Spectra-trait PLSR example using leaf-level spectra and leaf mass per area (LMA) data from 36 species growing in Rosa rugosa invaded coastal grassland communities in Belgium

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Overview

This is an R Markdown Notebook to illustrate how to retrieve a dataset from the EcoSIS spectral database, choose the "optimal" number of plsr components, and fit a plsr model for leaf-mass area (LMA)

Getting Started

Step 1. Load libraries needed to run example script

```
list.of.packages <- c("pls", "dplyr", "reshape2", "here", "plotrix", "ggplot2", "gridExtra",</pre>
                       "spectratrait")
invisible(lapply(list.of.packages, library, character.only = TRUE))
##
## Attaching package: 'pls'
## The following object is masked from 'package:stats':
##
##
       loadings
##
## Attaching package: 'dplyr'
## The following objects are masked from 'package:stats':
##
##
       filter, lag
## The following objects are masked from 'package:base':
##
##
       intersect, setdiff, setequal, union
## here() starts at /Users/sserbin/Data/GitHub/PLSR_for_plant_trait_prediction
##
## Attaching package: 'gridExtra'
## The following object is masked from 'package:dplyr':
##
##
       combine
```

Step 2. Setup other functions and options

```
### Setup other functions and options
# not in
`%notin%` <- Negate(`%in%`)
# Script options
pls::pls.options(plsralg = "oscorespls")
pls::pls.options("plsralg")
## $plsralg
## [1] "oscorespls"
# Default par options
opar <- par(no.readonly = T)</pre>
# What is the target variable?
inVar <- "LMA_g_m2"</pre>
# What is the source dataset from EcoSIS?
ecosis_id <- "9db4c5a2-7eac-4e1e-8859-009233648e89"
# Specify output directory, output_dir
# Options:
# tempdir - use a OS-specified temporary directory
# user defined PATH - e.q. "~/scratch/PLSR"
output_dir <- "tempdir"</pre>
```

Step 3. Set working directory (scratch space)

[1] "/private/var/folders/xp/h3k9vf3n2jx181ts786_yjrn9c2gjq/T/Rtmp8hJkLD"

Step 4. Pull example dataset from EcoSIS (ecosis.org)

```
print(paste0("Output directory: ",getwd())) # check wd
## [1] "Output directory: /Users/sserbin/Data/GitHub/PLSR_for_plant_trait_prediction/vignettes"
### Get source dataset from EcoSIS
dat_raw <- spectratrait::get_ecosis_data(ecosis_id = ecosis_id)</pre>
## [1] "**** Downloading Ecosis data ****"
## Downloading data...
##
## cols(
##
    .default = col_double(),
    `Latin Species` = col_character(),
##
##
    ids = col_character(),
##
    `plot code` = col_character(),
    `species code` = col_character()
##
## )
```

```
## i Use `spec()` for the full column specifications.
## Download complete!
head(dat_raw)
## # A tibble: 6 x 2,164
     `Cw/EWT (cm3/cm2~ `Latin Species`
                                         `Leaf area (mm2~ `Leaf calcium content pe~
##
                 <dbl> <chr>
                                                     <dbl>
                                                                               <dbl>
               0.00887 Arrhenatherum el~
                                                      696.
                                                                              0.0291
## 2
               0.00824 Bromus sterilis
                                                      447.
                                                                              0.0230
## 3
               0.0280 Jacobaea vulgaris
                                                     2418.
                                                                              0.0950
## 4
               0.0106 Rubus caesius
                                                     5719.
                                                                              0.0700
## 5
               0.00851 Arrhenatherum el~
                                                                              0.0286
                                                      671.
## 6
               0.0153 Crepis capillaris
                                                                              0.0470
                                                     1401.
## # ... with 2,160 more variables:
       Leaf magnesium content per leaf area (mg/mm2) <dbl>,
       Leaf mass per area (g/cm2) <dbl>,
       Leaf nitrogen content per leaf area (mg/mm2) <dbl>,
## #
## #
       Leaf phosphorus content per leaf area (mg/mm2) <dbl>,
## #
       Leaf potassium content per leaf area (mg/mm2) <dbl>,
       Plant height vegetative (cm) <dbl>, ids <chr>, plot code <chr>,
       species code <chr>, 350 <dbl>, 351 <dbl>, 352 <dbl>, 353 <dbl>, 354 <dbl>,
## #
## #
       355 <dbl>, 356 <dbl>, 357 <dbl>, 358 <dbl>, 359 <dbl>, 360 <dbl>,
## #
       361 <dbl>, 362 <dbl>, 363 <dbl>, 364 <dbl>, 365 <dbl>, 366 <dbl>,
## #
       367 <dbl>, 368 <dbl>, 369 <dbl>, 370 <dbl>, 371 <dbl>, 372 <dbl>,
## #
       373 <dbl>, 374 <dbl>, 375 <dbl>, 376 <dbl>, 377 <dbl>, 378 <dbl>,
## #
       379 <dbl>, 380 <dbl>, 381 <dbl>, 382 <dbl>, 383 <dbl>, 384 <dbl>,
## #
       385 <dbl>, 386 <dbl>, 387 <dbl>, 388 <dbl>, 389 <dbl>, 390 <dbl>,
## #
       391 <dbl>, 392 <dbl>, 393 <dbl>, 394 <dbl>, 395 <dbl>, 396 <dbl>,
## #
       397 <dbl>, 398 <dbl>, 399 <dbl>, 400 <dbl>, 401 <dbl>, 402 <dbl>,
## #
       403 <dbl>, 404 <dbl>, 405 <dbl>, 406 <dbl>, 407 <dbl>, 408 <dbl>,
       409 <dbl>, 410 <dbl>, 411 <dbl>, 412 <dbl>, 413 <dbl>, 414 <dbl>,
       415 <dbl>, 416 <dbl>, 417 <dbl>, 418 <dbl>, 419 <dbl>, 420 <dbl>,
## #
       421 <dbl>, 422 <dbl>, 423 <dbl>, 424 <dbl>, 425 <dbl>, 426 <dbl>,
## #
       427 <dbl>, 428 <dbl>, 429 <dbl>, 430 <dbl>, 431 <dbl>, 432 <dbl>,
       433 <dbl>, 434 <dbl>, 435 <dbl>, 436 <dbl>, 437 <dbl>, 438 <dbl>,
       439 <dbl>, 440 <dbl>, ...
names(dat_raw)[1:40]
##
    [1] "Cw/EWT (cm3/cm2)"
##
   [2] "Latin Species"
   [3] "Leaf area (mm2)"
##
   [4] "Leaf calcium content per leaf area (mg/mm2)"
##
   [5] "Leaf magnesium content per leaf area (mg/mm2)"
   [6] "Leaf mass per area (g/cm2)"
   [7] "Leaf nitrogen content per leaf area (mg/mm2)"
   [8] "Leaf phosphorus content per leaf area (mg/mm2)"
   [9] "Leaf potassium content per leaf area (mg/mm2)"
## [10] "Plant height vegetative (cm)"
## [11] "ids"
## [12] "plot code"
## [13] "species code"
## [14] "350"
## [15] "351"
```

```
## [16] "352"
## [17] "353"
## [18] "354"
## [19] "355"
## [20] "356"
## [21] "357"
## [22] "358"
## [23] "359"
## [24] "360"
## [25] "361"
## [26] "362"
## [27] "363"
## [28] "364"
## [29] "365"
## [30] "366"
## [31] "367"
## [32]
       "368"
## [33] "369"
## [34] "370"
## [35] "371"
## [36] "372"
## [37] "373"
## [38] "374"
## [39] "375"
## [40] "376"
```

