eu-circle_case-study-1

Rasmus Benestad

May 2, 2016

Extreme Dryness and forest fires on electricity and transport networks

Simultaneous forest fires ignite in the Bouche du Rhone department near Aix en Porvence, and in the Alpes Maritimes Department, at the French/Italian frontier, near a highway (A8) used by thousands of tourists. Due to the important smoke production, visibility is strongly reduced so that highway has to be closed, leading to an important traffic on the secondary road networks. The crossing of the frontier by car being completely impossible, traffic between France and Italy has to be diverted. Tourists are confined on highway rest areas. People, blocked on the roads, have difficulties to breathe because of the smoke and leave their cars, scattering into the nature. Additional accidents are caused because of the panic of people. Due to aerial firefighting, electricity lines have to be cut. Due to the fire smoke, aerial traffic in Nice airport has to be stopped. Numerous dwellings are without electricity and of course without telephones. Other emergency operations are disturbed because of the large delay of alert, major dispersion of means, decrease of available means.

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 strip off all the text and make a pure R-script, then use `purl`as shown below:

```
## Extract just the R-code
library(knitr)
purl('~/git/esd_Rmarkdown/EU-Circle/eu-circle_case-study-1.Rmd', output='~/git/esd_Rmarkdown/EU-Circle/
```

Precipitation

Station data

Represent the station data with lower-case x

```
library(esd)
```

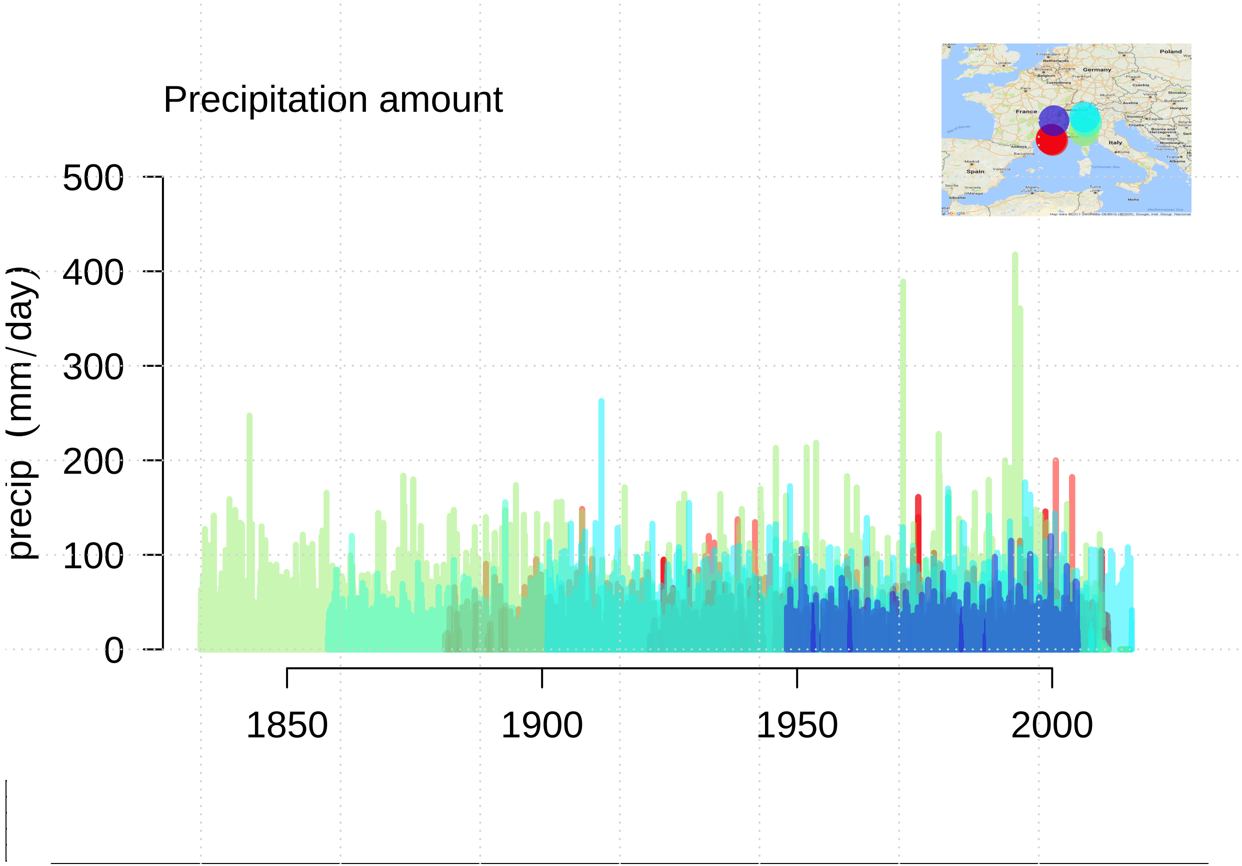
```
if (!file.exists('eu-circle_case-study-1_precio.rda')) {
  ss <- select.station(param='precip',lon=c(5,10),lat=c(42,45),nmin=50,src=c('ecad','ghcnd'))
  x <- station(ss)
  x <- subset(x,is=list(alt=-400))
  save(file='eu-circle_case-study-1_precio.rda',x)
} else load('eu-circle_case-study-1_precio.rda')
## Only keep the ECAD data
x <- subset(x,is=is.element(src(x),'ECAD'))
map(x,FUN='q95',new=TRUE)
diagnose(x)
```

The raw daily precipitation data. The colour of the curves correspond to the colour marker of the location. There have been some instances with very large precipitation amounts in the past.

```
plot(x,new=FALSE)
```

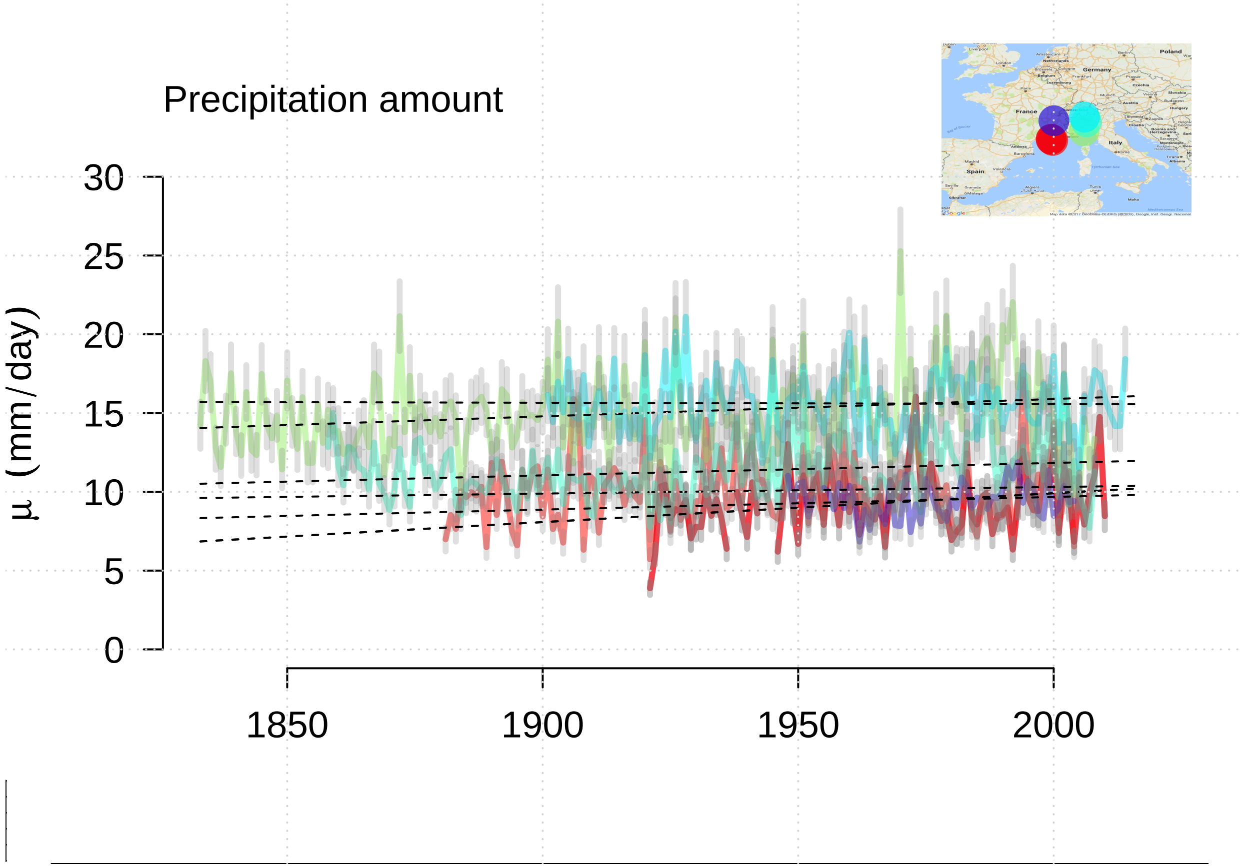
```
## Loading required package: RgoogleMaps
```

```
grid()
```



