Analysis of HPC results 2

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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(hydromad)
library(Kendall)
library(mgcv)
```

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 seventh part of the series that performs the Mann-Kendall and gam trend analysis on the residuals calculated in part 6, as well as comparing the non-parametric ϵ from the fifth part of the series with the numerical modelling ϵ following Chiew (2006).

FRANCIS H. S. CHIEW (2006) Estimation of rainfall elasticity of streamflow in Australia, Hydrological Sciences Journal, 51:4, 613-625, DOI: 10.1623/hysj.51.4.613

This script also generates final versions of *Figure 3* and *Figure 9* in the manuscript.

To recap, we have residuals for predictions between 1980 - 2010 of calibrated models across 13 catchments (calibrated on 1970 - 1980). However, there are results for both station rainfall and gridded rainfall for both the SimHyd and GR4J models to make sure there is no difference between these. For all the fits, performances were extracted and initial plots made in part 6 of the series. It is clear from those plots (which will be partly repeated here) that SimHyd performed more poorly than GR4J and that the models using the gridded rainfall data performed consistently worse compared to the station rainfall data. As a result, the manuscript concentrates only on the station rainfall data as this gives the best model performances across the catchments.

The overall performance of the models across the catchments in this analysis are much worse than the performances reported in the orginal paper (Chiew, 2006), but this could be due to several major differences:

- Monthly data in Chiew (2006), daily data in this paper
- Several much larger catchments
- Silo gridded monthly rainfall

In particular the difference between daily and monthly data would have made a major difference in the calibration performance. However, overall, the calibration performance needs to be taken into account in relation to the Mann-Kendall trends in the residuals and the derived ϵ.

Apart from running a Mann Kendall trend analysis on the residuals, this document also fits a linear trend using GAMM as a comparison to the Mann-Kendall

```
load("data/ClimCh_project_MD.Rdata")

Results <- data.frame(station=character(length=10),trend=numeric(length=10),
                      p_trend=numeric(length=10),r_sq=numeric(length=10),
                      tau=numeric(length=10),p_tau=numeric(length=10),
                      Mod.r.sq=numeric(length=10), Mod.bias=numeric(length=10))
```

Mann Kendall and GAMM trend analysis of the residuals

GR4J model results with station data

```
# read in the residual data list from part 6 for all
load(file="../ProjectData/residuals/GR4JHPCresiduals.Rdata")

GR4J_results <- list()

# also read in the model performance from part 6 (OutputMod)
load("../ProjectData/ModelResults.Rdata")
Modelperf <- OutputMod[OutputMod$model=="GR4JStationData",]

# run through a loop
for (i in seq_along(Stations[,1])){
  Results[,1] <- Stations[i,1]
  # run over the 10 calibrations
  for (j in 1:ncol(Residuals[[i]])) {
# Create the residual data set for the GAM model
    mod_df <- data.frame(resid=Residuals[[i]][,j],trend=1:nrow(Residuals[[i]]))
    # run the GAMM and store results
    mod_test <- gam(resid~trend,data=mod_df,
                    na.action=na.omit,correlation=corCAR1())
    Results[j,2:4] <- c(as.numeric(summary(mod_test)$p.table[2,c(1,4)]),
                        as.numeric(summary(mod_test)$r.sq))
    # run the mann-kendall and store results
    MKout <- MannKendall(mod_df$resid)
    Results[j,5:6] <- as.numeric(MKout[1:2])

    # add the model performance
    Results[j,7:8] <- Modelperf[(i-1)+j,1:2]
  }
  GR4J_results[[i]] <- Results
}
```

GR4J results with gridded rainfall data

```
# read in the residual data list from part 6 for all stations
load(file="../ProjectData/residuals/GR4JGridHPCresiduals.Rdata")
```

```r
GR4JGrid_results <- list()
# from section 6 model performance
Modelperf <- OutputMod[OutputMod$model=="GR4JGriddedData",]


# run through a loop
for (i in seq_along(Stations[,1])){
  Results[,1] <- Stations[i,1]
  # run over the 10 calibrations
  for (j in 1:ncol(Residuals[[i]])) {
# Create the residual data set for the GAM model
    mod_df <- data.frame(resid=Residuals[[i]][,j],trend=1:nrow(Residuals[[i]]))
    # run the GAMM and store results
    mod_test <- gam(resid~trend,data=mod_df,
                    na.action=na.omit,correlation=corCAR1())
    Results[j,2:4] <- c(as.numeric(summary(mod_test)$p.table[2,c(1,4)]),
                        as.numeric(summary(mod_test)$r.sq))
    # run the mann-kendall and store results
    MKout <- MannKendall(mod_df$resid)
    Results[j,5:6] <- as.numeric(MKout[1:2])

    # add the model performance
    Results[j,7:8] <- Modelperf[(i-1)+j,1:2]
  }
  GR4JGrid_results[[i]] <- Results
}
```

SimHyd results with station rainfall data

