eu-circle_case-study-1

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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/e
```

Precipitation

Station data

Represent the station data with lower-case x

```
library(esd)
```

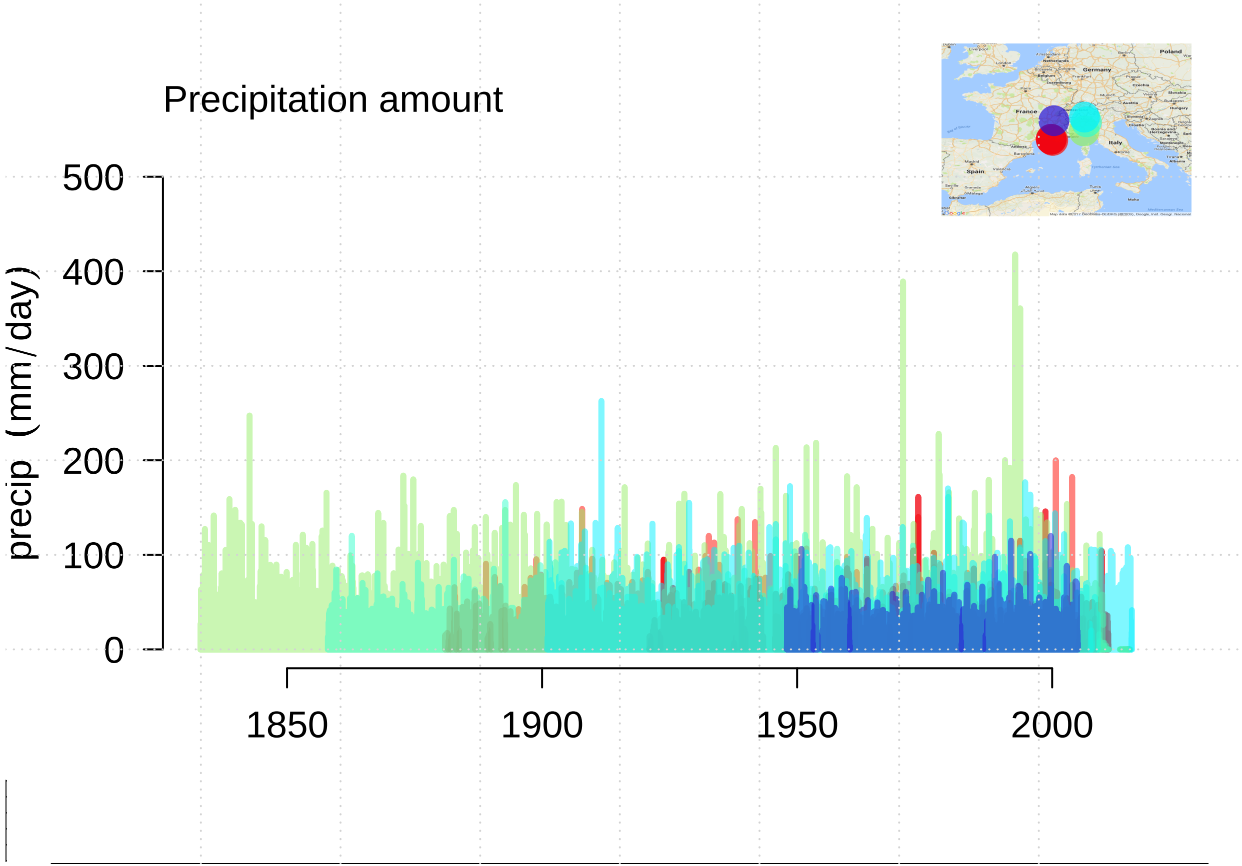
```
if (!file.exists('eu-circle_case-study-1_precio.rda')) {
  ss <- select.station(param='precip',lon=c(5,10),lat=c(42,45),nmin=50,src=c('ecad','ghcnd'))
  x <- station(ss)
  x <- subset(x,is=list(alt=-400))
  save(file='eu-circle_case-study-1_precio.rda',x)
} else load('eu-circle_case-study-1_precio.rda')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

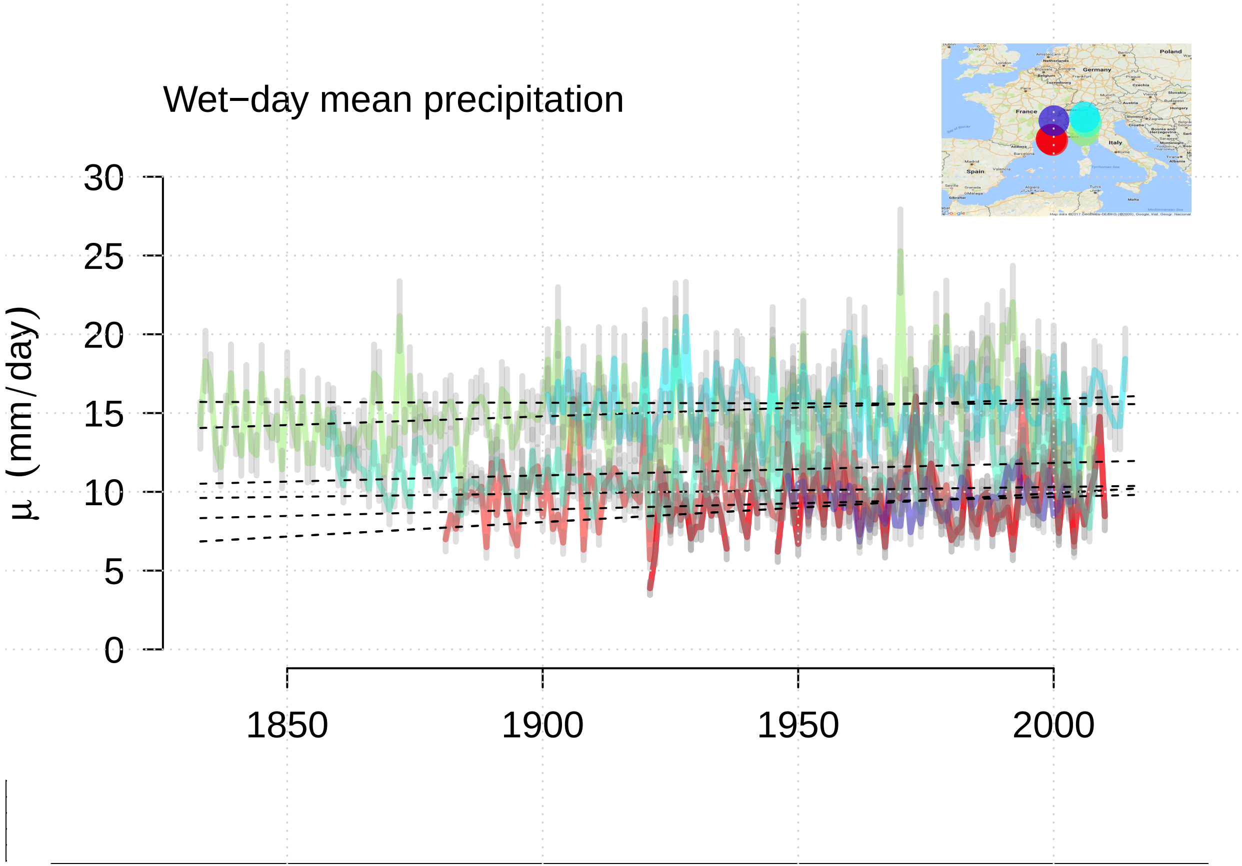
```
## Loading required package: RgoogleMaps
```

```
grid()
```



