Tree water deficit: data exploration

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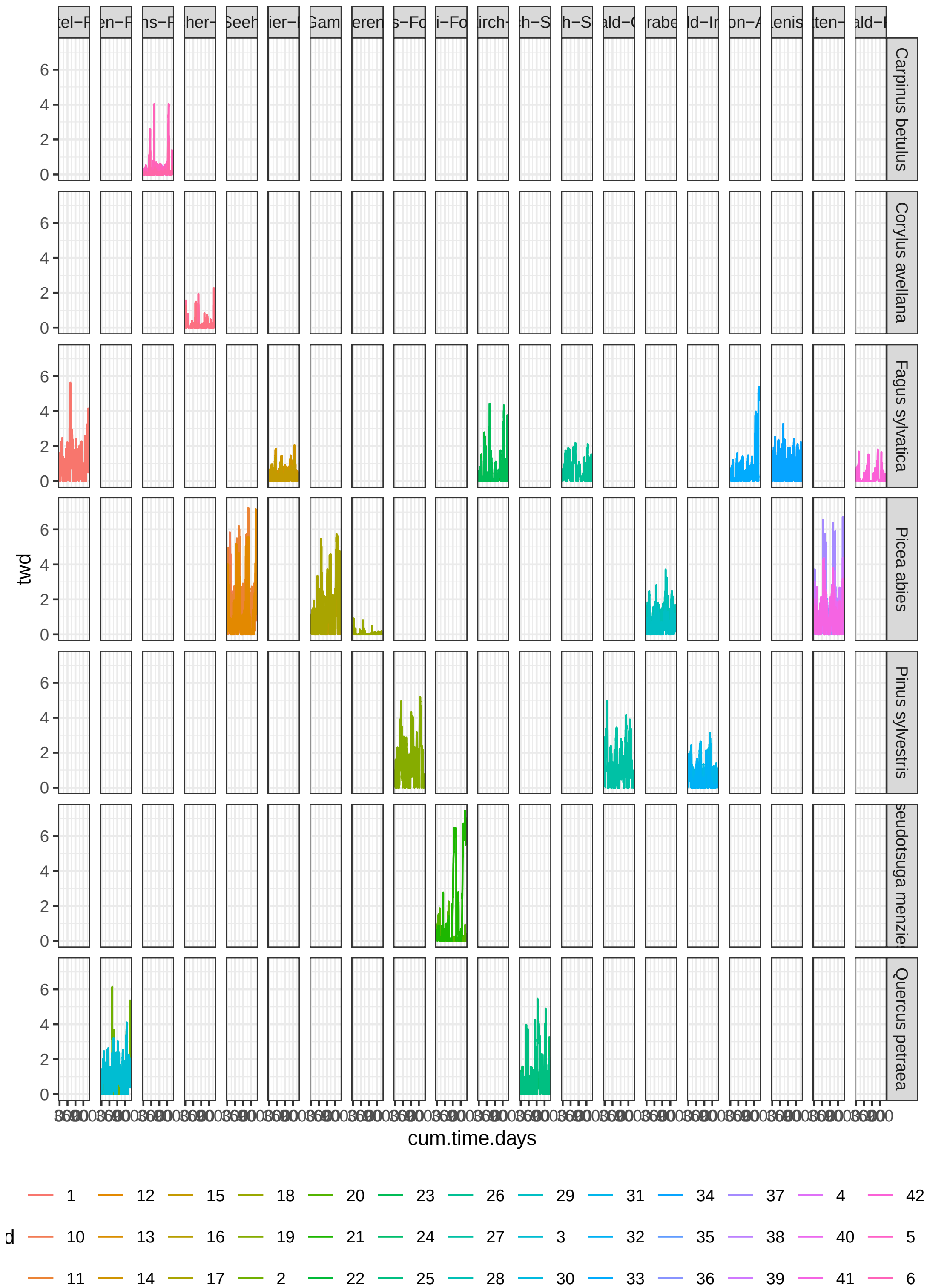
```r
require(dplyr)
require(ggplot2)
require(car)
require(stringr)
require(lubridate)
require(zoo)
#require(flextable)
library(broom)
library(ggplot2)
library(forecast)

knitr::opts_chunk$set(fig.width=7, fig.height=7)
```

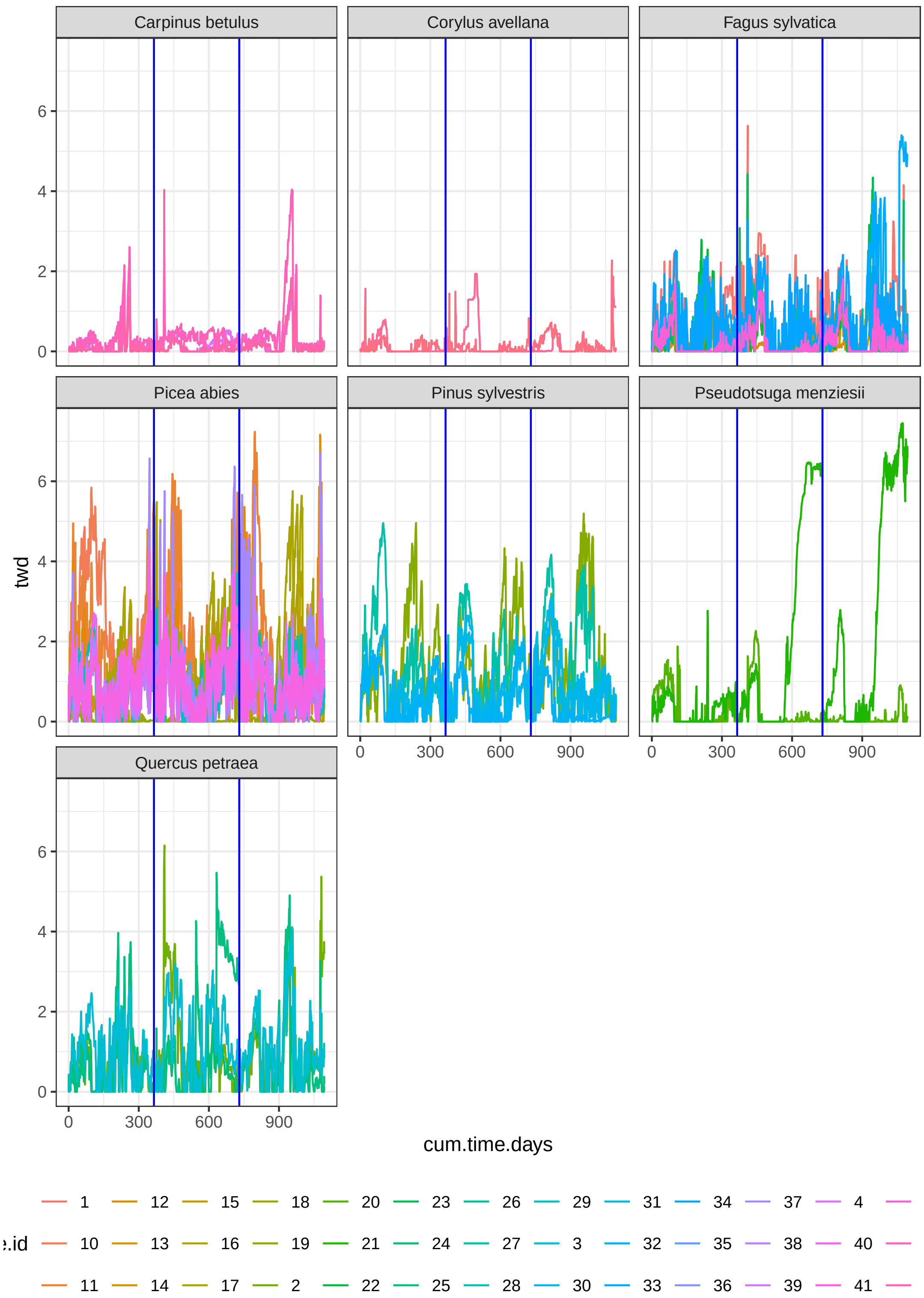
```r
bool_run_dataset <- TRUE

if(bool_run_dataset){source("read.datasets.r")
  } else {
  df.ts.series2 <- read.csv("df.ts.series2.csv")
  num.cols <- c("twd", "pr", "at", "ws", "dp", "sr", "lr", "day.of.year")
  }
```

```r
plot_basic <- ggplot(df.ts.series2, aes(x = cum.time.days, y = twd, group = tree.id)) +
  geom_line(aes(color = tree.id)) +
  theme_bw() +
  theme(legend.position='bottom') +
  guides(color = guide_legend(nrow = 3))

plot_basic +
  facet_grid(vars(species), vars(site))
```



twd
cum.time.days
Carpinus betulus
Corylus avellana
Fagus sylvatica
Picea abies
Pinus sylvestris
Quercus petraea

```
plot_basic +
  geom_vline(xintercept = 365, color = "blue") +
  geom_vline(xintercept = 730, color = "blue") +
  facet_wrap(~species)
```



Carpinus betulus
Corylus avellana
Fagus sylvatica
Picea abies
Pinus sylvestris
Pseudotsuga menziesii
Quercus petraea
twd
0
2
4
6
0
300
600
900
cum.time.days
.id
1 12 15 18 20 23 26 29 31 34 37 4
10 13 16 19 21 24 27 3 32 35 38 40
11 14 17 2 22 25 28 30 33 36 39 41

```r
ggplot(
  df.ts.series2,
  aes(x = day.of.year, y = twd,
  group = interaction(year, tree.id))) +
  geom_line(aes(color = year)) +
  facet_wrap(~species) +
  theme(legend.position='bottom')
```

Carpinus betulus
Corylus avellana
Fagus sylvatica
Picea abies
Pinus sylvestris
Pseudotsuga menziesii
Quercus petraea
twd
day.of.year
0
2
4
6
0
100
200
300
year
2020
2021
2022

```r
#lapply(df.ts.series2, class)

num.vars.df <- df.ts.series2[,num.cols]
cor_matrix <- cor(num.vars.df, use = "complete.obs")
#flextable(cor_matrix)
cor_matrix
```

```
                     twd           pr           at          ws          dp
twd          1.000000000 -0.131262923 -0.119470916 -0.12483220 -0.22037315
pr          -0.131262923  1.000000000  0.002590598  0.08997804  0.16716389
at          -0.119470916  0.002590598  1.000000000  0.08083005  0.90584762
ws          -0.124832202  0.089978045  0.080830051  1.00000000  0.02792756
dp          -0.220373147  0.167163893  0.905847623  0.02792756  1.00000000
sr           0.008947053 -0.276992037  0.614793728  0.04611393  0.38822556
lr          -0.198775942  0.344976601  0.764139599  0.08014614  0.88312535
day.of.year  0.053890048  0.032564700  0.189554518 -0.13950669  0.28942973
                      sr          lr day.of.year
twd          0.008947053 -0.19877594  0.05389005
pr          -0.276992037  0.34497660  0.03256470
at           0.614793728  0.76413960  0.18955452
ws           0.046113925  0.08014614 -0.13950669
dp           0.388225562  0.88312535  0.28942973
sr           1.000000000  0.16082884 -0.17224888
lr           0.160828837  1.00000000  0.26590182
day.of.year -0.172248882  0.26590182  1.00000000
```

```r
#pairs(num.vars.df)
```

```r
list_species <- unique(df.ts.series2$species)

for(iter_species in list_species){
  iter_df <- df.ts.series2 %>%
    filter(species == iter_species)

  print(iter_species)
  print(cor(iter_df[,num.cols]))
}
```

```
[1] "Fagus sylvatica"
                     twd          pr          at          ws         dp
twd          1.000000000 -0.18137627  0.02541095  0.009627288 -0.1405810
```

