Analysis of Monthly HPC results

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```r
# root dir
knitr::opts_knit$set(root.dir = "C:/Users/rver4657/ownCloud/Virtual Experiments/VirtExp")
knitr::opts_chunk$set(echo = TRUE)
# LOAD REQUIRED PACKAGES # #####
library(pander)
library(tidyverse)
library(xts)
library(zoo)
library(ggplot2)
library(reshape2)
library(Rcpp)
library(hydromad)
```

This rmarkdown document and the resulting pdf are stored on github. All directories (apart from the root working directory) refer to the directories in this repository.

Introduction

This document is related to the manuscript "Disentangling climate change trends in Australian streamflow" (vervoort et al.), submitted to Journal of Hydrology. This is the 9^{th} part of the series that analyses the monthly results from the GR4J and SimHyd model fitting on the High Performance computer Artemis at the University of Sydney.

This is a coomparison to part 6 of the series in which the daily data were analysed and also a comparison to the original Chiew (2006) paper that was based on monthly data.

In particular, this part extracts the best parameters of the modelling, plots the performance distributions and extracts the residuals to be analysed in a further script using Mann Kendall (this is separated because this takes quite long to run). Finally a comparison between the non-parametric epsilon (sensitivity) and the model based epsilon is plotted for both gridded and non-gridded rainfall.

To recap, we have 2 different High Performance Computing monthly results for each of the 13 catchments. The two models (GR4J and SimHyd) were fitted to monhtly data for 10 years of climate data (1970 - 1980). Here we are only using the station data and not using the gridded data.

The model fitting is based on the shuffled complex evolution optimisation in Hydromad as described in more detail in the paper. Essentially the model was fitted 10 times using the `FitBySCE()` function in the Hydromad package. The scripts related to the high performance computing and the HPC scripts are stored in the Rcode/HPC folder. However, in contrast to the daily modelling, this analysis cannot run use Viney's objective function as this does not work on the monthly data, so the monthly fit are (also following Chiew, 2006) based on fitting to the Nash Sutcliffe Efficiency (NSE), which in hydromad is `~hmadstat("r.squared")`, as explained in the hydromad helpfile for `hmadstat()` and on the website.

The HPC results are not stored on Github, as the files are too large, but are stored in the Cloudstor data directory.

1. Load basic data and define storage

This loads all the basic climate data and the catchment characteristics.
It also compiles the SimHyd model code.

```
load("../projectData/MonthlyDataOut.Rdata")
flow_zoo_m <- dataOut_Month[[1]]
rain_zoo_m <- dataOut_Month[[2]]
maxT_zoo_m <- dataOut_Month[[3]]
flow_rain_maxT_monthly <-dataOut_Month[[4]]
Stations <- read.csv("Data/CatchmentCharact.csv")

# compile SimHyd
rcode_dir <- paste(getwd(),"RCode/HPC",sep="/")
source(paste(rcode_dir,"Simhyd.r",sep="/"))
```

Define the beginning and end date for the modelling

```
start.date <- "Jan 1981"
end.date <- "Dec 2010"
```

As a first step define storage for the results of the modelling. These will get renamed for each of the individual modelling results

```
sum_Res <- list()
Chiew_Res <- list()

mod_Res <- list()

Chiew <- data.frame(station=character(length=10),eta_p=numeric(length=10),
                    eta_e=numeric(length=10),pvalue_eta_p=numeric(length=10),
                    pvalue_eta_e=numeric(length=10))

Results <- data.frame(station=character(length=10),
                      Mod.r.sq=numeric(length=10),
                      Mod.bias=numeric(length=10))

Residuals <- list()

# some other auxillary data frames
pred_results <- data.frame(Pmin15ET0=numeric(length=nrow(flow_zoo_m)),
                              Pmin10ET0=numeric(length=nrow(flow_zoo_m)),
                              P0ET0=numeric(length=nrow(flow_zoo_m)),
                              Pplus10ET0=numeric(length=nrow(flow_zoo_m)),
                              Pmin15ETplus5=numeric(length=nrow(flow_zoo_m)),
                              Pmin10ETplus5=numeric(length=nrow(flow_zoo_m)),
                              P0ETplus5=numeric(length=nrow(flow_zoo_m)),
                              Pplus10ETplus5=numeric(length=nrow(flow_zoo_m)),
                              Pmin15ETplus10=numeric(length=nrow(flow_zoo_m)),
                              Pmin10ETplus10=numeric(length=nrow(flow_zoo_m)),
                              P0ETplus10=numeric(length=nrow(flow_zoo_m)),
                              Pplus10ETplus10=numeric(length=nrow(flow_zoo_m)))
```

2. GR4J model results with station rainfall

Extract the modelling results, rerun the model, do the Chiew (2006) amplification analysis and write away the results.

```r
# find the list of files with GR4J results
filelist <- dir("../Projectdata/HPCResults/Monthly",
                pattern = "GR4JMonthCalibOutput")

for (i in seq_along(filelist)) {
  #i <- 1
  # load the rainfall, ET and flow data
  pred_data <- merge(flow_zoo_m[,i], rain_zoo_m[,i], maxT_zoo_m[,i])
  pred_data <- pred_data[time(pred_data) >= start.date &
                           time(pred_data) <= end.date,]
  colnames(pred_data) <- c("Q","P","E")
  # # another storage data frame for the residuals
  resid_out <- data.frame(matrix(0,ncol=10,nrow=nrow(pred_data)))
  # load the relevant output
  load(paste("../Projectdata/HPCResults/monthly/",
             filelist[grep(Stations[i,1],filelist)],sep=""))
  # extract the model and update with the parameters
  Mod <- Output$mod

  mod_Res[[i]] <- Output$Store
  Chiew[,1] <- Stations[i,1]
  Results[,1] <- Stations[i,1]


  # run through all iterations
  for (j in 1:(nrow(Output$Store))) {
    # testing
    #j <- 1
    # update the model with the final fitted parameters, for each iteration
    Mod <- update(Mod, x1=Output$Store[j,8],x2=Output$Store[j,5],
                  x3=Output$Store[j,6],x4=Output$Store[j,7],
                  etmult=Output$Store[j,9],
                  return_state=F)