Examine the trend in the wet-day mean precipitation μ

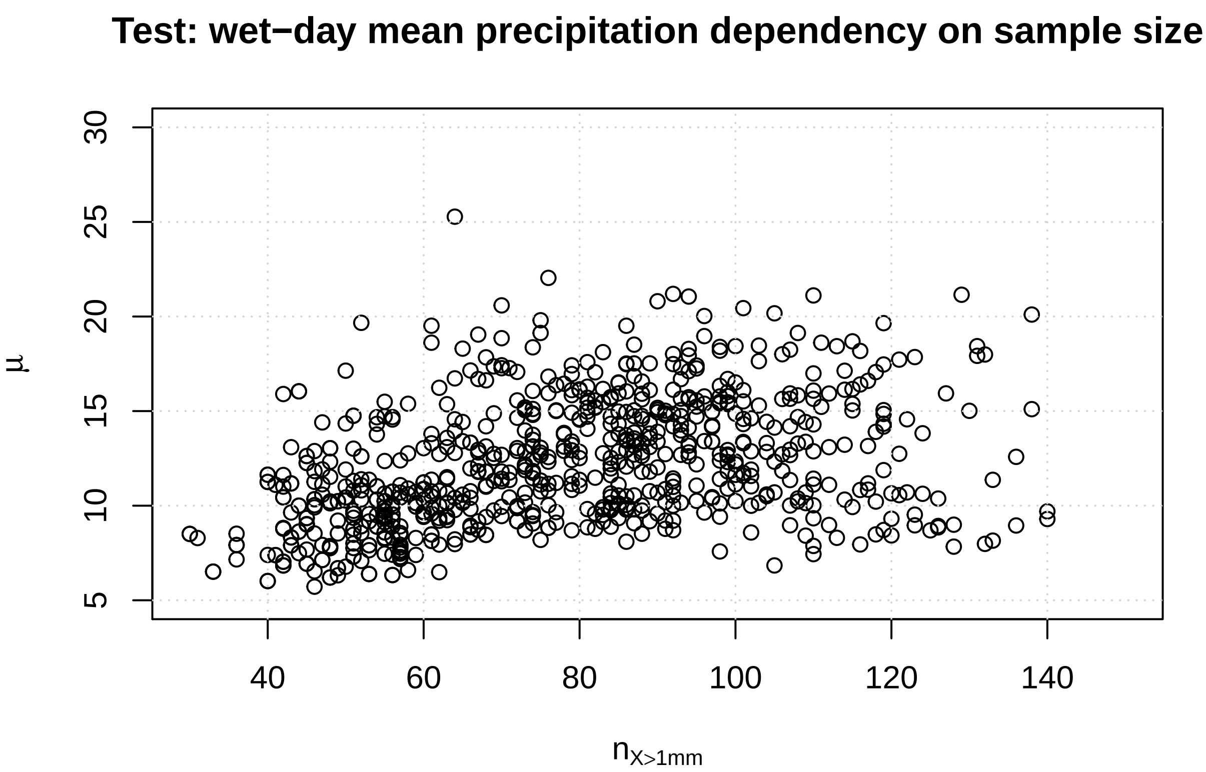
```
mu <- annual(x,'wetmean',nmin=250)
wq95 <- function(x) {x <- x[is.finite(x)]; x <- x[x >= 1]; wq95 <- quantile(x,probs=0.95); wq95}
q95 <- annual(x,'wq95')
plot(mu,new=FALSE)
for (i in 1:dim(mu)[2]) lines(trend(subset(mu,is=i)),lty=2)
grid()
```



There appears to be a slight increasing trend in μ for most stations, according to a linear regression analysis against time. There are also pronounced year-to-year variations in μ with high "spikes" in some years.

Need to check to see if μ is correlated with number of rainy days, e.g. can be high due to smaller samples and higher sampling fluctuations:

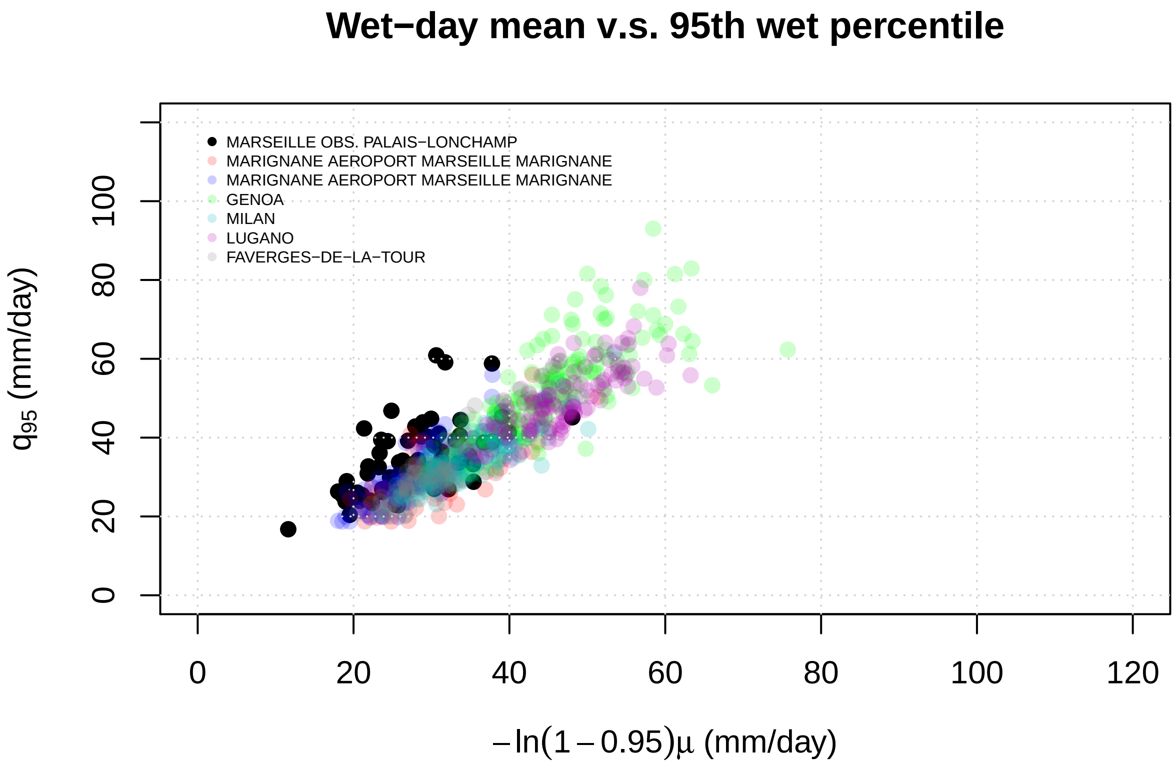
```
x1 <- zoo(subset(annual(x,'count',threshold=1),is=1))
y1 <- zoo(subset(mu,is=1))
plot(x1,y1,xlab=expression(n[X>1*mm]),ylab=expression(mu),xlim=c(30,150),ylim=c(5,30),
     main='Test: wet-day mean precipitation dependency on sample size')
for (i in 2:dim(mu)[2]) {
  x1 <- zoo(subset(annual(x,'count',threshold=1),is=i))
  y1 <- zoo(subset(mu,is=i))
  points(x1,y1)
}
grid()
```



There is no indication suggesting that high value of annual μ is connected with a low number of rain events.

For many purposes, it may be useful to assume that the daily precipitation amount is approximately exponentially distributed for the days when it rains and that the probability of the precipitation exceedin a threshold value x_0 can be estimated according to $Pr(X > x_0) = f_w e^{-x_0/\mu}$ where f_w is the wet-day frequency. Below is a test for whether the amount is close to exponential for a wet day.

