Benestad et al - Simple and approximate estimation of future precipitation return-values

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R set-up

First pre-amble that checks whether the esd-package is installed and installs it if needed. If it is not installed, install it from GitHub using devtools. Also install devtools if needed. This is only done once.

```
rm(list=ls())
xlim <- c(0,35); ylim <- c(45,70)
readecad <- FALSE
figshare=TRUE
nmin=50

## Check if you need to get the esd-package:
install.esd <- ("esd" %in% rownames(installed.packages()) == FALSE)

if (install.esd) {
  print('Need to install the esd package')
  ## Need online access.
  ## Use the devtools-package for simple facilitation of installing.
  if ("devtools" %in% rownames(installed.packages()) == FALSE)
    install.packages('devtools')
  library(devtools)
  ## Install esd directly from github
  install_github('metno/esd')
  print('The latest version of esd has been installed')
}

## Start the esd-library:
library(esd)
```

```
## Loading required package: ncdf4

## Loading required package: zoo

##
## Attaching package: 'zoo'

## The following objects are masked from 'package:base':
##
##     as.Date, as.Date.numeric

##
## Attaching package: 'esd'

## The following object is masked from 'package:base':
##
##     subset.matrix
```

```
## Information about the session
sessionInfo()
```

```
## R version 3.3.2 (2016-10-31)
```

```
## Platform: x86_64-pc-linux-gnu (64-bit)
## Running under: Ubuntu 16.04.2 LTS
##
## locale:
##  [1] LC_CTYPE=en_US.UTF-8       LC_NUMERIC=C
##  [3] LC_TIME=en_US.UTF-8        LC_COLLATE=en_US.UTF-8
##  [5] LC_MONETARY=en_US.UTF-8    LC_MESSAGES=en_US.UTF-8
##  [7] LC_PAPER=en_US.UTF-8       LC_NAME=C
##  [9] LC_ADDRESS=C               LC_TELEPHONE=C
## [11] LC_MEASUREMENT=en_US.UTF-8 LC_IDENTIFICATION=C
##
## attached base packages:
## [1] stats     graphics  grDevices utils     datasets  methods   base
##
## other attached packages:
## [1] esd_1.613  zoo_1.7-14 ncdf4_1.16
##
## loaded via a namespace (and not attached):
##  [1] Rcpp_0.12.8     lattice_0.20-34 digest_0.6.10   rprojroot_1.2
##  [5] grid_3.3.2      backports_1.0.5 magrittr_1.5    evaluate_0.10
##  [9] stringi_1.1.2   rmarkdown_1.3   tools_3.3.2     stringr_1.1.0
## [13] yaml_2.1.14     htmltools_0.3.5 knitr_1.15
```

Tools and functions

Below we define a number of functions used in the data processing and analysis. These functions are used to make the R-code more simple and improve clarity.

Simple functions to estimate various statistics

First we define the methods for calculating statistical measures of precipitation (mean, min, max, wettest month, and driest month), estimating percentiles assuming an exponential distribution, calculating skill-scores and regression coefficients.

```
## Return statistics for mean,min,max,wettest month,driest month
muclim <- function(x) {
  y <- coredata(x)
  iX <- mean((1:12)[is.element(y,max(y))])
  iN <- mean((1:12)[is.element(y,min(y))])
  stats <- c(mean(y,na.rm=TRUE),min(y,na.rm=TRUE),max(y,na.rm=TRUE),iX,iN)
  names(stats) <- c('mean','min','max','wettest month','driest month')
  stats
}
```

```
## Produce a set of percentiles and their counterparts for the exponential distribution
qqexp <- function(x,x0=1) {
  x[x < x0] <- NA
  if (sum(is.finite(x))>0) {
    mu <- mean(x,na.rm=TRUE)
    qx <- quantile(x,probs=seq(0,1,length=101),na.rm=TRUE)
    qy <- -log(1-seq(0,1,length=101))*mu
  } else {
    qx <- rep(NA,101); qy <- rep(NA,101)
  }
  return(cbind(qx,qy))
```

```
}
```

```
## Skill associated with predicting the wet-day mean mu
muskill <- function(x) {
  ## Estimate the skill of the calibration:
  r2 <- round(summary(lm(y ~ x,data=x))$r.squared,3)
  ## Negative slopes are not credible:
  if (summary(lm(y ~ x,data=x))$coefficients[2] < 0) r2 <- 0
  r2
}
```

```
## A function for extracting the regression coefficients and their
## error terms.
beta <- function(x,verbose=FALSE) {
  wc.model <- lm(y ~ x, data=x)
  if (verbose) print(summary(wc.model))
  beta <- summary(wc.model)$coefficients[c(2,4)]
  return(beta)
}
```

Data input and procesing

Here we define functions for reading and processing data so that it can be readily handled in the analysis.

```
## Read the data from the CMIP5 GCMs
readGCMs <- function(path='CMIP5.monthly/rcp45/',pattern='tas',
                     lon=c(-100,30),lat=c(0,40)) {
    ncfiles <- list.files(path=path,pattern=pattern,full.names=TRUE)
    n <- length(ncfiles)
    print(paste(n,'netCDF files'))
    X <- matrix(rep(NA,n*201),n,201)
    for (i in 1:n) {      print(paste(i,ncfiles[i]))
      ## Spatial average:
      gcm <- annual(spatial.avg.field(C.C.eq(retrieve(ncfiles[i],
                                                       lon=lon,lat=lat))))
      i1 <- is.element(1900:2100,year(gcm))
      i2 <- is.element(year(gcm),1900:2100)
      X[i,i1] <- coredata(gcm)[i2]
    }
    ## Extract the 5 & 95 percentile and the ensemble mean:
    print('Extract the 5 & 95 percentile and the ensemble mean')
    x <- apply(X,2,function(x) c(quantile(x,probs=c(0.05,0.95),na.rm=TRUE),mean(x,na.rm=TRUE)))
    print(dim(x))
    names(x) <- c('q05','q95','mean')
    x <- zoo(t(x),order.by=1900:2100)
    w2000 <- X[,is.element(1900:2100,2000)]
    w2050 <- X[,is.element(1900:2100,2020)]
    w2100 <- X[,is.element(1900:2100,2100)]
    plot(x,plot.type='single')
    attr(x,'path') <- path
    attr(x,'2000') <- w2000
    attr(x,'2050') <- w2050
    attr(x,'2100') <- w2100
    attr(x,'N') <- n
    attr(x,'region') <- paste(lon,lat,collapse=' ')
    return(x)
```

```
}
```

Model calibration and regression analysis

This is the main function that is used for calibrating the statistical model based on the mean seasonal cycles of the predictand (μ) and predictor (e_s, calculated from the temperature).

```
## Calibrate a model for the wet-day mean mu using temperature as input
mucal <- function(x,pre=NULL,lon=c(-100,30),lat=c(0,40),
                  plot=FALSE,verbose=FALSE) {

## If no pre, use the crude NCEP-reanalysis provided in esd
  if (is.null(pre)) {
    if (verbose) print('default predictor')
      t2m <- t2m.NCEP(lon=lon,lat=lat)
      pre <- spatial.avg.field(C.C.eq(t2m))
      if (plot) plot(EOF(t2m))
  } else
      if (is.character(pre))
          pre <- spatial.avg.field(C.C.eq(retrieve(ncfile=pre,lon=lon,lat=lat))) else
  if (inherits(pre,'field')) {
      if (is.T(pre)) pre <- spatial.avg.field(C.C.eq(pre)) else
      pre <- spatial.avg.field(pre)
  } else if (inherits(pre,'station')) pre <- pre
  z <- aggregate(pre,by=month,FUN='mean')

  cal <- data.frame(y=coredata(x),x=coredata(z))
  attr(cal,'standard.error') <- attr(x,'standard.error')
  stats <- cor.test(cal$y,cal$x)
  wc.model <- lm(y ~ x, data=cal)
  if (plot) {
      dev.new()
      par(bty='n',cex.sub=0.7,col.sub='grey40')
      ylim <- range(cal$y,na.rm=TRUE); xlim=range(cal$x,na.rm=TRUE)
      dy <- diff(ylim)/25
      plot(cal$x,cal$y,pch=19,cex=1.5,col='grey',
           ylab=expression(paste(mu,' (mm/day)')),
         xlab=expression(paste(e[s],' (Pa)')),
         ylim=ylim,xlim=xlim,
         main='Regression based on seasonal variations',
         sub=paste(loc(x),' (',round(lon(x),2),'E/',round(lat(x),2),'N; ',
             alt(x),'m.a.s.l.)',sep=''))
      segments(x0=cal$x,y0=cal$y,x1=cal$x,y1=cal$y+2*attr(x,'standard.error'),
             col='grey')
      segments(x0=cal$x,y0=cal$y,x1=cal$x,y1=cal$y-2*attr(x,'standard.error'),
             col='grey')
      segments(x0=cal$x,y0=cal$y,x1=cal$x+2*attr(z,'standard.error'),y1=cal$y,
             col='grey')
      segments(x0=cal$x,y0=cal$y,x1=cal$x-2*attr(z,'standard.error'),y1=cal$y,
             col='grey')
      points(cal$x,cal$y,pch=19,cex=1.5,col='grey')
      grid()
      abline(wc.model)
      text(xlim[1],ylim[2],paste('Correlation=',round(stats$estimate,2),
                               '(','p-value=',
```

```
                                   100*round(stats$p.value,4),'%)'),
           pos=4,cex=0.7,col='grey')
      text(xlim[1],ylim[2]-dy,paste('Regression: y=',
                                      round(wc.model$coeff[1],4), '+',
                                      round(wc.model$coeff[2],4), 'x (R2=',
                                      round(summary(wc.model)$r.squared,2),')'),
           pos=4,cex=0.7,col='grey')
      par(new=TRUE,fig=c(0.5,0.97,0.1,0.5),yaxt='n',xaxt='n',xpd=TRUE,
          cex.axis=0.7,col.axis='grey')
      plot((cal$x - mean(cal$x))/sd(cal$x),type='l',lwd=2,
           ylab='',xlab='',col=rgb(0.6,0.3,0))
      lines((cal$y - mean(cal$y))/sd(cal$y),type='l',lwd=2,col=rgb(0,0.3,0.6))
      par(xaxt = "s")
      axis(1,at=1:12,labels=month.abb,col='grey')
  }
  invisible(cal)
}
```

These functions apply the statistical model to GCM or reanalysis data in order to produce projections and predictions for the future/past:

```
## Projection based on the calibration with the annual cycle:
muproject <- function(x,gcm,verbose=FALSE,prct=TRUE) {
  #print('projection')
  wcmodel <- lm(y ~ x, data=x)
  if (verbose) {
    print(summary(wcmodel))
    print(dim(gcm))
  }
  pq05 <- data.frame(x=coredata(gcm[,1]))
  pq95 <- data.frame(x=coredata(gcm[,2]))
  pmea <- data.frame(x=coredata(gcm[,3]))
  y <- cbind(predict(wcmodel,newdata=pq05),
             predict(wcmodel,newdata=pq95),
             predict(wcmodel,newdata=pmea))
  if (verbose) print(dim(y))
  if (prct) {
    ii <- is.element(year(gcm),2000:2010)
    bline <- mean(y[ii,3])
    y <- 100*y/bline
  }
  y <- zoo(y,order.by=index(gcm))
  names(y) <- names(gcm)
  return(y)
}
```

```
## Predict values of the wet-day mean mu taking a given predictor
mupredict <- function(x,pre,verbose=FALSE,prct=TRUE) {
  if (verbose) print('projection')
  wcmodel <- lm(y ~ x, data=x)
  if (verbose) {
    print(summary(wcmodel))
  }
  eval <- data.frame(x=coredata(pre))
  y <- predict(wcmodel,newdata=eval)
```

```
  if (prct) {
    ii <- is.element(year(pre),1961:1990)
    bline <- mean(y[ii])
    if (verbose) print(length(bline))
    y <- 100*y/bline
  }
  y <- zoo(y,order.by=index(pre))
  names(y) <- 'mu'
  return(y)
}
```