Examine the trend in the wet-day mean precipitation μ

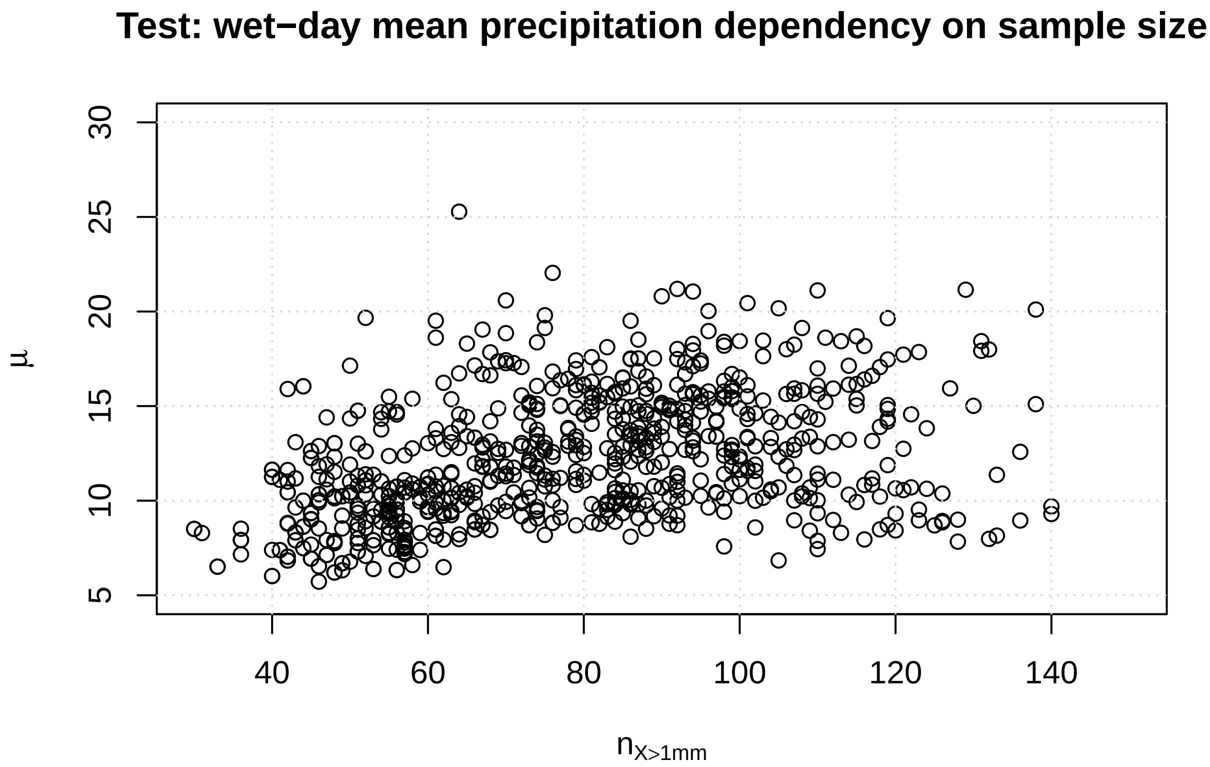
```
mu <- annual(x,'wetmean',nmin=250)
wq95 <- function(x) {x <- x[is.finite(x)]; x <- x[x >= 1]; wq95 <- quantile(x,probs=0.95); wq95}
q95 <- annual(x,'wq95')
plot(mu,new=FALSE)
for (i in 1:dim(mu)[2]) lines(trend(subset(mu,is=i)),lty=2)
grid()
```



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:

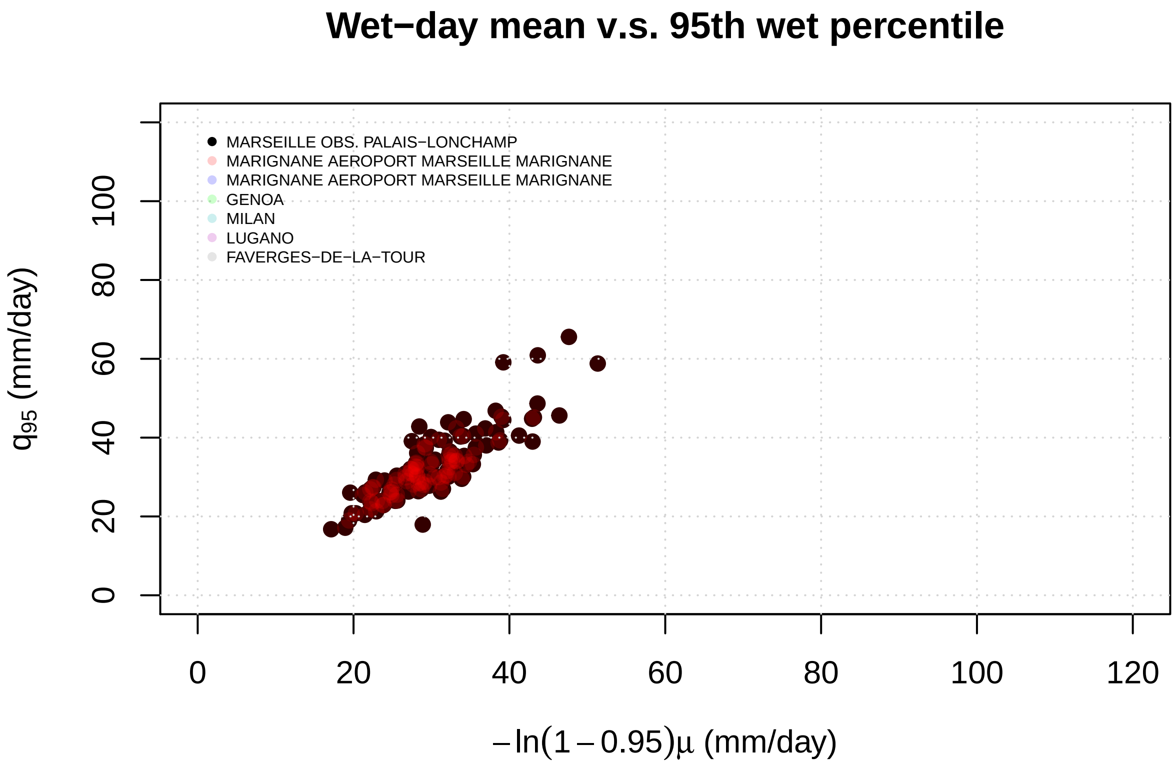
```
x1 <- zoo(subset(annual(x,'count',threshold=1),is=1))
y1 <- zoo(subset(mu,is=1))
plot(x1,y1,xlab=expression(n[X>1*mm]),ylab=expression(mu),xlim=c(30,150),ylim=c(5,30),
     main='Test: wet-day mean precipitation dependency on sample size')
for (i in 2:dim(mu)[2]) {
  x1 <- zoo(subset(annual(x,'count',threshold=1),is=i))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

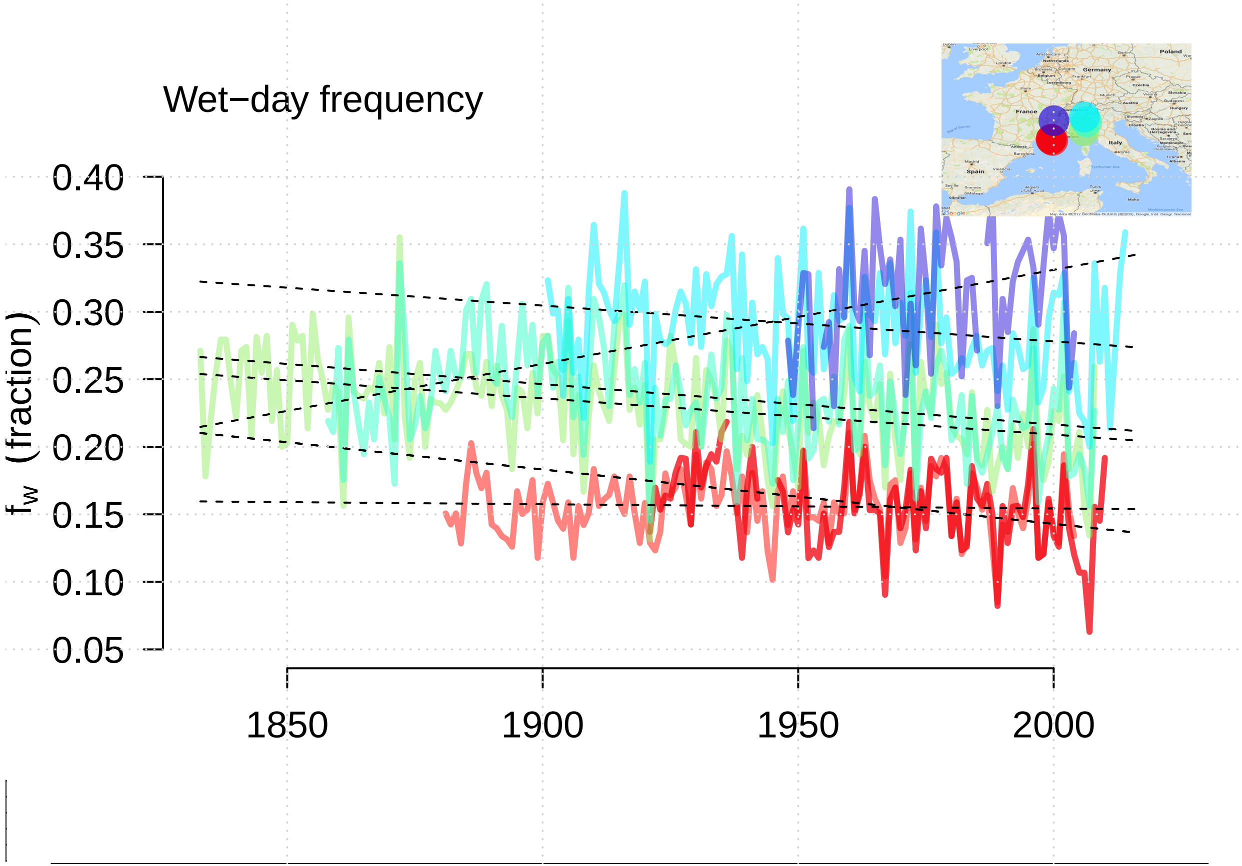
```
cols <- c(rgb(1,0,0,0.2),rgb(0,0,1,0.2),rgb(0,1,0,0.2),rgb(0,0.7,0.7,0.2),rgb(0.7,0,0.7,0.2),rgb(0.5,0.
## check the relationship between wet-day 95-percentile and wet-day mean
plot(-log(0.05)*zoo(mu[,1]),zoo(q95[,1]),pch=19,xlim=c(0,120),ylim=c(0,120),
     main='Wet-day mean v.s. 95th wet percentile',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



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:

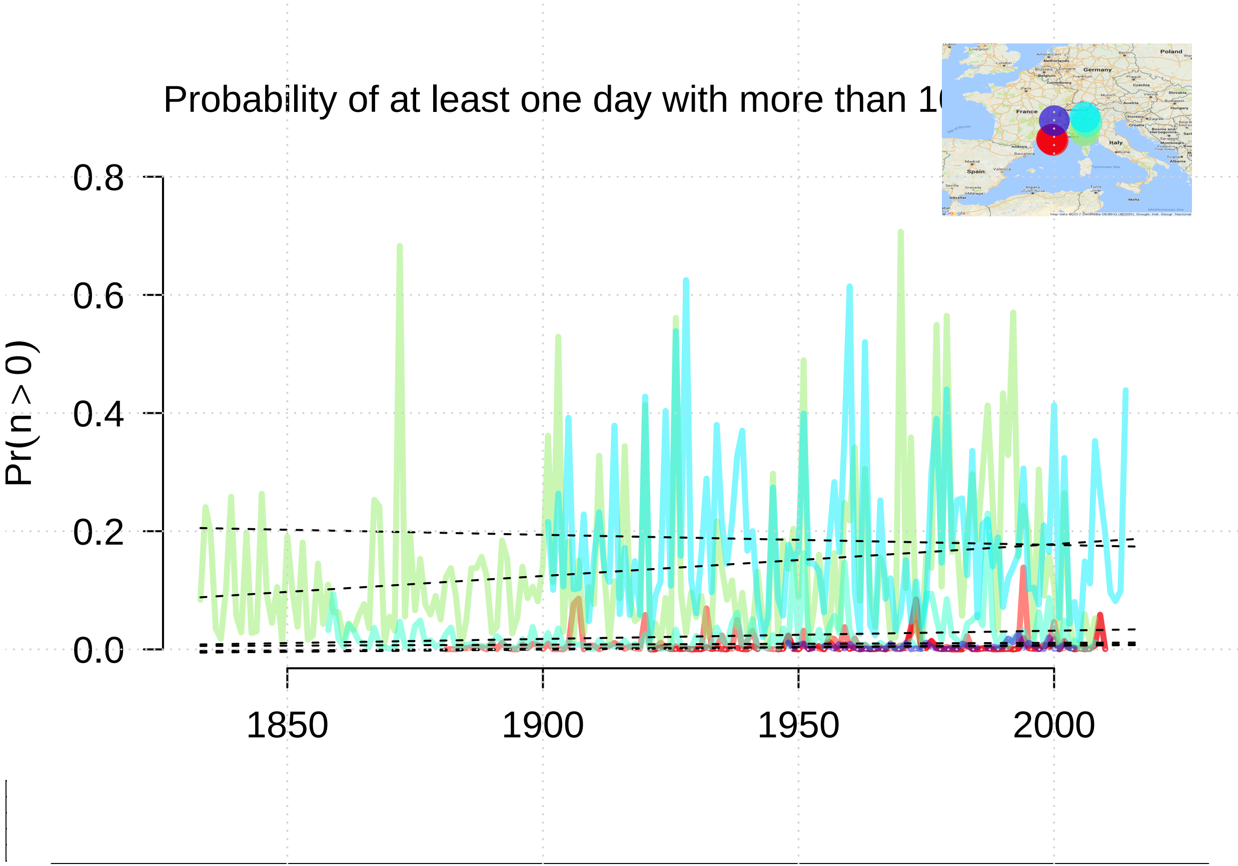
```
fw <- annual(x,'wetfreq',nmin=250)
plot(fw,new=FALSE)
for (i in 1:dim(fw)[2]) lines(trend(subset(fw,is=i)),lty=2)
grid()
```