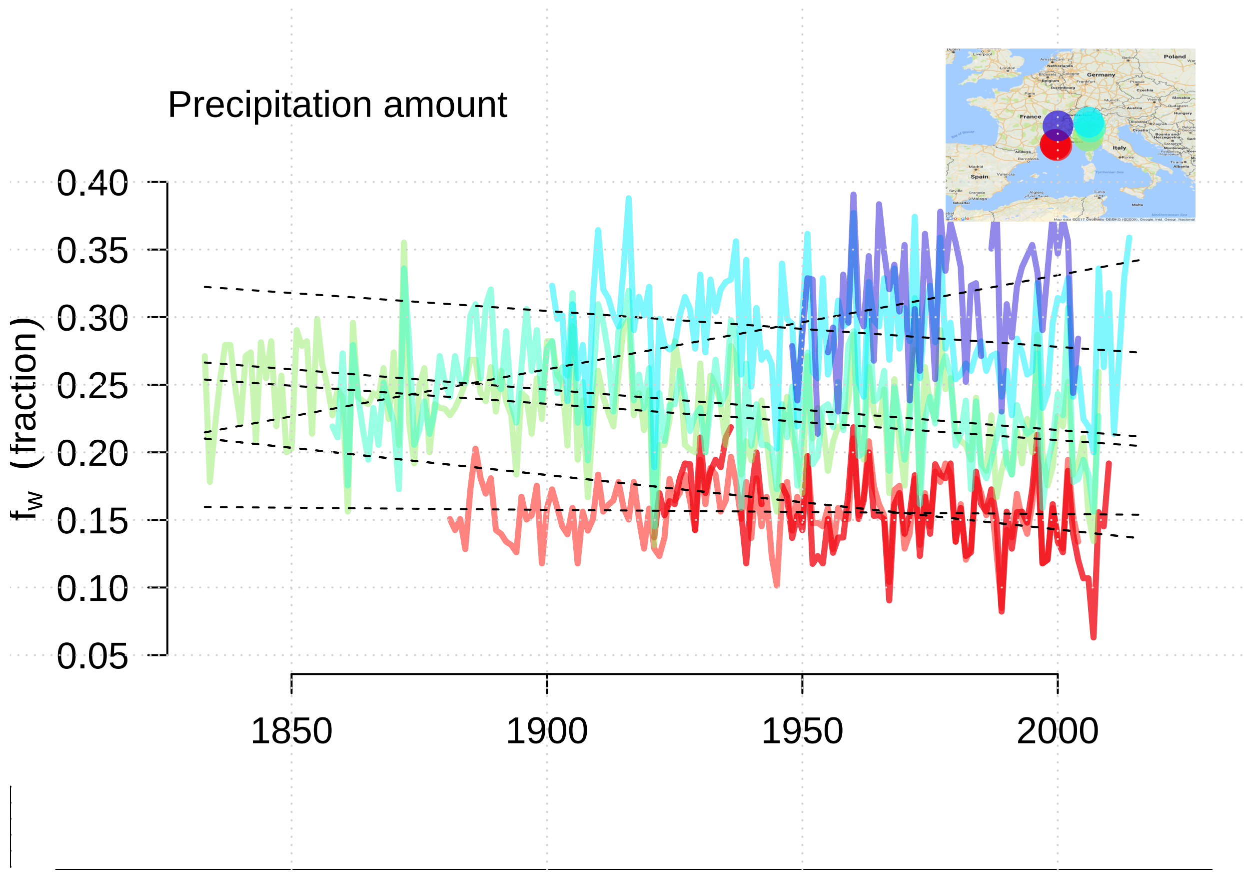
```
## check the relationship between wet-day 95-percentile and wet-day mean
plot(-log(0.05)*zoo(mu[,2]),zoo(q95[,1]),pch=19,xlim=c(0,120),ylim=c(0,120),
     main='Wet-day mean v.s. 95th wet percentile',
     xlab=expression(paste(-ln(1-0.95)*mu,' (mm/day)')), ylab=expression(paste(q[95],' (mm/day)')))
points(-log(0.05)*zoo(mu[,1]),zoo(q95[,2]),pch=19,col=rgb(1,0,0,0.2))
points(-log(0.05)*zoo(mu[,3]),zoo(q95[,3]),pch=19,col=rgb(0,0,1,0.2))
points(-log(0.05)*zoo(mu[,4]),zoo(q95[,4]),pch=19,col=rgb(0,1,0,0.2))
points(-log(0.05)*zoo(mu[,5]),zoo(q95[,5]),pch=19,col=rgb(0,0.7,0.7,0.2))
points(-log(0.05)*zoo(mu[,6]),zoo(q95[,6]),pch=19,col=rgb(0.7,0,0.7,0.2))
points(-log(0.05)*zoo(mu[,7]),zoo(q95[,7]),pch=19,col=rgb(0.5,0.5,0.5,0.2))
grid()
legend(0,120,loc(mu),pch=19,col=c('black',rgb(1,0,0,0.2),rgb(0,0,1,0.2),rgb(0,1,0,0.2),rgb(0,0.7,0.7,0.
```



The scatter plot suggests that the points are mainly clustered around the diagonal and hence the 24-hr precipitation amoun is approximately exponentially distributed. The Marseille data seem to be less similar to the exponential distribution than the other sites.

We also need to examine the trend in the wet-day frequency:

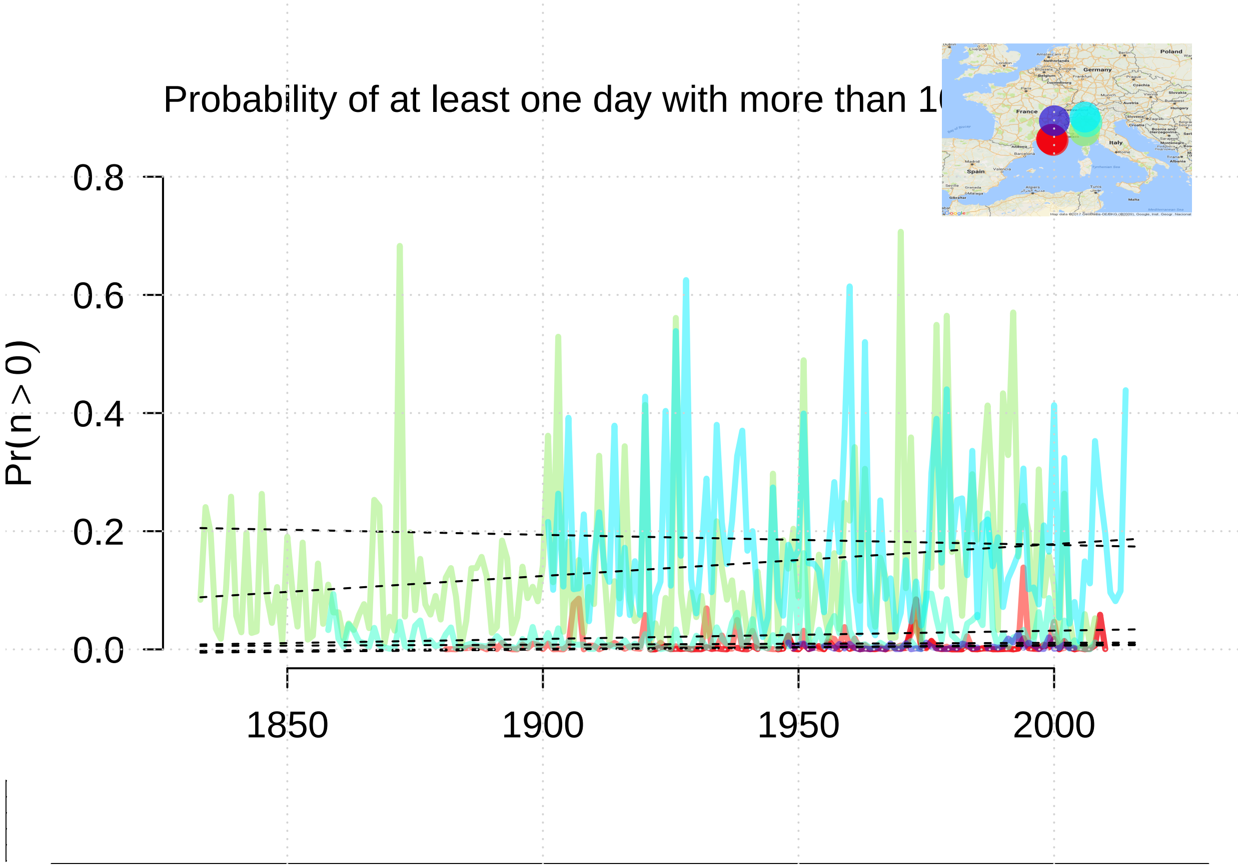
```
fw <- annual(x,'wetfreq',nmin=250)
plot(fw,new=FALSE)
for (i in 1:dim(fw)[2]) lines(trend(subset(fw,is=i)),lty=2)
grid()
```



The rain gauge data suggests decreasing trends in f_w for most locations, except for the highest station (360 m a.s.l.) further inland (Faverges-de-la-Tour) and with a short record.

Estimate the evolution in the probability for heavy precipitation: $Pr(X > x) = f_w e^{-x_0/\mu}$.

```
x0 <- 100 #mm
Pr <- zoo(1-pbinom(0,size=365,prob=coredata(fw)*exp(-x0/coredata(mu))),order.by=year(fw))
class(Pr) <- class(mu)
Pr <- attrcp(mu,Pr)
attr(Pr,'variable') <- 'Pr'
attr(Pr,'unit') <- 'probability'
attr(Pr,'longname') <- paste('probability of at least one day with more than',x0,'mm')
plot(Pr,ylab=expression(Pr(n>0)),xlab='',new=FALSE,errorbar=FALSE,
          main=paste('Probability of at least one day with more than',x0,'mm'))
for (i in 1:dim(Pr)[2]) lines(trend(subset(Pr,is=i)),lty=2)
grid()
```



The results indicate large annual variations in the probability of extreme precipitation ($X > 100mm$), suggesting a high sensitivity to both μ and f_w. This sensitivity is also seen in the different estimates for different locations, even if the difference between the mean μ is not as dramatic.

One relevant parameter is the duration of dry and wet spells (number of dry/wet consecutive days). The grapghic below shows the length of dry (red) and wet (blue) intervals (dry are plotted with negative sign for clarity).

