mestrado-renata-ml

Carregando os pacotes exigidos

```
library(readxl)
library(tidyverse)
library(geobr)
library(skimr)
library(tidymodels)
library(ISLR)
library(modeldata)
library(vip)
library(ggpubr)
source("R/my_functions.R")
```

Listando os arquivos com os mapas de cada área separadamente

```
files_eu <- list.files("data/EU espacial/",full.names = TRUE)
files_sp <- list.files("data/SP espacial/",full.names = TRUE)
```

Carregando os mapa para Eucalipto

```
eu <- map_df(files_eu,grd_read)
```

Arquivo com os dados de emissão, temperatura e umidade (temporal)

```
temporal_eu <- eu %>%
  filter(str_detect(nome,"^[F|U|T]")) %>%
  mutate(numero = as.numeric(str_remove(nome,"F|T|U")),
         ano = numero %% 10000,
         mes = numero %% 1000000 %/% 10000,
         dia = numero %/% 1e6,
         nome = str_remove_all(nome,"[0-9]")) %>%
  pivot_wider(names_from = nome,
              values_from = vetor)
```

Arquivo com os dados dos atributos do solo, somente

geoespacializados

```
spatial_eu <- eu %>%
  filter(!str_detect(nome,"^[F|U|T]")) %>%
  mutate(nome = str_remove(nome,"_EU")) %>%
  pivot_wider(names_from = nome,
              values_from = vetor)
```

Unindo as bases de dados, ou seja, repetindo os dados do solo para cada dia de avaliação

```
data_eu <- left_join(temporal_eu, spatial_eu, by="id") %>%
  select(-numero) %>%
  mutate(data = make_date(year= ano, month=mes, day=dia)) %>%
  relocate(id,data)
```

Carregando os mapa para Sistema Silvipastoril

```
sp <- map_df(files_sp,grd_read)
```

Arquivo com os dados de emissão, temperatura e umidade (temporal)

```
temporal_sp <- sp %>%
  filter(str_detect(nome,"^[F|U|T]")) %>%
  mutate(numero = as.numeric(str_remove(nome,"F|T|U")),
         ano = numero %% 10000,
         mes = numero %% 1000000 %/% 10000,
         dia = numero %/% 1e6,
         nome = str_remove_all(nome,"[0-9]")) %>%
  pivot_wider(names_from = nome,
              values_from = vetor)
```

Arquivo com os dados dos atributos do solo, somente geoespacializados

```
spatial_sp <- sp %>%
  filter(!str_detect(nome,"^[F|U|T]")) %>%
  mutate(nome = str_remove(nome,"_SP")) %>%
  pivot_wider(names_from = nome,
              values_from = vetor)
```

Unindo as bases de dados, ou seja, repetindo os dados do solo

para cada dia de avaliação

```
data_sp <- left_join(temporal_sp, spatial_sp, by="id") %>%
  select(-numero) %>%
  mutate(data = make_date(year= ano, month=mes, day=dia)) %>%
  relocate(id,data)
```

```
tibble(xnames=names(data_eu), ynames=names(data_sp)) %>%
  mutate(logic_test = xnames == ynames)
#> # A tibble: 21 × 3
#>    xnames ynames logic_test
#>    <chr>  <chr>  <lgl>
#>  1 id     id     TRUE
#>  2 data   data   TRUE
#>  3 ano    ano    TRUE
#>  4 mes    mes    TRUE
#>  5 dia    dia    TRUE
#>  6 F      F      TRUE
#>  7 T      T      TRUE
#>  8 U      U      TRUE
#>  9 Al     Al     TRUE
#> 10 Ca     Ca     TRUE
#> # ℹ 11 more rows
```

Unindo toda a base de dados

```
data_set <- rbind(data_eu %>%
                    mutate(local="EU"),
                  data_sp %>%
                    mutate(local="SP")) %>%
  relocate(local)
```

Aprendizado de Máquina

```
# Definindo a base de treino e a base de teste
locais <- data_set %>% pull(local) %>% unique()
for(i in seq_along(locais)){
  lo <- locais[i]
  data <- data_set %>% filter(local == lo)
  dias <- data$data %>% unique()
  for(j in seq_along(dias)){
    di <- dias[j]
    df <- data %>% filter(data == di)
    fco2_initial_split <- initial_split(df  %>%
select(-c(id,ano,mes,dia,local)) %>%                                    sample_n
(trunc(nrow(df)*.51289)), prop = 0.75)
    fco2_train <- training(fco2_initial_split)

    hist_fco2 <- fco2_train  %>%
      ggplot(aes(x=F, y=..density..))+
      geom_histogram(bins = 30, color="black",  fill="lightgray")+
      geom_density(alpha=.05,fill="red")+
      theme_bw() +
      labs(x="FCO2", y = "Densidade",title = paste(lo,di))
    print(hist_fco2)

    fco2_train   %>%
      select(where(is.numeric)) %>%
      drop_na() %>%
      cor()  %>%
      corrplot::corrplot()

    fco2_recipe <- recipe(F ~ ., data = fco2_train) %>%
      step_novel(all_nominal_predictors()) %>%
      step_zv(all_predictors()) %>%
      step_dummy(all_nominal_predictors())
    bake(prep(fco2_recipe), new_data = NULL)
    # visdat::vis_miss(bake(prep(fco2_recipe), new_data = NULL))

    fco2_resamples <- vfold_cv(fco2_train, v = 5) #<-------

    ### DECISION TREE
    print("ARVORE DE DECISÃO")
    fco2_dt_model <- decision_tree(
      cost_complexity = tune(),
      tree_depth = tune(),
      min_n = tune()
    )  %>%
      set_mode("regression")  %>%
      set_engine("rpart")

    fco2_dt_wf <- workflow()   %>%
      add_model(fco2_dt_model) %>%
```

```
    add_recipe(fco2_recipe)

  grid_dt <- grid_random(
    cost_complexity(c(-6, -4)),
    tree_depth(range = c(8, 18)),
    min_n(range = c(42, 52)),
    size = 2 # <-----------------------------
  )

  fco2_dt_tune_grid <- tune_grid(
    fco2_dt_wf,
    resamples = fco2_resamples,
    grid = grid_dt,
    metrics = metric_set(rmse)
  )
  print(autoplot(fco2_dt_tune_grid))

  fco2_dt_best_params <- select_best(fco2_dt_tune_grid, "rmse")
  fco2_dt_wf <- fco2_dt_wf %>% finalize_workflow(fco2_dt_best_params)
  fco2_dt_last_fit <- last_fit(fco2_dt_wf, fco2_initial_split)

  fco2_test_preds <- bind_rows(
    collect_predictions(fco2_dt_last_fit)  %>%   mutate(modelo = "dt")
  )
  pre_obs_plot <- fco2_test_preds %>%
    ggplot(aes(x=.pred, y=F)) +
    geom_point()+
    theme_bw() +
    geom_smooth(method = "lm") +
    stat_regline_equation(ggplot2::aes(
      label =  paste(..eq.label.., ..rr.label.., sep = "*plain(\",\")~~")))+
    labs(title = paste(lo,di))
  print(pre_obs_plot)

  fco2_modelo_final <- fco2_dt_wf %>% fit(df)
  saveRDS(fco2_modelo_final,
          paste0("models-3/fco2_modelo_dt_",lo,"_",di,".rds"))

  fco2_dt_last_fit_model <- fco2_dt_last_fit$.workflow[[1]]$fit$fit
  vip_plot <- vip(fco2_dt_last_fit_model,
      aesthetics = list(color = "grey35", size = 0.8, fill="orange")) +
    theme_bw()
  print(vip_plot)
  da <- fco2_test_preds %>%
filter(F > 0, .pred>0 )

  my_r <- cor(da$F,da$.pred)
  my_r2 <- my_r*my_r
  my_mse <- Metrics::mse(da$F,da$.pred)
  my_rmse <- Metrics::rmse(da$F,
                           da$.pred)
  my_mae <- Metrics::mae(da$F,da$.pred)
```

```
my_mape <- Metrics::mape(da$F,da$.pred)*100
vector_of_metrics <- c(r=my_r, R2=my_r2, MSE=my_mse,
                       RMSE=my_rmse, MAE=my_mae, MAPE=my_mape)
print(data.frame(vector_of_metrics))


# ##RANDOM FOREST
print("RANDOM FOREST")
fco2_rf_model <- rand_forest(
  min_n = tune(),
  mtry = tune(),
  trees = tune()
)   %>%
  set_mode("regression")  %>%
  set_engine("randomForest")

fco2_rf_wf <- workflow()   %>%
  add_model(fco2_rf_model) %>%
  add_recipe(fco2_recipe)

grid_rf <- grid_random(
  min_n(range = c(20, 30)),
  mtry(range = c(5, 10)),
  trees(range = c(100, 500) ),
  size = 2
)
fco2_rf_tune_grid <- tune_grid(
  fco2_rf_wf,
  resamples = fco2_resamples,
  grid = grid_rf,
  metrics = metric_set(rmse)
)
print(autoplot(fco2_rf_tune_grid))

fco2_rf_best_params <- select_best(fco2_rf_tune_grid, "rmse")
fco2_rf_wf <- fco2_rf_wf %>% finalize_workflow(fco2_rf_best_params)
fco2_rf_last_fit <- last_fit(fco2_rf_wf, fco2_initial_split)

fco2_test_preds <- bind_rows(
  collect_predictions(fco2_rf_last_fit)  %>%   mutate(modelo = "rf")
)
pre_obs_plot <- fco2_test_preds %>%
  ggplot(aes(x=.pred, y=F)) +
  geom_point()+
  theme_bw() +
  geom_smooth(method = "lm") +
  stat_regline_equation(ggplot2::aes(
    label =  paste(..eq.label.., ..rr.label.., sep = "*plain(\",\")~~")))+
  labs(title = paste(lo,di))
print(pre_obs_plot)

fco2_modelo_final <- fco2_rf_wf %>% fit(df)
```

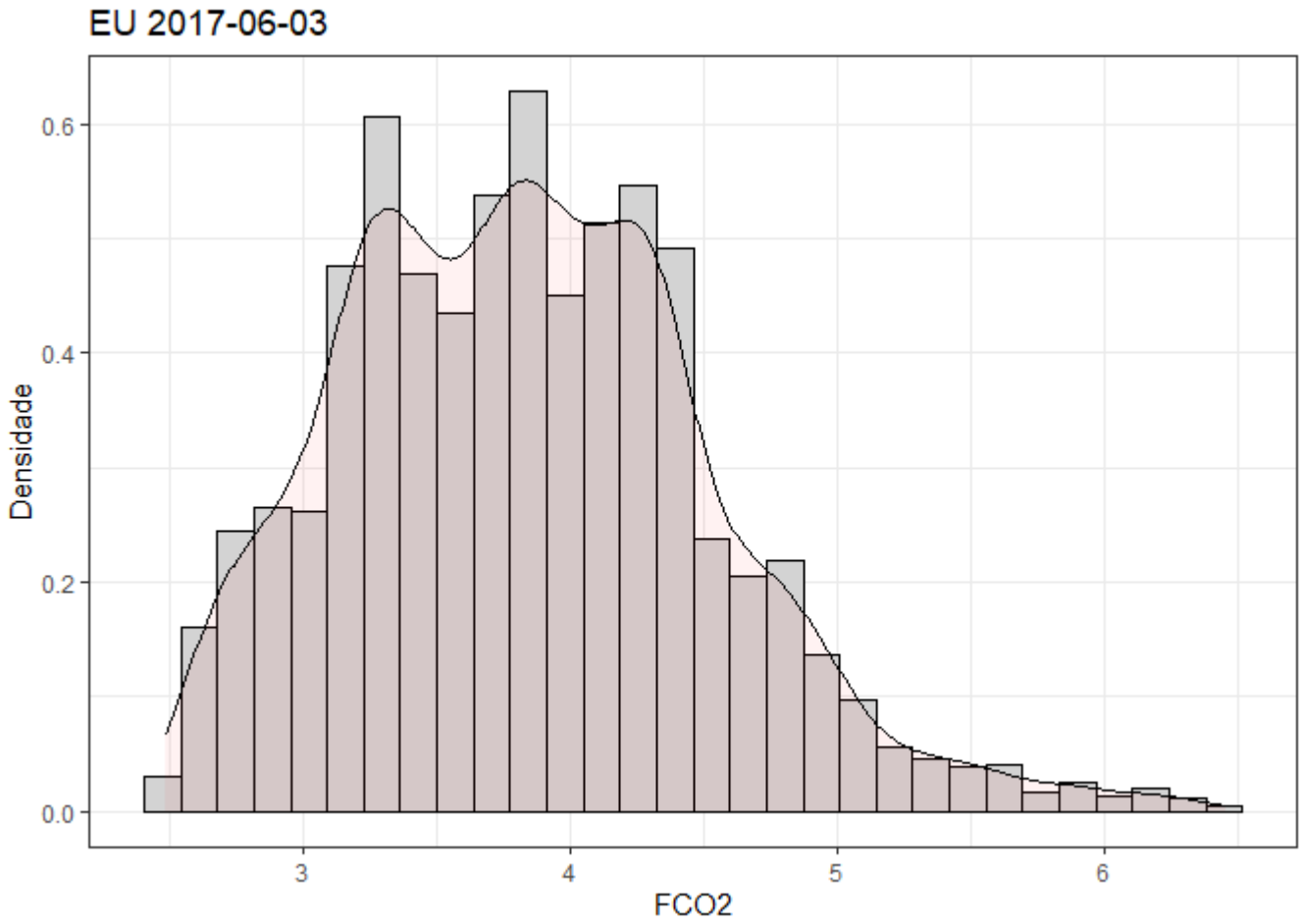
```
  saveRDS(fco2_modelo_final,
          paste0("models-3/fco2_modelo_rf_",lo,"_",di,".rds"))

  fco2_rf_last_fit_model <- fco2_rf_last_fit$.workflow[[1]]$fit$fit
  vip_plot <- vip(fco2_rf_last_fit_model,
      aesthetics = list(color = "grey35", size = 0.8, fill="orange")) +
    theme_bw()
  print(vip_plot)
      da <- fco2_test_preds %>%
filter(F > 0, .pred>0 )

  my_r <- cor(da$F,da$.pred)
  my_r2 <- my_r*my_r
  my_mse <- Metrics::mse(da$F,da$.pred)
  my_rmse <- Metrics::rmse(da$F,
                           da$.pred)
  my_mae <- Metrics::mae(da$F,da$.pred)
  my_mape <- Metrics::mape(da$F,da$.pred)*100
  vector_of_metrics <- c(r=my_r, R2=my_r2, MSE=my_mse,
                         RMSE=my_rmse, MAE=my_mae, MAPE=my_mape)
  print(data.frame(vector_of_metrics))

  ##XGBOOST
  cores = 6
  fco2_xgb_model <- boost_tree(
    mtry = 0.8,
    trees = tune(), # <---------------
    min_n = 5,
    tree_depth = 4,
    loss_reduction = 0, # lambda
    learn_rate = tune(), # epsilon
    sample_size = 0.8
  )  %>%
    set_mode("regression")  %>%
    set_engine("xgboost", nthread = cores, counts = FALSE)

  fco2_xgb_wf <- workflow()  %>%
    add_model(fco2_xgb_model) %>%
    add_recipe(fco2_recipe)

  grid_xgb <- expand.grid(
    learn_rate =  c(0.05, 0.3),
    trees = c(2, 250, 500)
  )

  #passo 1
  fco2_xgb_tune_grid <- tune_grid(
    fco2_xgb_wf,
    resamples = fco2_resamples,
    grid = grid_xgb,
    metrics = metric_set(rmse)
  )
```

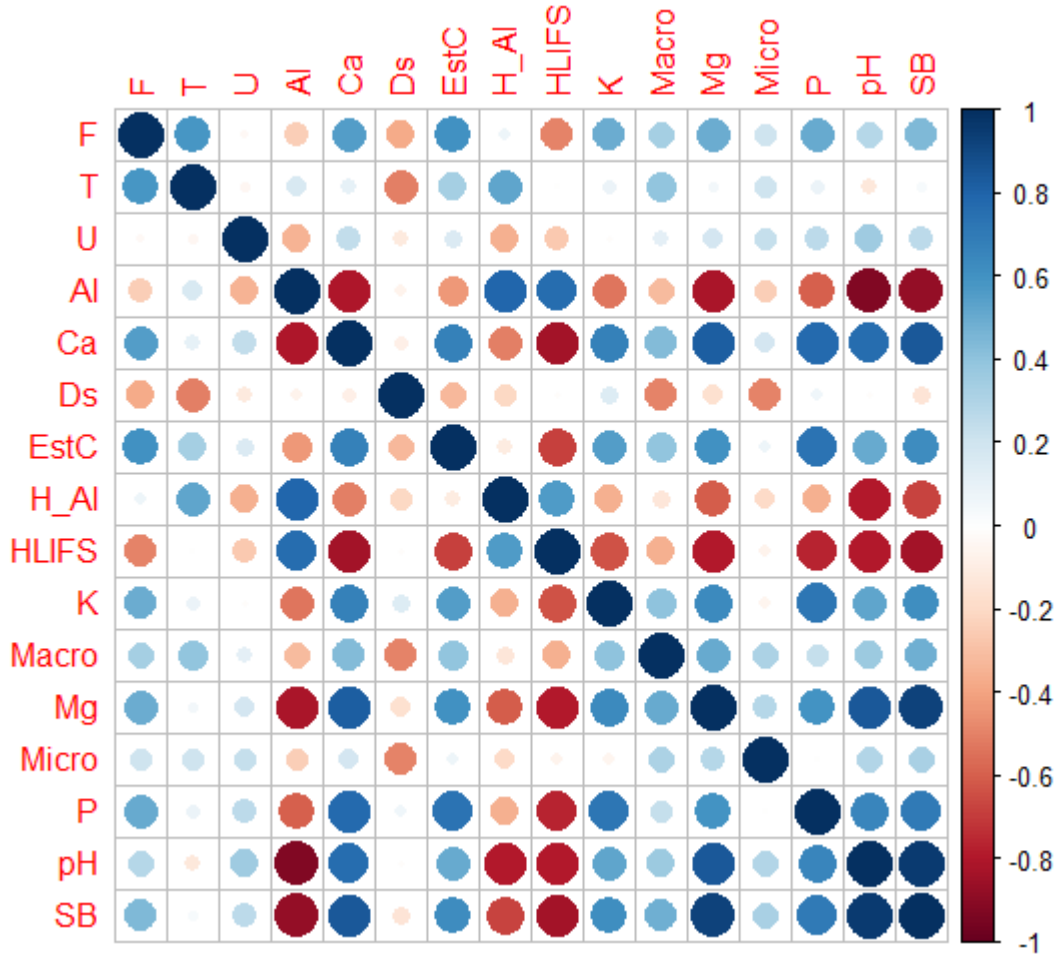
```
    # print(autoplot(fco2_xgb_tune_grid))
    fco2_xgb_select_best_passo1 <- fco2_xgb_tune_grid %>%
      select_best(metric = "rmse")

    # passo 2
    fco2_xgb_model <- boost_tree(
      mtry = 0.8,
      trees = fco2_xgb_select_best_passo1$trees,
      min_n = tune(),
      tree_depth = tune(),
      loss_reduction = 0,
      learn_rate = fco2_xgb_select_best_passo1$learn_rate,
      sample_size = 0.8
    ) %>%
      set_mode("regression")  %>%
      set_engine("xgboost", nthread = cores, counts = FALSE)
    fco2_xgb_wf <- workflow() %>%
      add_model(fco2_xgb_model)   %>%
      add_recipe(fco2_recipe)

    fco2_xgb_grid <- expand.grid(
      tree_depth = c(1, 3, 4),
      min_n = c(5, 30, 60)
    )

    fco2_xgb_tune_grid <- fco2_xgb_wf   %>%
      tune_grid(
        resamples =fco2_resamples,
        grid = fco2_xgb_grid,
        control = control_grid(save_pred = TRUE, verbose = FALSE, allow_par = TRUE),
        metrics = metric_set(rmse)
      )
    fco2_xgb_select_best_passo2 <- fco2_xgb_tune_grid  %>%   select_best(metric = "rms
e")

    # passo 3
    fco2_xgb_model <- boost_tree(
      mtry = 0.8,
      trees = fco2_xgb_select_best_passo1$trees,
      min_n = fco2_xgb_select_best_passo2$min_n,
      tree_depth = fco2_xgb_select_best_passo2$tree_depth,
      loss_reduction =tune(),
      learn_rate = fco2_xgb_select_best_passo1$learn_rate,
      sample_size = 0.8
    )  %>%
      set_mode("regression")  %>%
      set_engine("xgboost", nthread = cores, counts = FALSE)

    fco2_xgb_wf <- workflow()  %>%
      add_model(fco2_xgb_model)  %>%
      add_recipe(fco2_recipe)
```

```
    #### Grid
    fco2_xgb_grid <- expand.grid(
      loss_reduction = c(0.01, 0.05, 1, 2, 4, 8)
    )

    fco2_xgb_tune_grid <- fco2_xgb_wf   %>%
      tune_grid(
        resamples = fco2_resamples,
        grid = fco2_xgb_grid,
        control = control_grid(save_pred = TRUE, verbose = FALSE, allow_par = TRUE),
        metrics = metric_set(rmse)
      )
    fco2_xgb_select_best_passo3 <- fco2_xgb_tune_grid %>% select_best(metric = "rmse")

    # passo 4
    fco2_xgb_model <- boost_tree(
      mtry = tune(),
      trees = fco2_xgb_select_best_passo1$trees,
      min_n = fco2_xgb_select_best_passo2$min_n,
      tree_depth = fco2_xgb_select_best_passo2$tree_depth,
      loss_reduction = fco2_xgb_select_best_passo3$loss_reduction,
      learn_rate = fco2_xgb_select_best_passo1$learn_rate,
      sample_size = tune()
    )%>%
      set_mode("regression")  |>
      set_engine("xgboost", nthread = cores, counts = FALSE)

      fco2_xgb_wf <- workflow()  %>%
      add_model(fco2_xgb_model)  %>%
      add_recipe(fco2_recipe)

    fco2_xgb_grid <- expand.grid(
      sample_size = seq(0.5, 1.0, length.out = 2), ## <---
      mtry = seq(0.1, 1.0, length.out = 2) ## <---
    )

    fco2_xgb_tune_grid <- fco2_xgb_wf   %>%
      tune_grid(
        resamples = fco2_resamples,
        grid = fco2_xgb_grid,
        control = control_grid(save_pred = TRUE, verbose = FALSE, allow_par = TRUE),
        metrics = metric_set(rmse)
      )
    fco2_xgb_select_best_passo4 <- fco2_xgb_tune_grid   %>%   select_best(metric = "rms
e")

    # passo 5
    fco2_xgb_model <- boost_tree(
      mtry = fco2_xgb_select_best_passo4$mtry,
      trees = tune(),
      min_n = fco2_xgb_select_best_passo2$min_n,
      tree_depth = fco2_xgb_select_best_passo2$tree_depth,
```

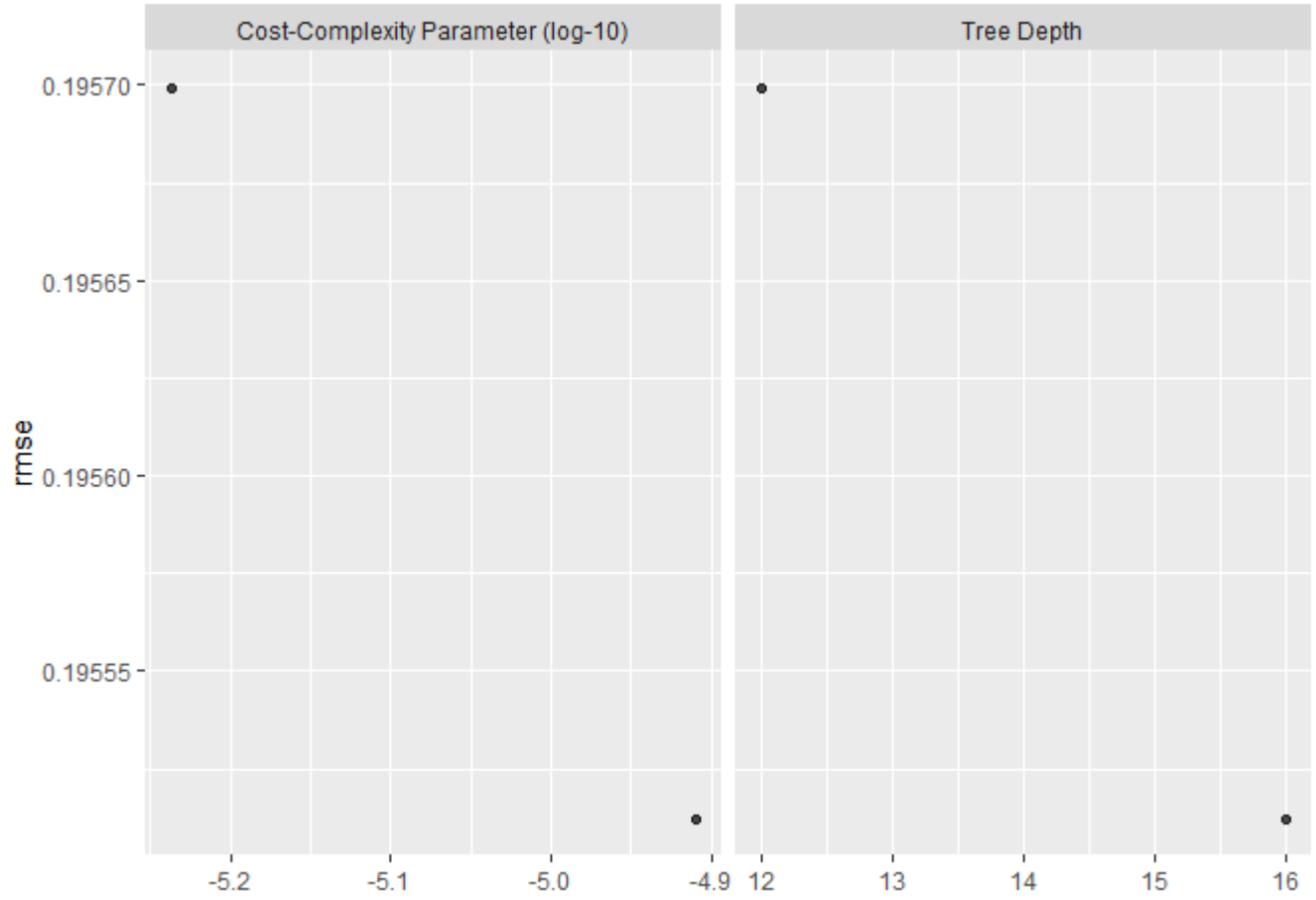
```
      loss_reduction = fco2_xgb_select_best_passo3$loss_reduction,
      learn_rate = tune(),
      sample_size = fco2_xgb_select_best_passo4$sample_size
    )  %>%
      set_mode("regression")  %>%
      set_engine("xgboost", nthread = cores, counts = FALSE)


    fco2_xgb_wf <- workflow() %>%
      add_model(fco2_xgb_model)  %>%
      add_recipe(fco2_recipe)


    fco2_xgb_grid <- expand.grid(
      learn_rate = c(0.05, 0.10, 0.15, 0.25),
      trees = c(100, 250, 500)
    )

    fco2_xgb_tune_grid <- fco2_xgb_wf   %>%
      tune_grid(
        resamples = fco2_resamples,
        grid = fco2_xgb_grid,
        control = control_grid(save_pred = TRUE, verbose = FALSE, allow_par = TRUE),
        metrics = metric_set(rmse)
      )
    fco2_xgb_select_best_passo5 <- fco2_xgb_tune_grid   %>%   select_best(metric = "rms
e")

    ## modelos final desempenho
    fco2_xgb_model <- boost_tree(
      mtry = fco2_xgb_select_best_passo4$mtry,
      trees = fco2_xgb_select_best_passo5$trees,
      min_n = fco2_xgb_select_best_passo2$min_n,
      tree_depth = fco2_xgb_select_best_passo2$tree_depth,
      loss_reduction = fco2_xgb_select_best_passo3$loss_reduction,
      learn_rate = fco2_xgb_select_best_passo5$learn_rate,
      sample_size = fco2_xgb_select_best_passo4$sample_size
    ) %>%
      set_mode("regression")  %>%
      set_engine("xgboost", nthread = cores, counts = FALSE)

    df_par <- data.frame(
      mtry = fco2_xgb_select_best_passo4$mtry,
      trees = fco2_xgb_select_best_passo5$trees,
      min_n = fco2_xgb_select_best_passo2$min_n,
      tree_depth = fco2_xgb_select_best_passo2$tree_depth,
      loss_reduction = fco2_xgb_select_best_passo3$loss_reduction,
      learn_rate = fco2_xgb_select_best_passo5$learn_rate,
      sample_size = fco2_xgb_select_best_passo4$sample_size
    )
    fco2_xgb_wf <- fco2_xgb_wf %>% finalize_workflow(df_par) # <------
    fco2_xgb_last_fit <- last_fit(fco2_xgb_wf, fco2_initial_split)
```

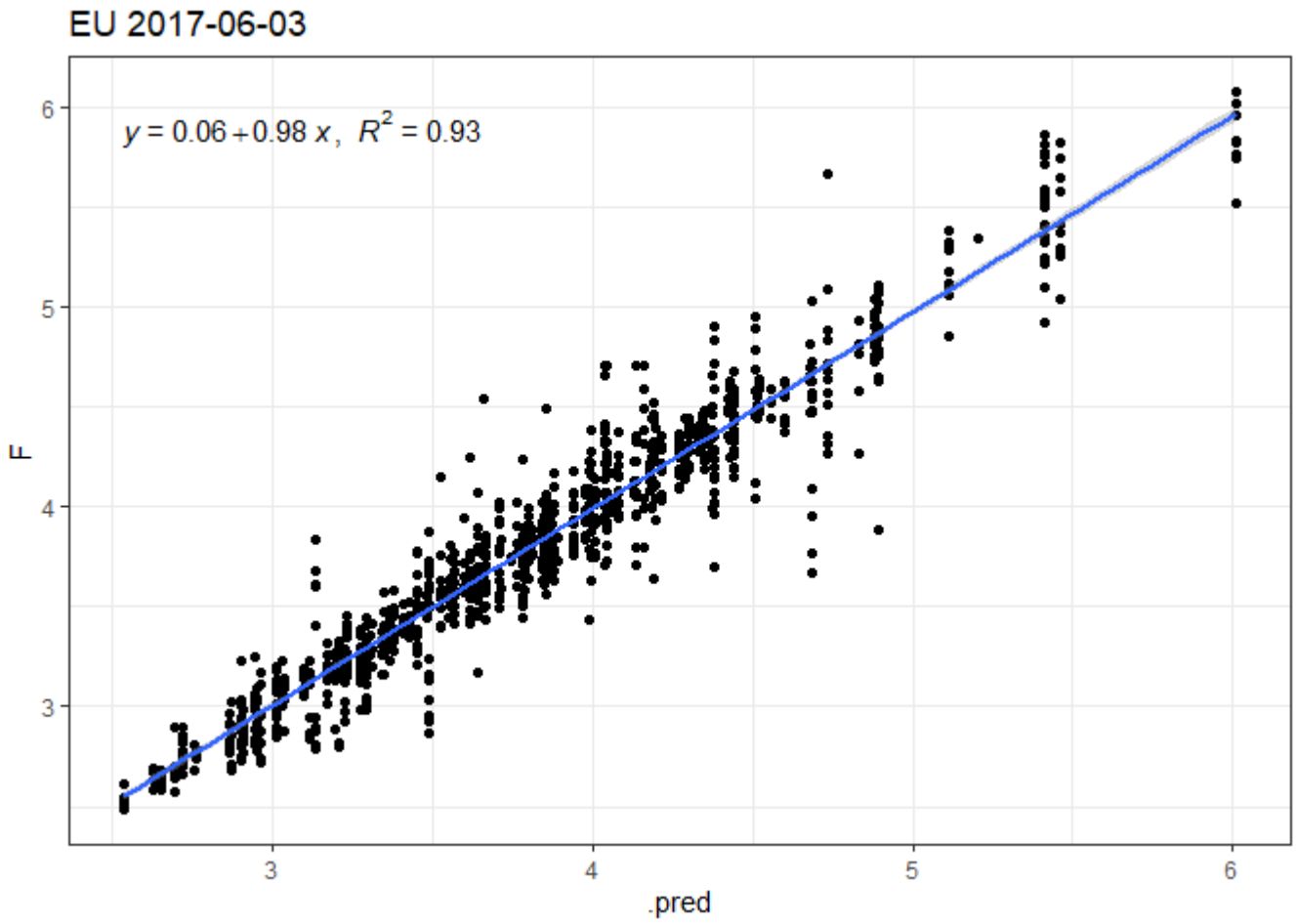
```
    fco2_test_preds <- bind_rows(
      collect_predictions(fco2_xgb_last_fit)  %>%   mutate(modelo = "xgb")
    )
    pre_obs_plot <- fco2_test_preds %>%
      ggplot(aes(x=.pred, y=F)) +
      geom_point()+
      theme_bw() +
      geom_smooth(method = "lm") +
      stat_regline_equation(ggplot2::aes(
        label =  paste(..eq.label.., ..rr.label.., sep = "*plain(\",\")~~")))+
      labs(title = paste(lo,di))
    print(pre_obs_plot)

    fco2_modelo_final <- fco2_xgb_wf %>% fit(df)
    saveRDS(fco2_modelo_final,
            paste0("models-3/fco2_modelo_xgb_",lo,"_",di,".rds"))

    fco2_xgb_last_fit_model <- fco2_xgb_last_fit$.workflow[[1]]$fit$fit
    vip_plot <- vip(fco2_xgb_last_fit_model,
        aesthetics = list(color = "grey35", size = 0.8, fill="orange")) +
      theme_bw()
    print(vip_plot)

        da <- fco2_test_preds %>%
  filter(F > 0, .pred>0 )

    my_r <- cor(da$F,da$.pred)
    my_r2 <- my_r*my_r
    my_mse <- Metrics::mse(da$F,da$.pred)
    my_rmse <- Metrics::rmse(da$F,
                             da$.pred)
    my_mae <- Metrics::mae(da$F,da$.pred)
    my_mape <- Metrics::mape(da$F,da$.pred)*100
    vector_of_metrics <- c(r=my_r, R2=my_r2, MSE=my_mse,
                           RMSE=my_rmse, MAE=my_mae, MAPE=my_mape)
    print(data.frame(vector_of_metrics))
  }
}
```

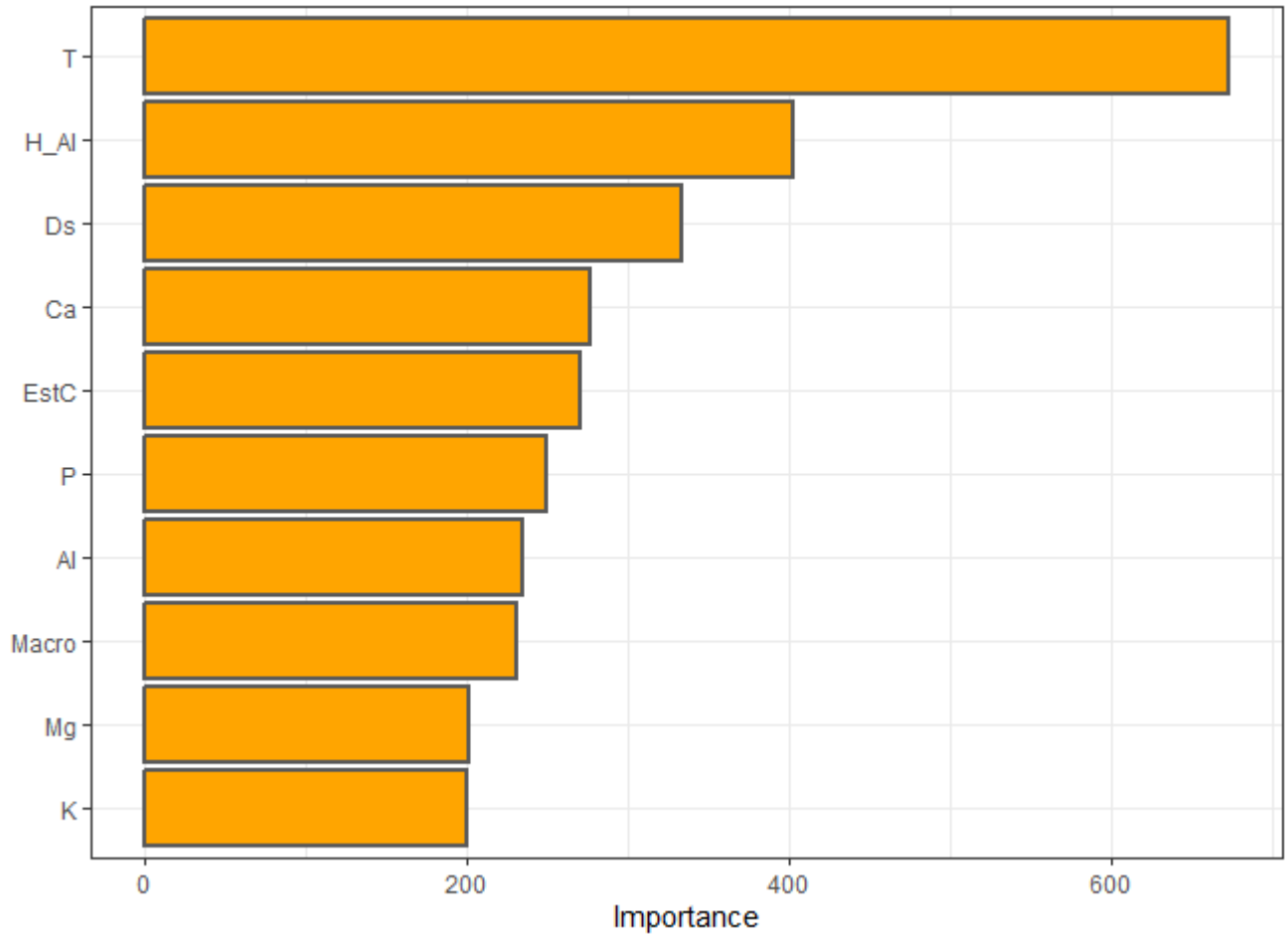

EU 2017-06-03
Densidade
0.0
0.2
0.4
0.6
3
4
5
6
FCO2


F
T
U
Al
Ca
Ds
EstC
H_Al
HLIFS
K
Macro
Mg
Micro
P
pH
SB
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1

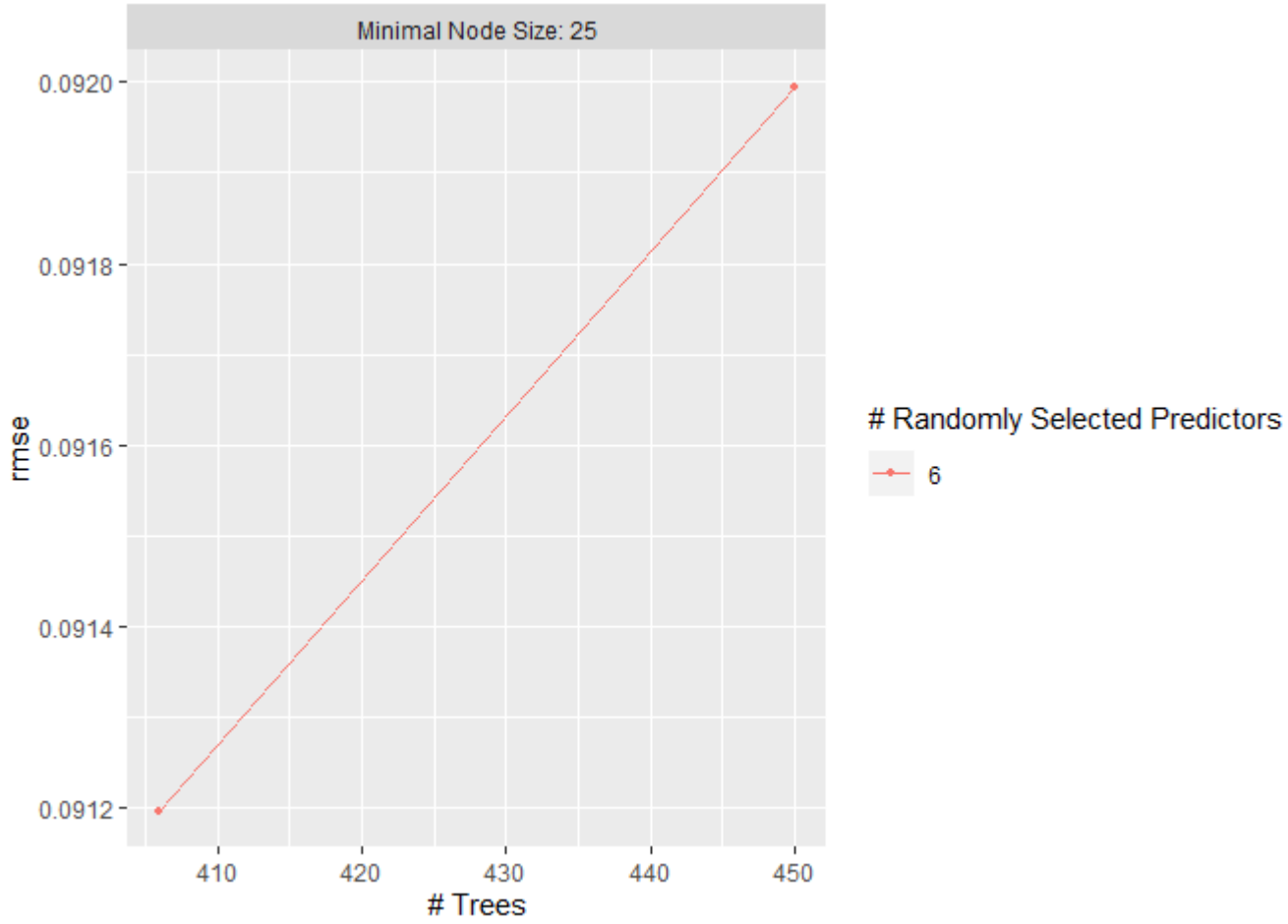
```
#> [1] "ARVORE DE DECISÃO"
```

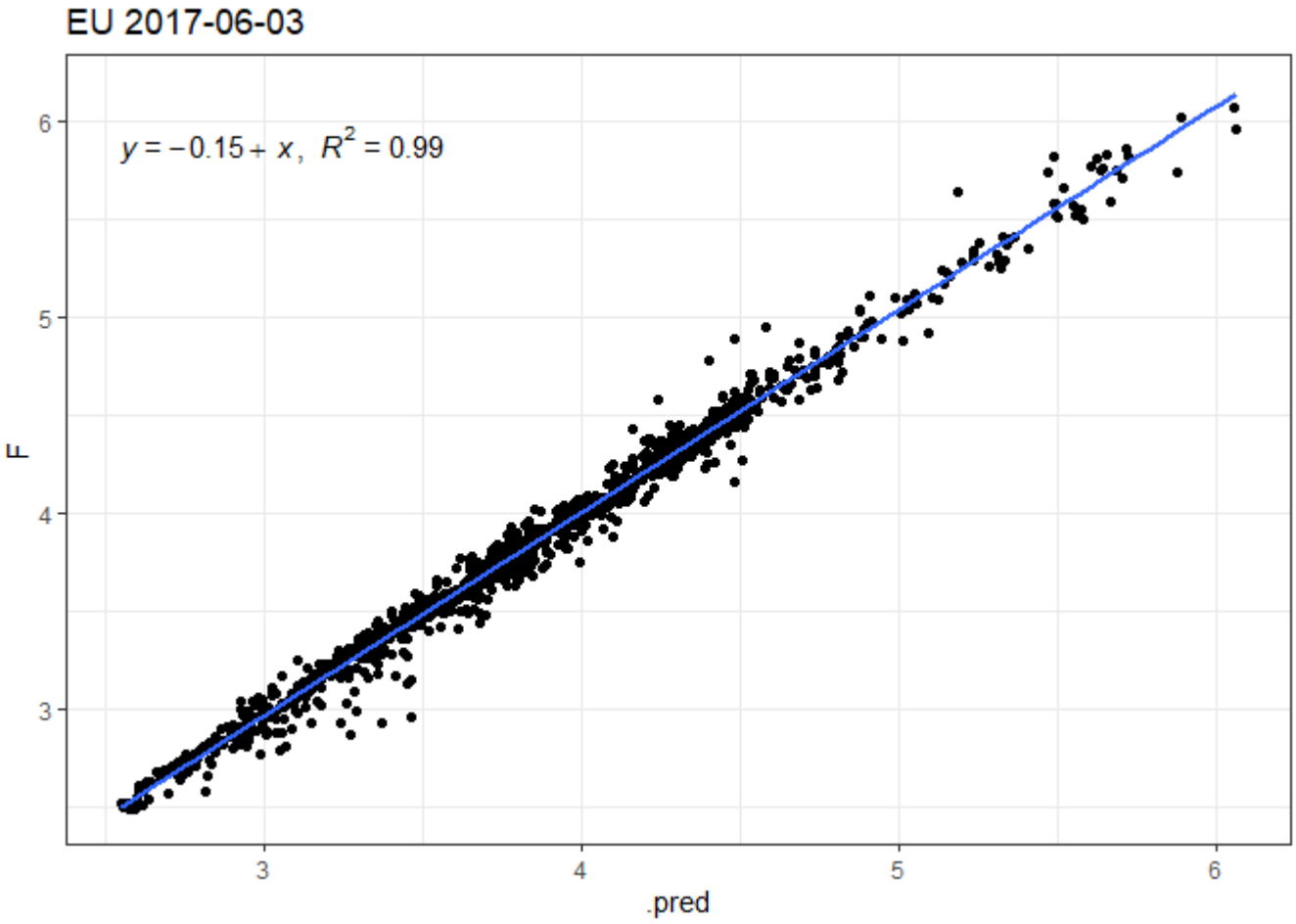

Cost-Complexity Parameter (log-10)
Tree Depth
rmse
0.19570
0.19565
0.19560
0.19555
-5.2
-5.1
-5.0
-4.9
12
13
14
15
16

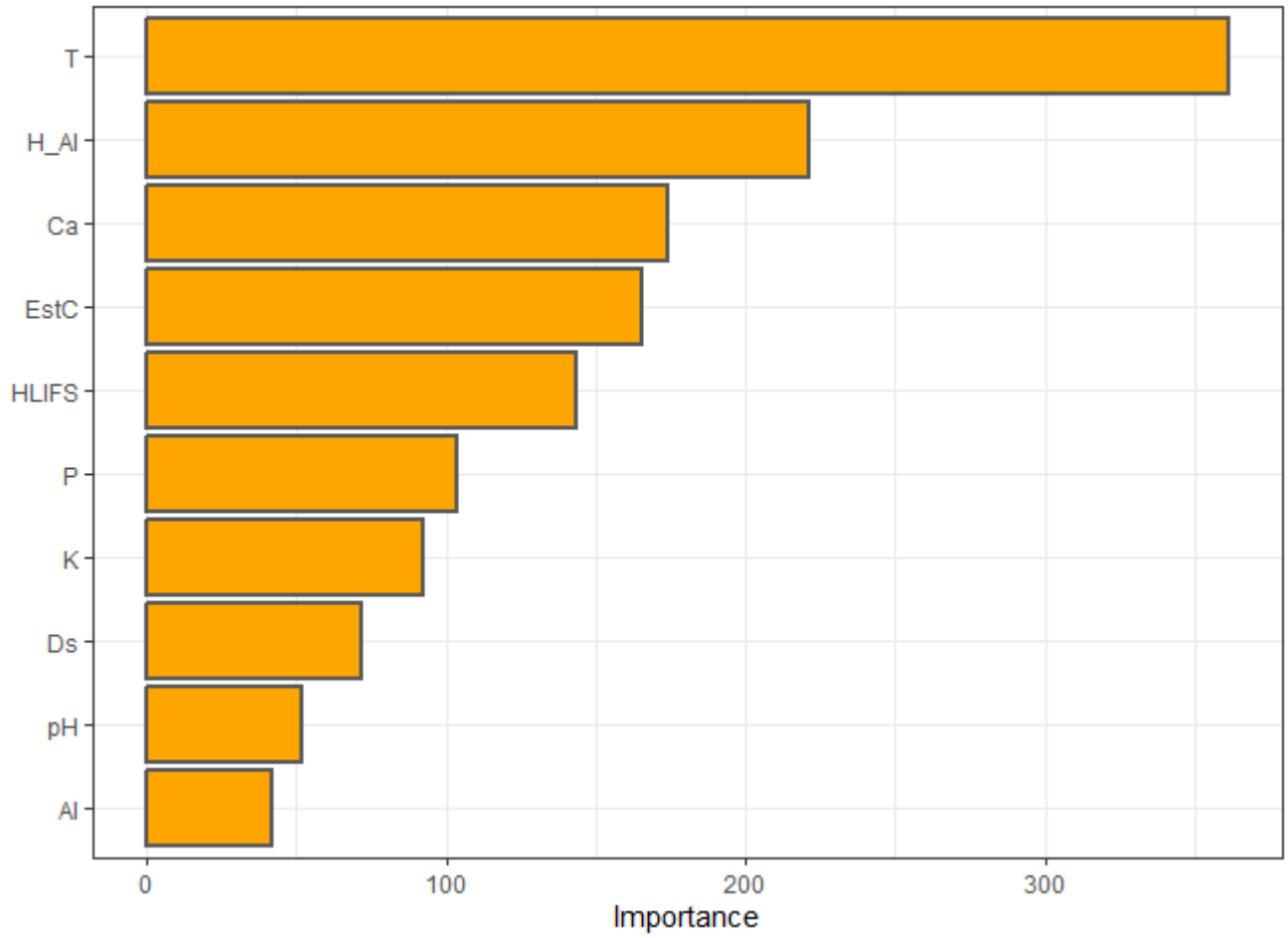

EU 2017-06-03
$y = 0.06 + 0.98\,x$, $R^2 = 0.93$
F
.pred
3
4
5
6



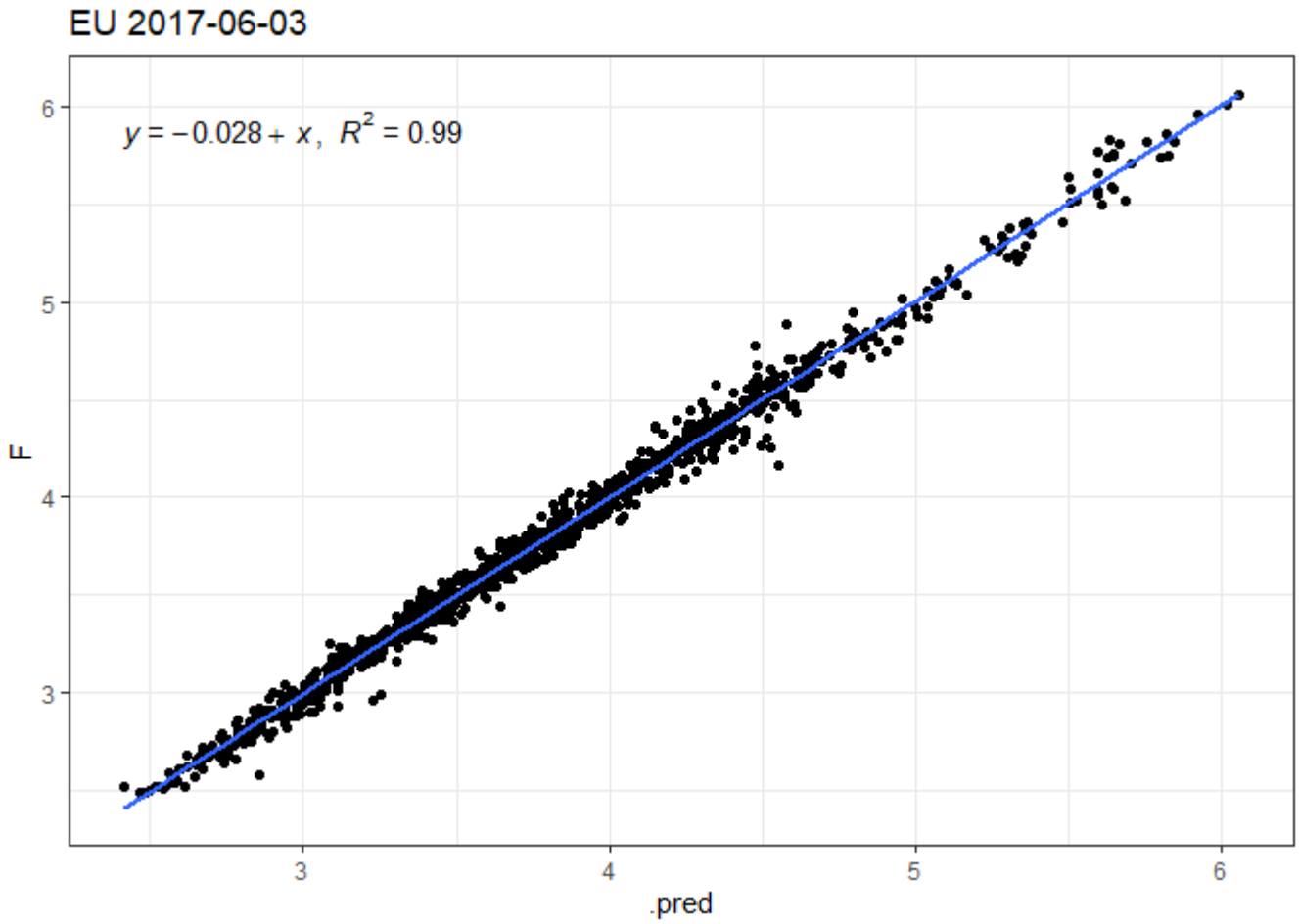

```
#>      vector_of_metrics
#> r           0.96524046
#> R2          0.93168914
#> MSE         0.03172493
#> RMSE        0.17811493
#> MAE         0.12042865
#> MAPE        3.15630146
#> [1] "RANDOM FOREST"
```

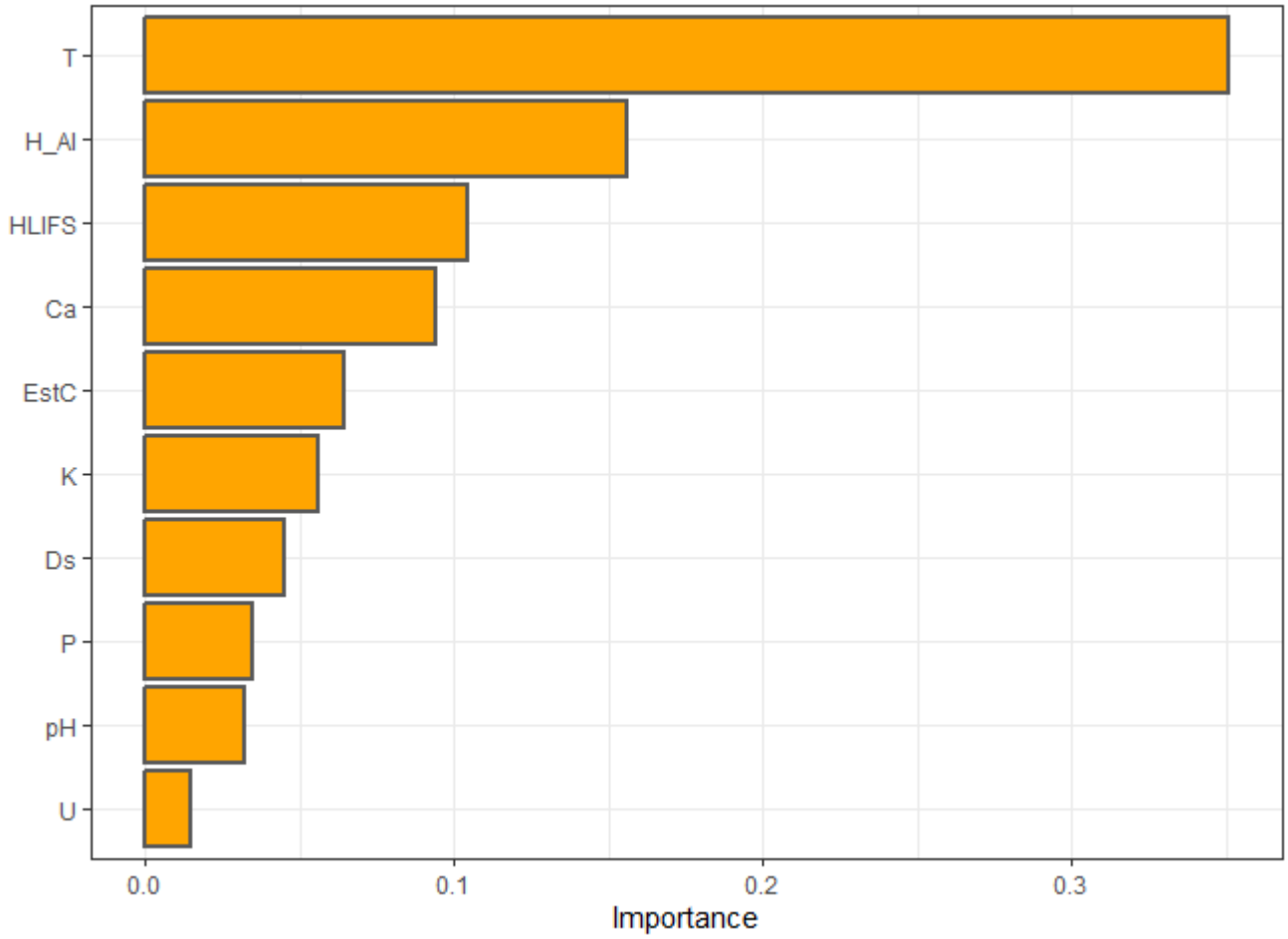

Minimal Node Size: 25
0.0920
0.0918
0.0916
0.0914
0.0912
rmse
410
420
430
440
450
Trees
Randomly Selected Predictors
6


EU 2017-06-03
$y = -0.15 + x$, $R^2 = 0.99$
6
5
4
3
F
3
4
5
6
.pred

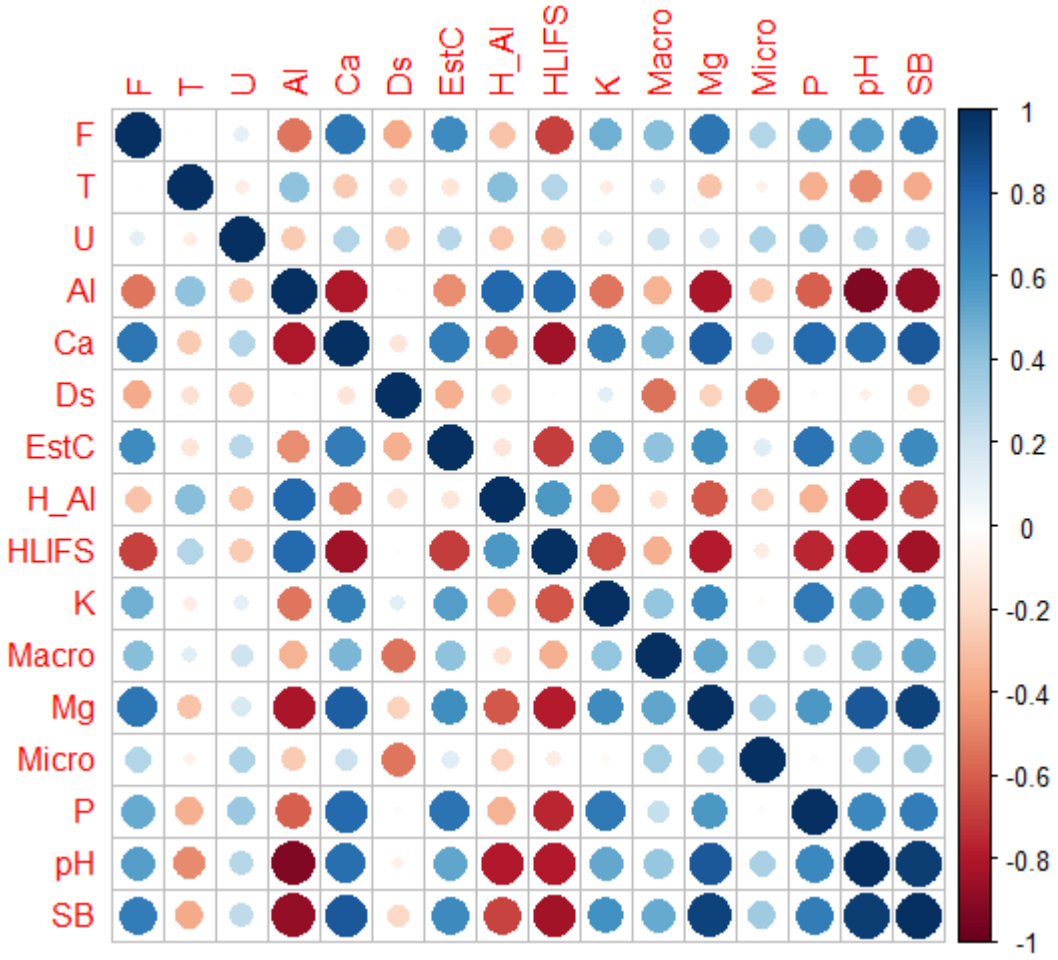



```
#>      vector_of_metrics
#> r           0.993642797
#> R2          0.987326009
#> MSE         0.006501958
#> RMSE        0.080634719
#> MAE         0.055129353
#> MAPE        1.479109132
```

