# Modern analogue technique

To run this .Rmd file, you have to change file paths in lines *134* and *290*.

## 1 Dissimilarity / distance metrics

The modern analogue technique is a statistical technique used to reconstruct past environments and climates. To reconstruct past environments, we need three data sets:

- modern species assemblages
- modern environmental variables
- fossil species assemblages

The basic assumption of the modern analogue technique is that similar environments result in similar species assemblages. In a first step a fossil species assemblage is compared to all modern species assemblages. Then the environmental values associated with the $k$ closest *modern analogues* are averaged to infer past environmental conditions.

The distance/dissimilarity metric used to compare modern and fossil species assemblages is crucial. In a first step we will compare three distance/dissimilarity metrics:

- Euclidean distance
- Chord distance
- Bray-Curtis distance

We will test these metrics on the the North American Modern Pollen Database (Whitmore et al. 2005). These modern data are available from the *analogue* r-package by Gavin Simpson.

```
library(analogue)
library(rioja)
library(vegan)
library(maps)
```

```
data(Pollen)
data(Climate)
data(Location)
head(Pollen)
```

```
##   ABIES ACNEGUNA ACPENSYL ACRUBRUM ACSACNUM ACSACRUM ACERX ALCRISPA
## 1     0        0        0        0        0        0     2      176
## 2     4        0        0        0        0        0     0        0
## 3     4        0        0        0        0        0     0       16
## 4     0        1        0      102        0        0     0        0
## 5     1        0        0        0        0       14     0        6
## 6    48        0        0        0        0        2     1       19
##   ALRUBRA ALRUGOSA ALNUSX AMBROSIA AMORPHA ANACARDI APIACEAE AQUIFOLI
## 1       0        0      0        5       0        0        0        0
## 2       0        0      3        0       0        0        0        0
## 3       0        2      0        1       0        0        0        0
## 4       0        0     80       73       0        0        0        0
## 5       0        2      0        1       0        0        0        0
## 6       0       34      0        9       0        0        0        0
##   ARCEUTHOBI ARECACEAE ARMERIA ARTEMISIA ASTERX ASTERCICHO BETULA
## 1          0         0       0         6      1          0     70
## 2          0         0       0         0      0          0     55
```

```
## 3          0         0       0         0      0          0      25
## 4          0         0       0         0      5          0       4
## 5          0         0       0         1      0          0     120
## 6          0         0       0         1      1          0     322
##   BORAGINACEAE BOTRYCHIUM BRASSICACEAE CACTACEAE CAMPANULACEA CAPRIFOLIA
## 1            0          0            0         0            0          0
## 2            0          0            0         0            0          0
## 3            0          0            0         0            0          0
## 4            0          0            0         0            0          0
## 5            0          0            0         0            0          0
## 6            0          0            0         0            0          0
##   CARYA CARYOPHYLL CASTANEA CEANOTHUS CELTIS CEPHALANTH CERCOCAR CHENOAMX
## 1     0          0        0         0      0          0        0        0
## 2     0          0        0         0      0          0        0        0
## 3     0          0        0         0      0          0        0        0
## 4    19          0        0         0      6         26        0        2
## 5     5          0        0         0      0          0        0        0
## 6     1          0        0         0      0          0        0        0
##   CHRYSOLEP CORNUS CORYLUS CUPRESSA CYPERACE DODECATH DRYAS ELAEAGNX
## 1         0      0       0        0       72        0     0        0
## 2         0      0       1        0        0        0     0        0
## 3         0      0       1        0        4        0     0        0
## 4         0      0       0        1        7        0     0        0
## 5         0      0       0        3        4        0     0        0
## 6         0      0       7        4        1        0     0        0
##   EPHEDRA EQUISETU ERILEDCH ERIVACCI ERICACEX ERICALES ERIOGONUM EUPHORB
## 1       0        0        0        0        5        0         0       0
## 2       0        0        0        0        0        0         0       0
## 3       0        0        0        0        1        0         0       0
## 4       0        0        0        0        0        0         0       0
## 5       0        0        0        0        0        0         0       0
## 6       0        0        0        0        3        0         0       0
##   FABACEAE FAGUS FRAXNIGR FRAXPNAM FRAXINUX IVA JUGCINER JUGNIGRA JUGLANSX
## 1        0     0        0        0        0   0        0        0        0
## 2        0     1        0        0        0   0        0        0        0
## 3        0     0        0        0        0   0        0        0        0
## 4        0     1        5        1        3   1        0        2        1
## 5        0    45        8        0        0   0        2        1        0
## 6        0     4        2        0        0   0        0        0        0
##   KOENISLD LAMIACEAE LARIXPSEU LARREA LILIACEAE LIQUIDAM LIRIODEN LYCOANNO
## 1        0         0         0      0         0        0        0        1
## 2        0         0         0      0         0        0        0        0
## 3        0         0         0      0         0        0        0        0
## 4        0         0         0      0         0        8        0        0
## 5        0         0         0      0         0        0        0        0
## 6        0         0         0      0         0        0        0        0
##   LYCOCLAV LYCOCOMP LYCOSELA LYCOPODX MAGNOLIACE MALVACEAE MORACEAX
## 1        0        0        2        0          0         0        0
## 2        0        0        0        0          0         0        0
## 3        0        0        0        2          0         0        0
## 4        0        0        0        0          0         0        0
## 5        0        0        0        0          0         0        0
## 6        1        0        0        0          0         0        0
##   MYRICACX NYSSA ONAGRACEAE OSMUNDACEA OSTRYCAR OXYRIA PAPAVERX PEDICULARI
```

```
## 1        0     0          0          0        0      0        0          0
## 2        0     0          0          0        0      0        0          0
## 3        1     0          0          0        0      0        0          0
## 4        0     5          0          0        4      0        0          0
## 5        0     0          0          0        1      0        0          0
## 6        2     0          0          0        1      0        0          0
##   PICGLAUC PICMARIA PICEAX PINDIPLO PINHAPLO PINUSX PLANTAGINX PLATANUS
## 1        0      107     18       20        0      1          0        0
## 2        0        0      5        0        0     32          0        0
## 3        0        0    286        2        2      0          0        0
## 4        0        0      0        7        1     19          0        8
## 5        0        6      1       19       31     28          0        0
## 6        0       48     28        4        6     11          0        0
##   POACEAE POLEMONI POLYGONAX POLYGBIS POLYGONMX POLYGVIV POLYPOD POPULUS
## 1       6        0         0        0         0        0       0       0
## 2       0        0         0        0         0        0       0       0
## 3       3        0         0        0         0        0       3       1
## 4      18        0         0        0         0        0       0       1
## 5       2        0         0        0         0        0       0       3
## 6      21        0         0        0         0        0       0       3
##   POTENTILLA PROSOPIS PTERIDIUM QUERCUS RANUNCUL RHAMNACEAE ROSACEAX
## 1          0        0         0       0        0          0        0
## 2          0        0         0       2        0          0        0
## 3          0        0         0       0        0          0        0
## 4          0        0         0      95        0          0        0
## 5          0        0         0      14        0          0        0
## 6          0        0         0       2        0          0        1
##   RUBIACEAE RUBUS RUMEX RUMEOXYR SALIX SANGUI SARCOBATUS SXFRACER SXFRAHIE
## 1         0     0     0        0    14      0          0        0        0
## 2         0     0     0        0     1      0          0        0        0
## 3         0     0     0        0     2      0          0        0        0
## 4         0     3     0        0     2      0          0        0        0
## 5         0     0     0        0     1      0          0        0        0
## 6         0     0     0        7     2      0          0        0        0
##   SXFRAOPP SXFRATRI SXFRAGAX SCROPHUL SELAGINE SHEPHERDIA SPHAGNUM
## 1        0        0        0        0        0          0        0
## 2        0        0        0        0        0          0        0
## 3        0        0        0        0        0          0        4
## 4        0        0        8        0        0          0        0
## 5        0        0        0        0        0          0        0
## 6        0        0        0        0        0          0        2
##   TAXODIUM TAXUS THALICTRUM TILIA TSUGHETE TSUGMERT TSUGAX ULMUS URTICACX
## 1        0     0          0     0        0        0      0     0        0
## 2        0     0          0     0        0        0      8     2        0
## 3        0     0          0     0        0        0      0     0        0
## 4        0     0          0     0        0        0      0    12        0
## 5        0     0          0     9        0        0     41    10        0
## 6        0     0          0     0        0        0      0     2        0
##   XANTHIUM
## 1        0
## 2        0
## 3        0
## 4        1
## 5        0
```

```
## 6        0
```

```
head(Climate)
```

```
##   Sitename    lon    lat   tapr  tmay  tjun  tjul  taug  tsep  toct  tnov  tdec pjan
## 1    -23.1 -23.6 -20.5 -13.1 -4.0  1.5  5.8  5.6  2.2 -3.1 -8.7 -17.9   21
## 2    -12.1 -10.3  -4.3   4.2 11.4 15.7 18.9 17.5 12.7  6.6  0.1  -8.6   62
## 3    -13.7 -13.2  -8.6  -3.0  2.1  6.6 10.9 10.9  7.3  2.2 -2.7  -9.7  105
## 4      1.6   3.8   9.3  14.2 18.5 22.7 24.5 24.0 20.6 14.4  9.2   4.0  124
## 5    -10.7  -9.1  -3.0   5.3 12.4 17.4 20.2 18.7 13.9  7.6  1.0  -7.4   76
## 6    -15.0 -14.1  -8.1  -0.6  6.6 12.7 15.4 13.8  9.0  3.1 -4.2 -12.1  101
##   pfeb pmar papr pmay pjun pjul paug psep poct pnov pdec       tave tmax
## 1   19   19   22   25   43   63   59   43   40   33   23 -8.2416667 25.8
## 2   51   63   67   77   94   95  101  114   93   89   73  4.3166667 37.2
## 3   85  106   81   67   92   92   99   90   89   95  105 -0.9083333 31.9
## 4  116  147  115  129  107  124   92  101   81  118  136 13.9000000 40.4
## 5   65   74   78   82   93   95  104   94   84   99   96  5.5250000 37.0
## 6   86  105  103  122  124  128  125  118  108  116  122  0.5416667 33.6
##    tmin   gdd0   gdd5  mtco mtwa annp
## 1 -45.4  427.2   25.6 -23.6  5.8  410
## 2 -43.2 2632.6 1588.3 -12.1 18.9  979
## 3 -37.1 1188.2  446.8 -13.7 10.9 1106
## 4 -25.5 5096.2 3410.9   1.6 24.5 1390
## 5 -38.6 2911.0 1824.9 -10.7 20.2 1040
## 6 -45.0 1820.8  957.2 -15.0 15.4 1358
```

```
head(Location)
```

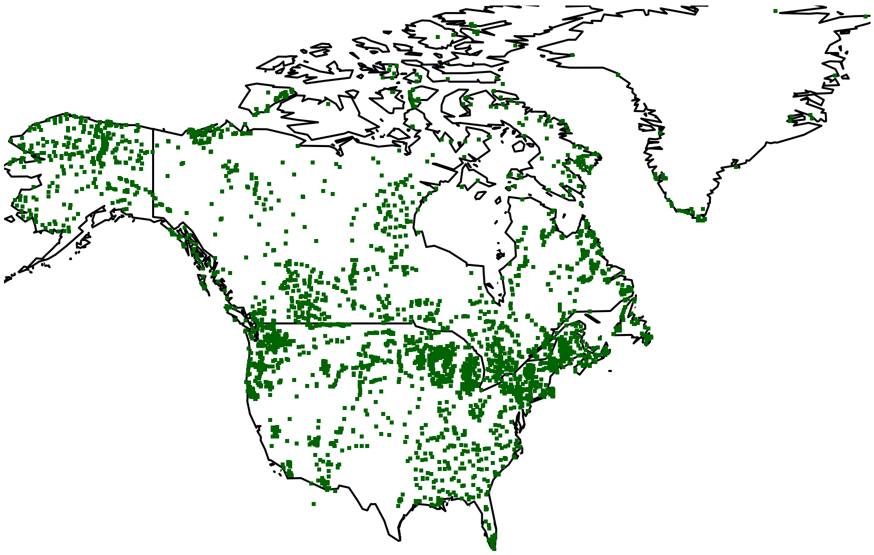
```
##   Latitude Longitude
## 1   60.979   -69.992
## 2   46.050   -79.200
## 3   52.517   -57.033
## 4   36.033   -85.500
## 5   45.543   -73.311
## 6   47.482   -70.685
```

The first three columns of the *climate* data seem odd. Latitudes and longitudes are different from lats and lons found in *location* and site names are real numbers and not characters. Additionally, January through March temperatures are missing. I therefore assume that the first three columns of *climate* are January through March temperatures. The pollen data are given as count data and contain *NAs*. To compare species assemblages, we need species composition / proportions and not absolute abundances. We therefore have to transform count data to proportions.

```
colnames(Climate)[1:3] <- c('tjan','tfeb','tmar')
Pollen.corrected <- replace(Pollen,is.na(Pollen),0)
pollen.prop <- Pollen.corrected/rowSums(Pollen.corrected)
```

To get an overview of the North American Modern Pollen Database we can make a map of pollen samples

```
lon <- Location$Longitude
lat <- Location$Latitude
map(regions=c('USA','Canada','Greenland'),xlim=c(range(lon)),ylim=range(lat))
points(lon,lat,pch = 15,cex =0.25,col='darkgreen')
```



Lets look at dissimilarities with the NAMPD. We will compare the distance / dissimilarity among the northernmost and southernmost sample, two spatially close samples and 1000 distances / dissimilarities between randomly drawn samples. Keep in mind that the minimum of all dissimilarity metrics is 0 while the chord distance has a maximum of 1.4142136 and the Bray-Curtis distance has a maximum of 1.

```
nm.pollen <- pollen.prop[which.max(lat), ]
sm.pollen <- pollen.prop[which.min(lat), ]
pollen.sn <- rbind(nm.pollen, sm.pollen)
pollen.prop.lat.order <- pollen.prop[order(lat), ]


dist.sn.chord <- analogue::distance(pollen.sn, method = "chord")
dist.sn.euclidean <- analogue::distance(pollen.sn, method = "euclidean")
dist.sn.bray <- analogue::distance(pollen.sn, method = "bray")

dist.sn <- data.frame(chord = dist.sn.chord[1, 2], euclidean = dist.sn.euclidean[1,
    2], bray = dist.sn.bray[1, 2])

dist.adj.chord <- analogue::distance(pollen.prop.lat.order[2:3, ], method = "chord")
dist.adj.euclidean <- analogue::distance(pollen.prop.lat.order[2:3, ], method = "euclidean")
dist.adj.bray <- analogue::distance(pollen.prop.lat.order[2:3, ], method = "bray")

dist.adj <- data.frame(chord = dist.adj.chord[1, 2], euclidean = dist.adj.euclidean[1,
    2], bray = dist.adj.bray[1, 2])
#-----------------------------------------------------------------------------------------
# 1000 random distances
#-----------------------------------------------------------------------------------------
dist.rand <- replicate(1000, {
    sample.nr <- sample(1:ncol(Pollen), 2, replace = FALSE)
    pollen.sample <- pollen.prop[sample.nr, ]
    dist.r.chord <- analogue::distance(pollen.sample, method = "chord")
    dist.r.euclidean <- analogue::distance(pollen.sample, method = "euclidean")
    dist.r.bray <- analogue::distance(pollen.sample, method = "bray")
    data.frame(chord = dist.r.chord[1, 2], euclid = dist.r.euclidean[1, 2],
        bray = dist.r.bray[1, 2])
})
```

```r
dist.rand.matrix <- matrix(unlist(dist.rand), nrow = 1000, ncol = 3, byrow = TRUE)
colnames(dist.rand.matrix) <- c("chord", "euclidean", "bray")

dist.rand.quantiles <- apply(dist.rand.matrix, 2, function(x) quantile(x, probs = c(0.025,
    0.25, 0.5, 0.75, 0.975)))

round(rbind(dist.adj, dist.rand.quantiles, dist.sn), 3)
```

```
##       chord euclidean  bray
## 1     0.721     0.467 0.554
## 2.5%  0.576     0.225 0.355
## 25%   0.844     0.397 0.587
## 50%   0.988     0.518 0.718
## 75%   1.155     0.624 0.840
## 97.5% 1.336     0.881 0.959
## 11    1.293     0.767 0.952
```

