**EU-Circle case study 3

title: Coastal Flooding (surface water, highway, sewer and watercourse flooding) across Torbay, UK
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output: pdf_document
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Torbay is located in South Devon (UK) and covers an area of approximately 62 km2 . 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 th 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.

Summary

Synoptic storms (low-pressure systems) represent an important factor that may affect flooding and innuation in the Torbay region, as they are both associated with precipitation, wind and storm surges. Their influence depends on their intensity as well as the amount of rain that they bring. The storm statistics exhibits a seasonal dependency, with more frequent and intense storms during autumn and winter. The number of storms and intensity are sensitive to sea surface temperatures and large-scale atmospheric conditions such as the North Atlantic Oscillation and the location of the upper air jet. The severity of storm surges that they cause is increased with a sea-level rise.

Other phenomena that may cause local flooding can be connected to convective events and cloud bursts. Observations so far have suggested that the amount of precipitation from such local phenomena has been secondary to synoptic storms for places like Torbay.

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())
```

Definition of functions

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
```

```
## Get files on the outgoing long-wave radiation (OLR).
cmip5.urls <- function(experiment='rcp45',varid='rlut',
                       url="http://climexp.knmi.nl/CMIP5/monthly/",
                       path=NULL,off=FALSE,force=FALSE,verbose=FALSE) {
  urlfiles <- "NA"
  if(verbose) print("cmip5.urls")
  if(is.null(path)) path <- getwd()
  for (iexp in experiment) {
    if(verbose) print(iexp)
    for (ivar in varid) {
      if(verbose) print(ivar)
      ## Loop on the number of experiments
      for (irun in 0:110) { ##
        if(verbose) print(paste(irun))
        ## Update experiment number
        if (irun < 10) run.id = paste("00",as.character(irun),sep="")
        else if (irun < 100) run.id = paste("0",as.character(irun),sep="")
        else run.id <- as.character(irun)

        ## Create output directory for the climate experiment
        path.exp <- file.path(path,experiment[grep(iexp,experiment)],
                              fsep = .Platform$file.sep)
        if (!file.exists(path.exp)) dir.create(path.exp)
        if (verbose) print(path.exp[grep(iexp,experiment)])
        ## Define the output file
```

```
        destfile <- paste(path.exp,varid[grep(ivar,varid)],sep="/")
        destfile <- paste(destfile,"_Amon_ens_",sep="")
        destfile <- paste(destfile,iexp,sep="")
        destfile <- paste(destfile,run.id,sep="_")
        destfile <- paste(destfile,".nc",sep="")

        if (!file.exists(destfile) | force) {
          ## Update output filename with attributes:
          urlfile  <- paste(url,ivar,sep="")              # add var directory
          urlfile  <- paste(urlfile,ivar,sep="/")         # add v.name
          urlfile  <- paste(urlfile,"_Amon_ens_",sep="") # add text
          urlfile  <- paste(urlfile,iexp,sep="")          # add exp.name
          urlfile  <- paste(urlfile,run.id,sep="_")       # add exp ID number
          urlfile  <- paste(urlfile,".nc",sep="")         # add file ext
        }
        urlfiles <- c(urlfiles,urlfile)
        if (verbose) print(urlfile)
      }
    } # End for
  }
  return(urlfiles[-1])
}

## download the CMIP5-files from the KNMI ClimateExplorer
urls <- cmip5.urls()
for (i in 1:length(urls)) if (!file.exists(substr(urls[i],43,70))) download.file(urls[i],substr(urls[i]
```

Function to estimate probabilty for daily amount of exceeding a threshold x0 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)
}
```

The data analysis

Precipitation

First, we examine historical observed precipitation to get a picture of what has happened until now. Global warming has taken place for a few decades (especially since the 1980s), and we ought to see some trends already as a concequence of an increased greenhouse effect. Past changes will give some indication of how sensitive the local consequences are to the large-scale changes. The following lines load the data and weed out stations with lots of missing values

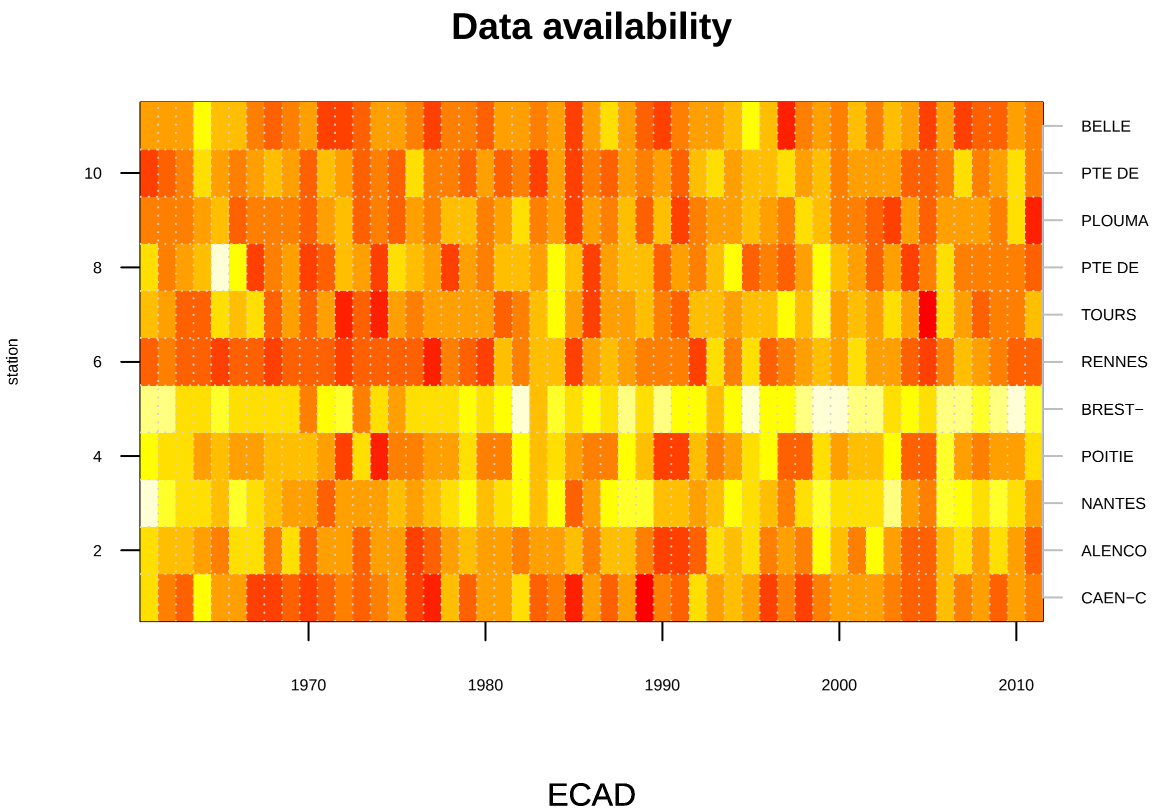
```
## Get MIDAS preciptation data that has laready been retrieved
## from the MIDAS data base (UK Met Office)
load('pr.eu-circle-torbay.rda')
pr <- subset(pr,it=c(1960,2013))

## 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))
```

Need to fill in missing values to proceed with the analysis, 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 larer spatial scales. In any case, these are used to assist the interpolation for the MIDAS sations.

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

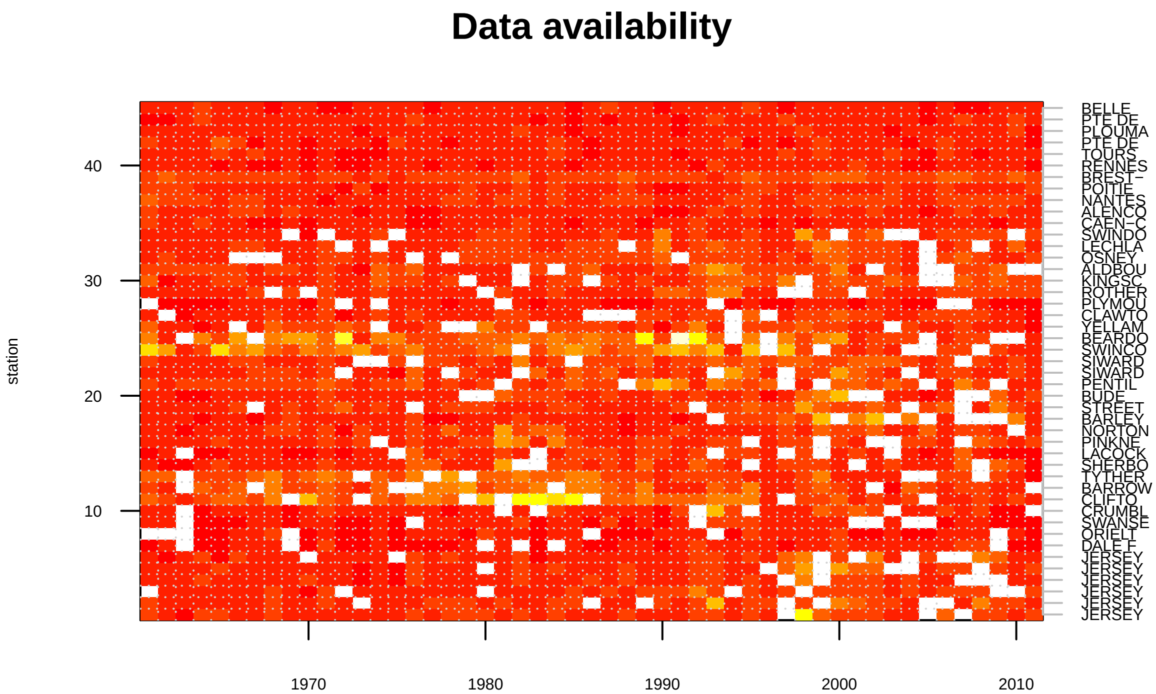
```
mu.ecad <- subset(annual(pr.ecad,'wetmean',nmin=100),it=c(1961,2011))
fw.ecad <- subset(annual(pr.ecad,'wetfreq',nmin=100),it=c(1961,2011))
## Second weeding of stations with many missing values in annual
## aggregate
nok <- apply(coredata(mu.ecad),2,'nv')
mu.ecad <- subset(mu.ecad,is=(nok>= 50))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



supplement ECA&D 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)
```

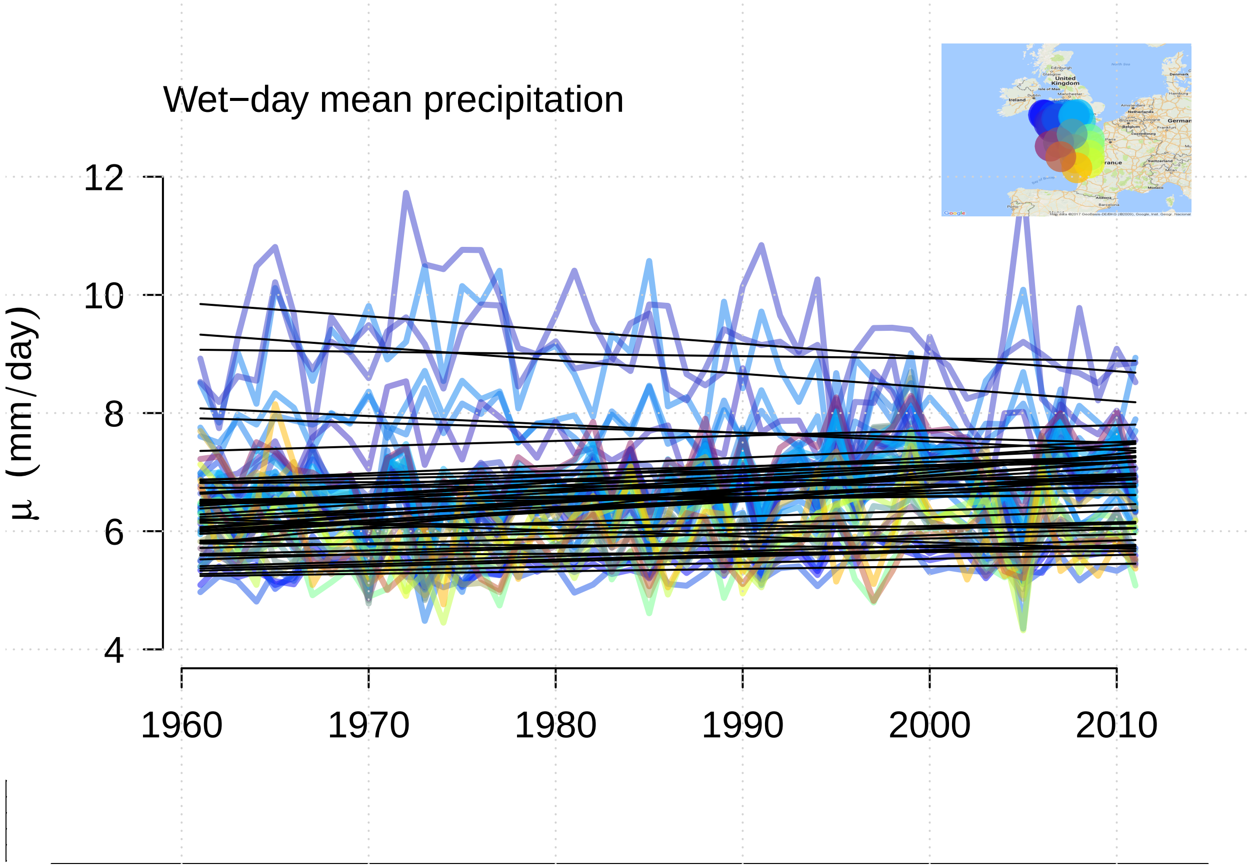


MIDAS (UK MetOffice) ECAD

```
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]))
```

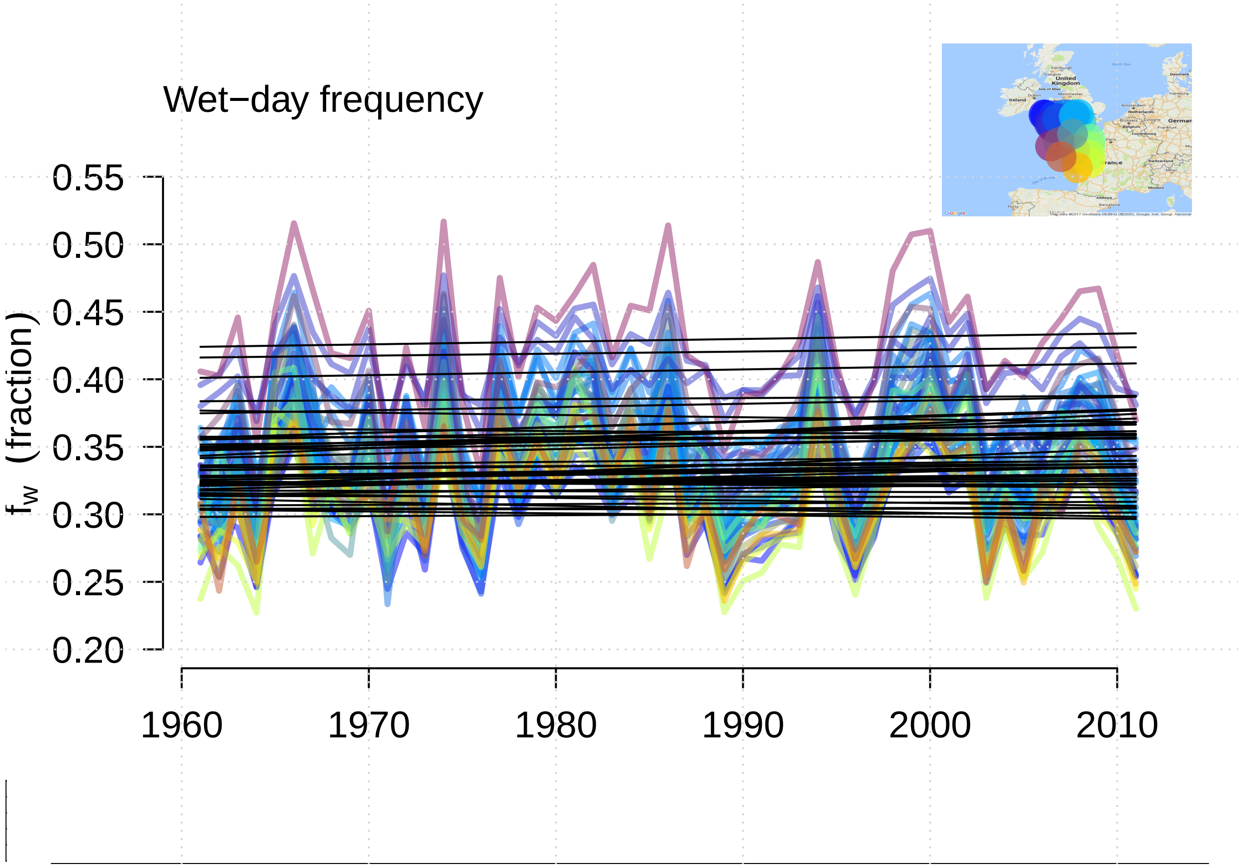


The five stations with the highest mean wet-day precipitation suggest a decline in the intensity between 1960-2010, but most of the stations with smaller means suggest an increase over the same period.