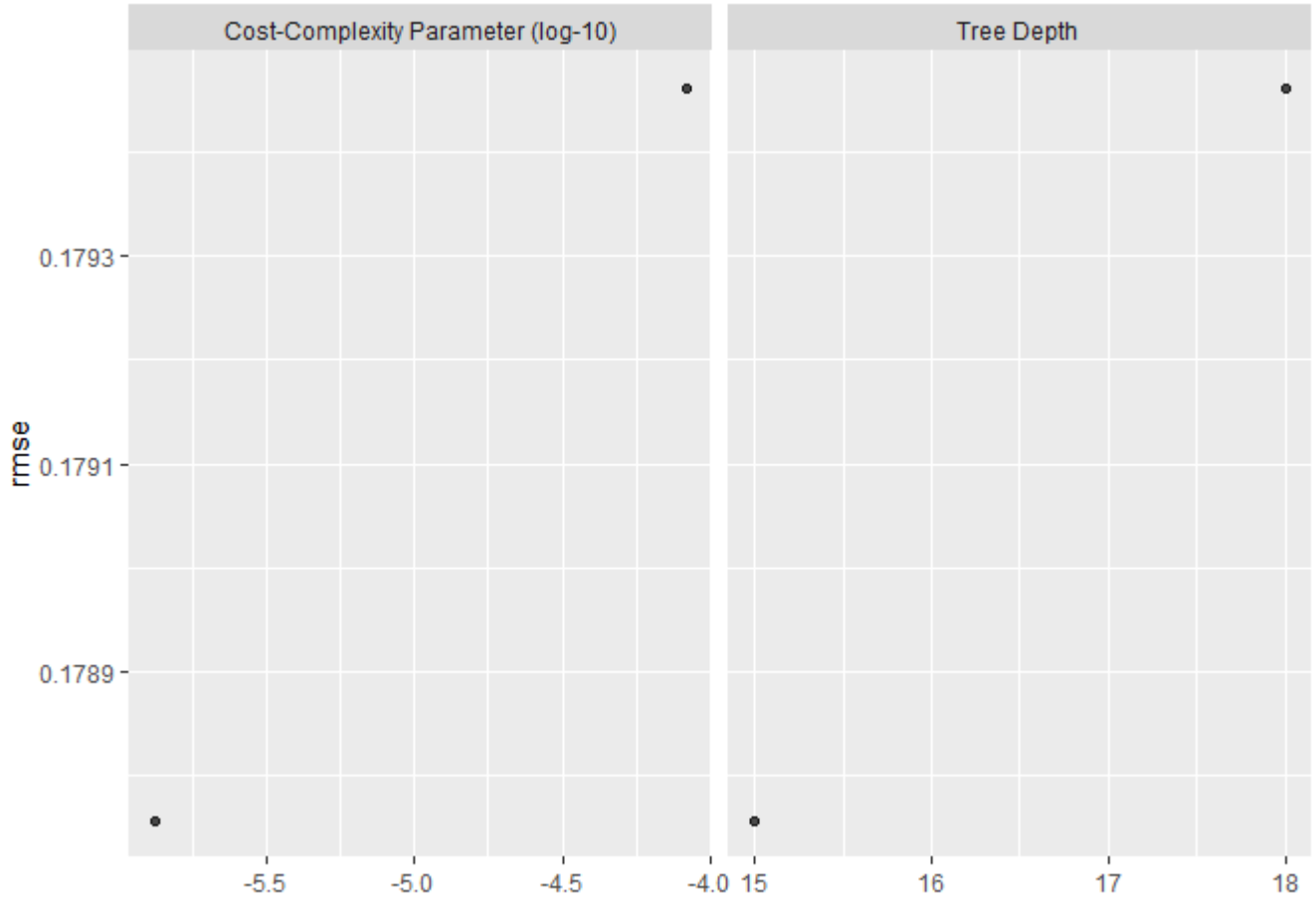

EU 2017-06-03
$y = -0.028 + x$, $R^2 = 0.99$
F
.pred
3
4
5
6

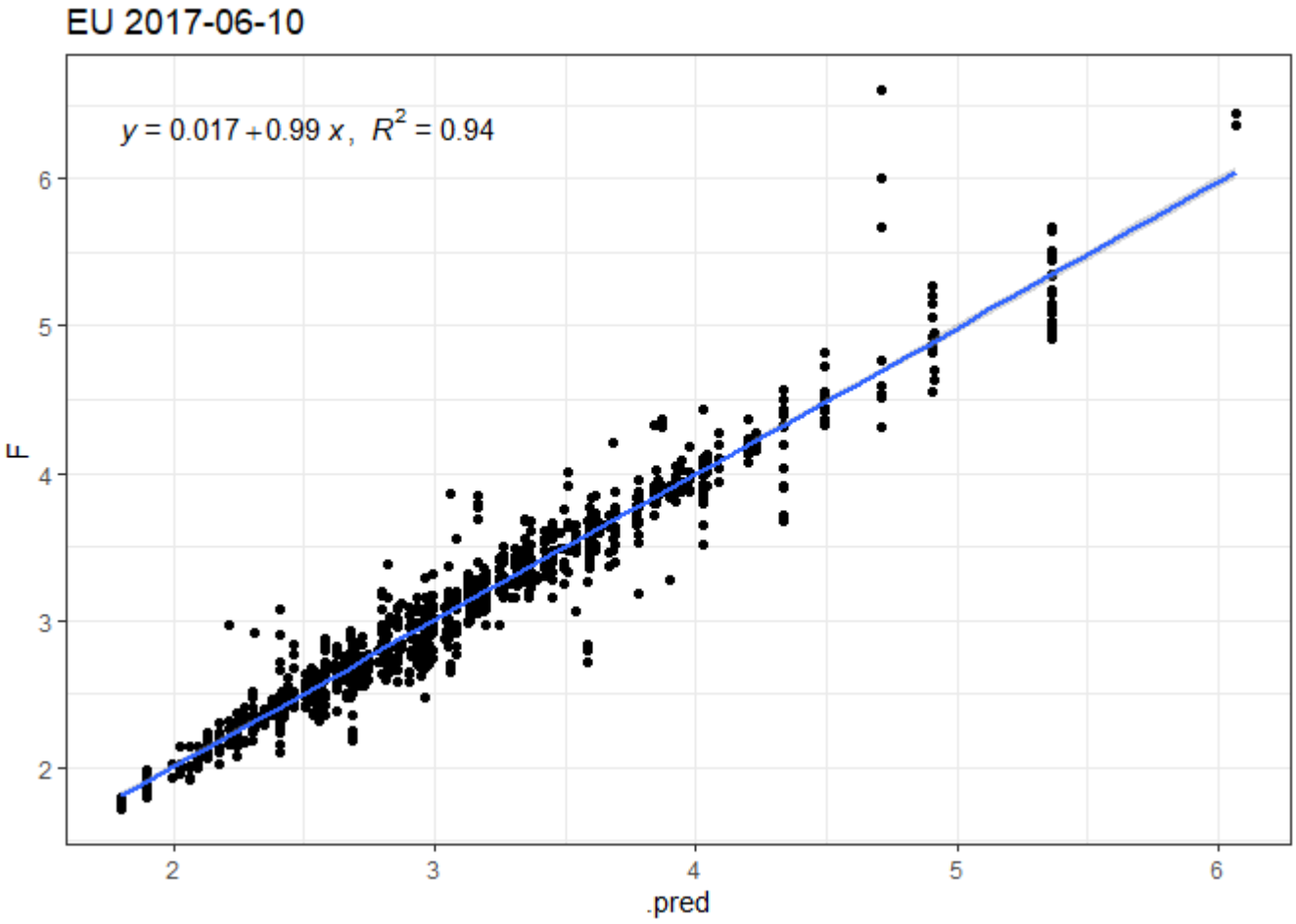

T
H_Al
HLIFS
Ca
EstC
K
Ds
P
pH
U
0.0
0.1
0.2
0.3
Importance

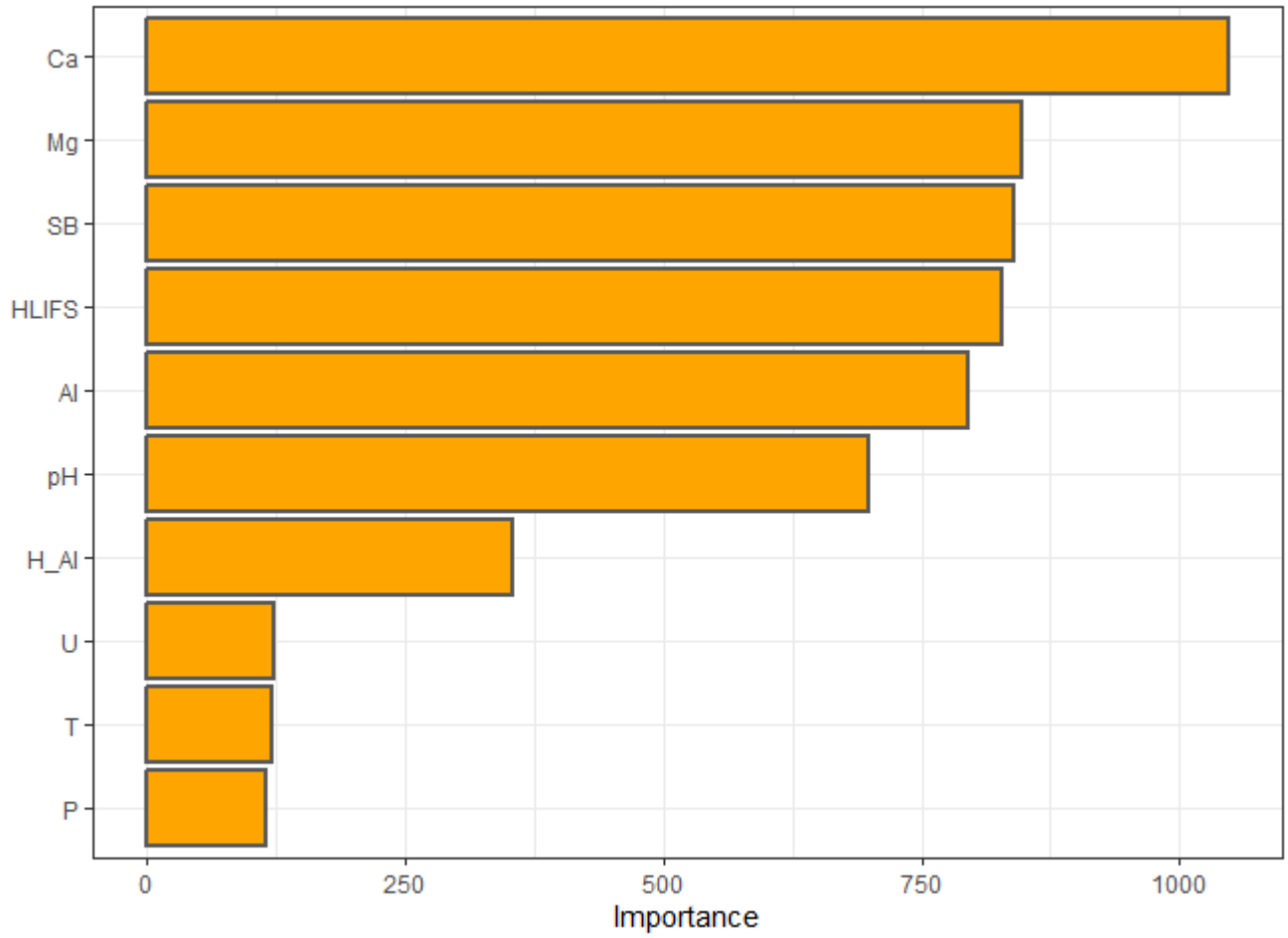
```
#>       vector_of_metrics
#> r           0.995602984
#> R2          0.991225302
#> MSE         0.004079066
#> RMSE        0.063867566
#> MAE         0.046851884
#> MAPE        1.245854370
```



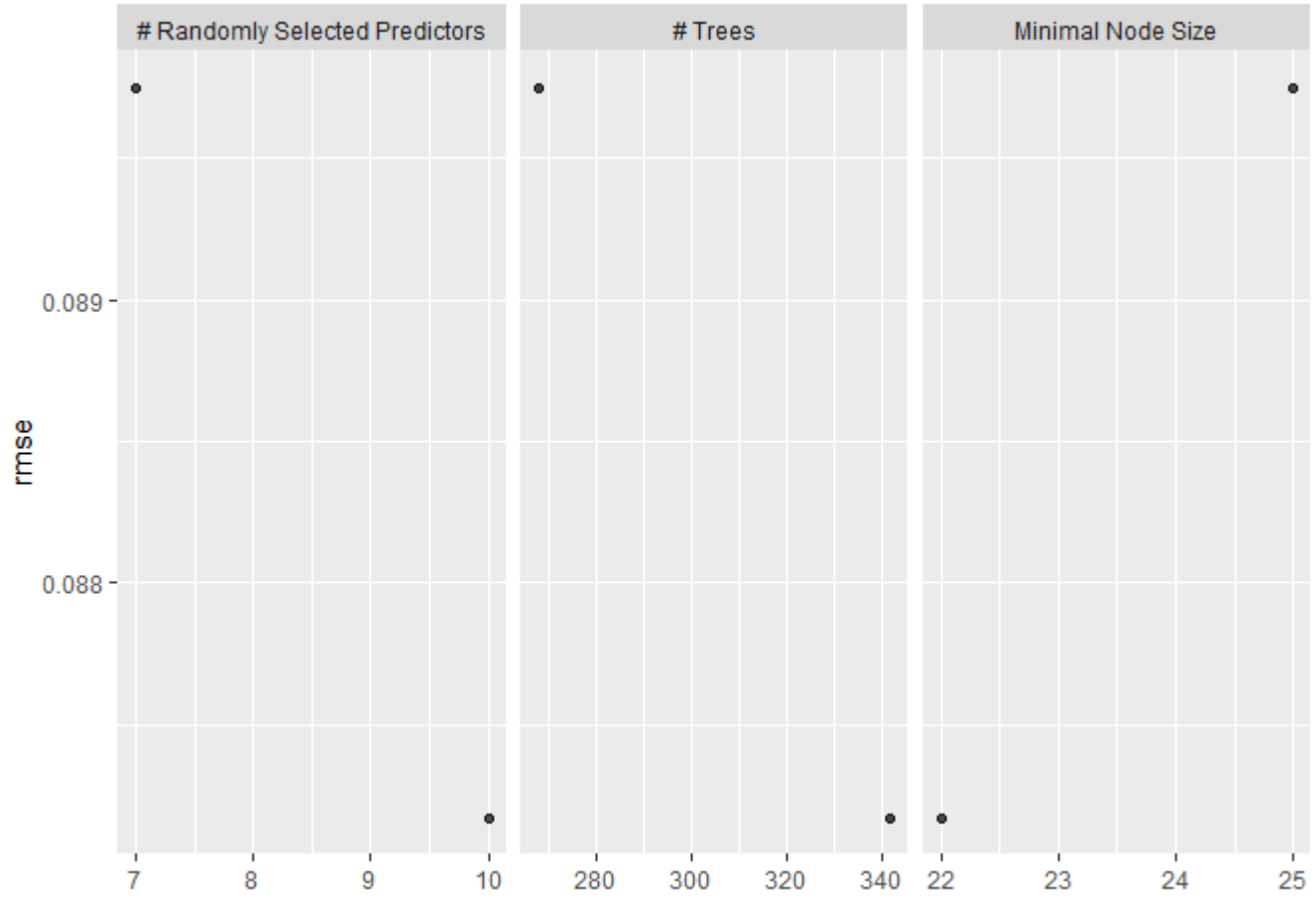

```
#> [1] "ARVORE DE DECISÃO"
```

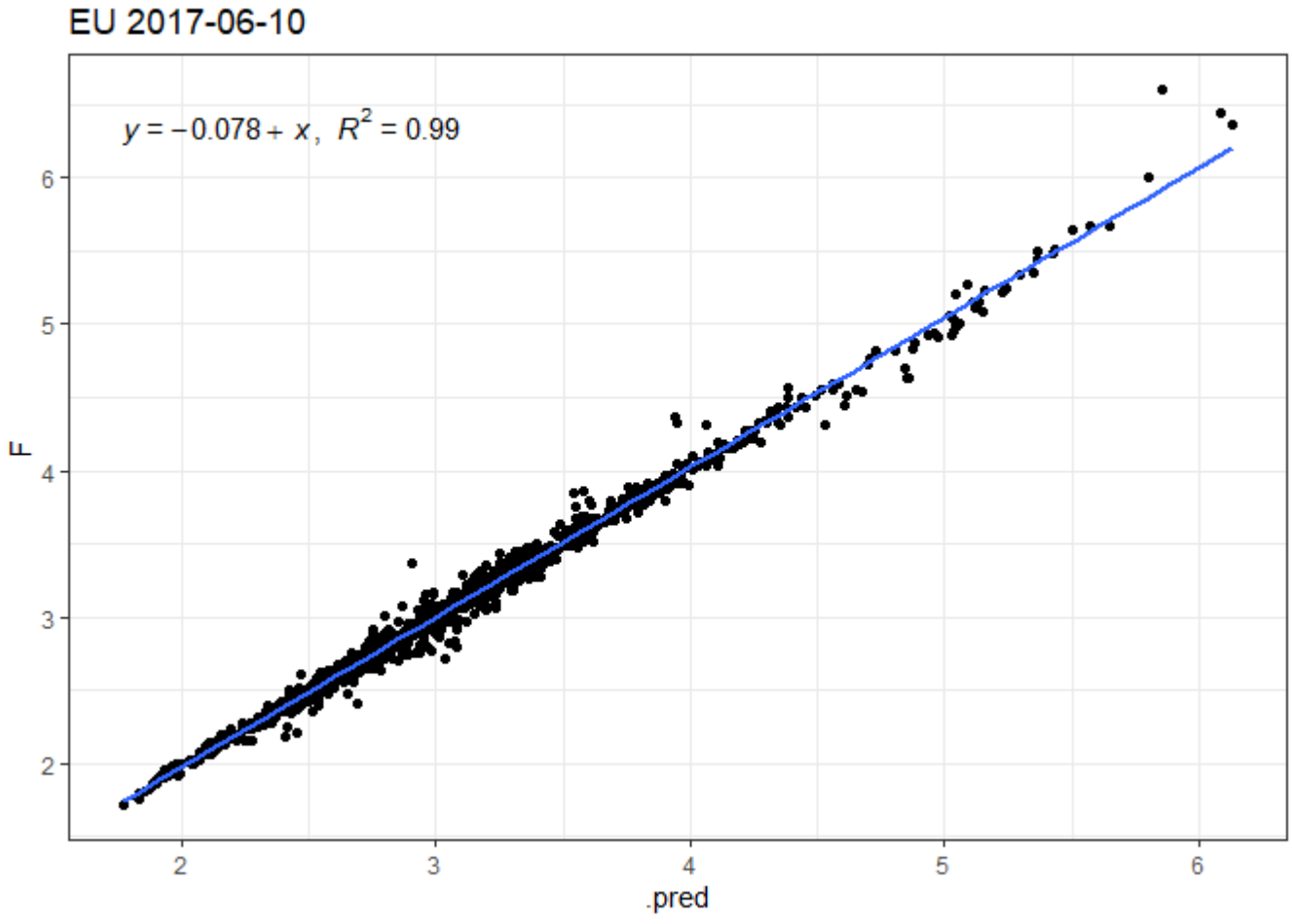

Cost-Complexity Parameter (log-10)
Tree Depth
rmse
0.1793
0.1791
0.1789
-5.5
-5.0
-4.5
-4.0
15
16
17
18

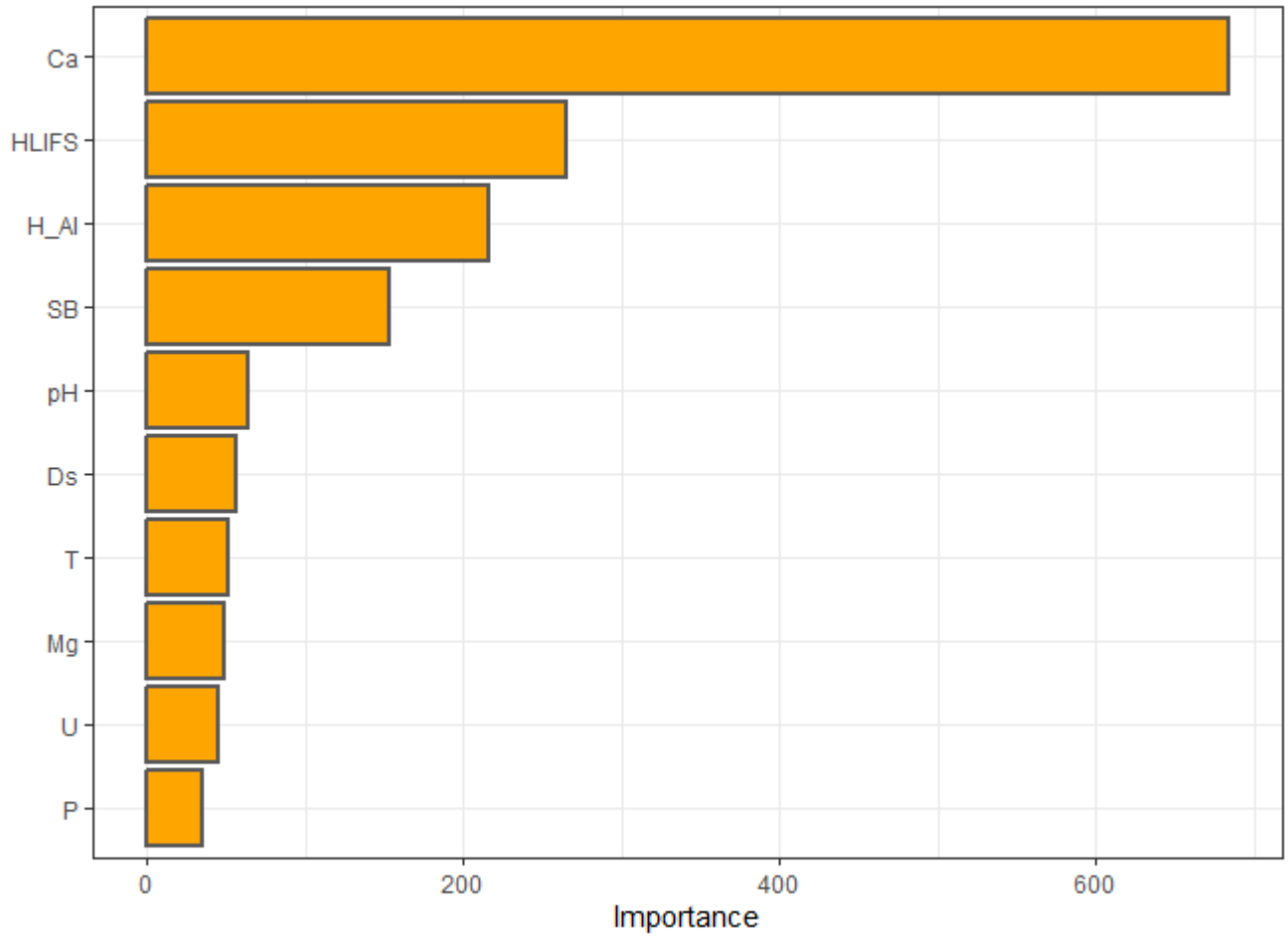

EU 2017-06-10
$y = 0.017 + 0.99\,x$, $R^2 = 0.94$
F
.pred
2
3
4
5
6




```
#>      vector_of_metrics
#> r           0.97111955
#> R2          0.94307318
#> MSE         0.03026605
#> RMSE        0.17397141
#> MAE         0.10825675
#> MAPE        3.43045078
#> [1] "RANDOM FOREST"
```

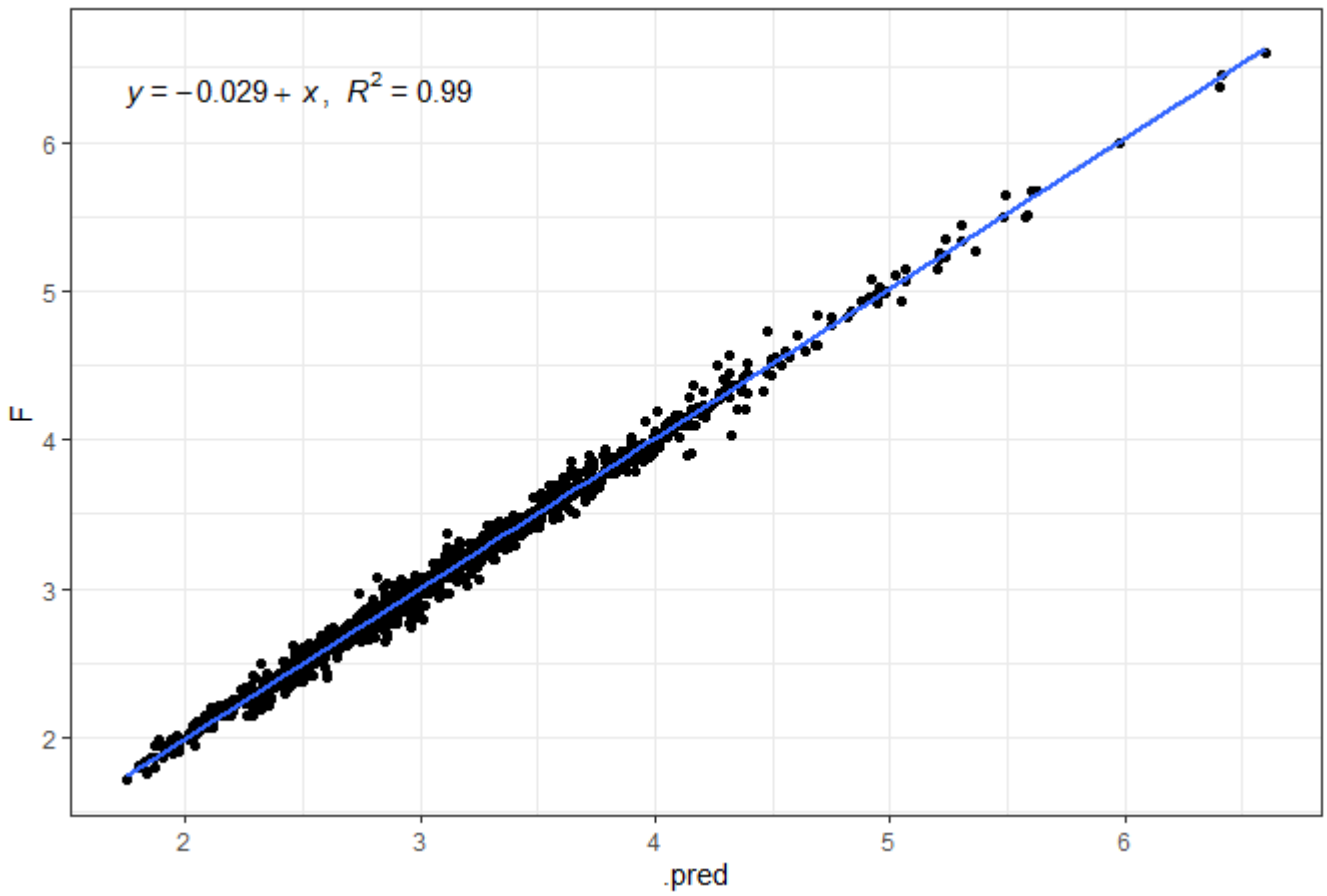

Randomly Selected Predictors
Trees
Minimal Node Size
rmse
0.089
0.088
7
8
9
10
280
300
320
340
22
23
24
25

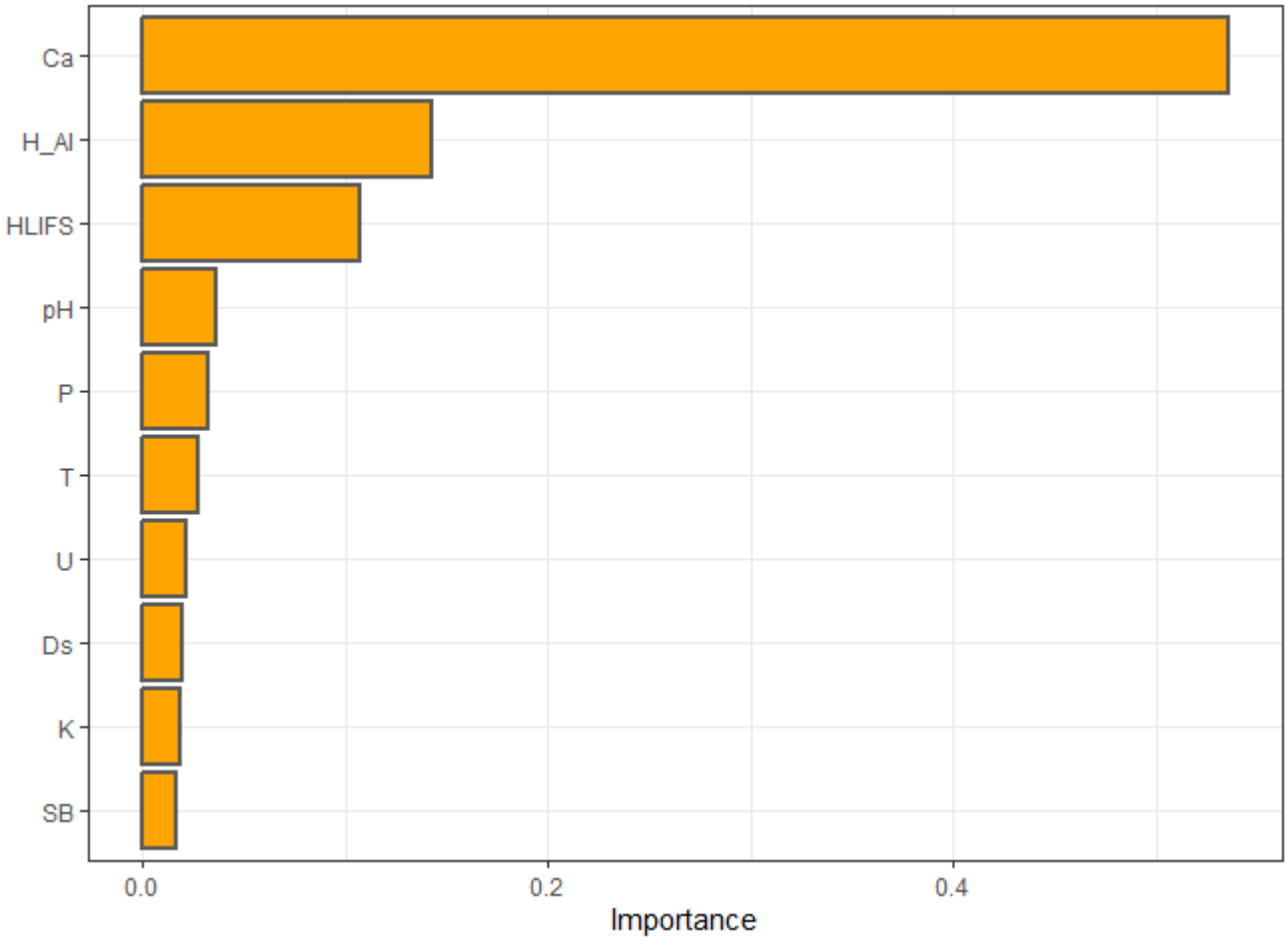

EU 2017-06-10
$y = -0.078 + x,\ R^2 = 0.99$
F
.pred
2
3
4
5
6



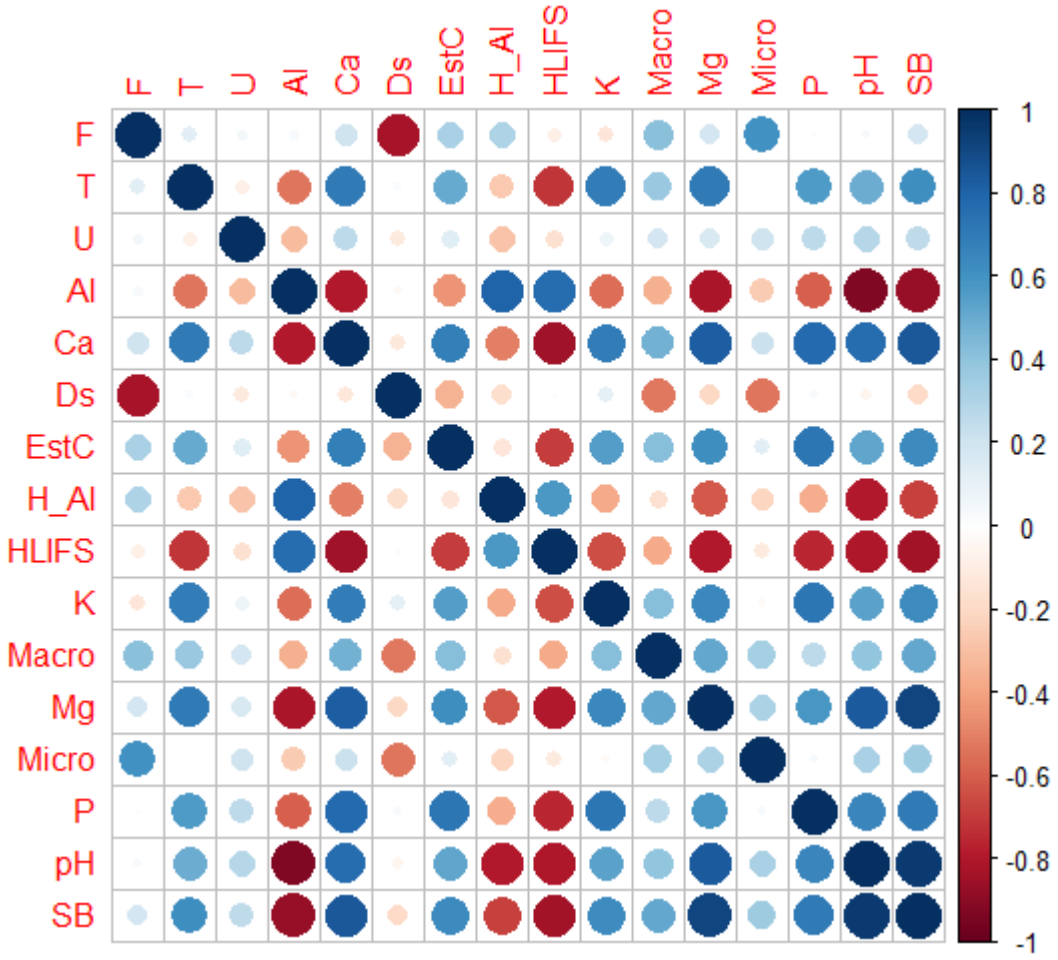

```
#>      vector_of_metrics
#> r           0.995428377
#> R2          0.990877653
#> MSE         0.005166783
#> RMSE        0.071880341
#> MAE         0.046755716
#> MAPE        1.507643081
```

EU 2017-06-10

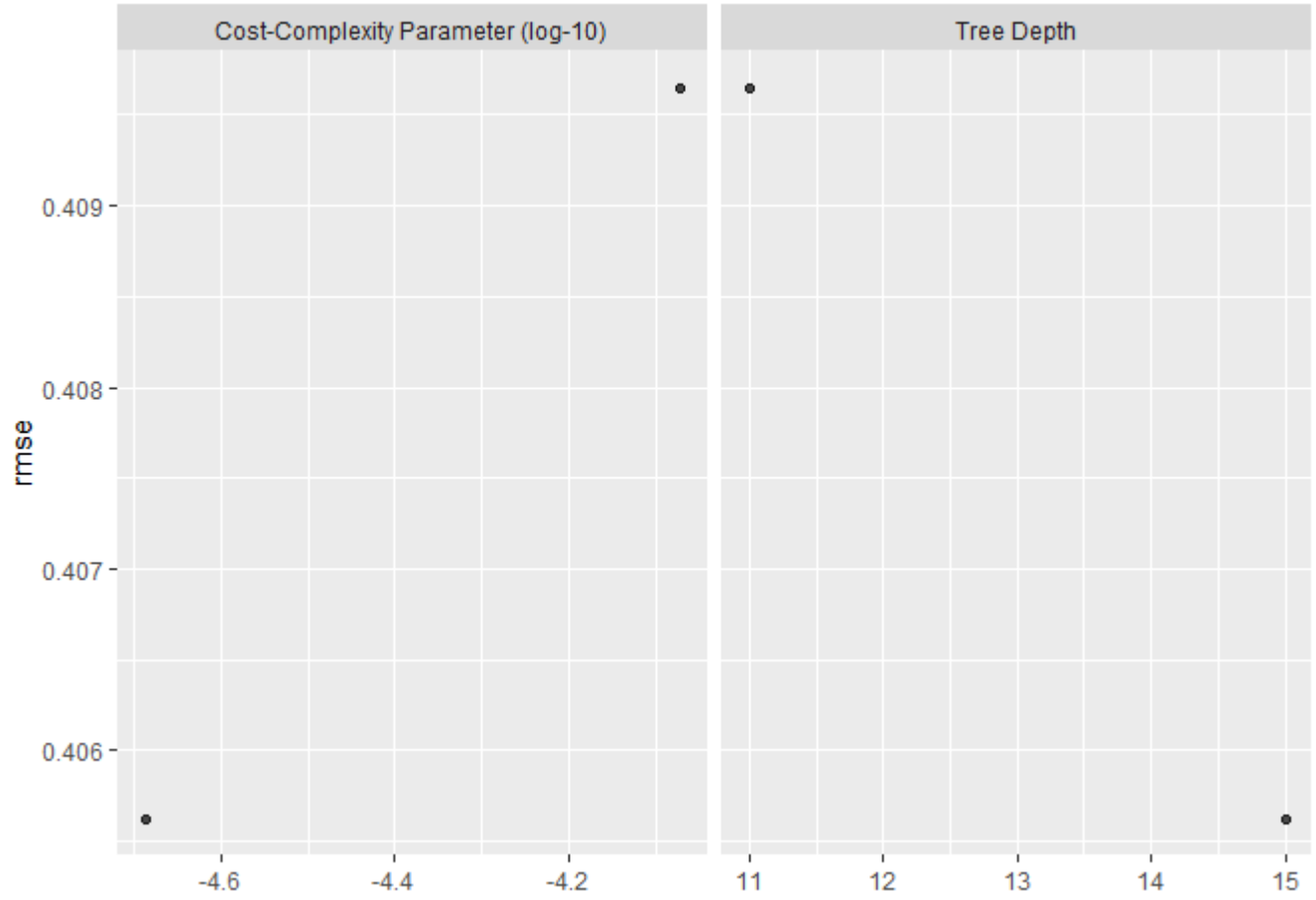

$y = -0.029 + x$, $R^2 = 0.99$
F
.pred
2
3
4
5
6

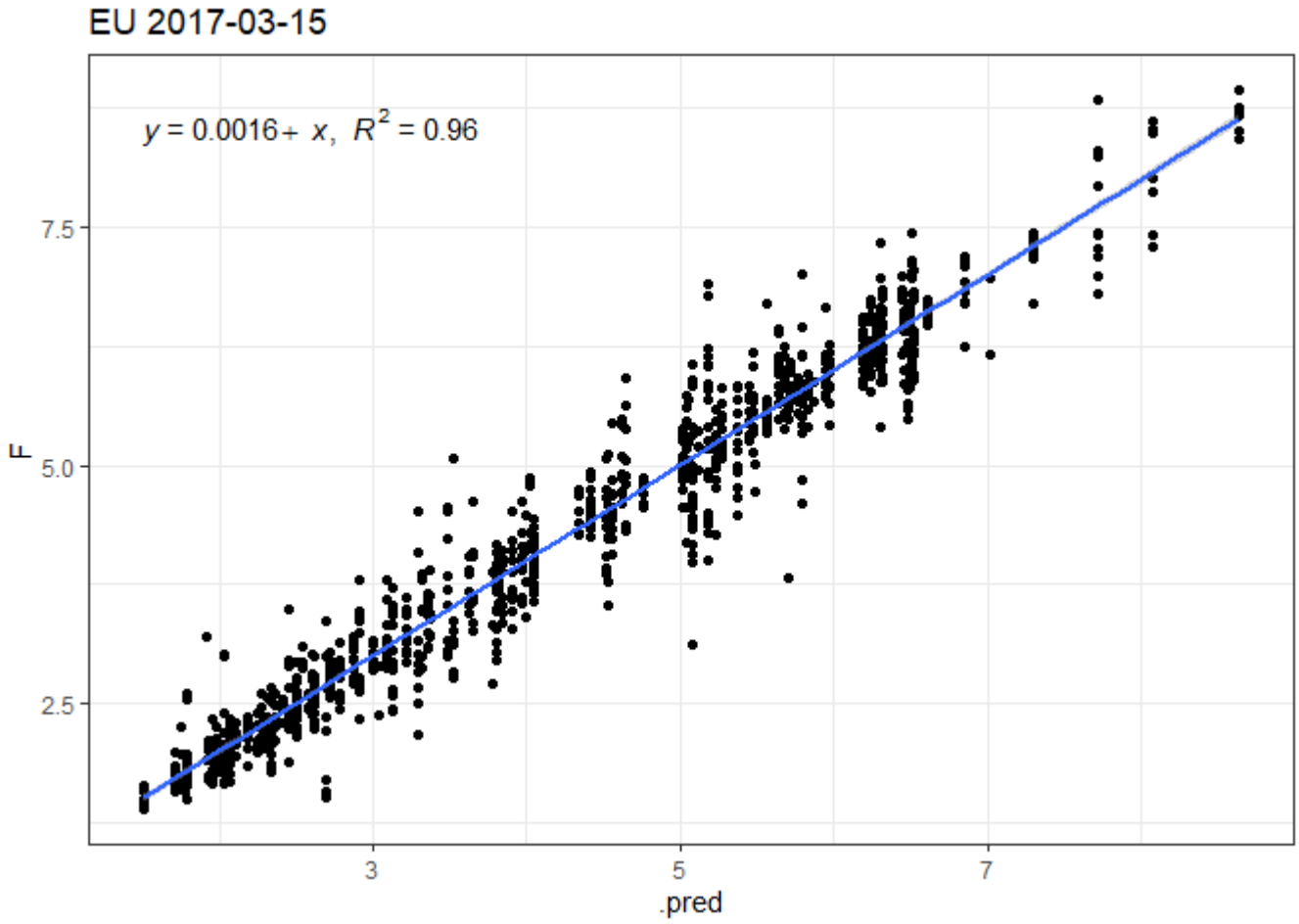

Ca
H_Al
HLIFS
pH
P
T
U
Ds
K
SB
0.0
0.2
0.4
Importance

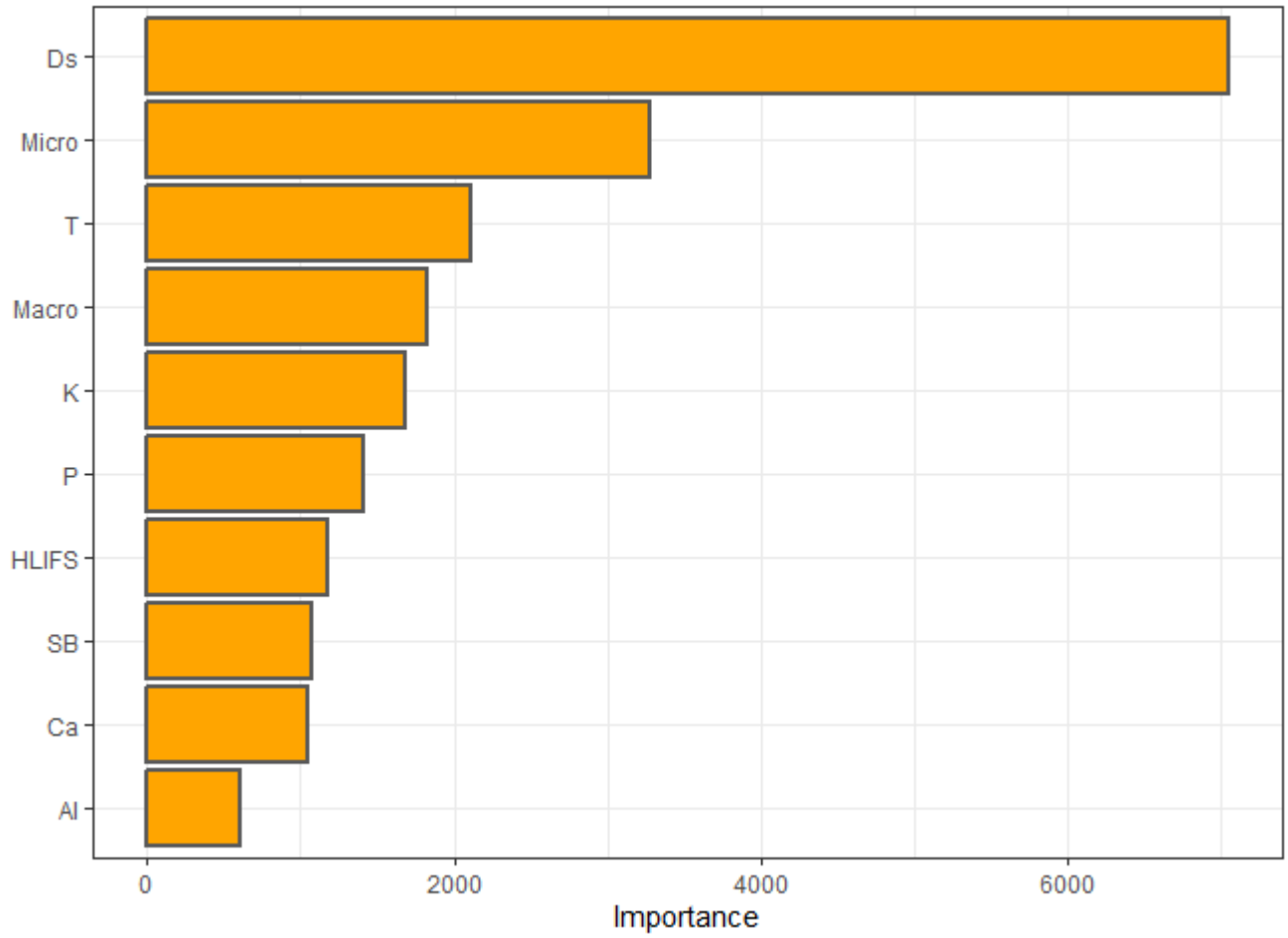
```
#>       vector_of_metrics
#> r           0.996044243
#> R2          0.992104134
#> MSE         0.004238968
#> RMSE        0.065107361
#> MAE         0.048306473
#> MAPE        1.584811887
```



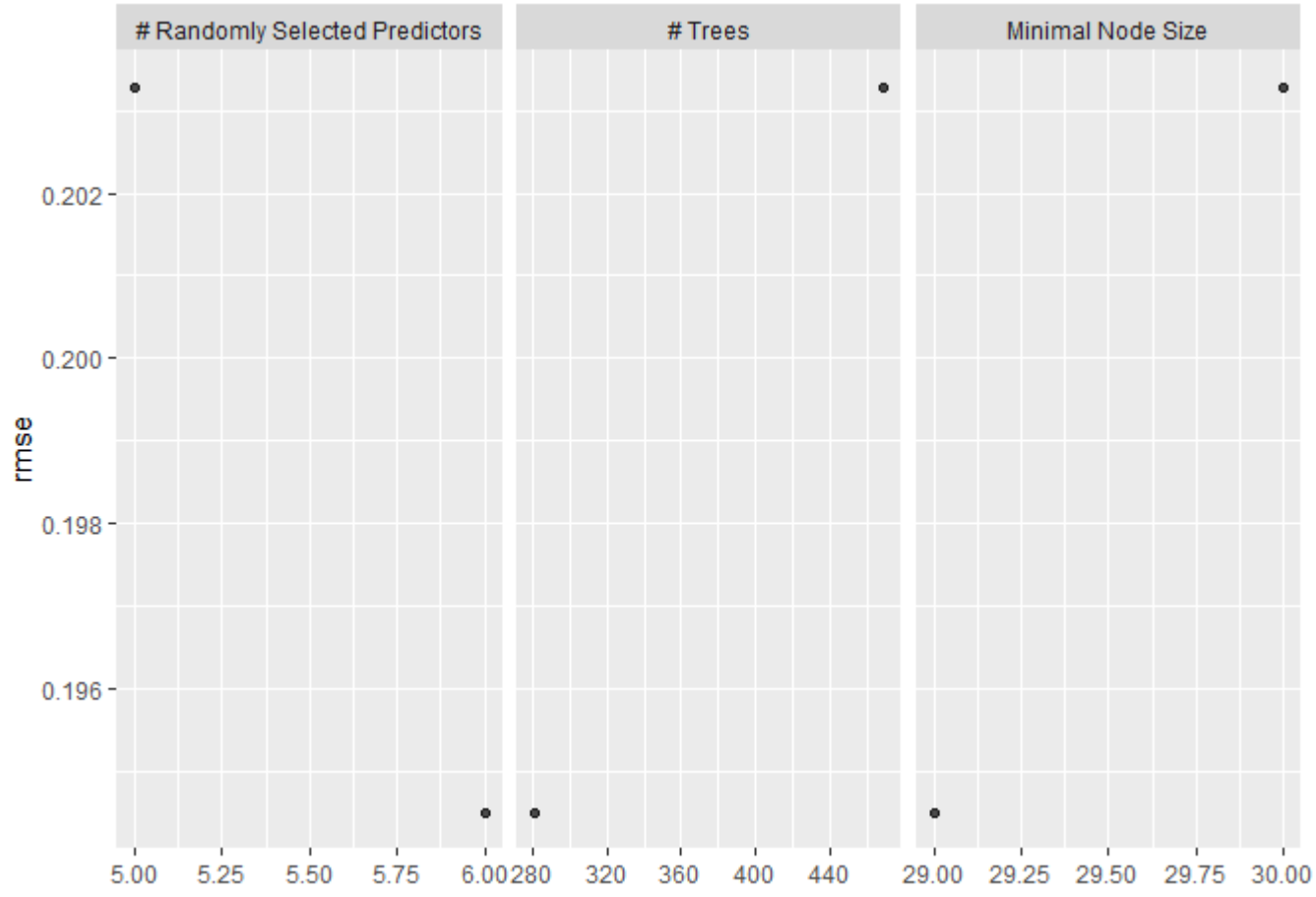

```
#> [1] "ARVORE DE DECISÃO"
```

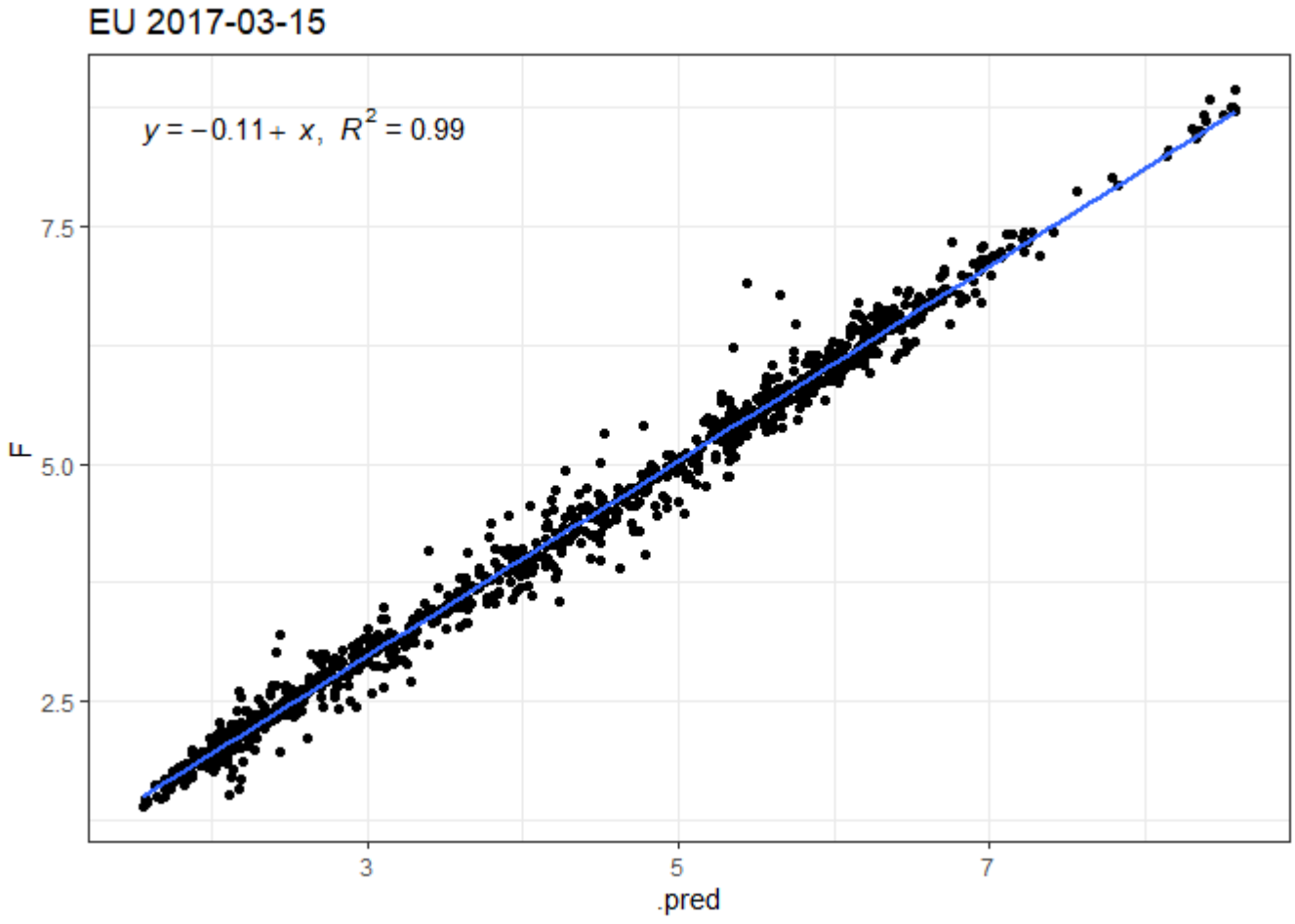

Cost-Complexity Parameter (log-10)
Tree Depth
rmse
0.409
0.408
0.407
0.406
-4.6
-4.4
-4.2
11
12
13
14
15

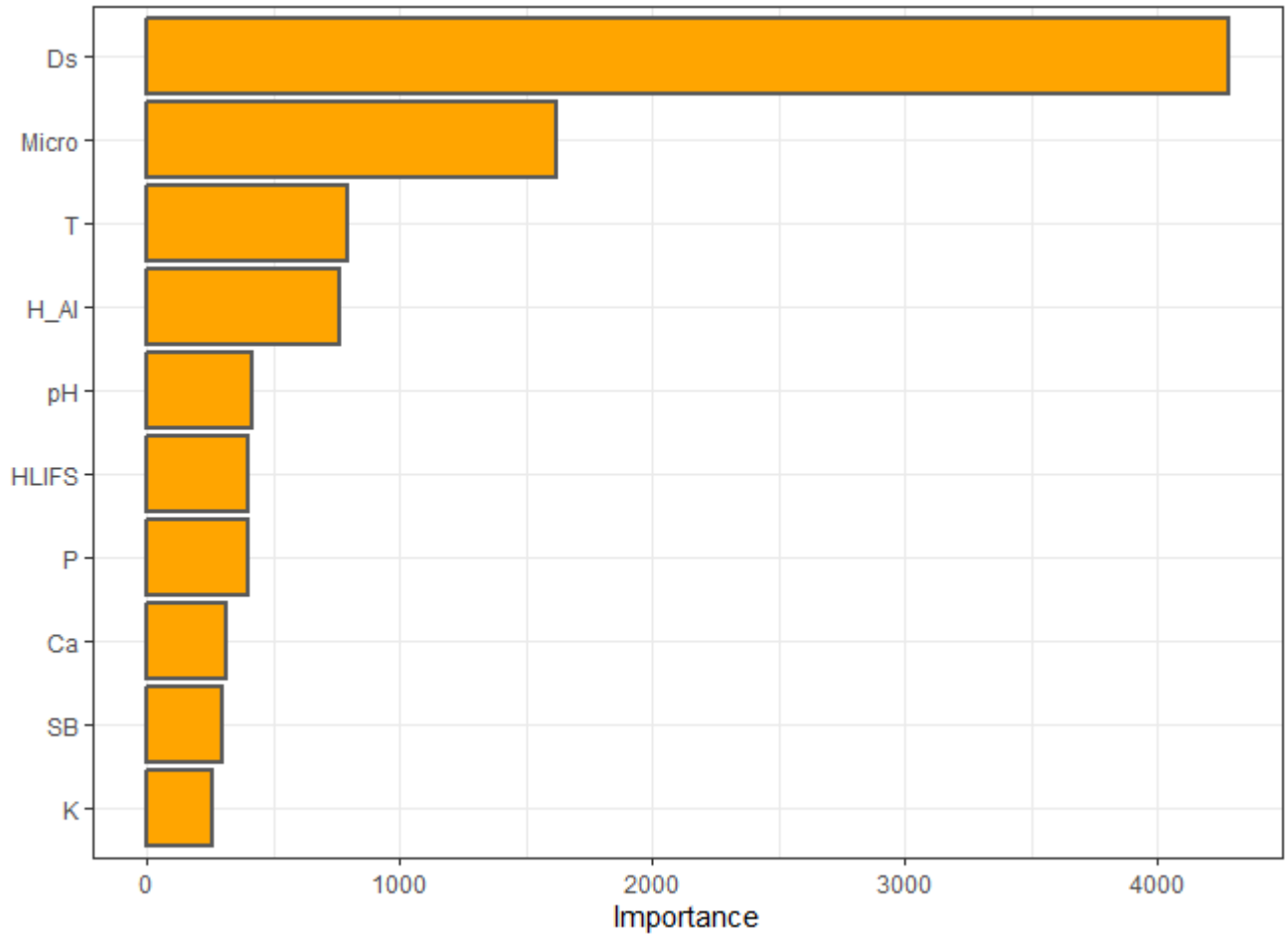

EU 2017-03-15
$y = 0.0016 + x$, $R^2 = 0.96$
F
7.5
5.0
2.5
3
5
7
.pred



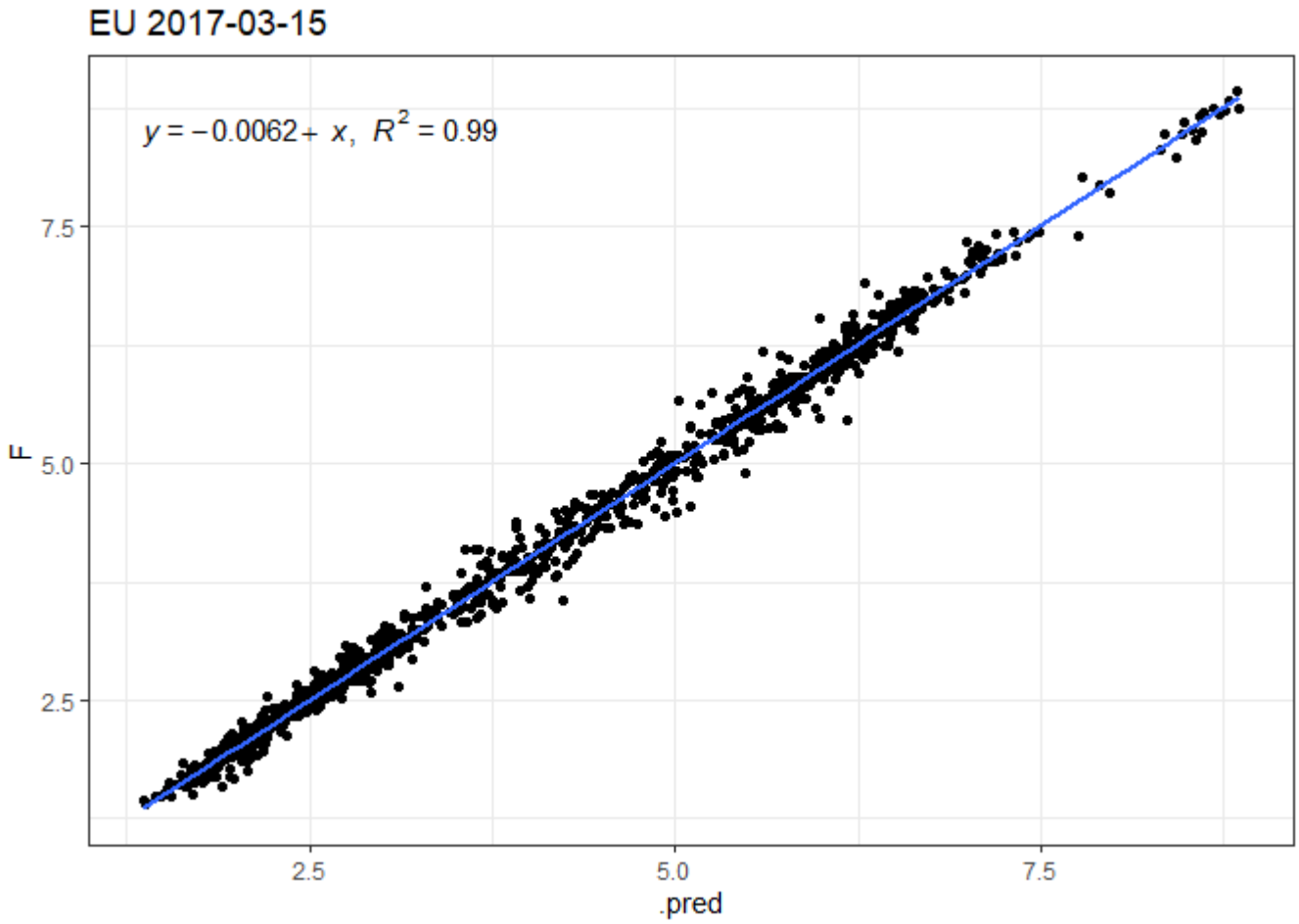

```
#>      vector_of_metrics
#> r            0.9791578
#> R2           0.9587501
#> MSE          0.1306334
#> RMSE         0.3614325
#> MAE          0.2498442
#> MAPE         6.5773152
#> [1] "RANDOM FOREST"
```

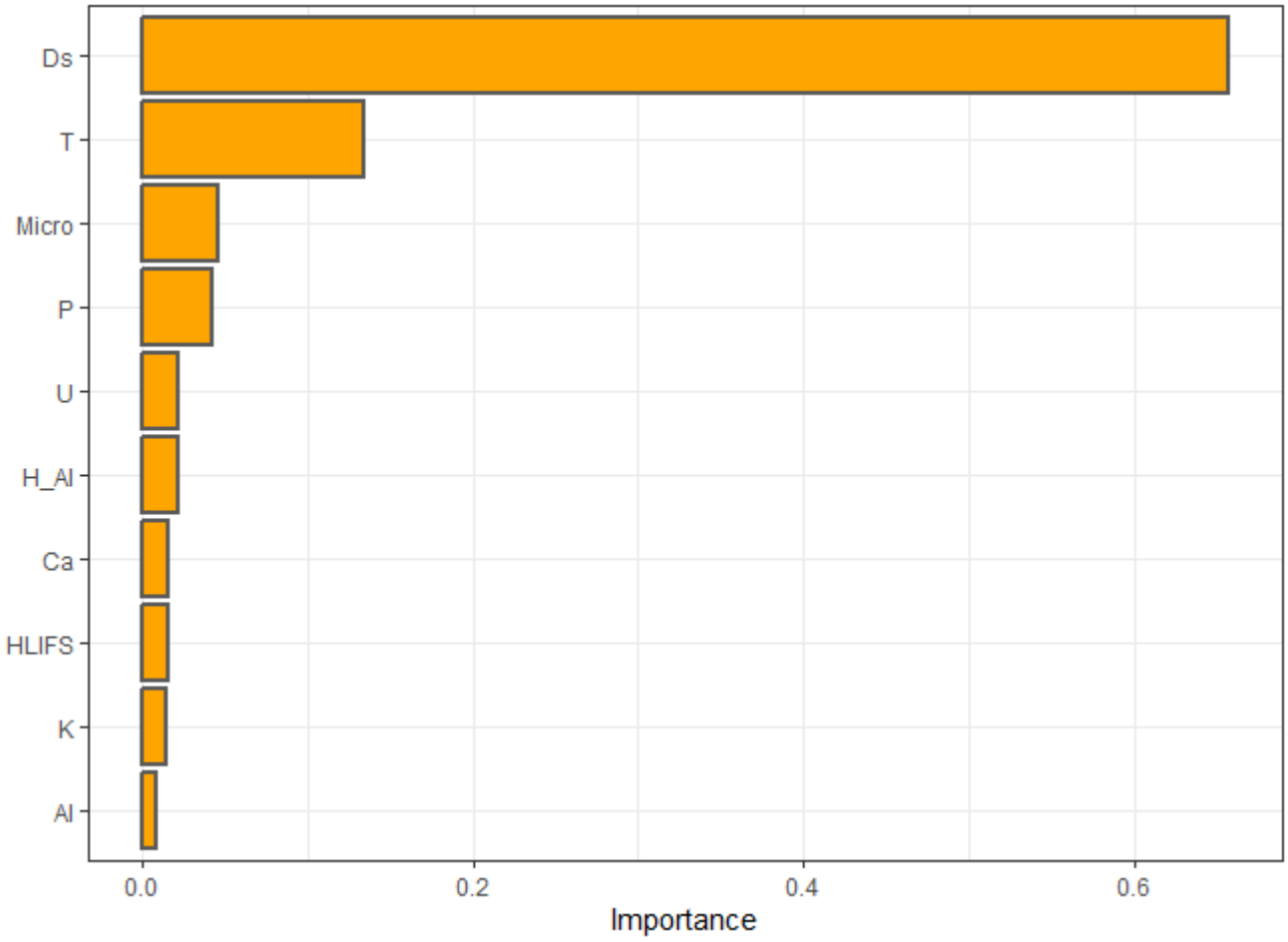

Randomly Selected Predictors
Trees
Minimal Node Size
rmse
0.202
0.200
0.198
0.196
5.00
5.25
5.50
5.75
6.00
280
320
360
400
440
29.00
29.25
29.50
29.75
30.00