Let's compare the three dissimilarity metrics based on dissimilarities among all samples.

```r
distance.all.chord <- dist(sqrt(pollen.prop), diag = FALSE, upper = FALSE, method = "euclidean")
distance.all.euclid <- dist(pollen.prop, diag = FALSE, upper = FALSE, method = "euclidean")
distance.all.bray <- vegan::vegdist(pollen.prop, diag = FALSE, upper = FALSE,
    method = "bray")


summary(distance.all.chord)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.0000  0.9222  1.0914  1.0571  1.2262  1.4142
```

```r
summary(distance.all.bray)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.0000  0.6492  0.7937  0.7556  0.8966  1.0000
```

```r
summary(distance.all.euclid)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.0000  0.4766  0.6034  0.6072  0.7321  1.3760
```

```r
total.distances <- cbind(distance.all.chord, distance.all.euclid, distance.all.bray)
colnames(total.distances) <- c("chord", "euclidean", "bray")

# jpeg('~/teaching/R/distance_pairs.jpeg',height=10,width=10,units='in',res
# =300) pairs(total.distances,pch = 16,cex = 0.5) dev.off()
```

From *Fig. 2* it is clear that the euclidean distance is quite different from the two other dissimilarity metrics. Euclidean distances vary widely for large chord and Bray-Curtis distances. The Bray-Curtis distance is designed to quantify compositional dissimilarity between sites. The chord distance is the euclidean distance between square root transformed proportions. By square root transforming, all compositional vector are standardized to have a length of 1 (i.e. all these points are on the surface of a n-dimensional sphere, hence the name chord distance). The chord distance is therefore a distance metric appropriate to compare proportions whereas euclidean distances are not appropriate for compositional data.

People interested in further comparisons between Bray-Curtis and euclidean distances can work through the next section. In this section we have a closer look at samples with large Bray-Curtis but low euclidean distances. In this example, we also encounter issues with taxonomic resolution: One analyst identified *

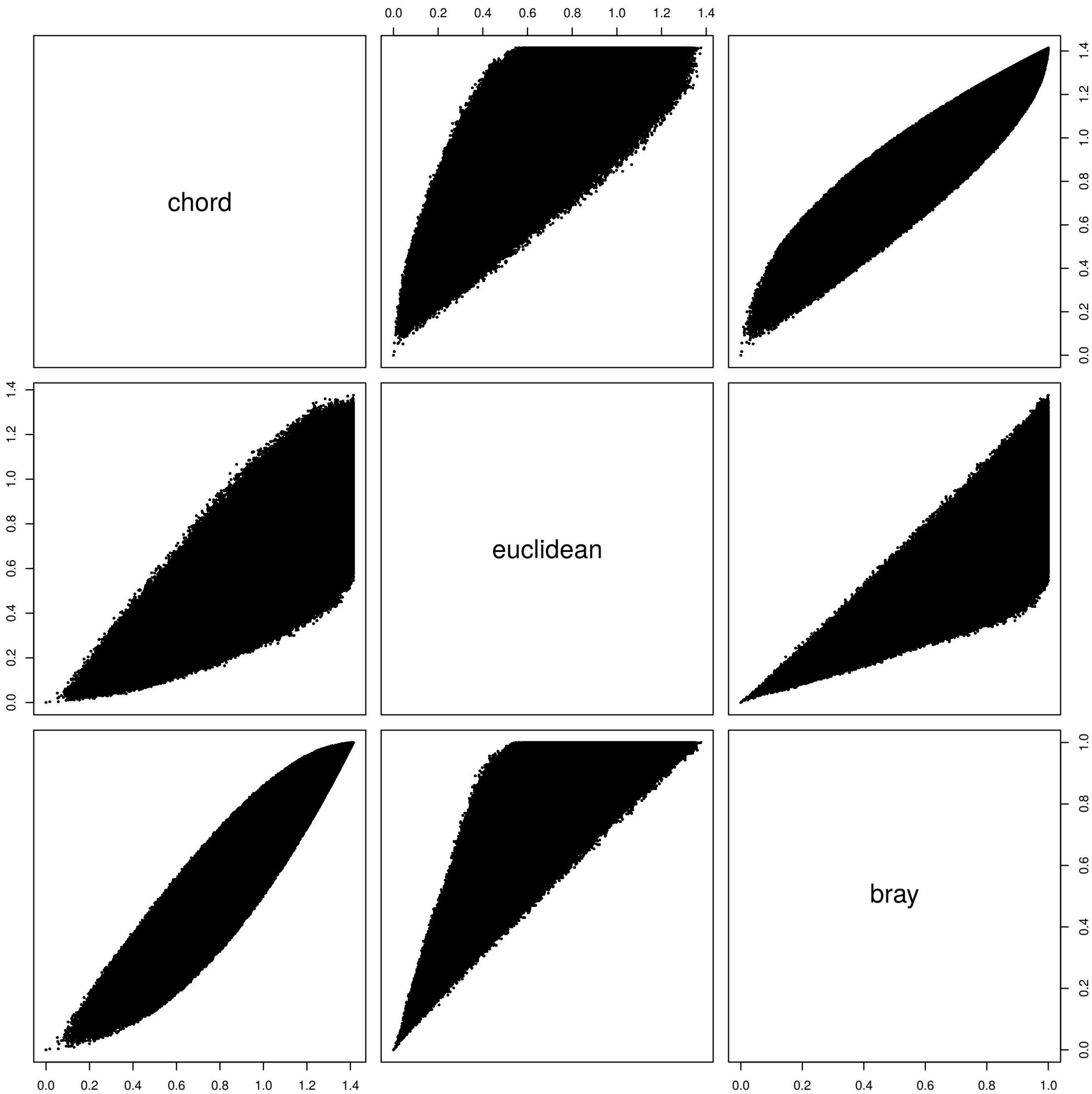



Figure 1: *Fig 2. Comparison of dissimilarity metrics*

Alnus viridis subsp. crispa* whereas another analyst only identified *Alnus undiff.* You will have to set options *echo = TRUE* and *eval=TRUE* to show code and results in your output file.

---

## 2 The modern analogue technique

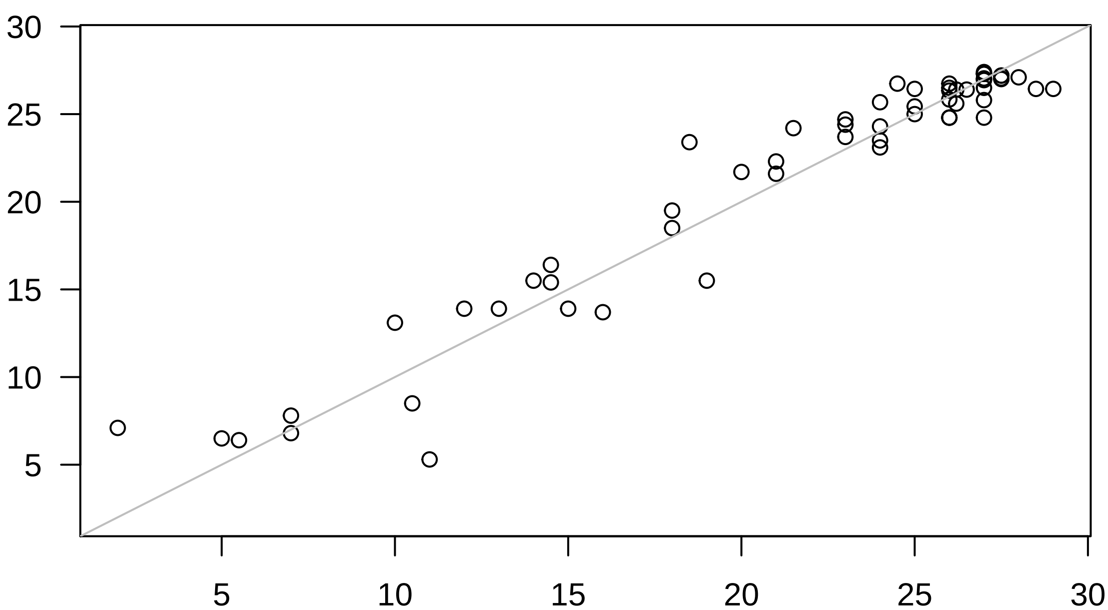
Before reconstructing an environmental variable, we usually assess how MAT performs in the modern species assemblage. This step is usually referred to as calibration

### Calibration

We will use the foraminifera data set by Imbrie and Kipp (1971) available in the *rioja* r-package by Steve Juggins. We will evaluate a MAT model for summer sea surface temperature (SumSST) using the *MAT* function from the *rioja* r-package (as default this function uses *squared chord-distances*). (I generally recommend to specify the r-package from which a function is called. For instance there are *crossval* and *performance* functions in *rioja* as well as *analogue*. The aforementioned packages also define functions *Merge* and *merge*, *MAT* and *mat* asf)

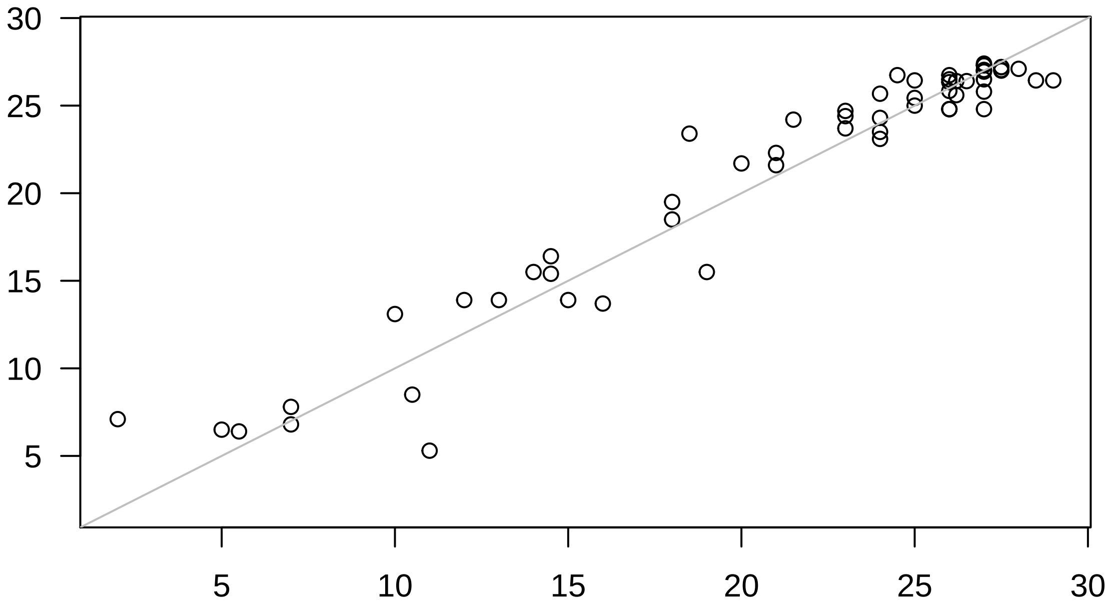
```
data(IK)
# ?IK
spp <- IK$spec/100
fossil <- IK$core/100
sppfos <- Merge(spp, fossil, split = TRUE)
spp <- sppfos$spp
fossil <- sppfos$fossil
SumSST <- IK$env$SumSST

sumsst.mat.model <- rioja::MAT(spp, SumSST, k = 5, lean = FALSE, dist.method = "chord")
plot(sumsst.mat.model)
```




Ideally, a calibration function is trained on one portion of the modern species assemblages (calibration set) and tested on another portion of the modern species assemblages (validation set). This two data sets are mutually exclusive and hopefully independent. To validate or cross-validate MAT, we usually use a technique called k-fold cross-validation. In k-fold cross-validation the modern data set is split into *k* mutually exclusive parts. *k-1* parts are used for calibration and one part is used for validation (test).

```
cv.sumsst.mat.model <- rioja::crossval(sumsst.mat.model, cv.method = "lgo",
    verbose = FALSE)
plot(cv.sumsst.mat.model)
```




```
perf.cv.sumsst.mat.model <- rioja::performance(cv.sumsst.mat.model)
perf.cv.sumsst.mat.model
```

```
## $RMSE0
## [1] 7.019838
##
## $object
##            RMSE        R2    Avg.Bias Max.Bias    Skill
## N01    2.472935 0.8806064 -0.31803279 9.000000 87.59001
## N02    1.902684 0.9277029 -0.21721311 6.000000 92.65353
## N03    1.783536 0.9357997 -0.10000000 5.166667 93.54480
## N04    1.731930 0.9392722 -0.08319672 5.125000 93.91296
## N05    1.745768 0.9391509 -0.21344262 5.100000 93.81530
## N01.wm 2.472935 0.8806064 -0.31803279 9.000000 87.59001
## N02.wm 1.908583 0.9272212 -0.19868306 6.159230 92.60790
## N03.wm 1.786369 0.9356327 -0.10331394 5.468770 93.52428
## N04.wm 1.724006 0.9398568 -0.09179193 5.385207 93.96853
## N05.wm 1.742435 0.9390537 -0.18057997 5.366950 93.83889
##
## $crossval
##            RMSE        R2   Avg.Bias Max.Bias    Skill
## N01    2.617063 0.8684654 -0.4409836 9.000000 86.10131
## N02    1.947918 0.9246910 -0.2663934 6.000000 92.30006
## N03    1.888509 0.9284656 -0.1721311 5.166667 92.76258
## N04    1.906173 0.9268506 -0.1692623 5.125000 92.62656
## N05    1.903345 0.9278363 -0.2527869 5.100000 92.64842
## N01.wm 2.617063 0.8684654 -0.4409836 9.000000 86.10131
## N02.wm 1.979285 0.9223329 -0.2615894 6.159230 92.05009
## N03.wm 1.892957 0.9282625 -0.1899128 5.468770 92.72845
```

```
## N04.wm 1.880309 0.9288591 -0.1614494 5.385207 92.82529
## N05.wm 1.877979 0.9293962 -0.2157188 5.366950 92.84306
```