```r
# read in the residual data list from part 6 for all stations
load(file="../ProjectData/residuals/SimHydHPCresiduals.Rdata")

Simhyd_results <- list()

# from section 6 model performance
Modelperf <- OutputMod[OutputMod$model=="SimHydStationData",]


# run through a loop
for (i in seq_along(Stations[,1])){
  Results[,1] <- Stations[i,1]
  # run over the 10 calibrations
  for (j in 1:ncol(Residuals[[i]])) {
# Create the residual data set for the GAM model
    mod_df <- data.frame(resid=Residuals[[i]][,j],trend=1:nrow(Residuals[[i]]))
    # run the GAMM and store results
    mod_test <- gam(resid~trend,data=mod_df,
                    na.action=na.omit,correlation=corCAR1())
    Results[j,2:4] <- c(as.numeric(summary(mod_test)$p.table[2,c(1,4)]),
                        as.numeric(summary(mod_test)$r.sq))
    # run the mann-kendall and store results
    MKout <- MannKendall(mod_df$resid)
```

```
    Results[j,5:6] <- as.numeric(MKout[1:2])

    # add the model performance
    Results[j,7:8] <- Modelperf[(i-1)+j,1:2]
  }
  Simhyd_results[[i]] <- Results
}
```

SimHyd results with gridded rainfall data

```
# read in the residual data list from part 6 for all stations
load(file="../ProjectData/residuals/SimHydGridHPCresiduals.Rdata")

SimhydGrid_results <- list()

# from section 6 model performance
Modelperf <- OutputMod[OutputMod$model=="SimHydGridStationData",]


# run through a loop
for (i in seq_along(Stations[,1])){
  Results[,1] <- Stations[i,1]
  # run over the 10 calibrations
  for (j in 1:ncol(Residuals[[i]])) {
# Create the residual data set for the GAM model
    mod_df <- data.frame(resid=Residuals[[i]][,j],trend=1:nrow(Residuals[[i]]))
    # run the GAMM and store results
    mod_test <- gam(resid~trend,data=mod_df,
                    na.action=na.omit,correlation=corCAR1())
    Results[j,2:4] <- c(as.numeric(summary(mod_test)$p.table[2,c(1,4)]),
                        as.numeric(summary(mod_test)$r.sq))
    # run the mann-kendall and store results
    MKout <- MannKendall(mod_df$resid)
    Results[j,5:6] <- as.numeric(MKout[1:2])

    # add the model performance
    Results[j,7:8] <- Modelperf[(i-1)+j,1:2]
  }
  SimhydGrid_results[[i]] <- Results
}
```

Plotting of all the trends (MK and GAMM)

```
# I need to make one df wich stacks MK and trend, best to do this via tibble
# first merge the lists into dataframes, add the model name and stack
OverallResults <- rbind(cbind(model="GR4J",do.call(rbind,GR4J_results)),
                        cbind(model="GR4JGrid",do.call(rbind,GR4JGrid_results)),
                        cbind(model="SimHyd",do.call(rbind,Simhyd_results)),
                        cbind(model="SimHydGrid",
                              do.call(rbind,SimhydGrid_results)))
```

```r
# now split the MK from the GAMM
OverallResults_GAMM <- cbind("Linear Trend",OverallResults[,c(1:4,8:9)])
OverallResults_MK <- cbind("Mann Kendall", OverallResults[,c(1:2,6:9)])
# make column names the same
colnames(OverallResults_GAMM) <-
  colnames(OverallResults_MK) <-
  c("Method", "Model","Station","trend","p_trend","rel.bias","r.squared")

# Now stack again
plot.df <- rbind(OverallResults_GAMM,OverallResults_MK)
plot.df$sig <- ifelse(plot.df$p_trend < 0.05,1,0)
```

Summary table of the trend values found in the analysis

From this data, we can also derive a summary table that summarises the slopes and Kendall tau values and indicates whether they are significant, by calculating the average of the "sig" column. A value of 1 would indicate all slopes are significant, while a value of 0 indicates all slopes are not significant.

