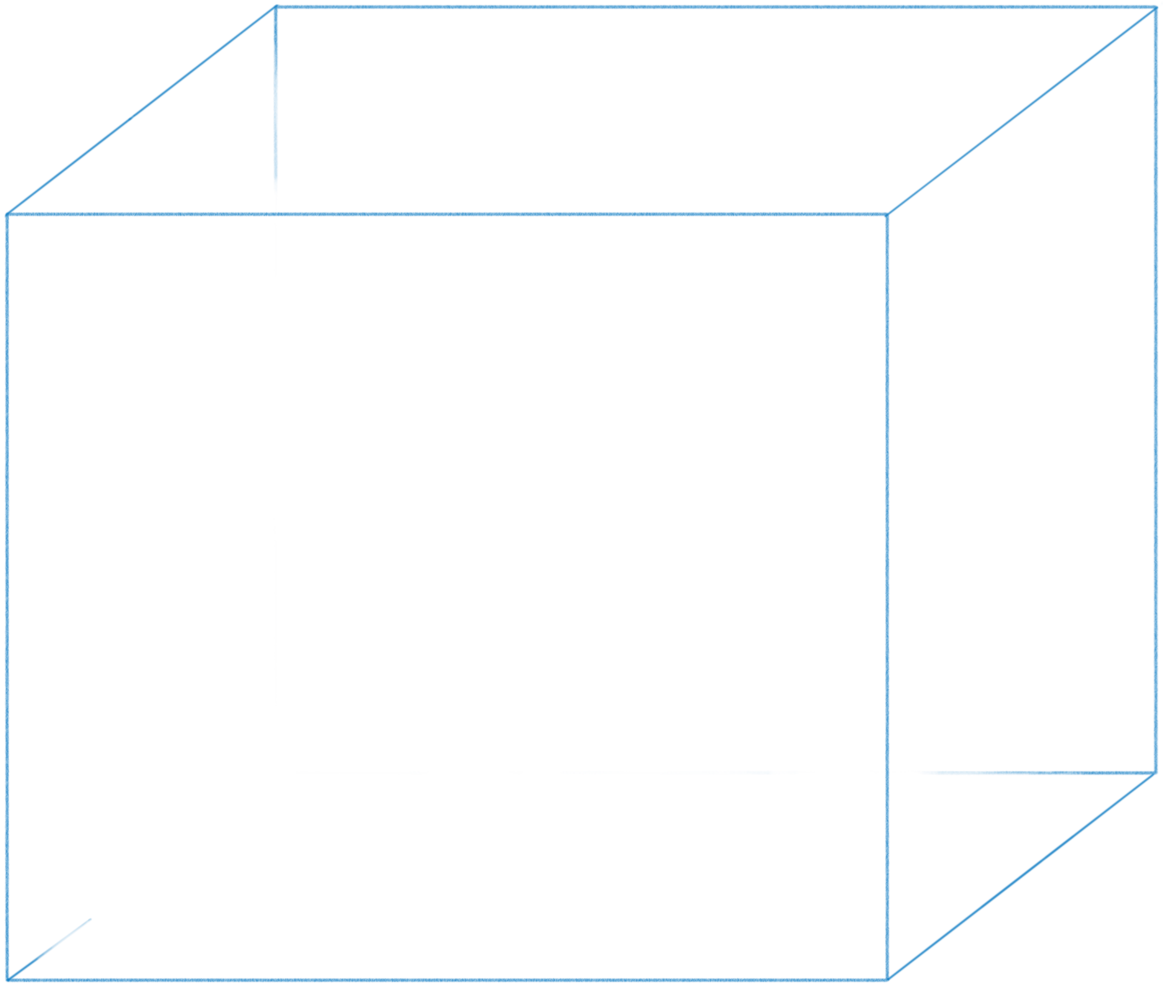
Comparison of the global distribution of functional and phylogenetic diversity in plant communities.

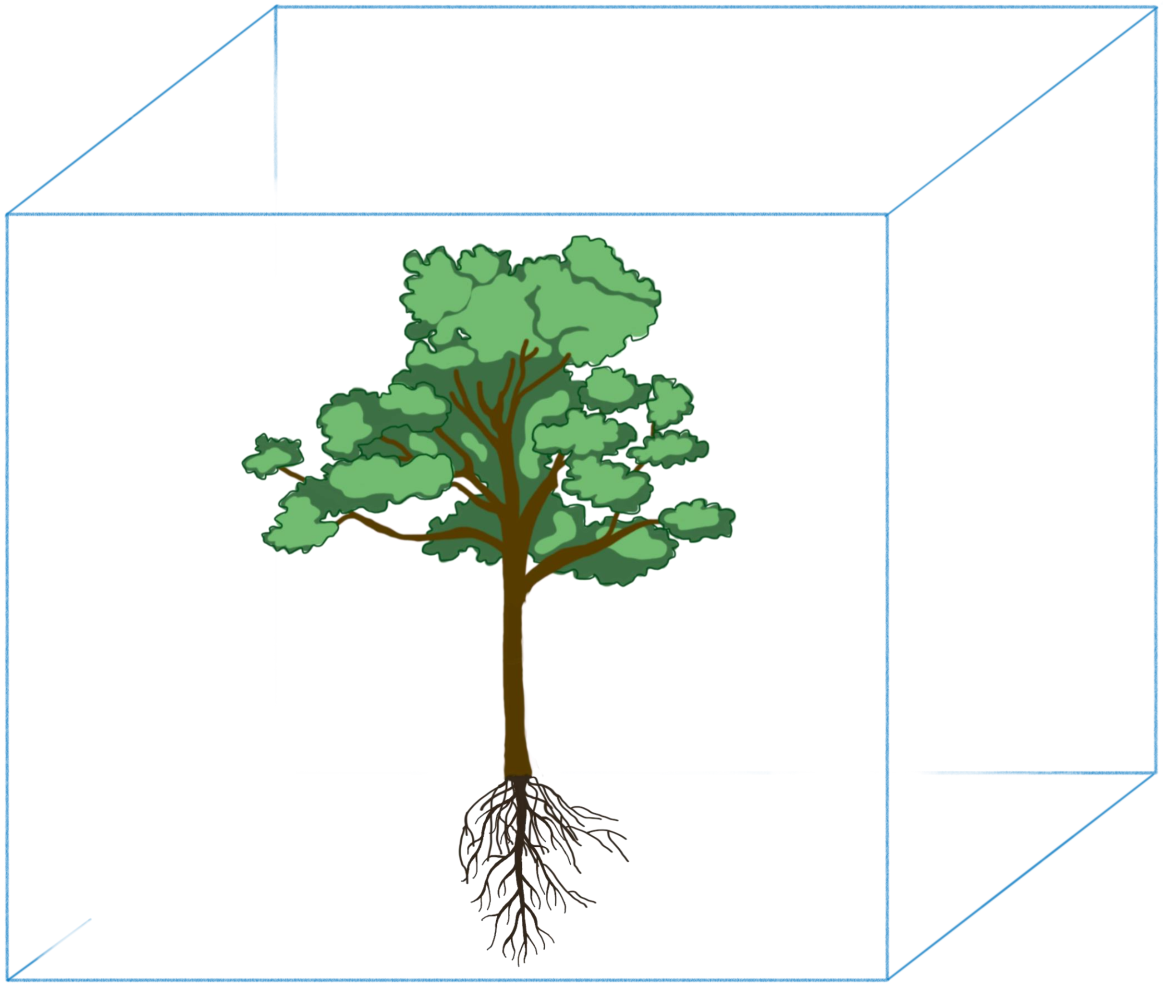
A study to highlight commonalities and differences in the distribution of vascular plants.

Introduction – Environmental space



[1] Hutchinson 1978

Introduction – Environmental space



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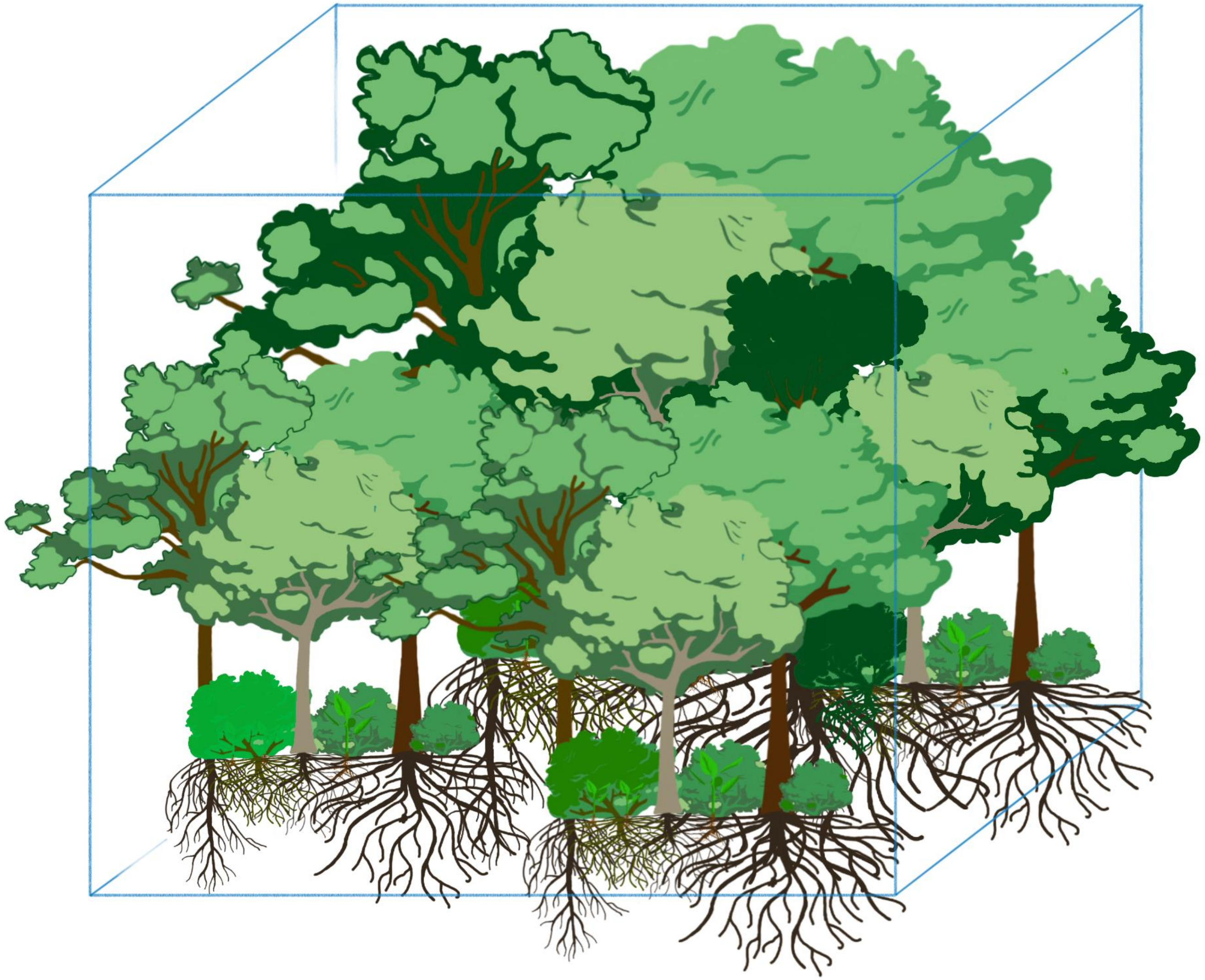
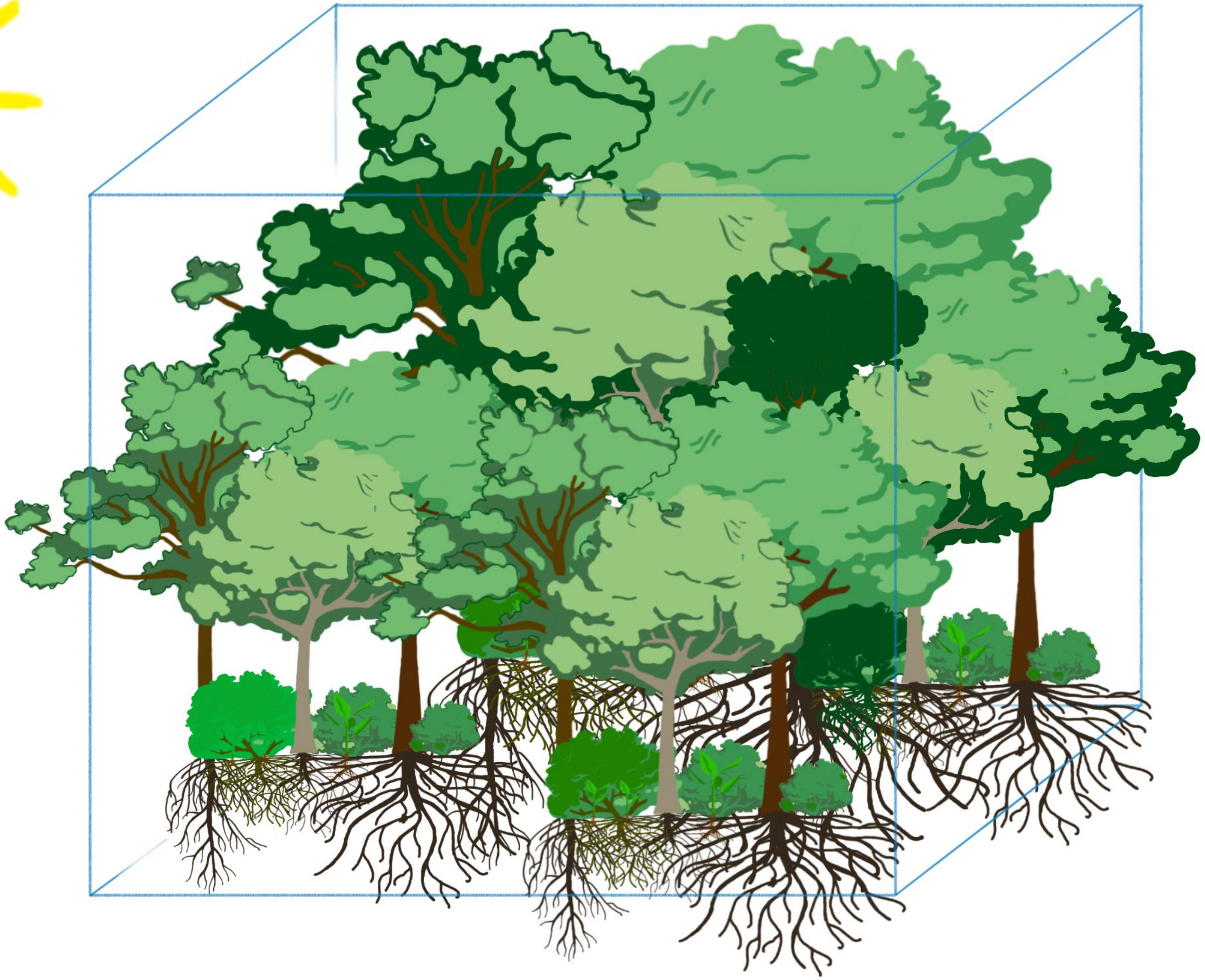


[1] Hutchinson 1978 [2] Gallego-Tévar et al. 2018

Introduction – Environmental space



[1] Hutchinson 1978 [3] Reich et al. 2003

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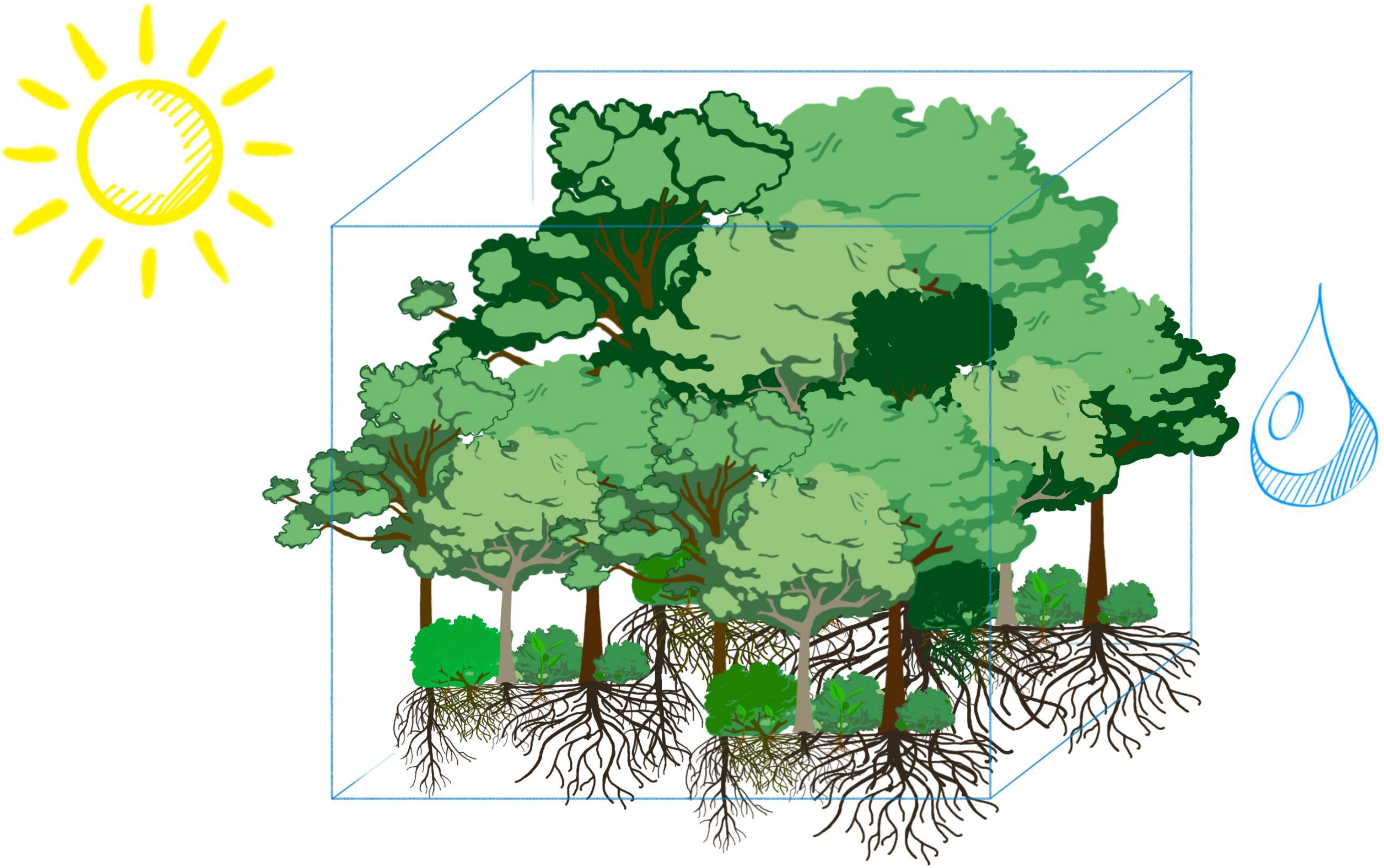