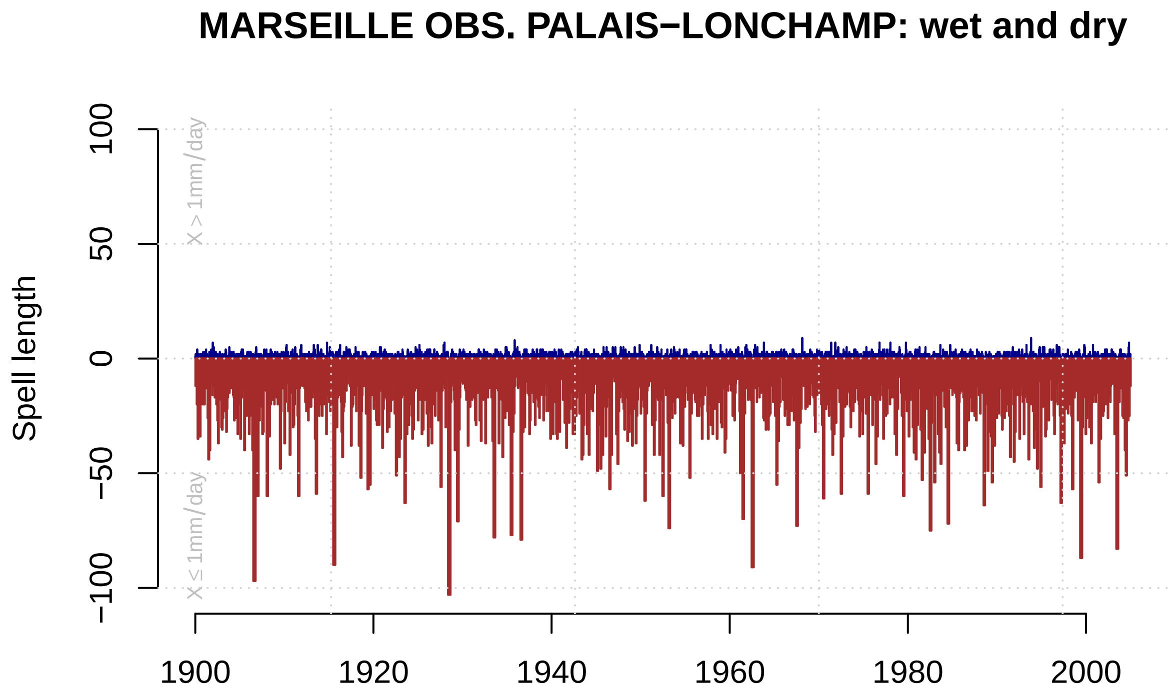
```
z <- subset(x,it=c(1900,2016),is=1)
ncd <- spell(z,threshold=1)
```

```
## [1] "Warning:  4235 missing values ( 10  %) filled by interpolation"
```

```
plot(ncd)
```

```
## NULL
```

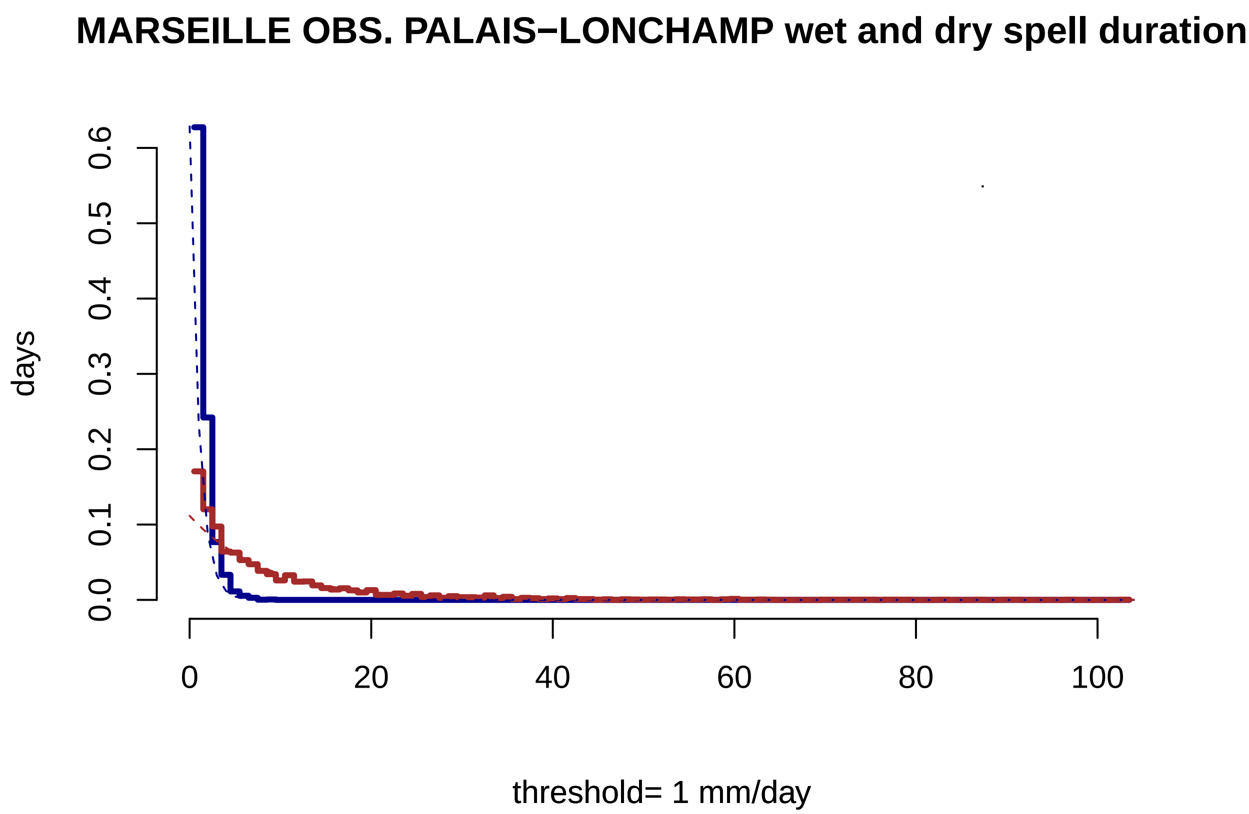
```
grid()
```



The dry runs usually last longer than the wet runs. some of the longest dry spells have lasted for ~100 days, but it has rarely rained more than 5 days in a row. One question is whether the dry/wet spell statistics can be considered to be a result of random/stochastic processes, or if they contain more structure.

If there is only a fixed probability for wet/dry day that detemines the outcome, then we can use the geometric distribution to represent the statistics of the wet/dry spells: https://en.wikipedia.org/wiki/Geometric_distribution. The question then is how closely the duration of wet/dry spells follow the geometric distribution. The histogram below compares the data to the pdfs for the geometric distribution and suggest a good match.

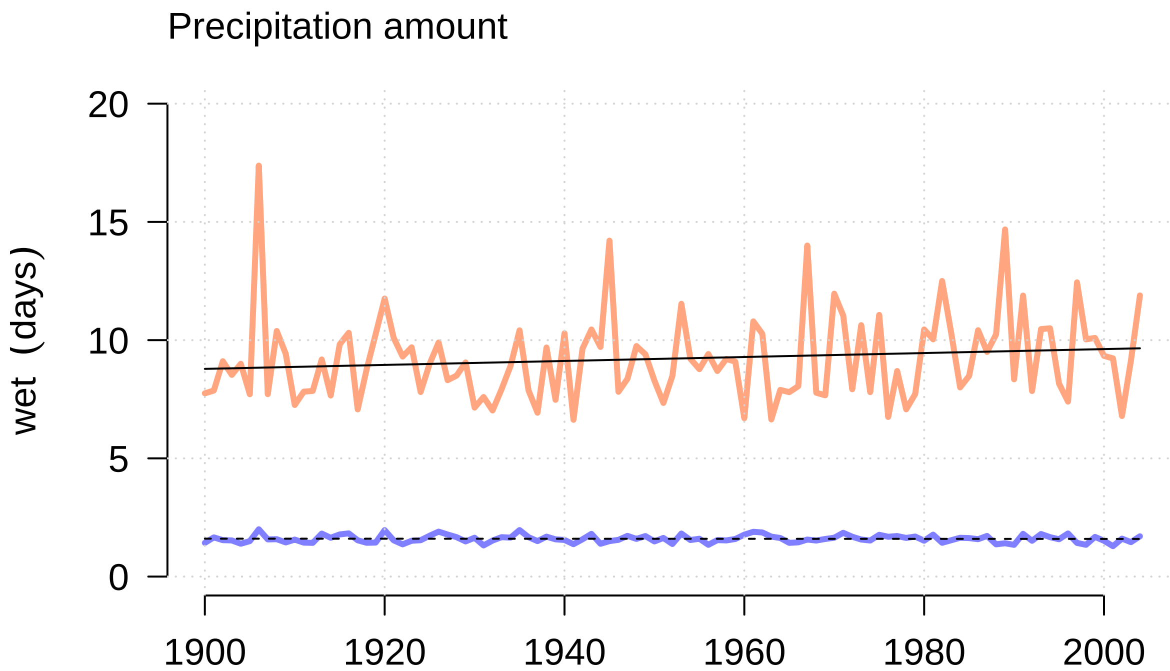
```
hist(ncd)
```



The mean value if the parameter that describes the shape of the geometric distribution. The comparison suggests that it does not give a bad representation of the observed charactereistics.