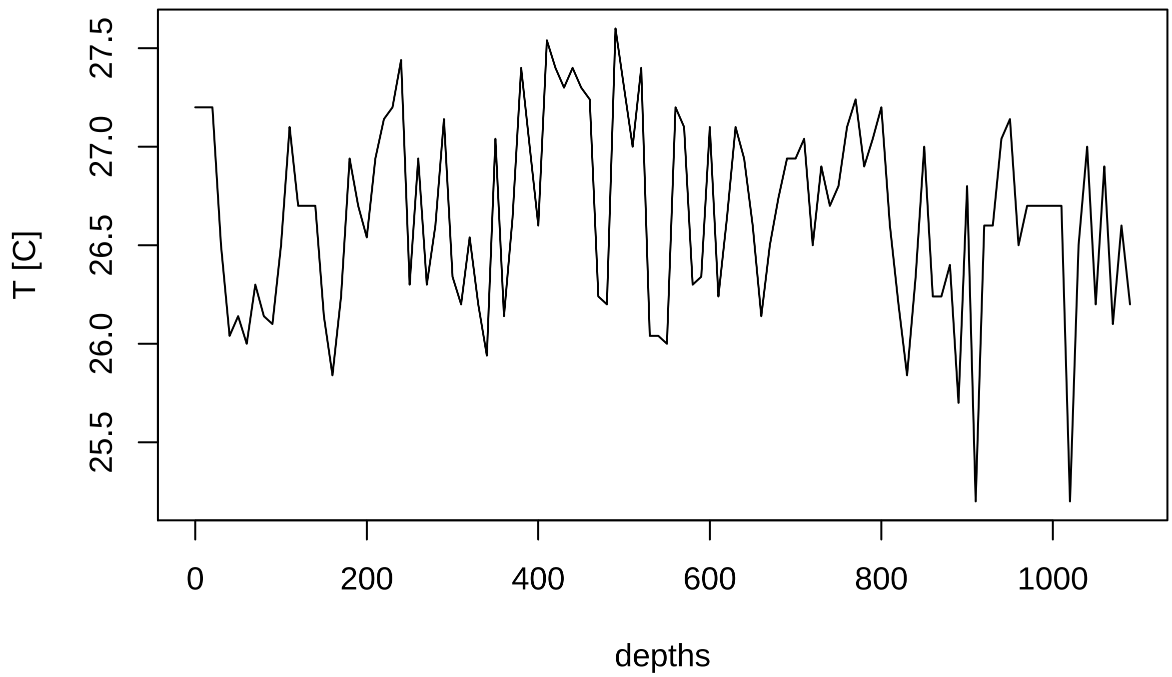
The code returns an object with three named components:

- RMSE0: The root mean square error when using the mean of all SumSST values instead of predicted values
- object: apparent performance statistics (all data are used for calibration)
- crossval: cross-validated performance statistics (model is tested on a hopefully independent test set)

### Reconstruction

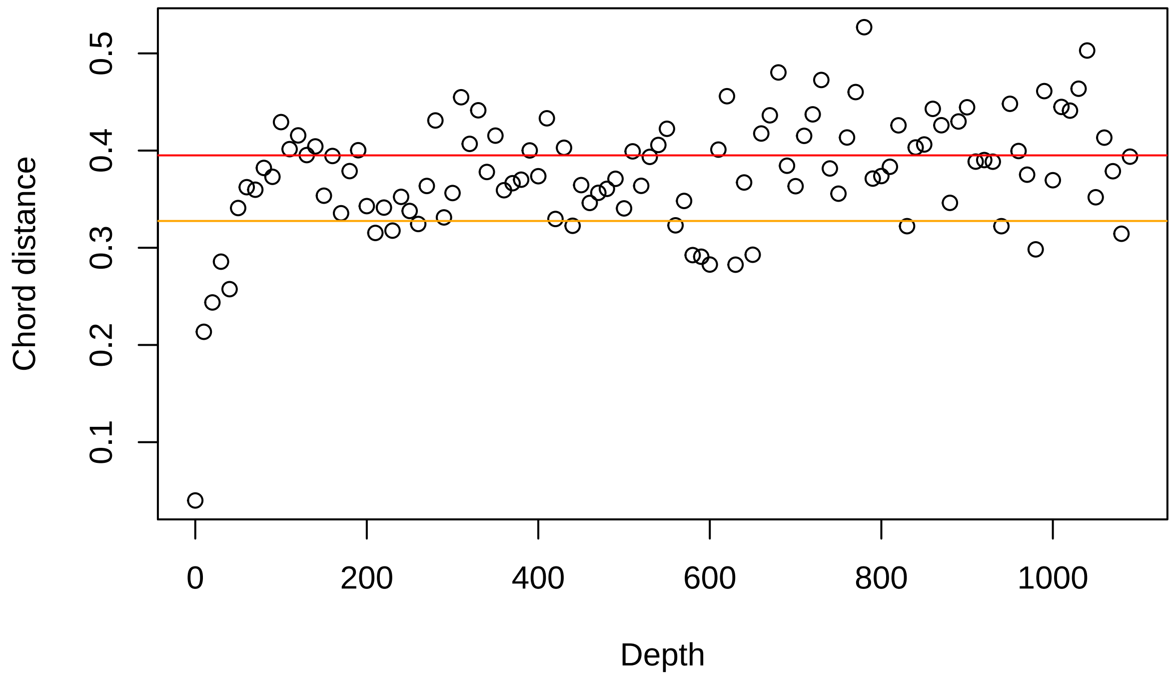
We can apply this transfer function to foraminifera from a sediment core.

```
depths <- as.numeric(rownames(fossil))
pred <- predict(sumsst.mat.model ,fossil)
plot(depths, pred$fit[,'MAT'],type='l',ylab ='T [C]')
```




It is crucial to assess the quality of modern analogues by looking at the dissimilarity between a fossil assemblage and the closest (least dissimilar) modern assemblage. If the shortest distance between a fossil assemblage and the modern assemblages is typical of distances between similar assemblages in the calibration set, then we can declare that the analogue match is good. The usual rule-of-thumb is that distances shorter than the 5th percentile of all distances between calibration set assemblages represent good analogues, and distances greater than the 10th percentile represent no-analogue assemblages.

```
goodpoorbad<-quantile(paldist(spp,dist.method='chord'), prob=c(0.05, 0.1))
plot(depths, pred$dist.n[,1], ylab="Chord distance", xlab="Depth")
abline(h=goodpoorbad, col=c("orange", "red"))
```



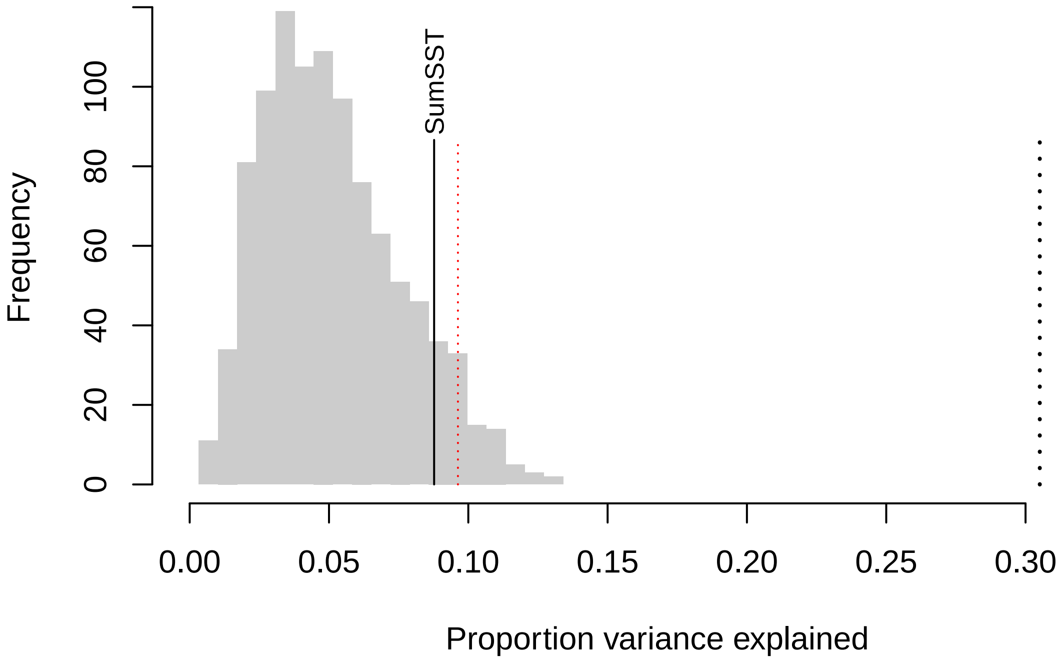

After assessing analogue quality we should (if possible) compare our reconstruction to other reconstructions. We can also tentatively assess the significance of our reconstruction comparing the variance of the fossil species assemblages explained by our reconstruction to the variance explained by reconstructions trained on random data.

```
library(palaeoSig)
IKrand <- randomTF(spp = spp, env = data.frame(SumSST = SumSST),fos = fossil,fun =MAT, dist.method = 'c
```

```
## Warning in Merge(object$y, newdata, split = TRUE): Some row names were
## changed to avoid duplicates.

## Warning in Merge(object$y, newdata, split = TRUE): Some row names were
## changed to avoid duplicates.
```

```
plot(IKrand)
```




**How many variables can we reconstruct?**

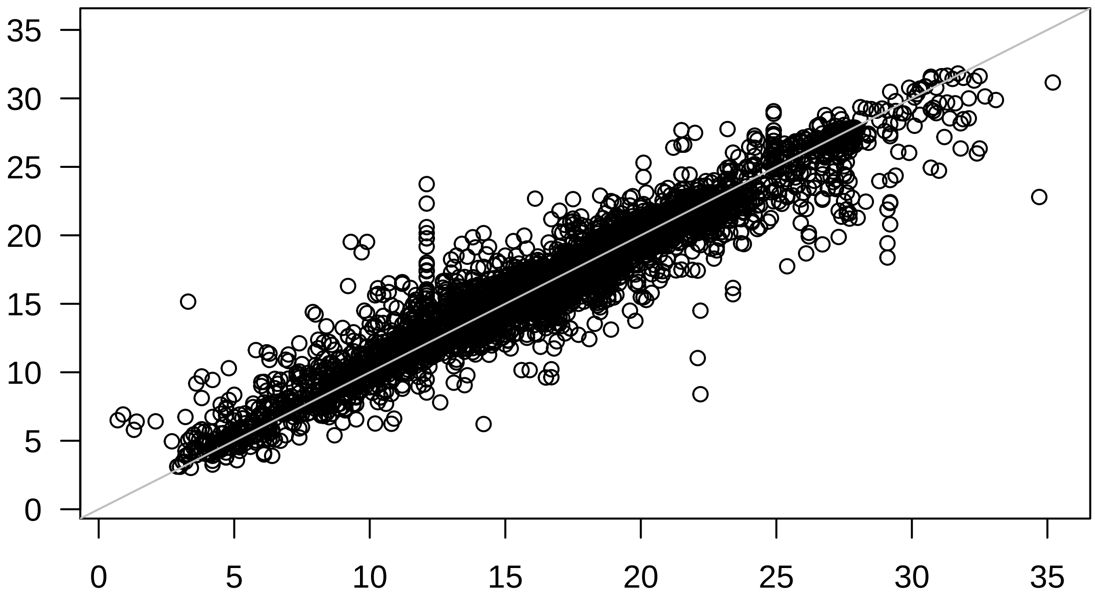
We will try to answer this question using the NAMPD.

First lets have a look at a model for temperatures of the warmest month.

```
mat.model.mtwa <- rioja::MAT(pollen.prop,Climate$mtwa,lean=FALSE)
```

```
## Warning in rioja::MAT(pollen.prop, Climate$mtwa, lean = FALSE): Inter-sample distances < 1.0E-6 foun
## These have been replaced by 1.0E-6
```

```
#mat.model.mtwa <- rioja::MAT(sqrt(pollen.prop),as.vector(Climate$mtwa),lean=FALSE,method='euclidean')
#-----------------------------------------------------------------------------------------------------
#curcial step: cross-validation, apply calibrate on one part of the dataset and validate on a (hopefull
# independent dataset, with the MAT one usually uses 10-fold cross-validation
cv.mat.model.mtwa <- rioja::crossval(mat.model.mtwa,verbose=FALSE)
plot(cv.mat.model.mtwa)
```




```
per.mat.model.mtwa <- rioja::performance(cv.mat.model.mtwa)
per.mat.model.mtwa
```

```
## $RMSE0
## [1] 5.675775
##
## $object
##             RMSE        R2    Avg.Bias Max.Bias    Skill
## N01     1.755352 0.9057596 0.009786882 2.528571 90.43515
## N02     1.585639 0.9220596 0.019635837 3.242857 92.19526
## N03     1.537631 0.9266250 0.023884406 3.695238 92.66071
## N04     1.564229 0.9240765 0.018823712 3.933929 92.40461
## N05     1.575463 0.9229897 0.016639768 3.910000 92.29511
## N01.wm 1.755352 0.9057596 0.009786882 2.528571 90.43515
## N02.wm 1.562163 0.9243370 0.016671005 3.183174 92.42466
## N03.wm 1.507905 0.9294337 0.021232569 3.632620 92.94174
## N04.wm 1.519929 0.9283328 0.017950688 3.853938 92.82873
## N05.wm 1.526585 0.9277150 0.015305734 3.813363 92.76578
##
## $crossval
##             RMSE        R2   Avg.Bias Max.Bias    Skill
## N01     1.791543 0.9018480 0.01466998 2.785714 90.03667
## N02     1.617819 0.9188788 0.01806331 3.371429 91.87526
## N03     1.556578 0.9247948 0.01529761 3.390476 92.47873
## N04     1.579793 0.9225468 0.01270950 3.717857 92.25271
## N05     1.573929 0.9231464 0.01360232 3.661429 92.31011
## N01.wm 1.791543 0.9018480 0.01466998 2.785714 90.03667
## N02.wm 1.594467 0.9211932 0.01697569 3.276072 92.10812
## N03.wm 1.529053 0.9274315 0.01480572 3.373534 92.74237
## N04.wm 1.534752 0.9269154 0.01348062 3.653481 92.68817
## N05.wm 1.528321 0.9275567 0.01297447 3.560738 92.74932
```