Generation of graphics

The following functions are used for the presentation of the results.

```
## Generate a map for the PC weights for the different modes of the
## wet-day mean mu annual cycle.
mupcamap <- function(mu,pca,ipca,xlim,ylim,r2) {
  r2 <- as.numeric(r2)
  colpc <- rev(colscal("budrd",n=100))
  cz <- round(100*abs(pca$v[,ipca])/quantile(abs(pca$v[,ipca]),0.95))
  cz[cz > 100] <- 100; cz[cz < 1] <- 1
  col <- colpc[cz]
  pch <- rep(19,length(r2))
  mo <- c(r2) > 0.4
  hi <- c(r2) > 0.6
  pch[!hi] <- 1
  pch[!mo] <- 4
  cex <- 1.2*c(r2) + 0.5
  map(mu, xlim=xlim,ylim=ylim,bg='grey90',col='grey90',cex=0.5,gridlines=FALSE,new=FALSE)
  points(lon(mu),lat(mu),pch=pch,col=col,cex=cex)
  par(xpd=TRUE)
  text(10,73,paste('Annual cycle in PC',ipca,
      'with variance of',round(100*pca$d[ipca]^2/sum(pca$d^2)),'%'),pos=4)

  colbar(pretty(pca$v[,ipca],n=100),colpc,fig = c(0.08, 0.12, 0.05, 0.2))

  par(xaxt = "n", yaxt = "s", fig = c(0.05,0.25,0.80,0.95),
      mar = c(0, 1, 0, 0), new = TRUE, las = 1, cex.axis = 0.5,bty='n')
  plot(pca$u[,ipca],type='l',lwd=3,col="red")
  par(xaxt = "s")
  axis(1,at=1:12,labels=month.abb)
}
```

```
## Plot shaded regions
shade <- function(x,col=rgb(0.5,0.5,0.5,0.3),border=NULL) {
  t <- index(x)
  if (is.null(border)) border <- col
  y <- coredata(x)
  polygon(c(t,rev(t)),c(y[,1],rev(y[,2])),col=col,border=border)
  lines(t,y[,3],lwd=5,col=col)
}
```

```
## Estimate correlation between different sets of wet-day mean mu
## The function is designed to be used in apply for best efficiency
cormu <- function(x) {
```

```
  n <- length(x); nh <- n/2
  x1 <- x[1:nh]; x2 <- x[(nh+1):n]
  ok <- is.finite(x1) & is.finite(x2)
  return(cor(x1[ok],x2[ok]))
}
```

Calculations and analysis

The definition of functions is followed by code that carry out the analysis based on these. First get the data needed - if they are not stored locally, download from Figshare where they are stored.

Access and prepare data

```
##------------------------------------------------------------------------------------------

## Need to obtain some of the data files - fetch from Figshare:

if (!file.exists("mu.worstcasemu.rda") & figshare) {
  download.file("http://files.figshare.com/2193033/mu.worstcasemu.rda",destfile="mu.worstcasemu.rda")
}

if (!file.exists("pre.worstcasemu.rda") & figshare) {
  download.file("http://files.figshare.com/2193038/pre.worstcasemu.rda",destfile="pre.worstcasemu.rda")
}

if (!file.exists("cmip5.rda") & figshare) {
  download.file("http://files.figshare.com/2193041/cmip5.rda",destfile="cmip5.rda")
}
```

The data can also be refreshed or updated with ECA&D data:

```
## Preparations that only needs to be done once.
if (readecad) {
## This section generates a processed data file from scratch using ECA&D data:
  pr <- station(src=c('metnod','ecad'),param='precip',nmin=nmin,it=c(1961,2010),lon=xlim,lat=ylim)
  pr <- subset(pr,it=c(1961,2014))
  nt <- apply(pr,2,FUN='nv')
  pr <- subset(pr,is=(nt >=19000))
  cpr <- coredata(pr)
  cpr[cpr > 250] <- NA
  coredata(pr) <- cpr
  save(file='pr.worstcasemu.rda',pr)
  file.remove('mu.worstcasemu.rda')
}

if (!file.exists('mu.worstcasemu.rda')) {
## pr.worstcasemu.rda is a huge file with daily precipdata based on ECA&D - generated above
  load('pr.worstcasemu.rda')

  ## Time series of the annual wet-day freq & mean - for evaluation
  ## Randomly sub-sample due to excessive volume:
  FW <- annual(pr,FUN='wetfreq',nmin=350)
  MU <- annual(pr,FUN='wetmean',nmin=350)
  fw <- aggregate(pr,month,FUN='wetfreq')
```

```r
  mu <- aggregate(pr,month,FUN='wetmean')

  ## Strip away stations with a lot of missing data
  n <- apply(pr,2,FUN='nv')
  y1 <- subset(subset(pr,is=(n==max(n))),is=1)
  save(file='mu.worstcasemu.rda',mu,MU,fw,FW,y1,n)
} else load('mu.worstcasemu.rda')
```

The convention here is that the wet-day mean precipitation (precipitation intensity) is represented by symbol μ and the variable name 'mu' in the R-scripts. The wet-day frequency f_w is referred to as 'fw'. Lower and upper case refer to the mean seasonal cycle and annually aggregated values respectively. There are some stations with many missing values and some with short series. Also exclude data records with unrealistic long-term trends (due to dubious data or short series).

```r
## Keep stations with no missing data and stations
## without suspect outlier trends
nok <- n
ok <- apply(mu,2,function(x) sum(!is.finite(x))==0) &
      apply(fw,2,function(x) sum(!is.finite(x))==0) &
      abs(apply(MU,2,FUN='trend.coef')) <= 1 &
      abs(apply(FW,2,FUN='trend.coef')) <= 0.02
mu <- subset(mu,is=ok) # REB 2015-03-01
MU <- subset(MU,is=ok) # REB 2015-03-01
fw <- subset(fw,is=ok)
FW <- subset(FW,is=ok)

## Remove stations with little data
nval <- apply(MU,2,nv)
mu <- subset(mu,is=(nval > 50))
MU <- subset(MU,is=(nval > 50))
fw <- subset(fw,is=(nval > 50))
FW <- subset(FW,is=(nval > 50))
nval <- apply(FW,2,nv)
mu <- subset(mu,is=(nval > 50))
MU <- subset(MU,is=(nval > 50))
fw <- subset(fw,is=(nval > 50))
FW <- subset(FW,is=(nval > 50))
```

Get and process the predictor data. Then the predictand data is processed: estimate annual mean aggregates and the mean seasonal cycle. Remove stations with large gaps of missing values.

```r
print("predictor")
```

```
## [1] "predictor"
```

```r
if (!file.exists('pre.worstcasemu.rda')) {
  t2m <- retrieve('air.mon.mean.nc',lon=c(-100,30),lat=c(0,40))
  pre <- spatial.avg.field(C.C.eq(t2m))
  attr(pre,'region') <- '100W,30E/0N,40N'
  save(file='pre.worstcasemu.rda',pre)
} else load('pre.worstcasemu.rda')
```

Statistical downscaling and analysis

Now the data is ready for the analysis. Calibrate the regression models and extract the regression coefficients. Use 'apply' to speed up the process for multiple stations.

```r
## Extract the monthly aggregates for all stations
print('apply mucal')
```

```
## [1] "apply mucal"
```

```r
V <- apply(mu,2,FUN='mucal',pre=pre)
Beta <- lapply(V,FUN='beta')

## Collect the R-squared statistics from lm(y ~ x) for each site
print('muskill')
```

```
## [1] "muskill"
```

```r
r2 <- lapply(V,muskill)
```

Figure 1

Figure 1 illustrates how the mean seasonal cycle in μ and the area mean predictor compare and what the regression results for one example station.

```r
## Extract the mean, min, max, wettest month, and driest months
##  in terms of mu for all stations:
print('muclim')
```

```
## [1] "muclim"
```

```r
X <- apply(mu,2,FUN='muclim')
print(table(X[4,]))
```

```
##
##   1   6   7   8   9  10  11  12
##   4  19 469 218 132 129  22  36
```

```r
wmns <- as.numeric(rownames(table(X[4,])))
nc <- max(wmns) - min(wmns) + 1
cols <- colscal(n=nc)
col1 <- cols[c(X[4,])]
cex <- 1.5*n/max(n)

## The relationship between mu and e_s for one station
## to show the calibration procedure
is <- (1:length(n))[X[4,]==8][1]
print(paste('plot mucal - is=',is))
```

```
## [1] "plot mucal - is= 3"
```

```r
mucal(subset(mu,is=is),pre=pre,verbose=TRUE,plot=TRUE)
figlab('Figure 1')
```

Figure 2a+b

Figure 2a+b show the principal component analysis (PCA) applied to the mean seasonal cycle for the different locations to show how it varies geographically.

```r
## Remove locations with missing values for PCA
print('Mu - matrix for PCA')
```

```
## [1] "Mu - matrix for PCA"
```

```
Mu <- as.matrix(coredata(mu))

## Anomalies wrt the mean value at each location.
Mu <- apply(Mu,2,function(x) (x - mean(x)))
pca <- svd(Mu)

## Plot maps with PCs:
print('Maps with PCs')
```

```
## [1] "Maps with PCs"
```

```
mupcamap(mu,pca,1,xlim,ylim,r2)
figlab('Figure 2a')
```

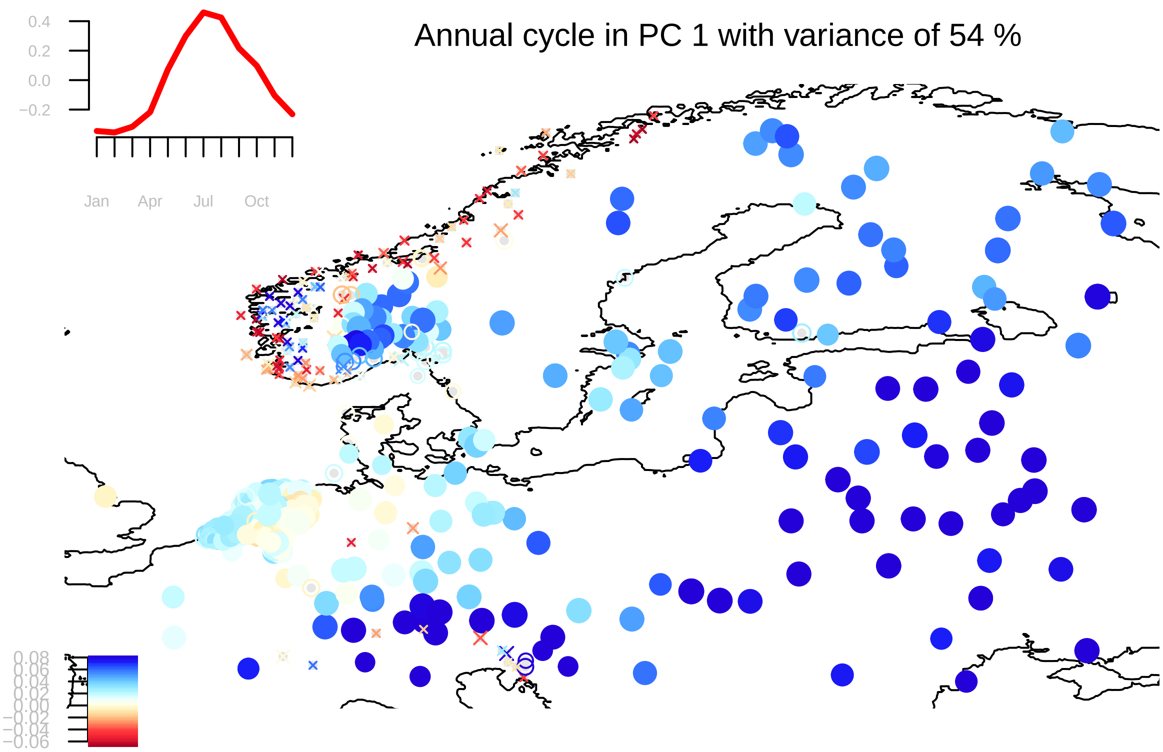
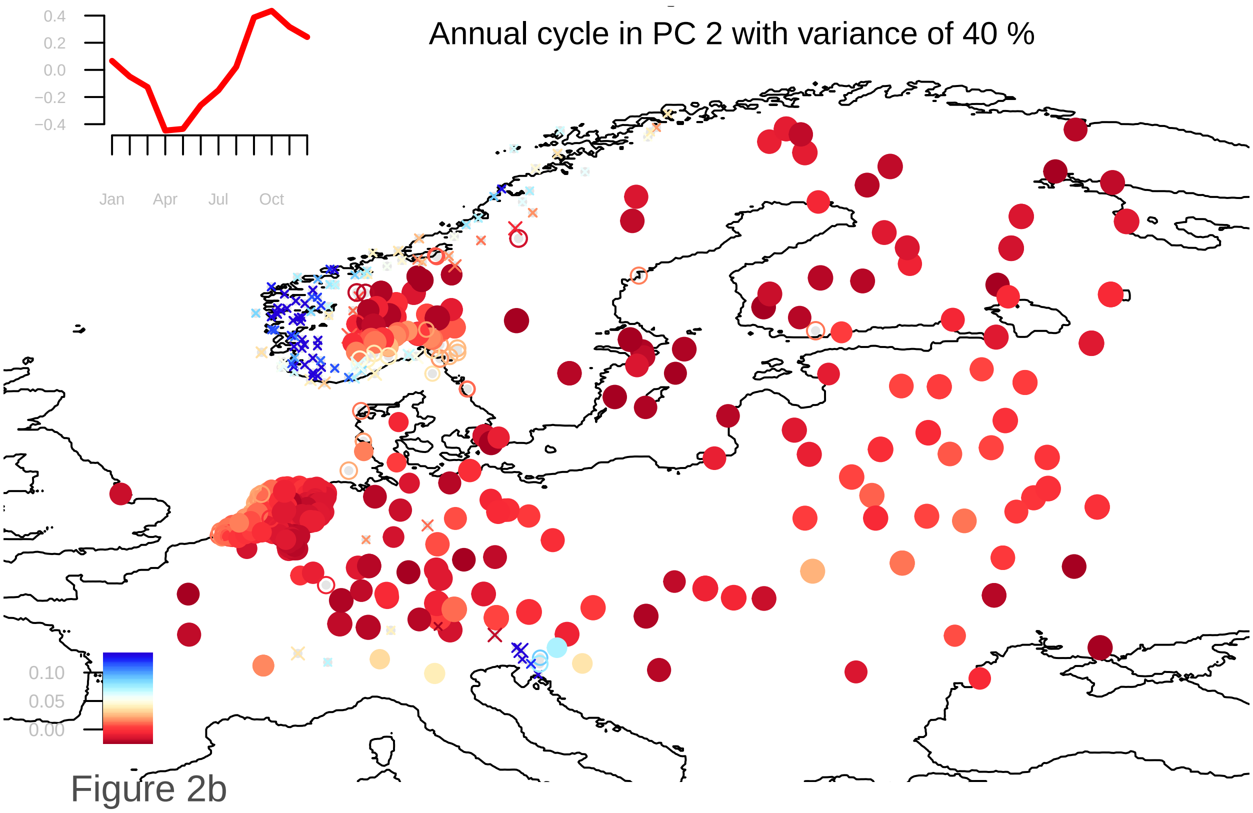