```
plot(fw,new=FALSE); grid()
```

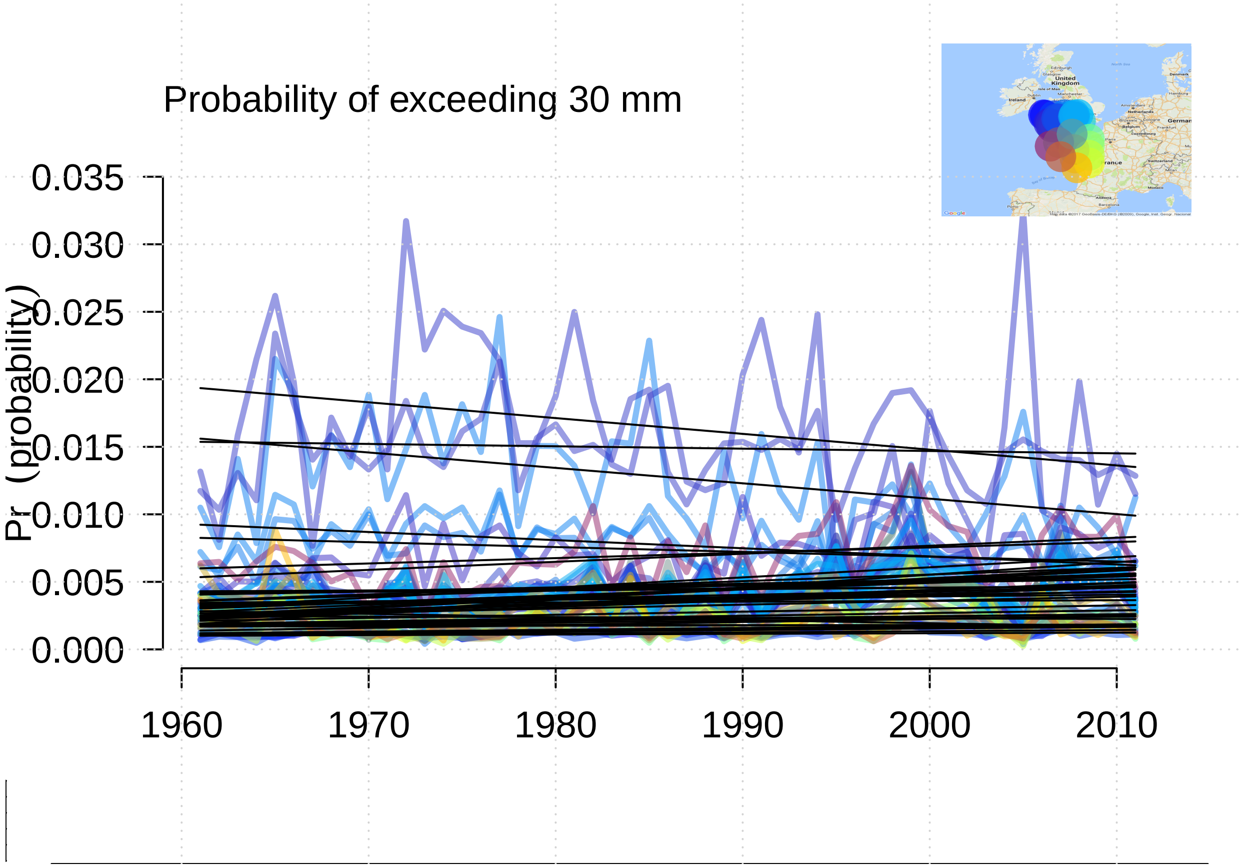
```
## Warning in plotmap(lat(x), lon(x), bgmap, pch = 19, col = col, cex = 2):
## NAs introduced by coercion
```

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



The number of rainy days appears to be fairly stable with a frequency of around 0.35, or 120-130 days per year (it may rain for only a fraction of the day).

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

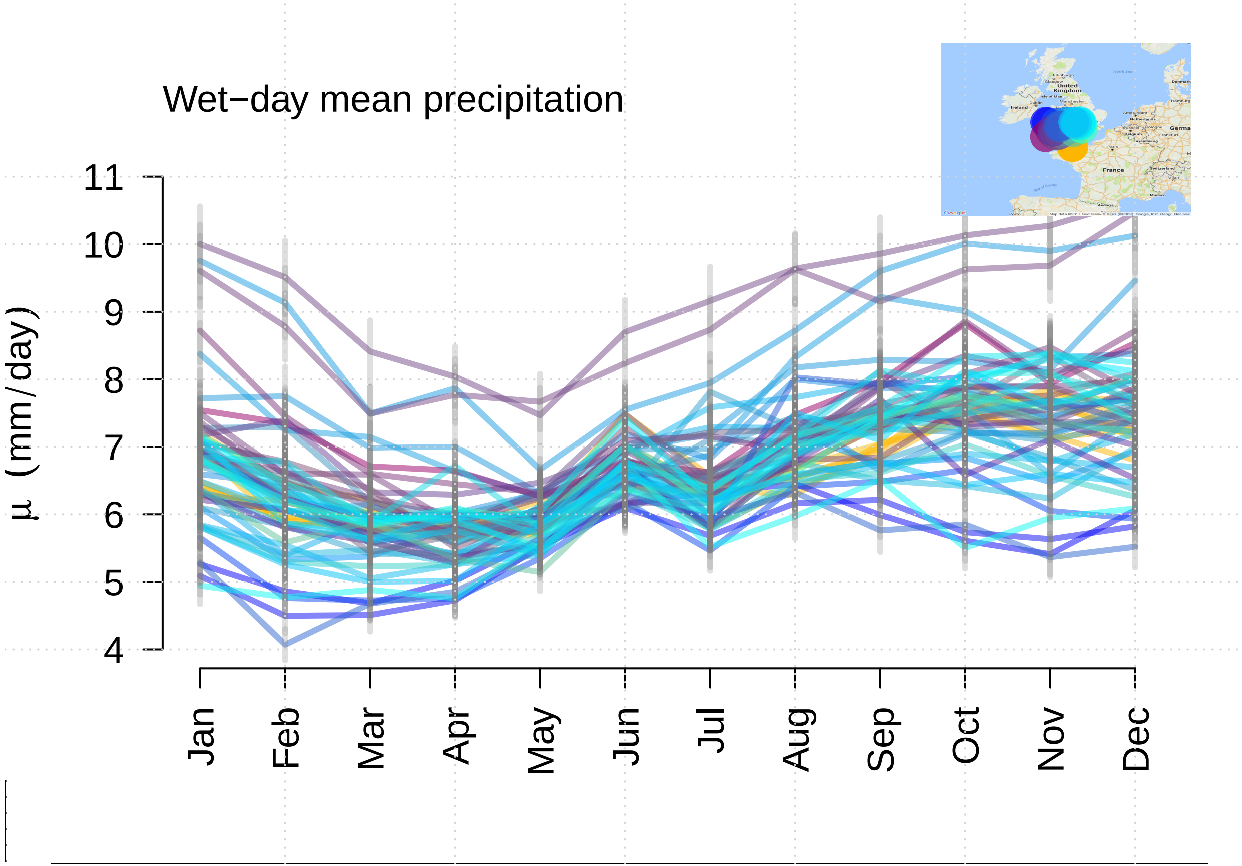


Useful information in the mean seasonal cycle?

Another attempt to search for systematic influences on the precipitation statistics (μ) is to examine the mean seasonal cycle. This type of approach may give som indication of how sensitive precipitation is to changing conditions.

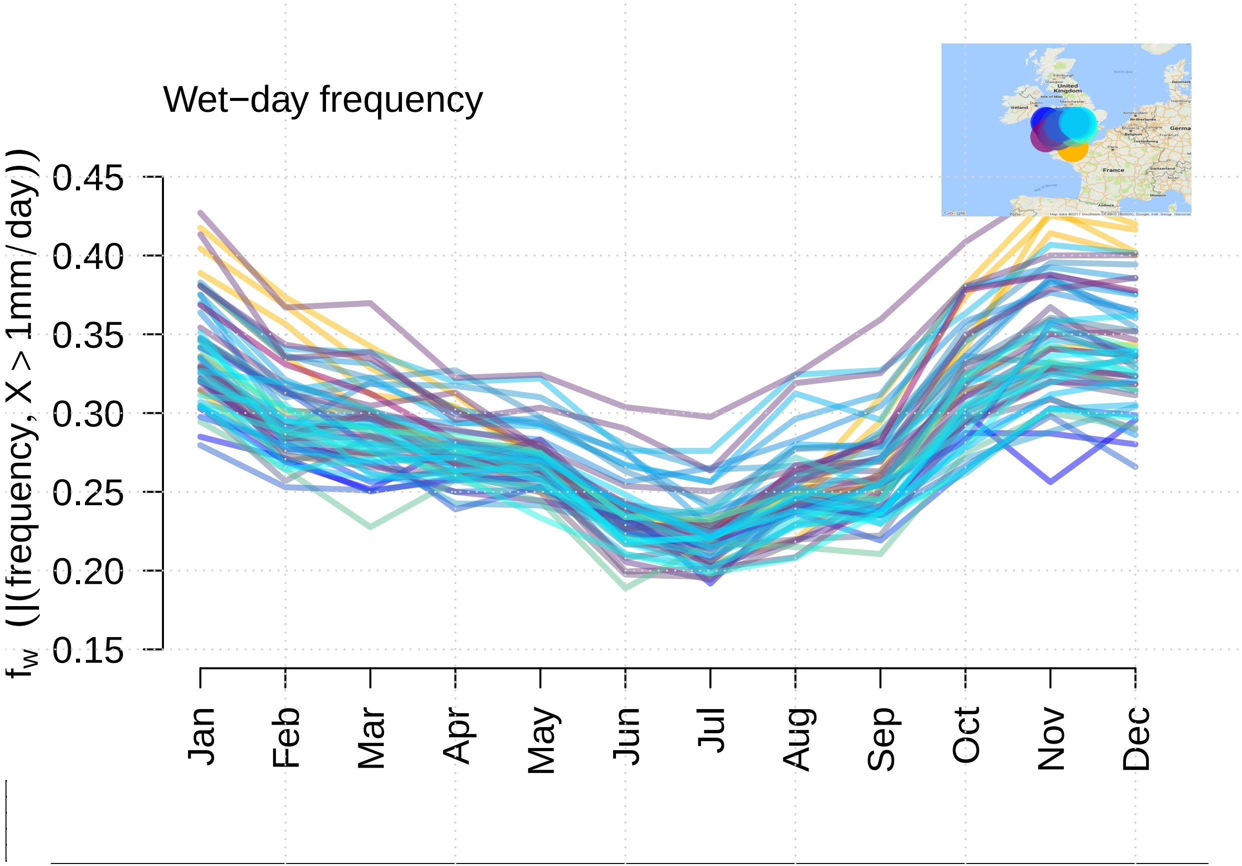
```
## Estimate the mean seasonal cycle in the wet-day mean precipitaiton
MU <- aggregate(x,month,FUN='wetmean')
## Estimate the mean seasonal cycle in wet-day mean frequency
FW <- aggregate(x,month,FUN='wetfreq')
## Estimate the mean seasonal cycle in wet-day mean frequency
MP <- aggregate(x,month,FUN='mean')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

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



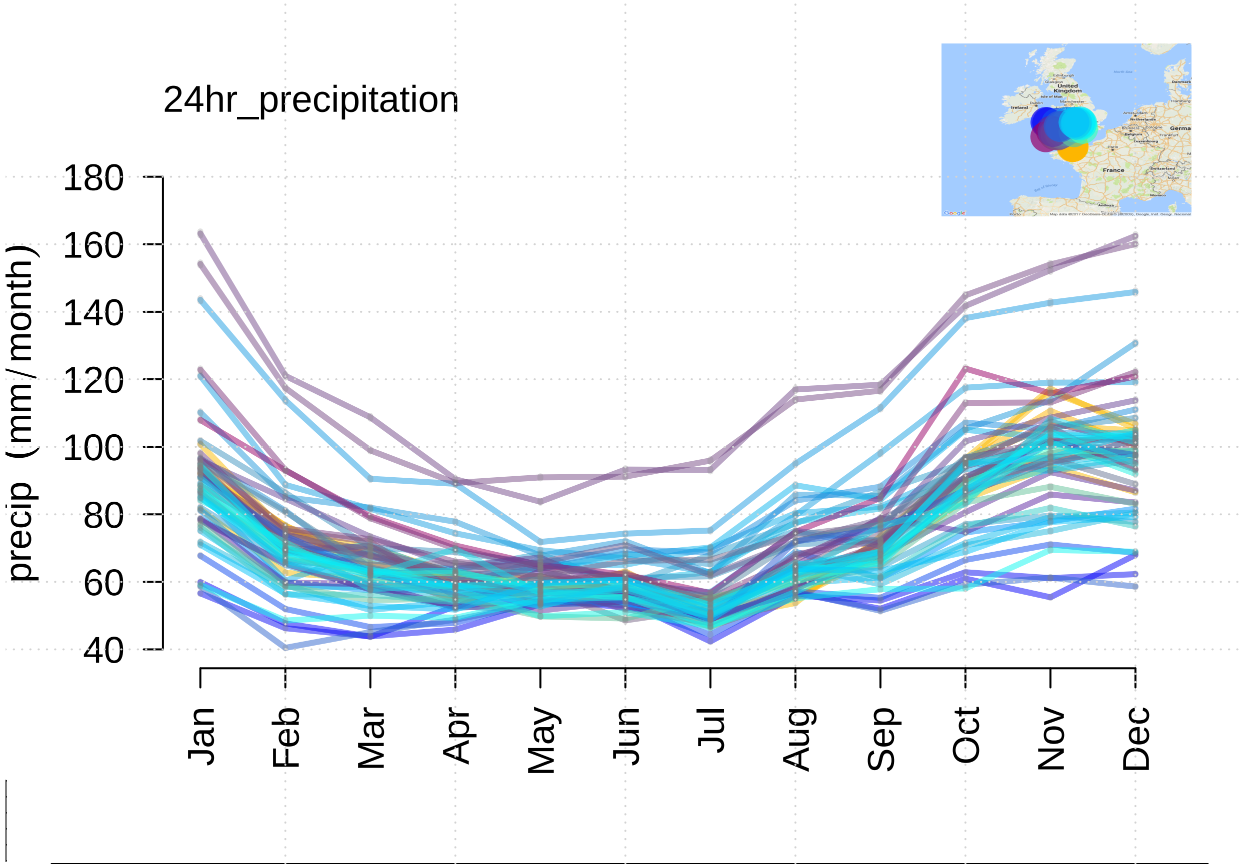
There is some indication of a mean seasonal cycle in μ, with minimum values in late winter spring and higher values in late summer and autumn. This suggest that the intensity is driven more by precipitation associated with autumn storms (low-pressure systems) than summer-time convective events.

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



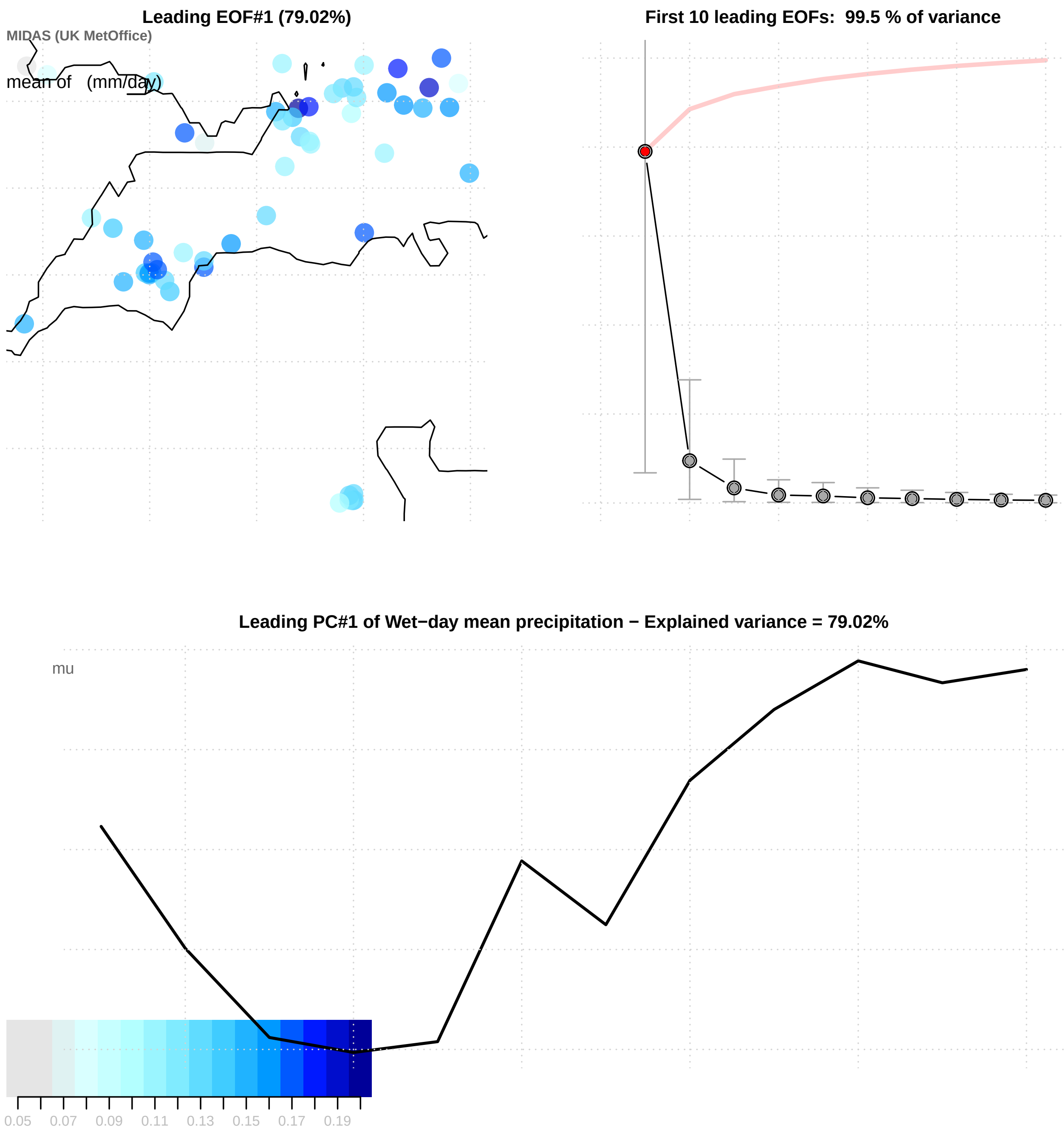
There is a clear seasonal cycle in the wet-day occurrence - more rainy days in the autumn. This too may be connected to storms. The minimum tends to be in June-August when convective events are expected to be more dominant.

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

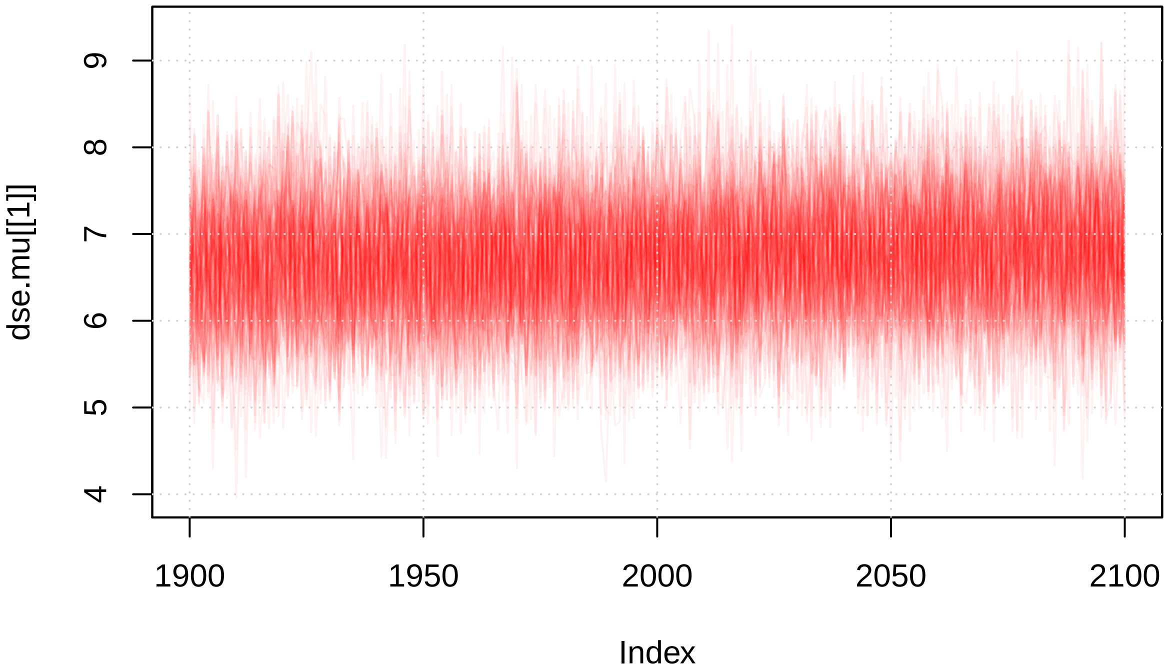


Most stations have the same features when it comes to a mean seasonal cycle in μ, with the leading PCA accounting for 80% of the variance. There is some variations in the amplitude from place to place, and the mean precipitation is influenced by geography and the local environment.