    # now predict the model output and use pred_data
    pred_mod <- predict(Mod,newdata=pred_data, all=T,na.rm=F)

    # store the residuals
    resid_out[,j] <- pred_data$Q-pred_mod

    Results[j,2:3] <- c(summary(Mod)$r.squared,summary(Mod)$rel.bias)

    # Now run the Chiew 2006 simulations on all the data
    mu <- cbind(rep(c(-15,-10,0,10),3),c(rep(0,4),rep(5,4),rep(10,4)))
    # Create the precipitation and ET data variations
    # station data
    RAIN <- rain_zoo_m
    test <- list()
```

```r
    for (k in 1:nrow(mu)) {
      temp <- as.data.frame(cbind((1+mu[k,1]/100)*RAIN[,i],
                          (1+mu[k,2]/100)*maxT_zoo_m[,i]))
      test[[k]] <- do.call(cbind,apply(temp,2,function(x) aggregate(x,
                     list(year=format(time(flow_zoo_m),"%Y")),sum,na.rm=T)))
      test[[k]] <- test[[k]][,-3]
    }
    clim_adj <- do.call(rbind,test)

    # now run the different pred results
    for (k in 1:ncol(pred_results)) {
      # run the model over all data
      pred_data2 <- window(merge(flow_zoo_m[,i],
                             (1+mu[k,1]/100)*RAIN[,i],
                             (1+mu[k,2]/100)*maxT_zoo_m[,i]))
      colnames(pred_data2) <- c("Q","P","E")

      pred_results[,k] <- predict(Mod,newdata=pred_data2, all=T,na.rm=F)
    }
    # summarise the data annually
    pred_ann <- apply(pred_results,2,
         function(x) aggregate(x,list(year=format(time(flow_zoo_m),"%Y")),
                                  sum,na.rm=T))
    ann_flow <- rep(pred_ann[[1]][,2],6)
    pred_t <- do.call(rbind,pred_ann)
    # Now add the ET and precipitation data
    pred_ann <- data.frame(pred_t,rain=clim_adj[,2],maxT=clim_adj[,3])
    # summarise base rain and temp
    ann_rain <- rep(aggregate(RAIN[,i],list(year=format(time(flow_zoo_m),"%Y")),
                          sum,na.rm=T),6)
    ann_maxT <- rep(aggregate(maxT_zoo_m[,i],
                          list(year=format(time(flow_zoo_m),"%Y")),
                          sum,na.rm=T),6)

    # Now calculate the difference
    pred_diff <- pred_ann
    pred_diff[,2] <- pred_diff[,2] - ann_flow
    pred_diff[,3] <- pred_diff[,3] - ann_rain
    pred_diff[,4] <- pred_diff[,4] - ann_maxT
    # Now fit a linear model (least squares (Chiew, 2006))
    fit <- lm(x~rain + maxT,data=pred_diff)
    # store the results
    Chiew[j,2:5] <- c(coef(fit)[2:3],summary(fit)$coefficients[2:3,4])

  }
  Chiew_Res[[i]] <- Chiew
  sum_Res[[i]] <- Results
  Residuals[[i]] <- resid_out
}
```

We can now temporary write away the results and the residuals and make some initial plots. Further plots will be generated later when comparing to the non-parametric epsilon (ϵ).

```r
# write away the results
OutputTrends <- do.call(rbind,sum_Res)
write.csv(OutputTrends,
          file="../ProjectData/MonthlyGR4JHPC_modelperformance.csv",
          row.names=F)

OutputChiew <- do.call(rbind,Chiew_Res)
write.csv(OutputChiew,file="../ProjectData/MonthlyGR4JHPC_ChiewAnalysis.csv",
          row.names=F)