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).

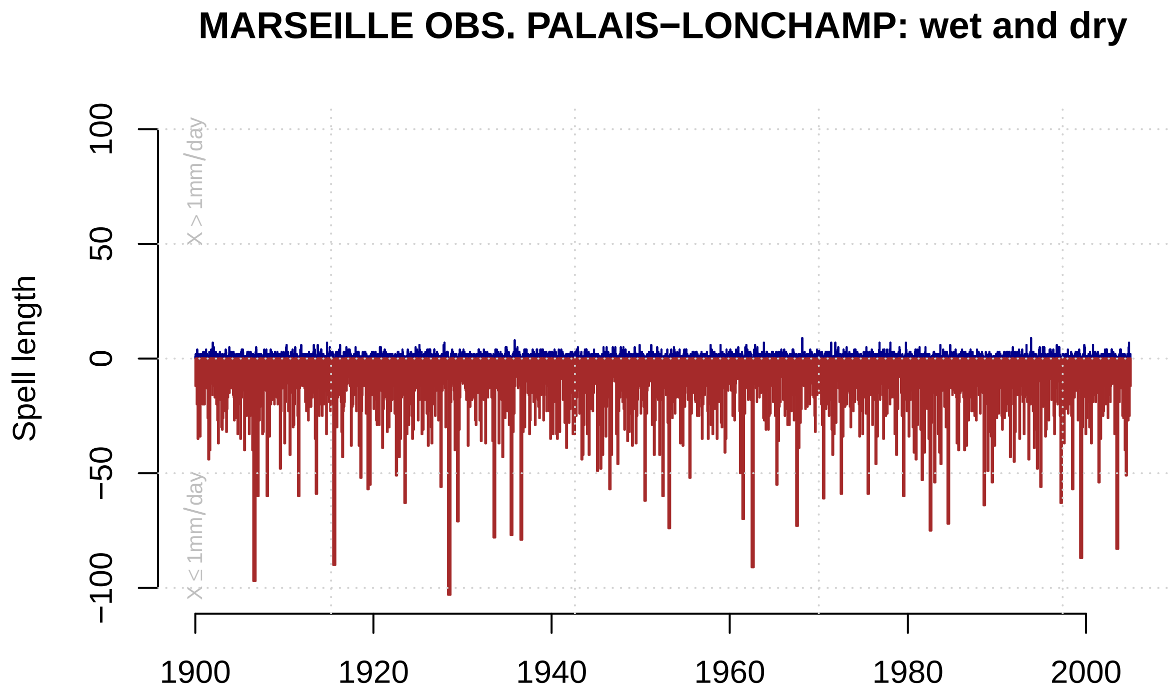
```
z <- subset(x,it=c(1900,2016),is=1)
ncd <- spell(z,threshold=1)
```

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

```
plot(ncd)
```

```
## NULL
```