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()
```



Empirical-statistical downscaling of the wet-day mean precipitation (intensity) suggests a slight increase for the future, although the analysis is very simple and far from perfect. The method is described in Benestatet al. (2017) http://www.nat-hazards-earth-syst-sci.net/17/993/2017/. This method was appropriate for convective events, but not suitable for precipitation associated with synoptic storms/low pressure systems (see below for storms).

EOBS gridded daily precipitation

This script retreives 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 cohernt 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(50,51.5))
```

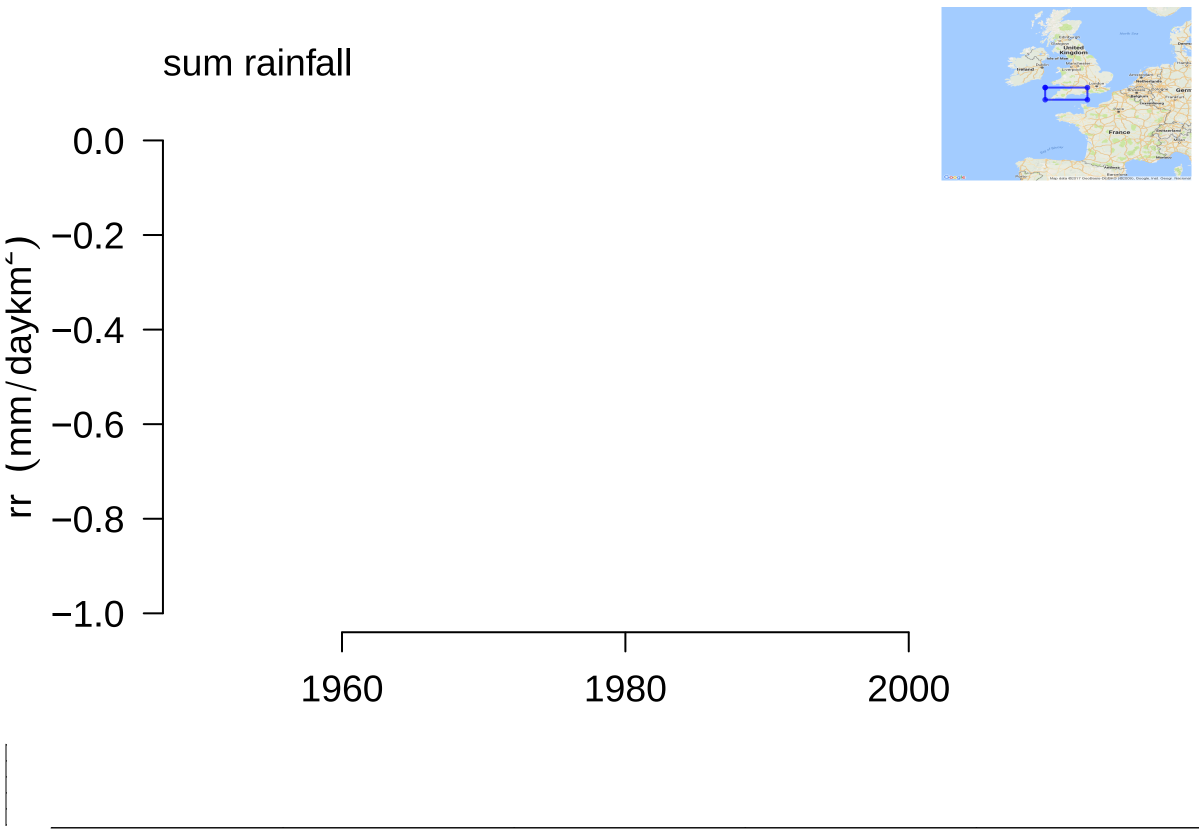
```
## [1] "Warning : Calendar attribute has not been found in the meta data and will be set automatically.
```

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

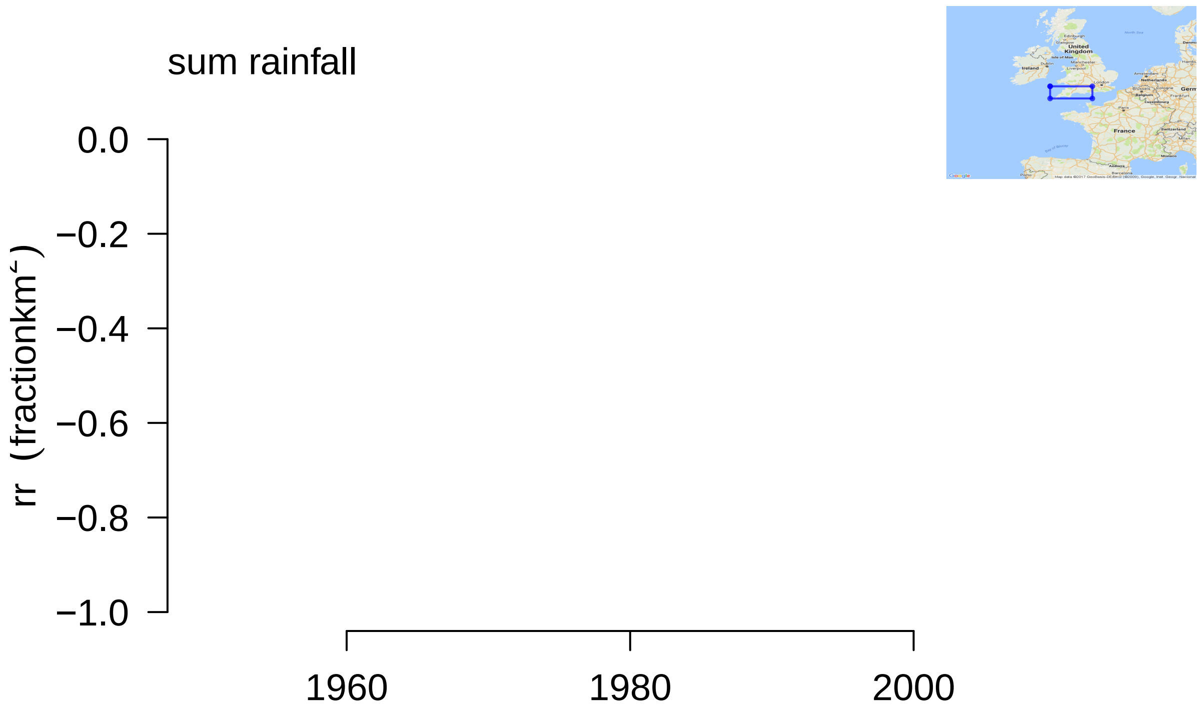
Past trends

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 μ or wet-day frequency f_w are sensitive to a global warming:

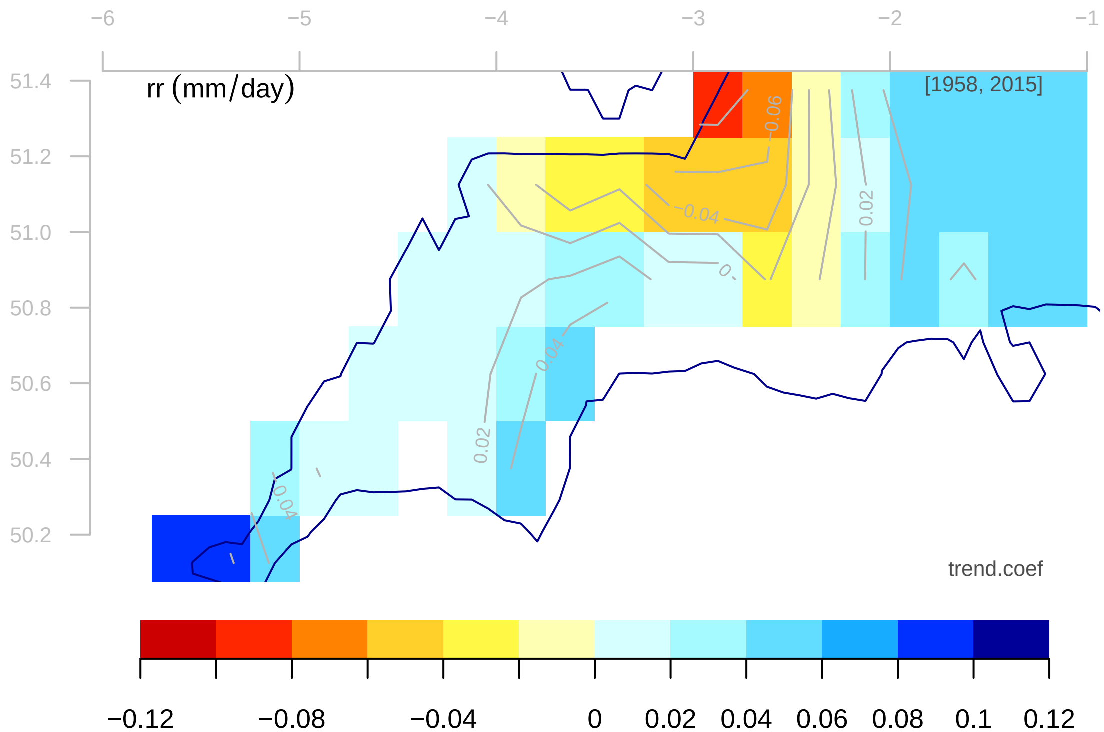
```
## The area mean wet-day mean precipitation
plot(aggregate.area(mu,FUN='mean'),new=FALSE)
```



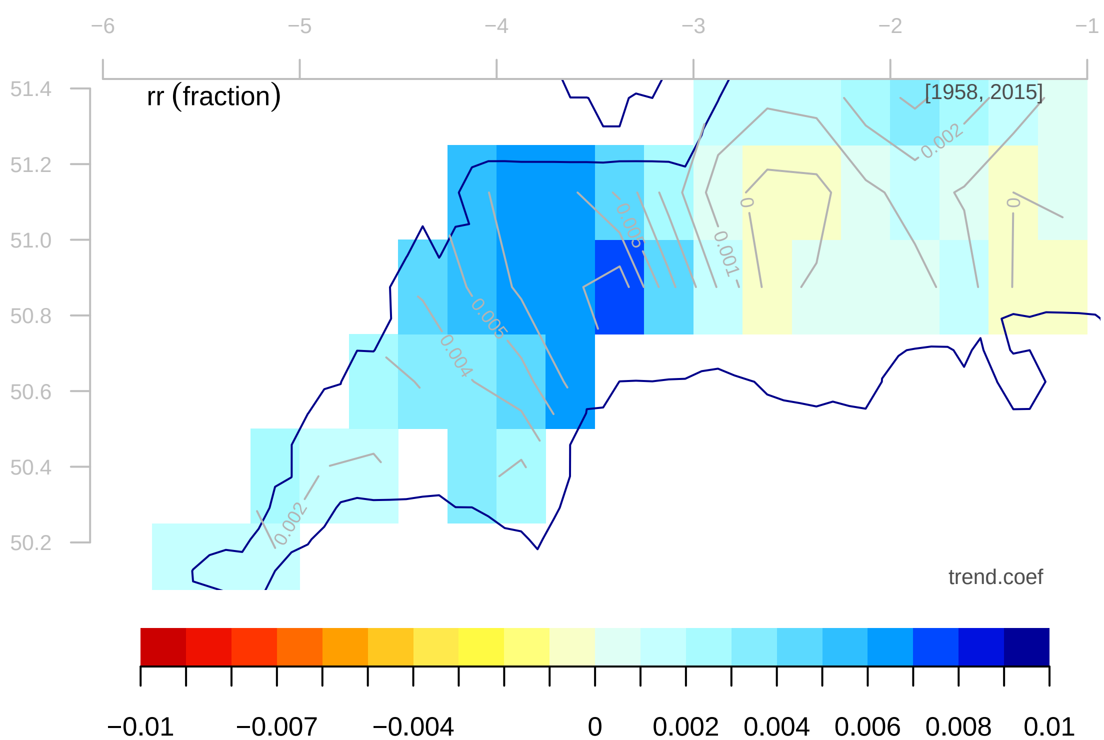

```
## The area mean wet-day frequency
plot(aggregate.area(fw,FUN='mean'),new=FALSE)
```




```
## 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),new=FALSE)
```



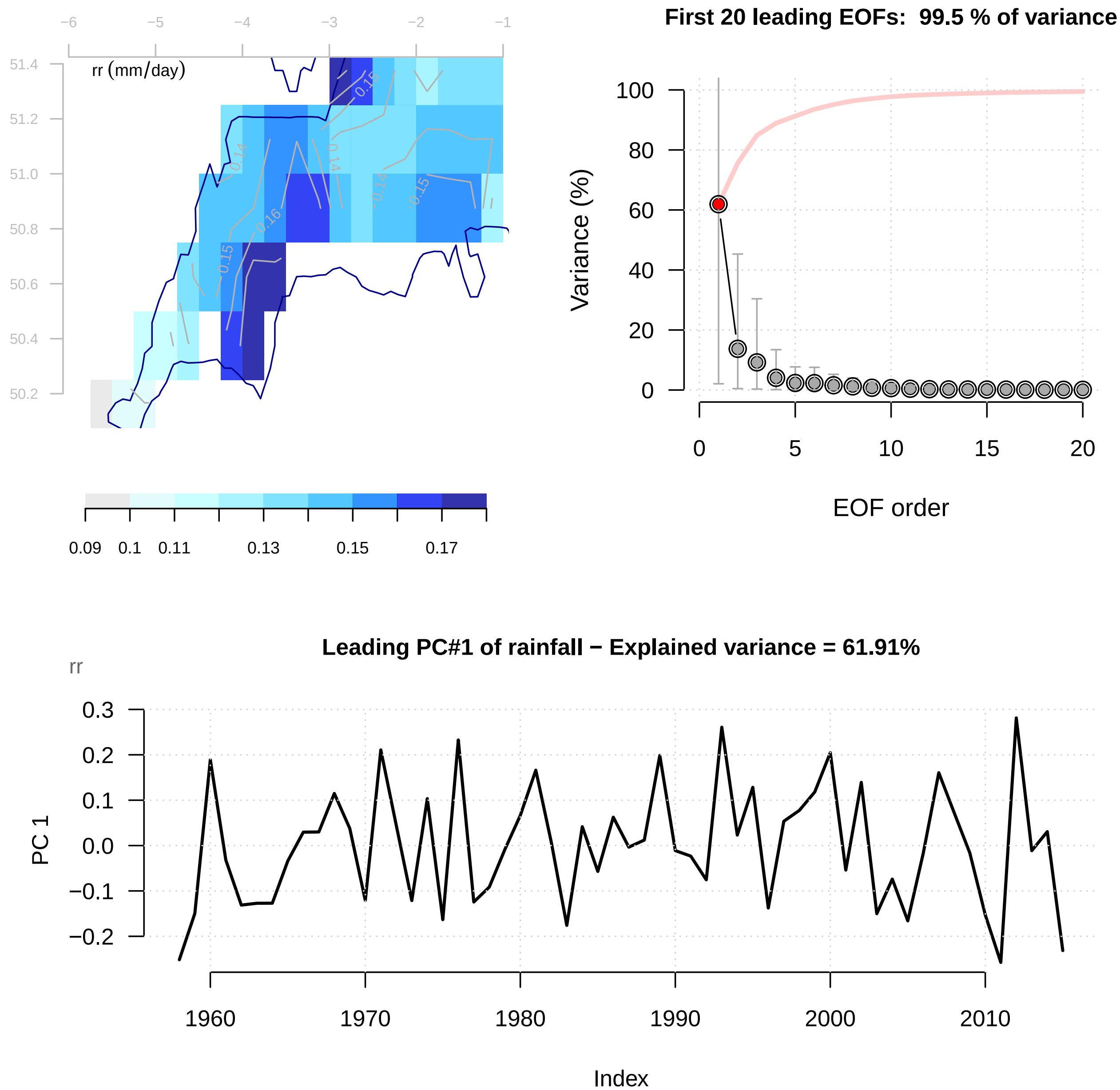

```
## Map of trends in wet-day frequency:
map(fw,FUN='trend',
    colbar=list(breaks=seq(-0.01,0.01,by=0.001),pal='t2m',rev=TRUE),new=FALSE)
```



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

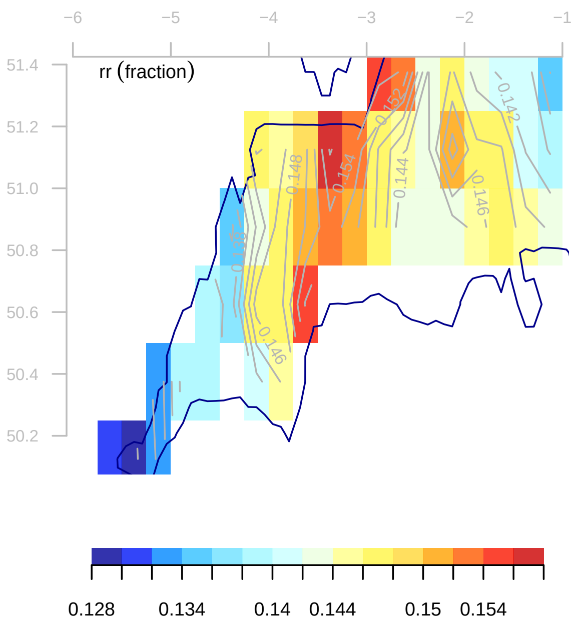
The predictors can be organised as EOFs to simplify the analysis and make use of properties as the products being orthogonal. Here are the EOFS for the annual wet-day mean precipitation μ

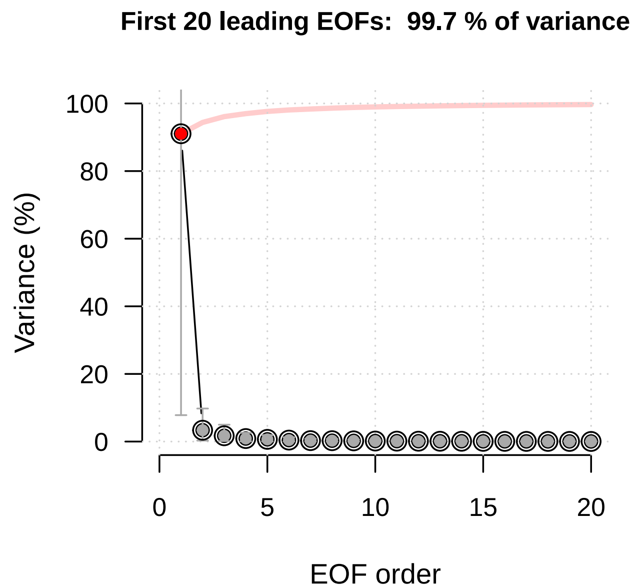
```
## The area mean wet-day mean precipitation
eof.mu <- EOF(mu)
## The area mean wet-day frequency
plot(eof.mu,new=FALSE)
```