EU 2017-03-15
$y = -0.11 + x,\ R^2 = 0.99$
F
7.5
5.0
2.5
3
5
7
.pred

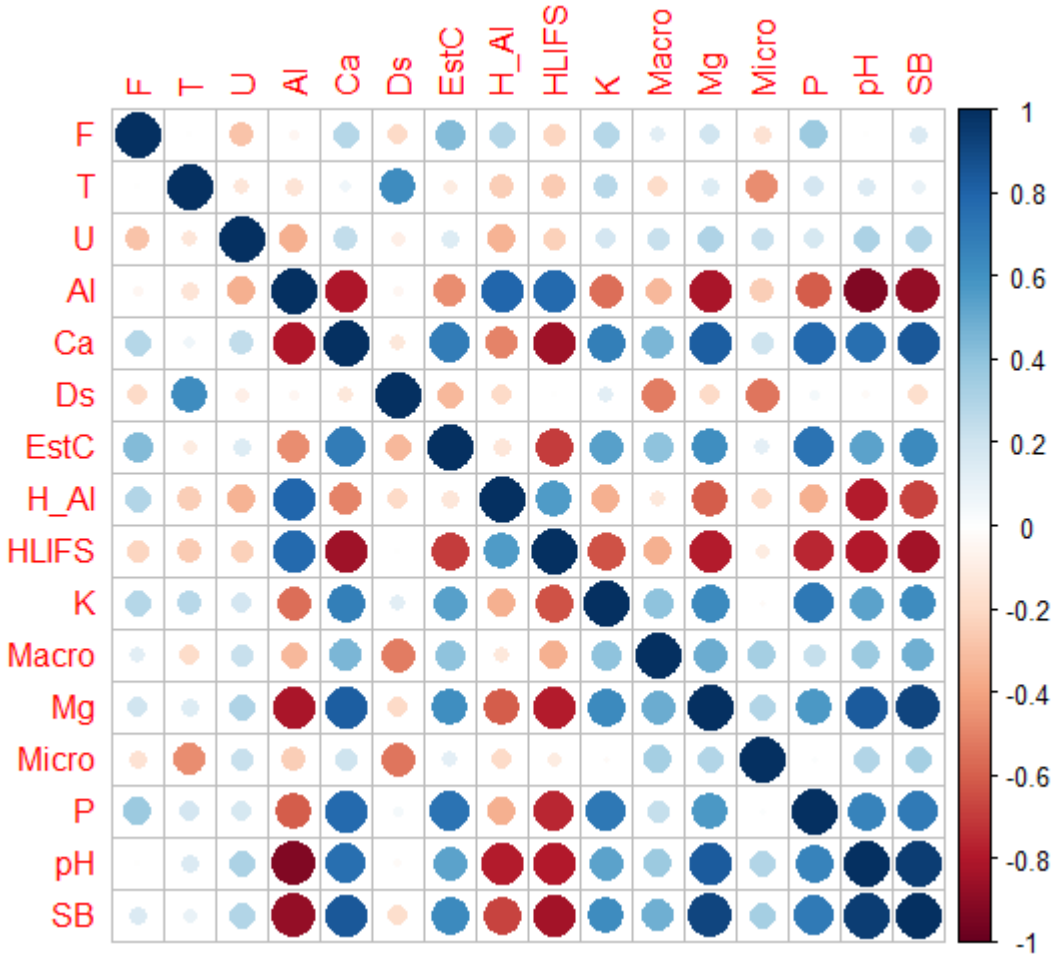



```
#>      vector_of_metrics
#> r           0.99497434
#> R2          0.98997394
#> MSE         0.03399734
#> RMSE        0.18438369
#> MAE         0.12596408
#> MAPE        3.38838653
```

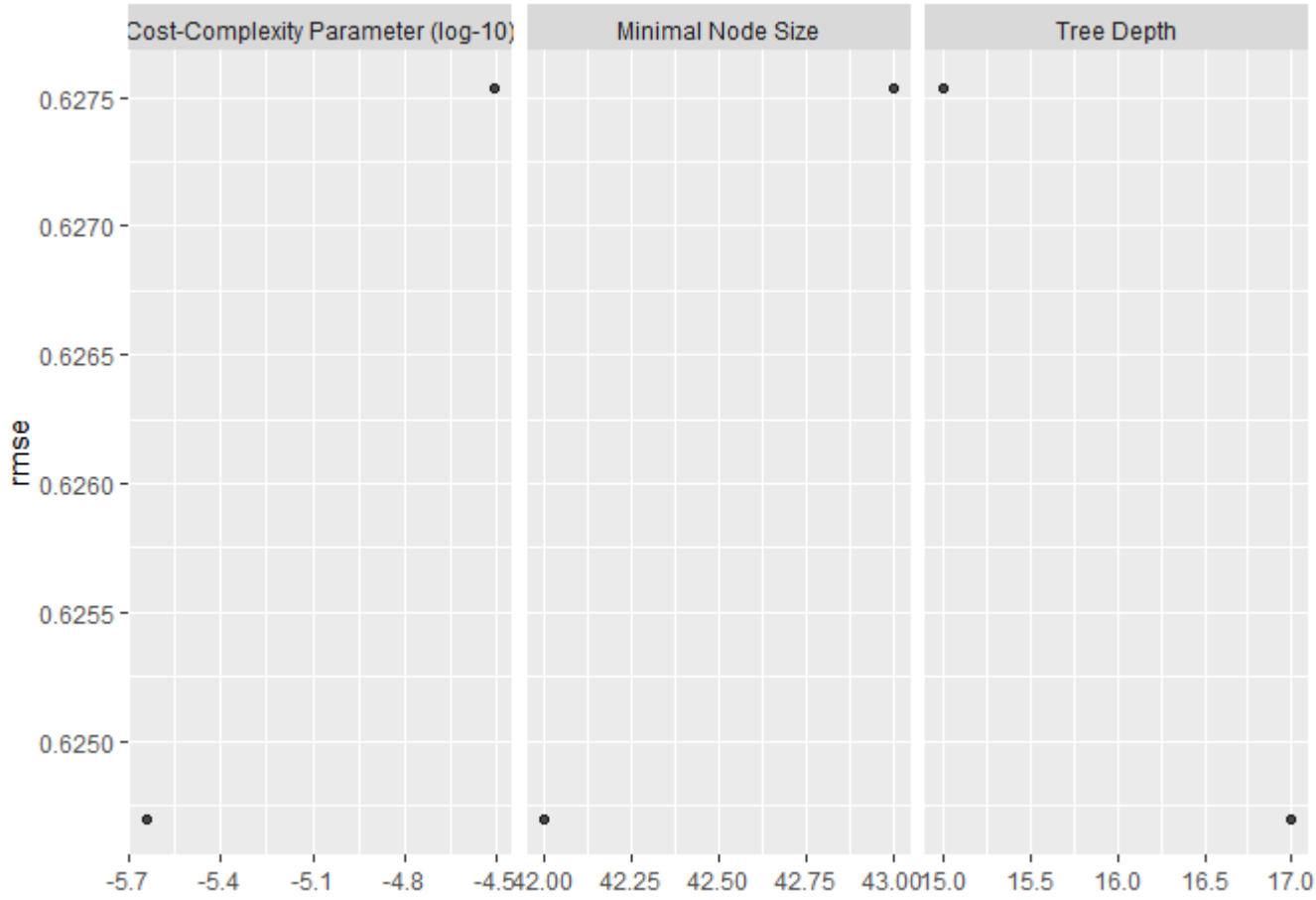

EU 2017-03-15
$y = -0.0062 + x,\ R^2 = 0.99$
7.5
5.0
2.5
F
2.5
5.0
7.5
.pred

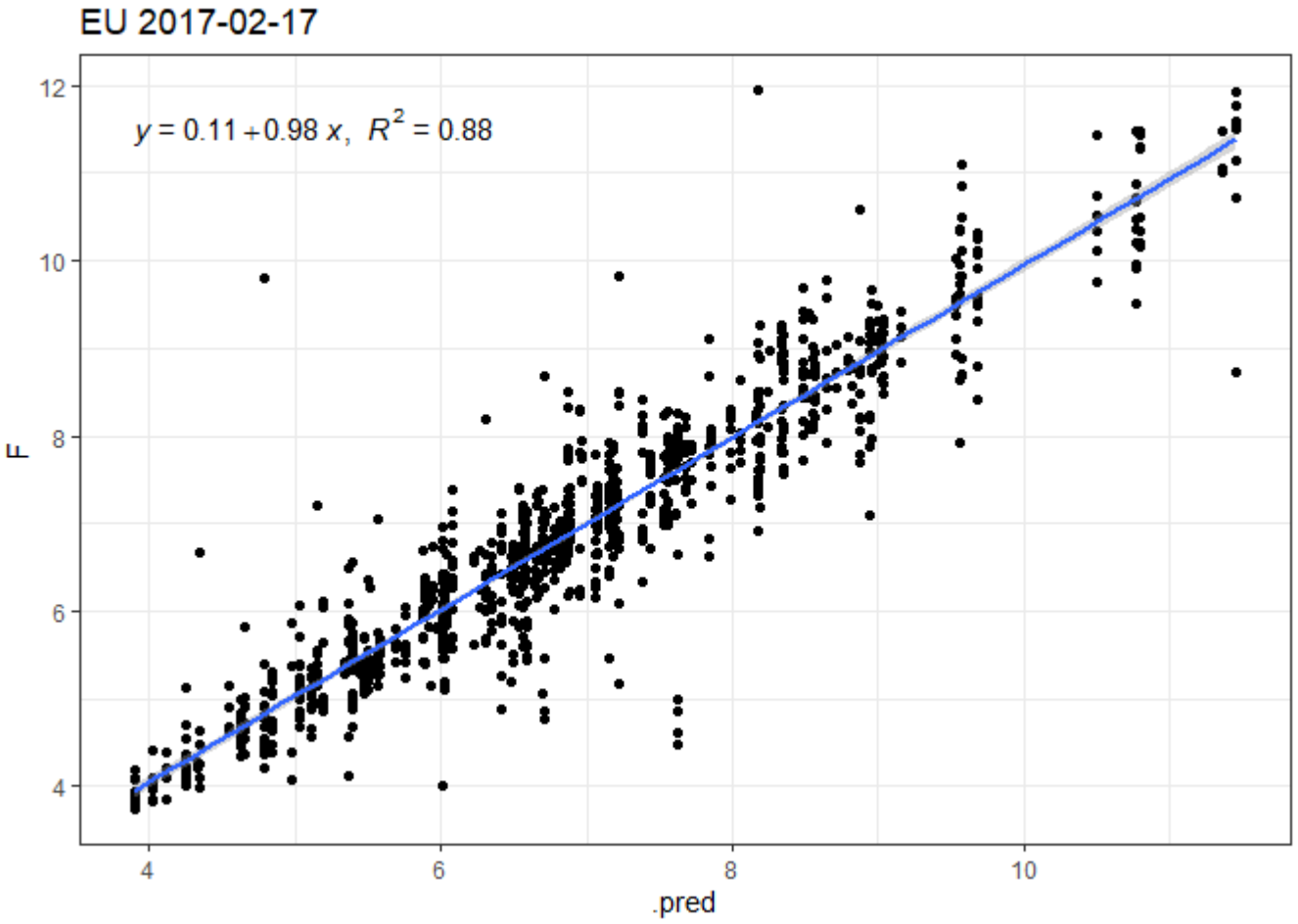

Ds
T
Micro
P
U
H_Al
Ca
HLIFS
K
Al
0.0
0.2
0.4
0.6
Importance

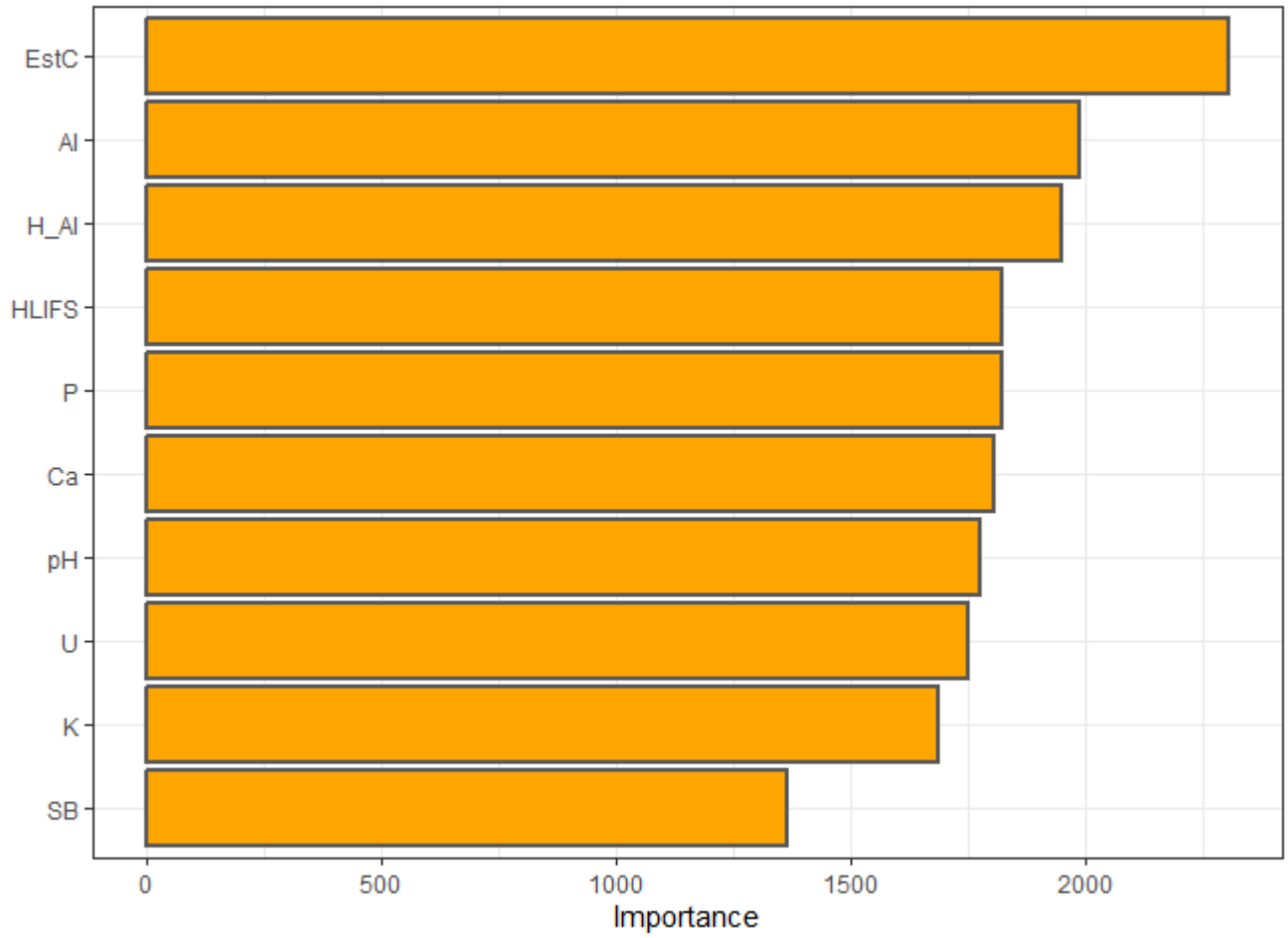
```
#>       vector_of_metrics
#> r            0.99680631
#> R2           0.99362282
#> MSE          0.02025893
#> RMSE         0.14233389
#> MAE          0.10093043
#> MAPE         2.69793849
```



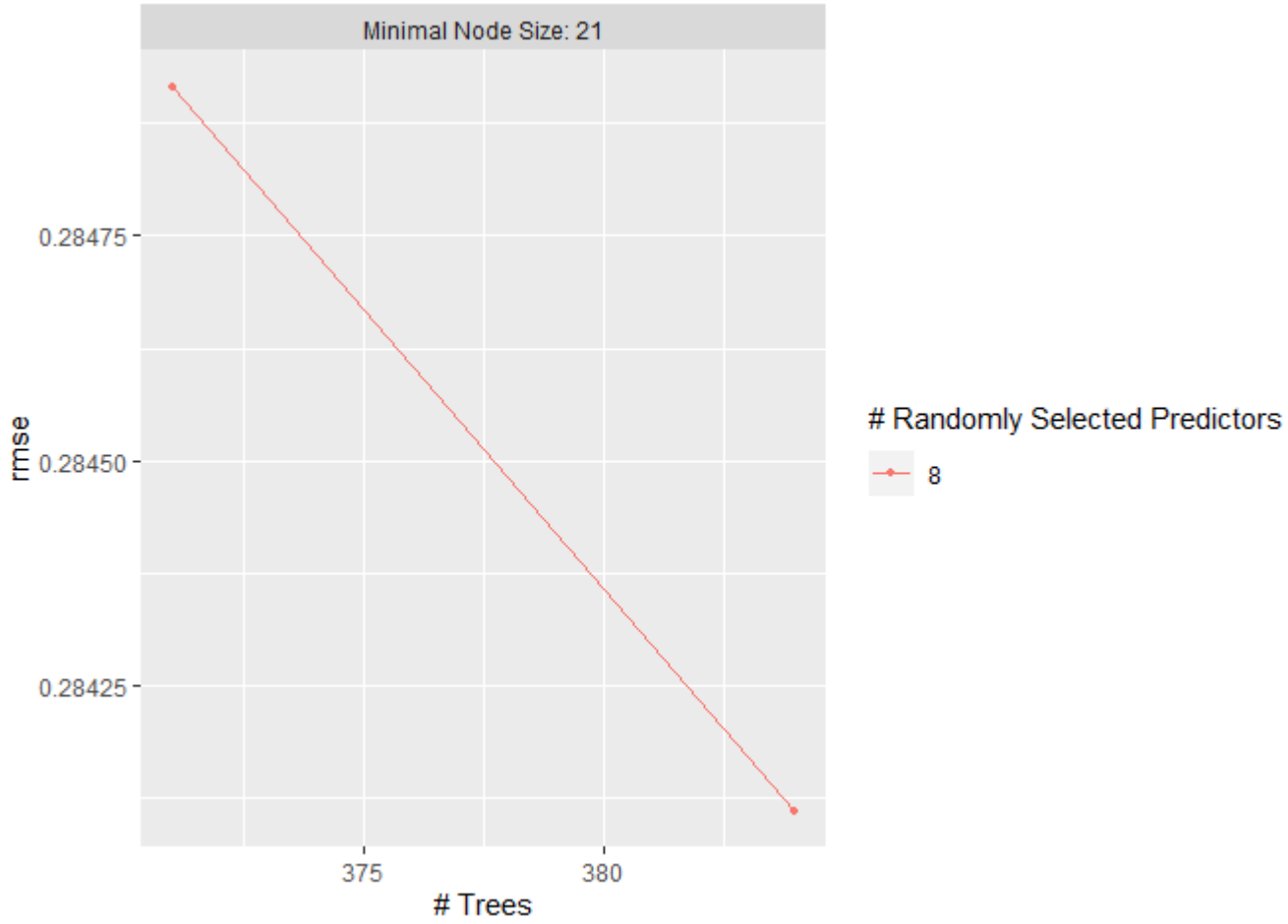

```
#> [1] "ARVORE DE DECISÃO"
```

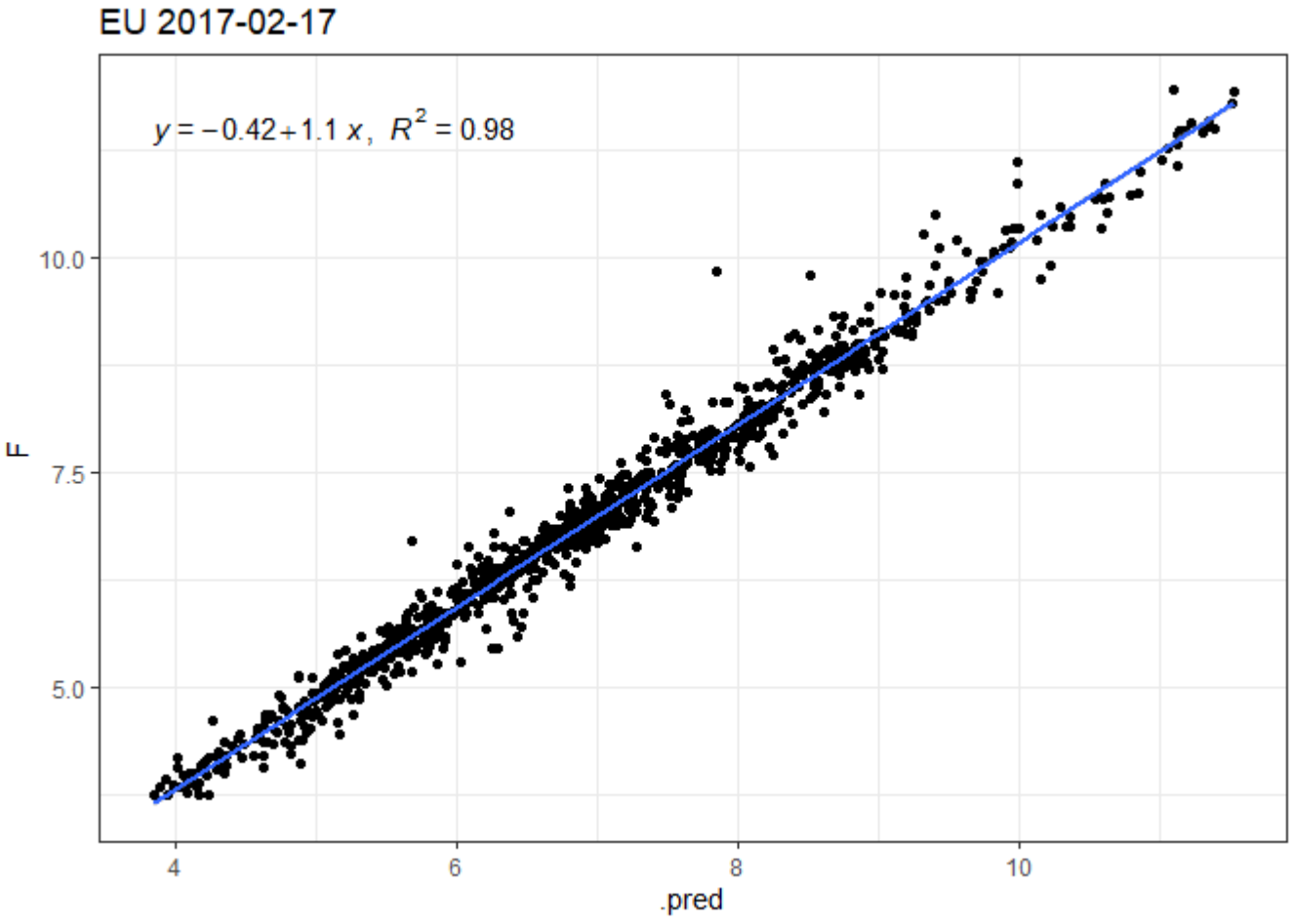

Cost-Complexity Parameter (log-10)
Minimal Node Size
Tree Depth
rmse
0.6275
0.6270
0.6265
0.6260
0.6255
0.6250
-5.7
-5.4
-5.1
-4.8
-4.5
42.00
42.25
42.50
42.75
43.00
15.0
15.5
16.0
16.5
17.0

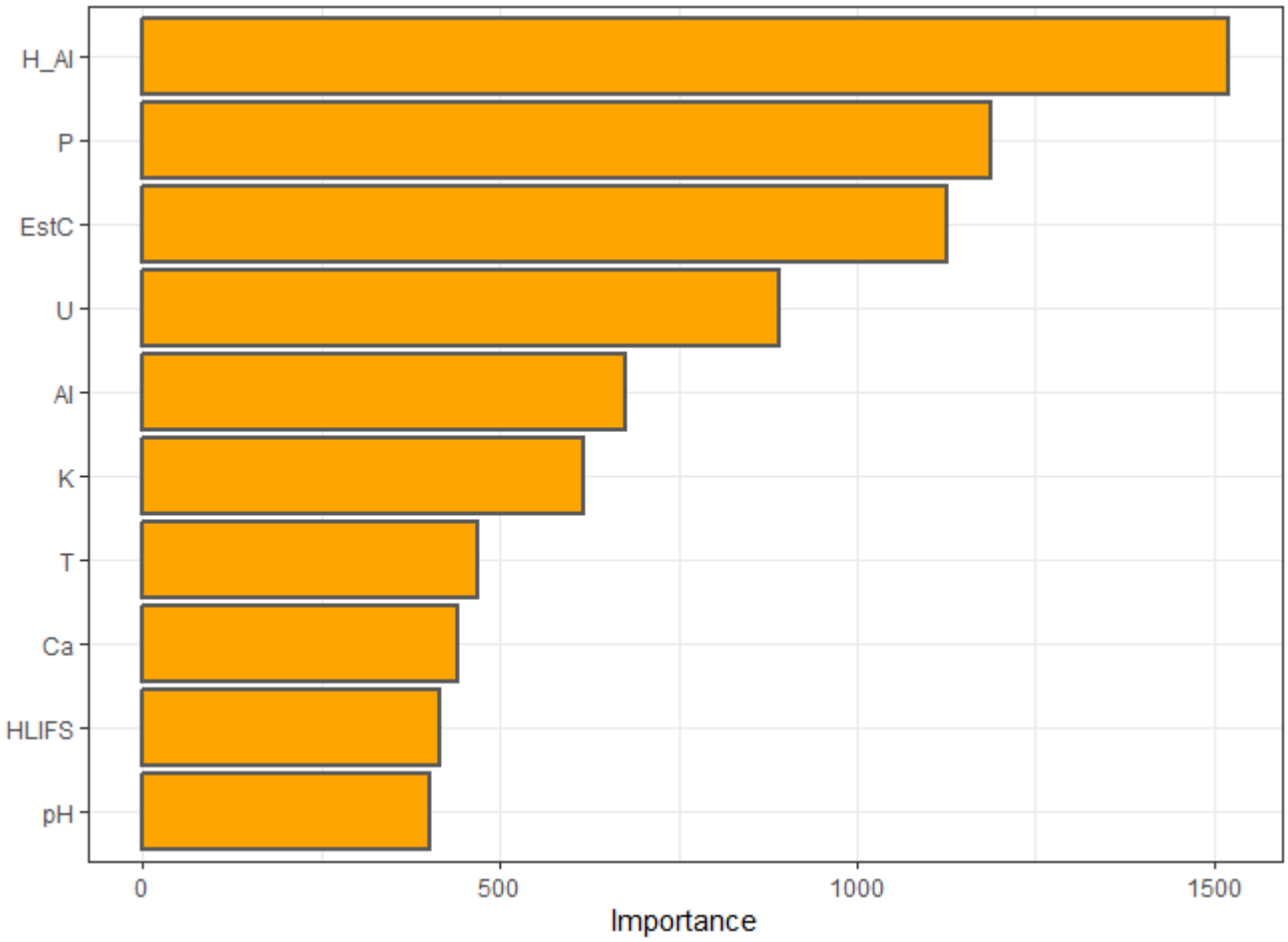

EU 2017-02-17
$y = 0.11 + 0.98\,x,\ R^2 = 0.88$
F
.pred
12
10
8
6
4
4
6
8
10



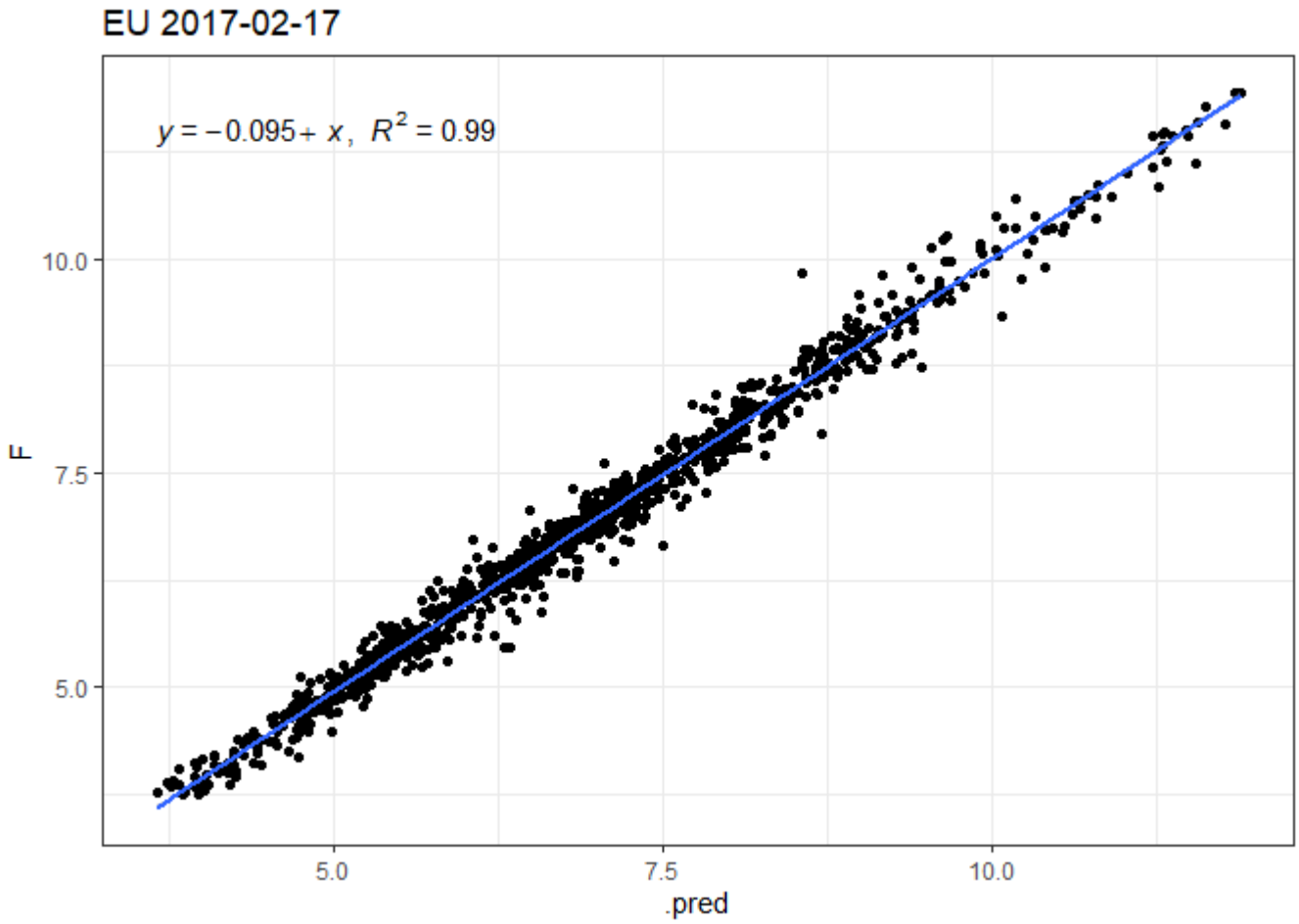

```
#>      vector_of_metrics
#> r            0.9399454
#> R2           0.8834973
#> MSE          0.3064829
#> RMSE         0.5536090
#> MAE          0.3625507
#> MAPE         5.3718164
#> [1] "RANDOM FOREST"
```

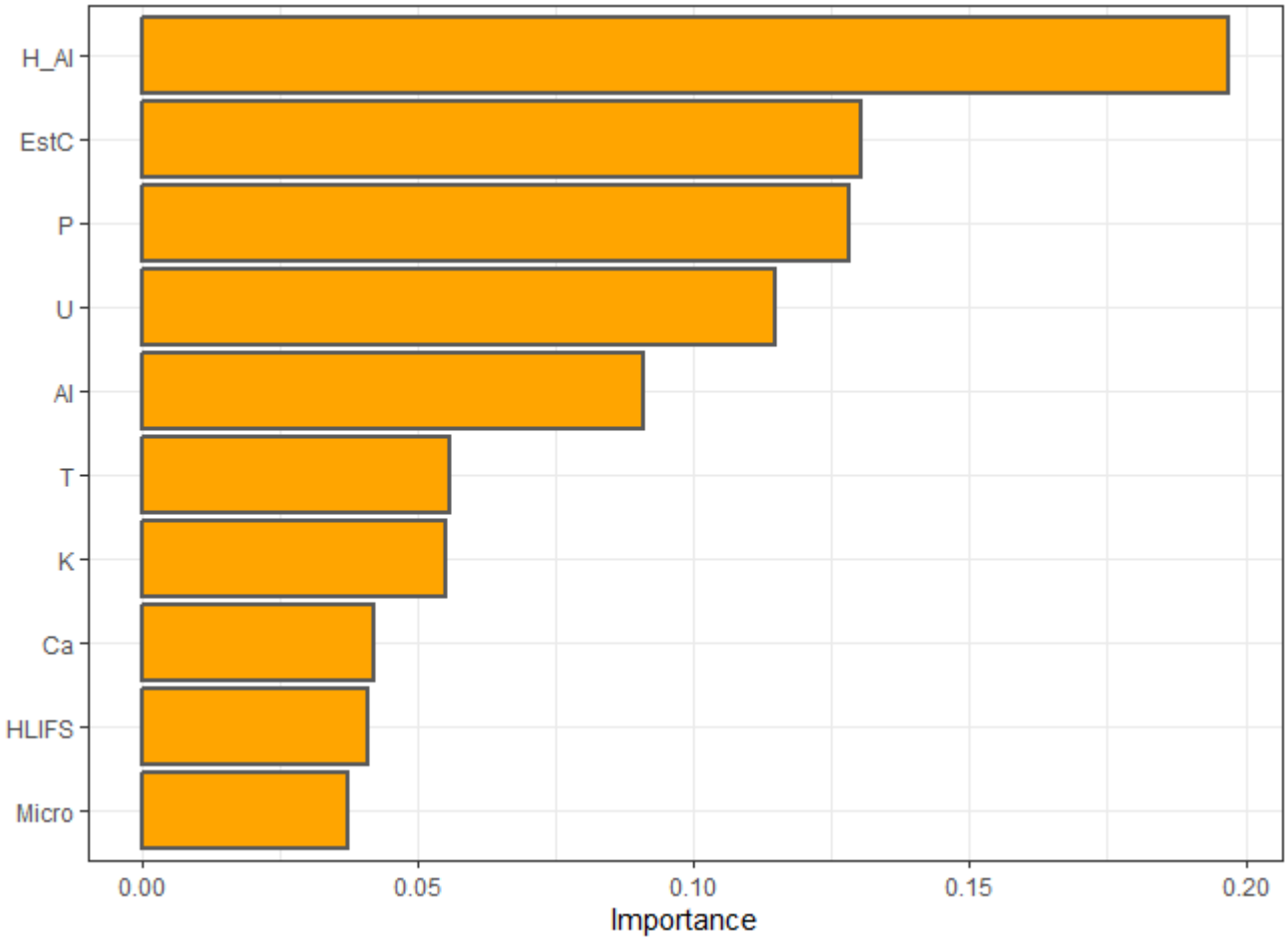

Minimal Node Size: 21
0.28475
0.28450
0.28425
rmse
375
380
Trees
Randomly Selected Predictors
8


EU 2017-02-17
$y = -0.42 + 1.1\,x,\ R^2 = 0.98$
10.0
7.5
5.0
F
4
6
8
10
.pred

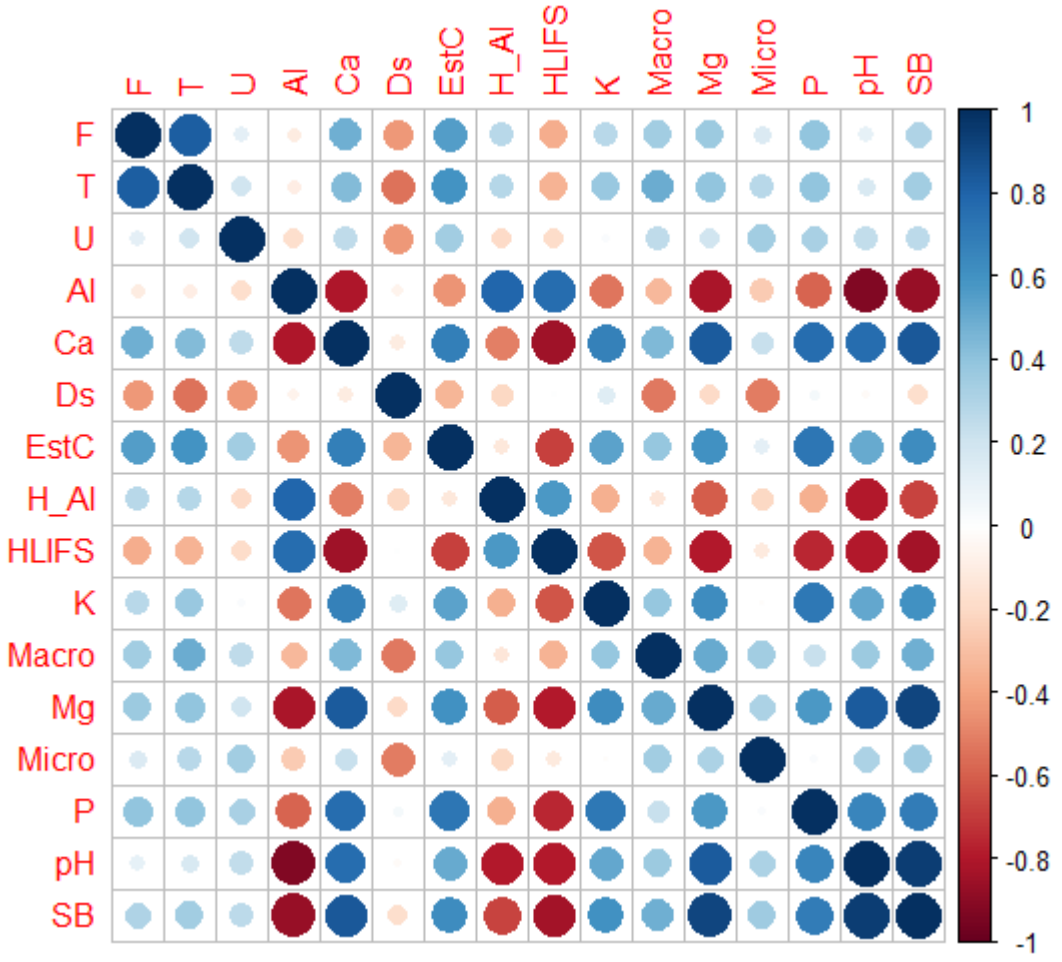



```
#>      vector_of_metrics
#> r            0.9910449
#> R2           0.9821701
#> MSE          0.0550342
#> RMSE         0.2345937
#> MAE          0.1597102
#> MAPE         2.4212565
```

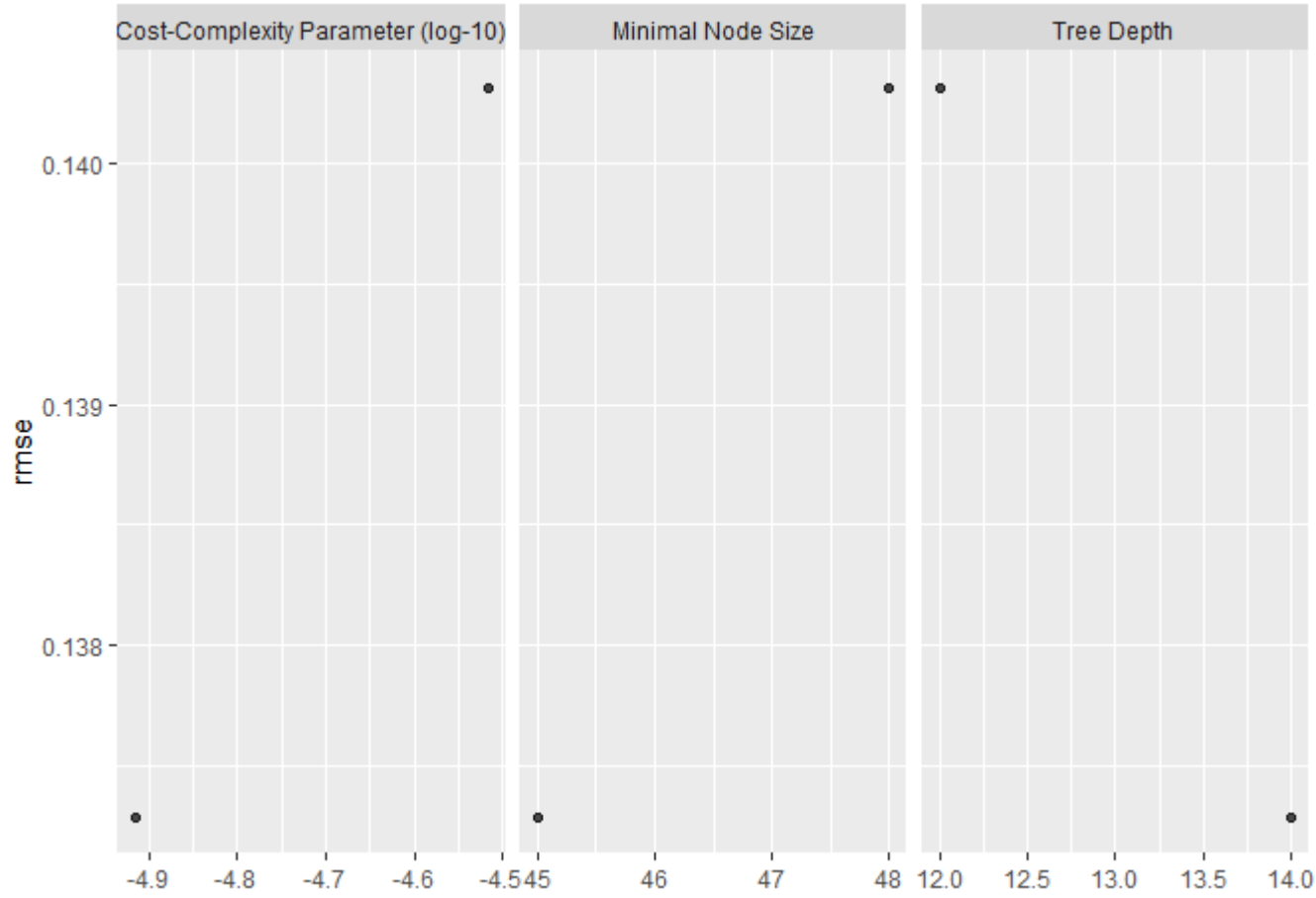

EU 2017-02-17
$y = -0.095 + x$, $R^2 = 0.99$
10.0
7.5
5.0
F
5.0
7.5
10.0
.pred

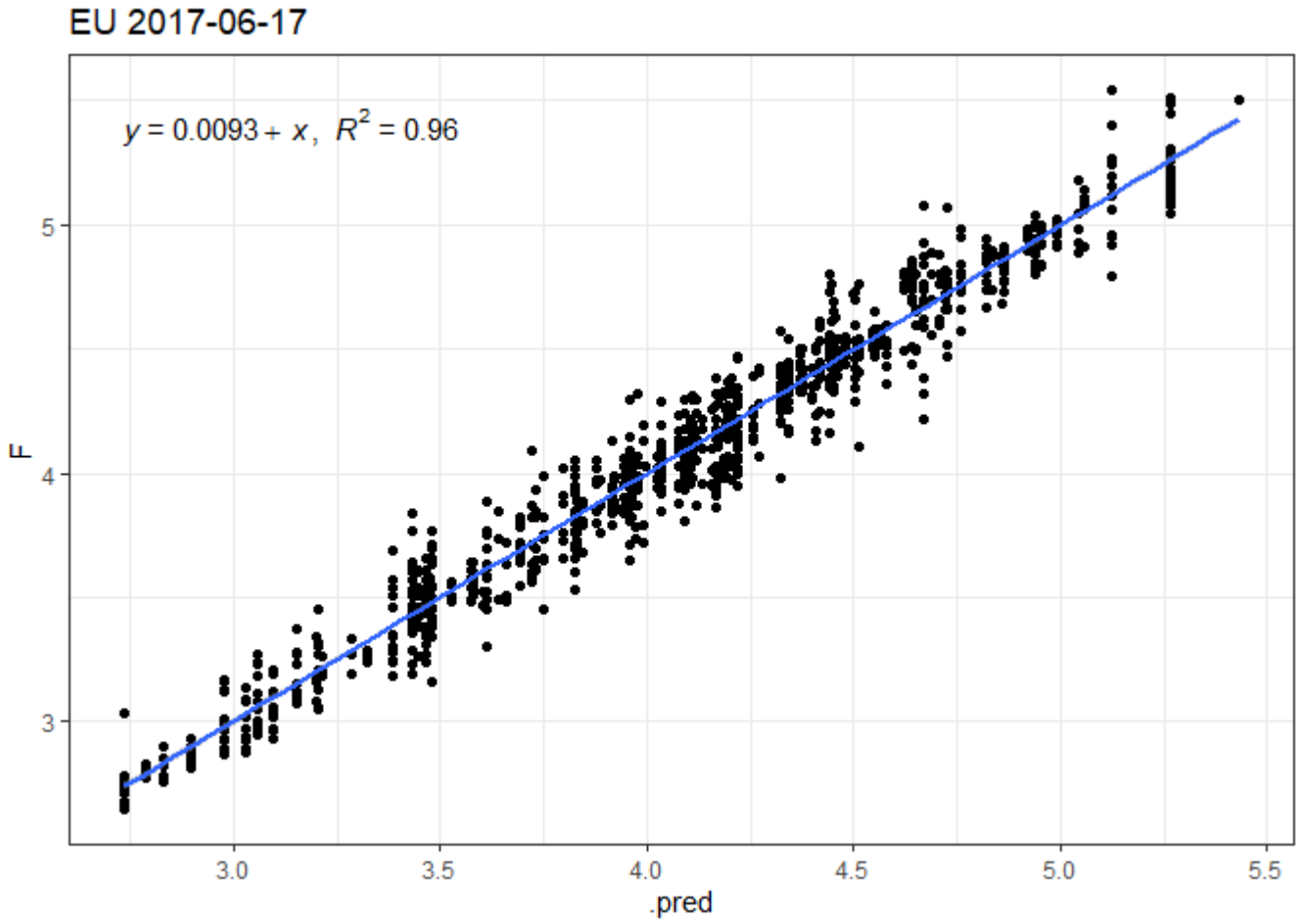

H_Al
EstC
P
U
Al
T
K
Ca
HLIFS
Micro
0.00
0.05
0.10
0.15
0.20
Importance

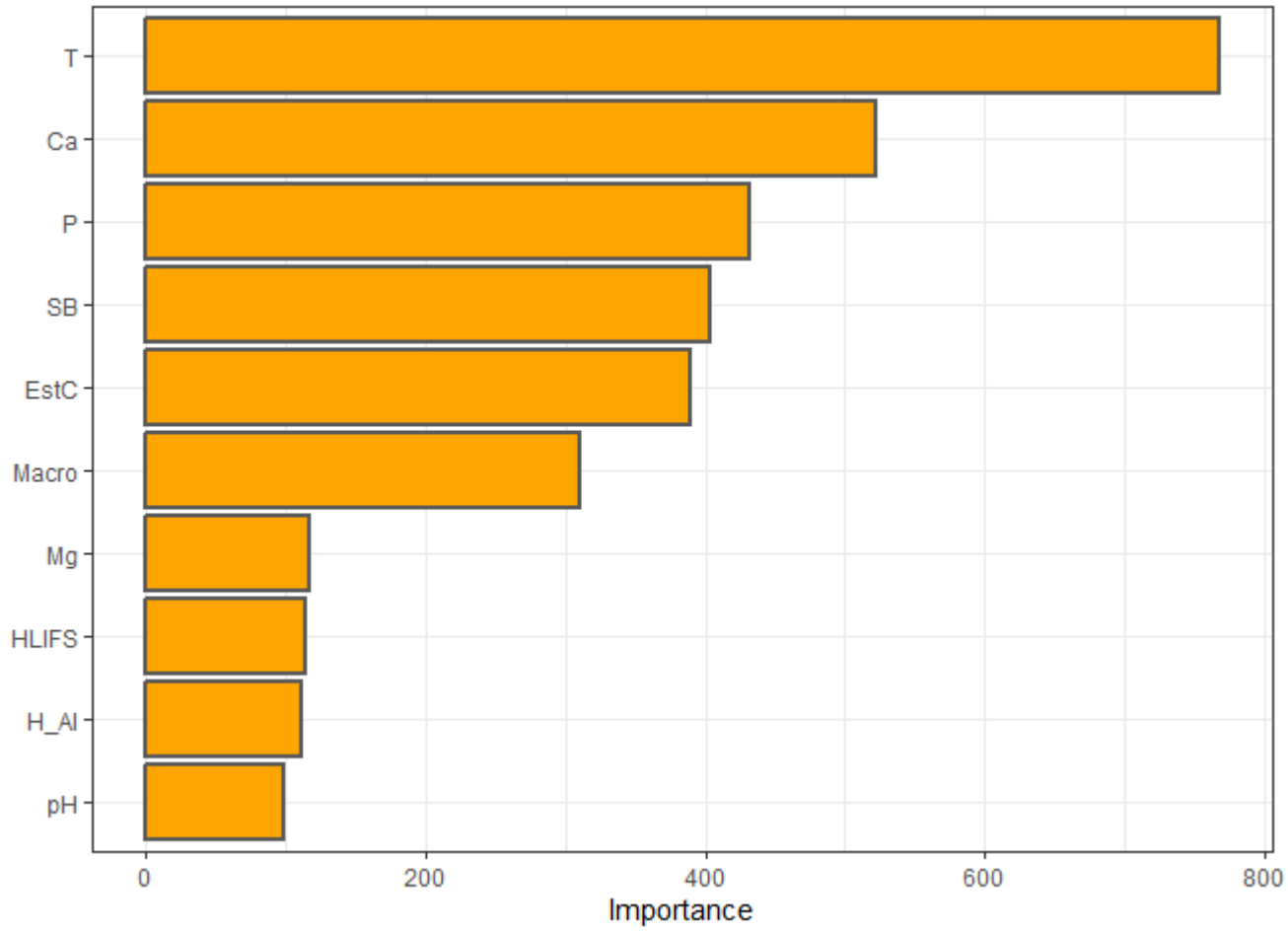
```
#>      vector_of_metrics
#> r           0.99263061
#> R2          0.98531552
#> MSE         0.03929455
#> RMSE        0.19822853
#> MAE         0.14270433
#> MAPE        2.16523663
```



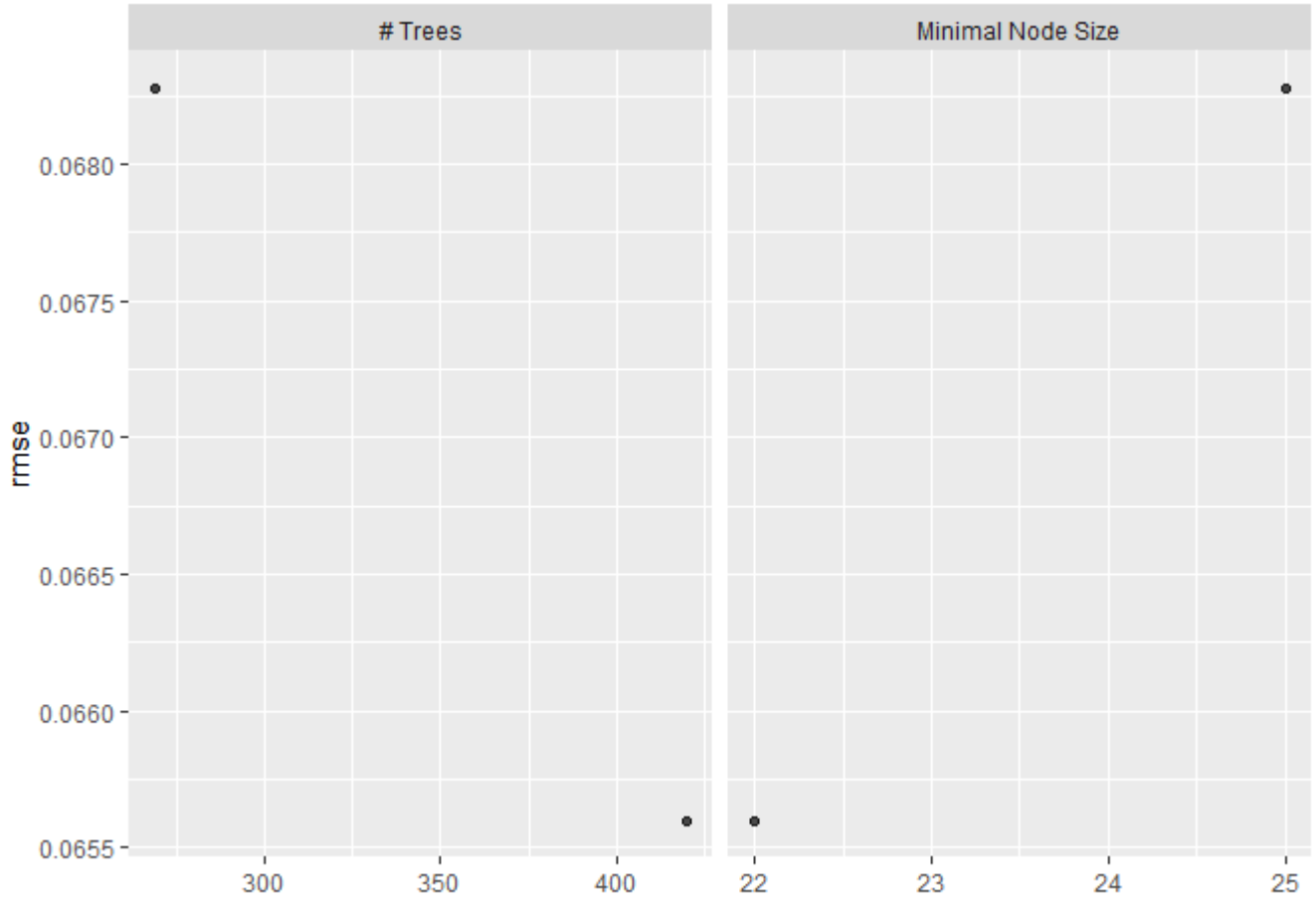

```
#> [1] "ARVORE DE DECISÃO"
```

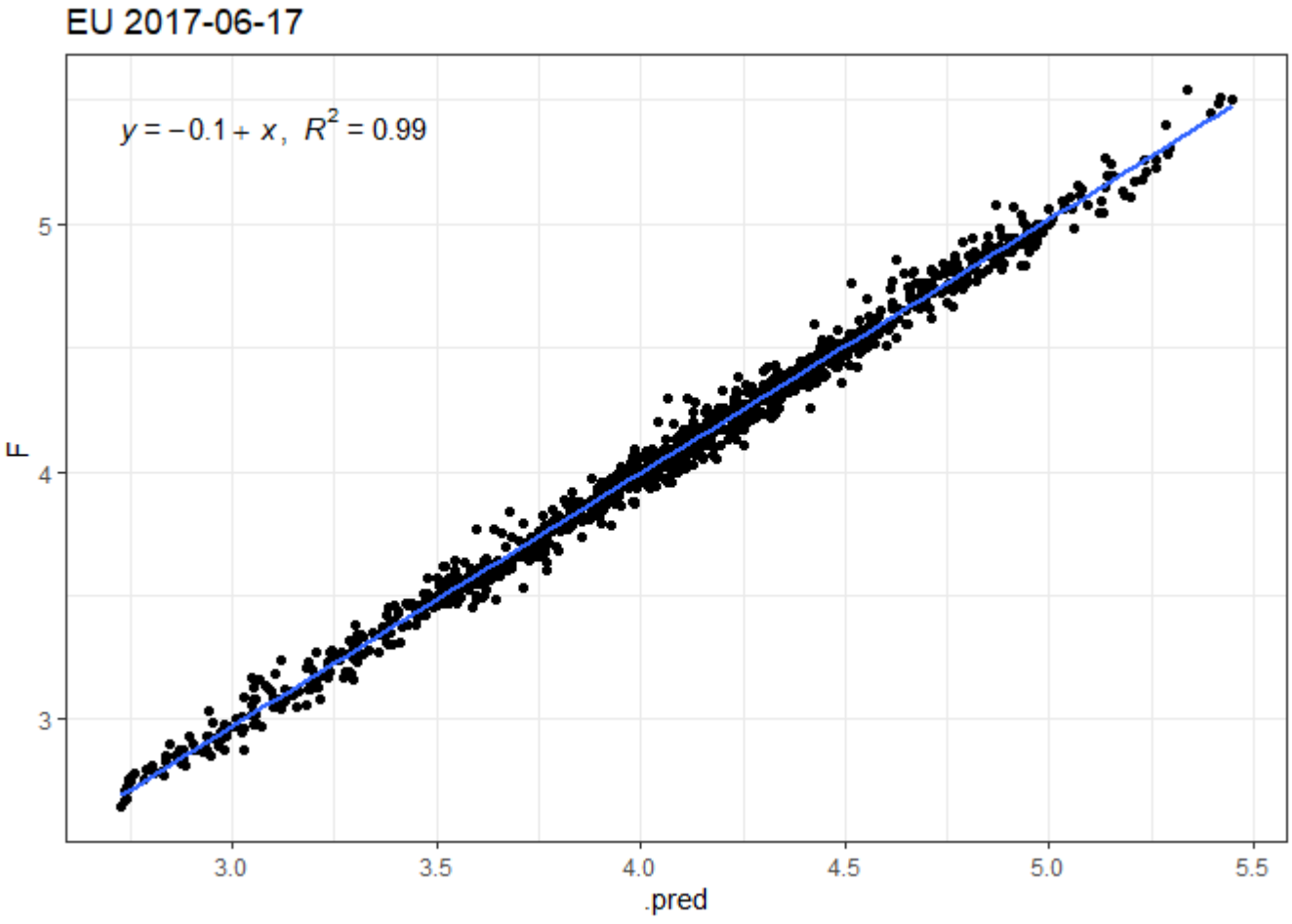

Cost-Complexity Parameter (log-10)
Minimal Node Size
Tree Depth
rmse
0.140
0.139
0.138
-4.9
-4.8
-4.7
-4.6
-4.5
45
46
47
48
12.0
12.5
13.0
13.5
14.0

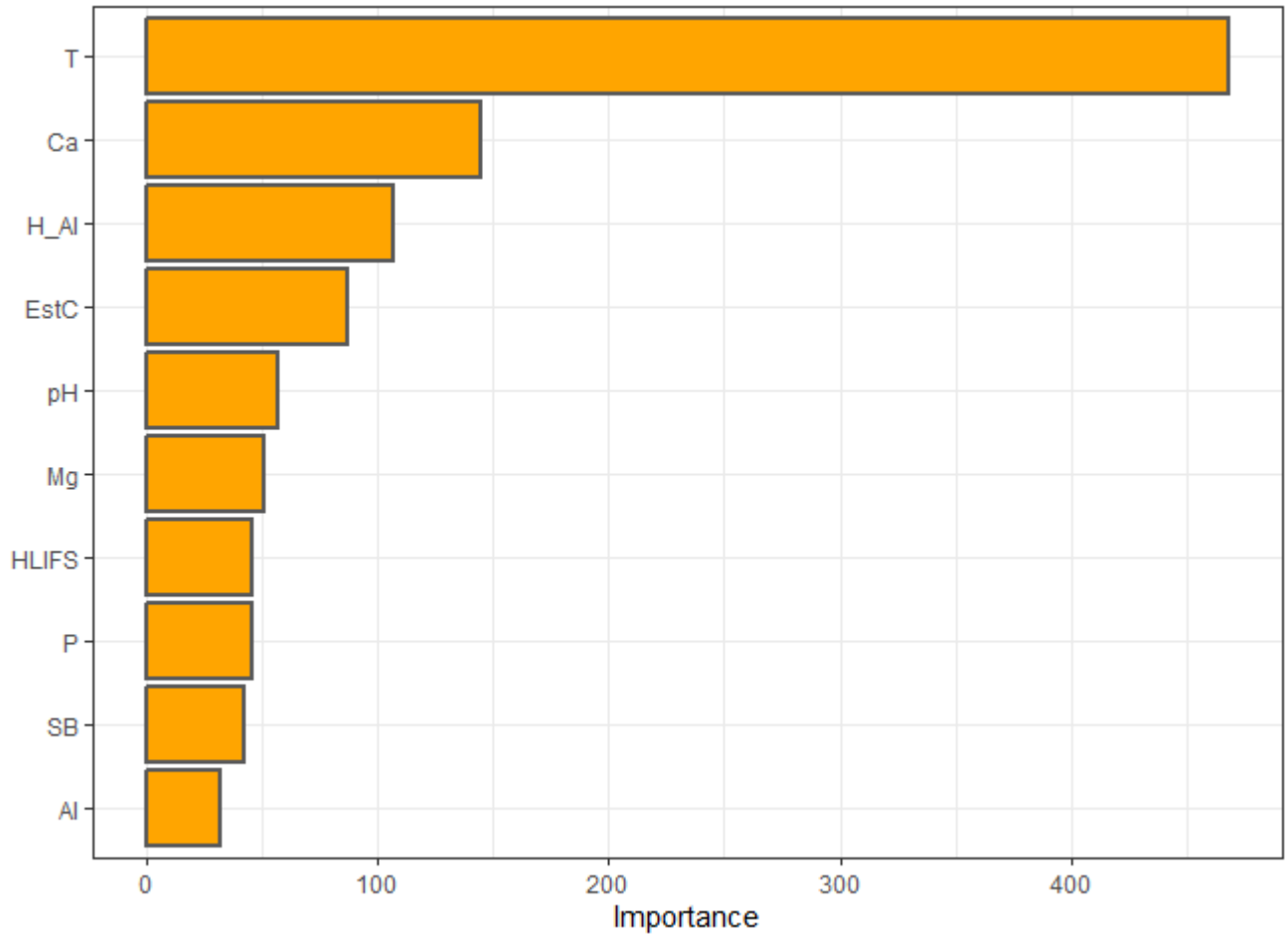

EU 2017-06-17
$y = 0.0093 + x$, $R^2 = 0.96$
F
5
4
3
3.0
3.5
4.0
4.5
5.0
5.5
.pred




```
#>      vector_of_metrics
#> r           0.98229706
#> R2          0.96490752
#> MSE         0.01235039
#> RMSE        0.11113233
#> MAE         0.08195672
#> MAPE        2.04118523
#> [1] "RANDOM FOREST"
```

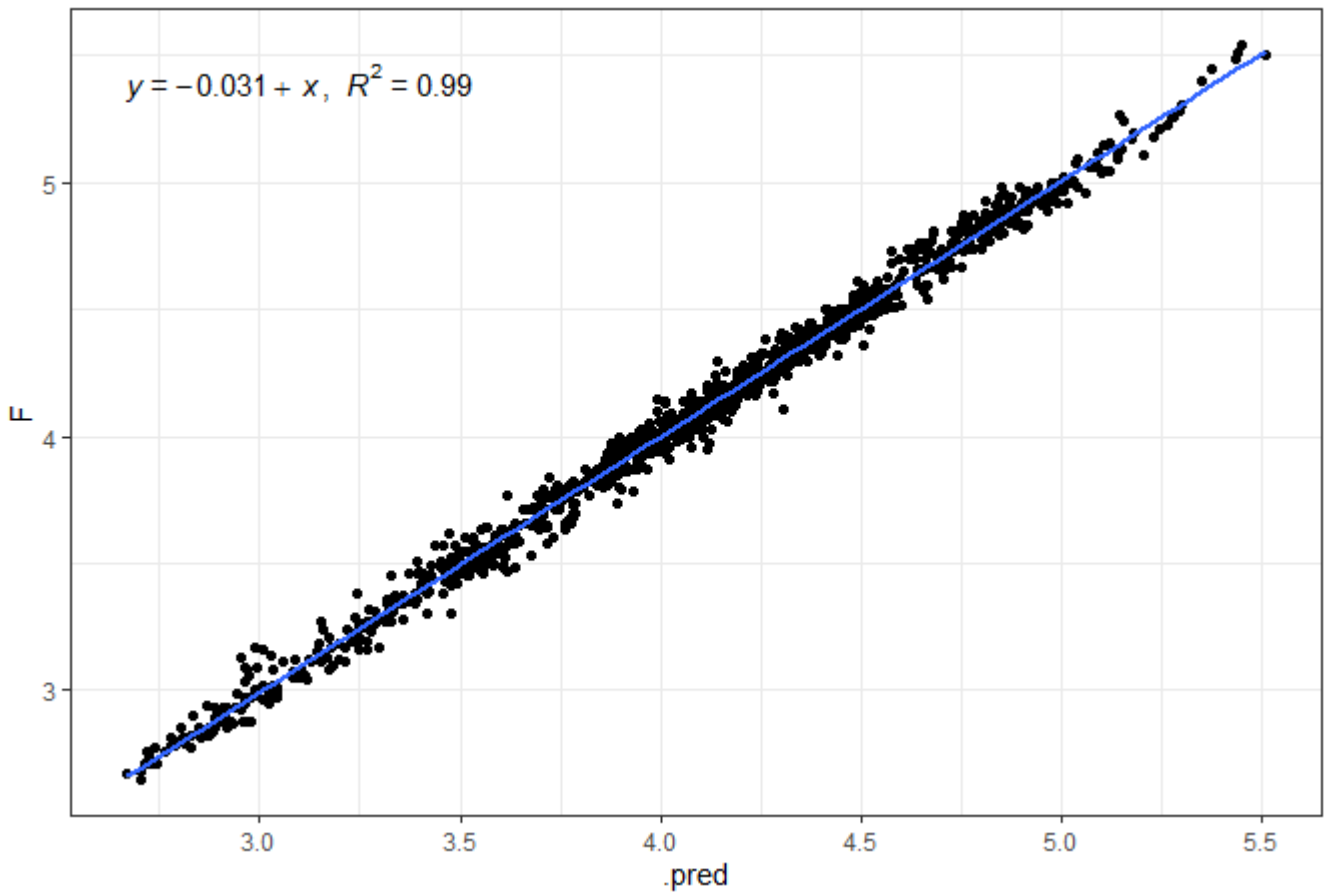

Trees
Minimal Node Size
rmse
0.0680
0.0675
0.0670
0.0665
0.0660
0.0655
300
350
400
22
23
24
25