Step 5. Create full plsr dataset

```
### Create plsr dataset
Start.wave <- 500
End.wave <- 2400
wv <- seq(Start.wave,End.wave,1)</pre>
Spectra <- as.matrix(dat_raw[,names(dat_raw) %in% wv])</pre>
colnames(Spectra) <- c(paste0("Wave_",wv))</pre>
sample_info <- dat_raw[,names(dat_raw) %notin% seq(350,2500,1)]</pre>
head(sample_info)
## # A tibble: 6 x 13
     `Cw/EWT (cm3/cm2~ `Latin Species`
                                           `Leaf area (mm2~ `Leaf calcium content pe~
##
                 <dbl> <chr>
                                                      <dbl>
                                                                                  <dbl>
## 1
               0.00887 Arrhenatherum el~
                                                       696.
                                                                                0.0291
## 2
               0.00824 Bromus sterilis
                                                       447.
                                                                                0.0230
## 3
               0.0280 Jacobaea vulgaris
                                                      2418.
                                                                                0.0950
## 4
               0.0106 Rubus caesius
                                                      5719.
                                                                                0.0700
## 5
               0.00851 Arrhenatherum el~
                                                       671.
                                                                                0.0286
               0.0153 Crepis capillaris
## 6
                                                      1401.
                                                                                0.0470
## # ... with 9 more variables:
## #
       Leaf magnesium content per leaf area (mg/mm2) <dbl>,
## #
       Leaf mass per area (g/cm2) <dbl>,
       Leaf nitrogen content per leaf area (mg/mm2) <dbl>,
## #
## #
       Leaf phosphorus content per leaf area (mg/mm2) <dbl>,
## #
       Leaf potassium content per leaf area (mg/mm2) <dbl>,
## #
       Plant height vegetative (cm) <dbl>, ids <chr>, plot code <chr>,
```