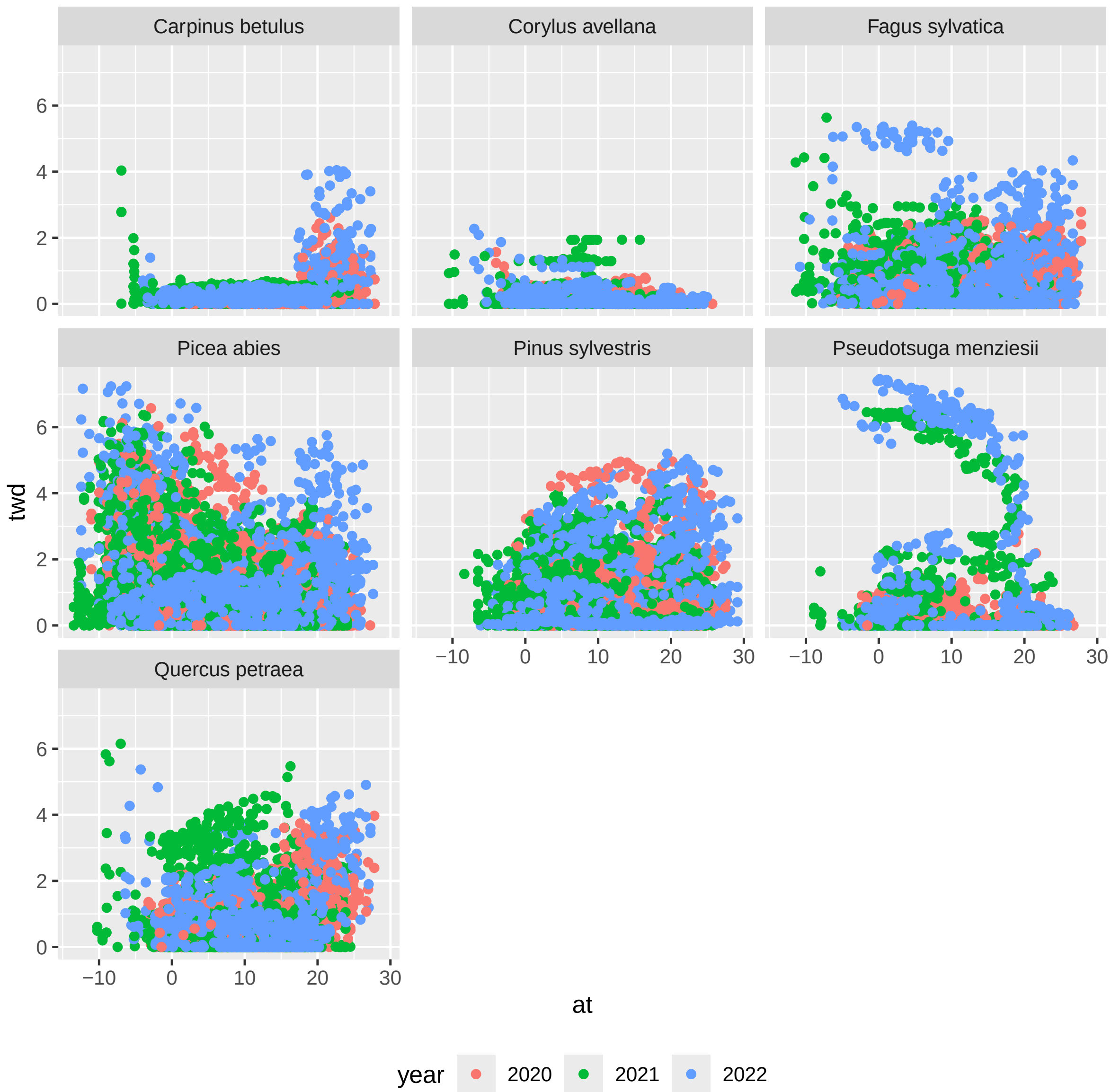
```
pr          -0.181376267  1.00000000 -0.02701793  0.094676772  0.1350574
at           0.025410953 -0.02701793  1.00000000 -0.035522186  0.9010553
ws           0.009627288  0.09467677 -0.03552219  1.000000000 -0.1330824
dp          -0.140581022  0.13505742  0.90105530 -0.133082399  1.0000000
sr           0.132248373 -0.29568173  0.67872372  0.067925142  0.4252621
lr          -0.172377333  0.34107498  0.72575852 -0.040340079  0.8641839
day.of.year -0.045990926  0.03258924  0.18032814 -0.189827925  0.3046255
                     sr          lr day.of.year
twd          0.13224837 -0.17237733 -0.04599093
pr          -0.29568173  0.34107498  0.03258924
at           0.67872372  0.72575852  0.18032814
ws           0.06792514 -0.04034008 -0.18982793
dp           0.42526205  0.86418388  0.30462553
sr           1.00000000  0.15077338 -0.16281669
lr           0.15077338  1.00000000  0.28660976
day.of.year -0.16281669  0.28660976  1.00000000
[1] "Quercus petraea"
                    twd          pr          at           ws          dp
twd          1.00000000 -0.19798010  0.14448897 -0.046200810  0.03319407
pr          -0.19798010  1.00000000  0.03682531  0.196605657  0.17324305
at           0.14448897  0.03682531  1.00000000 -0.115668256  0.91545158
ws          -0.04620081  0.19660566 -0.11566826  1.000000000 -0.16557647
dp           0.03319407  0.17324305  0.91545158 -0.165576472  1.00000000
sr           0.15232695 -0.24692796  0.67703942 -0.080532493  0.43101430
lr          -0.03945657  0.36513048  0.73197573  0.007775018  0.86106870
day.of.year  0.08598431  0.04182131  0.17383576 -0.228046338  0.30951107
                     sr           lr day.of.year
twd          0.15232695 -0.039456566  0.08598431
pr          -0.24692796  0.365130482  0.04182131
at           0.67703942  0.731975733  0.17383576
ws          -0.08053249  0.007775018 -0.22804634
dp           0.43101430  0.861068700  0.30951107
sr           1.00000000  0.134456029 -0.16368994
lr           0.13445603  1.000000000  0.29969086
day.of.year -0.16368994  0.299690856  1.00000000
[1] "Carpinus betulus"
                    twd          pr         at          ws          dp
twd          1.00000000 -0.14113324  0.2115865  0.06602011  0.08622268
pr          -0.14113324  1.00000000 -0.0223143  0.01205931  0.16028541
at           0.21158648 -0.02231430  1.0000000 -0.13926057  0.89930083
ws           0.06602011  0.01205931 -0.1392606  1.00000000 -0.23337661
dp           0.08622268  0.16028541  0.8993008 -0.23337661  1.00000000
sr           0.21104317 -0.34360907  0.6914149  0.07728482  0.40995724
```

```
lr           0.05302899  0.36085692  0.7467854 -0.18408455  0.86892949
day.of.year  0.01610075  0.06524682  0.1779694 -0.14404783  0.32035788
                     sr          lr day.of.year
twd          0.21104317  0.05302899  0.01610075
pr          -0.34360907  0.36085692  0.06524682
at           0.69141491  0.74678538  0.17796937
ws           0.07728482 -0.18408455 -0.14404783
dp           0.40995724  0.86892949  0.32035788
sr           1.00000000  0.17154998 -0.16269968
lr           0.17154998  1.00000000  0.28413664
day.of.year -0.16269968  0.28413664  1.00000000
[1] "Corylus avellana"
                    twd          pr          at          ws         dp
twd          1.00000000 -0.07676496 -0.15355564  0.06325104 -0.2518433
pr          -0.07676496  1.00000000  0.03552847  0.15382165  0.1728802
at          -0.15355564  0.03552847  1.00000000 -0.22953204  0.9248918
ws           0.06325104  0.15382165 -0.22953204  1.00000000 -0.2471297
dp          -0.25184328  0.17288019  0.92489175 -0.24712970  1.0000000
sr           0.07053484 -0.26731509  0.68725381 -0.15772881  0.4290405
lr          -0.23748086  0.38456779  0.69517075 -0.10127215  0.8497979
day.of.year -0.14072546  0.03335630  0.17507330 -0.21332874  0.3075513
                     sr          lr day.of.year
twd          0.07053484 -0.23748086  -0.1407255
pr          -0.26731509  0.38456779   0.0333563
at           0.68725381  0.69517075   0.1750733
ws          -0.15772881 -0.10127215  -0.2133287
dp           0.42904050  0.84979791   0.3075513
sr           1.00000000  0.06950637  -0.1729543
lr           0.06950637  1.00000000   0.3402204
day.of.year -0.17295428  0.34022041   1.0000000
[1] "Picea abies"
                    twd          pr          at          ws         dp
twd          1.00000000 -0.11592144 -0.25278882 -0.02901937 -0.3240365
pr          -0.11592144  1.00000000  0.01610968  0.09792613  0.1832309
at          -0.25278882  0.01610968  1.00000000  0.18377905  0.9194638
ws          -0.02901937  0.09792613  0.18377905  1.00000000  0.1295812
dp          -0.32403648  0.18323095  0.91946383  0.12958120  1.0000000
sr          -0.08383383 -0.26611184  0.55808405  0.06462908  0.3973794
lr          -0.29126816  0.36264903  0.76861616  0.19288153  0.8906218
day.of.year  0.09163775  0.02764386  0.22703349 -0.08269904  0.2947178
                     sr         lr day.of.year
twd         -0.08383383 -0.2912682  0.09163775
pr          -0.26611184  0.3626490  0.02764386
```

```
at           0.55808405  0.7686162  0.22703349
ws           0.06462908  0.1928815 -0.08269904
dp           0.39737939  0.8906218  0.29471780
sr           1.00000000  0.1573929 -0.19097898
lr           0.15739289  1.0000000  0.25129408
day.of.year -0.19097898  0.2512941  1.00000000
[1] "Pinus sylvestris"
                    twd          pr          at           ws           dp
twd          1.00000000 -0.17198315 -0.01632060  0.030783564 -0.152361842
pr          -0.17198315  1.00000000 -0.00797577 -0.065317673  0.202258877
at          -0.01632060 -0.00797577  1.00000000  0.200675846  0.886176720
ws           0.03078356 -0.06531767  0.20067585  1.000000000  0.000612399
dp          -0.15236184  0.20225888  0.88617672  0.000612399  1.000000000
sr           0.10575641 -0.24077228  0.74514516  0.284416006  0.492799530
lr          -0.16483295  0.32570466  0.81373988  0.108458914  0.910680491
day.of.year -0.09338251  0.02089943  0.16894938 -0.243834125  0.291081706
                    sr         lr day.of.year
twd          0.1057564 -0.1648329 -0.09338251
pr          -0.2407723  0.3257047  0.02089943
at           0.7451452  0.8137399  0.16894938
ws           0.2844160  0.1084589 -0.24383412
dp           0.4927995  0.9106805  0.29108171
sr           1.0000000  0.3899210 -0.15308436
lr           0.3899210  1.0000000  0.23804080
day.of.year -0.1530844  0.2380408  1.00000000
[1] "Pseudotsuga menziesii"
                    twd           pr          at          ws          dp
twd          1.00000000 -0.028627835 -0.16211835 -0.07723890 -0.08096724
pr          -0.02862784  1.000000000  0.05674352  0.28023423  0.14857411
at          -0.16211835  0.056743523  1.00000000 -0.02143595  0.94181408
ws          -0.07723890  0.280234234 -0.02143595  1.00000000 -0.13053257
dp          -0.08096724  0.148574107  0.94181408 -0.13053257  1.00000000
sr          -0.28368267 -0.245028300  0.67765399  0.02164081  0.46844137
lr          -0.02895595  0.348268450  0.75399104  0.01009687  0.86082813
day.of.year  0.35193517  0.007705166  0.17007220 -0.23853848  0.30313531
                     sr          lr  day.of.year
twd         -0.28368267 -0.02895595  0.351935169
pr          -0.24502830  0.34826845  0.007705166
at           0.67765399  0.75399104  0.170072196
ws           0.02164081  0.01009687 -0.238538479
dp           0.46844137  0.86082813  0.303135309
sr           1.00000000  0.15082065 -0.177108728
lr           0.15082065  1.00000000  0.326631339
```

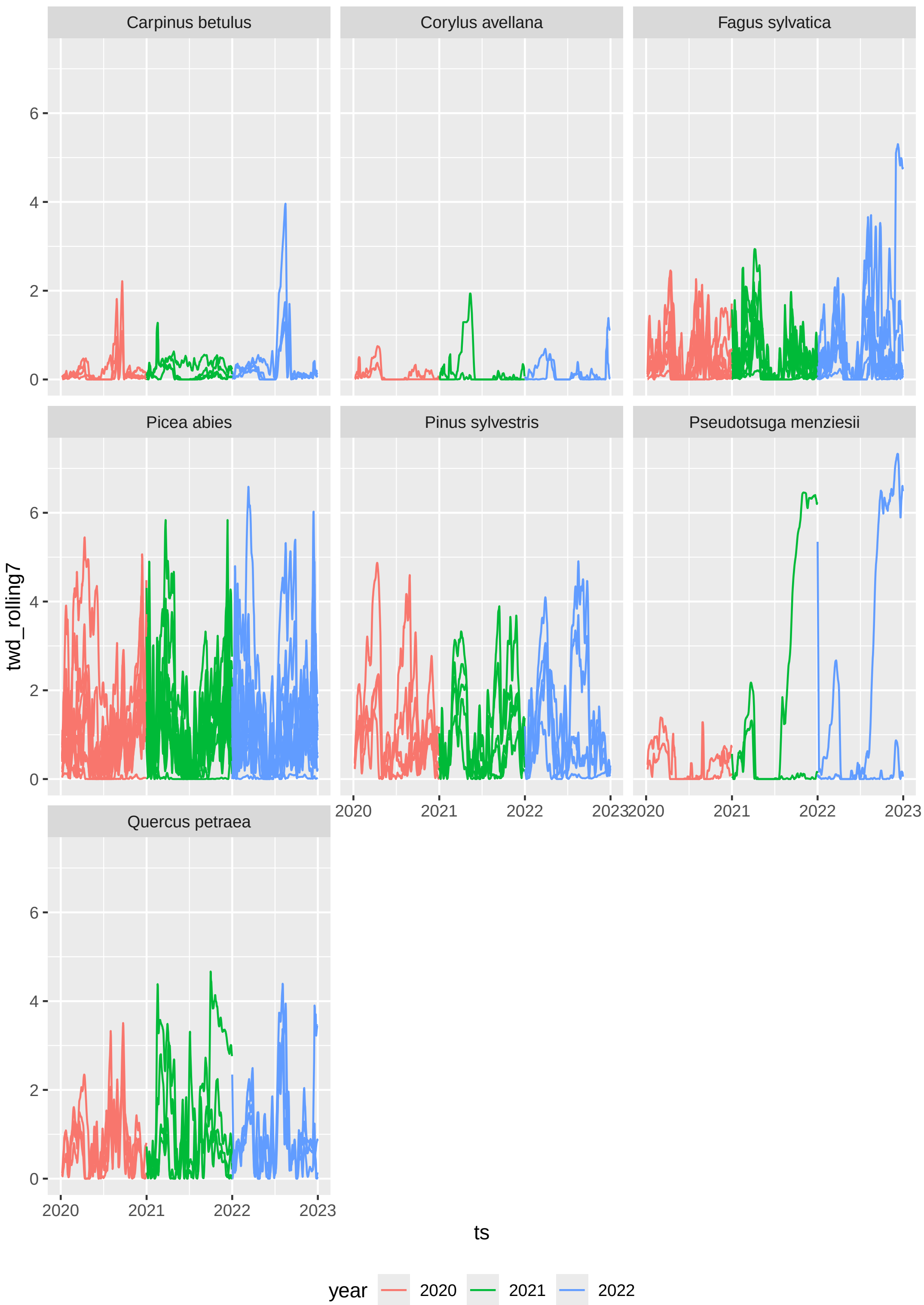
```
day.of.year -0.17710873  0.32663134  1.000000000
```

```
ggplot(
  df.ts.series2,
  aes(x = at, y = twd,
  group = interaction(year, tree.id))) +
  geom_point(aes(color = year)) +
  facet_wrap(~species) +
  theme(legend.position='bottom')
```



```r
ggplot(
  df.ts.series2,
  aes(x = ts, y = twd_rolling7,
  group = interaction(year, tree.id))) +
  geom_line(aes(color = year)) +
  facet_wrap(~species) +
  theme(legend.position='bottom')
```

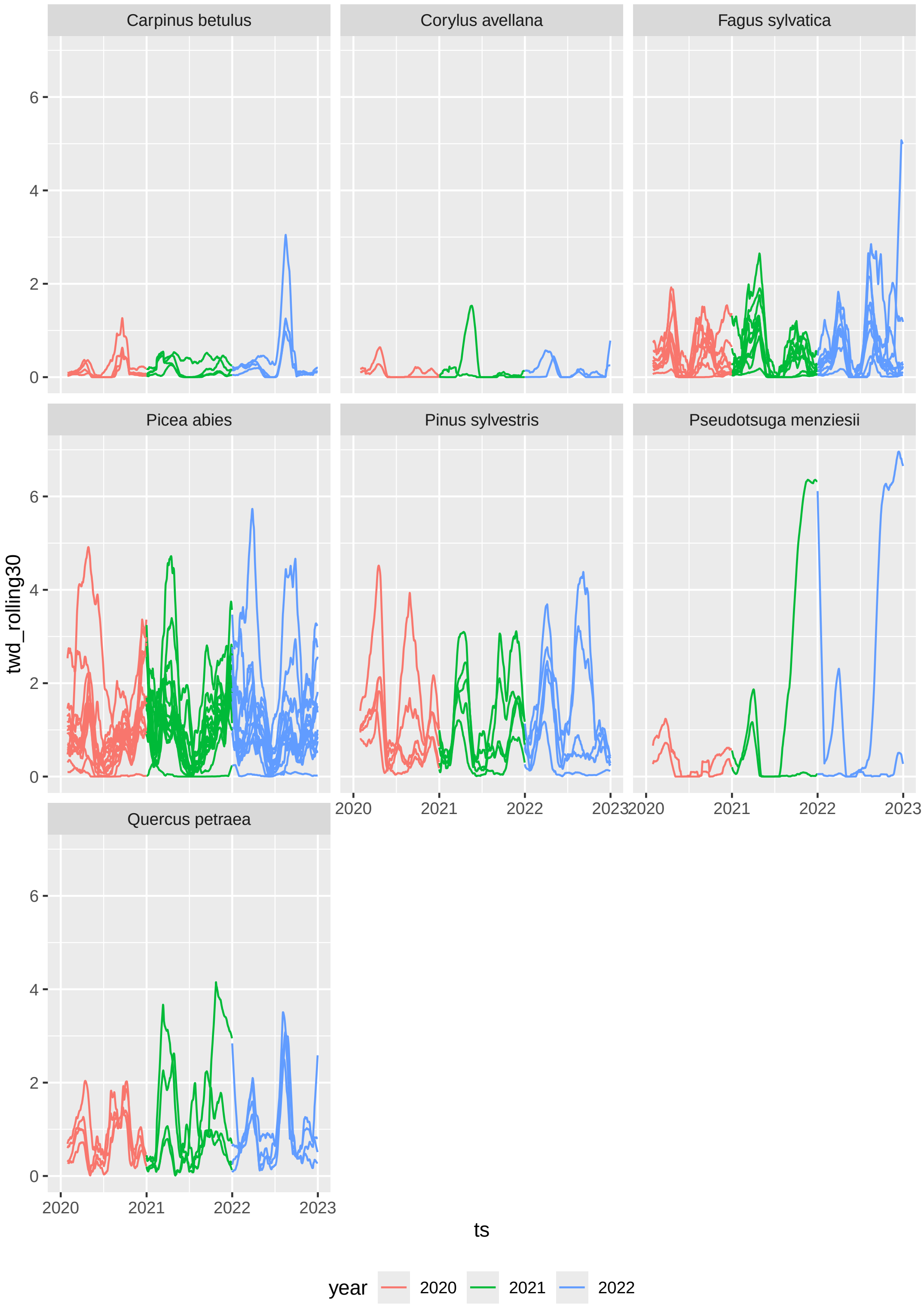
```
Warning: Removed 252 rows containing missing values or values outside the scale range
(`geom_line()`).
```



