_species <-
 read_csv(here("draft-02/manuscript_ver3/SWAFR-species.csv")) %>%
 filter(n_collections < 5) %>%
 pull(species)
species_occ <- rbind(GCFR_species_occ, SWAFR_species_occ)</pre>
species_occ$EDS <- species_occ %over%</pre>
 Larsen_grid %>%
 pull(edgc)
species occ@data$EDS %<>% as.character()
species_occ$QDS <- str_remove(species_occ$EDS, ".$")</pre>
species_occ$HDS <- str_remove(species_occ$QDS, ".$")</pre>
species_occ$DS <- str_remove(species_occ$HDS, ".$")</pre>
species_occ_data <- species_occ@data %>%
 filter(!(species %in% c(GCFR_bad_species, SWAFR_bad_species)))
QDS_richness <- species_occ_data %>%
  group_by(QDS) %>%
  summarise(
    n_EDS
                  = length(unique(EDS)),
    n_collections = length(species),
    QDS_richness = length(unique(species))
 )
mean QDS richness <- QDS richness %>%
 mutate(HDS = str remove(QDS, ".$")) %>%
 group_by(HDS) %>%
 summarise(
    mean QDS richness = mean(QDS richness)
HDS_richness <- species_occ_data %>%
 group_by(HDS) %>%
  summarise(
                  = length(unique(QDS)),
    n_collections = length(species),
    HDS_richness = length(unique(species))
 )
```

```
mean_HDS_richness <- HDS_richness %>%
  mutate(DS = str_remove(HDS, ".$")) %>%
  group_by(DS) %>%
  summarise(
   mean_HDS_richness = mean(HDS_richness)
DS_richness <- species_occ_data %>%
  group_by(DS) %>%
  summarise(
   n_HDS
                 = length(unique(HDS)),
   n_collections = length(species),
   DS_richness = length(unique(species))
data <- heterogeneity[-1]</pre>
data$QDS %<>%
  as_tibble() %>%
  full_join(QDS_richness) %>%
  na.exclude() %>%
  filter(n EDS == 4)
data$HDS %<>%
  as_tibble() %>%
  full_join(mean_QDS_richness) %>%
  full_join(HDS_richness) %>%
  na.exclude() %>%
  filter(n_QDS == 4) %>%
  mutate(
    QDS_turnover = HDS_richness - mean_QDS_richness,
    QDS_turnover_prop = QDS_turnover / HDS_richness
  )
data$DS %<>%
  as tibble() %>%
  full_join(mean_HDS_richness) %>%
  full_join(DS_richness) %>%
  na.exclude() %>%
  filter(n_HDS == 4) %>%
  mutate(
    HDS_turnover = DS_richness - mean_HDS_richness,
    HDS_turnover_prop = HDS_turnover/DS_richness,
 )
m1 <- lm(QDS richness ~ PC1, data$QDS)
m2 <- lm(log(QDS_richness) ~ PC1, data$QDS)</pre>
m3 <- lm(log10(QDS_richness) ~ PC1, data$QDS)
AIC(m1, m2, m3)
##
     df
## m1 3 9655.6932
## m2 3 1626.4966
## m3 3 487.2083
# Choose m3
m4 <- lm(log10(QDS_richness) ~ PC1 + region, data$QDS)
m5 <- lm(log10(QDS_richness) ~ PC1 * region, data$QDS)
AIC(m3, m4, m5)
##
     df
## m3 3 487.2083
## m4 4 488.4461
```

```
## m5 5 490.1653
```

```
# Choose m3
summary(m3)
```

```
##
## Call:
## lm(formula = log10(QDS_richness) ~ PC1, data = data$QDS)
##
## Residuals:
       Min
                1Q
                     Median
                                 3Q
                                        Max
## -1.49045 -0.17294 0.05534 0.24052 0.87306
##
## Coefficients:
##
             Estimate Std. Error t value Pr(>|t|)
0.007038 7.494 2.08e-13 ***
             0.052746
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.3447 on 681 degrees of freedom
## Multiple R-squared: 0.07619, Adjusted R-squared: 0.07484
## F-statistic: 56.17 on 1 and 681 DF, p-value: 2.076e-13
ggplot(data$QDS, aes(PC1, QDS_richness)) +
 geom_smooth(method = lm, colour = "black") +
 geom_point(aes(colour = region)) +
 scale_y_log10()
```



```
data$QDS$PC1_residual <- m3$residuals

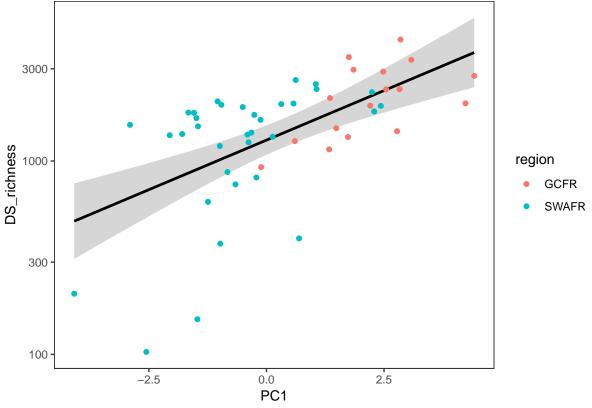
m1 <- lm(HDS_richness ~ PC1, data$HDS)

m2 <- lm(log(HDS_richness) ~ PC1, data$HDS)</pre>
```

```
m3 <- lm(log10(HDS_richness) ~ PC1, data$HDS)
AIC(m1, m2, m3)
##
              AIC
     df
## m1 3 3031.5108
## m2 3 459.3537
## m3 3 125.7407
# Choose m3
m4 <- lm(log10(HDS_richness) ~ PC1 + region, data$HDS)
m5 <- lm(log10(HDS_richness) ~ PC1 * region, data$HDS)
AIC(m3, m4, m5)
     df
             AIC
##
## m3 3 125.7407
## m4 4 125.1210
## m5 5 126.7163
# Choose m3
summary(m3)
##
## Call:
## lm(formula = log10(HDS_richness) ~ PC1, data = data$HDS)
## Residuals:
##
                 1Q Median
       Min
                                   3Q
                                           Max
## -1.51825 -0.09608 0.09299 0.19342 0.67349
## Coefficients:
##
              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 2.84889 0.02342 121.652 < 2e-16 ***
## PC1
               0.06038
                          0.01271 4.752 3.86e-06 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## Residual standard error: 0.3281 on 198 degrees of freedom
## Multiple R-squared: 0.1024, Adjusted R-squared: 0.09786
## F-statistic: 22.59 on 1 and 198 DF, p-value: 3.858e-06
ggplot(data$HDS, aes(PC1, HDS_richness)) +
 geom_smooth(method = lm, colour = "black") +
 geom_point(aes(colour = region)) +
 scale_y_log10()
```

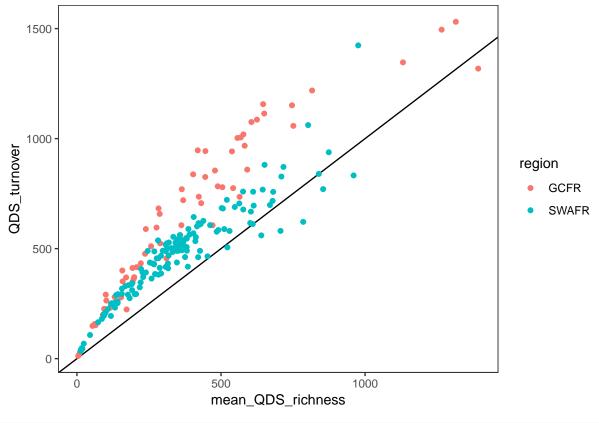
```
3000
   1000
HDS_richness
                                                                               region
    300
                                                                                   GCFR
                                                                                   SWAFR
    100
     30
                     -2
                                    0
                                        PC1
data$HDS$PC1_residual <- m3$residuals</pre>
m1 <- lm(DS_richness ~ PC1, data$DS)</pre>
m2 <- lm(log(DS_richness) ~ PC1, data$DS)</pre>
m3 <- lm(log10(DS_richness) ~ PC1, data$DS)
AIC(m1, m2, m3)
                AIC
##
      df
## m1 3 812.69955
## m2 3 98.49444
## m3 3 13.42313
# Choose m3
m4 <- lm(log10(DS_richness) ~ PC1 + region, data$DS)
m5 <- lm(log10(DS_richness) ~ PC1 * region, data$DS)</pre>
AIC(m3, m4, m5)
##
      df
              AIC
## m3 3 13.42313
## m4 4 15.05489
## m5 5 16.87791
# Choose m3
summary(m3)
##
## Call:
## lm(formula = log10(DS_richness) ~ PC1, data = data$DS)
## Residuals:
        Min
                   1Q
                       Median
                                      ЗQ
                                              Max
## -0.83339 -0.12455 0.07006 0.19871 0.37622
##
```

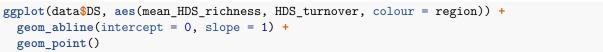
```
## Coefficients:
##
              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 3.10819 0.03792 81.975 < 2e-16 ***
## PC1
               0.10252
                          0.02008
                                  5.106 5.37e-06 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2655 on 49 degrees of freedom
## Multiple R-squared: 0.3473, Adjusted R-squared: 0.334
## F-statistic: 26.08 on 1 and 49 DF, p-value: 5.365e-06
ggplot(data$DS, aes(PC1, DS_richness)) +
 geom_smooth(method = lm, colour = "black") +
 geom_point(aes(colour = region)) +
 scale_y_log10()
```

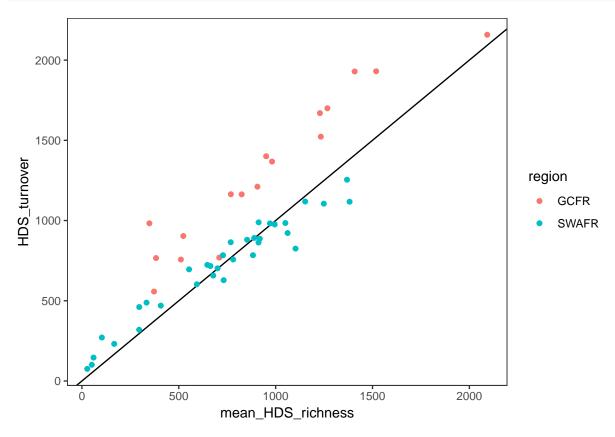