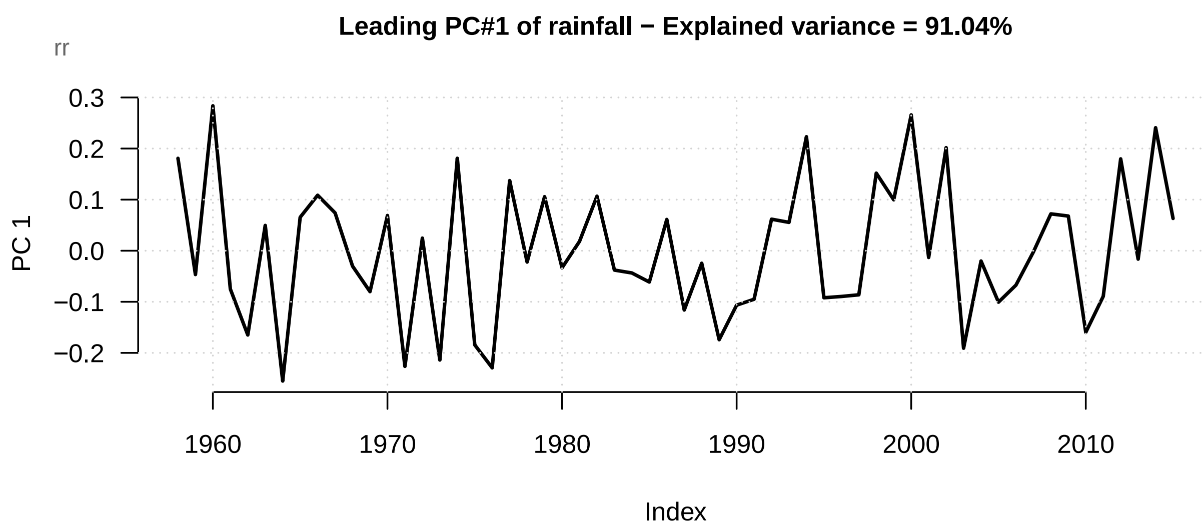


and the annual wet-day frequency f_w

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







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 predictor describes larg-scale conditions on which the local precipitation is expected to depend. The occurrence (frequency) of precipitation depends om the atmospheric circulation pattern (captured by mean sea-level pressure - SLP - patterns). The intensity is assumed to be influenced by the atmospheric humidity, which is influenced by the rate of evaporation and hence maritime temperatures.

```
## The mean sea-level pressure
slp <- retrieve('~/Downloads/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('~/Downloads/air.mon.mean.nc',lon=c(-80,0),lat=c(10,70))
```

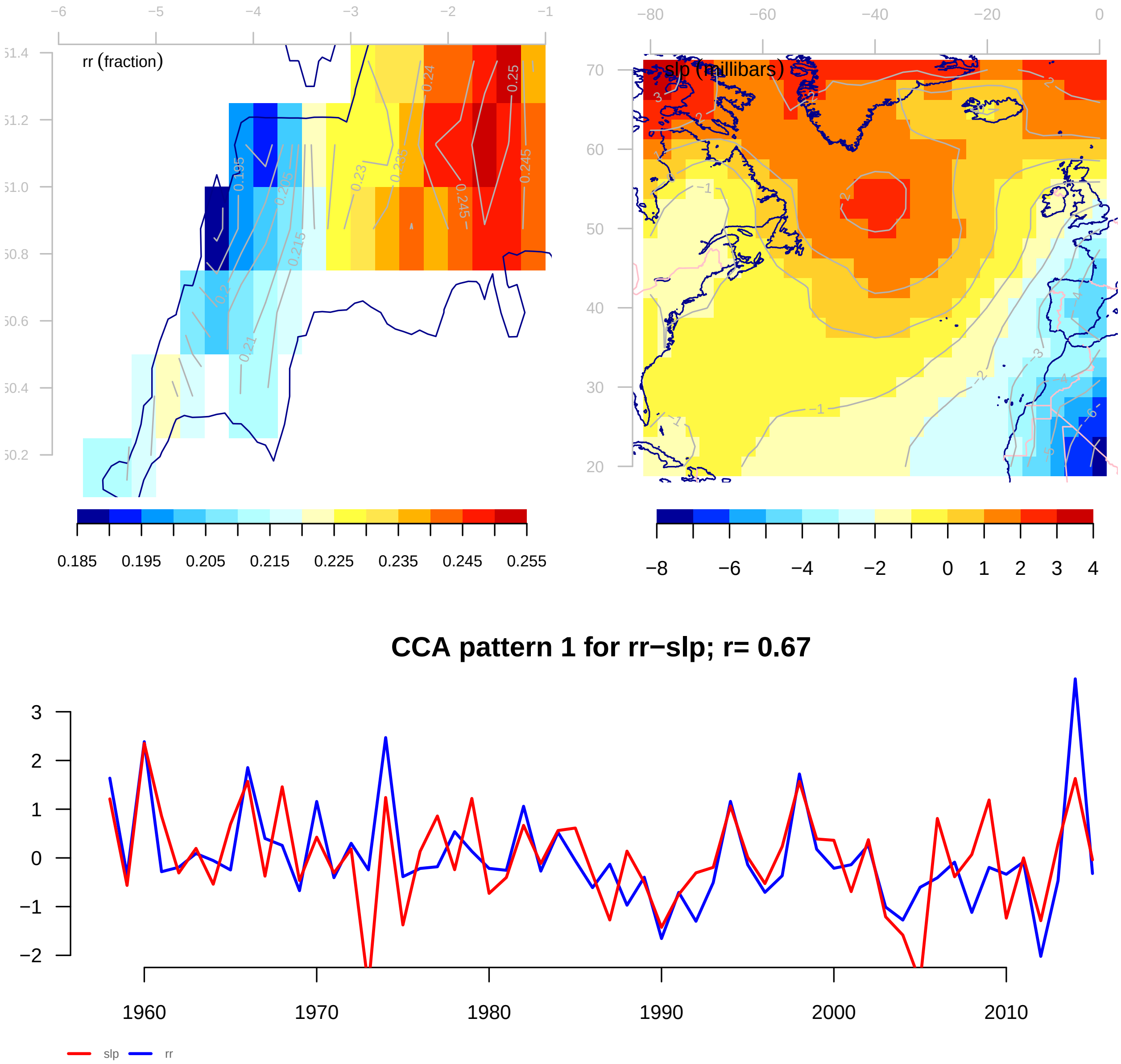
```
## [1] "Warning : Calendar attribute has not been found in the meta data and will be set automatically.
```

```
## 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'))
```

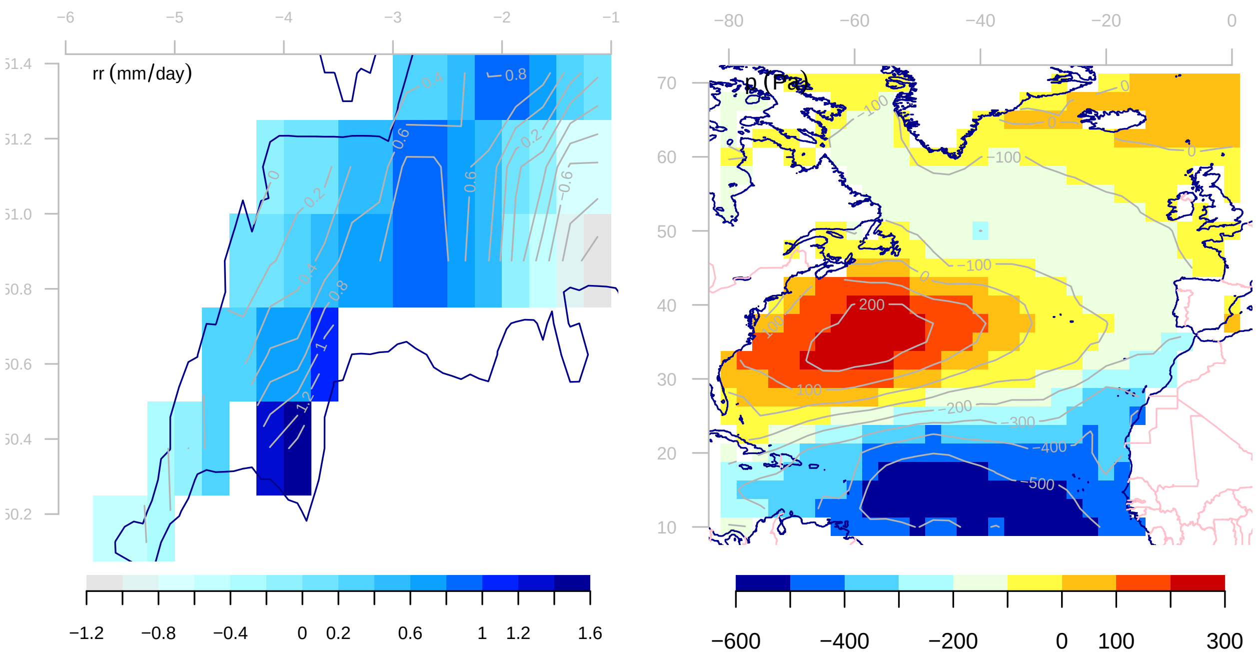
Cannical Correlation analysis

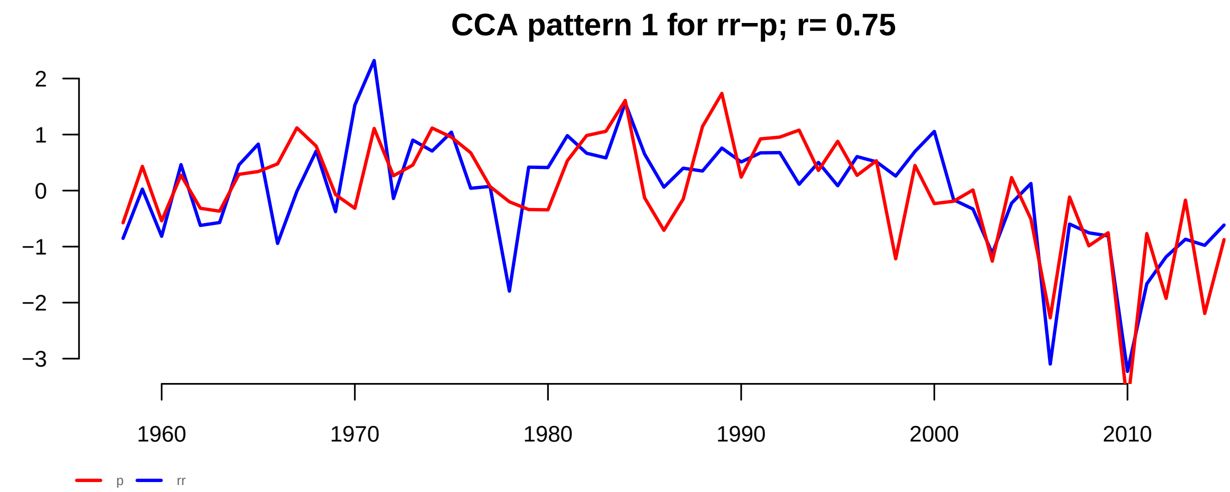
Carry out canonical correlation analysis (CCA) to explore relationships between the large-scale conditions such as SLP/temperature and the precipitation over soutwestern England:

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




```
cca.mu <- CCA(eof.mu,eof.es)
plot(cca.mu,new=FALSE)
```





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

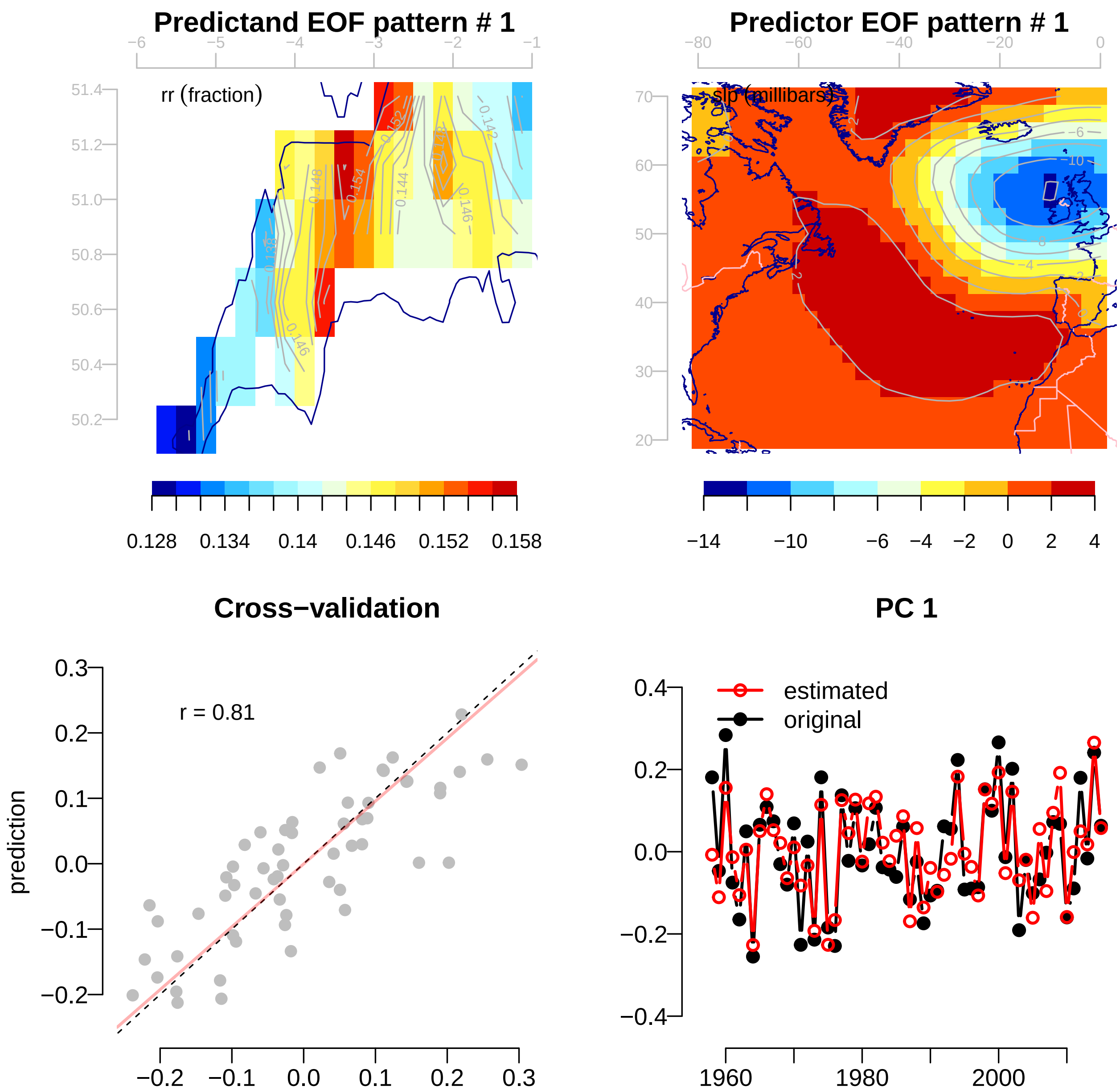
The downscaling emplies a multiple regression applied to each of the principal components for the EOFs of μ and f_w.

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

```
##
  |
  |                                                                      |   0%
  |
  |=================                                                     |  25%
```

```
|
|================================                                  |  50%
|
|=================================================                 |  75%
|
|==================================================================| 100%
```

```
plot(ds.fw,new=FALSE)
```



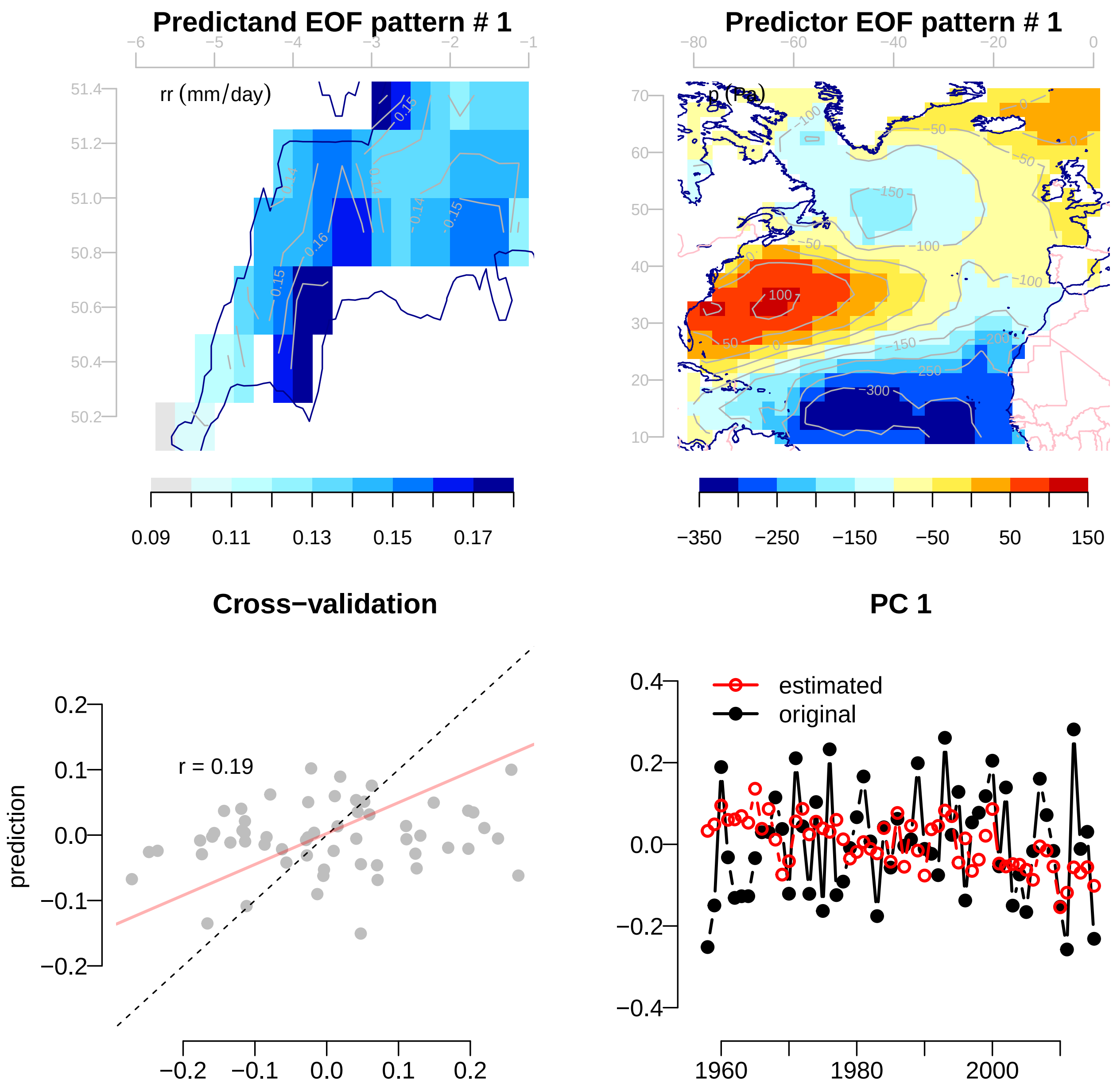

```
## NULL
```

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

```
##
|
|                                                                  |   0%
|
```

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

```
plot(ds.mu,new=FALSE)
```