Carpinus betulus
Corylus avellana
Fagus sylvatica
Picea abies
Pinus sylvestris
Pseudotsuga menziesii
Quercus petraea
twd_rolling7
0
2
4
6
2020
2021
2022
2023
ts
year
2020
2021
2022

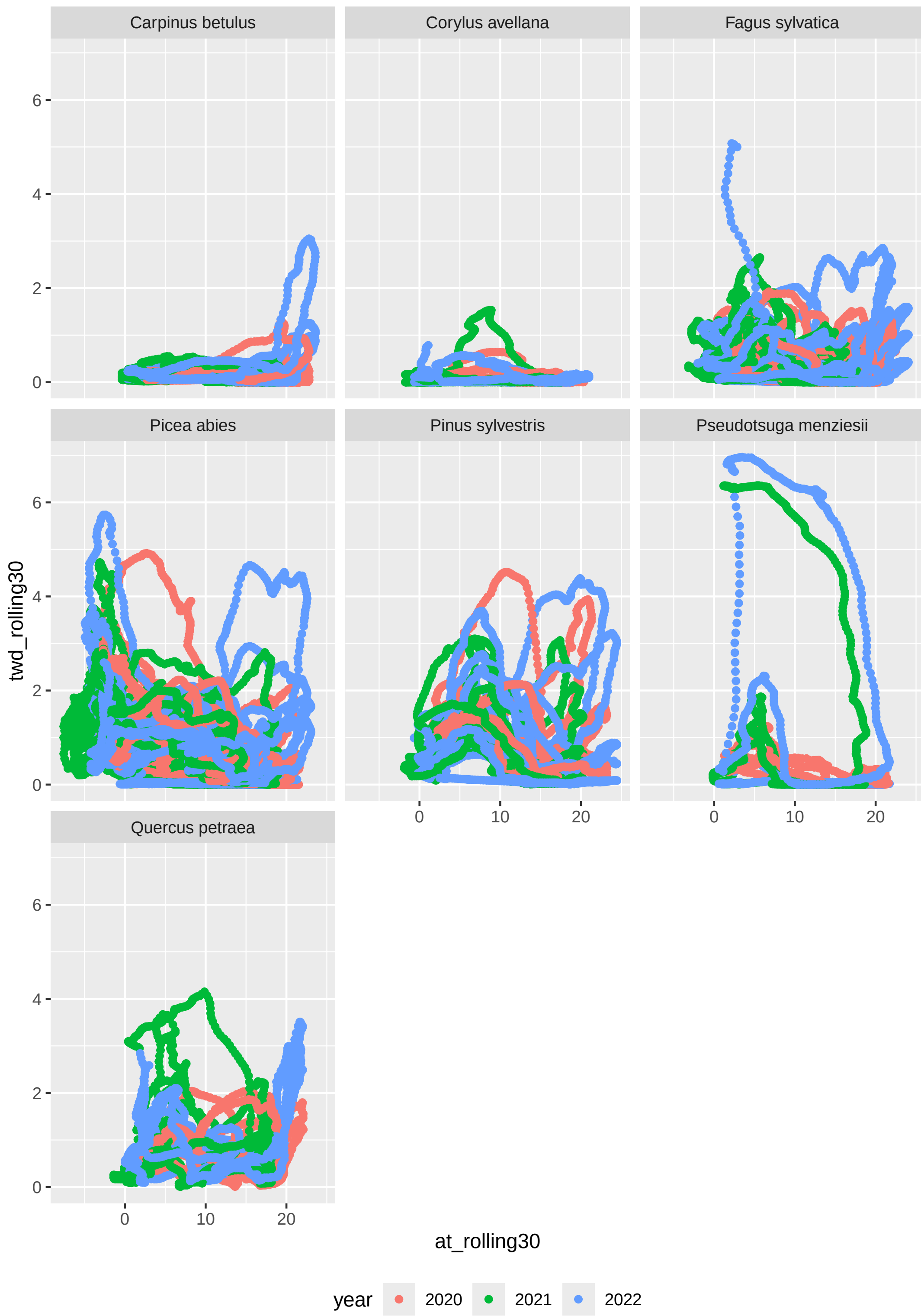
```r
ggplot(
  df.ts.series2,
  aes(x = ts, y = twd_rolling30,
  group = interaction(year, tree.id))) +
  geom_line(aes(color = year)) +
  #geom_point(aes(color = year), size = 1)+
  facet_wrap(~species) +
  theme(legend.position='bottom')
```

```
Warning: Removed 1218 rows containing missing values or values outside the scale range
(`geom_line()`).
```


Carpinus betulus
Corylus avellana
Fagus sylvatica
Picea abies
Pinus sylvestris
Pseudotsuga menziesii
Quercus petraea
twd_rolling30
ts
0
2
4
6
2020
2021
2022
2023
year
2020
2021
2022

```r
ggplot(
  df.ts.series2,
  aes(x = at_rolling30, y = twd_rolling30,
  group = interaction(year, tree.id))) +
  geom_point(aes(color = year)) +
  facet_wrap(~species) +
  theme(legend.position='bottom')
```

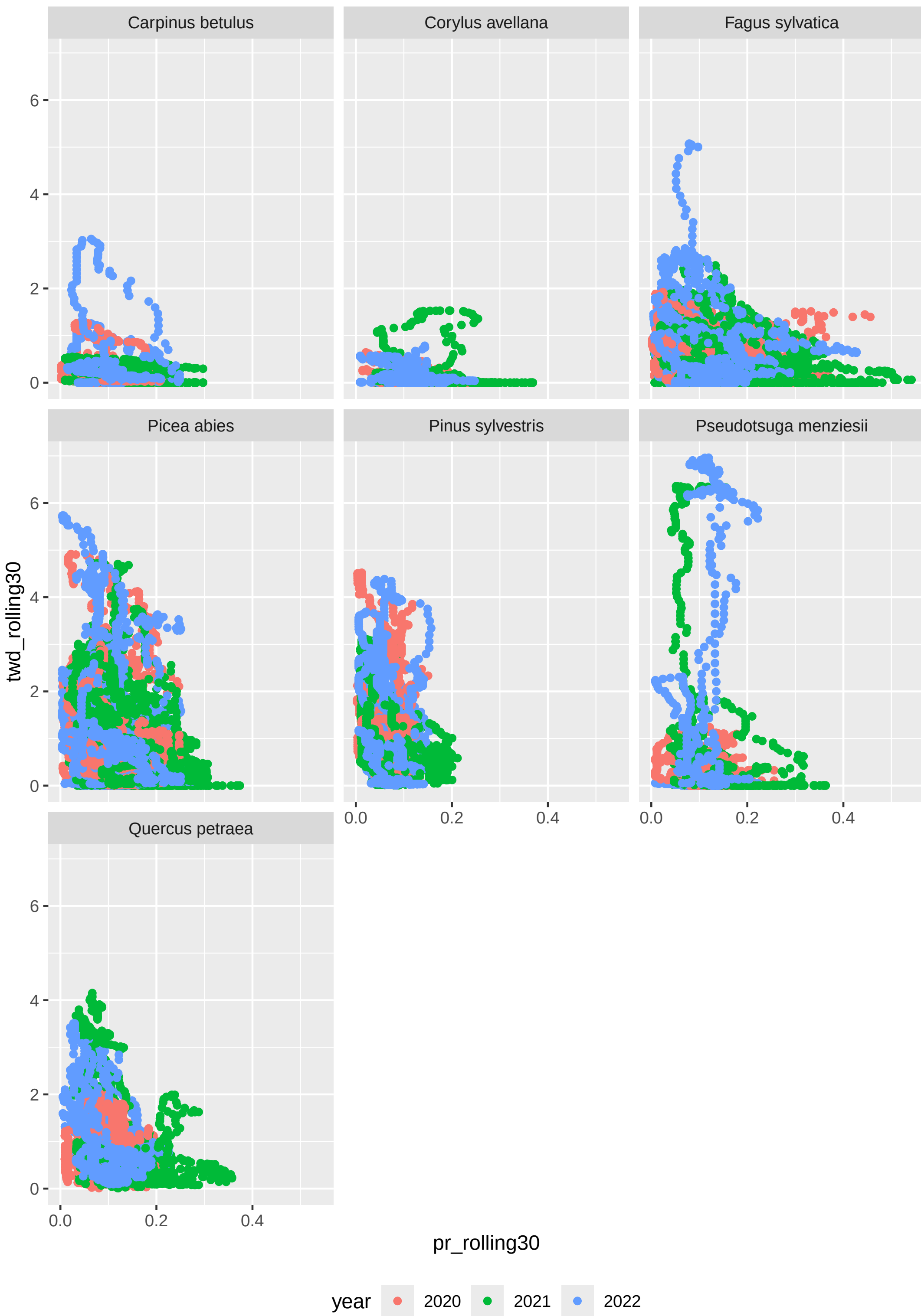
```
Warning: Removed 1218 rows containing missing values or values outside the scale range
(`geom_point()`).
```



Carpinus betulus
Corylus avellana
Fagus sylvatica
Picea abies
Pinus sylvestris
Pseudotsuga menziesii
Quercus petraea
twd_rolling30
at_rolling30
0
2
4
6
0
10
20
year
2020
2021
2022

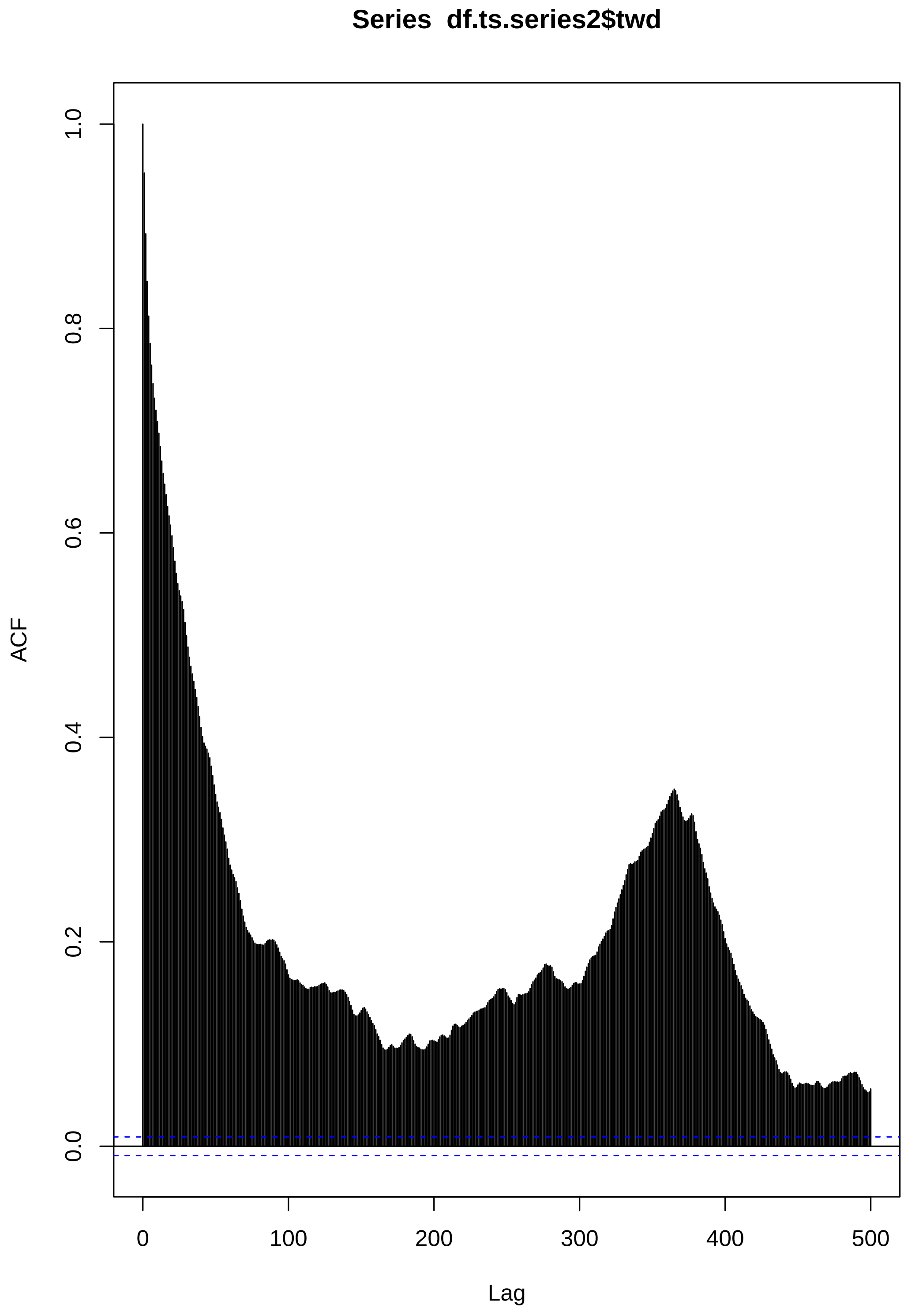
```r
ggplot(
  df.ts.series2,
  aes(x = pr_rolling30, y = twd_rolling30,
  group = interaction(year, tree.id))) +
  geom_point(aes(color = year)) +
  facet_wrap(~species) +
  theme(legend.position='bottom')
```

```
Warning: Removed 1218 rows containing missing values or values outside the scale range
(`geom_point()`).
```



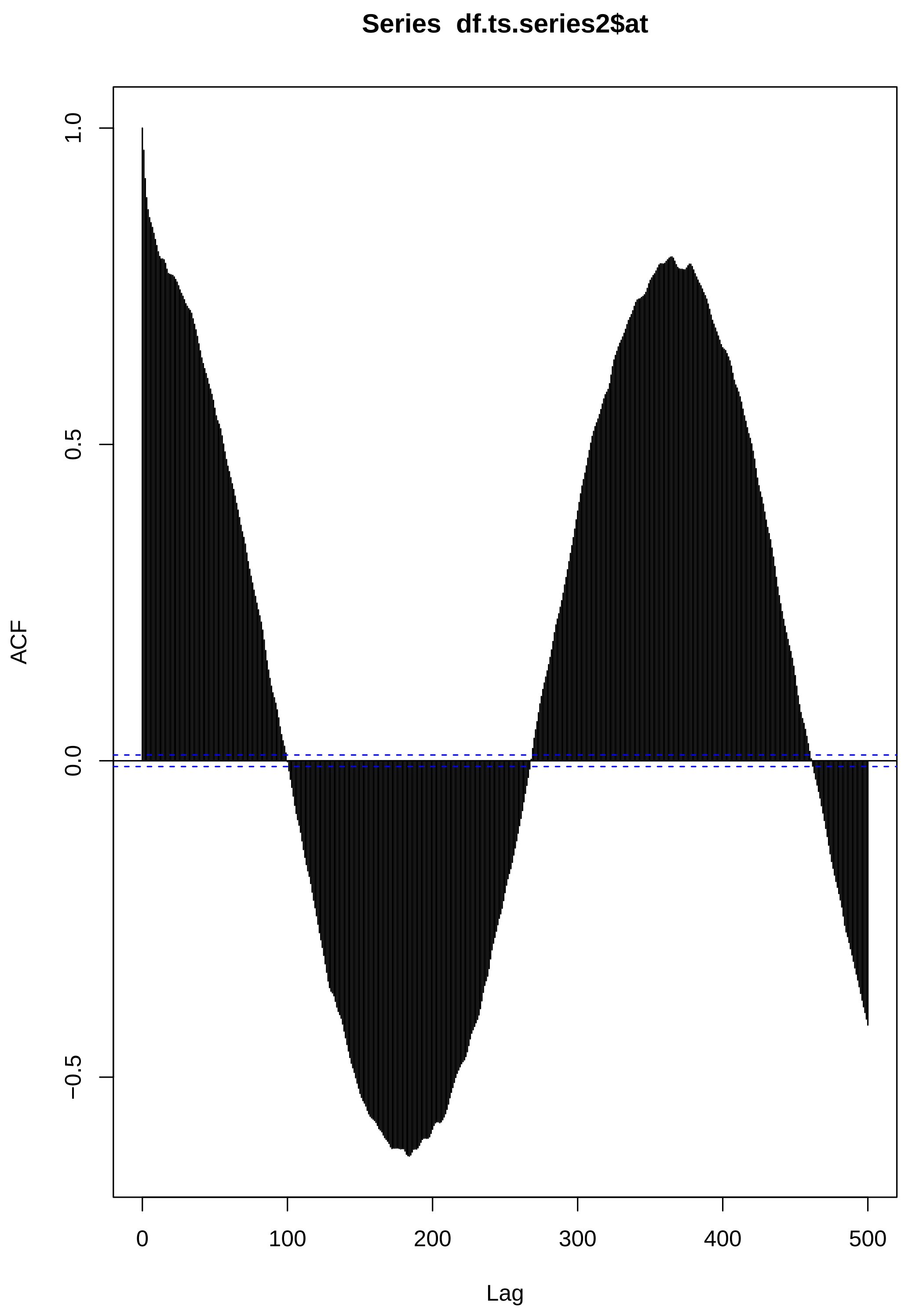
Carpinus betulus
Corylus avellana
Fagus sylvatica
Picea abies
Pinus sylvestris
Pseudotsuga menziesii
Quercus petraea
twd_rolling30
pr_rolling30
0
2
4
6
0.0
0.2
0.4
year
2020
2021
2022

```r
acf(df.ts.series2$twd, lag.max = 500)
```