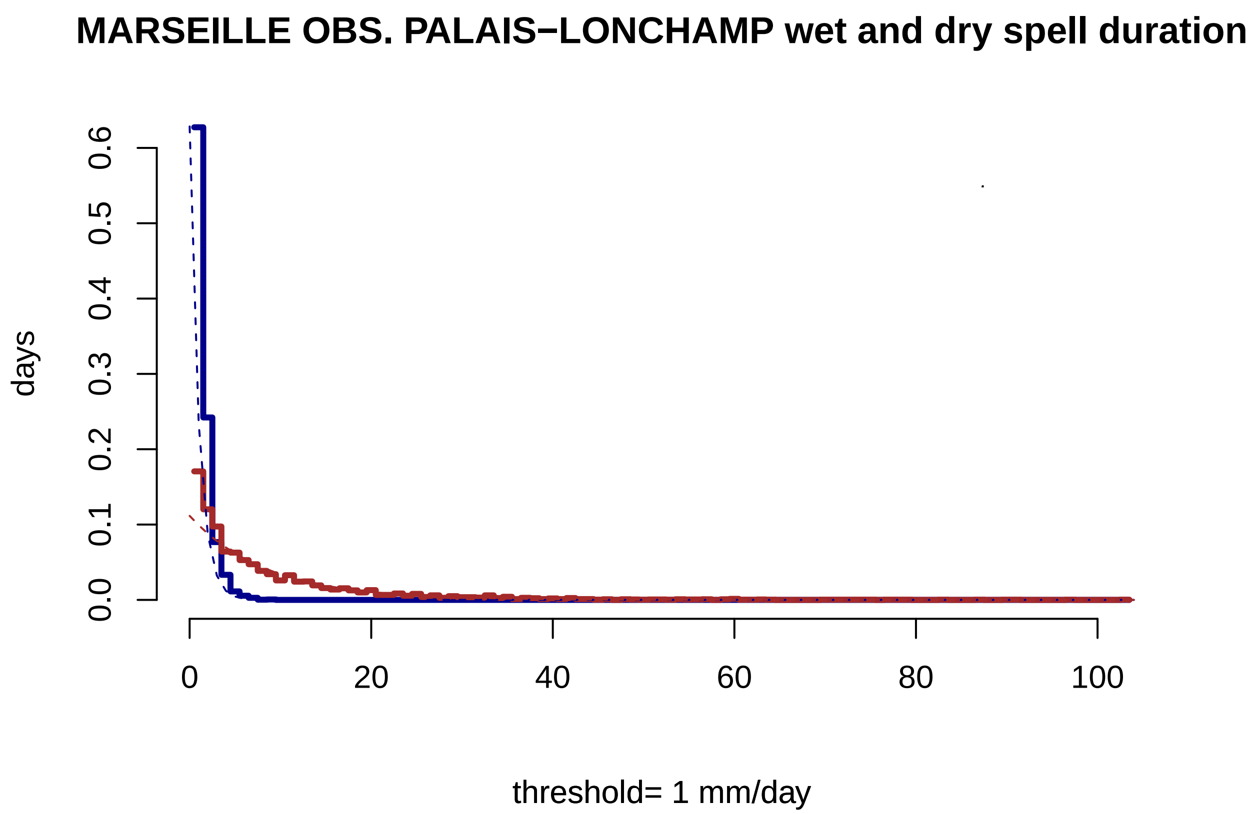
```
grid()
```



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.

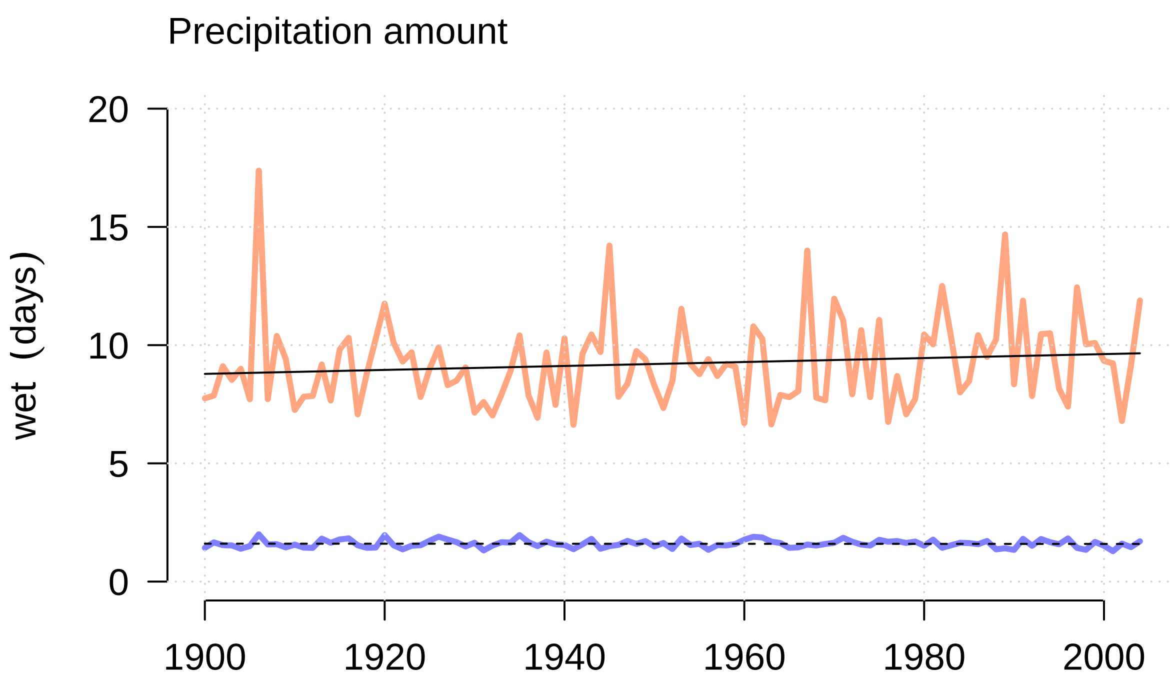
```
hist(ncd)
```



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)
```

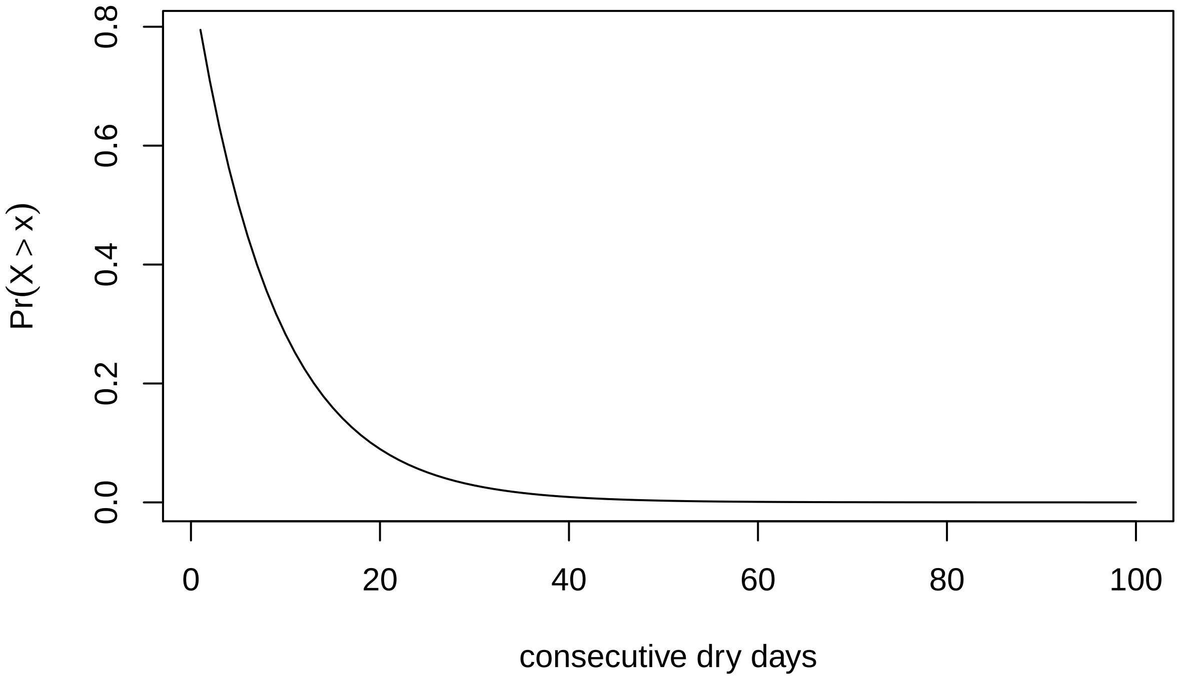



