Approximate estimation of an upper limit to changes in future precipitation return-values

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Supporting Material

What does “upper limit” refer to?

The precipitation statistics is expected to respond to changes in the rate of evaporation and the atmospheric moisture, and given a link between the vapour saturation pressure (a function of temperature) and the wet-day mean precipitation μ, the maximum systematic influence of the temperature on μ can be taken be proportional change between the mean seasonal variations in both. It is, however, possible that the effect is weaker and that there are other factors which play a role and also exhibit a seasonal cycle.

Why use the 100°W-30°E/0°N-40°N region of the North Atlantic as predictor?

This is an area which can be considered as an important source of the moisture brought in over Europe. The data analysis presented here suggests a good match between the seasonal variations of the temperature averaged over this region and the local wet-day mean (Figure 1). The choice of predictor in this study was motivated by the idea that the North Atlantic ocean is an important moisture source for precipitation over Europe and prevailing winds suggest that the moisture is transported from the west. Also, the sea surface temperature is highest at low latitudes, which suggest highest evaporation closer to the equator. Here the predictor was crudely defined as the area mean saturation vapour pressure. The area domain was set after some trials for some test stations, but this crude trial did not involve any systematic study nor any type of fitting/tuning.

Why using the wet-day mean rather than the mean precipitation?

A traditional approach for modelling and analysing precipitation involves monthly mean precipitation[1-5], however, it is not the optimal quantity for describing precipitation statistics. It doesn't rain every day in most places, and the proportion of wet days to total number of days in a monthly sample may have implications on the statistical parameters describing the distribution. A central question is whether the dry and wet days should be blended or kept apart, as different physical processes are present during days with and without precipitation.

A reductionist approach can involve a splitting of the precipitation data into two categories: one for zero-precipitation with a trivial non-distribution (dry days) and one for non-zero precipitation (wet days). For all intents and purposes, a threshold of 1mm/day was used to make this distinction. One implication of the categorisation of precipitation is that each month has about 10 data points for locations if only 30% of the days have non-zero precipitation. A month's worth of rain gauge data only corresponds to a small statistical sample subject to large sampling fluctuations, and statistical parameters such as the mean are not well-constrained. Furthermore, mean estimates based on small samples do not conform to the central limit theorem[6]. To avoid problems associated with small sample sizes, we analyse seasonal rather than monthly mean values of the wet-day mean precipitation.

How does the wet-day mean relate to the more traditional mean and total precipitation amounts?

The traditional mean precipitation can be expressed as the product between the wet-day frequency and the wet-day mean precipitation according to

$$x = f_w \mu \qquad (1).$$

The distinction between the two categories is clearer for rain gauge data that samples spatially heterogeneous precipitation accumulated over 24 hr at a smaller spatial scale than satellite-borne instruments which measure precipitation as a snapshot and coarser spatial resolution.

While one may argue for a distinction of wet and dry days based on different physical conditions being present during dry and wet days, it is also supported by empirical observations. A simple demonstration is the seasonal variation in the wet-day mean and the monthly mean respectively (Figure SM13), as the seasonal variations constitute some of the most pronounced and systematic climate variability that takes place on earth with reasonably well-understood causes. Hence we have made use of the hypothesis that precipitation involves two categories: wet and dry days is supported by a more pronounced seasonal cycle.

What are the implications of changes in the wet-day frequency?

Changes in the wet-day frequency will influence the probability for heavy precipitation amounts in the future according to $Pr(X > x) = f_w e^{-x/\mu'}$, and hence future return-values according to $x_{1year} = \mu' \ln(365.25 * f_w)$. This goes for both long-term changes (trends) as well as interannual-to-decadal variations. The historical estimates account for interannual variability, but short historical periods (limited sample size) may preclude a complete account of the effect from decadal changes.

Is the wet-day frequency stationary?

The wet-day frequency responds weakly to the seasonally varying conditions (Figure SM13; grey curve), which suggests that it is not as sensitive to systematic changes in the state of the local environment. We can also make use of some information from past trends in the wet-day frequency, as climate change is already happening (Figures SM6-SM7). Historical data suggest different tendencies in different regions (Figure SM7), but previous analysis suggests that the wet-day frequency f_w is strongly influenced by the circulation patterns[7]. Overall, there is little trend when taking the mean over all locations (Figure SM6).

One explanation for the weak historical trends is slow natural variations such as the North Atlantic Oscillation (NAO). Such natural variations are hard to predict and there is little evidence suggesting a systematic shift in the frequency of different circulation patterns.

Why use the seasonal cycle for model calibration?

Precipitation is generated by different atmospheric processes and depends on a number of factors. Hence the signal-to-noise ratio is often low for traditional model calibration based on chronological matching between the amount and some large-scale variable such as regional temperature. One technique commonly used in physics and electronics for optimising the information from systems and measurements with low signal-to-noise ratio involves cycles with well-established frequencies (eg. FM in radio, phase-locking), and in meteorology/climatology seasonal variations is the most pronounced cycle.

There has also been some analysis of tropical cyclone frequencies based on the seasonal variations[8], but there is an important caveat associated with such studies: the seasonal variations in the local insolation may affect both the large-scale conditions and the local variable under investigation, and their correlation may reflect the common dependency on this forcing rather than common link. Thus, the assumption that the seasonal cycle in the temperature over the North Atlantic is linked with the seasonal precipitation statistics is the weakest point of this study if one interprets the results as the most likely estimate of the wet-day mean precipitation. Nevertheless, from a physics perspective, it is expected that higher temperatures result in higher evaporation and higher humidity, hence, an increased capacity for greater rainfall amounts. The link is also assessed by extending the analysis to the spatial as well as the temporal dimension. Another important point is that we use this link to estimate an *upper limit* of the effect of a change in temperature on the precipitation, rather than the *most likely estimate* of the wet-day mean precipitation itself.

Is there other information indicating a connection between temperature and the wet-day mean precipitation?

There is a link between the wet-day mean and temperature found both in time and space. The fact that this exists in two different dimensions is a stronger indicator of a physical link than if it were to be limited to only one.

Figure SM8 shows a scatter plot between the saturation vapour pressure e_s calculated based on the local mean daily maximum temperature and the wet-day mean precipitation μ. The fitted line shows the regression between climatological values for mean wet-day mean and local mean climatological temperature for 1420 locations (CLARIS data) in South america, Europe (stations selected for the COST-VALUE experiment 1), and the US (GDCN) indicates that the wet-day mean (y) increases by 0.4 mm/day per degree C (x) increase in the local temperature if the elevation (z) is accounted for:

```
Call:
lm(formula = y ~ x, data = calmu, weights = fw)

Weighted Residuals:
```

```
          Min       1Q  Median      3Q        Max
-3.4489 -0.9975 -0.0333  0.6501  7.6932

Coefficients:
          Estimate Std. Error t value Pr(>|t|)
(Intercept)  2.88501    0.24159   11.94   <2e-16 ***
x          0.40359          0.01261   32.01   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.215 on 1418 degrees of freedom
Multiple R-squared:  0.4195,    Adjusted R-squared:  0.419
F-statistic:  1025 on 1 and 1418 DF,  p-value: < 2.2e-16
```

Why not use year-by-year correlation in temperature and wet-day mean?

A correlation analysis of annual year-to-year variations in temperature and wet-day mean gave close-to-zero correlations:

```
summary(cor)
Min.        1st Qu.     Median     Mean      3rd Qu.    Max.        NA's
-0.2891     0.1177      0.2163     0.2020    0.3021     0.5728
summary(f_w)
Min.        1st Qu.     Median     Mean      3rd Qu.            Max.        NA's
 0.0943     0.1766      0.2545     0.2345    0.2790     0.3439     1204
```

There may be other factors influencing the precipitation statistics on shorter time scales, such as the track of cyclones, low-pressure systems, and fronts. The effect of temperature is expected to be found on the longer time scales[9] both for physical reasons as well as statistical ones: (a) the temperature influences the surface evaporation and atmospheric moisture and hence a background level for precipitation mechanisms; (b) for about half of the locations, the number of rainy days in a year was less than 100 implying a limited sample size. Furthermore, this estimate represents an upper limit to the wet-day mean precipitation, and it is not clear whether the upper limit should be expected to correlate on an annual basis. Figure SM3 presents correlation between long-term trends predicted for the upper limit in μ and actual trends in μ derived from the observations. The observed values are scattered over a wider range, as other factors play a role and affect the trends over the observed intervals, however, the predicted upper limit are roughly of similar magnitude. The discrepancies can be interpreted as that the upper limit linked to temperature changes explain part of the long-term change in μ and that contributions from other conditions may come on top of that.

Why include the CLARIS and GDCN only in supporting analysis?

The point of this exercise is to demonstrate a link between the temperature and the wet-day mean that is not a result of a common external factor influencing both. It is expected that the analysis of the match in seasonal cycle will not give the same results for Latin America and the US, as there will be different dependencies to ocean temperature in different regions. For instance, precipitation falling over parts of the US is linked to the El Niño southern Oscillation and sea surface temperatures in the North Pacific[10]. Furthermore, the supporting analysis on the local climatological mean precipitation and temperature is limited to sites where both temperature and precipitation are measured. There are many more sites with rain gauges than thermometers, and hence, the analysis of the seasonal cycle can provide results to more sites within a region than an analysis that also requires local temperatures.

These results also suggest that it may be possible to get a rough and approximate estimate for the change in the wet-day mean precipitation for locations where good rain gauge records are lacking but where it is possible to downscale the temperature.

How well do the dependencies with local temperature and large-scale maritime temperature correspond?

Saturation vapour pressure was estimated from the mean climatological temperature, based on the Clausius-Clapeyron equation, to match the dimensions of the input used in the comparison between the seasonal cycle. A regression analysis was then applied to the local climatological mean temperature and the local wet-day mean:

```
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
```

It is not expected that the results should be identical, as the climatological temperature involves the mean of the local daily maximum temperature from the stations, whereas the seasonal temperatures were taken from a large region of the ocean and represented daily mean temperature. Nevertheless, similar values for the scaling factor (regression coefficients) between the saturation vapour pressure and the wet-day mean precipitation μ supports the hypothesis that the precipitation amounts are linked to temperature in a way that gives similar changes through the seasonal variations as in spatial variations. The results of this comparison are shown in Figure SM12, where the results shown in blue are based on the seasonal cycle and the grey the regression over space. The two approaches give results which overlap within the estimated error bars, except for a group of stations with poor match in the seasonal cycle (low R^2 from the regression). The stations with diverging results are located in regions where convective precipitation is less dominant (Figure 2).

Why use mean maximum temperature for the climatological analysis and mean daily mean temperature for the seasonal cycle?

Maximum temperature was available in all of the data sets used here, GDCN, CLARIS and ECA&D, and to obtain an estimate for the daily mean temperature, it would have to involve a crude calculation taking *mean=(min + max)/2*. However, the daily mean temperature was not estimated in this analysis because the geometrical distribution of mean daily maximum temperature was expected to be similar to mean daily maximum.

Is the model ensemble spread a good proxy for probabilities?

Model ensembles do not provide estimates of probabilities because they cannot be considered as a random sample of data and because they do not give a perfect reproduction of the observed quantities. According to the IPCC "*Ensemble members may not represent estimates of the climate system behaviour (trajectory) entirely independent of one another. This is likely true of members that simply represent different versions of the same model or use the same initial conditions. But even different models may share components and choices of parameterizations of processes and may have been calibrated using the same data sets. There is currently no 'best practice' approach to the characterization and combination of inter-dependent ensemble members, in fact there is no straight-forward or unique way to characterize model dependence*"[11].

Nevertheless, the spread of downscaled annual mean temperature from ensemble experiments such as CMIP5 is often comparable to the magnitude of the observed year-to-year temperature variations, and the 95-percentile has been used as an approximate estimate of one-in-twenty year hot summer season[12].

Can the comparison between two single years represent the mean change?

The comparisons shown here were made using the entire ensemble. Hence, for RCP4.5, the difference between years 2100 and 2010 involved comparing two data samples with the size *n=108*. The ensemble for RCP8.5 was smallest of the ones examined (*n=65*), however, nevertheless taken to be sufficient for such analysis (Table 1). The estimates of the differences between the data samples corresponding to 2100 and 2010 would of course be more accurate with more years since *n* would be increasing, but it could also be misleading as it would be much smaller than the uncertainties associated with the GCMs' ability to project the future.

What does the leading PCs possibly represent?

The PCs derived through principal component analysis (PCA) describe the most prominent features in the data. They can be viewed as a set of components which together can mimic the original data if each is given an appropriate weight, just like sinusoids can make up a time series in a Fourier transform (FT). In FT, a spectrum tells which frequency is strongly present through a comparison between the weight for each sinusoid (spectral coefficient), and in the same way, the weight associated with each PC provides information about how strongly present they are. The main difference between FT and PCA is that the former is restricted to having sinusoidal shapes whereas PCs can have any shape.

For the seasonal cycle in precipitation, the leading PC tends to describe higher values during summer and lower values in winter. The second PC provides an additional feature, with more heavy precipitation during the autumn.

Does variation in the wet-day mean precipitation really correspond to changing probabilities?

The framework adopted here can be formulated as $Pr(X < x \mid \mu)$, hence conditional on the sample mean μ and the distribution being exponential. Previous studies have found that the wet-day daily precipitation is approximately exponentially distributed[7,13,14,15], albeit with a systematic bias connected to the location. Here the assumption can be assessed by comparing the quantiles estimated for different samples with different μ (annual mean wet-day precipitation) using the formula for exponentially distributed data $q_p = -ln(1-p)\ \mu$ with the actual percentiles (Figure SM1). The exponential distribution implies a similar proportional change for all percentiles, which is roughly consistent a near-constant ratio of increase in daily precipitation percentiles above 90th percentage[16]. The two quantities should be similar and the data scattered along the diagonal in a scatter plot, indicating that a high percentile associated with a low wet-day mean μ is consistent with a more moderate percentile for a sample with a higher wet-day mean value.

Why calculate the saturation vapour pressure?

It is often wise to make use of terms with similar physical dimensions when calibrating statistical models[17], vapour pressure is proportional to its density (ideal gas law: e_s = ρ $R_{specific}$

T), and the total mass is the product between volume and density. If temperature was used, on the other hand, then the relationship would be expected to be nonlinear due to the Clausius-Clapeyron equation ($e_s=10^{(11.40–2353/T)}$ where T is temperature in degree Kelvin).

What is the connection between the mean seasonal cycle and long time scales?

The mean seasonal cycle is estimated by taking the mean value over all January months, then over all February months and so on until one mean is found for each of the 12 calendar months. This type of aggregation both implies having larger sample size compared to analyses applied on individual years, and that each sample stretches over longer time periods. Calibration on larger sample sizes stretching over longer time periods puts more weight on slow processes with long time scales.

What are the error bars?

Error bars were estimated as part of the regression analysis, and are shown in Figures SM3 and SM9. These are different from the error bars shown in Figure 1, which indicate the year-to-year variations (two standard deviation) about the seasonal mean. The error bars from the regression analysis were not explicitly used here other than in Figure SM9, because we wanted to condense the information and there was already too much to show in the figures. The error bars estimated can be applied to single stations to investigate the probable range of outcomes. However, we have made use of the R^2 statistic, indicating what fraction of the seasonal cycle that can be attributed to the ocean temperatures in the North Atlantic.

Supporting figures

Figure SM1. Test for assessing the consistency between the percentiles taken from observations and estimated values using q_p=-$ln(1$-$p)$μ where the value for the values for q_p is estimated using different value for p to compensate for variations in annual mean μ. A critical threshold x can correspond to different percentiles p according to $x = q_{p1}=-ln(1-p_1)\mu_2$ $=q_{p2}=-ln(1-p_2)\mu_2$ and if x is exponentially distributed and $p_1 = (p_2 - 1) \, exp\{\mu_2 - \mu_1\} - 1.$

Figure SM2. The statistics of the R^2 from the regression between the seasonal cycle in the saturation water vapour, estimated from the temperature over the seasonal cycles in the saturation water vapor from the surface temperature over 100°W-30°E/0°N-40°N, and the local wet-day mean μ. There is a portion of stations with very low variance explained by this regression, but most stations suggest a variance exceeding 60%.

Figure SM3. A comparison between the long-term linear trends estimated from the annual mean μ and estimated using equation 1, taking the saturation water vapor from the surface temperature over 100°W-30°E/0°N-40°N. The scatter in the observed trends is greater than in the predicted ones, which is consistent with the wet-day mean also being affected by factors other than e_s. The historical trends have furthermore been weak compared to interannual-to-decadal variations, and the skill assessment is limited due to low signal-to-noise ratio. The error bars were estimated through linear regression, taking two times the standard error estimate, were wider for the observations than projections owing to the stronger presence of natural variability in the observations.

Figure SM4. Map of the geographical distribution in the historical trends in the wet-day mean μ. The trend is generally increasing, but there are some outliers showing a decrease. These outliers are probably spurious, as they do not match the bulk of the data.

Figure SM5. The wet-day percentile that corresponds a one-year return-value x_{1year} given the observed mean wet-day frequency. In this case, a one-year precipitation return-value corresponds roughly to the 99-percentile for the wet-day 24-hr precipitation if the wet-day frequency is accounted for [Pr(X > x) = 1/365.25 = f_w*(1-p); p = 1 - 1/(365.25*f_w)]. The comparison between the 99-percentile and the exponential distribution suggests a good match if geographical biases are accounted for[7].

Figure SM6. Trend estimates in the wet-day frequency f_w for the 1032 locations suggests values scattered around zero. A general zero-trend is consistent with the annual wet-day frequency being stationary.

Figure SM7. The geographical distribution in the historical trends in the wet-day frequency f_w. There has been a general increase in the number of wet days in southern scandinavia and regions exposed to the sea.

Figure SM8. Scatter plot showing the correlation between the climatological mean daily maximum temperature (converted to saturation vapour pressure) and the wet-day mean μ. The size of the symbols is proportional to the number of rainy days. Insert map shows locations of stations used to compare the climatological mean wet-day mean against the mean surface temperature. The colours of symbols in the scatter plot match those in the map. The data included CLARIS data set from South America, a subset of the ECA&D in Europe used in the COST-VALUE experiment 1[w] and a subset of station data from GDCN as in reference [10] but selecting the stations with the longest records. The selection of location was also limited to sites where both temperature and precipitation had been recorded.

Figure SM9. Comparison between the regression coefficients estimated for each location based on the seasonal cycles in μ and e_s (blue) and based on the regression analysis of spatially varying mean climatology as in Fig SM11 (grey). Error bars represent two standard errors. The size of the symbols is proportional to the R^2-statistics from the regression analysis between the two mean seasonal cycles. The comparison between the results from the two types of analyses suggests a consistency within the margin of error for those locations where the mean seasonal cycle in μ matched that of the predictor from 100°W-30°E/0°N-40°N.

Figure SM10. Map showing the actual return-values estimated for 2100 for an RCP4.5 emissions scenario. The results here were estimated according to $x_{20year} = \mu_{95} \ln(365.25\, \overline{f_w})$, where μ_{95} was the 95-percentile of the values for μ downscaled from the CMIP5 RCP4.5 simulations (108 runs). Here $\overline{f_w}$ was the mean wet-day frequency, assuming that the number of rainy days is stationary. The downscaling of μ was based on statistical models calibrated on the mean seasonal cycle (Figure 1).

Figure SM11. An example of projected annual wet-day mean precipitation μ for the three different emission scenarios RCP 4.5 (grey), RCP2.6 (green) and RCP8.0 (red) as the percentage of the 2010 values (see Table 1).