```r
test <- group_by(plot.df,Station,Method,Model)
test2 <- summarize(test, Mean_slope=mean(trend),
                   significance=mean(sig))
LinearTrends <- filter(test2, Method=="Linear Trend")
MKtaus <- filter(test2, Method=="Mann Kendall")
final_table <- cbind(as.data.frame(LinearTrends)[,c(1,3:5)],
                     as.data.frame(MKtaus[,c(4,5)]))
colnames(final_table) <- c(colnames(test2)[c(1,3)],
                           "slope Linear","sign. Linear",
                           "MK tau", "sign. tau")
pander(final_table, caption="summary of slopes for models, methods and stations")
```

Table 1: summary of slopes for models, methods and stations

Station	Model	slope Linear	sign. Linear	MK tau	sign. tau
COCH	GR4J	-3.362e-05	1	0.03981	1
COCH	GR4JGrid	-0.0001033	1	-0.08689	1
COCH	SimHyd	-0.0001902	1	-0.03855	0.7
COCH	SimHydGrid	-7.117e-05	0.9	-0.02752	1
COEN	GR4J	2.497e-05	1	0.137	1
COEN	GR4JGrid	-1.79e-05	0	0.007133	0
COEN	SimHyd	2.214e-06	1	0.03271	1
COEN	SimHydGrid	-7.045e-06	0	0.01103	0.1
CORA	GR4J	-9.081e-06	0	0.008616	0
CORA	GR4JGrid	-0.0002112	1	-0.4397	1
CORA	SimHyd	0.02738	0.1	-0.05354	0.9
CORA	SimHydGrid	-7.354e-05	1	-0.07924	1
COTT	GR4J	-8.59e-07	0	-0.0401	1
COTT	GR4JGrid	-7.786e-05	1	-0.233	1
COTT	SimHyd	-1.948e-05	0.8	-0.0405	0.8
COTT	SimHydGrid	-8.239e-05	1	-0.07832	1
DOMB	GR4J	-9.475e-06	1	-0.09122	1
DOMB	GR4JGrid	2.894e-05	1	0.03613	1
DOMB	SimHyd	-5.689e-06	0	-0.01421	0.5

Station	Model	slope Linear	sign. Linear	MK tau	sign. tau
DOMB	SimHydGrid	6.437e-05	1	0.0248	1
ELIZ	GR4J	6.078e-05	1	0.009909	0
ELIZ	GR4JGrid	0.0001088	1	0.00963	0
ELIZ	SimHyd	6.561e-05	1	-0.01086	0.2
ELIZ	SimHydGrid	0.0001125	1	-0.009511	0.8
HELL	GR4J	-3.728e-05	1	-0.06094	1
HELL	GR4JGrid	2.008e-05	0	-0.01688	1
HELL	SimHyd	-2.897e-05	1	-0.03843	1
HELL	SimHydGrid	6.404e-05	1	0.01143	0.1
MURR	GR4J	-1.58e-05	1	-0.06759	1
MURR	GR4JGrid	-8.279e-05	1	-0.2598	1
MURR	SimHyd	-3.823e-05	1	-0.08879	1
MURR	SimHydGrid	-7.816e-05	1	-0.1151	1
NIVE	GR4J	3.684e-05	1	0.01694	1
NIVE	GR4JGrid	6.434e-05	1	0.01998	1
NIVE	SimHyd	6.66e-05	1	0.02474	0.8
NIVE	SimHydGrid	6.006e-05	1	0.006919	0
RUTH	GR4J	-6.625e-05	1	-0.2461	1
RUTH	GR4JGrid	-0.0001621	1	-0.3875	1
RUTH	SimHyd	-3.975e-05	0.9	-0.2099	1
RUTH	SimHydGrid	-0.0001128	1	-0.1137	1
SCOT	GR4J	-3.036e-06	0	-0.00438	0
SCOT	GR4JGrid	-1.378e-05	0.9	-0.01018	1
SCOT	SimHyd	-3.749e-06	0	-0.01559	1
SCOT	SimHydGrid	-1.669e-05	0.9	-0.01501	0.8
SOUT	GR4J	2.38e-05	1	0.03046	1
SOUT	GR4JGrid	-0.000109	1	-0.1293	1
SOUT	SimHyd	-2.357e-05	1	-0.04189	1
SOUT	SimHydGrid	-8.975e-05	1	-0.06327	1
YARR	GR4J	-7.109e-07	1	0.03566	1
YARR	GR4JGrid	2.332e-06	1	0.1069	1
YARR	SimHyd	4.285e-05	0.9	-0.009199	0.9
YARR	SimHydGrid	4.007e-05	1	-0.005332	0.1

Trends against r-squared of model calibration

