

---

\*\*EU-Circle case study 3

---

title: Coastal Flooding (surface water, highway, sewer and watercourse flooding) across Torbay, UK

author: "Rasmus Benestad"

date: "April 6, 2016"

output: pdf\_document

fig\_width: 8

fig\_height: 8

---

Torbay is located in South Devon (UK) and covers an area of approximately 62 km<sup>2</sup>. The area has suffered from flooding over many years from a number of different sources, including surface water run-off, highway flooding, sewer flooding, main river and ordinary watercourse flooding during intense rainfall events. In addition the coastal areas of Torbay suffer coastal flooding due to overtopping of the sea defences during high tides that coincide with easterly winds. It should be noted that the surface water, highway, sewer, main river and watercourse flooding is exacerbated in the low lying areas around the coast of Torquay, Paignton and Brixham during high tidal cycles when the capacity of the surface water outfalls discharging to coastal waters is impeded. In addition to the property flooding, during all of these flood events numerous roads have flooded to some extent, with some of the roads having to be closed to traffic until the flood water has subsided.

The main coast road linking Torquay to Paignton and Brixham has to be closed on a regular basis due to overtopping of the sea wall during high tides that coincide with easterly wind conditions. These closures result in long traffic diversions and delays. In addition, as a result of surface water flooding from watercourses and main rivers during intense rainfall events the main inland route linking Torquay, Paignton and Brixham has also been closed for periods resulting in no major roads being available between the towns until flooding has subsided. During the last major flooding event, which occurred on 24<sup>th</sup> October 1999, over 200 properties across all three towns were affected by flooding. Approximately 50% of these properties were commercial properties including shops, restaurants, hotels, bars and a cinema. In addition to the property flooding both the major roads linking Torquay to Paignton and Brixham were closed for a significant period making travel within the Bay extremely difficult and affecting emergency response.

Obviously climate change can affect local flood risk in several ways. Impacts will depend on local conditions and vulnerability. Wetter winters and more of this rain falling in wet spells will increase river and watercourse flooding. More intense rainfall causes more surface run-off, increasing localised flooding and erosion. In turn this will increase pressure on drains, sewers and water quality. Rising sea levels, as a result of climate change, will increase local flood risk both in coastal regions from increased risk of overtopping of the sea wall and inland from main rivers and watercourses due to the interaction with drains, sewers and smaller watercourses. As sea level is predicted to rise by over 1m in Torbay over the next 100 years the frequency and impact of overtopping of the sea defences will increase resulting in more infrastructure and properties being affected by flooding.

**Analysis** The downscaling of the wet-day mean precipitation used the surface temperature as predictor.

This is an R Markdown document. Markdown is a simple formatting syntax for authoring HTML, PDF, and MS Word documents. For more details on using R Markdown see <http://rmarkdown.rstudio.com>. To execute this type:

```
library(rmarkdown); render('eu-circle_case-study-3.Rmd',pdf_document())
```

Load the esd and ncdf packages.

```
## Load the necessary R-package  
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 system and session
```

---

Function to estimate probability for daily amount of exceeding a threshold  $x_0$  given that the distribution follows an exponential distribution and the records of the wet-day mean precipitation and frequency.

```
PrexpPr <- function(mu,fw,x0=10) {
  Pr <- zoo(coredata(fw)*exp(-x0/coredata(mu)),order.by=year(fw))

  Pr.mu <- zoo(mean(coredata(fw))*exp(-x0/coredata(mu)),order.by=year(fw))
  Pr.fw <- zoo(coredata(fw)*exp(-x0/mean(coredata(mu))),order.by=year(fw))
  attr(Pr,'prob.f(mu)') <- Pr.mu
  attr(Pr,'prob.f(fw)') <- Pr.fw
  Pr <- attrcp(mu,Pr)
  attr(Pr,'variable') <- 'Pr'
  attr(Pr,'unit') <- 'probability'
  attr(Pr,'longname') <- paste('Probability of exceeding',x0,'mm')
  class(Pr) <- class(mu)
  invisible(Pr)
}
```

Load the data and weed out stations with lots of missing values

```
## Get MIDAS precipitation data that has already been retrieved
## from the MIDAS data base (UK Met Office)
load('pr.eu-circle-torbay.rda')
pr <- subset(pr,it=c(1960,2013))

## First weeding of stations with many missing values
nok <- apply(coredata(pr),2,'nv')
x <- subset(pr,is=(nok> 15000))

## Quality check: remove outliers days with more than 300 mm - set to NA
xc <- coredata(x); xc[xc > 300] <- NA; xc -> coredata(x); rm('xc')
```

```
## Estimate the annual wet-day mean precipitaiton
mu <- subset(annual(x, 'wetmean', nmin=100), it=c(1961, 2011))
## Estimate the annual wet-day mean frequency
fw <- subset(annual(x, 'wetfreq', nmin=100), it=c(1961, 2011))

## Second weeding of stations with many missing values in annual
## aggregate
nok <- apply(coredata(mu), 2, 'nv')
mu <- subset(mu, is=(nok >= 44))
fw <- subset(fw, is=(nok >= 44))
```

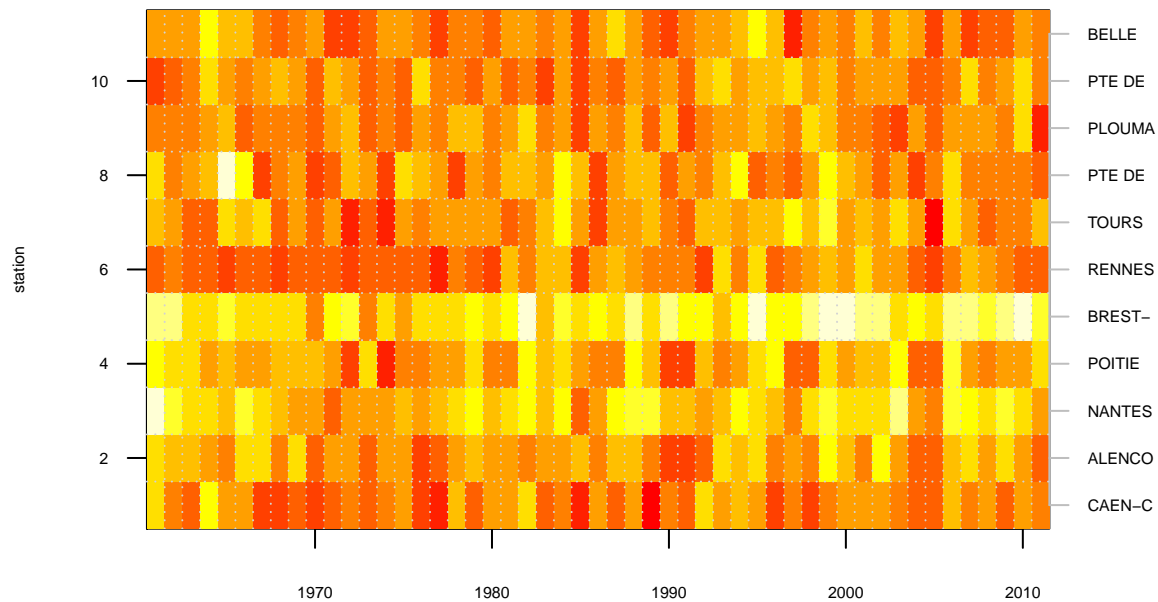
Fill in missing values, but since there are too many missing values, we need to get some more data from the region. This is ok since we are working with annual aggregated values, which may imply larger spatial scales. In any case, these are used to assist the interpolation for the MIDAS stations.

```
ss <- select.station(param='precip', src='ecad', cntr=c('United Kingdom', 'France'), lat=c(45, 55), lon=c(-10, 10))
pr.ecad <- station(ss)
```

```
## [1] "Retrieving data from 19 records ..."
## [1] "1 PRECIP 101265 WADDINGTON UNITED KINGDOM ECAD"
## [1] "2 PRECIP 104044 CAEN-CARPIQUET FRANCE ECAD"
## [1] "3 PRECIP 104052 ALENCON FRANCE ECAD"
## [1] "4 PRECIP 104060 NANTES-BOUGUENNAIS FRANCE ECAD"
## [1] "5 PRECIP 104088 POITIERS - BIARD FRANCE ECAD"
## [1] "6 PRECIP 104484 BREST-GUIPAVAS FRANCE ECAD"
## [1] "7 PRECIP 104924 RENNES-ST JACQUES FRANCE ECAD"
## [1] "8 PRECIP 104943 BALLOTS FRANCE ECAD"
## [1] "9 PRECIP 104974 LEZAY FRANCE ECAD"
## [1] "10 PRECIP 104979 MONTMORILLON FRANCE ECAD"
## [1] "11 PRECIP 106190 TOURS FRANCE ECAD"
## [1] "12 PRECIP 119361 HULL UNITED KINGDOM ECAD"
## [1] "13 PRECIP 119364 ARMAGH UNITED KINGDOM ECAD"
## [1] "14 PRECIP 119367 OXFORD UNITED KINGDOM ECAD"
## [1] "15 PRECIP 146808 ARMAGH UNITED KINGDOM ECAD"
## [1] "16 PRECIP 171623 PTE DE CHASSIRON FRANCE ECAD"
## [1] "17 PRECIP 171627 PLOUMANAC'H FRANCE ECAD"
## [1] "18 PRECIP 171628 PTE DE LA HAGUE FRANCE ECAD"
## [1] "19 PRECIP 171636 BELLE ILE - LE TALUT FRANCE ECAD"
```

```
mu.ecad <- subset(annual(pr.ecad, 'wetmean', nmin=100), it=c(1961, 2011))
fw.ecad <- subset(annual(pr.ecad, 'wetfreq', nmin=100), it=c(1961, 2011))
## Second weeding of stations with many missing values in annual
## aggregate
nok <- apply(coredata(mu.ecad), 2, 'nv')
mu.ecad <- subset(mu.ecad, is=(nok >= 50))
fw.ecad <- subset(fw.ecad, is=(nok >= 50))
diagnose(mu.ecad)
```

## Data availability



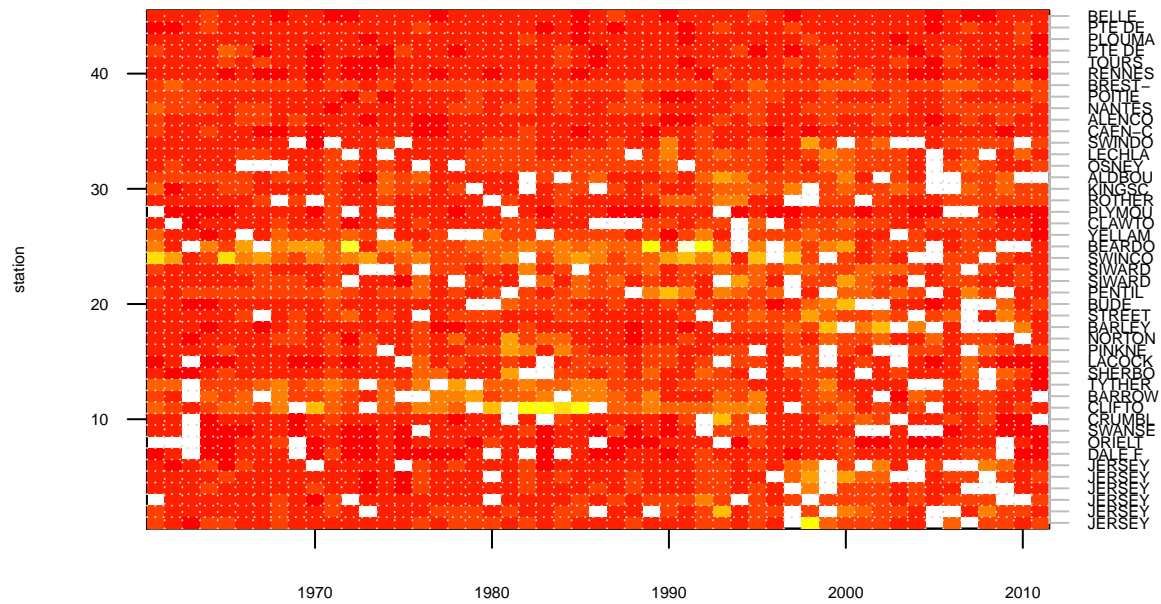
## ECAD

supplement these to the MIDAS data:

```
mu <- combine.stations(mu,mu.ecad)
fw <- combine.stations(fw,fw.ecad)
```

```
##Fill in the remaining gaps using a PCA-based interpolation scheme
## Check the records
diagnose(mu)
```