Figure SM12. The mean temperature over the chosen predictor area 100°W-30°E/0°N-40°N.

Figure SM13. A comparison between the seasonal cycle in the mean precipitation, the wet-day mean precipitation, the wet-day frequency, as well as the wet and dry spell lengths. The most pronounced seasonal variations tends to be associated with the wet-day mean rather than the mean precipitation or the wet-day frequency.

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Appendix

Figures

R-script (Rmarkdown) used to produce the plots

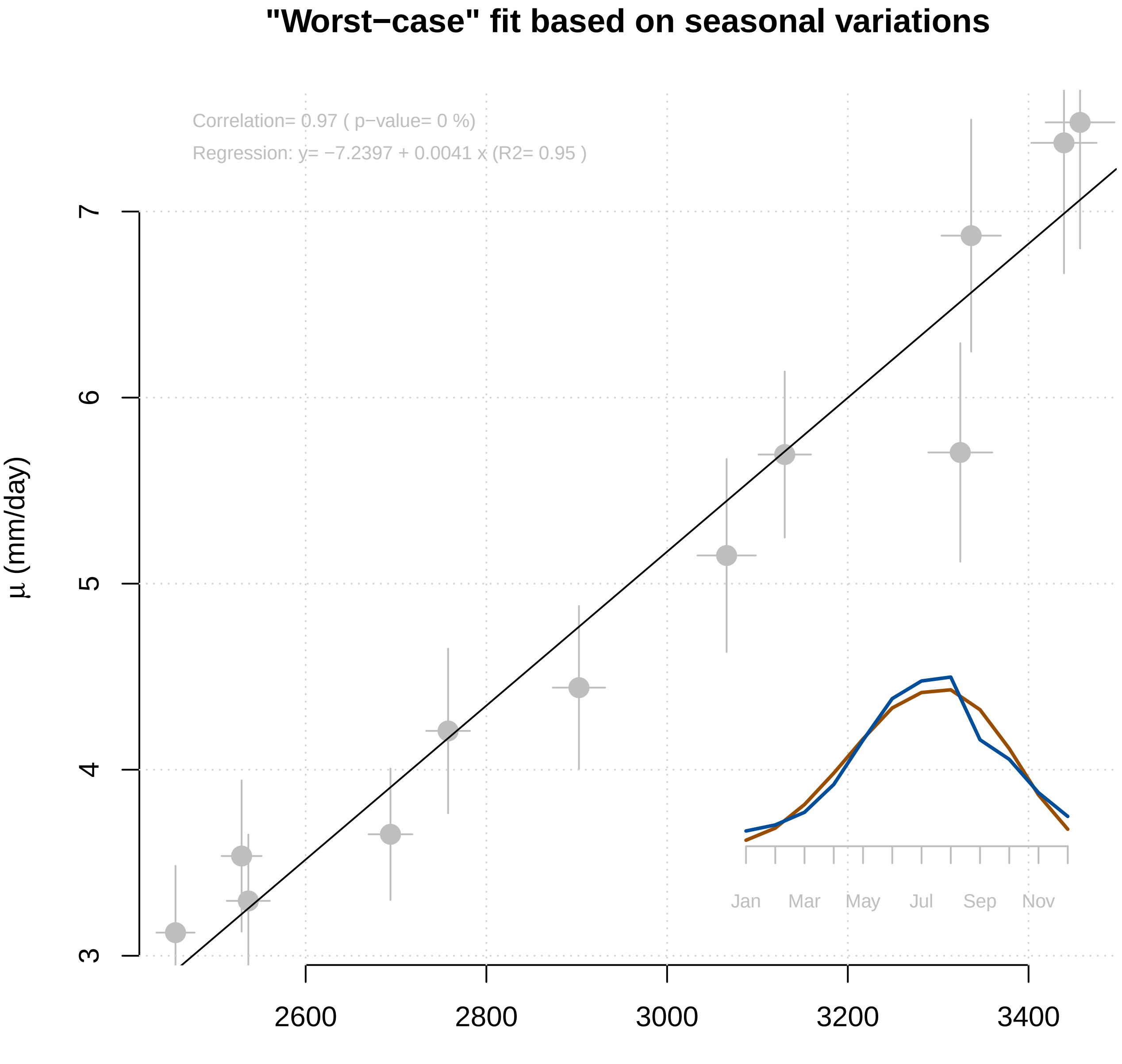


Figure 1

VELIKIE LUKI (30.62E/56.35N; 97m.a.s.l.)

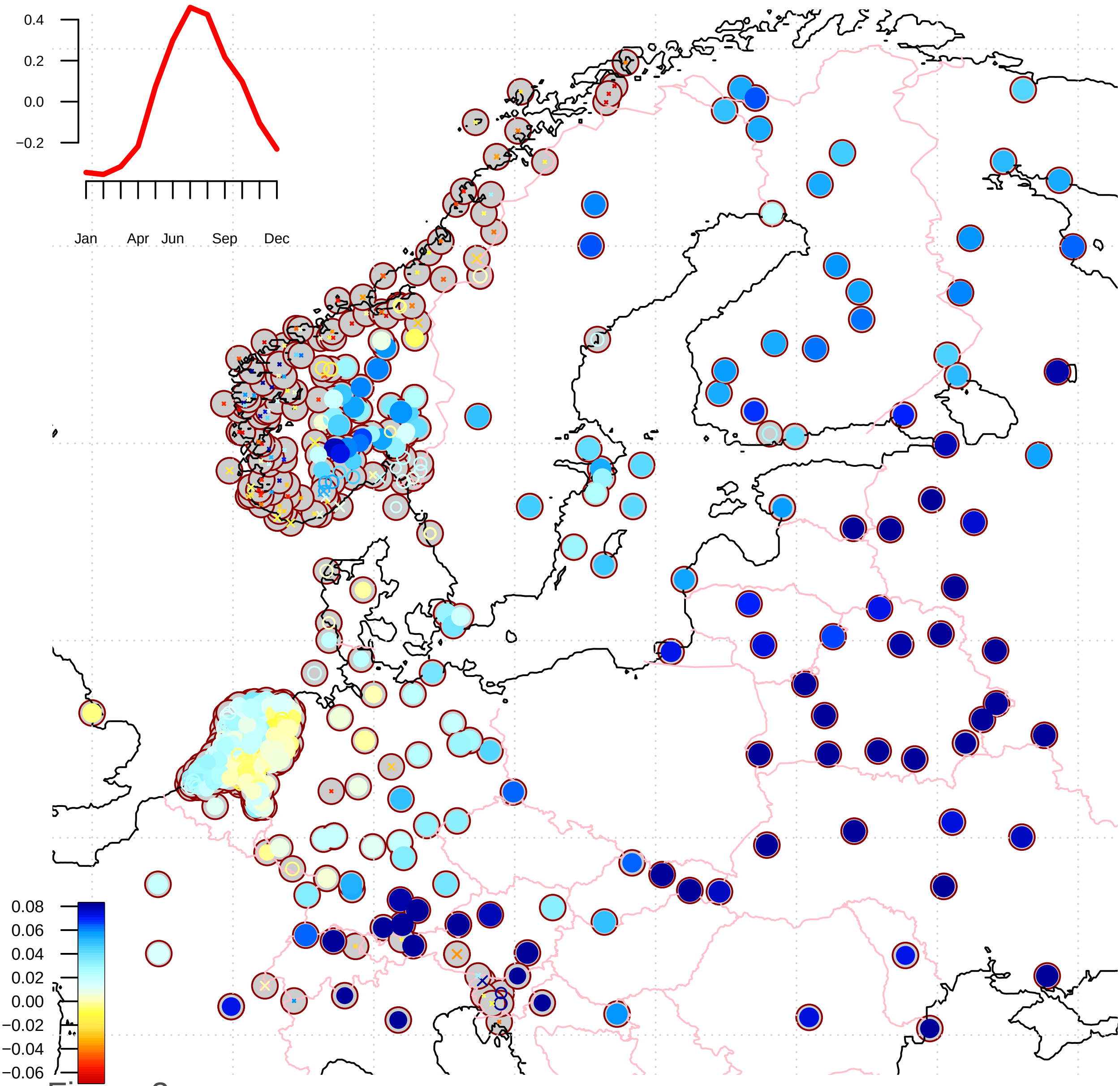


Figure 2a

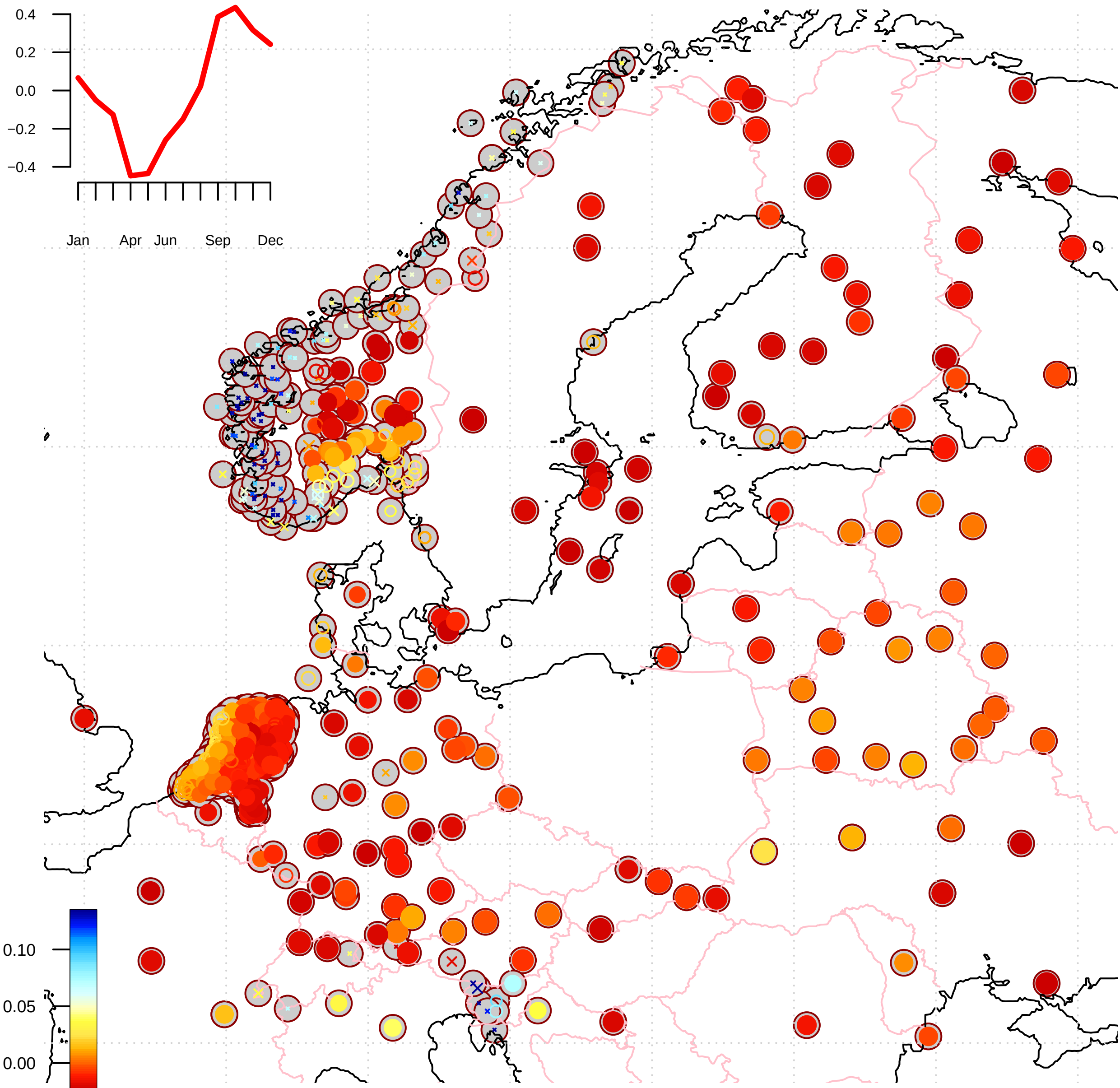


Figure 2b

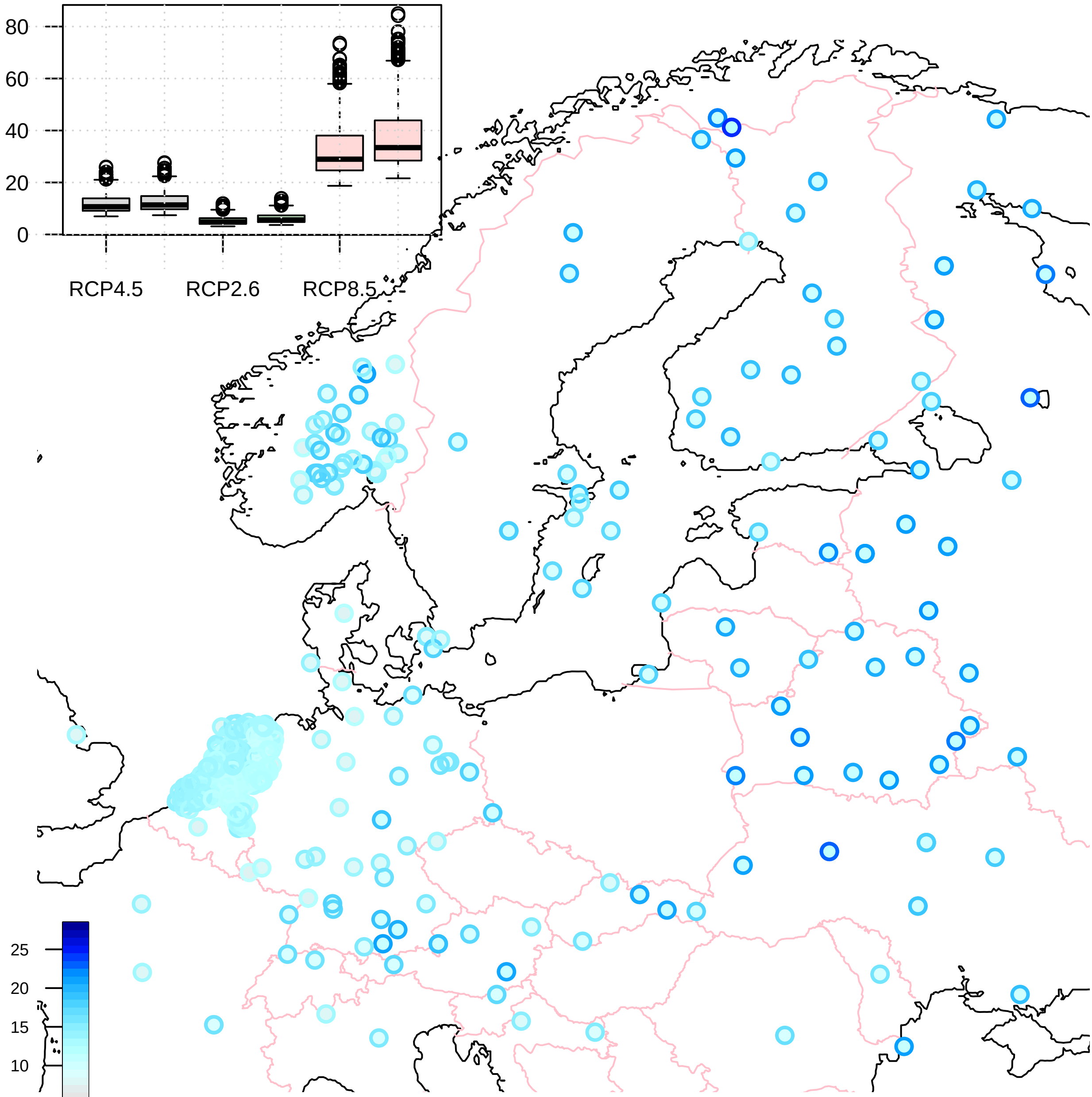


Figure 3

Supporting figures

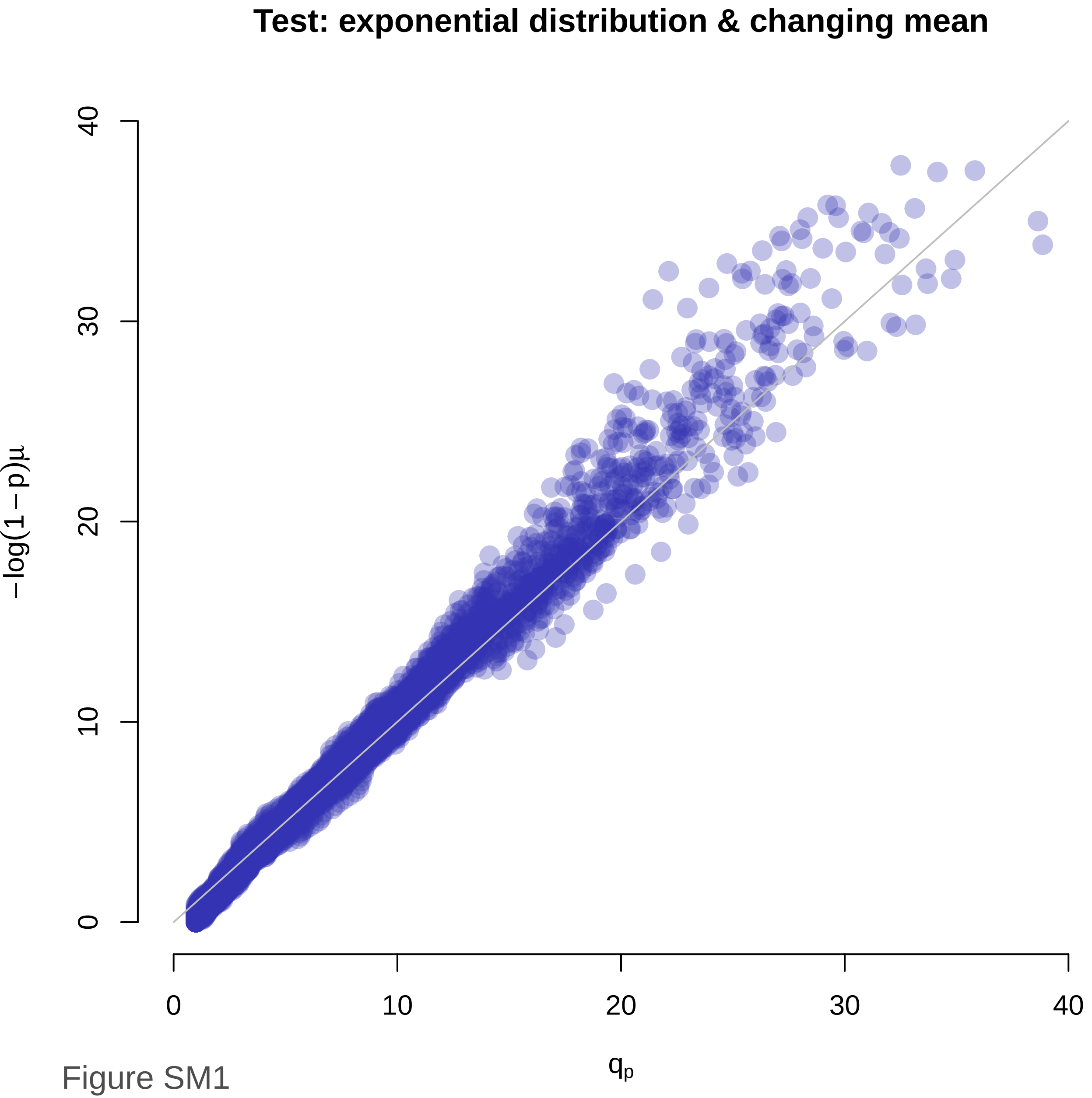

Test: exponential distribution & changing mean
40
30
20
10
0
−log(1 − p)μ
0
10
20
30
40
qp