pander(OutputChiew, caption="Results GR4J epsilon fit with significance")
```

Table 1: Results GR4J epsilon fit with significance

station	eta_p	eta_e	pvalue_eta_p	pvalue_eta_e
COTT	0.6686	-0.04063	1.324e-104	5.056e-07
COTT	0.6686	-0.04063	1.321e-104	5.055e-07
COTT	0.6686	-0.04063	1.322e-104	5.057e-07
COTT	0.6686	-0.04063	1.318e-104	5.061e-07
COTT	0.5749	-0.0266	1.281e-101	0.0001699
COTT	0.5749	-0.0266	1.283e-101	0.00017
COTT	0.6912	-0.04809	1.57e-97	5.55e-08
COTT	0.6685	-0.04062	1.315e-104	5.075e-07
COTT	0.6685	-0.04062	1.323e-104	5.067e-07
COTT	0.6685	-0.04063	1.32e-104	5.063e-07
RUTH	0.991	-0.03949	6.454e-151	2.092e-08
RUTH	0.991	-0.03949	6.43e-151	2.09e-08
RUTH	0.991	-0.03949	6.488e-151	2.093e-08
RUTH	0.991	-0.03949	6.424e-151	2.091e-08
RUTH	0.991	-0.03949	6.442e-151	2.091e-08
RUTH	0.991	-0.03949	6.427e-151	2.091e-08
RUTH	0.8702	-0.04734	2.503e-133	1.19e-11
RUTH	0.991	-0.03949	6.393e-151	2.089e-08
RUTH	0.991	-0.03949	6.538e-151	2.093e-08
RUTH	0.991	-0.03949	6.452e-151	2.092e-08
CORA	0.8366	-0.0449	9.585e-149	4.12e-16
CORA	0.8367	-0.0449	9.323e-149	4.124e-16
CORA	0.8367	-0.04489	9.407e-149	4.135e-16
CORA	0.8367	-0.04489	9.326e-149	4.127e-16
CORA	0.8367	-0.0449	9.314e-149	4.127e-16
CORA	0.8367	-0.04489	9.358e-149	4.128e-16
CORA	0.8367	-0.0449	9.348e-149	4.121e-16
CORA	0.8367	-0.04489	9.362e-149	4.132e-16
CORA	0.8367	-0.04489	9.365e-149	4.137e-16
CORA	0.8367	-0.0449	9.578e-149	4.13e-16
ELIZ	0.8985	-0.05602	4.615e-160	8.088e-12
ELIZ	0.8985	-0.05602	4.62e-160	8.089e-12
ELIZ	0.8985	-0.05602	4.676e-160	8.102e-12
ELIZ	0.8985	-0.05602	4.593e-160	8.083e-12
ELIZ	0.8985	-0.05602	4.645e-160	8.095e-12
ELIZ	0.8516	-0.05213	3.237e-168	1.937e-12
ELIZ	0.8985	-0.05602	4.588e-160	8.082e-12
ELIZ	0.8985	-0.05602	4.659e-160	8.098e-12

station	eta_p	eta_e	pvalue_eta_p	pvalue_eta_e
ELIZ	0.8985	-0.05602	4.596e-160	8.084e-12
ELIZ	0.8985	-0.05602	4.614e-160	8.088e-12
COCH	1.011	-0.09007	1.96e-232	1.203e-17
COCH	1.011	-0.0901	1.975e-232	1.187e-17
COCH	1.007	-0.08977	2.594e-235	3.844e-18
COCH	1.011	-0.09008	1.896e-232	1.183e-17
COCH	1.011	-0.09011	1.801e-232	1.162e-17
COCH	1.007	-0.08978	2.481e-235	3.812e-18
COCH	1.007	-0.08978	2.577e-235	3.833e-18
COCH	0.9867	-0.07831	1.599e-232	1.609e-14
COCH	1.011	-0.09009	1.846e-232	1.174e-17
COCH	1.007	-0.08978	2.817e-235	3.904e-18
COEN	0.9396	-0.03004	5.995e-218	1.228e-11
COEN	0.9396	-0.03004	5.984e-218	1.226e-11
COEN	0.9396	-0.03004	6.025e-218	1.223e-11
COEN	0.9396	-0.03004	6.008e-218	1.225e-11
COEN	0.9396	-0.03004	6.007e-218	1.225e-11
COEN	0.9396	-0.03004	5.983e-218	1.225e-11
COEN	0.9306	-0.03056	2.492e-215	6.934e-12
COEN	0.9396	-0.03004	5.996e-218	1.225e-11
COEN	0.9307	-0.03056	2.497e-215	6.92e-12
COEN	0.9307	-0.03056	2.499e-215	6.918e-12
SCOT	0.5402	-0.03173	5.667e-159	8.549e-20
SCOT	0.5146	-0.02864	9.087e-171	2.291e-20
SCOT	0.54	-0.03171	6.557e-159	9.049e-20