The second question is then: Are there any trends in the annual mean durations?

```
amncd <- annual(ncd)
plot(amncd,col=c(rgb(0,0,1),rgb(1,0.3,0)),new=FALSE,map.show=FALSE)
grid()
lines(trend(subset(amncd,is=1)),lty=2)
mcdd <- trend(subset(amncd,is=2))
lines(mcdd,lty=1)
```

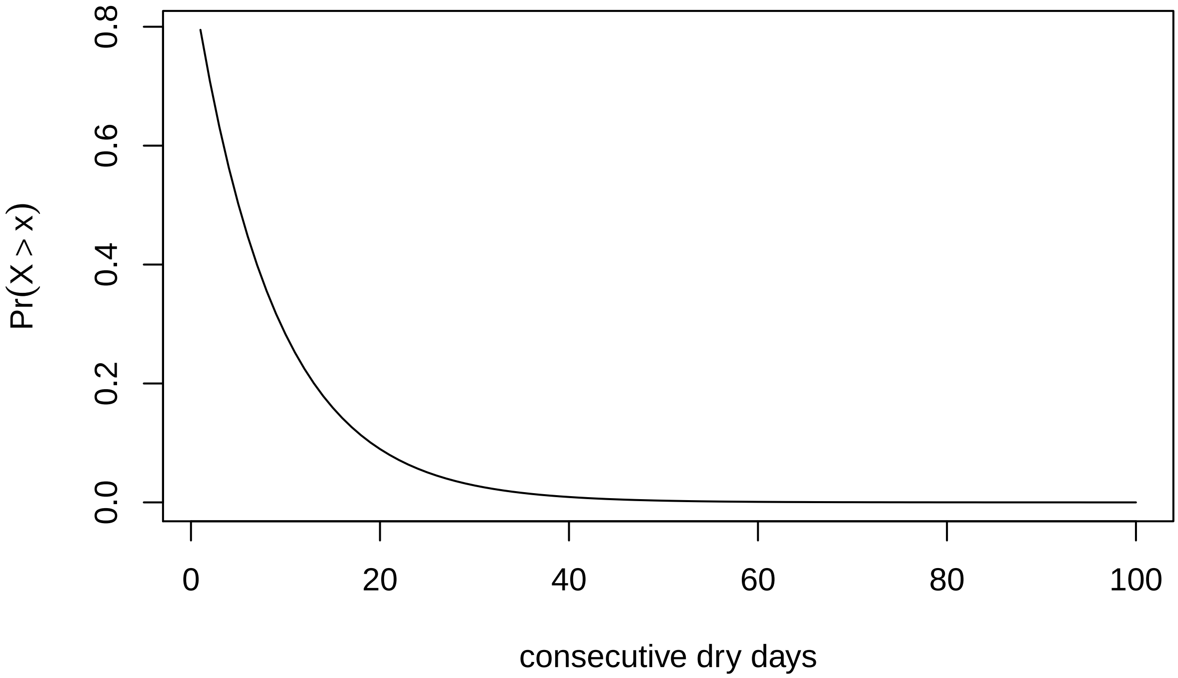



```
print(attr(mcdd,'coefficients'))
```

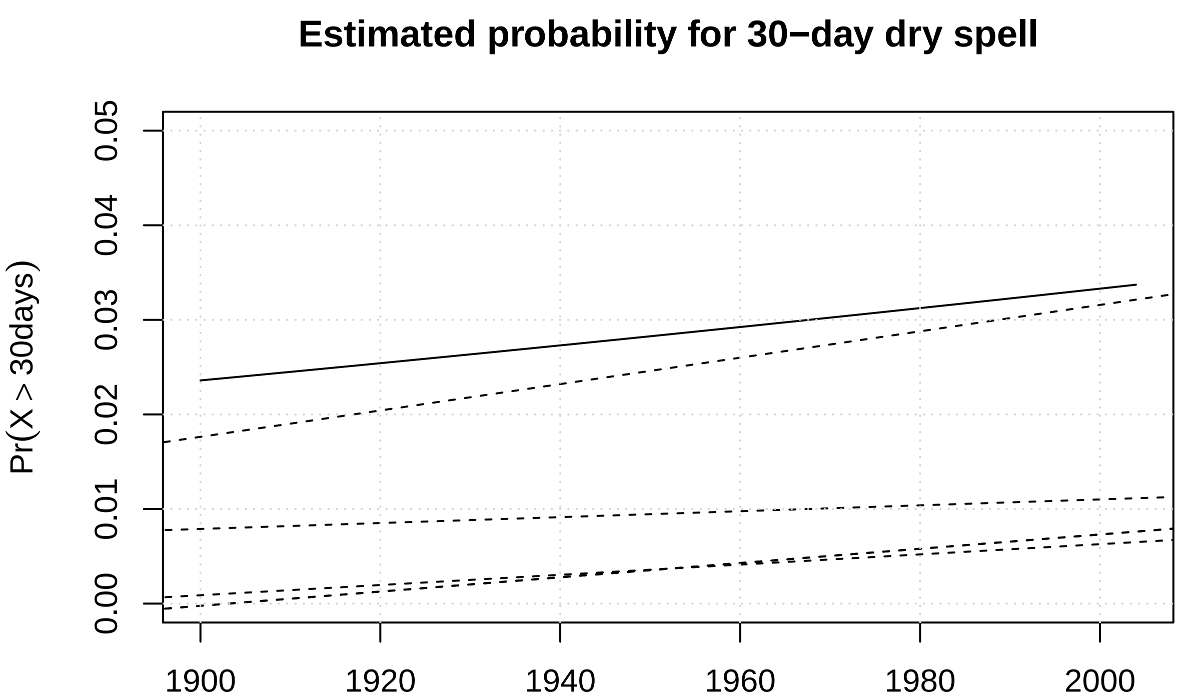
```
##                Estimate  Std. Error    t value  Pr(>|t|)
## (Intercept) -7.112431978 11.52234617 -0.6172729 0.5384170
## t            0.008366542  0.00590213  1.4175462 0.1593413
```

There is a slight increasing trend in the annual mean duration of dry spells, which also has a consequence for the probability of long-lasting meteorological droughts.

```
plot(1-pgeom(1:100,1/mean(mcdd)),type='l',xlab='consecutive dry days',ylab=expression(Pr(X > x)))
```




```
plot(index(mcdd),1-pgeom(30, 1/mcdd),type='l',xlab='',ylab=expression(Pr(X > 30*days)),
     main='Estimated probability for 30-day dry spell',ylim=c(0,0.05))
for (i in 1:dim(Pr)[2]) lines(trend(subset(Pr,is=i)),lty=2)
grid()
```



Linear trend analysis applied to both the duration of dry spells (solid line for one site in figure above) and the probability of more than 100 mm rain per day (dashed line showing several sites) both exhibit long-term increases over the last ~100 years. This tendency can be interpreted as the risk of long dry periods increases while the amount that falls as rain gets more extreme for the wet days. In other words, there has been a growing risk for both droughts and flash floods.

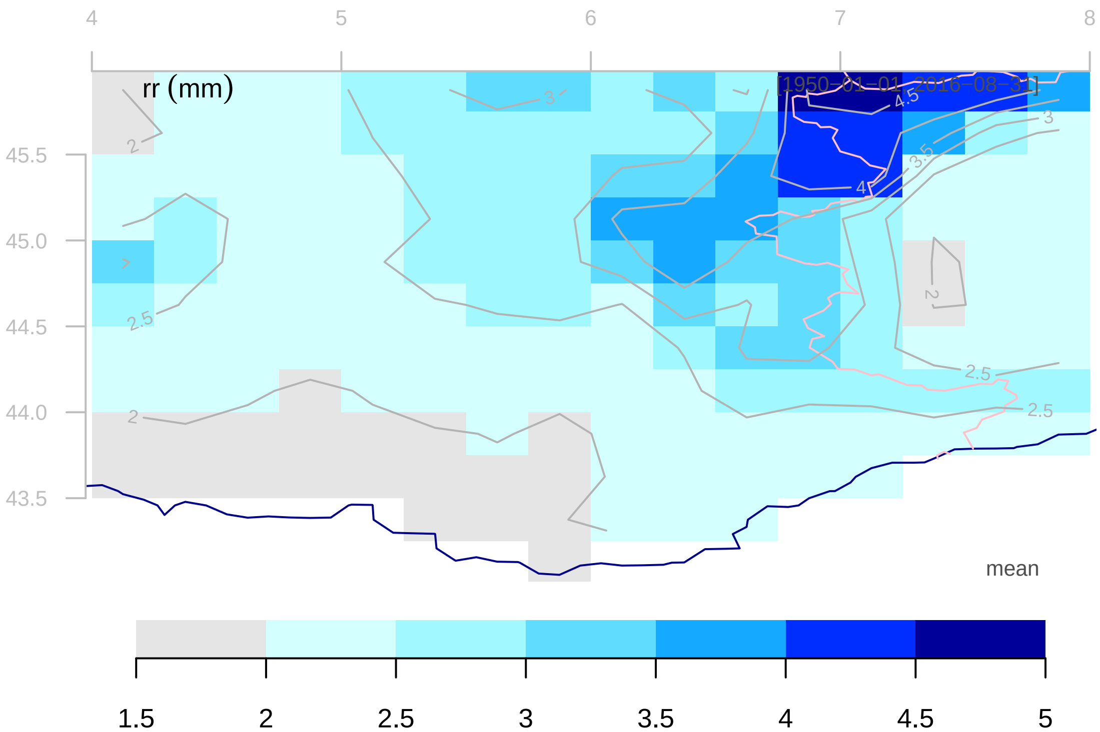
Gridded precipitation

The geographical pattern of trend in dry spell duration can be analysed using gridded data from EOBs (based on the ECA&D station records) Here gridded precipitation is represented with upper-case X. Gridded data are not ideal when it comes to extremes, as the gridding process makes the data spatially inhomogeneous. There are geographical variations in the climatological precipitation, with more precipitation over the higher elevations and the southern Alps.

```
X <- retrieve('~/data/data.ECAD/rr_0.25deg_reg.nc',lon=c(4,8),lat=c(43,46))
```