Figure SM1

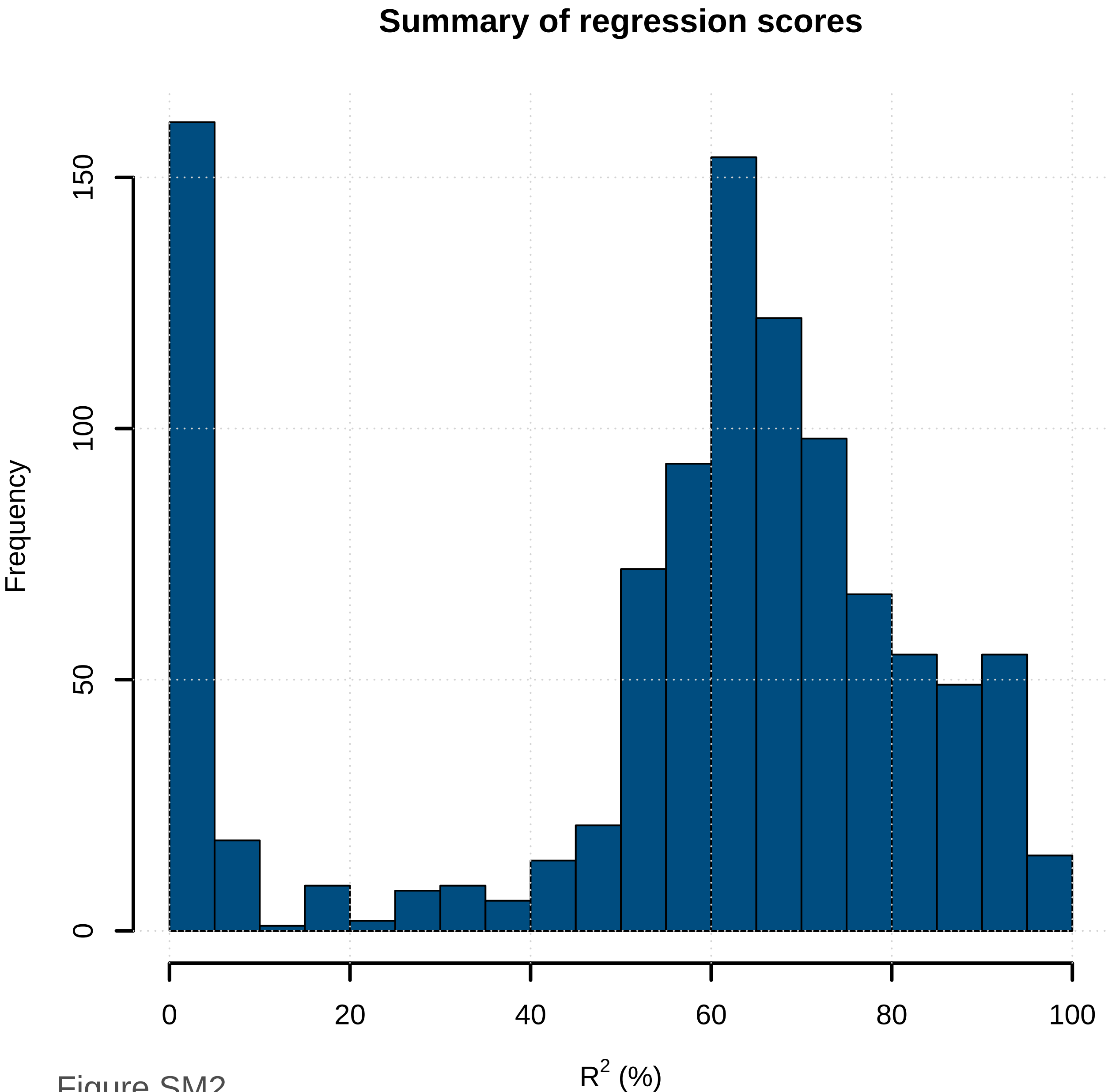

Summary of regression scores
Frequency
150
100
50
0
0
20
40
60
80
100
R2 (%)

Figure SM2

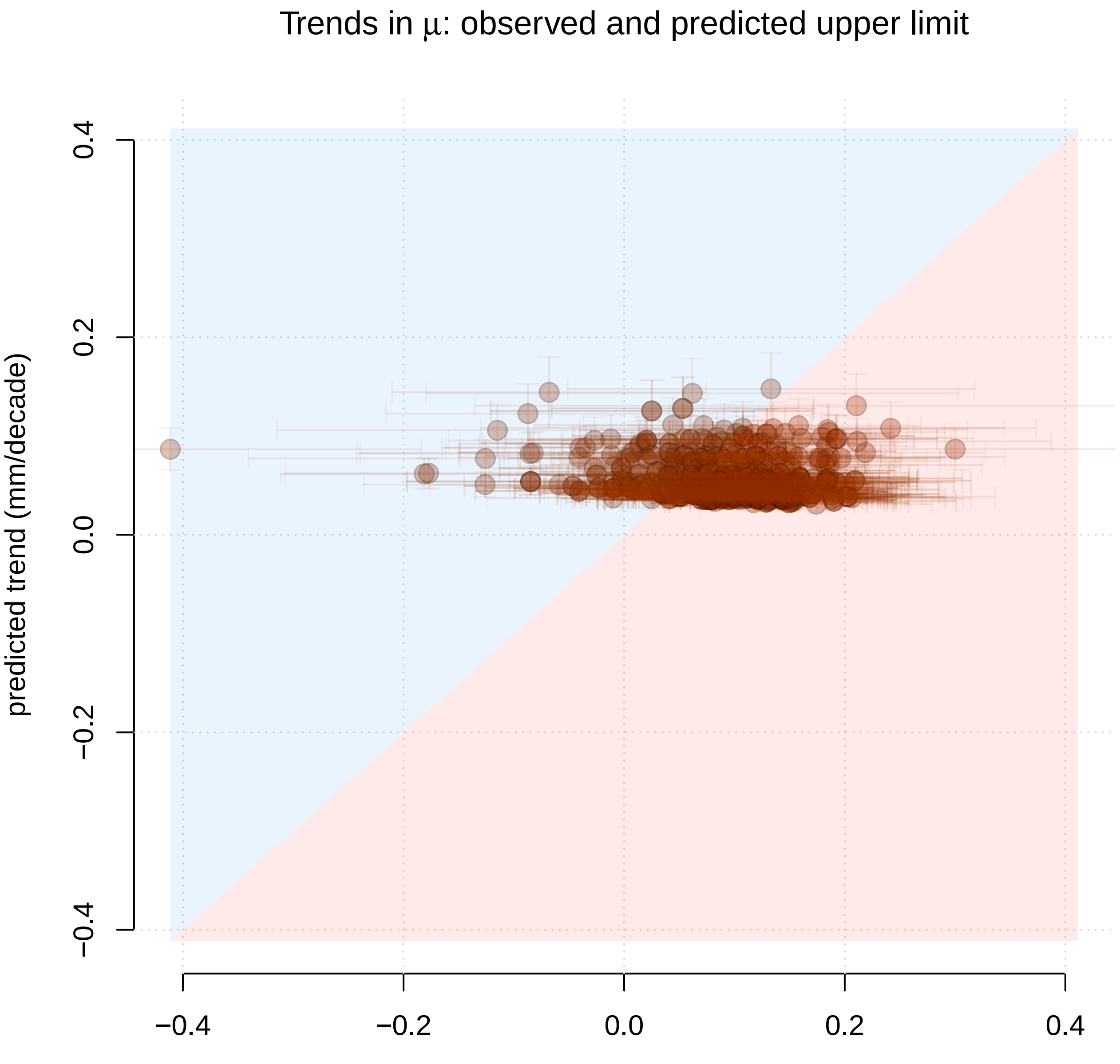
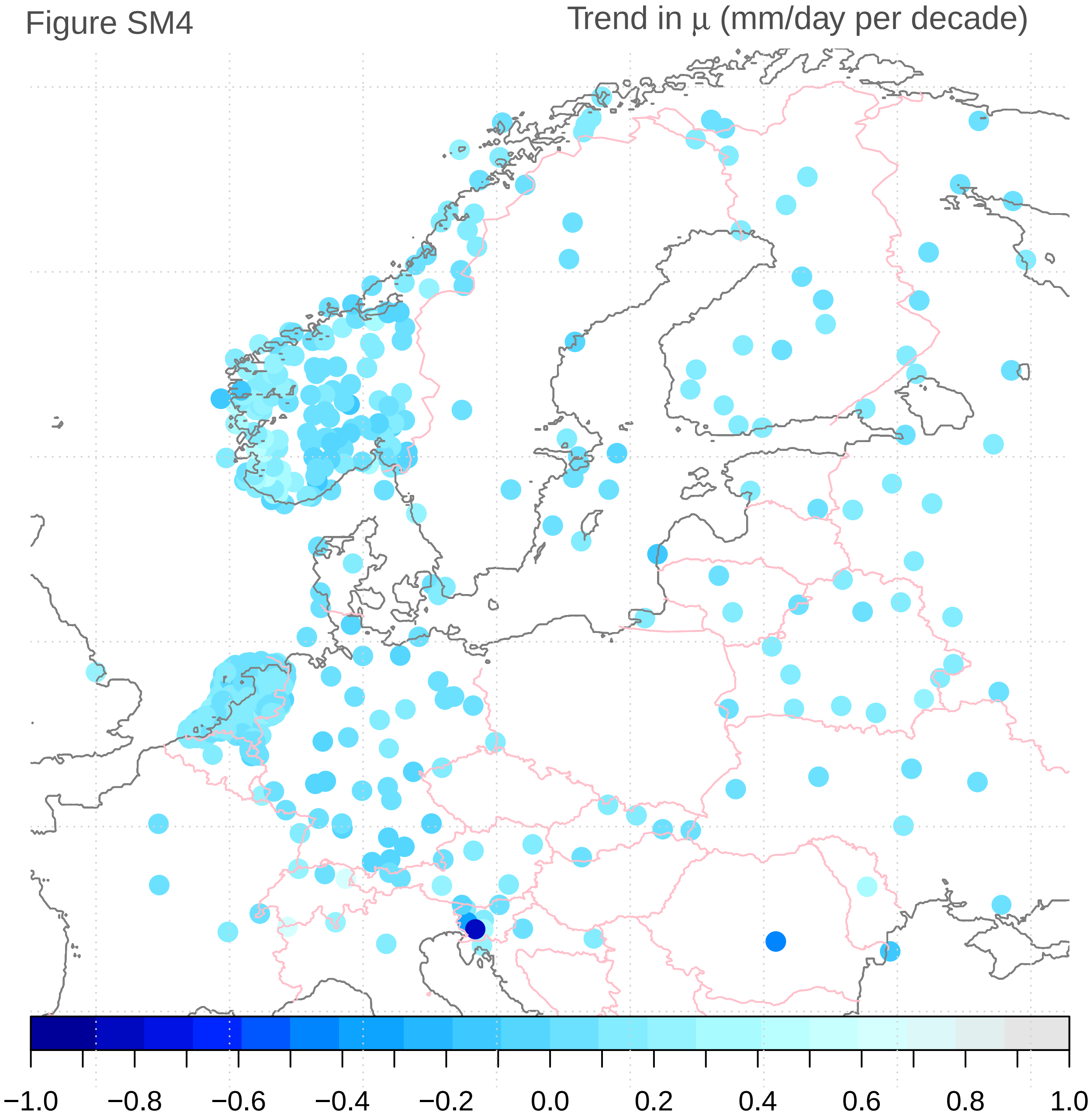


Figure SM3

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

Figure SM4



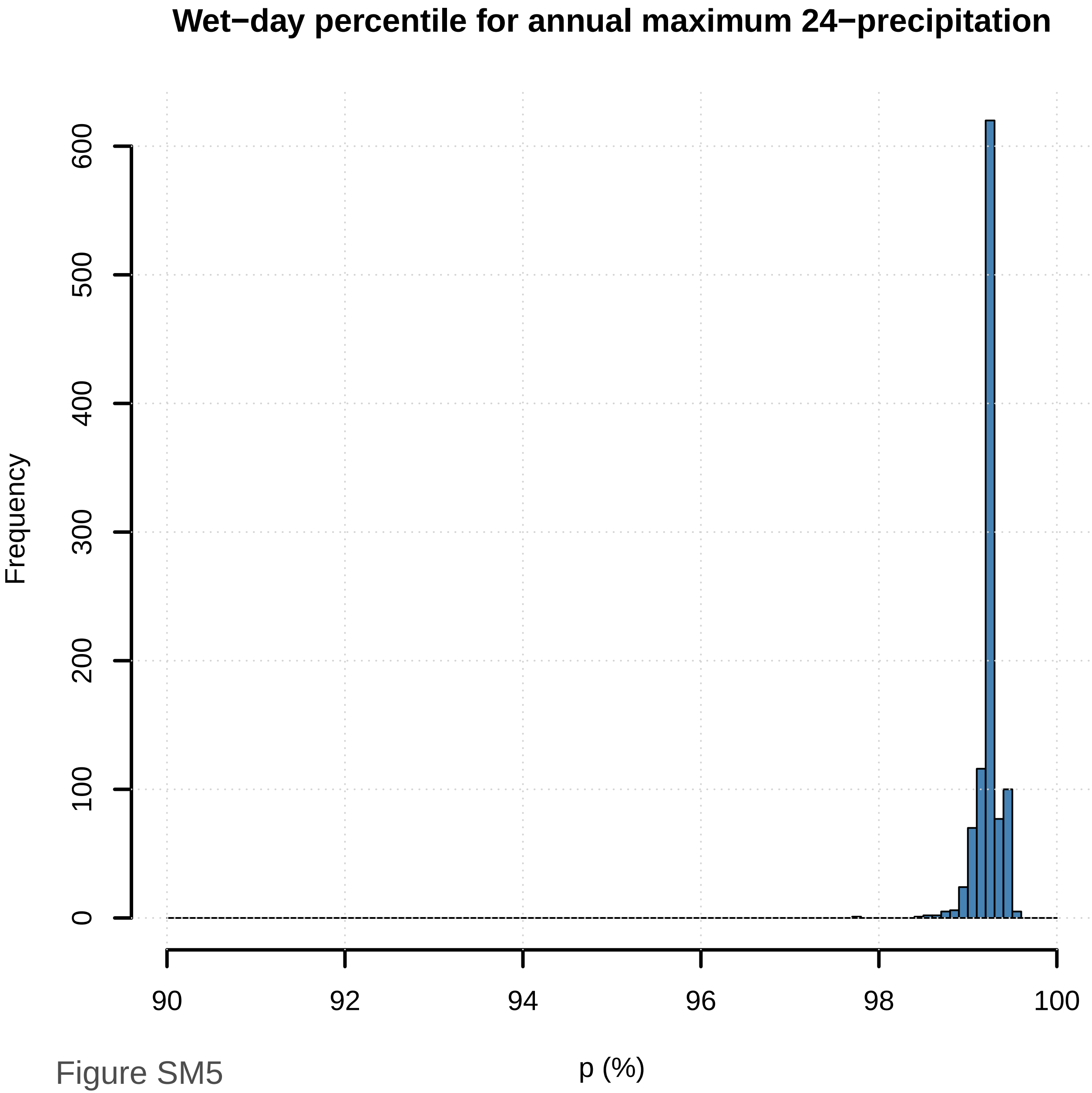

Wet−day percentile for annual maximum 24−precipitation
Frequency
0
100
200
300
400
500
600
90
92
94
96
98
100
p (%)