```
print(attr(mcdd,'coefficients'))
```

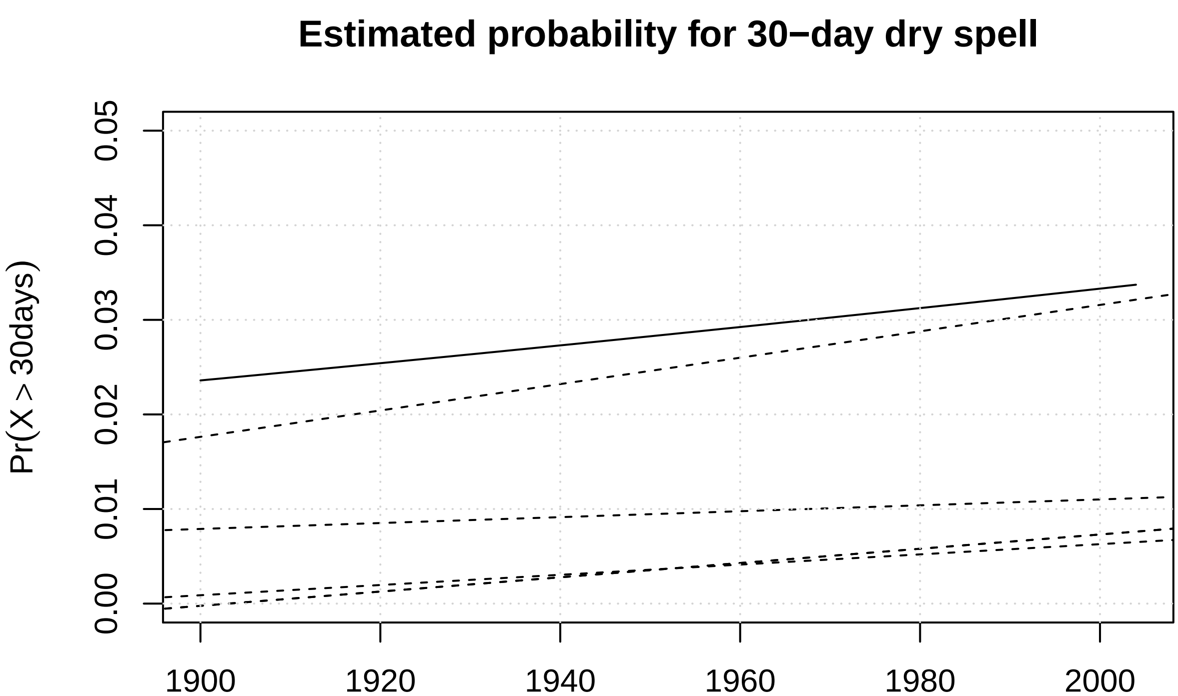
```
##                 Estimate  Std. Error    t value  Pr(>|t|)
## (Intercept) -7.112431978 11.52234617 -0.6172729 0.5384170
## t            0.008366542  0.00590213  1.4175462 0.1593413
```

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.

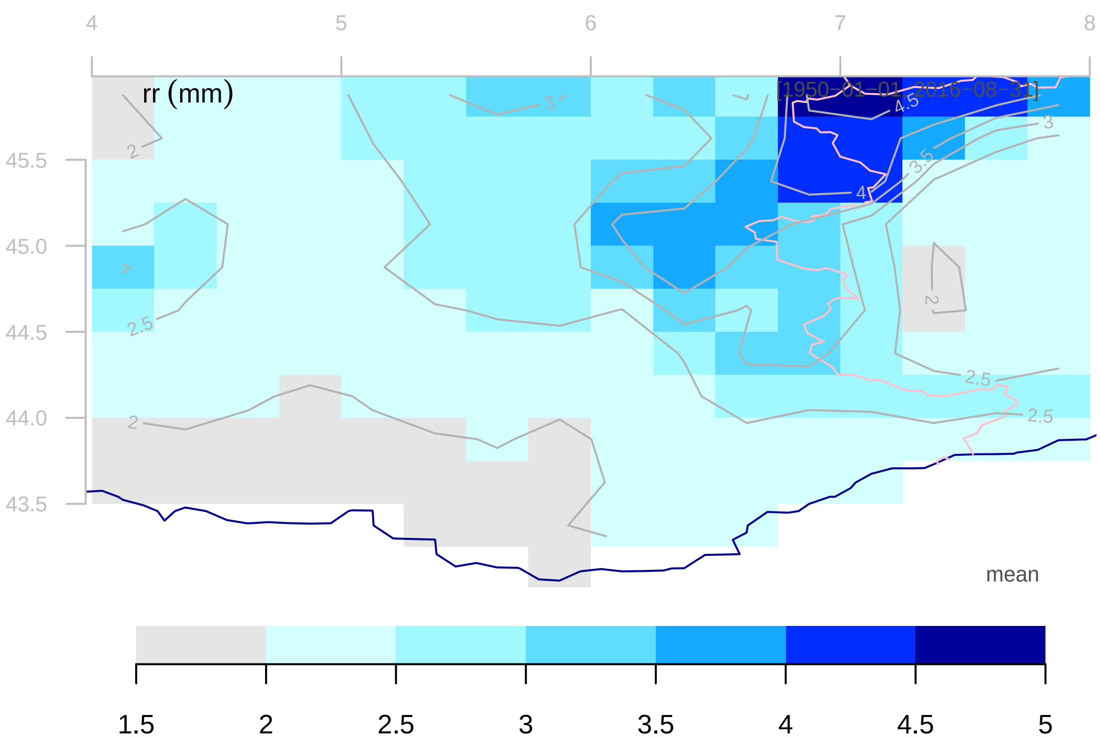
Gridded precipitation

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))
```

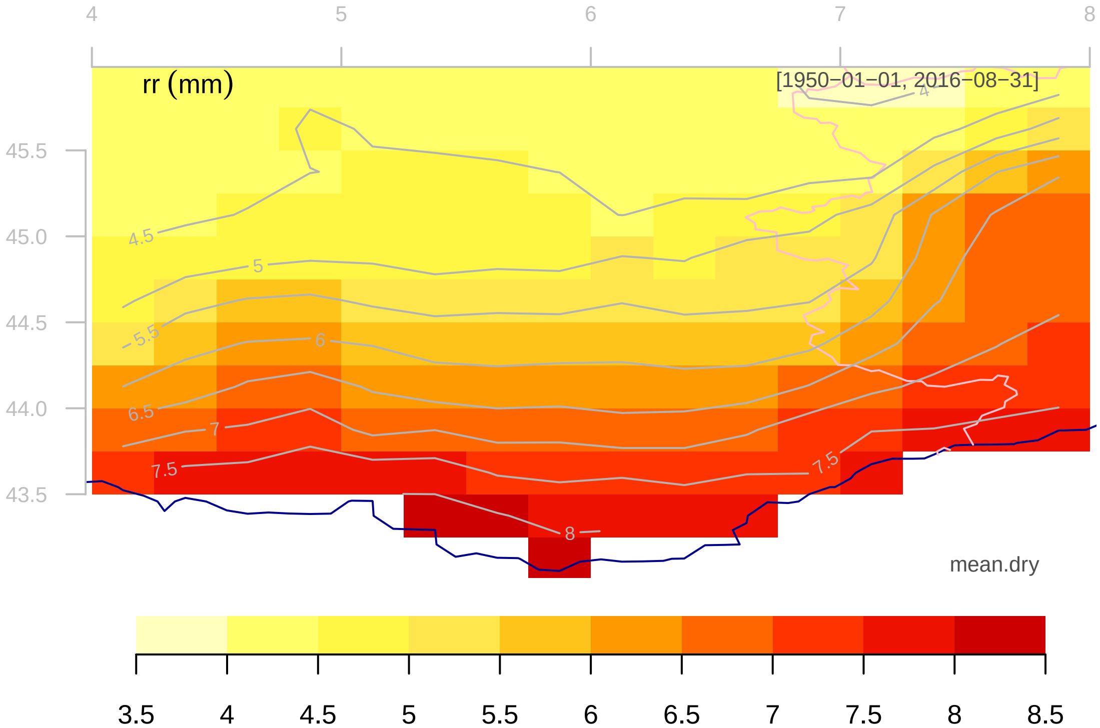
```
## [1] "Warning : Calendar attribute has not been found in the meta data and will be set automatically.
```