Series df.ts.series2$twd
ACF
0.0
0.2
0.4
0.6
0.8
1.0
0
100
200
300
400
500
Lag

```r
# clear cycl because high correlation again at 365 days

acf(df.ts.series2$at, lag.max = 500)
```



Series df.ts.series2$at
ACF
1.0
0.5
0.0
−0.5
0
100
200
300
400
500
Lag

```r
rolling.cols <- paste0(num.cols, "_rolling7")

for(iter_species in list_species){
  iter_df <- df.ts.series2 %>%
    filter(species == iter_species)

  print(iter_species)
  print(cor(iter_df[,rolling.cols], use = "complete.obs"))
}
```

```
[1] "Fagus sylvatica"
                     twd_rolling7  pr_rolling7  at_rolling7  ws_rolling7
twd_rolling7          1.000000000 -0.229326842 -0.001806405  0.005359136
pr_rolling7          -0.229326842  1.000000000 -0.002580239  0.056071004
at_rolling7          -0.001806405 -0.002580239  1.000000000 -0.054980460
ws_rolling7           0.005359136  0.056071004 -0.054980460  1.000000000
dp_rolling7          -0.155296191  0.152297003  0.927948643 -0.169831250
sr_rolling7           0.114709687 -0.175259465  0.771449126  0.145150365
lr_rolling7          -0.190929474  0.316380407  0.834238844 -0.108341723
day.of.year_rolling7 -0.057689827  0.049836083  0.188586244 -0.343576437
                     dp_rolling7 sr_rolling7 lr_rolling7 day.of.year_rolling7
twd_rolling7          -0.1552962   0.1147097  -0.1909295          -0.05768983
pr_rolling7            0.1522970  -0.1752595   0.3163804           0.04983608
at_rolling7            0.9279486   0.7714491   0.8342388           0.18858624
ws_rolling7           -0.1698312   0.1451504  -0.1083417          -0.34357644
dp_rolling7            1.0000000   0.5658505   0.9292750           0.32569578
sr_rolling7            0.5658505   1.0000000   0.4319584          -0.18819698
lr_rolling7            0.9292750   0.4319584   1.0000000           0.34110600
day.of.year_rolling7   0.3256958  -0.1881970   0.3411060           1.00000000
[1] "Quercus petraea"
                     twd_rolling7 pr_rolling7 at_rolling7 ws_rolling7
twd_rolling7           1.00000000 -0.30638524   0.1291794 -0.06552551
pr_rolling7           -0.30638524  1.00000000   0.1019861  0.17175190
at_rolling7            0.12917941  0.10198611   1.0000000 -0.19133876
ws_rolling7           -0.06552551  0.17175190  -0.1913388  1.00000000
dp_rolling7            0.03770180  0.23915998   0.9337133 -0.27314040
sr_rolling7            0.13450279 -0.08281823   0.7746494 -0.04617898
lr_rolling7           -0.03377644  0.39795395   0.8283397 -0.14520137
day.of.year_rolling7   0.08436441  0.07337225   0.1802469 -0.40016896
                     dp_rolling7 sr_rolling7 lr_rolling7 day.of.year_rolling7
twd_rolling7           0.0377018  0.13450279 -0.03377644           0.08436441
pr_rolling7            0.2391600 -0.08281823  0.39795395           0.07337225
```

```
at_rolling7            0.9337133  0.77464945  0.82833967           0.18024690
ws_rolling7           -0.2731404 -0.04617898 -0.14520137          -0.40016896
dp_rolling7            1.0000000  0.57116163  0.92560242           0.33106272
sr_rolling7            0.5711616  1.00000000  0.40917217          -0.18825438
lr_rolling7            0.9256024  0.40917217  1.00000000           0.36296281
day.of.year_rolling7   0.3310627 -0.18825438  0.36296281           1.00000000
[1] "Carpinus betulus"
                     twd_rolling7 pr_rolling7 at_rolling7 ws_rolling7
twd_rolling7           1.00000000 -0.18378950  0.23034814   0.1080840
pr_rolling7           -0.18378950  1.00000000 -0.03441214  -0.1183427
at_rolling7            0.23034814 -0.03441214  1.00000000  -0.1927280
ws_rolling7            0.10808400 -0.11834274 -0.19272802   1.0000000
dp_rolling7            0.11815185  0.16405094  0.92631633  -0.3276740
sr_rolling7            0.21861630 -0.30876256  0.78498848   0.1226974
lr_rolling7            0.10235193  0.34682046  0.84670696  -0.2890144
day.of.year_rolling7   0.01473794  0.11614731  0.18483807  -0.2857379
                     dp_rolling7 sr_rolling7 lr_rolling7 day.of.year_rolling7
twd_rolling7           0.1181519   0.2186163   0.1023519           0.01473794
pr_rolling7            0.1640509  -0.3087626   0.3468205           0.11614731
at_rolling7            0.9263163   0.7849885   0.8467070           0.18483807
ws_rolling7           -0.3276740   0.1226974  -0.2890144          -0.28573789
dp_rolling7            1.0000000   0.5617652   0.9263391           0.34582198
sr_rolling7            0.5617652   1.0000000   0.4493856          -0.18602970
lr_rolling7            0.9263391   0.4493856   1.0000000           0.33152721
day.of.year_rolling7   0.3458220  -0.1860297   0.3315272           1.00000000
[1] "Corylus avellana"
                     twd_rolling7 pr_rolling7 at_rolling7 ws_rolling7
twd_rolling7           1.00000000 -0.07885975  -0.1682110   0.1546851
pr_rolling7           -0.07885975  1.00000000   0.1019305   0.1105735
at_rolling7           -0.16821102  0.10193045   1.0000000  -0.3865053
ws_rolling7            0.15468509  0.11057350  -0.3865053   1.0000000
dp_rolling7           -0.27561466  0.23804869   0.9410117  -0.4252089
sr_rolling7            0.07162170 -0.11374353   0.7803831  -0.2179102
lr_rolling7           -0.28348277  0.43425538   0.7940991  -0.3274269
day.of.year_rolling7  -0.16630779  0.05128859   0.1808164  -0.3781703
                     dp_rolling7 sr_rolling7 lr_rolling7 day.of.year_rolling7
twd_rolling7          -0.2756147   0.0716217  -0.2834828          -0.16630779
pr_rolling7            0.2380487  -0.1137435   0.4342554           0.05128859
at_rolling7            0.9410117   0.7803831   0.7940991           0.18081642
ws_rolling7           -0.4252089  -0.2179102  -0.3274269          -0.37817030
dp_rolling7            1.0000000   0.5654600   0.9164353           0.32683459
sr_rolling7            0.5654600   1.0000000   0.3352121          -0.20001558
lr_rolling7            0.9164353   0.3352121   1.0000000           0.41194148
```

```
day.of.year_rolling7   0.3268346  -0.2000156   0.4119415          1.00000000
[1] "Picea abies"
                     twd_rolling7 pr_rolling7 at_rolling7 ws_rolling7
twd_rolling7           1.00000000 -0.20874054  -0.2996081 -0.04517938
pr_rolling7           -0.20874054  1.00000000   0.1110258  0.11953581
at_rolling7           -0.29960813  0.11102580   1.0000000  0.22993358
ws_rolling7           -0.04517938  0.11953581   0.2299336  1.00000000
dp_rolling7           -0.35866377  0.26686138   0.9510824  0.17403626
sr_rolling7           -0.13222135 -0.07206777   0.6398348  0.11645644
lr_rolling7           -0.35930200  0.40184668   0.8844347  0.22414563
day.of.year_rolling7   0.08499879  0.04796793   0.2404778 -0.10711066
                     dp_rolling7 sr_rolling7 lr_rolling7 day.of.year_rolling7
twd_rolling7          -0.3586638 -0.13222135  -0.3593020           0.08499879
pr_rolling7            0.2668614 -0.07206777   0.4018467           0.04796793
at_rolling7            0.9510824  0.63983482   0.8844347           0.24047781
ws_rolling7            0.1740363  0.11645644   0.2241456          -0.10711066
dp_rolling7            1.0000000  0.54566641   0.9468367           0.31473699
sr_rolling7            0.5456664  1.00000000   0.4483337          -0.22695706
lr_rolling7            0.9468367  0.44833369   1.0000000           0.29285342
day.of.year_rolling7   0.3147370 -0.22695706   0.2928534           1.00000000
[1] "Pinus sylvestris"
                     twd_rolling7 pr_rolling7 at_rolling7 ws_rolling7
twd_rolling7           1.00000000 -0.27333886 -0.04136144  0.02710506
pr_rolling7           -0.27333886  1.00000000  0.04456262 -0.02295181
at_rolling7           -0.04136144  0.04456262  1.00000000  0.30524248
ws_rolling7            0.02710506 -0.02295181  0.30524248  1.00000000
dp_rolling7           -0.15757589  0.22765296  0.92877872  0.10103160
sr_rolling7            0.09045519 -0.09084960  0.81564605  0.45189083
lr_rolling7           -0.18601458  0.32015533  0.90516003  0.21152998
day.of.year_rolling7  -0.10346325  0.02338364  0.17750497 -0.40201000
                     dp_rolling7 sr_rolling7 lr_rolling7 day.of.year_rolling7
twd_rolling7          -0.1575759  0.09045519  -0.1860146          -0.10346325
pr_rolling7            0.2276530 -0.09084960   0.3201553           0.02338364
at_rolling7            0.9287787  0.81564605   0.9051600           0.17750497
ws_rolling7            0.1010316  0.45189083   0.2115300          -0.40201000
dp_rolling7            1.0000000  0.63756182   0.9520371           0.31554406
sr_rolling7            0.6375618  1.00000000   0.6294887          -0.17071344
lr_rolling7            0.9520371  0.62948873   1.0000000           0.26915669
day.of.year_rolling7   0.3155441 -0.17071344   0.2691567           1.00000000
[1] "Pseudotsuga menziesii"
                     twd_rolling7  pr_rolling7 at_rolling7 ws_rolling7
twd_rolling7           1.00000000 -0.069480132 -0.17336808 -0.13545554
pr_rolling7           -0.06948013  1.000000000  0.15756877  0.30883038
```

```
at_rolling7           -0.17336808  0.157568772  1.00000000 -0.07111409
ws_rolling7           -0.13545554  0.308830377 -0.07111409  1.00000000
dp_rolling7           -0.08813263  0.229368713  0.95678648 -0.18813102
sr_rolling7           -0.32407623 -0.039964409  0.77307368  0.08901946
lr_rolling7           -0.03583490  0.396940574  0.84393488 -0.10810573
day.of.year_rolling7   0.34901114  0.003027917  0.17559813 -0.40367532
                     dp_rolling7 sr_rolling7 lr_rolling7 day.of.year_rolling7
twd_rolling7         -0.08813263 -0.32407623  -0.0358349          0.349011137
pr_rolling7           0.22936871 -0.03996441   0.3969406          0.003027917
at_rolling7           0.95678648  0.77307368   0.8439349          0.175598130
ws_rolling7          -0.18813102  0.08901946  -0.1081057         -0.403675317
dp_rolling7           1.00000000  0.59765829   0.9268854          0.321053901
sr_rolling7           0.59765829  1.00000000   0.4111937         -0.206733747
lr_rolling7           0.92688540  0.41119369   1.0000000          0.389889946
day.of.year_rolling7  0.32105390 -0.20673375   0.3898899          1.000000000
```

```
rolling.cols <- paste0(num.cols, "_rolling30")

for(iter_species in list_species){
  iter_df <- df.ts.series2 %>%
    filter(species == iter_species)

  print(iter_species)
  print(cor(iter_df[,rolling.cols], use = "complete.obs"))
}
```

```
[1] "Fagus sylvatica"
                      twd_rolling30 pr_rolling30 at_rolling30 ws_rolling30
twd_rolling30            1.00000000 -0.212181423  -0.03078646  0.018716165
pr_rolling30            -0.21218142  1.000000000   0.06315059  0.007965456
at_rolling30            -0.03078646  0.063150594   1.00000000 -0.065010419
ws_rolling30             0.01871617  0.007965456  -0.06501042  1.000000000
dp_rolling30            -0.16949196  0.196012211   0.94343951 -0.200585211
sr_rolling30             0.08765254 -0.038768951   0.81300739  0.195894994
lr_rolling30            -0.18927300  0.268092193   0.91127770 -0.181026869
day.of.year_rolling30   -0.08776357  0.035581843   0.20287378 -0.546695779
                      dp_rolling30 sr_rolling30 lr_rolling30
twd_rolling30           -0.1694920   0.08765254   -0.1892730
pr_rolling30             0.1960122  -0.03876895    0.2680922
at_rolling30             0.9434395   0.81300739    0.9112777
ws_rolling30            -0.2005852   0.19589499   -0.1810269
dp_rolling30             1.0000000   0.63619694    0.9689818
```

```
sr_rolling30            0.6361969   1.00000000    0.5902994
lr_rolling30            0.9689818   0.59029936    1.0000000
day.of.year_rolling30   0.3539579  -0.20912885    0.3744793
                      day.of.year_rolling30
twd_rolling30                   -0.08776357
pr_rolling30                     0.03558184
at_rolling30                     0.20287378
ws_rolling30                    -0.54669578
dp_rolling30                     0.35395788
sr_rolling30                    -0.20912885
lr_rolling30                     0.37447927
day.of.year_rolling30            1.00000000
[1] "Quercus petraea"
                      twd_rolling30 pr_rolling30 at_rolling30 ws_rolling30
twd_rolling30           1.000000000  -0.36874741    0.1171246  -0.04895769
pr_rolling30           -0.368747408   1.00000000    0.2419541   0.01102331
at_rolling30            0.117124560   0.24195414    1.0000000  -0.29375871
ws_rolling30           -0.048957693   0.01102331   -0.2937587   1.00000000
dp_rolling30            0.052358998   0.37015391    0.9450605  -0.42147308
sr_rolling30            0.093396270   0.13566319    0.8203822  -0.01505648
lr_rolling30            0.006242791   0.45023222    0.8987315  -0.38354740
day.of.year_rolling30   0.077171644   0.07828934    0.1944483  -0.67546379
                      dp_rolling30 sr_rolling30 lr_rolling30
twd_rolling30            0.0523590   0.09339627  0.006242791
pr_rolling30             0.3701539   0.13566319  0.450232220
at_rolling30             0.9450605   0.82038215  0.898731476
ws_rolling30            -0.4214731  -0.01505648 -0.383547402
dp_rolling30             1.0000000   0.64314346  0.967311019
sr_rolling30             0.6431435   1.00000000  0.563999120
lr_rolling30             0.9673110   0.56399912  1.000000000
day.of.year_rolling30    0.3665343  -0.21069044  0.409349735
                      day.of.year_rolling30
twd_rolling30                    0.07717164
pr_rolling30                     0.07828934
at_rolling30                     0.19444828
ws_rolling30                    -0.67546379
dp_rolling30                     0.36653430
sr_rolling30                    -0.21069044
lr_rolling30                     0.40934974
day.of.year_rolling30            1.00000000
[1] "Carpinus betulus"
                      twd_rolling30 pr_rolling30 at_rolling30 ws_rolling30
twd_rolling30            1.00000000  -0.23788812   0.25038261   0.13044734
```

```
pr_rolling30            -0.23788812   1.00000000  -0.01315086  -0.08559449
at_rolling30             0.25038261  -0.01315086   1.00000000  -0.21996377
ws_rolling30             0.13044734  -0.08559449  -0.21996377   1.00000000
dp_rolling30             0.15077268   0.18238453   0.94397037  -0.37021966
sr_rolling30             0.21999877  -0.24996622   0.83255191   0.11796458
lr_rolling30             0.14878405   0.26446025   0.92790566  -0.31985430
day.of.year_rolling30    0.01098617   0.16153927   0.19685936  -0.52460399
                      dp_rolling30 sr_rolling30 lr_rolling30
twd_rolling30            0.1507727    0.2199988    0.1487840
pr_rolling30             0.1823845   -0.2499662    0.2644602
at_rolling30             0.9439704    0.8325519    0.9279057
ws_rolling30            -0.3702197    0.1179646   -0.3198543
dp_rolling30             1.0000000    0.6565611    0.9643534
sr_rolling30             0.6565611    1.0000000    0.6376992
lr_rolling30             0.9643534    0.6376992    1.0000000
day.of.year_rolling30    0.3740399   -0.2038241    0.3547322
                      day.of.year_rolling30
twd_rolling30                    0.01098617
pr_rolling30                     0.16153927
at_rolling30                     0.19685936
ws_rolling30                    -0.52460399
dp_rolling30                     0.37403987
sr_rolling30                    -0.20382410
lr_rolling30                     0.35473221
day.of.year_rolling30            1.00000000
[1] "Corylus avellana"
                      twd_rolling30 pr_rolling30 at_rolling30 ws_rolling30
twd_rolling30             1.0000000  -0.11878944   -0.1671747    0.2464720
pr_rolling30             -0.1187894   1.00000000    0.2465994   -0.0767915
at_rolling30             -0.1671747   0.24659940    1.0000000   -0.5759521
ws_rolling30              0.2464720  -0.07679150   -0.5759521    1.0000000
dp_rolling30             -0.2904390   0.35930843    0.9530411   -0.6438180
sr_rolling30              0.1081551   0.10711011    0.8222464   -0.2876951
lr_rolling30             -0.3301206   0.47807945    0.8707749   -0.6352241
day.of.year_rolling30    -0.2578483   0.02697776    0.1955792   -0.6281890
                      dp_rolling30 sr_rolling30 lr_rolling30
twd_rolling30           -0.2904390    0.1081551   -0.3301206
pr_rolling30             0.3593084    0.1071101    0.4780794
at_rolling30             0.9530411    0.8222464    0.8707749
ws_rolling30            -0.6438180   -0.2876951   -0.6352241
dp_rolling30             1.0000000    0.6386810    0.9624457
sr_rolling30             0.6386810    1.0000000    0.4973503
lr_rolling30             0.9624457    0.4973503    1.0000000
```