## Data availability

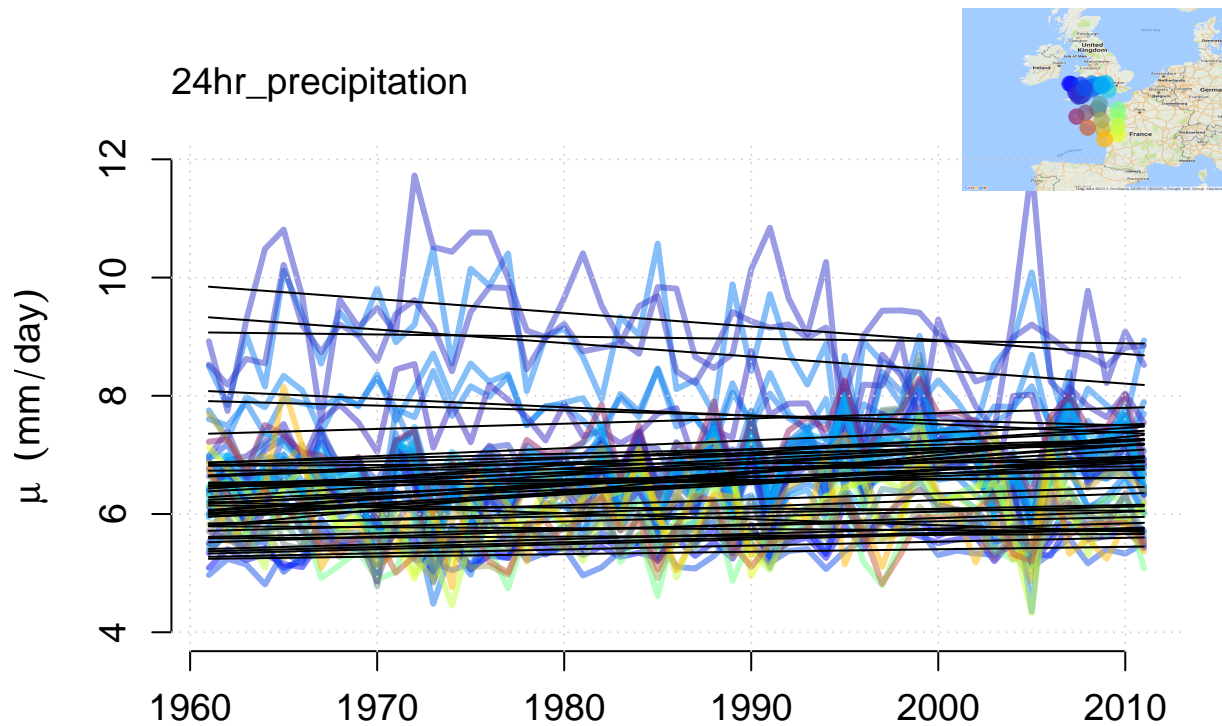


MIDAS (ECADetOffice)

```
pcafill(mu) -> mu
pcafill(fw) -> fw
```

Examine the long-term trends in the wet-day mean precipitation

```
plot(mu,new=FALSE); grid()
for (i in 1:dim(mu)[2]) lines(trend(mu[,i]))
```



```
plot(fw); grid()
```

```
## Warning in plotmap(lat(x), lon(x), bgmap, pch = 19, col = col): NAs
## introduced by coercion
```

```
for (i in 1:dim(mu)[2]) lines(trend(mu[,i]))
```

```
Pr.gt.30 <- PrexpPr(mu,fw,x0=30)
plot(Pr.gt.30); grid()
for (i in 1:dim(mu)[2]) lines(trend(Pr.gt.30[,i]))
```

## Useful information in the mean seasonal cycle?

another attempt to search for systematic influences on the precipitation statistics ( $\mu$ ) is to examine the mean seasonal cycle. This type of approach may

```
## Estimate the mean seasonal cycle in the wet-day mean precipitation
MU <- aggregate(x,month,FUN='wetmean')
## Estimate the mean seasonal cycle in wet-day mean frequency
FW <- aggregate(x,month,FUN='wetfreq')
## Estimate the mean seasonal cycle in wet-day mean frequency
MP <- aggregate(x,month,FUN='mean')
```

```
## Show the mean seasonal cycle in the wet-day mean precipitation
plot(MU)
grid()
```

There is some indication of a mean seasonal cycle in  $\mu$ , with minimum values in late winter spring and higher values in late summer and autumn.

```
## Show the mean seasonal cycle in the wet-day frequency
plot(FW)
grid()
```

There is a clear seasonal cycle in the wet-day occurrence - more rainy days in the uatumn.

```
## Show the mean seasonal cycle in the total precipitation
MP <- 30*MP
attr(MP,'unit') <- 'mm/month'
plot(MP)
grid()
```

Most of the rain falls during winter.

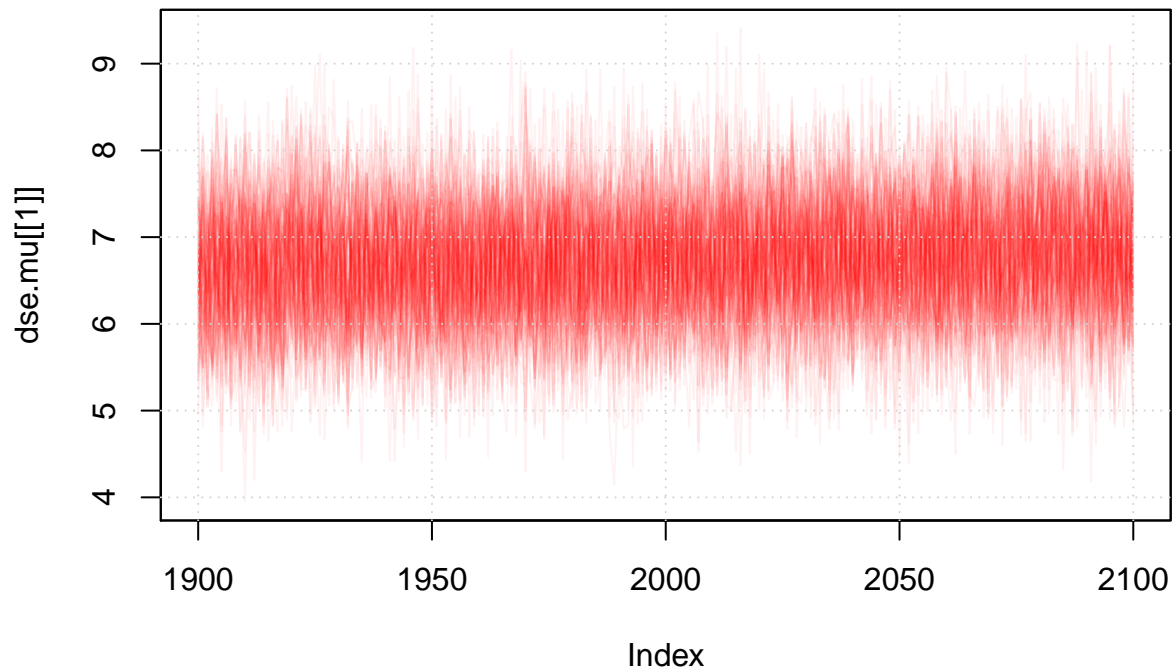
```
## Estimate the PCA for the annual cycle to identify the general features:
pca.MU <- PCA(MU,n=10)
plot(pca.MU)
```

Most stations have the same features when it comes to a mean seasonal cycle in  $\mu$ , with the leading PCA accounting for 80% of the variance.

## Downscaling based on mean seasonal variations

Estimating upper-limits can be an additional approach to exploring the effect of temperature on the precipitation intensity. This is a cruder means for quantifying and may provide further information when more traditional methods give limited information.

```
if (!file.exists('dse.mu.eu-circle-worstcase.rda')) {
  dse.mu <- DSensemble.mu.worstcase(x,biascorrect=TRUE,mask=TRUE,
                                   lon=c(-80,20),lat=c(10,60),
                                   rel.cord=FALSE,verbose=TRUE)
  save(file='dse.mu.eu-circle-worstcase.rda',dse.mu)
} else load('dse.mu.eu-circle-worstcase.rda')
#plot(dse.mu[[1]])
plot.zoo(dse.mu[[1]],plot.type='single',col=rgb(1,0,0,0.05))
grid()
```



## Sea-level

Analyse the sea-level trends and connection to global temperatures to assess future outcome. First the stations from the GLOSS dataset (global monthly data):

```
gloss <- aggregate(station.gloss(),year,FUN='max',na.rm=TRUE)
gloss <- subset(gloss,is=list(lon=c(-20,20),lat=c(45,55)))
```

Plot the GLOSS tidal data:

```
plot(gloss)
```

```
## Warning in plotmap(lat(x), lon(x), bgmap, pch = 19, col = col): NAs
## introduced by coercion
```

```
grid()
```

Single station with hourly data from Newlyn:

```
newlyn <- station.newlyn()
newlyn <- aggregate(newlyn,year,FUN='max',na.rm=TRUE)
```

Plot the Newlyn tidal data:

```
plot(newlyn)
```

```
## Warning in plotmap(lat(x), lon(x), bgmap, pch = 19, col = col): NAs
## introduced by coercion
```



```
grid()
```

French tidal stations along the northern/eastern coast (SONEL):

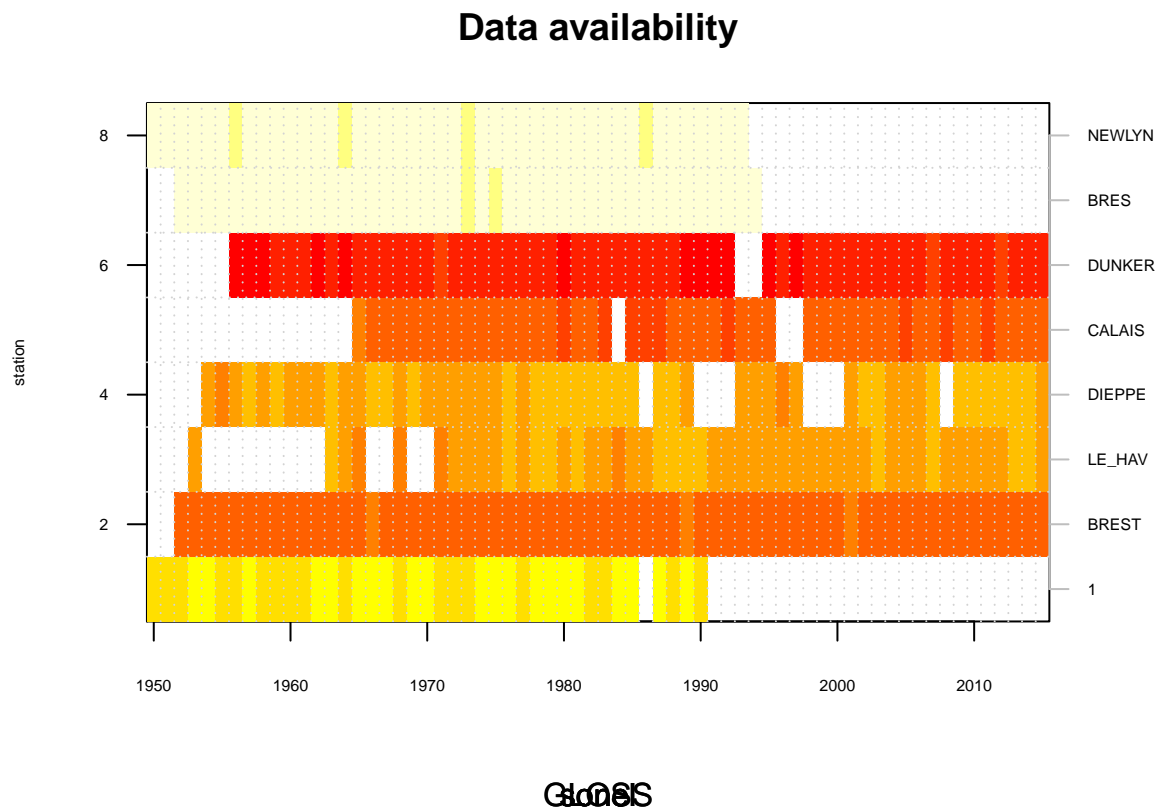
```
sonel <- aggregate(station.sonel(),year,FUN='max',na.rm=TRUE)
plot(sonel)
grid()
```

Combine the records from different sources

```
index(newlyn) <- year(newlyn)
index(sonel) <- year(sonel)
index(gloss) <- year(gloss)
Z <- combine.stations(newlyn,sonel,gloss)
nv <- apply(coredata(Z),2,FUN='nv')
Z <- subset(Z,is=(nv > 50))
Z <- subset(Z,it=c(1950,2015))
plot(Z); grid()
```

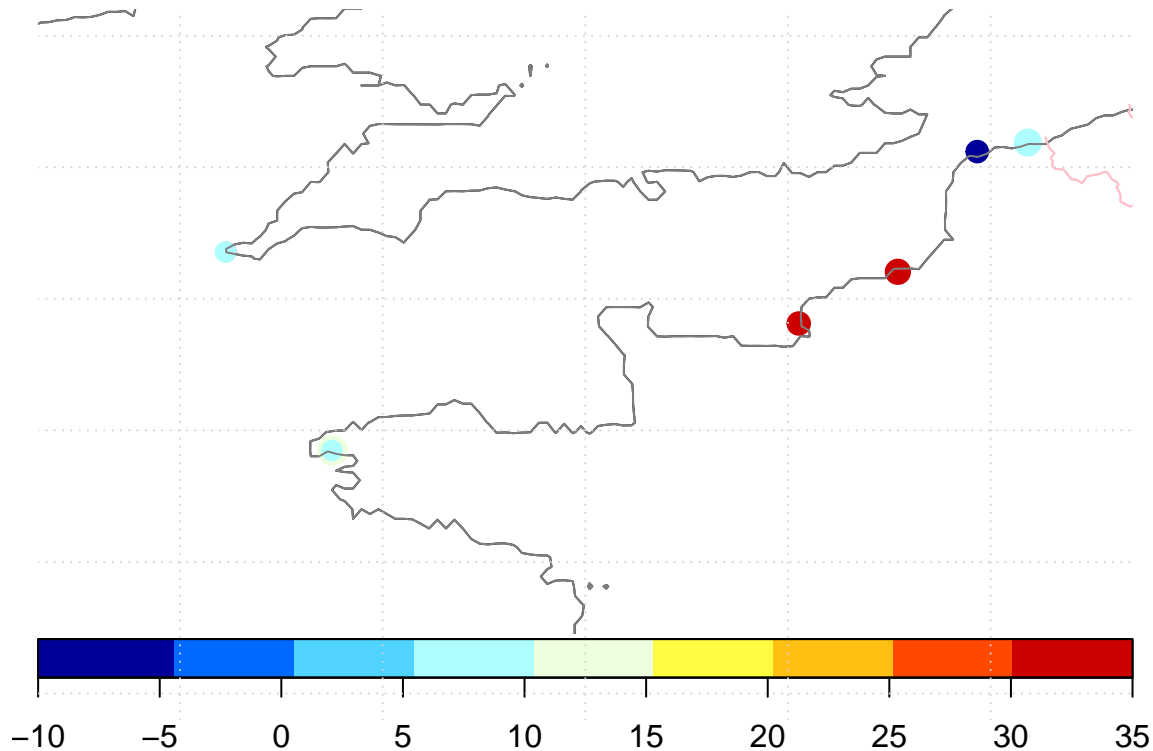
Check for data availability

```
diagnose(Z)
```