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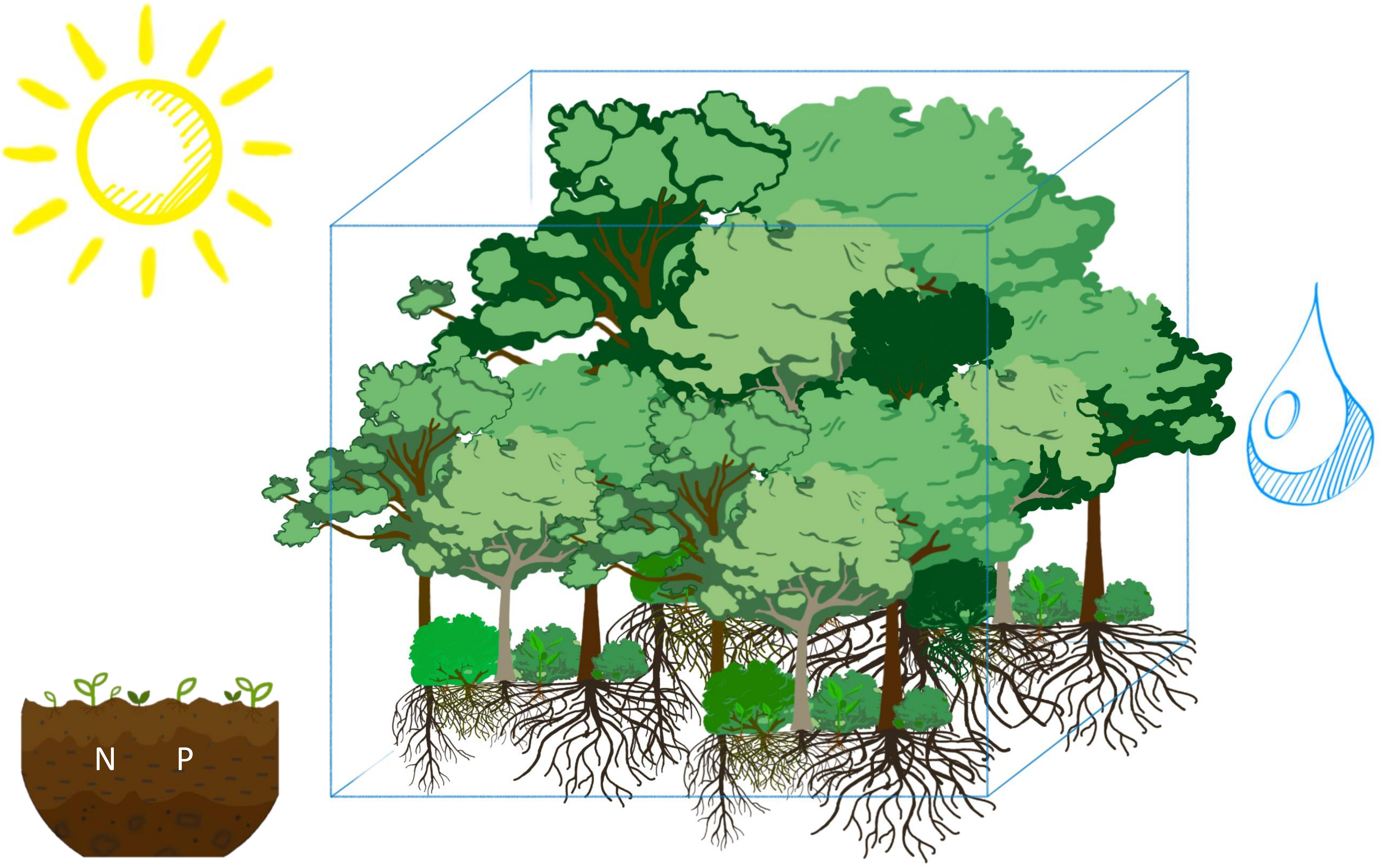
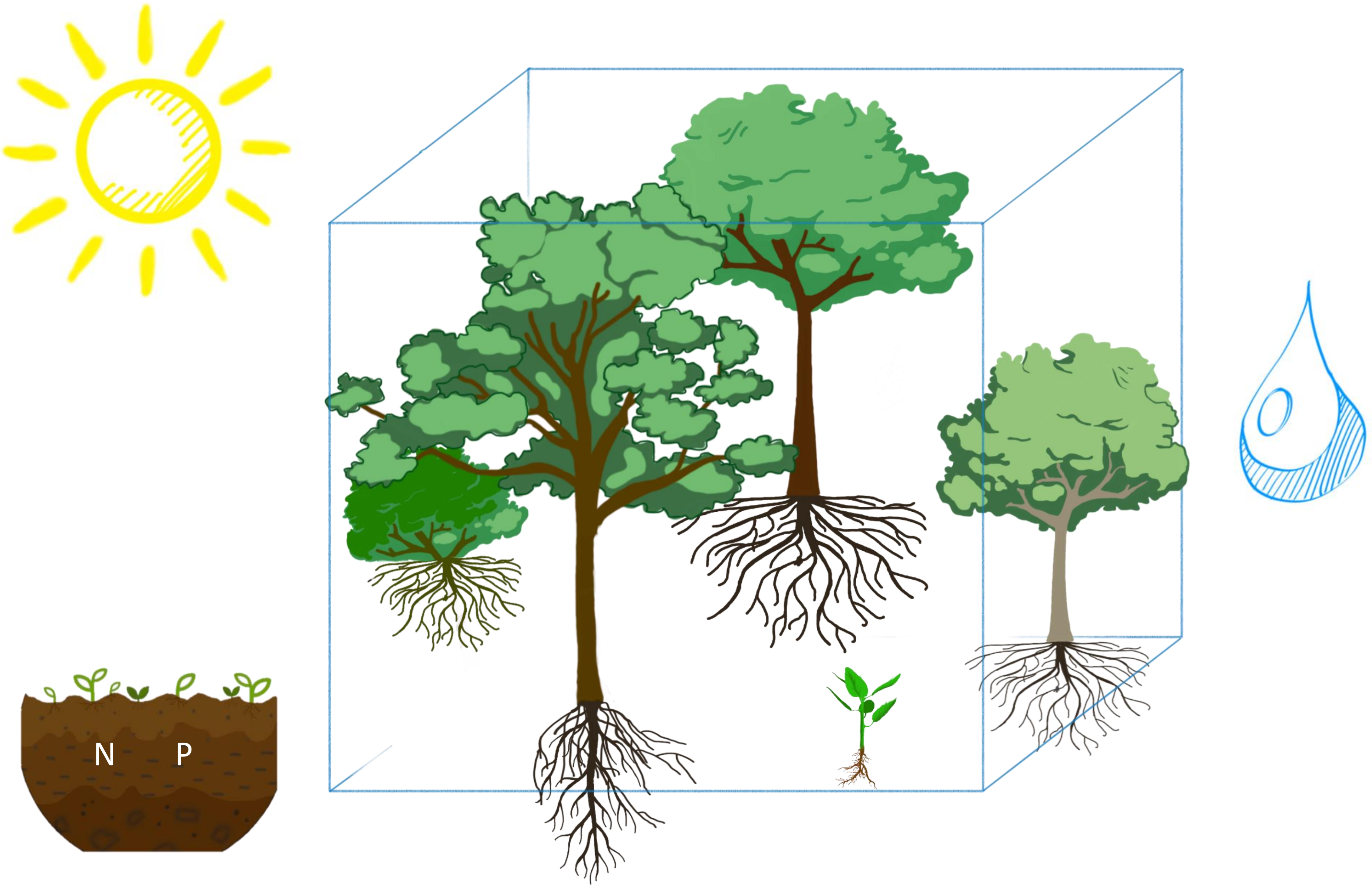
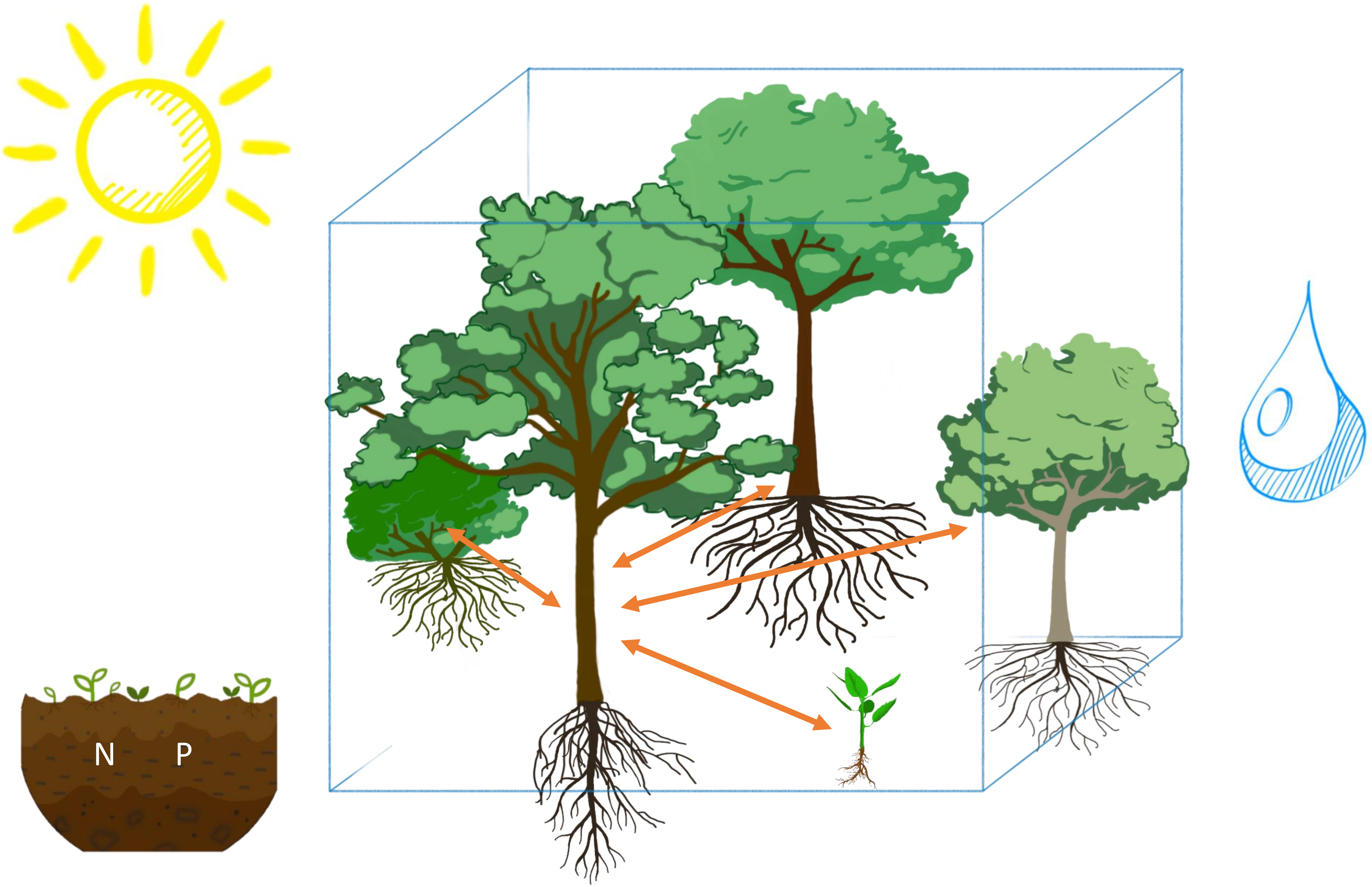


[1] Hutchinson 1978 [3] Reich et al. 2003 [4] García-Palacios et al. 2012



[5] McGill et al. 2006

Introduction – Community assemblage



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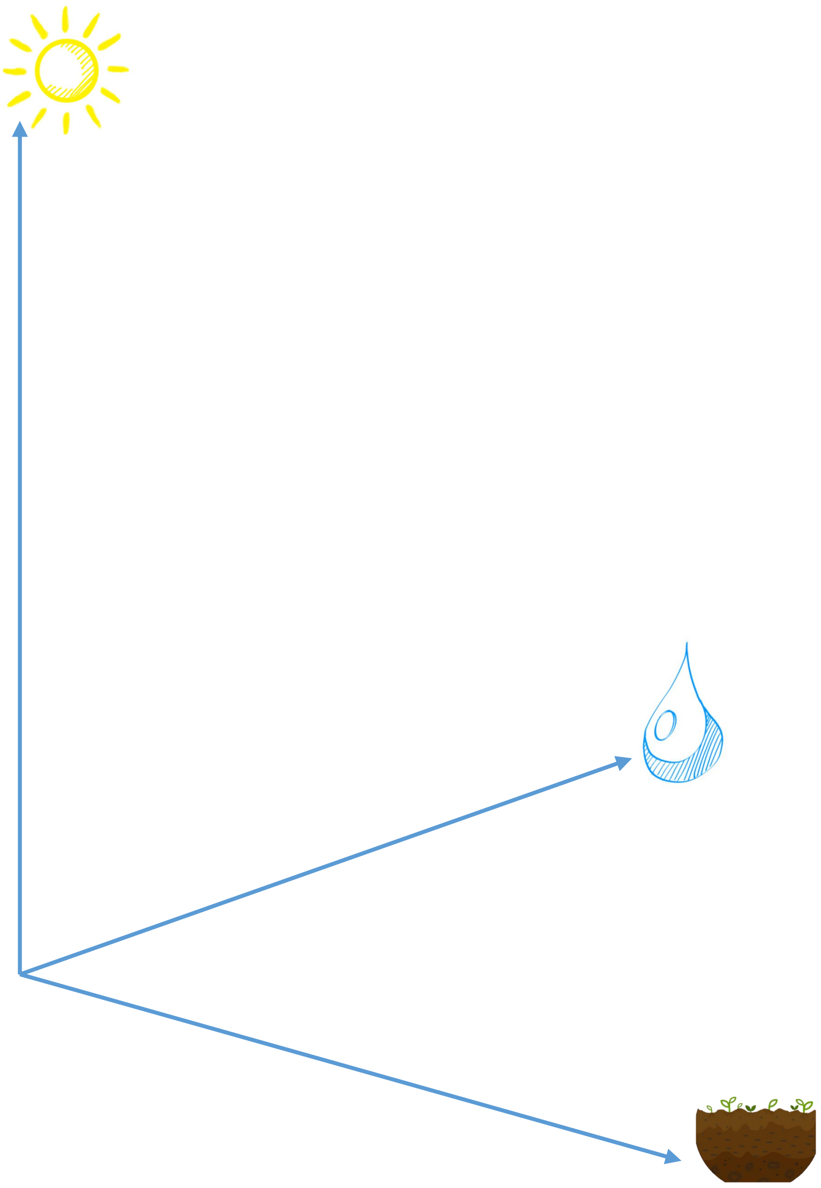
Introduction – Trait distances