This model is excellent! We can assess performances of models for all variables given in the *Climate* data set.

```
# mat.model <- lapply(colnames(Climate),function(x){
#   rioja::MAT(pollen.prop,as.vector(Climate[,x]),lean=FALSE)
```

```r
# })
#
# names(mat.model) <- colnames(Climate)
#
# crossval.mat <- lapply(names(mat.model),function(x){
#   rioja::crossval(mat.model[[x]],verbose=FALSE)
# })
#
# names(crossval.mat) <- colnames(Climate)
#
# perf.mat <- lapply(names(mat.model),function(x){
#   rioja::performance(crossval.mat[[x]])
# })
#
# names(perf.mat) <- colnames(Climate)
#
# saveRDS(perf.mat,'/data/calibration_MAT_RDS')

perf.mat <- readRDS('/home/mathias/teaching_uploads/data/calibration_MAT_RDS')
perf.mat
```

```
## $tjan
## $tjan$RMSE0
## [1] 11.16993
##
## $tjan$object
##            RMSE        R2  Avg.Bias Max.Bias    Skill
## N01    3.076891 0.9258860 0.1689841 1.958333 92.41207
## N02    2.946997 0.9313403 0.2311711 2.387917 93.03921
## N03    2.826226 0.9368197 0.2866956 2.637222 93.59804
## N04    2.906407 0.9330778 0.2964773 2.790417 93.22964
## N05    2.933883 0.9317542 0.2992262 2.852000 93.10103
## N01.wm 3.076891 0.9258860 0.1689841 1.958333 92.41207
## N02.wm 2.882170 0.9342716 0.2159023 2.289749 93.34208
## N03.wm 2.751688 0.9400345 0.2638521 2.506775 93.93128
## N04.wm 2.798213 0.9379220 0.2759178 2.641686 93.72432
## N05.wm 2.814062 0.9371861 0.2808181 2.699517 93.65303
##
## $tjan$crossval
##            RMSE        R2  Avg.Bias Max.Bias    Skill
## N01    3.115414 0.9240196 0.1607076 1.884167 92.22088
## N02    2.953643 0.9310549 0.2485206 2.345417 93.00778
## N03    2.897135 0.9334742 0.2748948 2.775833 93.27277
## N04    2.941325 0.9313973 0.2880923 2.722083 93.06598
## N05    2.973198 0.9299333 0.3099979 2.825333 92.91489
## N01.wm 3.115414 0.9240196 0.1607076 1.884167 92.22088
## N02.wm 2.894691 0.9337268 0.2334509 2.232874 93.28411
## N03.wm 2.809275 0.9374080 0.2577405 2.609394 93.67461
## N04.wm 2.829460 0.9364831 0.2704974 2.586257 93.58338
## N05.wm 2.845817 0.9357756 0.2902465 2.686562 93.50898
##
##
## $tfeb
## $tfeb$RMSE0
```

```
## [1] 11.47877
##
## $tfeb$object
##            RMSE        R2  Avg.Bias Max.Bias    Skill
## N01    3.046780 0.9311988 0.1617836 1.762319 92.95483
## N02    2.918202 0.9362220 0.2107904 2.439655 93.53691
## N03    2.797258 0.9413510 0.2649286 2.420690 94.06153
## N04    2.877997 0.9377963 0.2701014 2.887069 93.71377
## N05    2.908201 0.9364160 0.2699524 3.424828 93.58113
## N01.wm 3.046780 0.9311988 0.1617836 1.762319 92.95483
## N02.wm 2.852136 0.9390266 0.1963454 2.347610 93.82624
## N03.wm 2.725520 0.9442508 0.2428949 2.366017 94.36222
## N04.wm 2.772775 0.9422189 0.2511979 2.785355 94.16503
## N05.wm 2.792569 0.9413461 0.2534579 3.225749 94.08142
##
## $tfeb$crossval
##            RMSE        R2  Avg.Bias Max.Bias    Skill
## N01    3.195150 0.9243752 0.1762466 1.889372 92.25196
## N02    2.977014 0.9336872 0.2315849 2.525862 93.27378
## N03    2.883371 0.9376801 0.2775019 2.606897 93.69027
## N04    2.930550 0.9355173 0.2764070 2.843103 93.48210
## N05    2.981662 0.9332480 0.2921622 3.648966 93.25276
## N01.wm 3.195150 0.9243752 0.1762466 1.889372 92.25196
## N02.wm 2.912193 0.9364627 0.2159137 2.430782 93.56350
## N03.wm 2.806632 0.9408903 0.2593631 2.524173 94.02166
## N04.wm 2.829427 0.9398451 0.2591621 2.760663 93.92416
## N05.wm 2.863008 0.9384133 0.2739527 3.419195 93.77908
##
##
## $tmar
## $tmar$RMSE0
## [1] 10.97504
##
## $tmar$object
##            RMSE        R2  Avg.Bias Max.Bias    Skill
## N01    2.900090 0.9318327 0.1450652 1.220000 93.01750
## N02    2.757827 0.9376440 0.1861163 2.633333 93.68574
## N03    2.653832 0.9422074 0.2362025 2.846667 94.15298
## N04    2.729056 0.9387470 0.2359508 3.788333 93.81681
## N05    2.759227 0.9373131 0.2347983 4.556000 93.67934
## N01.wm 2.900090 0.9318327 0.1450652 1.220000 93.01750
## N02.wm 2.695750 0.9403610 0.1716775 2.487818 93.96681
## N03.wm 2.587763 0.9449701 0.2146252 2.749790 94.44048
## N04.wm 2.630988 0.9430182 0.2182355 3.598653 94.25320
## N05.wm 2.652027 0.9420551 0.2189809 4.278407 94.16093
##
## $tmar$crossval
##            RMSE        R2  Avg.Bias Max.Bias    Skill
## N01    3.011985 0.9266119 0.1401614 2.373333 92.46829
## N02    2.776059 0.9368322 0.2002586 2.593333 93.60198
## N03    2.742966 0.9382575 0.2469136 3.024444 93.75361
## N04    2.816798 0.9347563 0.2448014 4.108333 93.41282
## N05    2.808725 0.9350676 0.2457190 4.674667 93.45053
## N01.wm 3.011985 0.9266119 0.1401614 2.373333 92.46829
```

```
## NO2.wm 2.726172 0.9390257 0.1859398 2.575428 93.82987
## NO3.wm 2.669025 0.9414662 0.2254833 2.940904 94.08584
## NO4.wm 2.717834 0.9392092 0.2274552 3.933322 93.86755
## NO5.wm 2.706596 0.9396764 0.2318201 4.402349 93.91816
##
##
## $tapr
## $tapr$RMSE0
## [1] 9.313677
##
## $tapr$object
##            RMSE        R2   Avg.Bias Max.Bias    Skill
## NO1    2.544429 0.9270271 0.09834471 1.087435 92.53657
## NO2    2.382255 0.9351664 0.12322574 2.108824 93.45764
## NO3    2.305899 0.9391647 0.16099041 2.417647 93.87031
## NO4    2.363141 0.9359903 0.15730912 3.136765 93.56221
## NO5    2.390656 0.9344314 0.15441341 3.687059 93.41142
## NO1.wm 2.544429 0.9270271 0.09834471 1.087435 92.53657
## NO2.wm 2.331104 0.9378710 0.11203532 1.992778 93.73558
## NO3.wm 2.250226 0.9419975 0.14385835 2.319447 94.16273
## NO4.wm 2.281745 0.9402719 0.14317693 2.978351 93.99806
## NO5.wm 2.302320 0.9391505 0.14151677 3.467365 93.88933
##
## $tapr$crossval
##            RMSE        R2  Avg.Bias Max.Bias    Skill
## NO1    2.570474 0.9253667 0.1104283 1.336649 92.38299
## NO2    2.431061 0.9325767 0.1435444 2.123529 93.18683
## NO3    2.373071 0.9355553 0.1601283 2.705882 93.50799
## NO4    2.393900 0.9342959 0.1638734 3.294118 93.39353
## NO5    2.405346 0.9336317 0.1650610 3.880000 93.33020
## NO1.wm 2.570474 0.9253667 0.1104283 1.336649 92.38299
## NO2.wm 2.384055 0.9351000 0.1336717 2.005307 93.44776
## NO3.wm 2.310193 0.9388560 0.1444618 2.508299 93.84746
## NO4.wm 2.310361 0.9387541 0.1494672 2.991236 93.84657
## NO5.wm 2.313299 0.9385778 0.1510026 3.501177 93.83091
##
##
## $tmay
## $tmay$RMSE0
## [1] 7.271522
##
## $tmay$object
##            RMSE        R2   Avg.Bias  Max.Bias    Skill
## NO1    2.120279 0.9166732 0.04998965 0.9095541 91.49772
## NO2    1.951866 0.9283338 0.06734947 1.2089172 92.79474
## NO3    1.894791 0.9323407 0.09054418 1.3530786 93.20996
## NO4    1.930992 0.9296457 0.08600248 1.4898089 92.94803
## NO5    1.947941 0.9283672 0.08092282 1.5917197 92.82369
## NO1.wm 2.120279 0.9166732 0.04998965 0.9095541 91.49772
## NO2.wm 1.913131 0.9311110 0.05990943 1.1592823 93.07789
## NO3.wm 1.851164 0.9353729 0.07984929 1.2979398 93.51904
## NO4.wm 1.868066 0.9341249 0.07740933 1.4133965 93.40016
## NO5.wm 1.879837 0.9332694 0.07319765 1.4994071 93.31672
##
```

```
## $tmay$crossval
##            RMSE        R2   Avg.Bias Max.Bias    Skill
## N01    2.182969 0.9117364 0.06308711 1.084071 90.98752
## N02    1.986793 0.9257700 0.07549141 1.245133 92.53457
## N03    1.933401 0.9295441 0.08510242 1.384289 92.93043
## N04    1.964779 0.9271431 0.08063315 1.557166 92.69909
## N05    1.969097 0.9267849 0.07669357 1.606115 92.66697
## N01.wm 2.182969 0.9117364 0.06308711 1.084071 90.98752
## N02.wm 1.954982 0.9281033 0.07113685 1.230281 92.77172
## N03.wm 1.891121 0.9325677 0.08138236 1.324408 93.23624
## N04.wm 1.907322 0.9313225 0.07595396 1.475940 93.11986
## N05.wm 1.904379 0.9315157 0.07422342 1.517065 93.14107
##
##
## $tjun
## $tjun$RMSE0
## [1] 6.154688
##
## $tjun$object
##            RMSE        R2   Avg.Bias Max.Bias    Skill
## N01    1.922043 0.9042000 0.01665632 2.075000 90.24754
## N02    1.747541 0.9195519 0.02736396 2.745833 91.93801
## N03    1.696522 0.9240592 0.03658183 2.938889 92.40187
## N04    1.724737 0.9215017 0.03151252 3.131250 92.14703
## N05    1.736336 0.9204463 0.02614111 3.305000 92.04106
## N01.wm 1.922043 0.9042000 0.01665632 2.075000 90.24754
## N02.wm 1.717120 0.9223110 0.02307625 2.634529 92.21624
## N03.wm 1.660645 0.9272262 0.03153791 2.867400 92.71983
## N04.wm 1.672586 0.9261834 0.02823460 3.061887 92.61476
## N05.wm 1.679764 0.9255587 0.02331545 3.202591 92.55123
##
## $tjun$crossval
##            RMSE        R2   Avg.Bias Max.Bias    Skill
## N01    1.951394 0.9012450 0.03776122 3.283333 89.94741
## N02    1.778124 0.9167363 0.03524726 3.300000 91.65335
## N03    1.734974 0.9205687 0.03270570 3.180556 92.05354
## N04    1.740178 0.9200944 0.03494206 3.191667 92.00579
## N05    1.755388 0.9186969 0.02689841 3.501667 91.86544
## N01.wm 1.951394 0.9012450 0.03776122 3.283333 89.94741
## N02.wm 1.747327 0.9195765 0.03169127 3.250570 91.93998
## N03.wm 1.692766 0.9243804 0.03048772 3.137961 92.43547
## N04.wm 1.687559 0.9248588 0.03217668 3.154357 92.48194
## N05.wm 1.696122 0.9241086 0.02543206 3.410382 92.40545
##
##
## $tjul
## $tjul$RMSE0
## [1] 5.67824
##
## $tjul$object
##            RMSE        R2    Avg.Bias Max.Bias    Skill
## N01    1.759470 0.9054013 0.009228223 2.528571 90.39857
## N02    1.588917 0.9218035 0.018435754 3.242857 92.16976
## N03    1.540584 0.9264045 0.022249810 3.695238 92.63889
```

```
## N04    1.566268 0.9239423 0.016904614 3.933929 92.39140
## N05    1.577264 0.9228786 0.014297538 3.910000 92.28420
## N01.wm 1.759470 0.9054013 0.009228223 2.528571 90.39857
## N02.wm 1.565504 0.9240776 0.015553569 3.183174 92.39882
## N03.wm 1.510915 0.9292112 0.019808675 3.632620 92.91969
## N04.wm 1.522216 0.9281776 0.016294702 3.853938 92.81337
## N05.wm 1.528651 0.9275806 0.013318745 3.813363 92.75249
##
## $tjul$crossval
##            RMSE        R2    Avg.Bias Max.Bias    Skill
## N01    1.781392 0.9029169 0.011566315 2.785714 90.15782
## N02    1.612909 0.9194352 0.019397890 3.464286 91.93151
## N03    1.578073 0.9227736 0.017911580 3.745238 92.27627
## N04    1.608549 0.9197653 0.015797641 3.928571 91.97507
## N05    1.605237 0.9201058 0.007961928 3.960000 92.00809
## N01.wm 1.781392 0.9029169 0.011566315 2.785714 90.15782
## N02.wm 1.591335 0.9215584 0.016476976 3.399302 92.14591
## N03.wm 1.547615 0.9257242 0.016416983 3.661662 92.57155
## N04.wm 1.563213 0.9242346 0.014273874 3.802301 92.42105
## N05.wm 1.554744 0.9250746 0.008431392 3.853878 92.50295
##
##
## $taug
## $taug$RMSE0
## [1] 5.859118
##
## $taug$object
##            RMSE        R2   Avg.Bias Max.Bias    Skill
## N01    1.717530 0.9152020 0.02199462 2.614286 91.40701
## N02    1.555678 0.9296043 0.03557832 3.342857 92.95023
## N03    1.516474 0.9330691 0.04428581 3.792857 93.30107
## N04    1.542017 0.9308074 0.04043037 4.026786 93.07350
## N05    1.552813 0.9298449 0.04039313 4.002857 92.97618
## N01.wm 1.717530 0.9152020 0.02199462 2.614286 91.40701
## N02.wm 1.531006 0.9318043 0.03177828 3.283978 93.17206
## N03.wm 1.485202 0.9357963 0.04011835 3.731622 93.57451
## N04.wm 1.496286 0.9348674 0.03834779 3.948950 93.47824
## N05.wm 1.502833 0.9343083 0.03759693 3.908091 93.42105
##
## $taug$crossval
##            RMSE        R2   Avg.Bias Max.Bias    Skill
## N01    1.763067 0.9106674 0.02031864 2.614286 90.94532
## N02    1.599327 0.9256472 0.04983447 3.807143 92.54908
## N03    1.578116 0.9275317 0.05154838 4.102381 92.74540
## N04    1.574453 0.9278646 0.04492551 4.157143 92.77904
## N05    1.580276 0.9273271 0.04008690 4.048571 92.72553
## N01.wm 1.763067 0.9106674 0.02031864 2.614286 90.94532
## N02.wm 1.576284 0.9277564 0.04548159 3.690007 92.76223
## N03.wm 1.542835 0.9307298 0.04823008 4.005032 93.06615
## N04.wm 1.528798 0.9320053 0.04417645 4.074556 93.19174
## N05.wm 1.528751 0.9320159 0.03974260 3.981475 93.19217
##
##
## $tsep
```

```
## $tsep$RMSE0
## [1] 6.606156
##
## $tsep$object
##             RMSE        R2   Avg.Bias Max.Bias    Skill
## N01    1.810307 0.9258730 0.04624457 2.533333 92.49057
## N02    1.666199 0.9365755 0.07066005 3.012500 93.63855
## N03    1.623490 0.9397846 0.08854404 3.305556 93.96049
## N04    1.659724 0.9370676 0.08667494 3.481250 93.68789
## N05    1.674944 0.9359277 0.08864887 3.756667 93.57160
## N01.wm 1.810307 0.9258730 0.04624457 2.533333 92.49057
## N02.wm 1.635204 0.9388880 0.06416266 2.919117 93.87302
## N03.wm 1.586193 0.9424966 0.08029548 3.245589 94.23480
## N04.wm 1.605569 0.9411068 0.08040274 3.420789 94.09309
## N05.wm 1.615550 0.9403935 0.08161289 3.655295 94.01942
##
## $tsep$crossval
##             RMSE        R2   Avg.Bias Max.Bias    Skill
## N01    1.845562 0.9228419 0.04398924 2.533333 92.19524
## N02    1.699606 0.9340547 0.08420236 3.050000 93.38090
## N03    1.661462 0.9369422 0.09230981 3.419444 93.67467
## N04    1.698854 0.9340512 0.08610594 3.562500 93.38675
## N05    1.702133 0.9338159 0.08803642 3.571667 93.36121
## N01.wm 1.845562 0.9228419 0.04398924 2.533333 92.19524
## N02.wm 1.669913 0.9363011 0.07569302 3.002209 93.61016
## N03.wm 1.622336 0.9398536 0.08423351 3.344966 93.96908
## N04.wm 1.641251 0.9384536 0.08077765 3.495896 93.82762
## N05.wm 1.641009 0.9384919 0.08109143 3.503441 93.82945
##
##
## $toct
## $toct$RMSE0
## [1] 8.007366
##
## $toct$object
##             RMSE        R2   Avg.Bias Max.Bias    Skill
## N01    2.098266 0.9324488 0.07862611 1.463636 93.13340
## N02    1.981138 0.9391861 0.10647631 2.727273 93.87861
## N03    1.918444 0.9429197 0.13290572 2.757576 94.25991
## N04    1.968013 0.9398948 0.13679909 3.140909 93.95945
## N05    1.988854 0.9386194 0.14103455 3.512727 93.83083
## N01.wm 2.098266 0.9324488 0.07862611 1.463636 93.13340
## N02.wm 1.942113 0.9415207 0.09728206 2.601631 94.11740
## N03.wm 1.874632 0.9454533 0.12049803 2.677379 94.51909
## N04.wm 1.903909 0.9437141 0.12527830 3.025618 94.34656
## N05.wm 1.916673 0.9429624 0.12847533 3.332515 94.27050
##
## $toct$crossval
##             RMSE        R2  Avg.Bias Max.Bias    Skill
## N01    2.168002 0.9278636 0.1022553 1.518182 92.66939
## N02    2.019252 0.9368312 0.1169046 3.286364 93.64081
## N03    1.970838 0.9397475 0.1297607 3.409091 93.94210
## N04    1.996336 0.9381424 0.1361887 4.270455 93.78433
## N05    2.002399 0.9378009 0.1464598 3.945455 93.74652
```

```
## N01.wm 2.168002 0.9278636 0.1022553 1.518182 92.66939
## N02.wm 1.986926 0.9388044 0.1108661 3.139984 93.84279
## N03.wm 1.927982 0.9423025 0.1211300 3.223644 94.20269
## N04.wm 1.938831 0.9416317 0.1276855 3.802070 94.13726
## N05.wm 1.937271 0.9417515 0.1350715 3.625127 94.14669
##
##
## $tnov
## $tnov$RMSE0
## [1] 9.751704
##
## $tnov$object
##            RMSE        R2  Avg.Bias Max.Bias    Skill
## N01    2.757371 0.9218541 0.1326505 1.189785 92.00480
## N02    2.645419 0.9273175 0.1871095 2.604167 92.64084
## N03    2.557460 0.9319727 0.2322850 2.844444 93.12209
## N04    2.625245 0.9282324 0.2425667 3.918750 92.75266
## N05    2.654252 0.9266176 0.2503952 4.738333 92.59162
## N01.wm 2.757371 0.9218541 0.1326505 1.189785 92.00480
## N02.wm 2.590460 0.9302355 0.1727661 2.456524 92.94344
## N03.wm 2.493846 0.9352358 0.2123432 2.754883 93.45999
## N04.wm 2.534635 0.9330408 0.2240981 3.727328 93.24431
## N05.wm 2.550723 0.9321761 0.2315072 4.453262 93.15827
##
## $tnov$crossval
##            RMSE        R2  Avg.Bias Max.Bias    Skill
## N01    2.793185 0.9198839 0.1239189 1.150000 91.79576
## N02    2.687158 0.9249514 0.2022967 3.120833 92.40679
## N03    2.604339 0.9293418 0.2231740 4.063889 92.86763
## N04    2.664296 0.9260367 0.2403580 4.820833 92.53544
## N05    2.694869 0.9242744 0.2431078 5.908333 92.36315
## N01.wm 2.793185 0.9198839 0.1239189 1.150000 91.79576
## N02.wm 2.629470 0.9280773 0.1869717 2.926654 92.72931
## N03.wm 2.539515 0.9327598 0.2061610 3.881541 93.21827
## N04.wm 2.569567 0.9311430 0.2218458 4.624584 93.05681
## N05.wm 2.587615 0.9301396 0.2260893 5.399662 92.95894
##
##
## $tdec
## $tdec$RMSE0
## [1] 10.4617
##
## $tdec$object
##            RMSE        R2  Avg.Bias Max.Bias    Skill
## N01    2.909762 0.9244604 0.1676391 2.046154 92.26411
## N02    2.787397 0.9299688 0.2278605 2.365625 92.90107
## N03    2.685856 0.9349594 0.2805918 2.547756 93.40886
## N04    2.765757 0.9309439 0.2908287 3.351562 93.01087
## N05    2.793312 0.9295351 0.2970370 4.040000 92.87091
## N01.wm 2.909762 0.9244604 0.1676391 2.046154 92.26411
## N02.wm 2.725385 0.9329945 0.2133877 2.238275 93.21342
## N03.wm 2.614053 0.9383158 0.2587828 2.462779 93.75656
## N04.wm 2.662871 0.9359377 0.2710281 3.197940 93.52119
## N05.wm 2.678200 0.9351864 0.2780574 3.802799 93.44638
```

```
##
## $tdec$crossval
##             RMSE        R2  Avg.Bias Max.Bias    Skill
## N01    2.960662 0.9217886 0.1696876 2.481250 91.99110
## N02    2.832437 0.9276915 0.2318022 2.487500 92.66980
## N03    2.741080 0.9322358 0.2870888 2.862500 93.13503
## N04    2.784766 0.9299785 0.2932651 3.615625 92.91447
## N05    2.803810 0.9290484 0.3081688 3.720000 92.81722
## N01.wm 2.960662 0.9217886 0.1696876 2.481250 91.99110
## N02.wm 2.768259 0.9308728 0.2184936 2.427804 92.99822
## N03.wm 2.660521 0.9360977 0.2666143 2.820303 93.53261
## N04.wm 2.682383 0.9349829 0.2735814 3.502554 93.42589
## N05.wm 2.684794 0.9349011 0.2874504 3.566478 93.41407
##
##
## $pjan
## $pjan$RMSE0
## [1] 63.47676
##
## $pjan$object
##             RMSE        R2  Avg.Bias Max.Bias    Skill
## N01    30.73873 0.7789581 0.7581212 105.0000 76.55003
## N02    27.07690 0.8206003 1.5378647 176.0000 81.80432
## N03    27.14813 0.8188100 1.8768191 173.3333 81.70846
## N04    27.07279 0.8193685 2.1278709 162.7500 81.80984
## N05    27.10728 0.8189528 2.3045727 175.6000 81.76347
## N01.wm 30.73873 0.7789581 0.7581212 105.0000 76.55003
## N02.wm 26.71077 0.8255320 1.3754869 154.7160 82.29307
## N03.wm 26.37881 0.8288600 1.6530291 157.6370 82.73045
## N04.wm 26.27269 0.8298487 1.8664957 153.4448 82.86912
## N05.wm 26.16742 0.8311222 2.0393552 163.2062 83.00613
##
## $pjan$crossval
##             RMSE        R2 Avg.Bias Max.Bias    Skill
## N01    30.87995 0.7754958 1.041796 105.0000 76.33406
## N02    27.46601 0.8151599 1.822367 176.0000 81.27759
## N03    27.33733 0.8160601 1.945927 193.0000 81.45261
## N04    27.37961 0.8153081 2.284761 174.2500 81.39521
## N05    27.39497 0.8151947 2.412001 154.4000 81.37432
## N01.wm 30.87995 0.7754958 1.041796 105.0000 76.33406
## N02.wm 27.12482 0.8197365 1.685977 154.7160 81.73985
## N03.wm 26.57193 0.8260941 1.790653 168.3651 82.47667
## N04.wm 26.52330 0.8265655 2.077163 160.8718 82.54075
## N05.wm 26.41861 0.8279807 2.196211 149.8737 82.67830
##
##
## $pfeb
## $pfeb$RMSE0
## [1] 50.40512
##
## $pfeb$object
##             RMSE        R2  Avg.Bias Max.Bias    Skill
## N01    25.12457 0.7655046 0.6933582 139.5714 75.15448
## N02    22.34587 0.8064412 1.3183323 130.6429 80.34626
```