```
data$DS$PC1_residual <- m3$residuals

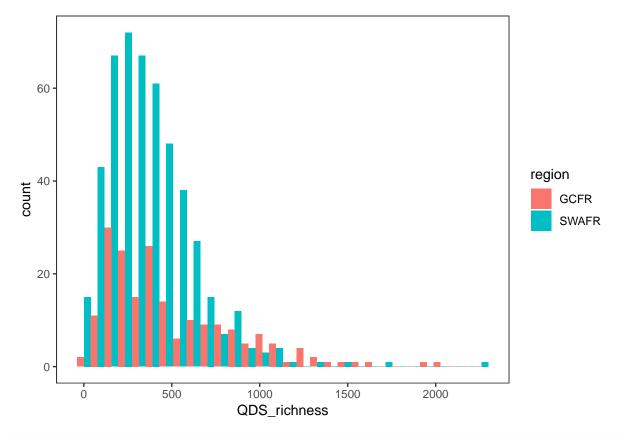
ggplot(data$HDS, aes(mean_QDS_richness, QDS_turnover, colour = region)) +
    geom_abline(intercept = 0, slope = 1) +
    geom_point()</pre>
```



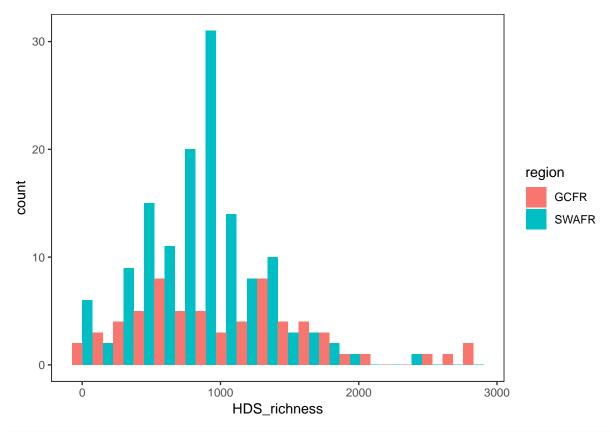




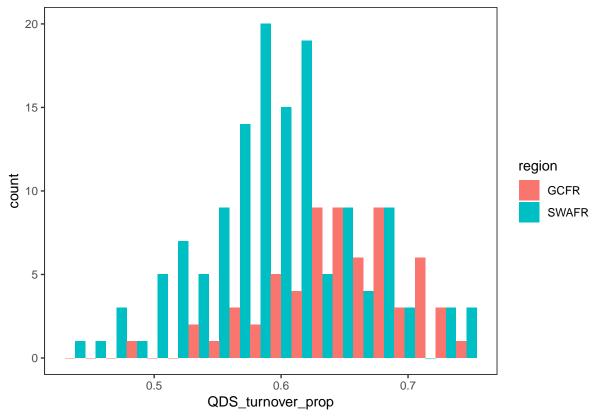
```
ggplot(data$QDS, aes(QDS_richness, fill = region)) +
  geom_histogram(bins = 30, position = "dodge")
```



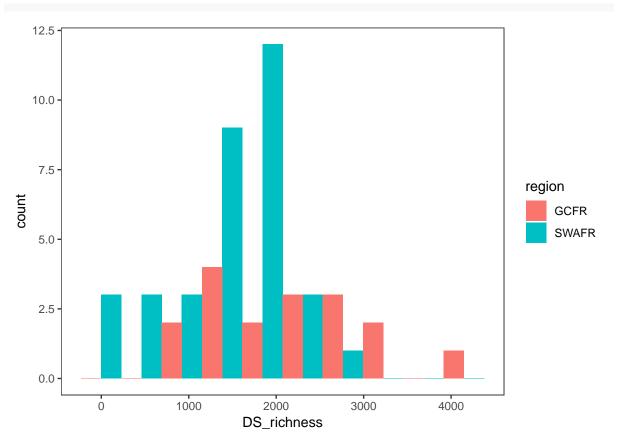
```
ggplot(data$HDS, aes(HDS_richness, fill = region)) +
  geom_histogram(bins = 20, position = "dodge")
```



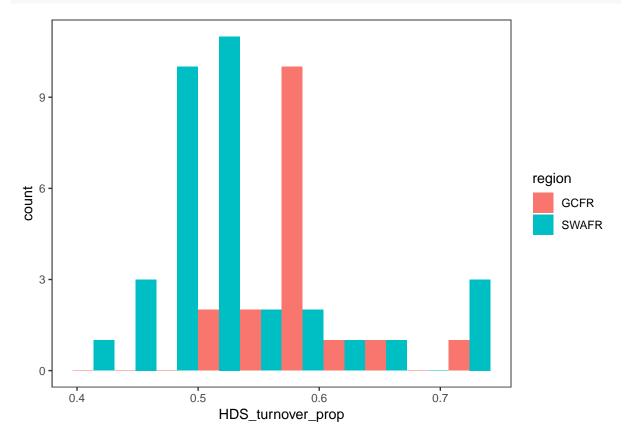
ggplot(data\$HDS, aes(QDS\_turnover\_prop, fill = region)) +
geom\_histogram(bins = 20, position = "dodge")



```
ggplot(data$DS, aes(DS_richness, fill = region)) +
  geom_histogram(bins = 10, position = "dodge")
```

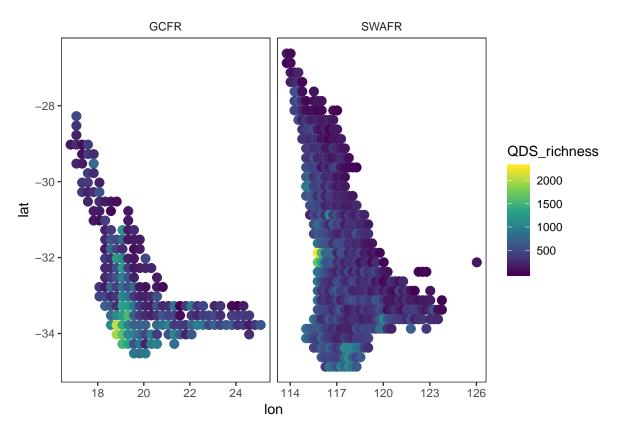


ggplot(data\$DS, aes(HDS\_turnover\_prop, fill = region)) +
geom\_histogram(bins = 10, position = "dodge")

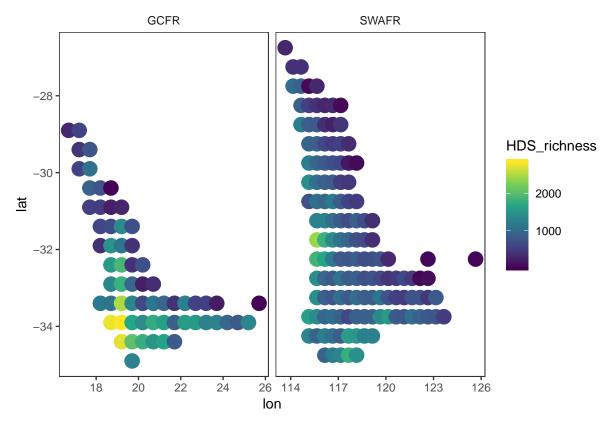