```r
# Now plot the actual trends
p <- ggplot(plot.df, aes(x = r.squared, y = trend)) +
  scale_colour_manual(name="Model", values=c("darkGreen", "Red","Blue","purple"))+
  scale_shape_discrete(name="Significance") +#,low="red", high="blue")  +
  geom_point(aes(col=Model, pch=as.factor(sig))) +  facet_wrap(~ Method, scales="free", ncol=1)
p
```

This plot suggests that there is no real relationship between the model performance and the trend derived from the modelled data.

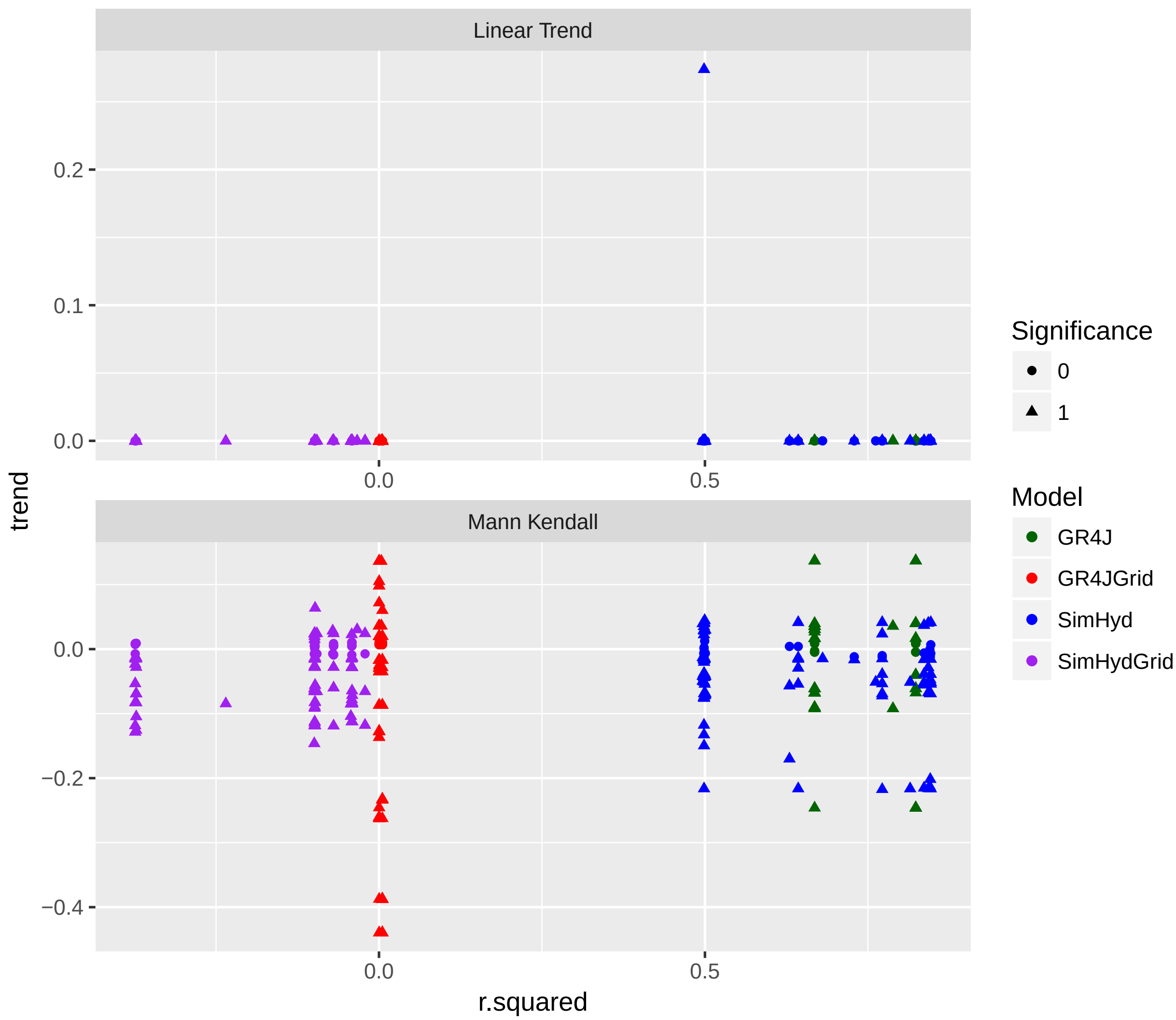

Figure 1: derived Mann Kendall trends and Linear Trends plotted agains the performance of the model

Figure 9

```
# Now plot the actual trends
p <- ggplot(plot.df, aes(x = Station, y = trend)) +
  scale_colour_continuous(name="significance",low="gray50", high="black")  +
  geom_boxplot(coef=0.5) +  facet_wrap(~ Model + Method,ncol=1)
p <- p + stat_summary(fun.y=mean, geom="point", shape=16,
                      aes(col=sig),lwd=2)

p <- p + ggtitle("Residual trends: predicted - observed 1980 - 2010") +
  theme(plot.title = element_text(lineheight=.8, face="bold"))+
  xlab("Station") +
  theme(axis.title.x = element_text(face="bold",  size=16),
        axis.text.x  = element_text(size=12)) +
  ylab("Trend estimate or Mann Kendall tau") +
  theme(axis.title.y = element_text(face="bold",  size=16),
        axis.text.y  = element_text(size=12)) +
  theme(legend.text = element_text(size = 12))+
  theme(legend.title = element_text(size=14, face="bold")) +
  theme(strip.text.x = element_text(size=10))

#save(p,file=paste(Today,"_ModelResidualTrendPlot.RData"))
p
```

This figure suggests that the overall slopes are small, and those close to 0 are not significant, which is the same as the earlier table.

Figure 9 publication quality

For this only plot the results from the non-gridded rainfall as the performance from the gridded rainfall modelling is poor.

