



Analysis and integration of omics data  
in a context of plant abiotic stress:  
an example of workflow with the `mixOmics` package

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Chargé de Recherches (INRAE, BioForA)





# Contribution of an integrative study to the understanding of plant adaptation to their environment: A focus on plant cell walls.

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Problem Solving Protocol

**A powerful framework for an integrative study with heterogeneous omics data: from univariate statistics to multi-block analysis**

Harold Duruflé, Merwann Selmani, Philippe Ranocha, Elisabeth Jamet, Christophe Dunand and Sébastien Déjean

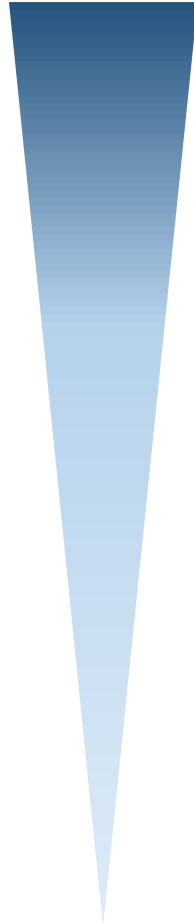


# Objectives & strategies

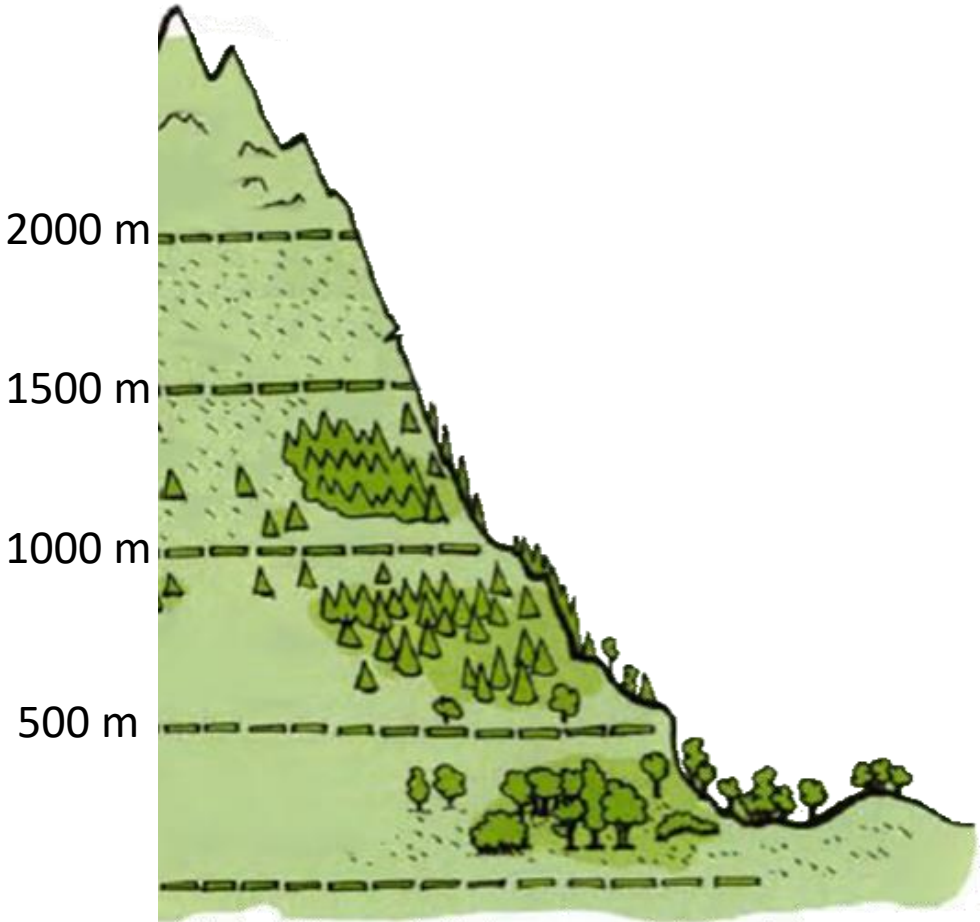
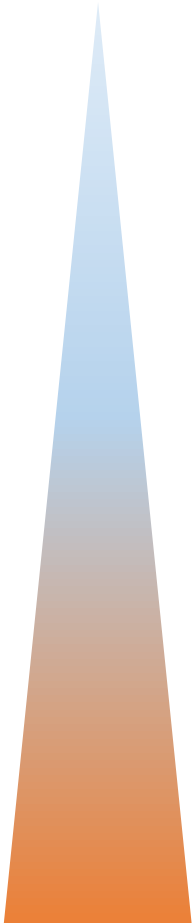