Figure SM5

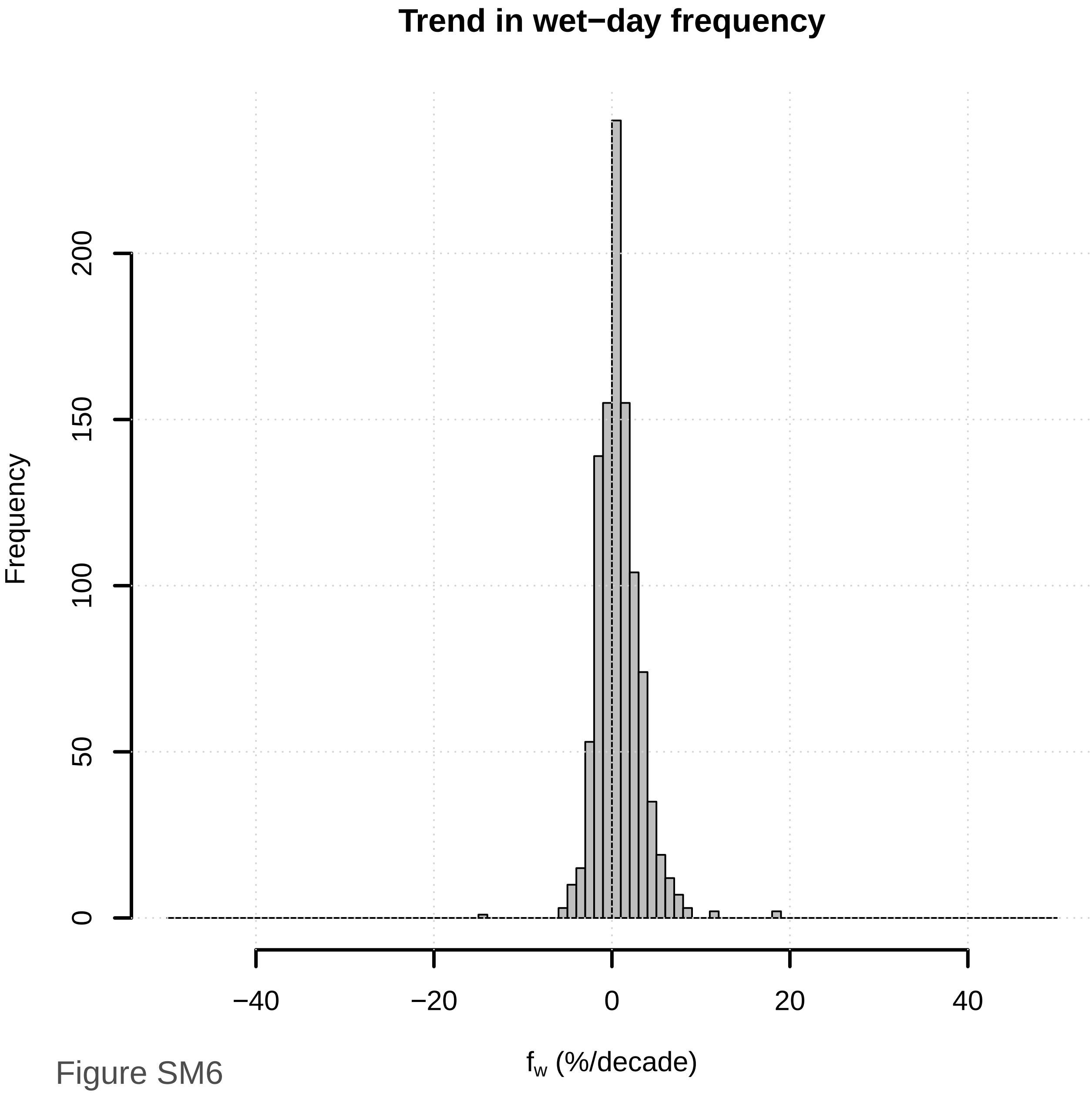
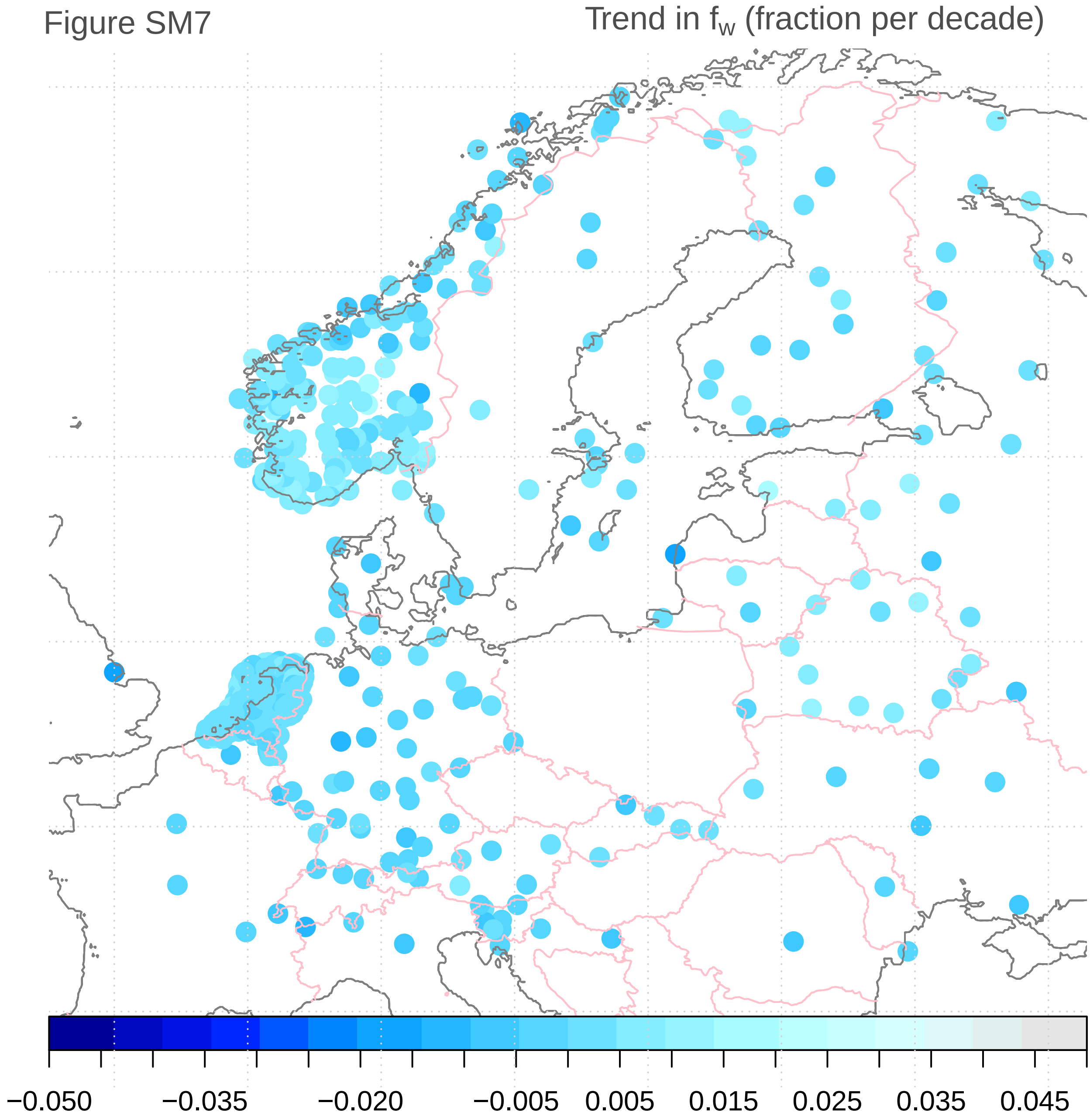
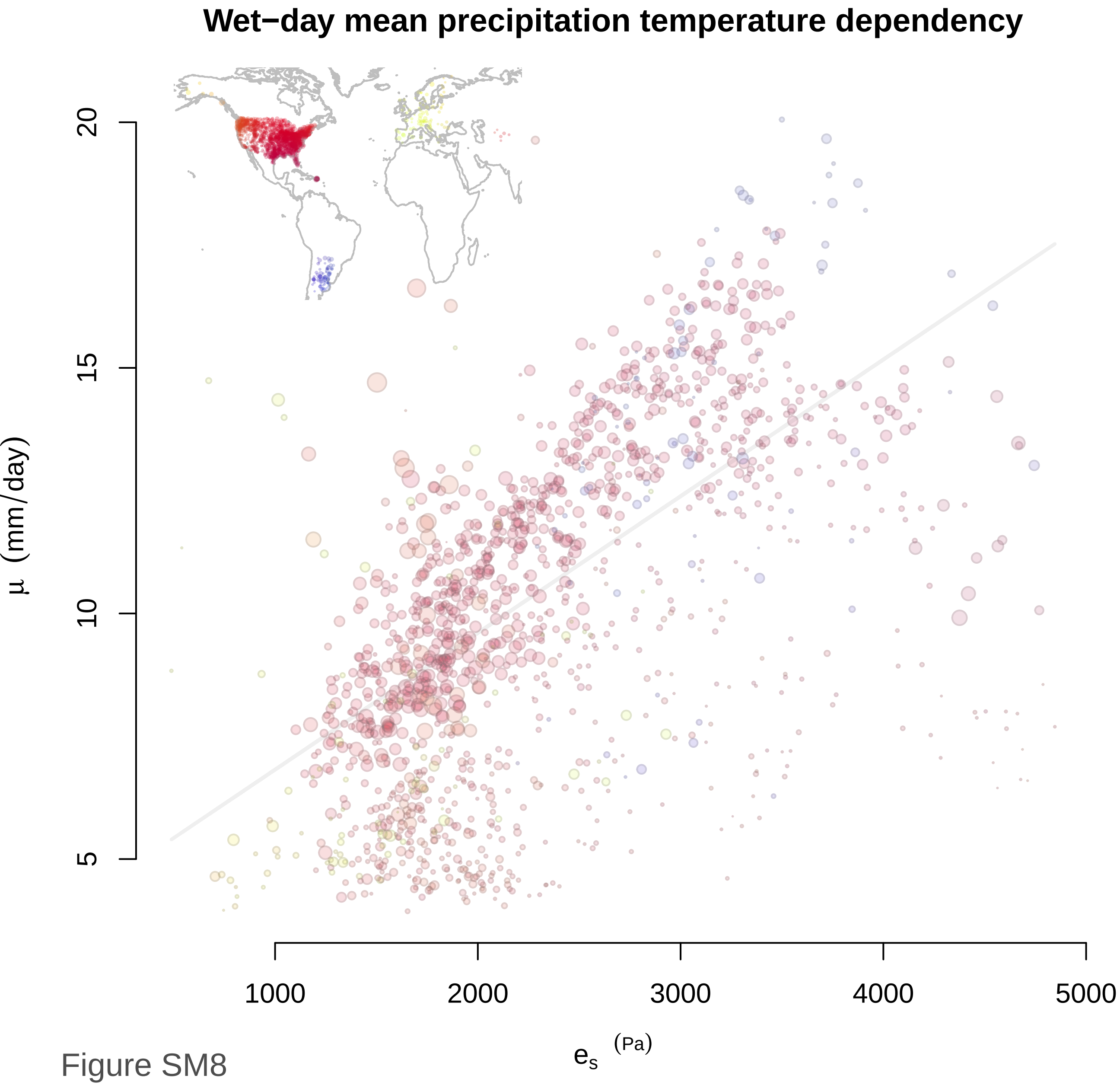

Trend in wet−day frequency
Frequency
0
50
100
150
200
−40
−20
0
20
40
f_w (%/decade)

Figure SM6

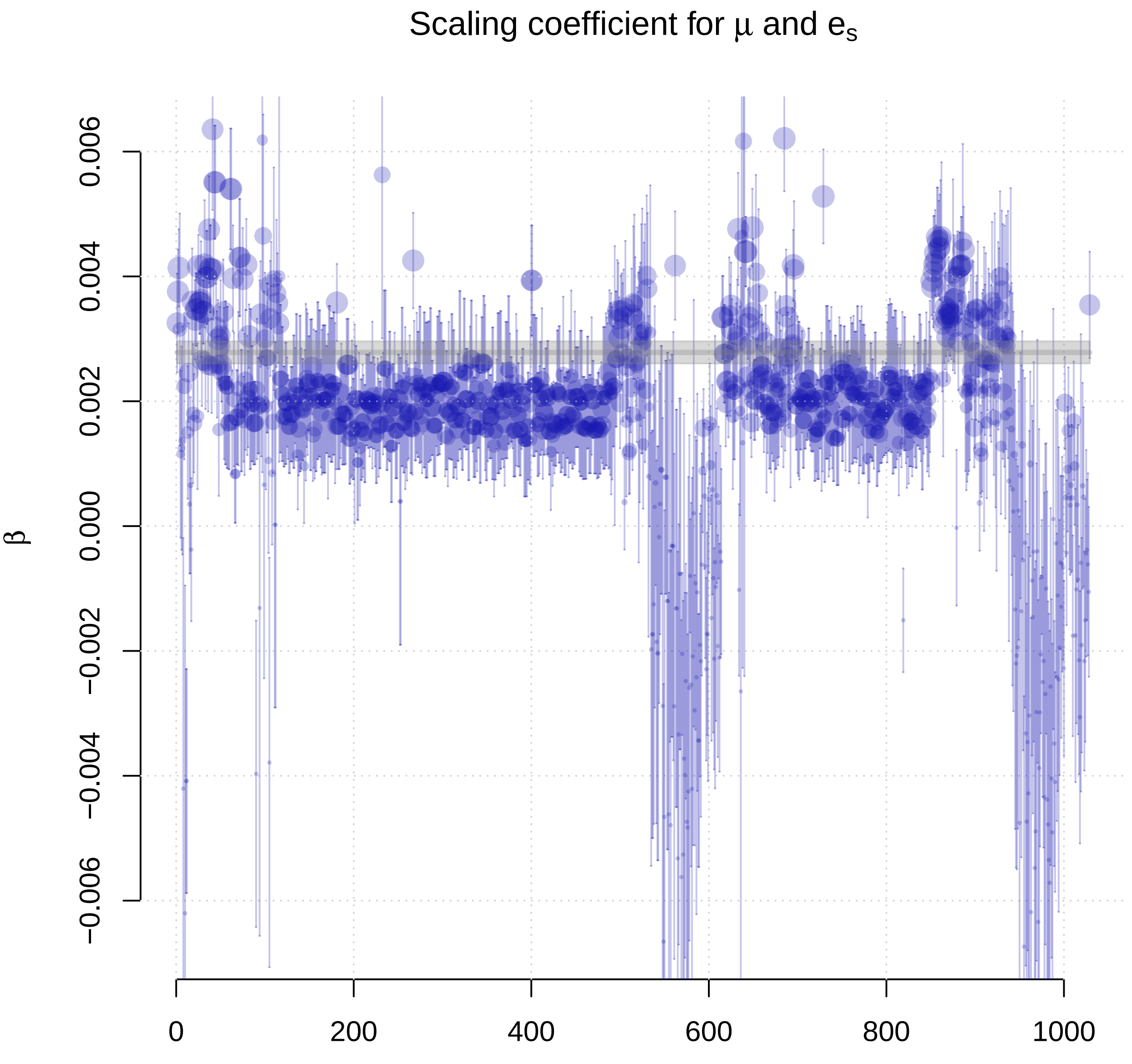
Figure SM7


Trend in f_w (fraction per decade)
−0.050
−0.035
−0.020
−0.005
0.005
0.015
0.025
0.035
0.045



Wet−day mean precipitation temperature dependency
20
15
10
5
μ (mm/day)
1000
2000
3000
4000
5000
e_s (Pa)

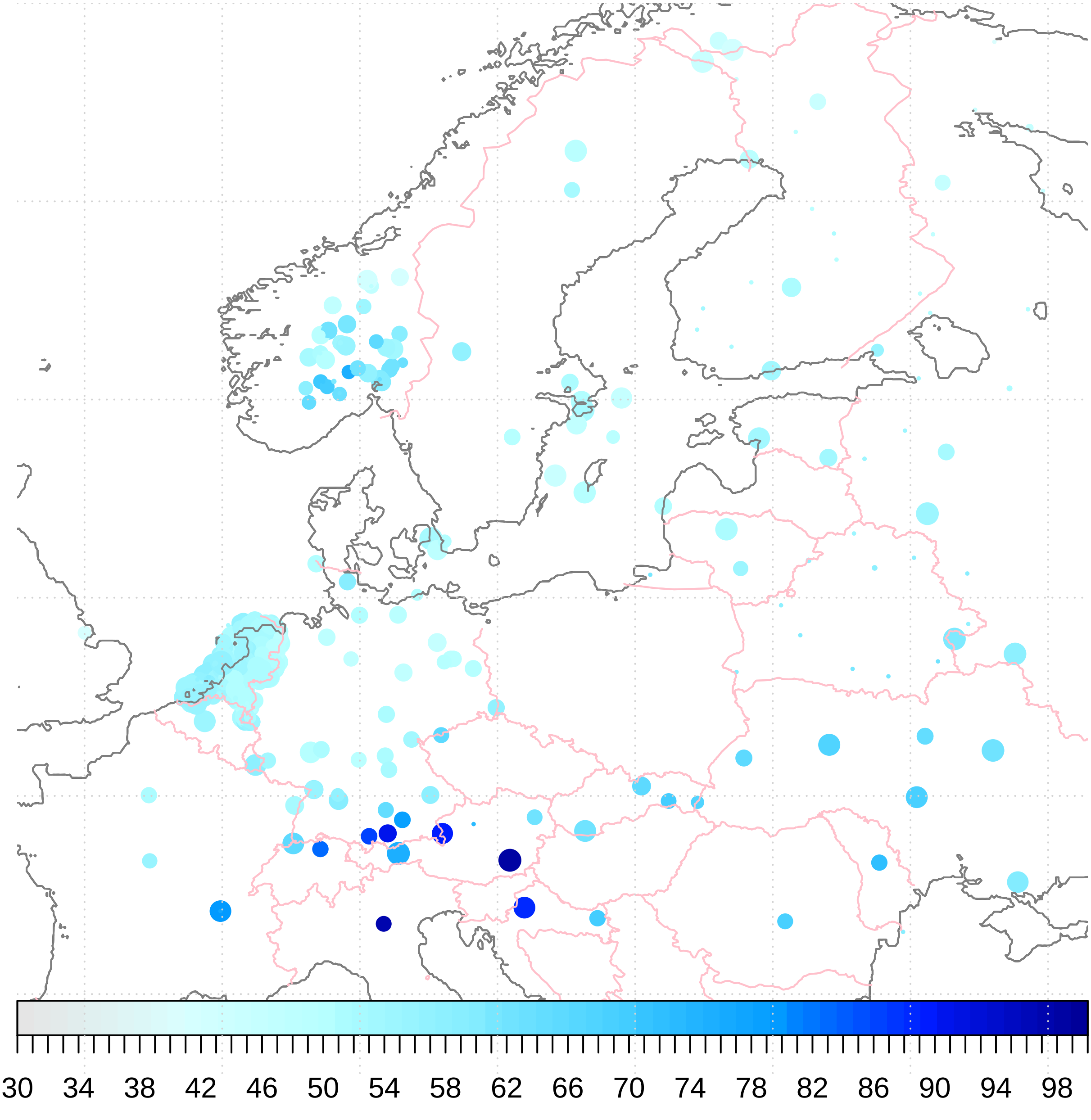
Figure SM8



Scaling coefficient for μ and e_s
β
0.006
0.004
0.002
0.000
−0.002
−0.004
−0.006
0
200
400
600
800
1000