Figure 2a

```
mupcamap(mu,pca,2,xlim,ylim,r2)
figlab('Figure 2b')
```



Mean seasonal cycle

Examine how the components of the mean seasonal cycle correlates with the skill-score of the empirical models.

```
print('Variance accounted for by the modes:')
```

```
## [1] "Variance accounted for by the modes:"
```

```
print(round(100*pca$d**2/sum(pca$d**2),1))
```

```
##  [1] 53.5 40.2  2.6  0.9  0.7  0.5  0.5  0.4  0.3  0.2  0.2  0.0
```

```
## The sign of PCs is arbitrary...
print(cor.test(pca$v[,1],as.numeric(r2)))
```

```
##
##  Pearson's product-moment correlation
##
## data:  pca$v[, 1] and as.numeric(r2)
## t = 46.835, df = 1027, p-value < 2.2e-16
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  0.8047705 0.8438465
## sample estimates:
##       cor
## 0.8252939
```

```
print(cor.test(pca$v[,2],as.numeric(r2)))
```

```
##
```

```
##  Pearson's product-moment correlation
##
## data:  pca$v[, 2] and as.numeric(r2)
## t = -49.436, df = 1027, p-value < 2.2e-16
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.8563167 -0.8200568
## sample estimates:
##        cor
## -0.8391165
```

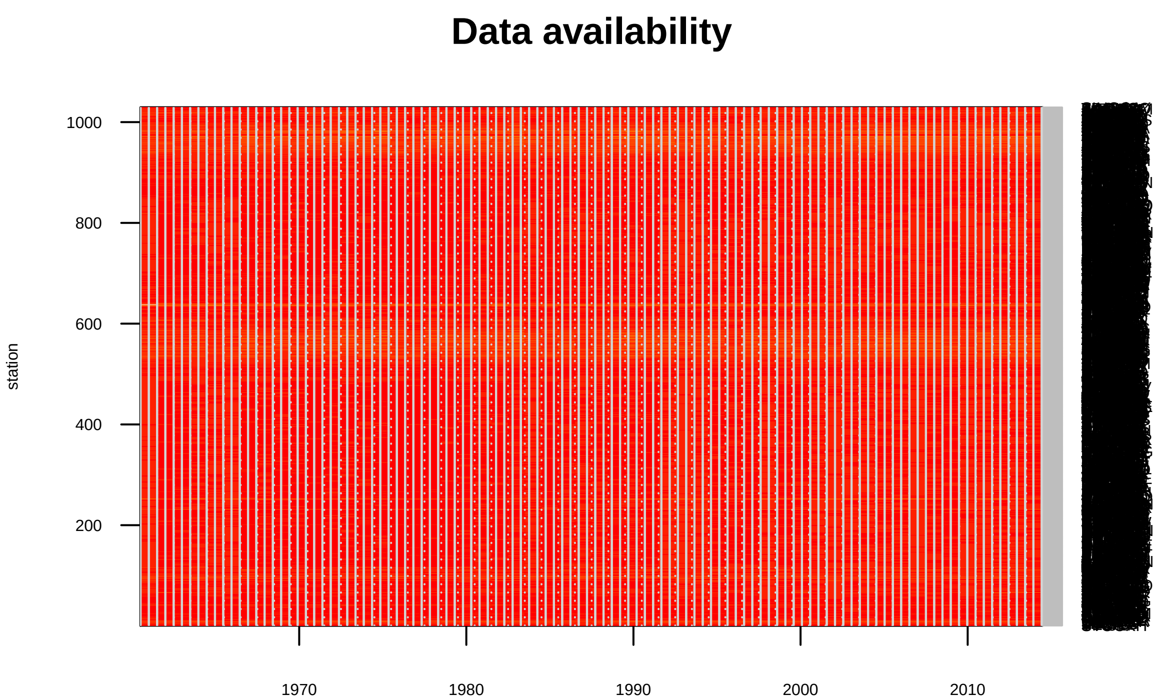
```
print(cor.test(pca$v[,3],as.numeric(r2)))
```

```
##
##  Pearson's product-moment correlation
##
## data:  pca$v[, 3] and as.numeric(r2)
## t = 0.061586, df = 1027, p-value = 0.9509
## alternative hypothesis: true correlation is not equal to 0
## 95 percent confidence interval:
##  -0.05919811  0.06302724
## sample estimates:
##         cor
## 0.001921741
```

Trend analysis

Estimate trend statistics if the historical wet-day mean and wet-day frequency.

```
## Estimate trend statistics for both fw and mu:
fw.trend <- 100*apply(subset(FW,it=c(1961,2014)),2,'trend.coef')/
                      apply(FW,2,'mean',na.rm=TRUE)
mu.trend <- 100*apply(subset(MU,it=c(1961,2014)),2,'trend.coef')/
                      apply(MU,2,'mean',na.rm=TRUE)
## Check data availability
diagnose(MU)
```



MECAND

Extract results (regression models, statistical information) only for locations where there is a good match between the seasonal cycles of μ and e_s ($R^2 > 0.6$). The models calibrated here only seem to be valid for regions dominated by convective precipitation and are poor over regions where orographically forced precipitation dominate.

```
## Select only the sites which have an R2 greater than 0.6:
is <- (1:length(r2))[as.numeric(r2)> 0.6]
mux <- subset(mu,is=is)
MUx <- subset(MU,is=is)
FWx <- subset(MU,is=is)
Xx <- X[,is]
Vx <- V[is]
```

Aggregated results from the GCMs

Collect aggregated GCM projections (CMIP5) and apply the empirical models to the ensembles.

```
## Read the GCM ensembles andestimate the 5 and 95 percentiles as well as
## the ensemble mean.
## Get the annual mean temperature from GCM ensembles:
if (!file.exists('cmip5.rda')) {
  print('get CMIP5 RCP4.5')
  rcp4.5 <- readGCMs(path='CMIP5.monthly/rcp45/',pattern='tas_Amon_ens_rcp')
  print('get CMIP5 RCP8.5')
  rcp8.5 <- readGCMs(path='CMIP5.monthly/rcp85/',pattern='tas_Amon_ens_rcp')
  print('get CMIP5 RCP2.6')
  rcp2.6 <- readGCMs(path='CMIP5.monthly/rcp26/',pattern='tas_Amon_ens_rcp')
  save(file='cmip5.rda',rcp4.5,rcp8.5,rcp2.6)
} else load('cmip5.rda')
```

```
## derive time series for each location:
Z.rcp4.5 <- lapply(Vx,'muproject',rcp4.5)
Z.rcp8.5 <- lapply(Vx,'muproject',rcp8.5)
Z.rcp2.6 <- lapply(Vx,'muproject',rcp2.6)
t <- index(rcp4.5)
```

Extract statistics of the wet-day mean associated with different emission scenarios and time slices and calculate the changes from the present (2010) to the far future (2100).

```
## Estimates for mu in 2010:
mu2010.rcp4.5 <- lapply(Z.rcp4.5,'window',start=2010,end=2010)
mu2010.rcp8.5 <- lapply(Z.rcp8.5,'window',start=2010,end=2010)
mu2010.rcp2.6 <- lapply(Z.rcp2.6,'window',start=2010,end=2010)
x2010 <- as.numeric(lapply(mu2010.rcp4.5,function(x) x[[3]])) ## Median value
x2010u <- as.numeric(lapply(mu2010.rcp4.5,function(x) x[[2]])) ## 95th percentile
y2010 <- as.numeric(lapply(mu2010.rcp8.5,function(x) x[[3]]))
y2010u <- as.numeric(lapply(mu2010.rcp8.5,function(x) x[[2]]))
z2010 <- as.numeric(lapply(mu2010.rcp2.6,function(x) x[[3]]))
z2010u <- as.numeric(lapply(mu2010.rcp2.6,function(x) x[[2]]))

## Repeat for 2100:
mu2100.rcp4.5 <- lapply(Z.rcp4.5,'window',start=2100,end=2100)
mu2100.rcp8.5 <- lapply(Z.rcp8.5,'window',start=2100,end=2100)
mu2100.rcp2.6 <- lapply(Z.rcp2.6,'window',start=2100,end=2100)
x2100 <- as.numeric(lapply(mu2100.rcp4.5,function(x) x[[3]]))
x2100u <- as.numeric(lapply(mu2100.rcp4.5,function(x) x[[2]]))
y2100 <- as.numeric(lapply(mu2100.rcp8.5,function(x) x[[3]]))
y2100u <- as.numeric(lapply(mu2100.rcp8.5,function(x) x[[2]]))
z2100 <- as.numeric(lapply(mu2100.rcp2.6,function(x) x[[3]]))
z2100u <- as.numeric(lapply(mu2100.rcp2.6,function(x) x[[2]]))

## Data frames with changes in percentages:
mu.2100 <- data.frame(median.RCP4.5=x2100 - x2010,q95.RCP4.5=x2100u - x2010u,
                      median.RCP2.6=z2100 - z2010,q95.RCP4.5=z2100u - z2010u,
                      median.RCP8.5=y2100 - y2010,q95.RCP8.5=y2100u - y2010u)
```

Print the projected changes in return-values from 2010 to 2100.

```
## Print the numbers:
print('--- Changes in 20% returnvalue in terms of % from 2010:')
```

```
## [1] "--- Changes in 20% returnvalue in terms of % from 2010:"
```

```
print(lapply(mu.2100,summary))
```

```
## $median.RCP4.5
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   6.958   9.111  10.660  12.170  13.890  26.040
##
## $q95.RCP4.5
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   7.398   9.688  11.340  12.940  14.770  27.690
##
## $median.RCP2.6
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   3.111   4.085   4.790   5.487   6.264  11.930
```

```
##
## $q95.RCP4.5.1
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   3.639   4.778   5.603   6.417   7.327  13.950
##
## $median.RCP8.5
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   18.71   24.64   28.96   33.31   38.04   73.70
##
## $q95.RCP8.5
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   21.59   28.43   33.41   38.43   43.88   85.02
```

```
print(paste('Summary for',length(mu.2100[[1]]),'locations'))
```

```
## [1] "Summary for 615 locations"
```