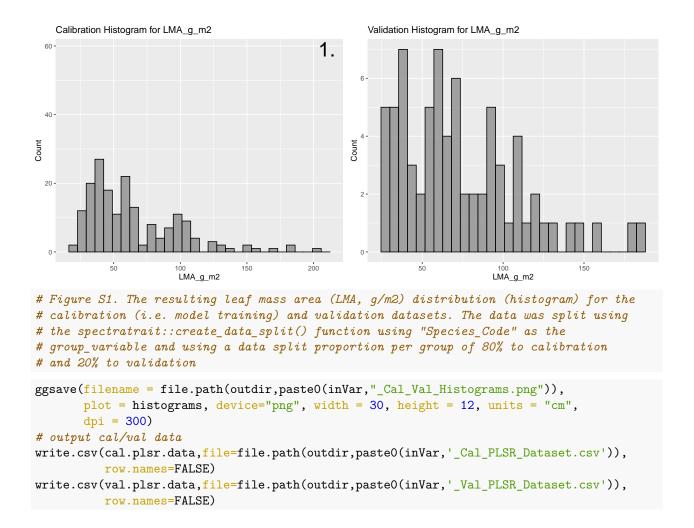
```
species code <chr>>
sample_info2 <- sample_info %>%
  select(Plant_Species=`Latin Species`,Species_Code=`species code`,Plot=`plot code`,
         LMA_g_cm2=`Leaf mass per area (g/cm2)`)
sample_info2 <- sample_info2 %>%
  mutate(LMA_g_m2=LMA_g_cm2*10000)
head(sample_info2)
## # A tibble: 6 x 5
##
    Plant Species
                           Species_Code Plot LMA_g_cm2 LMA_g_m2
##
     <chr>
                           <chr>
                                        <chr>
                                                  <dbl>
                                                           <dbl>
## 1 Arrhenatherum elatius Arrela
                                        DC1
                                                0.00342
                                                            34.2
## 2 Bromus sterilis
                                        DC1
                                                0.00282
                                                            28.2
                           Broste
## 3 Jacobaea vulgaris
                           Jacvul
                                        DC1
                                                0.00417
                                                            41.7
## 4 Rubus caesius
                                        DC1
                                                0.00566
                                                            56.6
                           Rubcae
## 5 Arrhenatherum elatius Arrela
                                        DC2
                                                0.00361
                                                            36.1
## 6 Crepis capillaris
                           Creves
                                        DC2
                                                0.00283
                                                            28.3
plsr_data <- data.frame(sample_info2,Spectra)</pre>
rm(sample_info,sample_info2,Spectra)
```

Step 6. Example data cleaning.

Step 7. Create cal/val datasets

```
method <- "dplyr" #base/dplyr</pre>
\# base R - a bit slow
# dplyr - much faster
split_data <- spectratrait::create_data_split(dataset=plsr_data, approach=method,</pre>
                                              split_seed=7529075, prop=0.8,
                                              group_variables="Species_Code")
names(split_data)
## [1] "cal data" "val data"
cal.plsr.data <- split_data$cal_data</pre>
head(cal.plsr.data)[1:8]
          Plant_Species Species_Code Plot LMA_g_cm2 LMA_g_m2 Wave_500 Wave_501
## 1 Ammophila arenaria
                              Ammare MC2 0.01679492 167.9492 0.135785 0.13685
## 2 Ammophila arenaria
                              Ammare WC3 0.01844376 184.4376 0.151750 0.15275
## 3 Ammophila arenaria
                              Ammare MC4 0.02030190 203.0190 0.156830 0.15790
                              Ammare ZC2 0.01591894 159.1894 0.144450 0.14525
## 4 Ammophila arenaria
## 5 Ammophila arenaria
                              Ammare ZC1 0.01483469 148.3469 0.147665 0.14910
## 6 Ammophila arenaria
                              Ammare ZC3 0.01802409 180.2409 0.130885 0.13175
##
   Wave_502
```

```
## 1 0.138150
## 2 0.154150
## 3 0.159065
## 4 0.146220
## 5 0.150330
## 6 0.132750
val.plsr.data <- split_data$val_data</pre>
head(val.plsr.data)[1:8]
##
            Plant Species Species Code Plot
                                             LMA_g_cm2 LMA_g_m2
                                                                     Wave 500
## 184 Jacobaea vulgaris
                                Jacvul WC2 0.003551614 35.51614 0.06736887
## 185 Potentilla reptans
                                Potrep WC2 0.005586320 55.86320 0.07125000
## 186
                                Rubcae WC2 0.005803902 58.03902 0.05993560
            Rubus caesius
                                Urtdio WC2 0.005215705 52.15705 0.06508300
## 187
            Urtica dioica
## 188 Ammophila arenaria
                                Ammare WC3 0.018443757 184.43757 0.15175000
       Jacobaea vulgaris
                                Jacvul WC3 0.004980002 49.80002 0.06805547
         Wave_501
                    Wave_502
## 184 0.06870667 0.07014220
## 185 0.07235000 0.07368350
## 186 0.06162000 0.06352233
## 187 0.06625000 0.06758350
## 188 0.15275000 0.15415000
## 189 0.06938000 0.07093553
rm(split_data)
# Datasets:
print(paste("Cal observations: ",dim(cal.plsr.data)[1],sep=""))
## [1] "Cal observations: 183"
print(paste("Val observations: ",dim(val.plsr.data)[1],sep=""))
## [1] "Val observations: 73"
text_loc <- c(max(hist(cal.plsr.data[,paste0(inVar)], plot=FALSE)$counts),</pre>
              max(hist(cal.plsr.data[,paste0(inVar)], plot=FALSE)$mids))
cal_hist_plot <- qplot(cal.plsr.data[,paste0(inVar)],geom="histogram",</pre>
                       main = paste0("Calibration Histogram for ",inVar),
                       xlab = paste0(inVar),ylab = "Count",fill=I("grey50"),col=I("black"),
                       alpha=I(.7)) +
 annotate("text", x=text_loc[2], y=text_loc[1], label= "1.", size=10)
val_hist_plot <- qplot(val.plsr.data[,paste0(inVar)],geom="histogram",</pre>
                       main = paste0("Validation Histogram for ",inVar),
                       xlab = paste0(inVar),ylab = "Count",fill=I("grey50"),col=I("black"),
                       alpha=I(.7))
histograms <- grid.arrange(cal_hist_plot, val_hist_plot, ncol=2)</pre>
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

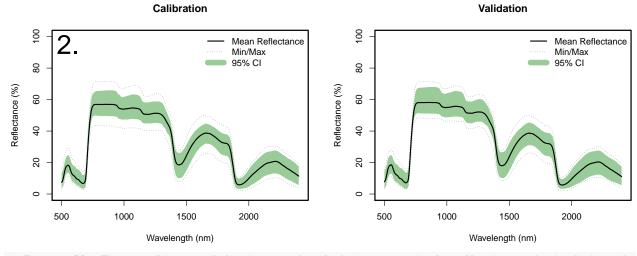


Step 8. Create calibration and validation PLSR datasets