Make a map of the trend in the local sea-level - mm/decade

```
zc <- coredata(Z)
zc[is.infinite(zc)] <- NA
zc -> coredata(Z)
map(Z,FUN='trend',cex=-2)
```



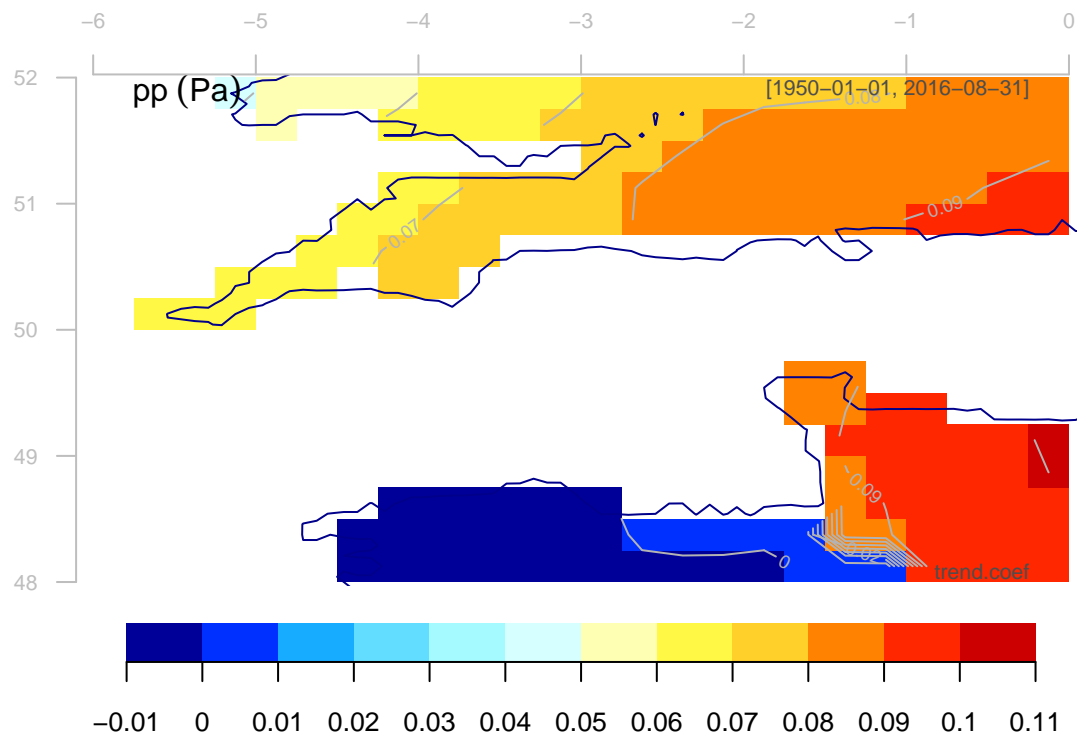
## Wind

Estimate wind windspeed from SLP measurements. Make use of the gridded EOBS data as the documentation for MIDAS data is poor and it's difficult to read the data and organise it, due to very large ASCII files and the way the data is stored.

```
slp.eobs <- retrieve('data.ECAD/pp_0.25deg_reg.nc',lon=c(-6,0),lat=c(48,52))
```

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

```
slp.eobs <- 10000*slp.eobs ## The data have some funny scaling factor
attr(slp.eobs,'unit') <- 'Pa'
map(slp.eobs,FUN='trend')
```



Pick three grid points from which we can estimate the geostrophic wind

```
## Fudge it - pick some windstations, but do not use their data. Reset the
## coordinates to select a triangle of SLP from the EOBS data.
ss <- select.station(param='slp',src='ecad',cntr=c('France','UNITED KINGDOM'))
fx <- station(ss)
```

```
## [1] "Retrieving data from 8 records ..."
## [1] "1 SLP 100102 BOURGES FRANCE ECAD"
## [1] "2 SLP 100106 TOULOUSE-BLAGNAC FRANCE ECAD"
## [1] "3 SLP 100110 BORDEAUX-MERIGNAC FRANCE ECAD"
## [1] "4 SLP 100114 CHATEAUROUX DEOLS FRANCE ECAD"
## [1] "5 SLP 100118 PERPIGNAN FRANCE ECAD"
## [1] "6 SLP 100122 LYON - ST EXUPERY FRANCE ECAD"
## [1] "7 SLP 100126 PARIS - MONTSOURIS FRANCE ECAD"
## [1] "8 SLP 146809 ARMAGH UNITED KINGDOM ECAD"
```

```
triangle <- subset(fx,is=1:3)
## The stations are not situated quite where there is valid slp data in the EOBS dataset
## It's only their coordinates that is used for interpolating SLP for three stations
## Using station objects as is-object makes the results a station object
attr(triangle,'longitude') <- c(-4,-2,-1.25)
attr(triangle,'latitude') <- c(50.50,51,49)
pp.eobs <- regrid(slp.eobs,is=triangle)
## Use triangulation for stations to estimate the wind
uv <- geostrophicwind(pp.eobs)
```

```
## [1] "3 stations gives 1 combinations of three."
##
|
```

```
|
|
|=====| 0%
|=====| 100%
```

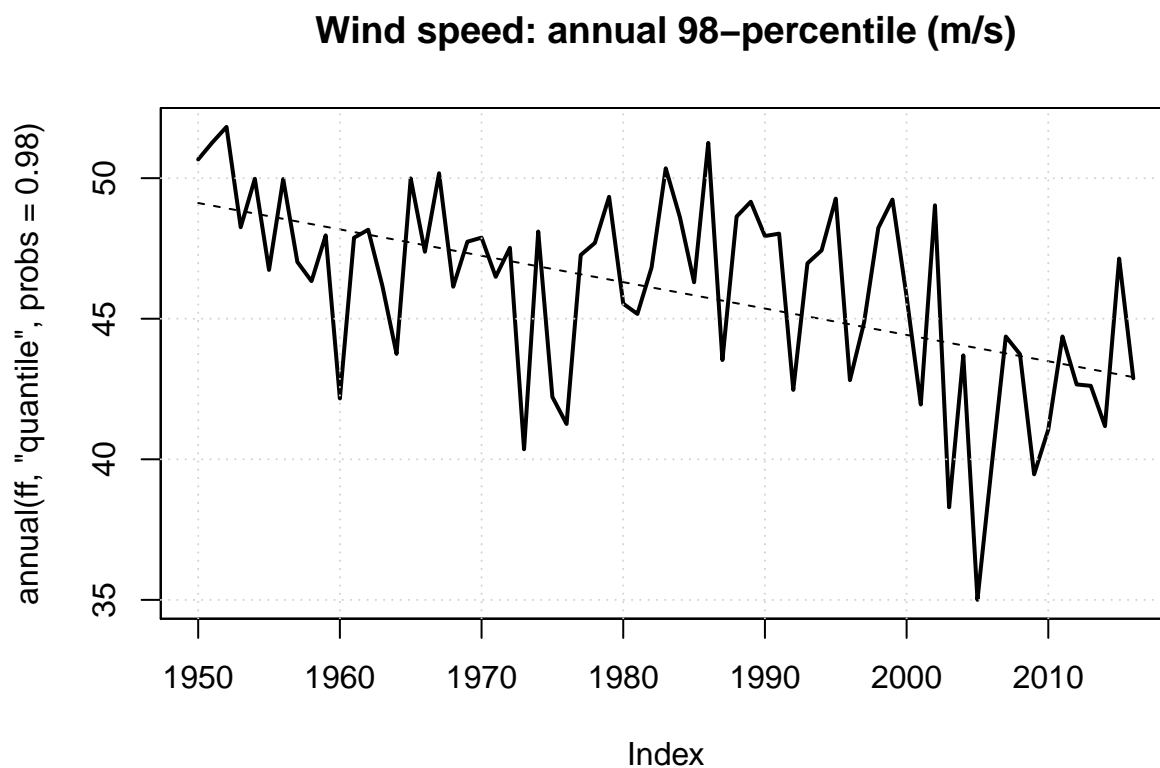
```
plot(annual(uv,nmin=300),main='zonal and meridional wind components',
      sub='Estimated from triangulation of mean sea-level pressure from EOBS',zoom=7)
grid()
```

The estimated annual mean geostrophic wind reveals that something changed between 2006 and 2010. The change seems to have taken place over 4 years.

```
plot(annual(uv,nmin=300),main='zonal and meridional wind components',
      xlim=c(2000,2010),map.show=FALSE)
grid()
```

This event also is seen in the upper tail of the wind speed distribution. There are four features concerning these wind speed estimates: a downward trend from moderate high wind speeds in the 1950s, two years with a large drop in values in the 1970s, a number of years with high values around year 2010, and a slight increasing trend in the upper wind speeds over the record.

```
## Trend in upper wind speed
ff <- sqrt(uv[,1]^2 + uv[,2]^2)
plot(annual(ff,"quantile",probs=0.98),lwd=2,
      main='Wind speed: annual 98-percentile (m/s)')
lines(trend(annual(ff,"quantile",probs=0.98)),lty=2)
grid()
```



```
trend.coef(annual(ff,"quantile",probs=0.98))
```

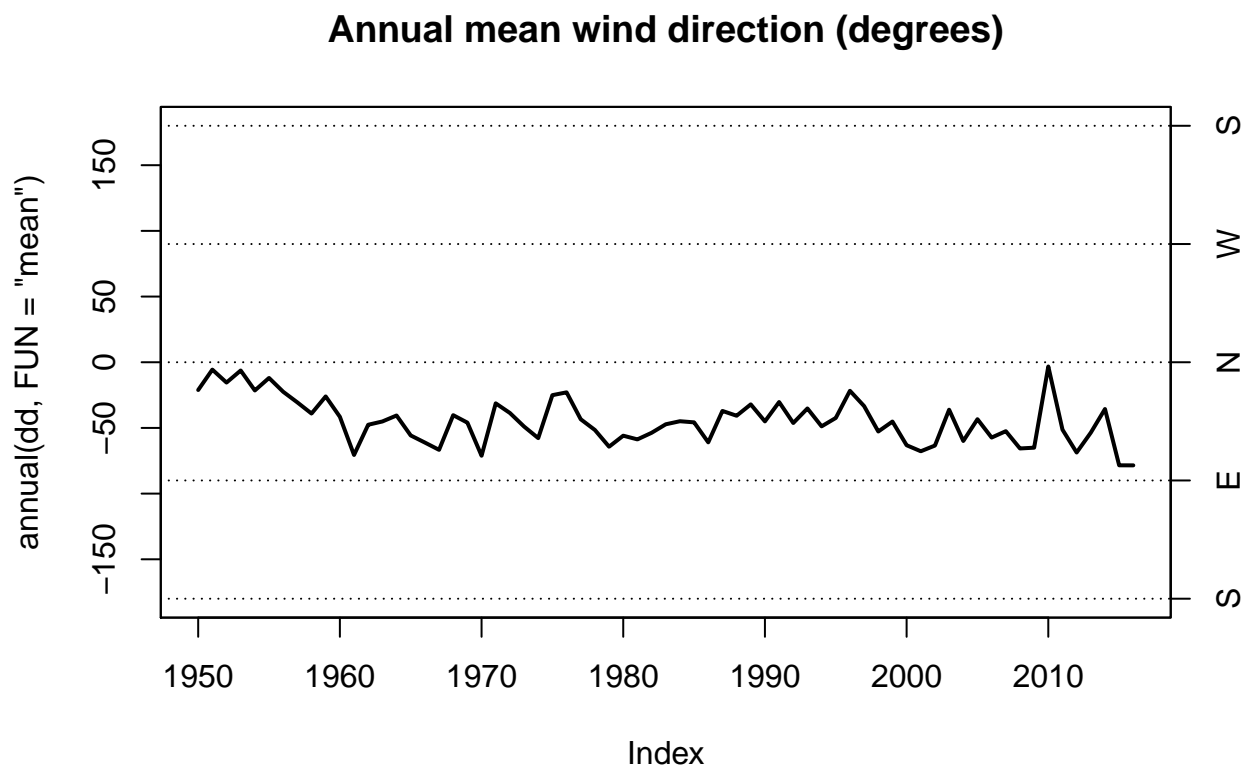
```
## trend.coefficients
##          -0.9383385
```

```
trend.err(annual(ff,"quantile",probs=0.98))
```

```
## trend.standard.error
##           0.1903132
```

The trend is not significant at the 5-percentage level.

```
## Trend in upper wind direction
dd <- zoo(180/pi*atan2(coredata(uv)[,1],coredata(uv)[,2]),order.by=index(uv))
plot(annual(dd,FUN='mean'),lwd=2,ylim=c(-180,180),
     main='Annual mean wind direction (degrees)')
axis(4,at=c(-180,-90,0,90,180),labels=c('S','E','N','W','S'))
for (j in c(-180,-90,0,90,180)) lines(range(index(dd)),rep(j,2),lty=3)
```