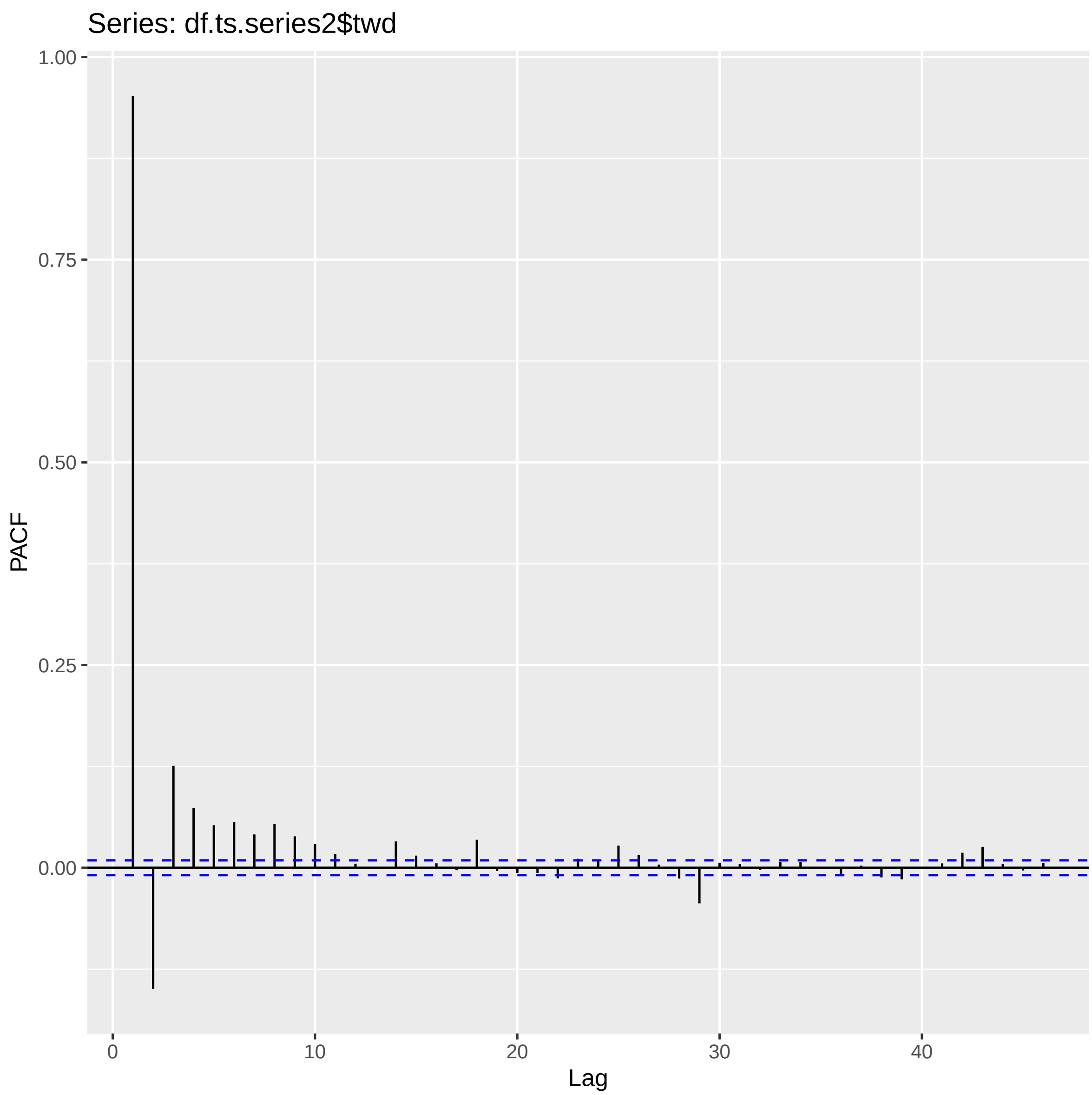
```
day.of.year_rolling30    0.3603965   -0.2236869    0.4627945
                      day.of.year_rolling30
twd_rolling30                   -0.25784831
pr_rolling30                     0.02697776
at_rolling30                     0.19557921
ws_rolling30                    -0.62818899
dp_rolling30                     0.36039651
sr_rolling30                    -0.22368692
lr_rolling30                     0.46279450
day.of.year_rolling30            1.00000000
[1] "Picea abies"
                      twd_rolling30 pr_rolling30 at_rolling30 ws_rolling30
twd_rolling30            1.00000000  -0.25361356   -0.3740038  -0.04551062
pr_rolling30            -0.25361356   1.00000000    0.2638959   0.08024032
at_rolling30            -0.37400381   0.26389586    1.0000000   0.26043912
ws_rolling30            -0.04551062   0.08024032    0.2604391   1.00000000
dp_rolling30            -0.41169556   0.39660243    0.9664684   0.19076659
sr_rolling30            -0.20270287   0.15082024    0.6686832   0.14211952
lr_rolling30            -0.41440303   0.43270205    0.9547638   0.22413467
day.of.year_rolling30    0.06133371   0.06301339    0.2580739  -0.12940025
                      dp_rolling30 sr_rolling30 lr_rolling30
twd_rolling30           -0.4116956   -0.2027029   -0.4144030
pr_rolling30             0.3966024    0.1508202    0.4327021
at_rolling30             0.9664684    0.6686832    0.9547638
ws_rolling30             0.1907666    0.1421195    0.2241347
dp_rolling30             1.0000000    0.6078743    0.9771511
sr_rolling30             0.6078743    1.0000000    0.5872998
lr_rolling30             0.9771511    0.5872998    1.0000000
day.of.year_rolling30    0.3339928   -0.2555050    0.3161751
                      day.of.year_rolling30
twd_rolling30                    0.06133371
pr_rolling30                     0.06301339
at_rolling30                     0.25807386
ws_rolling30                    -0.12940025
dp_rolling30                     0.33399281
sr_rolling30                    -0.25550496
lr_rolling30                     0.31617506
day.of.year_rolling30            1.00000000
[1] "Pinus sylvestris"
                      twd_rolling30 pr_rolling30 at_rolling30 ws_rolling30
twd_rolling30           1.000000000  -0.33879900  -0.08690945 -0.008164029
pr_rolling30           -0.338799001   1.00000000   0.18429644  0.016437757
at_rolling30           -0.086909445   0.18429644   1.00000000  0.346168111
```

```
ws_rolling30          -0.008164029  0.01643776  0.34616811  1.000000000
dp_rolling30          -0.167163341  0.31992692  0.95411170  0.146955607
sr_rolling30           0.051004139  0.10062858  0.84566925  0.532112219
lr_rolling30          -0.205035562  0.35441665  0.96331873  0.258206033
day.of.year_rolling30 -0.116665051 -0.03373590  0.18836405 -0.552914814
                     dp_rolling30 sr_rolling30 lr_rolling30
twd_rolling30           -0.1671633   0.05100414   -0.2050356
pr_rolling30             0.3199269   0.10062858    0.3544166
at_rolling30             0.9541117   0.84566925    0.9633187
ws_rolling30             0.1469556   0.53211222    0.2582060
dp_rolling30             1.0000000   0.70705369    0.9759720
sr_rolling30             0.7070537   1.00000000    0.7461934
lr_rolling30             0.9759720   0.74619340    1.0000000
day.of.year_rolling30    0.3381932  -0.18701580    0.2824684
                     day.of.year_rolling30
twd_rolling30                   -0.1166651
pr_rolling30                    -0.0337359
at_rolling30                     0.1883640
ws_rolling30                    -0.5529148
dp_rolling30                     0.3381932
sr_rolling30                    -0.1870158
lr_rolling30                     0.2824684
day.of.year_rolling30            1.0000000
[1] "Pseudotsuga menziesii"
                     twd_rolling30 pr_rolling30 at_rolling30 ws_rolling30
twd_rolling30           1.00000000  -0.15828309   -0.1792531   -0.2135736
pr_rolling30           -0.15828309   1.00000000    0.3402710    0.2040199
at_rolling30           -0.17925312   0.34027104    1.0000000   -0.1447002
ws_rolling30           -0.21357355   0.20401994   -0.1447002    1.0000000
dp_rolling30           -0.08823155   0.38739268    0.9654277   -0.2883100
sr_rolling30           -0.33875695   0.21909028    0.8164631    0.1727388
lr_rolling30           -0.04467526   0.48807141    0.9060974   -0.3017098
day.of.year_rolling30   0.33891713  -0.04237303    0.1881446   -0.6959699
                     dp_rolling30 sr_rolling30 lr_rolling30
twd_rolling30          -0.08823155   -0.3387570  -0.04467526
pr_rolling30            0.38739268    0.2190903   0.48807141
at_rolling30            0.96542774    0.8164631   0.90609741
ws_rolling30           -0.28830998    0.1727388  -0.30170975
dp_rolling30            1.00000000    0.6598778   0.97047002
sr_rolling30            0.65987783    1.0000000   0.55425872
lr_rolling30            0.97047002    0.5542587   1.00000000
day.of.year_rolling30   0.35204798   -0.2317087   0.43026229
                     day.of.year_rolling30
```

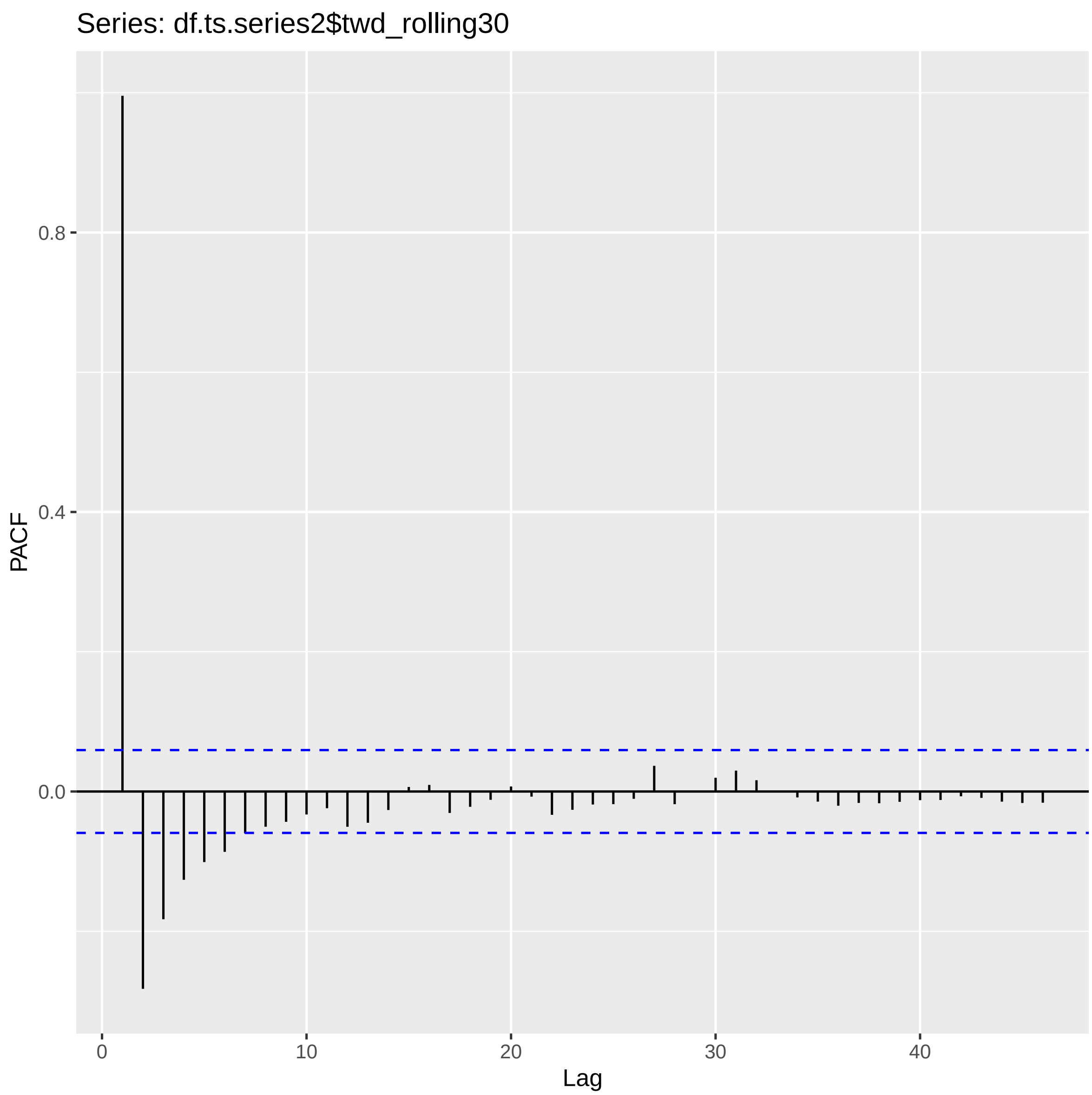
```
twd_rolling30                    0.33891713
pr_rolling30                    -0.04237303
at_rolling30                     0.18814460
ws_rolling30                    -0.69596994
dp_rolling30                     0.35204798
sr_rolling30                    -0.23170870
lr_rolling30                     0.43026229
day.of.year_rolling30            1.00000000
```

Partial Autocorrelation

```
# Plot PACF
ggPacf(df.ts.series2$twd)
```




```
ggPacf(df.ts.series2$twd_rolling30)
```




```r
plot_twd_lag <- function(df, x_col, twd_col, lag = 1) {

  # Arrange data by time
  df <- df %>% arrange(.data[[x_col]])

  # Create lagged TWD values
  df <- df %>%
    mutate(Lagged_TWD = lag(.data[[twd_col]], lag))
```

```
  # Plot TWD vs. lagged TWD
  ggplot(df, aes(x = ts, color = tree.id, y = .data[[twd_col]])) +
    geom_line() +
    geom_line(aes(y= Lagged_TWD))+
    labs(title = paste("Tree Water Deficit vs. Lagged TWD (Lag =", lag, ")"),
         x = paste("TWD at Lag", lag),
         y = "TWD at Current Time") +
    theme_bw() +
    facet_wrap(~species)
}

plot_twd_lag(df.ts.series2, "at", "twd", lag = 5)
```

Granger Causality

Granger Causality: Rather than testing whether X causes Y, the Granger causality tests whether X forecasts Y.