Figure 3

Figure 3 shows the projected changes in the median (inner marker) and 95th precentile of the wet-day mean from the present (2010) to the far future (2100).

```
## Fig 3
## Plot a map of projected values:
## Map showing RCP4.5 ensemble median and the upper 95% change in the
## outer part of the symbol. Also an insert with box-plot diagram
## showing the other RCPs.

cols <- colscal(n=100,col='precip')
cx2100 <- round(x2100 - x2010)
cx2100u <- round(y2100u - y2010u)
cx2100[cx2100 < 1] <- 1; cx2100[cx2100 > 100] <- 100
cx2100u[cx2100u < 1] <- 1; cx2100u[cx2100u > 100] <- 100
colx <- cols[cx2100]
coly <- cols[cx2100u]
Cex <- 1.25

print("Plot a map of projected values:")
```

```
## [1] "Plot a map of projected values:"
```

```
map(mux, xlim=xlim,ylim=ylim,cex=Cex,bg='grey70',col='grey70',gridlines=FALSE,
    colbar=list(col=cols,n=12,type="p",h=0.6,v=1))
points(lon(mux),lat(mux),pch=19,col=colx,cex=Cex)
points(lon(mux),lat(mux),pch=21,col=coly,cex=Cex,lwd=2)
par(xpd=TRUE)
text(20,72,'Wet-day mean: 2100')
legend(20,32,c(expression(bar(x)),expression(q[95])),
       pch=c(21,19),bty='n',col='grey',text.col='grey',horiz=TRUE)

colbar(pretty(c(x2100u- x2010u, x2100- x2010),n=15),cols,
       fig = c(0.05, 0.1, 0.05, 0.2))

par(new=TRUE,fig = c(0.05, 0.4, 0.75, 0.975),
    cex.axis=0.75,mar=c(1,1,0.1,0.1),xaxt='n')
boxplot(mu.2100,col=c(rep(rgb(0.5,0.5,0.5,0.3),2),
                      rep(rgb(0.5,1,0.5,0.3),2),
```

```
                          rep(rgb(1,0.5,0.5,0.3),2)))
par(xaxt='s')
axis(1,c(1,3,5),labels=c('RCP4.5','RCP2.6','RCP8.5'))
grid()

figlab('Figure 3')
```

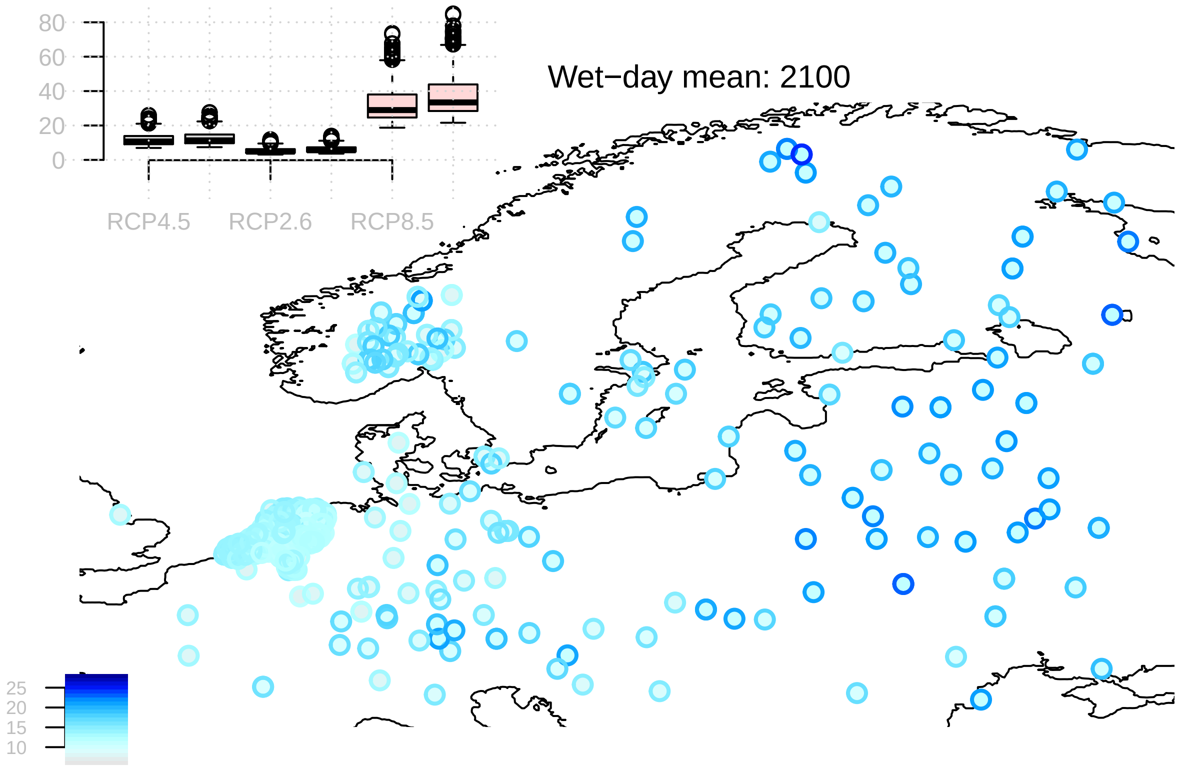


Figure 3

Supporting Material

The supporting material includes diagnostics and plots that checks a number of assumptions made in this study.

Reorganise data and statistical information Extract and reorganise essential information from previous analysis that will be used in the SM.

```
## Evaluation:
## Use the calibration strategy to predict the annual mu based on the predictor (t2m -> e_s)
print('evaluation: correlation')
```

```
## [1] "evaluation: correlation"
```

```
mu.eval <- lapply(Vx,'mupredict',annual(pre),prct=FALSE)
m <- length(mu.eval); n <- length(mu.eval[[1]])
MUz <- matrix(unlist(mu.eval),n,m)
MUz <- zoo(MUz,order.by=index(mu.eval[[1]]))
MUz <- subset(MUz,it=MUx)
MUx <- subset(MUx,it=MUz)
```

```
FWx <- subset(FWx,it=MUz)
r.eval <- apply(rbind(coredata(MUz),coredata(MUx)),2,'cormu')
print(summary(r.eval))
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -0.2891  0.1177  0.2163  0.2020  0.3021  0.5728
```

Now prepare the supporting figures.

```
## Supporting figures
par(xaxt='n',yaxt='n',bty='n')
plot(c(0,1),c(0,1),type='n',xlab='',ylab='')
text(0.5,0.5,'Supporting figures',cex=2,font=2)
```

Supporting figures

Figure SM2

Figure SM2 shows a test of the assumption that that the wet-day daily precipitation is approximately exponentially distributed, by comparing the actual percentiles with quantiles estimated for different samples with different annual mean wet-day precipitation using the formula for exponentially distributed data: $q_p = -ln(1-p)\mu$.

```
## Figure SM1.
## test: See if the quantiles are consistent when the mean mu varies.
qtest <- aggregate(y1,year,FUN='qqexp')
qx <- c(coredata(qtest[,1:101]))
qy <- c(coredata(qtest[,102:202]))

par(bty='n')
plot(qx,qy,xlim=c(0,40),ylim=c(0,40),
     pch=19,col=rgb(0.2,0.2,0.7,0.3),cex=cex,
     main='Test: exponential distribution & changing mean',
     xlab=expression(q[p]),ylab=expression(-log(1-p)*mu))
lines(c(0,40),c(0,40),col='grey')
figlab('Figure SM1')
```

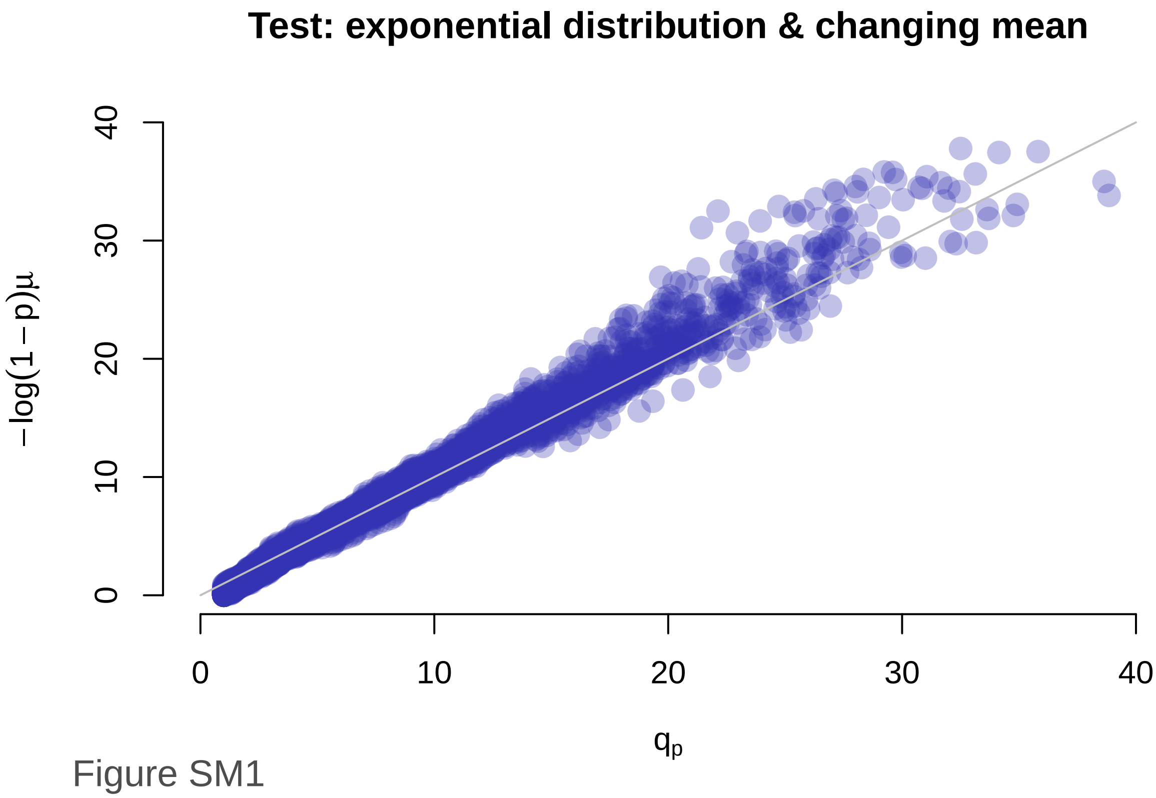


Figure SM2

Figure SM3 presents a map of the NCEP reanalysis temperature for the North Atlantic region that is used as predictor for the downscaling (see e.g., Figure 1 and 3).

```
## Show the predictor area:
X <- retrieve('air.mon.mean.nc',lon=c(-100,-30),lat=c(0,40))
```

```
## [1] "Warning : Calendar attribute has not been found in the meta data and will be set automatically.
```

```
map(X,projection='sphere',colbar=list(pal="budrd",breaks=seq(8,28,by=0.5)))
```

```
## [1] "Clip the value range to extremes of colour scale"
## [1] "0 set to highest colour and 0 to lowest"
```

```
figlab('Figure SM2',xpos=0.8,ypos=0.999)
```