SCOT	0.5401	-0.03172	6.042e-159	8.805e-20
SCOT	0.5402	-0.03172	5.837e-159	8.668e-20
SCOT	0.5146	-0.02864	9.077e-171	2.291e-20
SCOT	0.5146	-0.02864	9.101e-171	2.292e-20
SCOT	0.5403	-0.03174	5.698e-159	8.572e-20
SCOT	0.5403	-0.03173	5.563e-159	8.524e-20
SCOT	0.5402	-0.03172	5.805e-159	8.677e-20
HELL	1.027	-0.05568	1.071e-267	2.183e-20
HELL	1.027	-0.05568	1.075e-267	2.195e-20
HELL	1.027	-0.05568	1.066e-267	2.189e-20
HELL	1.027	-0.05568	1.071e-267	2.188e-20
HELL	1.027	-0.05568	1.052e-267	2.193e-20
HELL	1.027	-0.05568	1.073e-267	2.188e-20
HELL	1.027	-0.05568	1.096e-267	2.19e-20
HELL	1.068	-0.02795	1.393e-220	0.0002904
HELL	1.068	-0.02796	1.352e-220	0.0002885
HELL	1.027	-0.05568	1.076e-267	2.182e-20
NIVE	0.9359	-0.09052	1.519e-243	5.492e-25
NIVE	0.9358	-0.09051	1.537e-243	5.477e-25
NIVE	0.9359	-0.09053	1.484e-243	5.417e-25
NIVE	0.9359	-0.09052	1.508e-243	5.452e-25
NIVE	0.9359	-0.09053	1.488e-243	5.426e-25
NIVE	0.9358	-0.09052	1.489e-243	5.394e-25
NIVE	0.9358	-0.09052	1.506e-243	5.393e-25
NIVE	0.9358	-0.09052	1.507e-243	5.397e-25
NIVE	0.9358	-0.09051	1.537e-243	5.481e-25
NIVE	0.9357	-0.09051	1.53e-243	5.424e-25

station	eta_p	eta_e	pvalue_eta_p	pvalue_eta_e
MURR	0.7978	-0.02426	3.85e-226	2.777e-10
MURR	0.7978	-0.02426	3.872e-226	2.788e-10
MURR	0.9726	-0.08459	7.077e-182	1.498e-39
MURR	0.7978	-0.02426	3.832e-226	2.781e-10
MURR	0.7978	-0.02426	3.849e-226	2.776e-10
MURR	0.7978	-0.02426	3.86e-226	2.784e-10
MURR	0.7978	-0.02426	3.892e-226	2.78e-10
MURR	0.7978	-0.02426	3.85e-226	2.777e-10
MURR	0.7978	-0.02426	3.842e-226	2.771e-10
MURR	0.7536	-0.01796	4.071e-229	4.119e-07
SOUT	1.084	-0.08123	1.155e-262	1.962e-39
SOUT	1.084	-0.08123	1.158e-262	1.962e-39
SOUT	1.084	-0.08122	1.156e-262	1.967e-39
SOUT	1.084	-0.08123	1.155e-262	1.964e-39
SOUT	1.084	-0.08122	1.156e-262	1.964e-39
SOUT	1.084	-0.08123	1.157e-262	1.962e-39
SOUT	1.084	-0.08122	1.144e-262	1.971e-39
SOUT	1.084	-0.08122	1.156e-262	1.964e-39
SOUT	1.166	-0.07507	1.905e-267	4.564e-32
SOUT	1.084	-0.08122	1.154e-262	1.966e-39
YARR	0.1169	-0.01072	7.48e-80	3.223e-11
YARR	0.117	-0.01072	7.267e-80	3.207e-11
YARR	0.07156	-0.006437	2.392e-34	0.0001426
YARR	0.117	-0.01072	7.436e-80	3.22e-11
YARR	0.117	-0.01072	7.431e-80	3.22e-11
YARR	0.1169	-0.01072	7.451e-80	3.22e-11
YARR	0.117	-0.01072	7.362e-80	3.215e-11
YARR	0.117	-0.01072	7.386e-80	3.216e-11
YARR	0.07156	-0.006437	2.405e-34	0.0001427
YARR	0.117	-0.01072	7.453e-80	3.221e-11
DOMB	0.639	-0.03919	3.22e-244	2.392e-21
DOMB	0.639	-0.03918	3.097e-244	2.403e-21
DOMB	0.639	-0.03919	3.102e-244	2.372e-21
DOMB	0.639	-0.03918	3.134e-244	2.411e-21
DOMB	0.6389	-0.03916	3.047e-244	2.467e-21
DOMB	0.6389	-0.03917	3.127e-244	2.463e-21
DOMB	0.639	-0.0392	3.146e-244	2.334e-21
DOMB	0.639	-0.03919	3.28e-244	2.375e-21
DOMB	0.6391	-0.03921	3.124e-244	2.323e-21
DOMB	0.639	-0.03919	3.001e-244	2.381e-21