```
wilcox.test(QDS_richness ~ region, data$QDS)
##
## Wilcoxon rank sum test with continuity correction
##
## data: QDS_richness by region
## W = 56036, p-value = 0.0002828
\#\# alternative hypothesis: true location shift is not equal to 0
wilcox.test(HDS_richness ~ region, data$HDS)
##
## Wilcoxon rank sum test with continuity correction
##
## data: HDS_richness by region
## W = 5116.5, p-value = 0.0454
\#\# alternative hypothesis: true location shift is not equal to 0
wilcox.test(DS_richness ~ region, data$DS)
##
## Wilcoxon rank sum test
##
## data: DS_richness by region
## W = 423, p-value = 0.006739
\ensuremath{\mbox{\#\#}} alternative hypothesis: true location shift is not equal to 0
wilcox.test(QDS turnover
                               ~ region, data$HDS)
##
## Wilcoxon rank sum test with continuity correction
## data: QDS_turnover by region
## W = 5535, p-value = 0.001955
## alternative hypothesis: true location shift is not equal to 0
wilcox.test(QDS_turnover_prop ~ region, data$HDS)
##
## Wilcoxon rank sum test with continuity correction
## data: QDS_turnover_prop by region
## W = 6441, p-value = 4.507e-08
\#\# alternative hypothesis: true location shift is not equal to 0
wilcox.test(HDS_turnover
                          ~ region, data$DS)
##
## Wilcoxon rank sum test
##
## data: HDS_turnover by region
## W = 483, p-value = 4.736e-05
## alternative hypothesis: true location shift is not equal to 0
wilcox.test(HDS_turnover_prop ~ region, data$DS)
##
## Wilcoxon rank sum test
##
## data: HDS_turnover_prop by region
## W = 469, p-value = 0.0001875
\#\# alternative hypothesis: true location shift is not equal to 0
```

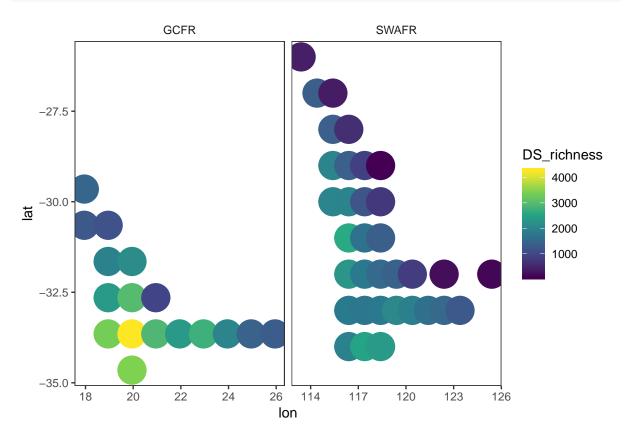
```
ggplot(data$QDS, aes(lon, lat, colour = QDS_richness)) +
geom_point(size = 3) +
facet_grid(~region, scales = "free_x") +
scale_colour_viridis_c()
```



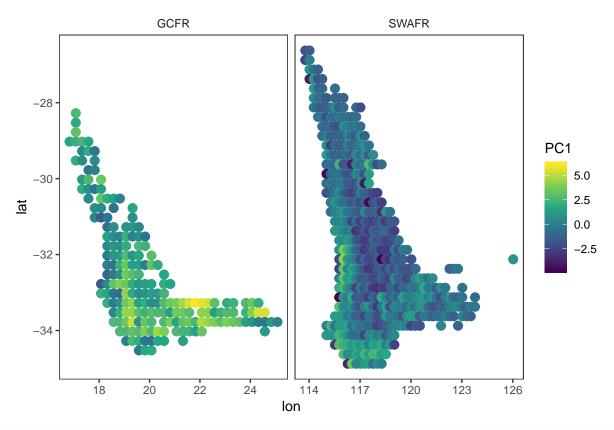
```
ggplot(data$HDS, aes(lon, lat, colour = HDS_richness)) +
geom_point(size = 5) +
facet_grid(~region, scales = "free_x") +
scale_colour_viridis_c()
```



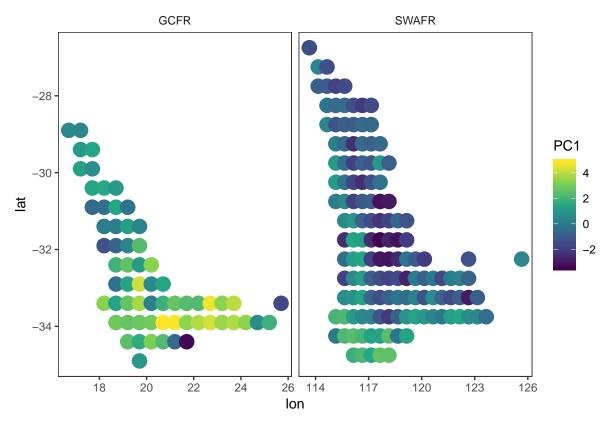
```
ggplot(data$DS, aes(lon, lat, colour = DS_richness)) +
  geom_point(size = 10) +
  facet_grid(~region, scales = "free_x") +
  scale_colour_viridis_c()
```



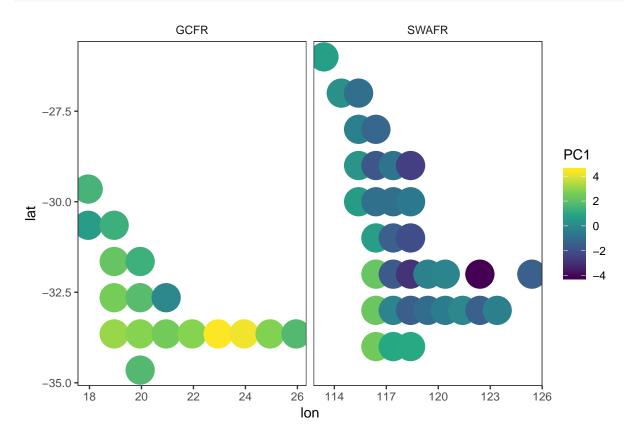
```
ggplot(data$QDS, aes(lon, lat, colour = PC1)) +
geom_point(size = 3) +
facet_grid(~region, scales = "free_x") +
scale_colour_viridis_c()
```



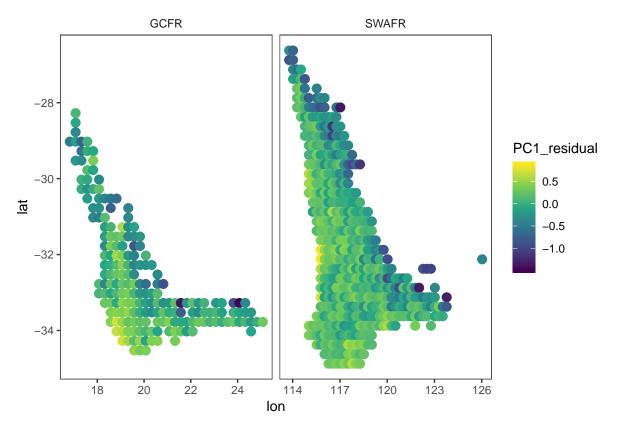
```
ggplot(data$HDS, aes(lon, lat, colour = PC1)) +
geom_point(size = 5) +
facet_grid(~region, scales = "free_x") +
scale_colour_viridis_c()
```



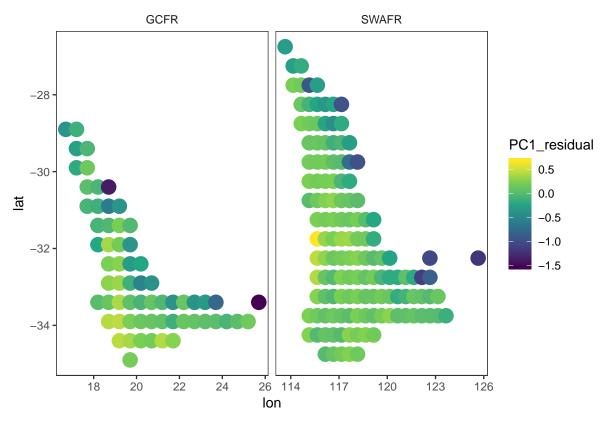
```
ggplot(data$DS, aes(lon, lat, colour = PC1)) +
geom_point(size = 10) +
facet_grid(~region, scales = "free_x") +
scale_colour_viridis_c()
```



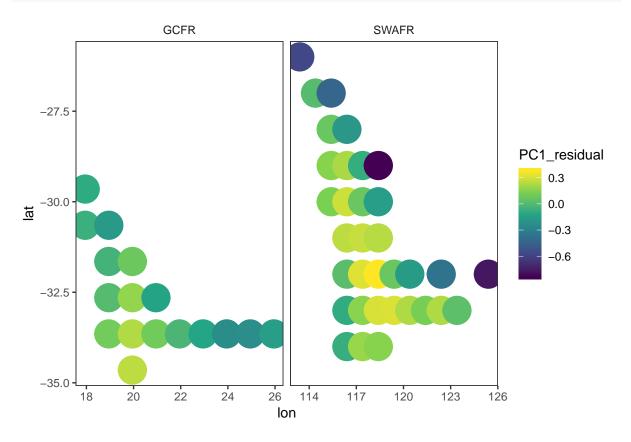
```
ggplot(data$QDS, aes(lon, lat, colour = PC1_residual)) +
geom_point(size = 3) +
facet_grid(~region, scales = "free_x") +
scale_colour_viridis_c()
```



```
ggplot(data$HDS, aes(lon, lat, colour = PC1_residual)) +
geom_point(size = 5) +
facet_grid(~region, scales = "free_x") +
scale_colour_viridis_c()
```



```
ggplot(data$DS, aes(lon, lat, colour = PC1_residual)) +
  geom_point(size = 10) +
  facet_grid(~region, scales = "free_x") +
  scale_colour_viridis_c()
```



# 3. Environmental heterogeneity as an explanation of species richness

#### 3.1. Univariate models

```
predictor_names <- c(str_replace_all(var_names, " ", "_"), "PC1")</pre>
models_non_region <- map(predictor_names,</pre>
  ~lm(paste("log10(QDS_richness) ~", .x), data$QDS)
names(models_non_region) <- predictor_names</pre>
models_add_region <- map(predictor_names,</pre>
  ~lm(paste("log10(QDS_richness) ~", .x, "+ region"), data$QDS)
names(models_add_region) <- predictor_names</pre>
models_int_region <- map(predictor_names,</pre>
  ~lm(paste("log10(QDS_richness) ~", .x, "* region"), data$QDS)
names(models_int_region) <- predictor_names</pre>
knitr::kable(pmap_dfr(
  .1 = list(models_non_region, models_add_region, models_int_region),
  .id = "variable",
  f = \text{AIC}(...1, ...2, ...3) \%
    mutate(
      model rank = 1:3,
      model_type = c(" ", "+", "x")[model_rank],
      delta_AIC = AIC - min(AIC),
      best_model = (model_rank == min(model_rank[delta_AIC < 2]))</pre>
    filter(best_model) %>%
    dplyr::select(-df, -AIC, -model_rank, -best_model)
))
```

variable	$model\_type$	delta_AIC
Elevation		0.0000000
MAP		0.0000000
PDQ		0.4844252
$Surface\_T$		0.1758586
NDVI	+	1.8932475
CEC	+	0.0000000
Clay	+	0.0000000
Soil_C	+	0.0000000
pН	+	0.0000000
PC1		0.0000000

```
names(models_int_region) <- predictor_names</pre>
pmap_dfr(
  .1 = list(models_non_region, models_add_region, models_int_region),
  .id = "variable",
  f = \text{AIC}(...1, ...2, ...3) \%
    mutate(
      model_rank = 1:3,
      model_type = c(" ", "+", "x")[model_rank],
      delta_AIC = AIC - min(AIC),
      best_model = (model_rank == min(model_rank[delta_AIC < 2]))</pre>
    ) %>%
    filter(best_model) %>%
    dplyr::select(-df, -AIC, -model_rank, -best_model)
)
##
      variable model_type delta_AIC
## 1 Elevation
                            0.0000000
## 2
            MAP
                            0.0000000
## 3
            PDQ
                           0.9498597
## 4 Surface_T
                           0.0000000
## 5
           NDVI
                           0.0000000
## 6
           CEC
                           0.2008189
## 7
           Clay
                           0.0000000
## 8
         Soil_C
                            0.0000000
## 9
                            0.7342033
            pН
## 10
            PC1
                            0.6197164
models_non_region <- map(predictor_names,</pre>
  ~lm(glue("log10(DS_richness) ~", .x), data$DS)
names(models_non_region) <- predictor_names</pre>
models_add_region <- map(predictor_names,</pre>
  ~lm(paste("log10(DS_richness) ~", .x, "+ region"), data$DS)
names(models_add_region) <- predictor_names</pre>
models_int_region <- map(predictor_names,</pre>
  ~lm(paste("log10(DS_richness) ~", .x, "* region"), data$DS)
names(models_int_region) <- predictor_names</pre>
pmap_dfr(
  .1 = list(models_non_region, models_add_region, models_int_region),
  .id = "variable",
  f = AIC(...1, ...2, ...3) \%
    mutate(
      model_rank = 1:3,
      model_type = c(" ", "+", "x")[model_rank],
      delta_AIC = AIC - min(AIC),
      best_model = (model_rank == min(model_rank[delta_AIC < 2]))</pre>
    ) %>%
    filter(best_model) %>%
    dplyr::select(-df, -AIC, -model_rank, -best_model)
)
##
       variable model_type delta_AIC
## 1 Elevation
                             0.000000
## 2
            MAP
                             0.000000
## 3
            PDQ
                             1.123590
## 4 Surface T
                         + 0.000000
                         + 0.000000
## 5
           NDVI
```