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



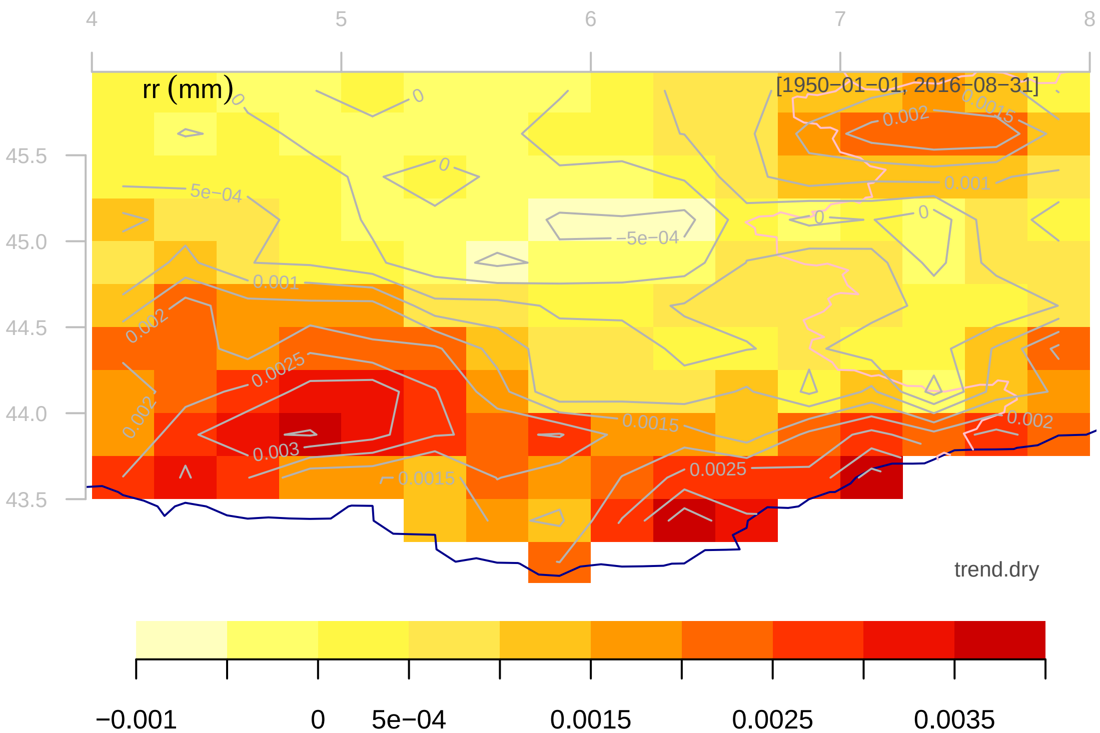
A similar analysis of the mean dry spell duration indictes that the dry periods typically last longer near the coast.

```
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'))
```



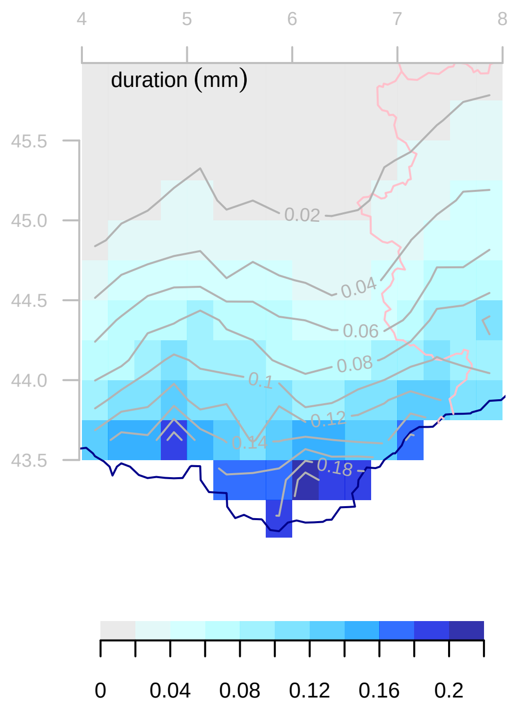
It is also along the coast where there has been a strongest trend in the mean duration of the dry spells, which has an implication for the probability of long dry periods according to the geometric distribution.

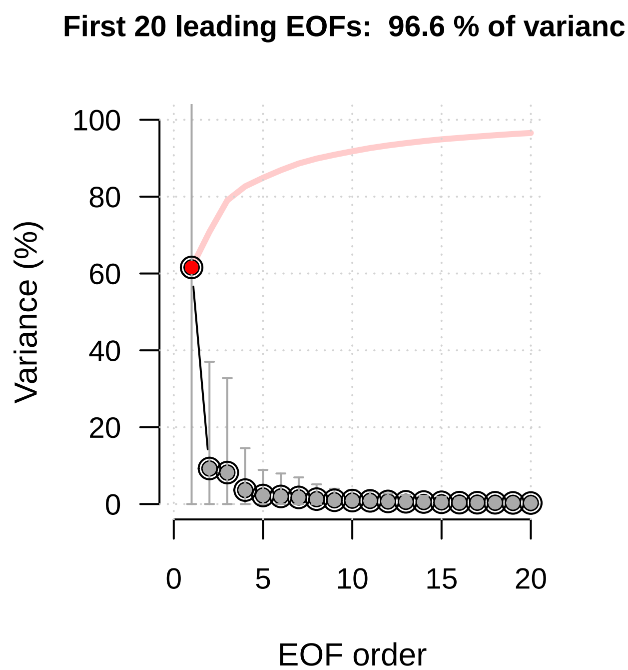
```
trend.dry <- function(x,na.rm=TRUE) trend.coef(subset(spell(x,threshold=1),is=2))
map(X,FUN='trend.dry',new=FALSE,colbar=list(pal='warm'))
```