```
plot.df1 <- plot.df[-(grep("GR4JGrid",plot.df$Model)),]
plot.df1 <- plot.df1[-(grep("SimHydGrid",plot.df1$Model)),]

p1 <- ggplot(plot.df1, aes(x = Station, y = trend)) +
  scale_colour_continuous(name="Significance\n",
                          low="gray50", high="black")  +
  geom_boxplot(coef=0.5) +  facet_wrap(~ Model + Method,ncol=1,
                               scales = "free")
p1 <- p1 + stat_summary(fun.y=mean, geom="point", shape=16,
                    aes(col=sig),lwd=2)

p1 <- p1 +   xlab("Station") +
  theme(axis.title.x = element_text(face="bold",  size=16),
        axis.text.x  = element_text(size=12)) +
  ylab("Trend estimate or Mann Kendall tau") +
  theme(axis.title.y = element_text(face="bold",  size=16),
        axis.text.y  = element_text(size=12)) +
  theme(legend.text = element_text(size = 12))+
  theme(legend.title = element_text(size=16, face="bold")) +
  theme(strip.text.x = element_text(size=14, face="bold"))
```

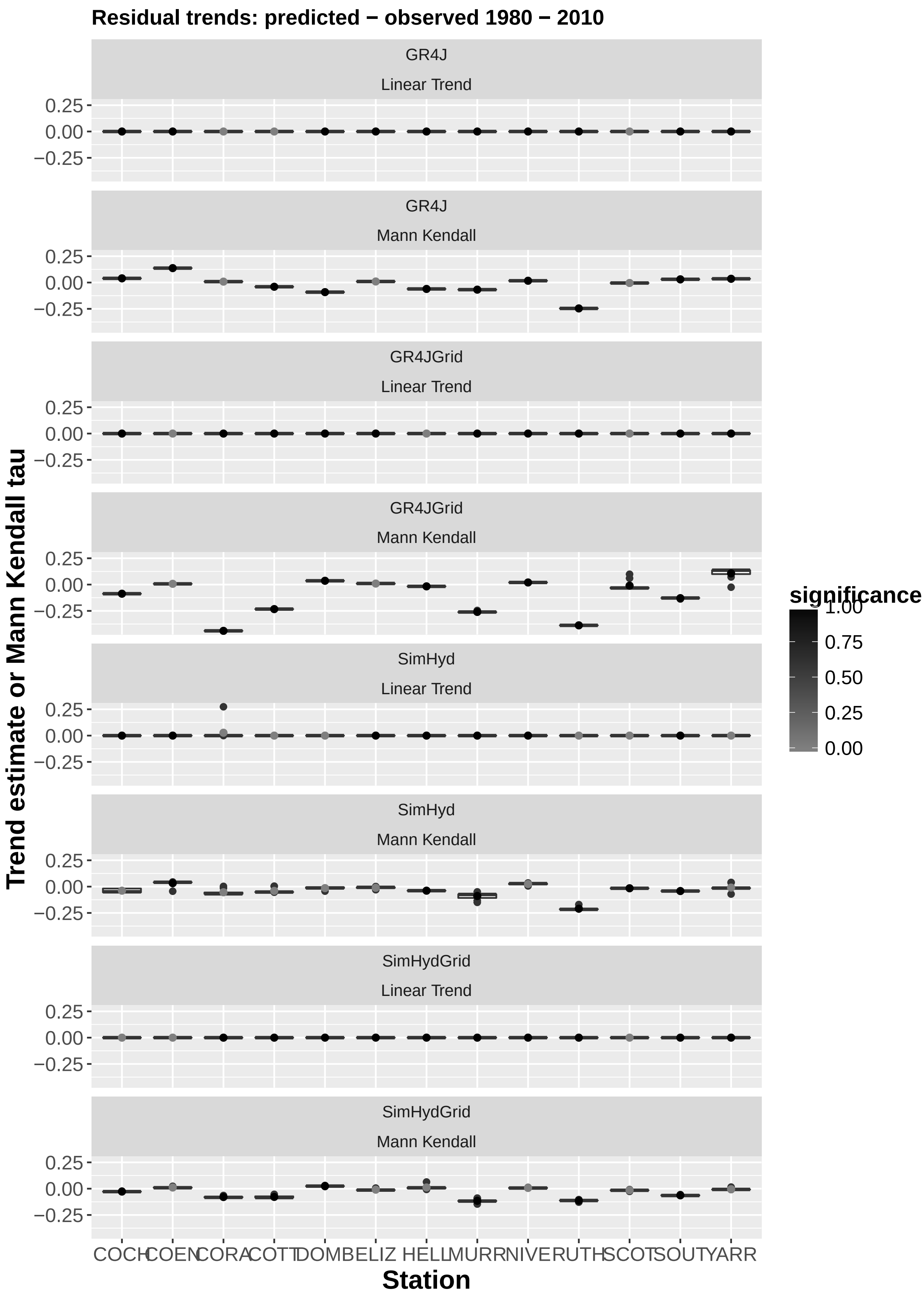

Figure 2: Analysis of residual trends between modelled and observed data for models calibrated on 1970 - 1979 and predicting 1980 - 2010. The level of gray colour indicates the significance, with dark coloured distributions being more significant. Boxplots represent the range of results from the 10 shuffled complex evolution calibrations.