# Mountains as areas of study

Precipitations



Temperature

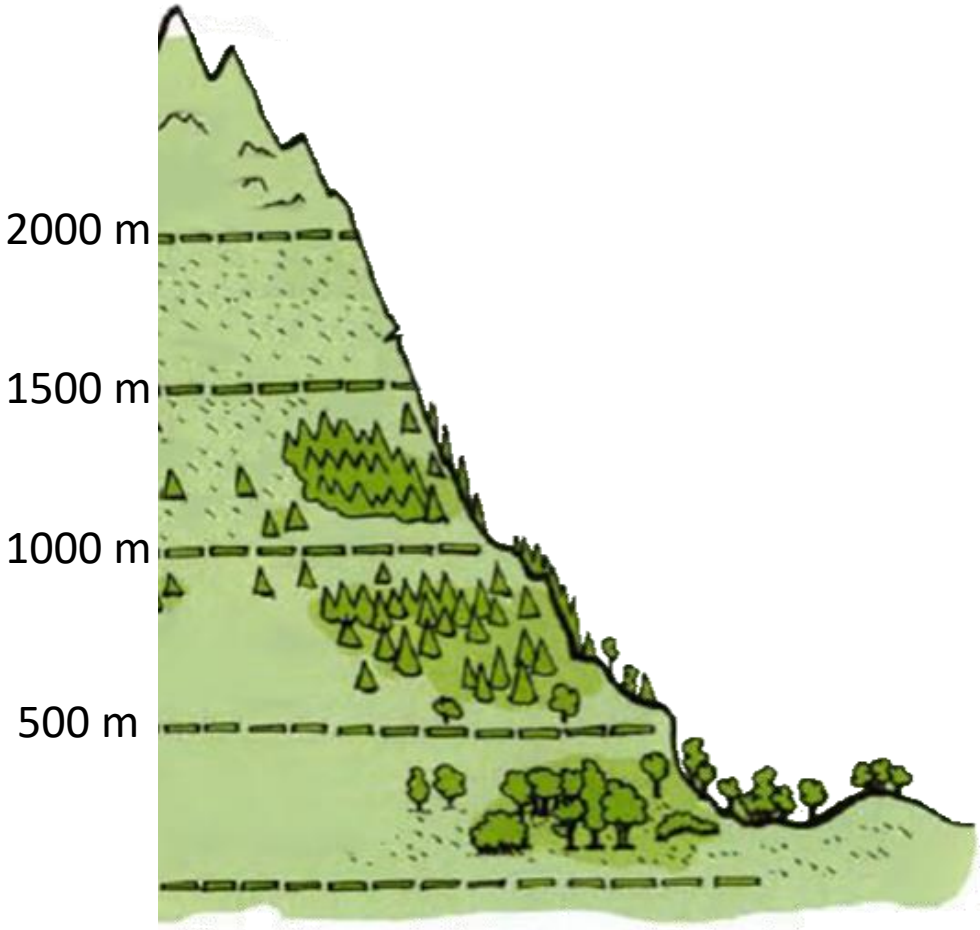


# Mountains as areas of study

Precipitations



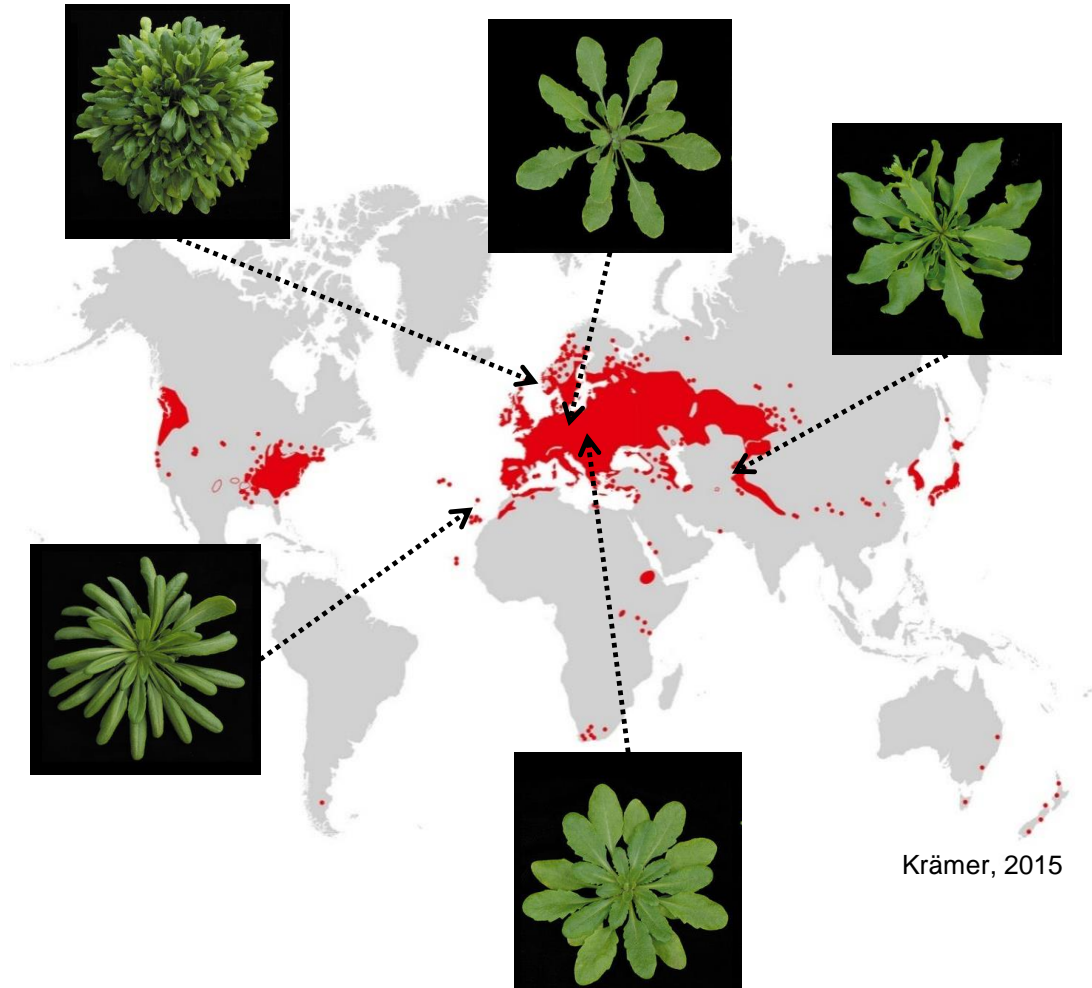
Temperature



# The model plant: *Arabidopsis thaliana*



PlantScreen Compact System



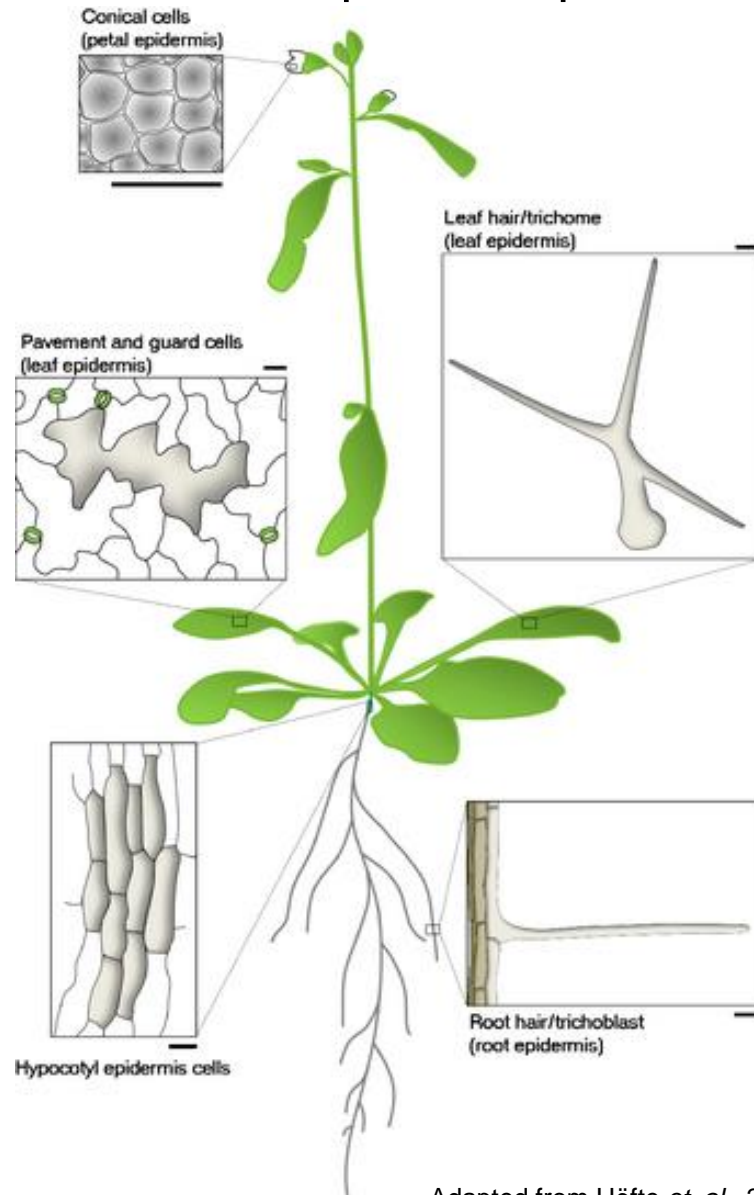
Krämer, 2015

# The cell wall: the plant skeleton

 The cell wall contributes to the cell and the plant shapes

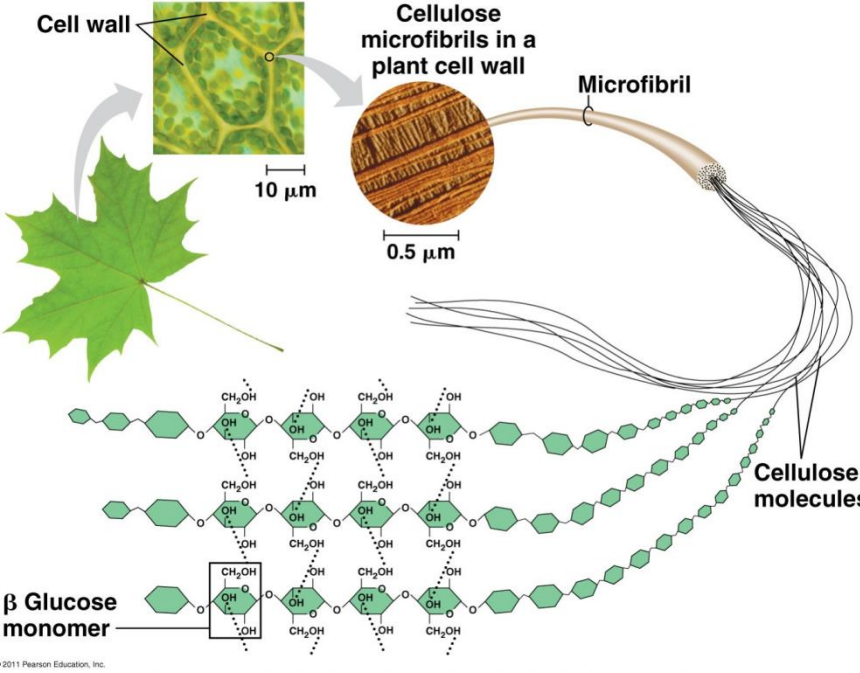
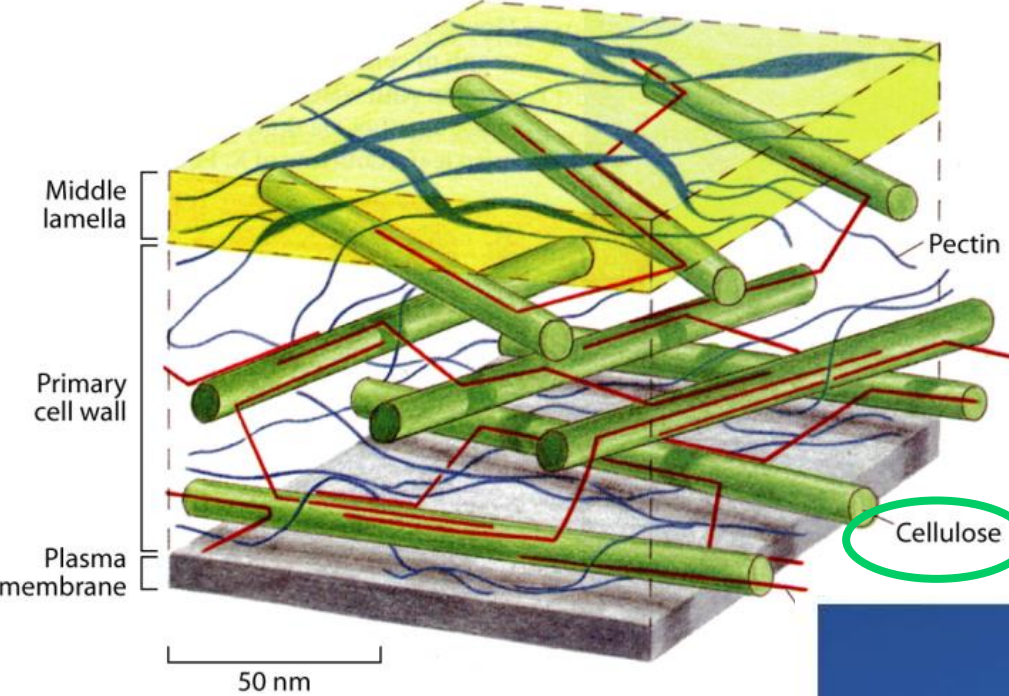
 Different functions

 Different compositions



# The cell wall: main constituents

## Cell wall polysaccharides



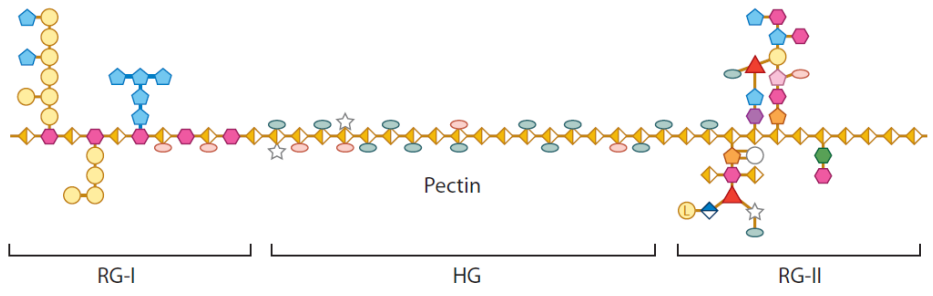
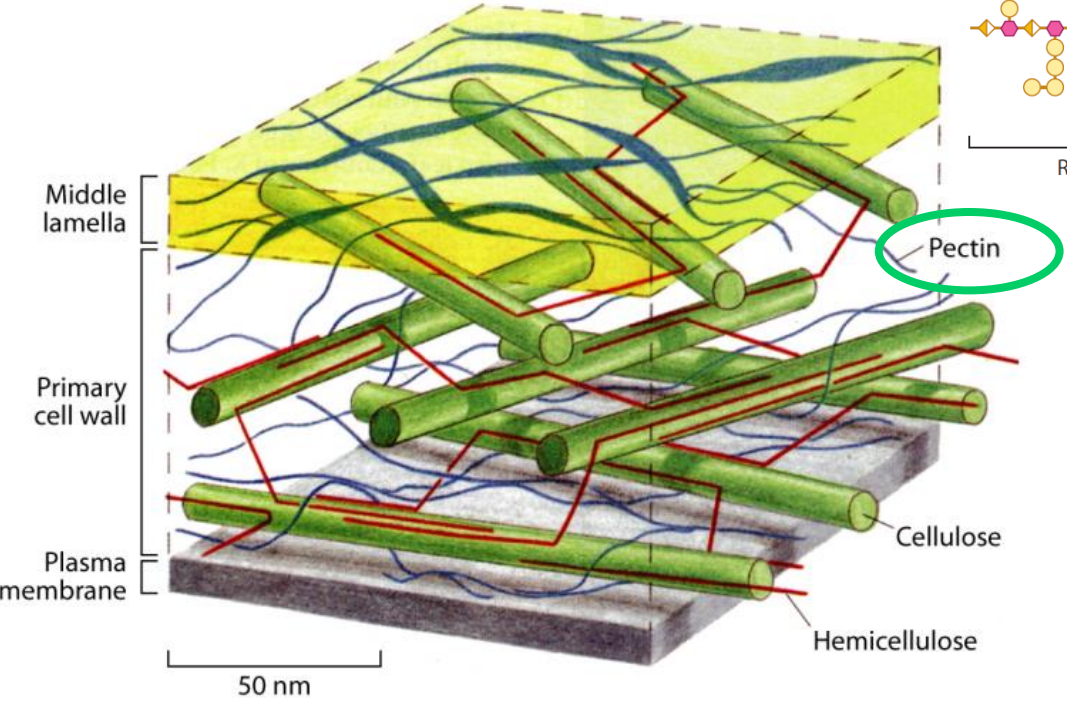
Scheller &