A time series X is said to Granger-cause Y if it can be shown, usually through a series of t-tests and F-tests on lagged values of X (and with lagged values of Y also included), that those X values provide statistically significant information about future values of Y.

A variable X that evolves over time Granger-causes another evolving variable Y if predictions of the value of Y based on its own past values and on the past values of X are better than predictions of Y based only on Y's own past values.

If the variables are non-stationary, then the test is done using first (or higher) differences. The number of lags to be included is usually chosen using an information criterion

```
library(vars)
library(urca)
library(vars)

summary(ur.df(df.ts.series2$twd, type="drift", lags=2))
```

```
###############################################
# Augmented Dickey-Fuller Test Unit Root Test #
###############################################

Test regression drift


Call:
lm(formula = z.diff ~ z.lag.1 + 1 + z.diff.lag)

Residuals:
    Min      1Q  Median      3Q     Max
-6.3454 -0.0568 -0.0214  0.0910  5.0259

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.035892   0.001730   20.74   <2e-16 ***
z.lag.1     -0.048081   0.001437  -33.45   <2e-16 ***
z.diff.lag1  0.161276   0.004593   35.11   <2e-16 ***
z.diff.lag2 -0.125885   0.004624  -27.22   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.2913 on 46025 degrees of freedom
Multiple R-squared:  0.06084,   Adjusted R-squared:  0.06077
F-statistic: 993.8 on 3 and 46025 DF,  p-value: < 2.2e-16


Value of test-statistic is: -33.4549 559.6152
```

```
Critical values for test statistics:
      1pct  5pct 10pct
tau2 -3.43 -2.86 -2.57
phi1  6.43  4.59  3.78
```

```r
summary(ur.df(df.ts.series2$at, type="drift", lags=2))
```

```
###############################################
# Augmented Dickey-Fuller Test Unit Root Test #
###############################################

Test regression drift


Call:
lm(formula = z.diff ~ z.lag.1 + 1 + z.diff.lag)

Residuals:
     Min       1Q   Median       3Q      Max
-15.8620  -1.1118   0.1609   1.2507  13.9444

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.291496   0.014314   20.36   <2e-16 ***
z.lag.1     -0.032011   0.001206  -26.54   <2e-16 ***
z.diff.lag1  0.183176   0.004529   40.45   <2e-16 ***
z.diff.lag2 -0.212788   0.004554  -46.72   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.97 on 46025 degrees of freedom
Multiple R-squared:  0.08551,   Adjusted R-squared:  0.08545
F-statistic:  1434 on 3 and 46025 DF,  p-value: < 2.2e-16


Value of test-statistic is: -26.5441 352.2943

Critical values for test statistics:
      1pct  5pct 10pct
tau2 -3.43 -2.86 -2.57
```

```
phi1  6.43  4.59  3.78
```

This tests the null hypothesis: The series has a unit root (i.e., non-stationary).

If the coefficient on z.lag.1 is significantly different from zero (with a very small p-value), then you can reject the null hypothesis and conclude the series is stationary.

```r
granger_test <- function(data, group = NA, x_col, y_col, lags = 10) {
  run_test <- function(df_sub) {
    df <- df_sub[, c(x_col, y_col)]
    names(df) <- c("x", "y")
    df <- df[complete.cases(df), ]

    if (nrow(df) <= lags + 1) {
      return("Not enough observations for VAR model.")
    }

    var_model <- VAR(df, p = lags, type = "const")
    return(causality(var_model, cause = "x"))
  }

  if (is.na(group)) {
    return(run_test(data))
  } else {
    group_list <- split(data, data[[group]])
    results <- lapply(group_list, run_test)
    return(results)
  }
}

granger_test(df.ts.series2, y_col= "twd", x_col= "at")
```

```
$Granger

	Granger causality H0: x do not Granger-cause y

data:  VAR object var_model
F-Test = 17.675, df1 = 10, df2 = 92002, p-value < 2.2e-16


$Instant
```

```
    H0: No instantaneous causality between: x and y

data:  VAR object var_model
Chi-squared = 520.16, df = 1, p-value < 2.2e-16
```

```r
granger_test(df.ts.series2, y_col = "twd", x_col= "dp")
```

```
$Granger

    Granger causality H0: x do not Granger-cause y

data:  VAR object var_model
F-Test = 81.642, df1 = 10, df2 = 92002, p-value < 2.2e-16


$Instant

    H0: No instantaneous causality between: x and y

data:  VAR object var_model
Chi-squared = 454.05, df = 1, p-value < 2.2e-16
```

Granger test by species

```r
granger_test(df.ts.series2, y_col= "twd", x_col= "at", group = "species")
```

```
$`Carpinus betulus`
$`Carpinus betulus`$Granger

    Granger causality H0: x do not Granger-cause y

data:  VAR object var_model
F-Test = 7.3404, df1 = 10, df2 = 8706, p-value = 1.099e-11


$`Carpinus betulus`$Instant

    H0: No instantaneous causality between: x and y
```

```
data:  VAR object var_model
Chi-squared = 24.933, df = 1, p-value = 5.937e-07



$`Corylus avellana`
$`Corylus avellana`$Granger

    Granger causality H0: x do not Granger-cause y

data:  VAR object var_model
F-Test = 2.68, df1 = 10, df2 = 4322, p-value = 0.002861


$`Corylus avellana`$Instant

    H0: No instantaneous causality between: x and y

data:  VAR object var_model
Chi-squared = 0.10641, df = 1, p-value = 0.7443



$`Fagus sylvatica`
$`Fagus sylvatica`$Granger

    Granger causality H0: x do not Granger-cause y

data:  VAR object var_model
F-Test = 6.9531, df1 = 10, df2 = 21858, p-value = 5.704e-11


$`Fagus sylvatica`$Instant

    H0: No instantaneous causality between: x and y

data:  VAR object var_model
Chi-squared = 311.05, df = 1, p-value < 2.2e-16



$`Picea abies`
$`Picea abies`$Granger
```

```
    Granger causality H0: x do not Granger-cause y

data:  VAR object var_model
F-Test = 13.061, df1 = 10, df2 = 32818, p-value < 2.2e-16


$`Picea abies`$Instant

    H0: No instantaneous causality between: x and y

data:  VAR object var_model
Chi-squared = 48.338, df = 1, p-value = 3.588e-12



$`Pinus sylvestris`
$`Pinus sylvestris`$Granger

    Granger causality H0: x do not Granger-cause y

data:  VAR object var_model
F-Test = 8.3564, df1 = 10, df2 = 10898, p-value = 1.141e-13


$`Pinus sylvestris`$Instant

    H0: No instantaneous causality between: x and y

data:  VAR object var_model
Chi-squared = 272.9, df = 1, p-value < 2.2e-16



$`Pseudotsuga menziesii`
$`Pseudotsuga menziesii`$Granger

    Granger causality H0: x do not Granger-cause y

data:  VAR object var_model
F-Test = 1.9786, df1 = 10, df2 = 4322, p-value = 0.03161
```

```
$`Pseudotsuga menziesii`$Instant

    H0: No instantaneous causality between: x and y

data:  VAR object var_model
Chi-squared = 15.741, df = 1, p-value = 7.264e-05



$`Quercus petraea`
$`Quercus petraea`$Granger

    Granger causality H0: x do not Granger-cause y

data:  VAR object var_model
F-Test = 3.9166, df1 = 10, df2 = 8706, p-value = 2.443e-05


$`Quercus petraea`$Instant

    H0: No instantaneous causality between: x and y

data:  VAR object var_model
Chi-squared = 184.65, df = 1, p-value < 2.2e-16
```

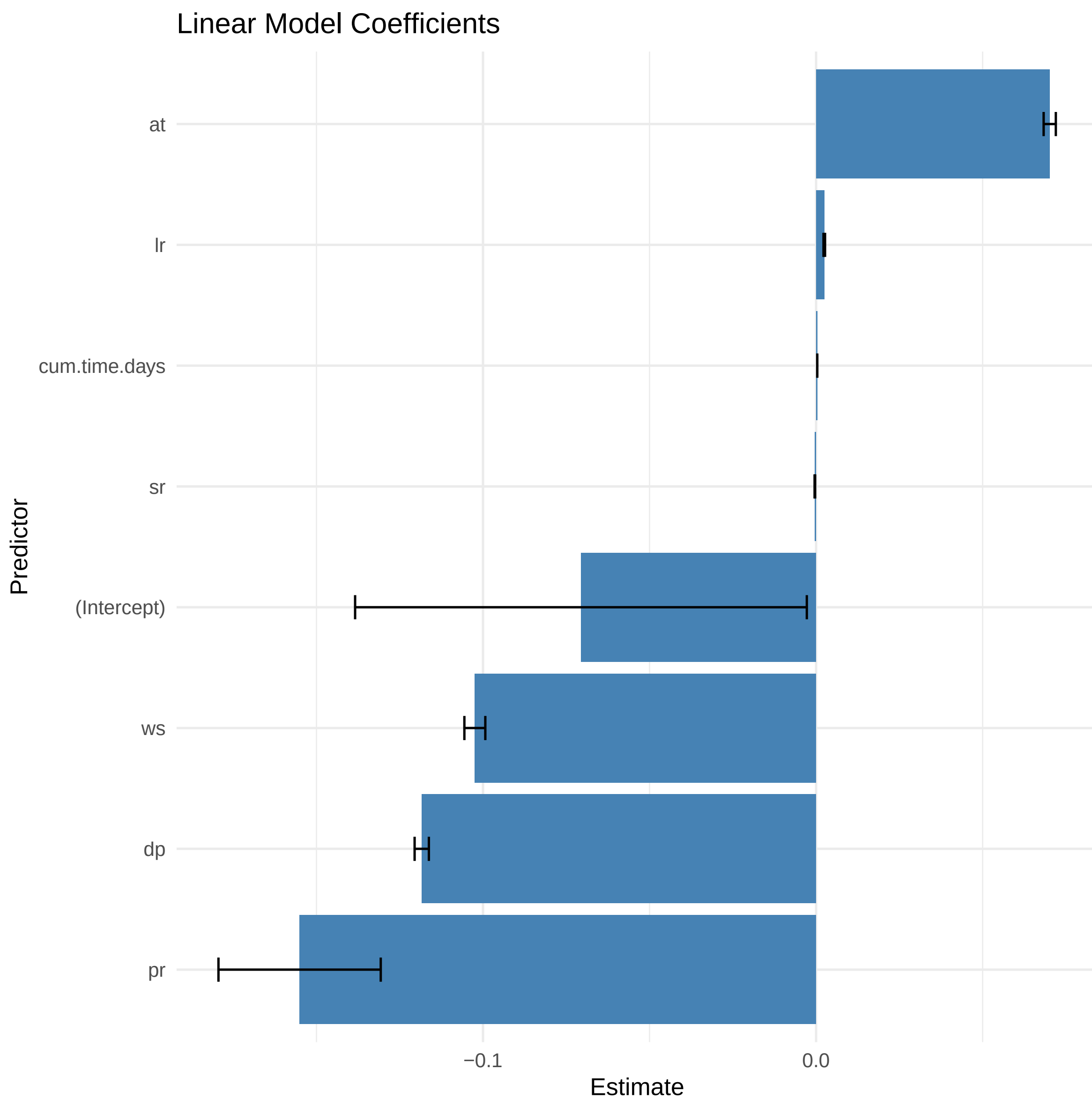
Linear regression

```
plot_coeffs <- function(my_coef_df){
  ggplot(my_coef_df, aes(x = reorder(term, estimate), y = estimate)) +
    geom_bar(stat = "identity", fill = "steelblue") +
    geom_errorbar(aes(ymin = estimate - std.error, ymax = estimate + std.error), width = 0.2
    coord_flip() +  # flip axes for readability
    labs(
      title = "Linear Model Coefficients",
      x = "Predictor",
      y = "Estimate"
    ) +
    theme_minimal()
}
```

```r
lm_fit <- lm(
  formula = twd ~ cum.time.days +  at + dp + pr + ws + sr + lr,
  data = df.ts.series2
)

summary(lm_fit)
```

```

Call:
lm(formula = twd ~ cum.time.days + at + dp + pr + ws + sr + lr,
    data = df.ts.series2)

Residuals:
    Min      1Q  Median      3Q     Max
-2.1275 -0.5348 -0.2398  0.2686  6.5412

Coefficients:
                Estimate Std. Error t value Pr(>|t|)
(Intercept)   -7.059e-02  6.781e-02  -1.041    0.298
cum.time.days  3.474e-04  1.364e-05  25.477  < 2e-16 ***
at             7.014e-02  1.826e-03  38.412  < 2e-16 ***
dp            -1.184e-01  2.142e-03 -55.269  < 2e-16 ***
pr            -1.551e-01  2.436e-02  -6.365 1.97e-10 ***
ws            -1.024e-01  3.145e-03 -32.578  < 2e-16 ***
sr            -3.721e-04  7.651e-05  -4.863 1.16e-06 ***
lr             2.454e-03  2.354e-04  10.422  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.9105 on 46024 degrees of freedom
Multiple R-squared:  0.1216,	Adjusted R-squared:  0.1215
F-statistic: 910.5 on 7 and 46024 DF,  p-value: < 2.2e-16
```