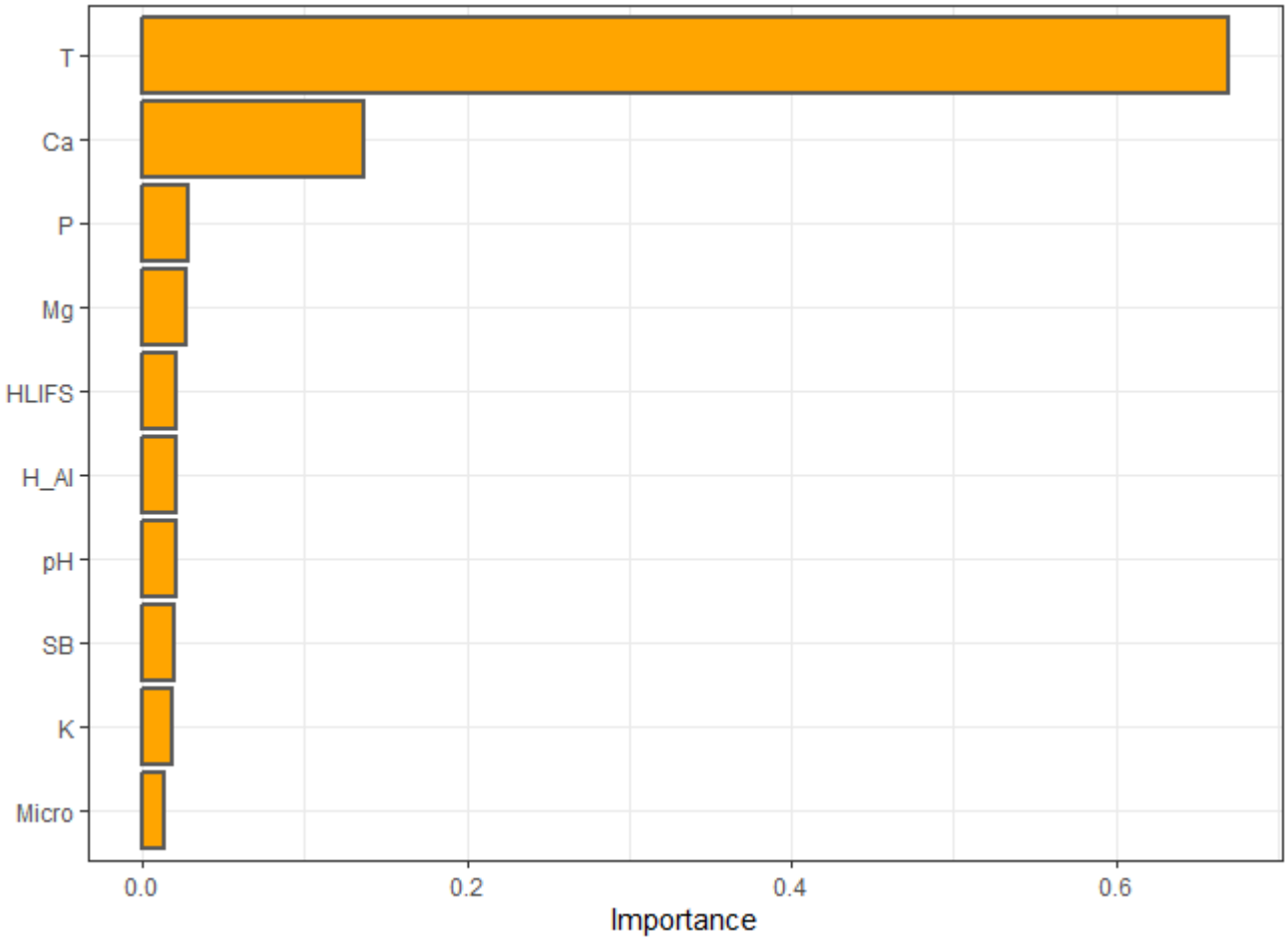

EU 2017-06-17
$y = -0.1 + x,\ R^2 = 0.99$
F
5
4
3
3.0
3.5
4.0
4.5
5.0
5.5
.pred



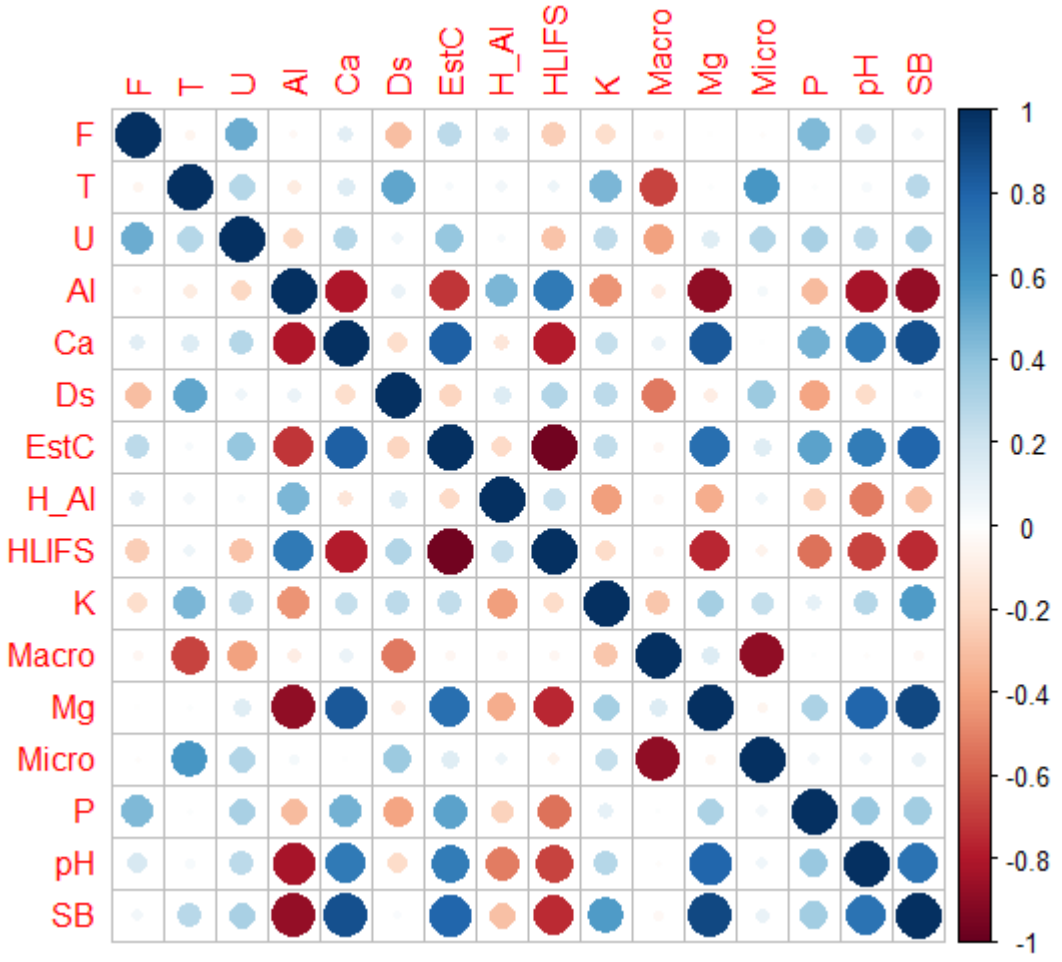

```
#>      vector_of_metrics
#> r           0.996033575
#> R2          0.992082882
#> MSE         0.002989187
#> RMSE        0.054673458
#> MAE         0.041105743
#> MAPE        1.029433203
```

EU 2017-06-17

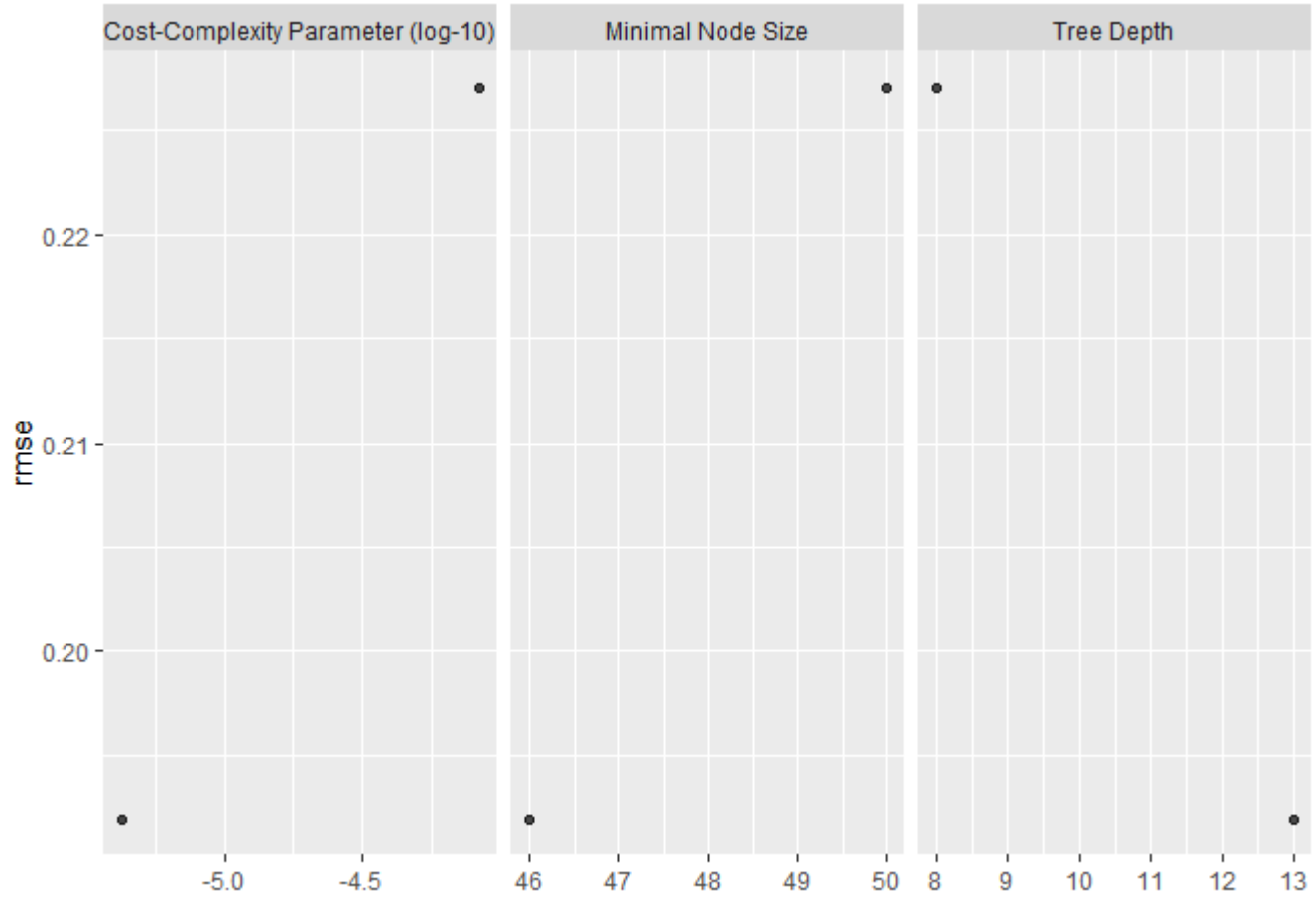

$y = -0.031 + x,\ R^2 = 0.99$
F
5
4
3
3.0
3.5
4.0
4.5
5.0
5.5
.pred

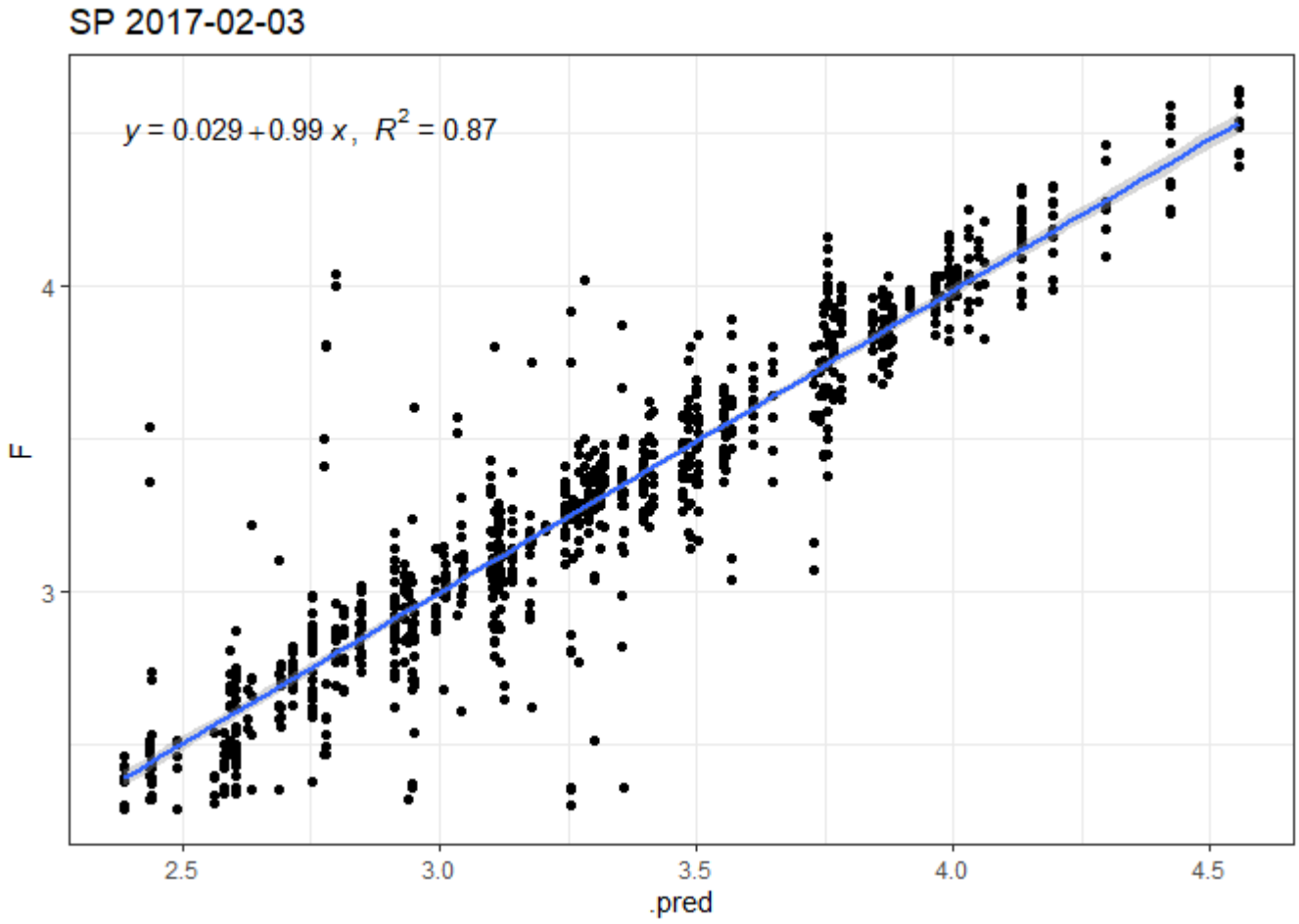

T
Ca
P
Mg
HLIFS
H_Al
pH
SB
K
Micro
0.0
0.2
0.4
0.6
Importance

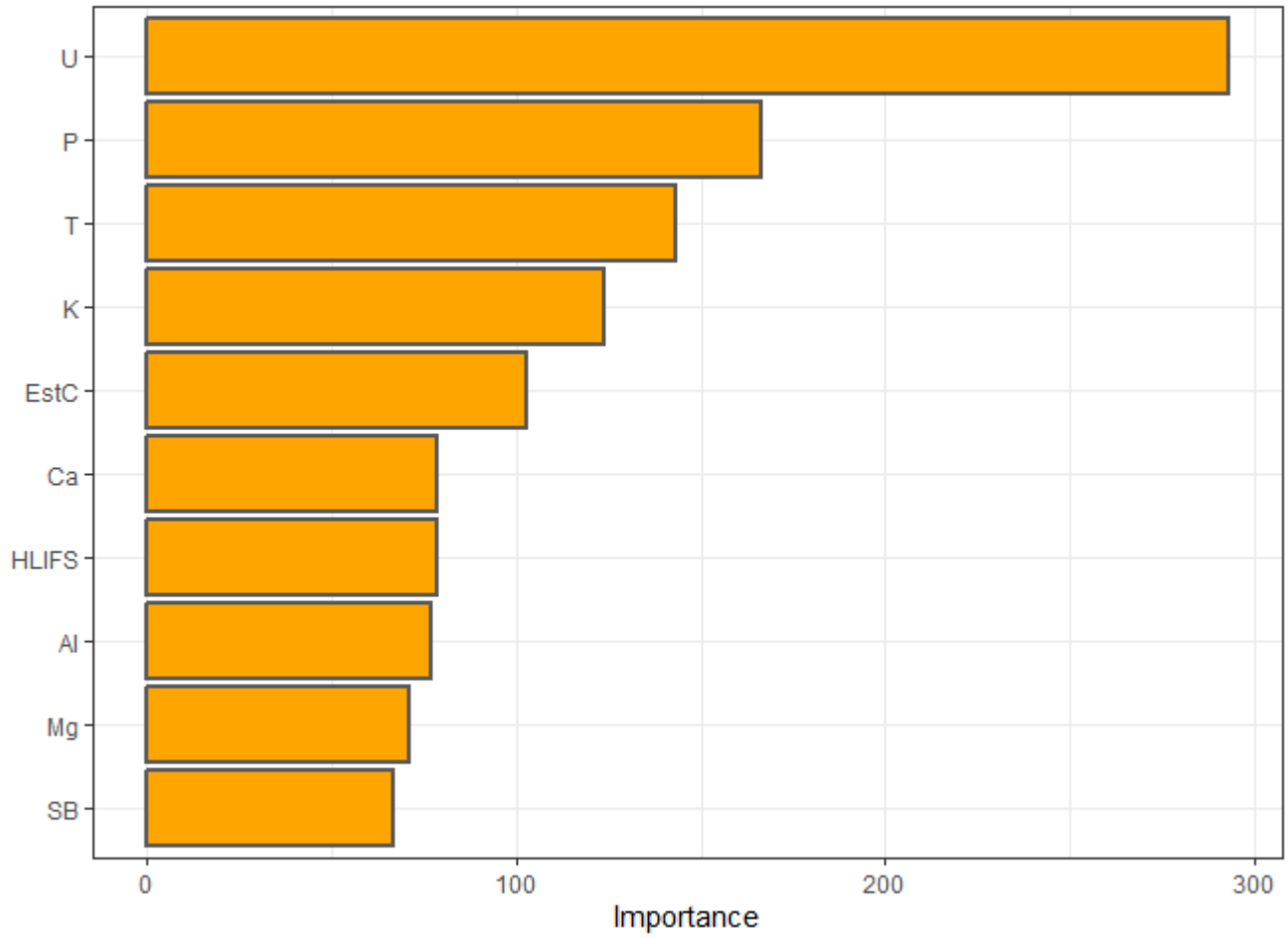
```
#>       vector_of_metrics
#> r           0.996101802
#> R2          0.992218799
#> MSE         0.002757562
#> RMSE        0.052512497
#> MAE         0.040387739
#> MAPE        1.016460934
```



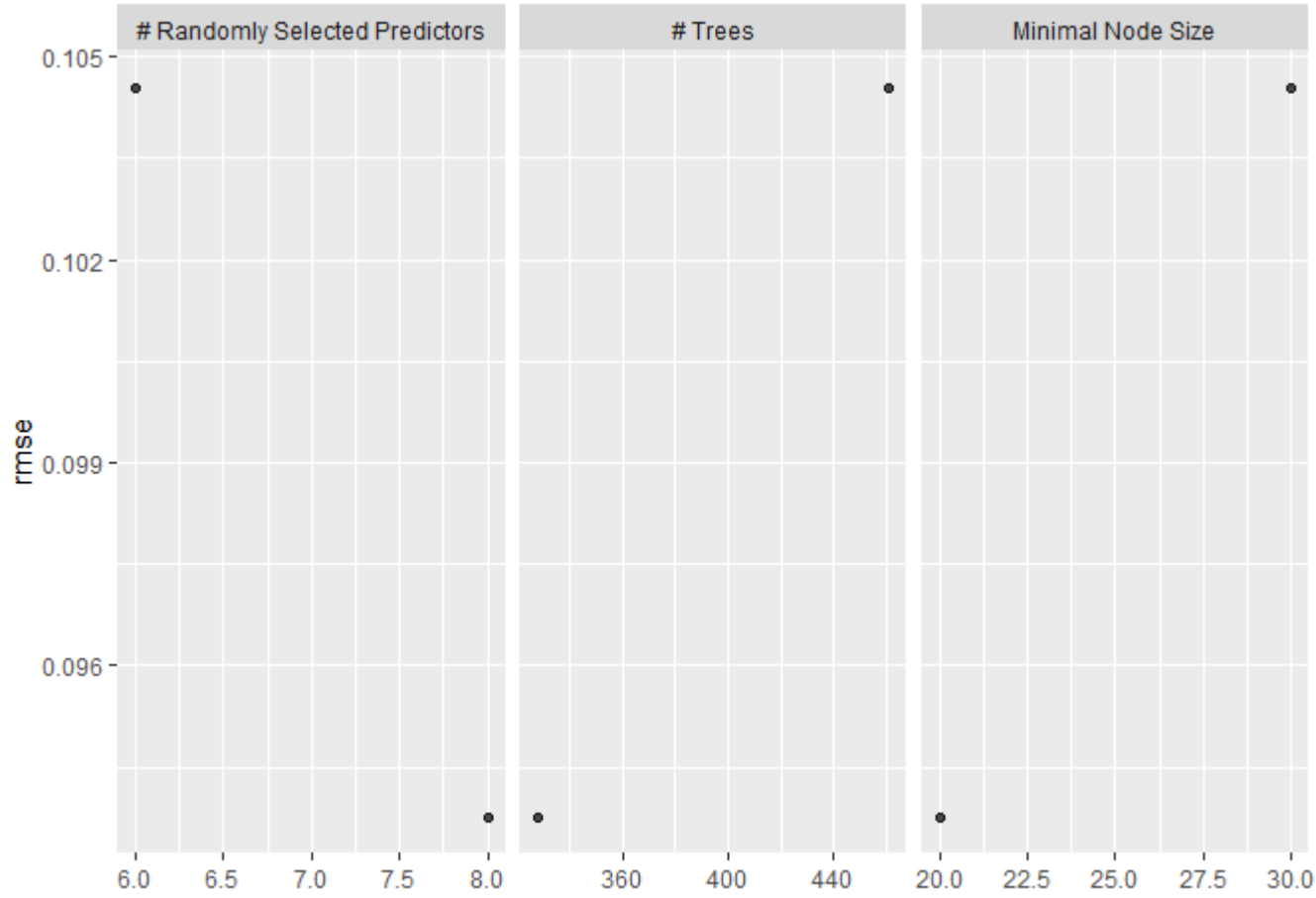

```
#> [1] "ARVORE DE DECISÃO"
```

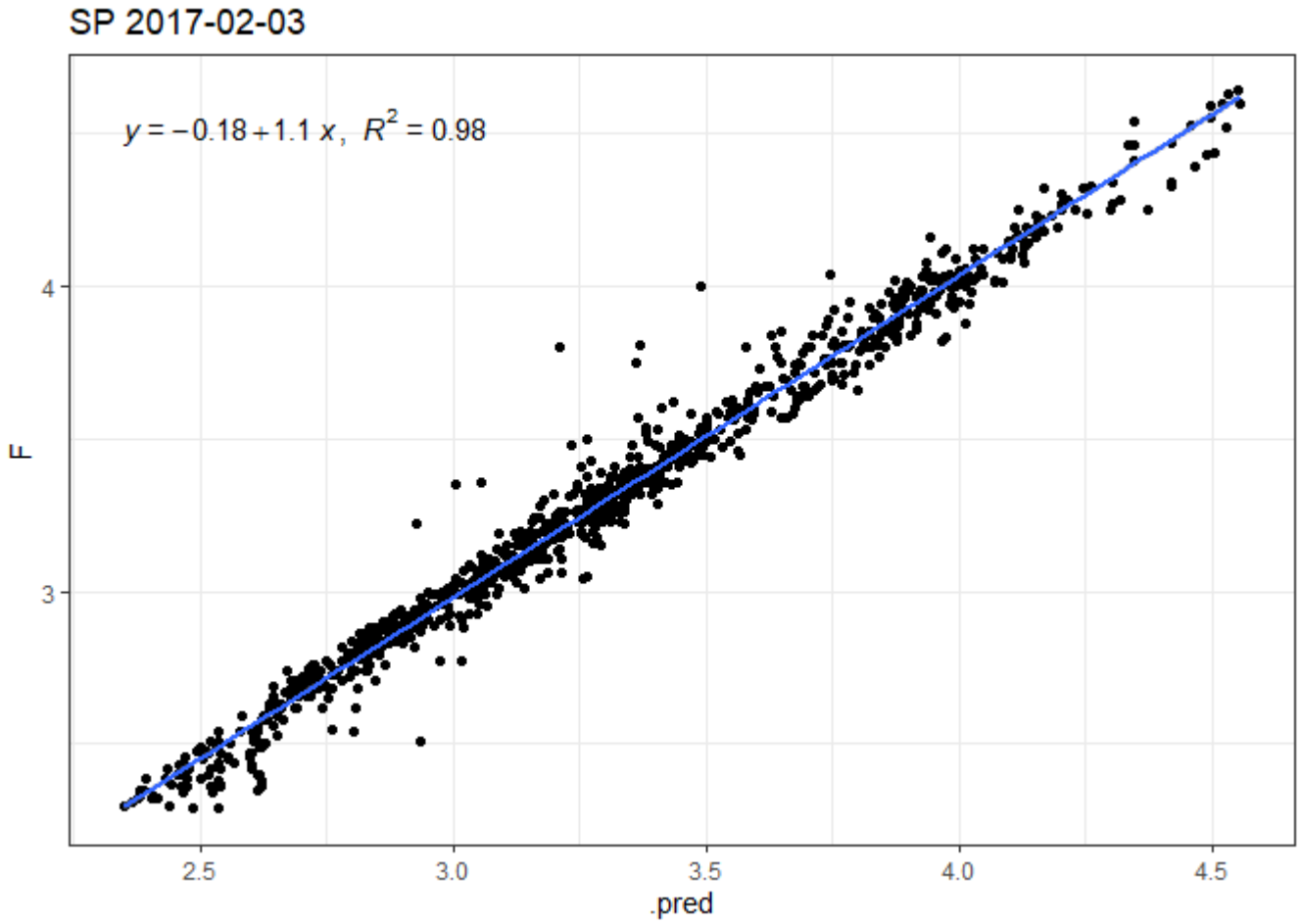

Cost-Complexity Parameter (log-10)
Minimal Node Size
Tree Depth
rmse
0.22
0.21
0.20
-5.0
-4.5
46
47
48
49
50
8
9
10
11
12
13

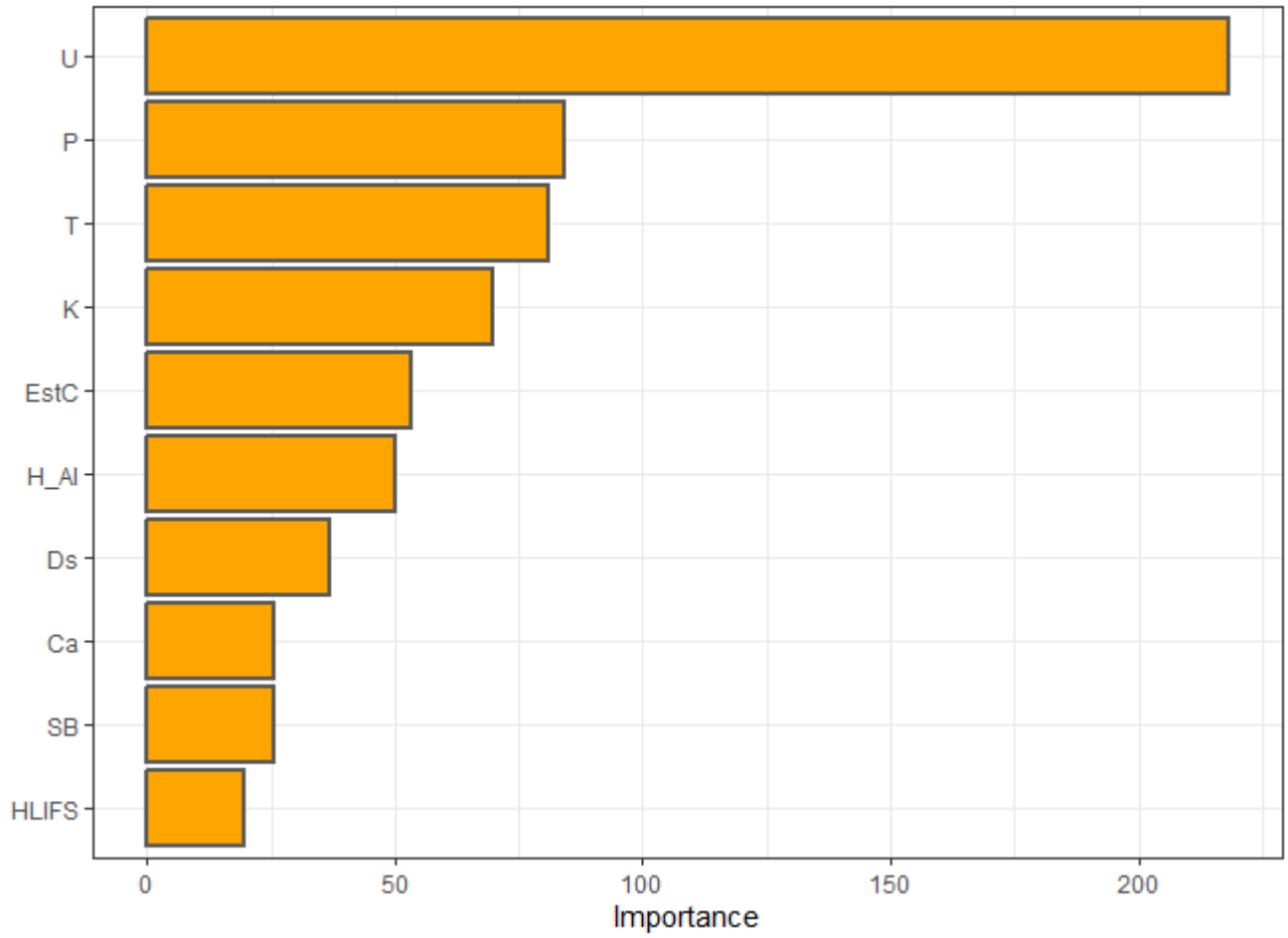

SP 2017-02-03
$y = 0.029 + 0.99\,x$, $R^2 = 0.87$
F
4
3
2.5
3.0
3.5
4.0
4.5
.pred



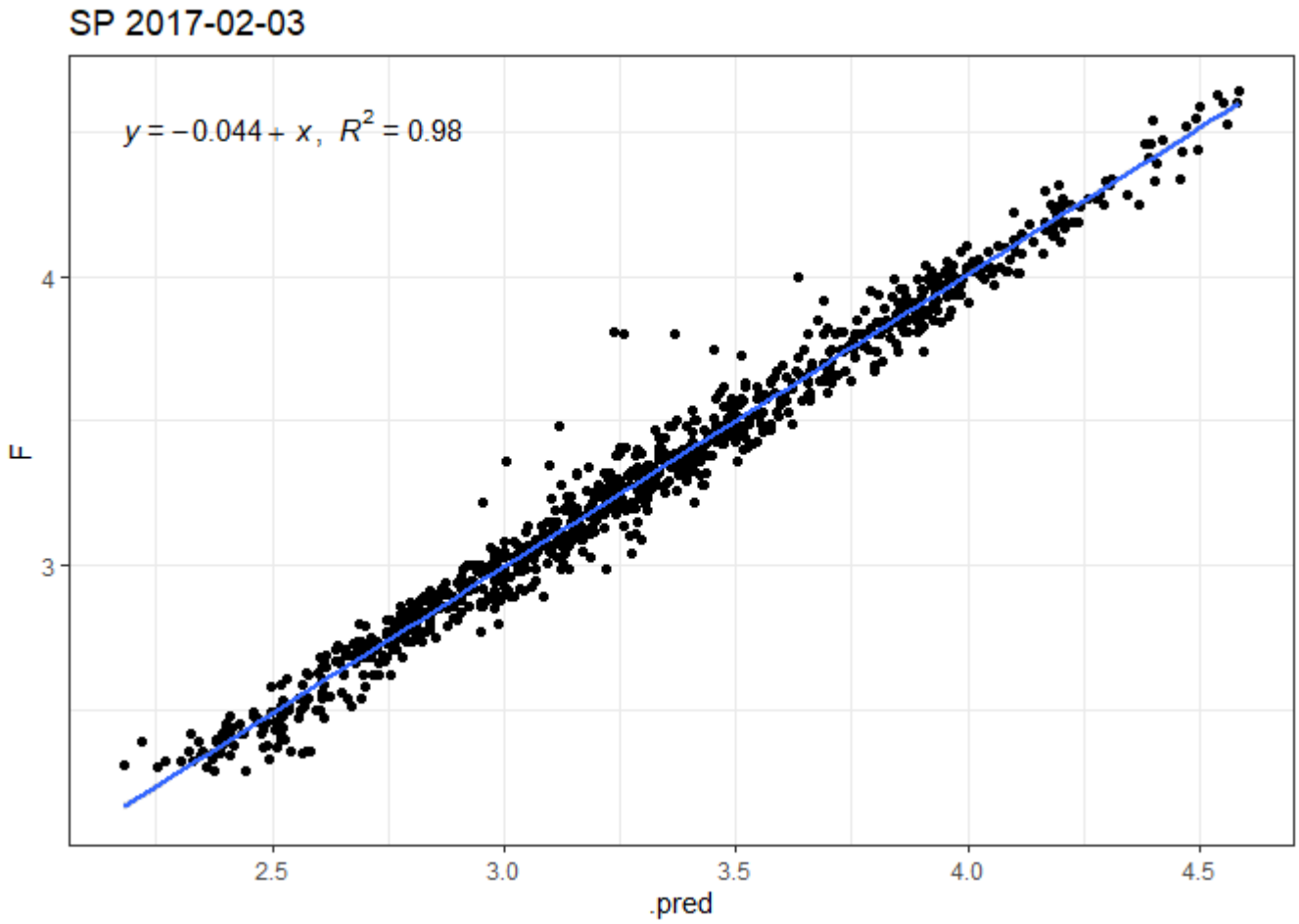

```
#>      vector_of_metrics
#> r           0.93147838
#> R2          0.86765196
#> MSE         0.03685642
#> RMSE        0.19198027
#> MAE         0.11962073
#> MAPE        3.78623359
#> [1] "RANDOM FOREST"
```

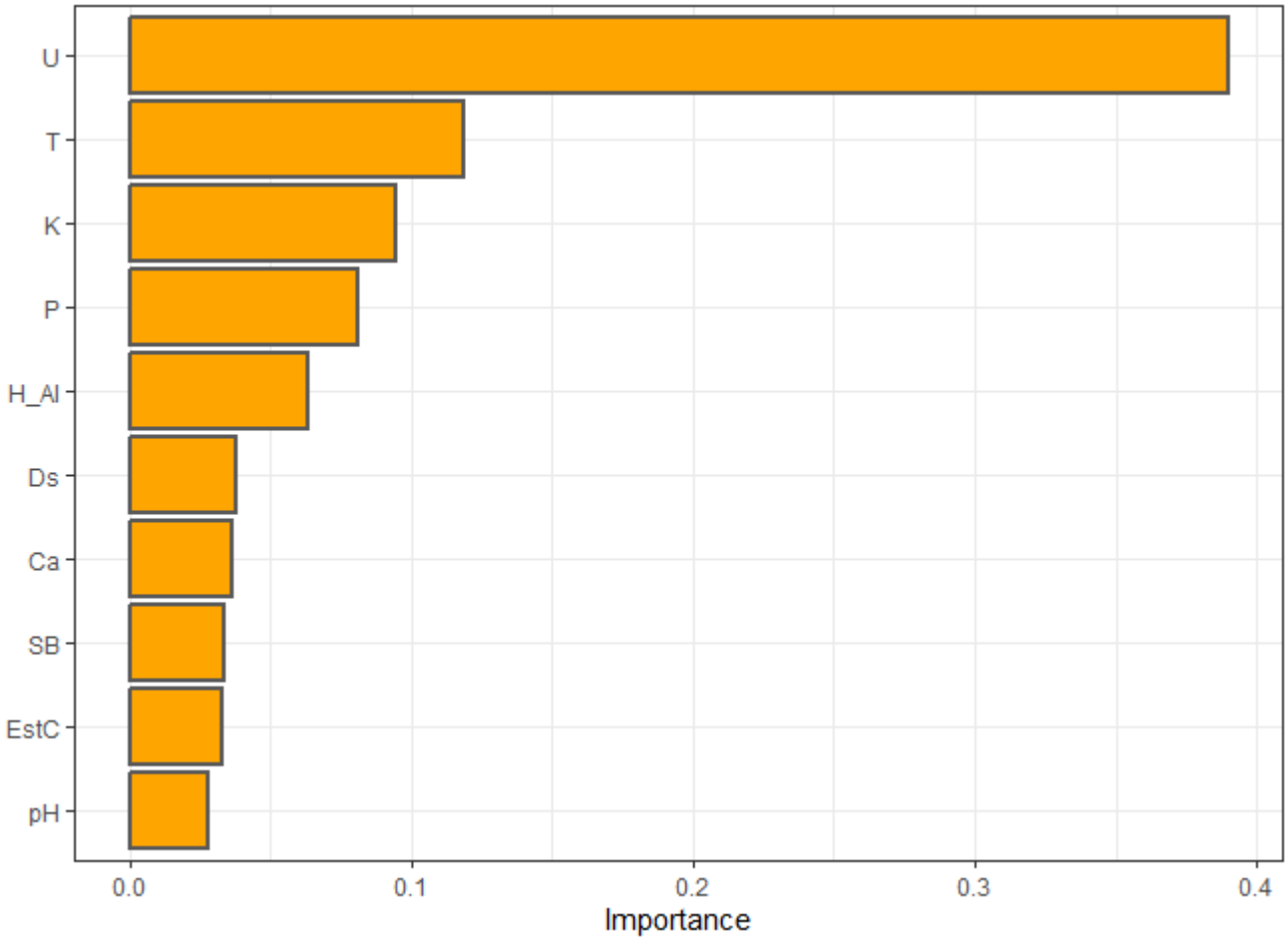

Randomly Selected Predictors
Trees
Minimal Node Size
rmse
0.105
0.102
0.099
0.096
6.0
6.5
7.0
7.5
8.0
360
400
440
20.0
22.5
25.0
27.5
30.0


SP 2017-02-03
$y = -0.18 + 1.1\,x,\ R^2 = 0.98$
F
4
3
2.5
3.0
3.5
4.0
4.5
.pred

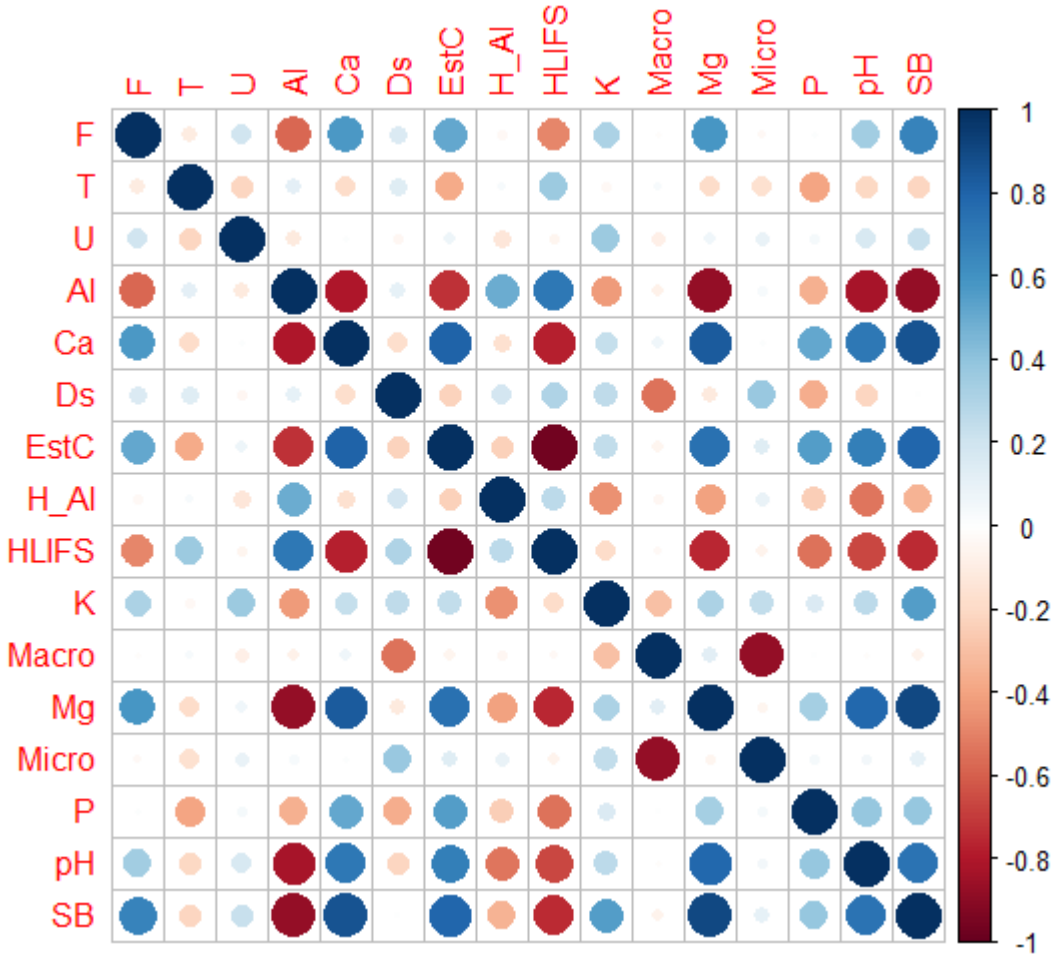



```
#>      vector_of_metrics
#> r          0.990131587
#> R2         0.980360560
#> MSE        0.006195856
#> RMSE       0.078713759
#> MAE        0.053432289
#> MAPE       1.674756432
```

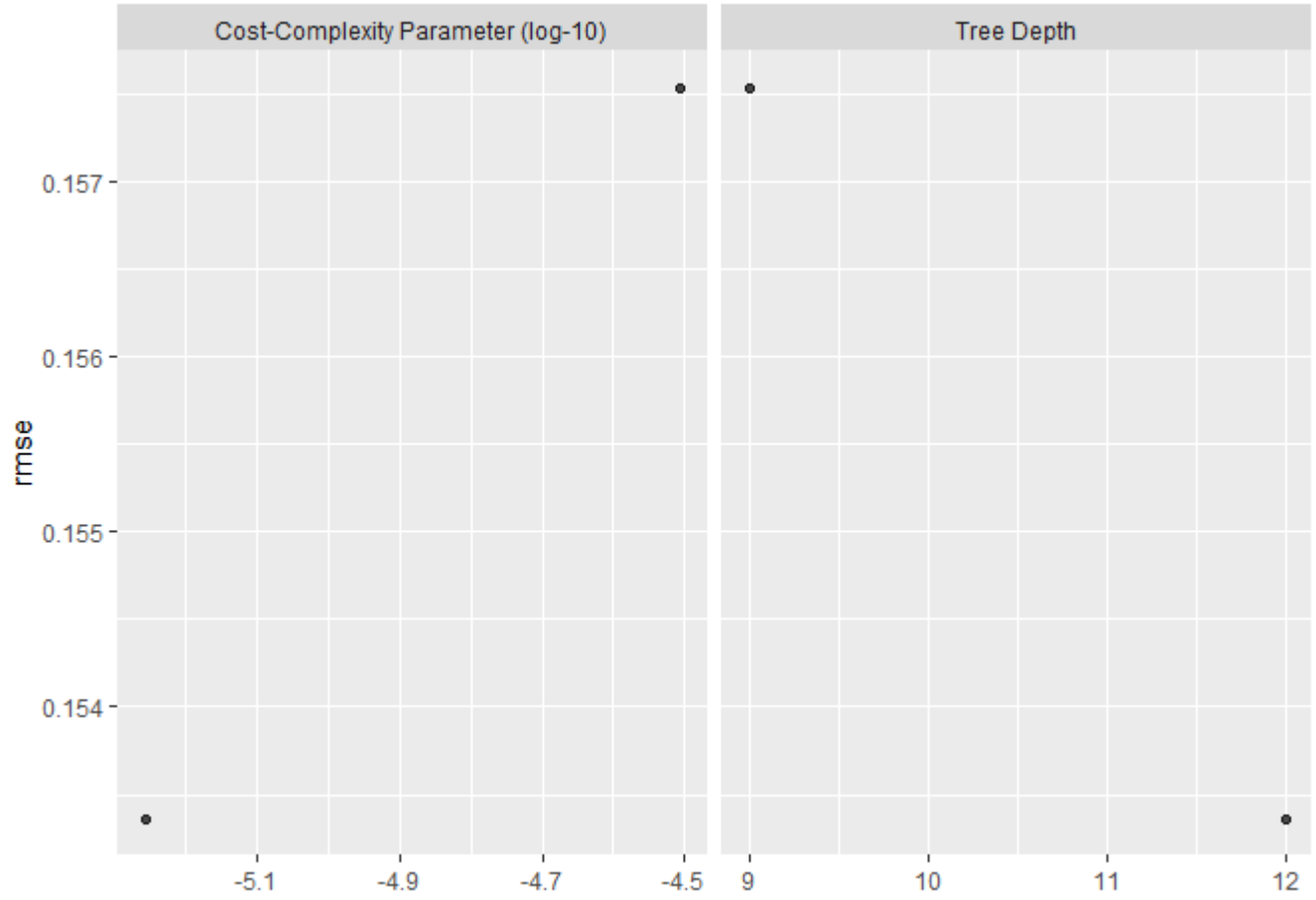

SP 2017-02-03
$y = -0.044 + x,\ R^2 = 0.98$
F
4
3
2.5
3.0
3.5
4.0
4.5
.pred

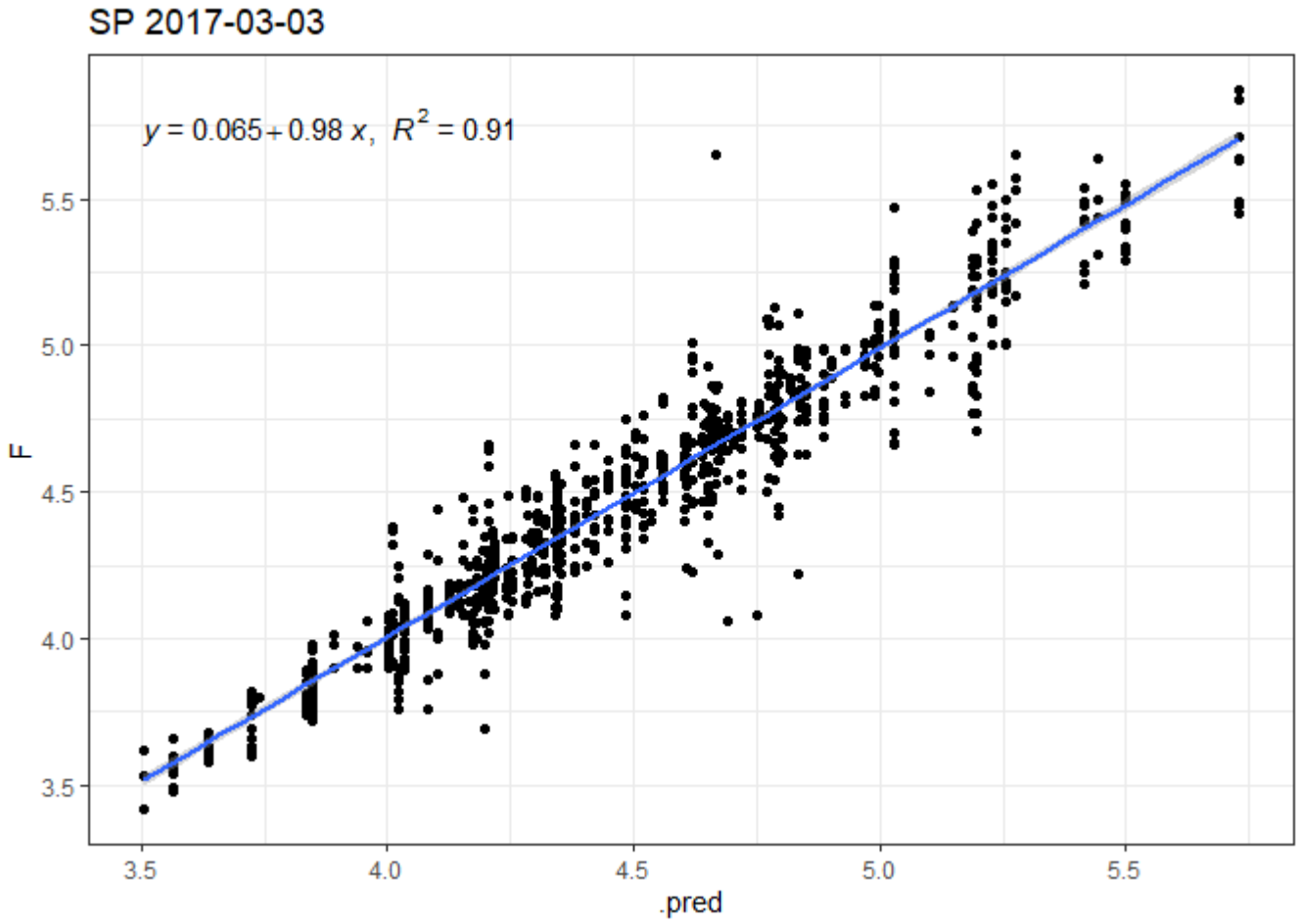

U
T
K
P
H_Al
Ds
Ca
SB
EstC
pH
0.0
0.1
0.2
0.3
0.4
Importance

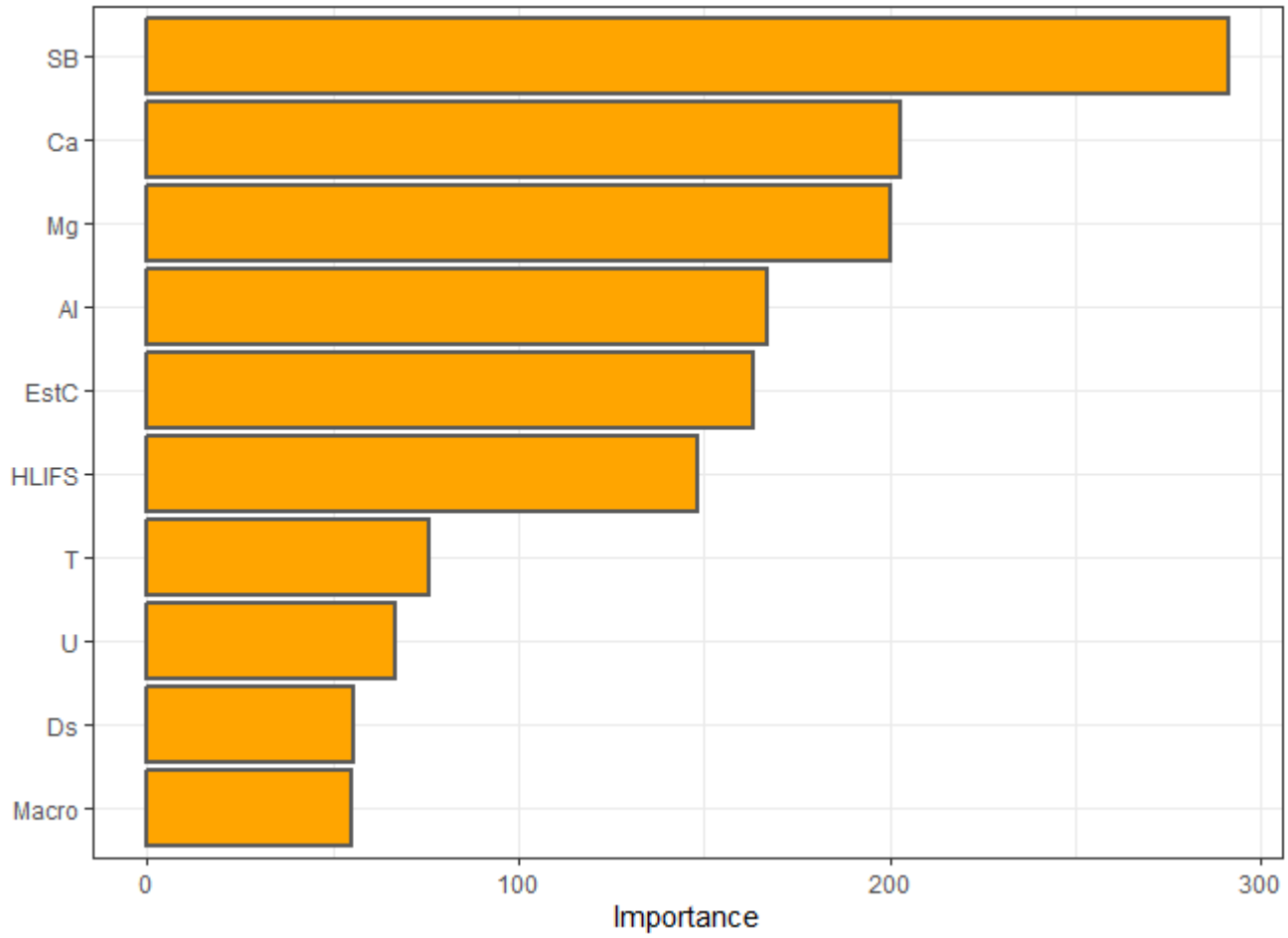
```
#>       vector_of_metrics
#> r           0.989513045
#> R2          0.979136066
#> MSE         0.005846852
#> RMSE        0.076464709
#> MAE         0.054457030
#> MAPE        1.694230862
```



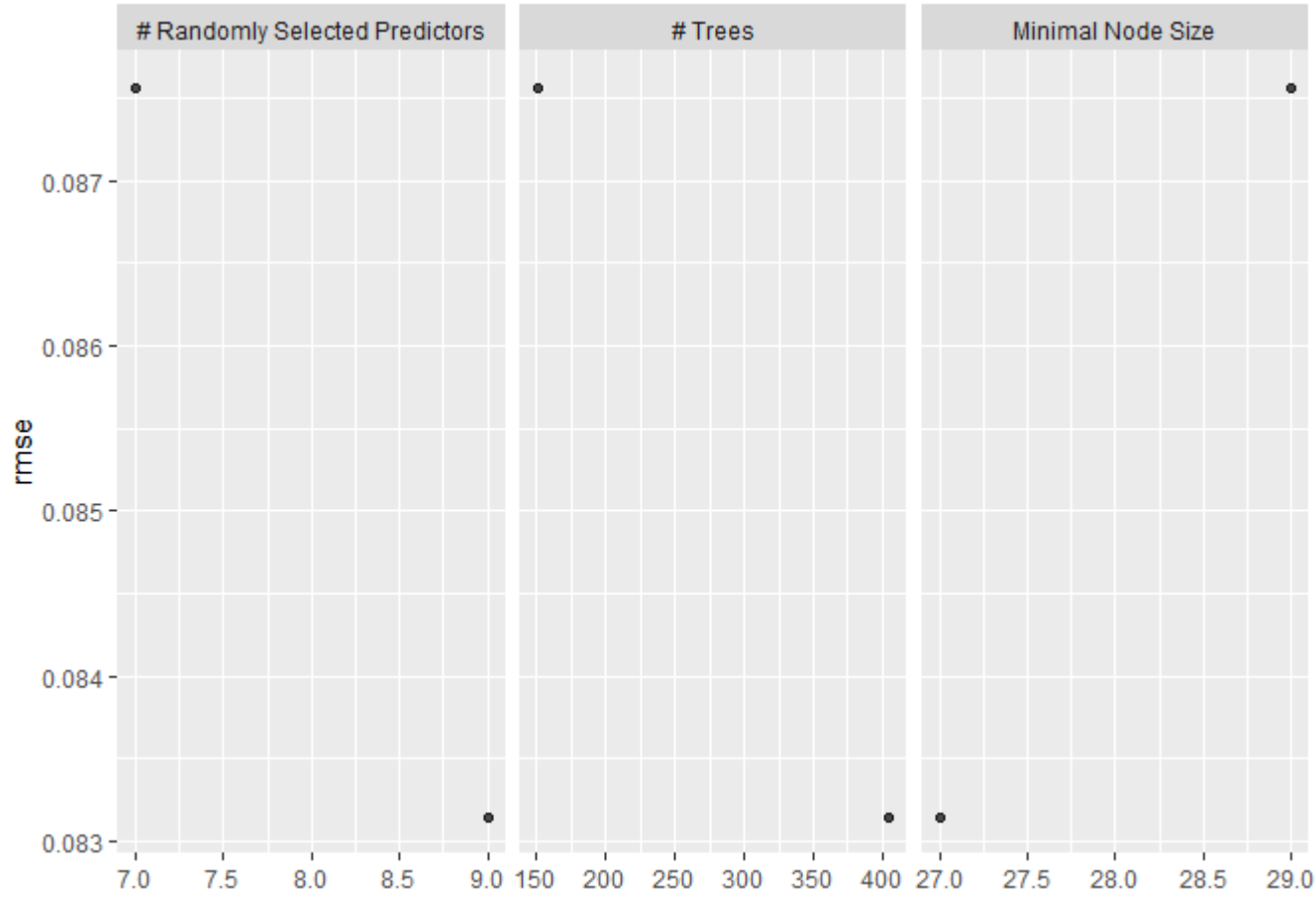

```
#> [1] "ARVORE DE DECISÃO"
```

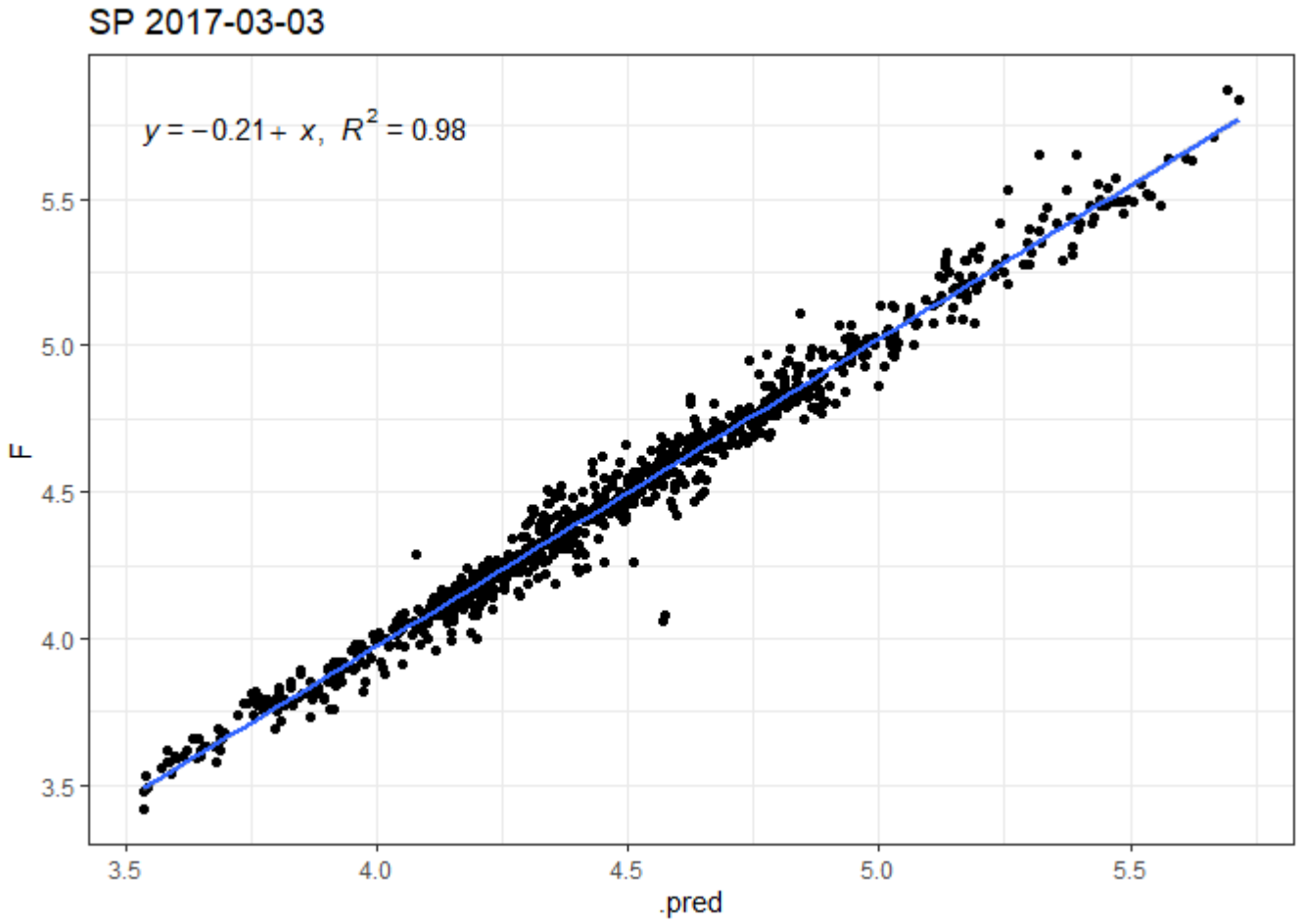

Cost-Complexity Parameter (log-10)
Tree Depth
rmse
0.157
0.156
0.155
0.154
-5.1
-4.9
-4.7
-4.5
9
10
11
12