```
## 6 CEC + 0.000000

## 7 Clay 0.000000

## 8 Soil_C 1.914403

## 9 pH + 0.000000

## 10 PC1 0.000000
```

#### 3.2. Multivariate models

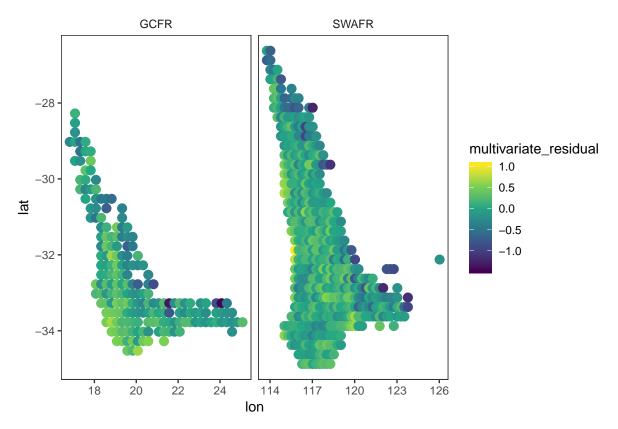
. . .

```
data$QDS %<>% mutate(log10_QDS_richness = log10(QDS_richness))
data$HDS %<>% mutate(log10_HDS_richness = log10(HDS_richness))
data$DS %<>% mutate(log10_DS_richness = log10(DS_richness))
full_formula <- predictor_names[predictor_names != "PC1"] %>%
  {c(., paste(., "* region"))} %>%
  paste(collapse = " + ")
m_QDS_richness1 <- lm(glue("QDS_richness ~ {full_formula}"), data$QDS)</pre>
m_QDS_richness <- lm(glue("log10_QDS_richness ~ {full_formula}"), data$QDS)</pre>
AIC(m_QDS_richness1, m_QDS_richness)
##
## m_QDS_richness1 21 9595.798
## m_QDS_richness 21 410.297
m_HDS_richness1 <- lm(glue("HDS_richness ~ {full_formula}"), data$HDS)</pre>
m_HDS_richness <- lm(glue("log10_HDS_richness ~ {full_formula}"), data$HDS)
AIC(m_HDS_richness1, m_HDS_richness)
                   df
                            AIC
## m_HDS_richness1 21 3006.9797
## m_HDS_richness 21 122.1338
m DS richness1 <- lm(glue("DS richness ~ {full formula}"), data$DS)
m_DS_richness <- lm(glue("log10_DS_richness ~ {full_formula}"), data$DS)</pre>
AIC(m_DS_richness1, m_DS_richness)
##
                  df
                          ATC
## m_DS_richness1 21 802.1799
## m_DS_richness 21 -20.9595
m QDS richness %<>% step(direction = "backward", trace = 0)
m_HDS_richness %<>% step(direction = "backward", trace = 0)
m_DS_richness %<>% step(direction = "backward", trace = 0)
# Reparameterise models to {*}:regionGCFR & {*}:regionSWAFR
# a.o.t. {*}*region, so that the figure of the effects actually represents
# each region, not the baseline (GCFR) and "relative SWAFR"
# (and that would cause inconsistencies too when their is no interaction with
# region term for a roughness variable).
reparameterise <- function(m) {</pre>
  response <- colnames(m$model)[[1]]
  data <- data %$% {
           (response == "log10_QDS_richness") QDS
    else if (response == "log10_HDS_richness") HDS
    else if (response == "log10_DS_richness") DS
  }
  preds_w_interactions <- m %$%</pre>
   coefficients %>%
   names() %>%
```

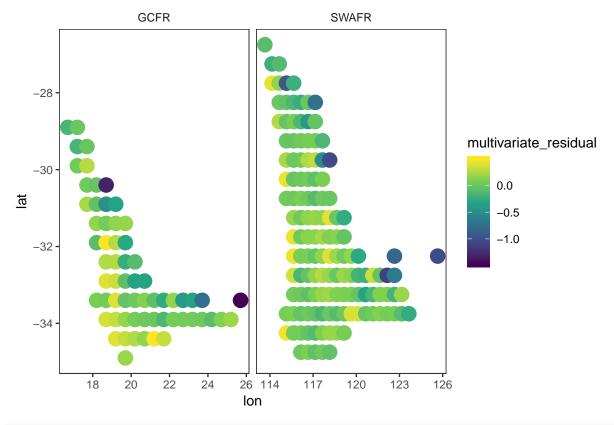
```
magrittr::extract(str_which(., ":regionSWAFR"))
  reparameterisation <- preds_w_interactions %<>%
    str_remove(":regionSWAFR") %>%
    {glue("-{.}")} %>%
    paste(collapse = " ")
  update(m,
    formula = glue(". ~ . {reparameterisation}"),
    data = data
  )
}
# Test:
# a <- m_HDS_richness
# b <- reparameterise(m HDS richness)</pre>
# AIC(a, b) # same model! :)
m_QDS_richness %<>% reparameterise()
m_HDS_richness %<>% reparameterise()
m_DS_richness %<>% reparameterise()
models <- list(</pre>
  QDS_richness = m_QDS_richness,
  HDS_richness = m_HDS_richness,
  DS_richness = m_DS_richness
models_summary <- models %>%
  map_df(.id = "response", tidy, conf.int = TRUE) %>%
  dplyr::select(-std.error, -statistic) %>%
  filter(term != "(Intercept)")
models_R2 <- models %>%
  map_df(.id = "response", glance) %>%
  dplyr::select(response, adj.r.squared)
models_summary %<>% full_join(models_R2)
glance(m_QDS_richness)
## # A tibble: 1 x 11
     r.squared adj.r.squared sigma statistic p.value
                                                          df logLik
                                                                      AIC
                       <dbl> <dbl>
         <dbl>
                                       <dbl>
                                                 <dbl> <int> <dbl> <dbl> <dbl> <dbl>
## 1
         0.212
                       0.203 0.320
                                         22.7 7.94e-31
                                                           9 -186. 392. 438.
## # ... with 2 more variables: deviance <dbl>, df.residual <int>
glance(m_HDS_richness)
## # A tibble: 1 x 11
     r.squared adj.r.squared sigma statistic p.value
                                                         df logLik
                                                                     AIC
                                                                           BIC
                                       <dbl>
                       <dbl> <dbl>
                                                <dbl> <int> <dbl> <dbl> <dbl> <dbl>
## 1
         0.240
                       0.208 0.307
                                        7.55 9.61e-9
                                                          9 -43.2 106. 139.
## # ... with 2 more variables: deviance <dbl>, df.residual <int>
glance(m_DS_richness)
## # A tibble: 1 x 11
     r.squared adj.r.squared sigma statistic p.value
                                                          df logLik
                                                                     AIC
         <dbl>
                       <dbl> <dbl>
                                    <dbl>
                                               <dbl> <int> <dbl> <dbl> <dbl> <dbl>
         0.827
                       0.778 0.153
                                        16.9 1.41e-11
                                                          12
                                                               30.1 -34.2 -9.06
## # ... with 2 more variables: deviance <dbl>, df.residual <int>
data$QDS$multivariate_residual <- m_QDS_richness$residuals</pre>
data$HDS$multivariate_residual <- m_HDS_richness$residuals</pre>
```

```
data$DS$multivariate_residual <- m_DS_richness$residuals

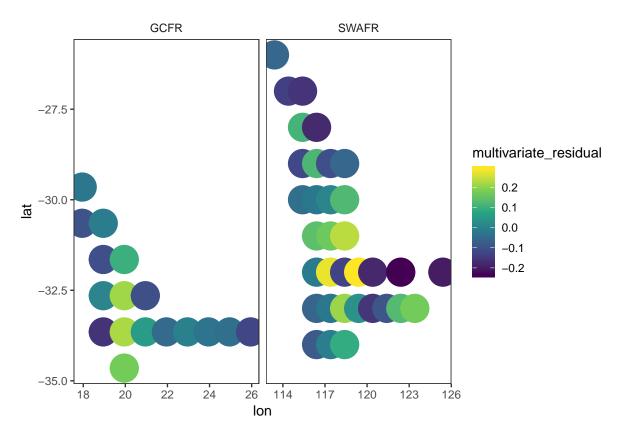
ggplot(data$QDS, aes(lon, lat, colour = multivariate_residual)) +
    geom_point(size = 3) +
    facet_grid(~region, scales = "free_x") +
    scale_colour_viridis_c()</pre>
```



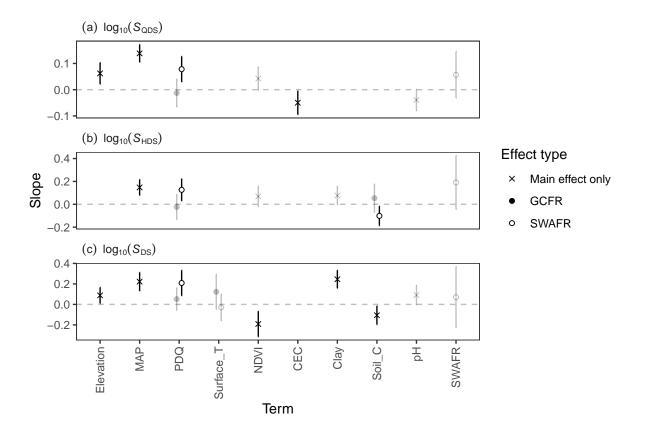
```
ggplot(data$HDS, aes(lon, lat, colour = multivariate_residual)) +
geom_point(size = 5) +
facet_grid(~region, scales = "free_x") +
scale_colour_viridis_c()
```