# The cell wall: main constituents

## Cell wall polysaccharides

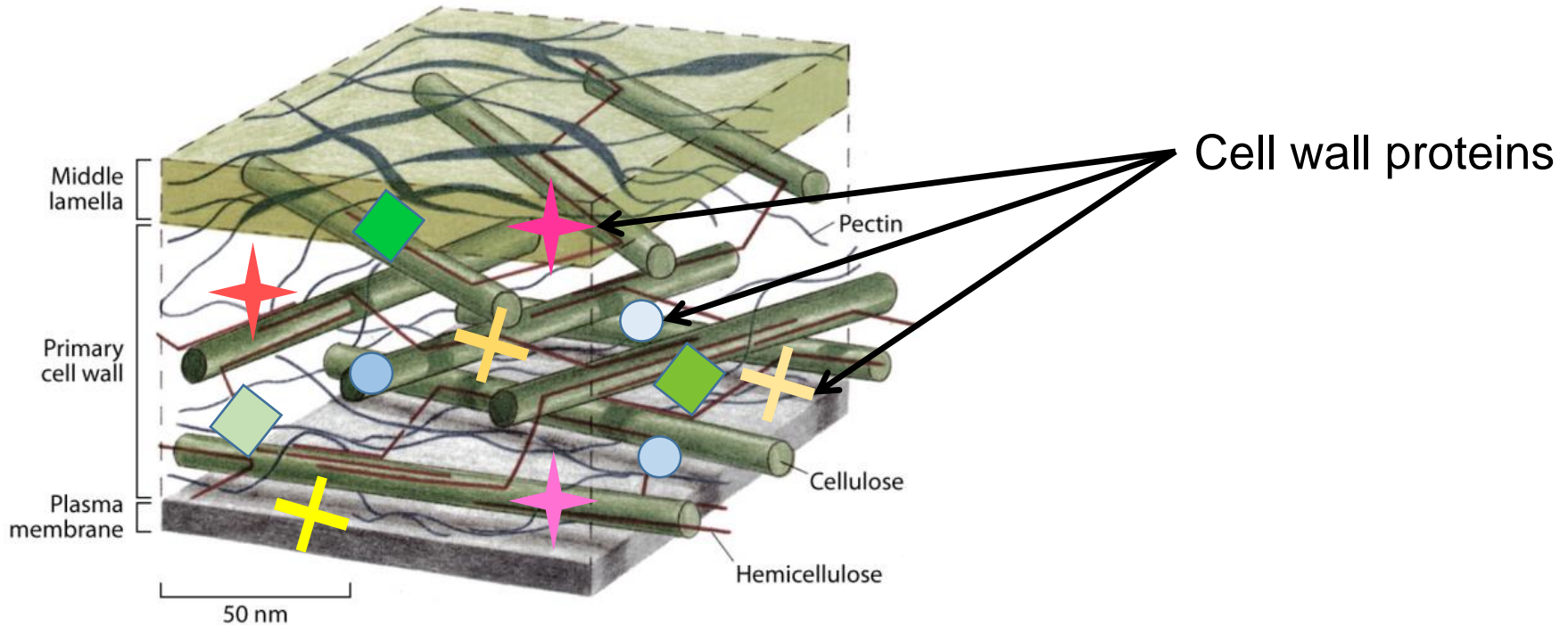


Scheller and Ulvskov 2010



# The cell wall: main constituents

## Cell wall polysaccharides



Scheller and Ulvskov 2010



Interlaced networks that can be reorganized at any time

- Dynamic and plastic

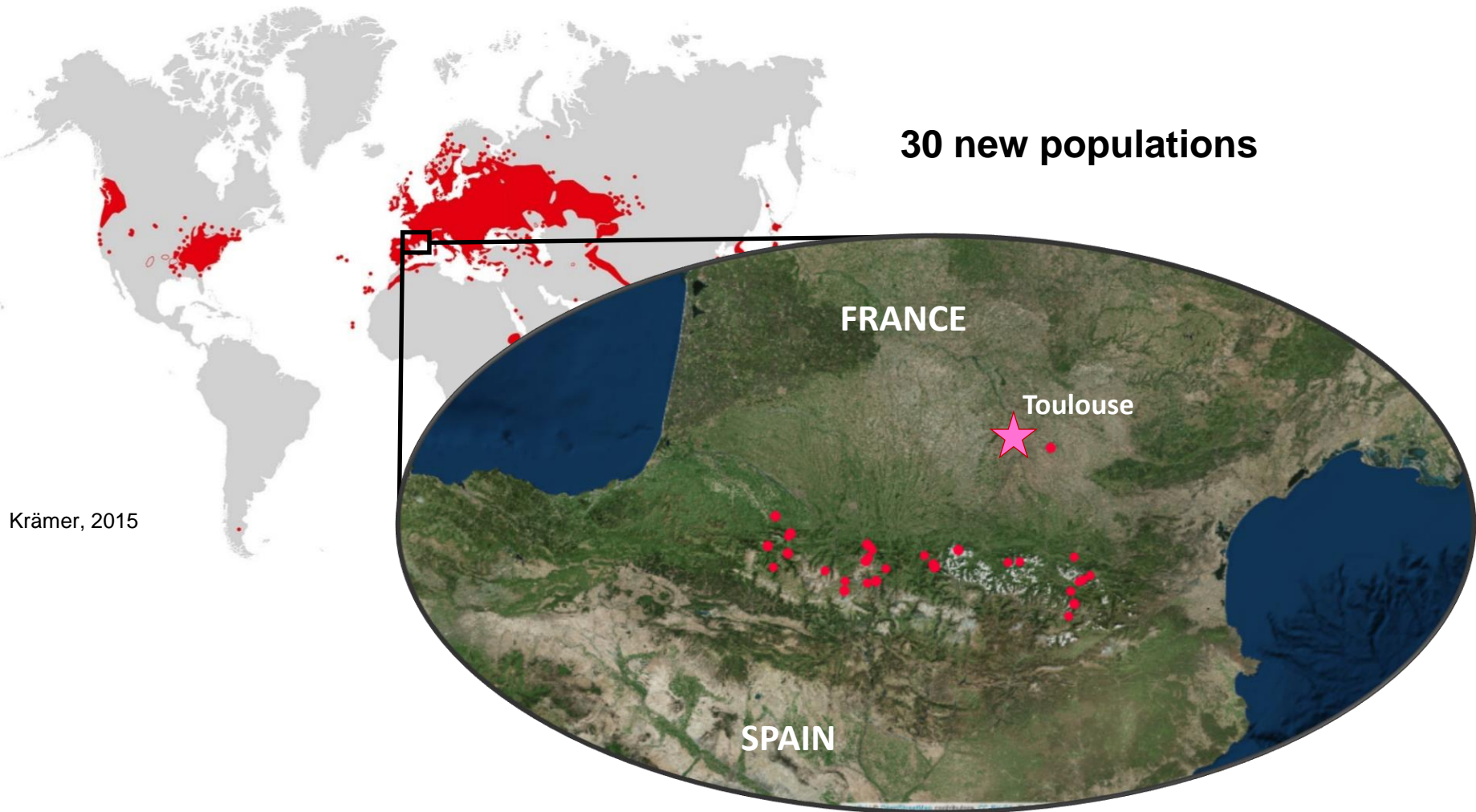


Proteins contribute to assemble and remodel the cell wall

- Different functional class

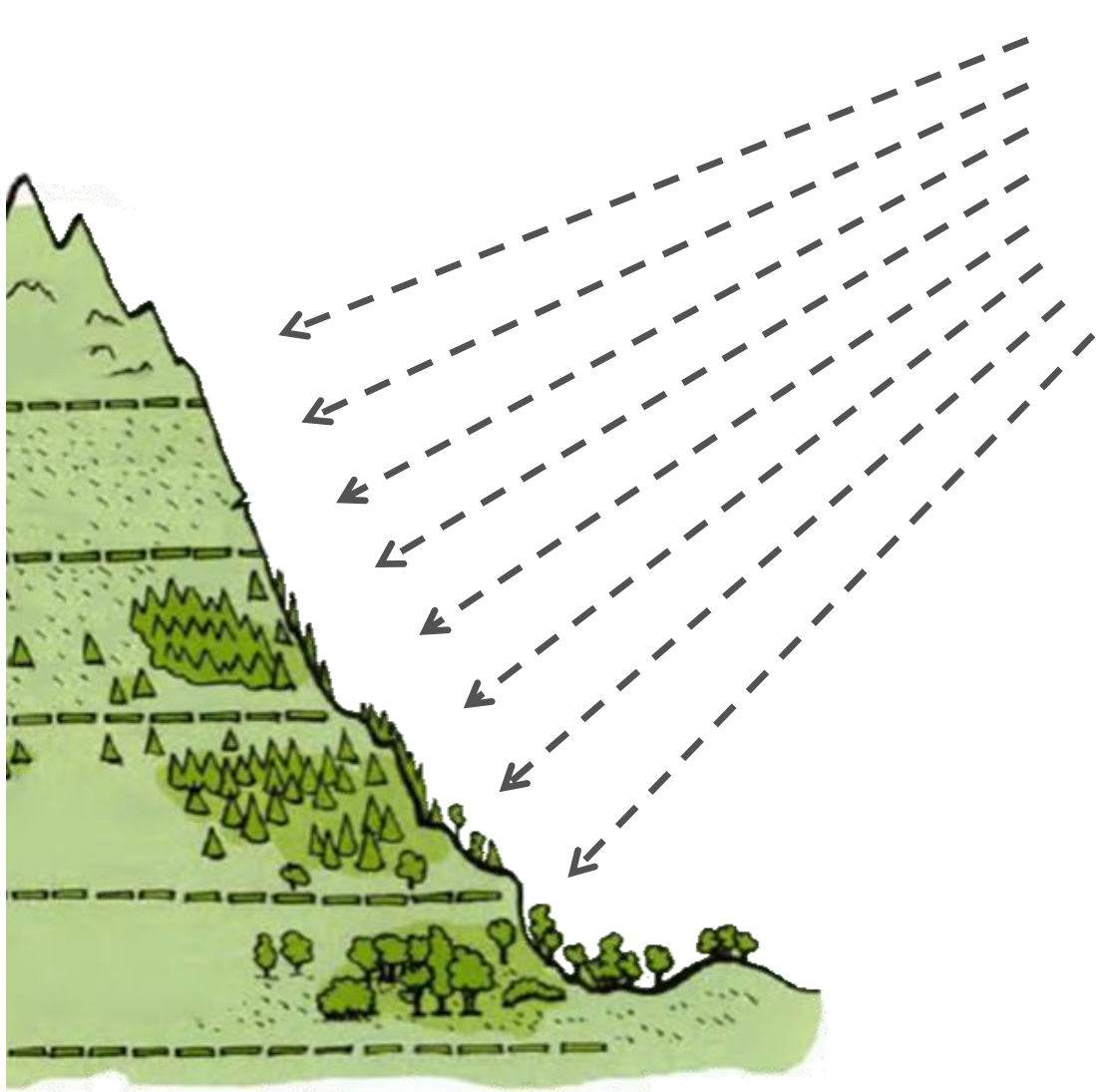
# Study of natural populations

Highlighting the natural diversity of *A. thaliana* populations in the Pyrenees.