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## N03    22.26990 0.8067669 1.6073522 139.4286 80.47966
## N04    22.21171 0.8072608 1.8120732 136.8929 80.58154
## N05    22.25669 0.8065188 1.9456238 148.0571 80.50281
## N01.wm 25.12457 0.7655046 0.6933582 139.5714 75.15448
## N02.wm 22.03785 0.8118520 1.1757145 125.9476 80.88434
## N03.wm 21.69355 0.8165711 1.4161637 130.0702 81.47698
## N04.wm 21.58724 0.8178925 1.5941357 130.4772 81.65807
## N05.wm 21.51993 0.8189348 1.7265155 139.8578 81.77228
##
## $pfeb$crossval
##            RMSE        R2  Avg.Bias Max.Bias    Skill
## N01    25.47117 0.7606289 0.7287399 124.0000 74.46426
## N02    23.13012 0.7932169 1.3915787 154.0714 78.94252
## N03    22.65587 0.7997814 1.6579074 159.7143 79.79717
## N04    22.42886 0.8034828 1.8251604 154.4286 80.20001
## N05    22.57703 0.8009348 1.9889096 154.0286 79.93753
## N01.wm 25.47117 0.7606289 0.7287399 124.0000 74.46426
## N02.wm 22.77066 0.7997257 1.2392422 147.5132 79.59193
## N03.wm 22.07499 0.8100439 1.4392255 148.4601 80.81985
## N04.wm 21.84586 0.8135237 1.6110077 146.9614 81.21595
## N05.wm 21.82649 0.8137686 1.7648039 146.3542 81.24926
##
##
## $pmar
## $pmar$RMSE0
## [1] 46.86869
##
## $pmar$object
##            RMSE        R2  Avg.Bias  Max.Bias    Skill
## N01    23.54762 0.7616780 0.7699152  84.60000 74.75772
## N02    21.07075 0.8010605 1.3357128  95.40000 79.78870
## N03    20.93976 0.8025142 1.6425271  97.26667 80.03921
## N04    20.88993 0.8029699 1.7928305  89.20000 80.13410
## N05    20.91233 0.8025617 1.8994413 105.32000 80.09147
## N01.wm 23.54762 0.7616780 0.7699152  84.60000 74.75772
## N02.wm 20.77514 0.8066293 1.2054828  86.63243 80.35182
## N03.wm 20.40174 0.8123937 1.4586577  87.18294 81.05176
## N04.wm 20.30714 0.8137051 1.5970670  84.47078 81.22707
## N05.wm 20.24405 0.8147949 1.7048797  95.94581 81.34354
##
## $pmar$crossval
##            RMSE        R2  Avg.Bias  Max.Bias    Skill
## N01    23.10492 0.7699930 0.8181254  78.40000 75.69793
## N02    21.29243 0.7974837 1.3639561  81.00000 79.36119
## N03    21.17034 0.7984011 1.7423271  91.26667 79.59720
## N04    21.04433 0.8001736 1.9151666 100.60000 79.83935
## N05    20.95282 0.8018800 1.9528243 104.52000 80.01431
## N01.wm 23.10492 0.7699930 0.8181254  78.40000 75.69793
## N02.wm 20.98305 0.8033208 1.2291527  72.27315 79.95660
## N03.wm 20.63315 0.8083610 1.5522525  80.49564 80.61947
## N04.wm 20.44528 0.8112477 1.7014452  89.42266 80.97081
## N05.wm 20.27094 0.8143816 1.7665329  93.95199 81.29395
##
##
```

```
## $papr
## $papr$RMSE0
## [1] 37.36176
##
## $papr$object
##             RMSE        R2  Avg.Bias Max.Bias    Skill
## N01     18.12897 0.7760283 0.5443824 116.2000 76.45539
## N02     16.48755 0.8081936 0.9424788 118.1000 80.52589
## N03     16.29556 0.8117309 1.1240775 111.1333 80.97678
## N04     16.26335 0.8119308 1.2293089 113.1500 81.05191
## N05     16.28450 0.8113434 1.3080074 109.1200 81.00259
## N01.wm 18.12897 0.7760283 0.5443824 116.2000 76.45539
## N02.wm 16.18074 0.8153114 0.8248037 117.7759 81.24392
## N03.wm 15.83294 0.8221401 0.9734364 112.7374 82.04156
## N04.wm 15.74225 0.8236720 1.0759192 115.0205 82.24671
## N05.wm 15.72362 0.8239656 1.1579152 111.9830 82.28870
##
## $papr$crossval
##             RMSE        R2  Avg.Bias Max.Bias    Skill
## N01     18.72848 0.7612982 0.6712187 116.8000 74.87243
## N02     16.55991 0.8062851 1.0592800  99.2000 80.35458
## N03     16.57728 0.8052816 1.2642941 103.4000 80.31334
## N04     16.49616 0.8067221 1.3845438 109.5500 80.50554
## N05     16.54410 0.8055083 1.4363335 108.0800 80.39208
## N01.wm 18.72848 0.7612982 0.6712187 116.8000 74.87243
## N02.wm 16.32877 0.8117651 0.9403232 100.1306 80.89917
## N03.wm 16.11107 0.8159660 1.0976545 104.7896 81.40509
## N04.wm 15.94689 0.8192280 1.2126925 108.9478 81.78215
## N05.wm 15.91960 0.8197388 1.2784314 108.6696 81.84443
##
##
## $pmay
## $pmay$RMSE0
## [1] 37.58397
##
## $pmay$object
##             RMSE        R2  Avg.Bias  Max.Bias    Skill
## N01     15.15907 0.8435267 0.4471343  90.66667 83.73178
## N02     14.37950 0.8558383 0.7037037 104.16667 85.36199
## N03     13.99801 0.8625520 0.9008897  90.55556 86.12838
## N04     14.01255 0.8619249 0.9424788  77.75000 86.09954
## N05     14.09251 0.8601992 0.9748810  76.53333 85.94046
## N01.wm 15.15907 0.8435267 0.4471343  90.66667 83.73178
## N02.wm 14.02742 0.8627291 0.6154065  99.53553 86.07002
## N03.wm 13.58641 0.8703802 0.7733912  88.49291 86.93215
## N04.wm 13.52461 0.8712407 0.8225320  79.41122 87.05077
## N05.wm 13.58256 0.8700211 0.8585116  79.54468 86.93955
##
## $pmay$crossval
##             RMSE        R2  Avg.Bias Max.Bias    Skill
## N01     15.53613 0.8354916 0.4409270 90.66667 82.91243
## N02     14.64923 0.8506930 0.6620112 89.33333 84.80767
## N03     14.34007 0.8558064 0.8783364 84.66667 85.44216
## N04     14.37693 0.8546619 0.9274778 73.91667 85.36722
```