```
### Format PLSR data for model fitting
cal_spec <- as.matrix(cal.plsr.data[, which(names(cal.plsr.data) %in%</pre>
                                               paste0("Wave_",wv))])
cal.plsr.data <- data.frame(cal.plsr.data[, which(names(cal.plsr.data) %notin%</pre>
                                                     paste0("Wave_",wv))],
                             Spectra=I(cal_spec))
head(cal.plsr.data)[1:5]
          Plant_Species Species_Code Plot LMA_g_cm2 LMA_g_m2
## 1 Ammophila arenaria
                              Ammare MC2 0.01679492 167.9492
## 2 Ammophila arenaria
                              Ammare WC3 0.01844376 184.4376
                              Ammare MC4 0.02030190 203.0190
## 3 Ammophila arenaria
## 4 Ammophila arenaria
                              Ammare ZC2 0.01591894 159.1894
## 5 Ammophila arenaria
                              Ammare ZC1 0.01483469 148.3469
## 6 Ammophila arenaria
                              Ammare ZC3 0.01802409 180.2409
val_spec <- as.matrix(val.plsr.data[, which(names(val.plsr.data) %in%</pre>
                                               paste0("Wave ",wv))])
val.plsr.data <- data.frame(val.plsr.data[, which(names(val.plsr.data) %notin%</pre>
                                                     paste0("Wave_",wv))],
```

Spectra=I(val_spec)) head(val.plsr.data)[1:5] Plant_Species Species_Code Plot ## LMA_g_cm2 LMA_g_m2 ## 184 Jacobaea vulgaris Jacvul WC2 0.003551614 35.51614 ## 185 Potentilla reptans Potrep WC2 0.005586320 55.86320 ## 186 Rubus caesius Rubcae WC2 0.005803902 58.03902 ## 187 Urtica dioica Urtdio WC2 0.005215705 52.15705 ## 188 Ammophila arenaria Ammare WC3 0.018443757 184.43757 Jacobaea vulgaris WC3 0.004980002 49.80002 ## 189 Jacvul

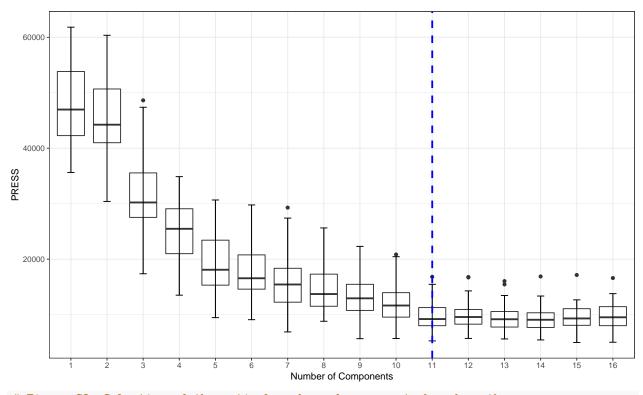
Step 9. Calibration and Validation spectra plot



```
## quartz_off_screen
## 3
dev.off();
## pdf
## 2
par(mfrow=c(1,1))
```

Step 10. Use permutation to determine the optimal number of components

```
### Use permutation to determine the optimal number of components
if(grepl("Windows", sessionInfo()$running)){
  pls.options(parallel = NULL)
} else {
  pls.options(parallel = parallel::detectCores()-1)
method <- "firstMin" #pls, firstPlateau, firstMin</pre>
random_seed <- 7529075</pre>
seg <- 80
maxComps <- 16
iterations <- 50
prop <- 0.70
if (method=="pls") {
  nComps <- spectratrait::find_optimal_components(dataset=cal.plsr.data, method=method,
                                                   maxComps=maxComps, seg=seg,
                                                   random_seed=random_seed)
  print(paste0("*** Optimal number of components: ", nComps))
} else {
  nComps <- spectratrait::find_optimal_components(dataset=cal.plsr.data, method=method,
                                                   maxComps=maxComps, iterations=iterations,
                                                   seg=seg, prop=prop,
                                                   random_seed=random_seed)
}
## [1] "*** Running permutation test. Please hang tight, this can take awhile ***"
## [1] "Options:"
## [1] "Max Components: 16 Iterations: 50 Data Proportion (percent): 70"
## [1] "*** Providing PRESS and coefficient array output ***"
## No id variables; using all as measure variables
## [1] "*** Optimal number of components based on t.test: 11"
```