Figure SM2

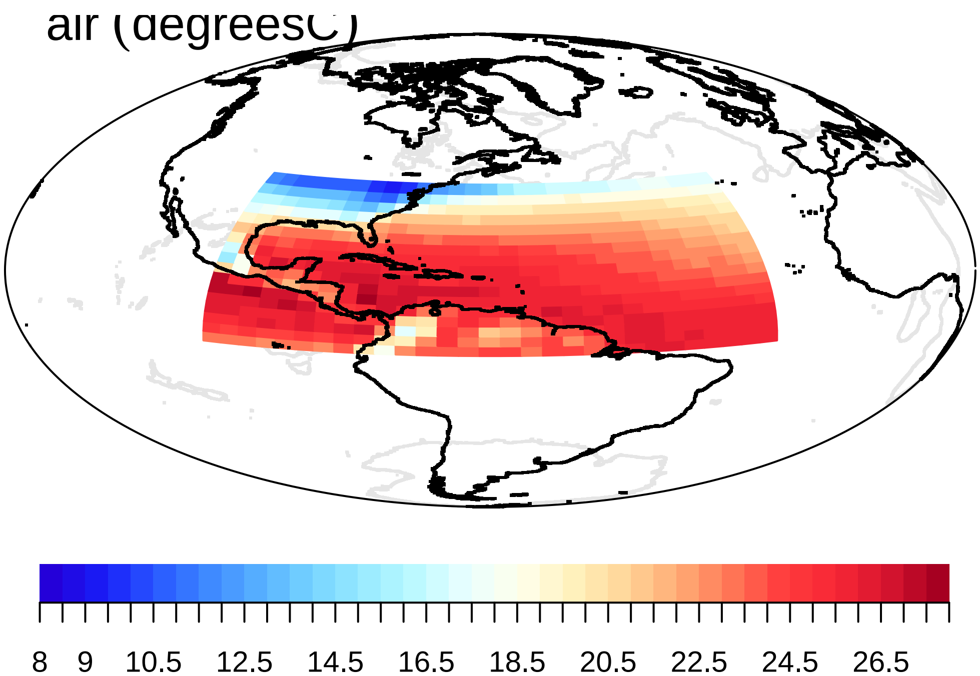


Figure SM3

Figure SM1 show the seasonal cycles of various precipitation statistics (mean, wet-day mean, wet-day frequency, mean consecutive wet days and dry days), calculated based on ECA&D observations for stations with long precipitation records.

```
# y1 contains precipitation observations from ECA&D stations with long records
pr.mean <- aggregate(y1,by=month,FUN='mean')
pr.mu <- aggregate(y1,by=month,FUN='wetmean')
pr.fw <- aggregate(y1,by=month,FUN='wetfreq')
y1.l <- spell(y1,threshold=1)
pr.wet <- aggregate(subset(y1.l,is=1),by=month,FUN='mean')
pr.dry <- aggregate(subset(y1.l,is=2),by=month,FUN='mean')

par(bty='n',xaxt='n')
plot(merge(pr.mean,pr.mu,10*pr.fw,pr.wet,pr.dry),plot.type='single',
     col=c('steelblue','darkblue','grey','darkgreen','red'),
     lwd=c(3,3,1,1,1),ylab="",xlab="Calendar month",main=loc(y1))
grid()
par(yaxt='s',xaxt='s')
axis(1,at=1:12,labels=month.abb,cex.lab=0.7, col='grey')
axis(4,at=10*pretty(pr.fw),pretty(pr.fw),col='grey')

legend(1,8.5,c(expression(bar(x)),expression(mu),expression(f[w]),
               expression(bar(n[c*w*d])),expression(bar(n[c*d*d]))),bty='n',
       col=c('steelblue','darkblue','grey','darkgreen','red'),lwd=c(3,3,1,1,1),
       ncol=2)
figlab('Figure SM3')
```

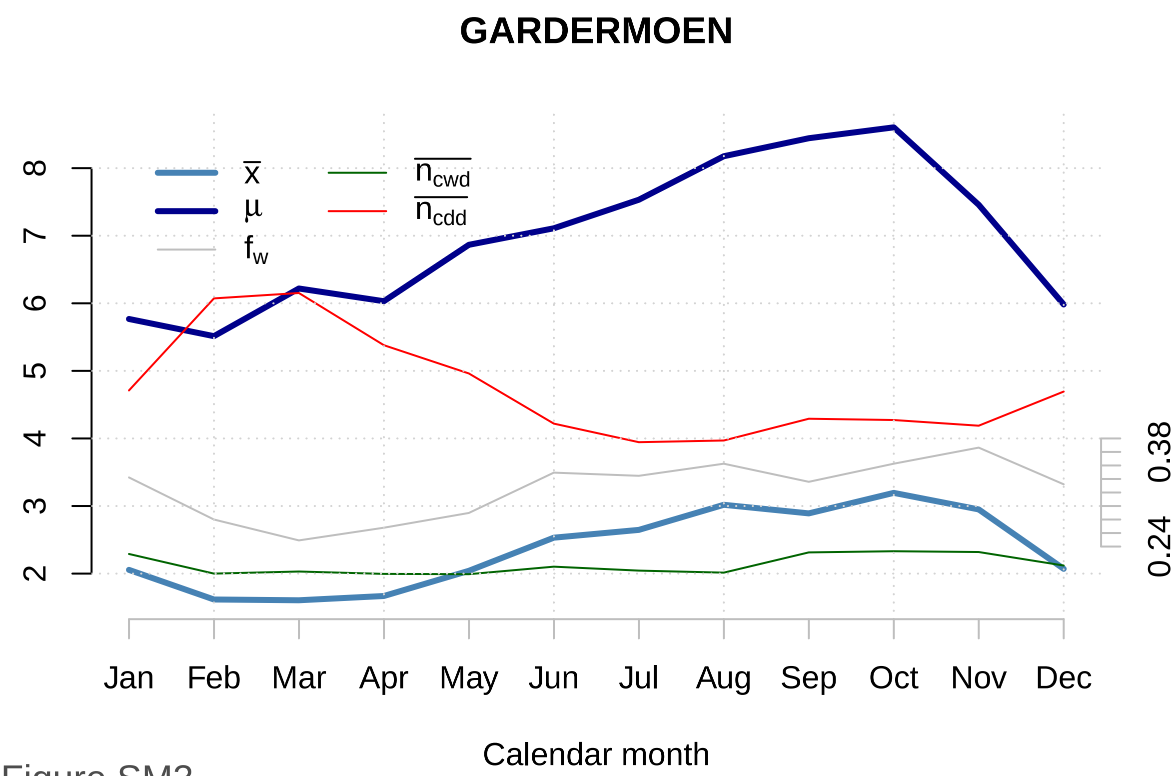


Figure SM3

Figure SM4

Figure SM4 shows an example of projections of the wet-day mean for one location, showing all three emission scenarios.

```
## Example of estimates for 2050:
print('Example plot - projections of mu')
```

```
## [1] "Example plot - projections of mu"
```

```
par(bty='n')
i <- 1
N <- length(Z.rcp4.5)
plot(Z.rcp4.5[[i]],plot.type='single',lty=c(2,2,1),lwd=c(1,1,2),
     xlab='Year',ylab='%',ylim=c(80,150),
     main=paste('Wet-day mean at',loc(subset(mux,is=i))))
shade(Z.rcp4.5[[i]],col=rgb(0.5,0.5,0.5,0.3))
shade(Z.rcp8.5[[i]],col=rgb(1,0.5,0.5,0.3))
shade(Z.rcp2.6[[i]],col=rgb(0.5,1,0.5,0.3))
grid()
legend("topleft",legend=c("RCP4.5","RCP8.5","RCP2.6"),lty=1,lwd=2,
       bty="o",box.lwd=0.2,
       col=c(rgb(0.5,0.5,0.5,0.5),rgb(1,0.5,0.5,0.5),rgb(0.5,1,0.5,0.5)))
figlab('Figure SM4')
```

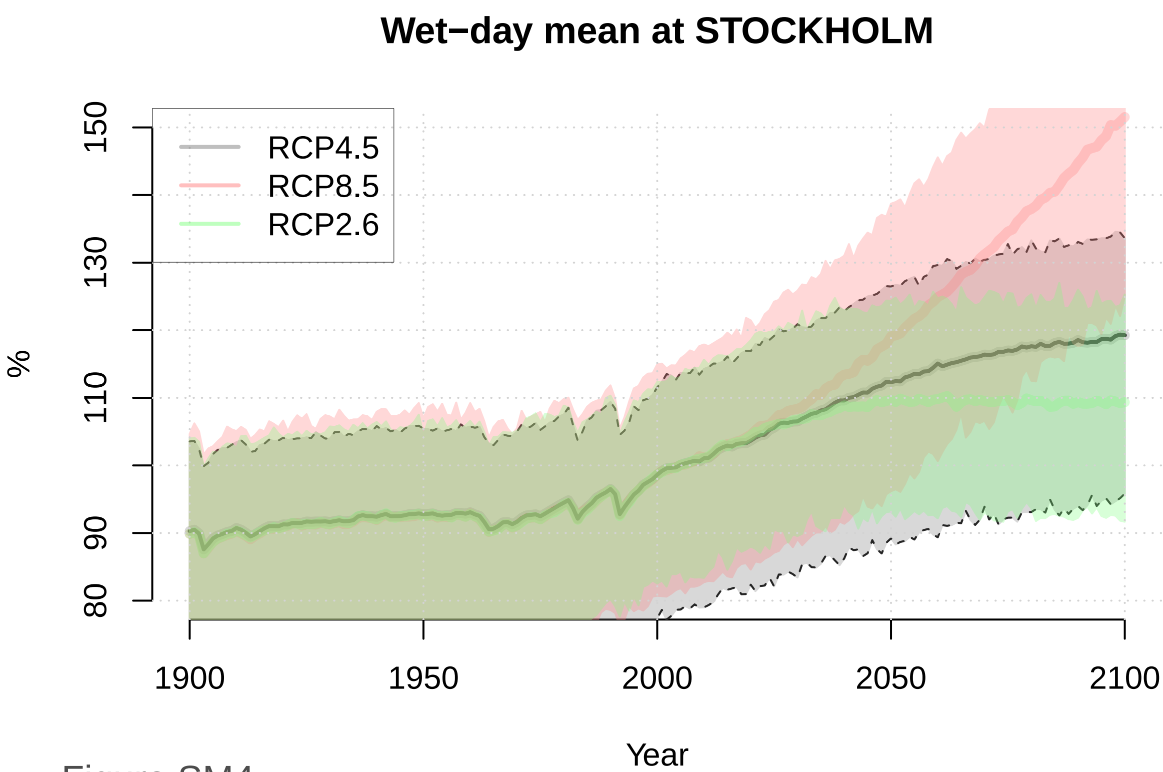


Figure SM4

Figure SM5

Figure SM5 presents the R^2 statistics from the model calibration (i.e., the regression between the seasonal cycles of μ and e_s) for different locations.

```
## Plot the statistics of R2:
hist(100*as.numeric(r2),breaks=seq(0,100,by=5),lwd=2,col=rgb(0,0.3,0.5),
     xlab=expression(paste(R^2,' (%)')),freq=TRUE,
     main="Summary of regression scores")
grid()
figlab('Figure SM5')
```