```r
save(Residuals,file="../ProjectData/residuals/MonthlyGR4JHPCresiduals.Rdata")

OutputMod_GR4J <- do.call(rbind,mod_Res)
save(OutputMod_GR4J,file="../ProjectData/MonthlyGR4JHPCModelResults.Rdata")

OutputMod_GR4J <- OutputMod_GR4J[,c(1:4,ncol(OutputMod_GR4J))]

OutputMod_GR4J$model <- "MonthlyGR4J"

p <- ggplot(OutputMod_GR4J,aes(station,r.squared)) +  geom_boxplot()
```

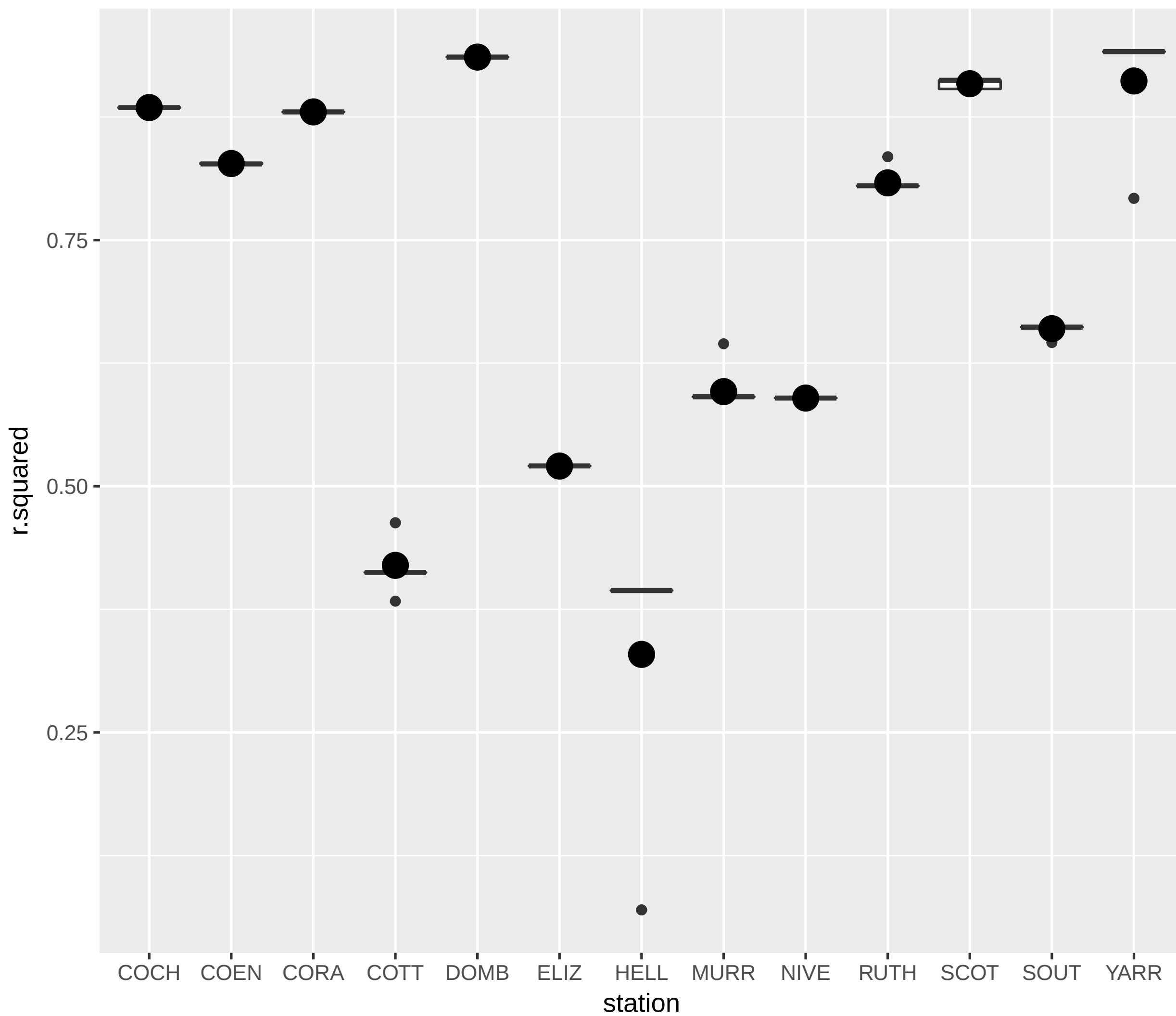

Figure 1: Calibration results for the GR4J model across 10 iterations using station rainfall data.