The change in 2006-2010 is also visible in the wind direction. This could be an event caused by a change in circulation, but it could also be due to changes in instrumentation, data used in the gridding or observational practices. It is possible to examine whether there were changes in the circulation by using ESD to compare the windspeeds with SLP from reanalyses.

```
## Trend in upper wind direction
SLP <- retrieve('slp.mon.mean.nc',lon=c(-50,30),lat=c(40,60))
```

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

```
eof.slp<- EOF(annual(SLP))
```

Apply the downscaling to the meridional wind component:

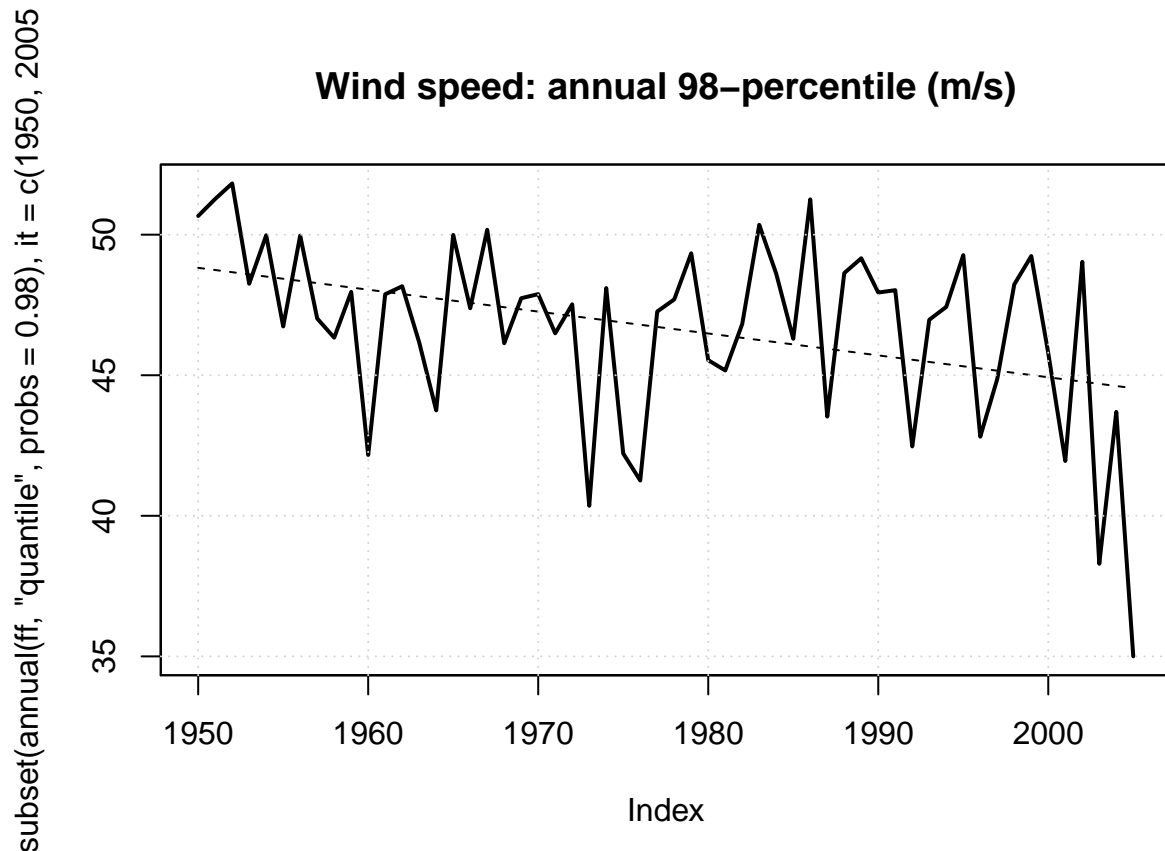
```
## Trend in upper wind direction
uam <- annual(subset(uv,is=2),nmin=300)
ds.u1 <- DS(uam,eof.slp,eofs=1:20)
plot(ds.u1)
```

The results suggest a mismatch between the reanalysis and the EOBS data, and the change after 2005 is not corroborated by other sources. We can therefore say that this feature is suspect.

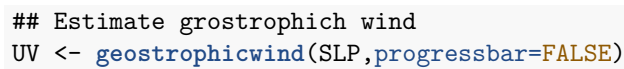
```
## Trend in upper wind direction
ds.u2 <- DS(subset(uam,it=c(1950,2005)),eof.slp,eofs=1:20)
plot(ds.u2)
```

When the test is repeated for the shorter period excluding data after 2005, there is a reasonably good match between the EOBS data and the reanalysis. The trend analysis can be repeated with this event excluded

```
## Trend in upper wind speed
plot(subset(annual(ff,"quantile",probs=0.98),it=c(1950,2005)),lwd=2,
      main='Wind speed: annual 98-percentile (m/s)')
lines(trend(subset(annual(ff,"quantile",probs=0.98),it=c(1950,2005))),lty=2)
grid()
```



```
##
require(MASS)
hist(coredata(subset(ff,it=c(1950,2005))),lwd=2,breaks=seq(0,70,by=1),
      main='Wind speed (m/s)',freq=FALSE,col=colscal(71))
grid()
## Maximum-likelihood fitting of the Weibull distribution - two parameters: shape and scale
f<-fitdistr(ff[is.finite(ff)], 'weibull')
lines(dweibull(seq(0,70,by=1),shape=f$estimate[1],scale=f$estimate[2]),lwd=3,col=rgb(1,0,0,0.3))
```



15

	==	4%
	===	4%
	===	5%
	====	5%
	====	6%
	====	7%
	=====	7%
	=====	8%
	=====	9%
	=====	10%
	=====	10%
	=====	11%
	=====	12%
	=====	13%
	=====	13%
	=====	14%
	=====	15%
	=====	15%
	=====	16%
	=====	16%
	=====	17%
	=====	18%
	=====	18%
	=====	19%
	=====	19%
	=====	20%
	=====	21%



=====		21%
=====		22%
=====		22%
=====		23%
=====		24%
=====		24%
=====		25%
=====		25%
=====		26%
=====		27%
=====		27%
=====		28%
=====		29%
=====		30%
=====		30%
=====		31%
=====		32%
=====		32%
=====		33%
=====		33%
=====		34%
=====		35%
=====		35%
=====		36%
=====		36%
=====		37%
=====		38%

			38%
	=====		39%
	=====		39%
	=====		40%
	=====		41%
	=====		41%
	=====		42%
	=====		42%
	=====		43%
	=====		44%
	=====		44%
	=====		45%
	=====		45%
	=====		46%
	=====		47%
	=====		47%
	=====		48%
	=====		48%
	=====		49%
	=====		50%
	=====		50%
	=====		51%
	=====		52%
	=====		52%
	=====		53%
	=====		53%
	=====		54%

			55%
	=====		55%
	=====		55%
	=====		56%
	=====		56%
	=====		57%
	=====		58%
	=====		58%
	=====		59%
	=====		59%
	=====		60%
	=====		61%
	=====		61%
	=====		62%
	=====		62%
	=====		63%
	=====		64%
	=====		64%
	=====		65%
	=====		65%
	=====		66%
	=====		67%
	=====		67%
	=====		68%
	=====		68%
	=====		69%
	=====		70%
	=====		70%

=====	71%
=====	72%
=====	73%
=====	73%
=====	74%
=====	75%
=====	75%
=====	76%
=====	76%
=====	77%
=====	78%
=====	78%
=====	79%
=====	79%
=====	80%
=====	81%
=====	81%
=====	82%
=====	82%
=====	83%
=====	84%
=====	84%
=====	85%
=====	85%
=====	86%
=====	87%
=====	87%

=====		88%
=====		89%
=====		90%
=====		90%
=====		91%
=====		92%
=====		93%
=====		93%
=====		94%
=====		95%
=====		95%
=====		96%
=====		96%
=====		97%
=====		98%
=====		98%
=====		99%
=====		99%
=====		100%[1] 10
##		
		0%
		1%
=		1%
=		2%
==		2%
==		3%
==		4%

===	4%
===	5%
=====	5%
=====	6%
=====	7%
=====	7%
=====	8%
=====	9%
=====	10%
=====	10%
=====	11%
=====	12%
=====	13%
=====	13%
=====	14%
=====	15%
=====	15%
=====	16%
=====	16%
=====	17%
=====	18%
=====	18%
=====	19%
=====	19%
=====	20%
=====	21%
=====	21%

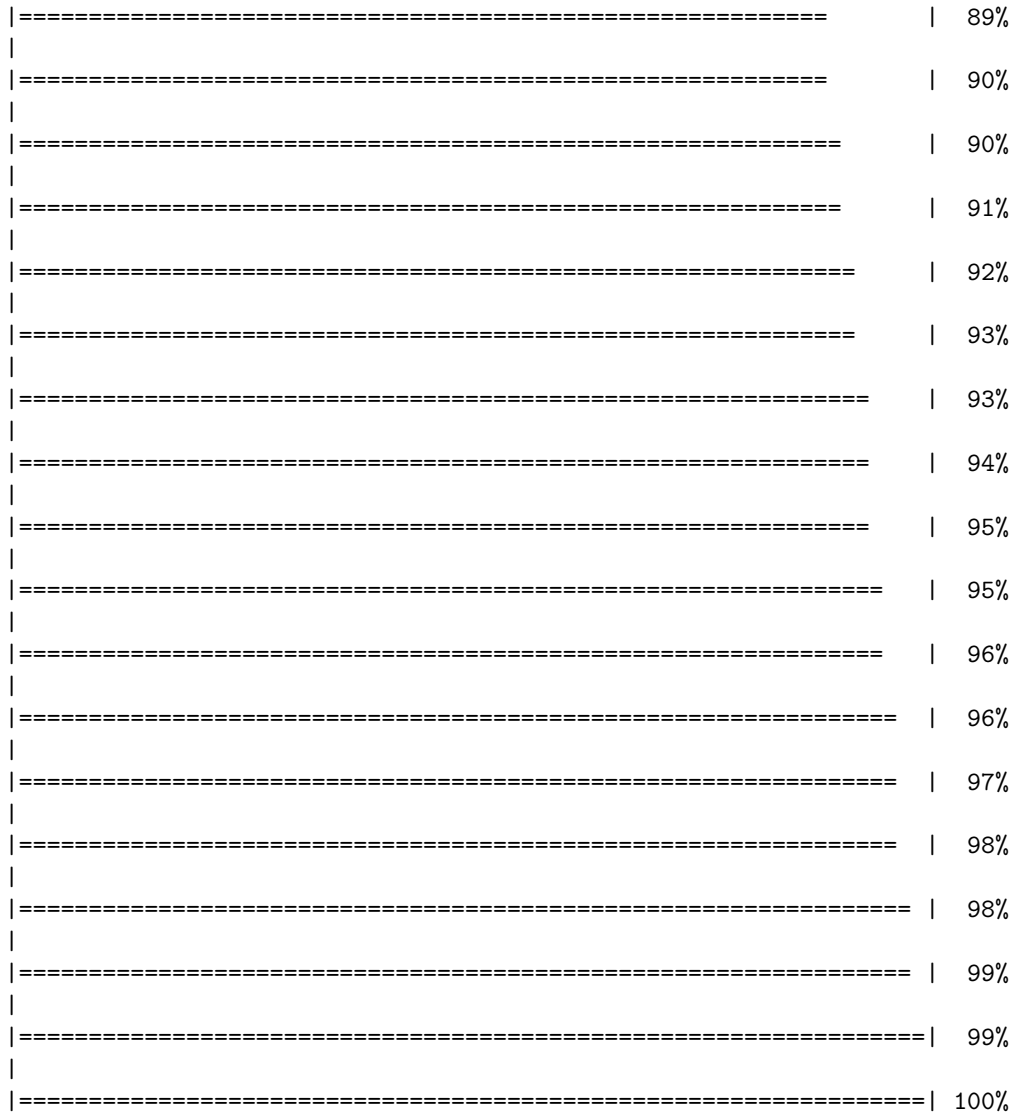
=====	22%
=====	22%
=====	23%
=====	24%
=====	24%
=====	25%
=====	25%
=====	26%
=====	27%
=====	27%
=====	28%
=====	29%
=====	30%
=====	30%
=====	31%
=====	32%
=====	32%
=====	33%
=====	33%
=====	34%
=====	35%
=====	35%
=====	36%
=====	36%
=====	37%
=====	38%
=====	38%

=====	39%
=====	39%
=====	40%
=====	41%
=====	41%
=====	42%
=====	42%
=====	43%
=====	44%
=====	44%
=====	45%
=====	45%
=====	46%
=====	47%
=====	47%
=====	48%
=====	48%
=====	49%
=====	50%
=====	50%
=====	51%
=====	52%
=====	52%
=====	53%
=====	53%
=====	54%
=====	55%