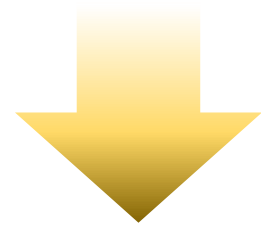
Krämer, 2015

# Natural populations from contrasted growth conditions



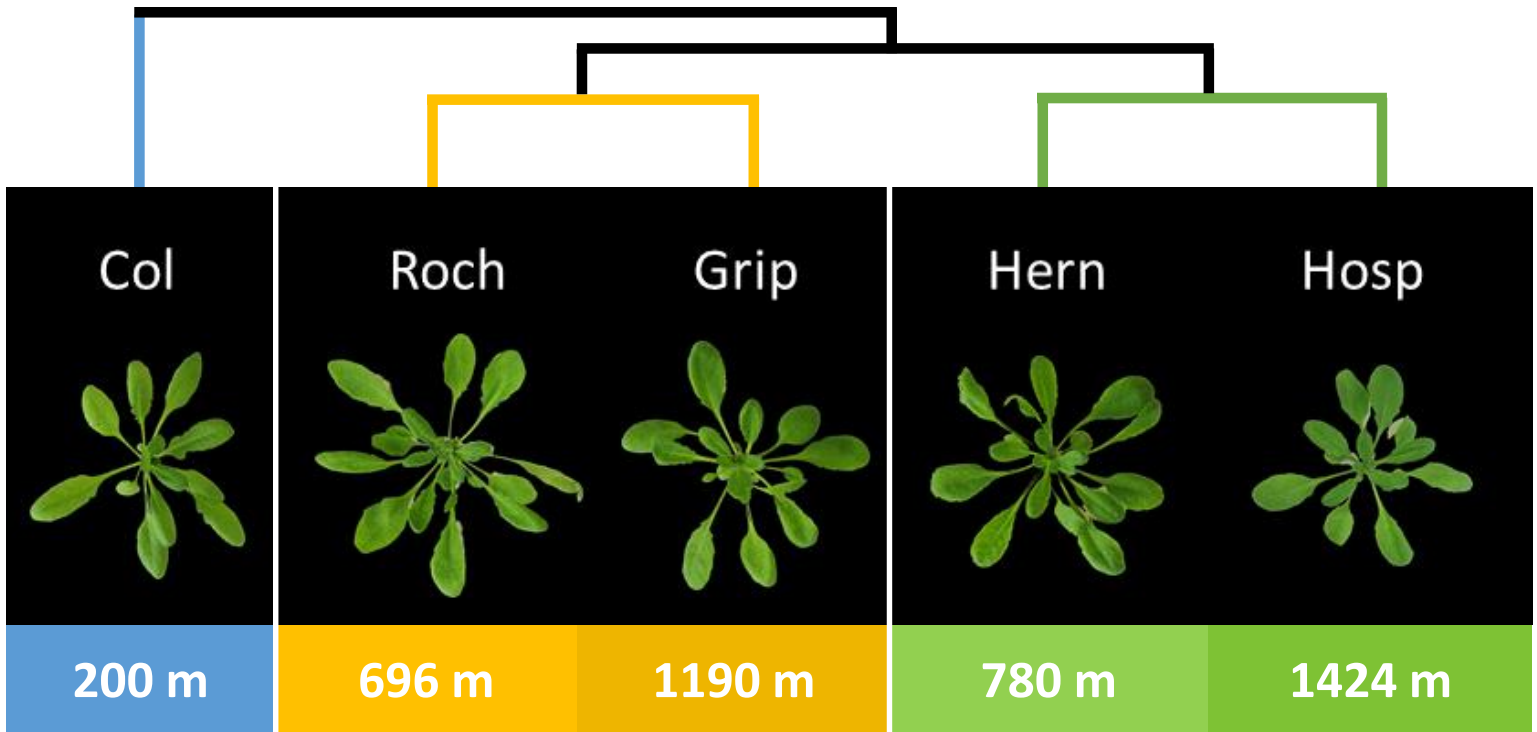
 Different altitude levels

 Different environments



**Adaptation ?**

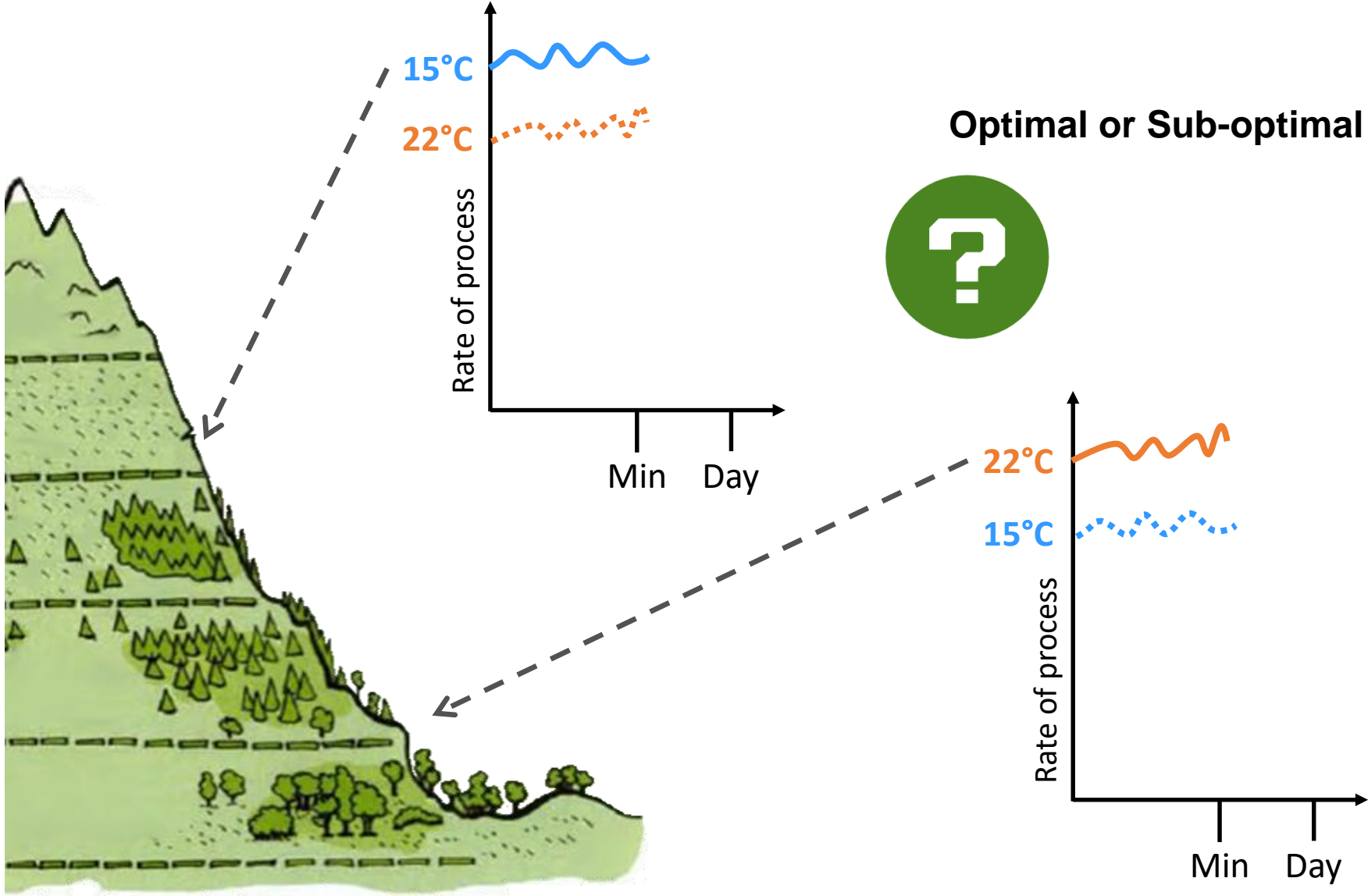
# Environmental adaptation of *A. thaliana*



 3 genetic clusters

 2 contrasted altitudes

# Choice of the temperatures growth conditions



# A system biology approach

## Two organs

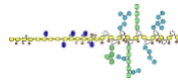


## Omics analysis



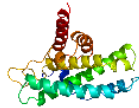
### Phenomics (Macro- and micro- phenotypic analyses)

- 5 and 4 phenotype on the rosette and the floral stems



### Metabolomics

- 6 cell wall polysaccharides



### Cell wall proteomics

- 364 and 414 cell wall proteins (CWPs) on rosette and floral stems



### Transcriptomics

- 19,763 and 22,570 transcripts on rosette and floral stems

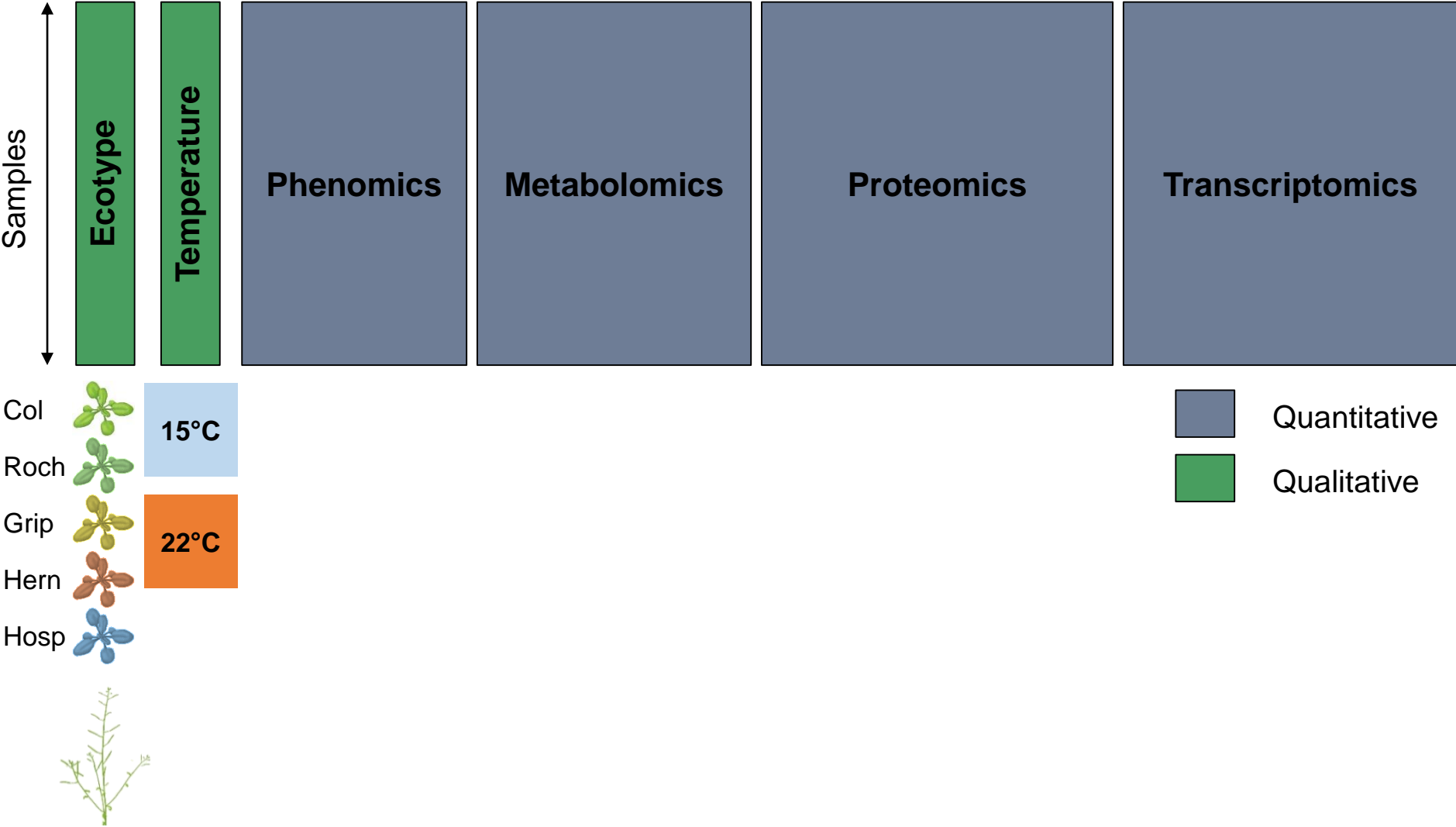
R Datasets Package “WallOmicsData”

Soon available (CRAN) for users needing benchmarking

- 3 biological replicates

- 20 plants per sample

# A system biology approach: principle of blocks





# mixOmics workflow

---

- 1) Ask a biological question
- 2) Run a method: `pca()`, `pls()`, `spls()`, `plsda()`, `block.pls()`, ...
- 3) Represent individuals: `plotIndiv()`
- 4) Represent variables: `plotVar()`, `plotLoadings()`, `cim()`, ...