```
## quartz_off_screen
## 3
dev.off();
```

pdf ## 2

Step 11. Fit final model

```
## (Intercept)
                                    2 comps
                                                  3 comps
                      1 comps
                                                                 4 comps
                                                                               5 comps
                        32.71
                                      30.36
                                                     23.51
                                                                   21.58
                                                                                 18.46
##
         37.79
       6 comps
                     7 comps
                                    8 comps
                                                  9 comps
                                                                10 comps
                                                                              11 comps
##
##
         15.89
                        15.44
                                      15.52
                                                     15.19
                                                                   15.14
                                                                                 13.68
plot(pls::RMSEP(plsr.out,estimate=c("test"),newdata = val.plsr.data), main="MODEL RMSEP",
     xlab="Number of Components", ylab="Model Validation RMSEP", lty=1, col="black", cex=1.5, lwd=2)
text(text_loc[1],text_loc[2],labels = "4.", cex=2)
box(1wd=2.2)
pls::R2(plsr.out, newdata = val.plsr.data)
## (Intercept)
                      1 comps
                                    2 comps
                                                  3 comps
                                                                 4 comps
                                                                               5 comps
      -0.06195
                     0.20461
                                    0.31467
                                                  0.58911
                                                                 0.65365
                                                                               0.74649
##
       6 comps
                     7 comps
                                    8 comps
                                                  9 comps
                                                                10 comps
                                                                              11 comps
##
                     0.82276
                                    0.82084
##
       0.81222
                                                  0.82841
                                                                 0.82945
                                                                               0.86090
plot(pls::R2(plsr.out,estimate=c("test"),newdata = val.plsr.data), main="MODEL R2",
     xlab="Number of Components",ylab="Model Validation R2",lty=1,col="black",cex=1.5,lwd=2)
box(1wd=2.2)
                     MODEL RMSEP
                                                                          MODEL R2
                                            4.
                                                       0.8
   35
Model Validation RMSEP
                                                      9.0
                                                   Model Validation R2
   30
                                                      0.4
   25
                                                       0.2
   20
                                                       0.0
   15
        0
              2
                            6
                                   8
                                         10
                                                                               6
                                                                                             10
                   Number of Components
                                                                      Number of Components
# Figure S4. A plot of the validation root mean square error of prediction (RMSEP, left)
# and coefficient of determination (right) for the O to optimal number of components
dev.copy(png,file.path(outdir,paste0(paste0(inVar,"_Validation_RMSEP_R2_by_Component.png"))),
         height=2800, width=4800, res=340)
## quartz_off_screen
dev.off();
## pdf
##
```

par(opar)

Step 12. PLSR fit observed vs. predicted plot data