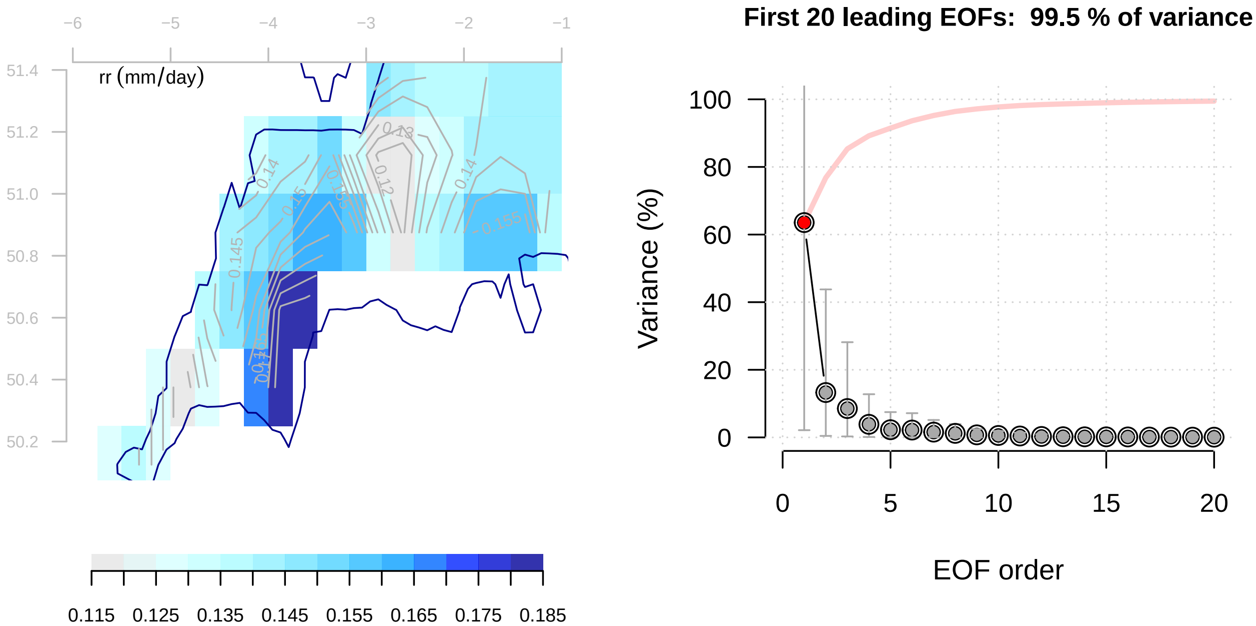


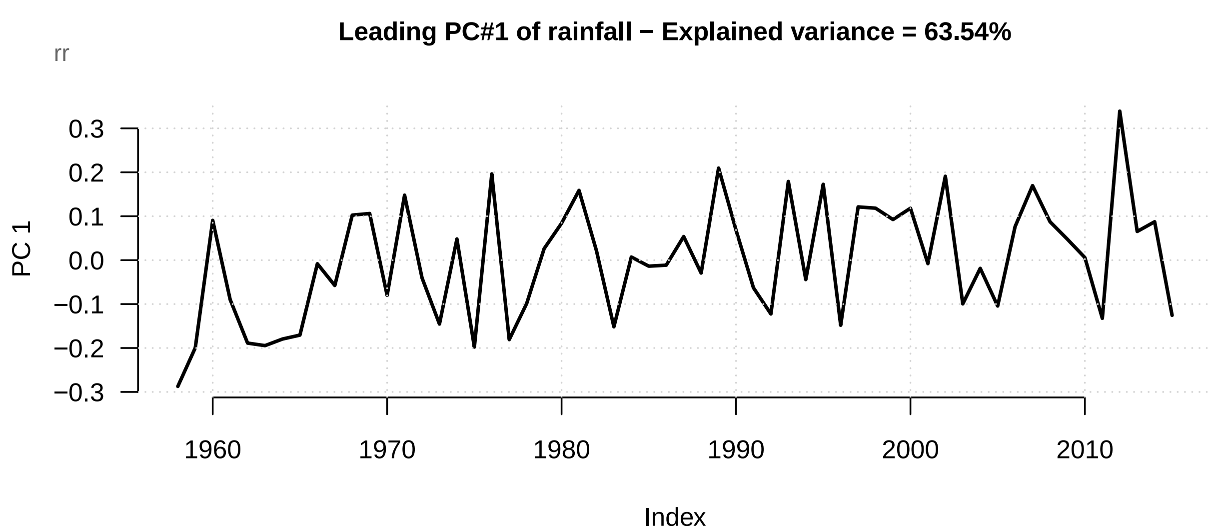

```
## NULL
```

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-stpatial 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,new=FALSE)
```

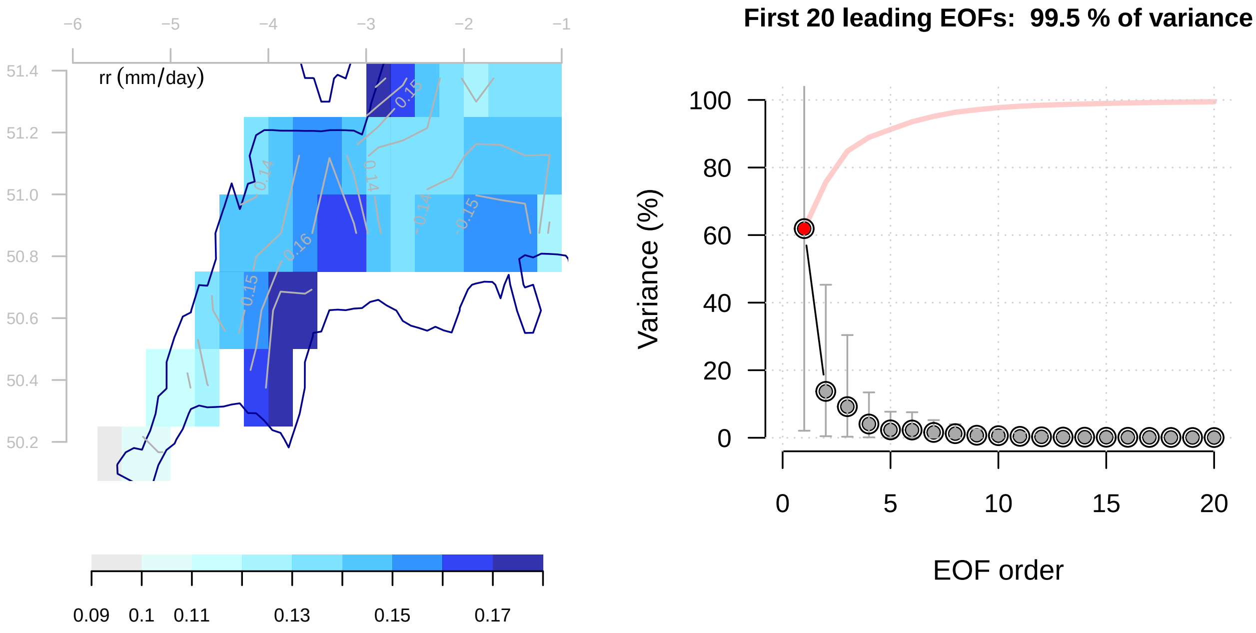


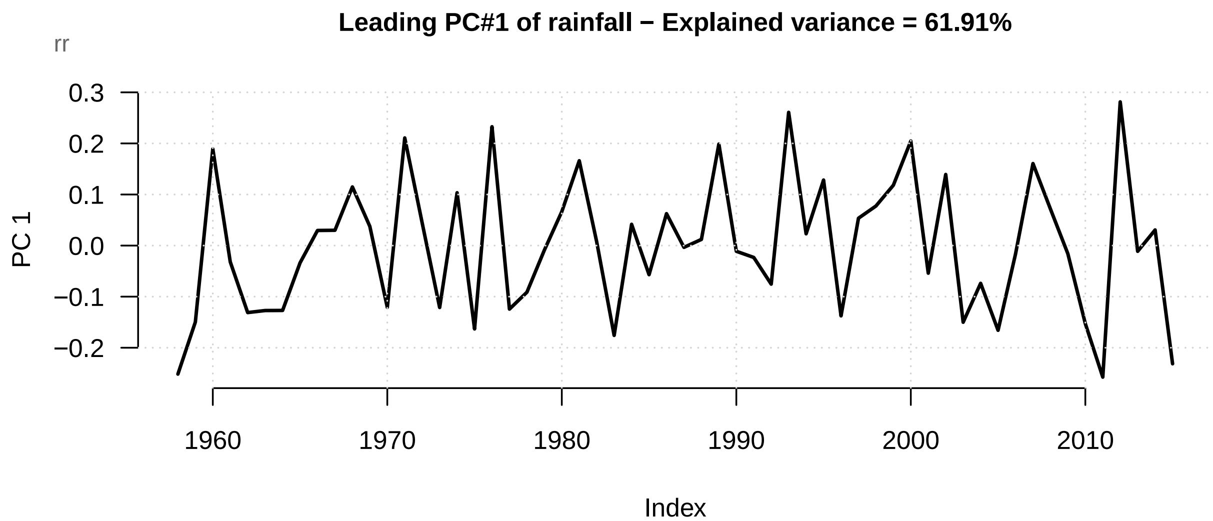


The residuals from the downscaling of μ still give eigenvalues which indicate that there are differnt coherent modes present associated with different variance. The spatial pattern is similar to the spatial patterns in the original data. This exercise suggests that the anaysis failed to capture any strong link between the predictor (vapour pressure estimated over the North Atlantic) and the predictand. One reason may be a shifting source region for moisture at different times of the year and from year to year.

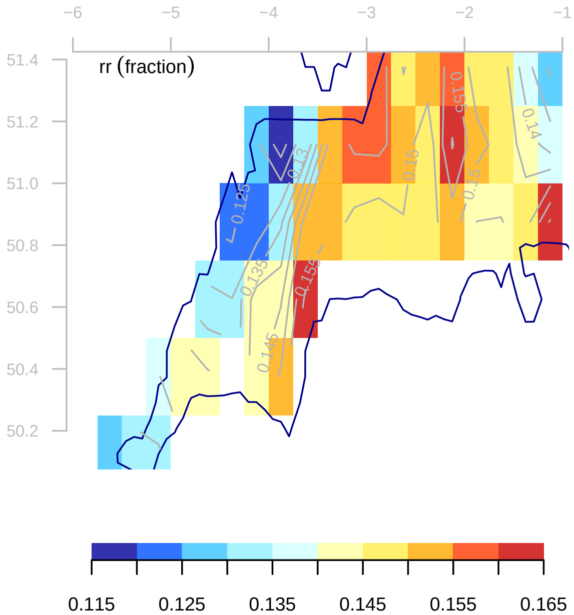
For comparison the original data look like this:

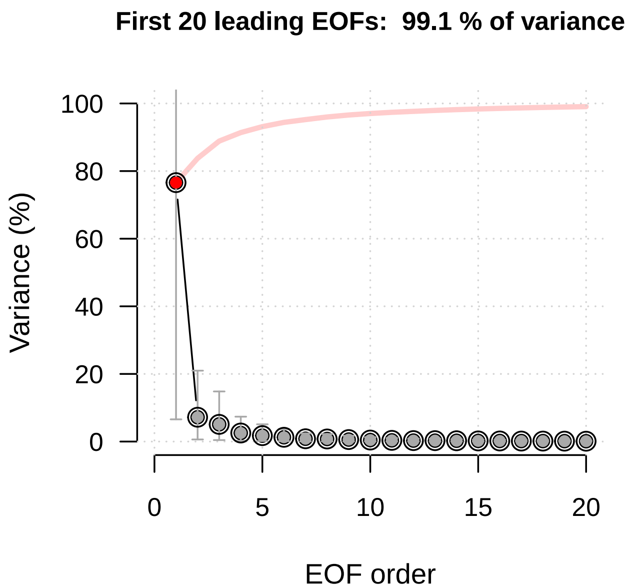
```
## The original of the wet-day precipitation
plot(EOF(mu),new=FALSE)
```

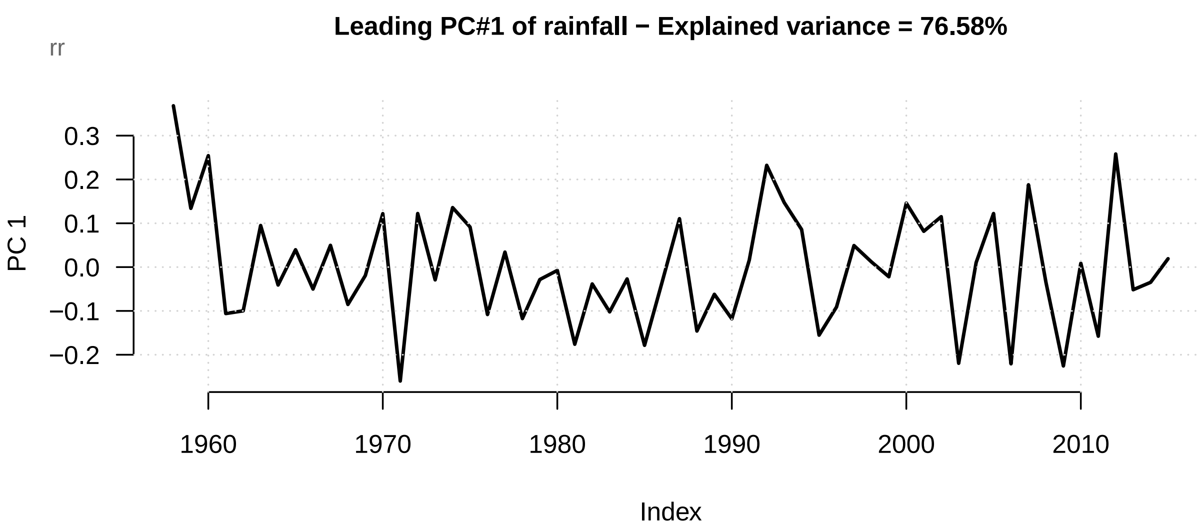





```
## Repeat with the wet-day frequency for the benefit of comparison
z.fw <- as.field(ds.fw)
#res.fw <- as.residual(ds.fw)
## Another way to estimate the residuals:
res.fw <- fw - z.fw
res.fw <- attrcp(fw,res.fw)
class(res.fw) <- class(fw)
eof.res.fw <- EOF(res.fw)
plot(eof.res.fw,new=FALSE)
```



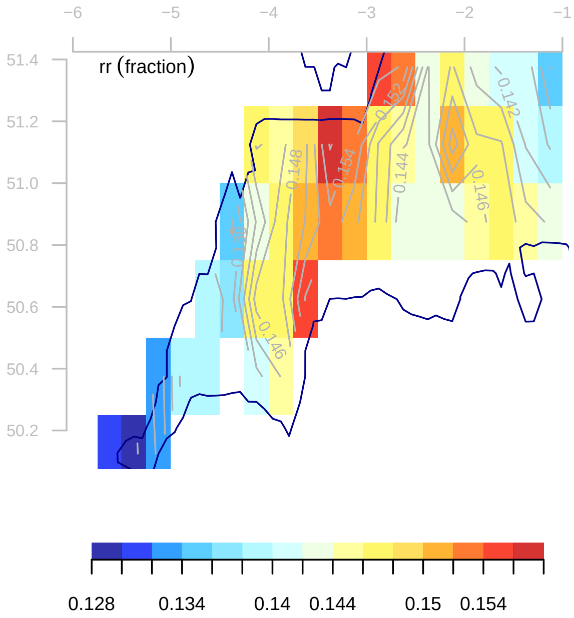


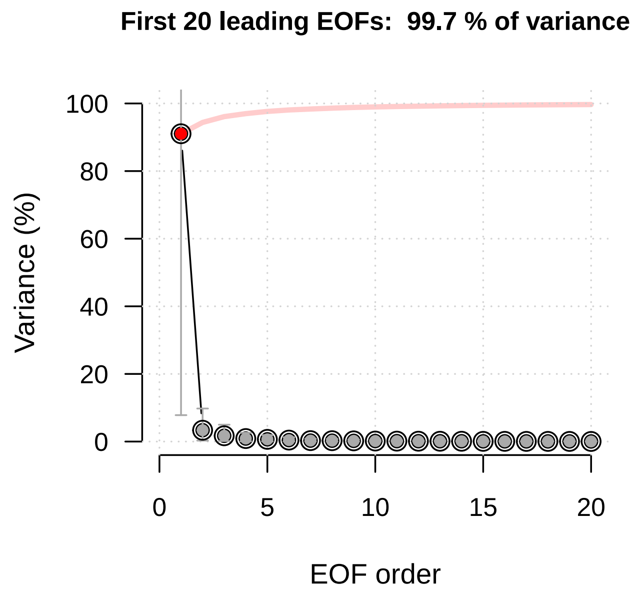


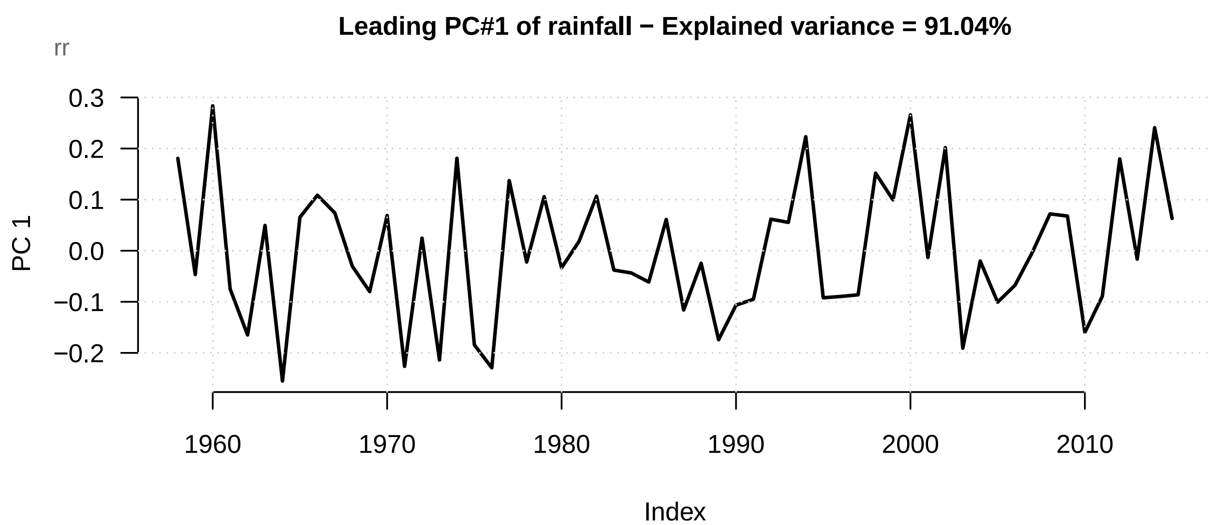
The residual for the wet-day frequency ...

For comparison the original data look like this:

```
## The original of the wet-day precipitation
plot(EOF(fw),new=FALSE)
```







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.

Sea-level

Coastal innundation is expected to worsen with rising sea-levels, given similar types of mid-latitude storms as at present. To explore this type of effect, we can analyse the sea-level trends and connection to global temperatures to assess future outcome. First the stations from the GLOSS dataset (global monthly data):

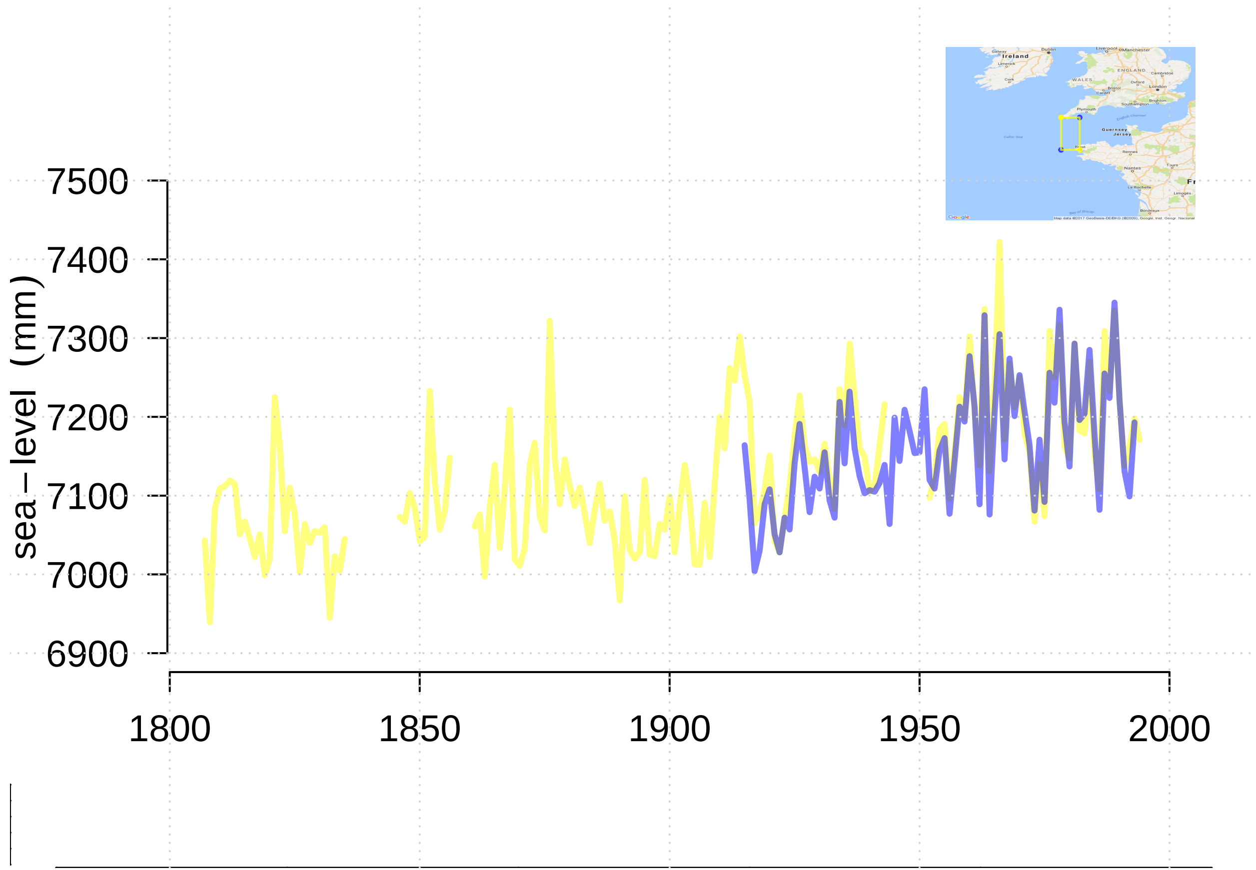
```
gloss <- aggregate(station.gloss(),year,FUN='max',na.rm=TRUE)
gloss <- subset(gloss,is=list(lon=c(-20,20),lat=c(45,55)))
```

Plot the GLOSS tidal data:

```r
plot(gloss,new=FALSE)
```

```
## Warning in plotmap(xx, yy, bgmap, pch = 19, col = col, cex = 0.25): NAs
## introduced by coercion
```

```r
grid()
```



Single station with hourly data from Newlyn:

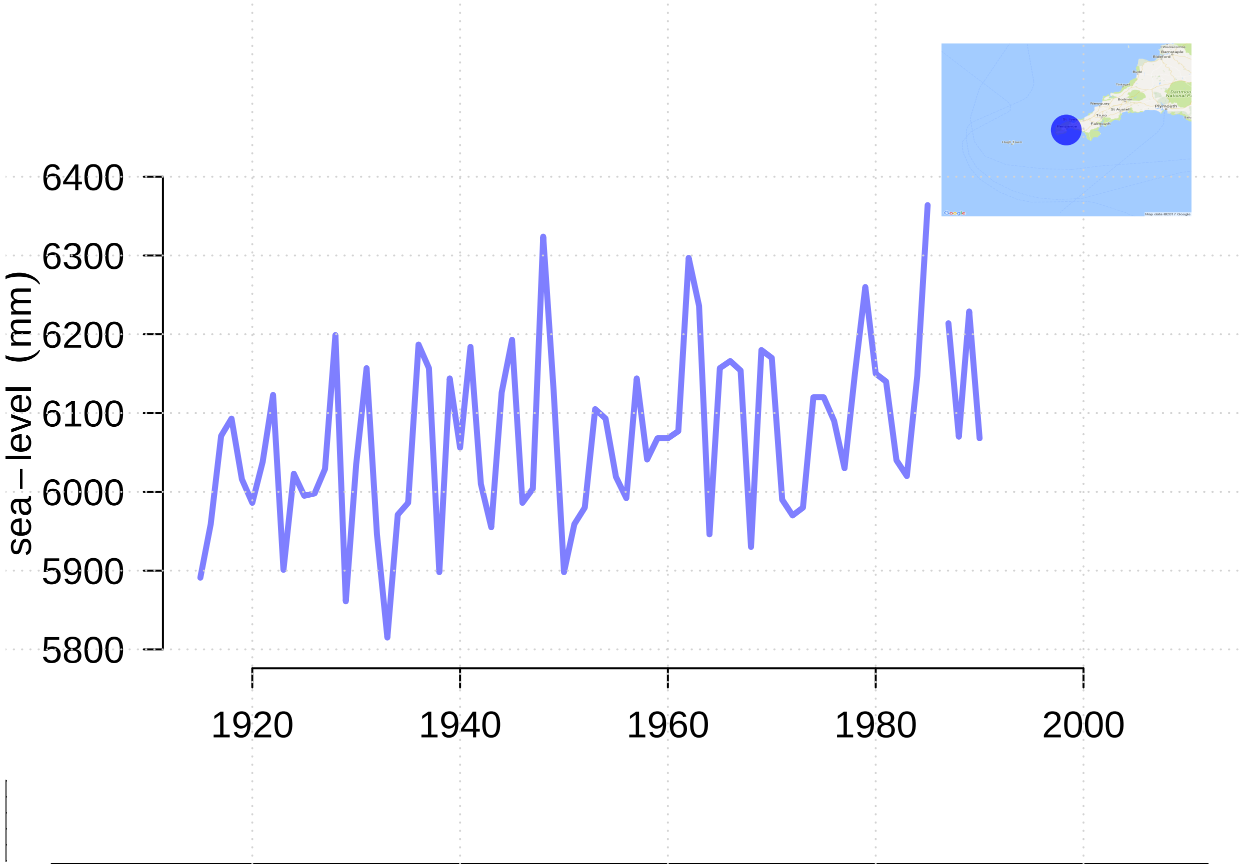
```r
if (!file.exists('newlyn.rda')) {
  newlyn <- station.newlyn()
  newlyn <- aggregate(newlyn,year,FUN='max',na.rm=TRUE)
  save(newlyn,file='newlyn.rda')
} else load('newlyn.rda')
```

Plot the Newlyn tidal data:

```r
plot(newlyn,new=FALSE)
```

```
## Warning in plotmap(lat(x), lon(x), bgmap, pch = 19, col = col, cex = 2):
## NAs introduced by coercion
```

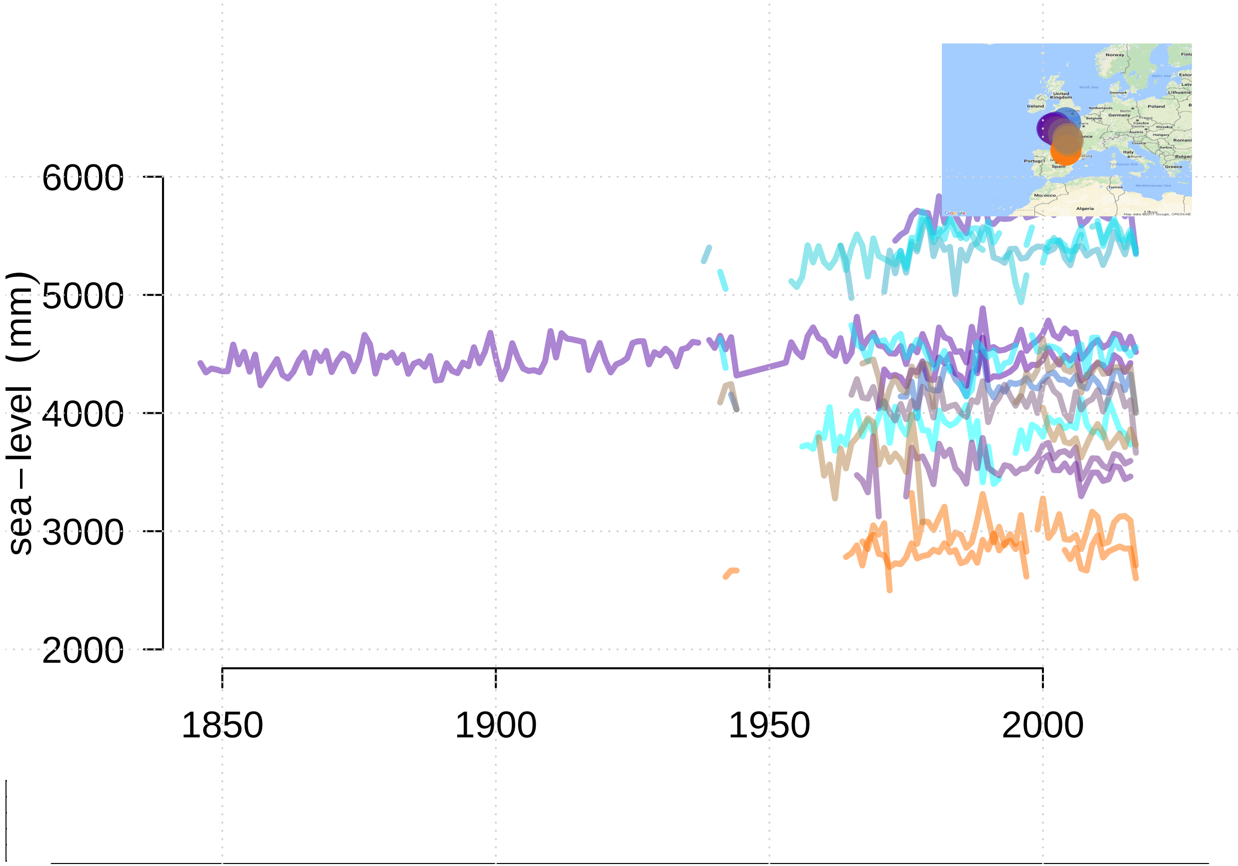
```r
grid()
```



The curve suggests a longterm increase since the early 20th century, but the data stops before 2000.

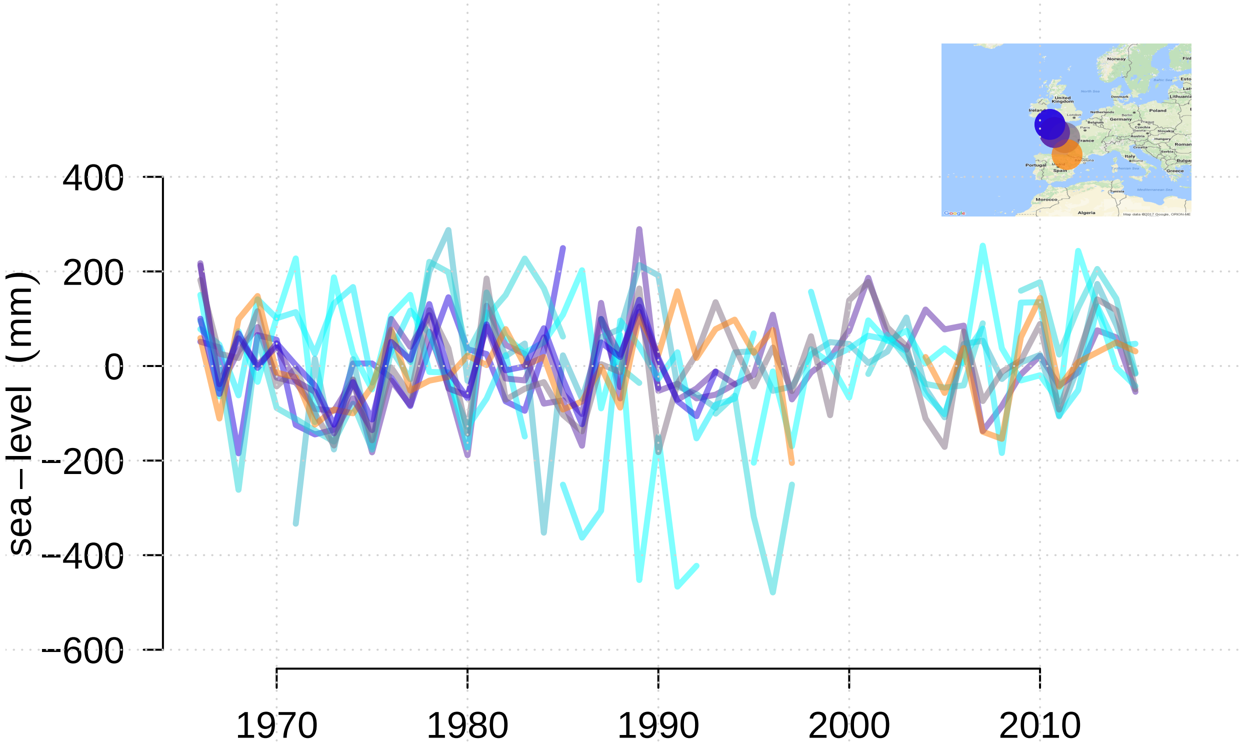
French tidal stations along the northern/eastern coast (SONEL):

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



Combine the records from different sources

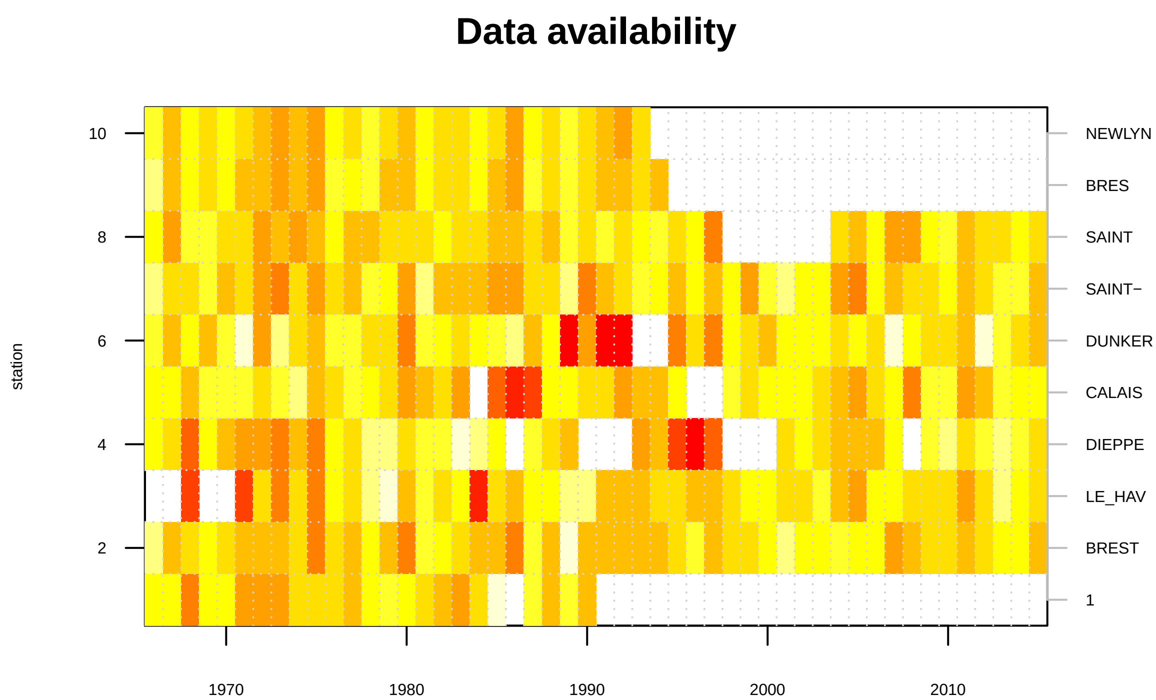
```
index(newlyn) <- year(newlyn)
index(sonel) <- year(sonel)
index(gloss) <- year(gloss)
Z <- combine.stations(newlyn,sonel,gloss)
nv <- apply(coredata(Z),2,FUN='nv')
Z <- subset(Z,is=(nv > 50))
Z <- subset(Z,it=c(1966,2015))
coredata(Z)[!is.finite(Z)] <- NA
coredata(Z) <- t(t(coredata(Z)) - colMeans(coredata(Z),na.rm=TRUE))
plot(Z,new=FALSE); grid()
```



There is a general increasing trend for the majority of the tidal stations, but the picture is clutterend by missing-data gaps, dupious outliers, and intermittent data availability.

Check for data availability

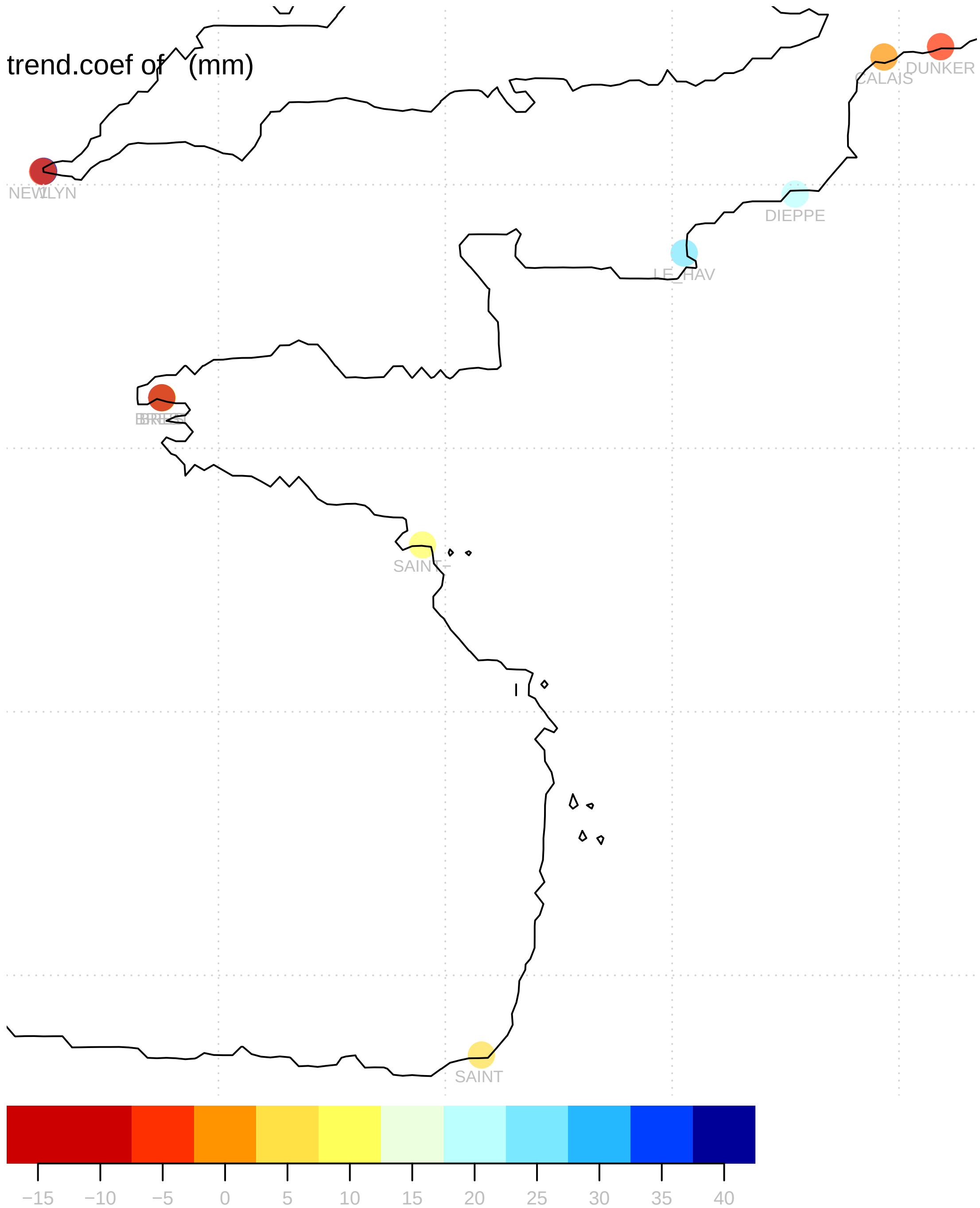
```
diagnose(Z)
```



GLOSS

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,pch=19,FUN='trend',cex=-2,add.text=TRUE,new=FALSE)
```



A trend analysis yields inconsistent results because missing-data gaps, of the inclusion of filled-in data by interpolation, and variable data quality. The map indicates different trends in the British Channel and the near-by parts of the Bay of Biscay.