```r
tiff("../manuscript/Figure9_ModelResidualTrendPlot.tif",
  width=16*480,height=12*480,
     res=600, compression="lzw")
print(p1)
dev.off()
```

```
## pdf
##   2
```

ϵ plotting

First read in the data from the previous analyses, and combine to create an overall data frame for plotting.

```
OutputChiewSimHyd <- read.csv("../ProjectData/SimHydHPC_ChiewAnalysis.csv")
OutputChiewSimHydGrid <-
  read.csv("../ProjectData/SimHydGridHPC_ChiewAnalysis.csv")
OutputChiewGR4J <- read.csv("../ProjectData/GR4JHPC_ChiewAnalysis.csv")
OutputChiewGR4JGrid <- read.csv("../ProjectData/GR4JGridHPC_ChiewAnalysis.csv")
non_par_eta <- read.csv("Data/non_par_eta.csv")


OutputChiewSimHyd$mod <- "SimHyd"
OutputChiewSimHydGrid$mod <- "SimHydGrid"
OutputChiewGR4J$mod <- "GR4J"
OutputChiewGR4JGrid$mod <- "GR4JGrid"

## combine everything into one df
OutputChiew <- cbind(rbind(OutputChiewSimHyd,OutputChiewSimHydGrid,
                           OutputChiewGR4J, OutputChiewGR4JGrid),
                     c(rep(non_par_eta$stn_eta,each=10),
                       rep(non_par_eta$grid_eta,each=10),
                       rep(non_par_eta$stn_eta,each=10),
                       rep(non_par_eta$grid_eta,each=10)))
colnames(OutputChiew)[7] <- "np_eta_p"
```

A plot comparing the model derived and the non-parametric ϵ values

This plot shows the non-parametric ϵ values in comparison with the model derived values. A thing to observe is thata the model derived ϵ values for SimHyd are essentially all the same (with some small variation), regardless of the gridded or non-gridded data. In contracst the values derived using the GR4J modelling are much more variable. However for both models, it is clear that the model derived ϵ values are much lower than most of the non-parametric values. However, it needs to be kept in mind that the model derived values are based on daily data, while the non-parametric values, which are much more aligned with the Chiew (2006) values, are again based on annual data.

This is *Figure 3* in the manuscript

```
p <- ggplot(OutputChiew, aes(x = station, y = eta_p)) +
  geom_boxplot(col="gray50", coef=0.5) +  facet_wrap(~ mod, ncol=1) +
  stat_summary(fun.y=mean, geom="point", shape=16, col="black",lwd=2)

p <- p +  geom_point(aes(x=station, y=np_eta_p),
           shape=17,size=3,colour="gray25", coef=0.5) +
        facet_wrap(~ mod,ncol=1)
```

```
## Warning: Ignoring unknown parameters: coef
```

```
p <- p +  xlab("Station") + ylim(-0.5,3) +
  theme(axis.title.x = element_text(face="bold",  size=14),
        axis.text.x  = element_text(size=12)) +
  ylab("Rainfall Elasticity") +
  theme(axis.title.y = element_text(face="bold",  size=16),
        axis.text.y  = element_text(size=12)) +
  theme(legend.text = element_text( size = 12))+
```

```r
  theme(legend.title = element_text(size=14, face="bold")) +
  theme(strip.text.x = element_text(size=14, face="bold"))
p
```

```
## Warning: Removed 1 rows containing non-finite values (stat_boxplot).
## Warning: Removed 1 rows containing non-finite values (stat_summary).
## Warning: Removed 20 rows containing missing values (geom_point).
```

```r
tiff("../manuscript/Figure3_RainfallElasticityPlot.tif",
  width=16*480,height=12*480,
     res=600, compression="lzw")
print(p)
```

```
## Warning: Removed 1 rows containing non-finite values (stat_boxplot).
## Warning: Removed 1 rows containing non-finite values (stat_summary).
## Warning: Removed 20 rows containing missing values (geom_point).
```