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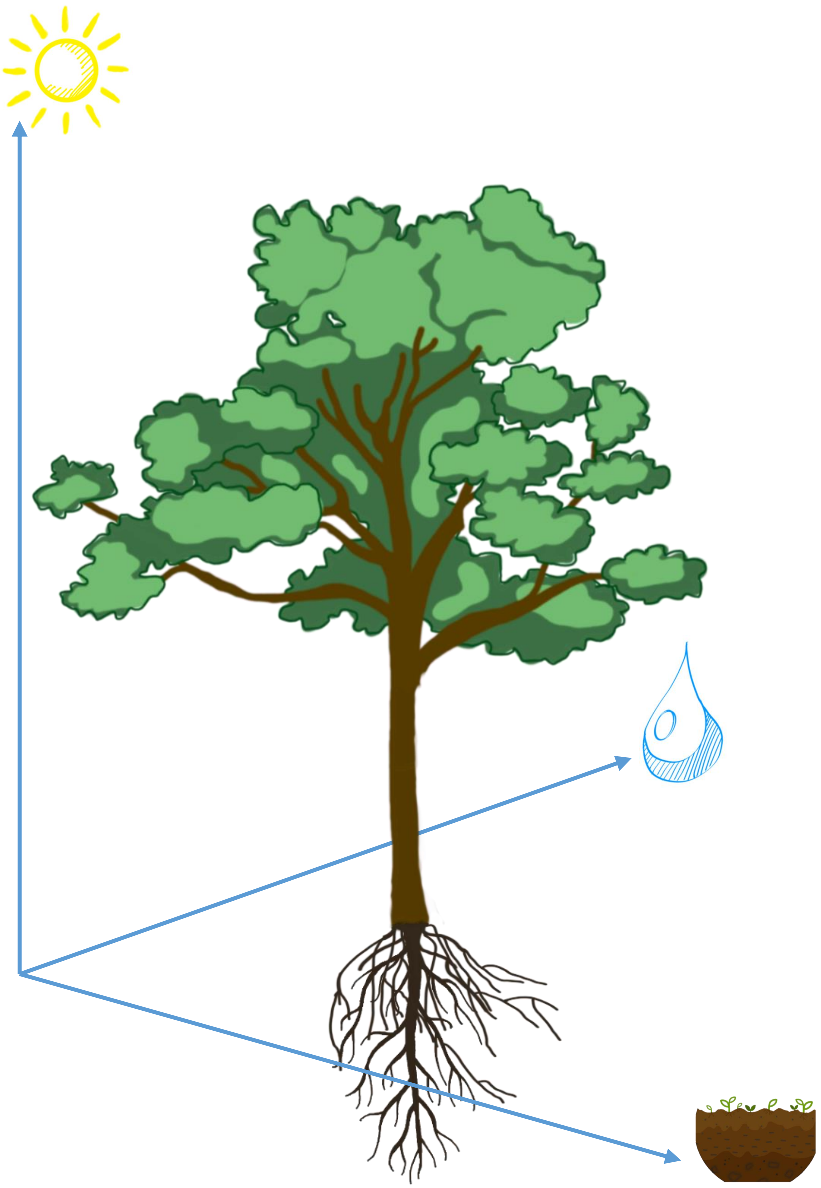
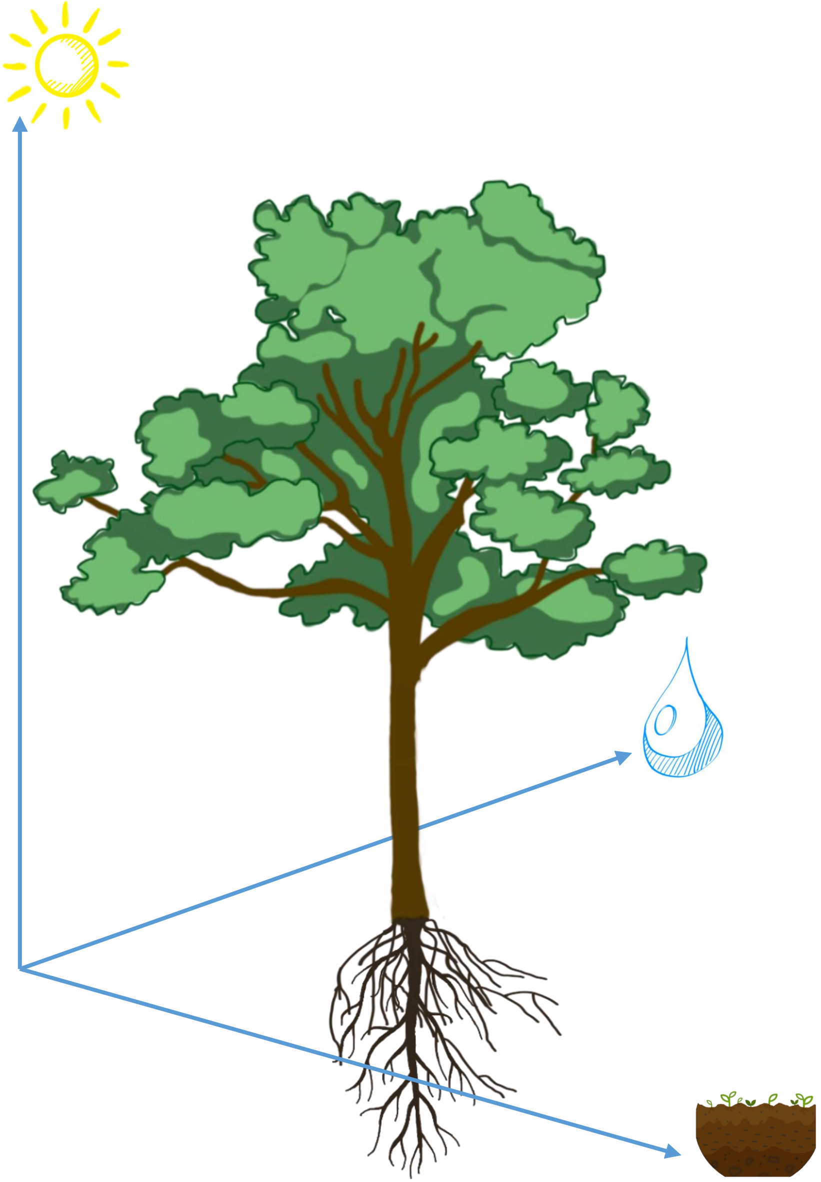


[5] McGill et al. 2006 [6] Wright et al. 2004

Introduction – Phylogenetic distances



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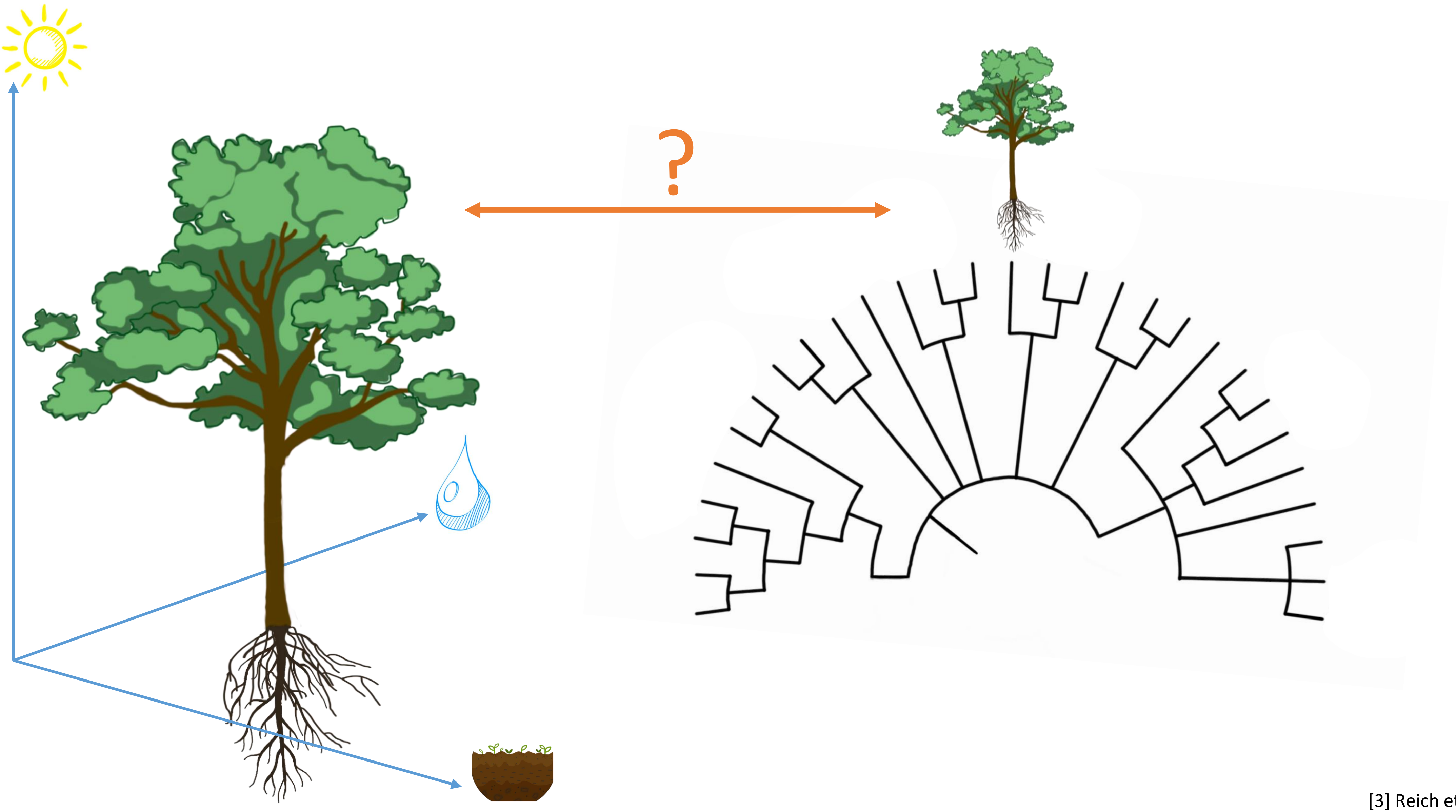

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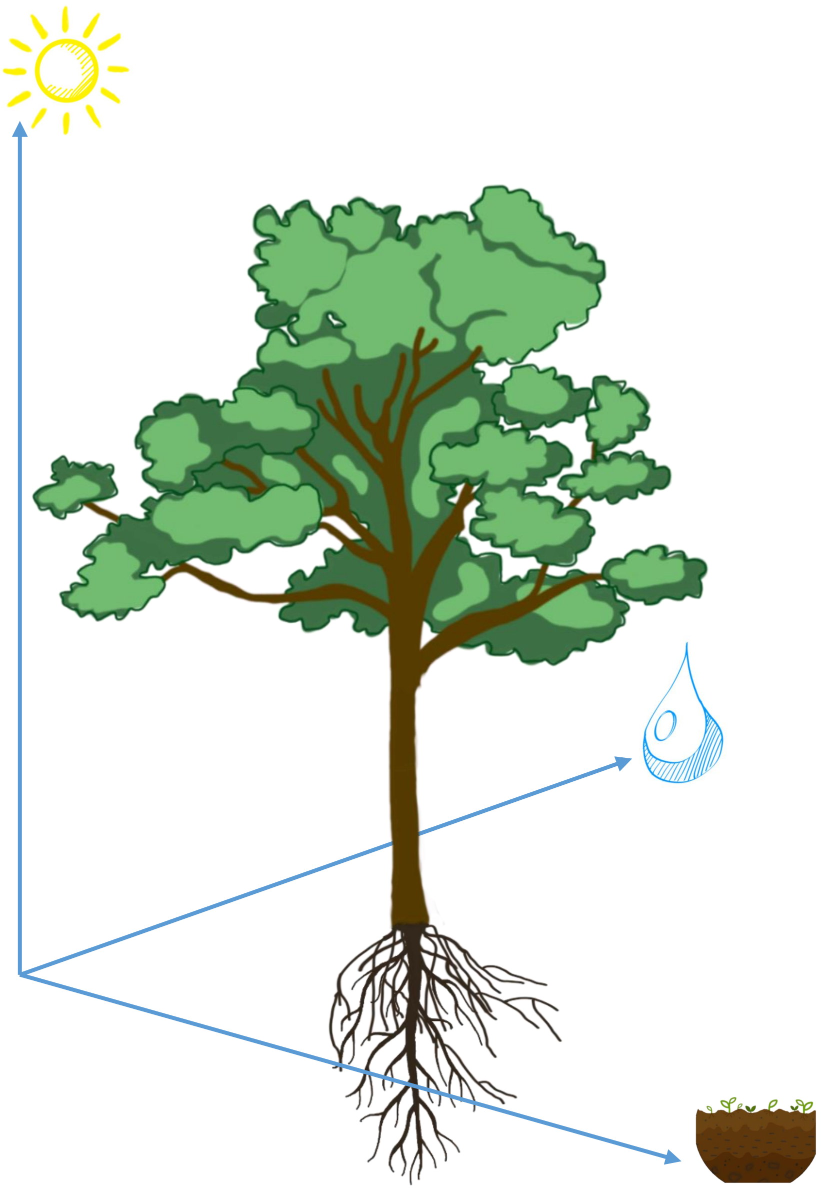
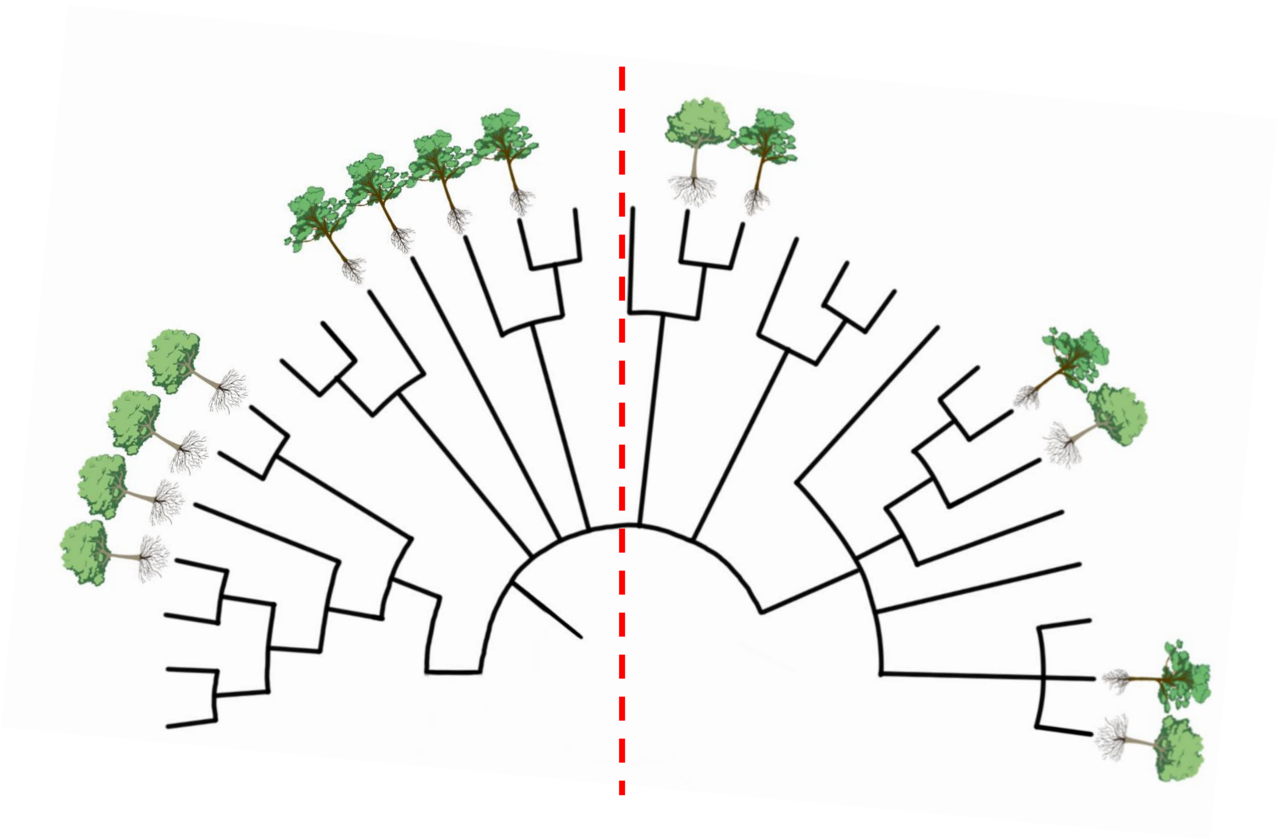
Introduction – Traits on the phylogeny





[7] Cavender-Bares et al. 2004 [8] Ackerly 2009 [9]