```
#calibration
cal.plsr.output <- data.frame(cal.plsr.data[, which(names(cal.plsr.data) %notin%</pre>
                                                       "Spectra")],
                              PLSR Predicted=fit,
                              PLSR_CV_Predicted=as.vector(plsr.out$validation$pred[,,
                                                                                     nComps]))
cal.plsr.output <- cal.plsr.output %>%
  mutate(PLSR_CV_Residuals = PLSR_CV_Predicted-get(inVar))
head(cal.plsr.output)
          Plant_Species Species_Code Plot LMA_g_cm2 LMA_g_m2 PLSR_Predicted
## 1 Ammophila arenaria
                              Ammare MC2 0.01679492 167.9492
                                                                      154.1892
## 2 Ammophila arenaria
                              Ammare WC3 0.01844376 184.4376
                                                                      147.0878
## 3 Ammophila arenaria
                              Ammare MC4 0.02030190 203.0190
                                                                      153.8674
## 4 Ammophila arenaria
                              Ammare ZC2 0.01591894 159.1894
                                                                      161.6047
## 5 Ammophila arenaria
                              Ammare ZC1 0.01483469 148.3469
                                                                      144.9268
                              Ammare ZC3 0.01802409 180.2409
## 6 Ammophila arenaria
                                                                      148.2100
     PLSR_CV_Predicted PLSR_CV_Residuals
## 1
                              -16.233027
              151.7161
## 2
              137.3863
                              -47.051273
## 3
              144.2584
                              -58.760574
## 4
              162.6250
                                3.435614
## 5
              142.9101
                                -5.436767
## 6
              142.5160
                              -37.724928
cal.R2 <- round(pls::R2(plsr.out)[[1]][nComps],2)</pre>
cal.RMSEP <- round(sqrt(mean(cal.plsr.output$PLSR_CV_Residuals^2)),2)</pre>
val.plsr.output <- data.frame(val.plsr.data[, which(names(val.plsr.data) %notin%</pre>
                                                        "Spectra")],
                              PLSR_Predicted=as.vector(predict(plsr.out,
                                                                newdata = val.plsr.data,
                                                                ncomp=nComps,
                                                                 type="response")[,,1]))
val.plsr.output <- val.plsr.output %>%
  mutate(PLSR Residuals = PLSR Predicted-get(inVar))
head(val.plsr.output)
##
            Plant_Species Species_Code Plot
                                               LMA_g_cm2 LMA_g_m2 PLSR_Predicted
## 184 Jacobaea vulgaris
                                Jacvul WC2 0.003551614
                                                          35.51614
                                                                          43.51586
## 185 Potentilla reptans
                                Potrep
                                                                          61.41726
                                        WC2 0.005586320
                                                          55.86320
## 186
            Rubus caesius
                                Rubcae WC2 0.005803902
                                                          58.03902
                                                                          45.55789
## 187
            Urtica dioica
                                Urtdio WC2 0.005215705
                                                          52.15705
                                                                          46.65139
## 188 Ammophila arenaria
                                Ammare WC3 0.018443757 184.43757
                                                                         147.08781
## 189
        Jacobaea vulgaris
                                Jacvul WC3 0.004980002 49.80002
                                                                          53.09532
##
       PLSR_Residuals
## 184
             7.999719
## 185
             5.554059
## 186
           -12.481126
## 187
            -5.505664
## 188
           -37.349758
             3.295298
## 189
```

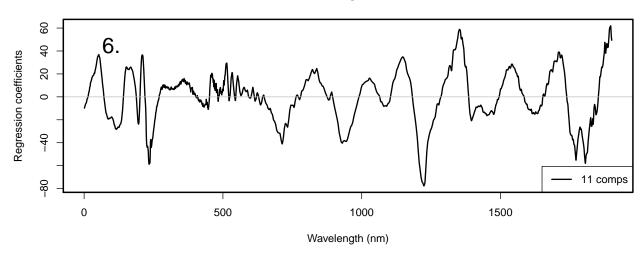
```
val.R2 <- round(pls::R2(plsr.out, newdata=val.plsr.data)[[1]][nComps],2)</pre>
val.RMSEP <- round(sqrt(mean(val.plsr.output$PLSR_Residuals^2)),2)</pre>
rng_quant <- quantile(cal.plsr.output[,inVar], probs = c(0.001, 0.999))</pre>
cal_scatter_plot <- ggplot(cal.plsr.output, aes(x=PLSR_CV_Predicted, y=get(inVar))) +</pre>
  theme_bw() + geom_point() + geom_abline(intercept = 0, slope = 1, color="dark grey",
                                           linetype="dashed", size=1.5) +
  xlim(rng quant[1], rng quant[2]) +
  ylim(rng quant[1], rng quant[2]) +
  labs(x=paste0("Predicted ", paste(inVar), " (units)"),
       y=paste0("Observed ", paste(inVar), " (units)"),
       title=paste0("Calibration: ", paste0("Rsq = ", cal.R2), "; ",
                    pasteO("RMSEP = ", cal.RMSEP))) +
  theme(axis.text=element_text(size=18), legend.position="none",
        axis.title=element_text(size=20, face="bold"),
        axis.text.x = element_text(angle = 0, vjust = 0.5),
        panel.border = element_rect(linetype = "solid", fill = NA, size=1.5)) +
  annotate("text", x=rng_quant[1], y=rng_quant[2], label= "5.",size=10)
cal_resid_histogram <- ggplot(cal.plsr.output, aes(x=PLSR_CV_Residuals)) +</pre>
  geom_histogram(alpha=.5, position="identity") +
  geom_vline(xintercept = 0, color="black",
             linetype="dashed", size=1) + theme_bw() +
  theme(axis.text=element_text(size=18), legend.position="none",
        axis.title=element text(size=20, face="bold"),
        axis.text.x = element text(angle = 0, vjust = 0.5),
        panel.border = element_rect(linetype = "solid", fill = NA, size=1.5))
rng_quant <- quantile(val.plsr.output[,inVar], probs = c(0.001, 0.999))</pre>
val_scatter_plot <- ggplot(val.plsr.output, aes(x=PLSR_Predicted, y=get(inVar))) +</pre>
  theme_bw() + geom_point() + geom_abline(intercept = 0, slope = 1, color="dark grey",
                                           linetype="dashed", size=1.5) +
  xlim(rng_quant[1], rng_quant[2]) +
  ylim(rng_quant[1], rng_quant[2]) +
  labs(x=paste0("Predicted ", paste(inVar), " (units)"),
       y=paste0("Observed ", paste(inVar), " (units)"),
       title=paste0("Validation: ", paste0("Rsq = ", val.R2), "; ",
                    paste0("RMSEP = ", val.RMSEP))) +
  theme(axis.text=element_text(size=18), legend.position="none",
        axis.title=element_text(size=20, face="bold"),
        axis.text.x = element_text(angle = 0, vjust = 0.5),
        panel.border = element_rect(linetype = "solid", fill = NA, size=1.5))
val_resid_histogram <- ggplot(val.plsr.output, aes(x=PLSR_Residuals)) +</pre>
  geom_histogram(alpha=.5, position="identity") +
  geom_vline(xintercept = 0, color="black",
             linetype="dashed", size=1) + theme_bw() +
  theme(axis.text=element_text(size=18), legend.position="none",
        axis.title=element_text(size=20, face="bold"),
        axis.text.x = element_text(angle = 0, vjust = 0.5),
        panel.border = element_rect(linetype = "solid", fill = NA, size=1.5))
# plot cal/val side-by-side
```

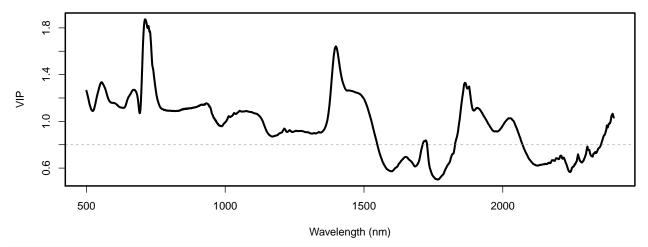
```
scatterplots <- grid.arrange(cal_scatter_plot, val_scatter_plot, cal_resid_histogram,</pre>
                                  val_resid_histogram, nrow=2, ncol=2)
## Warning: Removed 6 rows containing missing values (geom_point).
## Warning: Removed 6 rows containing missing values (geom_point).
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
## `stat bin()` using `bins = 30`. Pick better value with `binwidth`.
     Calibration: Rsq = 0.83; RMSEP = 12.84
                                                           Validation: Rsq = 0.83; RMSEP = 13.68
  200 5.
                                                    Observed LMA_g_m2 (units)
Observed LMA_g_m2 (units)
  150
  100
   50
                                                         50
               Predicted LMA_g_m2 (units)
                                                 200
                                                                     Predicted LMA_g_m2 (units)
  40
  30
20
                                                      count 6
  10
   0
                 PLSR_CV_Residuals
     -60
                                        30
                                                   60
                                                                 -<u>2</u>5
                                                                          PLSR_Residuals
                                                                                            25
                                                                                                         50
# Figure S5. The calibration model and independent validation scatter plot results for
```

the example LMA PLSR model (top row). Also shown are the calibration model and # validation PLSR residuals, where the calibration results are based on the internal # model cross-validation and the validation residuals are the predicted minus observed # values of LMA.

Step 13. Generate Coefficient and VIP plots

LMA_g_m2