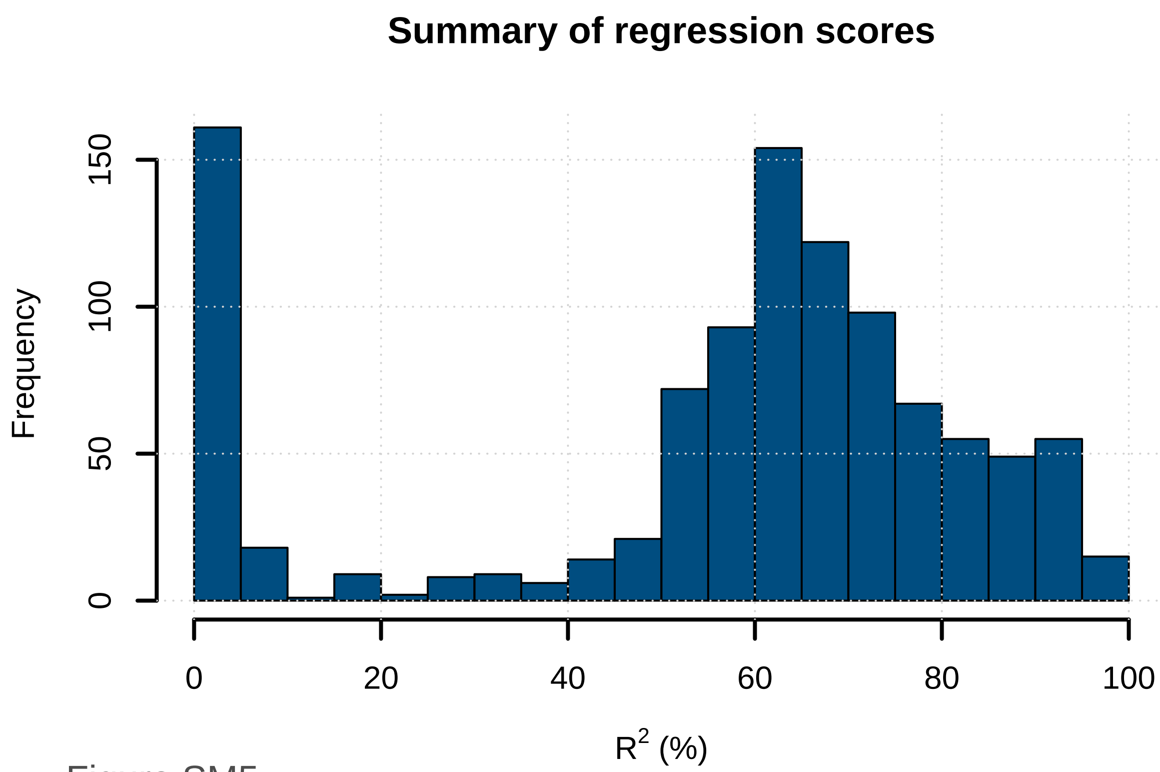


Figure SM5

Figure SM6

Figure SM6 compares the observed and predicted historical trends in the wet-day mean preciptation. First extract information about trends in μ.

```
## Trend in projected wet-day mean
trendbeta <- unlist(lapply(Z.rcp4.5,function(x) trend.coef(x[,3])))
## Strange results:
N <- length(Z.rcp4.5)
print((1:N)[trendbeta < 0])
```

```
## integer(0)
```

```
## test: Does the model predict observed trends?
print('evaluation: trends')
```

```
## [1] "evaluation: trends"
```

```
## Make sure to compare series with data for same times
mask <- !is.finite(coredata(MUx))
class(MUz) <- class(MUx)
muz <- coredata(MUz)
muz[mask] <- NA; dim(muz) <- dim(MUz)
coredata(MUz) <- muz

## Only look at stations with more than 50 years with data
ok <- (apply(coredata(MUx),2,nv) > 50)
MUz <- subset(MUz,is=ok)
MUx <- subset(MUx,is=ok)
FWx <- subset(FWx,is=ok)
```

```r
trend.mux <- apply(MUx,2,'trend.coef')
trend.pre <- apply(MUz,2,'trend.coef')
trenderr.mux <- apply(MUx,2,'trend.err')
trenderr.pre <- apply(MUz,2,'trend.err')

## Need to get a picture whether the predictions gives a plausible
## upper limit.
trend.sense <- data.frame(x=c(-trend.mux,trend.mux),
                          y=c(-trend.pre,trend.pre))

xylim <- max(abs(c(trend.mux,trend.pre)))*c(-1,1)
```

Then make a scatterplot comparing the observed and predicted trends.

```r
par(bty='n',col.sub='grey',cex.sub=0.8)
plot(trend.mux,trend.pre,pch=19,col=rgb(0.6,0.2,0,0.3),cex=1.5,
     xlab=expression(paste('Observed trend in ',mu,' (mm/decade)')),
     ylab=expression(paste('Predicted trend in ',mu,'(mm/decade)')),
     xlim=xylim,ylim=xylim,
     sub=paste('Mean correlation for local year-to-year variations over t=[',
       start(MUx),',',end(MUx),
       '] is ',round(mean(r.eval),2),' (',round(quantile(r.eval,0.05),2),', ',
       round(quantile(r.eval,0.95),2),
       ')',sep='') )
grid()

polygon(c(xylim[1],xylim[2],xylim[1],xylim[1]),c(xylim[1],xylim[2],xylim[2],xylim[1]),
        col=rgb(0.2,0.6,1,0.1),border=NA)
polygon(c(xylim[1],xylim[2],xylim[2],xylim[2]),c(xylim[1],xylim[2],xylim[2],xylim[1]),
        col=rgb(1,0.2,0.2,0.1),border=NA)
points(trend.mux,trend.pre,pch=1,col=rgb(0,0,0,0.1),cex=1.5)

## Plot error bars
apply(rbind(trend.mux,trend.pre,trenderr.mux,trenderr.pre),2,
      FUN=function(x) {lines(x[1]+c(-2,2)*x[3],x[2]+c(0,0),col=rgb(0.6,0.2,0,0.1))
                       lines(x[1]+c(0,0),x[2]+c(-2,2)*x[4],col=rgb(0.6,0.2,0,0.1))
                       lines(x[1]+c(-1,1)*0.01,x[2]+c(2,2)*x[4],col=rgb(0.6,0.2,0,0.05))
                       lines(x[1]+c(-1,1)*0.01,x[2]+c(-2,-2)*x[4],col=rgb(0.6,0.2,0,0.05))
                       lines(x[1]+c(-2,-2)*x[3],x[2]+c(-1,1)*0.01,col=rgb(0.6,0.2,0,0.05))
                       lines(x[1]+c(2,2)*x[3],x[2]+c(-1,1)*0.01,col=rgb(0.6,0.2,0,0.05))
                     })
```

```
## NULL
```

```r
figlab('Figure SM6')
```

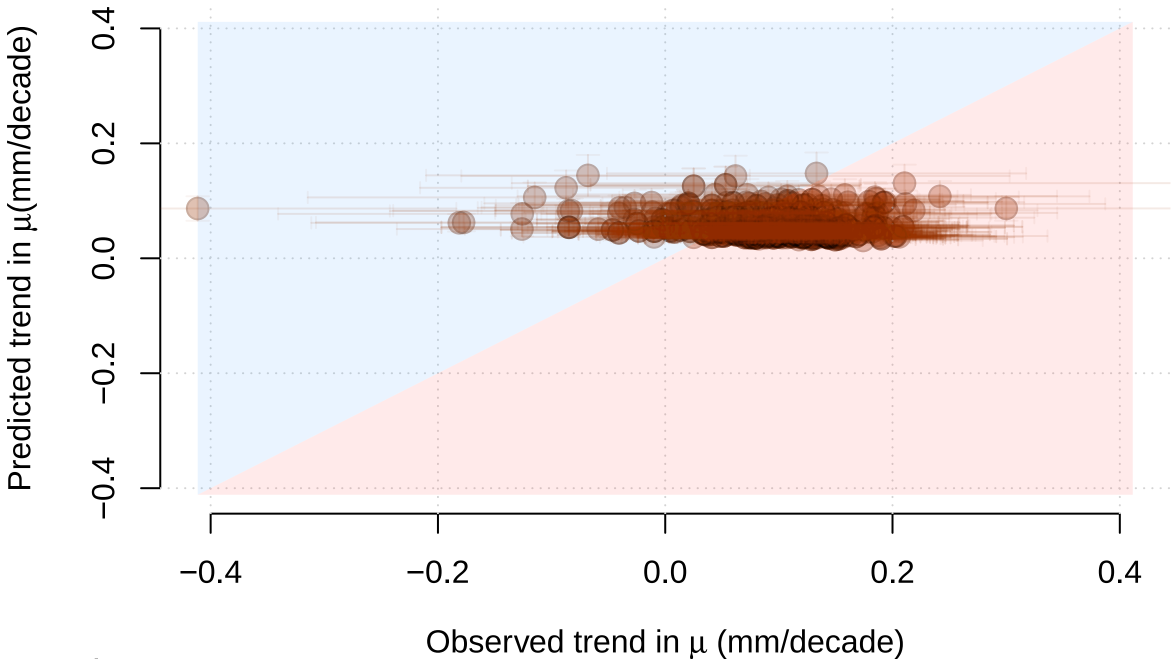


Figure SM6

Mean correlation for local year−to−year variations over t=[1961,2014] is 0.2 (−0.04, 0.41)

Figure SM7

Figure SM7 shows the historical trends in the wet-day mean preciptation. Locations with trends that are statistically significant at the 5%-level are shown with a ring around the symbol. The significance test was based on a regression analysis and the p-value associated with the fitted slope of a linear fit.

```
## Map showing trends in mu
map(MU,FUN='trend',cex=1,colbar=list(pal="budrd",breaks=pretty(c(-0.5,0.5),n=21)))
pval <- apply(coredata(MU),2,'trend.pval') <= 0.05
points(lon(subset(MU,is=pval)),lat(subset(MU,is=pval)),cex=1,col=rgb(0,0,0,0.2))
figlab('Figure SM7',ypos=0.999)
figlab(expression(paste('Trend in ',mu,' (mm/day per decade)')),xpos=0.5,ypos=0.999)
```

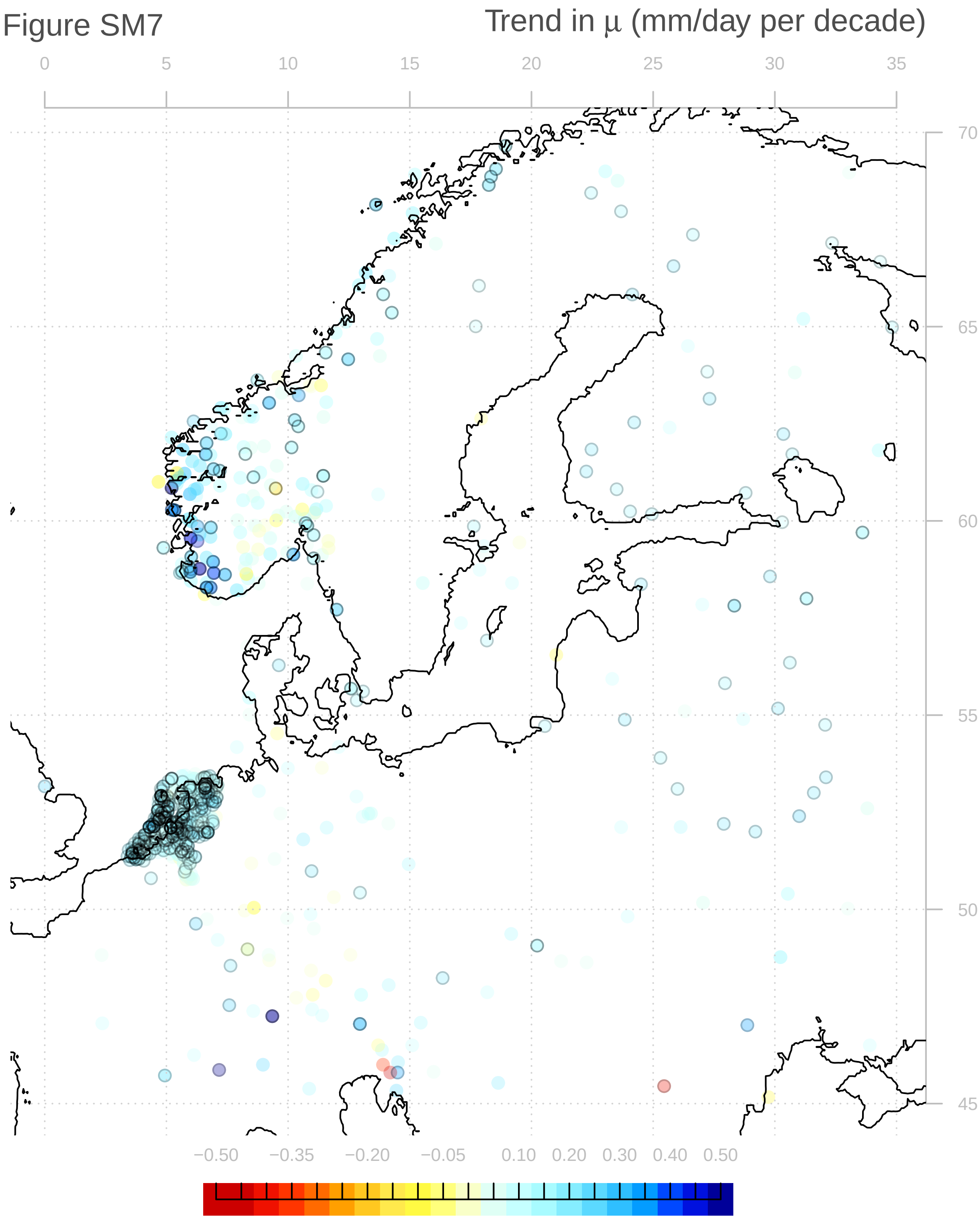


Figure SM8

Figure SM8 displays a histogram of historical trends in the wet-day frequency for the period… for the stations in Europe shown in Figure SM8.

```r
## Statistics of trend in wet-day frequency
print('Wet-day frequency statistics')
```

```
## [1] "Wet-day frequency statistics"
```

```
hist(fw.trend,breaks=seq(-50,50,by=1),col='grey',lwd=2,
     main='Trend in wet-day frequency',
     xlab=expression(paste(f[w],' (%/decade)')))
grid()
figlab('Figure SM8')
```