```
ggplot(data$DS, aes(lon, lat, colour = multivariate_residual)) +
  geom_point(size = 10) +
  facet_grid(~region, scales = "free_x") +
  scale_colour_viridis_c()
```

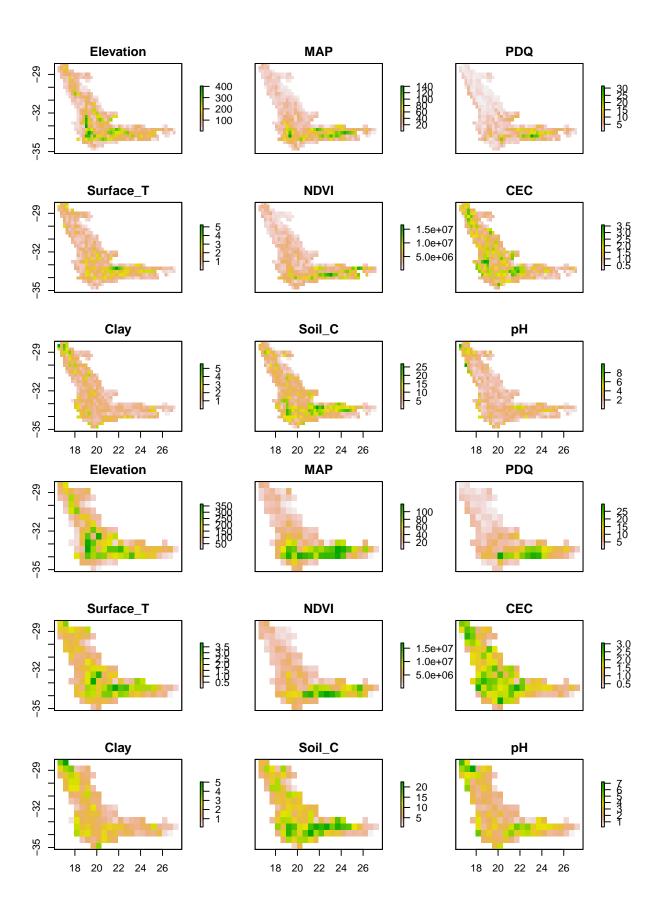


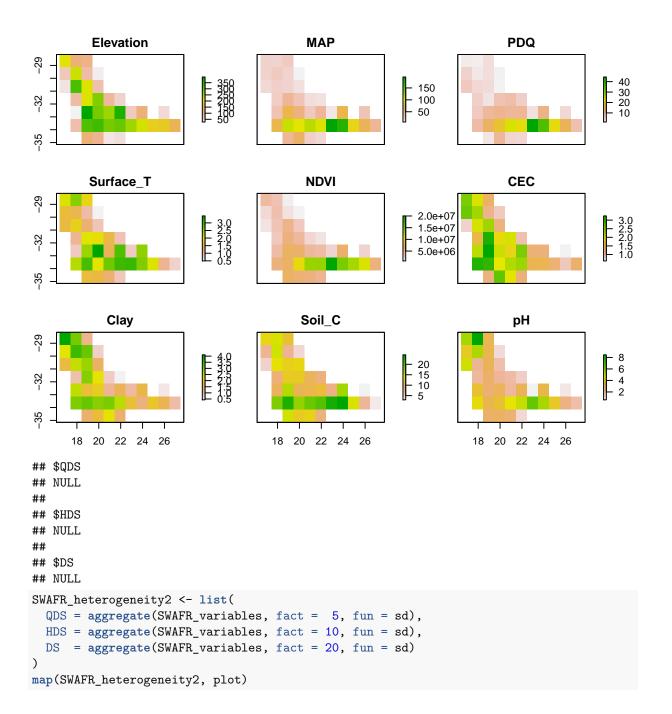
```
models_summary_for_plot <- models_summary %>%
 mutate(
   response = case when(
      response == "QDS_richness" ~ "(a)~~log[10](italic(S)[QDS])",
     response == "HDS_richness" ~ "(b)~~log[10](italic(S)[HDS])",
     response == "DS_richness" ~ "(c)~~log[10](italic(S)[DS])"
   ),
   region =
      case_when(
       str_detect(term, "regionSWAFR") ~ "SWAFR",
        str_detect(term, "regionGCFR") ~ "GCFR",
       TRUE
                                        ~ "Main effect only"
      ) %>%
     factor(levels = c("Main effect only", "GCFR", "SWAFR")),
    term = term %>%
      str_replace_all("\\.", " ") %>%
      str_remove_all("regionSWAFR:") %>%
     str_remove_all("regionGCFR:") %>%
     str_replace_all("regionSWAFR", "SWAFR") %>%
     factor(levels = c(str_replace_all(var_names, " ", "_"), "SWAFR")),
   sig = (p.value < 0.05)
  )
ggplot(models_summary_for_plot) +
 aes(
   term, estimate,
   fill = region, group = region, shape = region,
   alpha = sig
 geom_hline(yintercept = 0, linetype = "dashed", colour = "grey75") +
 geom_errorbar(
   aes(ymin = conf.low, ymax = conf.high),
   position = position_dodge(width = 0.25),
   width = 0
 ) +
 geom_point(position = position_dodge(width = 0.25)) +
 labs(x = "Term", y = "Slope") +
  scale_fill_manual(values = c(NA, "black", "white")) +
 scale_shape_manual(values = c(4, 21, 21)) +
 scale_alpha_manual(values = c(0.25, 1)) +
 facet_wrap(~response, nrow = 3, scales = "free_y", labeller = label_parsed) +
 guides(
   fill = FALSE,
   shape = guide_legend(
     title = "Effect type",
     override.aes = list(fill = c(NA, "black", "white"))
   ),
   alpha = FALSE
 ) +
 theme (
   axis.text.x = element_text(angle = 90, hjust = 1, vjust = 0.5),
   strip.text.x = element_text(angle = 0, hjust = 0)
```

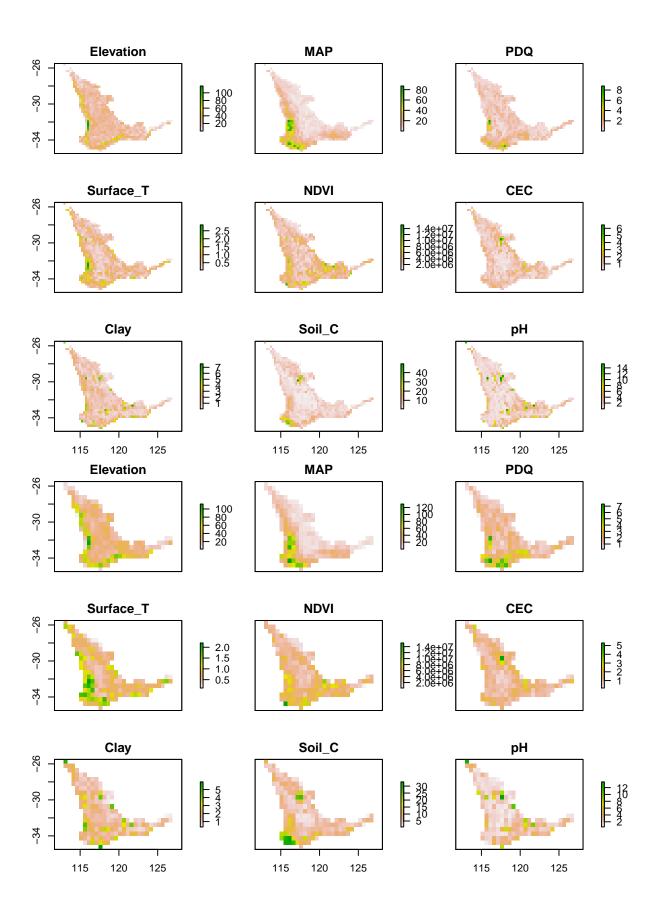


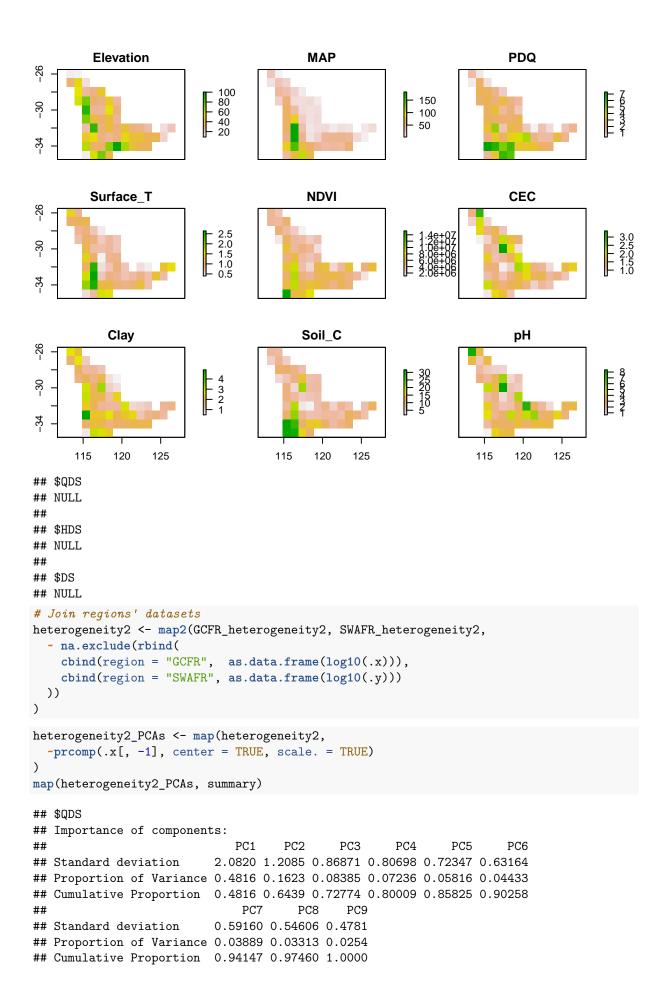
## Repeat 1.–3. with $EH_2$