```
# Figure S6. The calibration model PLSR regression coefficient (top) and variable
# importance of projection (bottom) plots

dev.copy(png,file.path(outdir,pasteO(inVar,'_Coefficient_VIP_plot.png')),
```

```
height=3100, width=4100, res=340)

## quartz_off_screen
## 3

dev.off();

## pdf
## 2
```

Step 14. Permutation analysis to derive uncertainty estimates

```
if(grepl("Windows", sessionInfo()$running)){
 pls.options(parallel =NULL)
} else {
 pls.options(parallel = parallel::detectCores()-1)
jk.plsr.out <- pls::plsr(as.formula(paste(inVar,"~","Spectra")), scale=FALSE,
                          center=TRUE, ncomp=nComps, validation="L00", trace=FALSE,
                          jackknife=TRUE,
                          data=cal.plsr.data)
pls.options(parallel = NULL)
Jackknife_coef <- spectratrait::f.coef.valid(plsr.out = jk.plsr.out,</pre>
                                               data_plsr = cal.plsr.data,
                                               ncomp = nComps, inVar=inVar)
Jackknife_intercept <- Jackknife_coef[1,,,]</pre>
Jackknife_coef <- Jackknife_coef[2:dim(Jackknife_coef)[1],,,]</pre>
interval <-c(0.025, 0.975)
Jackknife_Pred <- val.plsr.data$Spectra %*% Jackknife_coef +</pre>
  matrix(rep(Jackknife_intercept, length(val.plsr.data[,inVar])), byrow=TRUE,
         ncol=length(Jackknife_intercept))
Interval_Conf <- apply(X = Jackknife_Pred, MARGIN = 1, FUN = quantile,</pre>
                        probs=c(interval[1], interval[2]))
sd mean <- apply(X = Jackknife Pred, MARGIN = 1, FUN =sd)
sd_res <- sd(val.plsr.output$PLSR_Residuals)</pre>
sd_tot <- sqrt(sd_mean^2+sd_res^2)</pre>
val.plsr.output$LCI <- Interval_Conf[1,]</pre>
val.plsr.output$UCI <- Interval Conf[2,]</pre>
val.plsr.output$LPI <- val.plsr.output$PLSR_Predicted-1.96*sd_tot</pre>
val.plsr.output$UPI <- val.plsr.output$PLSR_Predicted+1.96*sd_tot</pre>
head(val.plsr.output)
##
            Plant_Species Species_Code Plot
                                                LMA_g_cm2 LMA_g_m2 PLSR_Predicted
                                 Jacvul WC2 0.003551614
                                                           35.51614
                                                                           43.51586
## 184 Jacobaea vulgaris
## 185 Potentilla reptans
                                                                           61.41726
                                 Potrep WC2 0.005586320 55.86320
## 186
            Rubus caesius
                                 Rubcae WC2 0.005803902 58.03902
                                                                           45.55789
## 187
            Urtica dioica
                                 Urtdio WC2 0.005215705 52.15705
                                                                           46.65139
```

UCI

7.999719 42.58086 44.15724 16.70642 70.32530

Ammare WC3 0.018443757 184.43757

Jacvul WC3 0.004980002 49.80002

LPI

147.08781

53.09532

188 Ammophila arenaria

Jacobaea vulgaris

LCI

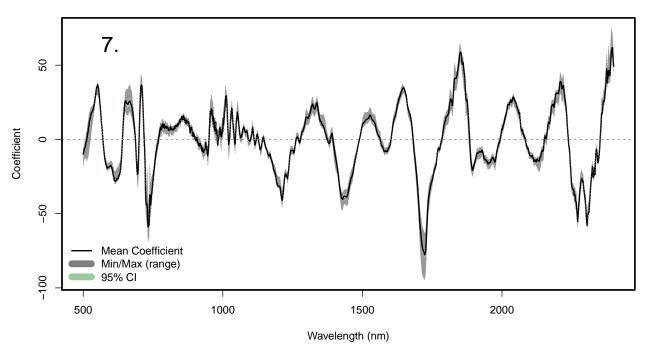
PLSR Residuals

189

184