```
## N05    14.23707 0.8572594 0.9676805 71.80000 85.65052
## N01.wm 15.53613 0.8354916 0.4409270 90.66667 82.91243
## N02.wm 14.32146 0.8571526 0.5829695 86.30383 85.47991
## N03.wm 13.91591 0.8640543 0.7621002 82.93912 86.29061
## N04.wm 13.89989 0.8640132 0.8124725 75.70854 86.32216
## N05.wm 13.76513 0.8664598 0.8537518 73.78545 86.58609
##
##
## $pjun
## $pjun$RMSE0
## [1] 42.72682
##
## $pjun$object
##            RMSE        R2  Avg.Bias Max.Bias    Skill
## N01    15.52673 0.8725084 0.2665011 23.65217 86.79438
## N02    15.03813 0.8778226 0.4207532 30.42857 87.61241
## N03    14.56019 0.8846343 0.6038347 32.23810 88.38731
## N04    14.78770 0.8806407 0.6645458 41.53571 88.02156
## N05    14.84743 0.8795443 0.6887234 40.02857 87.92461
## N01.wm 15.52673 0.8725084 0.2665011 23.65217 86.79438
## N02.wm 14.62545 0.8843825 0.3323427 26.96617 88.28298
## N03.wm 14.08980 0.8918779 0.4766192 28.82520 89.12552
## N04.wm 14.19121 0.8899883 0.5276479 37.96063 88.96842
## N05.wm 14.20912 0.8896056 0.5556041 37.37631 88.94056
##
## $pjun$crossval
##            RMSE        R2  Avg.Bias Max.Bias    Skill
## N01    16.59692 0.8546436 0.4454790 25.39130 84.91123
## N02    15.63624 0.8679504 0.5152079 38.85714 86.60744
## N03    15.21243 0.8741201 0.6533554 43.90476 87.32360
## N04    15.14879 0.8747211 0.6334058 41.57143 87.42943
## N05    15.28408 0.8724052 0.7714049 44.62857 87.20390
## N01.wm 16.59692 0.8546436 0.4454790 25.39130 84.91123
## N02.wm 15.22206 0.8747612 0.4465014 33.31947 87.30754
## N03.wm 14.75997 0.8814188 0.5511149 38.81176 88.06645
## N04.wm 14.59036 0.8837259 0.5344346 38.24632 88.33914
## N05.wm 14.66045 0.8825260 0.6412798 41.06948 88.22683
##
##
## $pjul
## $pjul$RMSE0
## [1] 38.08452
##
## $pjul$object
##            RMSE        R2   Avg.Bias Max.Bias    Skill
## N01    15.85532 0.8334825 0.07200497 18.68254 82.66782
## N02    15.01180 0.8469992 0.16035589 17.71429 84.46295
## N03    14.43986 0.8569782 0.29608939 17.86667 85.62430
## N04    14.59211 0.8535504 0.37797434 23.64167 85.31955
## N05    14.62877 0.8526648 0.43211256 24.22667 85.24571
## N01.wm 15.85532 0.8334825 0.07200497 18.68254 82.66782
## N02.wm 14.66858 0.8537926 0.12085275 17.53321 85.16530
## N03.wm 14.07311 0.8641020 0.21015269 17.11936 86.34527
## N04.wm 14.11967 0.8628146 0.27381289 20.96824 86.25478
```

```
## N05.wm 14.12445 0.8625871 0.33010981 21.76962 86.24545
##
## $pjul$crossval
##            RMSE        R2  Avg.Bias Max.Bias    Skill
## N01    16.51102 0.8194580 0.2967101 21.84127 81.20464
## N02    15.18088 0.8435475 0.2466377 19.70635 84.11100
## N03    14.80085 0.8498470 0.4509277 20.12222 84.89655
## N04    14.96803 0.8459839 0.4853611 25.30000 84.55342
## N05    14.90329 0.8470644 0.4736603 26.34667 84.68675
## N01.wm 16.51102 0.8194580 0.2967101 21.84127 81.20464
## N02.wm 14.89156 0.8493143 0.2143092 19.63332 84.71086
## N03.wm 14.39366 0.8578943 0.3461029 18.66216 85.71615
## N04.wm 14.46316 0.8561025 0.3776367 22.90283 85.57788
## N05.wm 14.37898 0.8575817 0.3780460 23.50756 85.74527
##
##
## $paug
## $paug$RMSE0
## [1] 38.35992
##
## $paug$object
##            RMSE        R2     Avg.Bias Max.Bias    Skill
## N01    16.06352 0.8312254 -0.104076143 117.5000 82.46418
## N02    15.30041 0.8434008  0.006207325 116.5000 84.09072
## N03    14.74514 0.8532194  0.113042279 114.6667 85.22450
## N04    14.93213 0.8490167  0.193461618 114.8750 84.84736
## N05    14.90629 0.8492775  0.229795158  91.9000 84.89977
## N01.wm 16.06352 0.8312254 -0.104076143 117.5000 82.46418
## N02.wm 14.97838 0.8498604 -0.042193361 117.1811 84.75336
## N03.wm 14.37887 0.8603493  0.037410621 115.7188 85.94943
## N04.wm 14.45836 0.8583759  0.089937024 116.0374 85.79364
## N05.wm 14.41896 0.8589185  0.129226368 100.9478 85.87097
##
## $paug$crossval
##            RMSE        R2    Avg.Bias Max.Bias    Skill
## N01    16.45193 0.8236046 -0.12849162 117.5000 81.60591
## N02    15.34741 0.8427914 -0.04365818 116.5000 83.99282
## N03    14.99320 0.8482793  0.11635285 114.6667 84.72316
## N04    15.24787 0.8426264  0.19092696 114.8750 84.19979
## N05    15.17351 0.8438350  0.22375336  91.9000 84.35351
## N01.wm 16.45193 0.8236046 -0.12849162 117.5000 81.60591
## N02.wm 15.10905 0.8476032 -0.07740878 117.1811 84.48617
## N03.wm 14.61829 0.8557147  0.05039732 115.7188 85.47762
## N04.wm 14.75315 0.8526121  0.09853907 116.0374 85.20844
## N05.wm 14.68354 0.8537235  0.12997327 100.9478 85.34769
##
##
## $psep
## $psep$RMSE0
## [1] 43.74038
##
## $psep$object
##            RMSE        R2  Avg.Bias Max.Bias    Skill
## N01    19.39127 0.8110104 0.2553280 171.5000 80.34615
```

```
## N02    18.48132 0.8246123 0.4220981 171.7500 82.14743
## N03    17.85523 0.8347616 0.5832816 169.8333 83.33651
## N04    18.16171 0.8284750 0.7134802 172.1250 82.75957
## N05    18.10633 0.8292912 0.7539003 137.7000 82.86454
## N01.wm 19.39127 0.8110104 0.2553280 171.5000 80.34615
## N02.wm 18.11809 0.8315085 0.3359950 172.7020 82.84227
## N03.wm 17.42322 0.8426221 0.4663892 171.1301 84.13312
## N04.wm 17.57423 0.8393217 0.5646561 173.0437 83.85688
## N05.wm 17.50691 0.8403204 0.6144346 150.5709 83.98032
##
## $psep$crossval
##            RMSE        R2  Avg.Bias Max.Bias    Skill
## N01    19.74509 0.8037078 0.4057521 171.5000 79.62239
## N02    18.75159 0.8195216 0.5415891 171.7500 81.62146
## N03    18.07175 0.8307554 0.6970136 169.8333 82.92993
## N04    18.52945 0.8215834 0.8340575 172.1250 82.05431
## N05    18.61361 0.8196603 0.8636044 137.7000 81.89093
## N01.wm 19.74509 0.8037078 0.4057521 171.5000 79.62239
## N02.wm 18.41227 0.8259935 0.4459557 172.7020 82.28058
## N03.wm 17.64473 0.8385977 0.5880990 171.1301 83.72709
## N04.wm 17.91442 0.8331119 0.6942781 173.0437 83.22585
## N05.wm 17.98309 0.8315772 0.7314338 150.5709 83.09702
##
##
## $poct
## $poct$RMSE0
## [1] 52.13169
##
## $poct$object
##            RMSE        R2  Avg.Bias Max.Bias    Skill
## N01    26.52068 0.7515471 0.4779640 291.0000 74.11991
## N02    24.22777 0.7875635 0.7888475 290.2500 78.40151
## N03    23.70457 0.7950449 1.0084144 246.3333 79.32428
## N04    23.81594 0.7922626 1.2136354 208.4167 79.12954
## N05    23.64724 0.7950040 1.3217463 203.6000 79.42417
## N01.wm 26.52068 0.7515471 0.4779640 291.0000 74.11991
## N02.wm 24.05606 0.7908363 0.6819525 290.6816 78.70658
## N03.wm 23.31881 0.8017373 0.8559173 251.3247 79.99174
## N04.wm 23.26910 0.8017479 1.0188999 218.1675 80.07695
## N05.wm 23.07987 0.8046836 1.1225663 217.9251 80.39968
##
## $poct$crossval
##            RMSE        R2  Avg.Bias Max.Bias    Skill
## N01    26.59805 0.7503822 0.6031450 291.0000 73.96870
## N02    24.02480 0.7912851 0.8153321 235.0000 78.76189
## N03    23.92384 0.7915118 1.0555900 256.5000 78.94001
## N04    23.90598 0.7908042 1.2771053 227.8750 78.97144
## N05    23.26337 0.8015649 1.3301055 199.8000 80.08677
## N01.wm 26.59805 0.7503822 0.6031450 291.0000 73.96870
## N02.wm 23.87928 0.7942006 0.6987343 241.1004 79.01839
## N03.wm 23.48458 0.7992028 0.8817460 259.7961 79.70627
## N04.wm 23.32970 0.8008057 1.0801517 237.4161 79.97306
## N05.wm 22.75104 0.8101463 1.1125136 214.9444 80.95421
##
```

```
##
## $pnov
## $pnov$RMSE0
## [1] 61.15229
##
## $pnov$object
##            RMSE        R2  Avg.Bias Max.Bias    Skill
## N01    28.92984 0.7871693 0.5872129 172.2500 77.61966
## N02    25.69012 0.8258576 1.1806331 181.0000 82.35154
## N03    25.63709 0.8257977 1.4821712 181.3333 82.42433
## N04    25.42869 0.8280480 1.7220670 171.6875 82.70891
## N05    25.36615 0.8288880 1.8838403 166.6500 82.79385
## N01.wm 28.92984 0.7871693 0.5872129 172.2500 77.61966
## N02.wm 25.40750 0.8298020 1.0448942 171.6999 82.73772
## N03.wm 25.04129 0.8337799 1.2956062 172.5619 83.23174
## N04.wm 24.80679 0.8363702 1.4934306 169.5862 83.54433
## N05.wm 24.63943 0.8384257 1.6461563 165.3000 83.76562
##
## $pnov$crossval
##            RMSE        R2 Avg.Bias Max.Bias    Skill
## N01    29.84698 0.7744972 0.809642 172.2500 76.17817
## N02    26.34896 0.8170456 1.426340 181.0000 81.43472
## N03    25.83658 0.8229921 1.563280 180.0000 82.14974
## N04    25.86952 0.8220614 1.807211 169.6875 82.10419
## N05    25.43152 0.8280572 1.940079 159.3500 82.70506
## N01.wm 29.84698 0.7744972 0.809642 172.2500 76.17817
## N02.wm 26.08431 0.8208115 1.298625 171.6999 81.80579
## N03.wm 25.41458 0.8287916 1.438643 171.1278 82.72809
## N04.wm 25.34563 0.8292308 1.619358 167.5745 82.82167
## N05.wm 24.81990 0.8361106 1.735916 157.0063 83.52693
##
##
## $pdec
## $pdec$RMSE0
## [1] 66.44646
##
## $pdec$object
##            RMSE        R2  Avg.Bias  Max.Bias    Skill
## N01    31.51098 0.7870579 0.7597765  96.36364 77.51048
## N02    27.92906 0.8257848 1.4696876 166.00000 82.33275
## N03    27.95963 0.8245986 1.8060556 178.16667 82.29405
## N04    27.75375 0.8266560 2.0648148 153.25000 82.55385
## N05    27.71104 0.8272286 2.2566936 165.00000 82.60750
## N01.wm 31.51098 0.7870579 0.7597765  96.36364 77.51048
## N02.wm 27.57182 0.8303225 1.3174741 131.72012 82.78182
## N03.wm 27.23186 0.8335581 1.5939316 141.68553 83.20380
## N04.wm 27.00782 0.8358460 1.8130964 134.13064 83.47903
## N05.wm 26.82834 0.8379115 1.9933515 142.32414 83.69788
##
## $pdec$crossval
##            RMSE        R2  Avg.Bias Max.Bias    Skill
## N01    32.28869 0.7779715 0.9650321  89.0000 76.38667
## N02    29.15727 0.8109960 1.4860335 166.0000 80.74471
## N03    28.59495 0.8166133 1.8561280 178.1667 81.48026
```

```
## N04    28.28017 0.8200655 2.1206290 153.2500 81.88574
## N05    28.08762 0.8225167 2.3023381 165.0000 82.13158
## N01.wm 32.28869 0.7779715 0.9650321  89.0000 76.38667
## N02.wm 28.80175 0.8156544 1.3563698 131.7201 81.21142
## N03.wm 27.96993 0.8246244 1.6505874 141.6855 82.28100
## N04.wm 27.60912 0.8285150 1.9075869 134.1306 82.73520
## N05.wm 27.26618 0.8326217 2.0674491 142.3241 83.16144
##
##
## $tave
## $tave$RMSE0
## [1] 8.239153
##
## $tave$object
##            RMSE        R2   Avg.Bias Max.Bias    Skill
## N01    2.144047 0.9334761 0.09143389 0.882734 93.22821
## N02    2.011704 0.9408484 0.12434478 1.678186 94.03840
## N03    1.946707 0.9445947 0.15640044 1.917810 94.41741
## N04    1.999667 0.9414782 0.15762984 2.479289 94.10952
## N05    2.021074 0.9401989 0.15810504 2.901961 93.98273
## N01.wm 2.144047 0.9334761 0.09143389 0.882734 93.22821
## N02.wm 1.968517 0.9433186 0.11448971 1.587100 94.29161
## N03.wm 1.898254 0.9472636 0.14237201 1.841314 94.69185
## N04.wm 1.928798 0.9455184 0.14580182 2.353836 94.51965
## N05.wm 1.943479 0.9446773 0.14682127 2.731938 94.43590
##
## $tave$crossval
##            RMSE        R2   Avg.Bias Max.Bias    Skill
## N01    2.227462 0.9280975 0.08434375 1.147120 92.69104
## N02    2.073226 0.9371917 0.13667753 1.443107 93.66818
## N03    2.027845 0.9398857 0.16101053 1.763562 93.94235
## N04    2.065171 0.9375886 0.16280218 2.540564 93.71729
## N05    2.063296 0.9376749 0.16212877 3.035000 93.72869
## N01.wm 2.227462 0.9280975 0.08434375 1.147120 92.69104
## N02.wm 2.035115 0.9394290 0.12555145 1.403732 93.89883
## N03.wm 1.977625 0.9427672 0.14698230 1.681998 94.23867
## N04.wm 1.997979 0.9415358 0.14883837 2.397948 94.11946
## N05.wm 1.989633 0.9420174 0.15021864 2.769809 94.16849
##
##
## $tmax
## $tmax$RMSE0
## [1] 5.61502
##
## $tmax$object
##            RMSE        R2    Avg.Bias Max.Bias    Skill
## N01    2.114118 0.8630960 -0.03252638 2.392500 85.82393
## N02    1.877027 0.8892279 -0.03433685 2.882500 88.82524
## N03    1.825280 0.8947197 -0.03265742 3.075000 89.43289
## N04    1.824513 0.8946198 -0.04704635 3.051250 89.44176
## N05    1.832459 0.8936511 -0.05501345 3.079000 89.34960
## N01.wm 2.114118 0.8630960 -0.03252638 2.392500 85.82393
## N02.wm 1.858567 0.8913756 -0.03687053 2.814839 89.04395
## N03.wm 1.791929 0.8984843 -0.03396245 3.037489 89.81551
```