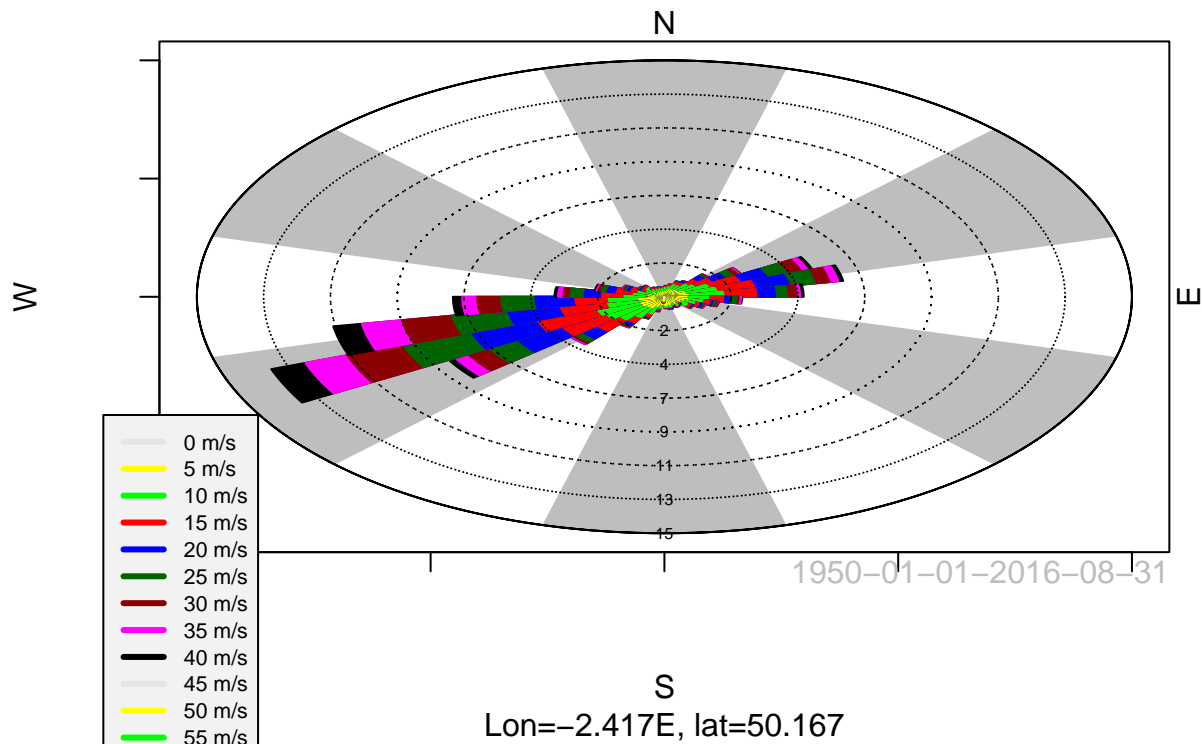
=====	55%
=====	56%
=====	56%
=====	57%
=====	58%
=====	58%
=====	59%
=====	59%
=====	60%
=====	61%
=====	61%
=====	62%
=====	62%
=====	63%
=====	64%
=====	64%
=====	65%
=====	65%
=====	66%
=====	67%
=====	67%
=====	68%
=====	68%
=====	69%
=====	70%
=====	70%
=====	71%

=====	72%
=====	73%
=====	73%
=====	74%
=====	75%
=====	75%
=====	76%
=====	76%
=====	77%
=====	78%
=====	78%
=====	79%
=====	79%
=====	80%
=====	81%
=====	81%
=====	82%
=====	82%
=====	83%
=====	84%
=====	84%
=====	85%
=====	85%
=====	86%
=====	87%
=====	87%
=====	88%



```
## wind rose  
windrose(uv)
```

## URGES-TOULOUSE-BLAGNAC-BORDEAUX-MERIGNAC wind rose; N



## EOBS gridded data

This script retrieves precipitation for Southwestern England from the EOBS data set and estimates the wet-day mean precipitation and frequency.

The EOBS data was chosen here because the rain gauge data from stations (MIDAS) was intermittent and not readily available for an analysis that makes use of PCA in order to make the most use of the information embedded in many parallel data records.

Rain gauges provide a very tiny sample of the rainfall, and previous work suggests that downscaling can provide a better picture if it's applied to a group of stations rather than single stations (Benestad et al., 2015; doi:10.342/tellusa.v67.28326). Downscaling applied to products from principal component analysis (PCA) benefits from an emphasis on coherent structure of variability in time and space, which can improve the signal-to-noise ratio. PCA requires no missing values, but the EOBS gridded data provides complete records.

```
pr.eobs <- retrieve('data.ECAD/rr_0.25deg_reg.nc',lon=c(-6,-1),lat=c(50,52))
```

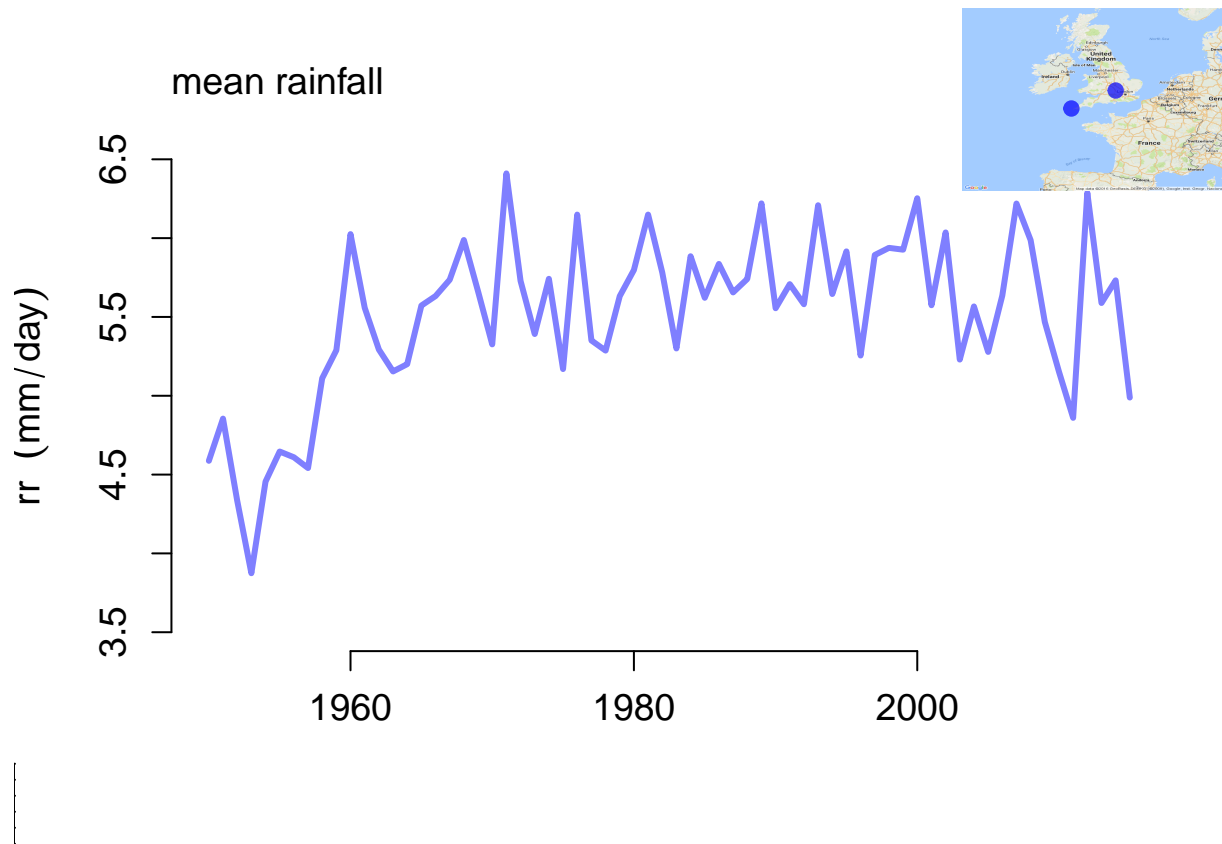
```
## [1] "Warning : Calendar attribute has not been found in the meta data and will be set automatically."
```

```
mu <- annual(pr.eobs,FUN='wetmean')
fw <- annual(pr.eobs,FUN='wetfreq')
```

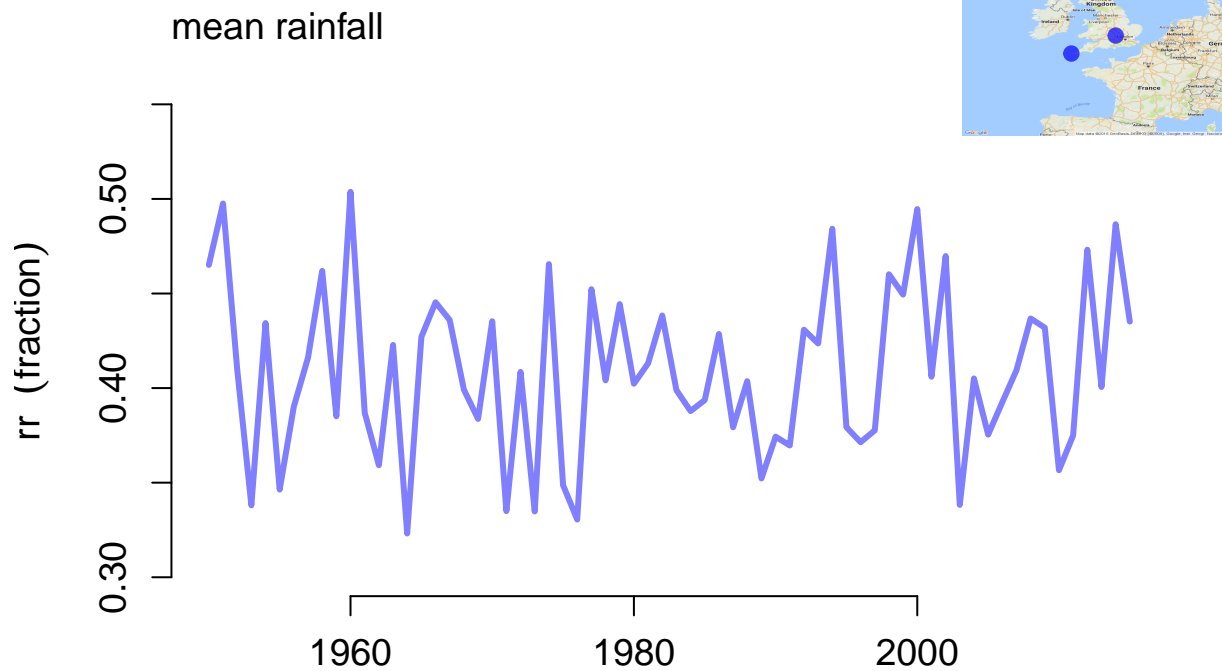
## Past trends

Climate change has taken place for some time, and past trends may provide some indication about whether a chosen climate parameter such as the wet-day mean precipitation  $\mu$  or wet-day frequency  $f_w$  are sensitive to a global warming:

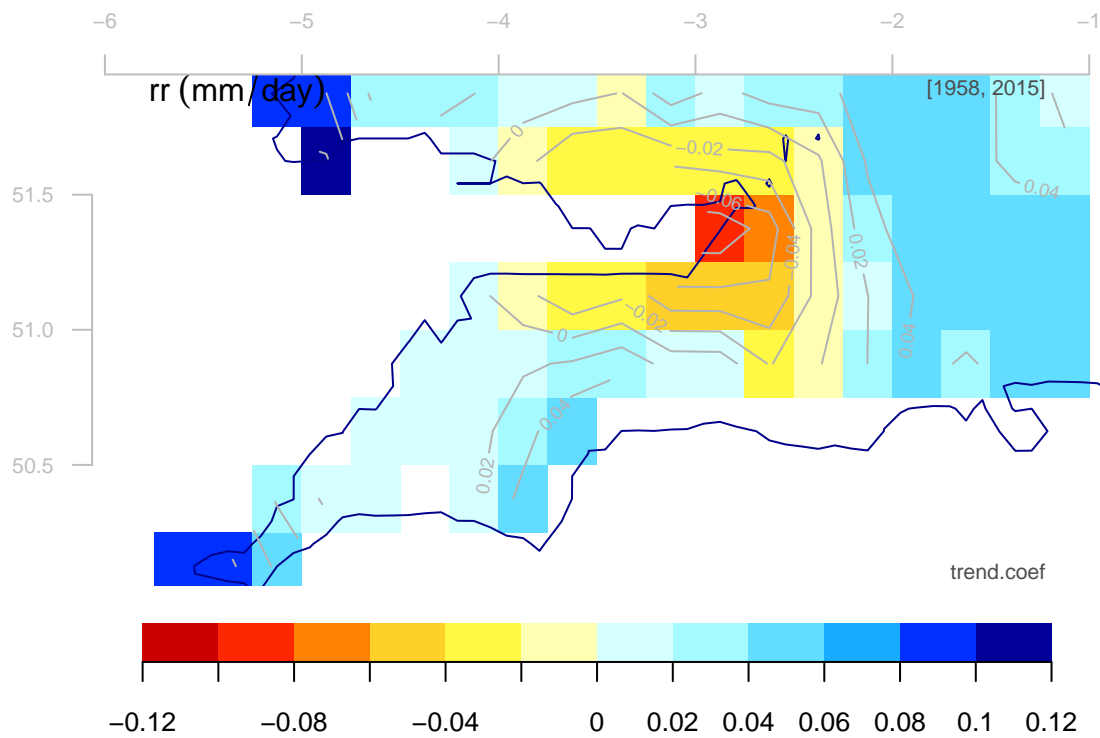
```
## The area mean wet-day mean precipitation  
plot(mu,new=FALSE)
```



```
## The area mean wet-day frequency  
plot(fw,new=FALSE)
```