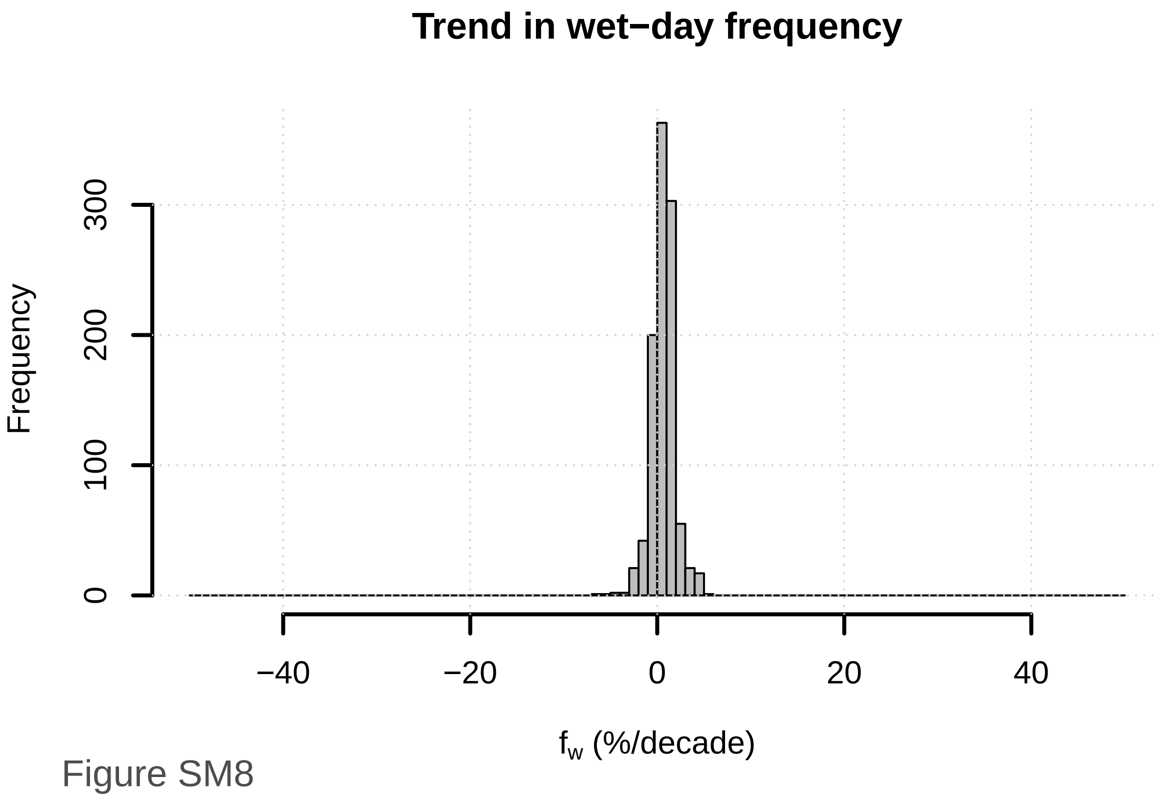
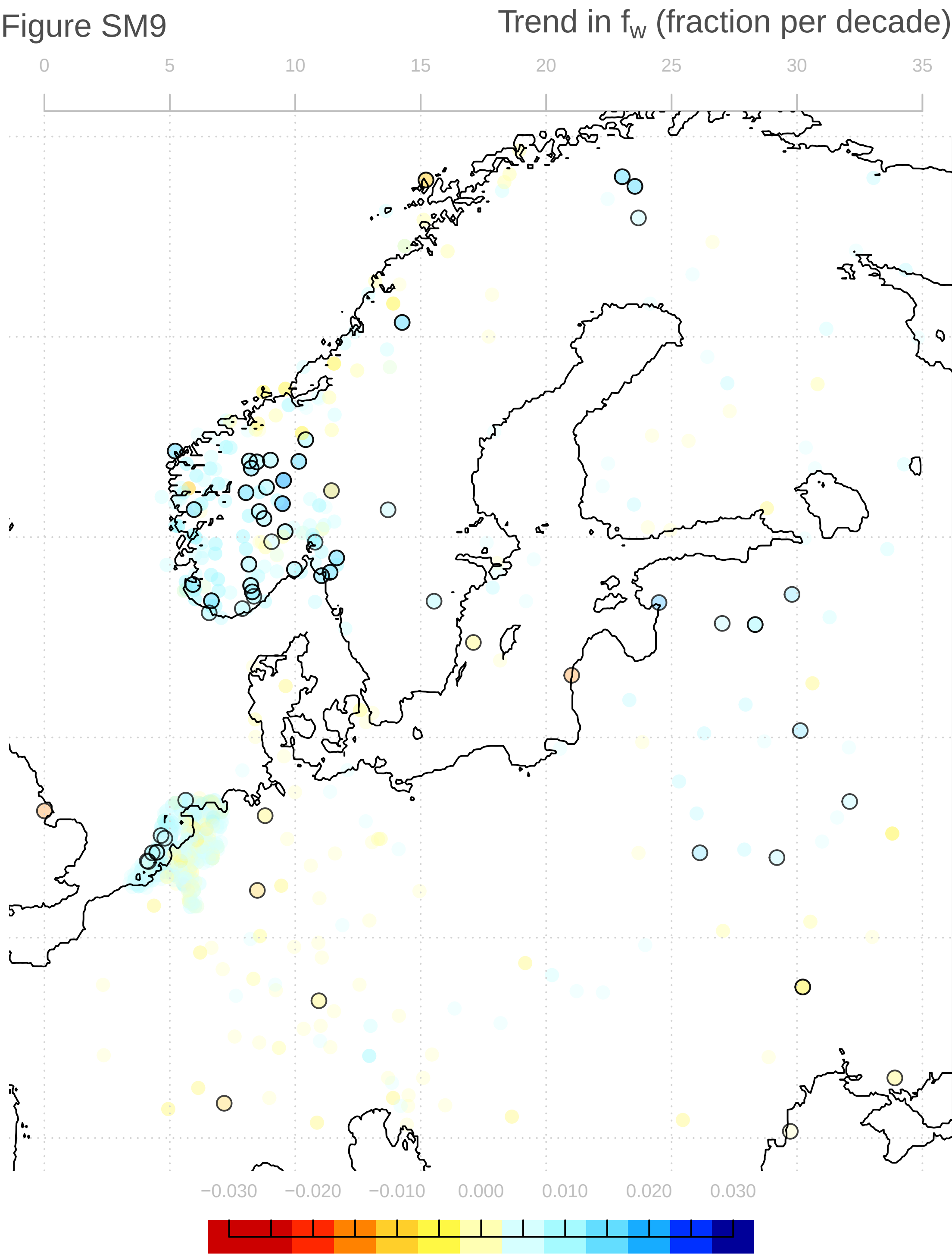


Figure SM9

Figure SM9 shows the spatial distribution of the historical trends in wet-day frequency on a map, similar to Fig SM7.

```
## Map showing trends in fw
map(FW,FUN='trend',cex=1,colbar=list(pal="budrd",breaks=pretty(c(-0.03,0.03),n=21)))
pval <- apply(coredata(FW),2,'trend.pval') <= 0.05
points(lon(subset(FW,is=pval)),lat(subset(FW,is=pval)),cex=1.2,col=rgb(0,0,0,0.75))
#points(lon(FW),lat(FW),cex=1.2,col=rgb(0,0,0,0.3))
figlab('Figure SM9',ypos=0.999)
figlab(expression(paste('Trend in ',f[w],' (fraction per decade)')),xpos=0.5,ypos=0.999)
```

Figure SM9



Analysis from other continents and with local temperature

Additional analysis testing the connection between local temperature and wet-day mean precipitation.

Regression analysis between the wet-day mean mu and the mean temperature

Load South American temperature and precipitation data from the climate database CLARIS and European observations that were used in COST-VALUE experiment 1.

```
## CLARIS
load('claris.Tx.rda')
load('claris.Pr.rda')

Tx1 <- Tx
Pr1 <- Pr

## COST-VALUE
load('stationsVALUE-exp1a.rda')
Tx2 <- Tx
Pr2 <- Pr
```

Load and prepare temperature and precipitation data from North America from the GDCN database.

```
## Read North american data:
if (!file.exists('mut2m.GDCN.rda')) {
  source('readGDCN.R')

  gdcn <- list.files('/disk1/GDCN-data_disk2',pattern='dly', full.names = TRUE)
  finfo <- file.info(gdcn)
  fok <- (finfo$size > 200000)
  gdcn <- gdcn[fok]
  n <- length(gdcn)

  plot(c(-180,180),c(-90,90),type='n',xlab='',ylab='')
  data(geoborders)
  lines(geoborders)

  for (i in 1:n) {
    pr <- readGDCN(gdcn[i])
    tx <- readGDCN(gdcn[i],param="tmax")
    if ( (nv(pr) >  20000) & (nv(tx) >  20000)) {
      pr <- subset(pr,it=c(1945,2015))
      tx <- subset(tx,it=c(1945,2015))

      if (i==1) {
        mu <- annual(pr,FUN='wetmean')
        fw <- annual(pr,FUN='wetfreq')
        t2m <- annual(tx,FUN='mean',na.rm=TRUE)
      } else {
        mu <- combine(mu,annual(pr,FUN='wetmean'))
        fw <- combine(fw,annual(pr,FUN='wetfreq'))
        t2m <- combine(t2m,annual(tx,FUN='mean',na.rm=TRUE))
      }
      print(paste(i,' (',n,'): ',loc(pr),', ',cntr(pr),' #validdata=',nv(pr),
                  'Tx: ',round(mean(tx,na.rm=TRUE),2),
                  round(min(tx,na.rm=TRUE),2),
                  round(max(tx,na.rm=TRUE),2),lat(tx)))
      points(lon(pr),lat(pr),pch=19,col='darkgreen')
    }
  }
  save(file='mut2m.GDCN.rda',mu,fw,t2m)
} else load('mut2m.GDCN.rda')
```

Combine the observational data from North America, Europe, and South America. Then fit a linear regression model comparing the mean μ and e_s values at different locations.

```
## Aggregate annual statistics based on the combined data sources:
MU <- combine(mu,annual(Pr1,FUN='wetmean'),annual(Pr2,FUN='wetmean'))
FW <- combine(fw,annual(Pr1,FUN='wetfreq'),annual(Pr2,FUN='wetfreq'))
T2M <- combine(t2m,annual(Tx1,FUN='mean'),annual(Tx2,FUN='mean'))
nval <- apply(coredata(MU),2,'nv')
attr(T2M,'variable') <- 't2m'
es <- C.C.eq(T2M)

calmu <- data.frame(x=as.numeric(apply(coredata(es),2,'mean',na.rm=TRUE)),
                    y=as.numeric(apply(coredata(MU),2,'mean',na.rm=TRUE)),
                    fw=as.numeric(apply(coredata(FW),2,'mean',na.rm=TRUE)),
                    z=alt(MU),lat=lat(MU),lon=lon(MU),nval=nval)
premu <- calmu; premu$x[0] <- 0
model.mutx <- lm(y ~ x, weights=fw,data=calmu)
print(summary(model.mutx))
```

```
##
## Call:
## lm(formula = y ~ x, data = calmu, weights = fw)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -4.3565 -1.0354 -0.0751  0.7310  6.0004
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 4.038e+00  2.094e-01   19.28   <2e-16 ***
## x           2.783e-03  8.788e-05   31.67   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.22 on 1418 degrees of freedom
## Multiple R-squared:  0.4142, Adjusted R-squared:  0.4138
## F-statistic:  1003 on 1 and 1418 DF,  p-value: < 2.2e-16
```

```
data(geoborders)
Fw <- apply(coredata(fw),2,'sum',na.rm=TRUE)
```

```
## Estimate the correlation between the annual mean es and mu at the different sites
corhalf <- function(x) {
  n <- length(x)
  x1 <- x[1:(n/2)]; x2 <- x[(n/2+1):n]
  ok <- is.finite(x1) & is.finite(x2)
  r <- cor(x1[ok],x2[ok])
  return(r)
}

X <- matchdate(MU,es)
Y <- matchdate(es,MU)
w <- apply(coredata(fw),2,'mean')
ok <- w > 0.25
Z <- rbind(coredata(X),coredata(Y))
r <- apply(Z,2,corhalf)
```

```r
hist(r)
```