```
GCFR_heterogeneity2 <- list(
   QDS = aggregate(GCFR_variables, fact = 5, fun = sd),
   HDS = aggregate(GCFR_variables, fact = 10, fun = sd),
   DS = aggregate(GCFR_variables, fact = 20, fun = sd)
)
map(GCFR_heterogeneity2, plot)</pre>
```

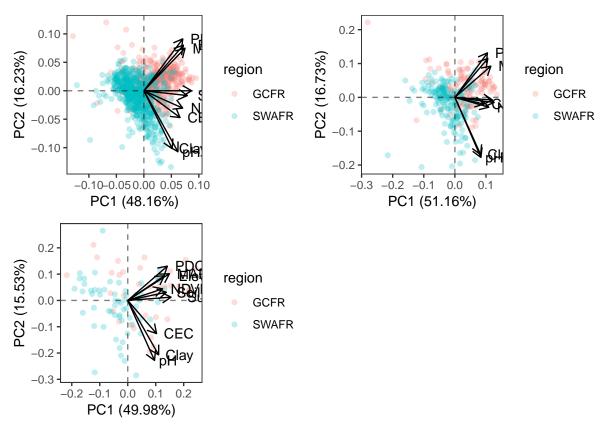








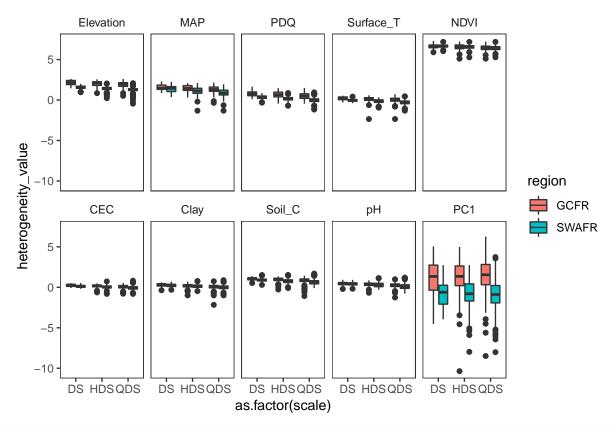
```
##
## $HDS
## Importance of components:
                             PC1
                                    PC2
                                             PC3
                                                     PC4
                                                             PC5
                                                                     PC6
                          2.1457 1.2270 0.89003 0.76637 0.66199 0.60262
## Standard deviation
## Proportion of Variance 0.5116 0.1673 0.08802 0.06526 0.04869 0.04035
## Cumulative Proportion 0.5116 0.6788 0.76687 0.83212 0.88082 0.92117
##
                             PC7
                                     PC8
                                             PC9
                          0.5450 0.49093 0.41413
## Standard deviation
## Proportion of Variance 0.0330 0.02678 0.01906
## Cumulative Proportion 0.9542 0.98094 1.00000
##
## $DS
## Importance of components:
                                    PC2
                                           PC3
                                                   PC4
                                                           PC5
                                                                  PC6
                             PC1
## Standard deviation
                          2.1210 1.1822 0.9973 0.8469 0.63505 0.6206 0.50295
## Proportion of Variance 0.4999 0.1553 0.1105 0.0797 0.04481 0.0428 0.02811
## Cumulative Proportion 0.4999 0.6551 0.7657 0.8454 0.89016 0.9330 0.96106
##
                              PC8
                                      PC9
## Standard deviation
                          0.47383 0.35484
## Proportion of Variance 0.02495 0.01399
## Cumulative Proportion 0.98601 1.00000
# Force PC1 scores to be positive if all vars rotations are negative
heterogeneity2 PCAs %<>% map(function(PCA) {
  if (all(PCA$rotation[, 1] <= 0)) {</pre>
    message("Multiplying this one by -1")
    PCA$rotation[, 1] %<>% multiply_by(-1)
    PCA$x[, 1]
                      %<>% multiply_by(-1)
  }
  PCA
})
plot_grid(plotlist = map2(
  .x = heterogeneity2_PCAs,
  .y = heterogeneity2,
  .f =
    ~ autoplot(.x, data = .y, colour = "region",
      alpha = 0.25,
      loadings
                     = TRUE, loadings.colour
                                                   = "black",
      loadings.label = TRUE, loadings.label.colour = "black",
      loadings.label.hjust = -0.25
    ggtitle(unique(.y$scale)) +
    geom_hline(yintercept = 0, linetype = "dashed", alpha = 0.5) +
    geom_vline(xintercept = 0, linetype = "dashed", alpha = 0.5)
))
```



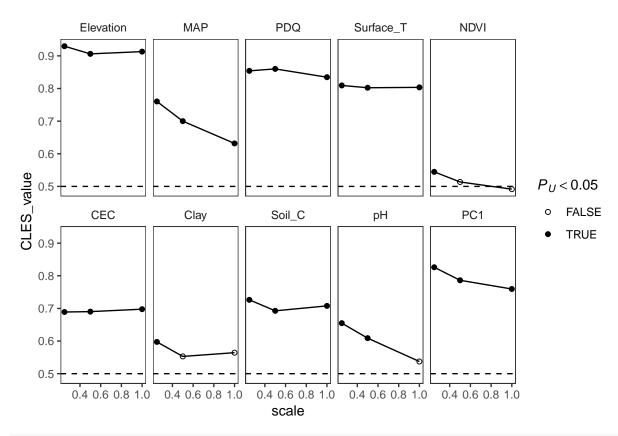
```
PC1s2 <- map(heterogeneity2_PCAs, ~tibble(PC1 = .x$x[, 1]))
heterogeneity2 %<>% map2(PC1s2, ~cbind(.x, .y))
CLES2_results <- map2_dfr(</pre>
  .x = heterogeneity2 %>%
    map(filter, region == "GCFR") %>%
    map(dplyr::select, -region),
  .y = heterogeneity2 %>%
    map(filter, region == "SWAFR") %>%
    map(dplyr::select, -region),
  .id = "scale", # for every spatial scale,
  ~ map2_df(
    .x = .x,
    .id = "variable", # for every variable in each region,
    ~ tibble(
      CLES_value = CLES(.y, .x), # calculate the CLES,
      U_test = wilcox.test(.x, .y, conf.int = TRUE) %>% # & Mann-Whitney U-test
        tidy() %>%
        list()
    )
  )
CLES2_results %<>% mutate(
  variable = factor(variable, levels = var_names %>%
    str_replace_all(" ", "_") %>%
    c("PC1")
  ),
  scale = case_when(
    scale == "point1" ~ 0.10,
    scale == "QDS" ~ 0.25,
   scale == "HDS"
                   ~ 0.50,
```

```
scale == "DS" ~ 1.00
  ),
 diff = map_dbl(U_test, "estimate"),
 P_U = map_dbl(U_test, "p.value"),
 U_low = map_dbl(U_test, "conf.low"),
  U_upp = map_dbl(U_test, "conf.high")
CLES2_results
## # A tibble: 30 x 8
     scale variable CLES_value U_test
                                              diff
                                                         P_U U_low U_upp
##
      <dbl> <fct>
                     <dbl> <list>
                                              <dbl>
                                                       <dbl>
                                                              <dbl> <dbl>
## 1 0.25 Elevation
                         0.930 <tibble [1 x~ 0.652 8.05e-114 0.613
                                                                     0.690
## 2 0.25 MAP
                         0.760 <tibble [1 x~ 0.415 5.90e- 43 0.363
                                                                     0.467
## 3 0.25 PDQ
                        0.854 <tibble [1 x~ 0.504 5.74e- 78 0.458
                                                                     0.551
## 4 0.25 Surface_T 0.809 <tibble [1 x~ 0.327 6.02e- 60 0.293
                                                                     0.361
## 5 0.25 NDVI
                        0.545 <tibble [1 x~ 0.0460 1.85e- 2 0.00748 0.0844
## 6 0.25 CEC
                         0.689 <tibble [1 x~ 0.157 1.93e- 23 0.128
## 7 0.25 Clay
                         0.597 <tibble [1 x~ 0.0827 2.76e- 7 0.0522 0.113
## 8 0.25 Soil_C
                         0.726 <tibble [1 x~ 0.252 6.53e- 33 0.214
                                                                     0.288
## 9 0.25 pH
                          0.655 <tibble [1 x~ 0.179 3.02e- 16 0.139
                                                                     0.219
## 10 0.25 PC1
                         0.826 <tibble [1 x~ 2.38 2.06e- 66 2.15
                                                                     2.60
## # ... with 20 more rows
CLES2_models <- CLES2_results %>%
  split(.$variable) %>%
  map(~lm(CLES_value ~ scale, .x))
CLES2_models$Elevation
##
## Call:
## lm(formula = CLES_value ~ scale, data = .x)
##
## Coefficients:
## (Intercept)
                     scale
                  -0.01698
      0.92611
# Summarise those models
CLES2_model_summaries <- CLES2_models %>%
  map_df(.id = "variable", tidy) %>%
  filter(term != "(Intercept)") %>%
  mutate(sig = case_when(
   p.value <= 0.05 ~ "*",
   p.value <= 0.10 ~ ".",
                   🕳 II II
   TRUE
  mutate(variable = factor(variable, levels = var_names %>%
     str_replace_all(" ", "_") %>%
     c("PC1")
  mutate_if(is.numeric, round, digits = 3) %>%
  dplyr::select(variable, estimate, p.value, sig)
CLES2_model_summaries
## # A tibble: 10 x 4
     variable estimate p.value sig
     <fct>
                 <dbl> <dbl> <chr>
                        0.638 " "
## 1 Elevation -0.017
               -0.166 0.098 .
## 2 MAP
## 3 PDQ
                -0.03 0.355 " "
```

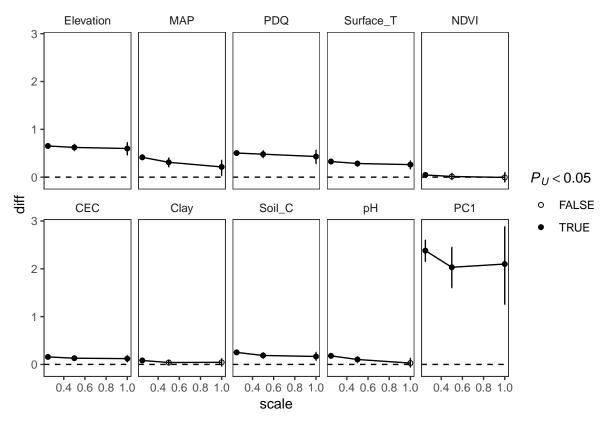
```
## 4 Surface_T
                  -0.006
                          0.553 " "
##
   5 NDVI
                  -0.067
                           0.183 " "
##
                  0.012
                          0.134 " "
   6 CEC
                           0.614 " "
                  -0.034
   7 Clay
## 8 Soil_C
                  -0.017
                           0.75 " "
## 9 pH
                  -0.155
                           0.041 *
## 10 PC1
                  -0.084
                           0.194 " "
heterogeneity2 %>% #heterogeneity_df %>%
  bind_rows(.id = "scale") %>%
  gather(
    variable, heterogeneity_value,
    -region, -scale#, -lon, -lat
  ) %>%
  mutate(variable = factor(variable, levels = var_names %>%
    str_replace_all(" ", "_") %>%
    c("PC1")
  )) %>%
  ggplot(aes(as.factor(scale), heterogeneity_value, fill = region)) +
    geom_boxplot() +
    facet_wrap(~variable, nrow = 2)
```



```
ggplot(CLES2_results) +
  aes(scale, CLES_value, group = variable) +
  geom_hline(yintercept = 0.5, lty = "dashed") +
  geom_line() +
  geom_point(aes(shape = P_U < 0.05)) +
  scale_shape_manual(name = bquote(italic("P"["U"]) < 0.05), values = c(1, 19)) +
  facet_wrap(~variable, nrow = 2)</pre>
```