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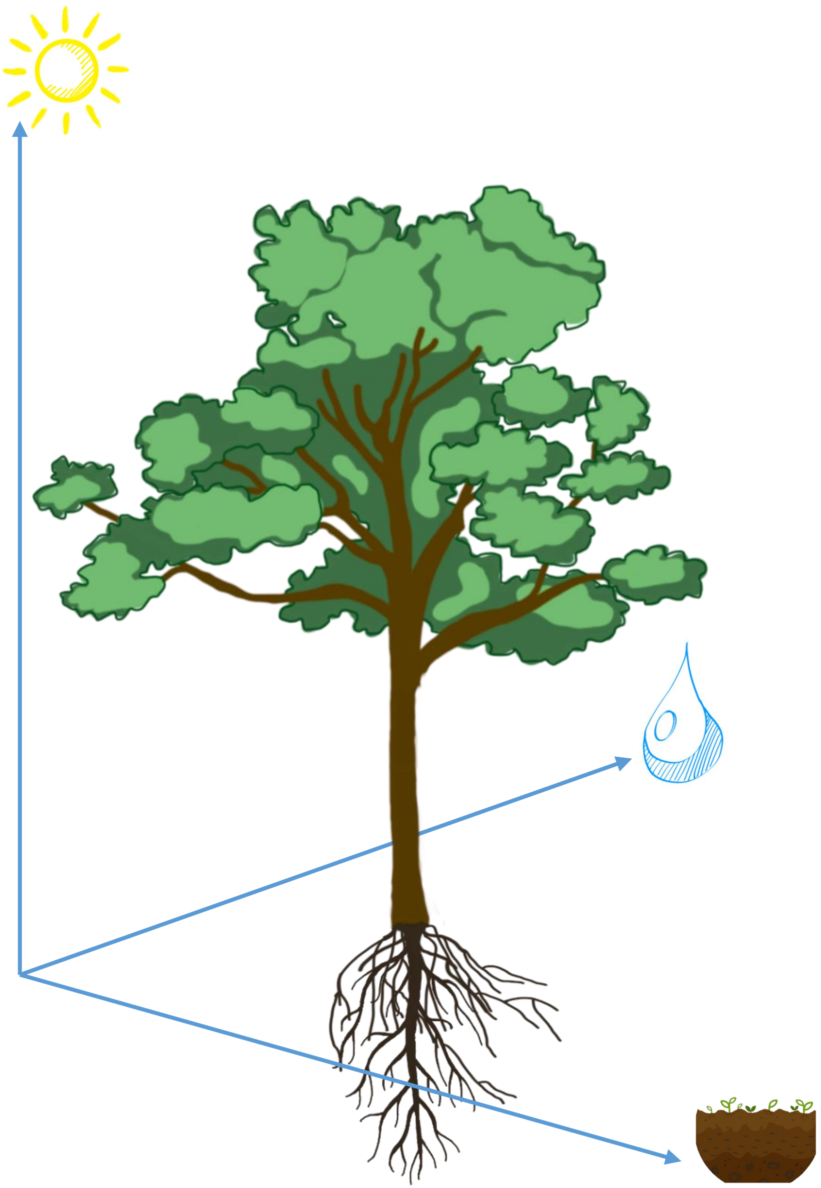
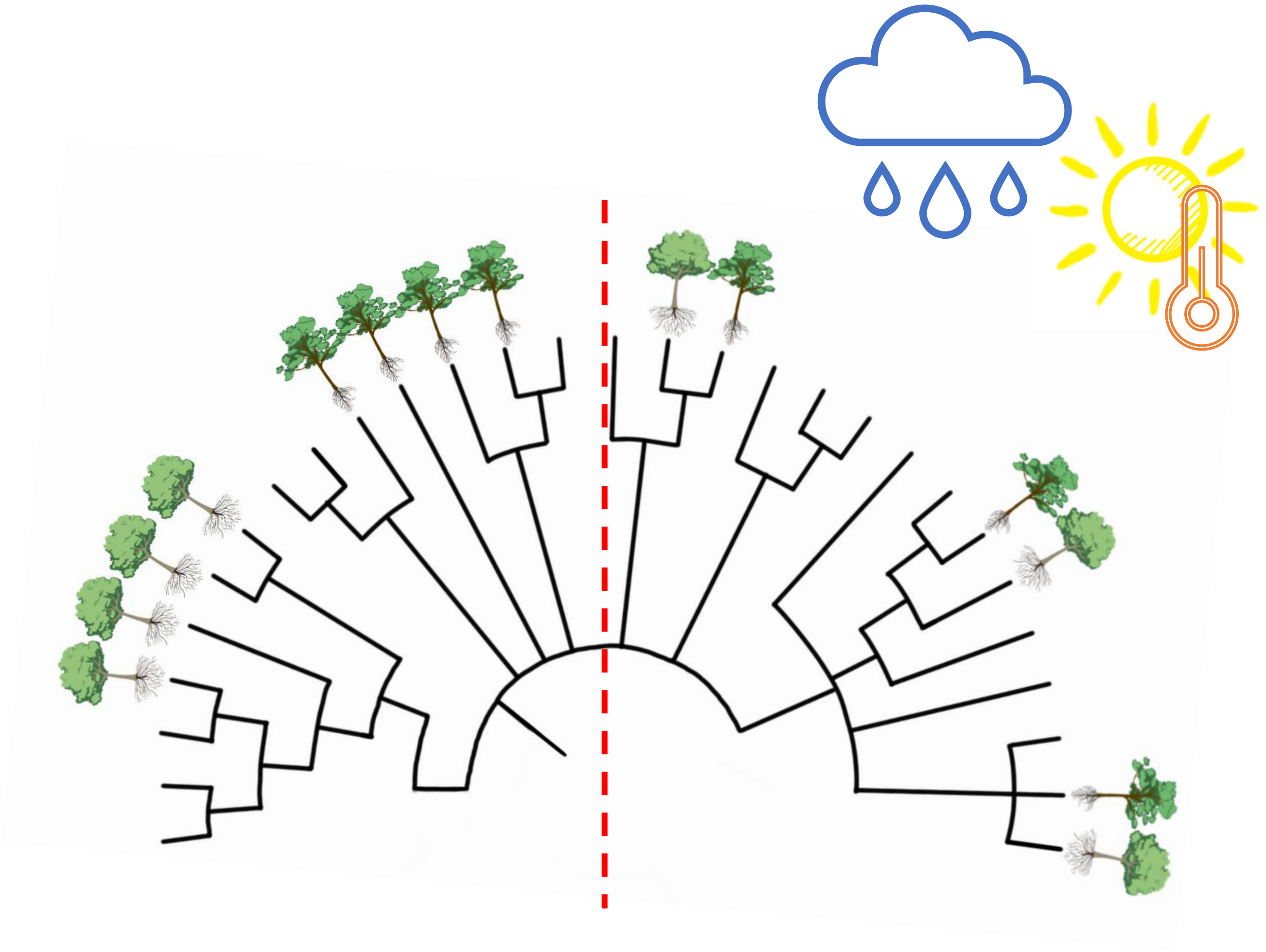
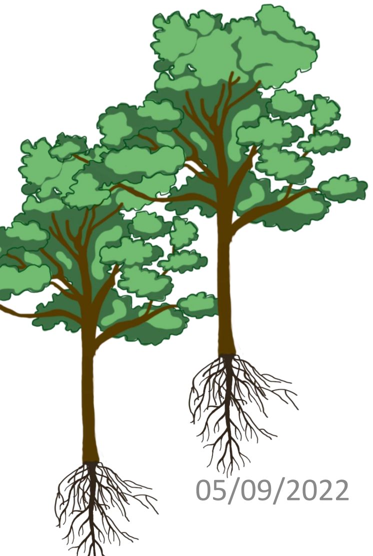




[9] Núñez-Farfán et al. 2007 [10] Castagneyrol et al. 2014

H1: Functional and phylogenetic diversity are related at the global scale.



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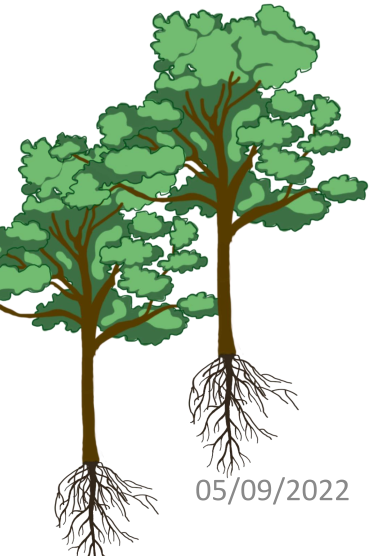
H2: Spatial patterns of functional and phylogenetic diversity differ from each other.



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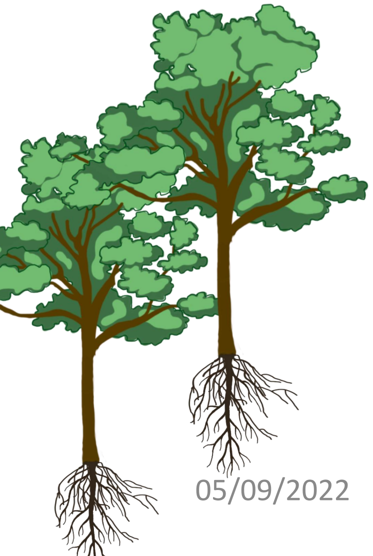

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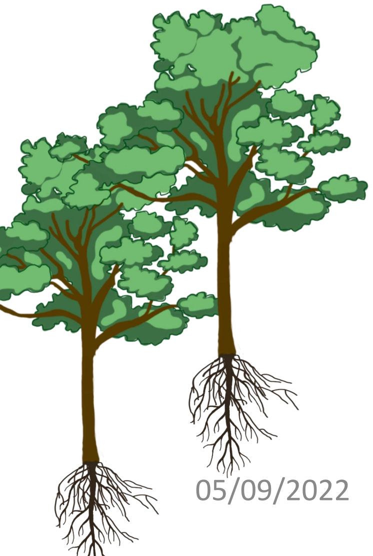
H4: Spatial pattern of phylogenetic diversity depends on past climatic events, i.e. climatic conditions after the last glacial maximum.



Methods – Species community data

sPlot

a project of iDiv

1,977,637 vegetation-plots

[11] Bruelheide et al. 2019

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GBOTB for seed plants[12]

Clade in the phylogeny for pteridophytes[13]

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TRY Plant Trait Database

Specific leaf area, plant height and specific root length from the gap-filled TRY traits[14, 15, 16, 17]

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50% of the total cover is represented by species present in the phylogeny and traits

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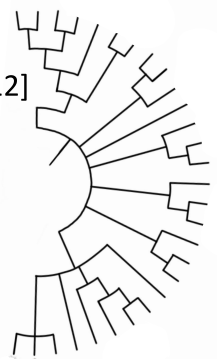

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Methods – Response variables

1,782,777 plots

Ref

Methods – Response variables

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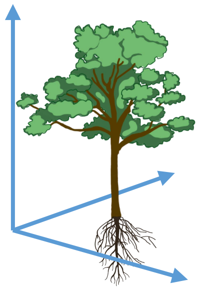

Functional diversity indices:

Rao`s Quadratic Entropy (RQEF)[18]

Functional dispersion (FDis)[19]

[18] Rao 1982 [19] Anderson et al. 2006

Methods – Response variables

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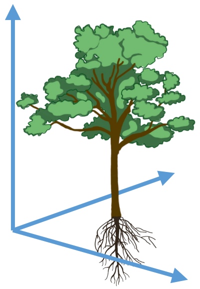

Functional diversity indices:

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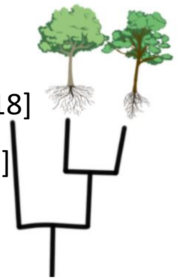
Phylogenetic diversity indices:

- Rao`s Quadratic Entropy (RQEP)[18]
- Mean pairwise distance (MPD)[20]



[18] Rao 1982 [19] Anderson et al. 2006 [20] Webb et al. 2002

Methods – Response variables

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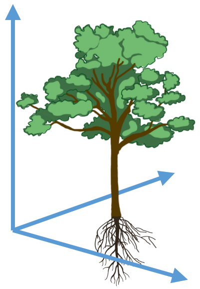

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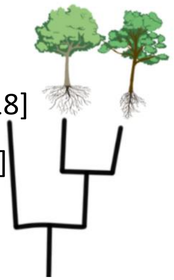

Correction for species richness dependencies[21]

$$SES.MPD = \frac{MPD_{obs} - \overline{MPD_{rand_{SR}}}}{\sigma_{rand_{SR}}}$$

[18] Rao 1982 [19] Anderson et al. 2006 [20] Webb et al. 2002 [21] Botta-Dukát 2018

CHELSA

Recent climate conditions: 19 bioclimatic variables from CHELSA v.2.1[22, 23]

Preselection with a principal component analyses

→ 5 climate variables

[22] Karger et al. 2017 [23] Karger et al. 2018

Methods – Explanatory variables

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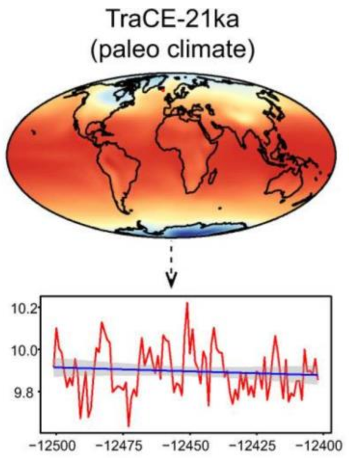

Worldwide stable climatic condition after the last glacial maximum (LGM) from StableClim v.1.1[24]

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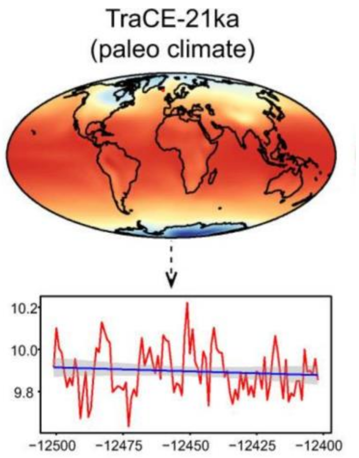

Worldwide stable climatic condition after the last glacial maximum (LGM) from StableClim v.1.1[24]

Plot size

Which plants were recorded

Categorization as forest or non-forest

Description of the vegetation type (biome)

[22] Karger et al. 2017 [23] Karger et al. 2018 [24] Brown et al. 2020

Methods – Statistical analyses

gam(SES.RQEF ~ SES.RQEP + s(Longitude, Latitude, bs = "sos"), family = "gaussian", method = "REML")

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Boosted regression trees (BRT) to select explanatory variables with most relevant influence

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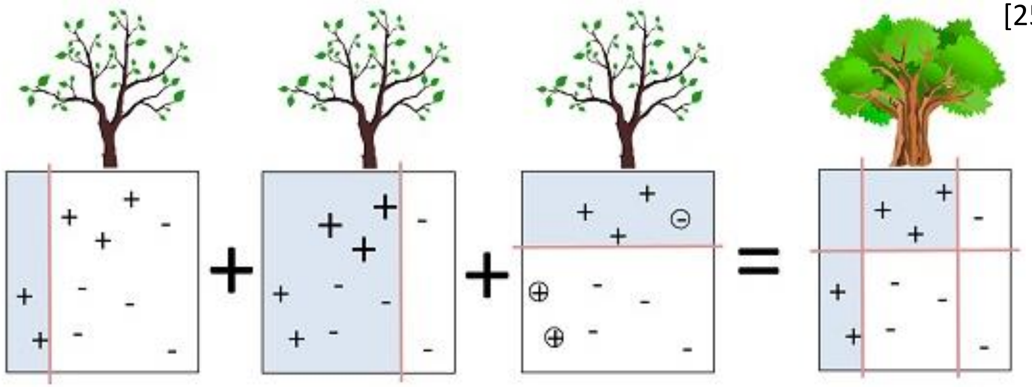

[25]

[25] Colin et al. 2018

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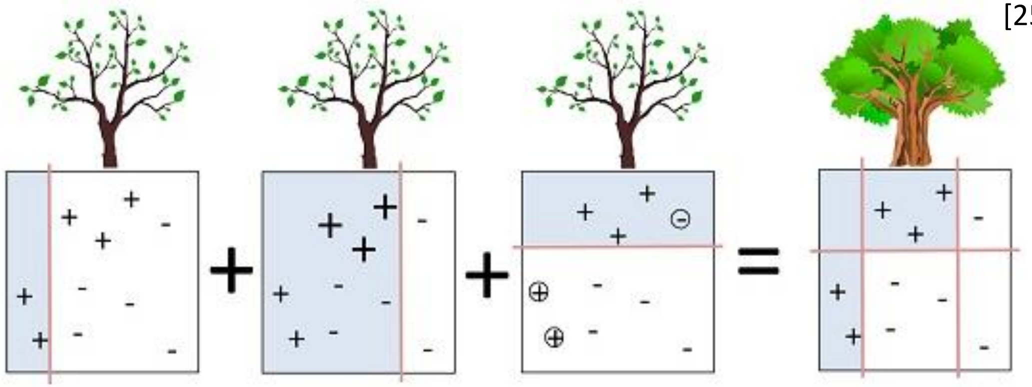

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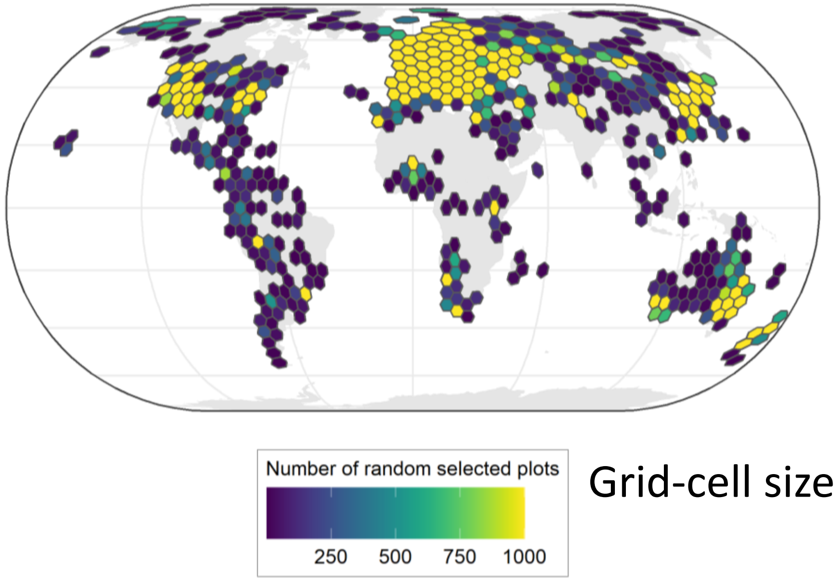