Get the annual mean global mean sea-level and analyse the correspondense between that and the local sea level - we can expect a link from heuristic physics. Also include an account of the mean sea-level pressure.

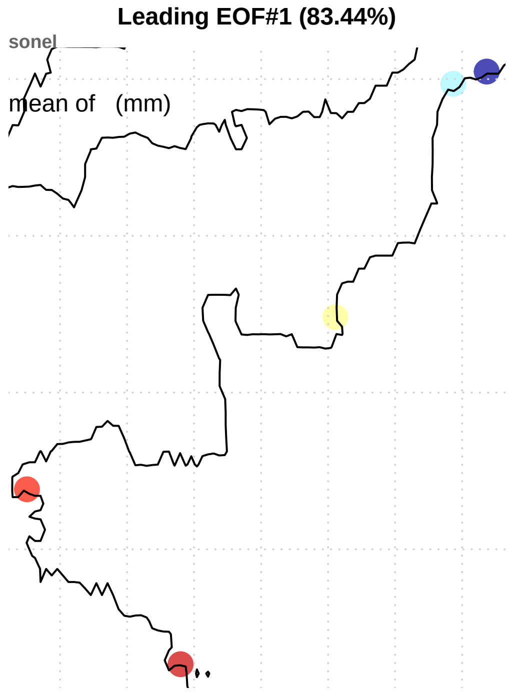
```
gsl <- annual(GSL())
plot(gsl)
slp <- annual(retrieve('~/Downloads/slp.mon.mean.nc',lon=c(-20,10),lat=c(45,60)))
```

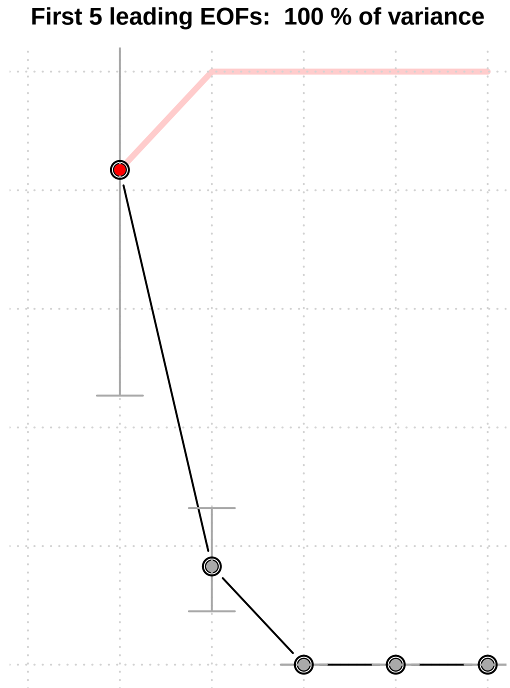
```
## [1] "Warning : Calendar attribute has not been found in the meta data and will be set automatically.
```

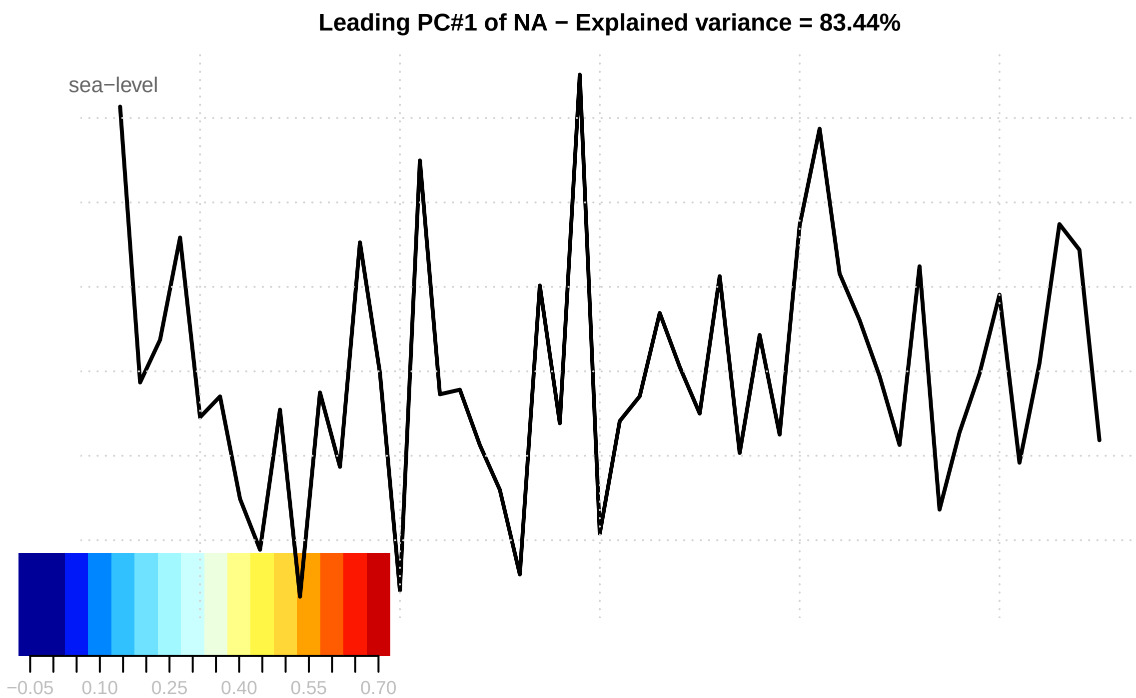
```
eof.slp <- EOF(slp,n=5)
## Manipulate the data: replace the last SLP EOF with the global sea-level and use DS to explore connect
i1 <- is.element(year(eof.slp),year(gsl))
i2 <- is.element(year(gsl),year(eof.slp))
coredata(eof.slp)[i1,5] <- coredata(gsl)[i2]
attr(eof.slp,'pattern')[,,5] <- 1
attr(eof.slp,'eigenvalue') <- 1
plot(eof.slp,ip=5,new=FALSE)
```

Prepare the local tidal data: PCA

```
nv <- apply(coredata(Z),2,'nv')
Z <- subset(Z,is=nv > 45)
Z <- pcafill(Z)
pca.Z <- PCA(Z)
plot(pca.Z, new=FALSE)
```







The PCA suggests stronger amplitude in the interannual variations in the sea-level near the Bay of Biscay, and less variation in the British Channel.

Wind

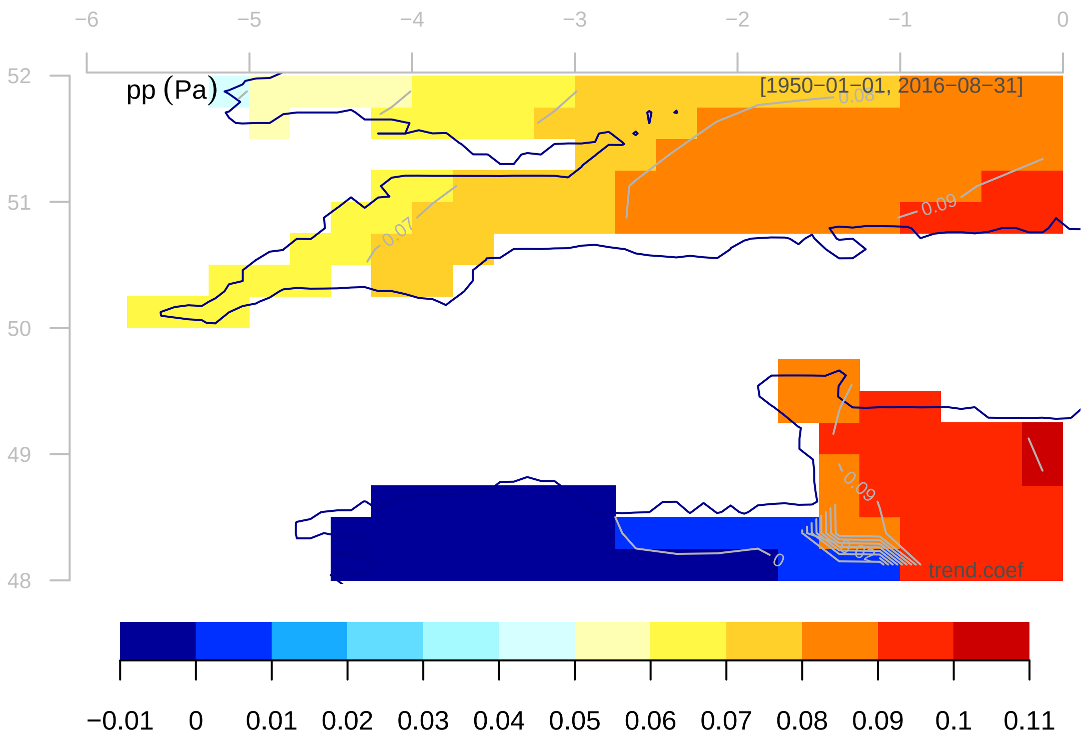
Wind affects wave heights and can cause flooding and innundation through storm surges. Wind measurements are often unavailable, but it is possible to reconstruct wind informatnion from barometric pressure - sea-level pressure (SLP).

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',new=FALSE)
```



The trend analysis indicates non-zero changes near the British Channel, although these may be due to natural variability.

Pick three grid points from which we can estimate the geostropic 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)
```

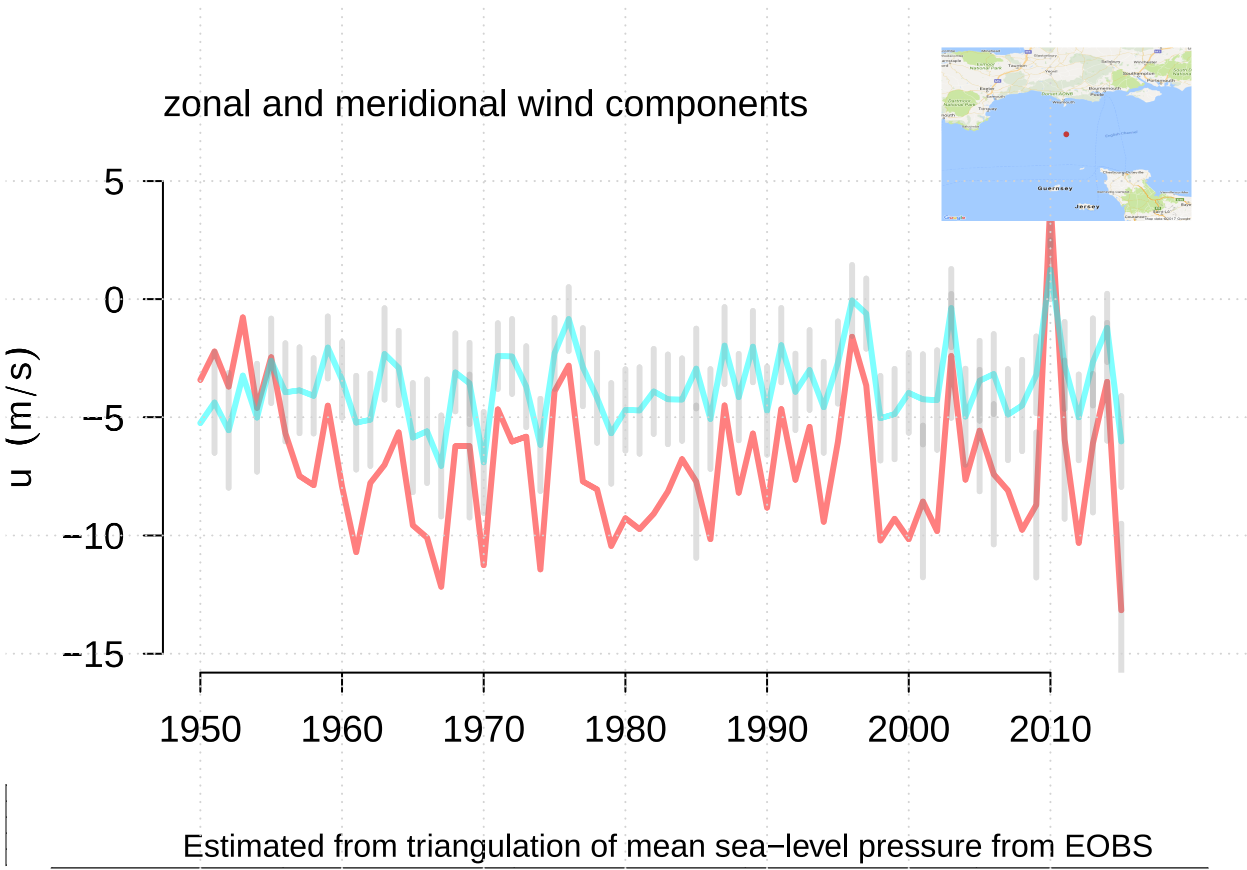
```
## [1] "Retrieving data from 8 records ..."
## [1] "1 SLP 100102 BOURGES FRANCE ECAD"
## [1] "2 SLP 100106 TOULOUSE-BLAGNAC FRANCE ECAD"
## [1] "3 SLP 100110 BORDEAUX-MERIGNAC FRANCE ECAD"
## [1] "4 SLP 100114 CHATEAUROUX DEOLS FRANCE ECAD"
## [1] "5 SLP 100118 PERPIGNAN FRANCE ECAD"
```

```
## [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 triagulation for stations to estimate the wind
uv <- geostrophicwind(pp.eobs)
```

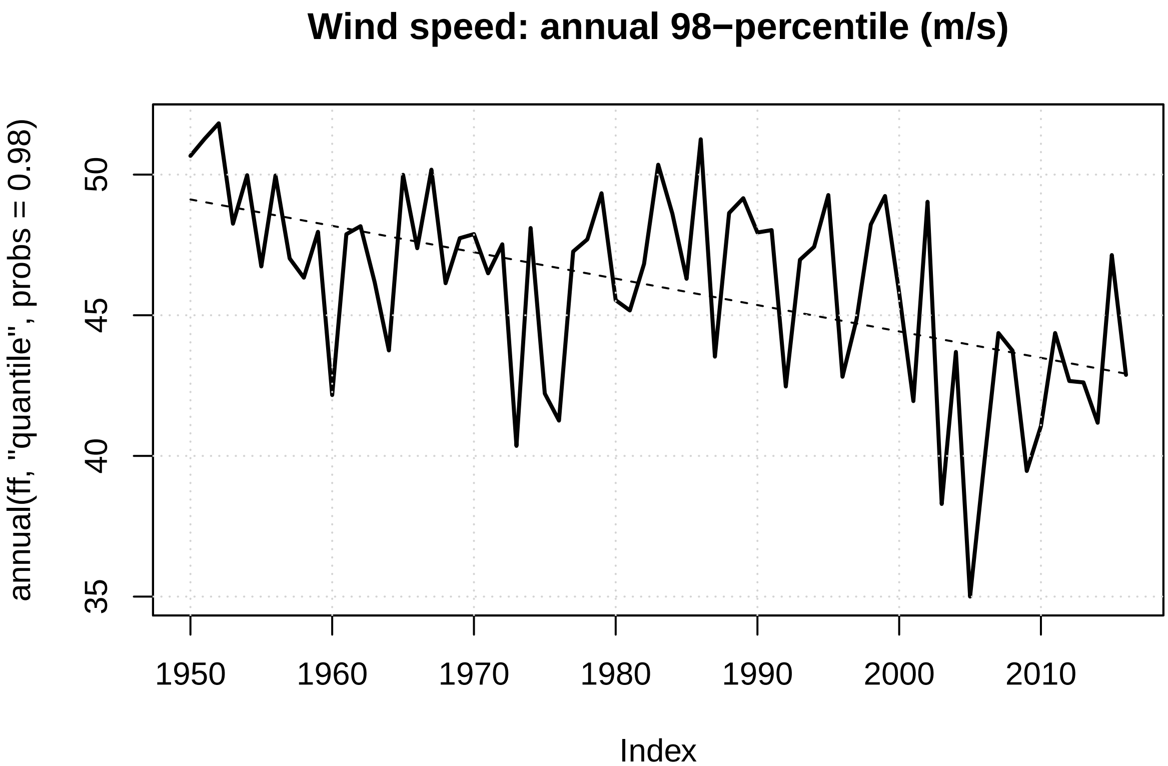
```
## [1] "3 stations gives  1 combinations of three."
##
  |
  |                                                                  |   0%
  |
  |==================================================================| 100%
```

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



THe level of the wind components seam fairly stable between 1950 and 2050, albeit with a number of peaks. 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 low values around year 2010, and a slight decreasing 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)',new=FALSE)
lines(trend(annual(ff,"quantile",probs=0.98)),lty=2)
grid()
```




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

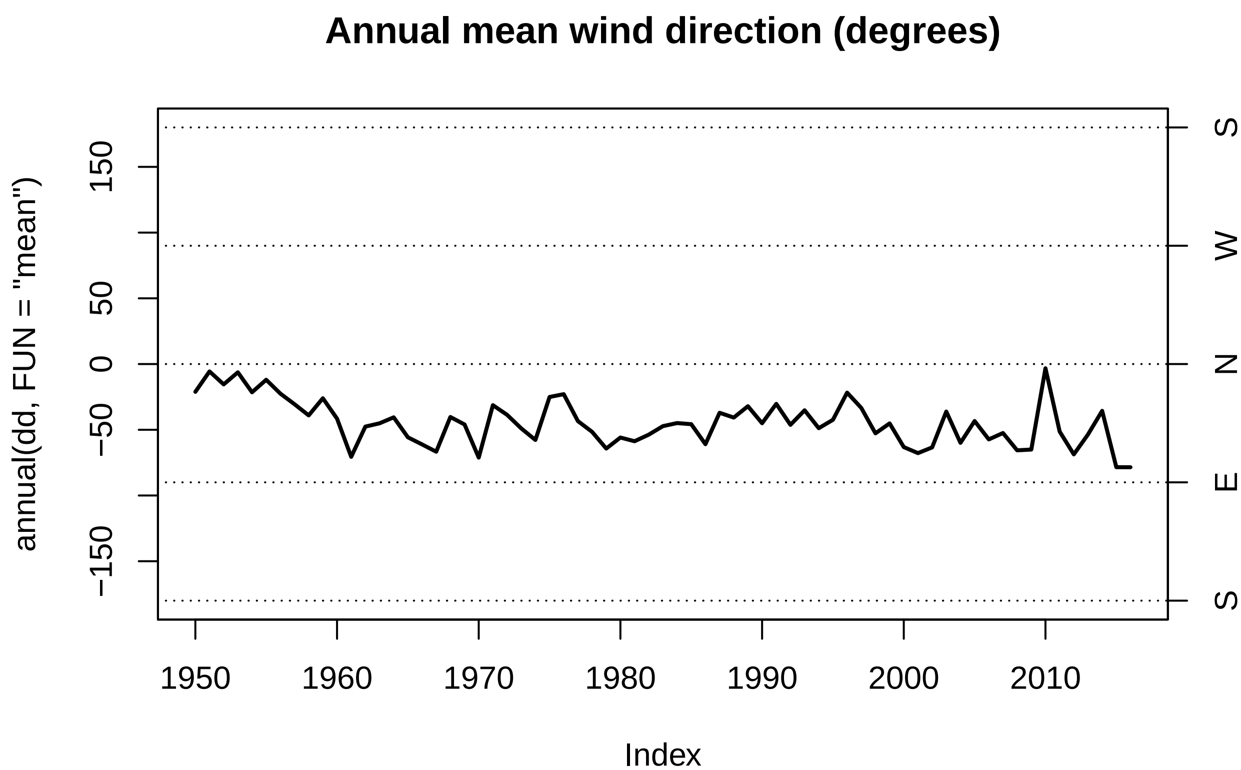
```
## trend.coefficients
##         -0.9383385
```

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

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

The trend is not siginificant 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)',new=FALSE)
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)
```



It is possible to examine whether there were changes in the criculation by using ESD to compare the windspeeds with SLP from reanalyses.