```r
dev.off()
```

```
## pdf
##   2
```

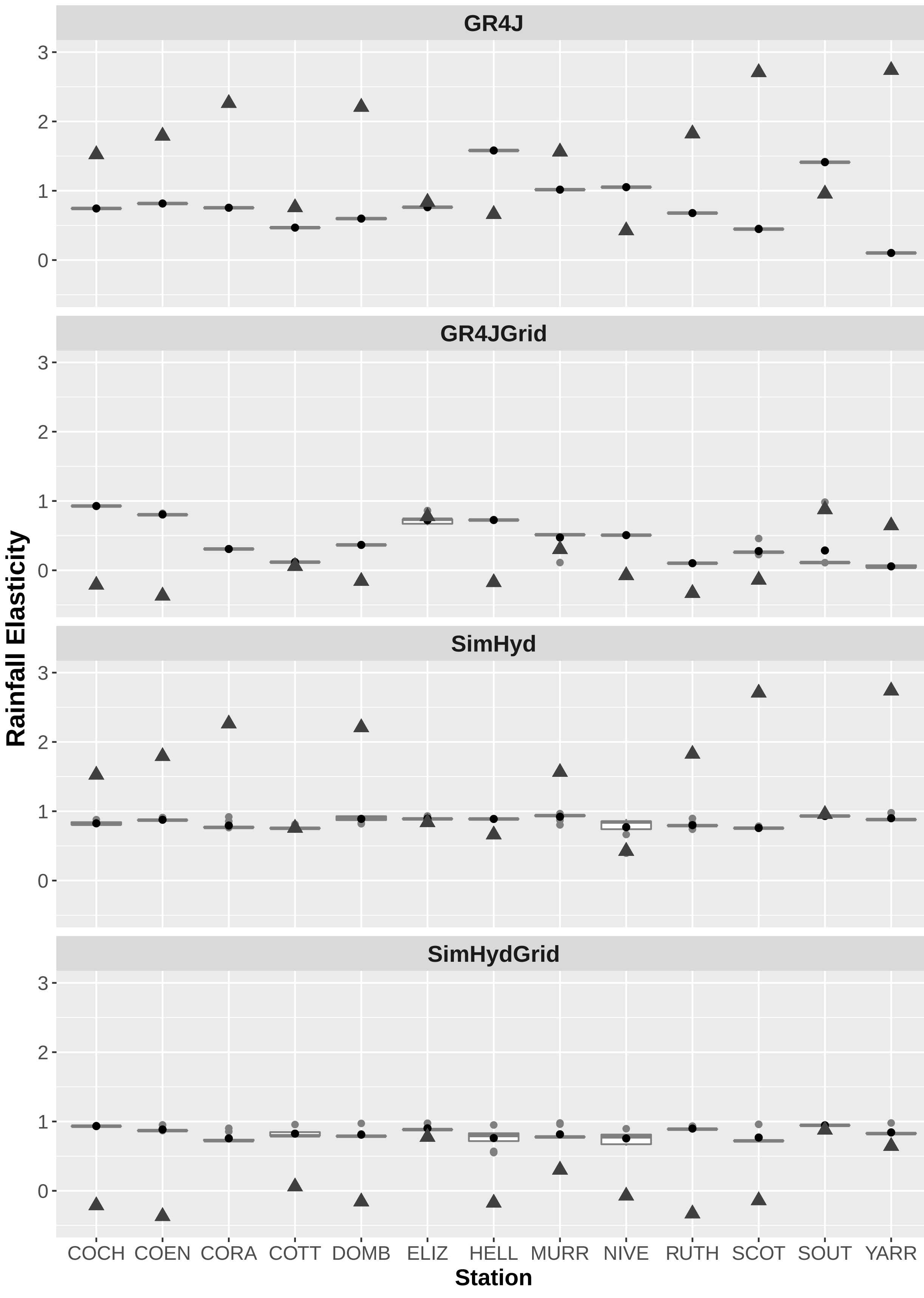

Figure 3: Rainfall elasticities calculated using a non-parametric method (Chiew, 2006) (grey triangles) and using two different rainfall runoff models (SimHyd and GR4J) and scaled gridded and non-griddd rainfall and temperature data (black dots (means) and grey boxplots with small black dots as outliers). The model calibrations were replicated 10 times to cover parameter equifinality. This equifinality is represented by the boxplots.

A plot of the performance of the models

This is a replotting of what was in part 6 of these documents to create *Figure 4* for the manuscript.

```
p <- ggplot(plot.df, aes(x = Station, y = r.squared)) +
  geom_boxplot(col="grey50", coef=0.75) +
  facet_wrap(~ Model,ncol=1, scales="free") +
  stat_summary(fun.y=mean, geom="point", shape=16,col="black",lwd=2)
p <- p + ggtitle("Model Calibration NSE") +
  theme(plot.title = element_text(lineheight=.8, face="bold"))+
  xlab("Station") +
  theme(axis.title.x = element_text(face="bold",  size=16),
        axis.text.x  = element_text(size=12)) +
  ylab("Nash Sutcliffe Efficiency") +
  theme(axis.title.y = element_text(face="bold",  size=16),
        axis.text.y  = element_text(size=12)) +
  theme(legend.text = element_text( size = 12))+
  theme(legend.title = element_text(size=14, face="bold")) +
  theme(strip.text.x = element_text(size=16))

p
```

```
#
```

Now replot just for the publication, without the title and only the station data results