```
## N04.wm 1.782531 0.8993890 -0.04687619 3.013941 89.92206
## N05.wm 1.779758 0.8996679 -0.05541567 3.033404 89.95339
##
## $tmax$crossval
##            RMSE        R2    Avg.Bias Max.Bias    Skill
## N01    2.130550 0.8606911 -0.02938134 2.720000 85.60271
## N02    1.878741 0.8888598 -0.04352369 3.213750 88.80481
## N03    1.843433 0.8926285 -0.04194772 3.159167 89.22166
## N04    1.835522 0.8933635 -0.05995758 3.128125 89.31397
## N05    1.853041 0.8912371 -0.05687978 3.206500 89.10900
## N01.wm 2.130550 0.8606911 -0.02938134 2.720000 85.60271
## N02.wm 1.861623 0.8908532 -0.04508441 3.160019 89.00790
## N03.wm 1.805520 0.8969271 -0.04327045 3.133812 89.66044
## N04.wm 1.790870 0.8984574 -0.05862081 3.081322 89.82755
## N05.wm 1.796154 0.8978028 -0.05830879 3.146110 89.76743
##
##
## $tmin
## $tmin$RMSE0
## [1] 11.70312
##
## $tmin$object
##            RMSE        R2  Avg.Bias Max.Bias    Skill
## N01    4.360605 0.8644515 0.1650528 16.14000 86.11678
## N02    4.057549 0.8806494 0.2207014 14.17000 87.97946
## N03    3.954610 0.8864058 0.2795158 15.95333 88.58163
## N04    4.028829 0.8821829 0.3052452 17.06500 88.14902
## N05    4.081816 0.8791676 0.3179061 18.40000 87.83524
## N01.wm 4.360605 0.8644515 0.1650528 16.14000 86.11678
## N02.wm 3.981631 0.8850265 0.2109272 14.51053 88.42506
## N03.wm 3.855746 0.8919691 0.2607065 15.36004 89.14541
## N04.wm 3.892169 0.8899984 0.2849181 16.27100 88.93936
## N05.wm 3.926468 0.8881534 0.2962803 17.48219 88.74357
##
## $tmin$crossval
##            RMSE        R2  Avg.Bias Max.Bias    Skill
## N01    4.489549 0.8564090 0.1783157 16.50000 85.28358
## N02    4.169988 0.8739542 0.2414442 13.41000 87.30402
## N03    4.058889 0.8804279 0.3119525 17.65333 87.97152
## N04    4.079732 0.8792314 0.3126681 18.13500 87.84766
## N05    4.118556 0.8769735 0.3080406 18.28000 87.61527
## N01.wm 4.489549 0.8564090 0.1783157 16.50000 85.28358
## N02.wm 4.106902 0.8776984 0.2281973 13.73624 87.68526
## N03.wm 3.959999 0.8861099 0.2870049 16.96093 88.55049
## N04.wm 3.956023 0.8863877 0.2907221 17.31885 88.57347
## N05.wm 3.970702 0.8856259 0.2899345 17.44434 88.48852
##
##
## $gdd0
## $gdd0$RMSE0
## [1] 1669.594
##
## $gdd0$object
##            RMSE        R2 Avg.Bias  Max.Bias    Skill
```

```
## N01    504.9038 0.9099869 13.28092  756.9146 90.85475
## N02    465.5658 0.9224976 20.39171  868.9104 92.22428
## N03    453.7839 0.9263700 25.87721  965.2146 92.61286
## N04    465.5722 0.9225288 27.05079  990.5344 92.22407
## N05    469.3619 0.9212804 26.92199 1031.4179 92.09696
## N01.wm 504.9038 0.9099869 13.28092  756.9146 90.85475
## N02.wm 457.0797 0.9252830 18.75657  856.6896 92.50516
## N03.wm 443.6053 0.9296088 23.73910  951.0129 92.94053
## N04.wm 449.3666 0.9278214 25.15990  974.6392 92.75597
## N05.wm 451.4700 0.9271664 24.92032 1010.6154 92.68800
##
## $gdd0$crossval
##            RMSE        R2 Avg.Bias  Max.Bias    Skill
## N01    505.8018 0.9096120 14.37763  764.0792 90.82219
## N02    462.9828 0.9233860 25.03027  830.3583 92.31032
## N03    463.6082 0.9231416 26.20296  944.4618 92.28953
## N04    474.7879 0.9194150 27.35164  983.0260 91.91318
## N05    475.1253 0.9193644 28.12746 1077.2821 91.90168
## N01.wm 505.8018 0.9096120 14.37763  764.0792 90.82219
## N02.wm 454.6711 0.9260874 23.13192  824.7611 92.58394
## N03.wm 450.5294 0.9273960 24.26943  932.7808 92.71844
## N04.wm 457.1680 0.9252854 25.64443  965.7124 92.50227
## N05.wm 456.2849 0.9256466 26.43529 1046.8544 92.53120
##
##
## $gdd5
## $gdd5$RMSE0
## [1] 1313.669
##
## $gdd5$object
##            RMSE        R2  Avg.Bias Max.Bias    Skill
## N01    396.9649 0.9100658  9.986571 543.5569 90.86870
## N02    369.5380 0.9210990 15.487689 621.9415 92.08690
## N03    359.4830 0.9253355 19.188661 663.5559 92.51167
## N04    369.4810 0.9211574 19.725641 660.0373 92.08935
## N05    372.4194 0.9199083 19.122404 698.0148 91.96302
## N01.wm 396.9649 0.9100658  9.986571 543.5569 90.86870
## N02.wm 362.5792 0.9240346 14.320555 615.4892 92.38212
## N03.wm 351.4182 0.9286277 17.833318 657.4328 92.84390
## N04.wm 356.4268 0.9266350 18.700110 652.3409 92.63845
## N05.wm 357.9248 0.9260328 18.047126 654.5996 92.57645
##
## $gdd5$crossval
##            RMSE        R2 Avg.Bias Max.Bias    Skill
## N01    408.3124 0.9048553 10.32603 572.5985 90.33919
## N02    380.0153 0.9165544 13.99483 663.7500 91.63183
## N03    372.7336 0.9196840 18.06521 635.4559 91.94945
## N04    380.9491 0.9161409 19.31838 738.8848 91.59066
## N05    386.8270 0.9135126 18.37843 744.9730 91.32915
## N01.wm 408.3124 0.9048553 10.32603 572.5985 90.33919
## N02.wm 373.7925 0.9192656 12.64941 651.4496 91.90365
## N03.wm 363.8855 0.9234302 16.54937 632.6193 92.32713
## N04.wm 367.2576 0.9220525 17.84971 663.6218 92.18426
## N05.wm 371.1544 0.9203839 17.07587 677.5395 92.01753
```

```
##
##
## $mtco
## $mtco$RMSE0
## [1] 11.28255
##
## $mtco$object
##            RMSE        R2  Avg.Bias Max.Bias    Skill
## N01    3.085239 0.9269521 0.1695013 2.255797 92.52239
## N02    2.955819 0.9322728 0.2287916 2.547101 93.13658
## N03    2.834591 0.9376771 0.2832264 2.778502 93.68801
## N04    2.915879 0.9339543 0.2932133 2.962862 93.32080
## N05    2.942782 0.9326789 0.2954604 3.411034 93.19699
## N01.wm 3.085239 0.9269521 0.1695013 2.255797 92.52239
## N02.wm 2.891215 0.9351473 0.2135149 2.469235 93.43332
## N03.wm 2.761116 0.9407946 0.2603413 2.664105 94.01100
## N04.wm 2.808805 0.9386705 0.2725546 2.824615 93.80233
## N05.wm 2.824548 0.9379505 0.2769522 3.213621 93.73266
##
## $mtco$crossval
##            RMSE        R2  Avg.Bias Max.Bias    Skill
## N01    3.133986 0.9248124 0.1841920 2.247101 92.28423
## N02    3.024981 0.9291002 0.2344610 2.679310 92.81163
## N03    2.909886 0.9342725 0.2723912 2.794203 93.34823
## N04    2.970817 0.9312914 0.2657097 3.456897 93.06675
## N05    2.975396 0.9311928 0.3029381 3.693103 93.04536
## N01.wm 3.133986 0.9248124 0.1841920 2.247101 92.28423
## N02.wm 2.958505 0.9321379 0.2193931 2.546619 93.12409
## N03.wm 2.835656 0.9375192 0.2496954 2.685238 93.68327
## N04.wm 2.868150 0.9359280 0.2475765 3.199953 93.53767
## N05.wm 2.860484 0.9363597 0.2804627 3.397077 93.57217
##
##
## $mtwa
## $mtwa$RMSE0
## [1] 5.675775
##
## $mtwa$object
##            RMSE        R2    Avg.Bias Max.Bias    Skill
## N01    1.755352 0.9057596 0.009786882 2.528571 90.43515
## N02    1.585639 0.9220596 0.019635837 3.242857 92.19526
## N03    1.537631 0.9266250 0.023884406 3.695238 92.66071
## N04    1.564229 0.9240765 0.018823712 3.933929 92.40461
## N05    1.575463 0.9229897 0.016639768 3.910000 92.29511
## N01.wm 1.755352 0.9057596 0.009786882 2.528571 90.43515
## N02.wm 1.562163 0.9243370 0.016671005 3.183174 92.42466
## N03.wm 1.507905 0.9294337 0.021232569 3.632620 92.94174
## N04.wm 1.519929 0.9283328 0.017950688 3.853938 92.82873
## N05.wm 1.526585 0.9277150 0.015305734 3.813363 92.76578
##
## $mtwa$crossval
##            RMSE        R2    Avg.Bias Max.Bias    Skill
## N01    1.800907 0.9011532 0.009207532 2.350000 89.93225
## N02    1.606301 0.9200164 0.022677426 3.089286 91.99053
```

```
## N03    1.567860 0.9237136 0.025118974 3.773810 92.36930
## N04    1.579199 0.9226179 0.022222222 3.751786 92.25853
## N05    1.584929 0.9220678 0.016751500 3.938571 92.20224
## N01.wm 1.800907 0.9011532 0.009207532 2.350000 89.93225
## N02.wm 1.584201 0.9221896 0.018124384 3.028472 92.20941
## N03.wm 1.537173 0.9266654 0.021638728 3.700738 92.66509
## N04.wm 1.534412 0.9269563 0.019756345 3.687029 92.69141
## N05.wm 1.533377 0.9270798 0.015230030 3.857673 92.70126
##
##
## $annp
## $annp$RMSE0
## [1] 478.9726
##
## $annp$object
##            RMSE        R2  Avg.Bias Max.Bias    Skill
## N01    224.2420 0.7906772  5.527623 1520.000 78.08141
## N02    204.0006 0.8212900 10.286675 1709.333 81.85982
## N03    202.3229 0.8233541 13.044555 1493.222 82.15697
## N04    202.4025 0.8227108 14.854542 1284.417 82.14292
## N05    202.3323 0.8227349 15.999338 1275.733 82.15531
## N01.wm 224.2420 0.7906772  5.527623 1520.000 78.08141
## N02.wm 200.8507 0.8268277  8.988212 1646.874 82.41569
## N03.wm 197.2119 0.8320641 11.210705 1467.665 83.04706
## N04.wm 196.5523 0.8327218 12.737630 1318.403 83.16028
## N05.wm 195.8526 0.8337577 13.878626 1325.542 83.27996
##
## $annp$crossval
##            RMSE        R2  Avg.Bias Max.Bias    Skill
## N01    231.4324 0.7765021  8.515001 2019.000 76.65323
## N02    206.3402 0.8169038 12.588144 1795.000 81.44135
## N03    205.2914 0.8178761 14.860749 1350.556 81.62954
## N04    205.8103 0.8166438 15.762156 1195.300 81.53655
## N05    205.5960 0.8170185 17.027974 1298.000 81.57498
## N01.wm 231.4324 0.7765021  8.515001 2019.000 76.65323
## N02.wm 204.3223 0.8204365 11.577526 1822.439 81.80256
## N03.wm 200.5051 0.8261763 13.311417 1438.541 82.47616
## N04.wm 199.4883 0.8276209 14.070813 1283.601 82.65342
## N05.wm 198.3264 0.8295646 15.165960 1369.167 82.85491
```

Can we really reconstruct 32 variables? Probably not! Why could 32 variables seem reconstructable?

- spatial correlation between variables (does not mean there is a temporal correlation)
- spatial autocorrelation

**To obtain a good reconstruction, we should first ask the question: does this reconstruction make sense ecologically?**

### Spatial autocorrelation

Environmental variables influencing species composition are often spatially autocorrelated (e.g. summer temperatures at spatially close locations are more similar than summer temperatures at spatially distant locations). This is not in itself a problem. If an environmental variable influencing species assemblages is spatially autocorrelated, spatially close assemblages tend to be similar. The similarity of spatially close assemblages in turn means that sites chosen as analogues are spatially close. This again means that any spatially autocorrelated variable will perform well under cross-validation, even if it is globally unrelated to the variable influencing species assemblages. As an example, we can evaluate the performance of a model for an (obviously nonsensical) variable: distance to Calgary:

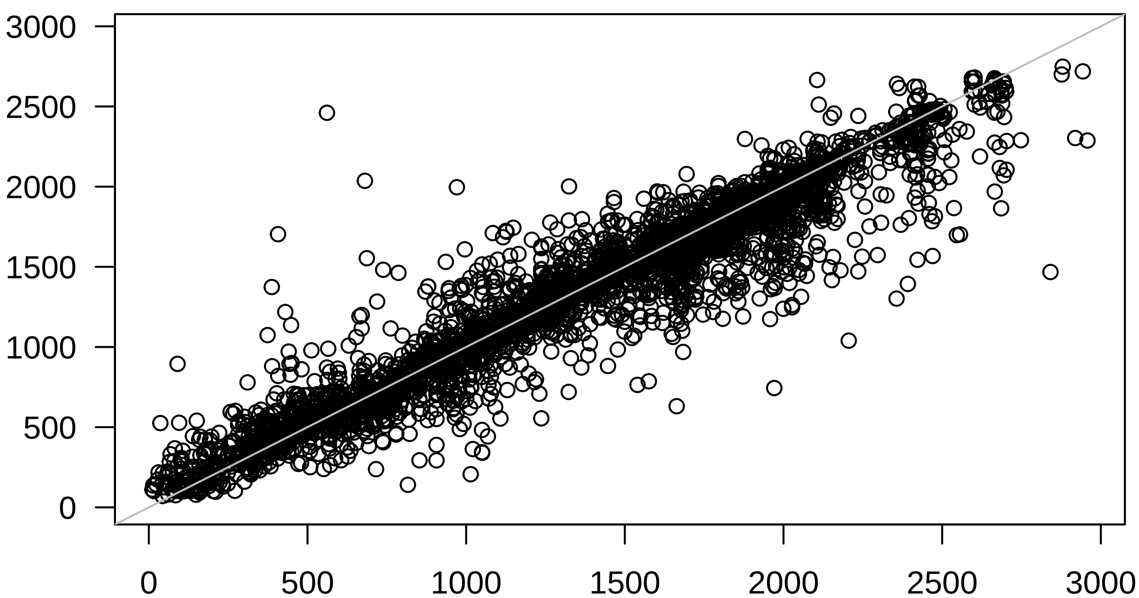
```
library(fields)
coord.calgary <- matrix(c(-114, 51), ncol = 2)

dist.calgary <- t(rdist.earth(coord.calgary, cbind(lon, lat)))