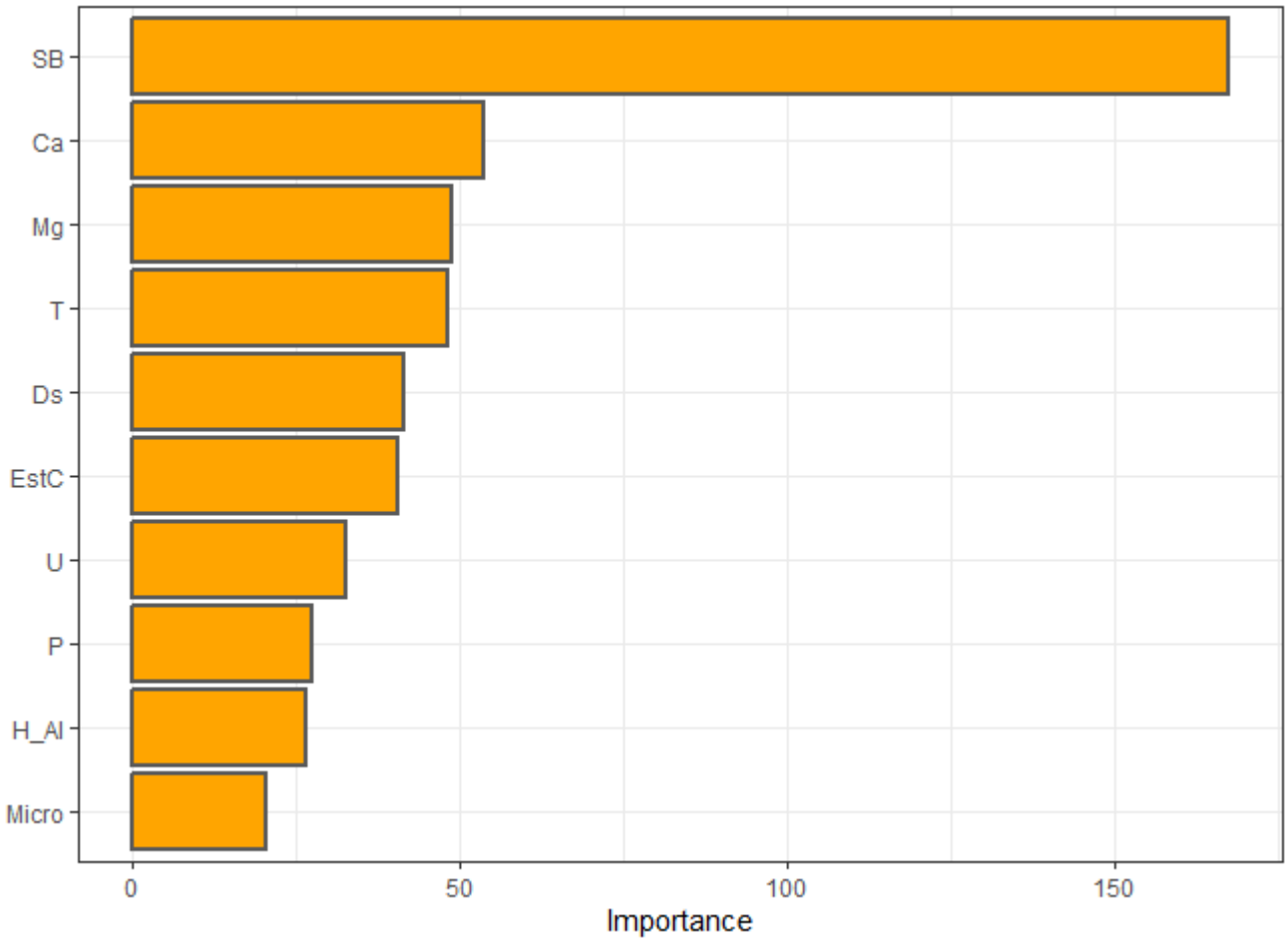

SP 2017-03-03
$y = 0.065 + 0.98\,x,\ R^2 = 0.91$
F
.pred
5.5
5.0
4.5
4.0
3.5
3.5
4.0
4.5
5.0
5.5



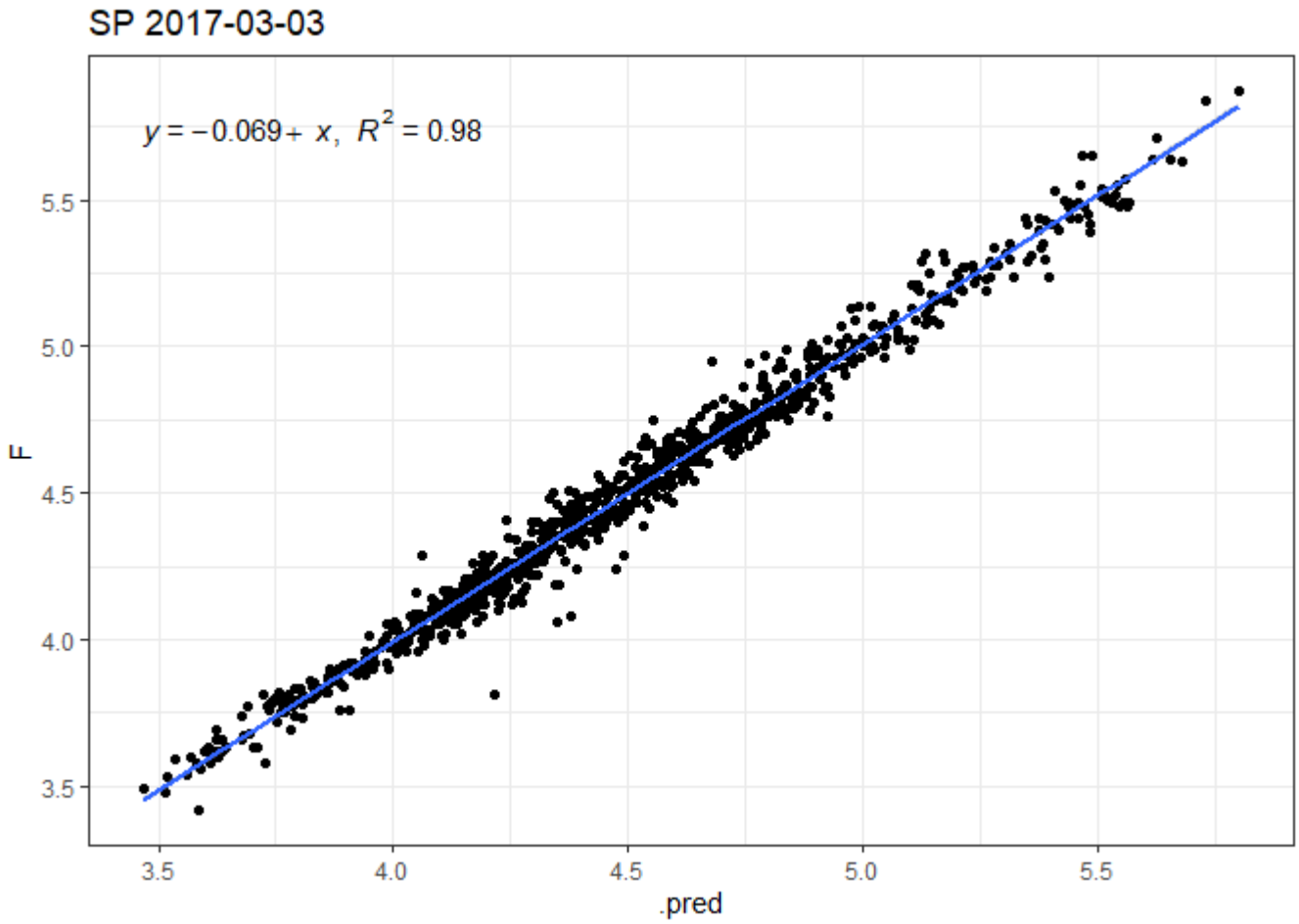

```
#>      vector_of_metrics
#> r           0.95489870
#> R2          0.91183152
#> MSE         0.01841117
#> RMSE        0.13568777
#> MAE         0.09467923
#> MAPE        2.09797525
#> [1] "RANDOM FOREST"
```

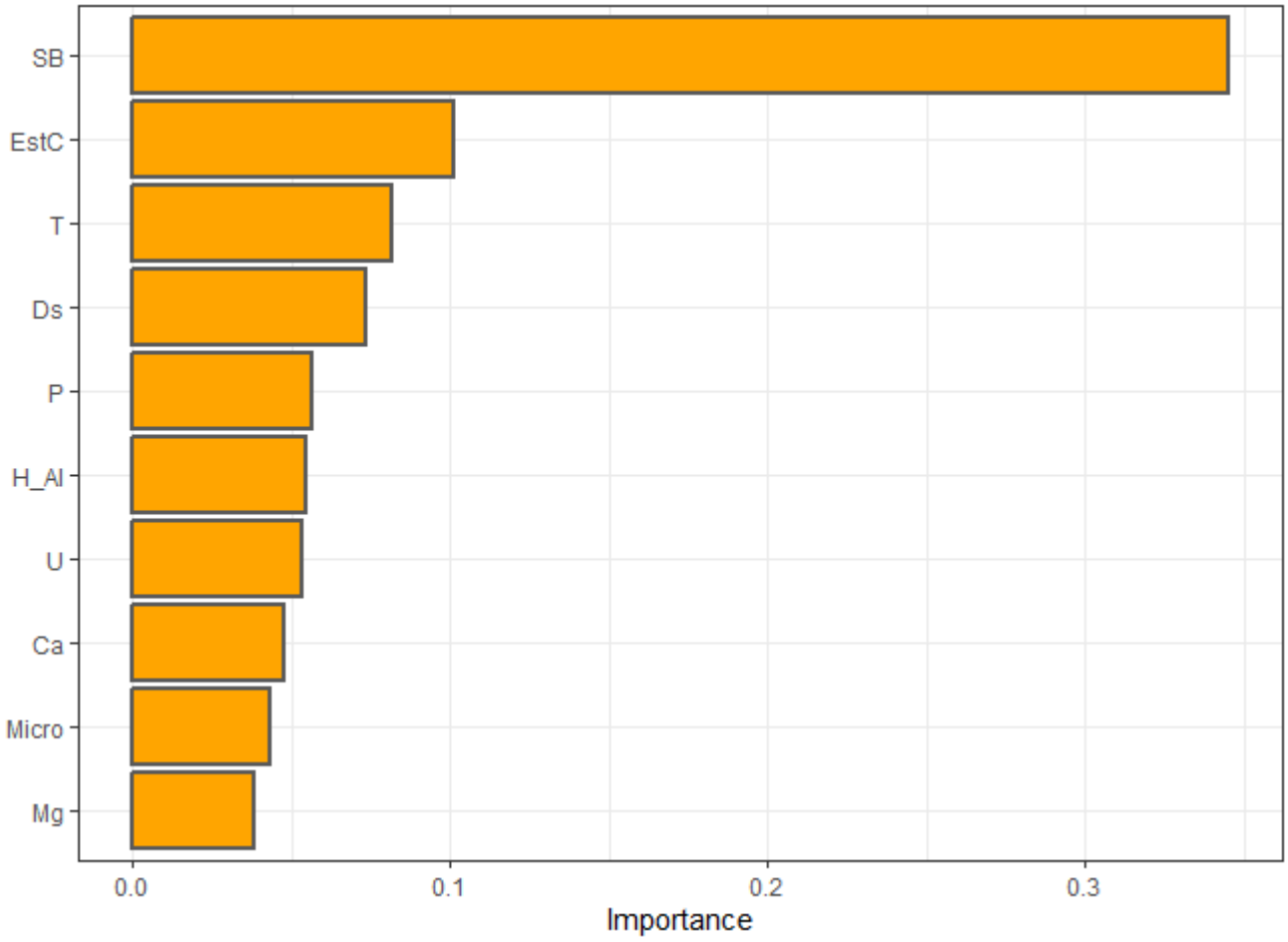

Randomly Selected Predictors
Trees
Minimal Node Size
rmse
0.087
0.086
0.085
0.084
0.083
7.0
7.5
8.0
8.5
9.0
150
200
250
300
350
400
27.0
27.5
28.0
28.5
29.0


SP 2017-03-03
$y = -0.21 + x,\ R^2 = 0.98$
F
5.5
5.0
4.5
4.0
3.5
3.5
4.0
4.5
5.0
5.5
.pred

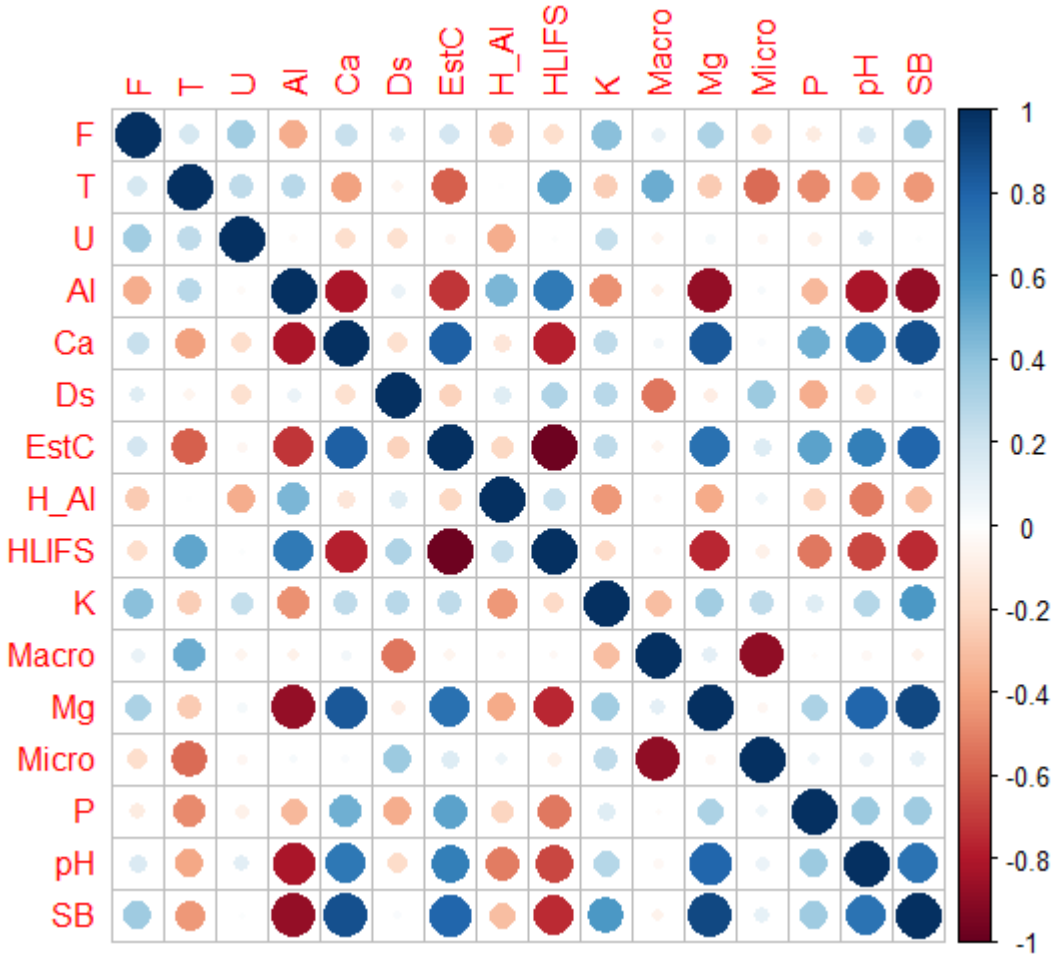



```
#>      vector_of_metrics
#> r           0.989917602
#> R2          0.979936858
#> MSE         0.004595255
#> RMSE        0.067788312
#> MAE         0.047173951
#> MAPE        1.051156636
```

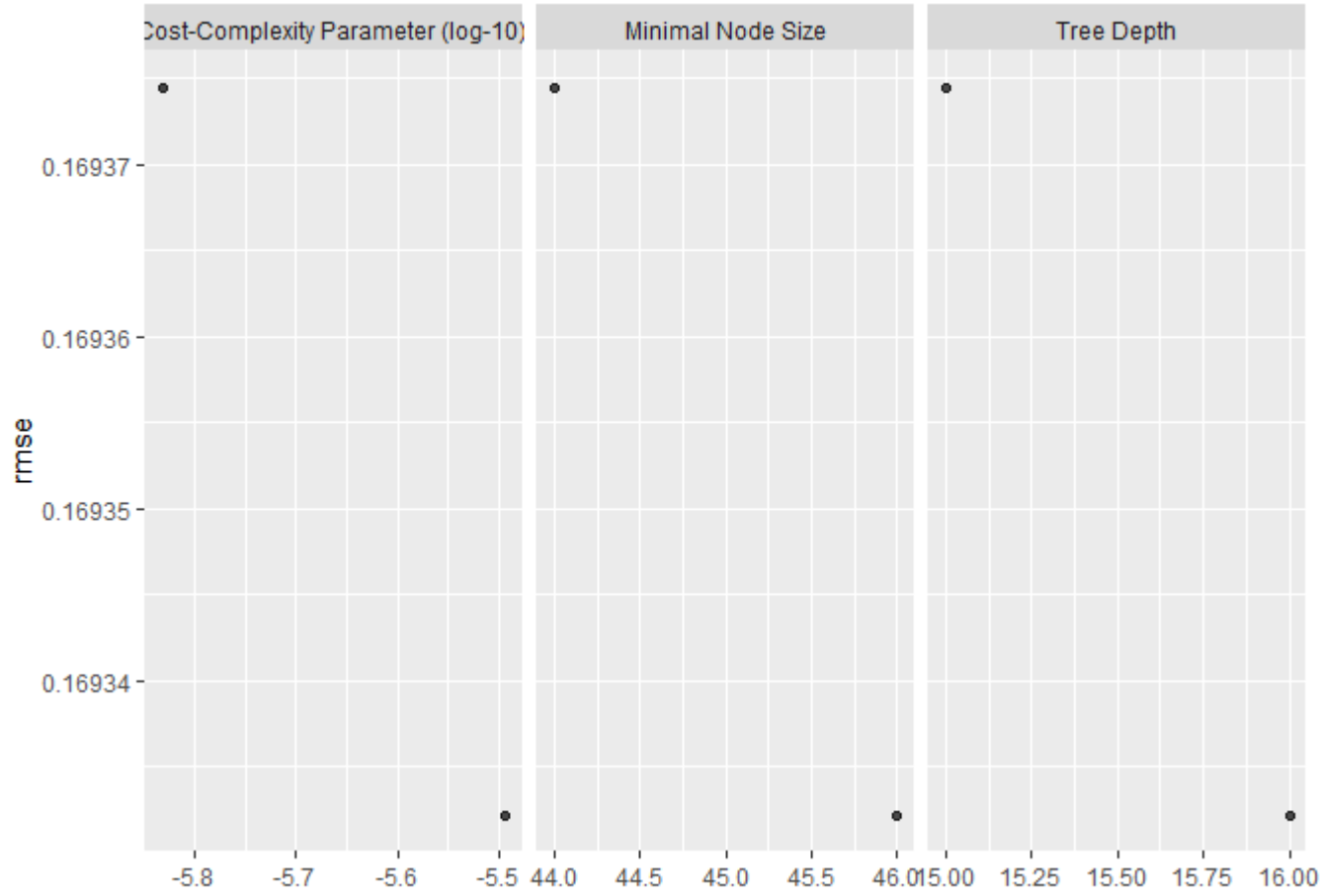

SP 2017-03-03
y = −0.069+ x, R² = 0.98
F
.pred
3.5
4.0
4.5
5.0
5.5

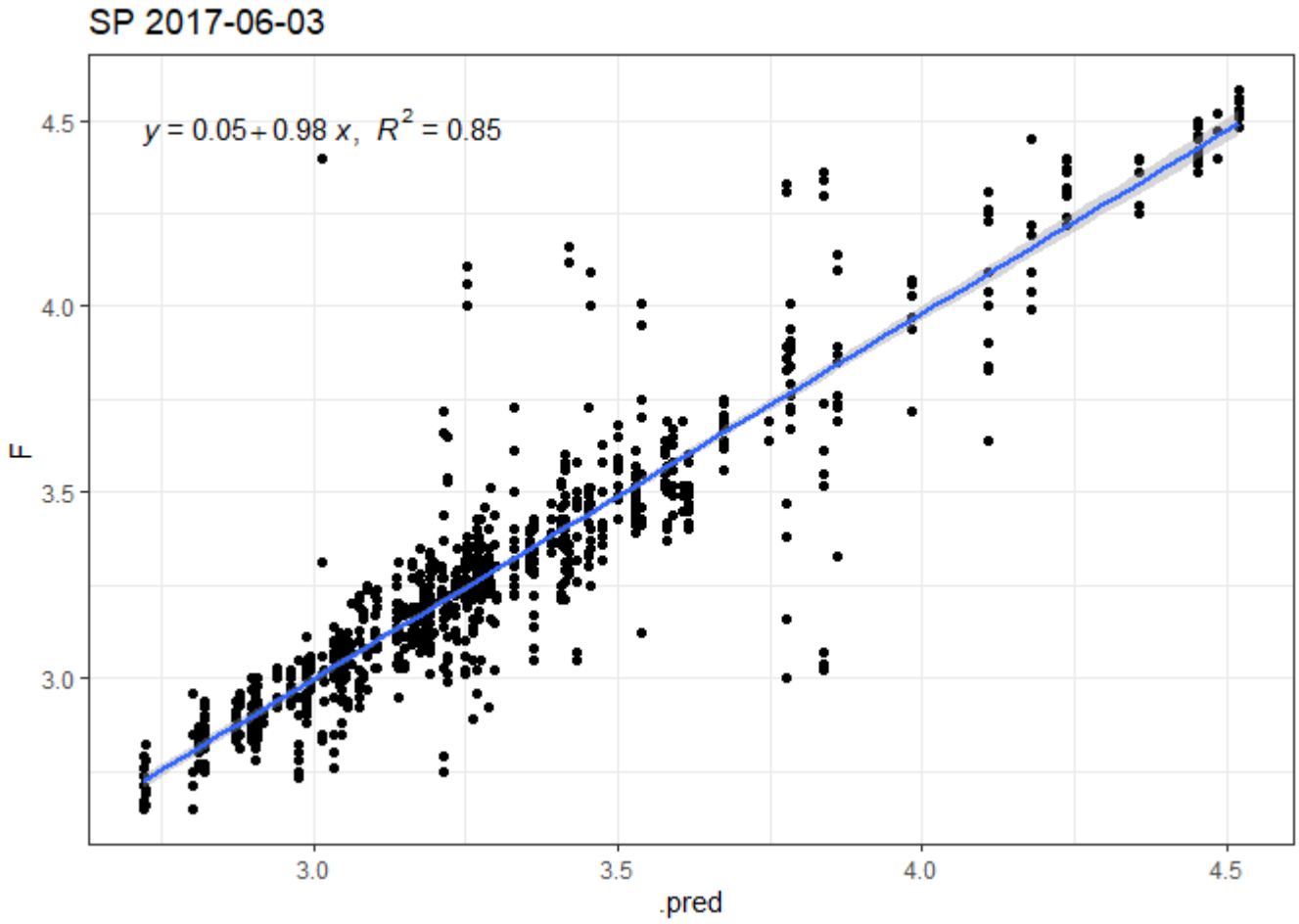

SB
EstC
T
Ds
P
H_Al
U
Ca
Micro
Mg
0.0
0.1
0.2
0.3
Importance

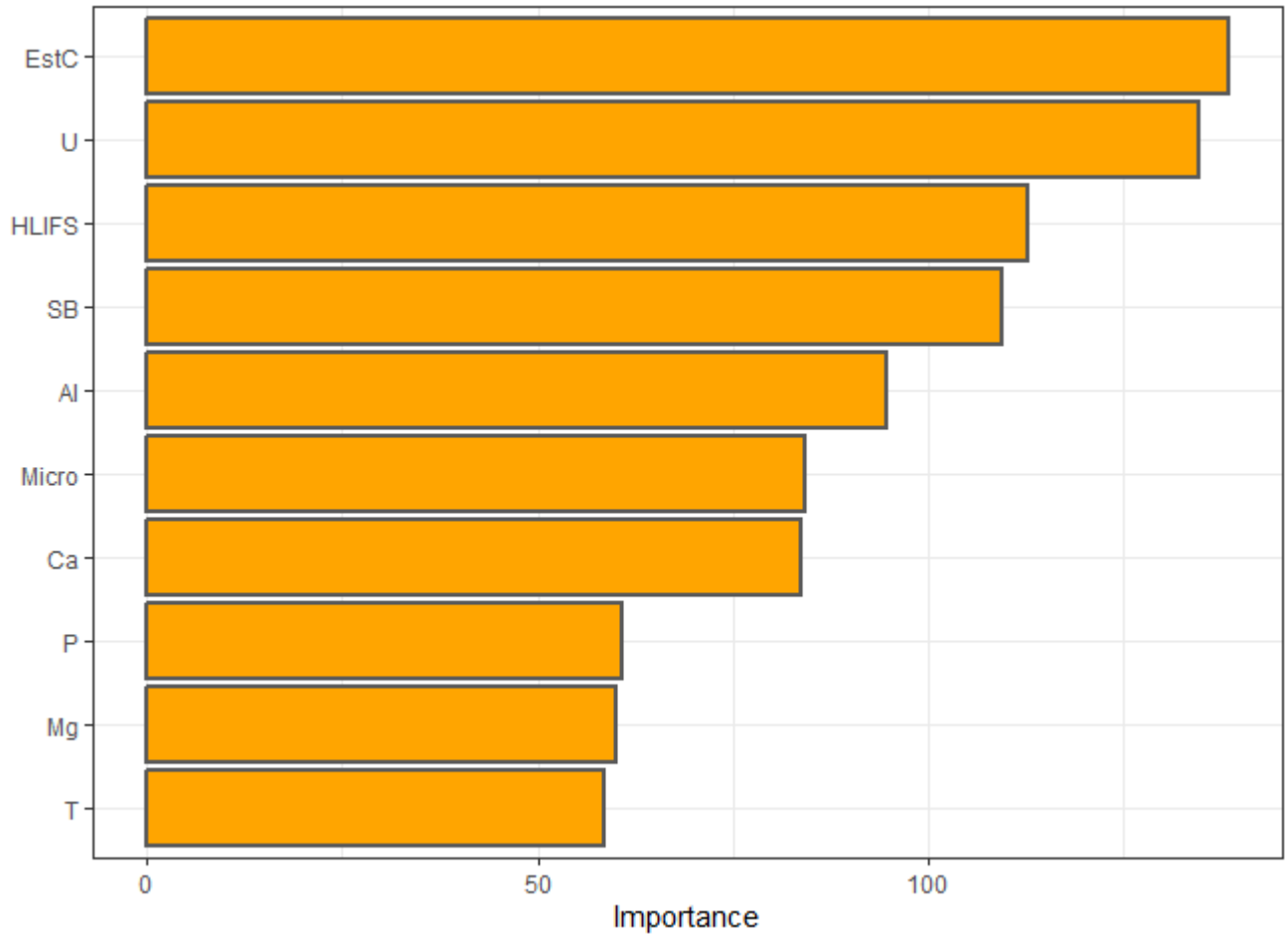
```
#>       vector_of_metrics
#> r           0.991277102
#> R2          0.982630292
#> MSE         0.003663334
#> RMSE        0.060525483
#> MAE         0.044493993
#> MAPE        0.993559371
```



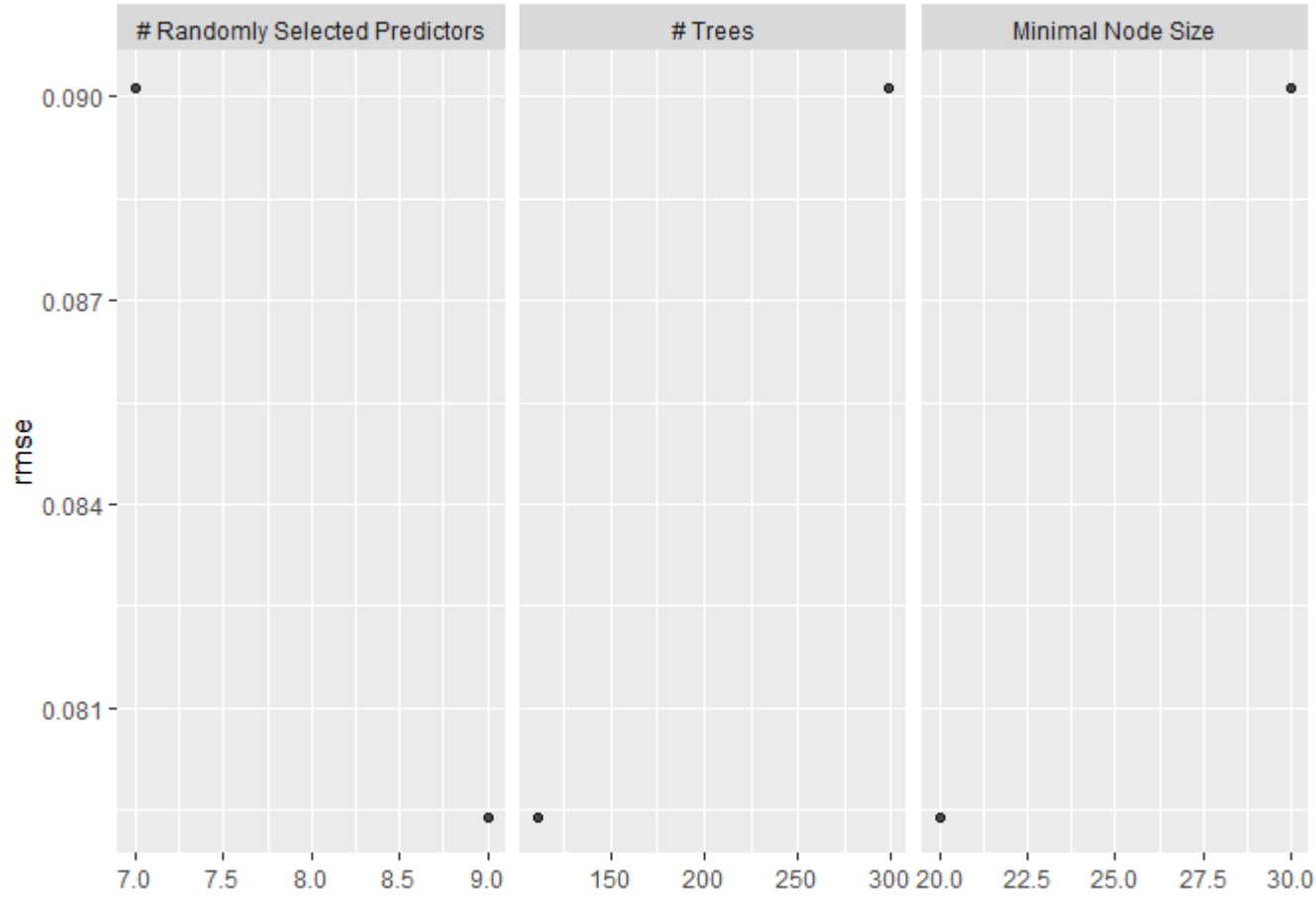

```
#> [1] "ARVORE DE DECISÃO"
```

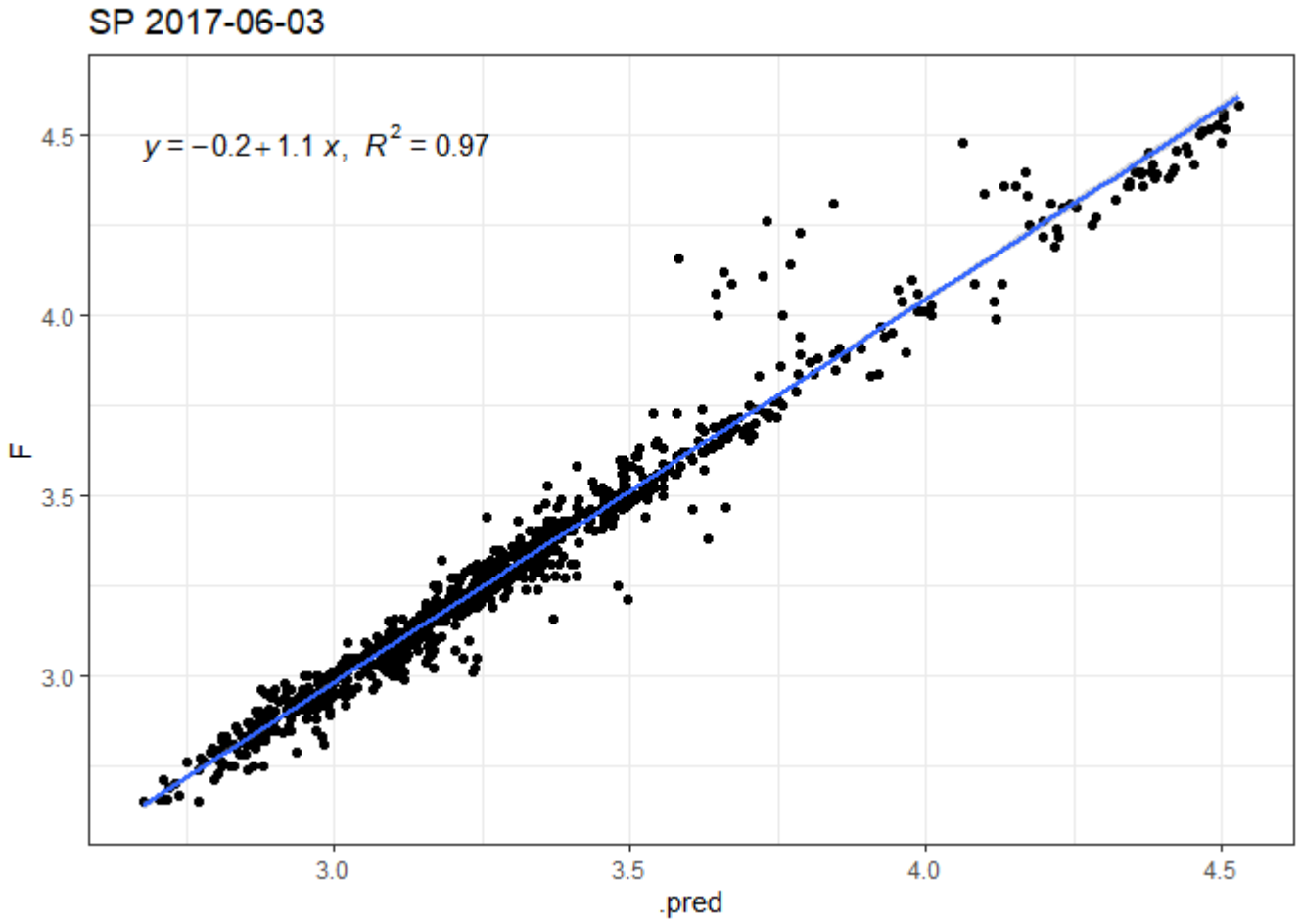

Cost-Complexity Parameter (log-10)
Minimal Node Size
Tree Depth
rmse
0.16937
0.16936
0.16935
0.16934
-5.8
-5.7
-5.6
-5.5
44.0
44.5
45.0
45.5
46.0
15.00
15.25
15.50
15.75
16.00

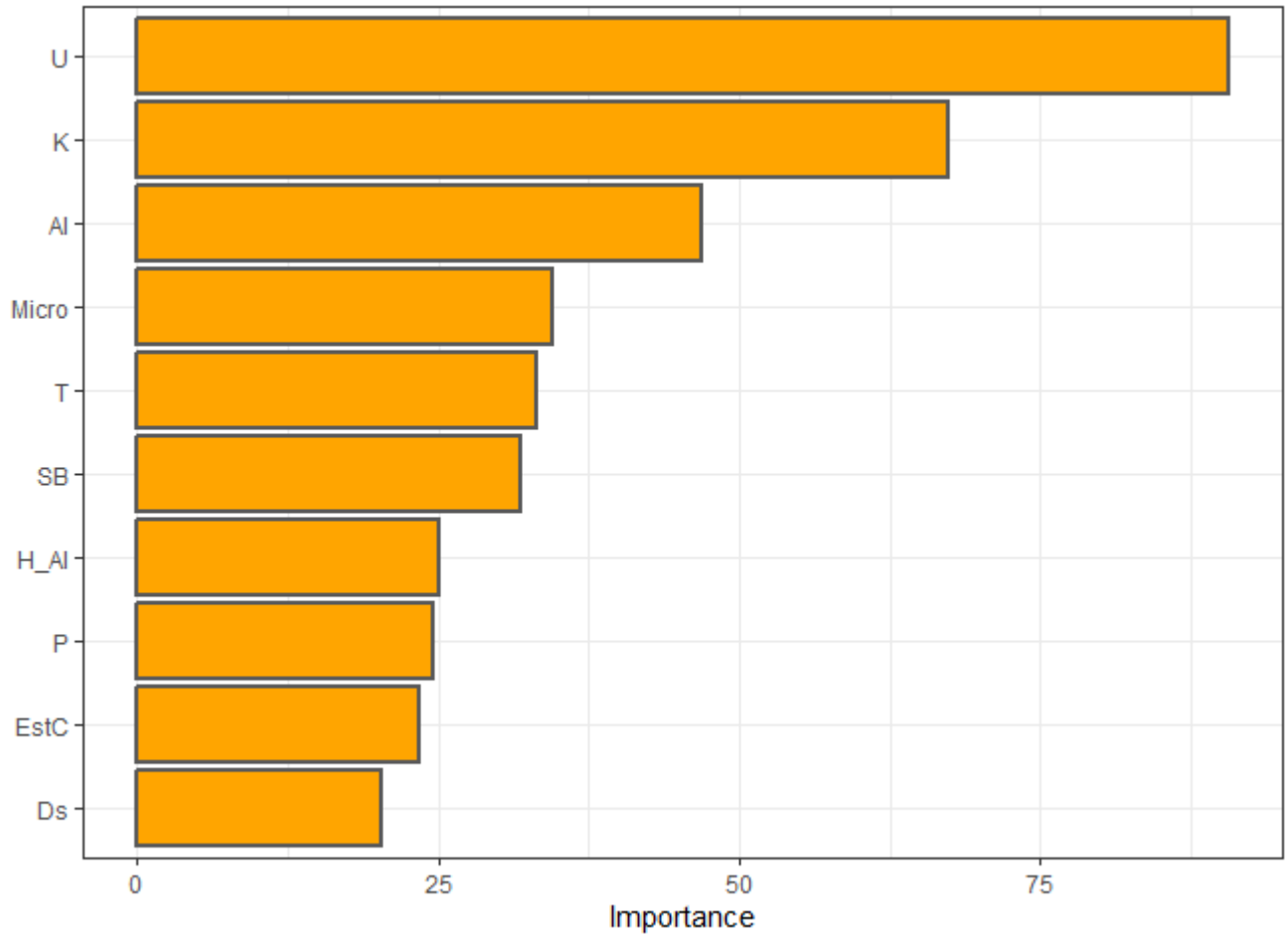

SP 2017-06-03
$y = 0.05 + 0.98\,x,\ R^2 = 0.85$
F
.pred
4.5
4.0
3.5
3.0
3.0
3.5
4.0
4.5



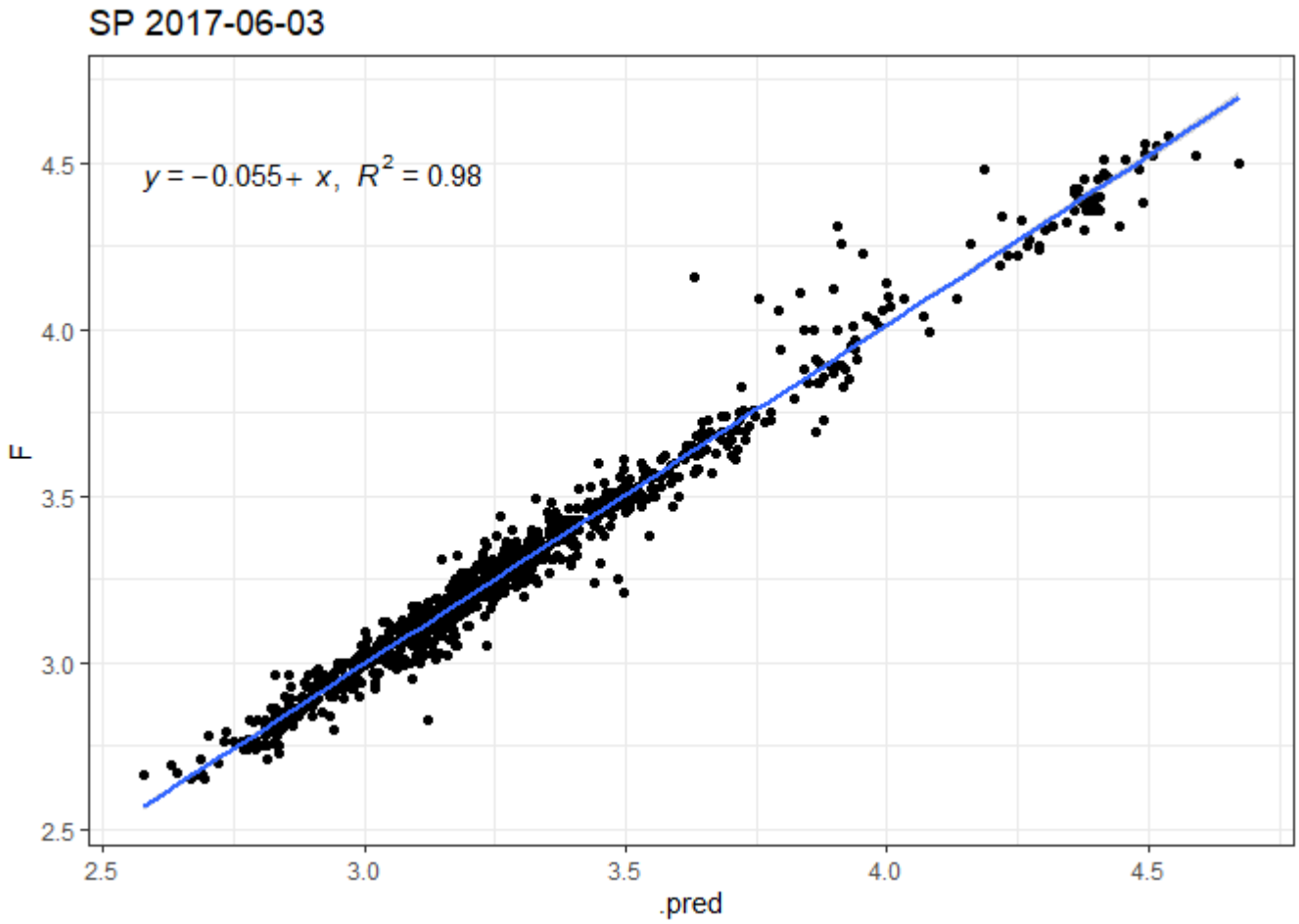

```
#>      vector_of_metrics
#> r           0.92349771
#> R2          0.85284802
#> MSE         0.02179714
#> RMSE        0.14763855
#> MAE         0.08757442
#> MAPE        2.61646309
#> [1] "RANDOM FOREST"
```

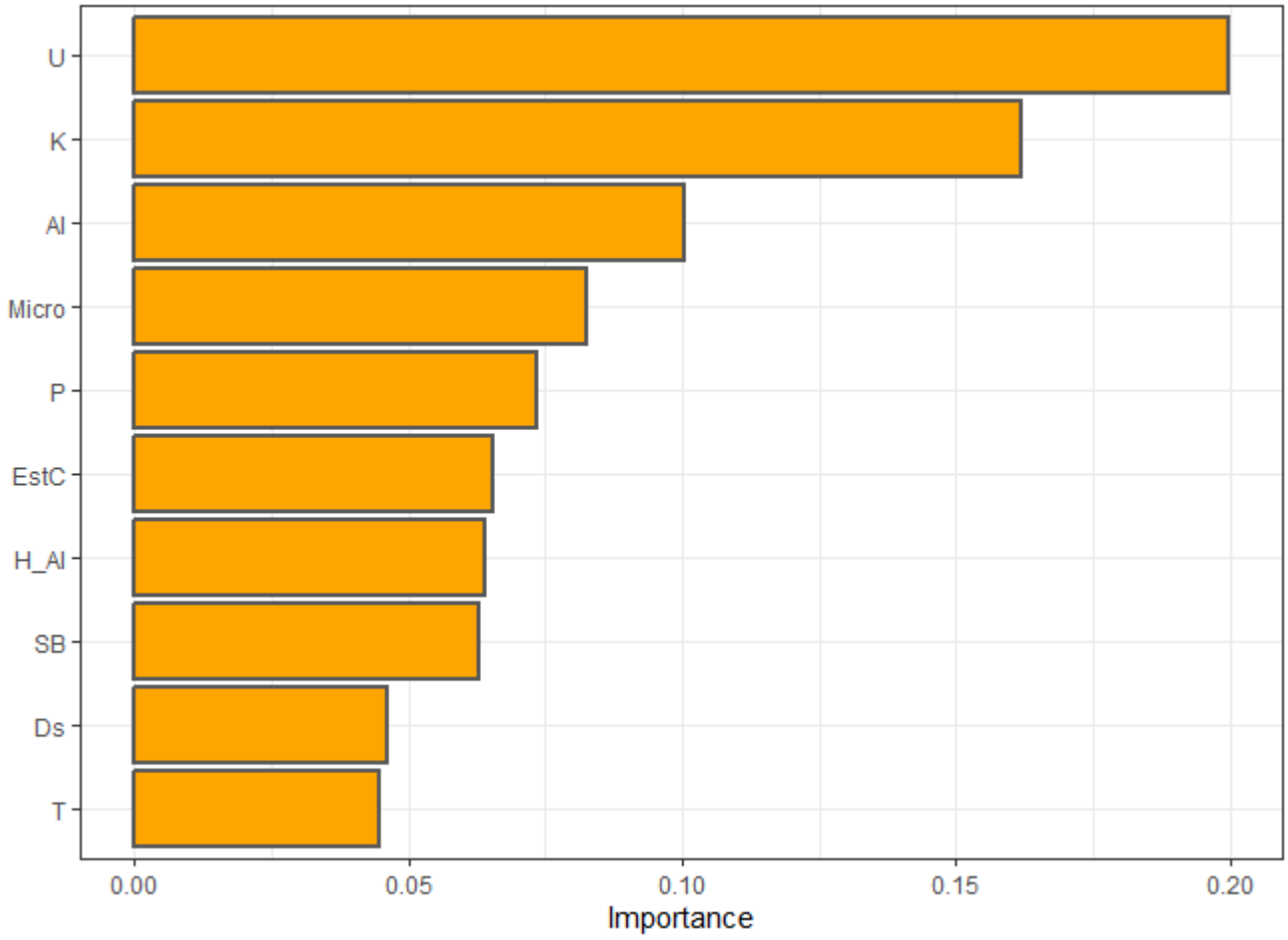

Randomly Selected Predictors
Trees
Minimal Node Size
rmse
0.090
0.087
0.084
0.081
7.0
7.5
8.0
8.5
9.0
150
200
250
300
20.0
22.5
25.0
27.5
30.0


SP 2017-06-03
$y = -0.2 + 1.1\,x,\ R^2 = 0.97$
F
4.5
4.0
3.5
3.0
3.0
3.5
4.0
4.5
.pred

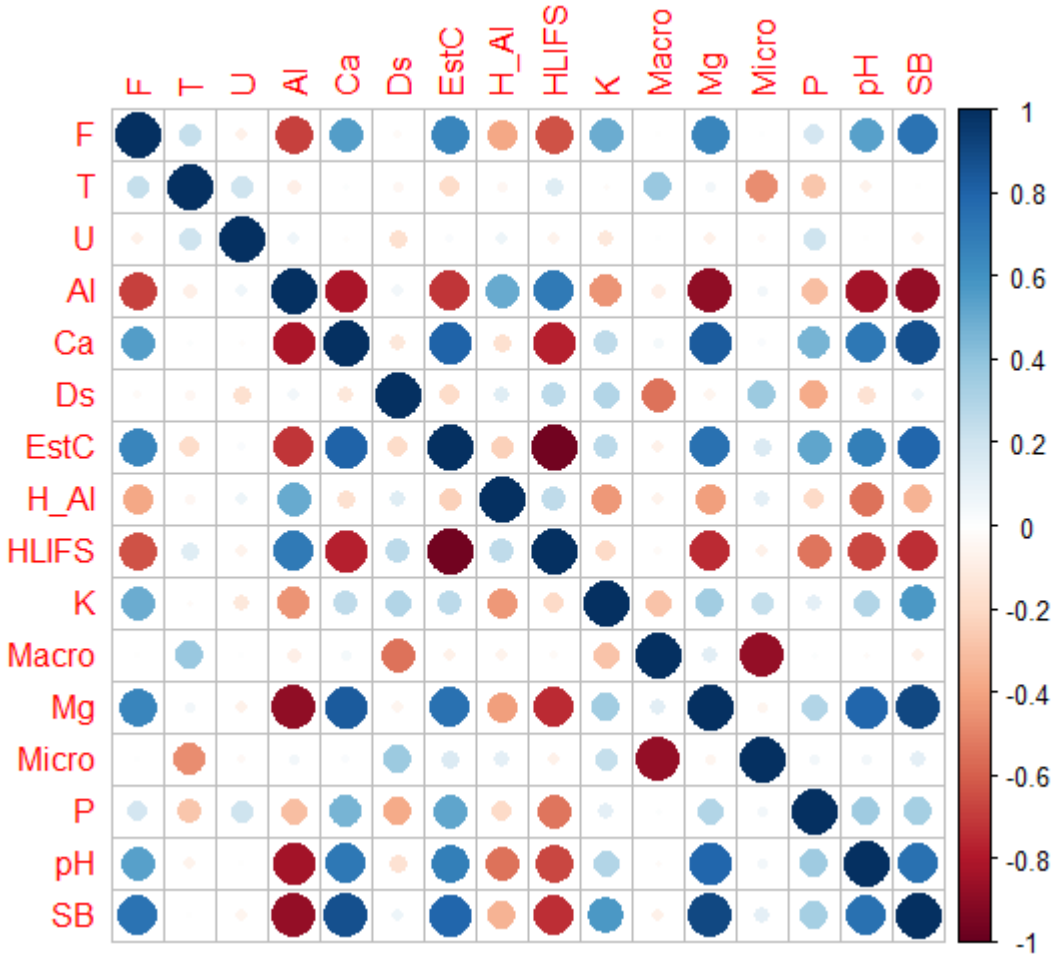



```
#>       vector_of_metrics
#> r           0.984272185
#> R2          0.968791735
#> MSE         0.005094213
#> RMSE        0.071373758
#> MAE         0.040790118
#> MAPE        1.212759521
```

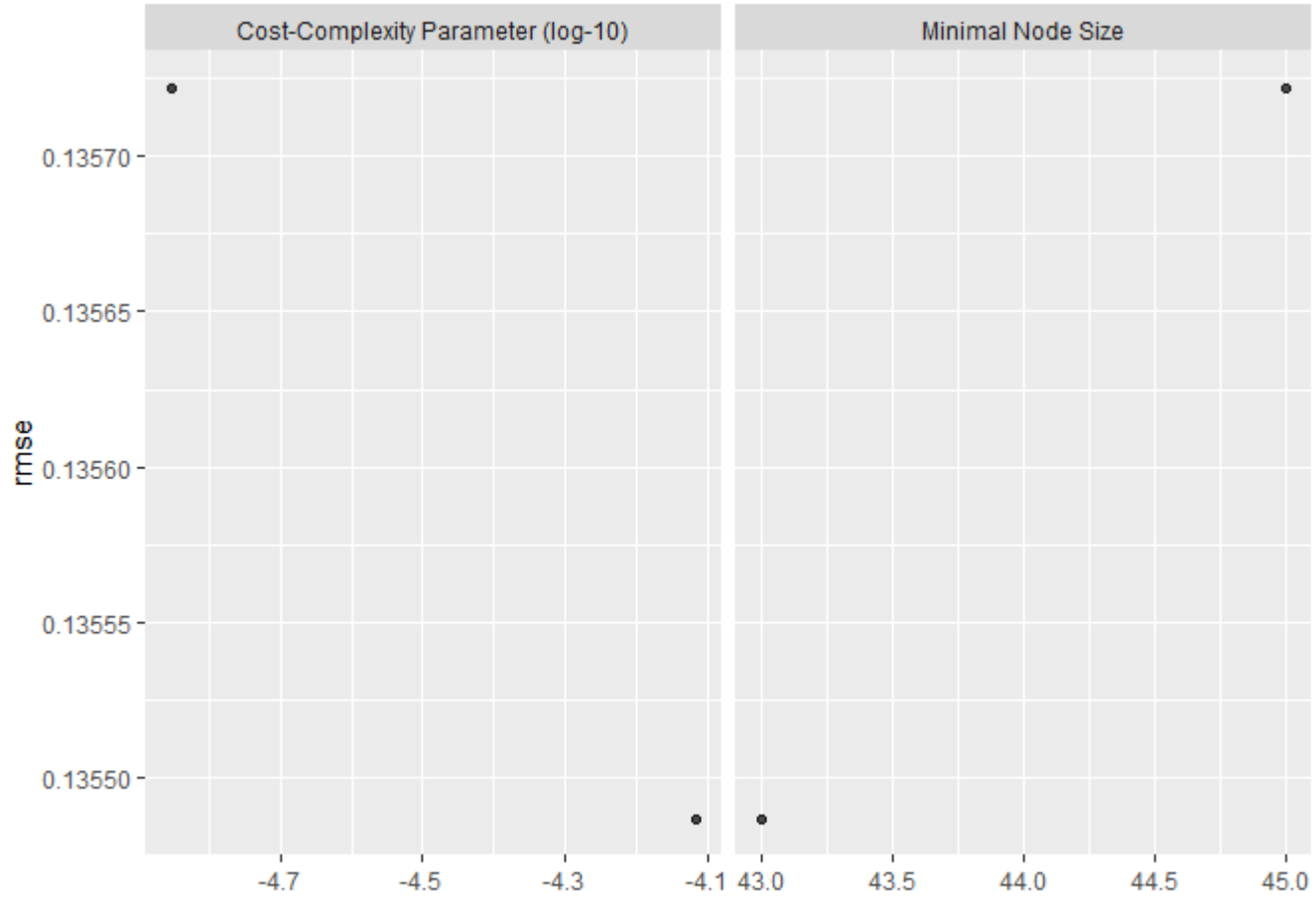

SP 2017-06-03
$y = -0.055 + x,\ R^2 = 0.98$
F
.pred
2.5
3.0
3.5
4.0
4.5

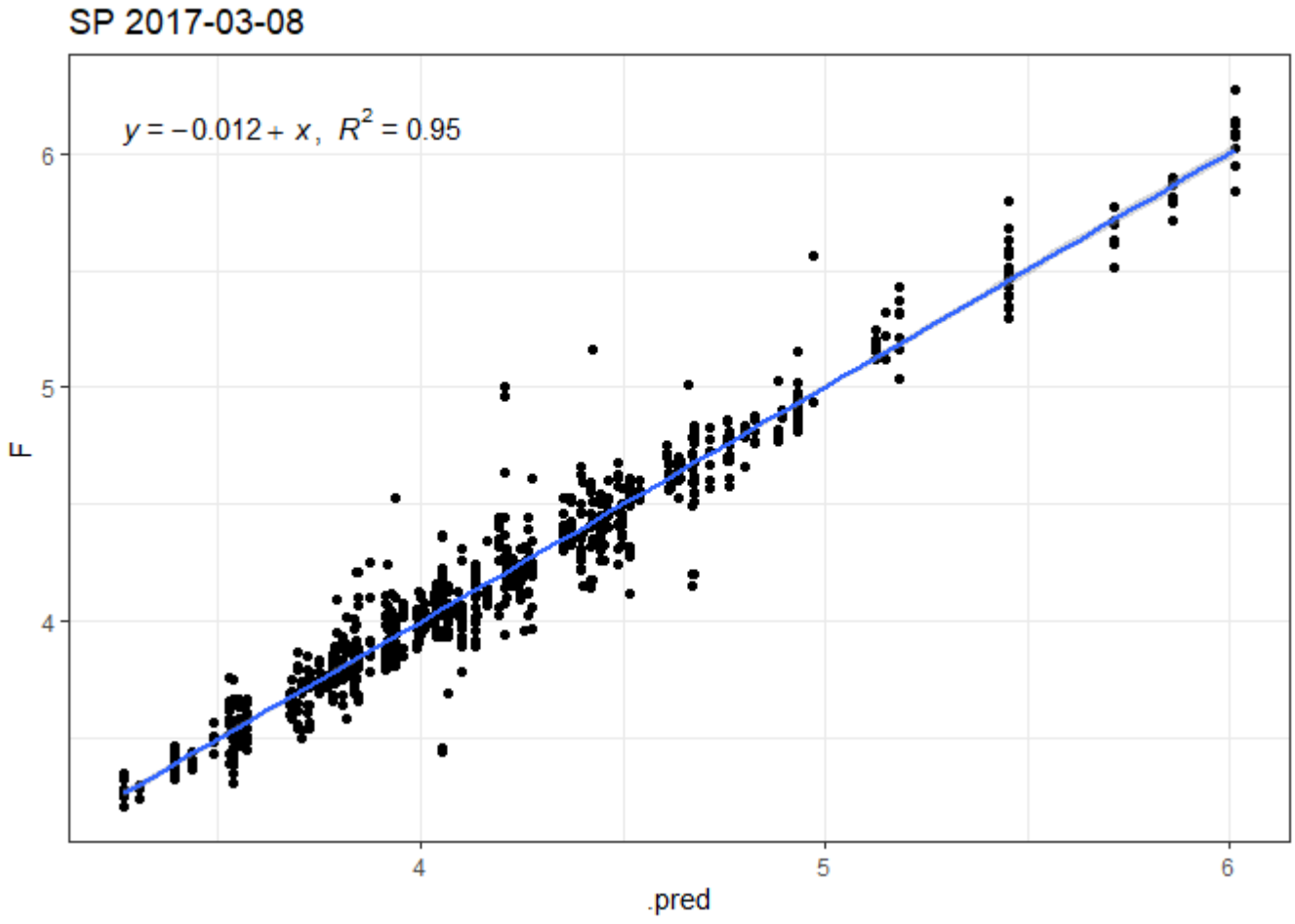

U
K
Al
Micro
P
EstC
H_Al
SB
Ds
T
0.00
0.05
0.10
0.15
0.20
Importance

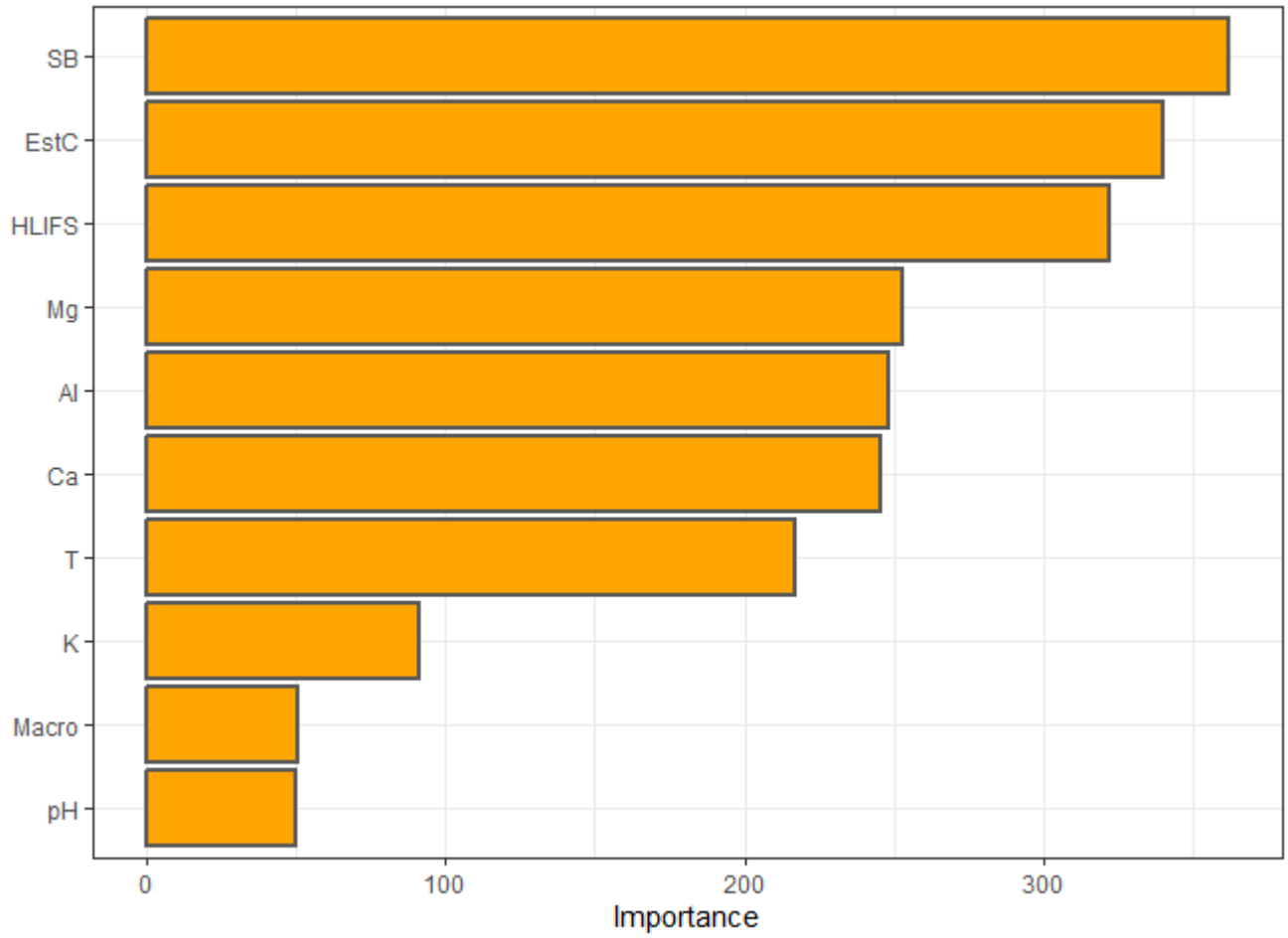
```
#>       vector_of_metrics
#> r           0.987586801
#> R2          0.975327690
#> MSE         0.003685666
#> RMSE        0.060709684
#> MAE         0.040244621
#> MAPE        1.207263383
```