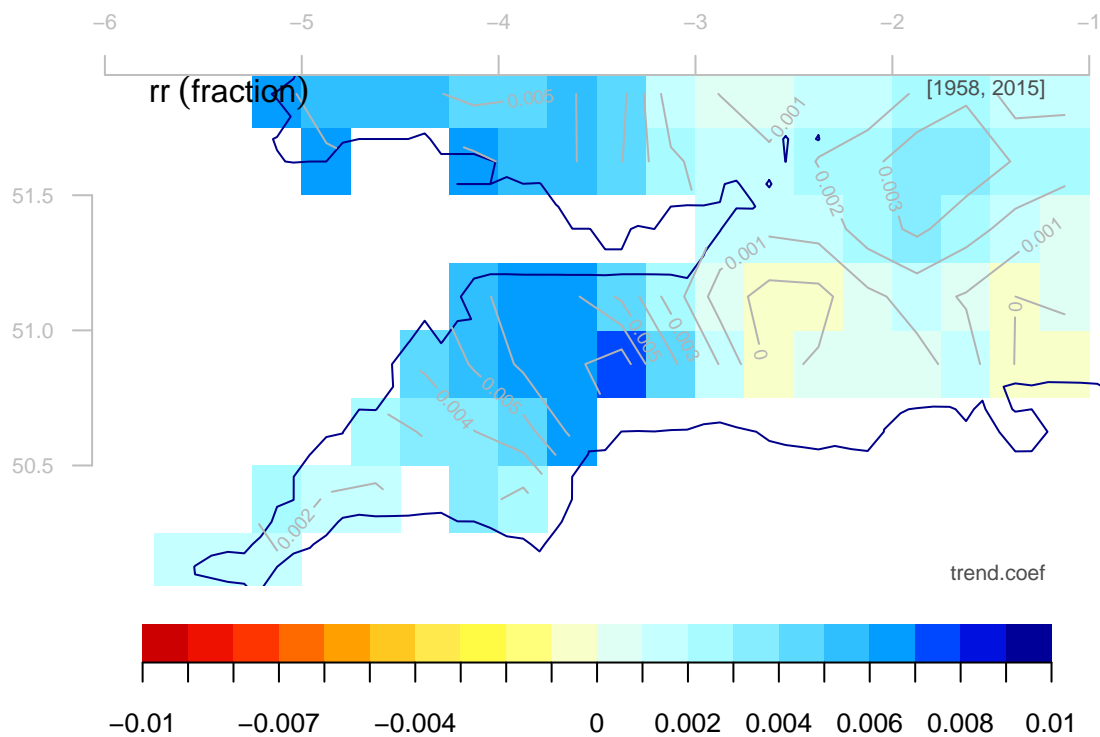


```
## The early part of the record looks suspect:
mu <- subset(mu,it=c(1958,2015))
fw <- subset(fw,it=c(1958,2015))
## Show maps of trends for the wet-day mean precipitation
map(mu,FUN='trend',
    colbar=list(breaks=seq(-0.12,0.12,by=0.02),pal='t2m',rev=TRUE))
```



## Map of trends in wet-day frequency:

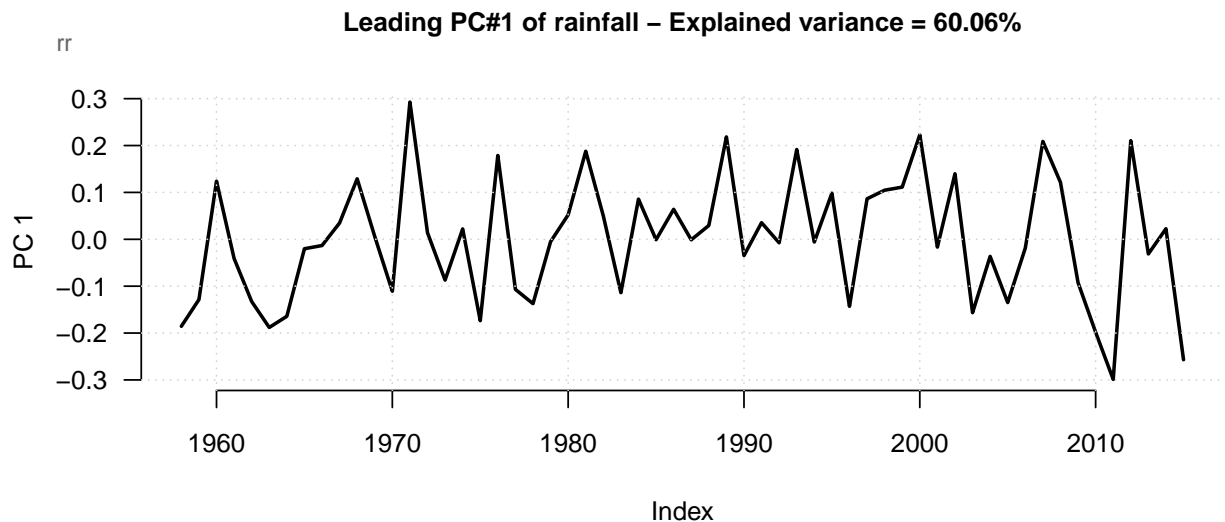
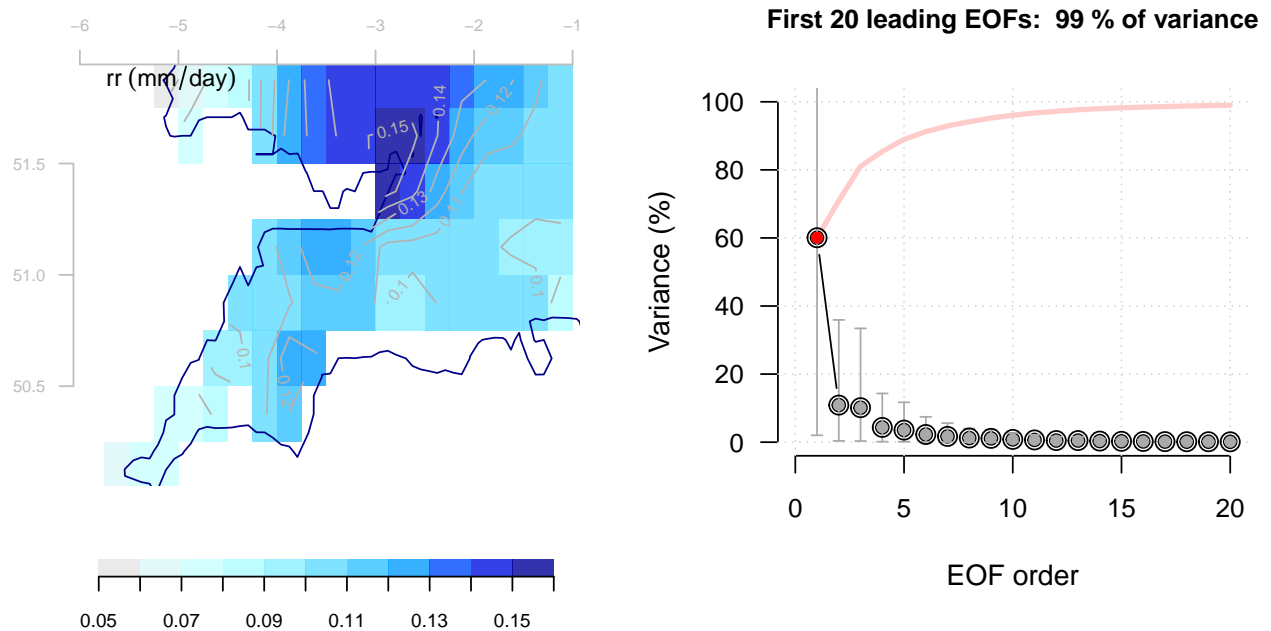
```
map(fw, FUN='trend',
    colbar=list(breaks=seq(-0.01, 0.01, by=0.001), pal='t2m', rev=TRUE))
```



The trend analysis for the wet-day frequency suggest a general increase in the number of wet-days over the period 1960–2015 while the intensity .

The predictors can be organised as EOFs to simplify the analysis and make use of properties as the products being orthogonal. Here are the EOFs for the annual wet-day mean precipitation  $\mu$

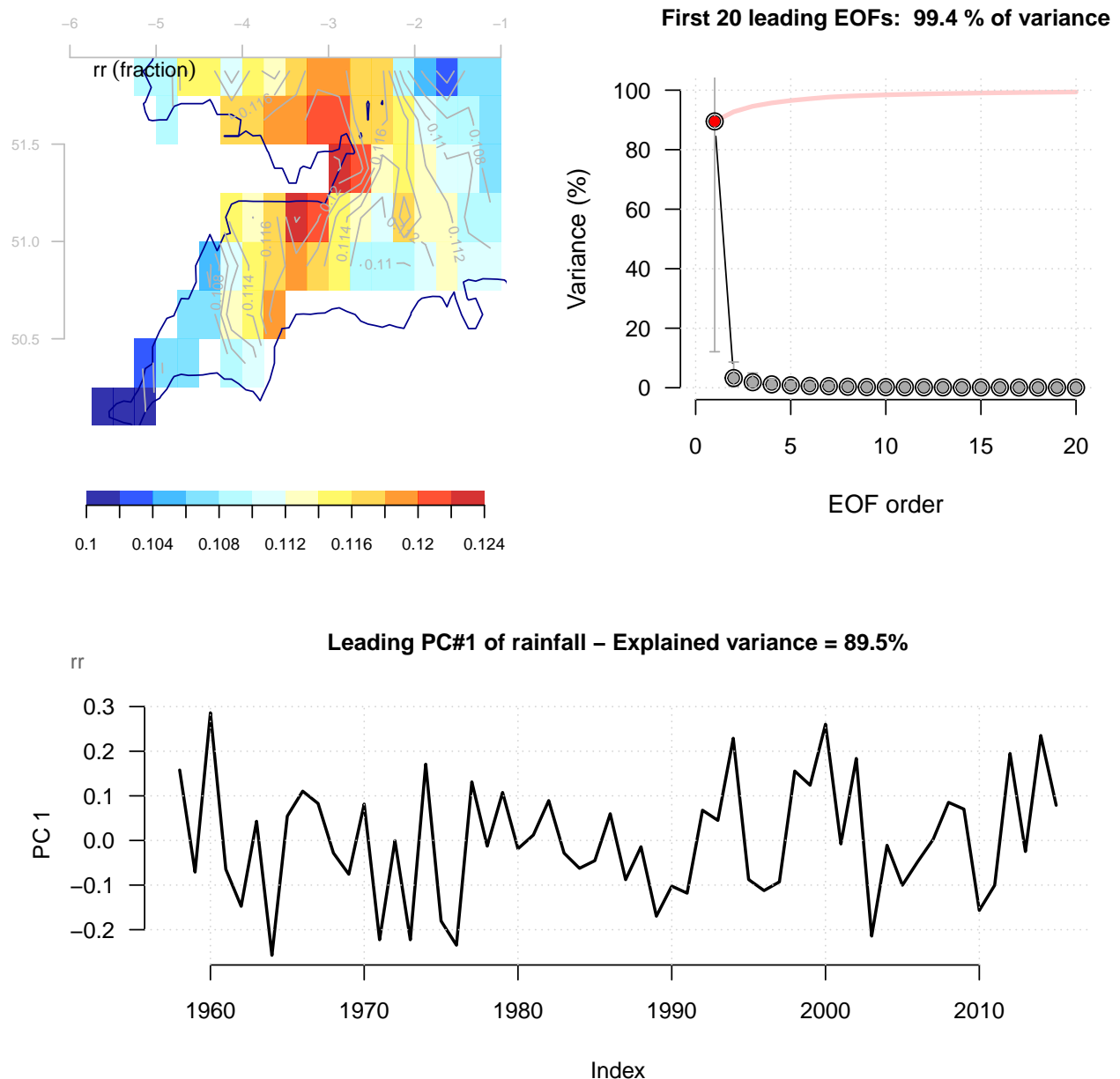
```
## The area mean wet-day mean precipitation
eof.mu <- EOF(mu)
## The area mean wet-day frequency
plot(eof.mu)
```



and the annual wet-day frequency  $f_w$

```
## Show maps of trends for the wet-day mean precipitation
eof.fw <- EOF(fw)
## Map of trends in wet-day frequency:
plot(eof.fw)
```





The diagnostics of the EOFs suggest that the leading mode explains a high proportion of the variability on an annual time scale.

The mean sea-level pressure (SLP) is used as predictor for the annual wet-day frequency, as this gives a good description of the circulation. A number of different spatial domains were tested, and for SLP and  $f_w$ , the results were fairly robust with respect to the choice of domain.

The predictor for the wet-day mean precipitation was taken to be the saturation vapour pressure over the North Atlantic, which is regarded as the main source for the atmospheric moisture over northern Europe.

## Predictor

```
## The mean sea-level pressure
slp <- retrieve('slp.mon.mean.nc',lon=c(-80,0),lat=c(20,70))
```

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

```
## The surface temperature
t2m <- retrieve('air.mon.mean.nc',lon=c(-80,0),lat=c(10,70))
```

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

```
## Saturation water pressure estimated from maritime temperatures
es <- C.C.eq(mask(t2m,land=TRUE))
eof.slp<- EOF(annual(slp))
eof.t2m <- EOF(annual(t2m))
eof.es <- EOF(annual(es,FUN='mean'))
```

## Cannical Correlation analysis

Carry out canonical correlation analysis (CCA) to explore relationships between the large-scale conditions such as SLP/temperature and the precipitation over southwestern England:

```
## The wet-day frequency and SLP
cca.fw <- CCA(eof.fw,eof.slp)
plot(cca.fw)
cca.mu <- CCA(eof.mu,eof.es)
plot(cca.mu)
```

The CCA identifies the two patterns in the data that have the highest correlation - this pattern may not necessarily be the ones with the highest variance.