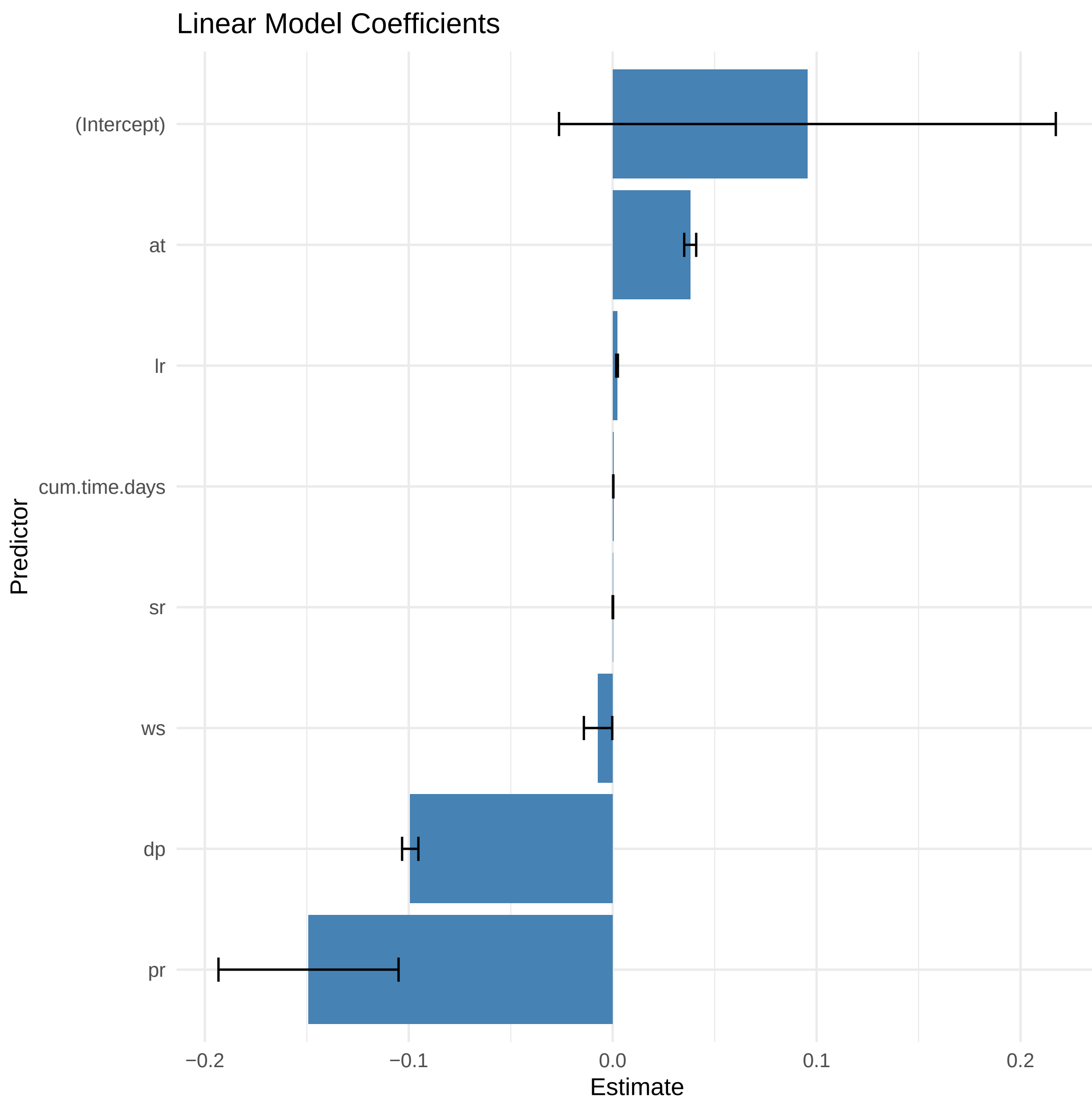
```r
coef_df <- tidy(lm_fit)  # gets estimate, std.error, etc.
plot_coeffs(coef_df)
```




```
lm_fit <- lm(
  formula = twd ~ cum.time.days + at + dp + pr + ws + sr + lr,
  data = df.ts.series2,
  subset = species %in% c("Picea abies")
)

summary(lm_fit)
```

```
Call:
lm(formula = twd ~ cum.time.days + at + dp + pr + ws + sr + lr,
    data = df.ts.series2, subset = species %in% c("Picea abies"))

Residuals:
    Min      1Q  Median      3Q     Max
-2.3254 -0.6140 -0.2014  0.3965  5.6093

Coefficients:
                Estimate Std. Error t value Pr(>|t|)
(Intercept)    9.549e-02  1.218e-01   0.784 0.433121
cum.time.days  2.939e-04  2.330e-05  12.615  < 2e-16 ***
at             3.801e-02  2.937e-03  12.942  < 2e-16 ***
dp            -9.928e-02  3.999e-03 -24.826  < 2e-16 ***
pr            -1.492e-01  4.416e-02  -3.378 0.000732 ***
ws            -7.186e-03  6.952e-03  -1.034 0.301363
sr             8.313e-05  1.170e-04   0.711 0.477347
lr             2.132e-03  4.145e-04   5.144 2.72e-07 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.9286 on 16432 degrees of freedom
Multiple R-squared:  0.1282,    Adjusted R-squared:  0.1278
F-statistic: 345.2 on 7 and 16432 DF,  p-value: < 2.2e-16
```

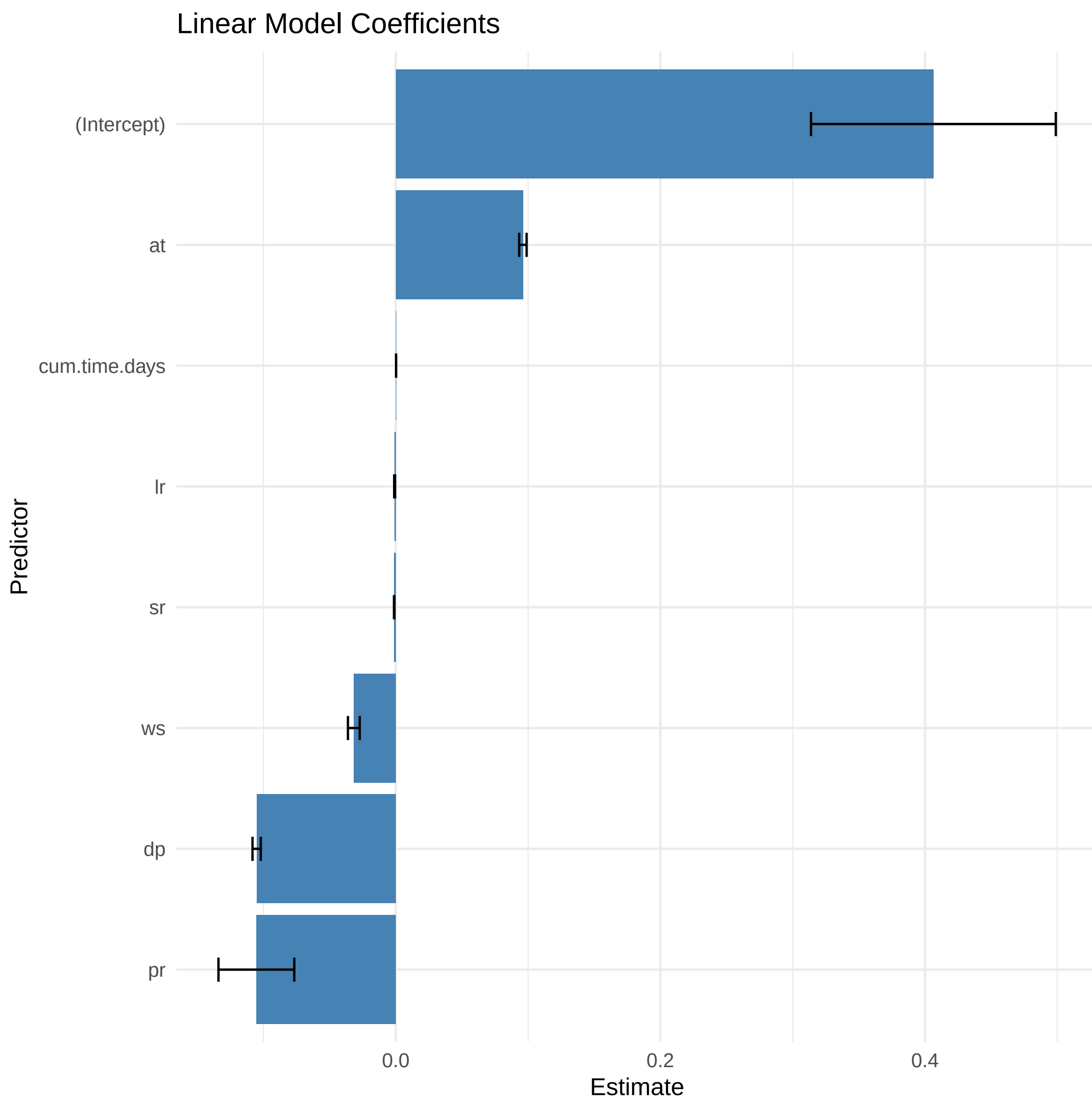
```r
coef_df <- tidy(lm_fit)  # gets estimate, std.error, etc.
plot_coeffs(coef_df)
```




```
lm_fit <- lm(
  formula = twd ~ cum.time.days +  at + dp + pr + ws + sr + lr,
  data = df.ts.series2,
  subset = species %in% c("Fagus sylvatica")
)

summary(lm_fit)
```

```
Call:
lm(formula = twd ~ cum.time.days + at + dp + pr + ws + sr + lr,
    data = df.ts.series2, subset = species %in% c("Fagus sylvatica"))

Residuals:
    Min      1Q  Median      3Q     Max
-1.5274 -0.3262 -0.1401  0.1694  4.9716

Coefficients:
                Estimate Std. Error t value Pr(>|t|)
(Intercept)    4.064e-01  9.252e-02   4.392 1.13e-05 ***
cum.time.days  2.595e-04  1.823e-05  14.234  < 2e-16 ***
at             9.608e-02  2.805e-03  34.256  < 2e-16 ***
dp            -1.051e-01  3.134e-03 -33.550  < 2e-16 ***
pr            -1.054e-01  2.865e-02  -3.678 0.000236 ***
ws            -3.170e-02  4.453e-03  -7.119 1.16e-12 ***
sr            -1.215e-03  1.195e-04 -10.170  < 2e-16 ***
lr            -8.737e-04  3.253e-04  -2.686 0.007242 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.5929 on 10952 degrees of freedom
Multiple R-squared:  0.1739,    Adjusted R-squared:  0.1734
F-statistic: 329.3 on 7 and 10952 DF,  p-value: < 2.2e-16
```

```r
coef_df <- tidy(lm_fit)  # gets estimate, std.error, etc.
plot_coeffs(coef_df)
```



Rollins SD

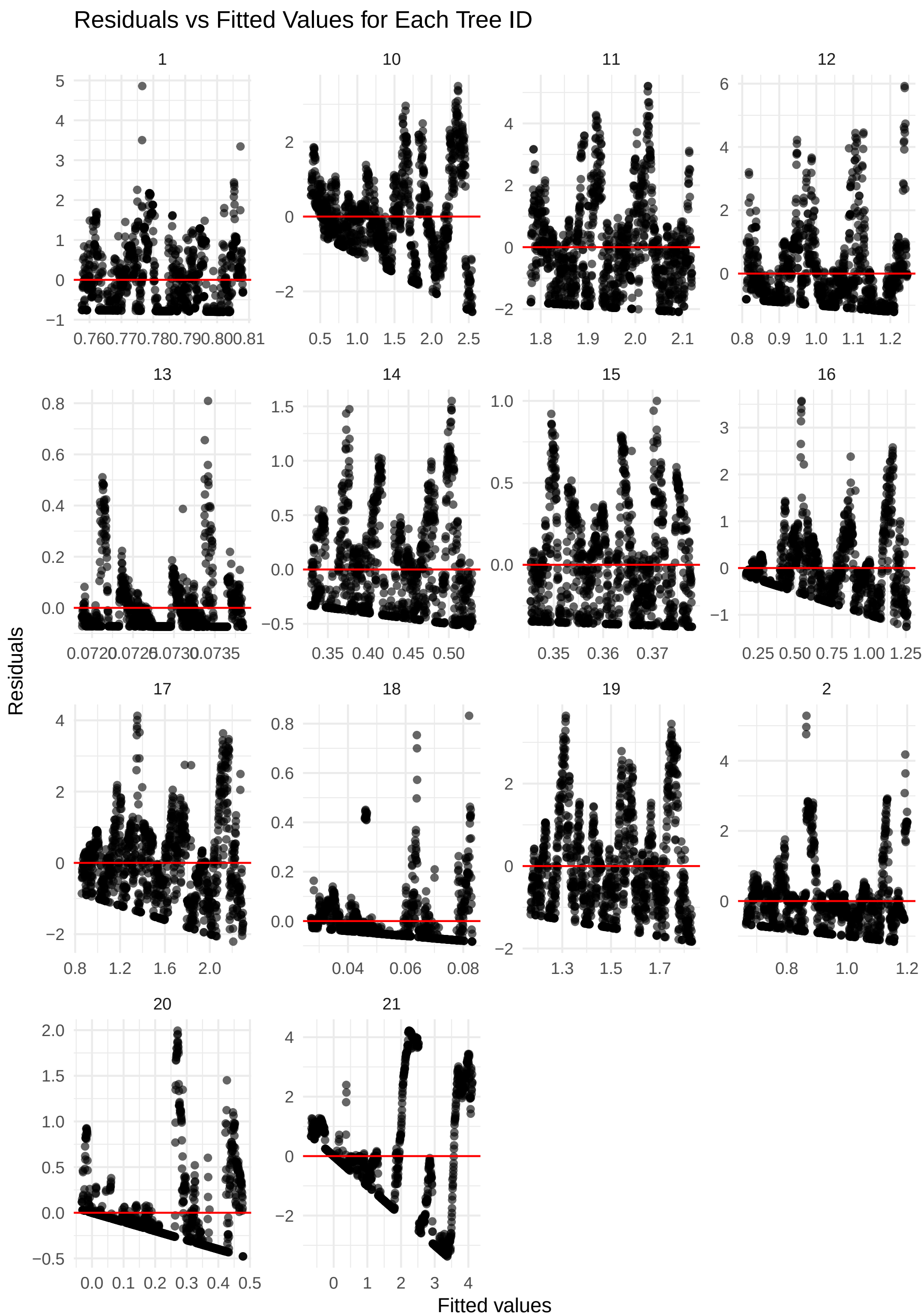
Confirm that timeseries are not stationary

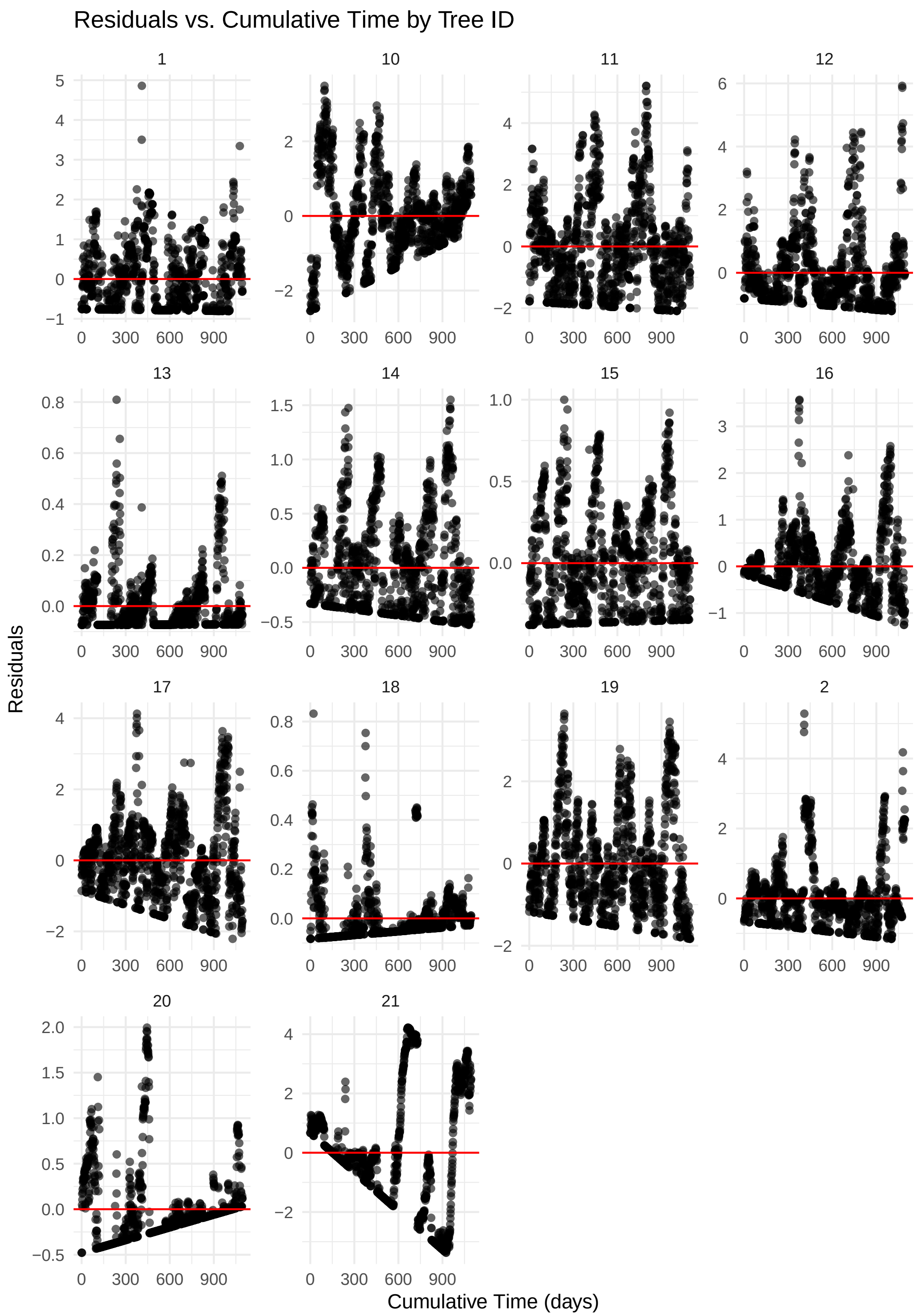
```
library(dplyr)
library(purrr)
```

```
Attaching package: 'purrr'


The following object is masked from 'package:car':

    some
```