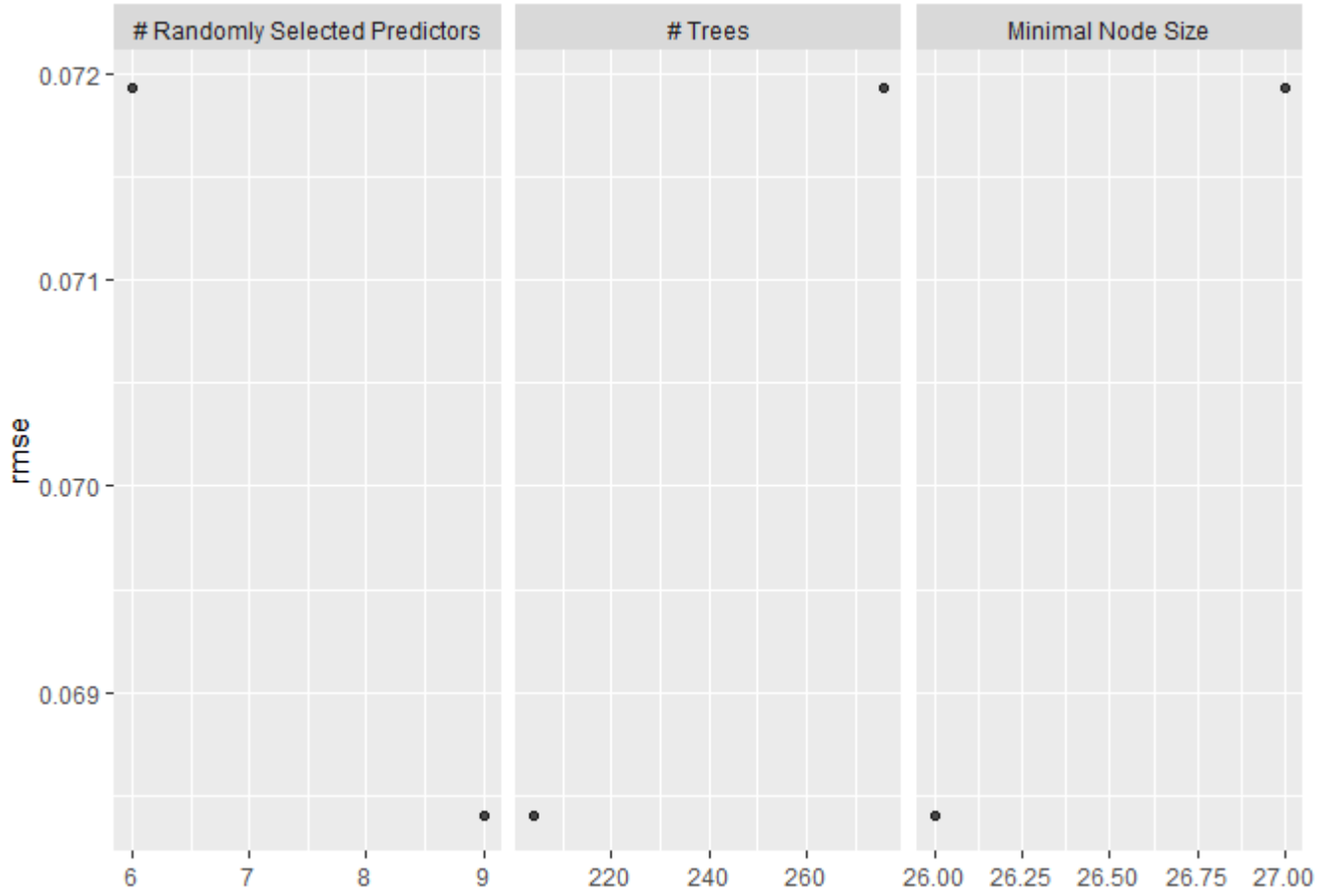

```
#> [1] "ARVORE DE DECISÃO"
```

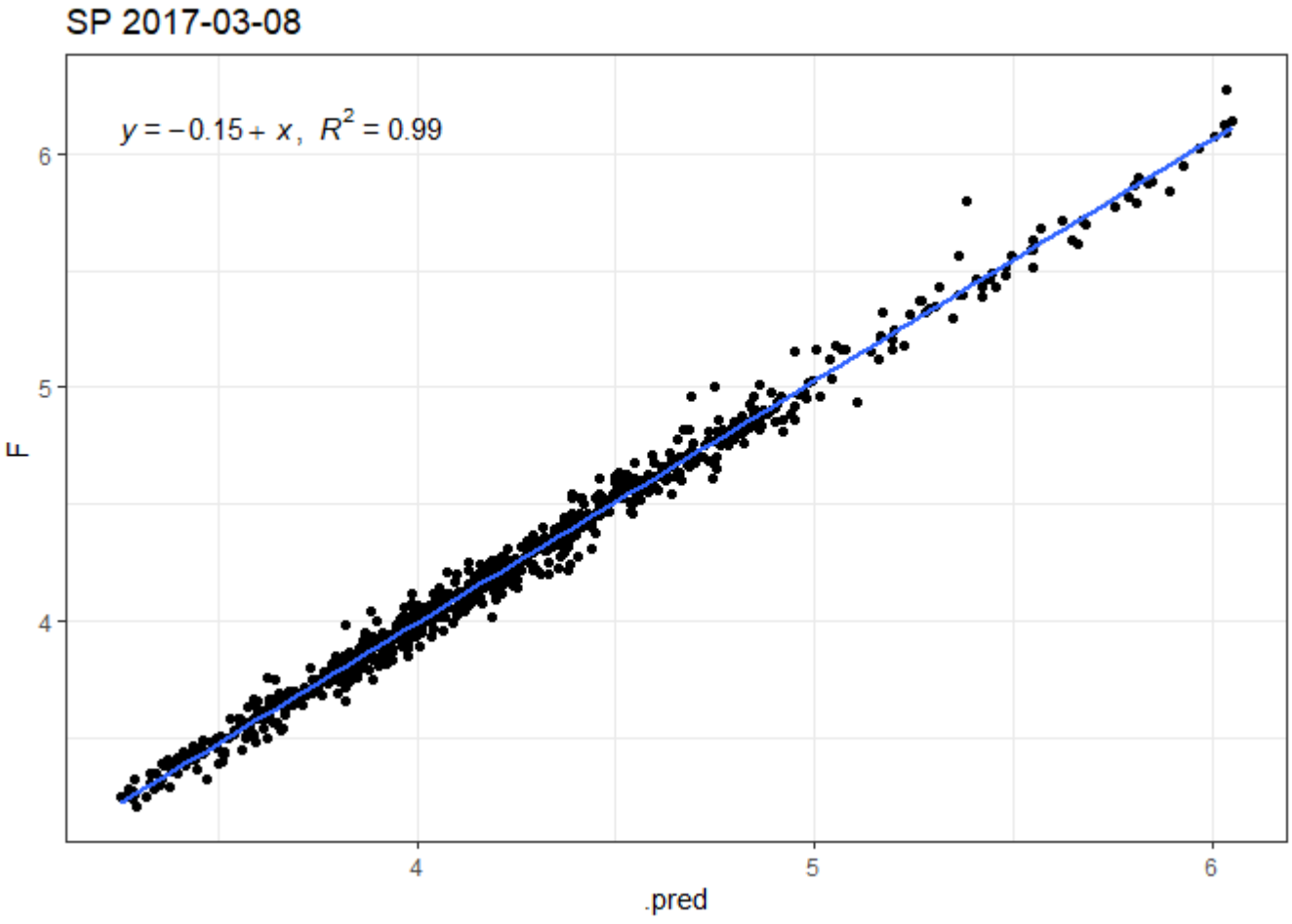

Cost-Complexity Parameter (log-10)
Minimal Node Size
rmse
0.13570
0.13565
0.13560
0.13555
0.13550
-4.7
-4.5
-4.3
-4.1
43.0
43.5
44.0
44.5
45.0

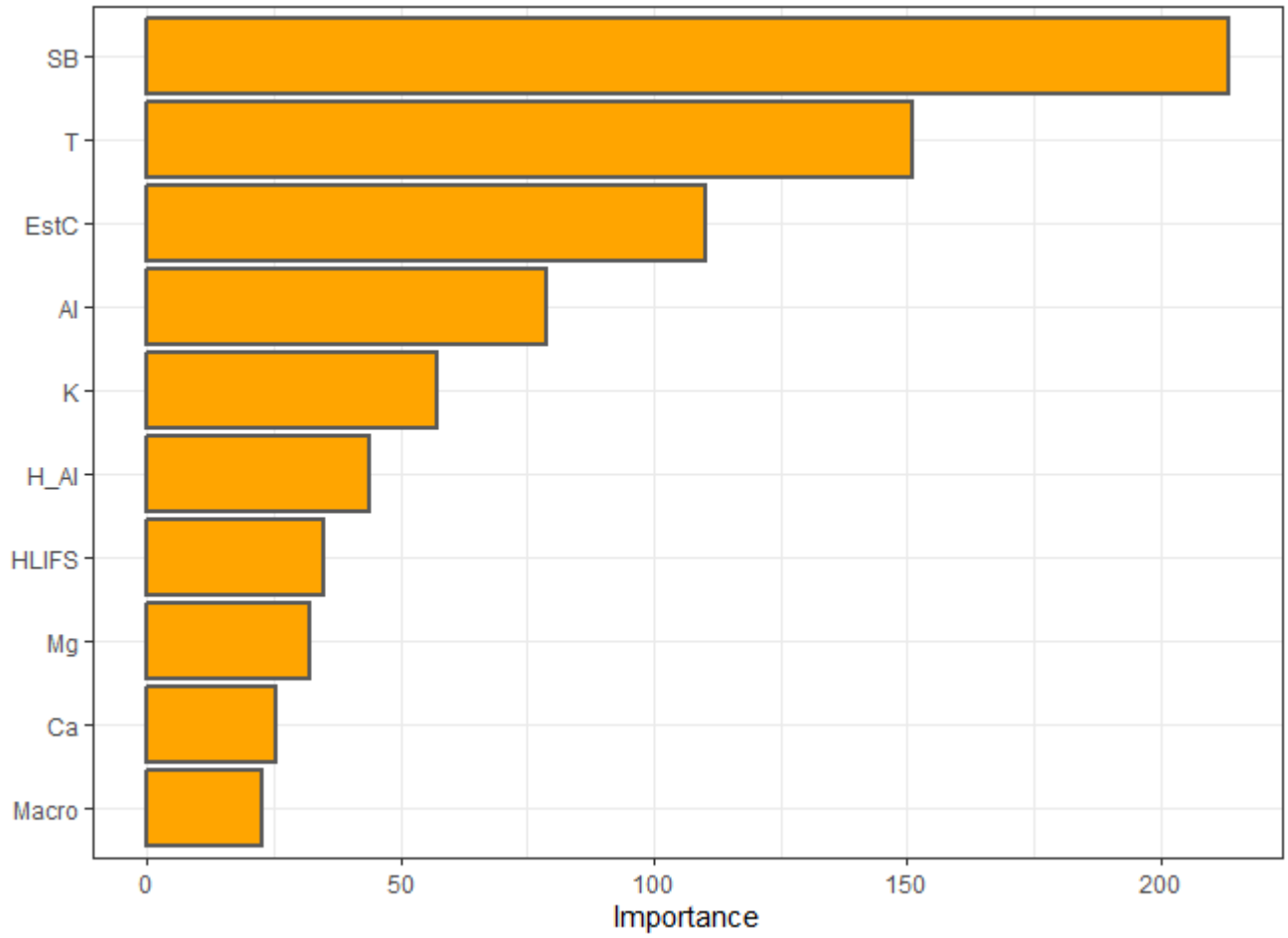

SP 2017-03-08
$y = -0.012 + x$, $R^2 = 0.95$
F
.pred
4
5
6



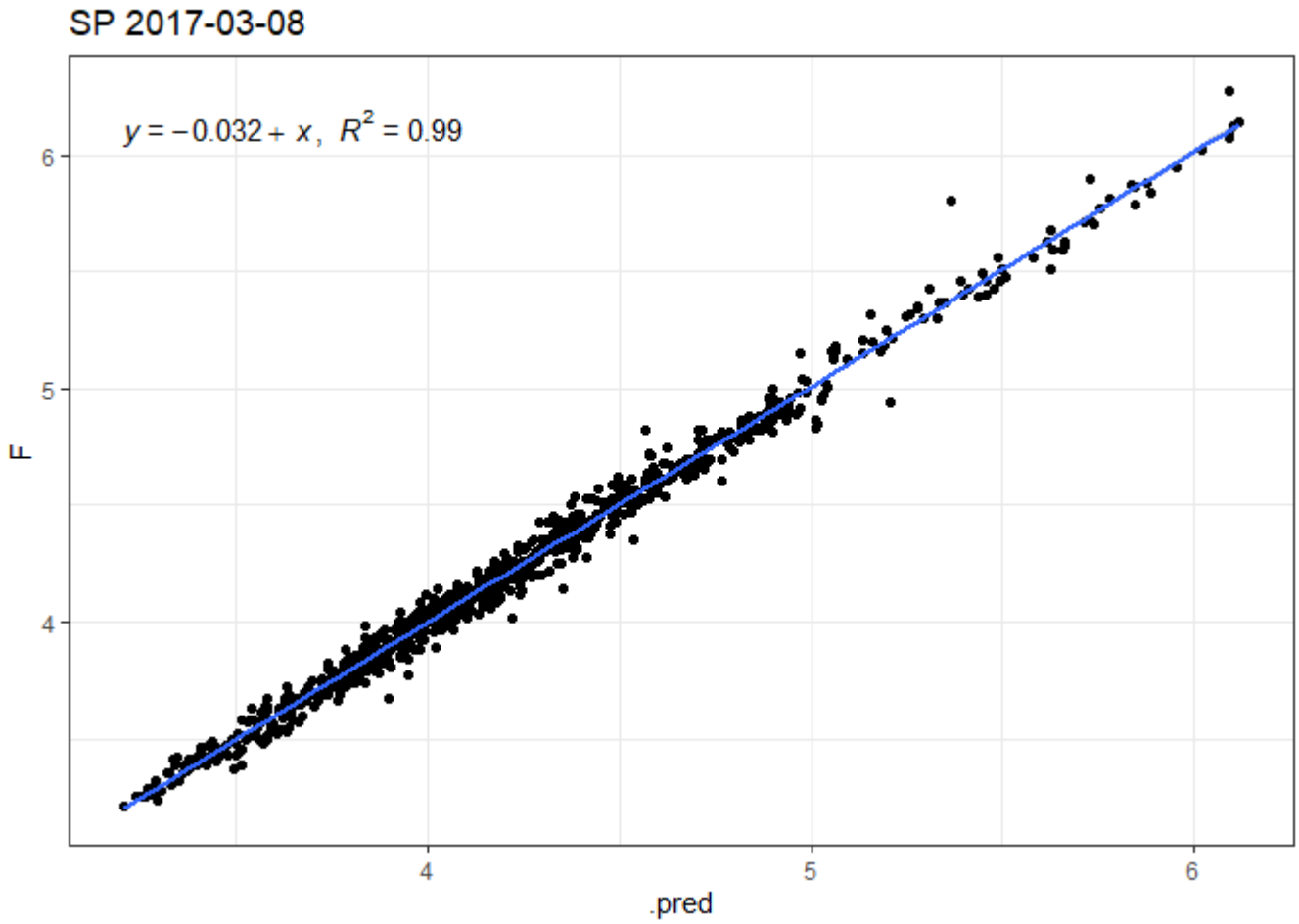

```
#>      vector_of_metrics
#> r           0.97529260
#> R2          0.95119566
#> MSE         0.01434486
#> RMSE        0.11977005
#> MAE         0.07896086
#> MAPE        1.87455167
#> [1] "RANDOM FOREST"
```

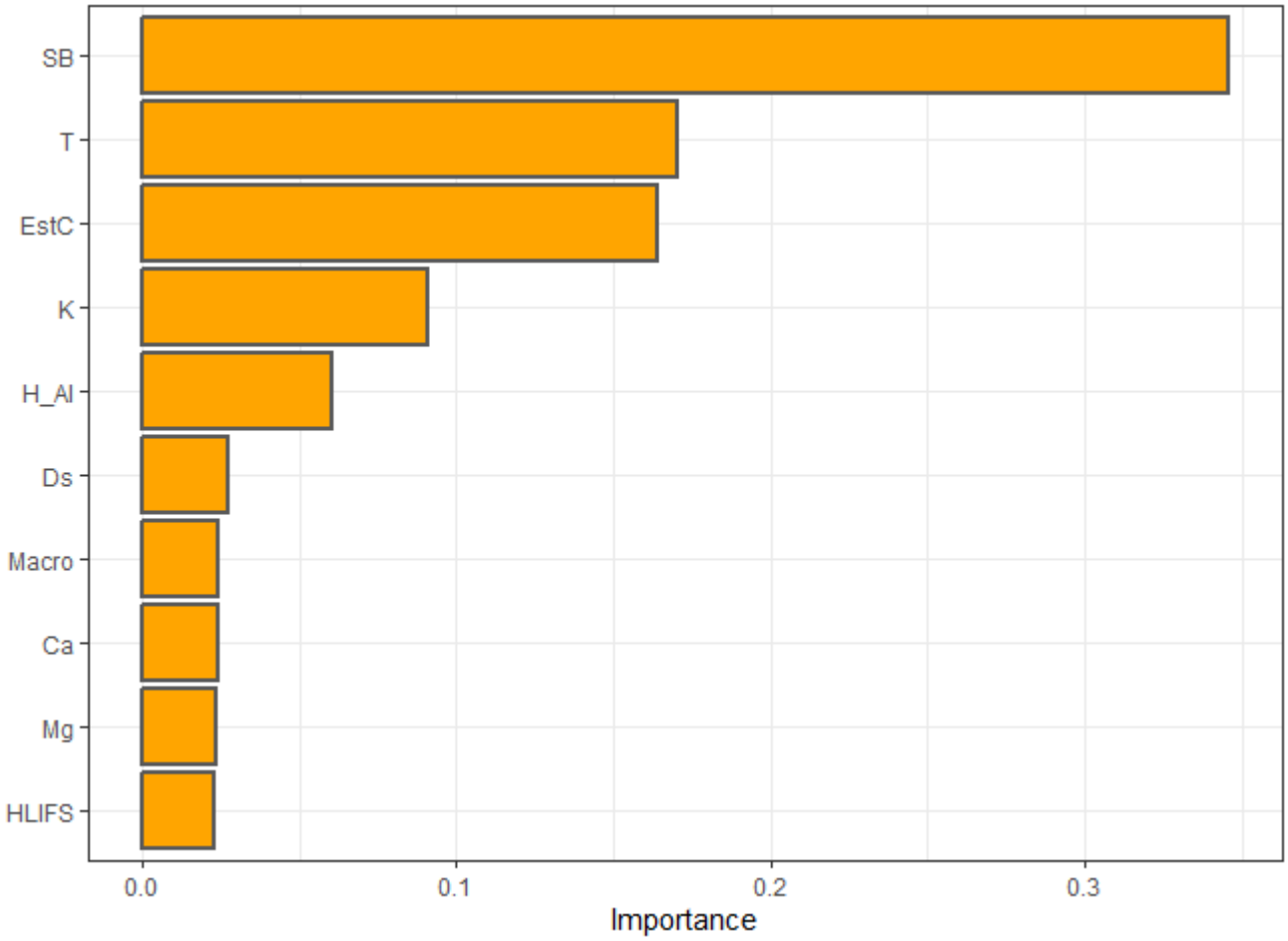

Randomly Selected Predictors
Trees
Minimal Node Size
rmse
0.072
0.071
0.070
0.069
6
7
8
9
220
240
260
26.00
26.25
26.50
26.75
27.00


SP 2017-03-08
$y = -0.15 + x$, $R^2 = 0.99$
F
.pred
4
5
6

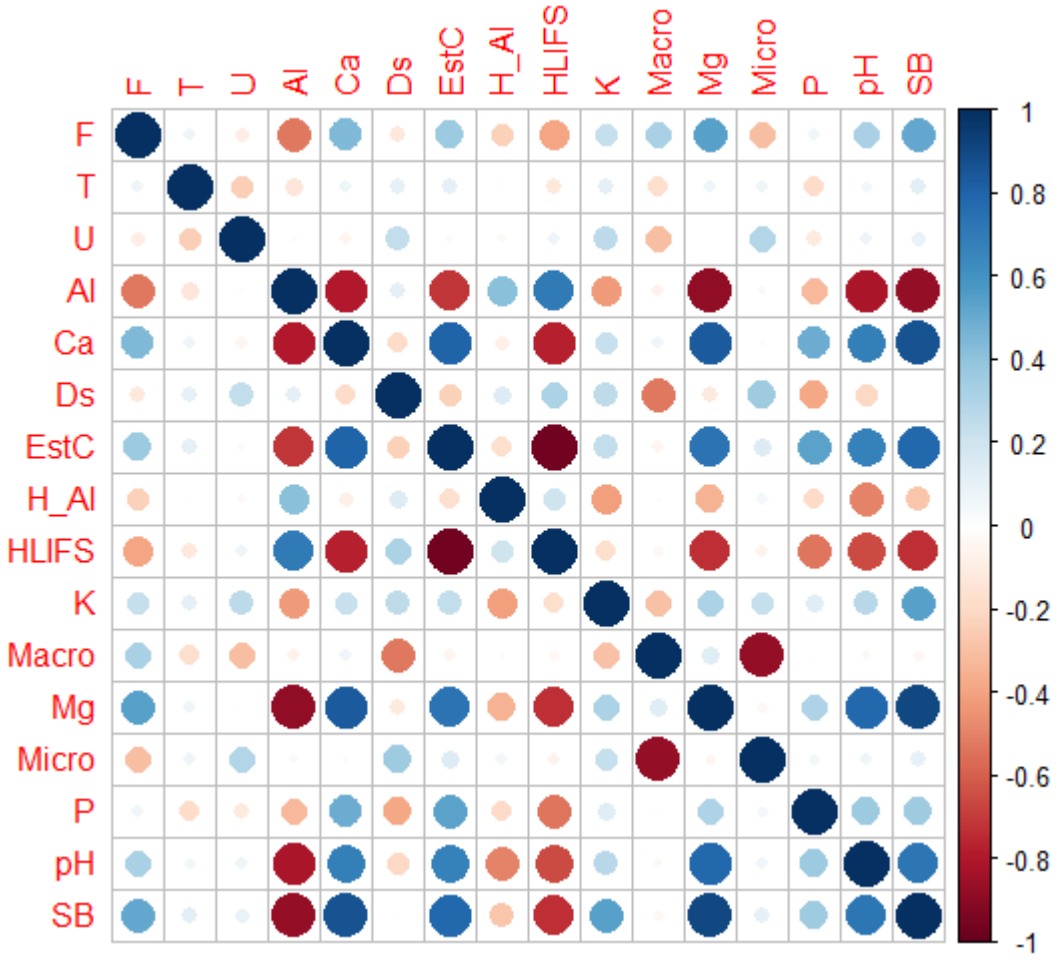



```
#>      vector_of_metrics
#> r           0.995292130
#> R2          0.990606424
#> MSE         0.003102094
#> RMSE        0.055696448
#> MAE         0.040301584
#> MAPE        0.954450574
```

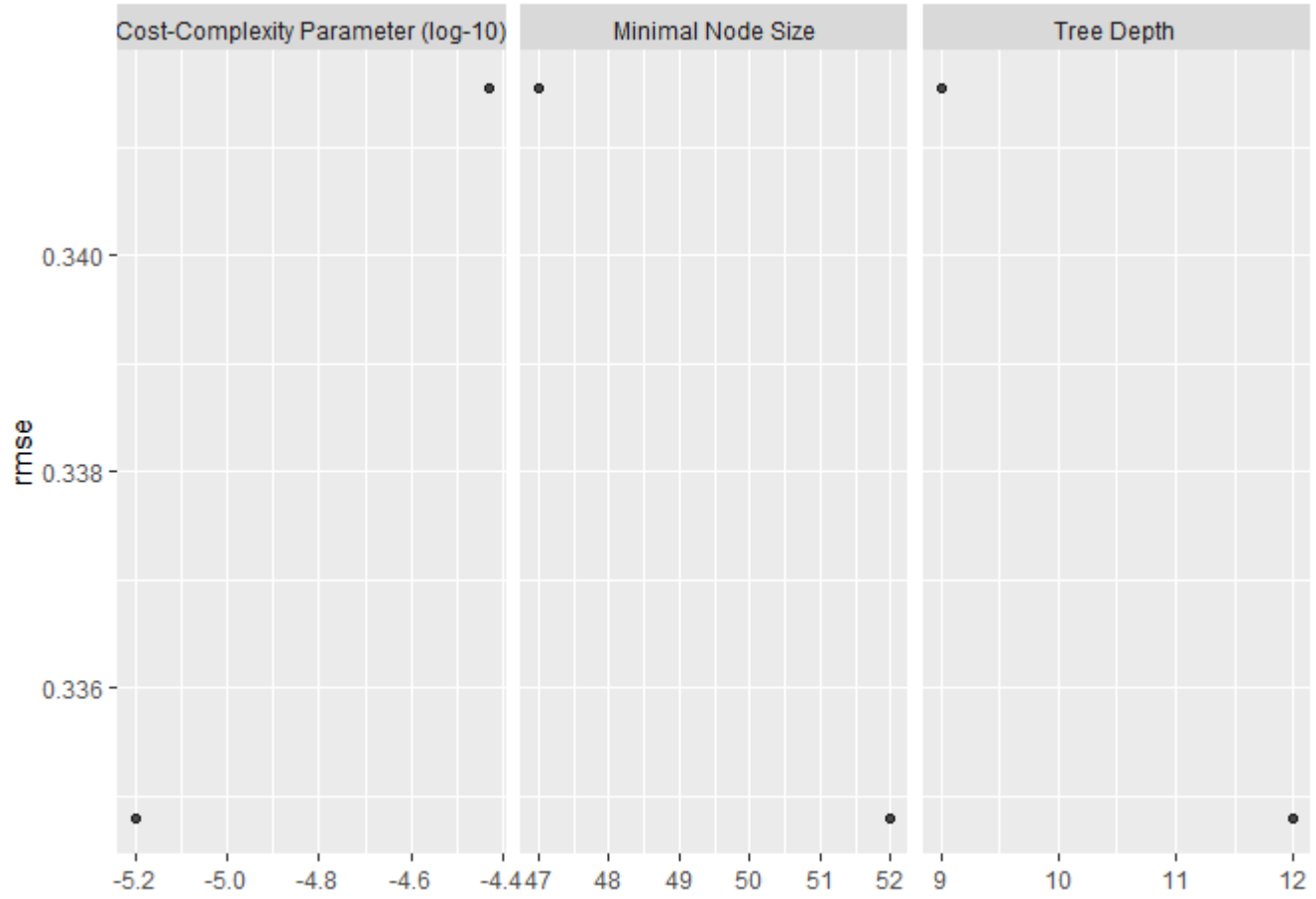

SP 2017-03-08
$y = -0.032 + x$, $R^2 = 0.99$
F
.pred
6
5
4
4
5
6

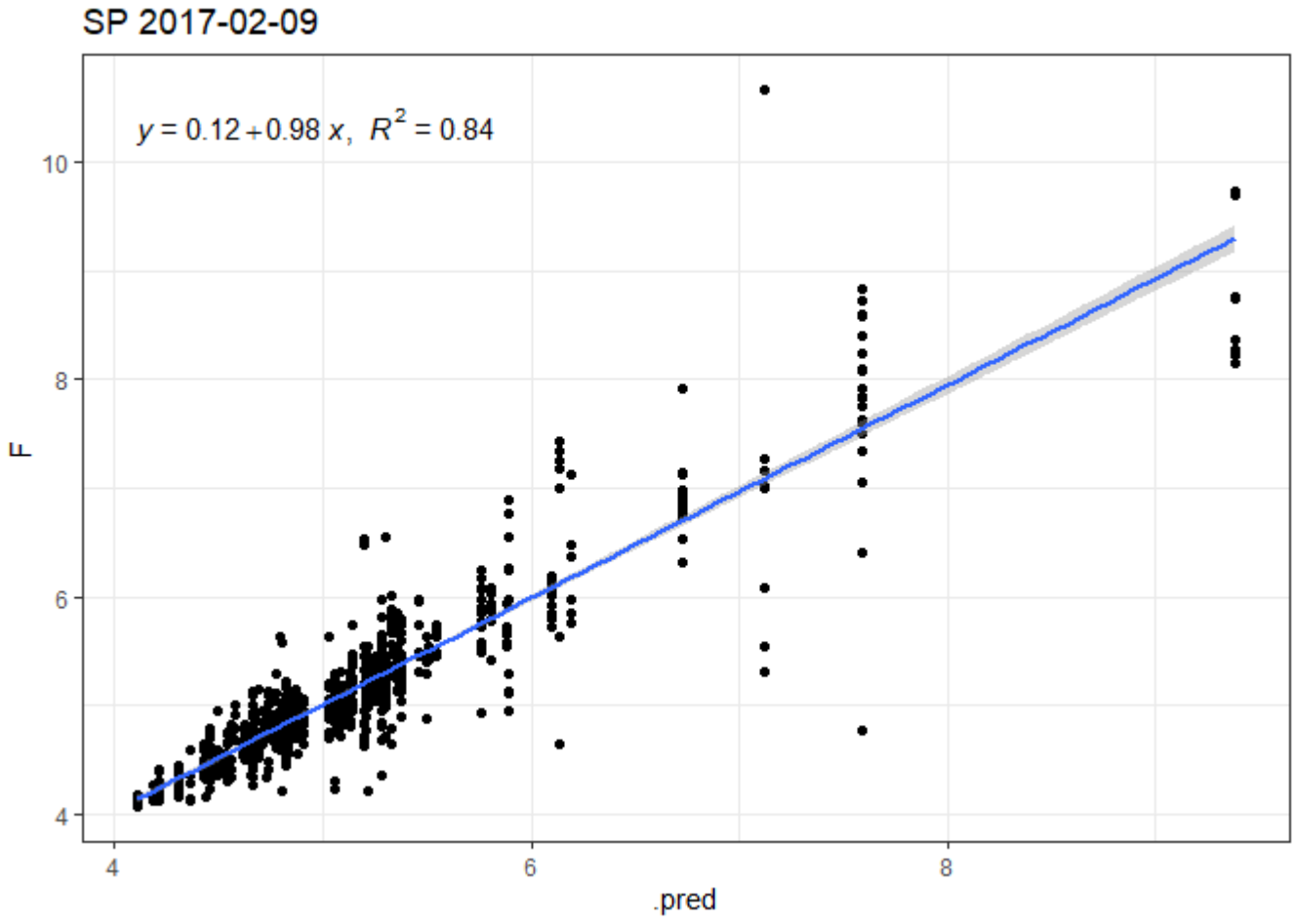

SB
T
EstC
K
H_Al
Ds
Macro
Ca
Mg
HLIFS
0.0
0.1
0.2
0.3
Importance

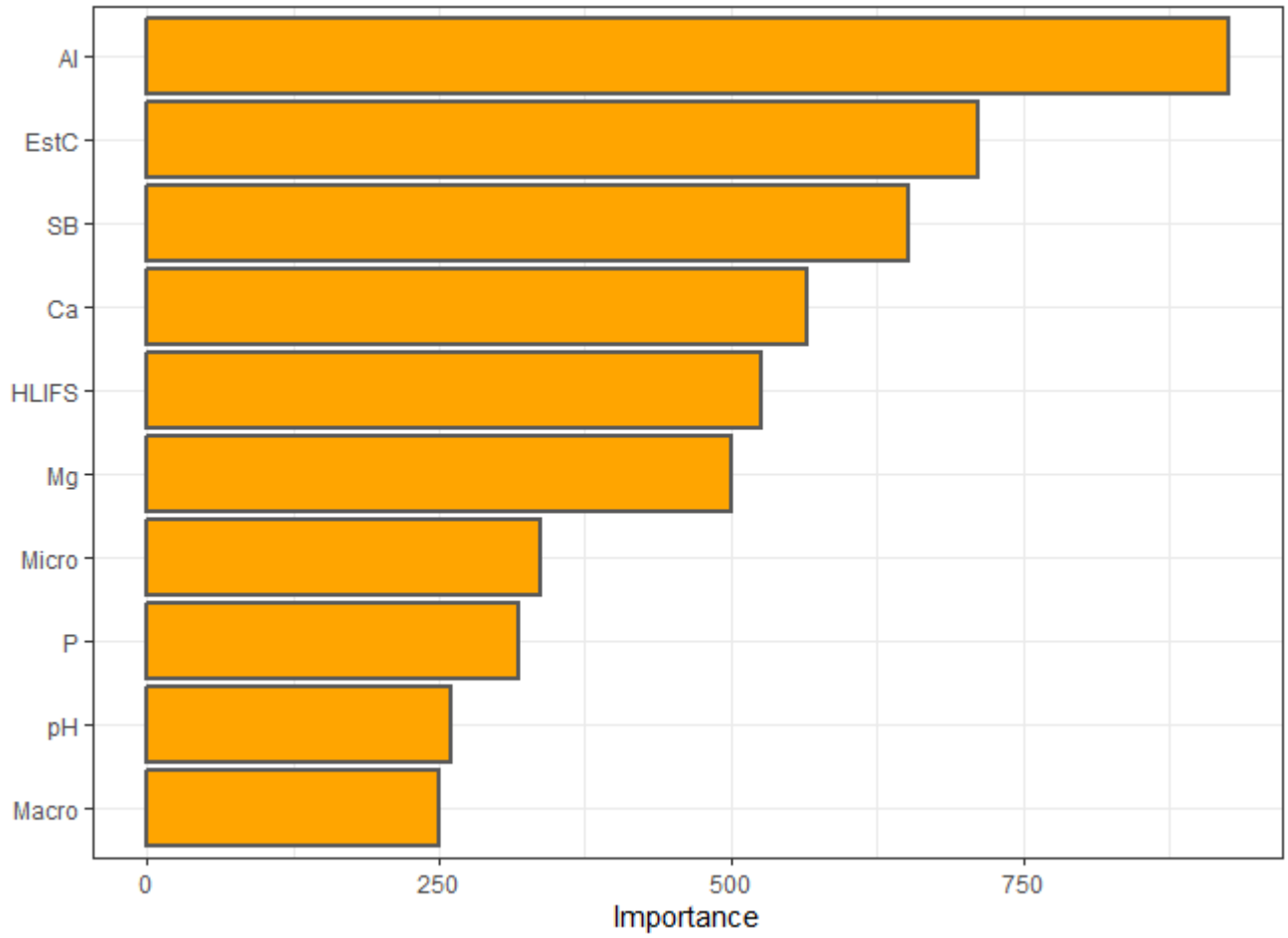
```
#>       vector_of_metrics
#> r           0.994978989
#> R2          0.989983188
#> MSE         0.002960119
#> RMSE        0.054406976
#> MAE         0.038916552
#> MAPE        0.921551793
```



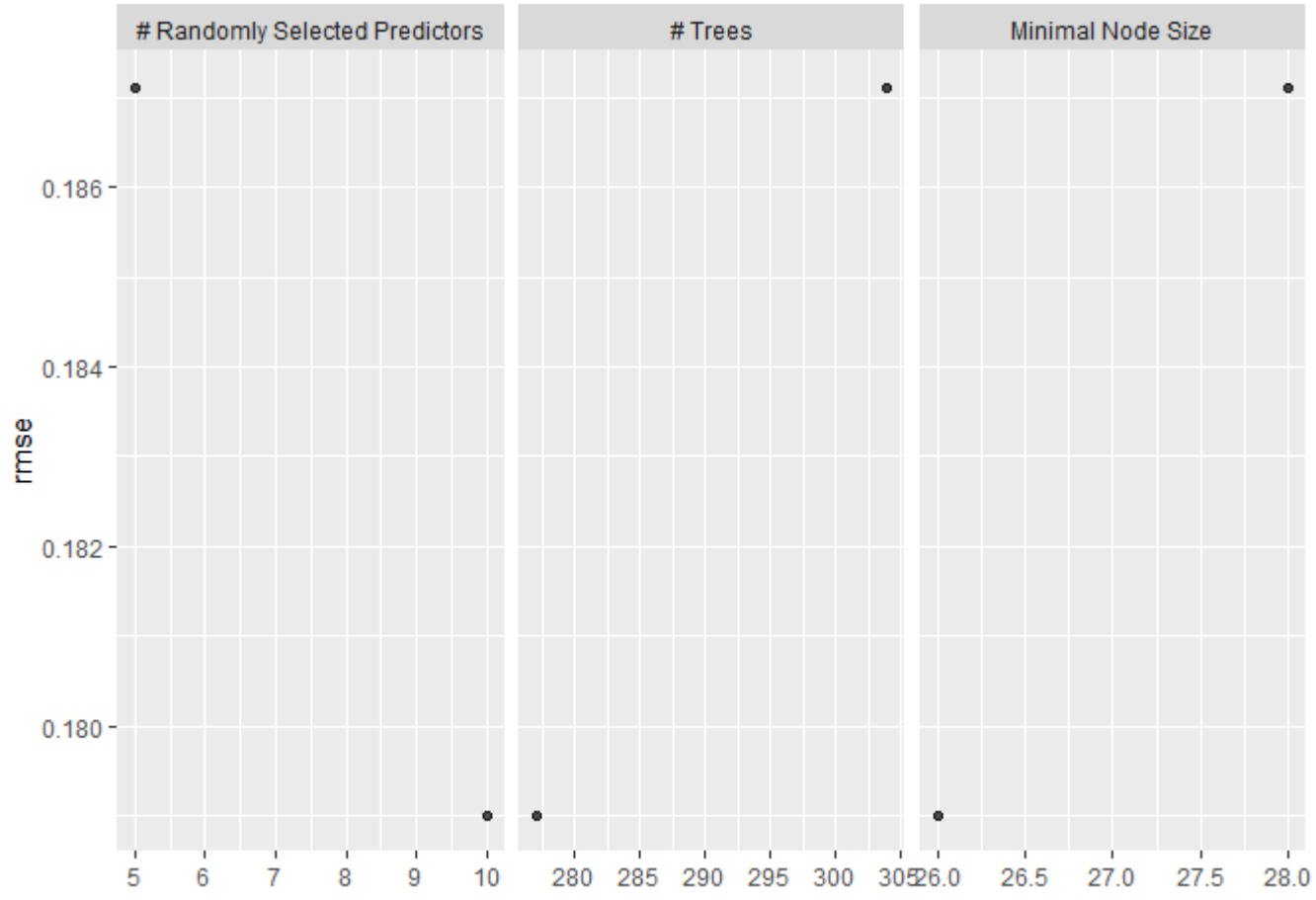

```
#> [1] "ARVORE DE DECISÃO"
```

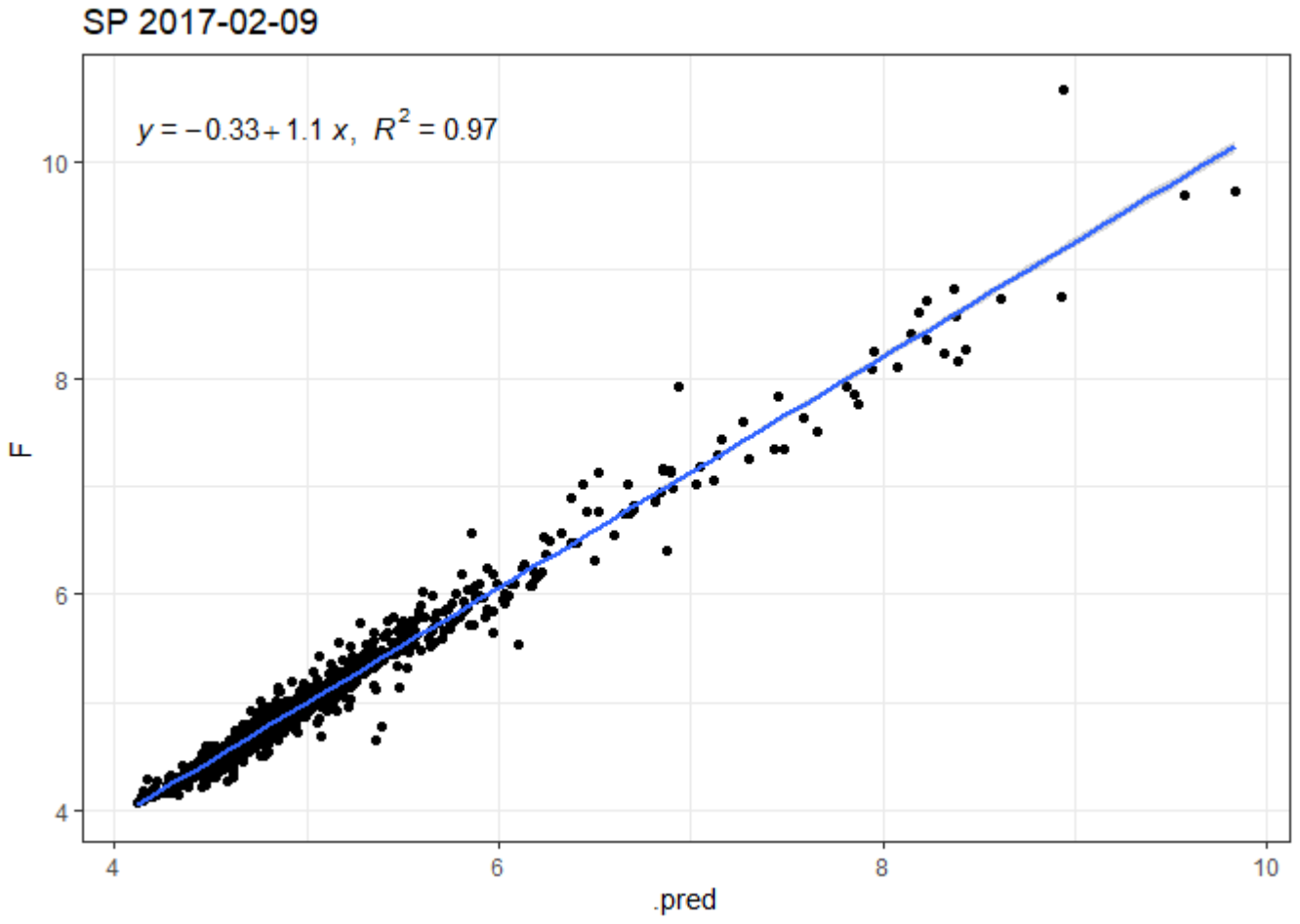

Cost-Complexity Parameter (log-10)
Minimal Node Size
Tree Depth
rmse
0.340
0.338
0.336
-5.2
-5.0
-4.8
-4.6
-4.4
47
48
49
50
51
52
9
10
11
12

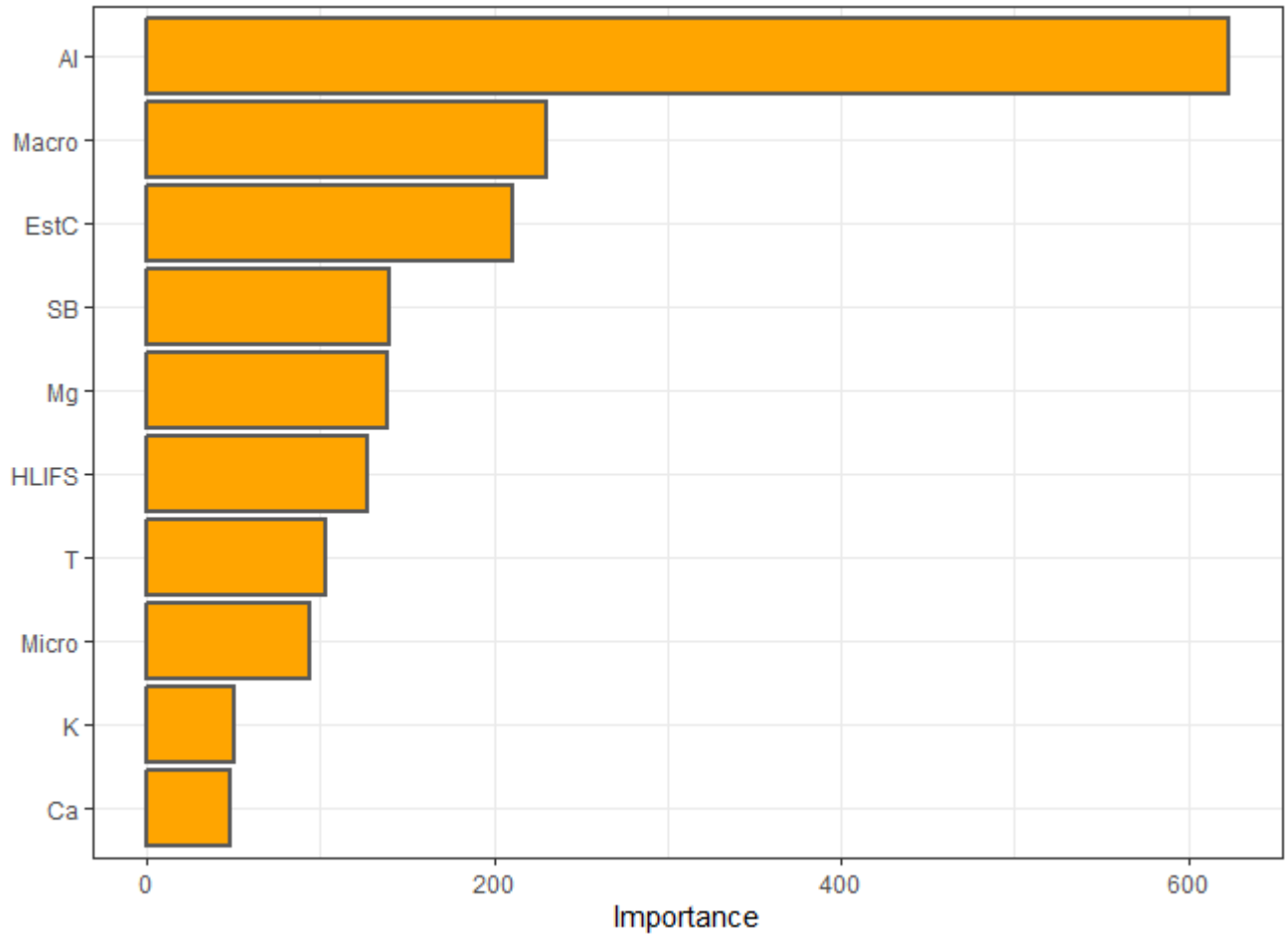

SP 2017-02-09
$y = 0.12 + 0.98\,x,\ R^2 = 0.84$
F
.pred
10
8
6
4
4
6
8



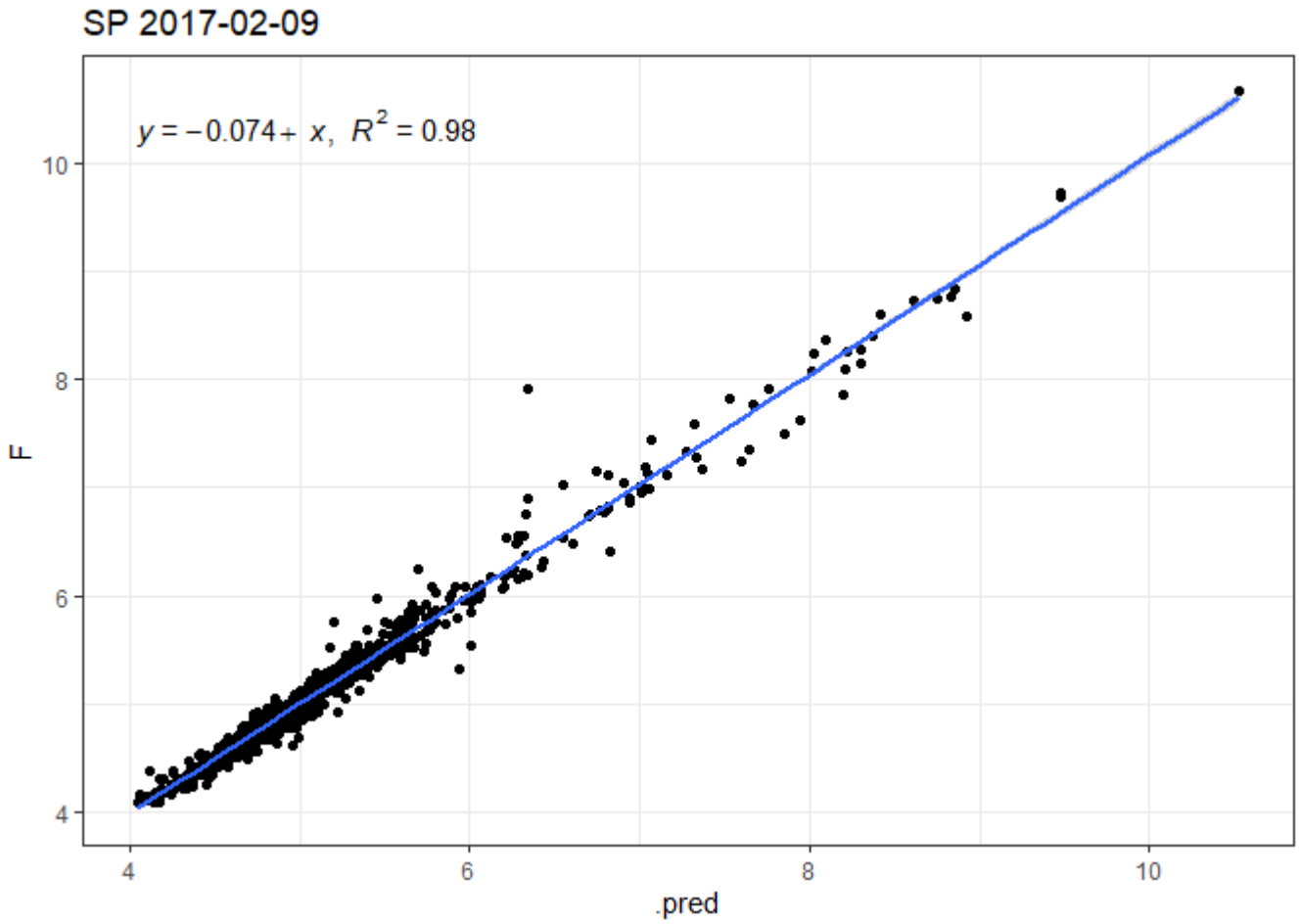

```
#>      vector_of_metrics
#> r            0.9145876
#> R2           0.8364705
#> MSE          0.1030590
#> RMSE         0.3210280
#> MAE          0.1807676
#> MAPE         3.3186413
#> [1] "RANDOM FOREST"
```

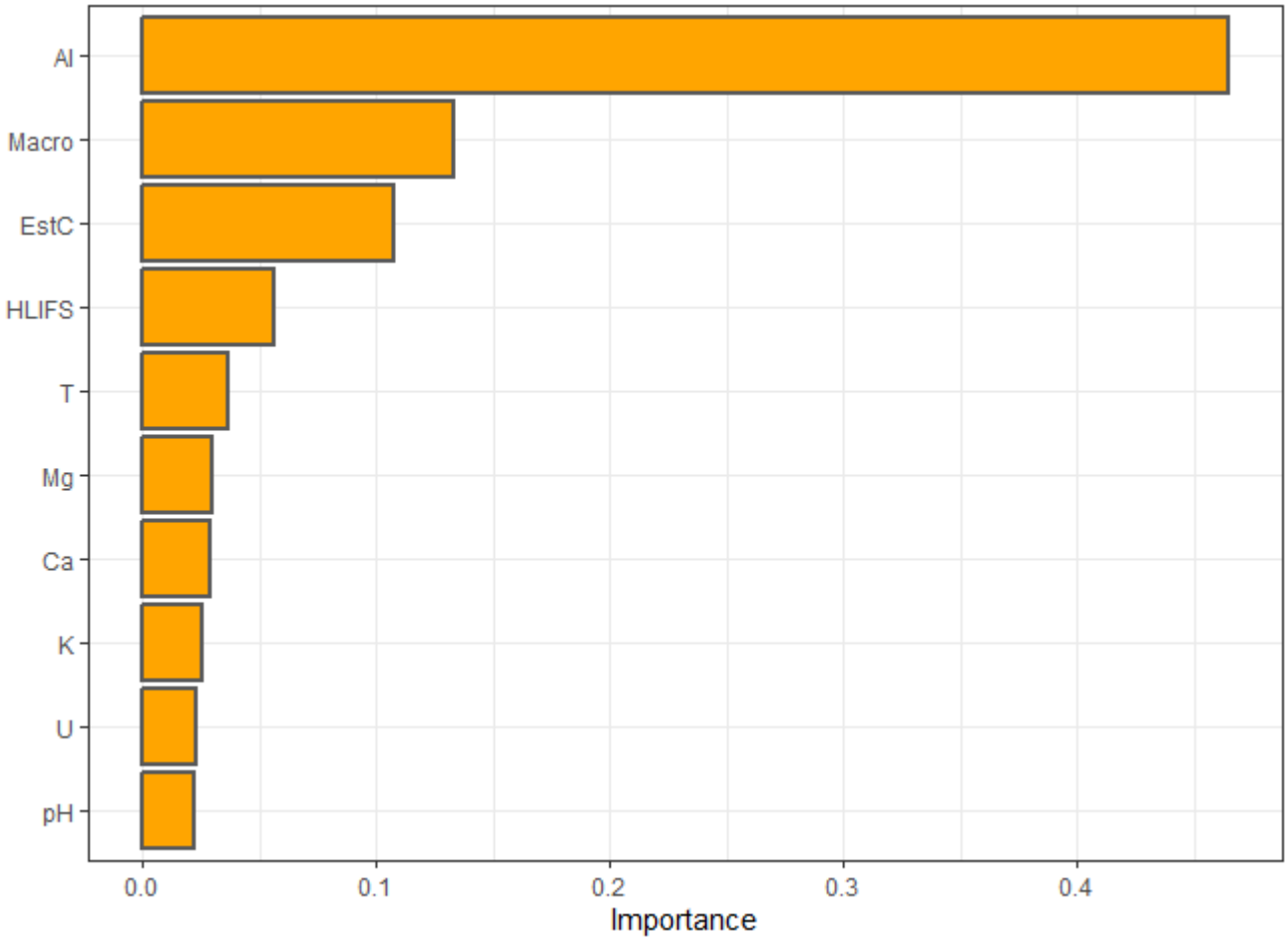

Randomly Selected Predictors
Trees
Minimal Node Size
rmse
0.186
0.184
0.182
0.180
5
6
7
8
9
10
280
285
290
295
300
305
26.0
26.5
27.0
27.5
28.0


SP 2017-02-09
$y = -0.33 + 1.1\,x,\ R^2 = 0.97$
F
.pred
4
6
8
10

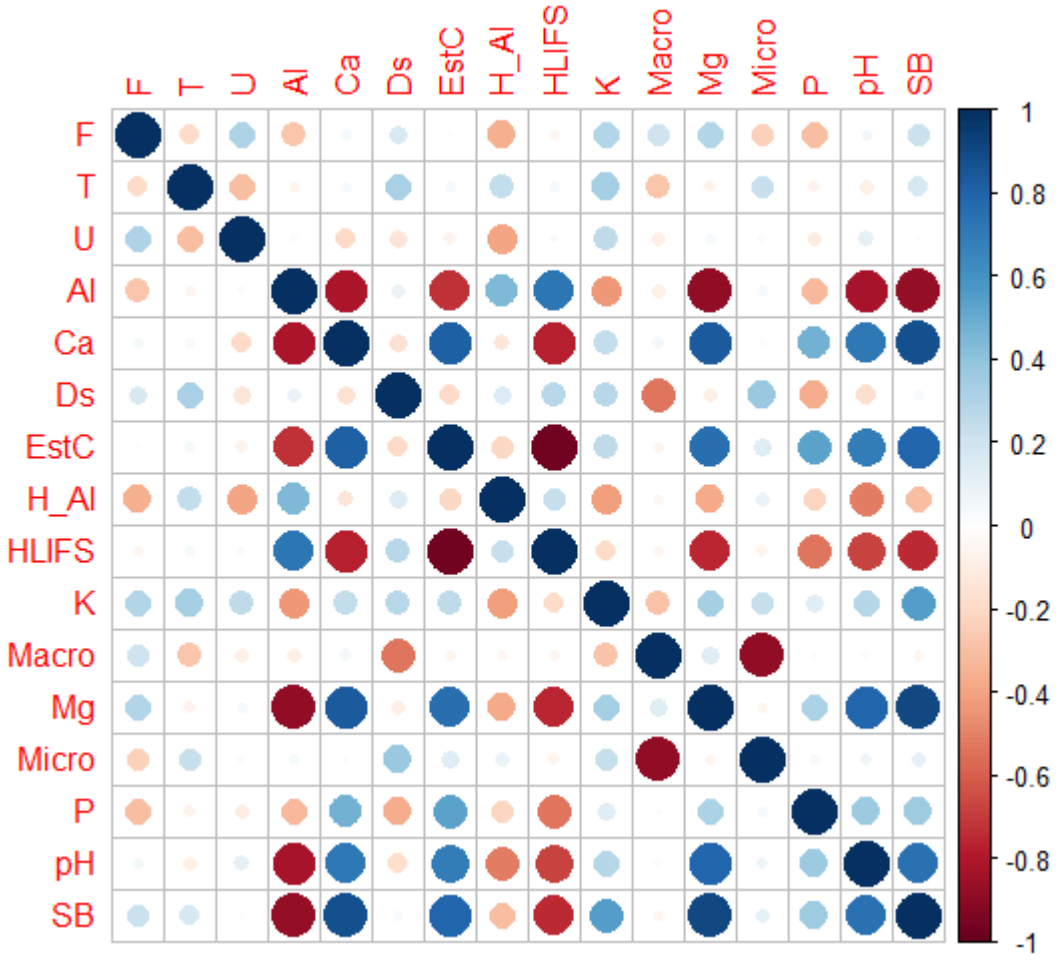



```
#>      vector_of_metrics
#> r           0.98657057
#> R2          0.97332149
#> MSE         0.01912989
#> RMSE        0.13831084
#> MAE         0.08470589
#> MAPE        1.58783995
```

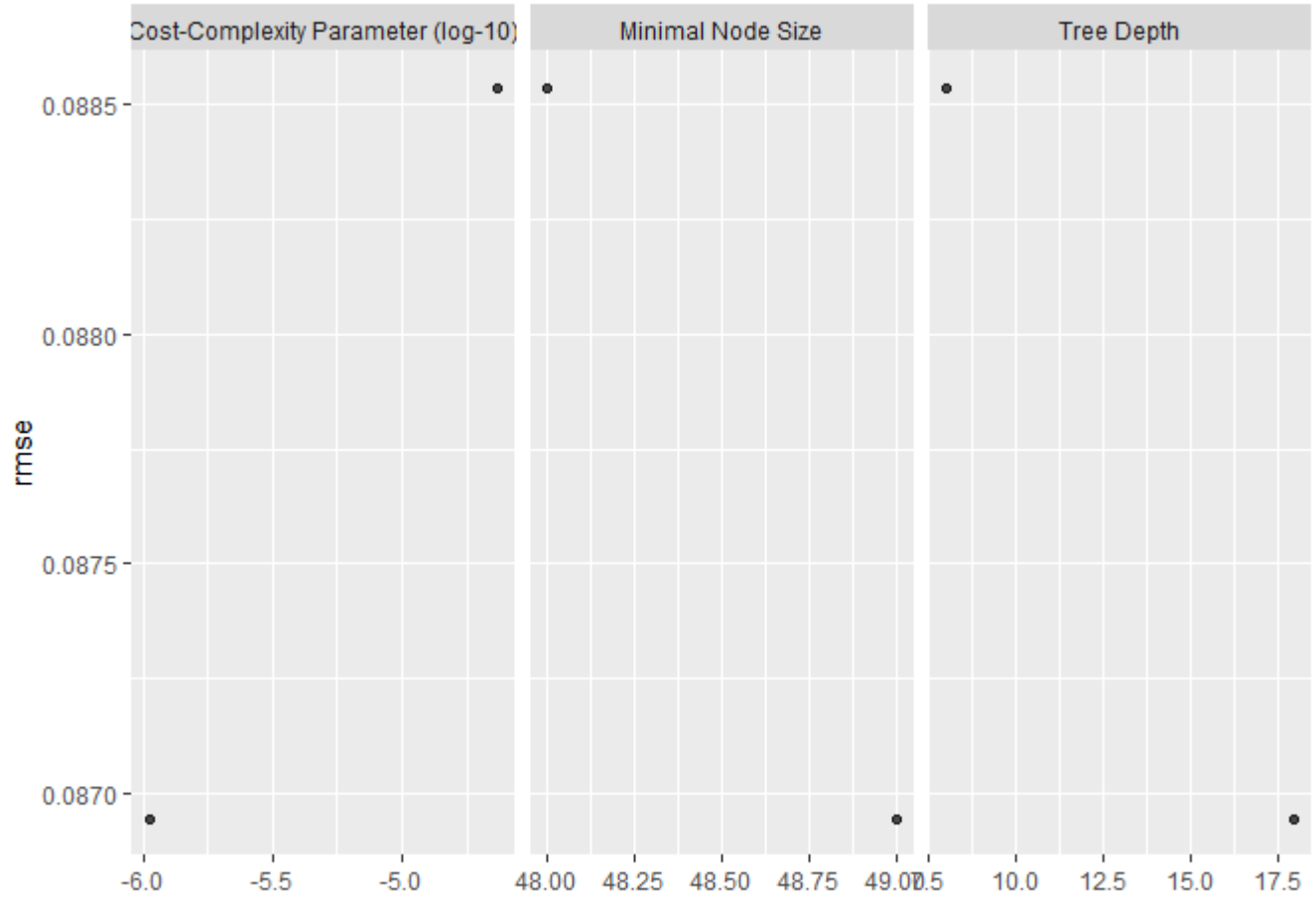

SP 2017-02-09
$y = -0.074 + x,\ R^2 = 0.98$
F
.pred
4
6
8
10

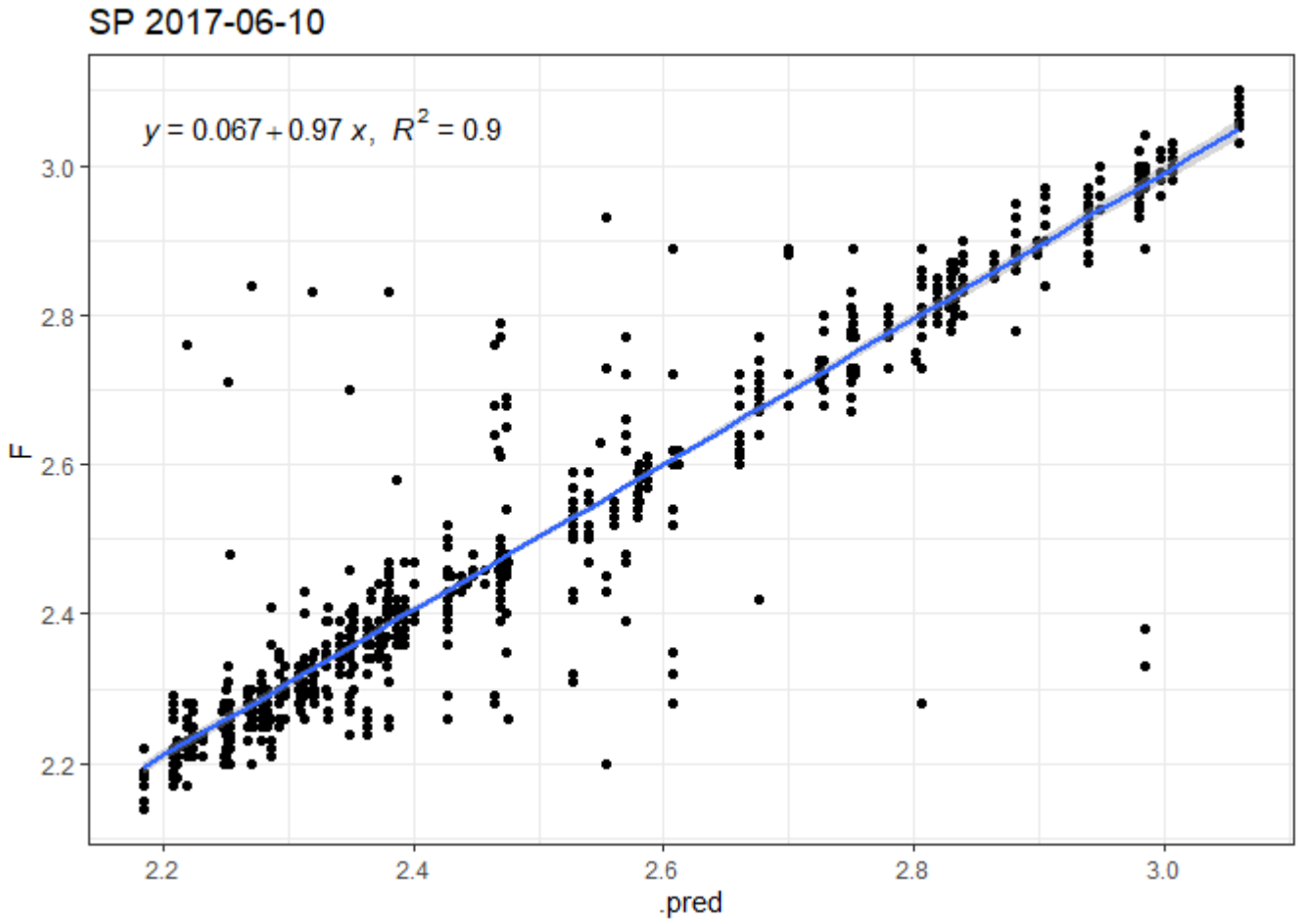

Al
Macro
EstC
HLIFS
T
Mg
Ca
K
U
pH
0.0
0.1
0.2
0.3
0.4
Importance

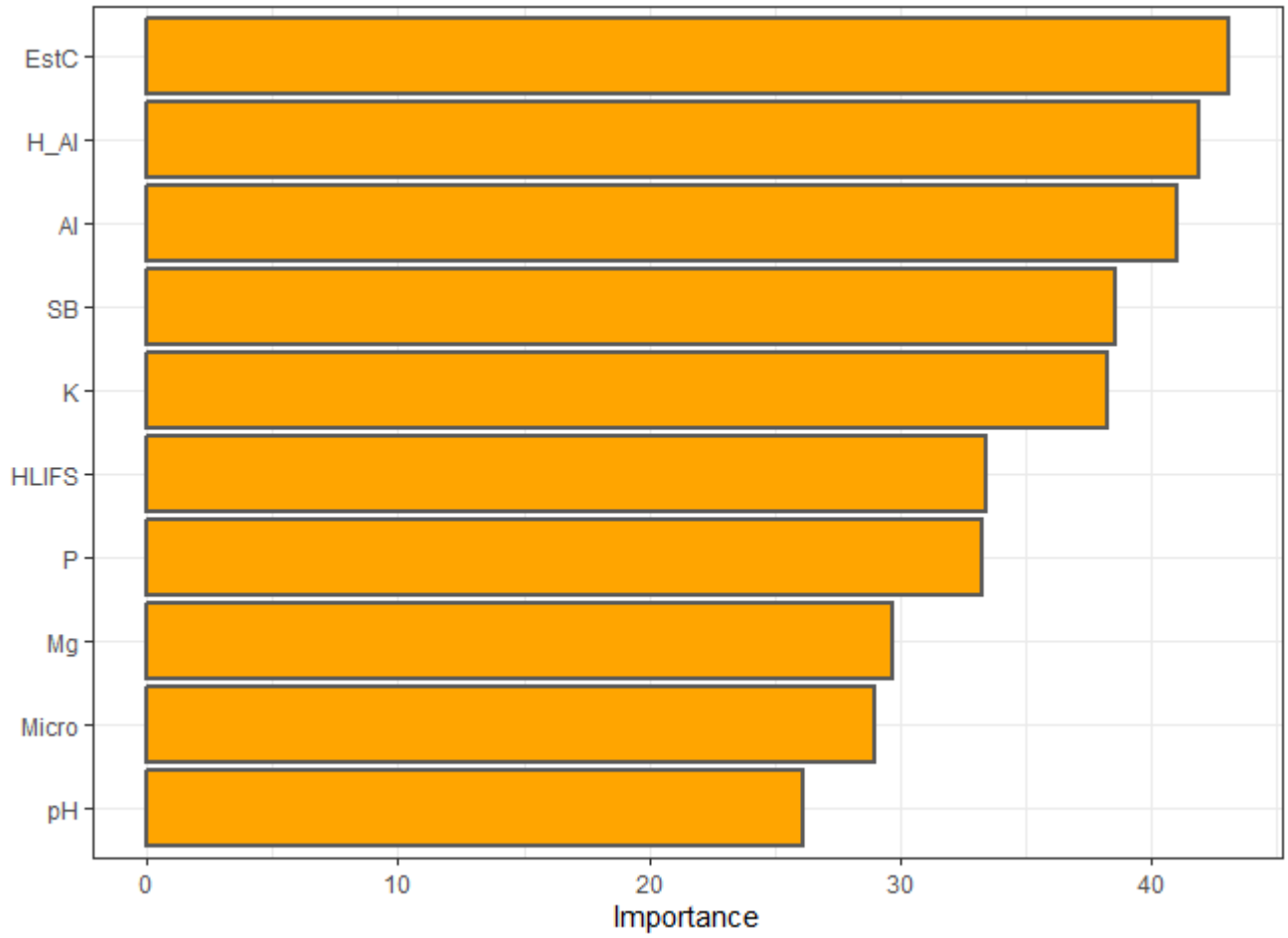
```
#>       vector_of_metrics
#> r            0.98950996
#> R2           0.97912996
#> MSE          0.01324195
#> RMSE         0.11507368
#> MAE          0.07097831
#> MAPE         1.32850426
```