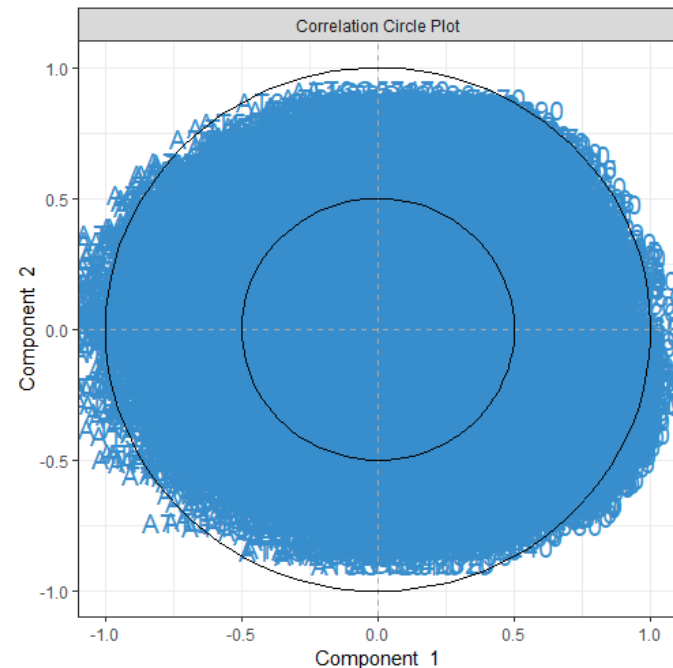
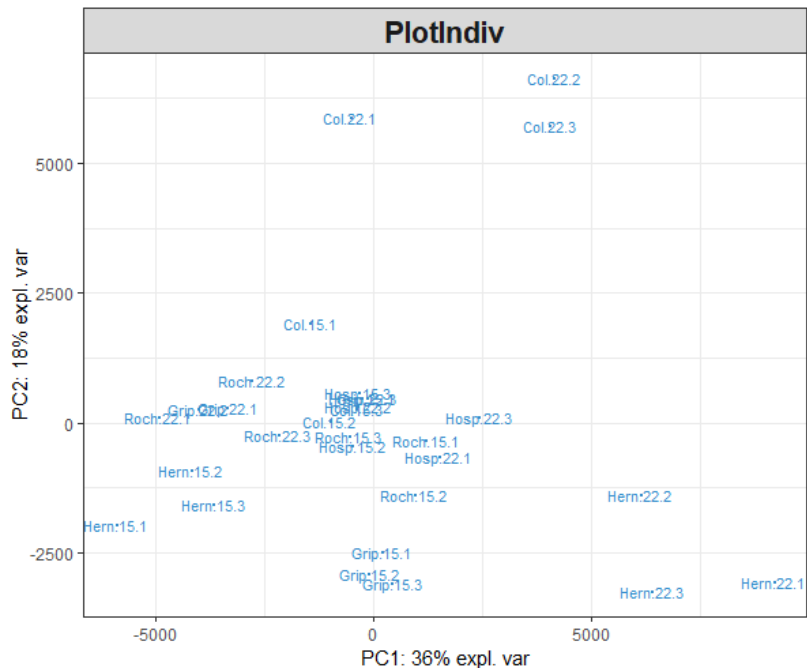
# Case study focused on the floral stem



Can we observe on the transcriptomics data, with no prior, the effect of different environmental growth conditions or different ecotypes?

→ Perform Principal Component Analysis

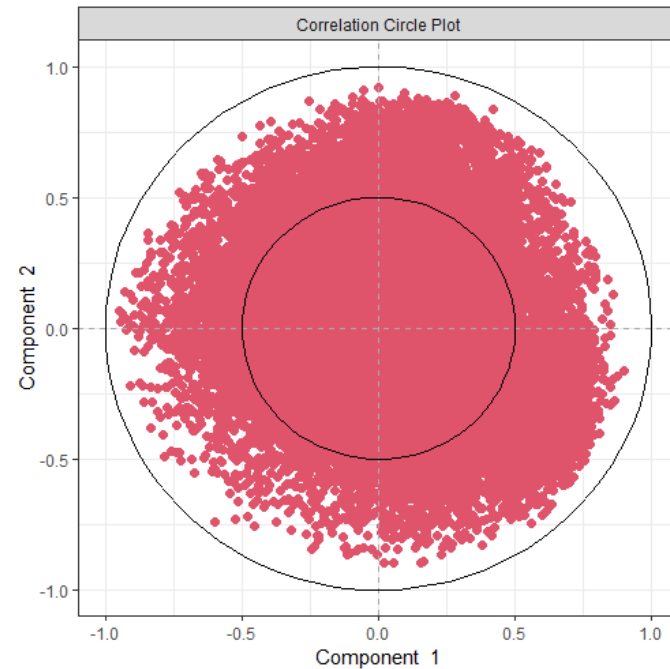
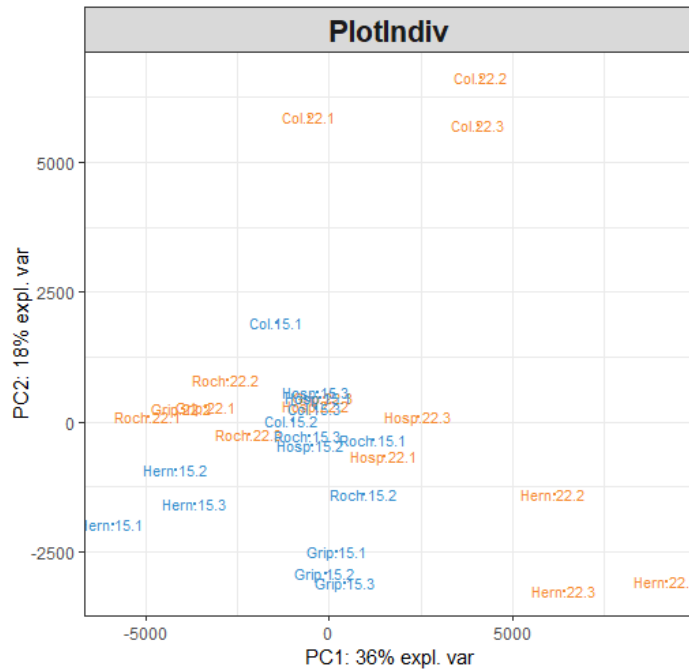
```
Result_PCA_stems_transcriptomics <- pca(Transcriptomics_Stems)  
plotIndiv(Result_PCA_stems_transcriptomics)  
plotVar(Result_PCA_stems_transcriptomics)
```



Can we observe on the transcriptomics data, with no prior, the effect of different environmental growth conditions or different ecotypes?

→ Perform Principal Component Analysis

```
plotIndiv(Result_PCA_stems_transcriptomics, group = Temperature, legend = TRUE)  
plotVar(Result_PCA_stems_transcriptomics, var.names = FALSE, pch = 16, cex = 2, col = 2)
```

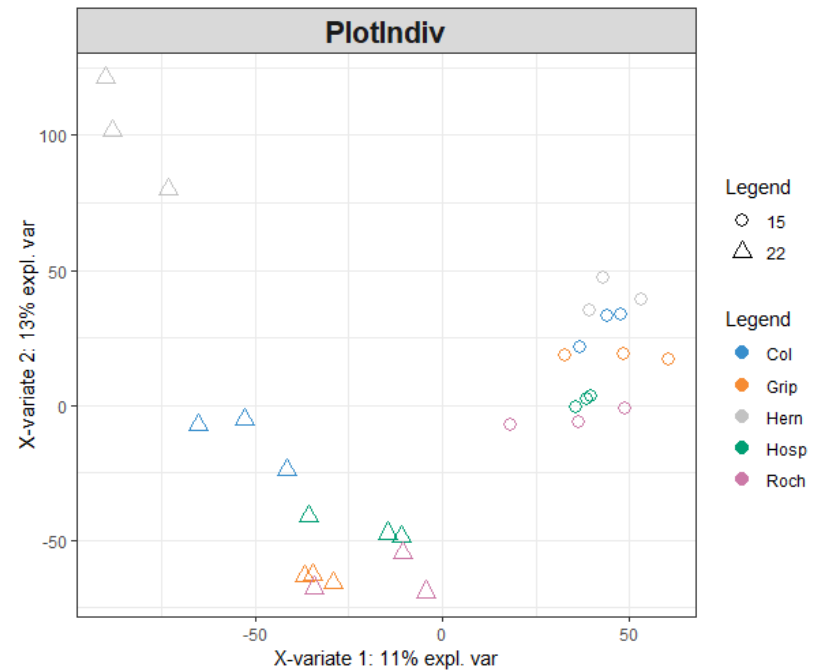
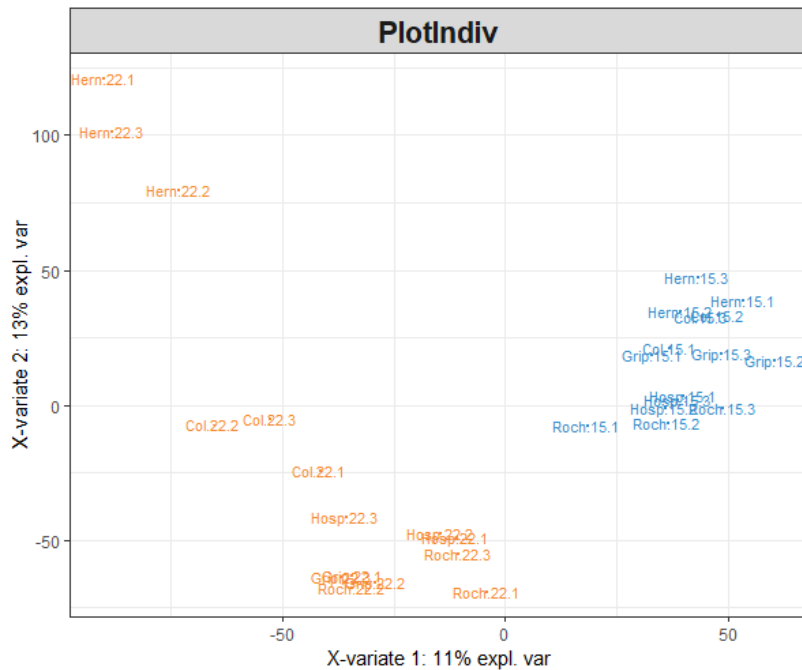