Grid-cell size of ~209,000 km^2

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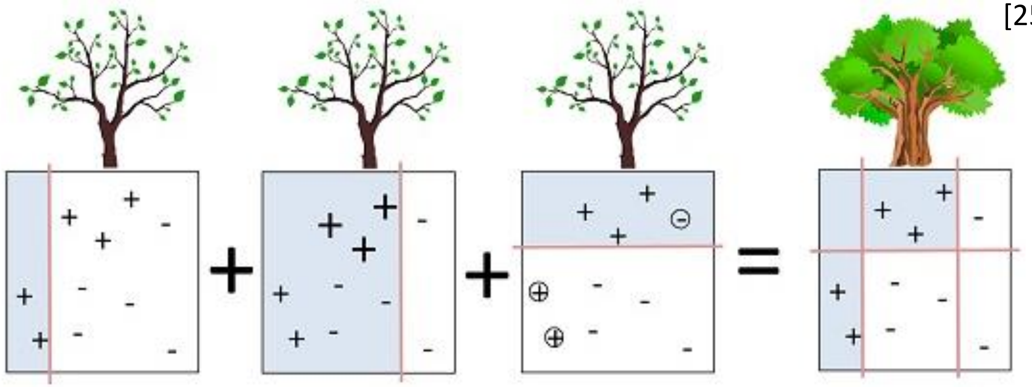
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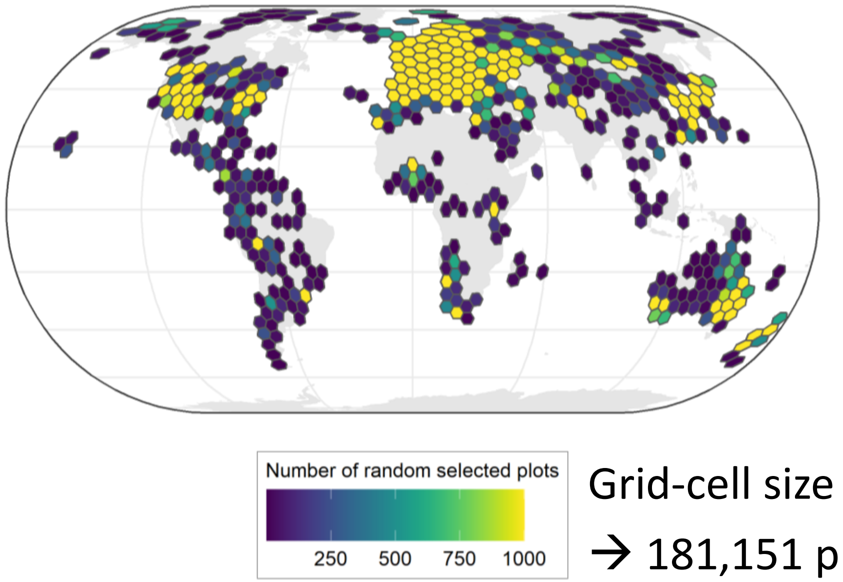

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→ 181,151 plots per run

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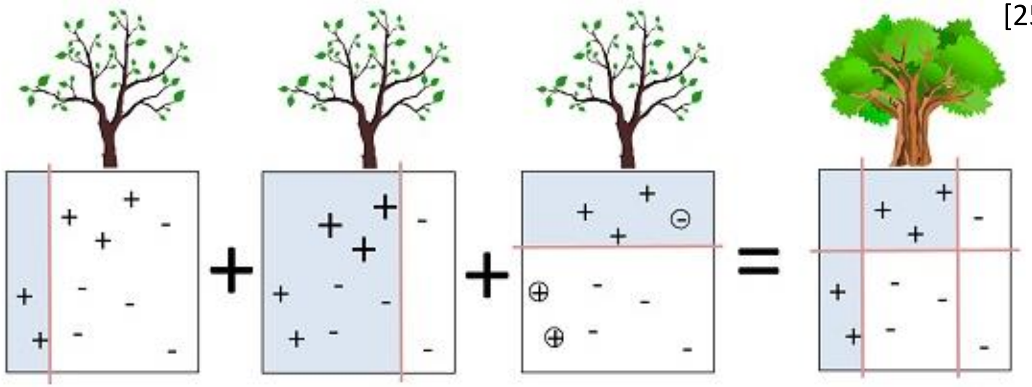

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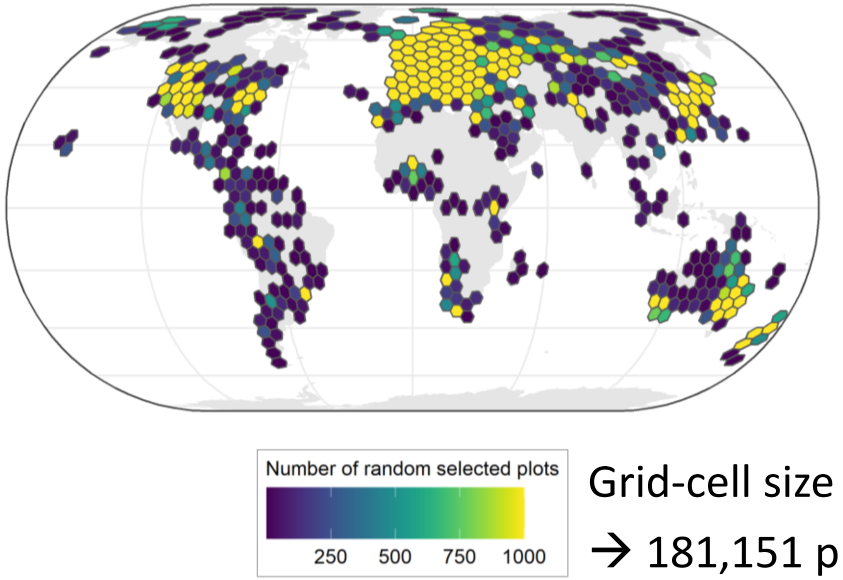

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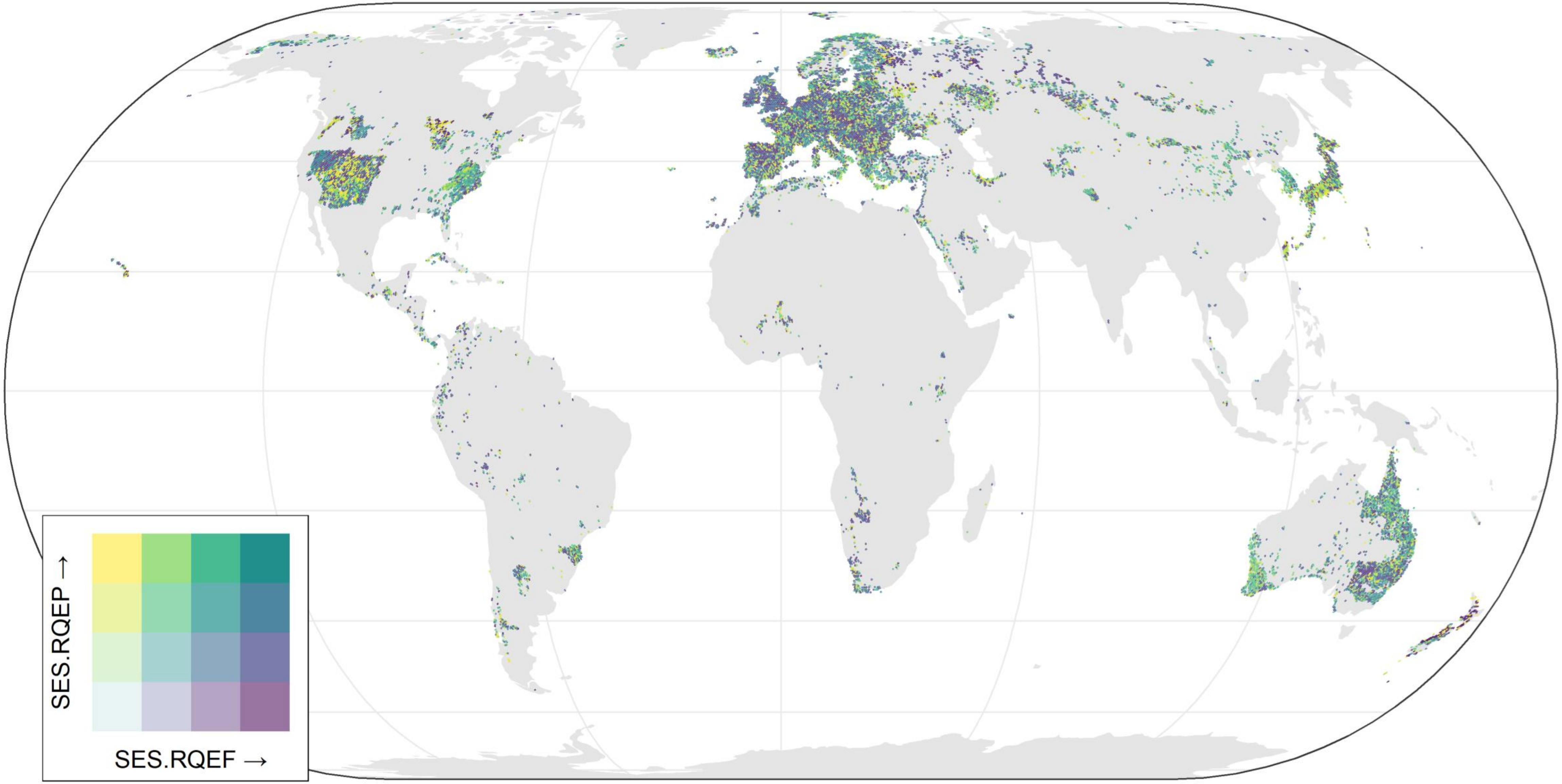

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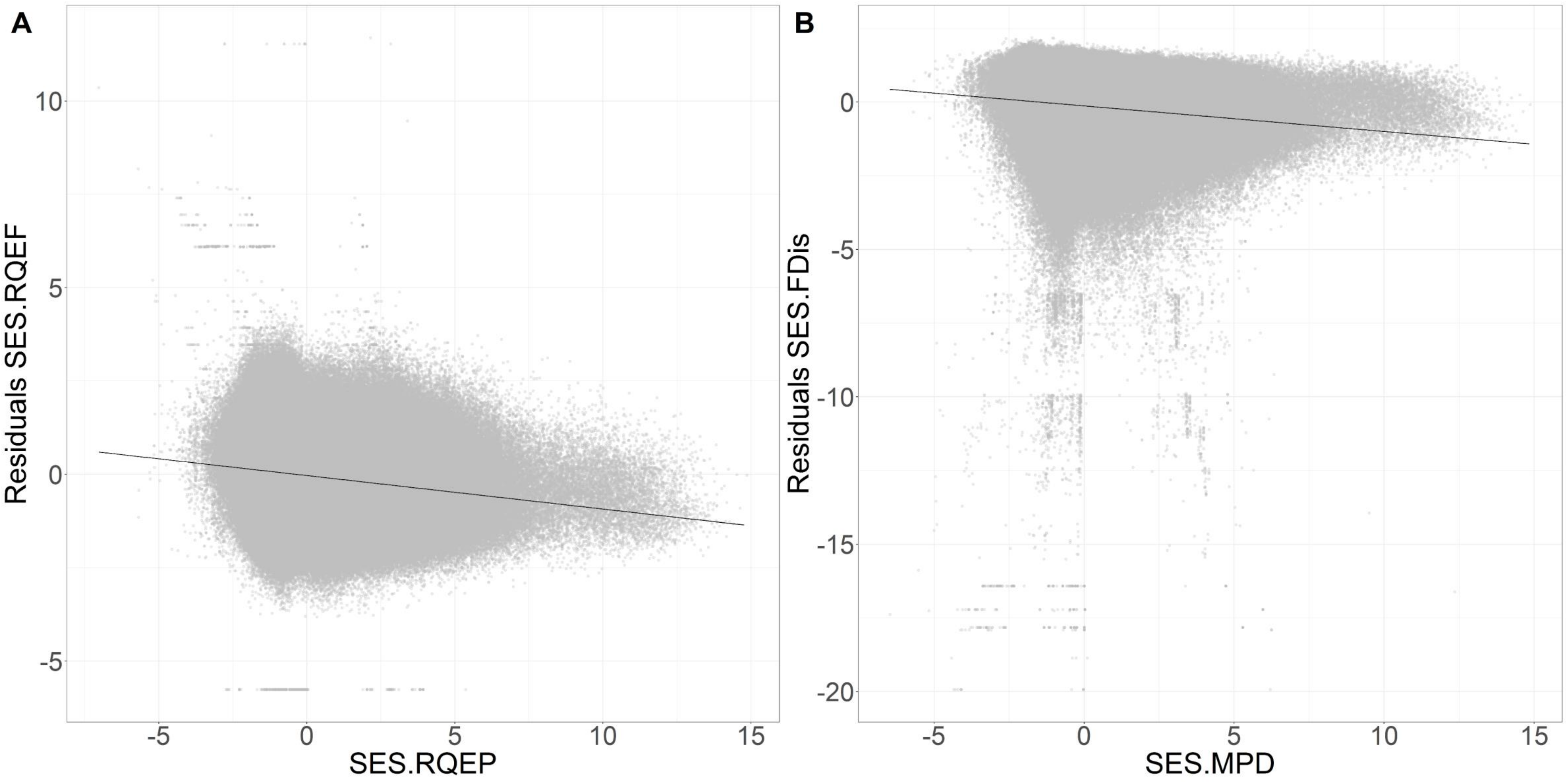
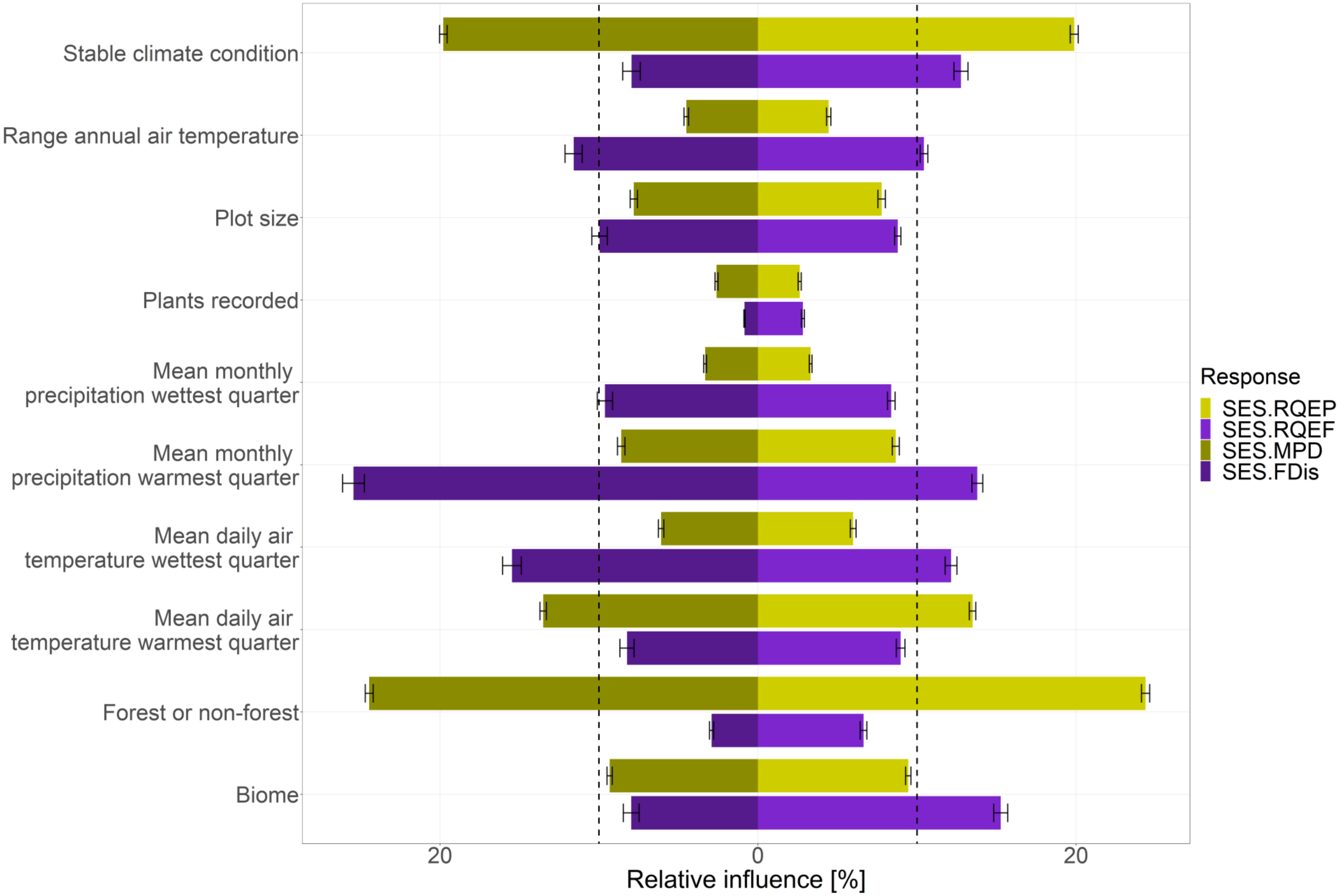