Figure SM9

Figure SM10 Return values for 2100 assuming RCP4.5



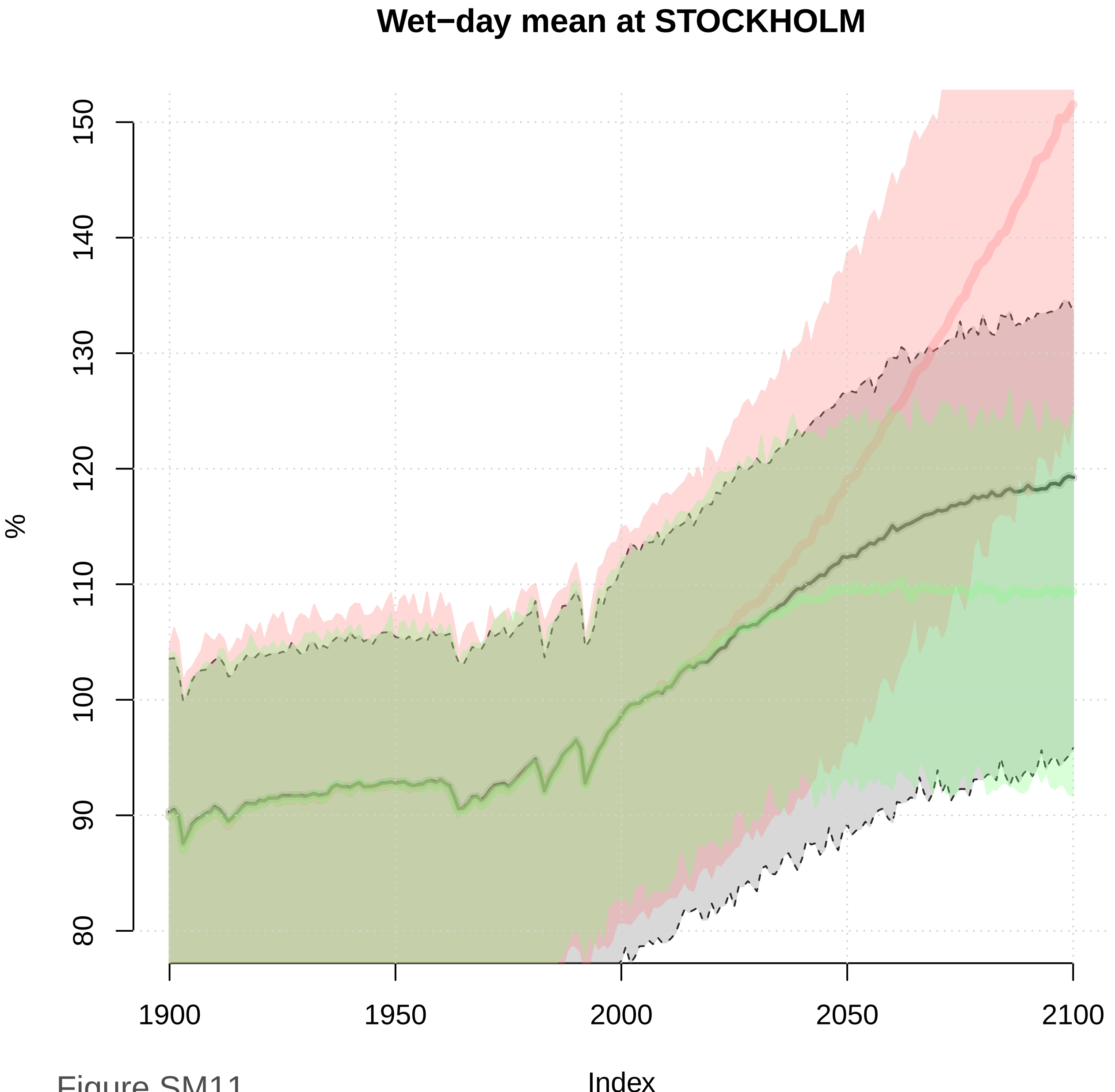
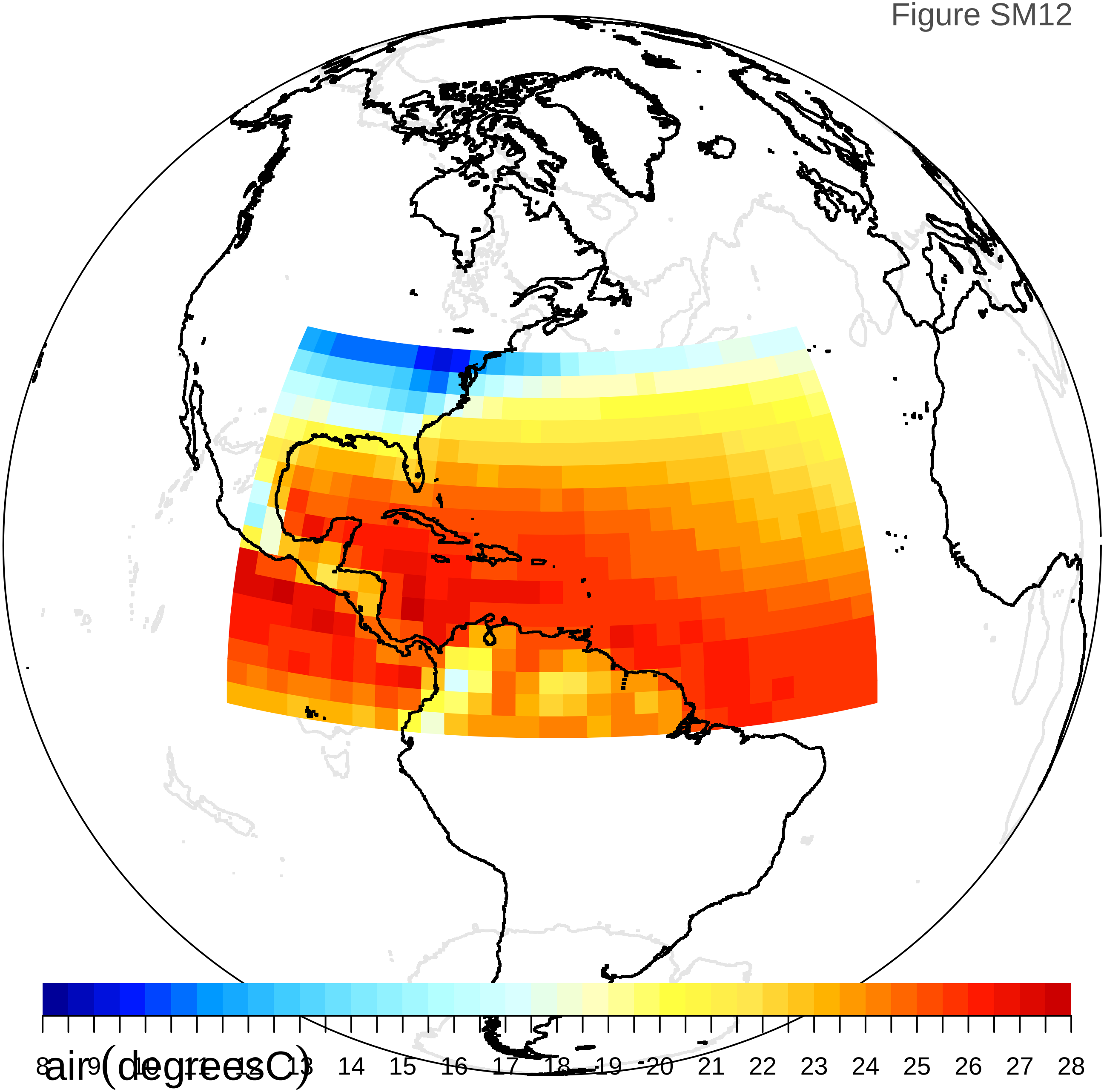

Wet−day mean at STOCKHOLM
%
80
90
100
110
120
130
140
150
1900
1950
2000
2050
2100
Index

Figure SM11


8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
27
28
air (degreesC)

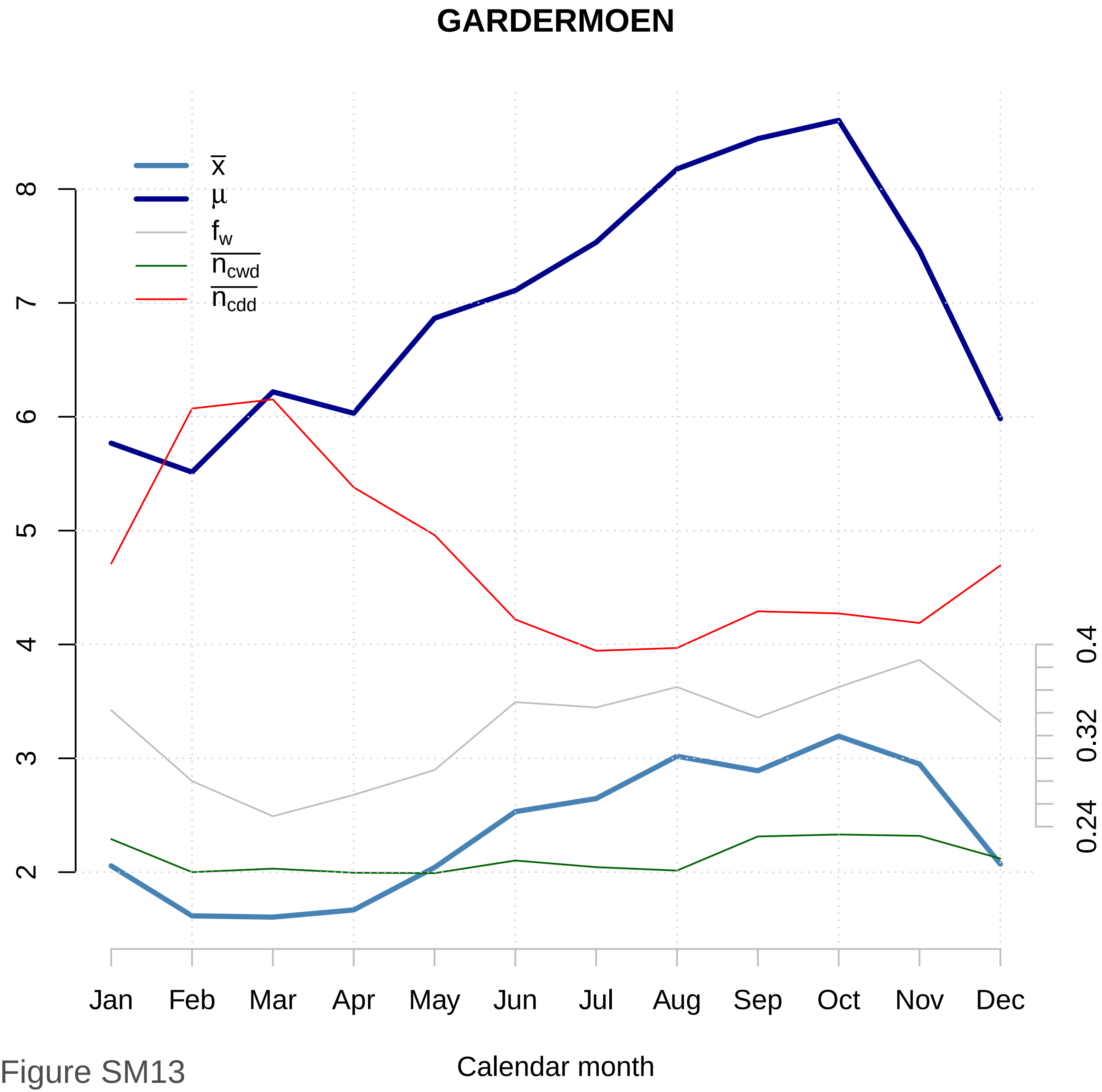

GARDERMOEN
x̄
μ
f_w
n̄_cwd
n̄_cdd
8
7
6
5
4
3
2
0.4
0.32
0.24
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Calendar month

Figure SM13

Benestad et al - Upper-limit estimation of future precipitation return-values

title: "Analysis and calculations in manuscript" author: "Rasmus Benestad" date: "April 4, 2016" output: pdf_document —

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)
## Information about the system and session
Sys.info()
```

```
##                                                   sysname
##                                                   "Linux"
##                                                   release
##                                       "3.8.0-26-generic"
##                                                   version
## "#38~precise2-Ubuntu SMP Thu Jun 20 18:29:36 UTC 2013"
##                                                  nodename
##                                                  "pc4409"
##                                                   machine
##                                                  "x86_64"
##                                                     login
##                                                 "unknown"
##                                                      user
##                                                 "rasmusb"
##                                            effective_user
##                                                 "rasmusb"
```

```r
sessionInfo()
```

```
## R version 3.1.3 (2015-03-09)
## Platform: x86_64-pc-linux-gnu (64-bit)
## Running under: Ubuntu precise (12.04.5 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=nb_NO.UTF-8       LC_NAME=C
##  [9] LC_ADDRESS=C               LC_TELEPHONE=C
## [11] LC_MEASUREMENT=nb_NO.UTF-8 LC_IDENTIFICATION=C
##
## attached base packages:
## [1] stats     graphics  grDevices utils     datasets  methods   base
##
## other attached packages:
## [1] esd_1.1         ncdf_1.8.6      zoo_1.7-12      ncdf4_1.15
## [5] rmarkdown_0.9.5
##
## loaded via a namespace (and not attached):
##  [1] digest_0.6.9    evaluate_0.8.3  formatR_1.3     grid_3.1.3
##  [5] htmltools_0.3   knitr_1.12.3    lattice_0.20-33 magrittr_1.5
##  [9] stringi_1.0-1   stringr_1.0.0   tools_3.1.3
```

Below are definition of a number of functions used in the data processing and analysis. The first are simple functions used in ploting.

Simple functions which estimate various statistics

Functions to extract the numbers for mean,min,max,wettest month,driest month, estimate percentiles assuming an exponential distribution, skill-scores, and regression coefficients. These are used to make the R-code simpler, shorter, and improve clarity.

```r
## 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
}
```

```r
## 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

Functions for reading the data and processing it so that it can readily be handelled 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

Main function that is used for calibrating the statistical model based on the mean seasonal cycle.

```
## 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='"Worst-case" fit 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)
}
```

Functions for projection and prediction 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)
}
```

```r
## 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/maps

The following functions are used for the presentation of the results

```r
## 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("t2m",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 <- 1.5*c(r2) + 0.2

  map(mu, xlim=xlim,ylim=ylim,bg='grey80',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(0.05, 0.1, 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]))
}
```

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.:

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

## 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')
  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 referret 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).

```
## 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.

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

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

```
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')
```

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

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

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

```
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"
```

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

Plot 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.

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

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

```
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
```

```
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"
```

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

```
## Warning in par(new = TRUE, pdx = NA, fig = c(0, 1, 0, 1), xaxt = "n", yaxt
## = "n", : "pdx" is not a graphical parameter
```

```
## Warning in text.default(xpos, ypos, x, type = 2, cex = 1.2, pos = 4, col =
## "grey30"): graphical parameter "type" is obsolete
```

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.

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

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

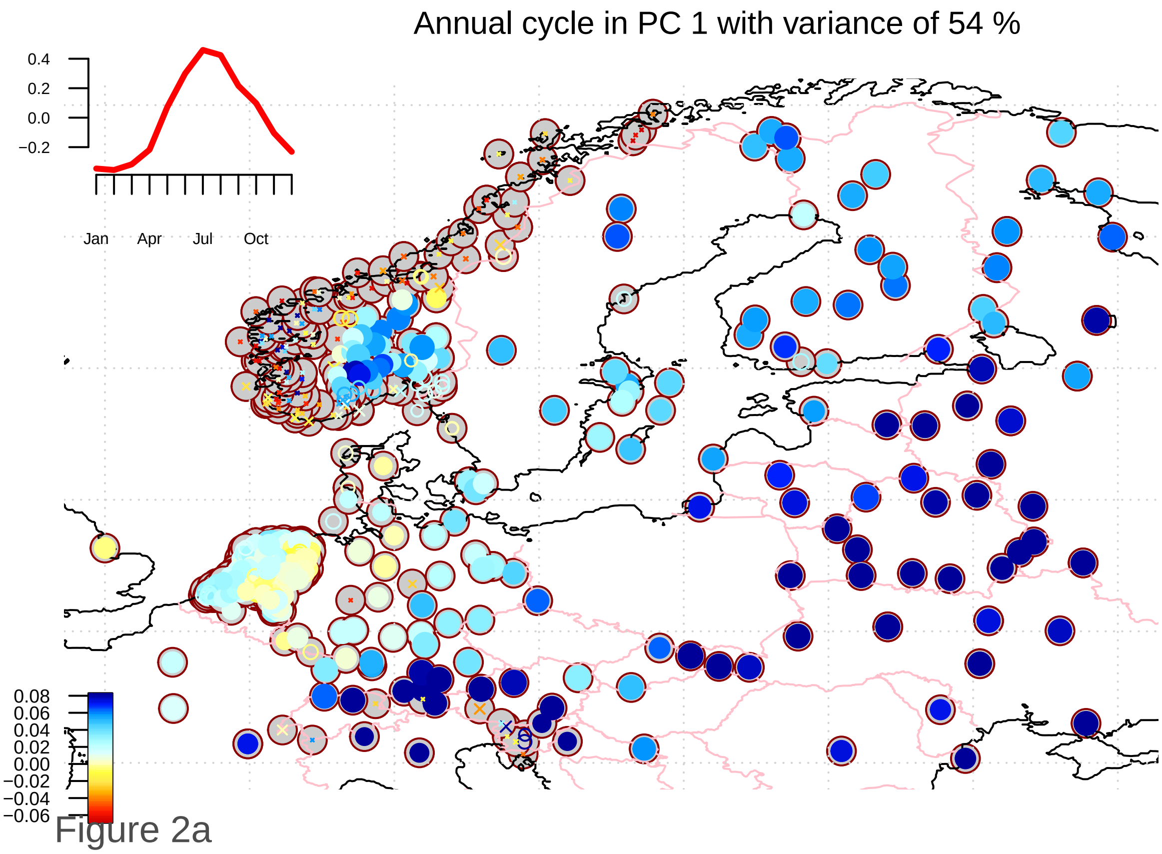
```
Mu <- as.matrix(coredata(mu))

## 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')
```

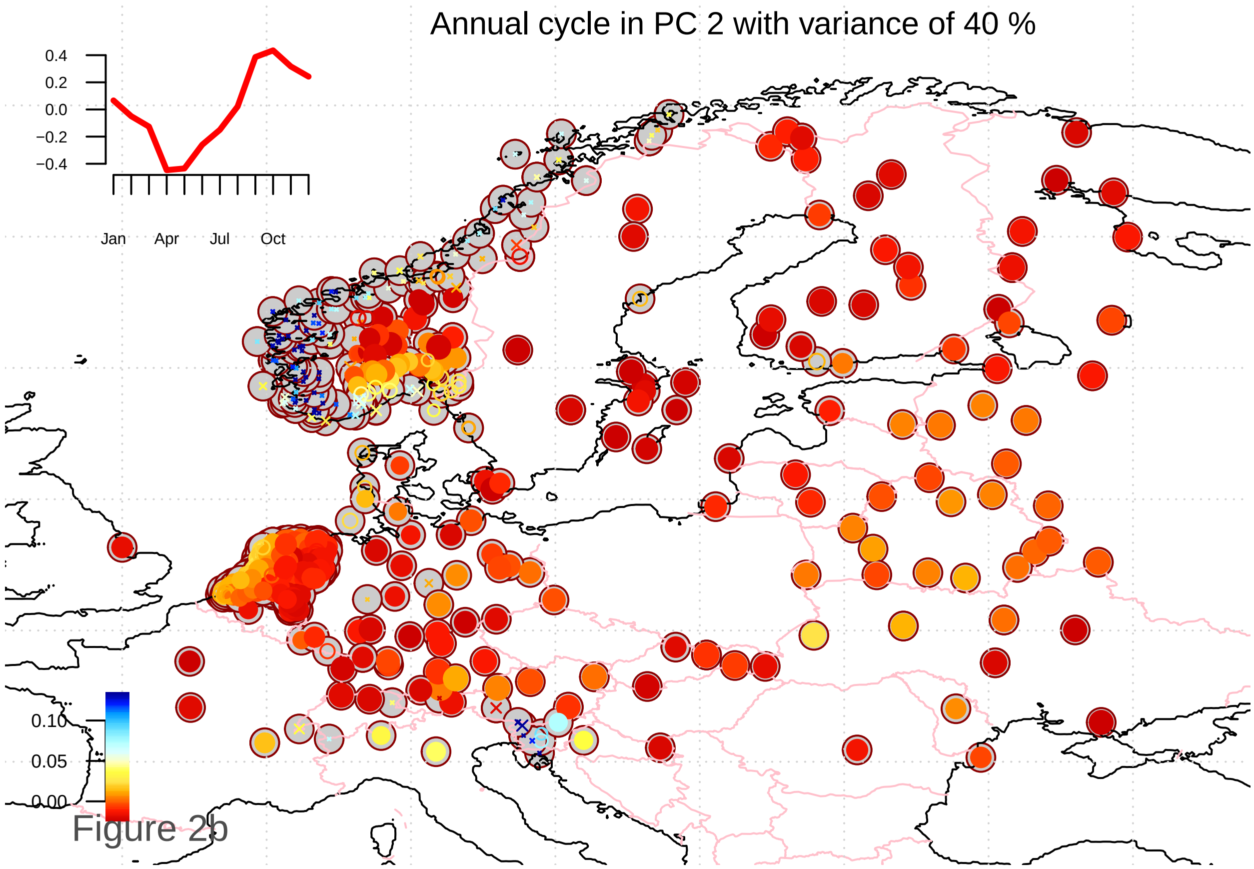
```
## Warning in par(new = TRUE, pdx = NA, fig = c(0, 1, 0, 1), xaxt = "n", yaxt
## = "n", : "pdx" is not a graphical parameter
```

```
## Warning in text.default(xpos, ypos, x, type = 2, cex = 1.2, pos = 4, col =
## "grey30"): graphical parameter "type" is obsolete
```




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

```
## Warning in par(new = TRUE, pdx = NA, fig = c(0, 1, 0, 1), xaxt = "n", yaxt
## = "n", : "pdx" is not a graphical parameter

## Warning in par(new = TRUE, pdx = NA, fig = c(0, 1, 0, 1), xaxt = "n", yaxt
## = "n", : graphical parameter "type" is obsolete
```



Mean seasonal cycle

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

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

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

```r
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
```

```r
## 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 = 46.8353, 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 = -49.4364, 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
```

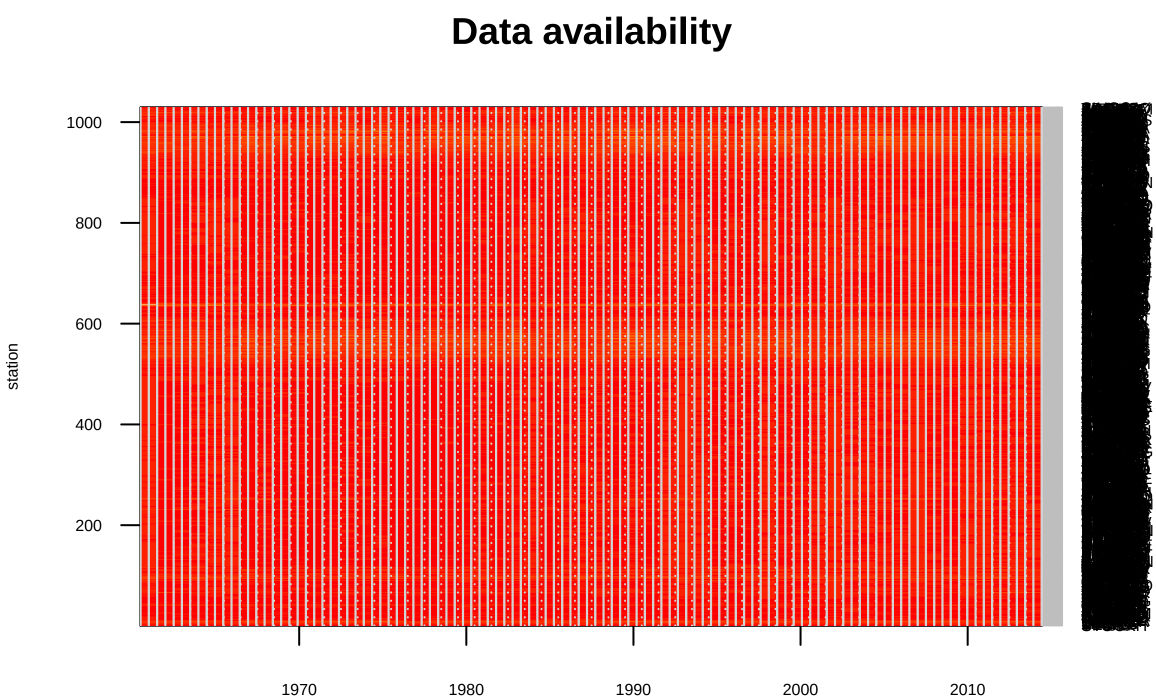
```
print(cor.test(pca$v[,3],as.numeric(r2)))
```

```
##
##  Pearson's product-moment correlation
##
## data:  pca$v[, 3] and as.numeric(r2)
## t = 0.0616, 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 and extract only the results for locations with a good match. 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.

```
## Estimate trend statistics for both fw and mu:
## Use subset - in the PCA there is something strange in the 1990s.
fw.trend <- 100*apply(subset(FW,it=c(1950,1990)),2,'trend.coef')/
                      apply(FW,2,'mean',na.rm=TRUE)
mu.trend <- 100*apply(subset(MU,it=c(1950,1990)),2,'trend.coef')/
                      apply(MU,2,'mean',na.rm=TRUE)

diagnose(MU)
```



MECAND

```
## 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

Need to collect aggregated results based on the ensembles of GCM projections.