```
## 185
            5.554059 60.10507 62.52674
                                          34.59536 88.23916
## 186
          -12.481126 44.66849
                                48.22967
                                          18.70489 72.41090
## 187
           -5.505664 45.70375 47.84938
                                          19.82512 73.47765
## 188
          -37.349758 145.09309 148.61694 120.18052 173.99510
## 189
            3.295298 52.40880 53.97806
                                          26.28498
                                                   79.90565
### Permutation coefficient plot
spectratrait::f.plot.coef(Z = t(Jackknife_coef), wv = wv,
           plot_label="Jackknife regression coefficients",position = 'bottomleft')
abline(h=0,lty=2,col="grey50")
legend("topleft",legend = "7.", cex=2, bty="n")
box(1wd=2.2)
```

Jackknife regression coefficients



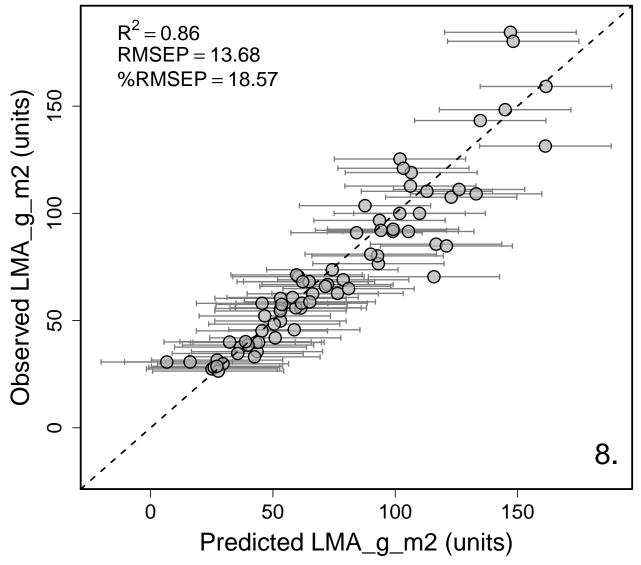


Figure S8. Independent validation results for the LMA PLSR model with associated # jackknife uncertainty estimate 95% prediction intervals for each estimate LMA # value. The %RMSEP is the model prediction performance standardized to the

Step 15. Output permutation coefficients for later use

```
out.jk.coefs <- data.frame(Iteration=seq(1,length(Jackknife_intercept),1),</pre>
                          Intercept=Jackknife_intercept,t(Jackknife_coef))
head(out.jk.coefs)[1:6]
        Iteration Intercept
                             Wave_500 Wave_501
                                                  Wave_502
                                                              Wave_503
                1 18.33909 -7.580446 -6.724083 -5.886226 -4.984744
## Seg 1
## Seg 2
                2 21.22164 -8.574931 -7.084795 -6.255716 -5.384000
                3 19.63843 -18.104491 -17.260522 -16.154983 -14.960119
## Seg 3
                4 15.90905 -10.715594 -9.874766 -8.926979 -8.007834
## Seg 4
                5 17.51805 -8.952143 -8.305344 -7.136167 -6.221407
## Seg 5
## Seg 6
                6 12.18563 -7.702160 -7.128890 -6.532276 -5.840220
write.csv(out.jk.coefs,file=file.path(outdir,
                                     pasteO(inVar,
                                            '_Jackkife_PLSR_Coefficients.csv')),
         row.names=FALSE)
```

Step 16. Output remaining core PLSR outputs

Step 17. Confirm files were written to temp space

```
print("**** PLSR output files: ")
## [1] "**** PLSR output files: "
print(list.files(outdir)[grep(pattern = inVar, list.files(outdir))])
   [1] "Figure_3_LMA_g_m2_PLSR_Component_Selection.png"
   [2] "LMA_g_m2_Cal_PLSR_Dataset.csv"
##
##
  [3] "LMA_g_m2_Cal_Val_Histograms.png"
## [4] "LMA_g_m2_Cal_Val_Scatterplots.png"
## [5] "LMA_g_m2_Cal_Val_Spectra.png"
##
   [6] "LMA_g_m2_Coefficient_VIP_plot.png"
## [7] "LMA_g_m2_Jackkife_PLSR_Coefficients.csv"
## [8] "LMA_g_m2_Jackknife_Regression_Coefficients.png"
## [9] "LMA_g_m2_Observed_PLSR_CV_Pred_11comp.csv"
## [10] "LMA_g_m2_PLSR_Coefficients_11comp.csv"
## [11] "LMA_g_m2_PLSR_Validation_Scatterplot.png"
## [12] "LMA_g_m2_PLSR_VIPs_11comp.csv"
## [13] "LMA_g_m2_Val_PLSR_Dataset.csv"
## [14] "LMA_g_m2_Validation_PLSR_Pred_11comp.csv"
## [15] "LMA_g_m2_Validation_RMSEP_R2_by_Component.png"
```