```
ggplot(CLES2_results) +
  aes(scale, diff, group = variable) +
  geom_hline(yintercept = 0.0, lty = "dashed") +
  geom_line() +
  geom_errorbar(aes(ymin = U_low, ymax = U_upp), width = 0) +
  geom_point(aes(shape = P_U < 0.05)) +
  scale_shape_manual(name = bquote(italic("P"["U"]) < 0.05), values = c(1, 19)) +
  facet_wrap(~variable, nrow = 2)</pre>
```

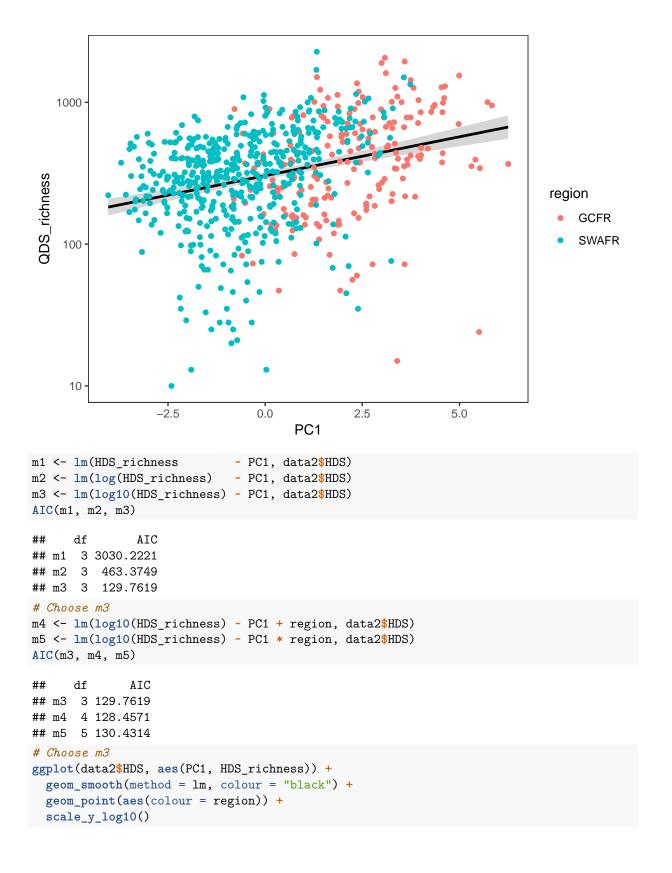


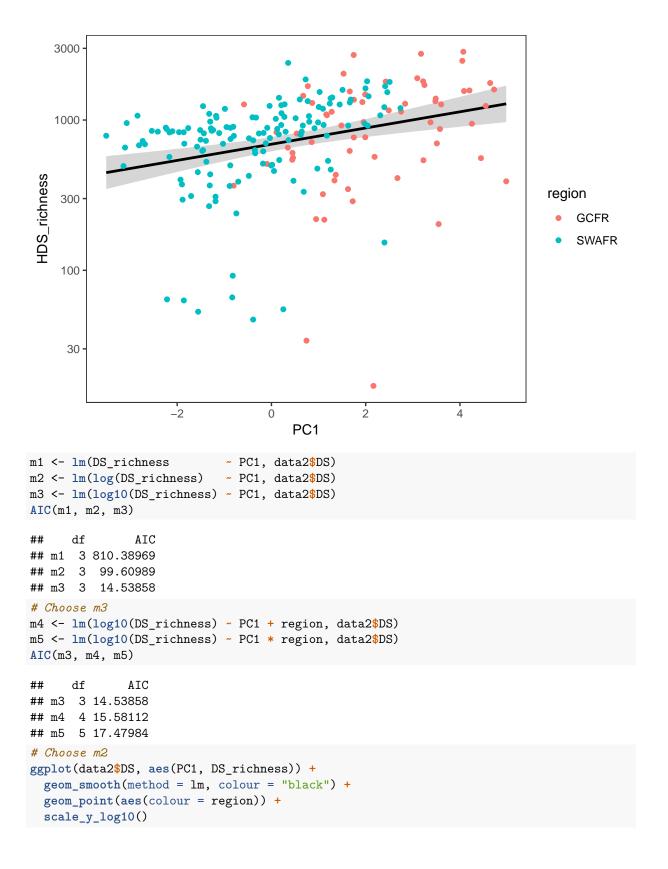
```
heterogeneity2_w_coords <- map2(GCFR_heterogeneity2, SWAFR_heterogeneity2,
  ~ na.exclude(rbind(
    cbind(region = "GCFR", raster2df(.x)),
    cbind(region = "SWAFR", raster2df(.y))
  ))
)
heterogeneity2 <- map2(heterogeneity2, heterogeneity2_w_coords, full_join)
heterogeneity2$QDS$QDS <- heterogeneity2$QDS %$%
  SpatialPoints(
               = data.frame(x = lon, y = lat),
    proj4string = crs(Larsen_grid)
  ) %over%
  Larsen_grid %>%
  pull(qdgc)
heterogeneity2$HDS$HDS <- heterogeneity2$HDS %$%
  SpatialPoints(
                = data.frame(x = lon, y = lat),
    coords
    proj4string = crs(Larsen_grid)
  ) %over%
  Larsen_grid %>%
  pull(hdgc)
heterogeneity2$DS$DS <- heterogeneity2$DS %$%
  SpatialPoints(
               = data.frame(x = lon, y = lat),
    coords
    proj4string = crs(Larsen_grid)
  ) %over%
  Larsen_grid %>%
  pull(dgc)
```

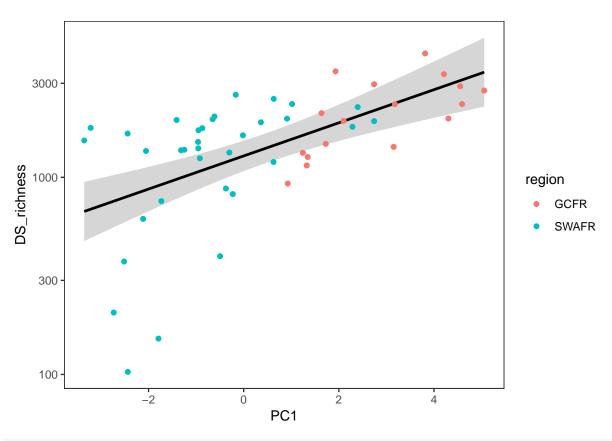
```
data2 <- heterogeneity2
data2$QDS %<>%
 as_tibble() %>%
 full join(QDS richness) %>%
 na.exclude() %>%
 filter(n_EDS == 4)
data2$HDS %<>%
 as tibble() %>%
 full_join(mean_QDS_richness) %>%
 full_join(HDS_richness) %>%
 na.exclude() %>%
 filter(n_QDS == 4) %>%
 mutate(
   QDS_turnover = HDS_richness - mean_QDS_richness,
   QDS_turnover_prop = QDS_turnover / HDS_richness
 )
data2$DS %<>%
 as_tibble() %>%
 full_join(mean_HDS_richness) %>%
 full_join(DS_richness) %>%
 na.exclude() %>%
 filter(n_HDS == 4) \%
 mutate(
   HDS_turnover = DS_richness - mean_HDS_richness,
   HDS_turnover_prop = HDS_turnover/DS_richness
```

### Univariate models

```
m1 <- lm(QDS richness
                            ~ PC1, data2$QDS)
m2 <- lm(log(QDS_richness) ~ PC1, data2$QDS)</pre>
m3 <- lm(log10(QDS_richness) ~ PC1, data2$QDS)</pre>
AIC(m1, m2, m3)
     df
## m1 3 9829.8053
## m2 3 1645.6538
## m3 3 484.6806
# Choose m3
m4 <- lm(log10(QDS_richness) ~ PC1 + region, data2$QDS)
m5 <- lm(log10(QDS_richness) ~ PC1 * region, data2$QDS)
AIC(m3, m4, m5)
      df
##
              AIC
## m3 3 484.6806
## m4 4 482.9581
## m5 5 484.3936
# Choose m3
ggplot(data2$QDS, aes(PC1, QDS_richness)) +
 geom_smooth(method = lm, colour = "black") +
  geom_point(aes(colour = region)) +
 scale_y_log10()
```







```
models_non_region <- map(predictor_names,</pre>
  ~lm(paste("log10(QDS_richness) ~", .x), data2$QDS)
names(models_non_region) <- predictor_names</pre>
models_add_region <- map(predictor_names,</pre>
  ~lm(paste("log10(QDS_richness) ~", .x, "+ region"), data2$QDS)
names(models_add_region) <- predictor_names</pre>
models_int_region <- map(predictor_names,</pre>
  ~lm(paste("log10(QDS_richness) ~", .x, "* region"), data2$QDS)
names(models_int_region) <- predictor_names</pre>
knitr::kable(pmap_dfr(
  .1 = list(models_non_region, models_add_region, models_int_region),
  .id = "variable",
  .f = ~AIC(..1, ...2, ...3) \%
    mutate(
      model_rank = 1:3,
      model_type = c(" ", "+", "x")[model_rank],
      delta_AIC = AIC - min(AIC),
      best_model = (model_rank == min(model_rank[delta_AIC < 2]))</pre>
    ) %>%
    filter(best_model) %>%
    dplyr::select(-df, -AIC, -model_rank, -best_model)
))
```

variable	$model\_type$	delta_AIC
Elevation	+	0.000000
MAP	+	0.000000
PDQ	X	0.000000
$Surface\_T$		0.000000

variable	$model\_type$	delta_AIC
NDVI	X	0.000000
CEC	+	0.000000
Clay	+	0.000000
$Soil\_C$	+	0.174429
рН	+	0.000000
PC1		1.722464