```
## 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)
```

```r
Z.rcp2.6 <- lapply(Vx,'muproject',rcp2.6)
t <- index(rcp4.5)
```

Extract the statistics of the different emission scenarios and time slices

```r
## 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]]))
x2010u <- as.numeric(lapply(mu2010.rcp4.5,function(x) x[[2]]))
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 frams with changes in percentages:
mu.2100 <- data.frame(mean.RCP4.5=x2100 - x2010,q95.RCP4.5=x2100u - x2010u,
                      mean.RCP2.6=z2100 - z2010,q95.RCP4.5=z2100u - z2010u,
                      mean.RCP8.5=y2100 - y2010,q95.RCP8.5=y2100u - y2010u)
```

Plot figure 3

```r
## Fig 3
## Plot a map of projected values:
## Map showing RCP4.5 ensemble mean 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:"
```

```r
map(mux, xlim=xlim,ylim=ylim,cex=Cex,bg='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(20,73,'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')
```

```
## Warning in par(new = TRUE, pdx = NA, fig = c(0, 1, 0, 1), xaxt = "n", yaxt
## = "n", : "pdx" is not a graphical parameter
```

```
## Warning in text.default(xpos, ypos, x, type = 2, cex = 1.2, pos = 4, col =
## "grey30"): graphical parameter "type" is obsolete
```

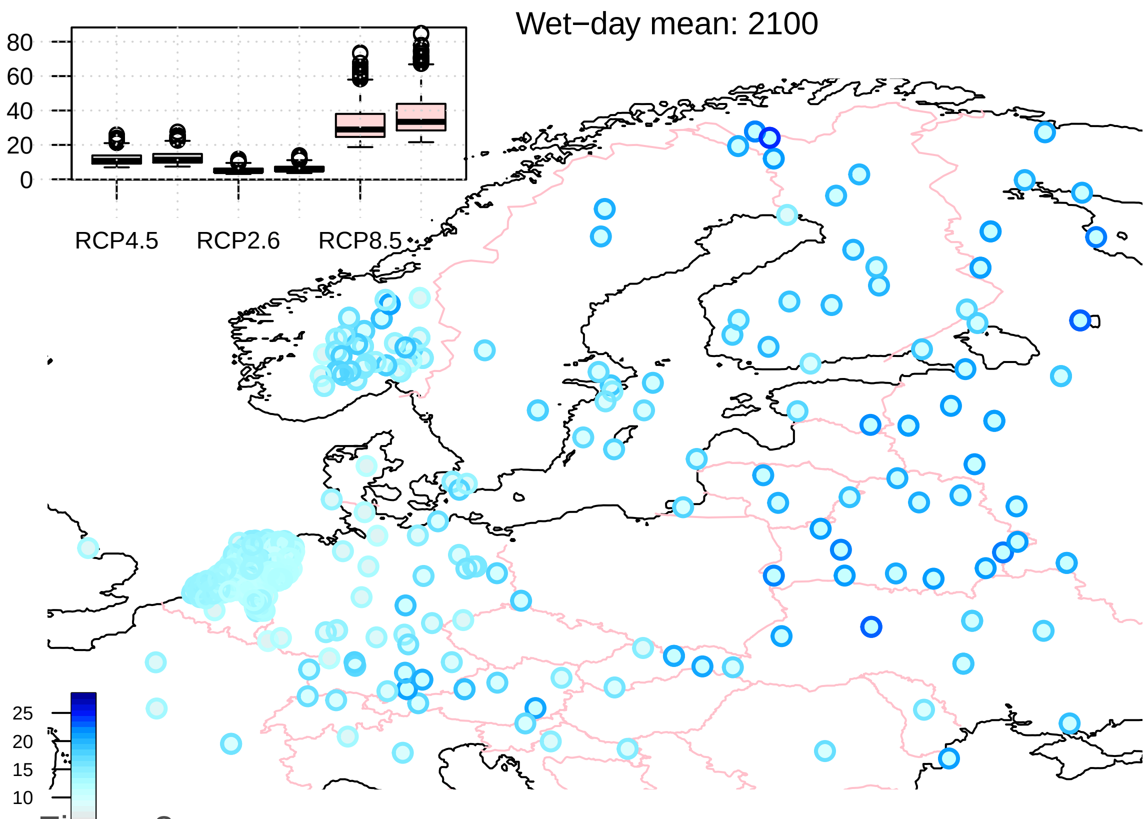


Figure 3

Supporting material/analysis (SM)

Extract the essential information

```
## 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
```

** ———— Supporting Material ——————————**

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

figure SM2

Presents the statistics of R^2 from the model calibration based on the different locations.

```
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

```
## 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 SM2')
```

```
## Warning in par(new = TRUE, pdx = NA, fig = c(0, 1, 0, 1), xaxt = "n", yaxt
## = "n", : "pdx" is not a graphical parameter
```

```
## Warning in text.default(xpos, ypos, x, type = 2, cex = 1.2, pos = 4, col =
## "grey30"): graphical parameter "type" is obsolete
```

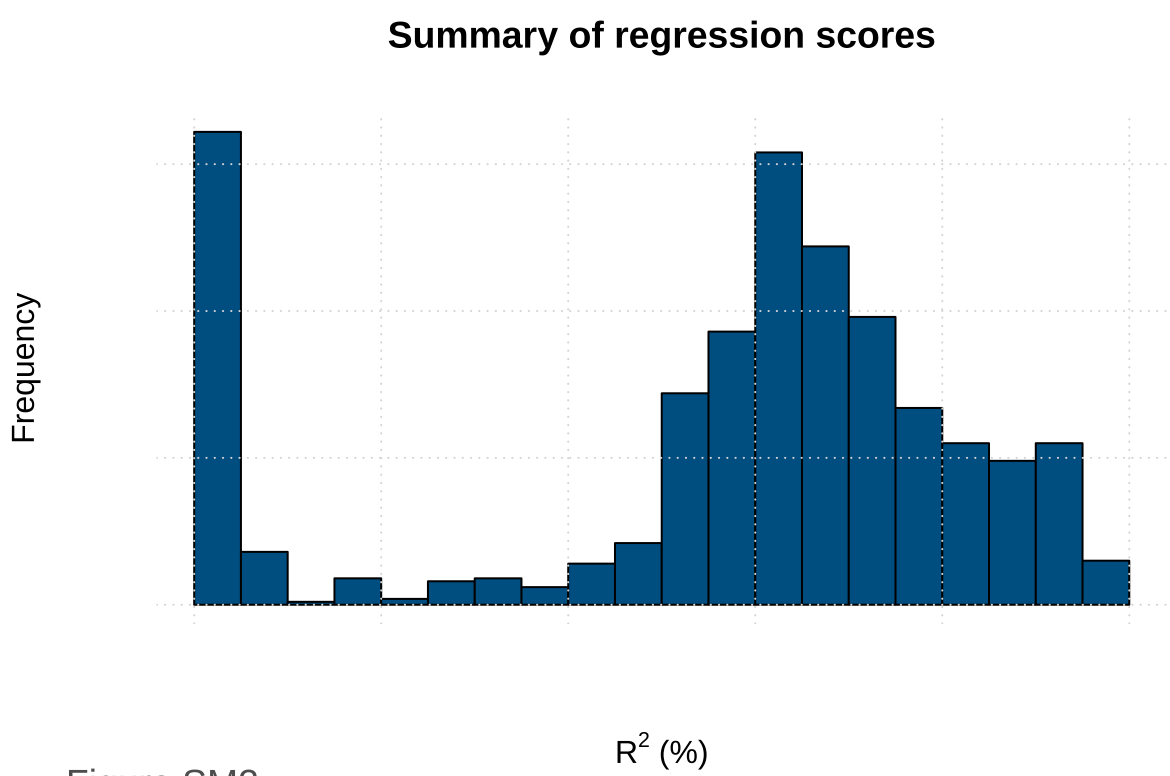


Figure SM2

##**Figure SM12**

A figure showing one example of projections for one location, showing all three emission scenarios.

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

```
## [1] "Example plot - evolution"
```

```
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),
     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()
figlab('Figure SM12')
```

```
## Warning in par(new = TRUE, pdx = NA, fig = c(0, 1, 0, 1), xaxt = "n", yaxt
## = "n", : "pdx" is not a graphical parameter
```

```
## Warning in text.default(xpos, ypos, x, type = 2, cex = 1.2, pos = 4, col =
## "grey30"): graphical parameter "type" is obsolete
```

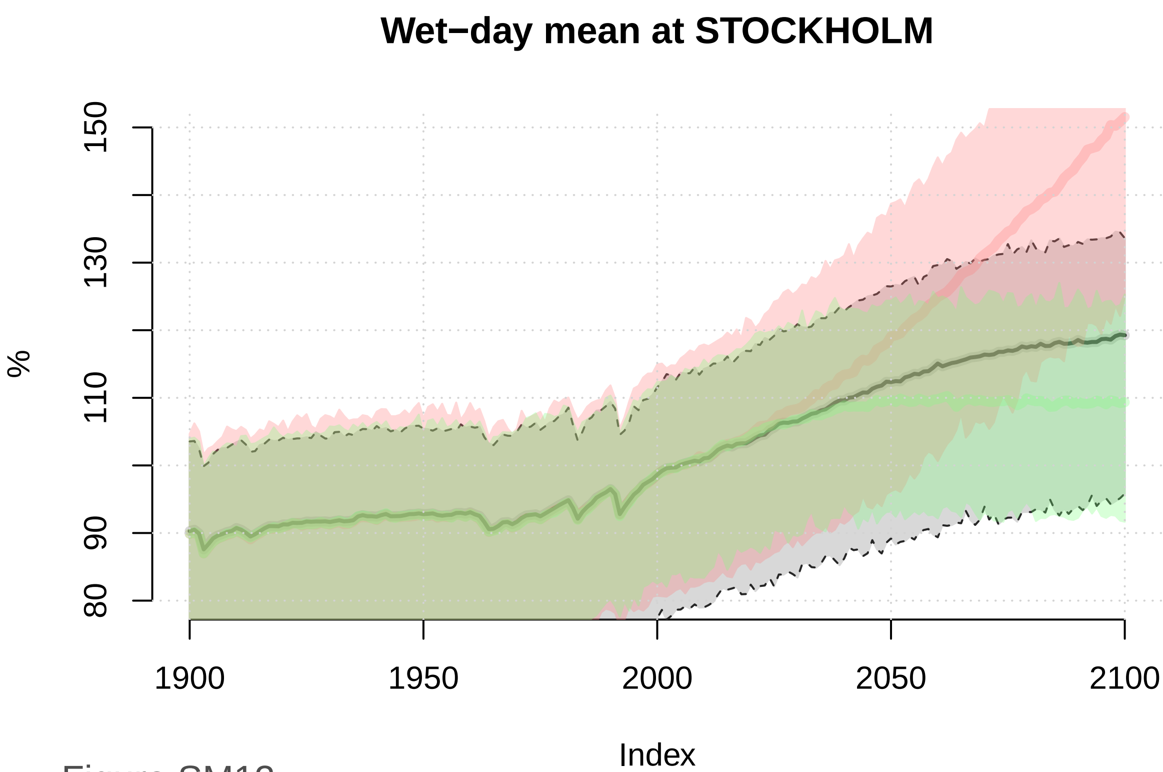


Figure SM12

Further processing for Fig SM3: 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:
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)
```

Figure SM3

Historical trends in the wet-day mean preciptation

```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,
     main=expression(paste('Trends in ',mu,': observed and predicted upper limit')),
     xlab='Observed trend (mm/decade)',ylab='predicted trend (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 SM3')
```

```
## Warning in par(new = TRUE, pdx = NA, fig = c(0, 1, 0, 1), xaxt = "n", yaxt
## = "n", : "pdx" is not a graphical parameter
```

```
## Warning in text.default(xpos, ypos, x, type = 2, cex = 1.2, pos = 4, col =
## "grey30"): graphical parameter "type" is obsolete
```

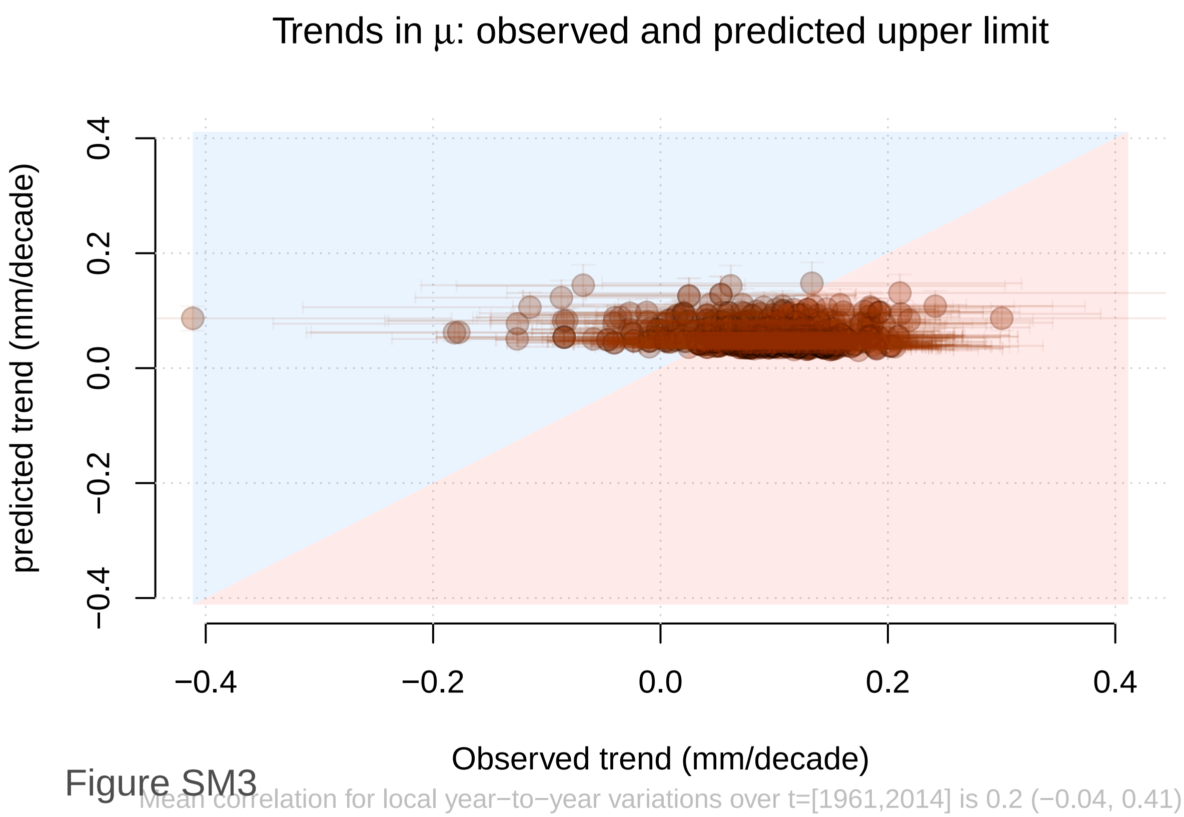


Figure SM4

```
## Map showing trends in mu
map(MU,FUN='trend',colbar=list(breaks=seq(-1,1,length=21),rev=TRUE),cex=cex)
```

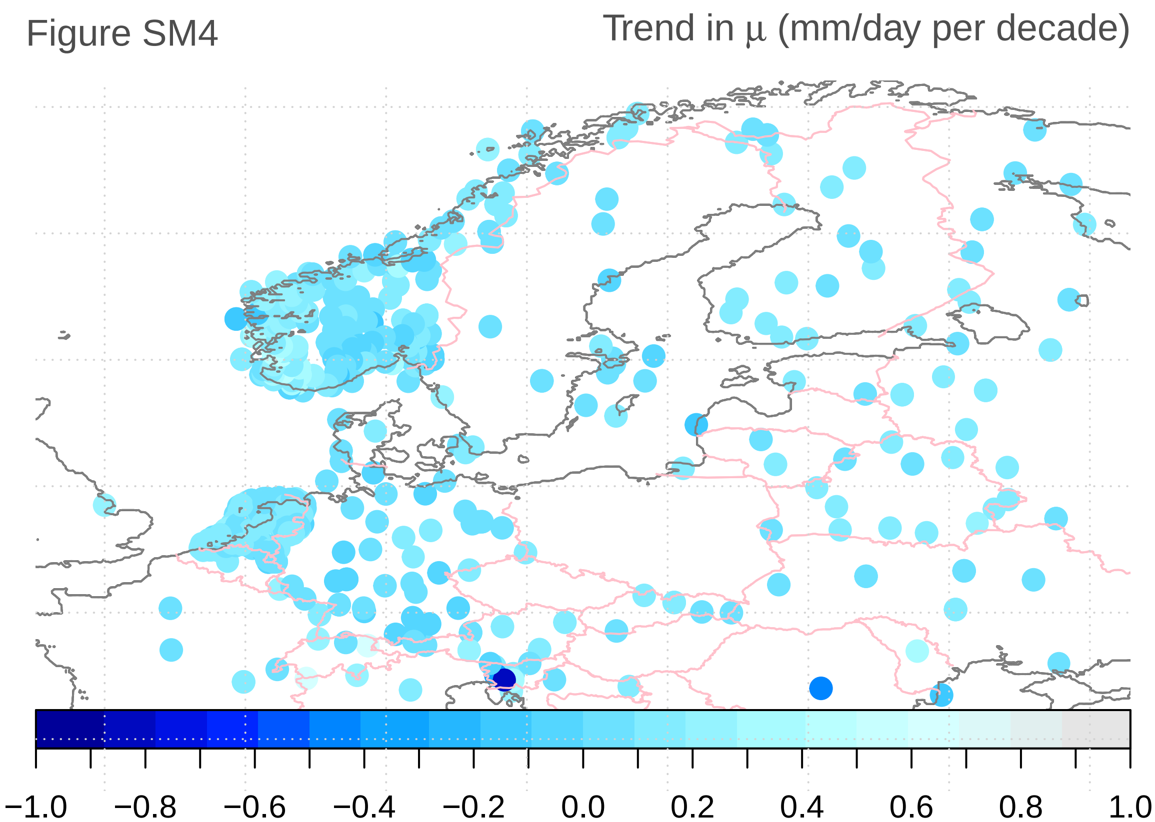
```
## Warning in if (cex == 0) cex <- 1.25 * nok/max(nok, na.rm = TRUE): the
## condition has length > 1 and only the first element will be used