Results – Drivers of plant diversity



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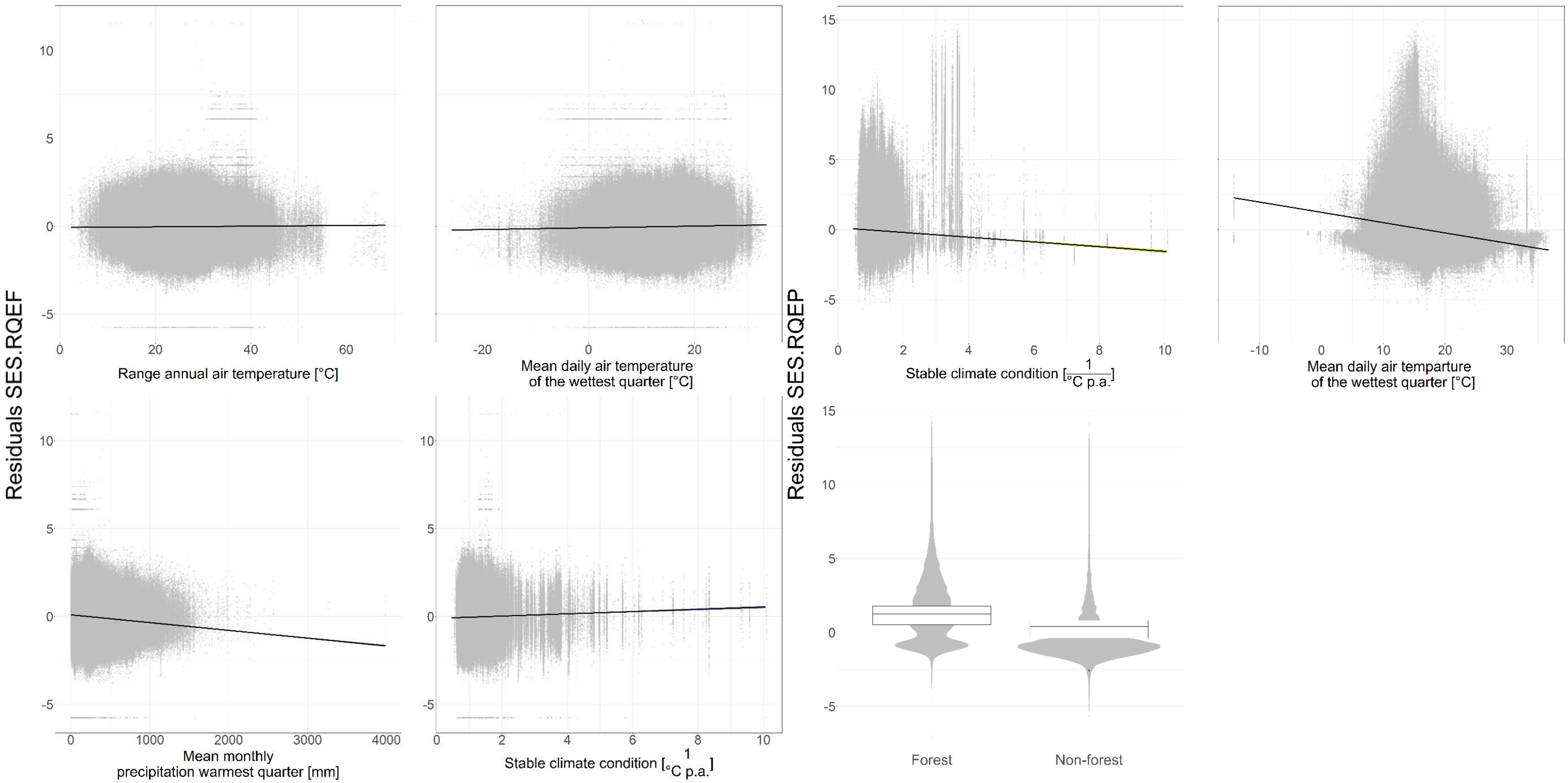

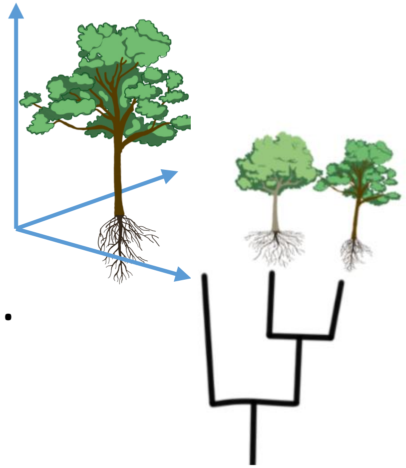

H1: Functional and phylogenetic diversity are related at the global scale.

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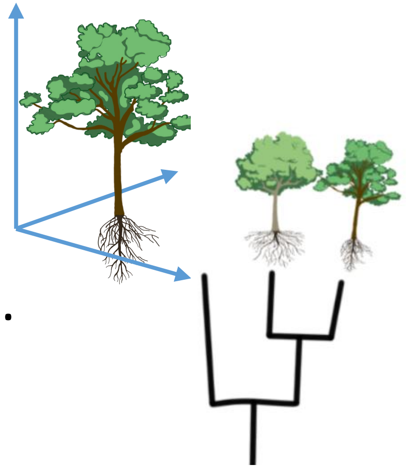

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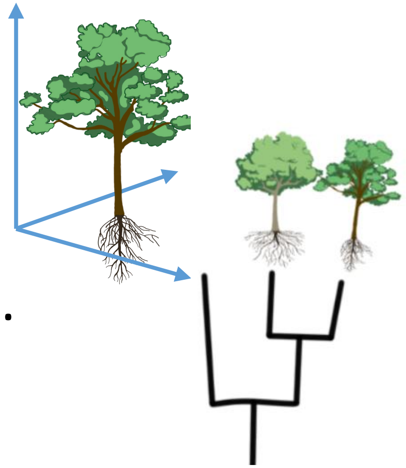

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Increasing with higher number of traits

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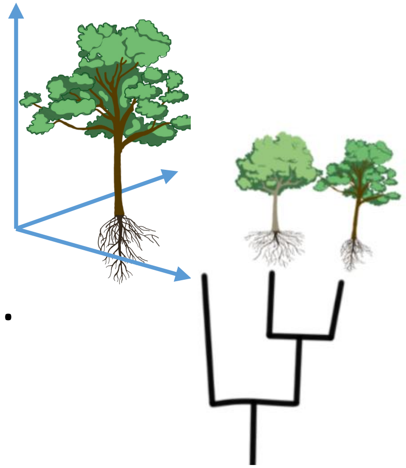

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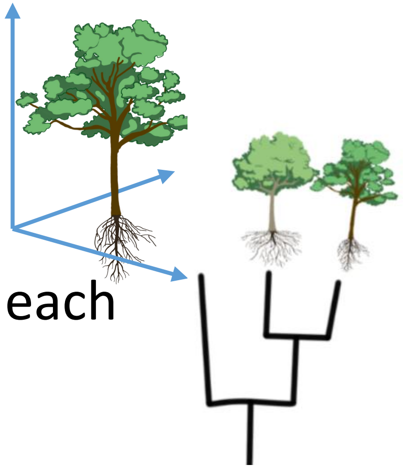
Increasing with higher number of traits

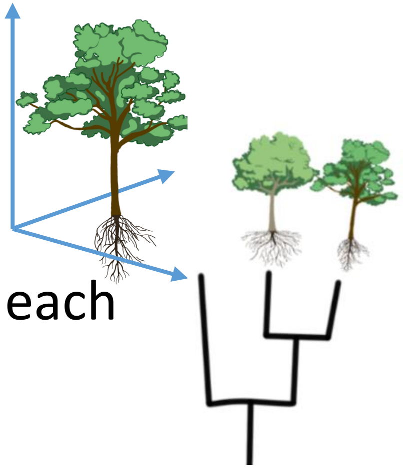
Traits map differently on the phylogeny at smaller spatial extent[7, 8]

[26] Tucker et al. 2018 [7] Cavender-Bares et al. 2004 [8] Ackerly 2009



H2: Spatial patterns of functional and phylogenetic diversity differ from each other.

[27] Zuo et al. 2021 [28] Massante et al. 2019 [29] Cai et al. 2020



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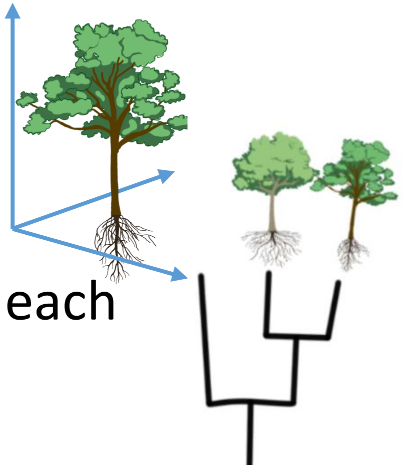

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Functional diversity differ along rain gradients[27]

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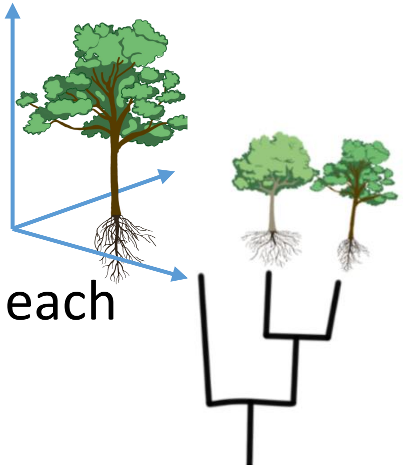

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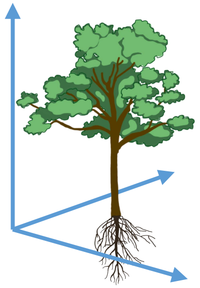
Functional diversity differ along rain gradients[27]

Phylogenetic diversity changes along latitudinal gradient[28] or to the North (e.g. China)[29]

[27] Zuo et al. 2021 [28] Massante et al. 2019 [29] Cai et al. 2020

H3: Distribution pattern of functional diversity depends on current climatic conditions.



[30] Del Toro et al. 2015 [31] Flynn et al. 2009 [32] Pauw et al. 2021

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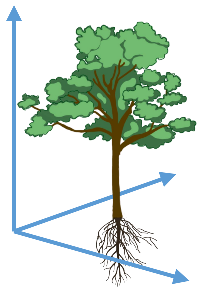
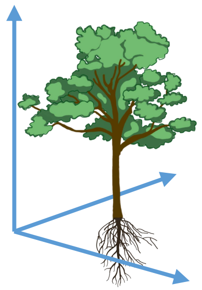


→ explained deviance was relatively low

[30] Del Toro et al. 2015 [31] Flynn et al. 2009 [32] Pauw et al. 2021

H3: Distribution pattern of functional diversity depends on current climatic conditions.

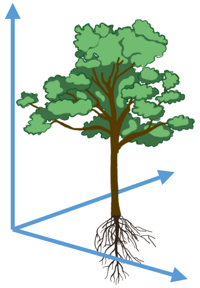


→ explained deviance was relatively low

Functional diversity can be linked to recent climate conditions on smaller spatial extent [30]

[30] Del Toro et al. 2015 [31] Flynn et al. 2009 [32] Pauw et al. 2021

H3: Distribution pattern of functional diversity depends on current climatic conditions.



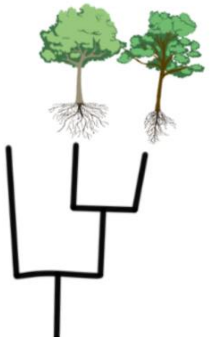
→ explained deviance was relatively low

Functional diversity can be linked to recent climate conditions on smaller spatial extent [30]

But local communities depend on local factors such as land-use[31] or soil properties[32]

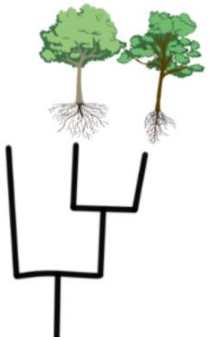
[30] Del Toro et al. 2015 [31] Flynn et al. 2009 [32] Pauw et al. 2021

H4: Spatial pattern of phylogenetic diversity depends on past climatic events, i.e. climatic conditions after the last glacial maximum.



[33] Cubino et al. 2021

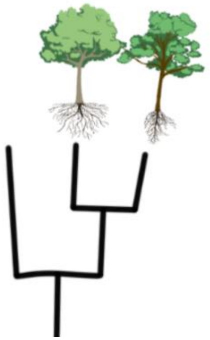
H4: Spatial pattern of phylogenetic diversity depends on past climatic events, i.e. climatic conditions after the last glacial maximum.



→ second most relative influence from BRT, negative correlation in the GAM

[33] Cubino et al. 2021

H4: Spatial pattern of phylogenetic diversity depends on past climatic events, i.e. climatic conditions after the last glacial maximum.

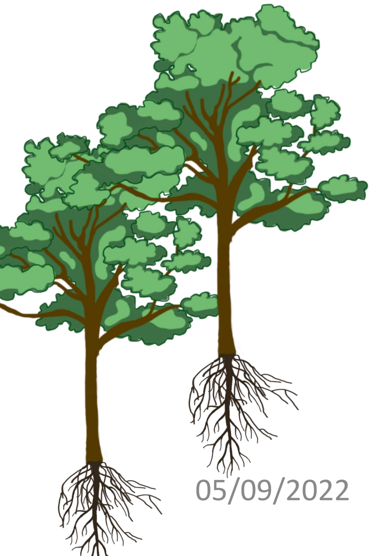


→ second most relative influence from BRT, negative correlation in the GAM

Phylogenetic turnovers in regions with high climatic changes after the LGM[33]

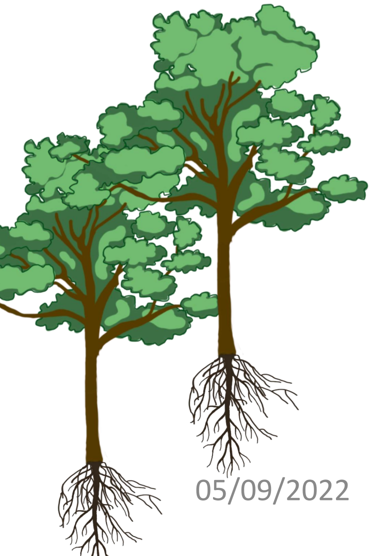
[33] Cubino et al. 2021

Abundance weighted indices could improve the understanding of the distribution patterns



Abundance weighted indices could improve the understanding of the distribution patterns

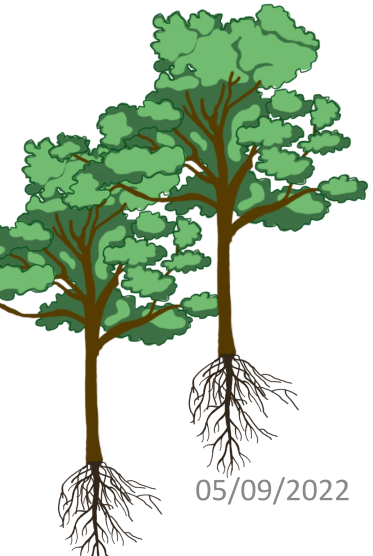
Addition of local factors could improve model explanation



Abundance weighted indices could improve the understanding of the distribution patterns

Addition of local factors could improve model explanation

Vegetation-plots from the global South could lead to a better understanding of the observed patterns



Thanks to:

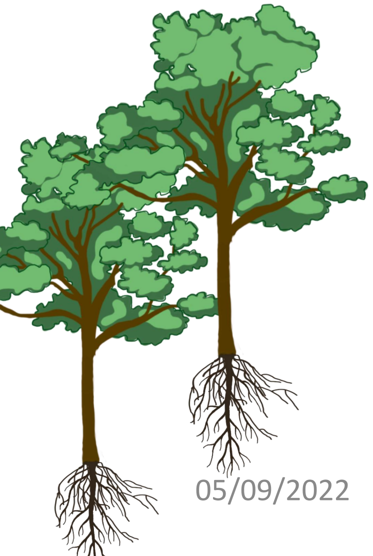
Helge Bruelheide

Francesco M. Sabatini

the IT of the iDiv and the UFZ

the whole working group at the botanical garden

my family and friends.