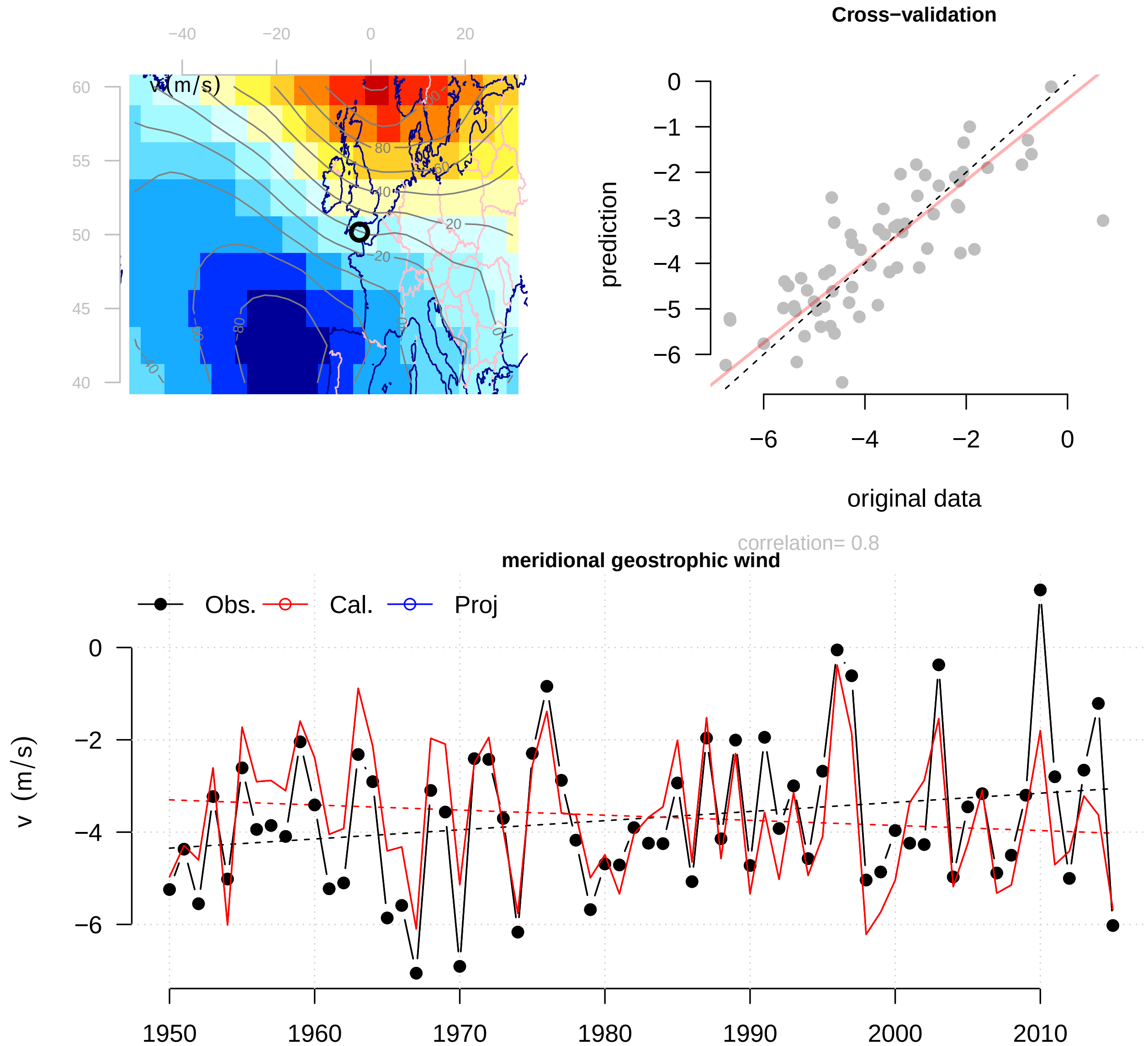
```
## Trend in upper wind direction
SLP <- retrieve('~/Downloads/slp.mon.mean.nc',lon=c(-50,30),lat=c(40,60))
```

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

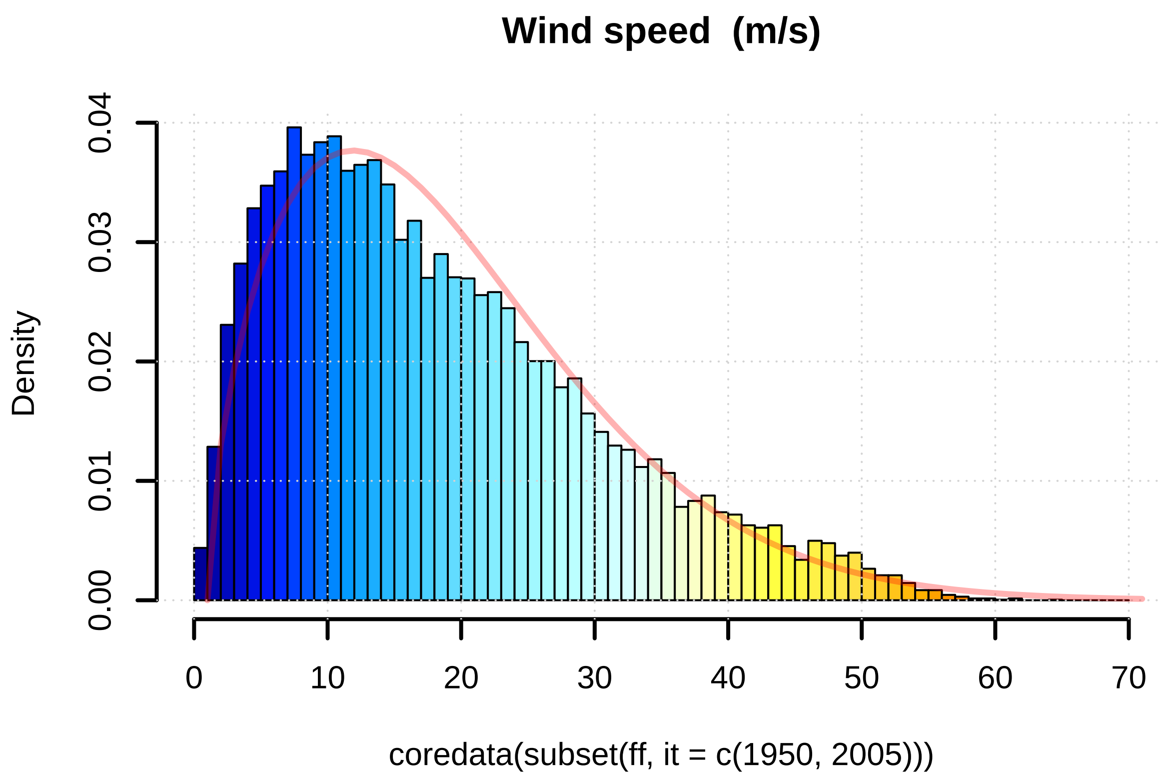
```
eof.slp<- EOF(annual(SLP))
```

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,new=FALSE)
```




```
##
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))
```



The windspeed statistics has a distribution that is close to being Weibul, although with a slight bias.

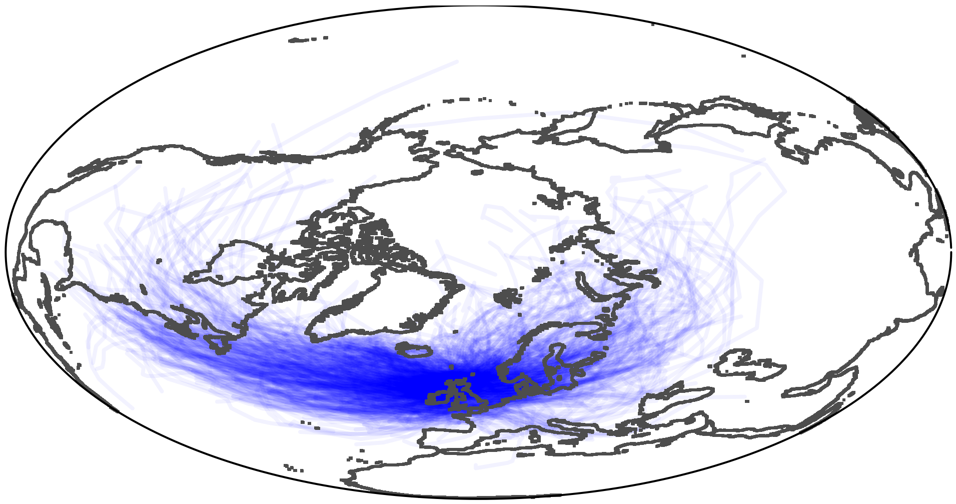
```
## Estimate grostrophich wind
#UV <- geostrophicwind(SLP,progressbar=FALSE)
```

```
## wind rose
#windrose(UV)
```

Storms

Synoptic storms are associated with winds, storm surges, precipitation, and waves. The storms (low pressure systems) tend to appear over the North Atlantic ("cyclogenesis"") between the coast of Newfoundland and the British Isles, and travel eastward and die off once they hit land (Scandinavia). These storms are a result of wind shear and temperature differences, due to barolinic instability, and tend to cluset around the upper air jet stream. The storm statistics is also influenced by the North Atlantic Oscillation (NAO). Since the storms travel a fair distance over the North Atlantic, they are expected to be subject to air-sea heat and moisture exchange before hitting the UK. The intensity of the storms may potentially be affected by affected by sea surface temperatures through air-sea interactions - higher temperatures favour more evaporation and more"fuel" for the storms.

```
load('cyclones.uk.rda')
map(cyclones.uk,new=FALSE)
```

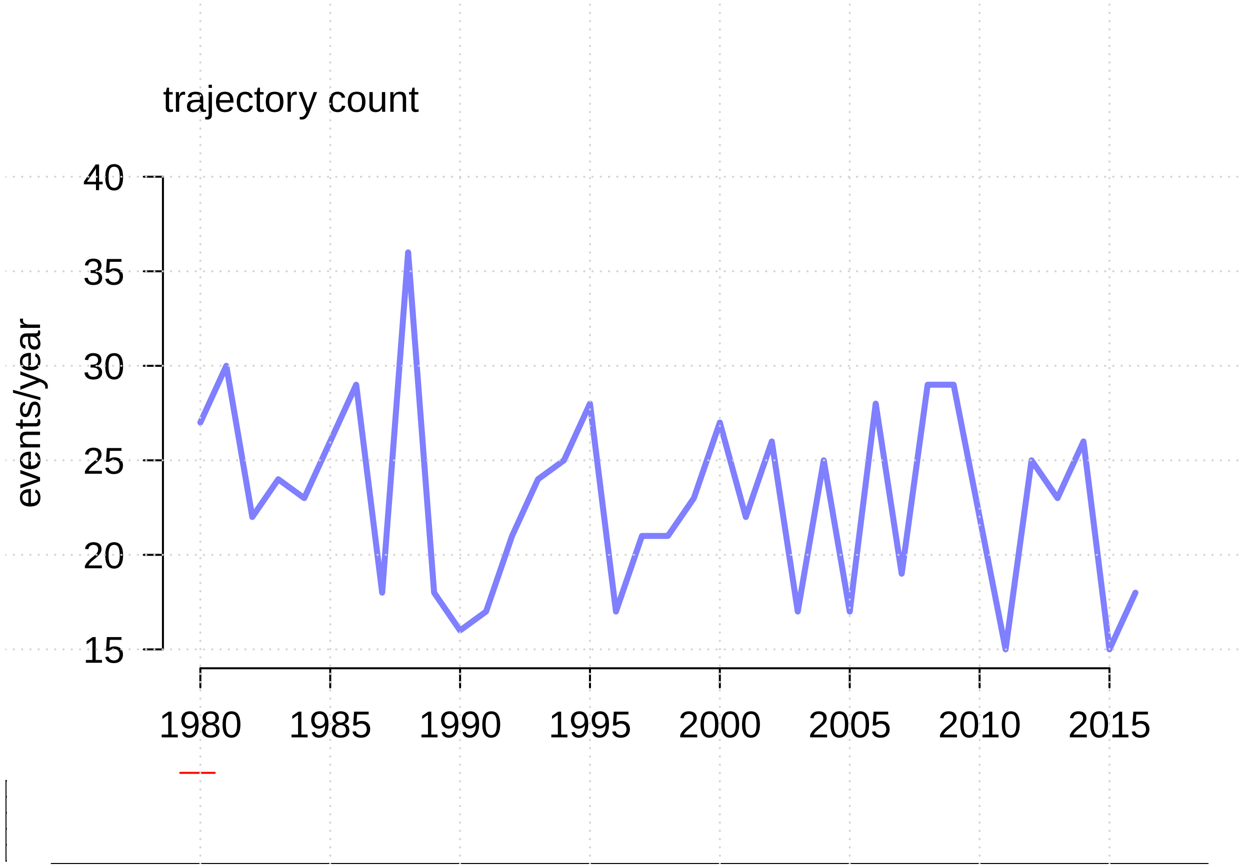


A plot of the number of trajectories over time suggests a weak declining trend over 1980-2015 in the number of storms sweeping over the Torbay region.

```
plot(cyclones.uk,new=FALSE)
```

```
## Warning in merge.zoo(nz, n0): Index vectors are of different classes:
## character integer

## Warning in is.na(lon(y)): is.na() applied to non-(list or vector) of type
## 'NULL'

## Warning in is.na(lat(y)): is.na() applied to non-(list or vector) of type
## 'NULL'

## Warning in is.na(lon(y)): is.na() applied to non-(list or vector) of type
## 'NULL'

## Warning in is.na(lat(y)): is.na() applied to non-(list or vector) of type
## 'NULL'
```

```
grid()
```

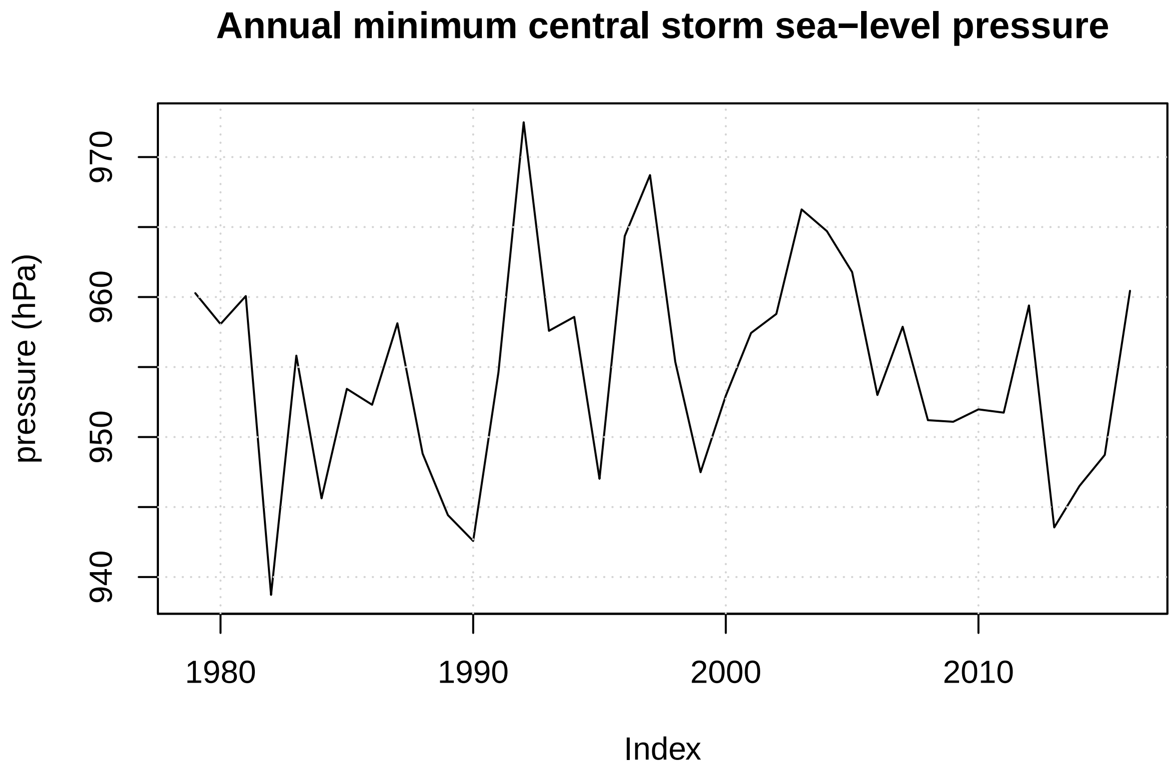


This curve does not indicate how the mean intensity of the storms has varied over the same period.

```
cdat <- as.character(cyclones.uk[,2])
press <- annual(zoo(apply(cyclones.uk[,is.element(colnames(cyclones.uk),'pcent')],1,min),
              order.by=as.Date(paste(substr(cdat,1,4),'-',substr(cdat,5,6),'-',
                                    substr(cdat,7,8),':',substr(cdat,9,10),':00',sep=''))),'min')
```

```
## Warning in zoo(apply(cyclones.uk[, is.element(colnames(cyclones.uk),
## "pcent")], : some methods for "zoo" objects do not work if the index
## entries in 'order.by' are not unique
```

```
plot(press,main='Annual minimum central storm sea-level pressure',ylab='pressure (hPa)')
grid()
```



The central pressure is more closely connected to the wind speeds in the storm systems, but the connection between amount of precipitation caused by such storms is less clear. The precipitation intensity is expected to be influenced by the air moisture and the rate of evaporation over the ocean where the storms cross.