## Warning in if (cex < 0) cex <- abs(cex) * nok/max(nok, na.rm = TRUE): the
## condition has length > 1 and only the first element will be used
```

```
figlab('Figure SM4',ypos=0.999)
```

```
## Warning in par(new = TRUE, pdx = NA, fig = c(0, 1, 0, 1), xaxt = "n", yaxt
## = "n", : "pdx" is not a graphical parameter

## Warning in text.default(xpos, ypos, x, type = 2, cex = 1.2, pos = 4, col =
## "grey30"): graphical parameter "type" is obsolete
```

```
figlab(expression(paste('Trend in ',mu,' (mm/day per decade)')),xpos=0.5,ypos=0.999)
```

```
## Warning in par(new = TRUE, pdx = NA, fig = c(0, 1, 0, 1), xaxt = "n", yaxt
## = "n", : "pdx" is not a graphical parameter

## Warning in par(new = TRUE, pdx = NA, fig = c(0, 1, 0, 1), xaxt = "n", yaxt
## = "n", : graphical parameter "type" is obsolete
```



##Figure SM5

```
## 99-percentile wet-day mean and typical wet-day frequency
## The Tellus paper on specification approximately annual maximum.
## Prob(X>x) for annual maximum for 24hr precip
## Pr(X > x) = 1/365.25 = fw*(1-p): p = 1 - 1/(365.25*fw)
par(bty='n')
W <- apply(fw,2,FUN='muclim')
hist(100*(1-1/(W[1,]*365.25)),col='steelblue',lwd=2,breaks=seq(90,100,by=0.1),
     main='Wet-day percentile for annual maximum 24-precipitation',
     xlab='p (%)')
grid()
figlab('Figure SM5')
```

```
## Warning in par(new = TRUE, pdx = NA, fig = c(0, 1, 0, 1), xaxt = "n", yaxt
## = "n", : "pdx" is not a graphical parameter

## Warning in text.default(xpos, ypos, x, type = 2, cex = 1.2, pos = 4, col =
## "grey30"): graphical parameter "type" is obsolete
```

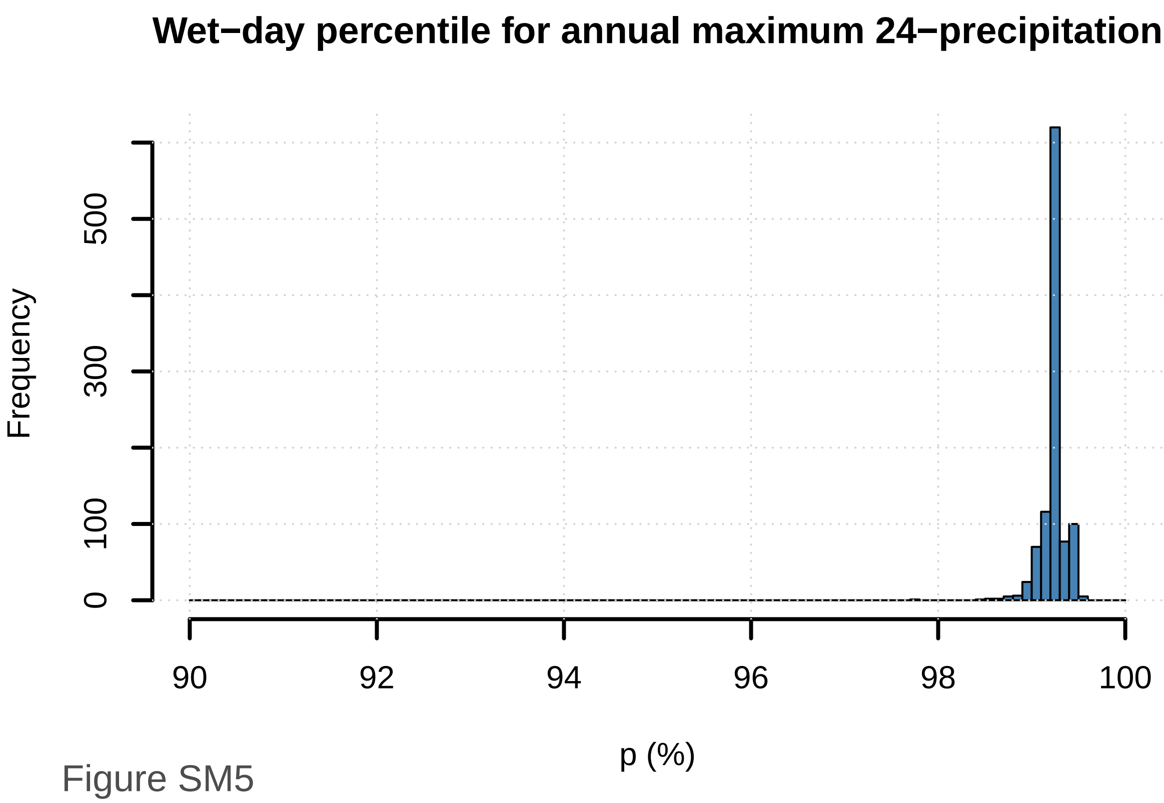


Figure SM6

```
## 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 SM6')
```

```
## Warning in par(new = TRUE, pdx = NA, fig = c(0, 1, 0, 1), xaxt = "n", yaxt
## = "n", : "pdx" is not a graphical parameter
```

```
## Warning in text.default(xpos, ypos, x, type = 2, cex = 1.2, pos = 4, col =
## "grey30"): graphical parameter "type" is obsolete
```

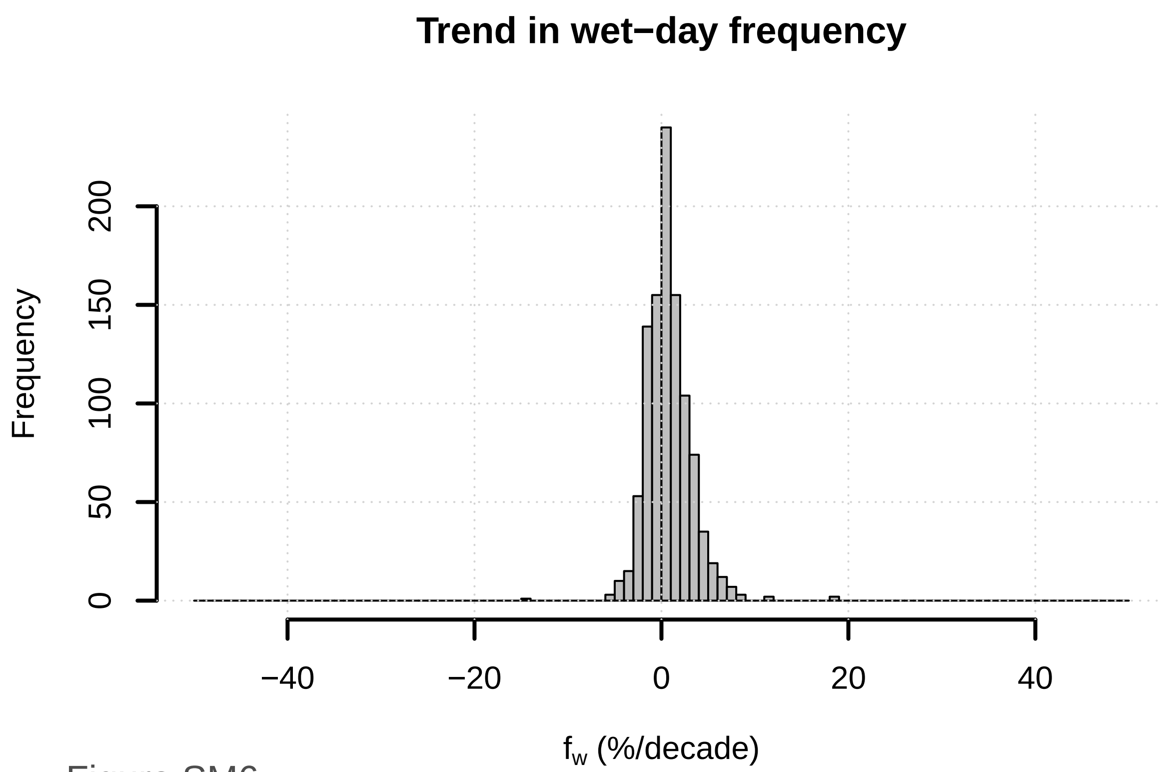


Figure SM6

##**Figure SM7**

```
## Map showing trends in fw
#dev.new()
map(FW,FUN='trend',colbar=list(breaks=seq(-0.05,0.05,length=21),rev=TRUE),cex=cex)
```

```
## Warning in if (cex == 0) cex <- 1.25 * nok/max(nok, na.rm = TRUE): the
## condition has length > 1 and only the first element will be used

## Warning in if (cex < 0) cex <- abs(cex) * nok/max(nok, na.rm = TRUE): the
## condition has length > 1 and only the first element will be used
```

```
figlab('Figure SM7',ypos=0.999)
```

```
## Warning in par(new = TRUE, pdx = NA, fig = c(0, 1, 0, 1), xaxt = "n", yaxt
## = "n", : "pdx" is not a graphical parameter

## Warning in text.default(xpos, ypos, x, type = 2, cex = 1.2, pos = 4, col =
## "grey30"): graphical parameter "type" is obsolete
```

```
figlab(expression(paste('Trend in ',f[w],' (fraction per decade)')),xpos=0.5,ypos=0.999)
```

```
## Warning in par(new = TRUE, pdx = NA, fig = c(0, 1, 0, 1), xaxt = "n", yaxt
## = "n", : "pdx" is not a graphical parameter

## Warning in par(new = TRUE, pdx = NA, fig = c(0, 1, 0, 1), xaxt = "n", yaxt
## = "n", : graphical parameter "type" is obsolete
```

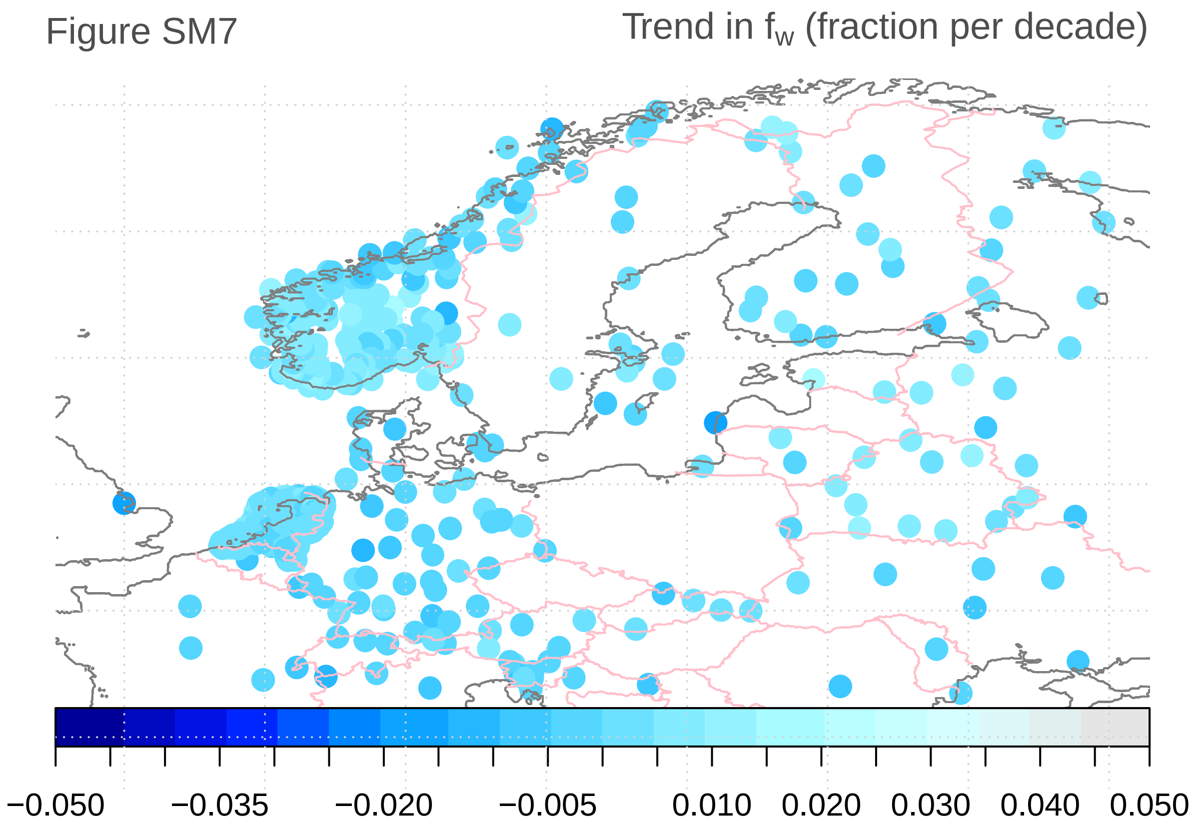


Figure SM1

```
## 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')
```

```
## Warning in par(new = TRUE, pdx = NA, fig = c(0, 1, 0, 1), xaxt = "n", yaxt
## = "n", : "pdx" is not a graphical parameter
```

```
## Warning in text.default(xpos, ypos, x, type = 2, cex = 1.2, pos = 4, col =
## "grey30"): graphical parameter "type" is obsolete
```

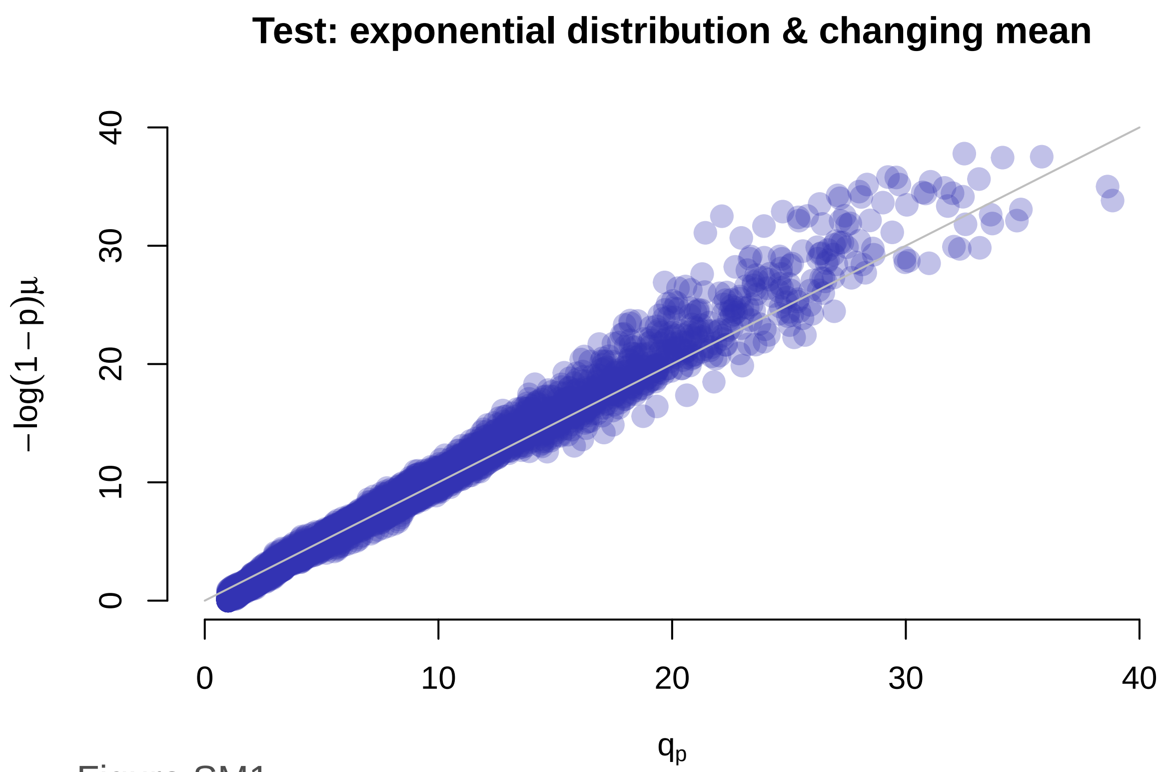


Figure SM1

Figure SM14: compare the mean seasonal variations in the different precipitation statistics

```
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))
figlab('Figure SM9')
```

```
## Warning in par(new = TRUE, pdx = NA, fig = c(0, 1, 0, 1), xaxt = "n", yaxt
## = "n", : "pdx" is not a graphical parameter
```

```
## Warning in text.default(xpos, ypos, x, type = 2, cex = 1.2, pos = 4, col =
## "grey30"): graphical parameter "type" is obsolete
```

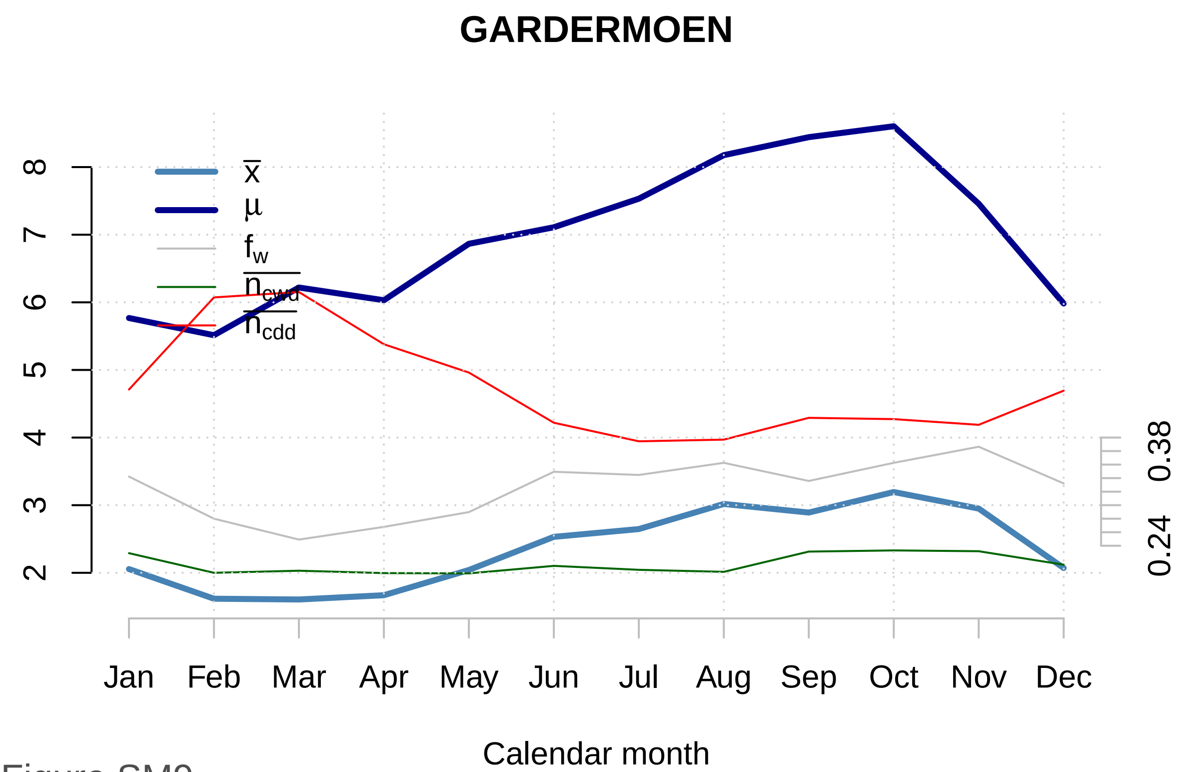


Figure SM9

Figure SM10: Map of the future return values