# Can we observe a global effect of temperature on the different ecotypes according to their transcriptomics profiles?

## → Perform Projection to Latent Structures - Discriminant Analysis

```
Result_PLSDA_stems_transcriptomics_temperature <- plsda(X=Transcriptomics_Stems,Y= Temperature)  
plotVar(Result_PLSDA_stems_transcriptomics_temperature)  
plotIndiv(Result_PLSDA_stems_transcriptomics_temperature)
```

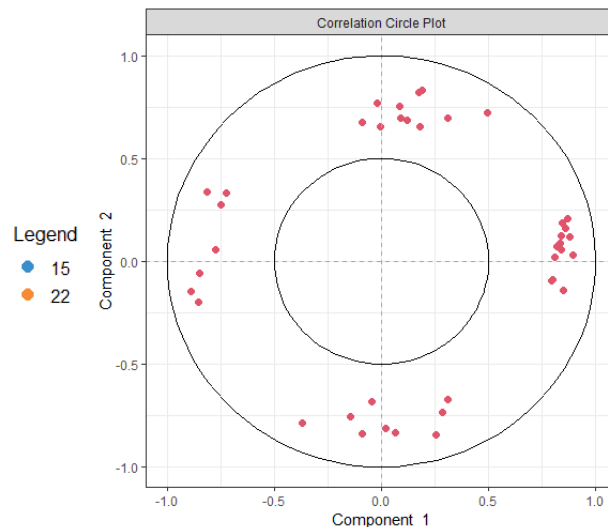
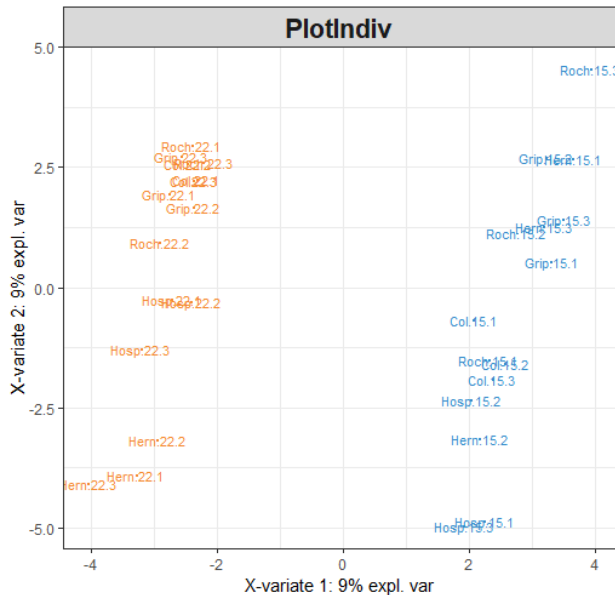
```
plotIndiv(Result_PLSDA_stems_transcriptomics_temperature,  
  ind.names = FALSE, pch = Temperature, group = Ecotype, legend = TRUE)
```



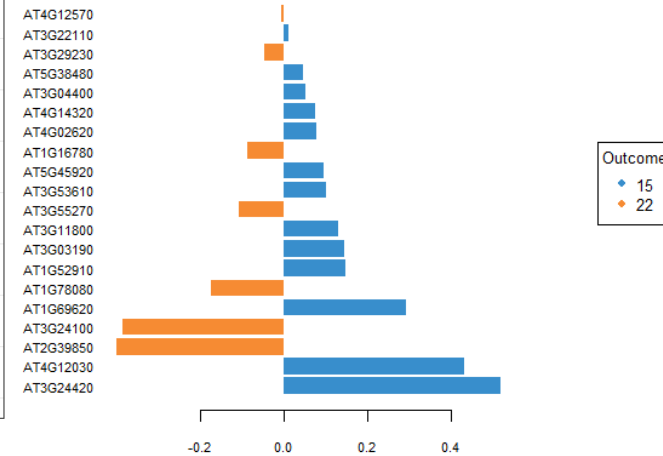
# How to know the best candidate genes for the global effect of temperature?

## → Perform Sparse Projection to Latent Structures - Discriminant Analysis

```
Result_sPLSDA_stems_transcriptomics_temperature <- splsda(X = Transcriptomics_Stems,  
Y = Temperature, keepX = c(20,20))  
plotIndiv(Result_sPLSDA_stems_transcriptomics_temperature)  
plotVar(Result_sPLSDA_stems_transcriptomics_temperature, var.names = FALSE, pch = 16, cex = 2, col = 2)  
plotLoadings(Result_sPLSDA_stems_transcriptomics_temperature, contrib = 'max', method = 'mean')
```

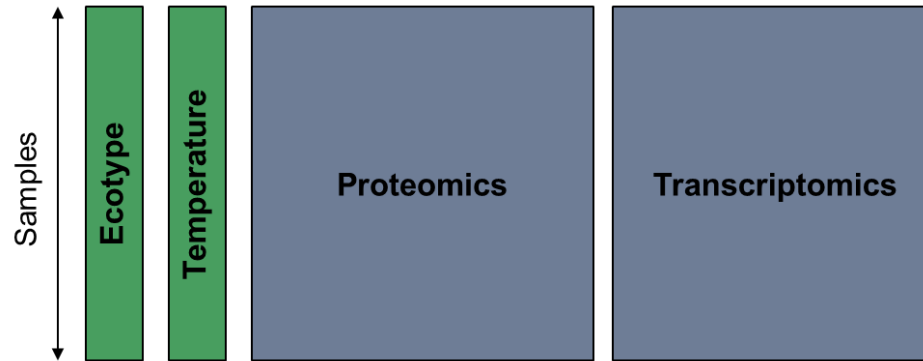


### Contribution on comp 1



```
Selected_transcripts_temperature <- selectVar(Result_sPLSDA_stems_transcriptomics_temperature, comp=1)
```

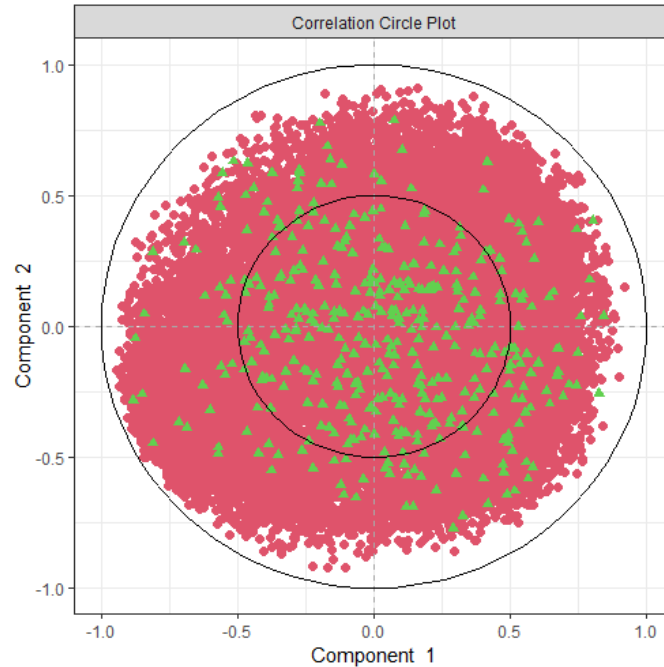
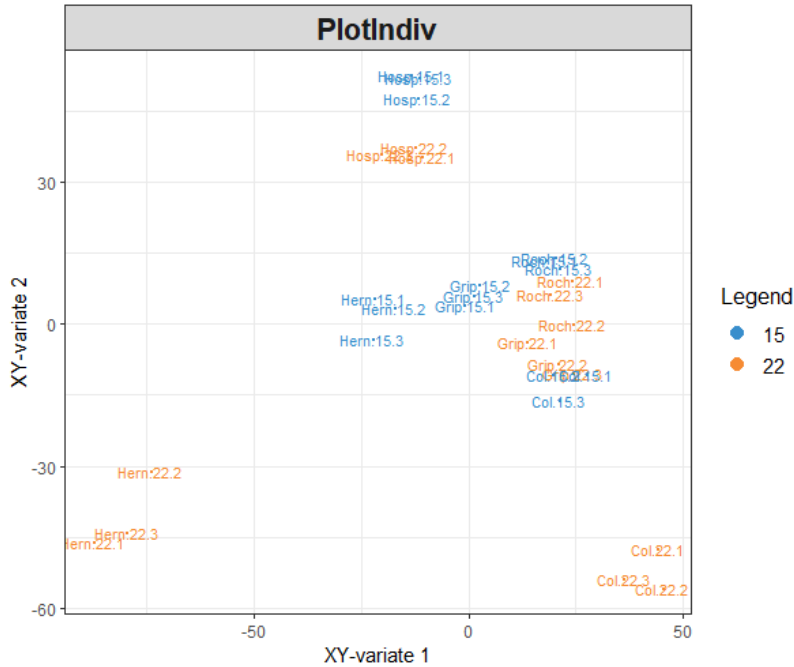
# Horizontal integration



# Can we highlight relationships between cell wall proteins and transcripts in stems?

## → Perform Projection to Latent Structures

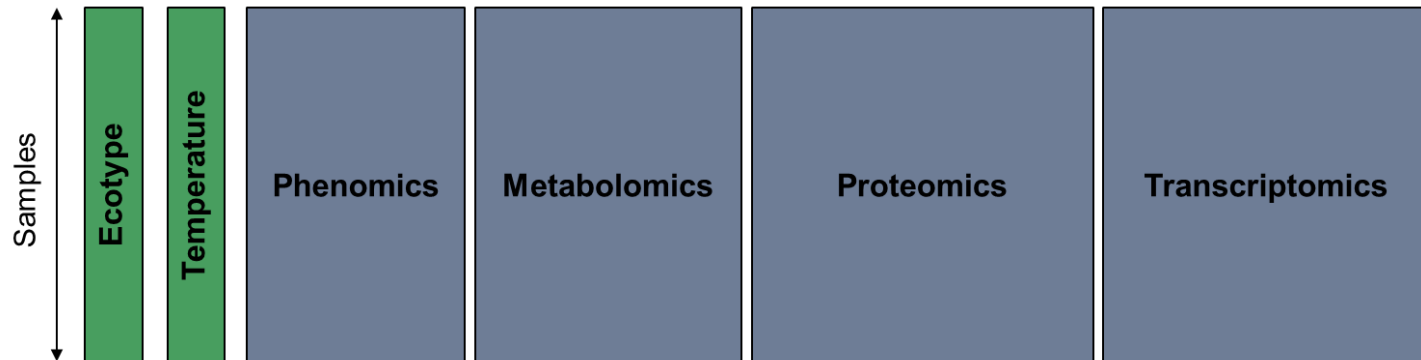
```
Result_PLS_stems_transcriptomics <- pls(X = Transcriptomics_Stems, Y = Proteomics_Stems_CW)
plotIndiv(Result_PLS_stems_transcriptomics, rep.space = "XY-variate", group = Temperature, legend = TRUE)
plotVar(Result_PLS_stems_transcriptomics, var.names = c(FALSE, FALSE), pch = c(16, 17),
        cex = c(2, 2), col = c(2, 3))
```



```
Result_sPLS_stems_transcriptomics <- spls(X = Transcriptomics_Stems, Y = Proteomics_Stems_CW,
        keepX = c(10, 10), keepY = c(10, 10))
plotLoadings(Result_sPLS_stems_transcriptomics, contrib = 'max')
```