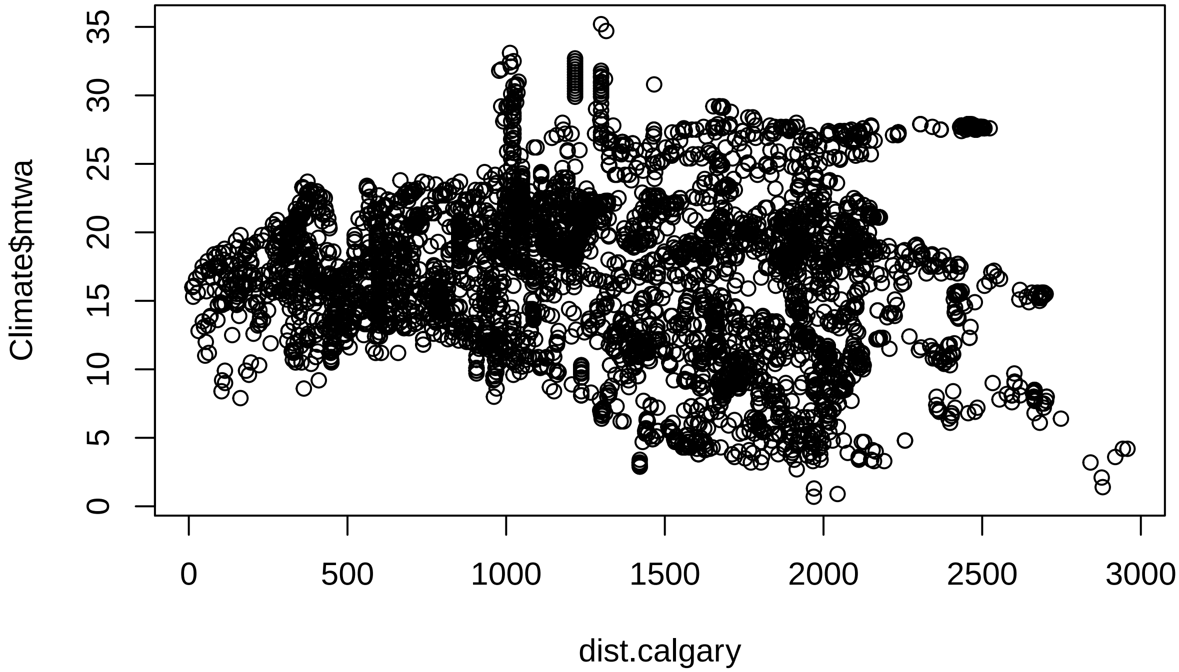
cor.env.var <- round(cor(dist.calgary, Climate), 2)
print(cor.env.var)
```

```
##       tjan  tfeb  tmar  tapr  tmay  tjun  tjul  taug  tsep  toct tnov
## [1,] -0.06 -0.14 -0.13 -0.12 -0.08 -0.05 -0.08 -0.09 -0.04 -0.07 0.01
##       tdec  pjan pfeb pmar papr pmay pjun pjul paug psep poct pnov  pdec
## [1,] -0.02 -0.05 0.02 0.07 0.18 0.25 0.32 0.48 0.55 0.42 0.19 0.03 -0.03
##       tave  tmax tmin gdd0 gdd5  mtco  mtwa annp
## [1,] -0.08 -0.35 0.17 0.05  0.1 -0.07 -0.08 0.21
```

```
mat.calgary <- rioja::MAT(y = pollen.prop, dist.calgary, lean = FALSE)
cv.calgary <- rioja::crossval(mat.calgary, verbose = FALSE)
perf.calgary <- rioja::performance(cv.calgary)
plot(cv.calgary)
```

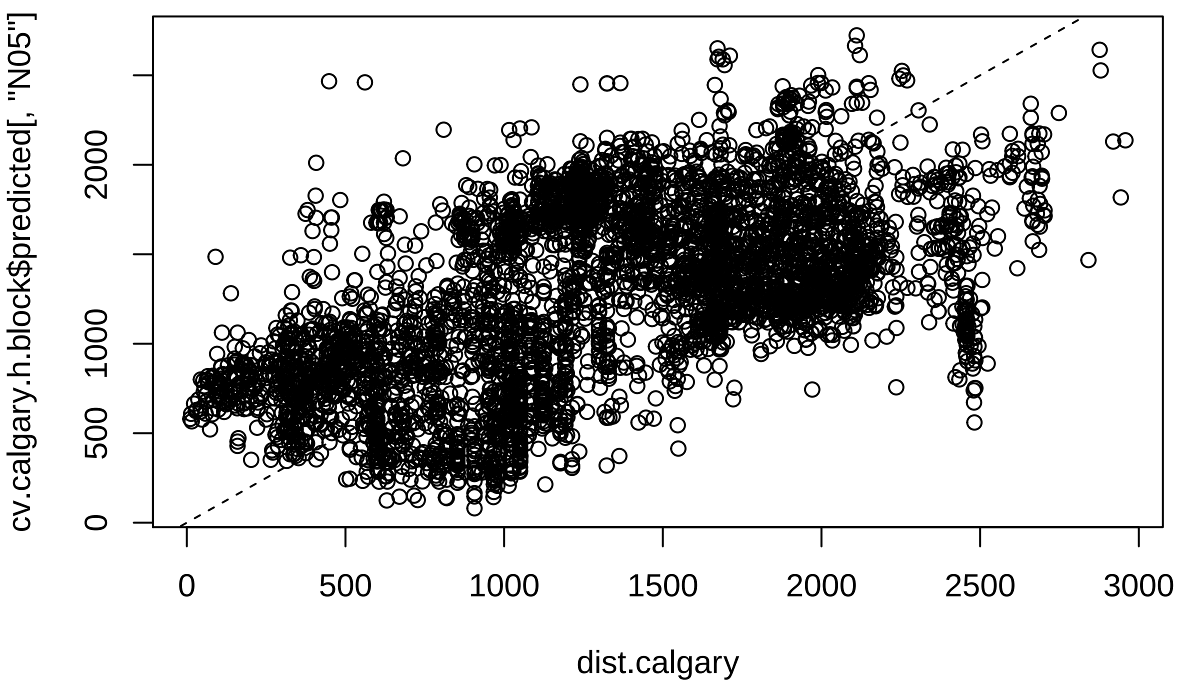



```
plot(dist.calgary, Climate$mtwa)
```




It is possible to assess the influence of spatial autocorrelation using h-block cross-validation. Under h-block cross-validation samples within radius $h$ of the predicted sample are removed from the calibration data set. One problem of h-block cross-validation is that we one the one hand account for artificial skill caused by spatial autocorrelation but on the other hand remove taxonomically close modern analogues also removing true skill.

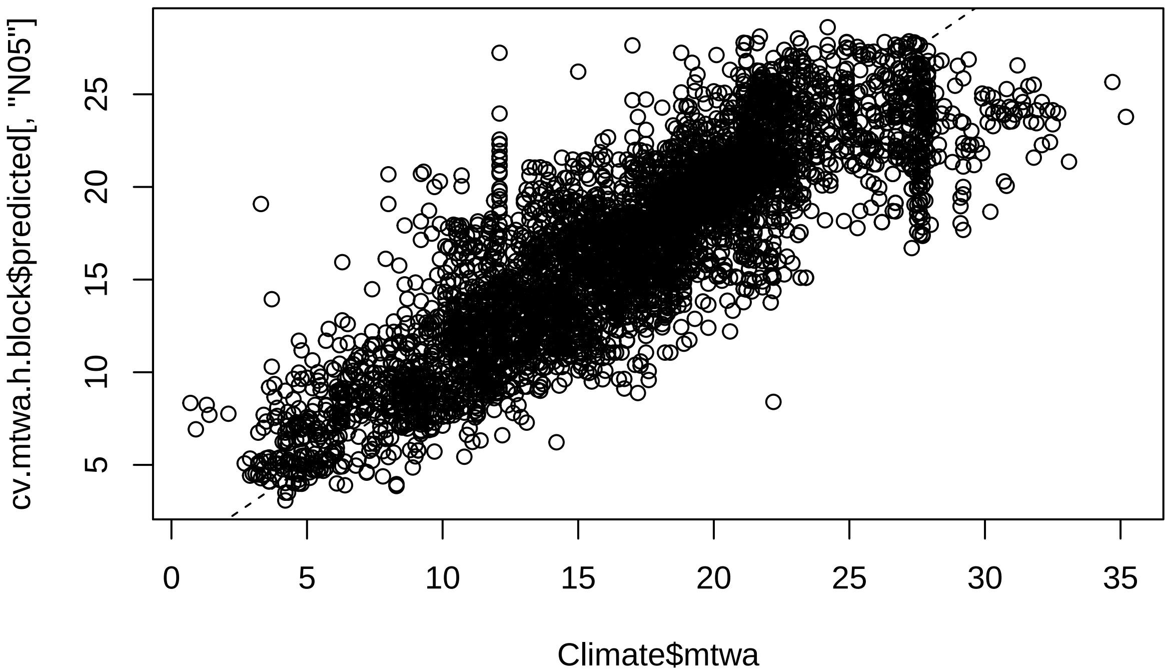
```
dist.h <- rdist.earth(cbind(lon,lat),cbind(lon,lat))
cv.calgary.h.block <- rioja::crossval(mat.calgary,h.cutoff = 500,h.dist=dist.h,cv.method = 'h-block',ve
plot(dist.calgary,cv.calgary.h.block$predicted[,'N05'])
abline(a=0,b=1,lty=2)
```



```r
rioja::performance(cv.calgary.h.block)
```

```
## $RMSE0
## [1] 604.8569
##
## $object
##             RMSE        R2  Avg.Bias Max.Bias    Skill
## N01    175.4432 0.9176049  9.581908 165.7415 91.58667
## N02    167.6362 0.9242311 16.143352 221.5481 92.31878
## N03    161.6631 0.9294875 18.234972 223.5527 92.85641
## N04    164.4657 0.9270958 19.411634 252.9188 92.60658
## N05    166.8169 0.9250363 19.891359 268.2763 92.39368
## N01.wm 175.4432 0.9176049  9.581908 165.7415 91.58667
## N02.wm 163.6981 0.9276830 15.294183 204.4796 92.67543
## N03.wm 156.6030 0.9337991 17.315141 204.5877 93.29660
## N04.wm 158.1477 0.9325818 18.589418 230.2196 93.16371
## N05.wm 159.2890 0.9316778 19.186584 244.6036 93.06468
##
## $crossval
##             RMSE        R2 Avg.Bias  Max.Bias     Skill
## N01    575.8696 0.2793825 39.72114  922.8722  9.355194
## N02    545.2385 0.3043462 43.54507  949.2802 18.741693
## N03    535.8628 0.3112115 44.65952  967.8120 21.512258
## N04    531.1431 0.3137231 45.07971  988.0042 22.888739
## N05    528.8426 0.3145171 45.24624 1003.5614 23.555281
## N01.wm 575.8696 0.2793825 39.72114  922.8722  9.355194
## N02.wm 544.6903 0.3057529 43.08618  945.4103 18.905027
## N03.wm 534.9175 0.3134133 44.12037  962.6767 21.788926
## N04.wm 530.0455 0.3163700 44.76910  981.6480 23.207104
## N05.wm 527.5792 0.3174565 44.96458  996.3462 23.920075
```

```r
#----------------------------------------------------------------------------------------------------
#compare this to h-block cross-validation of the mtwa model
cv.mtwa.h.block <- rioja::crossval(mat.model.mtwa,h.cutoff = 500,h.dist=dist.h,cv.method = 'h-block',ve
plot(Climate$mtwa,cv.mtwa.h.block$predicted[,'N05'])
abline(a=0,b=1,lty=2)
```




```r
rioja::performance(cv.mtwa.h.block)
```

```
## $RMSE0
## [1] 5.675775
##
## $object
##             RMSE        R2    Avg.Bias Max.Bias    Skill
## N01     1.755352 0.9057596 0.009786882 2.528571 90.43515
## N02     1.585639 0.9220596 0.019635837 3.242857 92.19526
## N03     1.537631 0.9266250 0.023884406 3.695238 92.66071
## N04     1.564229 0.9240765 0.018823712 3.933929 92.40461
## N05     1.575463 0.9229897 0.016639768 3.910000 92.29511
## N01.wm 1.755352 0.9057596 0.009786882 2.528571 90.43515
## N02.wm 1.562163 0.9243370 0.016671005 3.183174 92.42466
## N03.wm 1.507905 0.9294337 0.021232569 3.632620 92.94174
## N04.wm 1.519929 0.9283328 0.017950688 3.853938 92.82873
## N05.wm 1.526585 0.9277150 0.015305734 3.813363 92.76578
##
## $crossval
##             RMSE        R2   Avg.Bias Max.Bias    Skill
## N01     3.497870 0.6533017 0.03283675 8.614286 62.01982
## N02     3.155842 0.7034730 0.08319884 8.432143 69.08422
## N03     3.054308 0.7181089 0.09344782 8.838095 71.04154
## N04     2.997853 0.7265545 0.10683323 8.889286 72.10217
## N05     2.957338 0.7326645 0.09527002 9.044286 72.85113
## N01.wm 3.497870 0.6533017 0.03283675 8.614286 62.01982
## N02.wm 3.156126 0.7034911 0.08098981 8.419107 69.07865
## N03.wm 3.053097 0.7184444 0.09094883 8.765084 71.06451
## N04.wm 2.995682 0.7270433 0.10377125 8.814812 72.14256
## N05.wm 2.953507 0.7334150 0.09479722 8.971644 72.92143
```

Using h-block cross-validation, we can confirm that mean temperature of the warmest month is an ecologically meaningful variable whereas distance to Calgary does not influence pollen assemblages.

If you are interested in effects of spatial autocorrelation on transfer function performance and how to detect spatial autocorrelation you can work through some examples of the *palaeoSig* r-package by Richard Telford.

```
library(palaeoSig)
?rne
```