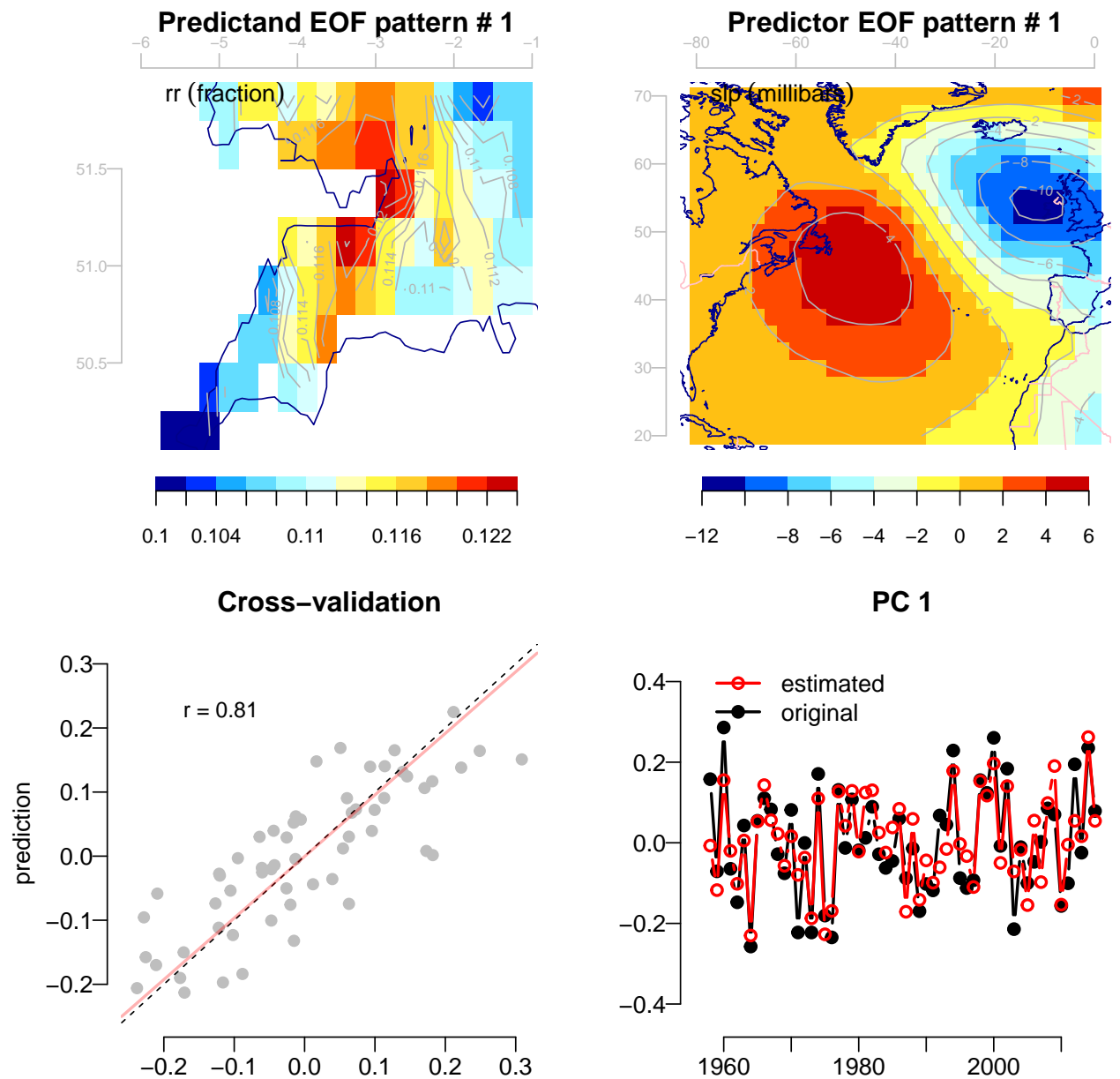
## Downscaling analysis

The downscaling emplies a multiple regression applied to each of the principal components for the EOFs of  $\mu$  and  $f_w$ .

```
## The wet-day frequency and SLP
ds.fw <- DS(subset(eof.fw,ip=1:4),eof.slp,eofs=1:5)
```

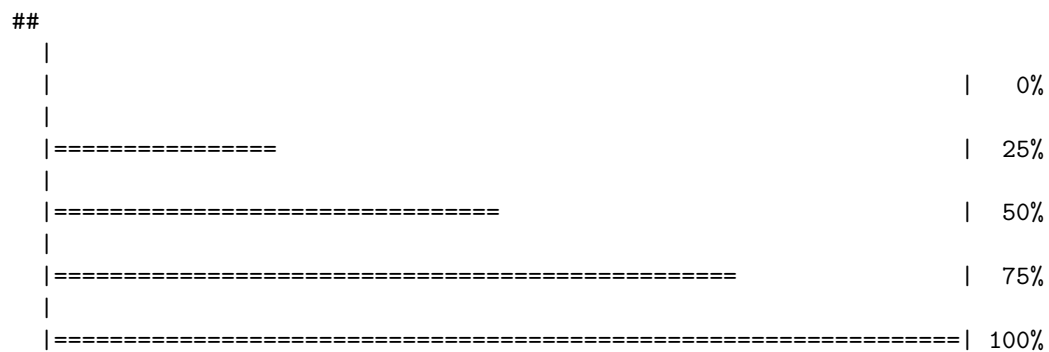
```
##
|
|
|
|=====| 25%
|
|=====| 50%
|
|=====| 75%
|
|=====| 100%
```

```
plot(ds.fw)
```

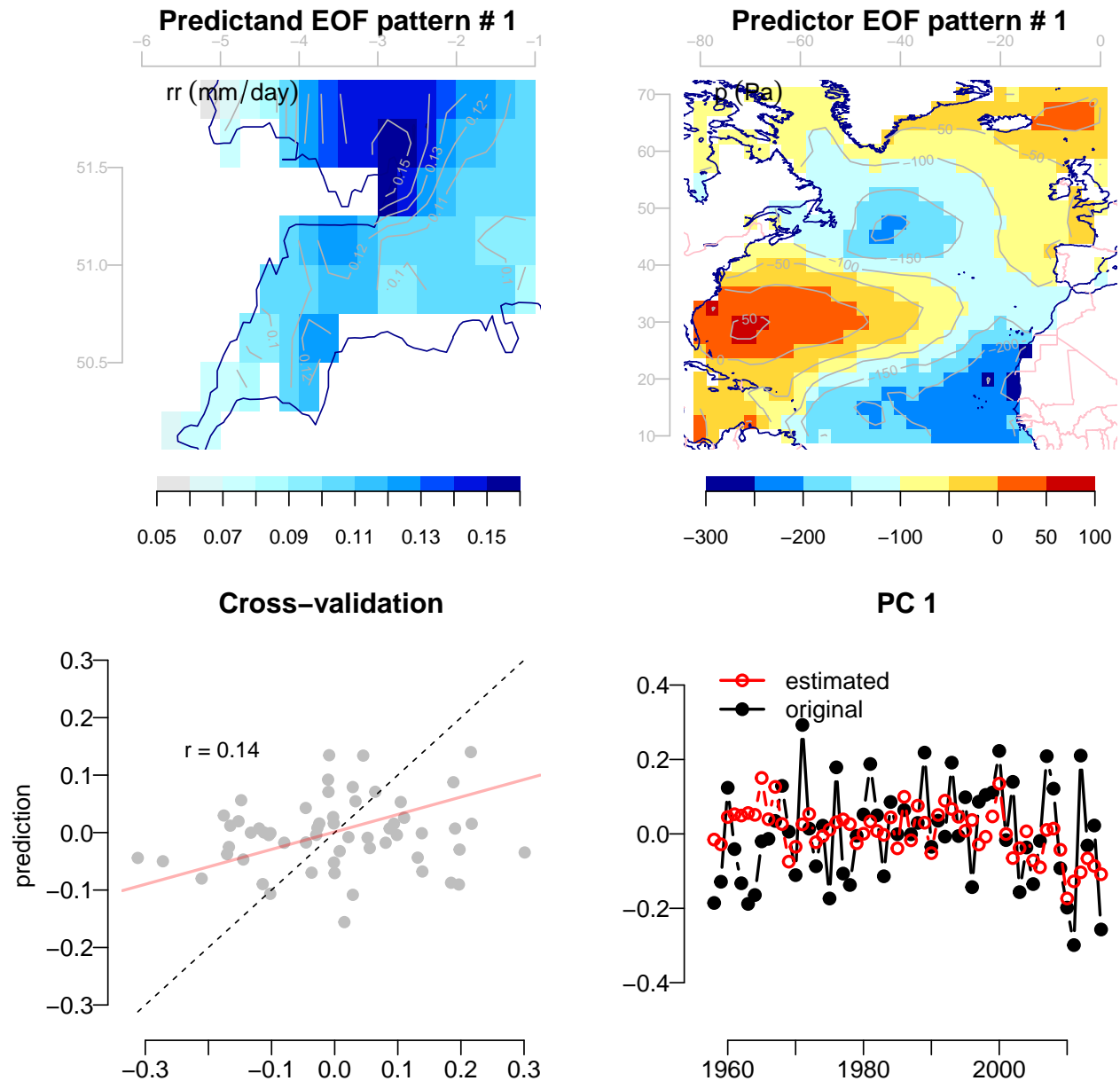


## NULL

```
ds.mu <- DS(subset(eof.mu,ip=1:4),eof.es,eofs=1:7)
```



```
plot(ds.mu)
```



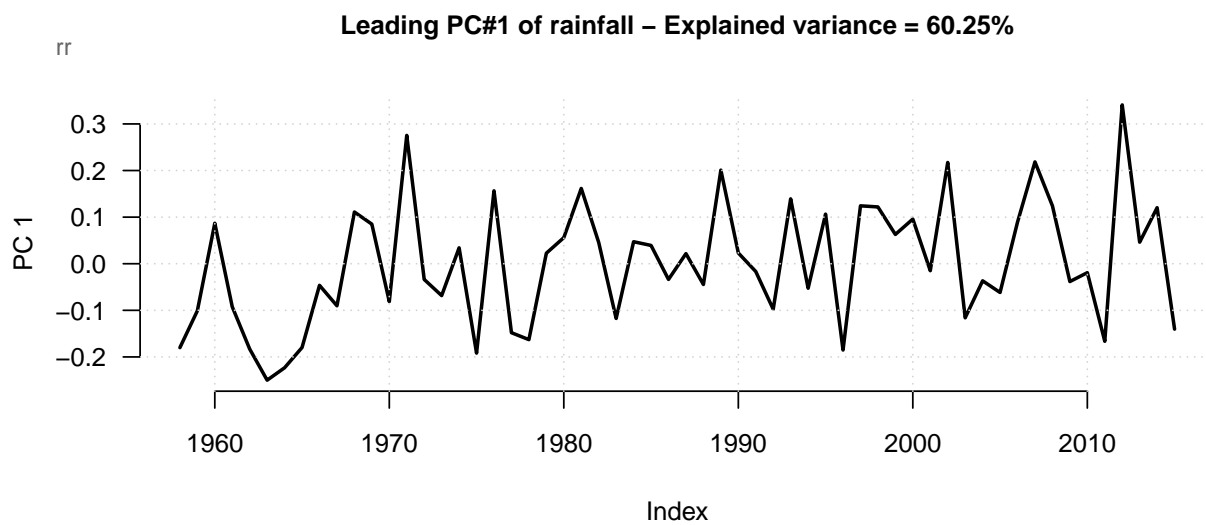
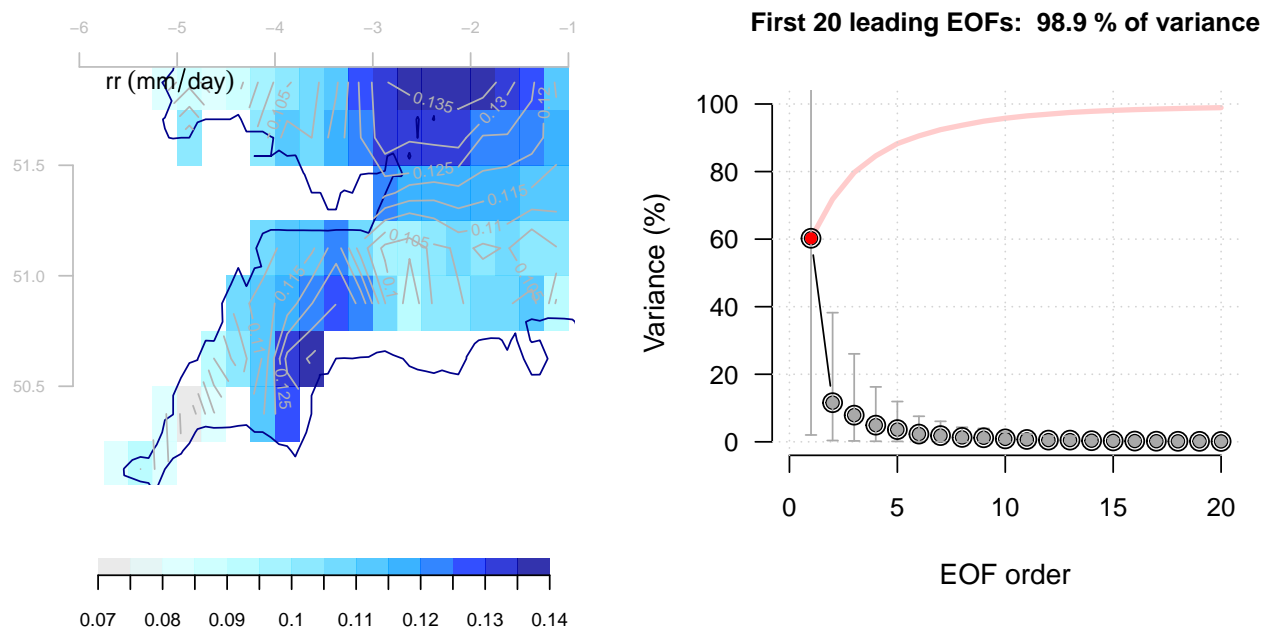
```
## NULL
```

The downscaling includes cross-validation analysis, and the results shown are for the leading EOF of the predictands. We do not expect that the downscaling will capture a large fraction of the wet-day mean precipitation; local processes are also likely influencing.