# Horizontal integration



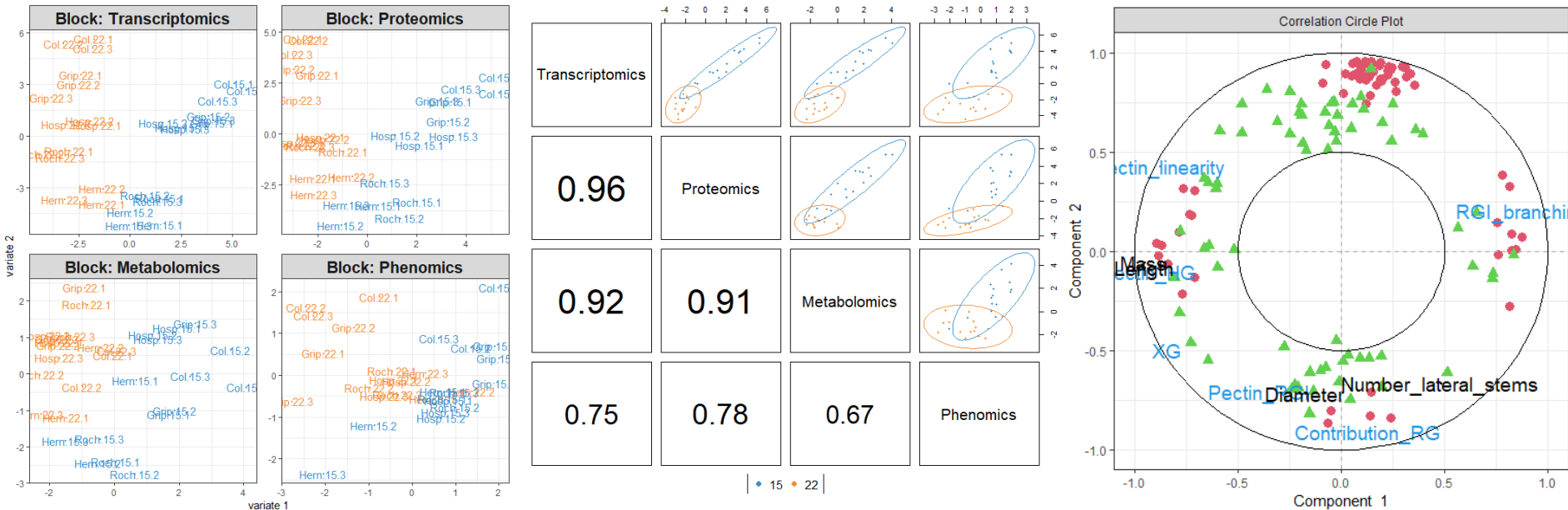
# Can we determine a multi-omics signature to classify ecotypes?

→ Perform multi-block Sparse Projection to Latent Structure - Discriminant Analysis (DIABLO)

```
Data_Stems <- list(Transcriptomics = Transcriptomics_Stems,  
                  Proteomics = Proteomics_Stems_CW,  
                  Metabolomics = Metabolomics_Stems,  
                  Phenomics = Phenomics_Stems)
```

```
Keepdata_Data_Stems <- list(Transcriptomics = c(20, 20),  
                             Proteomics = c(20, 20),  
                             Metabolomics = c(6, 6),  
                             Phenomics = c(4, 4))
```

```
Result_DIABLO_stems <- block.splsda(X = Data_Stems, Y = Temperature, keepX = Keepdata_Data_Stems)  
plotIndiv(Result_DIABLO_stems, cex=4)  
plotDiablo(Result_DIABLO_stems)  
plotVar(Result_DIABLO_stems, var.names = c(FALSE, FALSE, TRUE, TRUE), pch = c(16, 17, NA, NA),  
         cex = c(3, 3, 5, 5), col = c(2, 3, 7, 1))
```



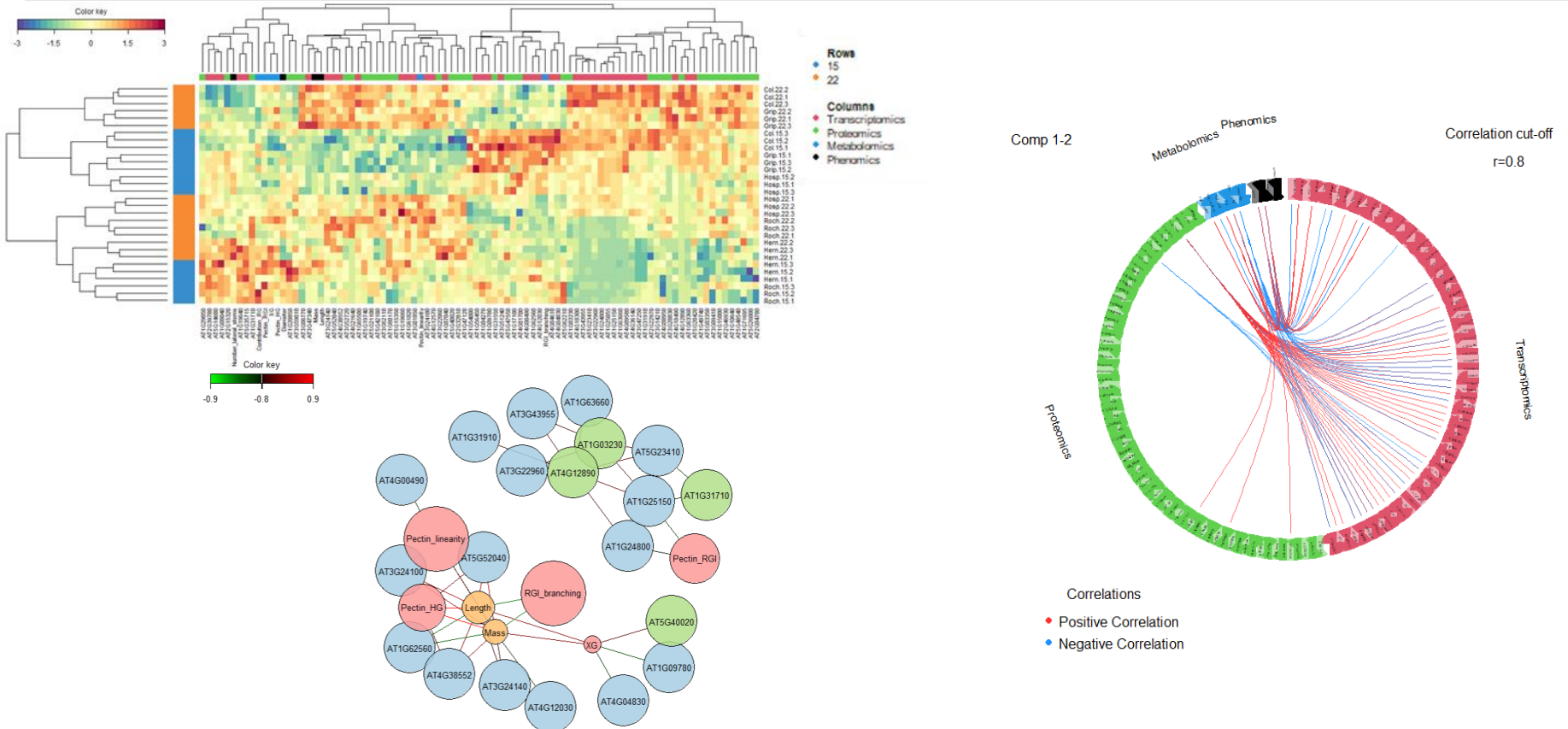
# Can we determine a multi-omics signature to classify ecotypes?

→ Perform multi-block Sparse Projection to Latent Structure - Discriminant Analysis (DIABLO)

```
cimDiablo(Result_DIABLO_stems, margins = c(8,10), size.legend = 0.5, color.blocks = c(2, 3, 7, 1),  
          legend.position = "topright")
```

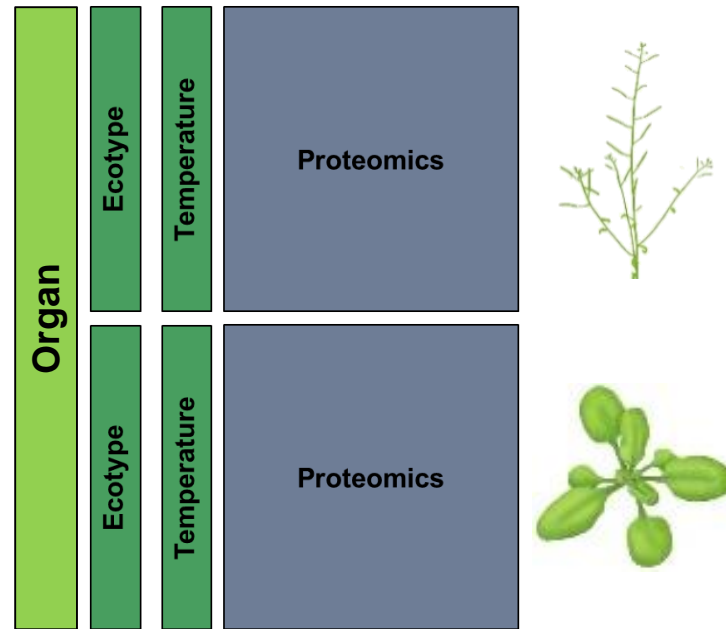
```
circosPlot(Result_DIABLO_stems, cutoff = 0.8, size.legend = 1, size.variables = 0.2, size.labels = 1,  
           color.blocks = c(2, 3, 7, 1))
```

```
network(Result_DIABLO_stems, blocks = c(1,2,3,4), block.var.names = c(T,T,T,T), cutoff = 0.8)
```



```
Candidates_Stems <- selectVar(Result_DIABLO_stems)  
Transcripts_Candidates <- Candidates_Stems$Transcriptomics$name
```

# Vertical integration



# Can we identify on the proteomics data behaviors that do not depend on the organ?

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→ Perform Multivariate INTegrative Method (MINT)

Need to format the data to assemble the proteomic data of these two organs

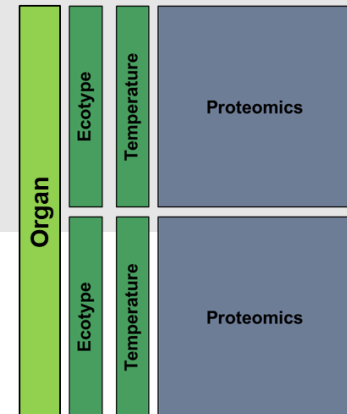
```
# To retrieve the list of common proteins between Stems and Rosettes
Common_List_Prot_Stem_Rosette <- intersect(colnames(Proteomics_Stems_CW),
                                           colnames(Proteomics_Rosettes_CW))

length(Common_List_Prot_Stem_Rosette) # 304 common variables

# To build one single dataset with stem and rosette data
Data_Prot_Mint <- rbind.data.frame(Proteomics_Rosettes_CW[,Common_List_Prot_Stem_Rosette],
                                   Proteomics_Stems_CW[,Common_List_Prot_Stem_Rosette])

# To add factors
Organ_Mint <- as.factor(rep(c("Rosette", "Stem"), each = 30))
Ecotype_Mint <- rep(Ecotype, 2)
Genetic_Cluster_Mint <- rep(Genetic_Cluster, 2)
Altitude_Cluster_Mint <- rep(Altitude_Cluster, 2)

# To make the rownames more explicit and not duplicated
rownames(Data_Prot_Mint)[31:60]<-paste0("Stem.", rownames(Data_Prot_Mint)[1:30])
rownames(Data_Prot_Mint)[1:30]<-paste0("Rosette.", rownames(Data_Prot_Mint)[1:30])
```