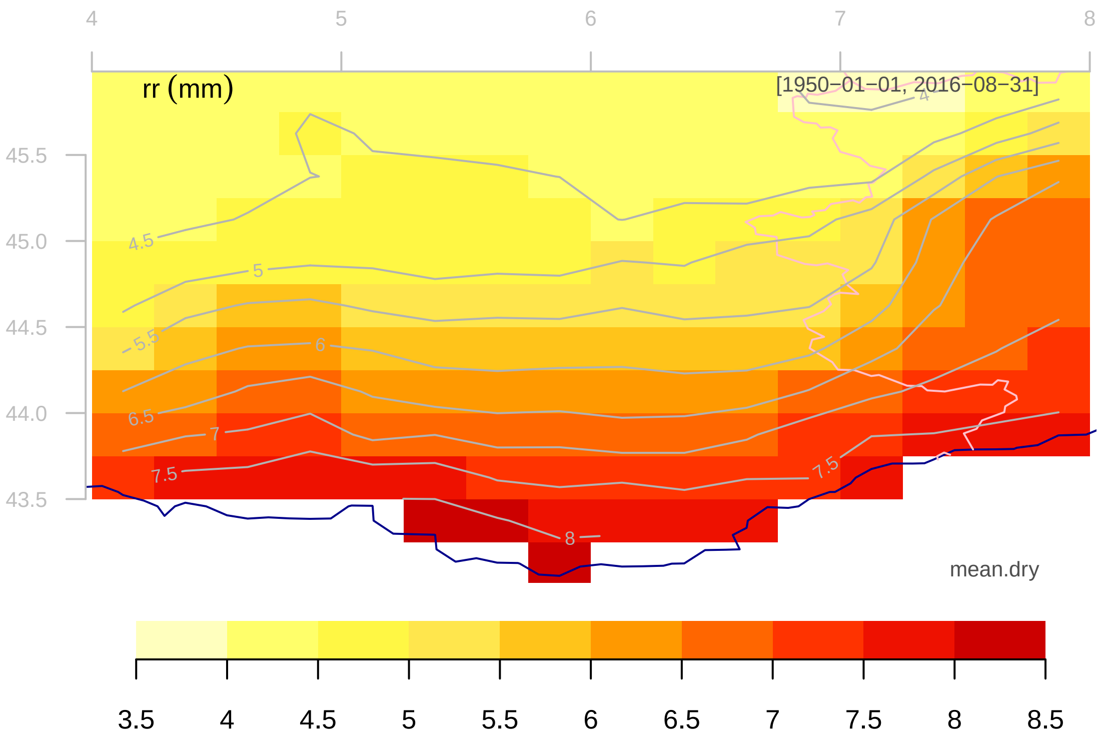
```
## [1] "Warning : Calendar attribute has not been found in the meta data and will be set automatically.
```

```
map(X,new=FALSE)
```



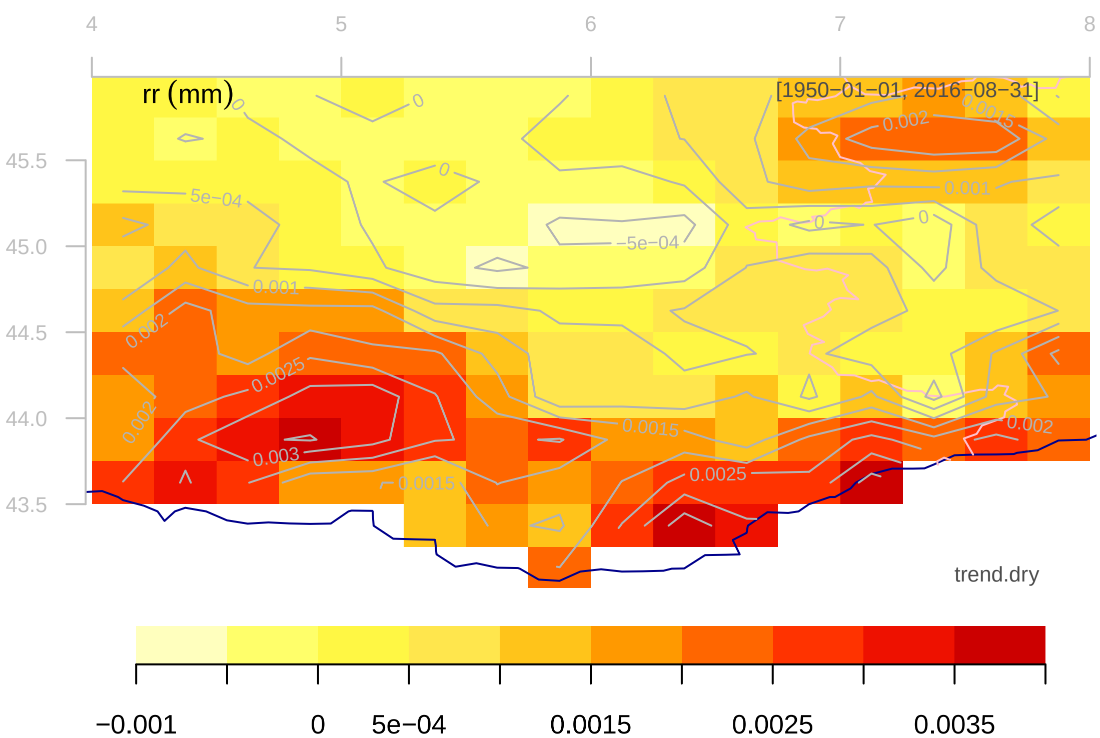
A similar analysis of the mean dry spell duration indictes that the dry periods typically last longer near the coast.

```
mean.dry <- function(x,na.rm=TRUE) mean(subset(spell(x,threshold=1),is=2),na.rm=na.rm)
map(X,FUN='mean.dry',new=FALSE,colbar=list(pal='warm'))
```