```
p <- p + stat_summary(fun.y=mean, geom="point", shape=16,
                      size=5,aes(col=rel.bias))
print(p)
```

4. SimHyd model results with station rainfall

Extract the modelling results from the SimHyd model, rerun the model, do the Chiew (2006) amplification analysis and write away the results.

```
# find the list of files with SimHyd results
filelist <- dir("../Projectdata/HPCResults/monthly/",
                pattern = "SimhydMonthCalibOutput")

for (i in seq_along(Stations[,1])) {
  # load the rainfall, ET and flow data
```

```r
pred_data <- merge(flow_zoo_m[,i], rain_zoo_m[,i], maxT_zoo_m[,i])
pred_data <- pred_data[time(pred_data) >= start.date &
                         time(pred_data) <= end.date,]
colnames(pred_data) <- c("Q","P","E")
# # another storage data frame for the residuals
resid_out <- data.frame(matrix(0,ncol=10,nrow=nrow(pred_data)))
# load the relevant output
load(paste("../Projectdata/HPCResults/monthly/",
           filelist[grep(Stations[i,1],filelist)],sep=""))
# extract the model and update with the parameters
Mod <- Output$mod

mod_Res[[i]] <- Output$Store
Chiew[,1] <- Stations[i,1]
Results[,1] <- Stations[i,1]


# run through all iterations
for (j in 1:(nrow(Output$Store))) {
  # testing
  #j <- 1
  # update the model with the final fitted parameters, for each iteration
  Mod <- update(Mod, INSC=Output$Store[j,7],COEFF=Output$Store[j,8],
                SQ=Output$Store[j,9],SMSC=Output$Store[j,10],
                SUB=Output$Store[j,11],CRAK=Output$Store[j,12],
                K=Output$Store[j,13],
              etmult=Output$Store[j,14], DELAY=Output$Store[j,5],
              X_m = Output$Store[j,6],
            return_state=F)


  # now predict the model output and use pred_data
  pred_mod <- predict(Mod,newdata=pred_data, all=T,na.rm=F)

  # store the residuals
  resid_out[,j] <- pred_data$Q-pred_mod

  Results[j,2:3] <- c(summary(Mod)$r.squared,summary(Mod)$rel.bias)

  # Now run the Chiew 2006 simulations on all the data
  mu <- cbind(rep(c(-15,-10,0,10),3),c(rep(0,4),rep(5,4),rep(10,4)))
  # Create the precipitation and ET data variations
  # station data
  RAIN <- rain_zoo_m
  test <- list()
  for (k in 1:nrow(mu)) {
    temp <- as.data.frame(cbind((1+mu[k,1]/100)*RAIN[,i],
                          (1+mu[k,2]/100)*maxT_zoo_m[,i]))
    test[[k]] <- do.call(cbind,apply(temp,2,function(x) aggregate(x,
                      list(year=format(time(flow_zoo_m),"%Y")),sum,na.rm=T)))
    test[[k]] <- test[[k]][,-3]
  }
  clim_adj <- do.call(rbind,test)
```

```r
    # now run the different pred results
    for (k in 1:ncol(pred_results)) {
      # run the model over all data
      pred_data2 <- window(merge(flow_zoo_m[,i],
                                 (1+mu[k,1]/100)*RAIN[,i],
                                 (1+mu[k,2]/100)*maxT_zoo_m[,i]))
      colnames(pred_data2) <- c("Q","P","E")

      pred_results[,k] <- predict(Mod,newdata=pred_data2, all=T,na.rm=F)
    }
    # summarise the data annually
    pred_ann <- apply(pred_results,2,
              function(x) aggregate(x,list(year=format(time(flow_zoo_m),"%Y")),
                                          sum,na.rm=T))
    ann_flow <- rep(pred_ann[[1]][,2],6)
    pred_t <- do.call(rbind,pred_ann)
    # Now add the ET and precipitation data
    pred_ann <- data.frame(pred_t,rain=clim_adj[,2],maxT=clim_adj[,3])
    # summarise base rain and temp
    ann_rain <- rep(aggregate(RAIN[,i],list(year=format(time(flow_zoo_m),"%Y")),
                              sum,na.rm=T),6)
    ann_maxT <- rep(aggregate(maxT_zoo_m[,i],
                              list(year=format(time(flow_zoo_m),"%Y")),
                              sum,na.rm=T),6)

    # Now calculate the difference
    pred_diff <- pred_ann
    pred_diff[,2] <- pred_diff[,2] - ann_flow
    pred_diff[,3] <- pred_diff[,3] - ann_rain
    pred_diff[,4] <- pred_diff[,4] - ann_maxT
    # Now fit a linear model (least squares (Chiew, 2006))
    fit <- lm(x~rain + maxT,data=pred_diff)
    # store the results
    Chiew[j,2:5] <- c(coef(fit)[2:3],summary(fit)$coefficients[2:3,4])


  }
  Chiew_Res[[i]] <- Chiew
  sum_Res[[i]] <- Results
  Residuals[[i]] <- resid_out
}
```

We can now temporary write away the results and the residuals and make some initial plots. Further plots will be generated later when comparing to the non-parametric epsilon (ϵ).