Extract the residual and examine to see if there is any temporal-spatial structure left: a tell-tale sign for noise is a flat eigenspectrum

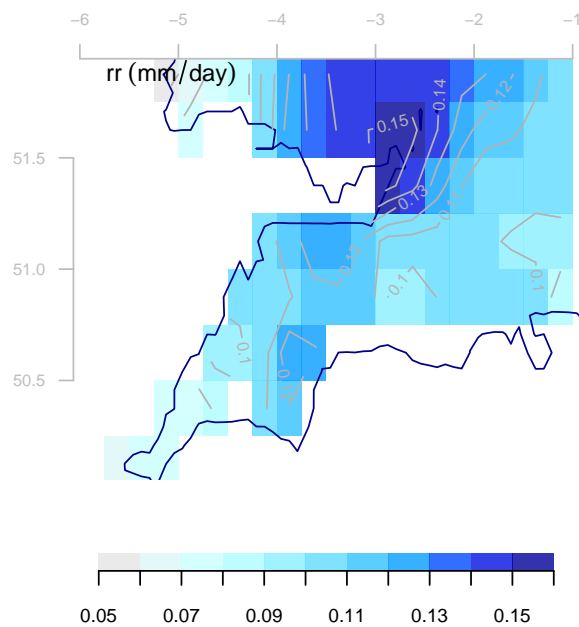
```
## The residual of the wet-day precipitation
z.mu <- as.field(ds.mu)
#res.mu <- as.residual(z.mu)
```

```
res.mu <- mu - z.mu
res.mu <- attrcp(mu,res.mu)
class(res.mu) <- class(mu)
eof.res.mu <- EOF(res.mu)
plot(eof.res.mu)
```

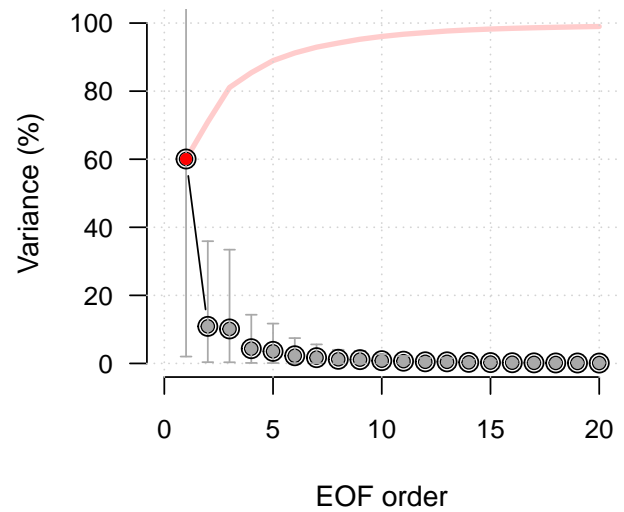


For comparison the original data look like this:

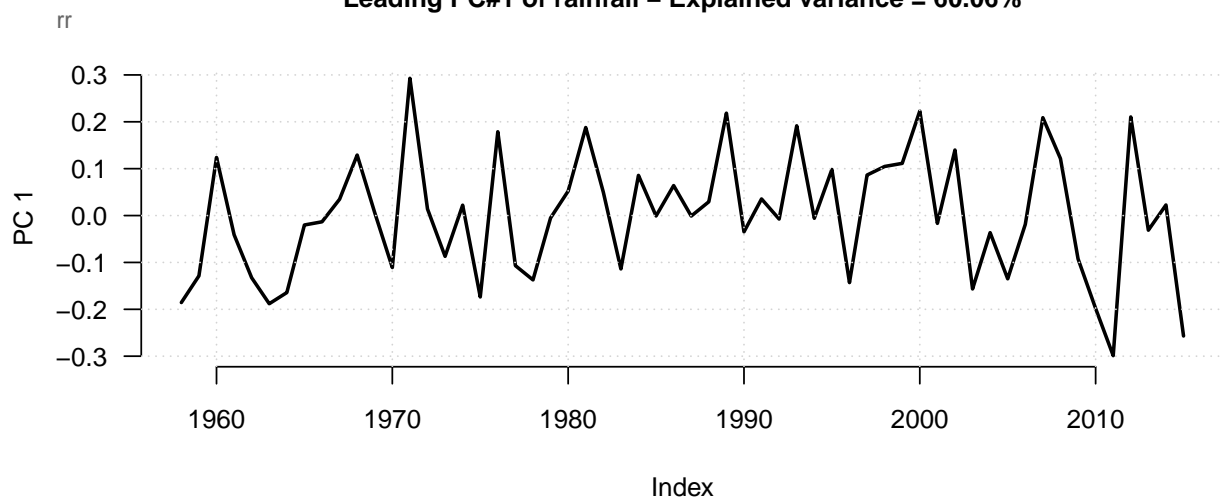
```
## The residual of the wet-day precipitation
plot(EOF(mu))
```



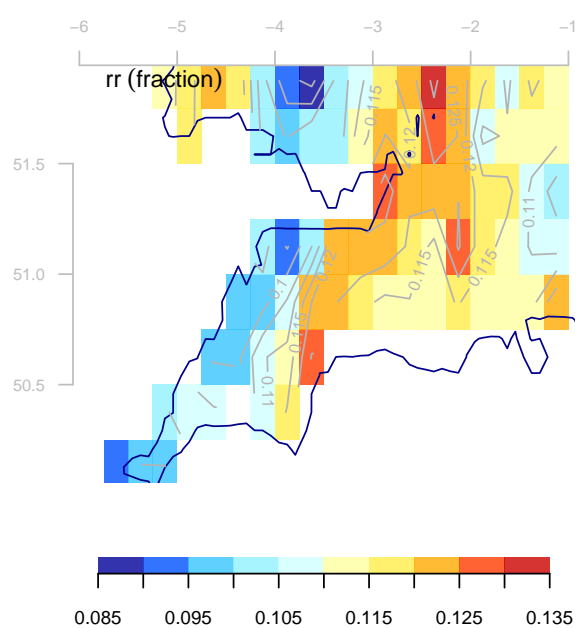
First 20 leading EOFs: 99 % of variance



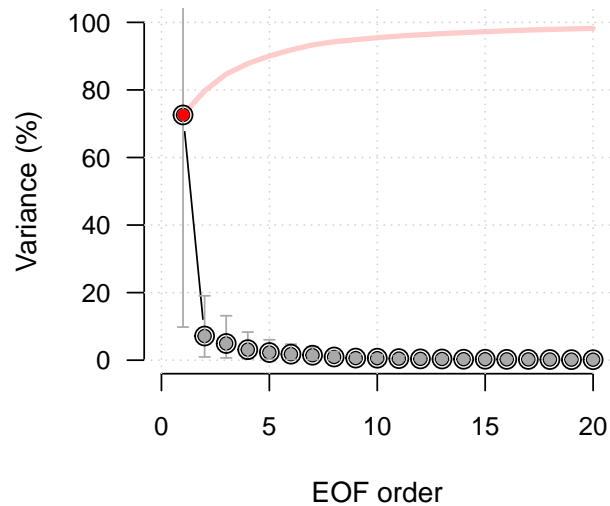
Leading PC#1 of rainfall – Explained variance = 60.06%



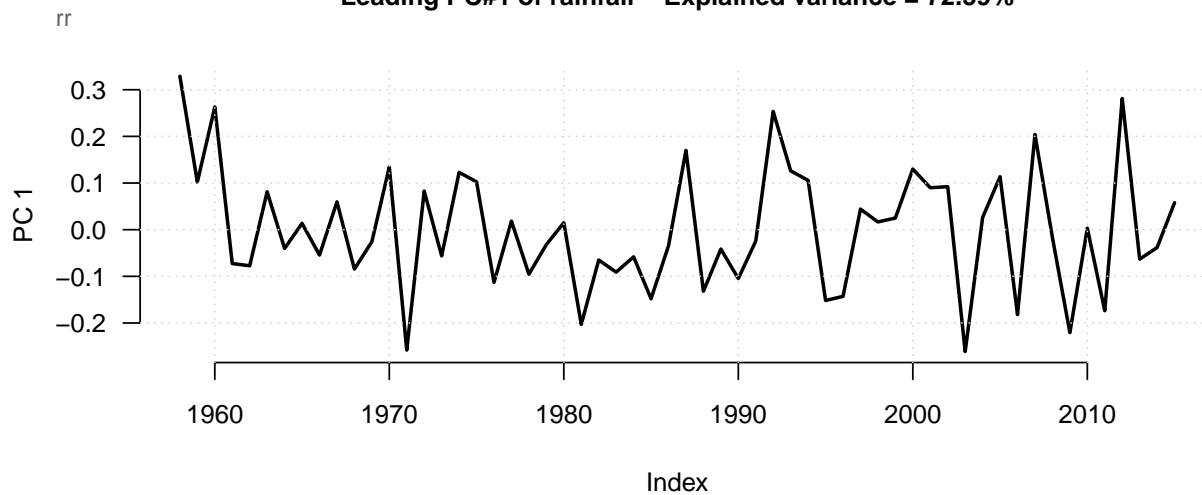
```
## Repeat with the wet-day frequency for the benefit of comparison
z.fw <- as.field(ds.fw)
#res.fw <- as.residual(ds.fw)
## Another way to estimate the residuals:
res.fw <- fw - z.fw
res.fw <- attrcp(fw, res.fw)
class(res.fw) <- class(fw)
eof.res.fw <- EOF(res.fw)
plot(eof.res.fw)
```



First 20 leading EOFs: 98.2 % of variance

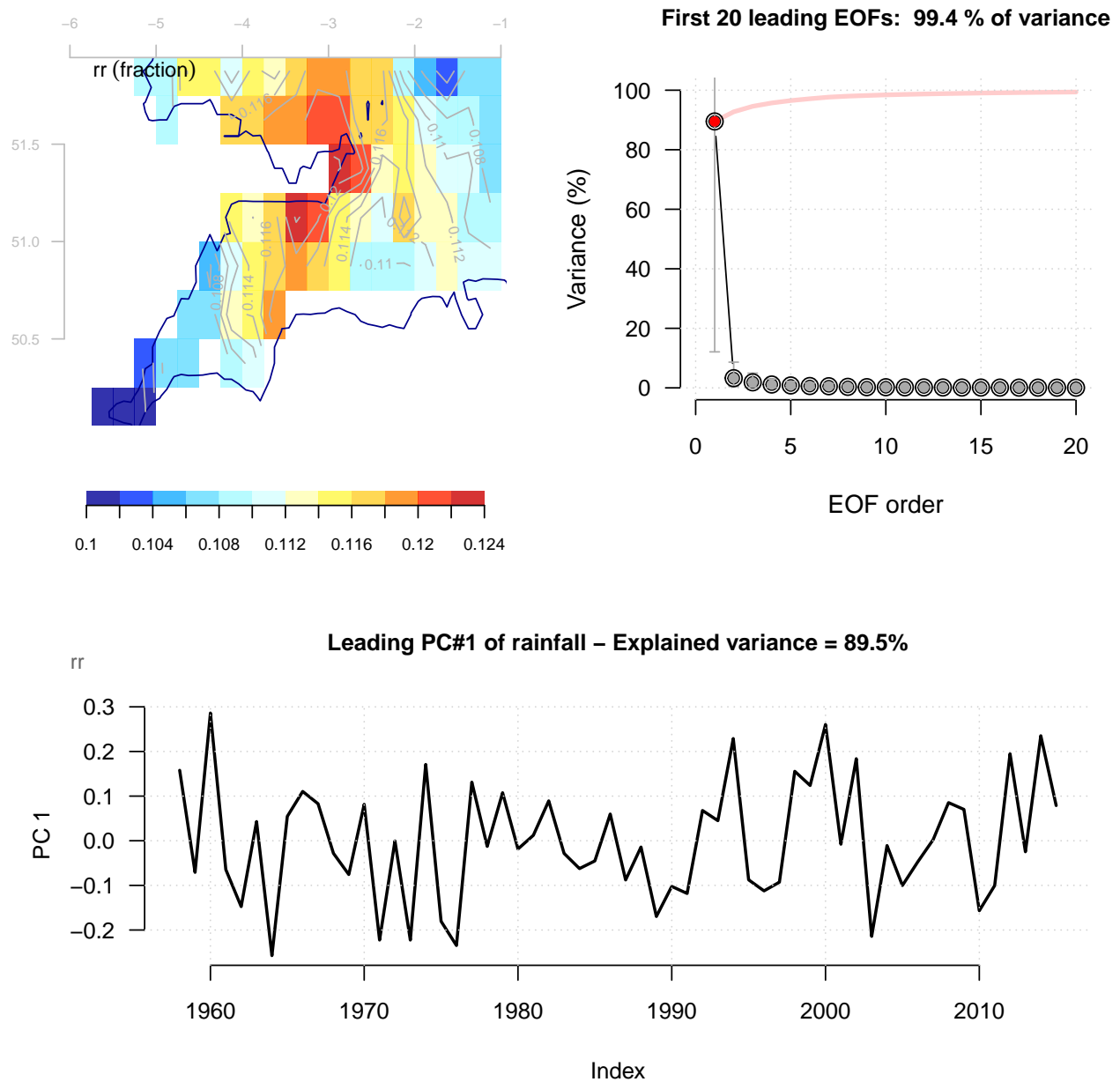


Leading PC#1 of rainfall – Explained variance = 72.59%



For comparison the original data look like this:

```
## The residual of the wet-day precipitation
plot(EOF(fw))
```



Hence, there is remaining spatio-temporal structure left in the residuals from the downscaling. The challenge is to identify further factors on which both the wet-day mean precipitation and the wet-day frequency depend. It's surprising to see such strong modes in the residual of the wet-day frequency still.