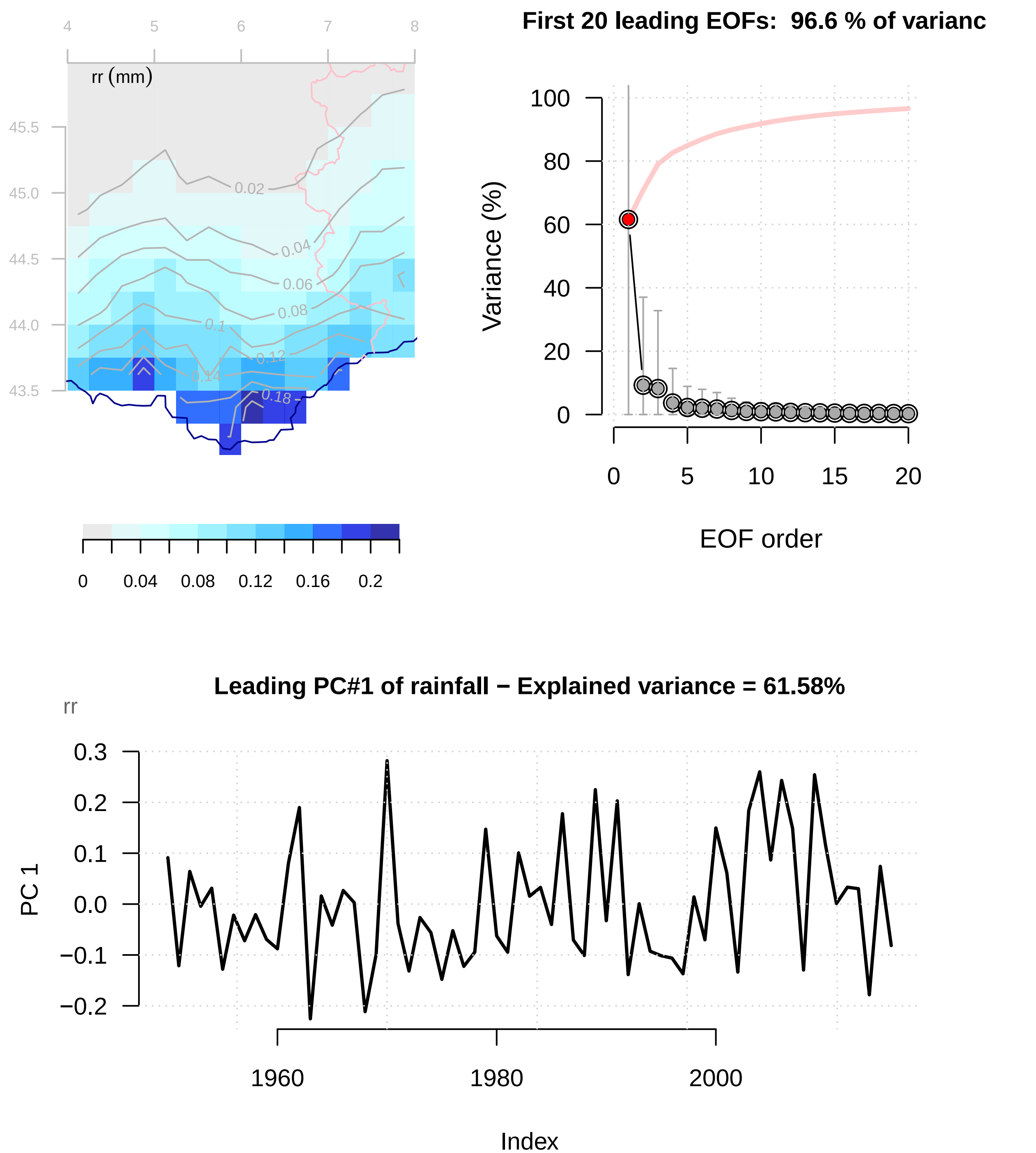
It is also along the coast where there has been a strongest trend in the mean duration of the dry spells, which has an implication for the probability of long dry periods according to the geometric distribution.

```
trend.dry <- function(x,na.rm=TRUE) trend.coef(subset(spell(x,threshold=1),is=2))
map(X,FUN='trend.dry',new=FALSE,colbar=list(pal='warm'))
```



Calculate EOFs which can serve as predictors for the downscaling.

```
dryseason <- function(x,na.rm=TRUE) if (sum(is.finite(x))>1) mean(subset(spell(x,threshold=1),is=2),na.
if (!file.exists('case1-dryseason.rda')) {
  z <- aggregate(subset(X,it='mjjas'),year,FUN='dryseason')
  save(z,file='case1-dryseason.rda')
} else load('case1-dryseason.rda')
eof.dry <- EOF(z)
plot(eof.dry)
```



Only the 4 leading EOFs for the seasonal mean dry spell length are relevant. The higher orders are noise. This is according to expectations, i.e. that droughts and heat waves are large-scale phenomena.

```r
eof.dry <- subset(eof.dry,ip=1:4)
```

Predictors for calibration: check for any dependency

```r
T2M <- aggregate(subset(retrieve('~/Downloads/air.mon.mean.nc',lon=c(-12,35),lat=c(27,50)),it='mjjas'),y
```

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

```r
SLP <- aggregate(subset(retrieve('~/Downloads/slp.mon.mean.nc',lon=c(-12,35),lat=c(27,50)),it='mjjas'),y
```

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

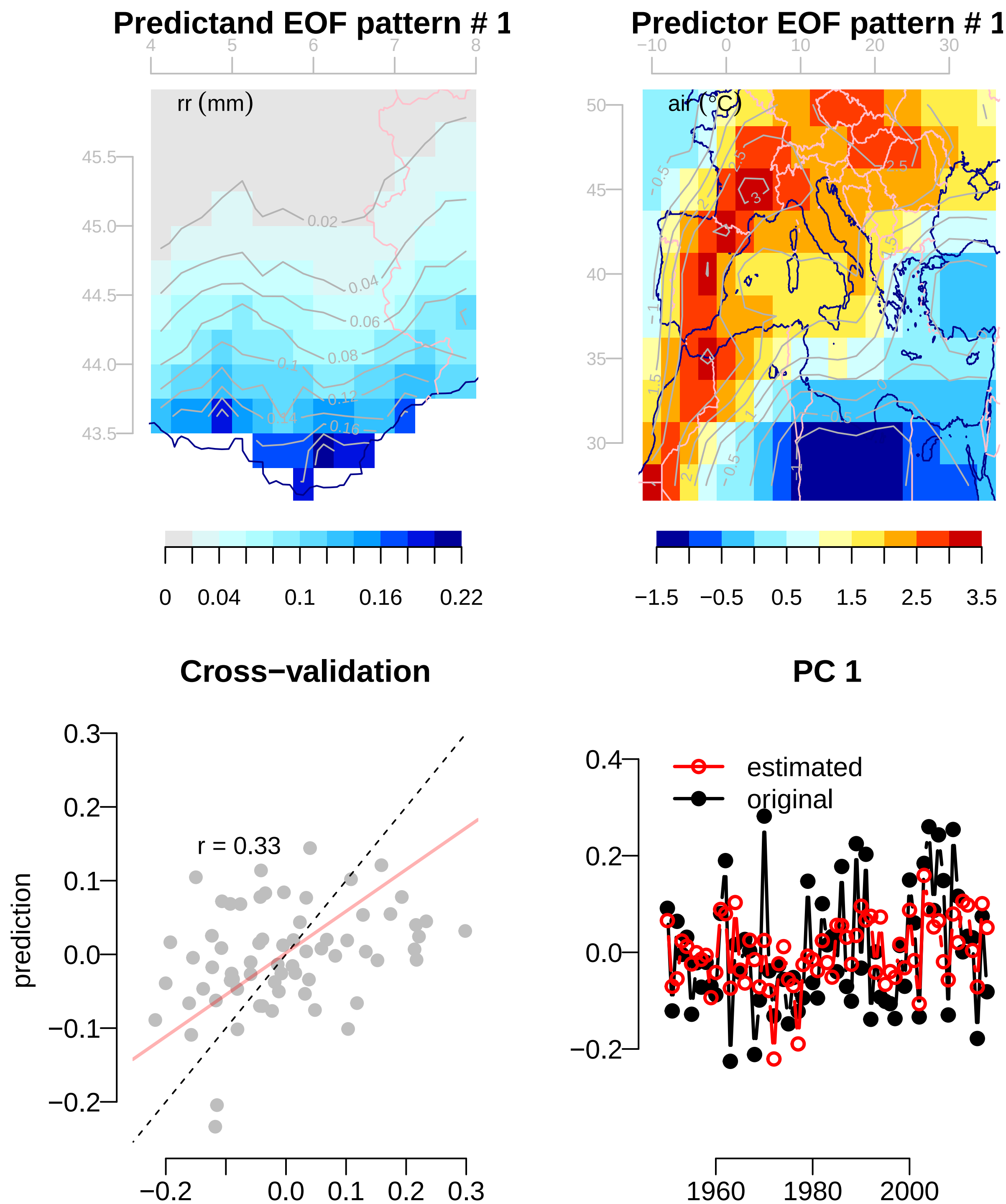
```r
eof.t2m <- EOF(T2M)
eof.slp <- EOF(SLP)
```

Examine the connection between temperature and dry spells:

```r
ds.t2m <- DS(eof.dry,eof.t2m)
```

```
##
  |
  |                                                                 |   0%
  |
  |================                                                 |  25%
  |
  |================================                                 |  50%
  |
  |=================================================                |  75%
  |
  |=================================================================| 100%
```

```r
plot(ds.t2m)
```




```
## NULL
```

Cross-validation scores of 0.33 for the leading EOF of the mean duration of dry spells and a temperature anomaly over Iberia and souther France suggest a real link.