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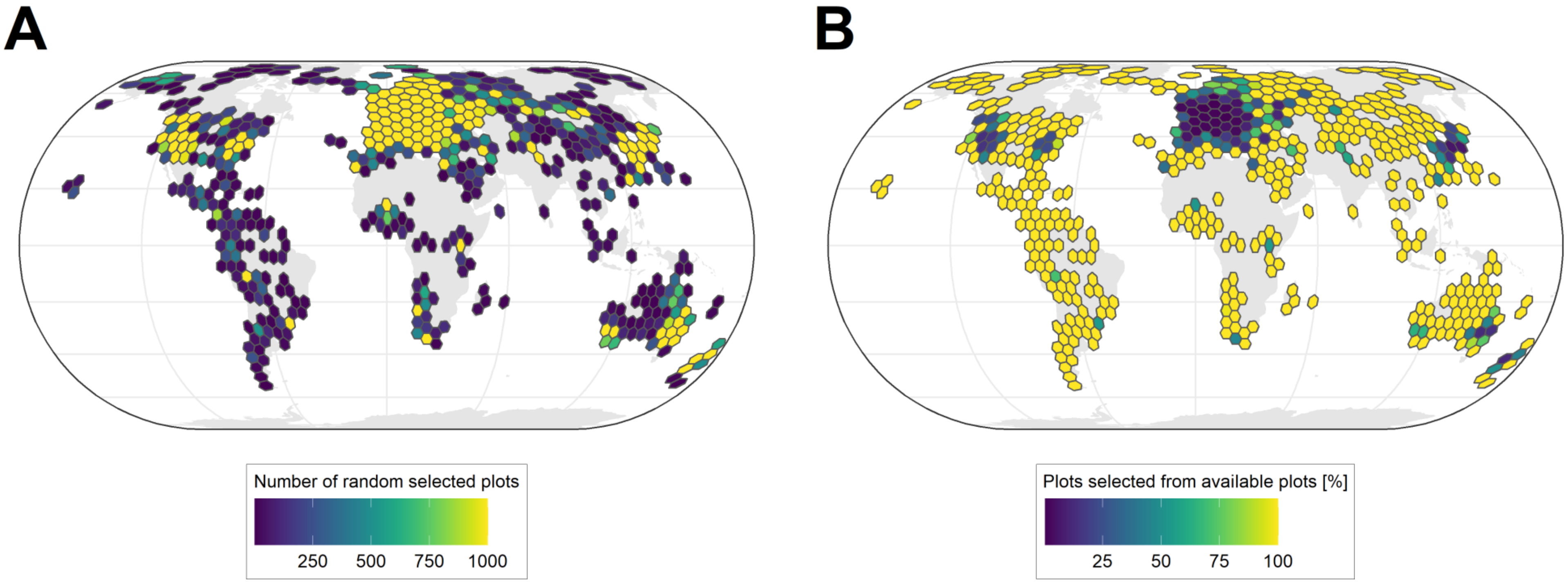
A
B
Number of random selected plots
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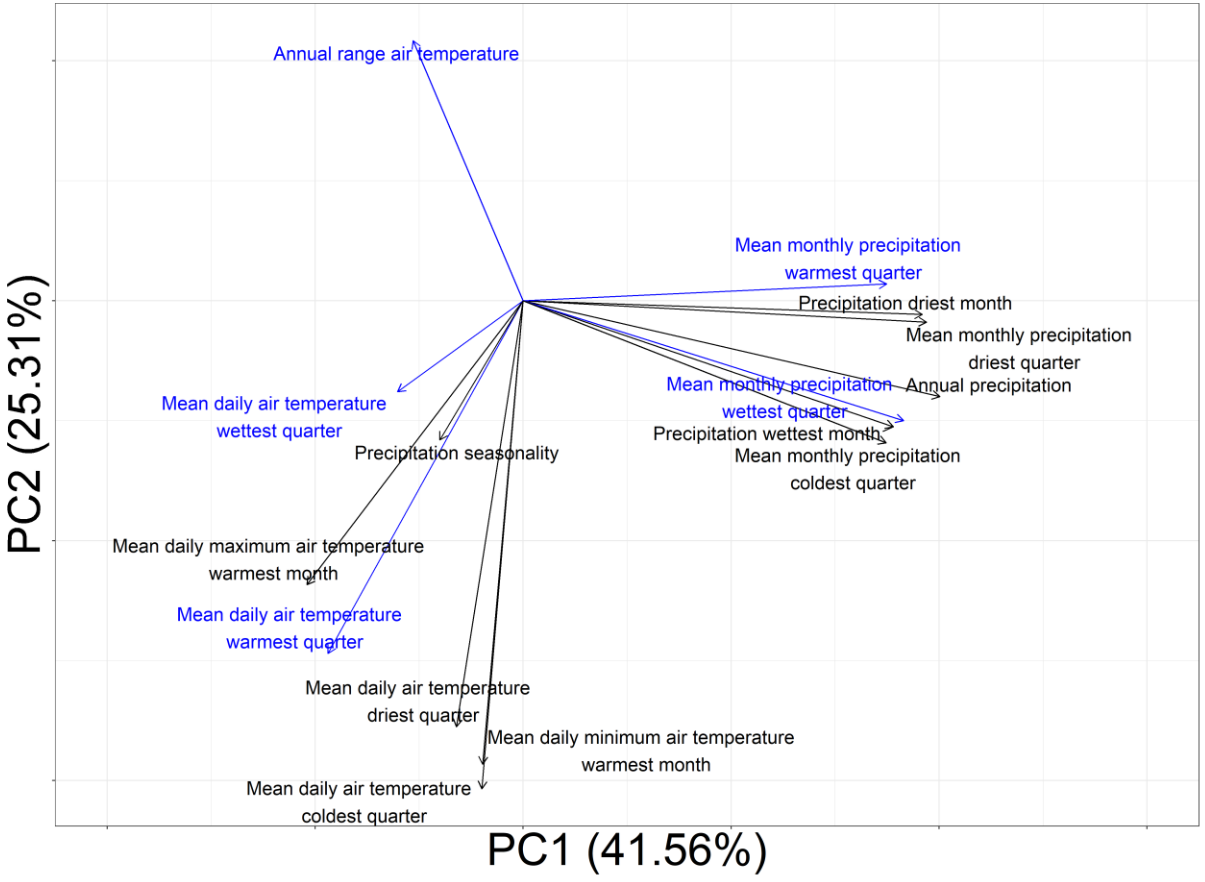
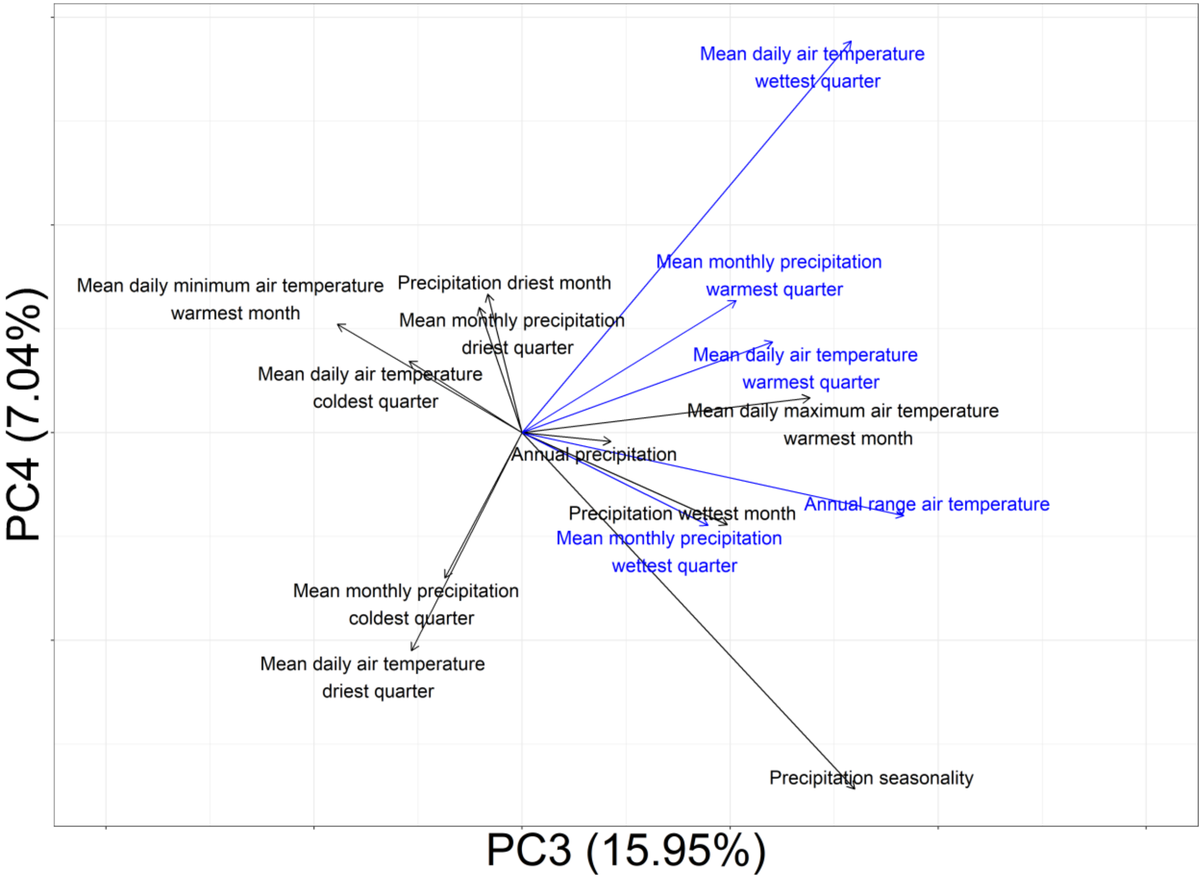
500
750
1000
Plots selected from available plots [%]
25
50
75
100

Supporting Information





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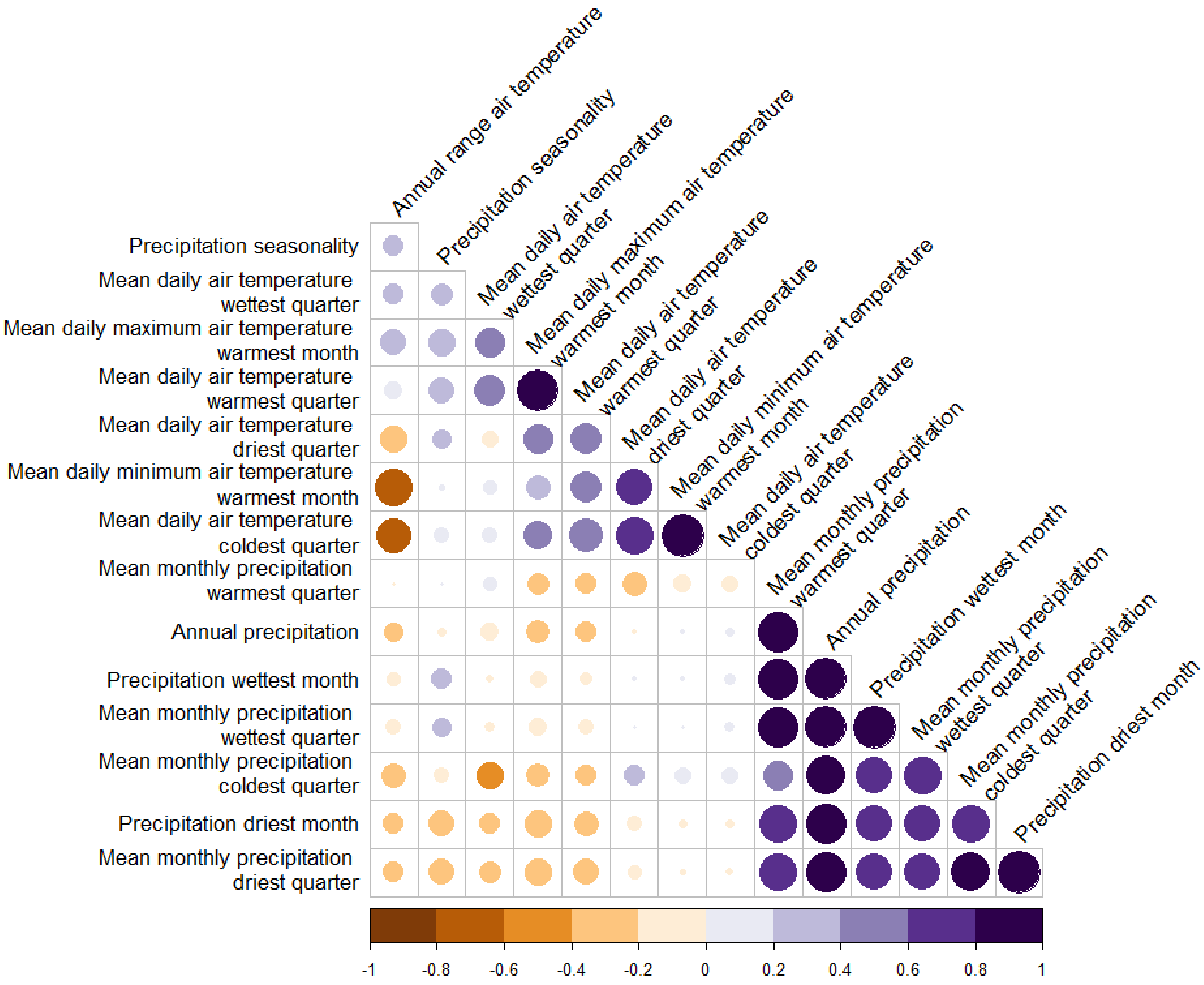

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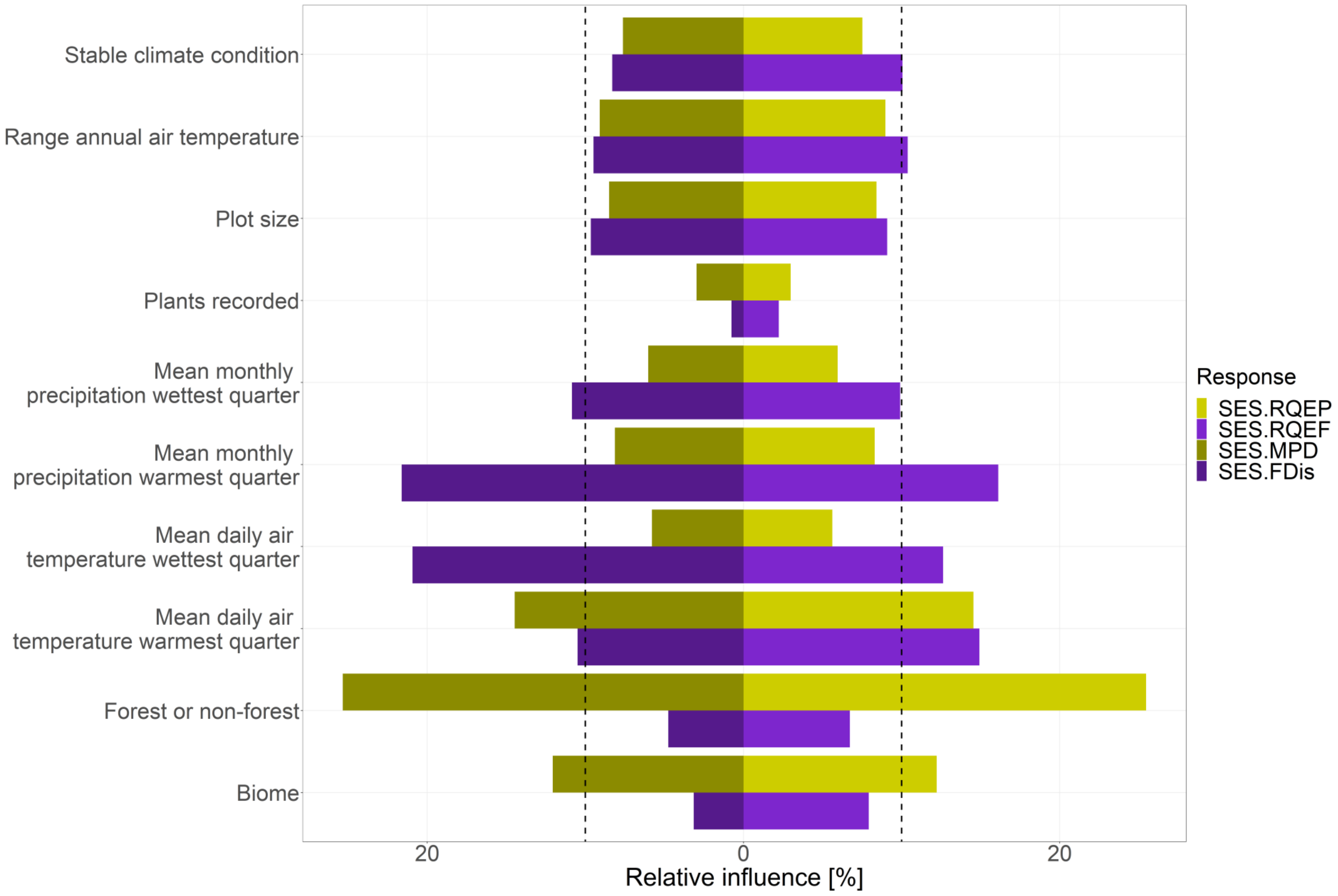