```r
# write away the results
OutputTrends <- do.call(rbind,sum_Res)
write.csv(OutputTrends,
          file="../ProjectData/MonthlySimHydHPC_modelperformance.csv",
          row.names=F)

OutputChiew <- do.call(rbind,Chiew_Res)
write.csv(OutputChiew,
          file="../ProjectData/MonthlySimHydHPC_ChiewAnalysis.csv",
```

```
         row.names=F)
pander(OutputChiew, caption="Results Simhyd epsilon fit with significance")
```

Table 2: Results Simhyd epsilon fit with significance

station	eta_p	eta_e	pvalue_eta_p	pvalue_eta_e
COTT	0.8731	-0.005486	2.966e-107	0.5914
COTT	0.873	-0.005482	2.736e-107	0.5916
COTT	0.8735	-0.005498	3.768e-107	0.591
COTT	0.8731	-0.005486	2.994e-107	0.5914
COTT	0.8738	-0.00551	3.123e-107	0.5901
COTT	0.8756	-0.005558	1.326e-106	0.5895
COTT	0.8756	-0.005558	1.326e-106	0.5895
COTT	0.8733	-0.005492	3.346e-107	0.5912
COTT	0.873	-0.005484	2.847e-107	0.5915
COTT	0.8751	-0.005531	7.217e-107	0.5903
RUTH	0.9163	-0.004606	6.7e-149	0.4782
RUTH	0.9163	-0.004606	6.7e-149	0.4782
RUTH	0.9163	-0.004606	6.698e-149	0.4782
RUTH	0.9163	-0.004606	6.7e-149	0.4782
RUTH	0.9163	-0.004606	6.699e-149	0.4782
RUTH	0.9163	-0.004606	6.697e-149	0.4782
RUTH	0.9163	-0.004606	6.709e-149	0.4782
RUTH	0.9163	-0.004606	6.7e-149	0.4782
RUTH	0.9163	-0.004606	6.7e-149	0.4782
RUTH	0.9163	-0.004606	6.7e-149	0.4782
CORA	0.945	-0.001059	1.552e-181	0.8305
CORA	0.945	-0.001059	1.552e-181	0.8305
CORA	0.945	-0.001059	1.552e-181	0.8305
CORA	0.945	-0.001059	1.561e-181	0.8305
CORA	0.945	-0.001059	1.552e-181	0.8305
CORA	0.945	-0.001059	1.52e-181	0.8305
CORA	0.945	-0.001059	1.552e-181	0.8305
CORA	0.945	-0.001059	1.552e-181	0.8305
CORA	0.945	-0.001059	1.558e-181	0.8305
CORA	0.9361	1.198	2.718e-83	0
ELIZ	0.9322	-0.0005869	6.222e-166	0.9416
ELIZ	0.9321	-0.0005881	7.771e-166	0.9415
ELIZ	0.932	-0.0005892	9.42e-166	0.9414
ELIZ	0.9325	-0.0009551	6.71e-166	0.9051
ELIZ	0.9316	-0.000593	1.952e-165	0.9411
ELIZ	0.9321	-0.0005882	7.816e-166	0.9415
ELIZ	0.9321	-0.0005875	6.884e-166	0.9415
ELIZ	0.9321	-0.0005877	7.163e-166	0.9415
ELIZ	0.9321	-0.0005883	7.936e-166	0.9415
ELIZ	0.9323	-0.0005864	5.763e-166	0.9416
COCH	0.9692	-0.004107	2.337e-246	0.6494
COCH	0.9692	-0.004107	2.337e-246	0.6494
COCH	0.9692	-0.004107	2.339e-246	0.6494
COCH	0.9692	-0.004107	2.337e-246	0.6494
COCH	0.9691	-0.004107	2.343e-246	0.6494
COCH	0.9692	-0.004107	2.337e-246	0.6494
COCH	0.9692	-0.004107	2.337e-246	0.6494

station	eta_p	eta_e	pvalue_eta_p	pvalue_eta_e
COCH	0.9692	-0.004107	2.337e-246	0.6494
COCH	0.9692	-0.004107	2.337e-246	0.6494
COCH	0.9692	-0.004107	2.337e-246	0.6494
COEN	0.9534	-0.001741	4.036e-213	0.6994
COEN	0.9534	-0.001741	4.028e-213	0.6994
COEN	0.9534	-0.001741	4.05e-213	0.6994
COEN	0.9534	-0.001741	4.027e-213	0.6994
COEN	0.9534	-0.001742	4.244e-213	0.6993
COEN	0.9533	-0.001744	5.333e-213	0.6991
COEN	0.9534	-0.001741	4.029e-213	0.6994
COEN	0.9534	-0.001741	4.029e-213	0.6994
COEN	0.9534	-0.001741	4.028e-213	0.6994
COEN	0.9534	-0.001741	4.028e-213	0.6994
SCOT	0.977	-0.000744	1.615e-294	0.7972
SCOT	0.977	-0.0007436	1.498e-294	0.7973
SCOT	0.977	-0.000744	1.601e-294	0.7972
SCOT	0.977	-0.00178	4.564e-295	0.5377
SCOT	0.9774	-0.000718	7.667e-299	0.8
SCOT	0.9769	-0.0007423	1.237e-294	0.7975
SCOT	0.9769	-0.0007422	9.8e-295	0.7975
SCOT	0.9769	-0.0007431	1.247e-294	0.7974
SCOT	0.977	-0.000744	1.624e-294	0.7972
SCOT	0.977	-0.002864	4.406e-295	0.3216
HELL	0.9754	-0.001877	3.069e-277	0.7184
HELL	0.9742	-0.004163	6.875e-269	0.443
HELL	0.9744	-0.001935	8.815e-269	0.7216
HELL	0.9191	-0.001845	2.143e-93	0.9005
HELL	0.9742	-0.001934	1.03e-268	0.7217
HELL	0.9754	-0.001872	7.424e-278	0.7183
HELL	0.9752	-0.001877	2.542e-277	0.7182
HELL	0.9519	-0.001858	2.771e-270	0.724
HELL	0.9755	-0.001873	1.266e-277	0.7185
HELL	0.9755	-0.001869	5.89e-278	0.7186
NIVE	0.9692	-0.0004891	1.87e-255	0.9517
NIVE	0.9691	-0.0004922	1.511e-255	0.9514
NIVE	0.9692	-0.0004892	1.831e-255	0.9517
NIVE	0.9692	-0.0004892	1.837e-255	0.9517
NIVE	0.9692	-0.0004891	1.867e-255	0.9517
NIVE	0.9694	-0.0004925	1.558e-255	0.9513
NIVE	0.9694	-0.0007286	1.544e-255	0.9281
NIVE	0.9692	-0.0004891	1.87e-255	0.9517
NIVE	0.9692	-0.0004891	1.864e-255	0.9517
NIVE	0.9692	-0.0004891	1.868e-255	0.9517
MURR	0.9645	-0.001225	2.214e-255	0.7536
MURR	0.9624	-0.001201	3.02e-257	0.7555
MURR	0.9643	-0.001233	1.382e-254	0.7529
MURR	0.9624	-0.001201	3.021e-257	0.7555
MURR	0.963	-0.001213	3.483e-256	0.7547
MURR	0.9624	-0.001201	3.021e-257	0.7555
MURR	0.9677	-0.001293	1.007e-249	0.7486
MURR	0.9624	-0.001201	3.021e-257	0.7555
MURR	0.964	-0.001229	5.393e-255	0.7533

station	eta_p	eta_e	pvalue_eta_p	pvalue_eta_e
MURR	0.9647	-0.00124	5.056e-254	0.7524
SOUT	0.9638	-0.002346	1.028e-254	0.6536
SOUT	0.9638	-0.002346	1.028e-254	0.6536
SOUT	0.9638	-0.002346	1.028e-254	0.6536
SOUT	0.9638	-0.002346	1.028e-254	0.6536
SOUT	0.9638	-0.002346	1.027e-254	0.6536
SOUT	0.9638	-0.002346	1.028e-254	0.6536
SOUT	0.9638	-0.002346	9.902e-255	0.6536
SOUT	0.9638	-0.002346	1.028e-254	0.6536
SOUT	0.9638	-0.002346	1.028e-254	0.6536
SOUT	0.9638	-0.002346	9.879e-255	0.6537
YARR	0.9814	-0.0009162	2.184e-295	0.7979
YARR	0.9813	-0.0009078	2.216e-297	0.7978
YARR	0.9814	-0.0009186	1.563e-296	0.7963
YARR	0.9812	-0.0009028	9.136e-298	0.7984
YARR	0.9813	-0.0009032	1.052e-297	0.7984
YARR	0.9814	-0.0009188	1.352e-296	0.7962
YARR	0.982	-0.0008218	4.368e-307	0.8077
YARR	0.9836	-0.0008974	1.5e-298	0.7993
YARR	0.9836	-0.0008982	1.494e-298	0.7992
YARR	0.9814	-0.0009162	2.184e-295	0.7979
DOMB	0.9858	-0.0001607	4.545e-322	0.9687
DOMB	0.9859	-0.000161	7.115e-322	0.9687
DOMB	0.9859	-0.0001609	7.115e-322	0.9687
DOMB	0.9859	-0.0001608	7.115e-322	0.9687
DOMB	0.9859	-0.0001608	7.115e-322	0.9687
DOMB	0.9859	-0.0001608	7.115e-322	0.9687
DOMB	0.9859	-0.0001608	7.115e-322	0.9687
DOMB	0.9859	-0.0001609	7.115e-322	0.9687
DOMB	0.9859	-0.0001608	7.115e-322	0.9687
DOMB	0.9859	-0.000161	7.115e-322	0.9687