```
models_non_region <- map(predictor_names,</pre>
  ~lm(paste("log10(HDS_richness) ~", .x), data2$HDS)
)
names(models_non_region) <- predictor_names</pre>
models_add_region <- map(predictor_names,</pre>
  ~lm(paste("log10(HDS_richness) ~", .x, "+ region"), data2$HDS)
names(models_add_region) <- predictor_names</pre>
models_int_region <- map(predictor_names,</pre>
  ~lm(paste("log10(HDS_richness) ~", .x, "* region"), data2$HDS)
names(models_int_region) <- predictor_names</pre>
pmap_dfr(
  .1 = list(models_non_region, models_add_region, models_int_region),
  .id = "variable",
  f = \text{AIC}(...1, ...2, ...3) \%
    mutate(
      model_rank = 1:3,
      model_type = c(" ", "+", "x")[model_rank],
      delta_AIC = AIC - min(AIC),
      best_model = (model_rank == min(model_rank[delta_AIC < 2]))</pre>
    ) %>%
    filter(best_model) %>%
    dplyr::select(-df, -AIC, -model_rank, -best_model)
)
##
       variable model_type delta_AIC
## 1 Elevation
                         + 1.13689775
## 2
            MAP
                            0.07858797
## 3
            PDQ
                         x 0.00000000
## 4 Surface_T
                            0.00000000
## 5
           NDVI
                            0.00000000
## 6
            CEC
                         x 0.00000000
## 7
           Clay
                            0.00000000
## 8
         Soil_C
                            0.00000000
## 9
                            0.00000000
            рΗ
            PC1
                            1.30479200
models_non_region <- map(predictor_names,</pre>
  ~lm(glue("log10(DS_richness) ~", .x), data2$DS)
names(models_non_region) <- predictor_names</pre>
models_add_region <- map(predictor_names,</pre>
  ~lm(paste("log10(DS_richness) ~", .x, "+ region"), data2$DS)
names(models_add_region) <- predictor_names</pre>
models_int_region <- map(predictor_names,</pre>
  ~lm(paste("log10(DS_richness) ~", .x, "* region"), data2$DS)
```

```
names(models_int_region) <- predictor_names</pre>
pmap_dfr(
  .1 = list(models_non_region, models_add_region, models_int_region),
  .id = "variable",
  f = \text{AIC}(...1, ...2, ...3) \%
   mutate(
     model_rank = 1:3,
      model_type = c(" ", "+", "x")[model_rank],
      delta_AIC = AIC - min(AIC),
     best_model = (model_rank == min(model_rank[delta_AIC < 2]))</pre>
    ) %>%
    filter(best_model) %>%
    dplyr::select(-df, -AIC, -model_rank, -best_model)
)
##
       variable model_type delta_AIC
## 1 Elevation
                           0.8578615
## 2
            MAP
                           0.0000000
## 3
           PDQ
                        x 0.0000000
## 4 Surface_T
                          0.0000000
## 5
          NDVI
                           0.0000000
## 6
           CEC
                        + 0.0000000
## 7
          Clay
                          0.9074850
## 8
         Soil_C
                           0.7398216
## 9
                        + 0.0000000
            рH
## 10
            PC1
                           0.0000000
Multivariate models
data2$QDS %<>% mutate(log10_QDS_richness = log10(QDS_richness))
data2$HDS %<>% mutate(log10_HDS_richness = log10(HDS_richness))
data2$DS %<>% mutate(log10_DS_richness = log10(DS_richness))
m_QDS_richness <- lm(glue("log10_QDS_richness ~ {full_formula}"), data2$QDS)
m_HDS_richness <- lm(glue("log10_HDS_richness ~ {full_formula}"), data2$HDS)
m_DS_richness <- lm(glue("log10_DS_richness ~ {full_formula}"), data2$DS)</pre>
m_QDS_richness %<>% step(direction = "backward", trace = 0)
m_HDS_richness %<>% step(direction = "backward", trace = 0)
m_DS_richness %<>% step(direction = "backward", trace = 0)
# Reparameterise models to \{*\}:regionGCFR & \{*\}:regionSWAFR
# a.o.t. {*}*region, so that the figure of the effects actually represents
# each region, not the baseline (GCFR) and "relative SWAFR"
# (and that would cause inconsistencies too when their is no interaction with
# region term for a roughness variable).
reparameterise <- function(m) {</pre>
  response <- colnames(m$model)[[1]]
  data <- data2 %$% {
```

(response == "log10\_QDS\_richness") QDS

else if (response == "log10\_HDS\_richness") HDS
else if (response == "log10\_DS\_richness") DS

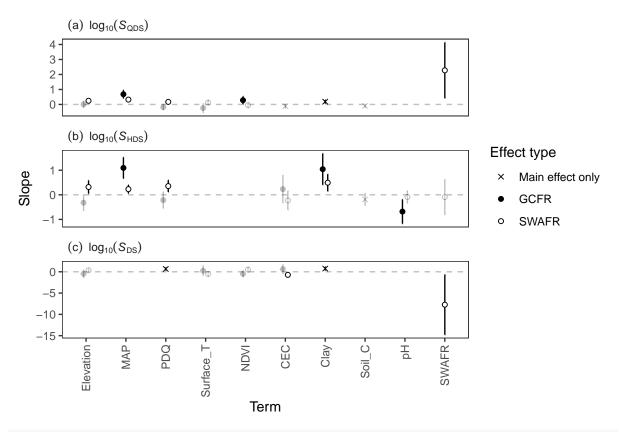
magrittr::extract(str\_which(., ":regionSWAFR"))
reparameterisation <- preds\_w\_interactions %<>%

preds\_w\_interactions <- m %\$%</pre>

coefficients %>%
names() %>%

```
str_remove(":regionSWAFR") %>%
    {glue("-{.}")} %>%
    paste(collapse = " ")
  update(m,
    formula = glue(". ~ . {reparameterisation}"),
    data = data
  )
}
# Test:
# a <- m_HDS_richness
  b <- reparameterise(m_HDS_richness)</pre>
# AIC(a, b) # same model! :)
m_QDS_richness %<>% reparameterise()
m HDS richness %<>% reparameterise()
m_DS_richness %<>% reparameterise()
models <- list(</pre>
  QDS richness = m QDS richness,
  HDS_richness = m_HDS_richness,
  DS_richness = m_DS_richness
)
models_summary <- models %>%
  map_df(.id = "response", tidy, conf.int = TRUE) %>%
  dplyr::select(-std.error, -statistic) %>%
  filter(term != "(Intercept)")
models_R2 <- models %>%
  map_df(.id = "response", glance) %>%
  dplyr::select(response, adj.r.squared)
models_summary %<>% full_join(models_R2)
glance(m_QDS_richness)
## # A tibble: 1 x 11
## r.squared adj.r.squared sigma statistic p.value
                                                       df logLik
                                                                    AIC
##
         <dbl>
                      <dbl> <dbl>
                                      <dbl>
                                              <dbl> <int> <dbl> <dbl> <dbl> <dbl>
                                                        15 -162. 356. 429.
## 1
         0.274
                       0.259 0.309
                                        18.3 5.18e-39
## # ... with 2 more variables: deviance <dbl>, df.residual <int>
glance(m_HDS_richness)
## # A tibble: 1 x 11
    r.squared adj.r.squared sigma statistic p.value
                                                         df logLik
                                                                     AIC
                                                                           BIC
##
                       <dbl> <dbl>
         <dbl>
                                      <dbl>
                                              <dbl> <int> <dbl> <dbl> <dbl> <dbl>
         0.377
## 1
                       0.330 0.283
                                        8.00 3.42e-13
                                                         15 -23.4 78.7 131.
## # ... with 2 more variables: deviance <dbl>, df.residual <int>
glance(m_DS_richness)
## # A tibble: 1 x 11
     r.squared adj.r.squared sigma statistic p.value
                                                        df logLik
                                                                    AIC
                      <dbl> <dbl>
         <dbl>
                                    <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <
                                                     12 16.6 -7.12 18.0
                                        8.48 2.25e-7
         0.705
                       0.622 0.200
## # ... with 2 more variables: deviance <dbl>, df.residual <int>
models_summary_for_plot <- models_summary %>%
  mutate(
   response = case_when(
   response == "QDS_richness" ~ "(a)~~log[10](italic(S)[QDS])",
```

```
response == "HDS_richness" ~ "(b)~~log[10](italic(S)[HDS])",
     response == "DS_richness" ~ "(c)~~log[10](italic(S)[DS])"
   ),
   region =
      case_when(
        str_detect(term, "regionSWAFR") ~ "SWAFR",
       str_detect(term, "regionGCFR") ~ "GCFR",
       TRUE
                                        ~ "Main effect only"
      ) %>%
     factor(levels = c("Main effect only", "GCFR", "SWAFR")),
   term = term %>%
     str_replace_all("\\.", " ") %>%
     str_remove_all("regionSWAFR:") %>%
     str remove all("regionGCFR:") %>%
     str_replace_all("regionSWAFR", "SWAFR") %>%
     factor(levels = c(str_replace_all(var_names, " ", "_"), "SWAFR")),
   sig = (p.value < 0.05)
ggplot(models_summary_for_plot) +
 aes(
   term, estimate,
   fill = region, group = region, shape = region,
   alpha = sig
 geom_hline(yintercept = 0, linetype = "dashed", colour = "grey75") +
 geom errorbar(
   aes(ymin = conf.low, ymax = conf.high),
   position = position_dodge(width = 0.25),
   width = 0
 ) +
 geom_point(position = position_dodge(width = 0.25)) +
 labs(x = "Term", y = "Slope") +
  scale_fill_manual(values = c(NA, "black", "white")) +
 scale_shape_manual(values = c(4, 21, 21)) +
 scale_alpha_manual(values = c(0.25, 1)) +
 facet_wrap(~response, nrow = 3, scales = "free_y", labeller = label_parsed) +
 guides(
   fill = FALSE,
   shape = guide_legend(
     title = "Effect type",
     override.aes = list(fill = c(NA, "black", "white"))
   ),
   alpha = FALSE
 ) +
 theme(
   axis.text.x = element_text(angle = 90, hjust = 1, vjust = 0.5),
   strip.text.x = element_text(angle = 0, hjust = 0)
```



```
ggplot(models_summary_for_plot[models_summary_for_plot$term != "SWAFR", ]) +
 aes(
   term, estimate,
   fill = region, group = region, shape = region,
   alpha = sig
 ) +
 geom_hline(yintercept = 0, linetype = "dashed", colour = "grey75") +
 geom_errorbar(
   aes(ymin = conf.low, ymax = conf.high),
   position = position_dodge(width = 0.25),
   width = 0
 ) +
  geom_point(position = position_dodge(width = 0.25)) +
 labs(x = "Term", y = "Slope") +
 scale_fill_manual(values = c(NA, "black", "white")) +
 scale_shape_manual(values = c(4, 21, 21)) +
  scale_alpha_manual(values = c(0.25, 1)) +
 facet_wrap(~response, nrow = 3, scales = "free_y", labeller = label_parsed) +
 guides(
   fill = FALSE,
    shape = guide_legend(
      title = "Effect type",
      override.aes = list(fill = c(NA, "black", "white"))
   ),
   alpha = FALSE
  ) +
 theme(
   axis.text.x = element_text(angle = 90, hjust = 1, vjust = 0.5),
    strip.text.x = element_text(angle = 0, hjust = 0)
 )
```