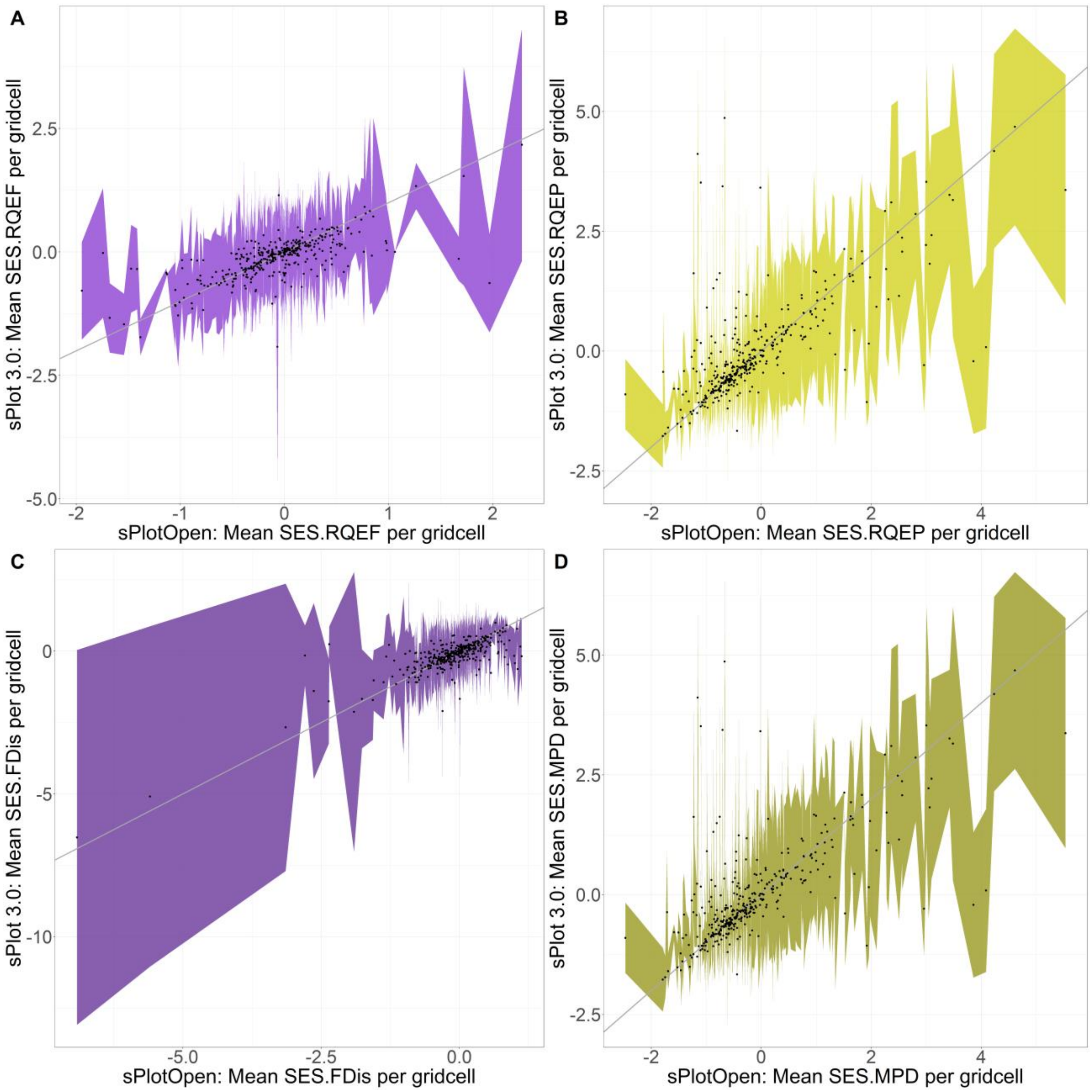
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sPlot 3.0: Mean SES.RQEF per gridcell
sPlotOpen: Mean SES.RQEF per gridcell
2.5
0.0
-2.5
-5.0
-2
-1
0
1
2
B
sPlot 3.0: Mean SES.RQEP per gridcell
sPlotOpen: Mean SES.RQEP per gridcell
5.0
2.5
0.0
-2.5
-2
0
2
4
C
sPlot 3.0: Mean SES.FDis per gridcell
sPlotOpen: Mean SES.FDis per gridcell
0
-5
-10
-5.0
-2.5
0.0
D
sPlot 3.0: Mean SES.MPD per gridcell
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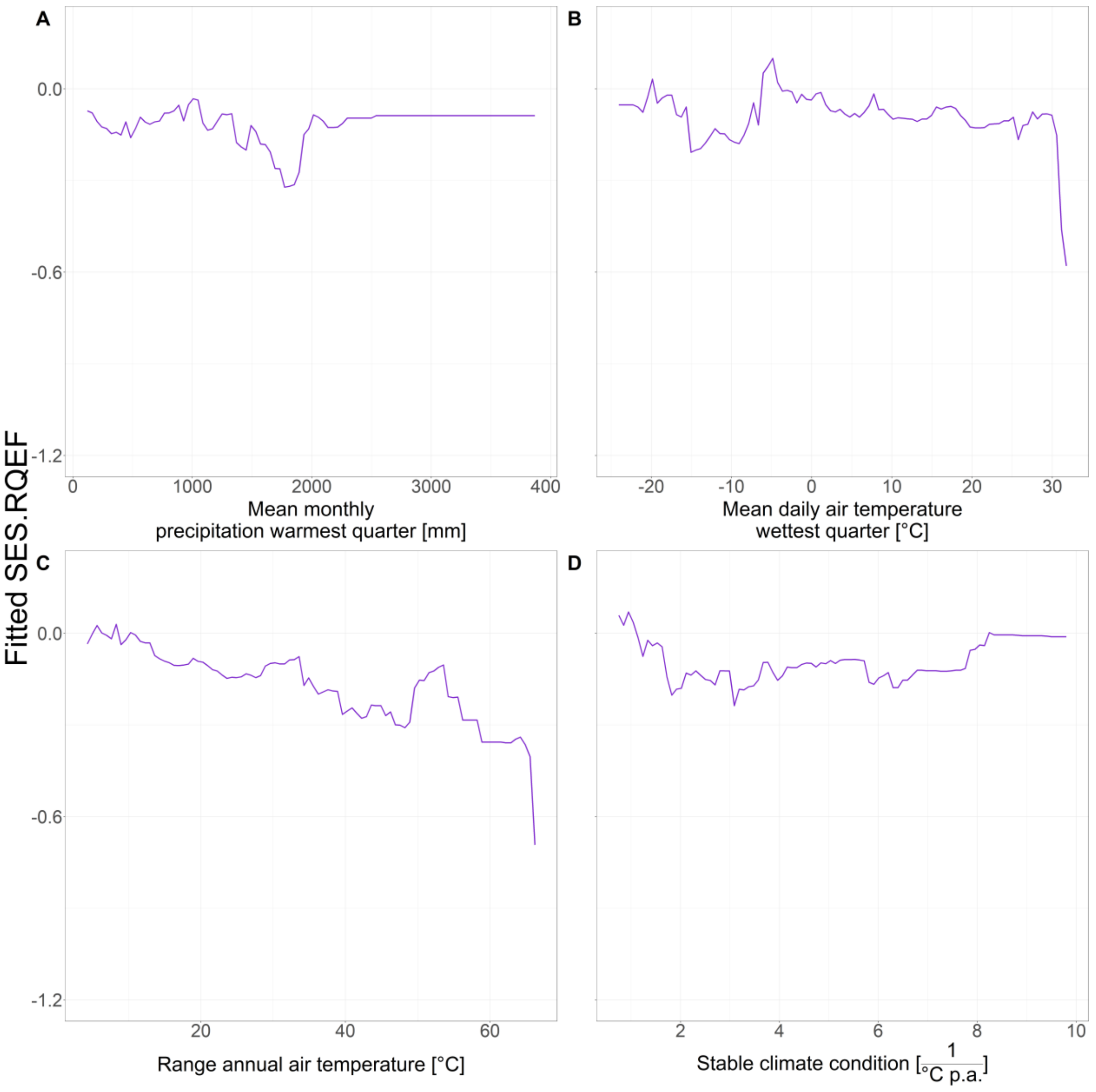
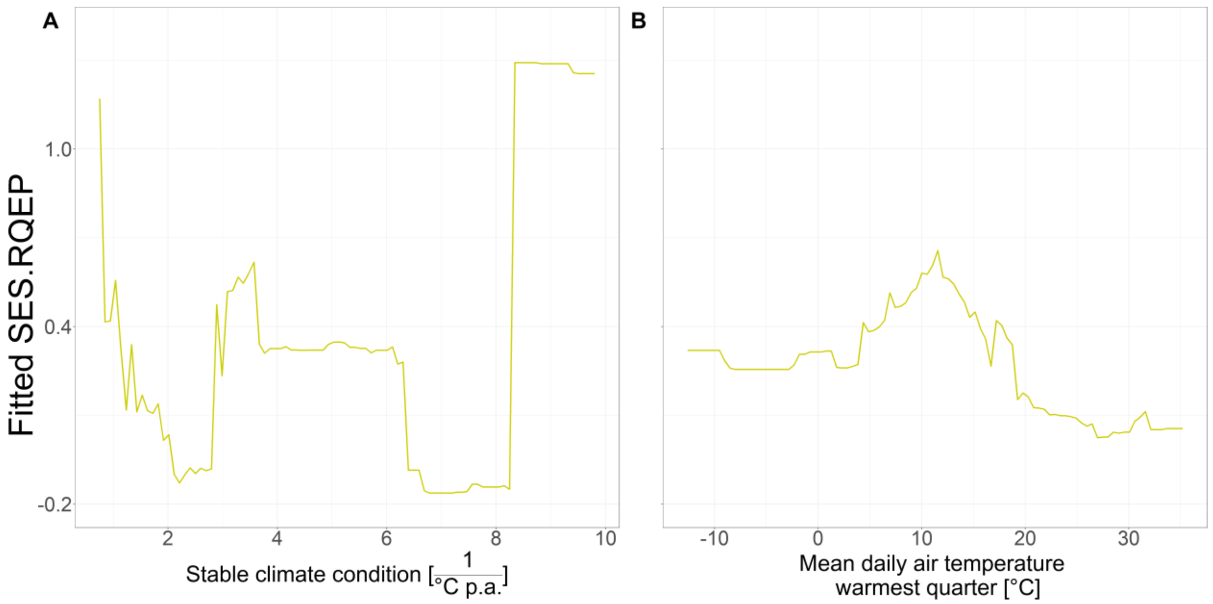
5.0
2.5
0.0
-2.5
-2
0
2
4

Supporting Information





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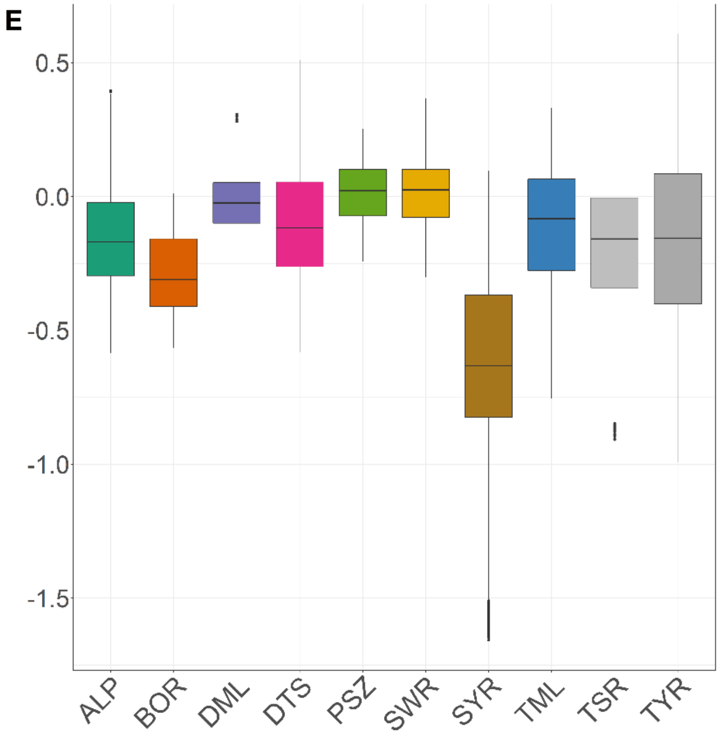

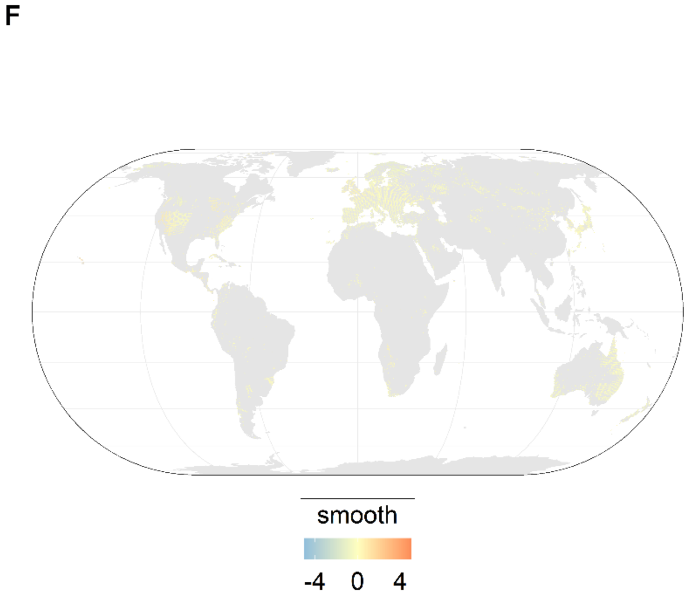

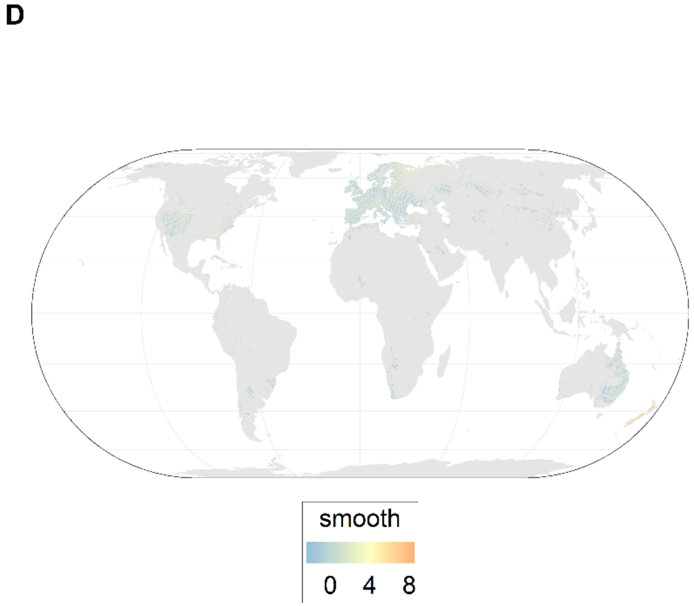

Supporting Information

```
Family: gaussian
Link function: identity

Formula:
SES.RQEF ~ SES.RQEP + s(Longitude, Latitude, bs = "sos")

Parametric coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.0001157  0.0007246    0.16    0.873
SES.RQEP    -0.0896341  0.0004374 -204.94   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Approximate significance of smooth terms:
                        edf Ref.df    F p-value
s(Longitude,Latitude) 48.94     49 1281  <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

R-sq.(adj) =  0.0581   Deviance explained = 5.81%
-REML = 2.4684e+06  Scale est. = 0.93336   n = 1782777
```

```
Family: gaussian
Link function: identity

Formula:
SES.RQEP ~ stable.clim + mean.daily.air.temp.warm.qu + s(Longitude,
    Latitude, bs = "sos") + is.forest

Parametric coefficients:
                              Estimate Std. Error t value Pr(>|t|)
(Intercept)                  1.0286811  0.0118456   86.84   <2e-16 ***
stable.clim                 -0.1694141  0.0071234  -23.78   <2e-16 ***
mean.daily.air.temp.warm.qu -0.0733673  0.0004541 -161.56   <2e-16 ***
is.forestTRUE                1.8155171  0.0027595  657.91   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Approximate significance of smooth terms:
                        edf Ref.df    F p-value
s(Longitude,Latitude) 48.96     49 4802  <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

R-sq.(adj) =  0.394   Deviance explained = 39.4%
-REML = 2.696e+06  Scale est. = 2.1407    n = 1498079
```

```
Family: gaussian
Link function: identity

Formula:
SES.RQEF ~ stable.clim + annual.range.air.temp + mean.monthly.prec.warm.qu +
    mean.daily.air.temp.wet.qu + biome + s(Longitude, Latitude,
    bs = "sos")

Parametric coefficients:
                                     Estimate Std. Error t value Pr(>|t|)
(Intercept)                        -4.923e-02  1.296e-02  -3.798 0.000146 ***
stable.clim                         6.378e-02  4.201e-03  15.181  < 2e-16 ***
annual.range.air.temp               1.986e-03  3.008e-04   6.604 4.01e-11 ***
mean.monthly.prec.warm.qu          -4.423e-04  7.611e-06 -58.106  < 2e-16 ***
mean.daily.air.temp.wet.qu          4.950e-03  1.846e-04  26.813  < 2e-16 ***
biomeBoreal zone                   -1.867e-01  9.579e-03 -19.485  < 2e-16 ***
biomeDry midlatitudes               4.680e-02  8.611e-03   5.435 5.48e-08 ***
biomeDry tropics and subtropics     4.159e-02  1.098e-02   3.789 0.000151 ***
biomePolar and subpolar zone        1.202e-01  2.021e-02   5.951 2.67e-09 ***
biomeSubtrop. with year-round rain -1.662e-01  1.009e-02 -16.473  < 2e-16 ***
biomeSubtropics with winter rain   -3.242e-02  7.556e-03  -4.290 1.79e-05 ***
biomeTemperate midlatitudes        -2.699e-02  6.463e-03  -4.176 2.96e-05 ***
biomeTropics with summer rain      -1.349e-02  1.671e-02  -0.808 0.419360
biomeTropics with year-round rain  -5.631e-03  1.903e-02  -0.296 0.767339
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Approximate significance of smooth terms:
                        edf Ref.df    F p-value
s(Longitude,Latitude) 48.93     49 1021  <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

R-sq.(adj) =  0.0397   Deviance explained = 3.98%
-REML = 2.4856e+06  Scale est. = 0.95156   n = 1782777
```

Supporting Information

```
R version 4.2.1 (2022-06-23)
Platform: x86_64-pc-linux-gnu (64-bit)
Running under: Ubuntu 20.04.5 LTS

Matrix products: default
BLAS:   /usr/lib/x86_64-linux-gnu/blas/libblas.so.3.9.0
LAPACK: /usr/lib/x86_64-linux-gnu/lapack/liblapack.so.3.9.0

locale:
 [1] LC_CTYPE=en_US.UTF-8       LC_NUMERIC=C               LC_TIME=en_US.UTF-8        LC_COLLATE=en_US.UTF-8     LC_MONETARY=en_US.UTF-8
 [6] LC_MESSAGES=en_US.UTF-8    LC_PAPER=en_US.UTF-8       LC_NAME=C                  LC_ADDRESS=C               LC_TELEPHONE=C
[11] LC_MEASUREMENT=en_US.UTF-8 LC_IDENTIFICATION=C

attached base packages:
[1] stats     graphics  grDevices utils     datasets  methods   base

other attached packages:
 [1] ggforce_0.3.3         viridis_0.6.2         viridisLite_0.4.1     marginaleffects_0.6.0 dggridR_3.0.0         sf_1.0-7
 [7] rlang_1.0.4           rnaturalearth_0.1.0   ncdf4_1.19            mgcv_1.8-40           gbm_2.1.8             dismo_1.3-5
[13] raster_3.5-21         sp_1.5-0              colorspace_2.0-3      castor_1.7.2          Rcpp_1.0.9            ggtreeExtra_1.7.0
[19] ggtree_3.5.0.900      treeio_1.21.0         funrar_1.4.1          FD_1.0-12.1           geometry_0.4.6.1      ade4_1.7-19
[25] furrr_0.3.0           future_1.26.1         picante_1.8.2         nlme_3.1-157          vegan_2.6-2           lattice_0.20-45
[31] permute_0.9-7         tidytree_0.3.9        phytools_1.0-3        maps_3.4.0            V.PhyloMaker_0.1.0    ape_5.6-2
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