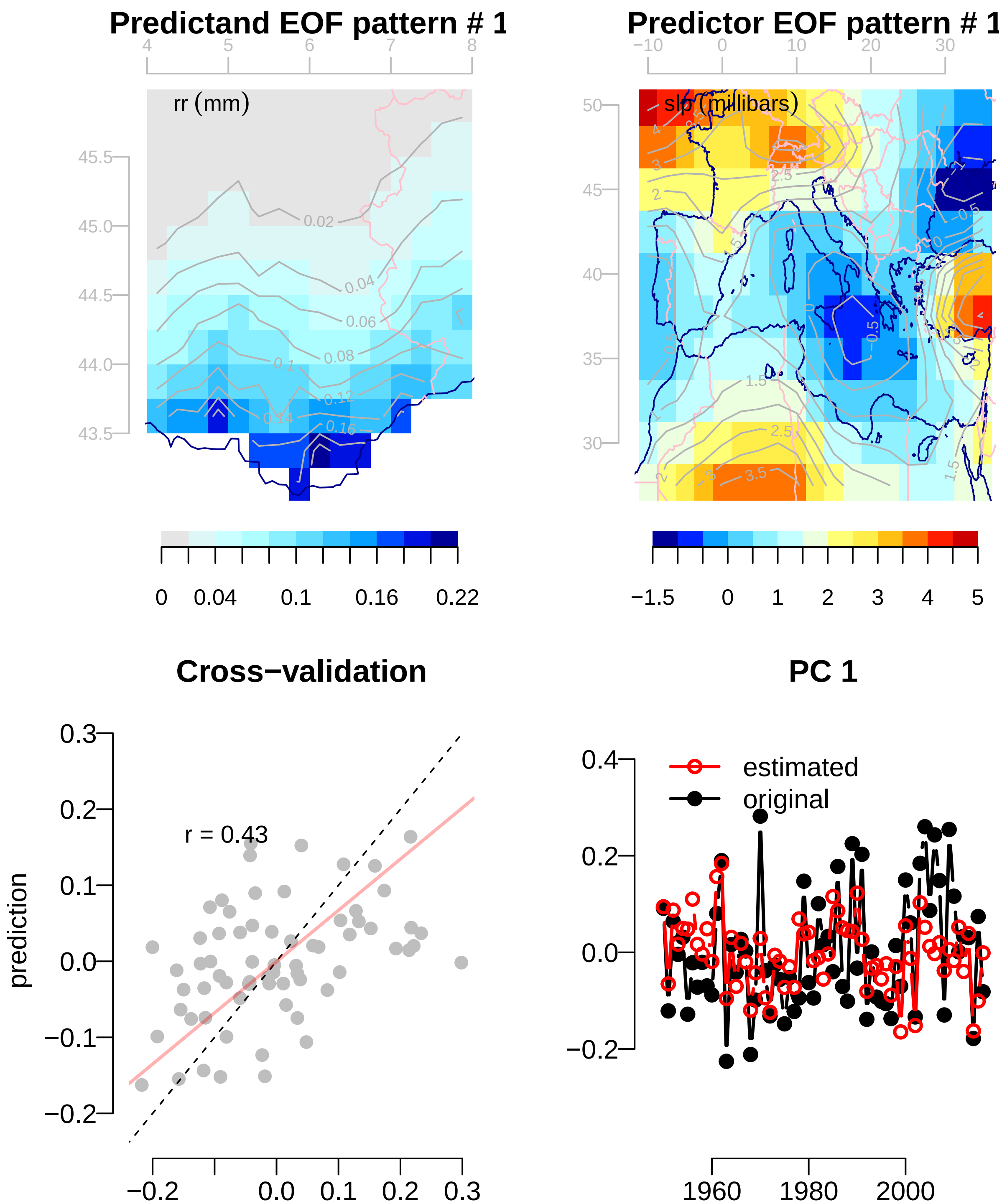
There is also a connection between sea-level pressure anomalies and dry spells.

```
ds.slp <- DS(eof.dry,eof.slp)
```

```
##
```

```
  |                                                                       
  |                                                                 |   0%
  |                                                                       
  |================                                                 |  25%
  |                                                                       
  |================================                                 |  50%
  |                                                                       
  |=================================================                |  75%
  |                                                                       
  |=================================================================| 100%
```

```r
plot(ds.slp)
```




```
## NULL
```

Cross-validation score of 0.43 and high SLP anomalies over France. The summertime temperature and SLP are expected to be related:

```
cca.slp.t2m <- CCA(eof.slp,eof.t2m)
plot(cca.slp.t2m)
```

The CCA suggests that there is covariance between SLP and temperature, and we need to avoid double counting of these effects.

Residual:

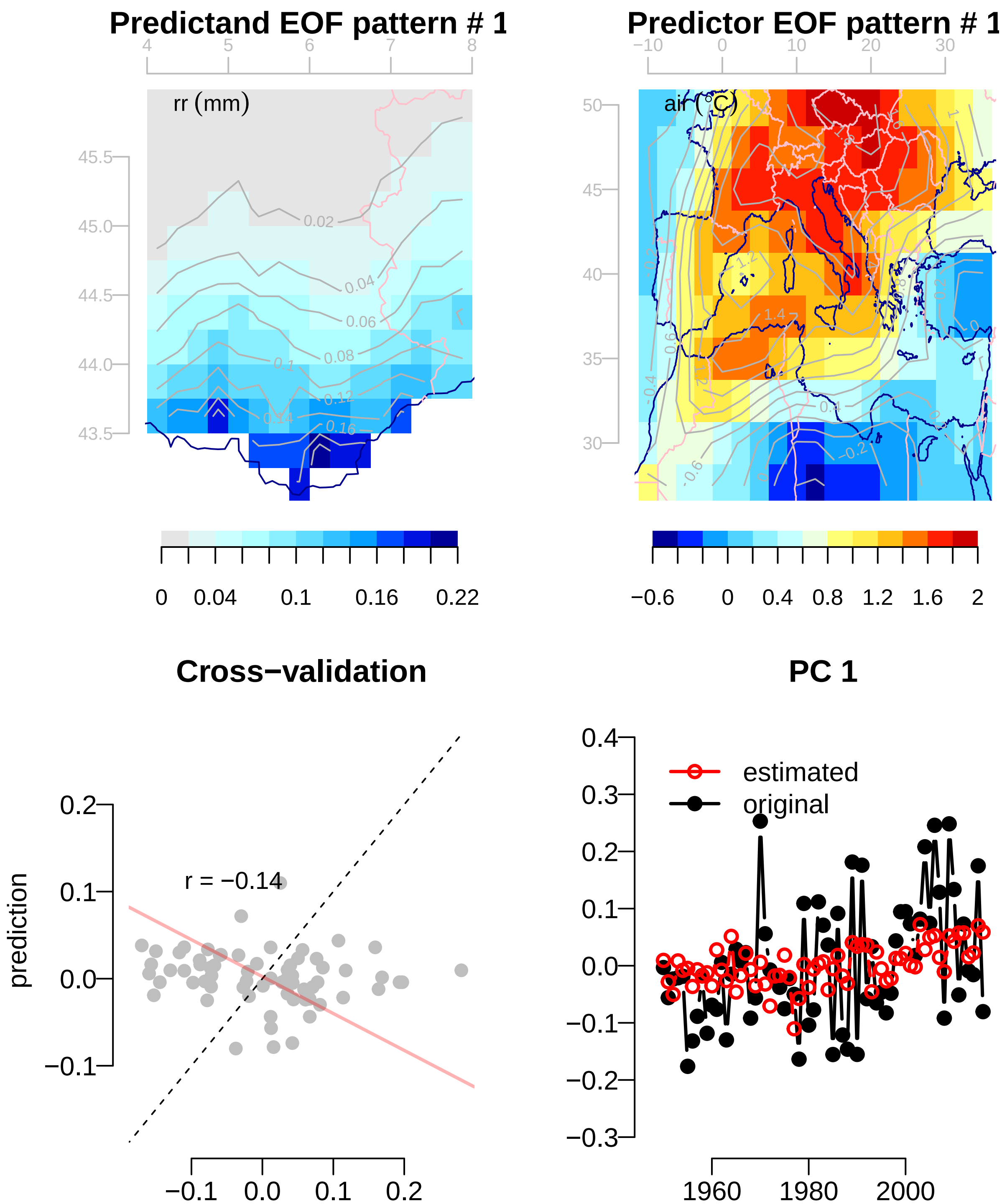
```
## Estimate the residuals
eof.res <- subset(eof.dry,it=ds.slp)
coredata(eof.res) <- coredata(eof.res) - coredata(ds.slp)
```

Check to see if the residual contains covariance with the temperature

```
ds.res <- DS(eof.res,eof.t2m)
```

```
##
  |
  |                                                                 |   0%
  |
  |================                                                 |  25%
  |
  |================================                                 |  50%
  |
  |=================================================                |  75%
  |
  |=================================================================| 100%
```

```
plot(ds.res)
```




```
## NULL
```

Dry conditions and wild fire statistics

Use the EOFs describing the dry conditions as predictors and wild fire statistics as predictand to assess the connection

```r
# z <- DS(wfire,eof.dry)
```

Projections for the future

Need to read the predictors again to get all months

```r
T2M <- retrieve('~/Downloads/air.mon.mean.nc',lon=c(-12,35),lat=c(27,50))
```

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

```r
SLP <- retrieve('~/Downloads/slp.mon.mean.nc',lon=c(-12,35),lat=c(27,50))
```

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

```r
## Also - fix the index of eof - set to year.
index(eof.dry) <- year(eof.dry)
```

Two seperate analyses based on SLP and temperature respectively, assuming the RCP 4.5 emission scenario. Start with the SLP and the original data

```r
if (!file.exists('dse.mld.slp.rda')) {
  dse.mld.slp <- DSensemble.eof(eof.dry,predictor=SLP,it='mjjas',path="~/data/CMIP5.monthly",pattern =
  save(dse.mld.slp,file = 'dse.mld.slp.rda')
} else load('dse.mld.slp.rda')
plot(dse.mld.slp)
```

Follow up with the residuals and the large-scale temperture

Add the the two components to get an estimate of the total change. The `dse`objects are lists which contain `zoo` time series:

Temperature

For heat waves, use a similar approach as described in the supporting material of where a GLM was used to estimate the number of events with a basis of the 'Poisson' distribution.