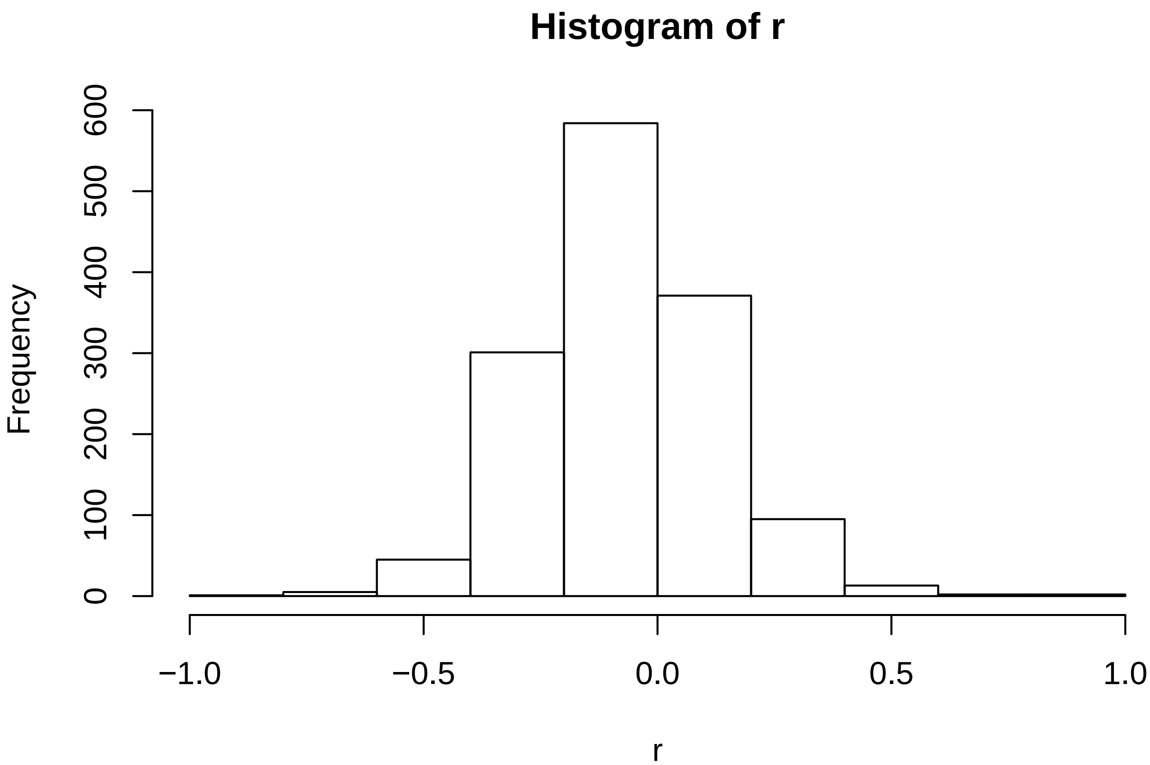


Figure SM10

Assess the connection between temperature and the wet-day mean precipitation in space, based on the regression models defined above.

```r
par(bty='n')
col <- rgb((1+sin(pi*calmu$lat/180))/2,
           cos(pi*calmu$lon/180)^2,
           1-(1+sin(pi*calmu$lat/180))/2,0.4)
cex <- 1.5*Fw/max(Fw,na.rm=TRUE)
plot(calmu$x,calmu$y,pch=19,col=col,cex=cex,
     main='Wet-day mean precipitation temperature dependency',
     ylab=expression(mu*phantom(0)*(mm/day)),
     xlab=expression(e[s]*phantom(0)**(Pa)))
points(calmu$x,calmu$y,pch=21,col=rgb(0.5,0.5,0.5,0.2),cex=cex)
lines(calmu$x,predict(model.mutx),col=rgb(0.4,0.4,0.4,0.1),lwd=2)

par(new=TRUE,fig=c(0.15,0.45,0.7,0.9),mar=rep(0,4),xaxt="n",yaxt="n")
plot(calmu$lon,calmu$lat,pch=19,col=col,cex=0.3*cex)
lines(geoborders,col='grey')
points(calmu$lon,calmu$lat,pch=19,col=col,cex=0.3*cex)
figlab('Figure SM10')
```

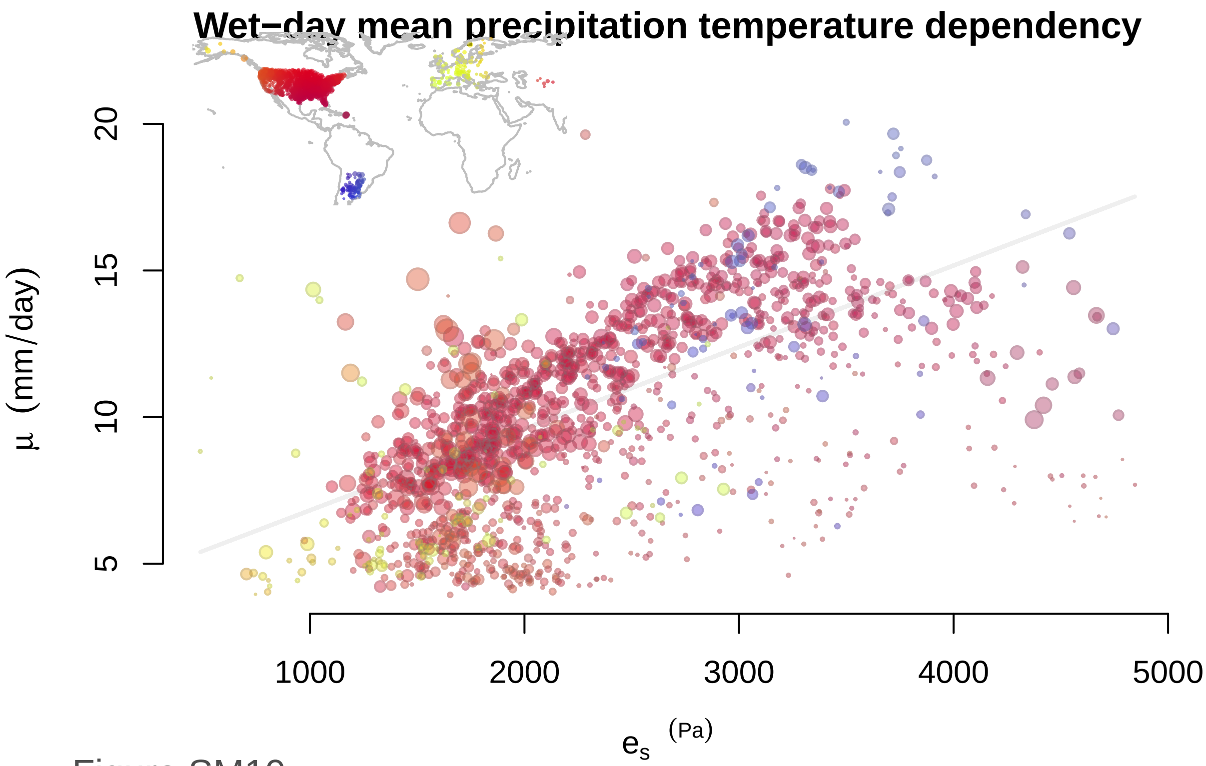


Figure SM10

```
mu.eq.f.tx <- model.mutx
attr(mu.eq.f.tx,'input') <- 'saturation water pressure e_s (Pa)'
attr(mu.eq.f.tx,'predictand') <- 'C.C.eq(tmax)'
attr(mu.eq.f.tx,'output') <- 'wet-day mean precipitation (mm/day)'
attr(mu.eq.f.tx,'calibration') <- 'mean climatology'
attr(mu.eq.f.tx,'source script') <- 'mut2m.R'
attr(mu.eq.f.tx,'timestamp') <- date()
attr(mu.eq.f.tx,'calibration_data') <- calmu
save(file='mu.eq.f.tx.rda',mu.eq.f.tx)
```

Figure SM11

Figure SM11 compares the regression coefficients derived from the seasonal cycles of μ and the North Atlantic e_s (see e.g. Figures 1 and 3), to the regression coefficient from the comparison between the mean μ and e_s from various sites (see Figure SM10).

```
## Compare the regression coefficients derived from individual
## seasonal cycles with that derived from mean climatology at different sites.

data(mu.eq.f.tx)

col <- rgb(0.1,0.1,0.7,0.25)
mutx <- summary(mu.eq.f.tx)$coefficients[c(2,4)]
b1 <- as.numeric(lapply(Beta,function(x) x[1]))
e1 <- as.numeric(lapply(Beta,function(x) x[2]))
cex.r2 <- 1.5*unlist(r2) + 0.2

par(bty='n')
plot(b1,pch=19,col=col,cex=cex.r2,xaxt="n",
     main=expression(paste('Scaling coefficient for ',mu,' and ',e[s])),
```

```r
     xlab='Observation site',ylab=expression(beta))
axis(side=1, seq(0,1000,200), labels = FALSE)
grid()
for (i in 1:length(b1)) {
  lines(rep(i,2),b1[i]+e1[i]*c(-2,2),col=col)
  lines(i+c(-0.45,0.45),b1[i]+e1[i]*c(-2,-2),col=col)
  lines(i+c(-0.45,0.45),b1[i]+e1[i]*c(2,2),col=col)
}
polygon(c(1,rep(length(b1),2),rep(1,2)),
        mutx[1]+mutx[2]*c(-2,-2,2,2,-2),
        border=rgb(0.5,0.5,0.5,0.4),col=rgb(0.5,0.5,0.5,0.3))
lines(c(1,length(b1)),rep(mutx[1],2),lwd=3,col=rgb(0.5,0.5,0.5,0.3))
legend(200,-4e-3,legend=c("seasonal regression","spatial regression"),
       col=c(col,rgb(0.5,0.5,0.5,0.4)),cex=0.8,lwd=2,box.lwd=0.5,
       lty=c(1,1),pch=c(19,NA),fill=c(NA,rgb(0.5,0.5,0.5,0.3)),
       border=c(NA,rgb(0.5,0.5,0.5,0.4)))
figlab('Figure SM11')
```

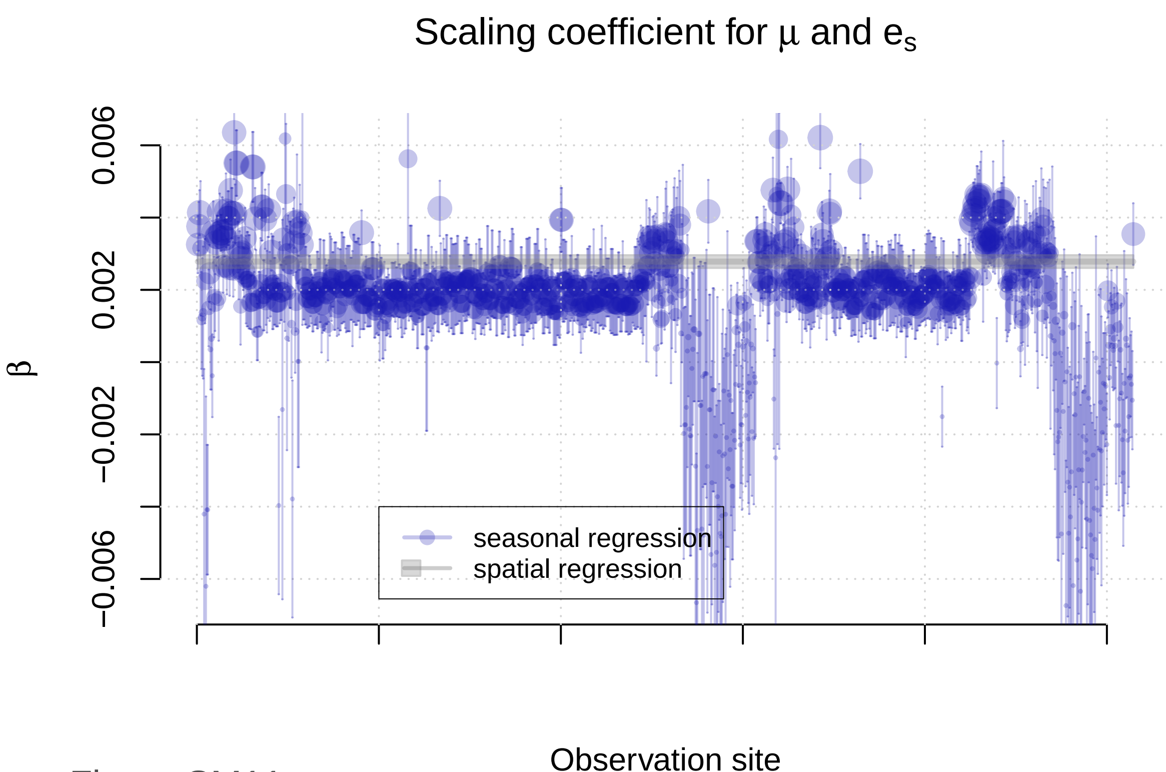


Figure SM11