```
print('Map of return values for 2100 with RCP4.5')
```

```
## [1] "Map of return values for 2100 with RCP4.5"
```

```
rv <- MUx
## x2100u gives the percentage of mu,
coredata(rv) <- t((x2100u/100)*apply(coredata(MUx),2,'mean')*log(365.25*t(coredata(FWx))))
cexr2 <- 1.5*c(as.numeric(r2)) + 0.2
map(rv,FUN='mean',cex=cexr2,colbar=list(breaks=seq(30,100,by=1)))
```

```
## Warning in if (cex == 0) cex <- 1.25 * nok/max(nok, na.rm = TRUE): the
## condition has length > 1 and only the first element will be used

## Warning in if (cex < 0) cex <- abs(cex) * nok/max(nok, na.rm = TRUE): the
## condition has length > 1 and only the first element will be used
```

```
figlab('Figure SM10',ypos=0.999)
```

```
## Warning in par(new = TRUE, pdx = NA, fig = c(0, 1, 0, 1), xaxt = "n", yaxt
## = "n", : "pdx" is not a graphical parameter
```

```
## Warning in text.default(xpos, ypos, x, type = 2, cex = 1.2, pos = 4, col =
## "grey30"): graphical parameter "type" is obsolete
```

```r
figlab('Return values for 2100 assuming RCP4.5',xpos=0.3,ypos=0.999)
```

```
## Warning in par(new = TRUE, pdx = NA, fig = c(0, 1, 0, 1), xaxt = "n", yaxt
## = "n", : "pdx" is not a graphical parameter

## Warning in par(new = TRUE, pdx = NA, fig = c(0, 1, 0, 1), xaxt = "n", yaxt
## = "n", : graphical parameter "type" is obsolete
```

Figure SM10 Return values for 2100 assuming RCP4.5

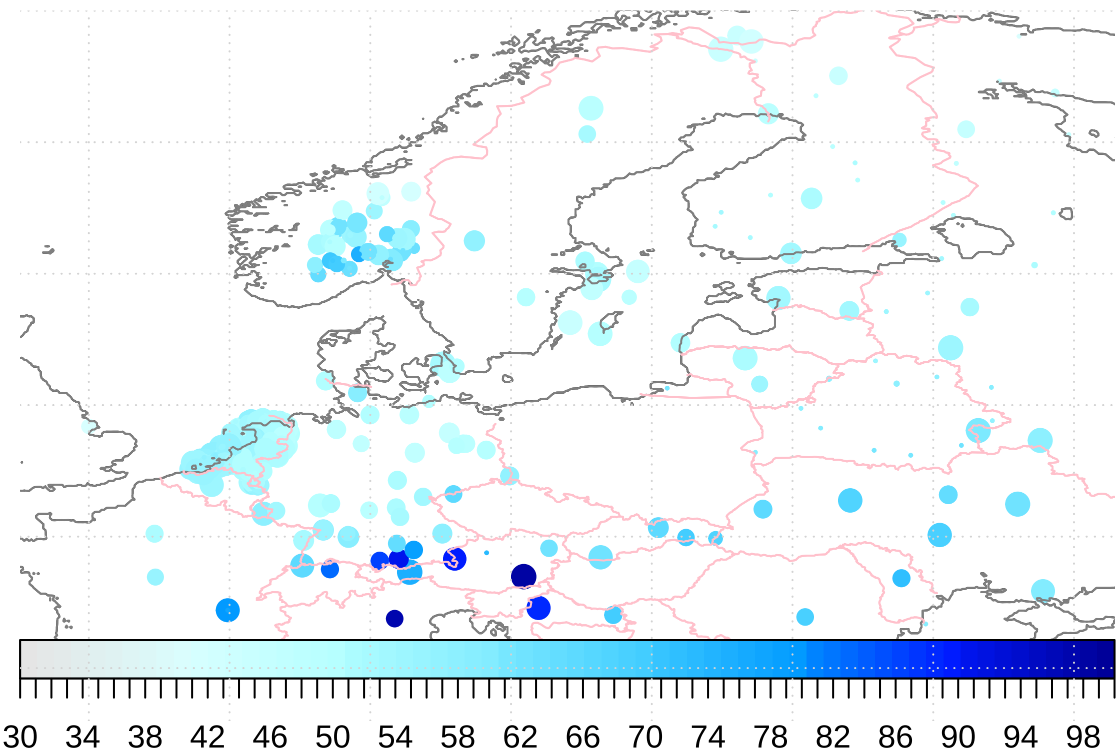


Figure SM9

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

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

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

```
## $mean.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
##
## $mean.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
##
## $mean.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"
```

```
## Compare the regression coefficients derived from individual
## seasonal cycle with that derived from mean climatology.

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]))

par(bty='n')
plot(b1,pch=19,col=col,cex=cexr2,
     main=expression(paste('Scaling coefficient for ',mu,' and ',e[s])),
     xlab='',ylab=expression(beta))
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))
figlab('Figure SM9')
```

```
## Warning in par(new = TRUE, pdx = NA, fig = c(0, 1, 0, 1), xaxt = "n", yaxt
## = "n", : "pdx" is not a graphical parameter
```

```
## Warning in text.default(xpos, ypos, x, type = 2, cex = 1.2, pos = 4, col =
## "grey30"): graphical parameter "type" is obsolete
```

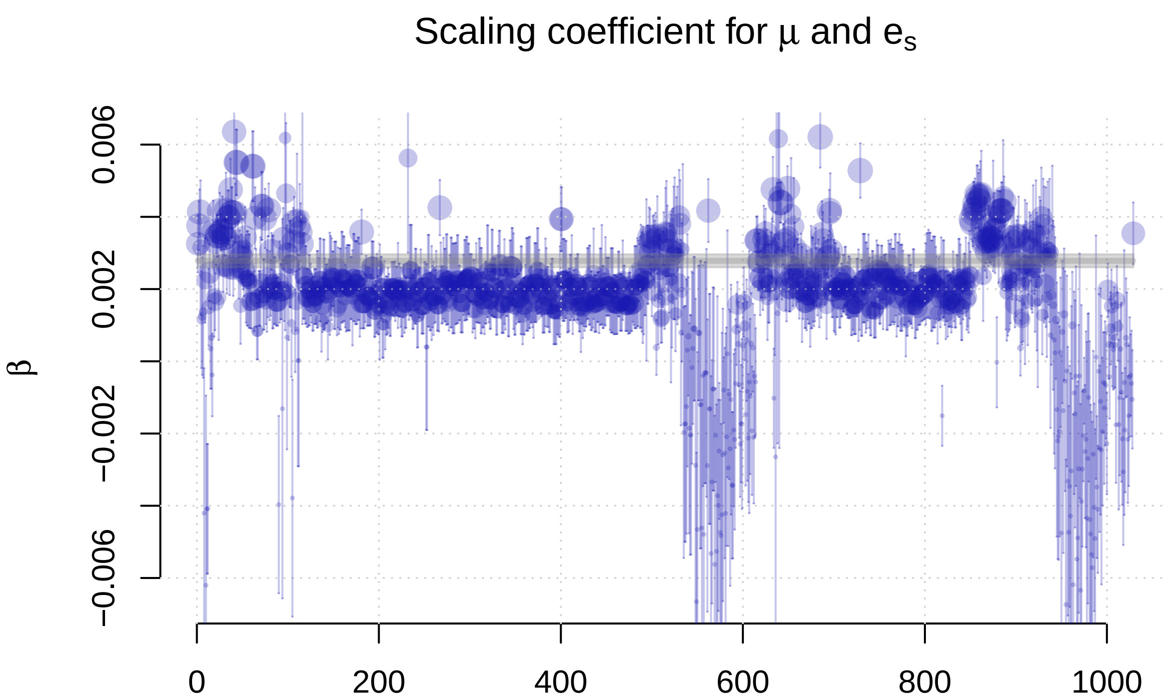


Figure SM9

Figure SM13

```
## 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(breaks=seq(8,28,by=0.5)))
```

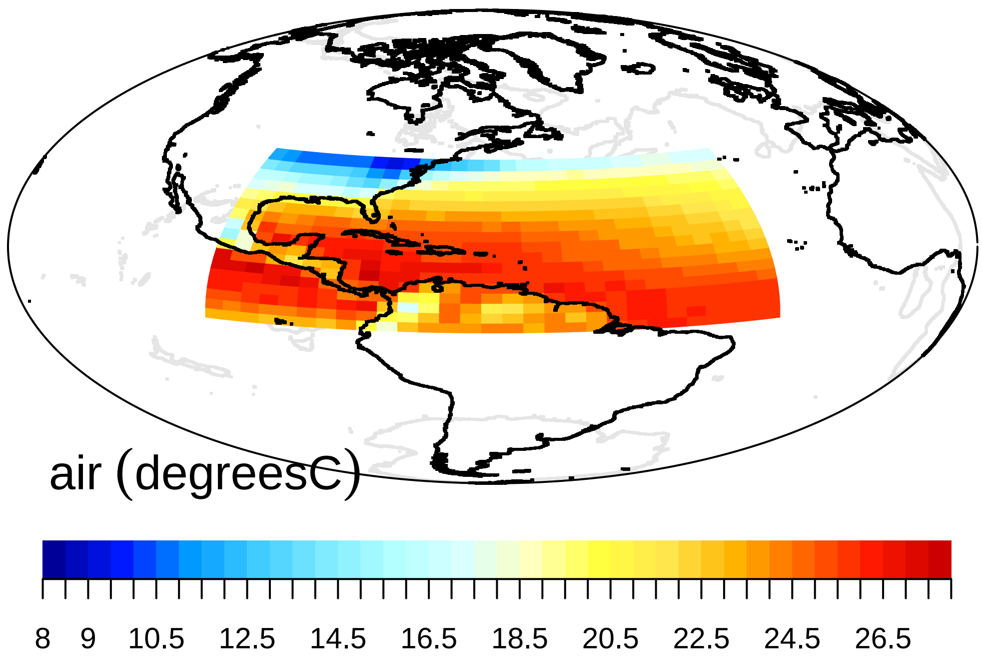
```
## [1] "Clip the value range to extremes of colour scale"
## [1] "0 set to highest colour and 0 to lowest"
```

```
figlab('Figure SM13',xpos=0.8,ypos=0.999)
```

```
## Warning in par(new = TRUE, pdx = NA, fig = c(0, 1, 0, 1), xaxt = "n", yaxt
## = "n", : "pdx" is not a graphical parameter
```

```
## Warning in text.default(xpos, ypos, x, type = 2, cex = 1.2, pos = 4, col =
## "grey30"): graphical parameter "type" is obsolete
```

Figure SM13



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.

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)
}
```

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

Tx1 <- Tx
Pr1 <- Pr

## COST-VALUE
load('VALUE_ECA_86_v2/stationsVALUE-exp1a.rda')
Tx2 <- Tx
Pr2 <- Pr
```

```
## 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')
```

```
## 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)

#map(MU,FUN='mean',cex=0)
#map(MU,FUN='trend',cex=0,colbar=list(rev=TRUE,breaks=seq(-1,1,length=21)))
#map(FW,FUN='trend',cex=0,colbar=list(rev=TRUE,breaks=seq(-0.01,0.01,length=21)))
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)
```

** Figure SM8**

Assess the connection between temperature and the wet-day mean precipitation.

```
par(bty='n')
col <- rgb((1+sin(pi*calmu$lat/180))/2,
           cos(pi*calmu$lon/180)^2,
           1-(1+sin(pi*calmu$lat/180))/2,0.15)
cex <- 1.5*Fw/max(Fw,na.rm=TRUE)
plot(calmu$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 SM8')
```

```
## Warning in par(new = TRUE, pdx = NA, fig = c(0, 1, 0, 1), xaxt = "n", yaxt
## = "n", : "pdx" is not a graphical parameter
```

```
## Warning in text.default(xpos, ypos, x, type = 2, cex = 1.2, pos = 4, col =
## "grey30"): graphical parameter "type" is obsolete
```

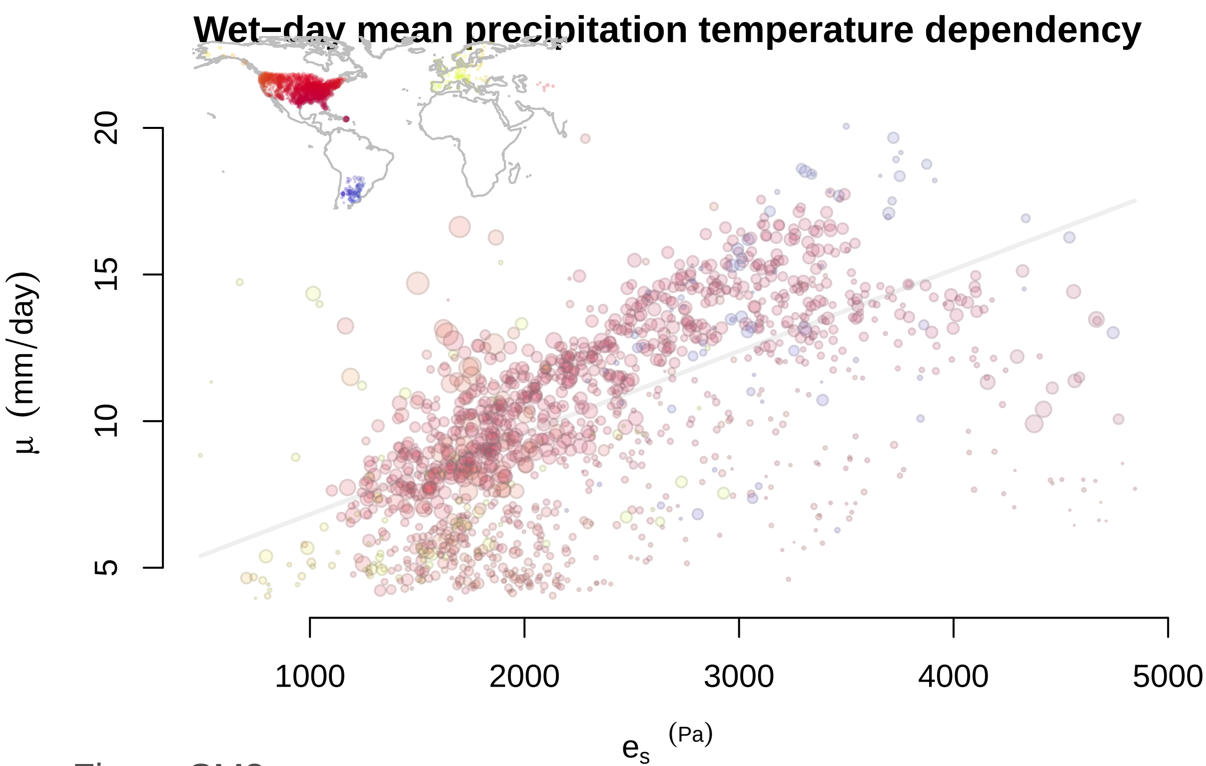
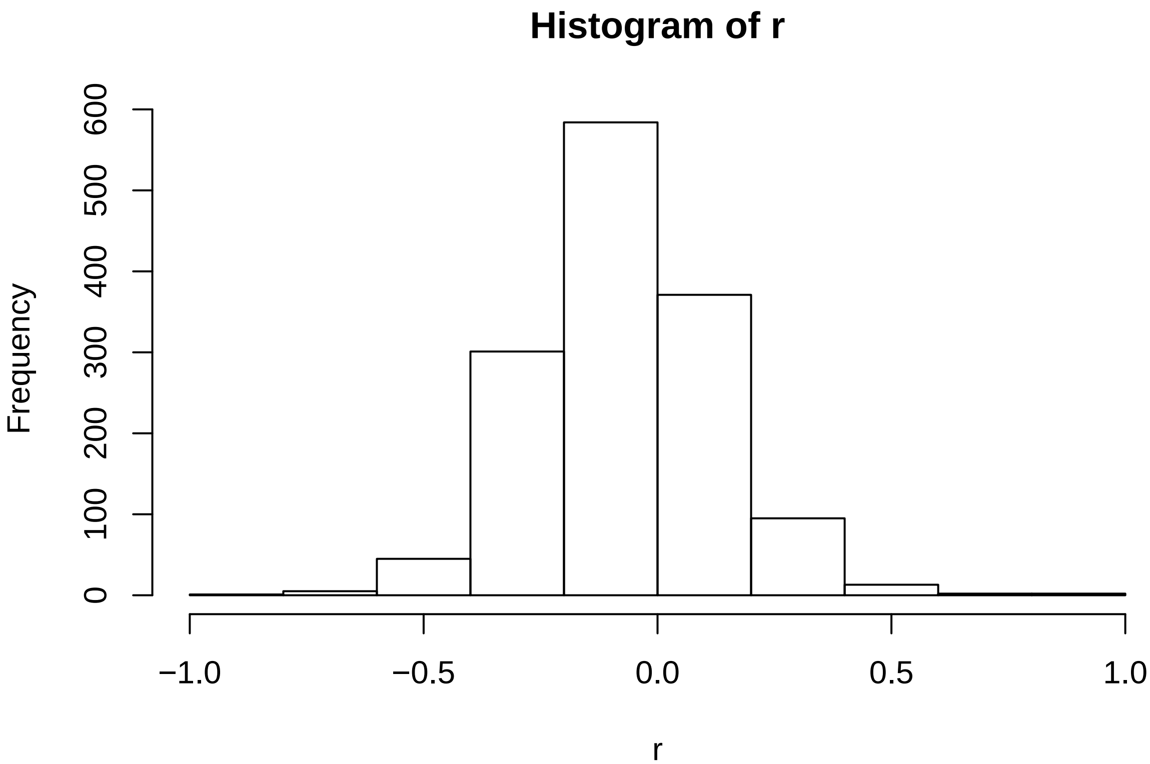


Figure SM8

```
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='esd/data/mu.eq.f.tx.rda',mu.eq.f.tx)
```

```
## Estimate the year-by-year correlation in es and mu

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)
hist(r)
```


Histogram of r
Frequency
0
100
200
300
400
500
600
−1.0
−0.5
0.0
0.5
1.0
r