```
p <- ggplot(plot.df1, aes(x = Station, y = r.squared)) +
  geom_boxplot(col="grey50", coef=0.5) +
  facet_wrap(~ Model,ncol=1) +
  stat_summary(fun.y=mean, geom="point", shape=16,col="black",lwd=2)
p <- p +  xlab("Station") + ylim(0.4,1) +
  theme(axis.title.x = element_text(face="bold",  size=16),
        axis.text.x  = element_text(size=12)) +
  ylab("Nash Sutcliffe Efficiency") +
  theme(axis.title.y = element_text(face="bold",  size=16),
        axis.text.y  = element_text(size=12)) +
  theme(legend.text = element_text( size = 12))+
  theme(legend.title = element_text(size=14, face="bold")) +
  theme(strip.text.x = element_text(size=16))

 # publication quality
 tiff("../manuscript/Figure4_ModelCalStats.tif",
      width=16*480,height=12*480,
      res=600, compression="lzw")
 print(p)
 dev.off()
```

```
## pdf
##   2
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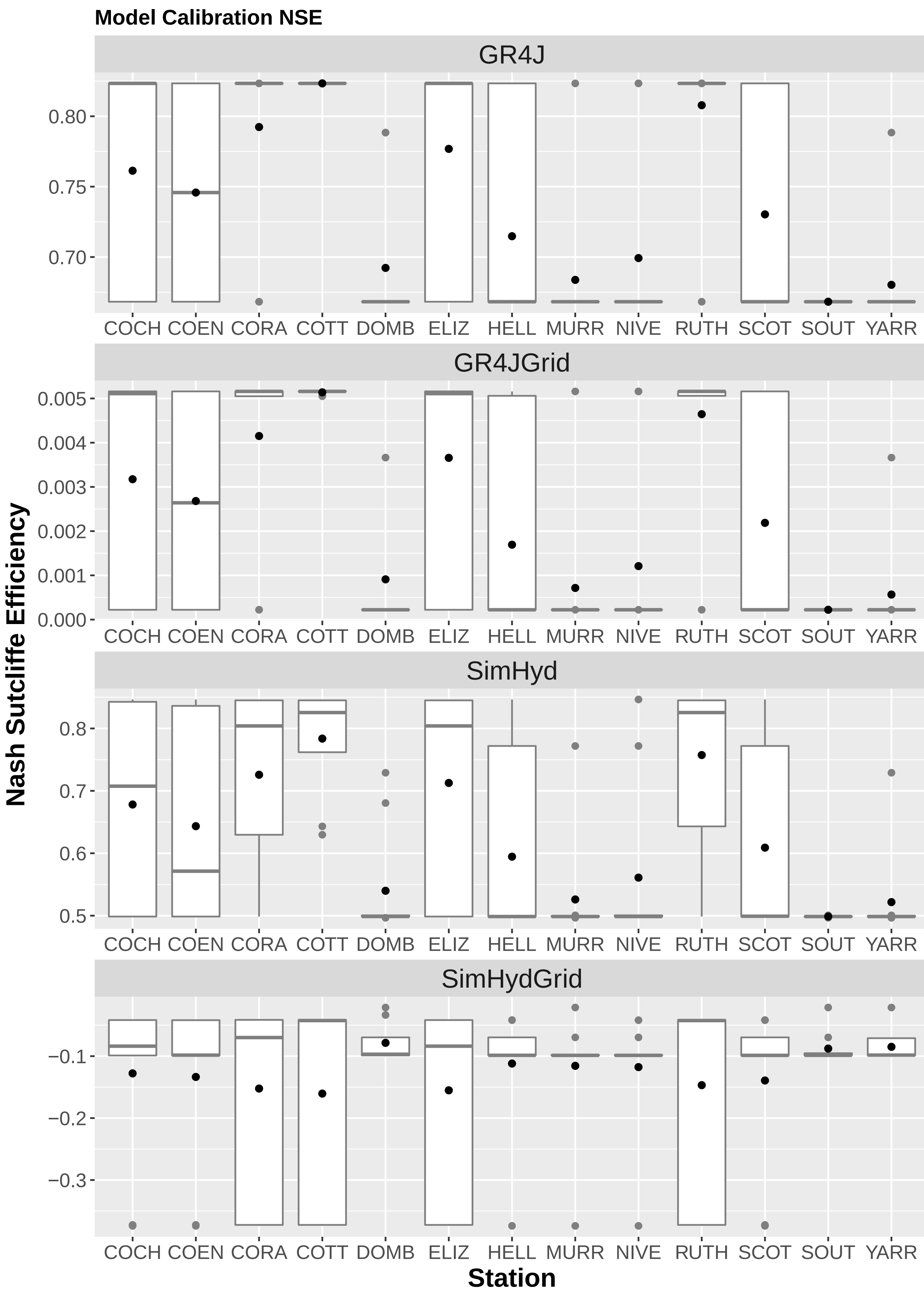

Figure 4: Boxplots and mean values (black dots) for goodness of fit of the GR4J and SimHyd calibrations on the 1970 - 1979 data using gridded and non-gridded data. The goodness of fit is indicated by the Nash Sutcliffe Efficiency, which is equal to 1 for a perfect fit, and 0 for a fit equal to the average streanflow.