```r
save(Residuals,
     file="../ProjectData/residuals/MonthlySimHydHPCresiduals.Rdata")

OutputMod_SimHyd <- do.call(rbind,mod_Res)
save(OutputMod_SimHyd,
     file="../ProjectData/MonthlySimHydHPCModelResults.Rdata")

OutputMod_SimHyd <- OutputMod_SimHyd[,c(1:4,ncol(OutputMod_SimHyd))]
OutputMod_SimHyd$model <- "MonthlySimHydStationData"

p <- ggplot(OutputMod_SimHyd,aes(station,r.squared)) +  geom_boxplot()
p <- p + stat_summary(fun.y=mean, geom="point", shape=16,
                      size=5,aes(col=rel.bias))
print(p)
```

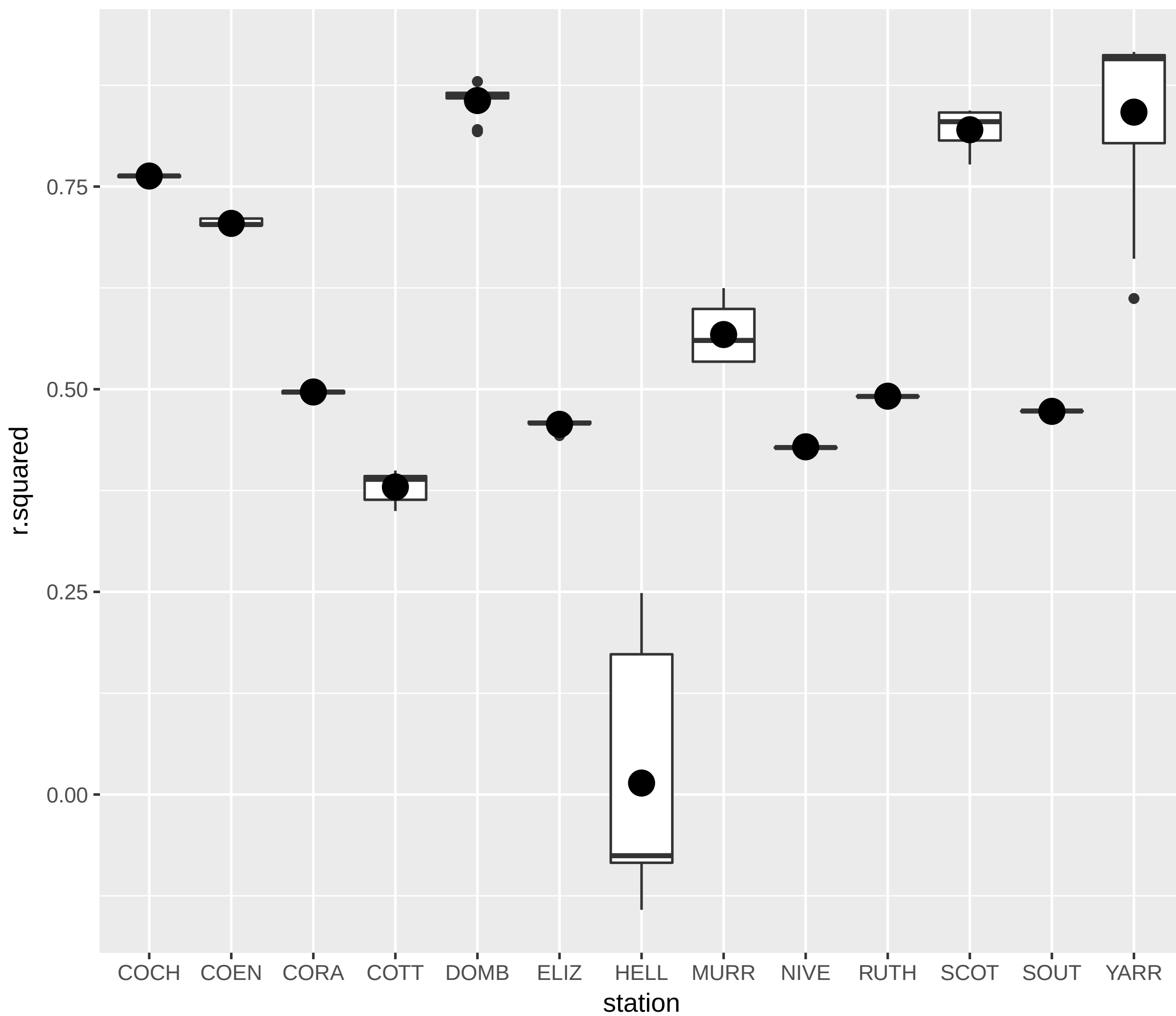

Figure 2: Calibration results for the SimHyd model across 10 iterations using station rainfall data.

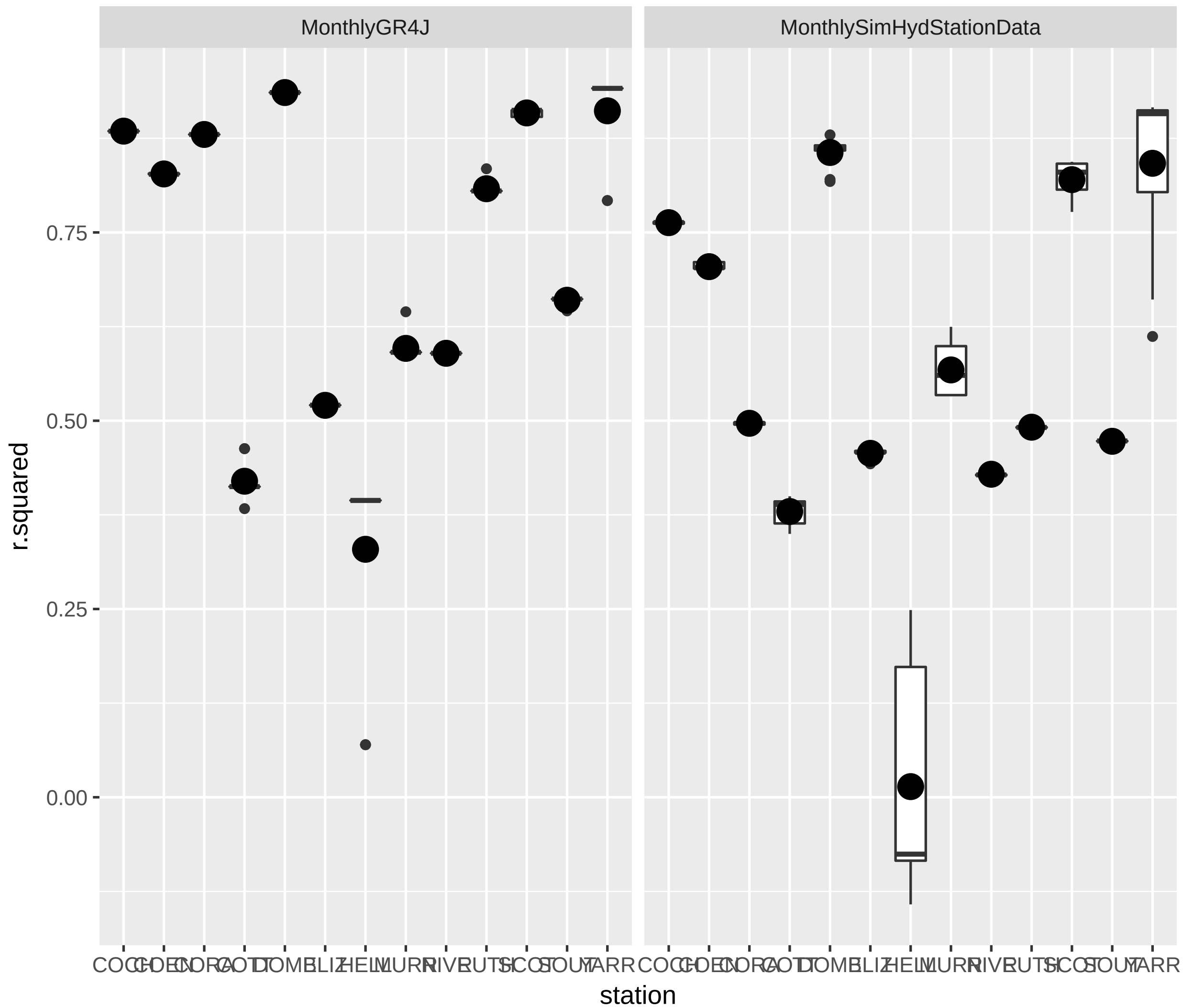

Figure 3: Comparing the performance of different models

6. Final plot comparing performance of all models

```
OutputMod <- rbind(OutputMod_GR4J, OutputMod_SimHyd)
p <- ggplot(OutputMod,aes(station,r.squared)) +  geom_boxplot()
p <- p + stat_summary(fun.y=mean, geom="point", shape=16,
                      size=5,aes(colour=rel.bias))
p <- p + facet_wrap(~model)
print(p)
```

```
# Write away the data
save(OutputMod,file="../ProjectData/MonthlyModelResults.Rdata")
```