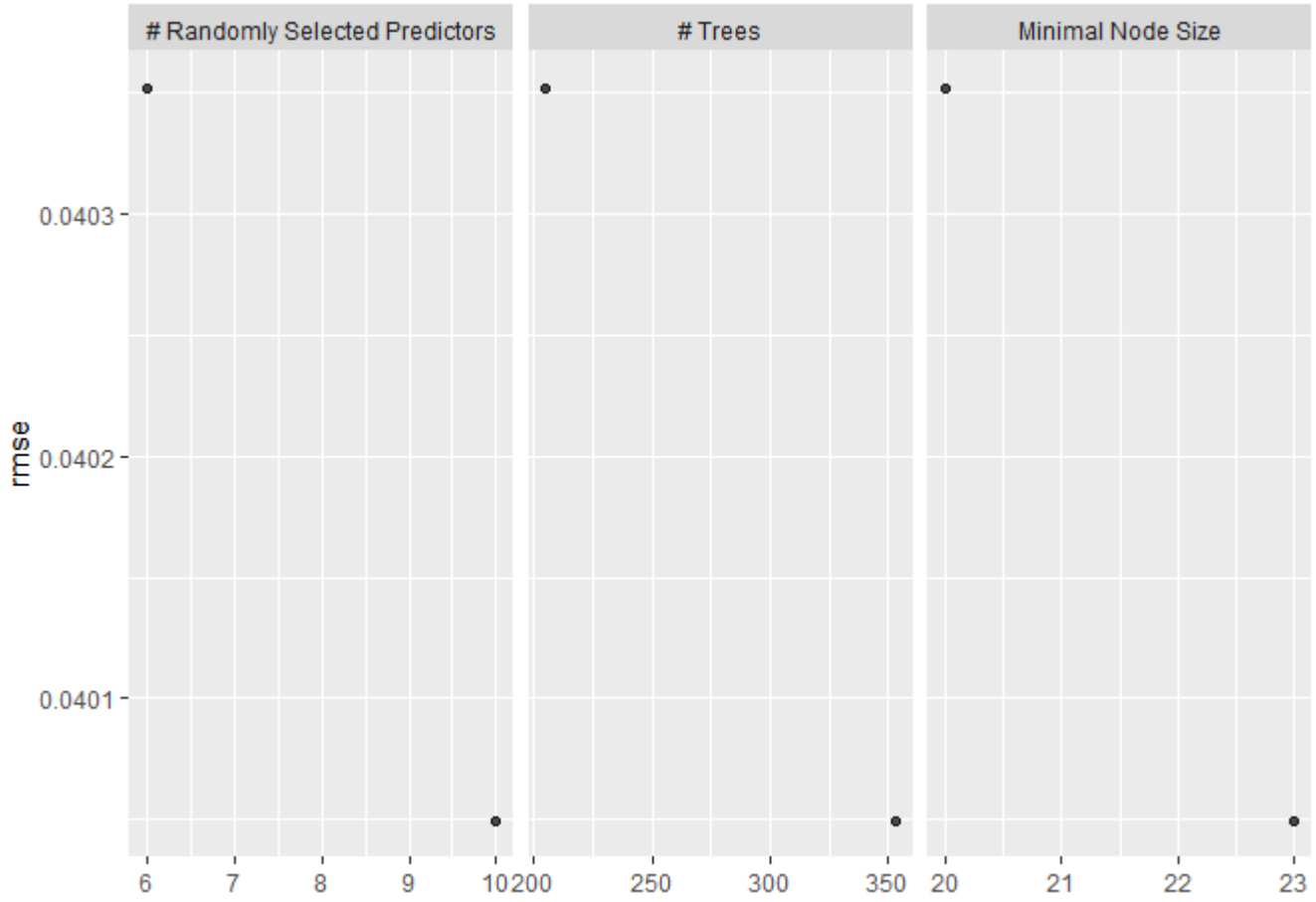

```
#> [1] "ARVORE DE DECISÃO"
```

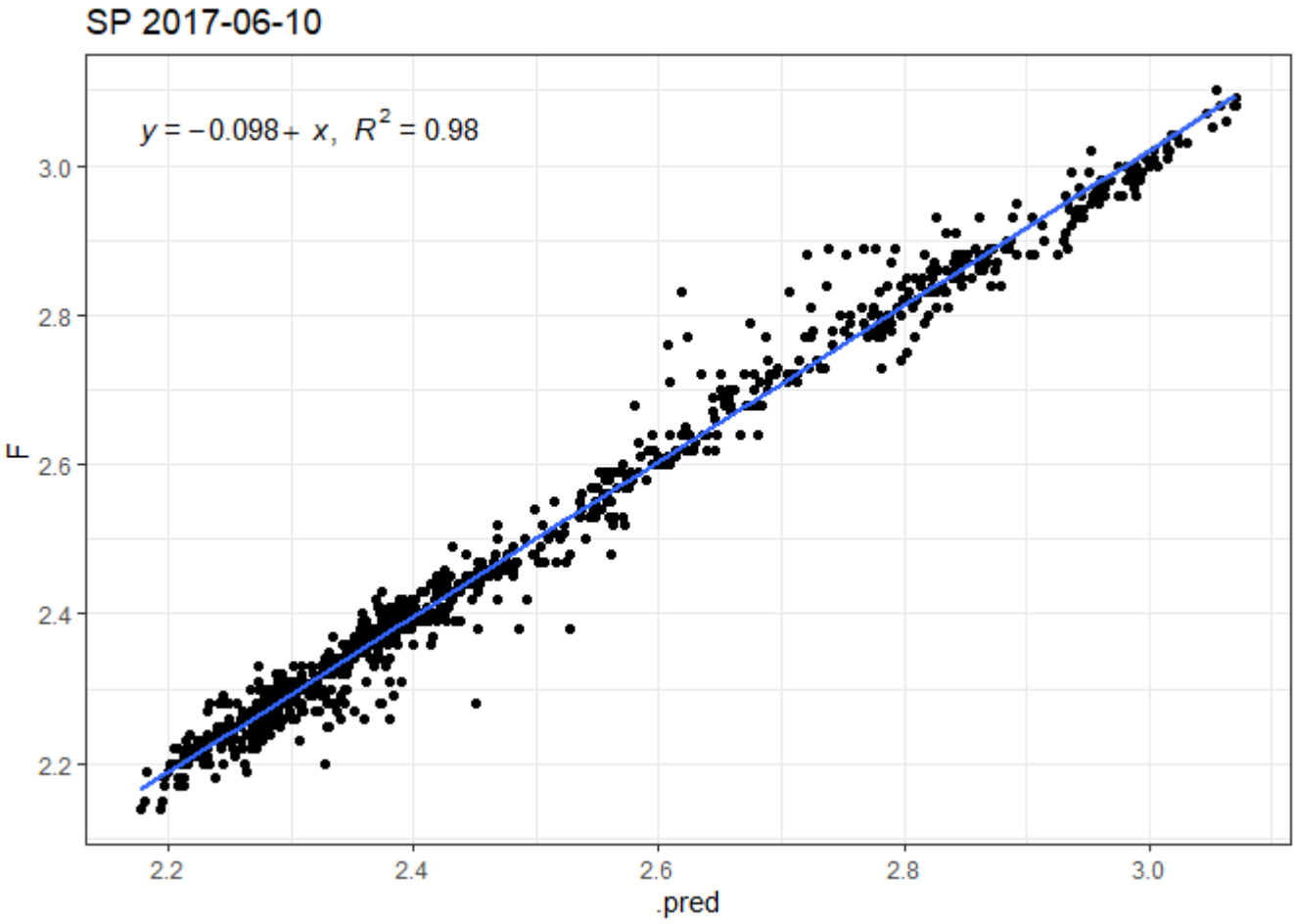

Cost-Complexity Parameter (log-10)
Minimal Node Size
Tree Depth
rmse
0.0885
0.0880
0.0875
0.0870
-6.0
-5.5
-5.0
48.00
48.25
48.50
48.75
49.00
10.0
12.5
15.0
17.5

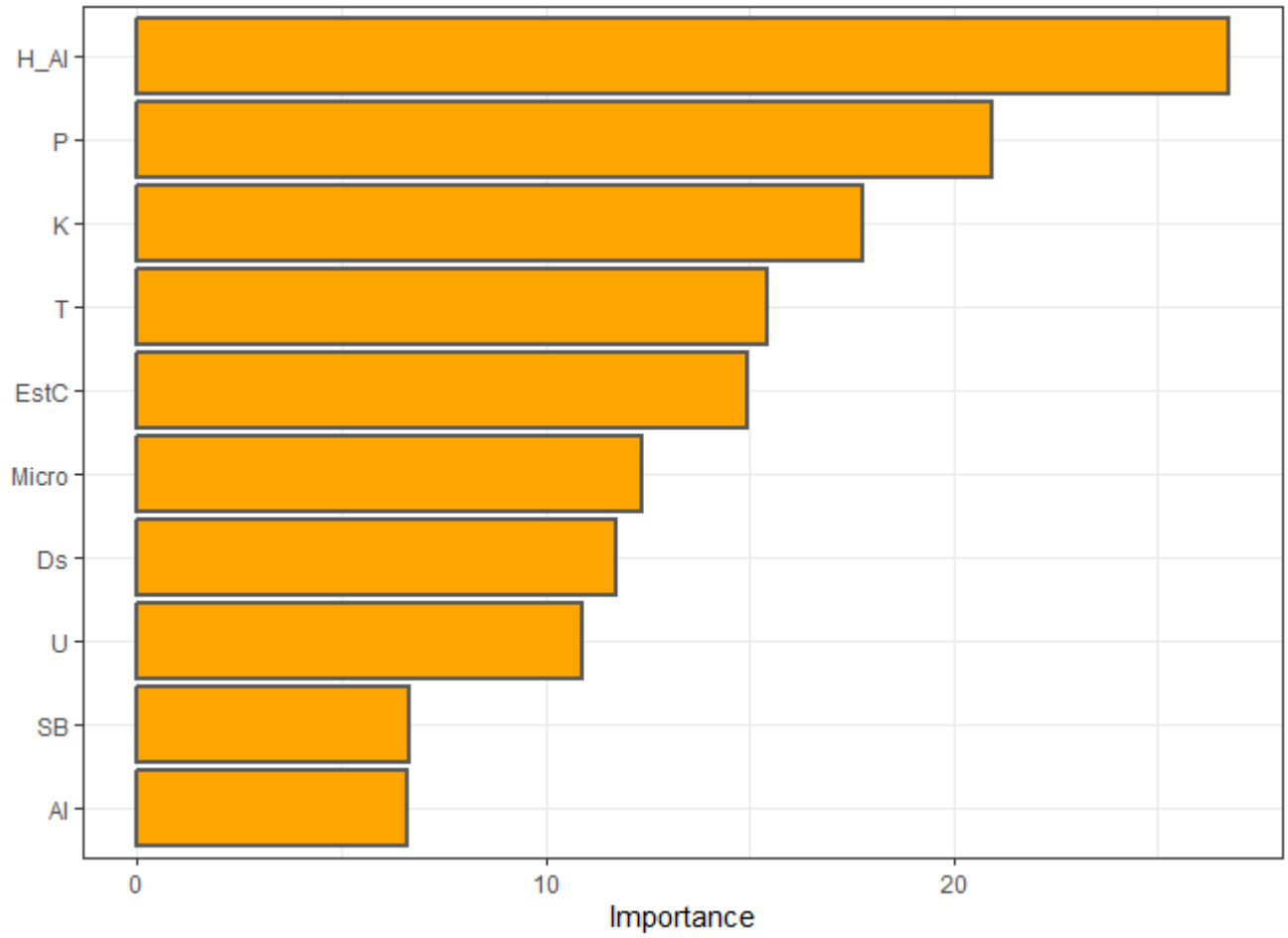

SP 2017-06-10
$y = 0.067 + 0.97\,x,\ R^2 = 0.9$
F
.pred
3.0
2.8
2.6
2.4
2.2
2.2
2.4
2.6
2.8
3.0



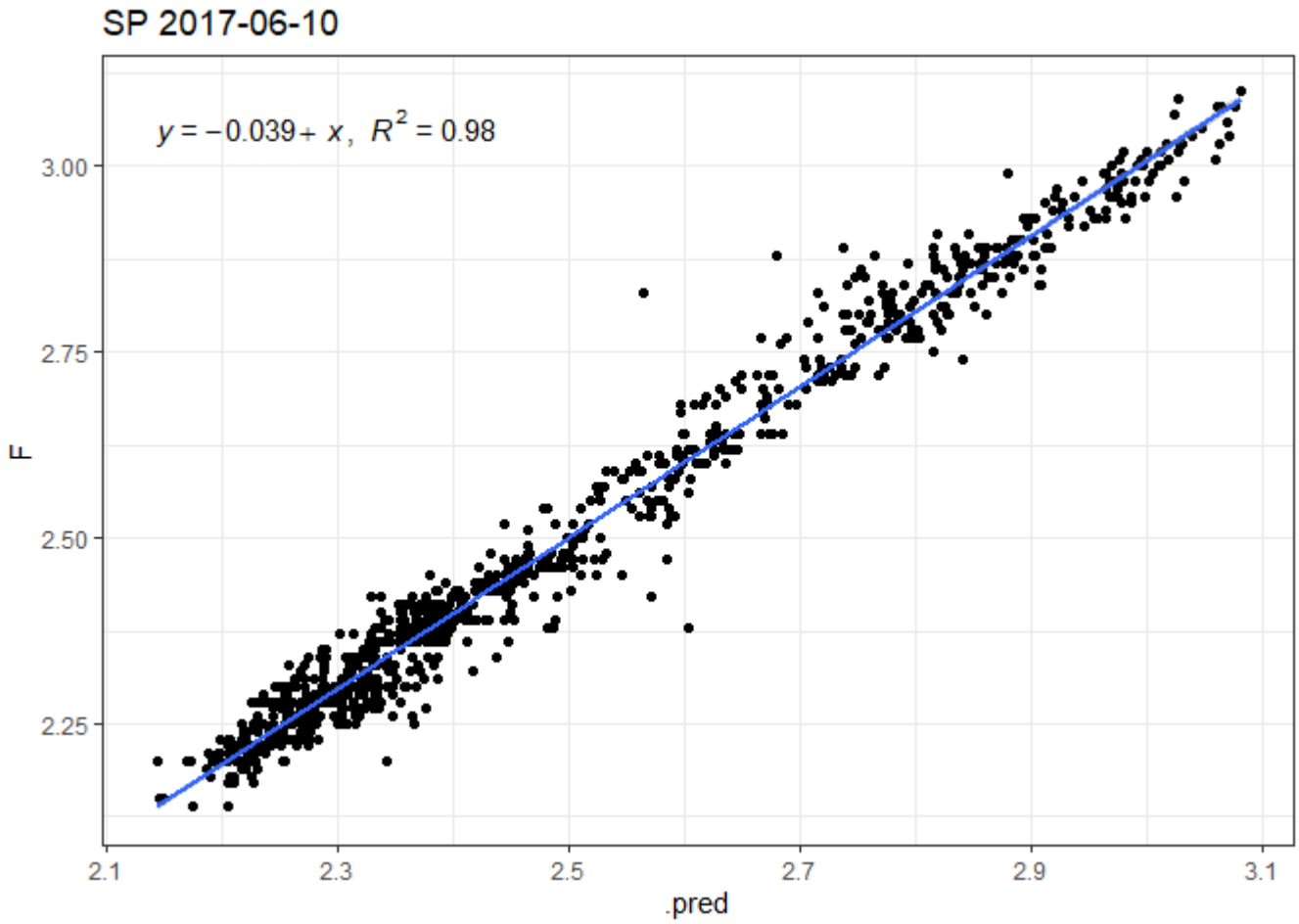

```
#>      vector_of_metrics
#> r           0.949618488
#> R2          0.901775273
#> MSE         0.005963251
#> RMSE        0.077222089
#> MAE         0.039160581
#> MAPE        1.560899252
#> [1] "RANDOM FOREST"
```

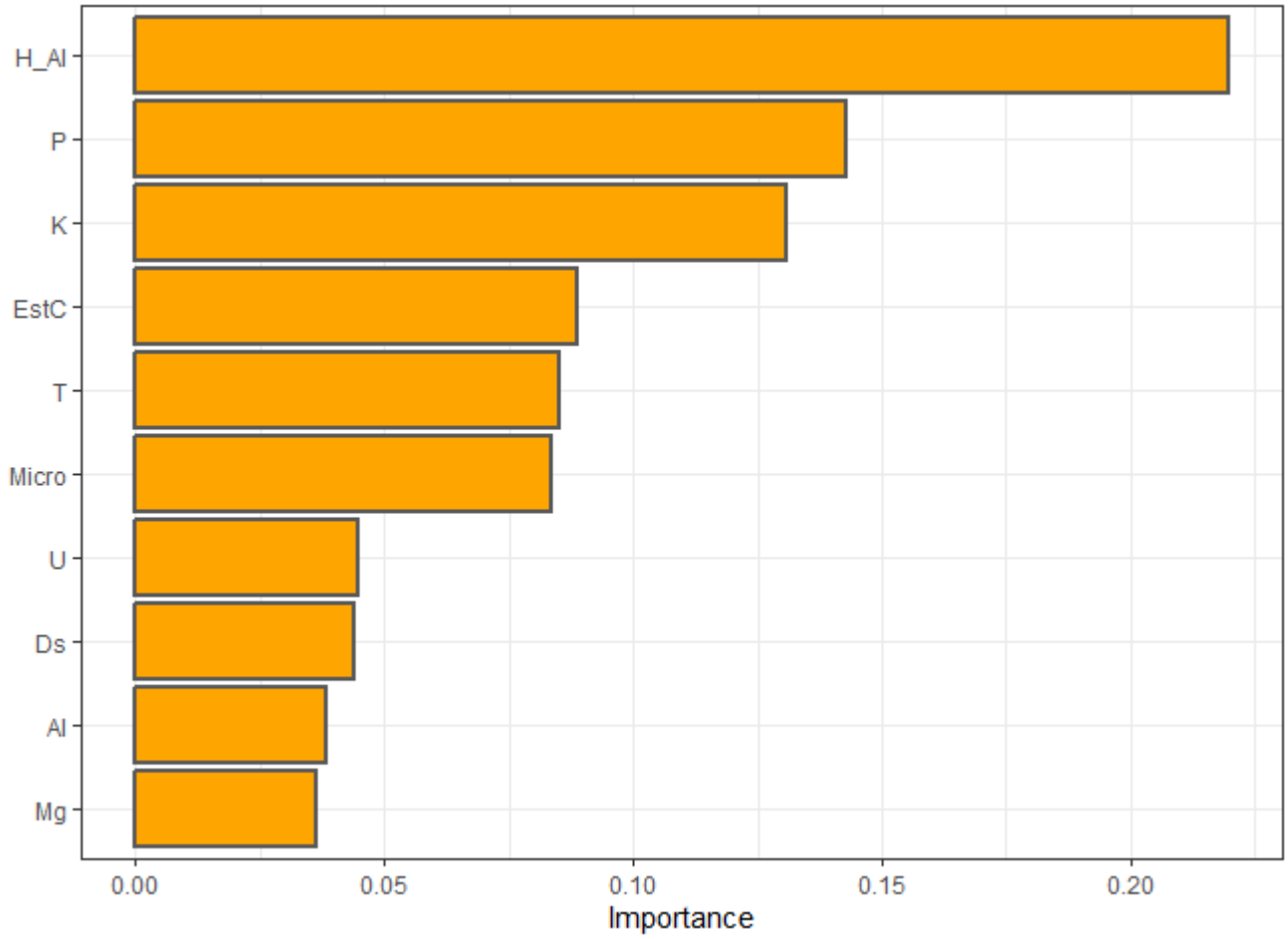

Randomly Selected Predictors
Trees
Minimal Node Size
rmse
0.0403
0.0402
0.0401
6
7
8
9
10
200
250
300
350
20
21
22
23


SP 2017-06-10
$y = -0.098 + x,\ R^2 = 0.98$
F
3.0
2.8
2.6
2.4
2.2
2.2
2.4
2.6
2.8
3.0
.pred

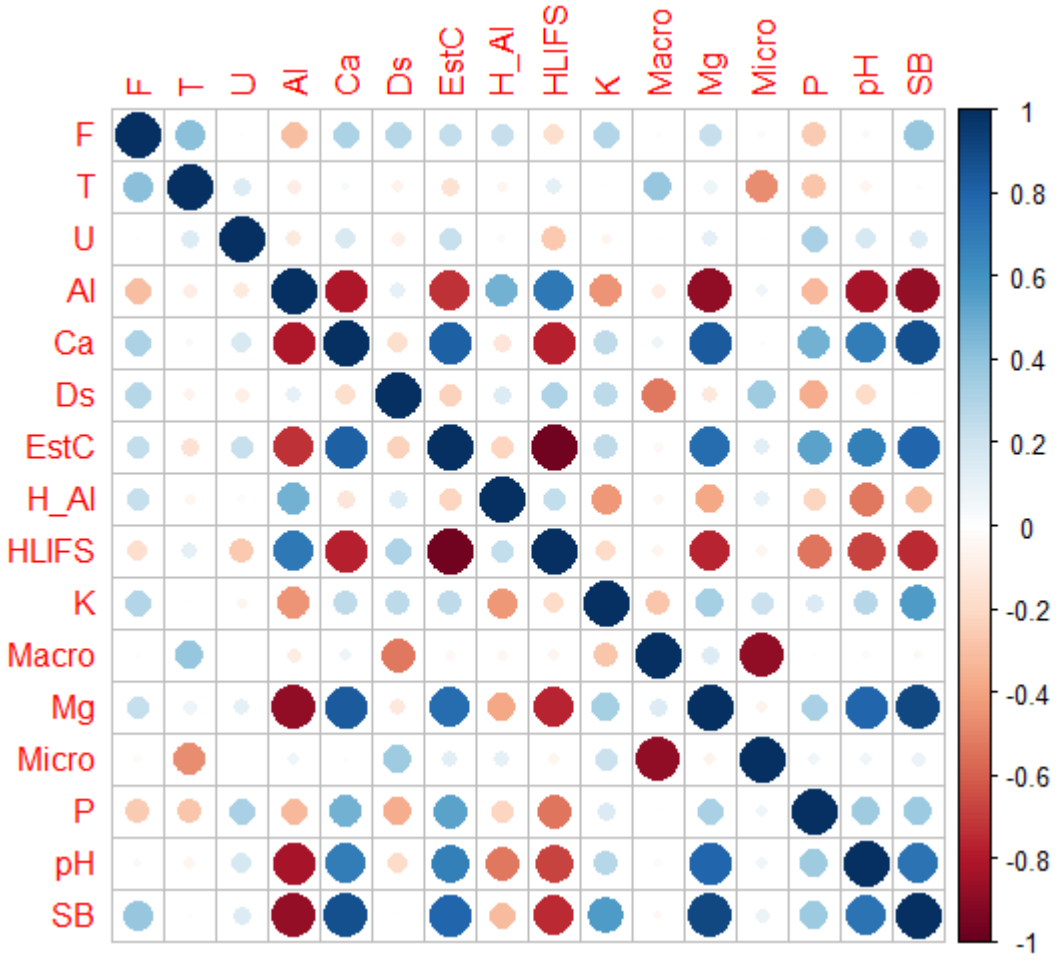



```
#>       vector_of_metrics
#> r           0.9924566884
#> R2          0.9849702783
#> MSE         0.0009918791
#> RMSE        0.0314941124
#> MAE         0.0202415375
#> MAPE        0.8089422794
```

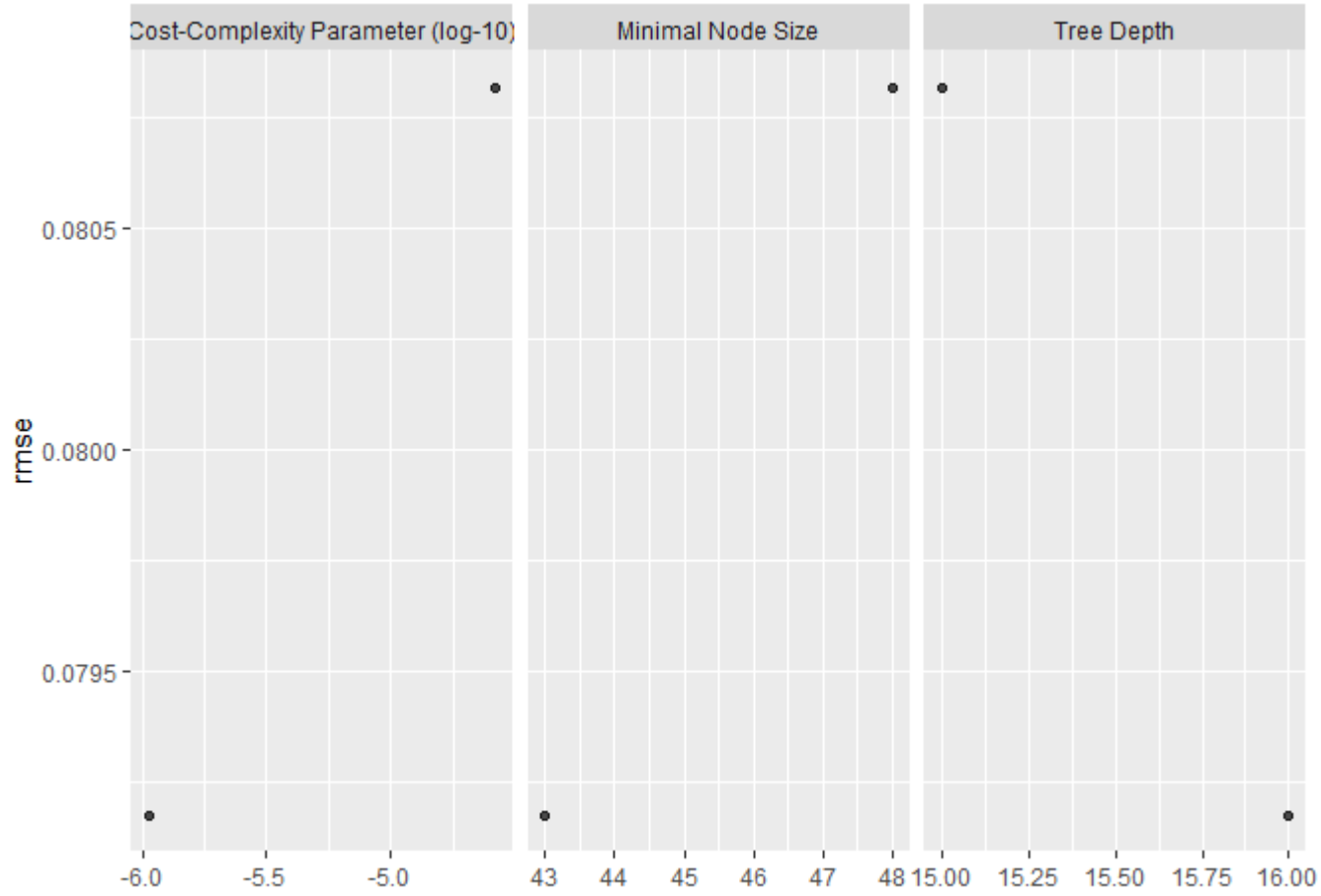

SP 2017-06-10
$y = -0.039 + x$, $R^2 = 0.98$
3.00
2.75
2.50
2.25
F
2.1
2.3
2.5
2.7
2.9
3.1
.pred

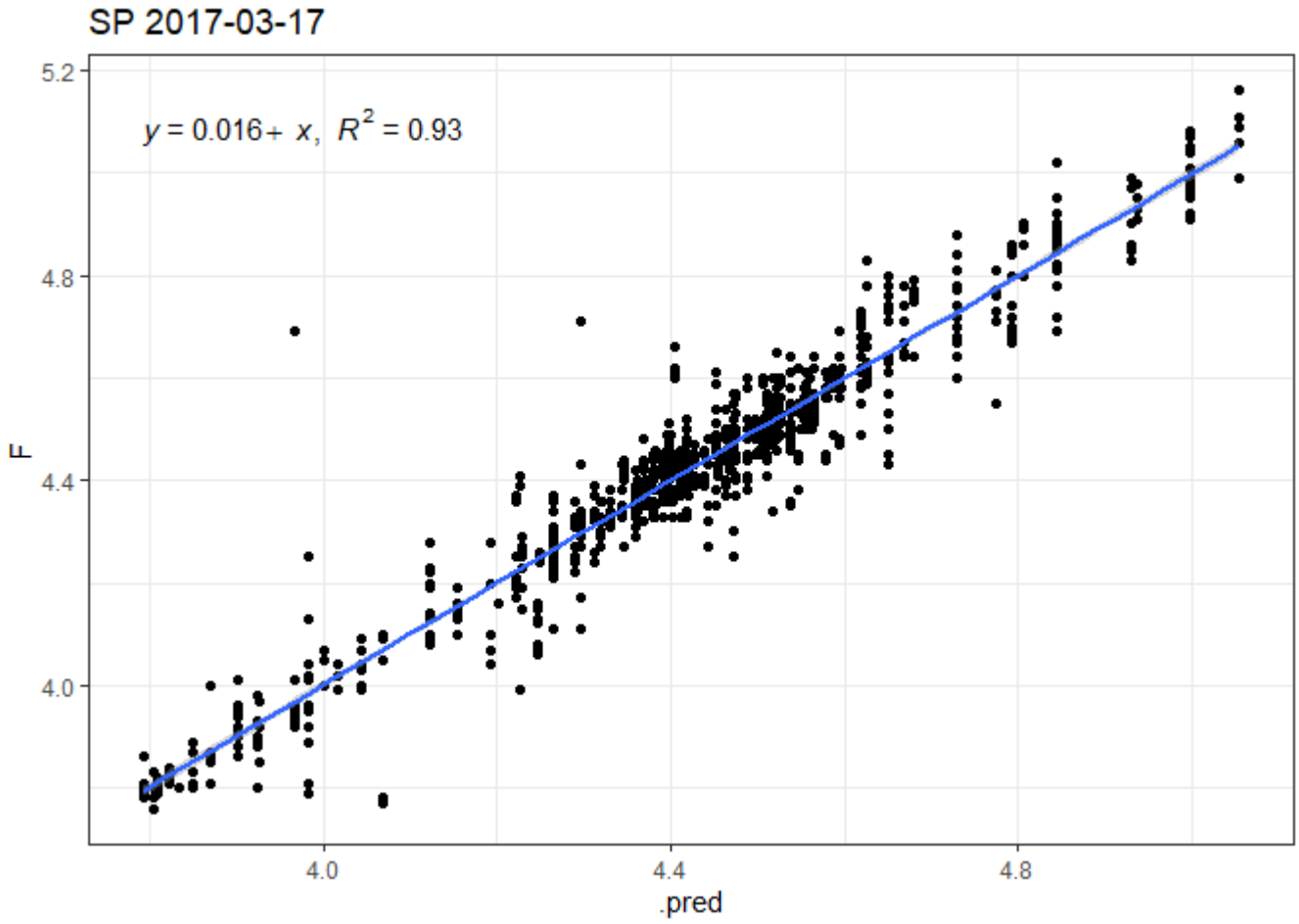

H_Al
P
K
EstC
T
Micro
U
Ds
Al
Mg
0.00
0.05
0.10
0.15
0.20
Importance

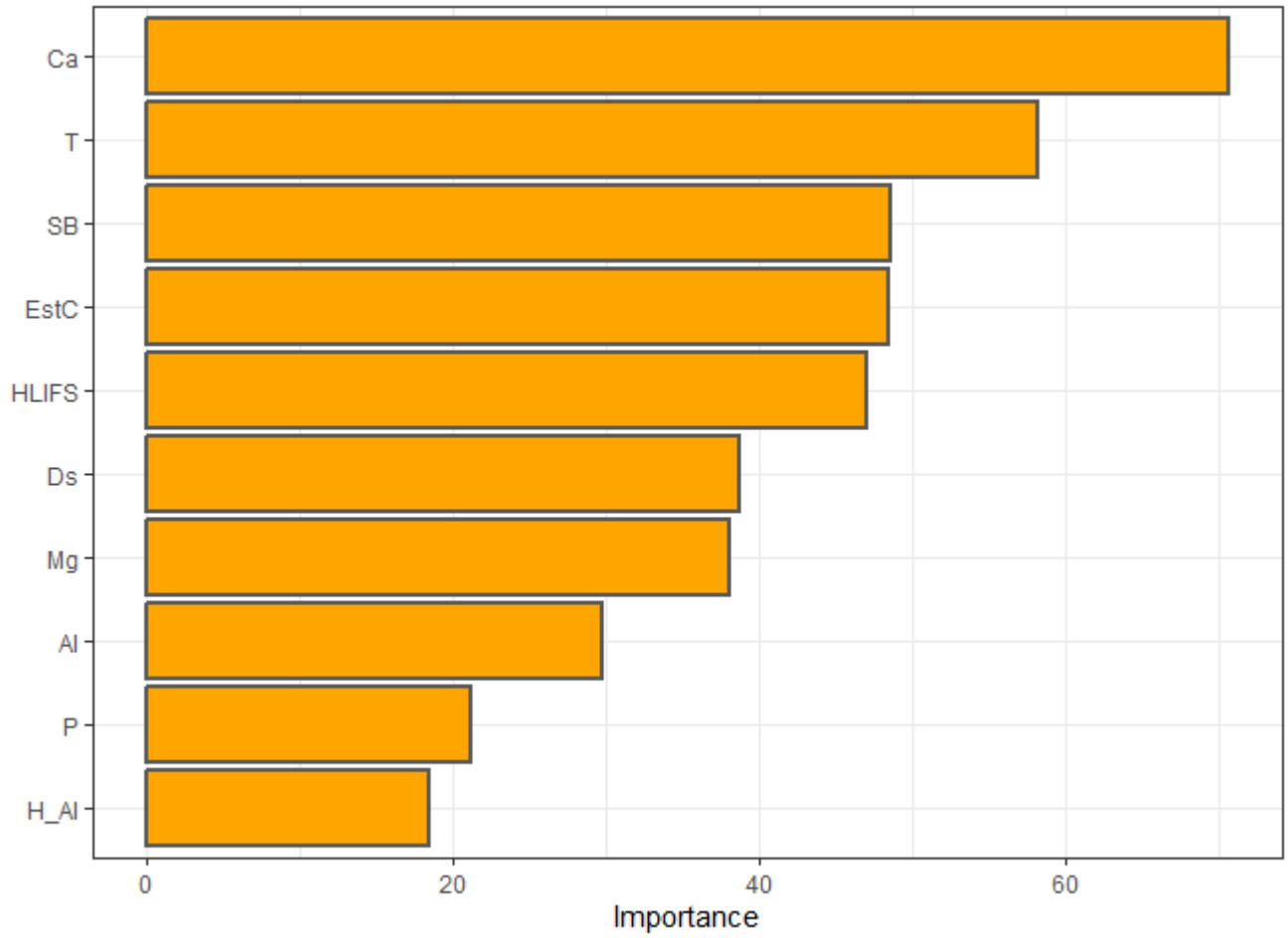
```
#>       vector_of_metrics
#> r           0.988437037
#> R2          0.977007775
#> MSE         0.001399825
#> RMSE        0.037414236
#> MAE         0.027067570
#> MAPE        1.085957842
```



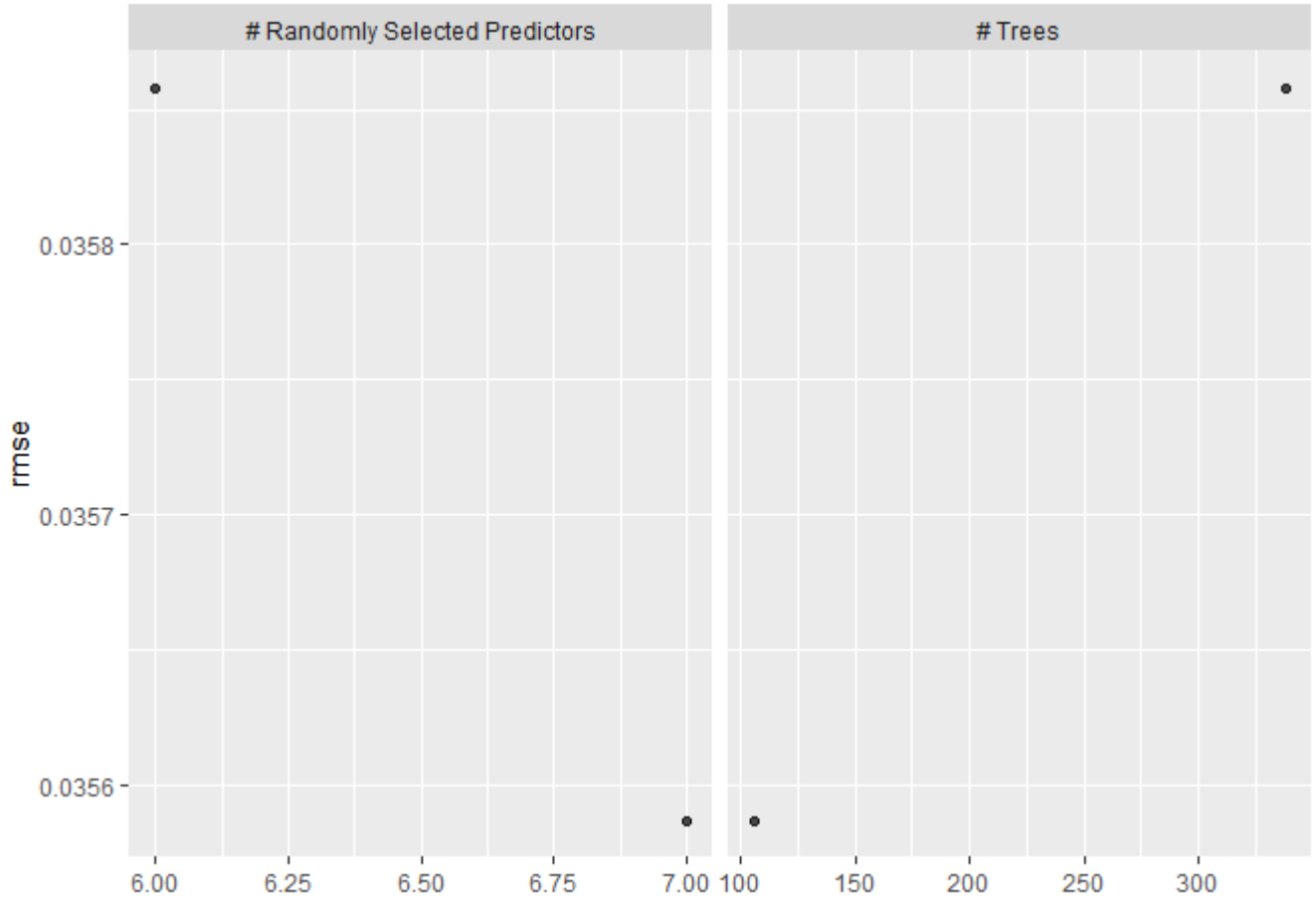

```
#> [1] "ARVORE DE DECISÃO"
```

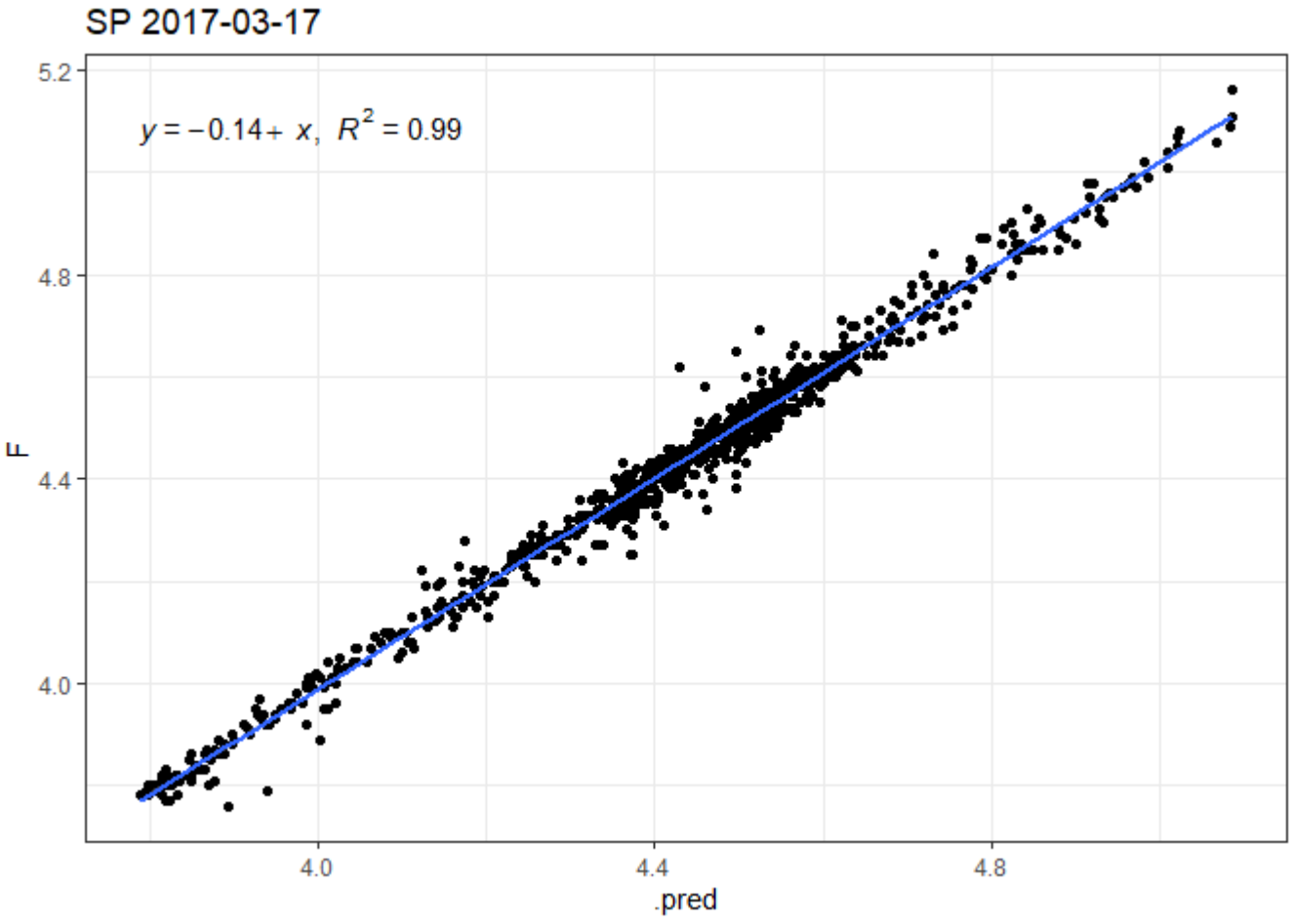

Cost-Complexity Parameter (log-10)
Minimal Node Size
Tree Depth
rmse
0.0805
0.0800
0.0795
-6.0
-5.5
-5.0
43
44
45
46
47
48
15.00
15.25
15.50
15.75
16.00

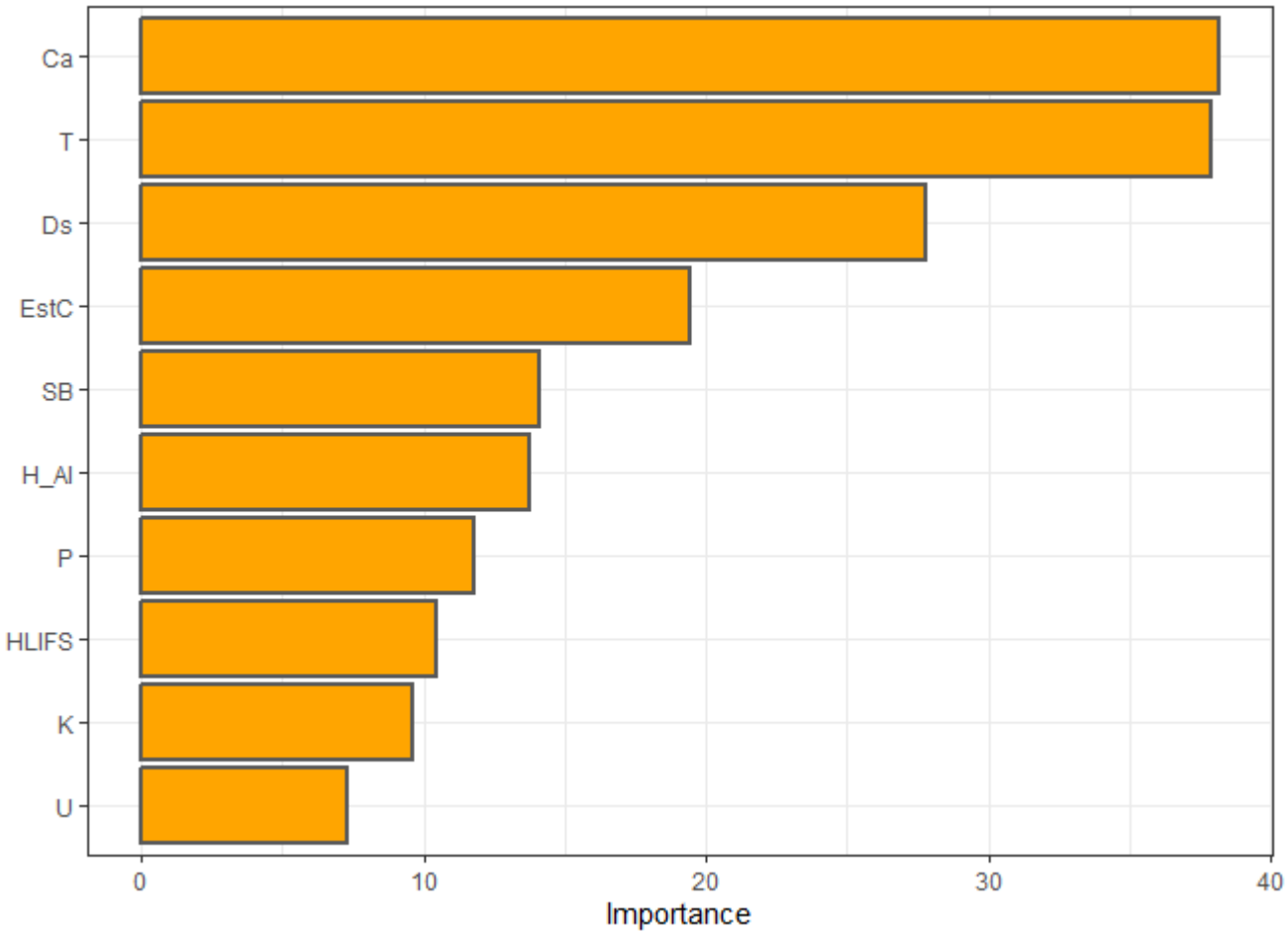

SP 2017-03-17
y = 0.016+ x, R2 = 0.93
F
5.2
4.8
4.4
4.0
4.0
4.4
4.8
.pred



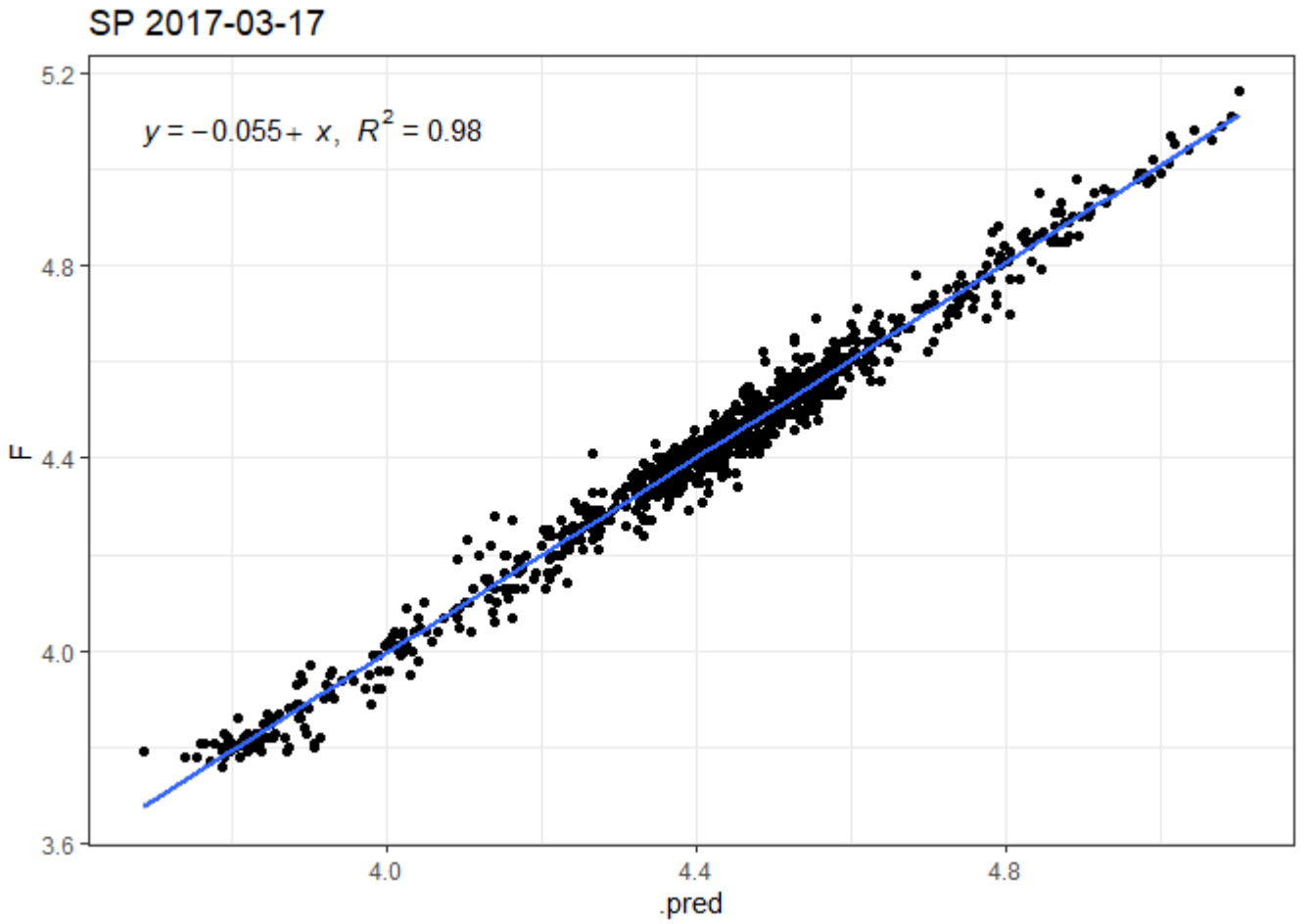

```
#>      vector_of_metrics
#> r           0.966878660
#> R2          0.934854343
#> MSE         0.004645566
#> RMSE        0.068158388
#> MAE         0.044200021
#> MAPE        1.003661751
#> [1] "RANDOM FOREST"
```

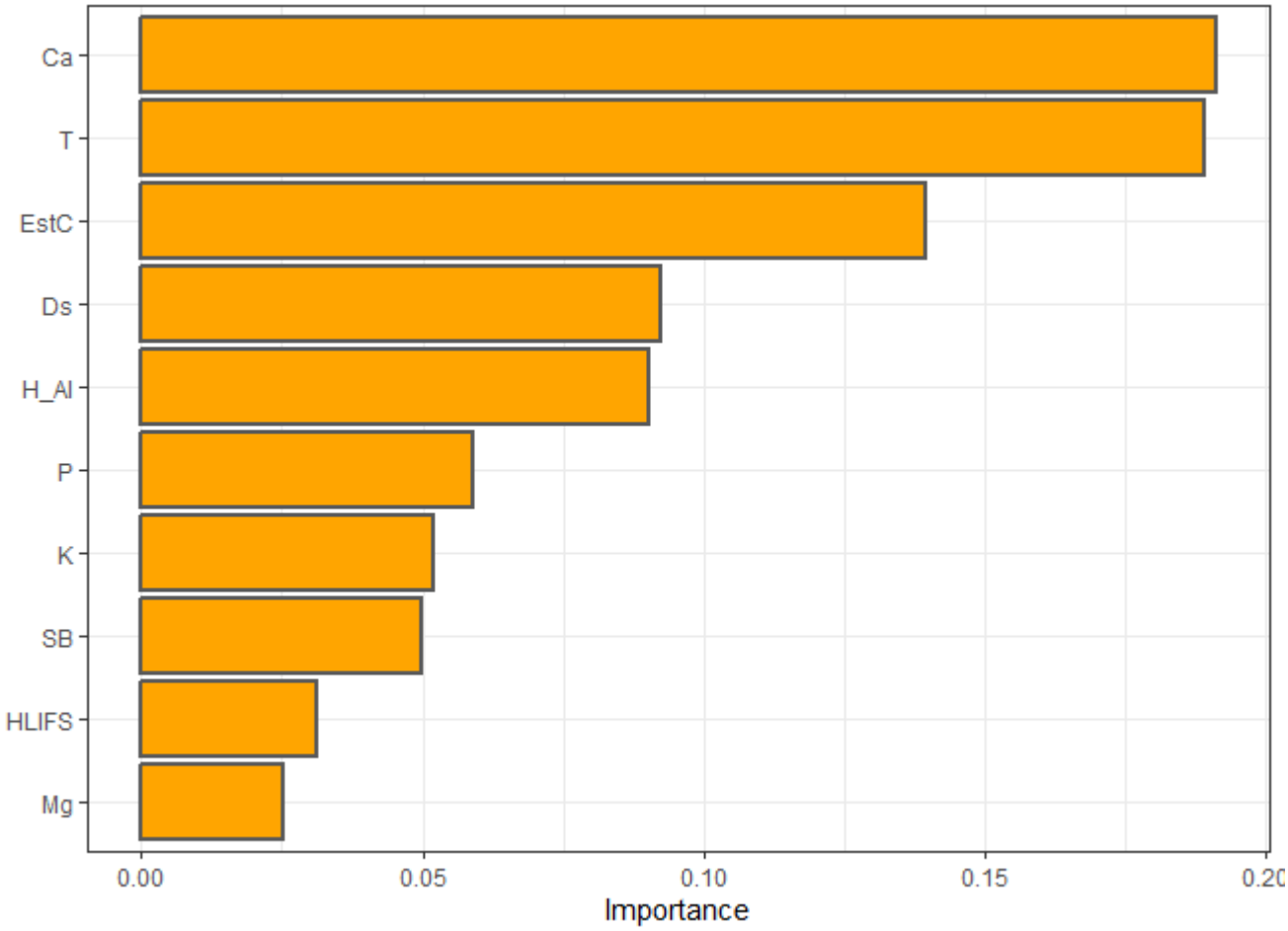

Randomly Selected Predictors
Trees
rmse
0.0358
0.0357
0.0356
6.00
6.25
6.50
6.75
7.00
100
150
200
250
300


SP 2017-03-17
$y = -0.14 + x,\ R^2 = 0.99$
F
5.2
4.8
4.4
4.0
4.0
4.4
4.8
.pred

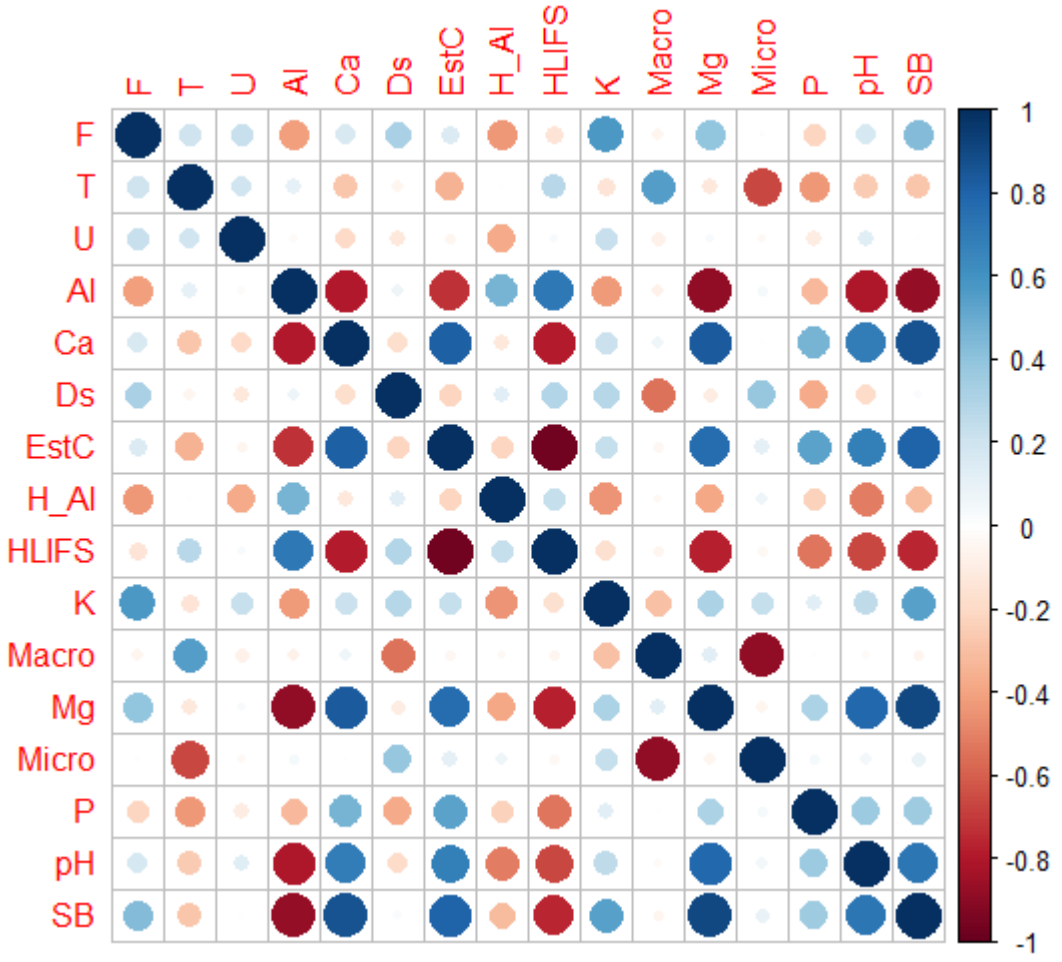



```
#>      vector_of_metrics
#> r          0.9935443100
#> R2         0.9871302958
#> MSE        0.0009893257
#> RMSE       0.0314535486
#> MAE        0.0220547888
#> MAPE       0.5003072126
```

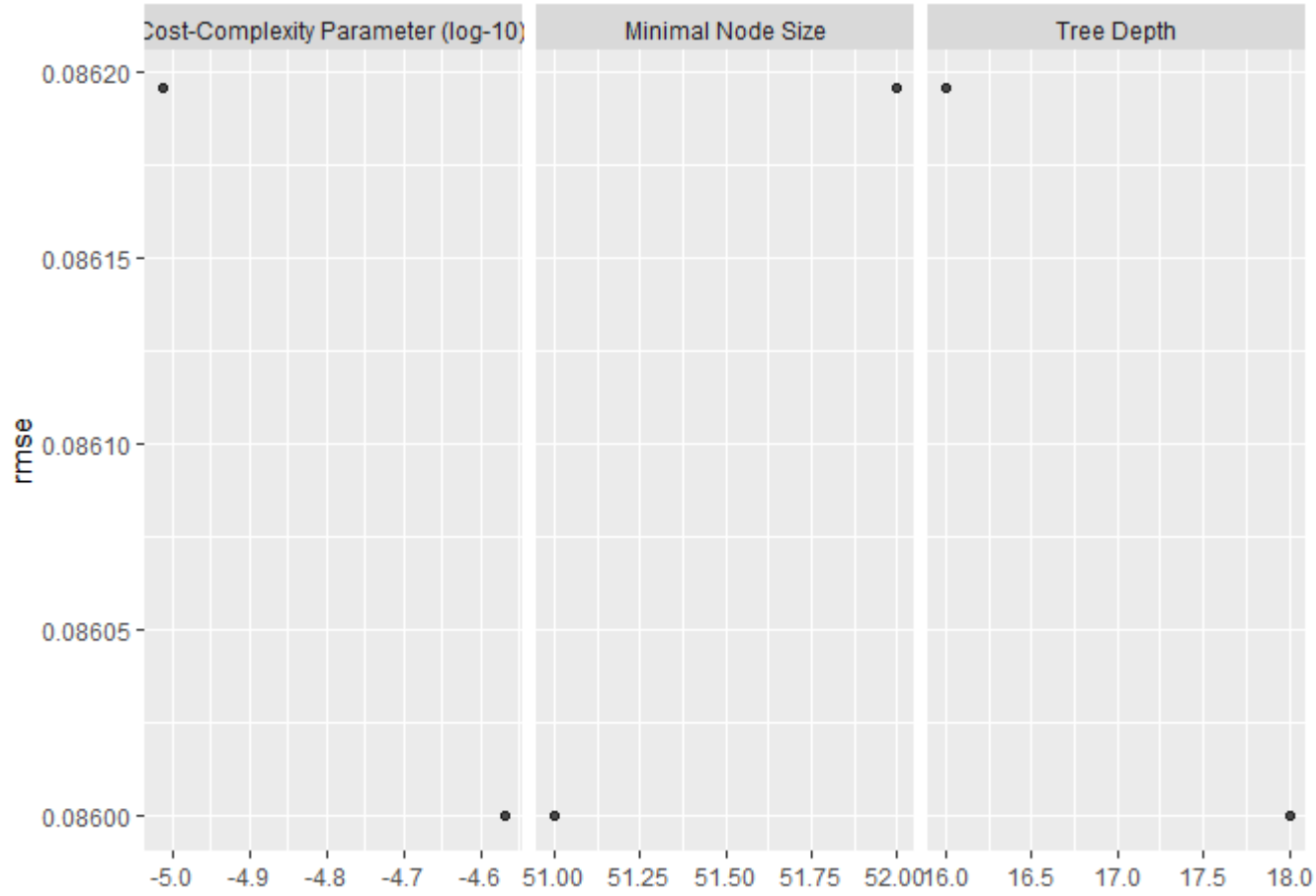

SP 2017-03-17
$y = -0.055 + x,\ R^2 = 0.98$
5.2
4.8
4.4
4.0
3.6
F
4.0
4.4
4.8
.pred