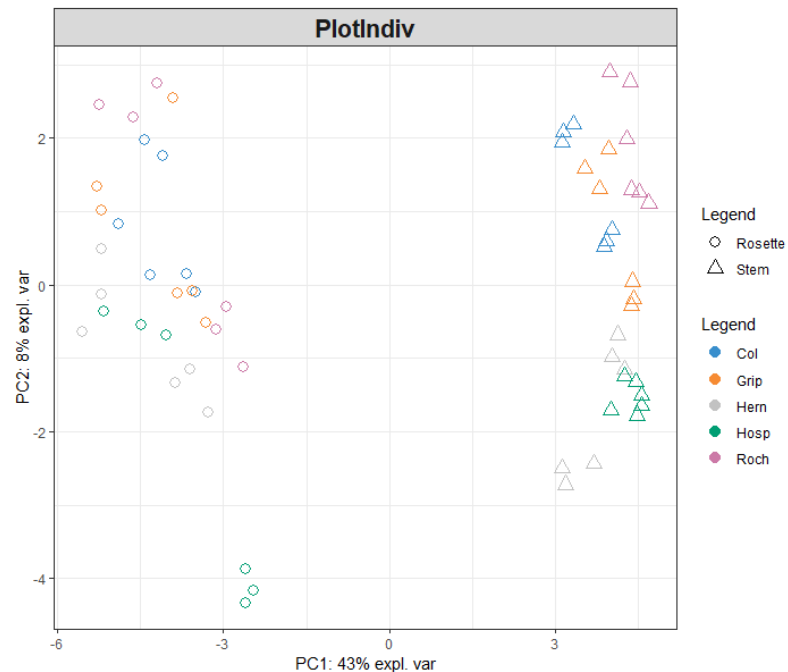
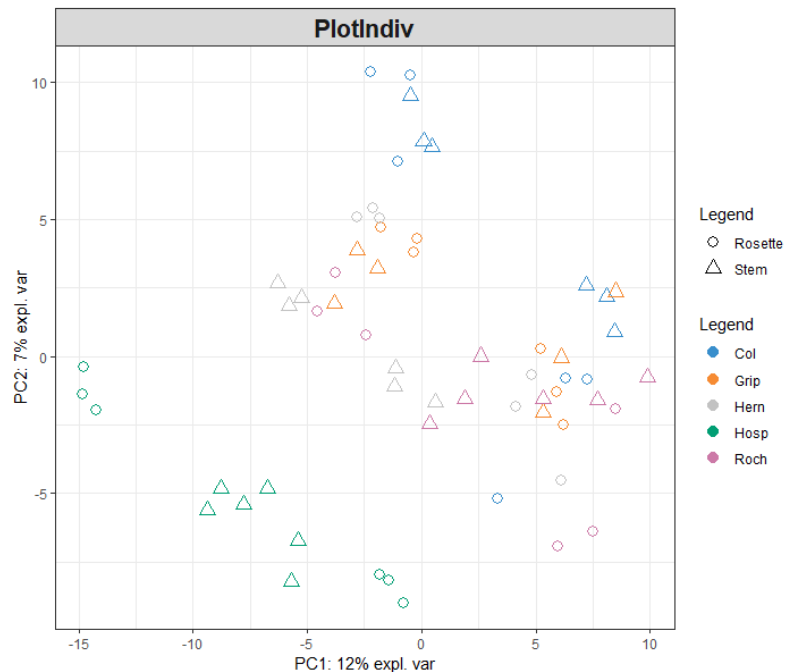


With no prior, what are the main effects of different environmental growth conditions or different ecotypes, when controlling the variations due to the organ?

→ Perform MINT-PCA

```
res_mint_pca <- mint.pca(X = Data_Prot_Mint, study = Organ_Mint, ncomp = 3)
plotIndiv(res_mint_pca, legend = TRUE, ind.names = FALSE, pch = Organ_Mint, group = Ecotype_Mint)

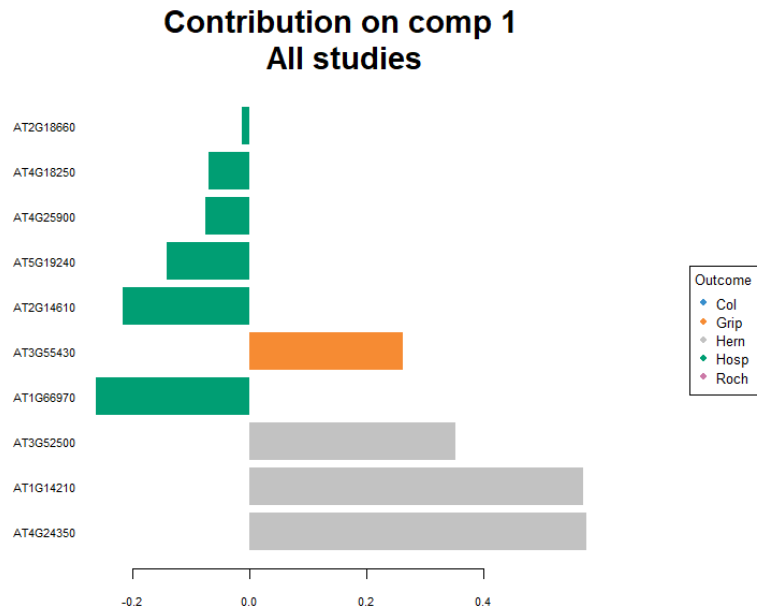
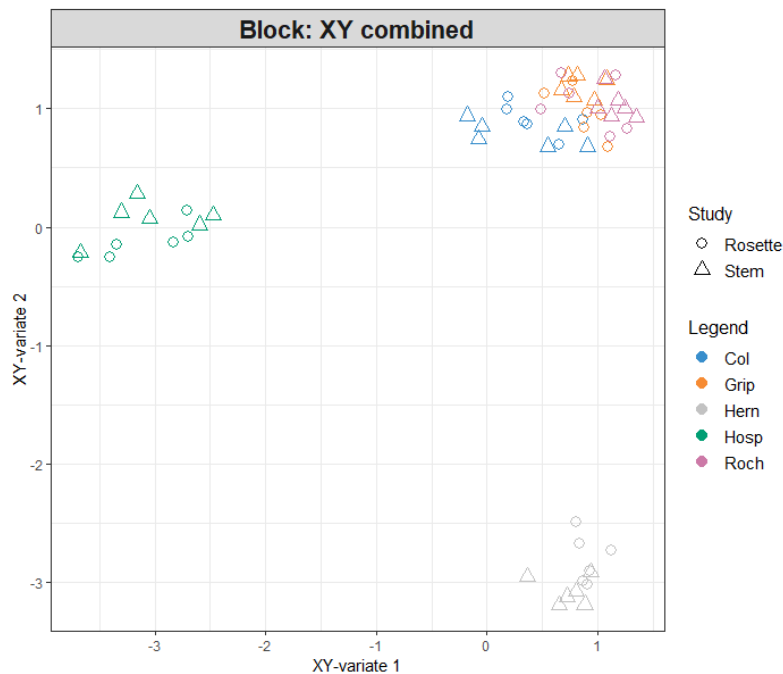
res_pca_no_mint <- pca(X = Data_Prot_Mint, ncomp = 3)
plotIndiv(res_pca_no_mint, legend = TRUE, ind.names = FALSE, pch = Organ_Mint, group = Ecotype_Mint)
```



# Can we determine a proteomics signature of the 5 ecotypes controlling the variations due to the organ?

→ Perform MINT-sPLS-DA

```
res_mint_splsda <- mint.splsda(X = Data_Prot_Mint, Y = Ecotype_Mint, study = Organ_Mint, ncomp = 3,  
                              keepX = c(10,10,10))  
plotIndiv(res_mint_splsda, legend = TRUE, rep.space = "XY-variate")  
plotLoadings(res_mint_splsda, comp = 1, method = "mean", contrib = "max")
```



# CONCLUSIONS

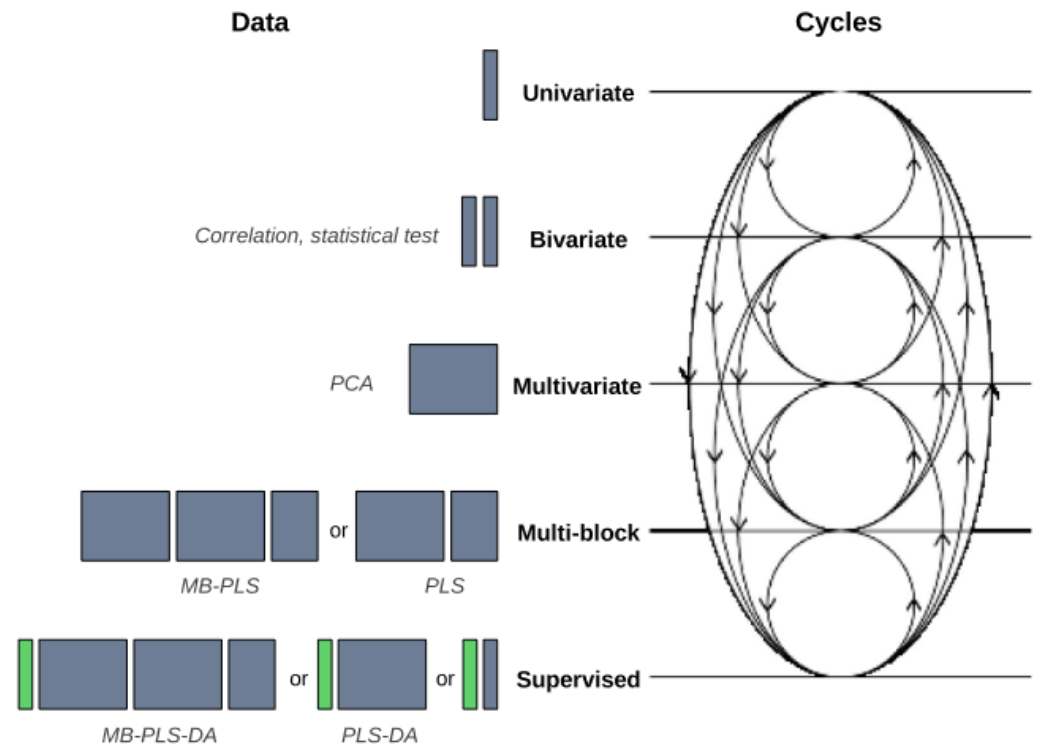




# Conclusions

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- Practice on your own data! The best way to understand what a method has to tell you.
- Do not bypass the elementary analyses (univariate, bivariate, multivariate single data set)
- Clearly identify the biological question to use the most appropriate methods



# Thanks for your attention



**Christophe Dunand**  
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Maxime Bonhomme



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Philippe Besse



Nathalie Escaravage  
Monique Burrus



Michel Zivy  
Thierry Balliau