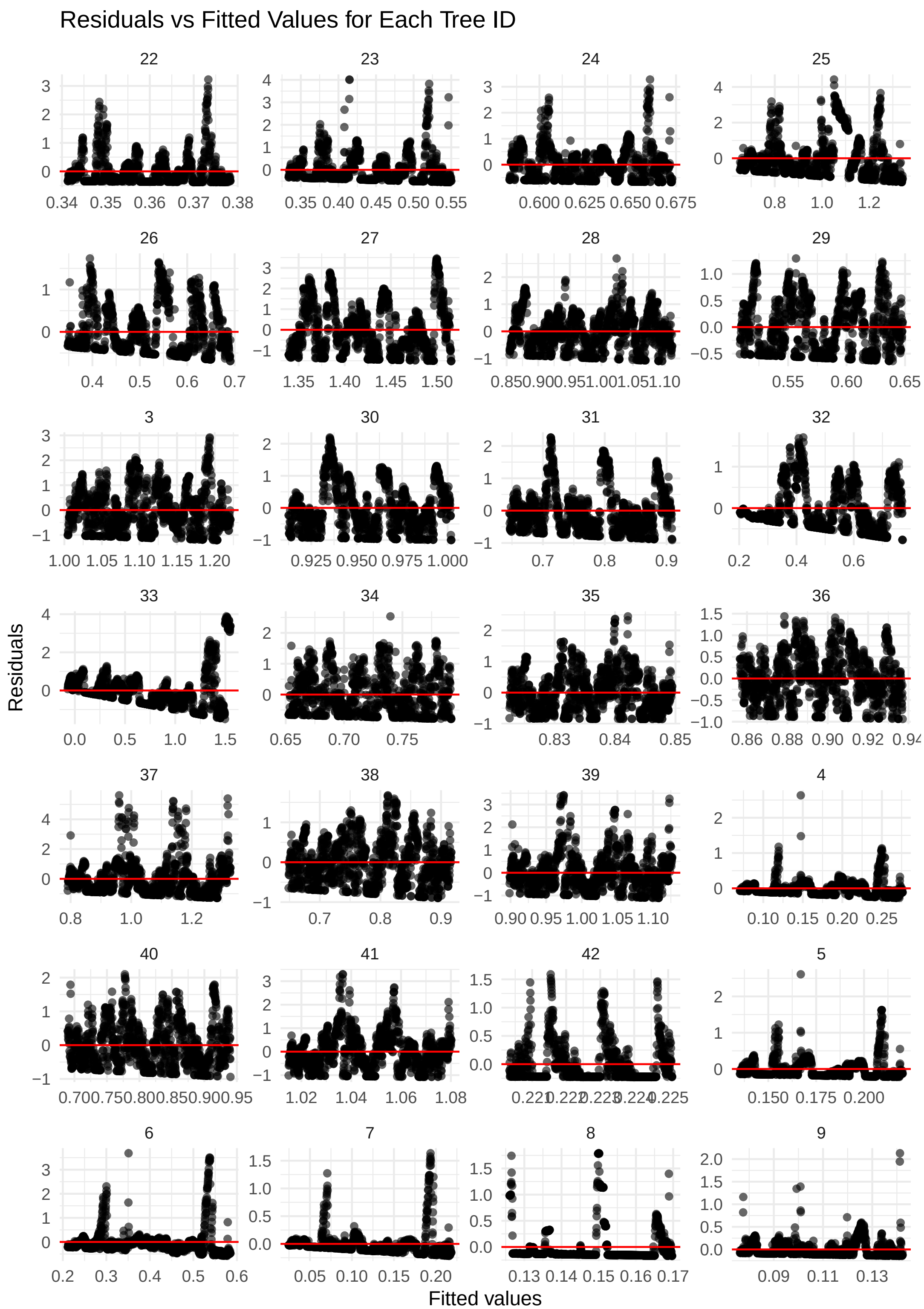
```r
library(ggplot2)
library(broom)
library(tidyr)
library(ggplot2)

# Nest data by tree.id
nested <- df.ts.series2 %>%
  group_by(tree.id) %>%
  nest()

# Fit model and extract residuals
residuals_by_tree <- nested %>%
  mutate(
    model = map(data, ~ lm(twd ~ cum.time.days, data = .x)),
    augmented = map(model, augment)
  ) %>%
  unnest(augmented)

residuals_by_tree_p1 <- residuals_by_tree %>%
  filter(tree.id < 22)
residuals_by_tree_p2 <- residuals_by_tree %>%
  filter(tree.id > 21)

plot_residuals <- function(df){
  # Plot residuals vs fitted for each tree
  print(ggplot(df, aes(.fitted, .resid)) +
    geom_point(alpha = 0.6) +
    geom_hline(yintercept = 0, color = "red") +
    facet_wrap(~ tree.id, scales = "free", ncol = 4) +
    labs(x = "Fitted values", y = "Residuals",
        title = "Residuals vs Fitted Values for Each Tree ID") +
    theme_minimal())

  print(ggplot(df, aes(x = cum.time.days, y = .resid)) +
    geom_point(alpha = 0.6) +
```

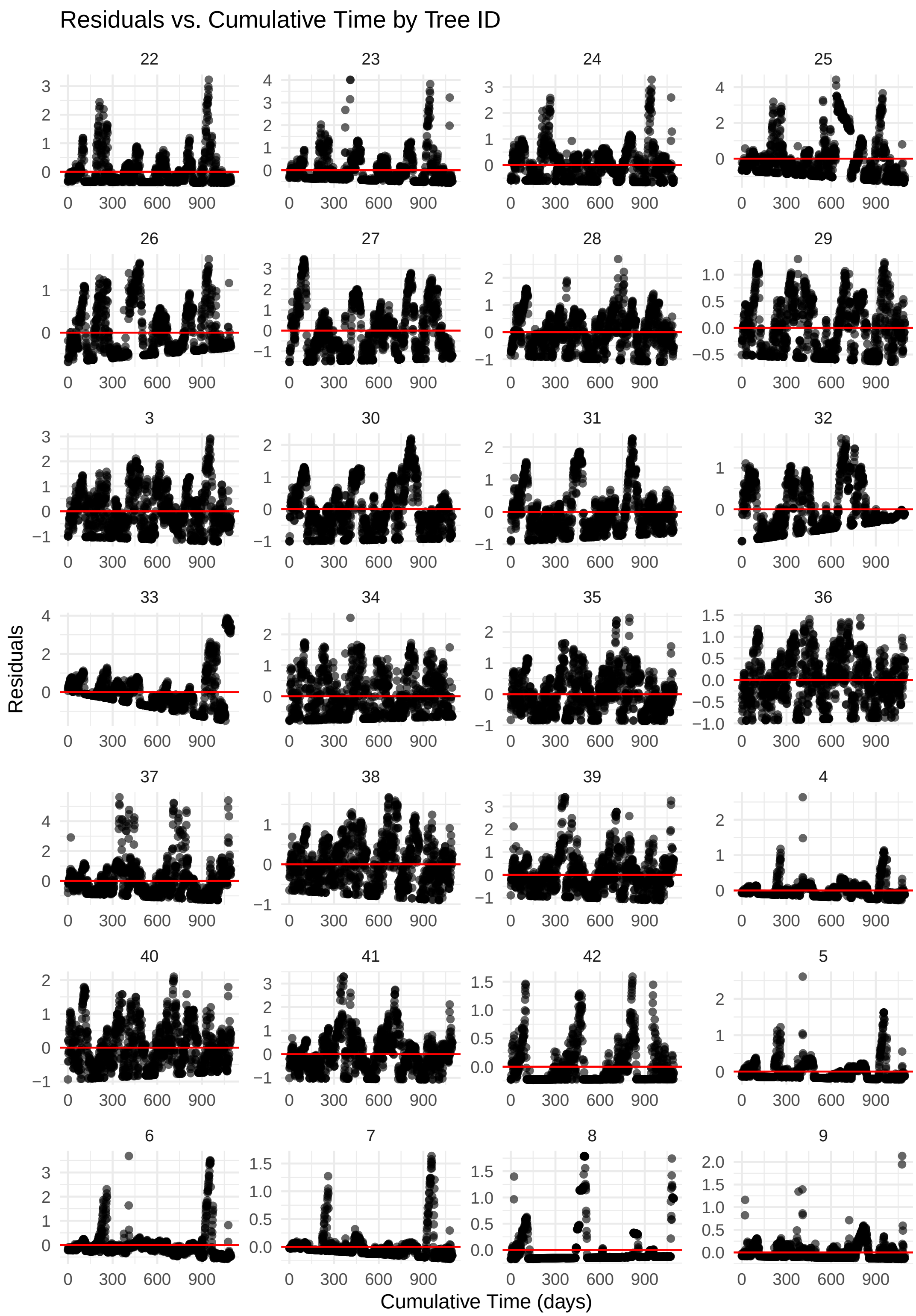
```
    geom_hline(yintercept = 0, color = "red") +
    facet_wrap(~ tree.id, scales = "free", ncol = 4) +
    labs(x = "Cumulative Time (days)", y = "Residuals",
        title = "Residuals vs. Cumulative Time by Tree ID") +
    theme_minimal())
}

plot_residuals(residuals_by_tree_p1)
```


Residuals vs Fitted Values for Each Tree ID
1
10
11
12
13
14
15
16
17
18
19
2
20
21
Residuals
Fitted values

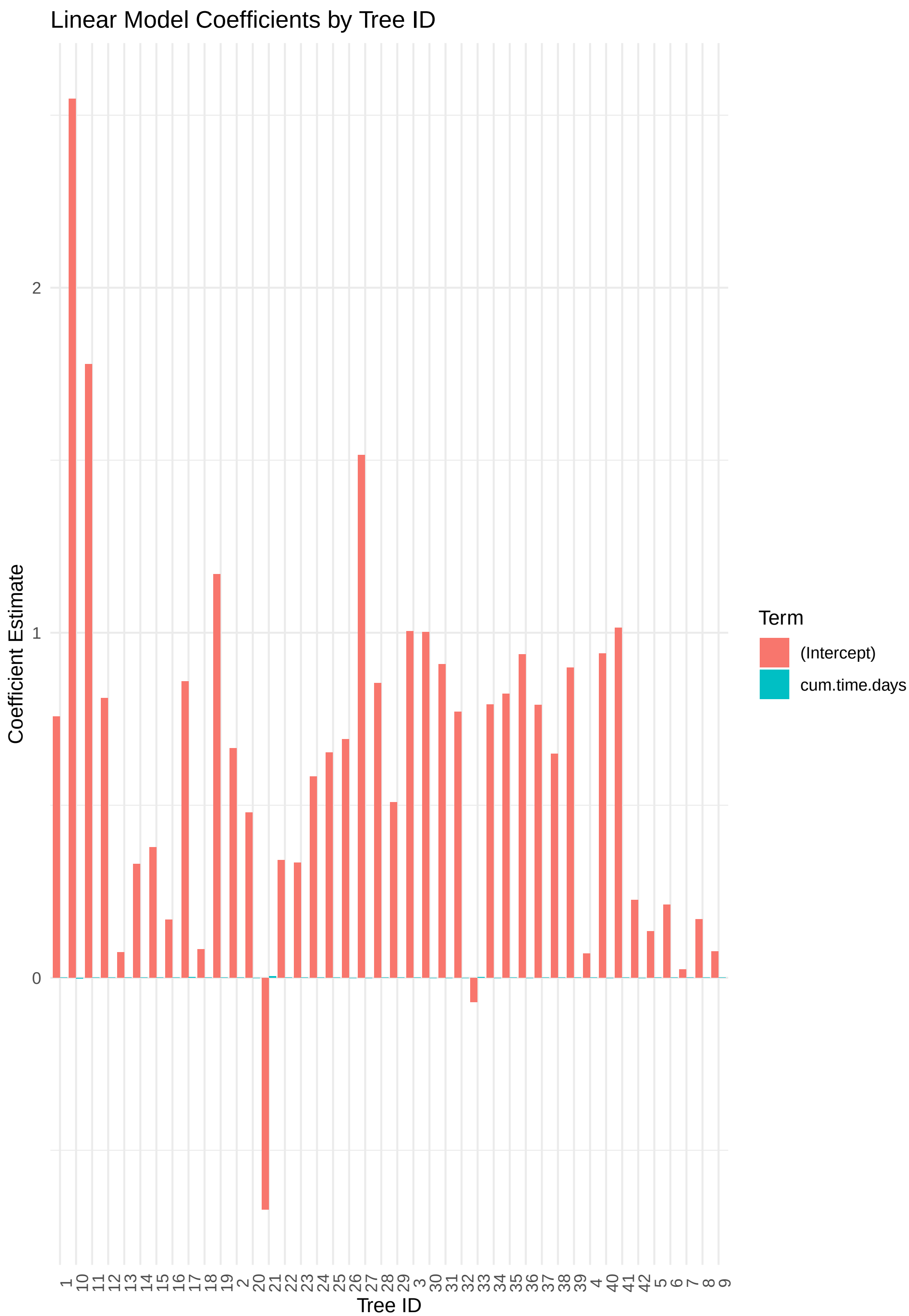

Residuals vs. Cumulative Time by Tree ID
Residuals
Cumulative Time (days)
1
10
11
12
13
14
15
16
17
18
19
2
20
21

```
plot_residuals(residuals_by_tree_p2)
```


Residuals vs Fitted Values for Each Tree ID
Residuals
Fitted values


Residuals vs. Cumulative Time by Tree ID
Residuals
Cumulative Time (days)

```
# Step 1: Fit a linear model for each tree
coeffs_by_tree <- df.ts.series2 %>%
  group_by(tree.id) %>%
  nest() %>%
  mutate(
    model = map(data, ~ lm(twd ~ cum.time.days, data = .x)),
    coef = map(model, tidy)
  ) %>%
  unnest(coef)

# Step 2: Plot coefficients
ggplot(coeffs_by_tree, aes(x = tree.id, y = estimate, fill = term)) +
  geom_bar(stat = "identity", position = position_dodge()) +
  labs(x = "Tree ID", y = "Coefficient Estimate", fill = "Term",
       title = "Linear Model Coefficients by Tree ID") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 90))
```


Linear Model Coefficients by Tree ID
Coefficient Estimate
Tree ID
Term
(Intercept)
cum.time.days
0
1
2
1 10 11 12 13 14 15 16 17 18 19 2 20 21 22 23 24 25 26 27 28 29 3 30 31 32 33 34 35 36 37 38 39 4 40 41 42 5 6 7 8 9