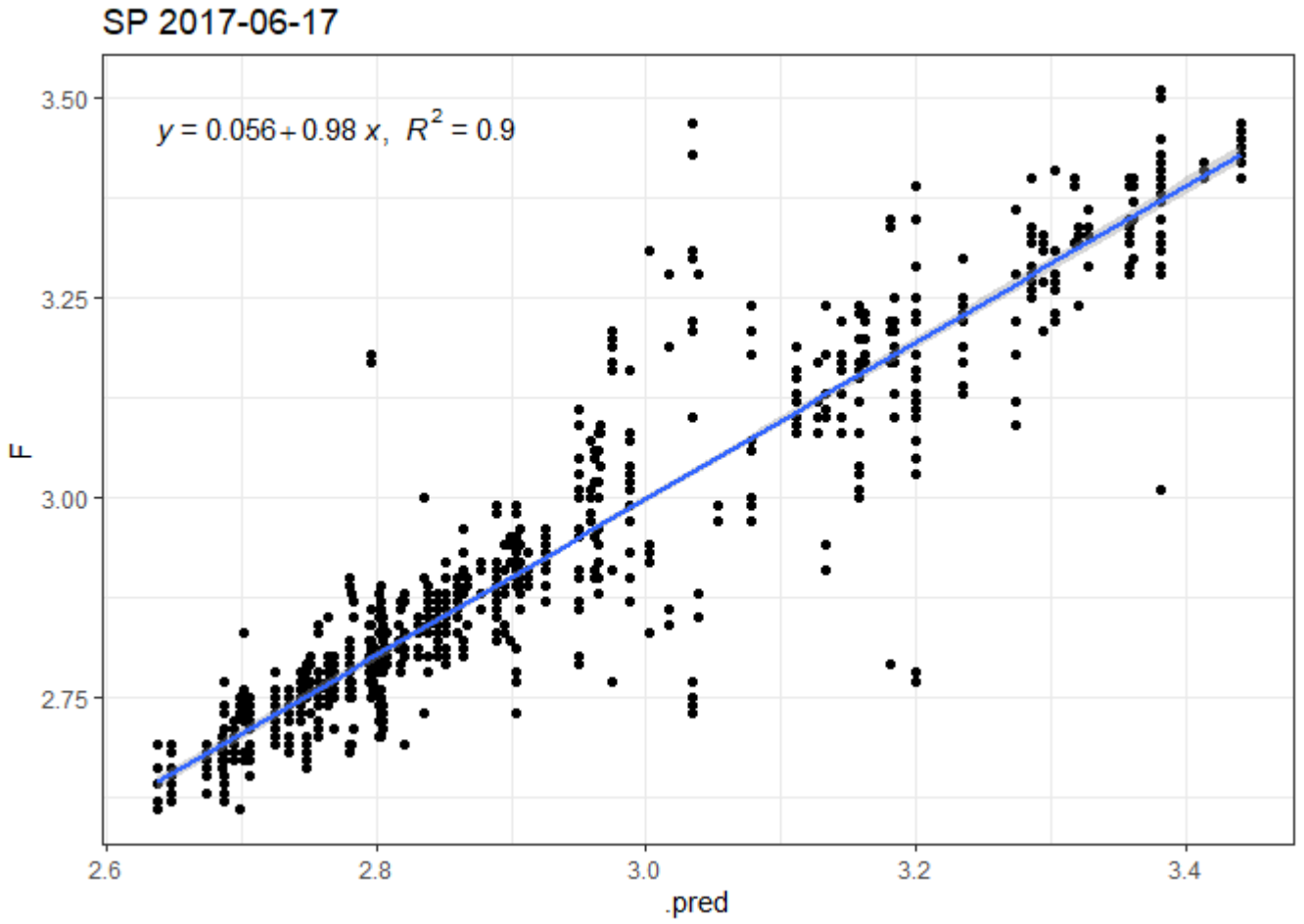

Ca
T
EstC
Ds
H_Al
P
K
SB
HLIFS
Mg
0.00
0.05
0.10
0.15
0.20
Importance

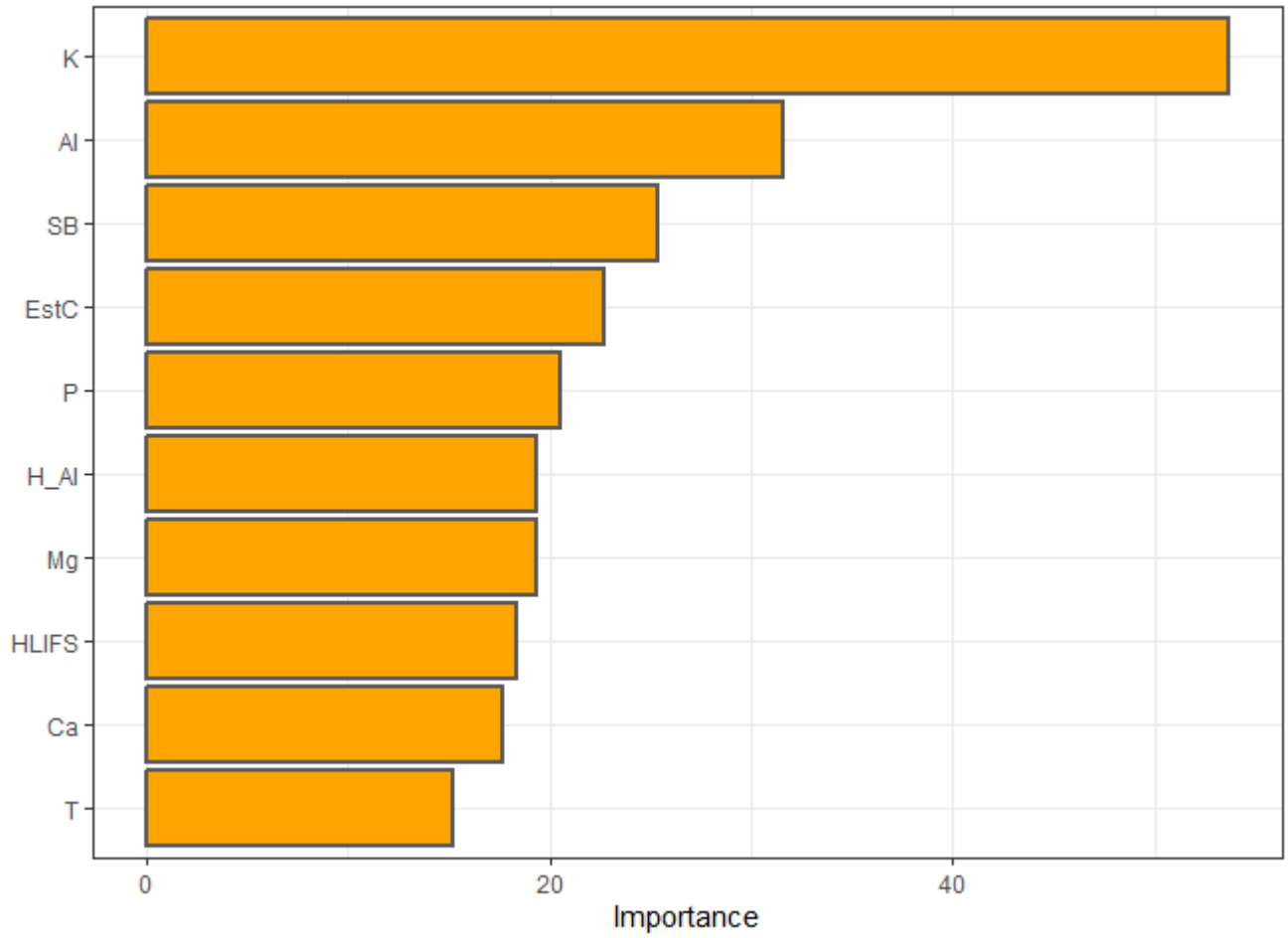
```
#>       vector_of_metrics
#> r           0.990930479
#> R2          0.981943214
#> MSE         0.001298142
#> RMSE        0.036029735
#> MAE         0.027232238
#> MAPE        0.621138991
```



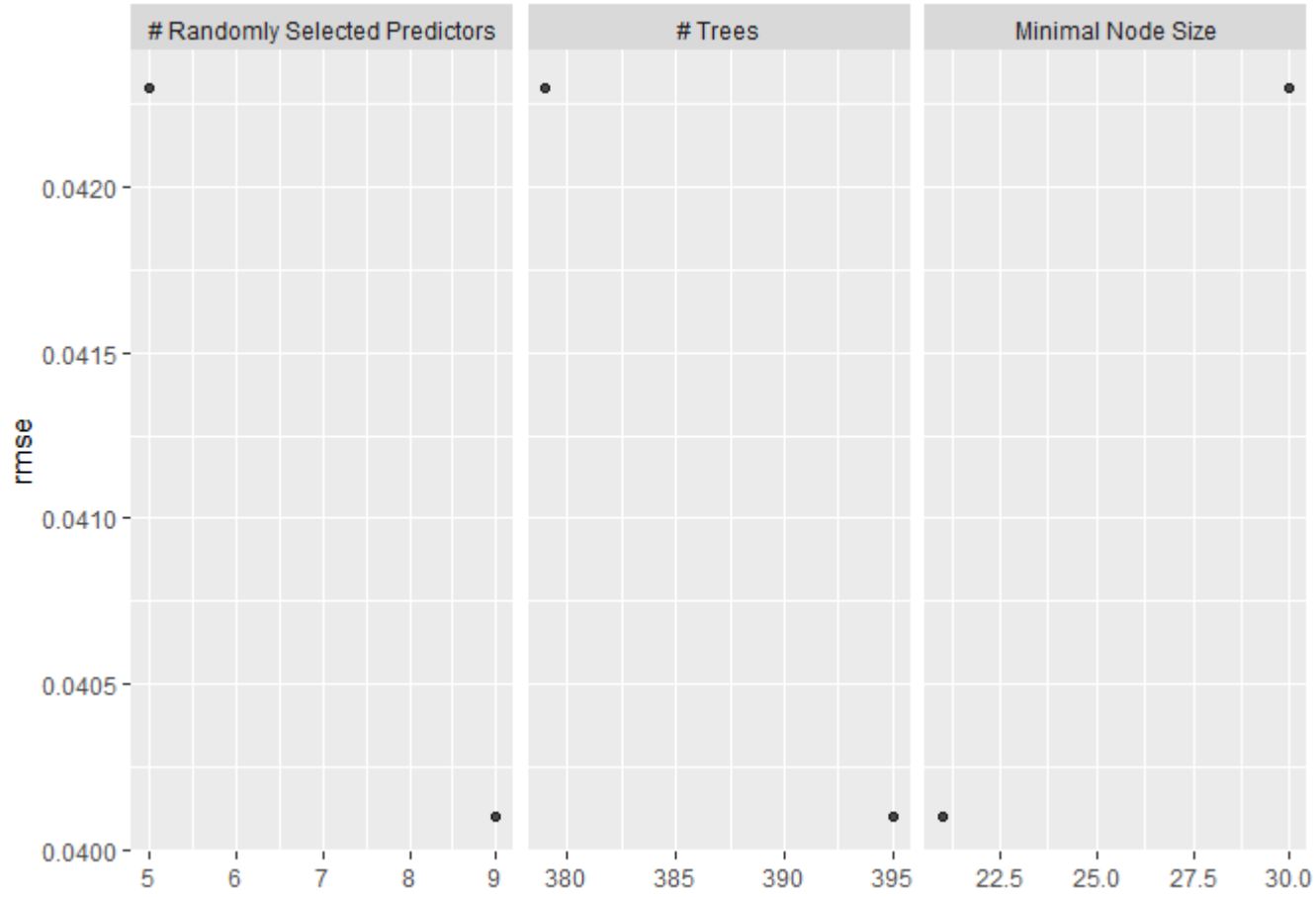

```
#> [1] "ARVORE DE DECISÃO"
```

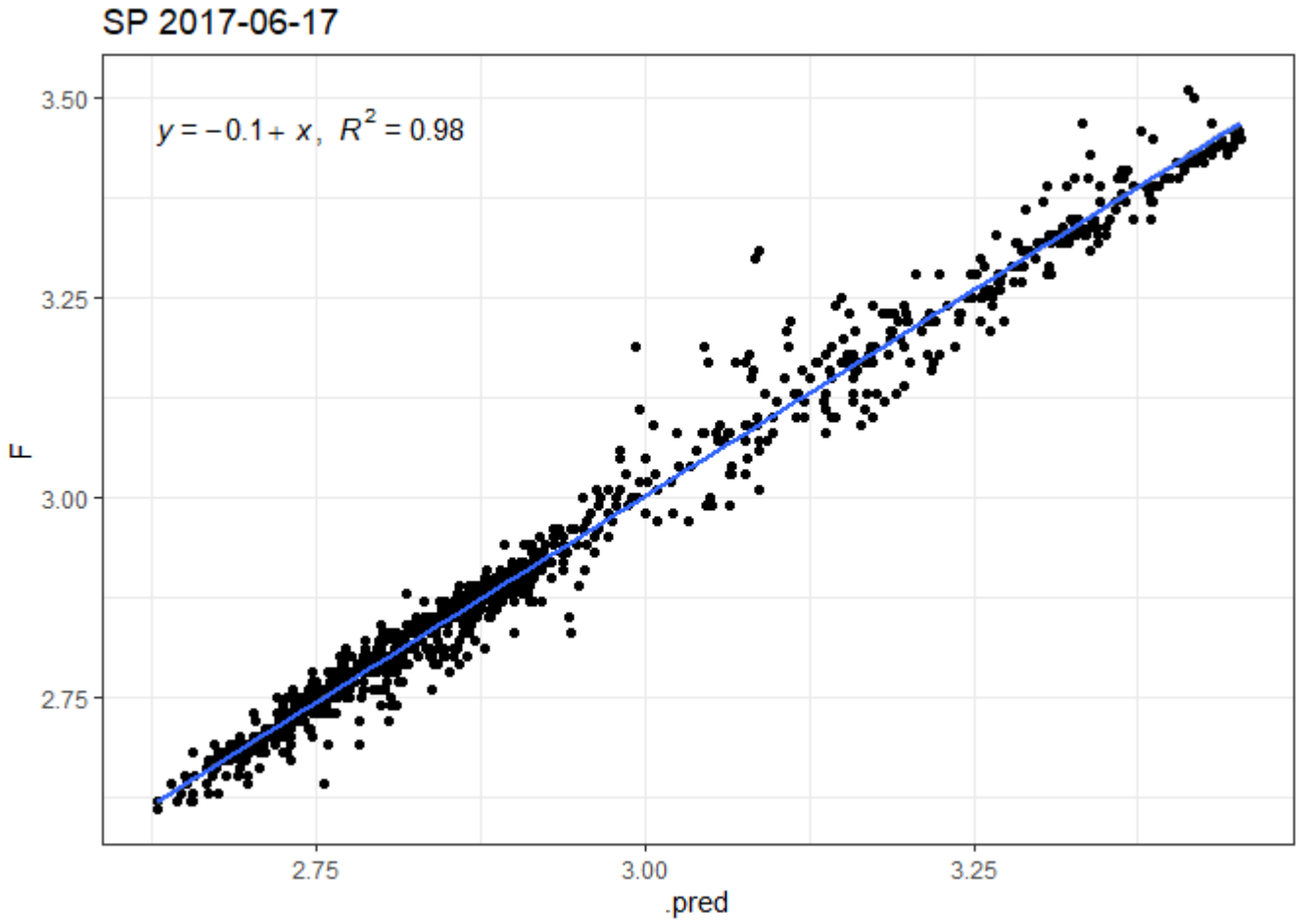

Cost-Complexity Parameter (log-10)
Minimal Node Size
Tree Depth
rmse
0.08620
0.08615
0.08610
0.08605
0.08600
-5.0
-4.9
-4.8
-4.7
-4.6
51.00
51.25
51.50
51.75
52.00
16.0
16.5
17.0
17.5
18.0

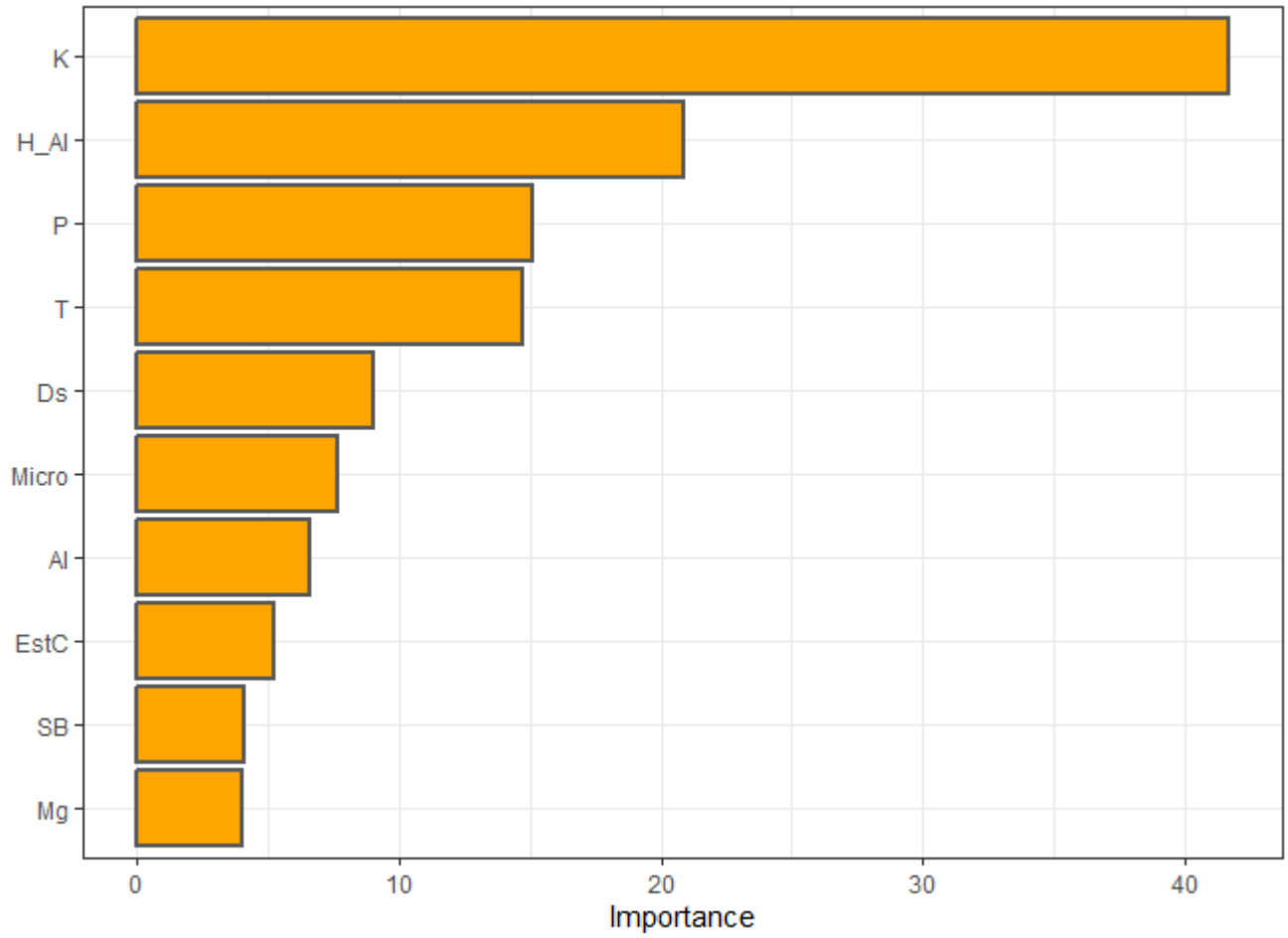

SP 2017-06-17
$y = 0.056 + 0.98\,x,\ R^2 = 0.9$
F
3.50
3.25
3.00
2.75
2.6
2.8
3.0
3.2
3.4
.pred



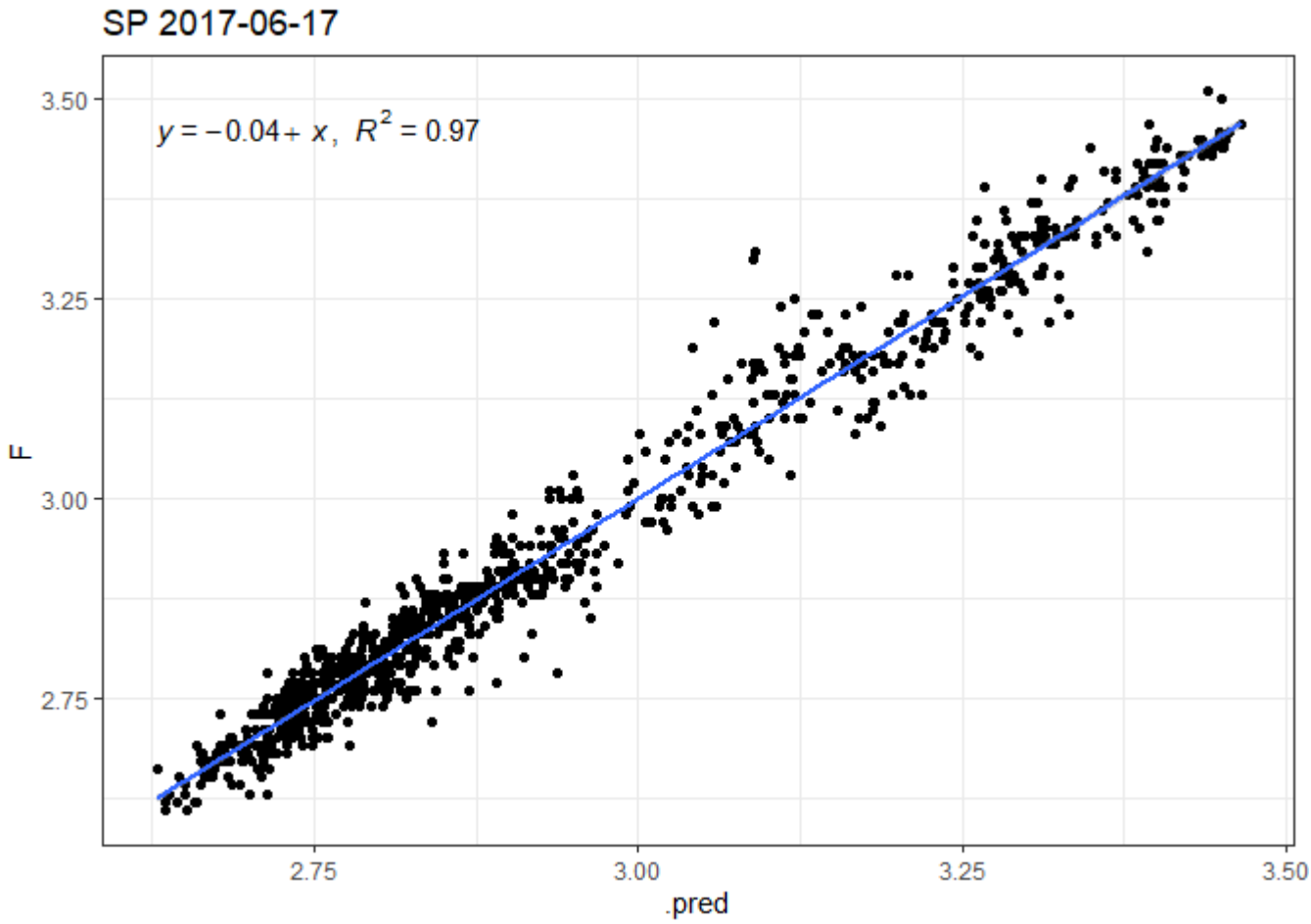

```
#>      vector_of_metrics
#> r           0.947523941
#> R2          0.897801619
#> MSE         0.005474458
#> RMSE        0.073989577
#> MAE         0.044391750
#> MAPE        1.496940101
#> [1] "RANDOM FOREST"
```

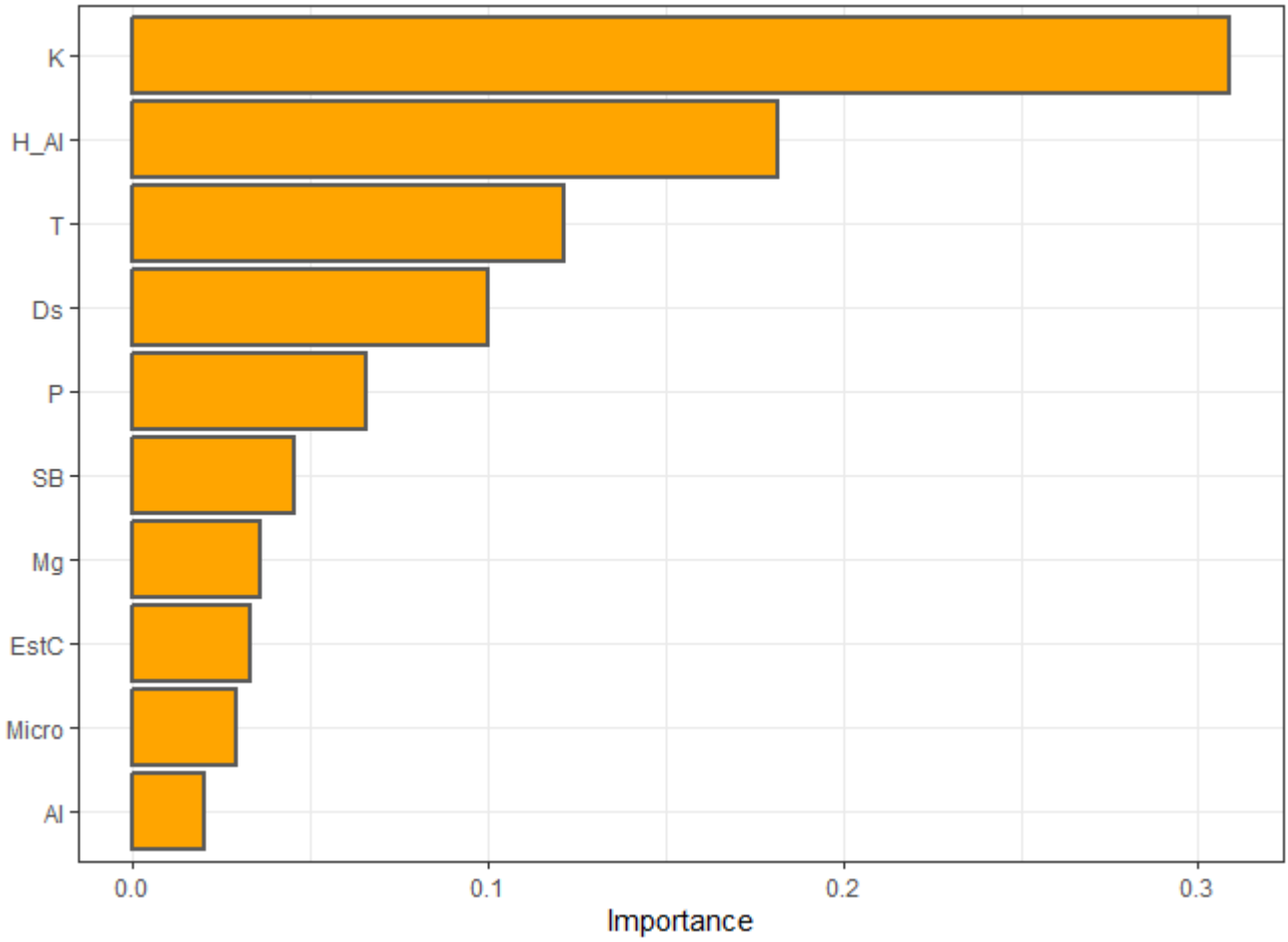

Randomly Selected Predictors
Trees
Minimal Node Size
rmse
0.0420
0.0415
0.0410
0.0405
0.0400
5
6
7
8
9
380
385
390
395
22.5
25.0
27.5
30.0


SP 2017-06-17
$y = -0.1 + x$, $R^2 = 0.98$
F
3.50
3.25
3.00
2.75
2.75
3.00
3.25
.pred

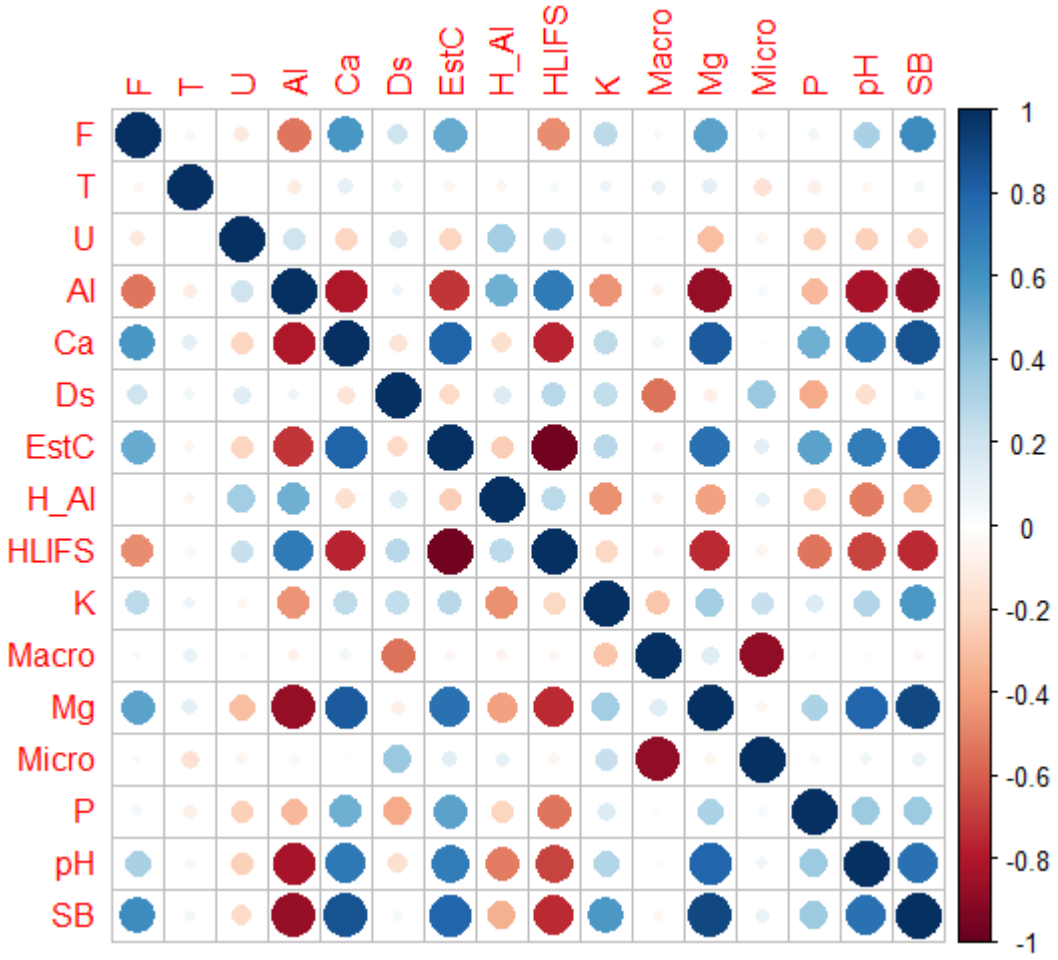



```
#>      vector_of_metrics
#> r          0.9914792221
#> R2         0.9830310479
#> MSE        0.0009654777
#> RMSE       0.0310721369
#> MAE        0.0201836590
#> MAPE       0.6790754991
```

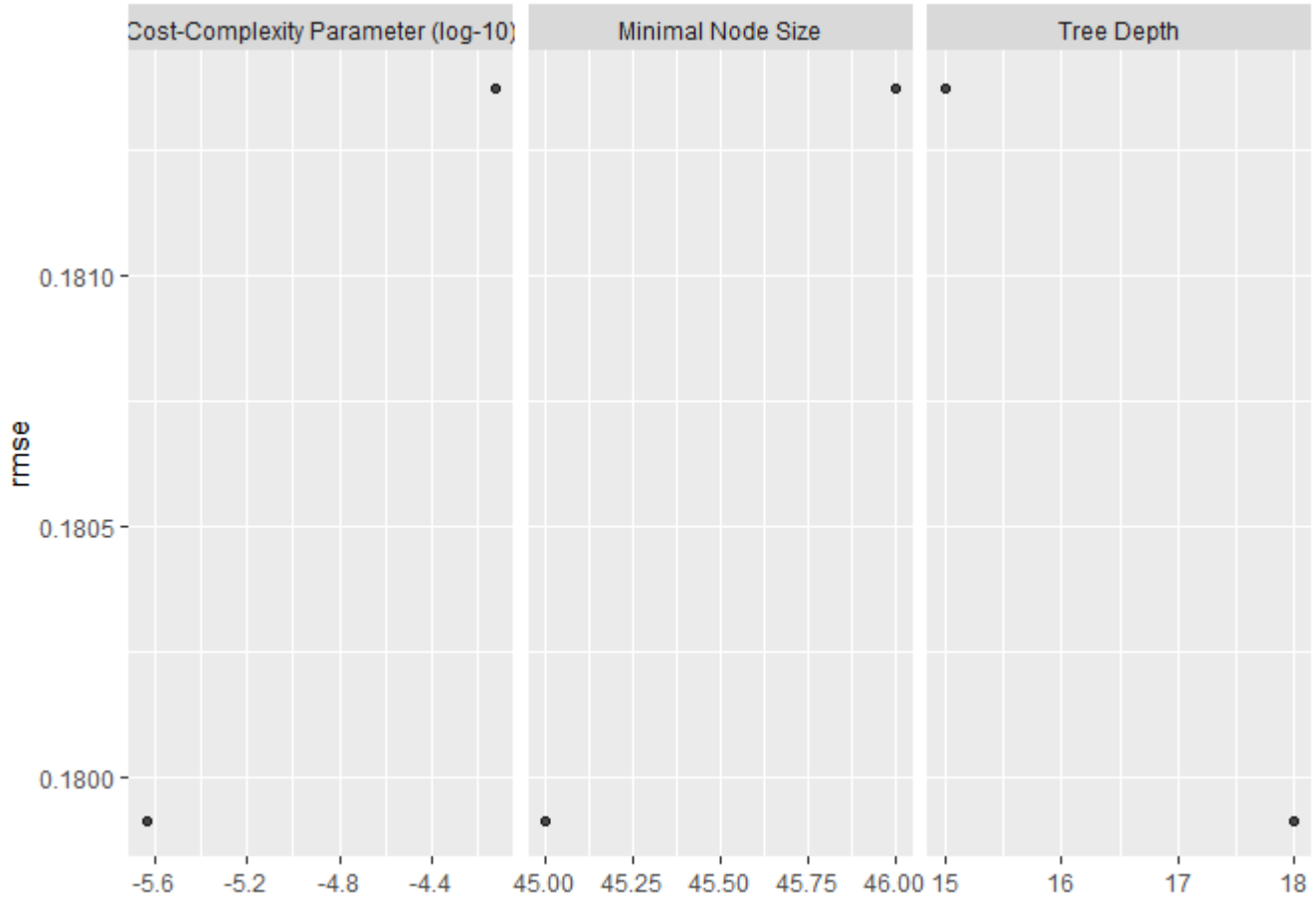

SP 2017-06-17
$y = -0.04 + x$, $R^2 = 0.97$
3.50
3.25
3.00
2.75
F
2.75
3.00
3.25
3.50
.pred

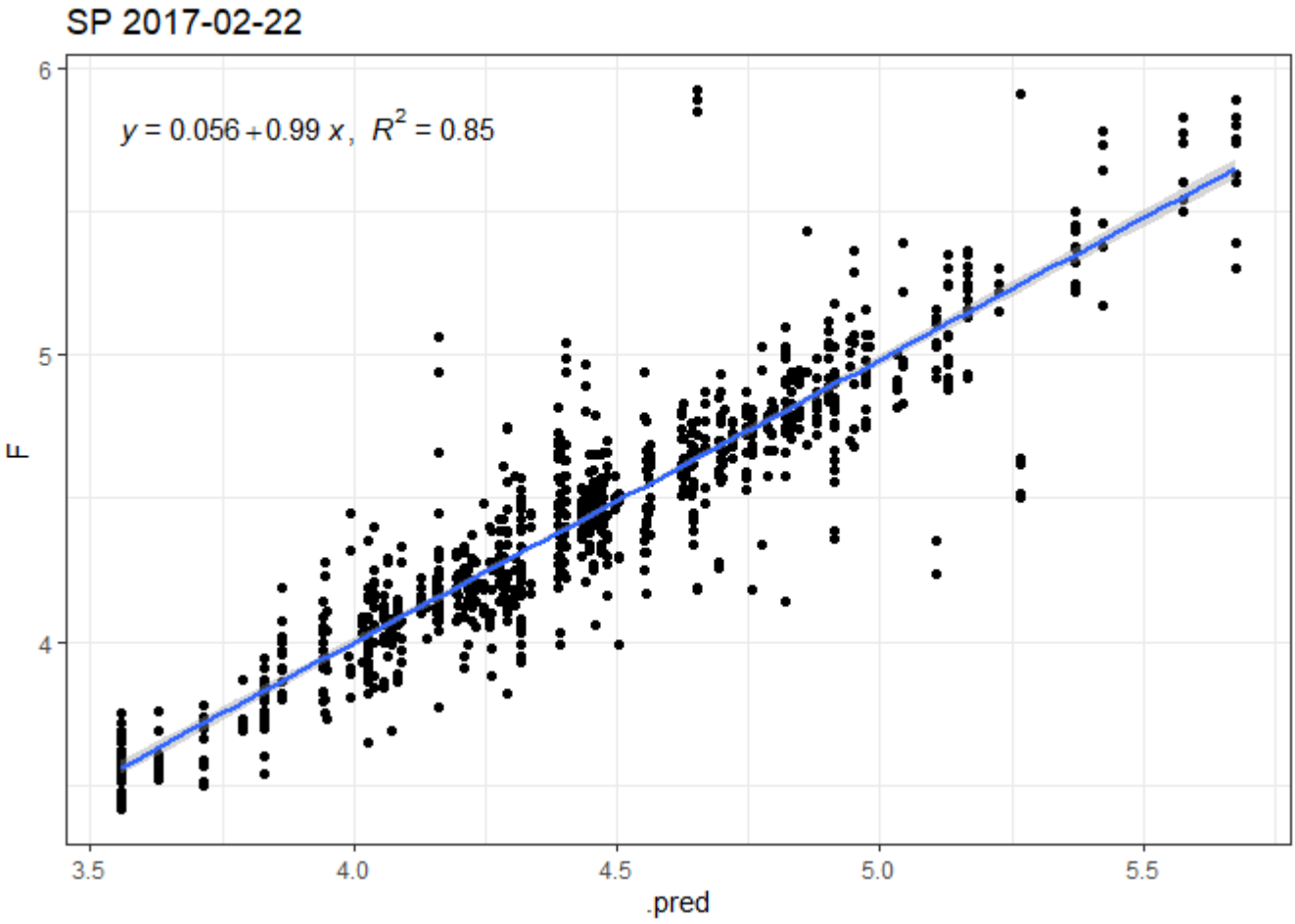

K
H_Al
T
Ds
P
SB
Mg
EstC
Micro
Al
0.0
0.1
0.2
0.3
Importance

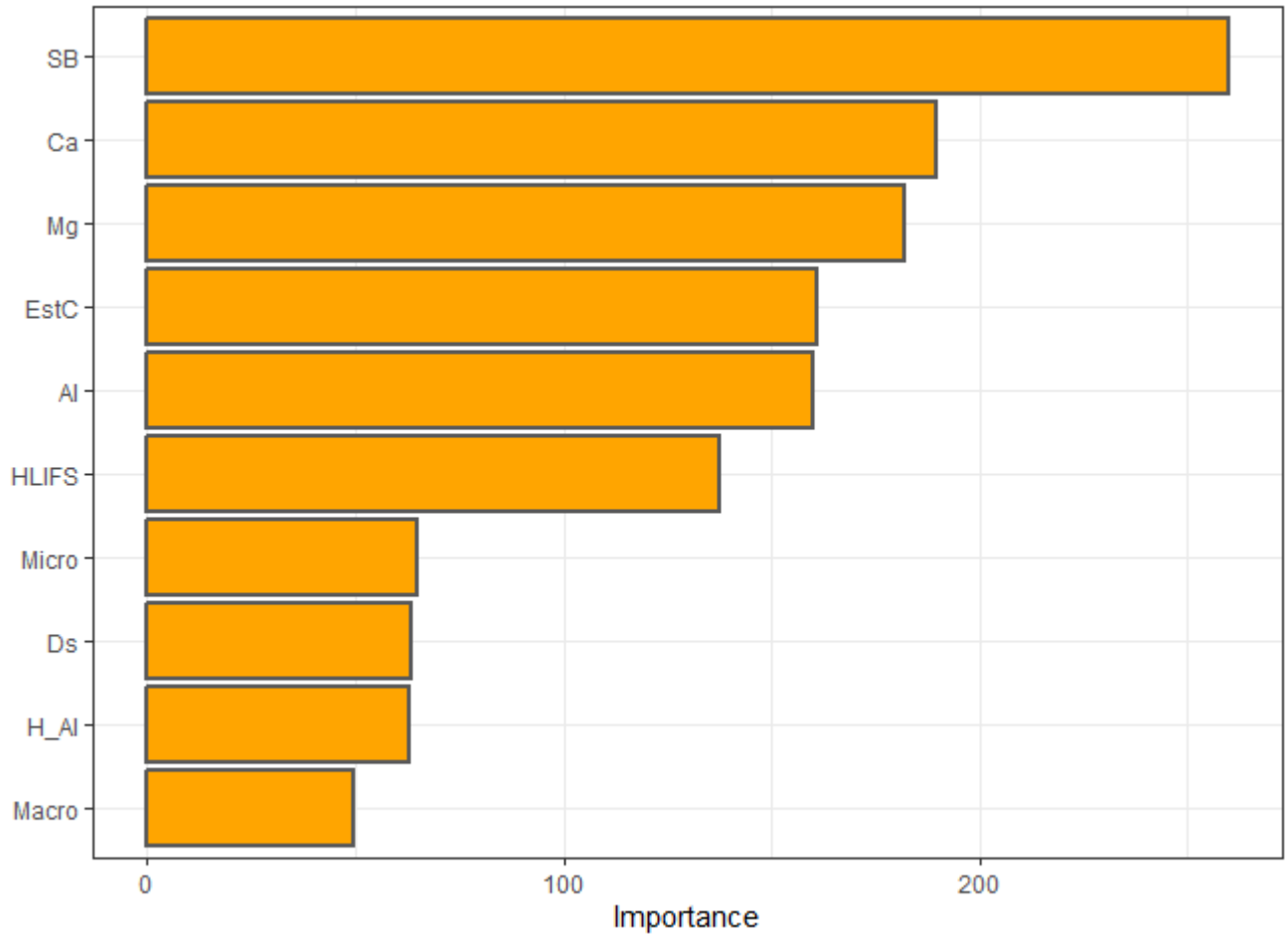
```
#>       vector_of_metrics
#> r           0.986915759
#> R2          0.974002716
#> MSE         0.001397126
#> RMSE        0.037378150
#> MAE         0.027181511
#> MAPE        0.920145168
```



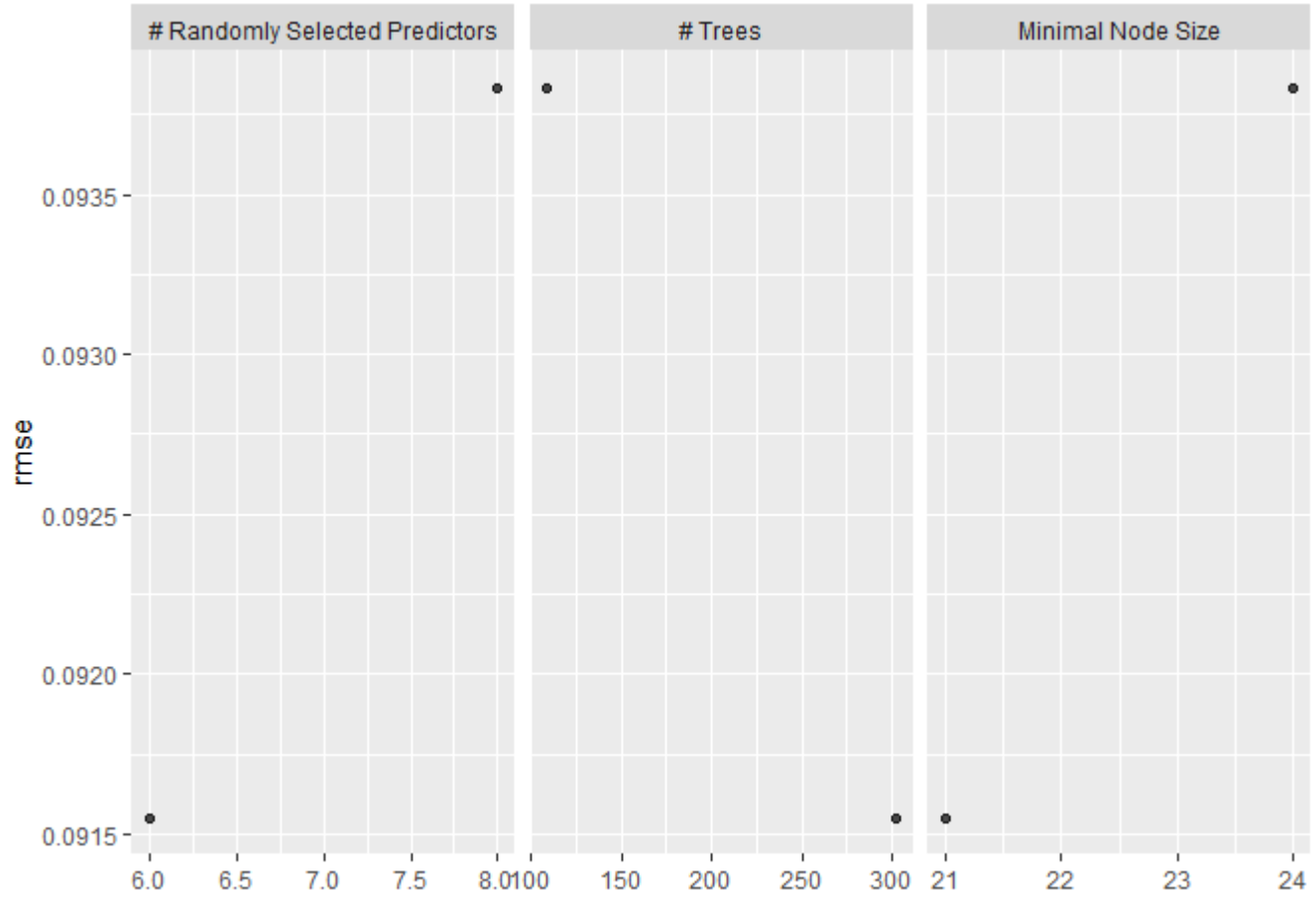

```
#> [1] "ARVORE DE DECISÃO"
```

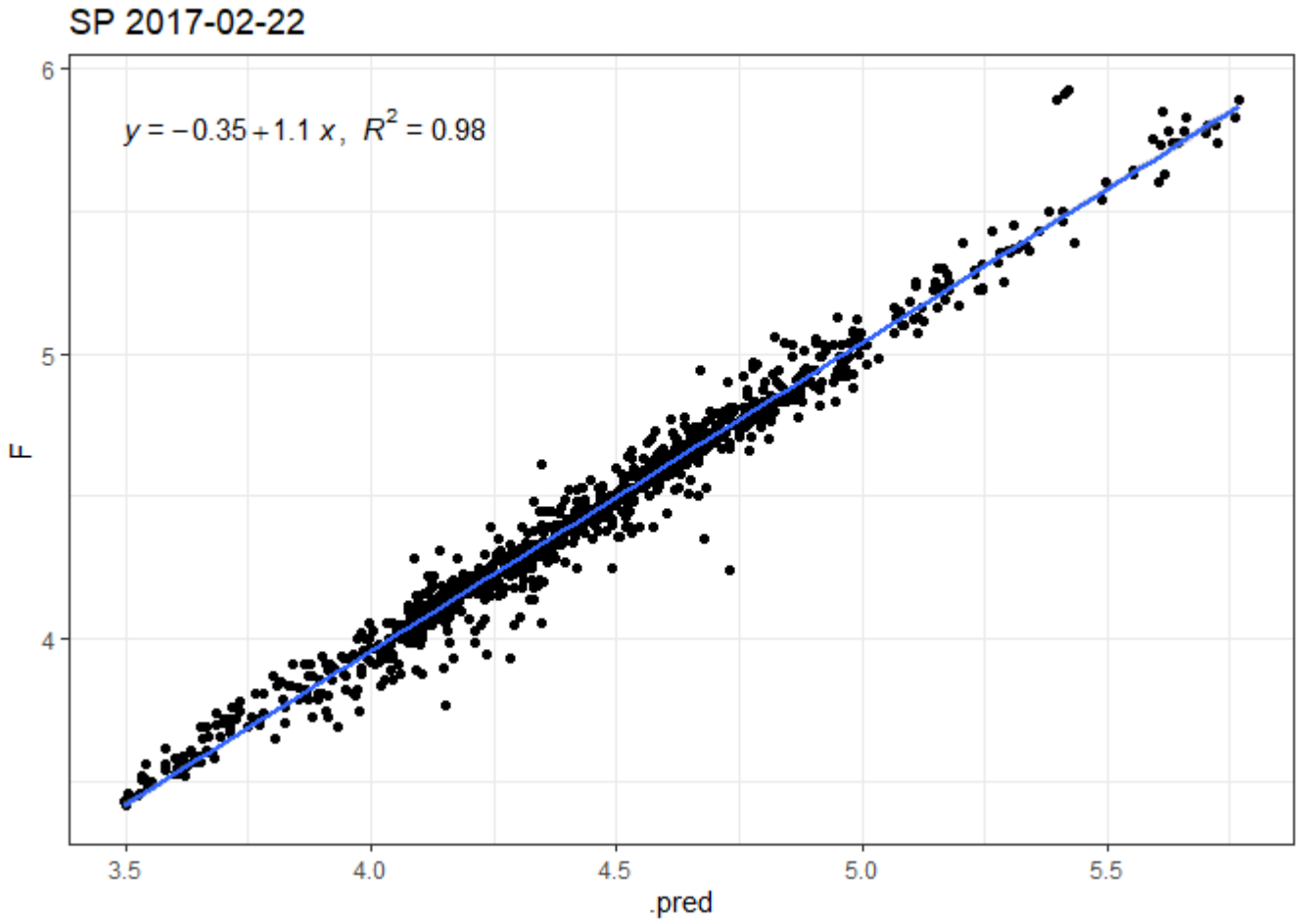

Cost-Complexity Parameter (log-10)
Minimal Node Size
Tree Depth
rmse
0.1810
0.1805
0.1800
-5.6
-5.2
-4.8
-4.4
45.00
45.25
45.50
45.75
46.00
15
16
17
18

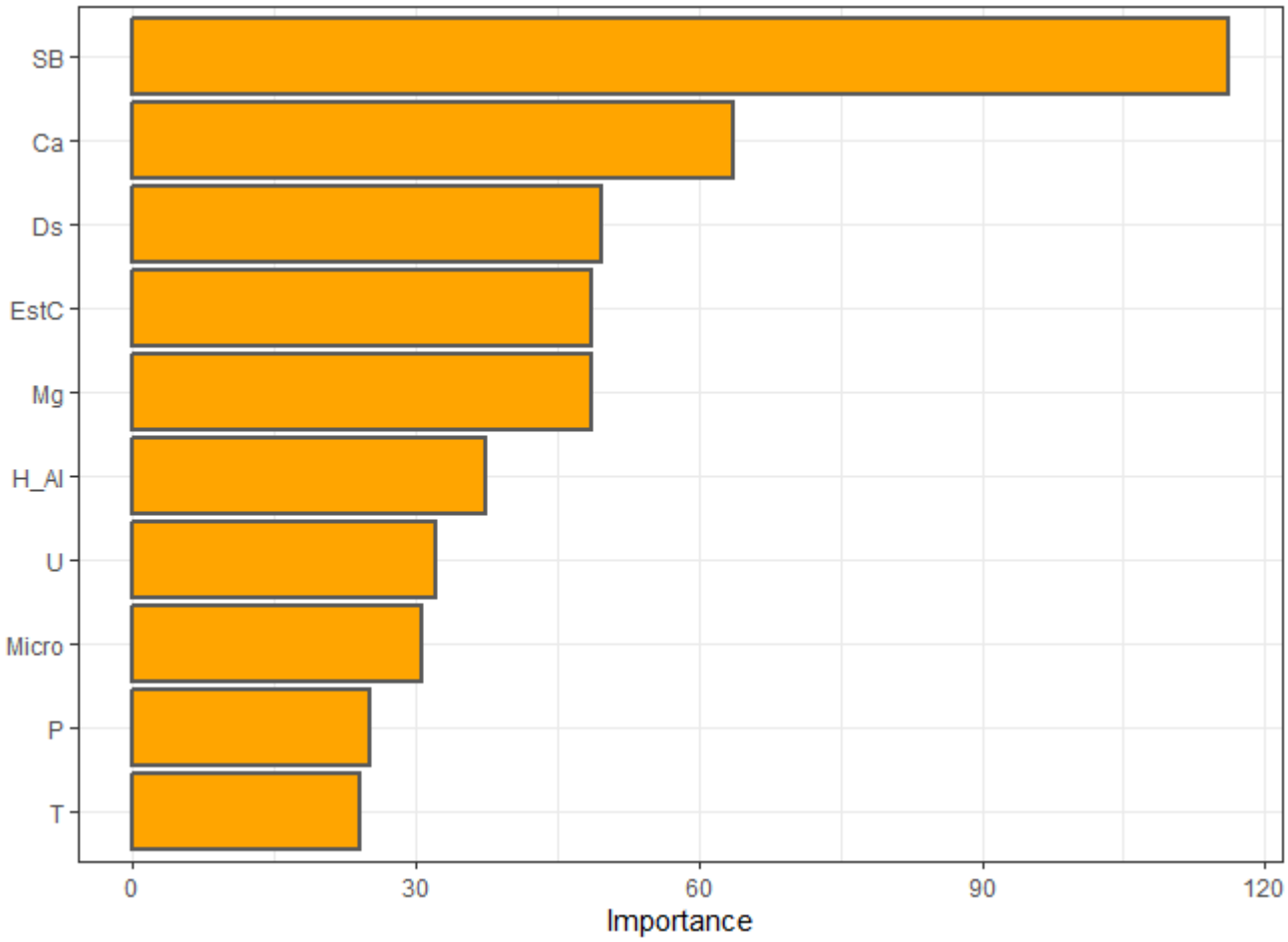

SP 2017-02-22
y = 0.056 + 0.99 x, R2 = 0.85
F
6
5
4
3.5
4.0
4.5
5.0
5.5
.pred



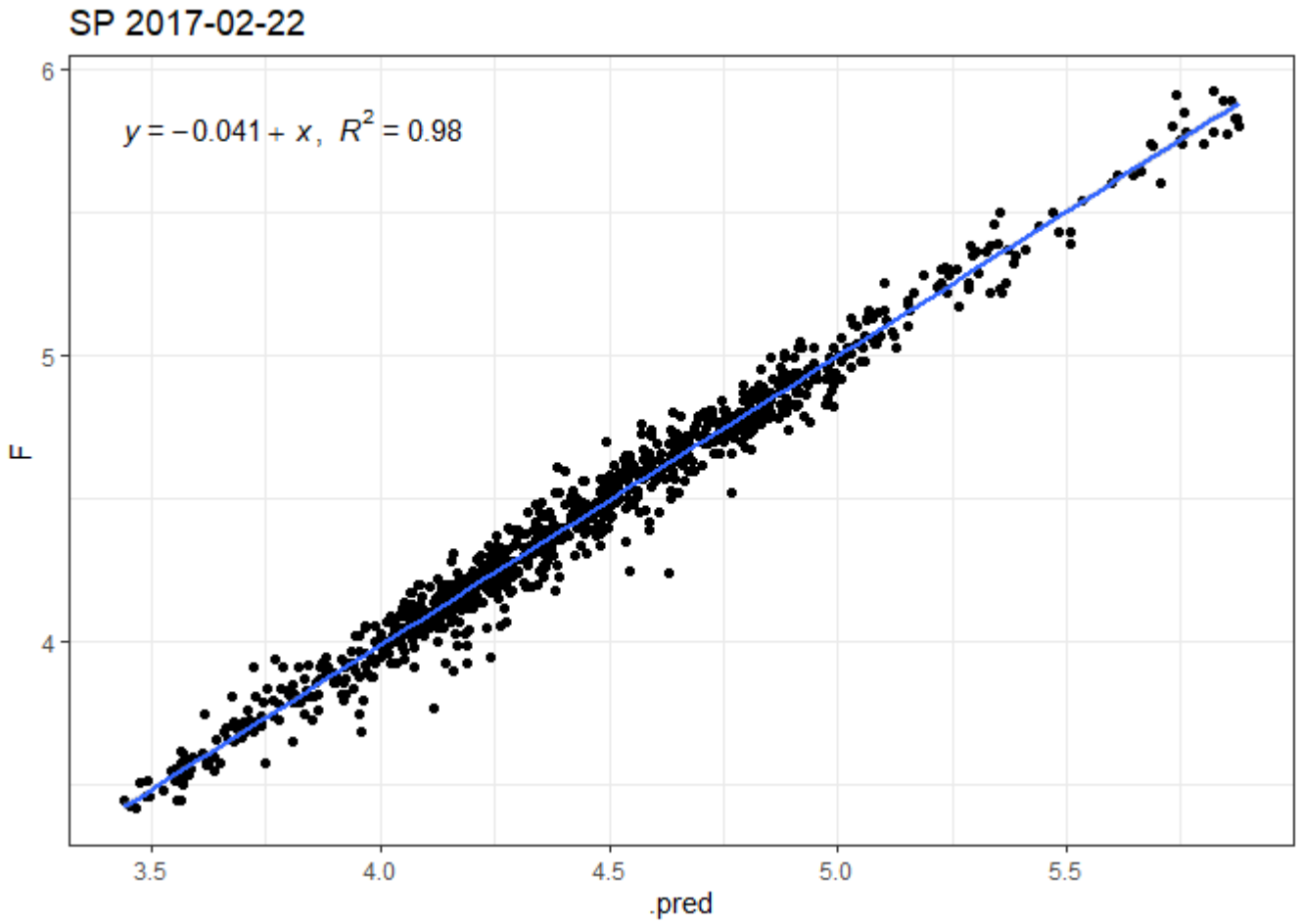

```
#>      vector_of_metrics
#> r           0.92116818
#> R2          0.84855081
#> MSE         0.03375386
#> RMSE        0.18372224
#> MAE         0.12170486
#> MAPE        2.72788257
#> [1] "RANDOM FOREST"
```

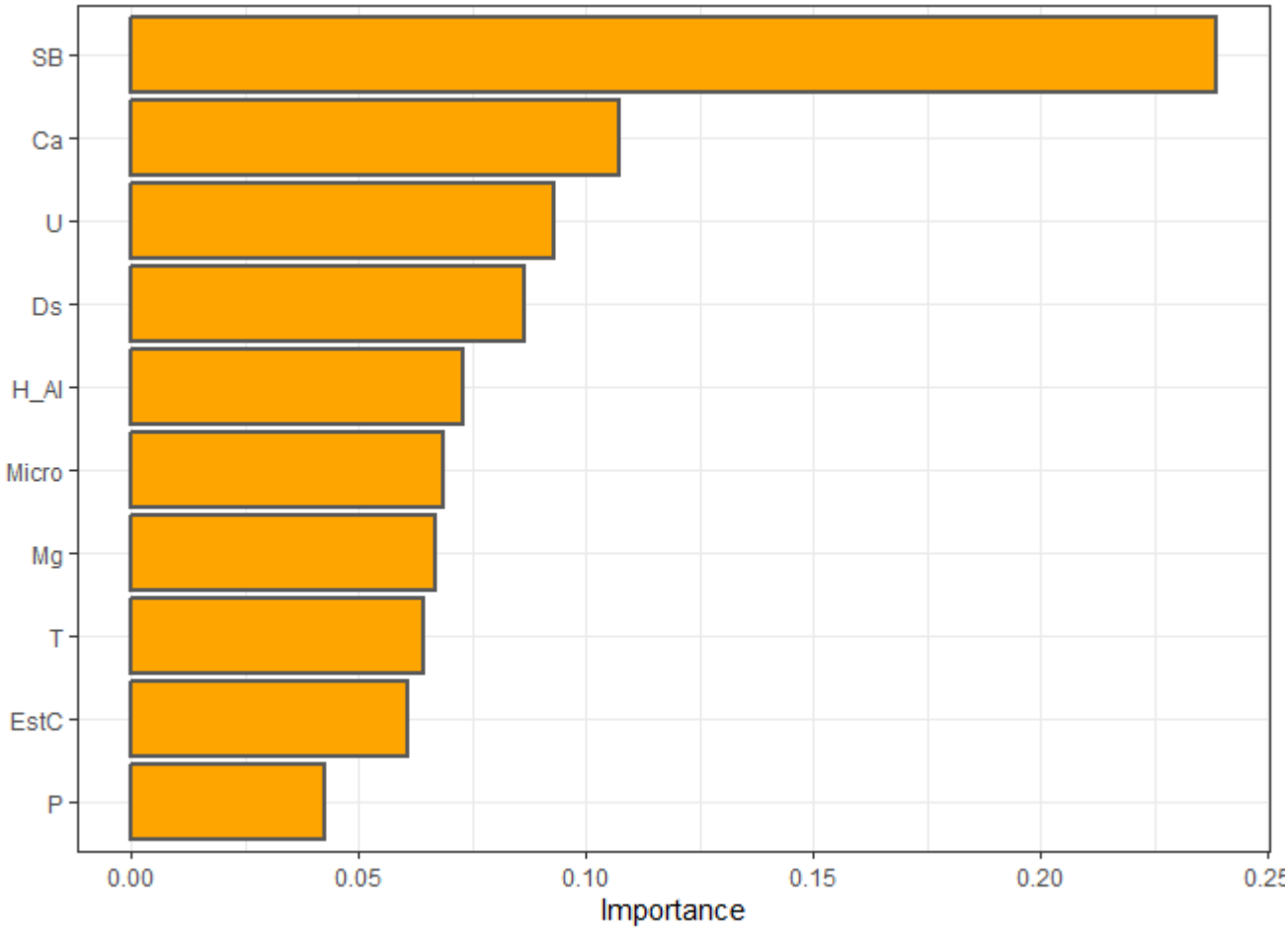

Randomly Selected Predictors
Trees
Minimal Node Size
rmse
0.0935
0.0930
0.0925
0.0920
0.0915
6.0
6.5
7.0
7.5
8.0
100
150
200
250
300
21
22
23
24


SP 2017-02-22
$y = -0.35 + 1.1\,x,\ R^2 = 0.98$
F
.pred
6
5
4
3.5
4.0
4.5
5.0
5.5




```
#>      vector_of_metrics
#> r           0.987638099
#> R2          0.975429015
#> MSE         0.006629223
#> RMSE        0.081420043
#> MAE         0.055692659
#> MAPE        1.262768560
```


SP 2017-02-22
$y = -0.041 + x,\ R^2 = 0.98$
F
.pred
6
5
4
3.5
4.0
4.5
5.0
5.5


SB
Ca
U
Ds
H_Al
Micro
Mg
T
EstC
P
0.00
0.05
0.10
0.15
0.20
Importance

```
#>      vector_of_metrics
#> r          0.988563291
#> R2         0.977257381
#> MSE        0.005104343
#> RMSE       0.071444688
#> MAE        0.052905387
#> MAPE       1.206445867
```

Material de Apêndice - Sinais (mapas dos atributos geoespacializados)

Mapas Eucalipto

```
# for(i in seq(files_eu)){
#   mp<-read.table(files_eu[i],skip = 5)
#   image(mp %>%  as.matrix(),xlab = files_eu[i])
# }
```

Mapas Silvipastoril

```
# for(i in seq(files_sp)){
#   mp<-read.table(files_sp[i],skip = 5)
#   image(mp %>%  as.matrix(),xlab = files_sp[i])
# }
```