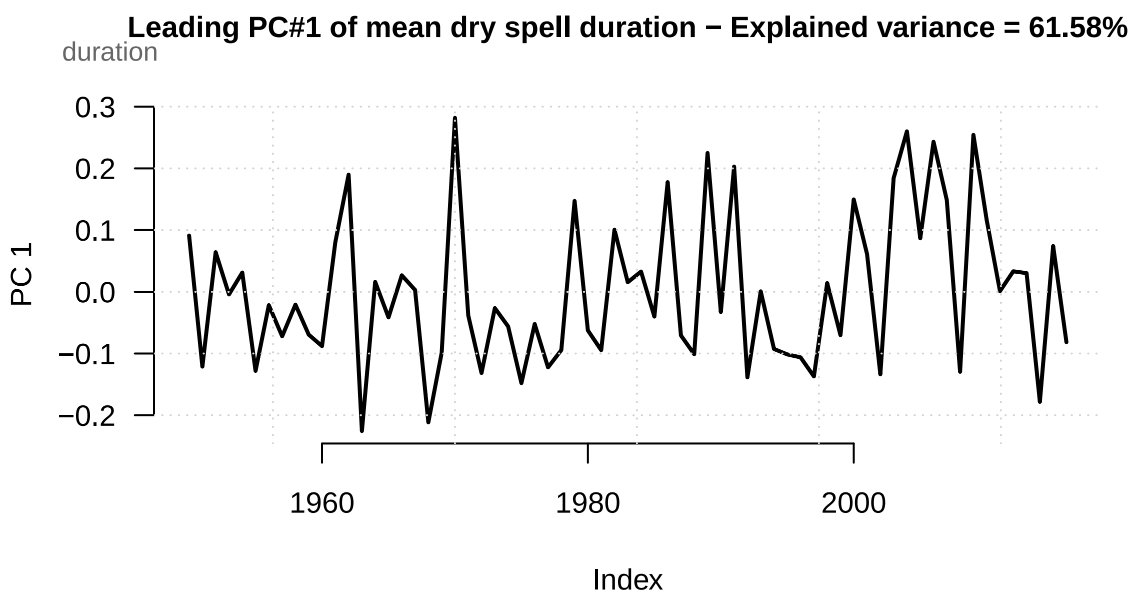


Calculate EOFs which can serve as predictors for the downscaling.

```
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')
attr(z,'variable') <- 'duration'
attr(z,'longname') <- 'mean dry spell duration'
eof.dry <- EOF(z)
plot(eof.dry,new=FALSE)
```







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.

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

Predictors for calibration: check for any dependency

```
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.
```

```
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.
```

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

Examine the connection between temperature and dry spells:

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

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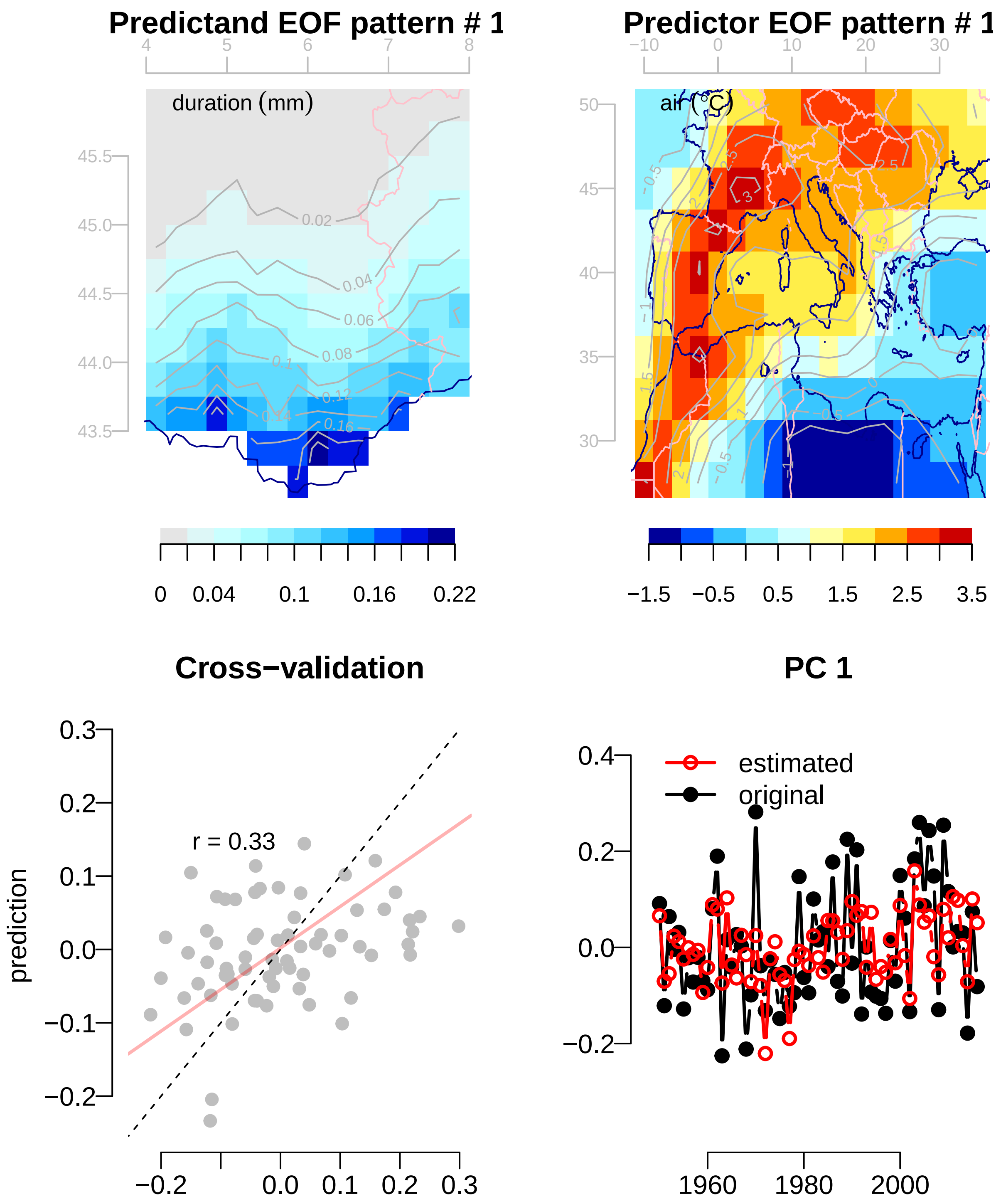

```
plot(ds.t2m,new=FALSE)
```




```
## 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.

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

```
##
```

```
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```
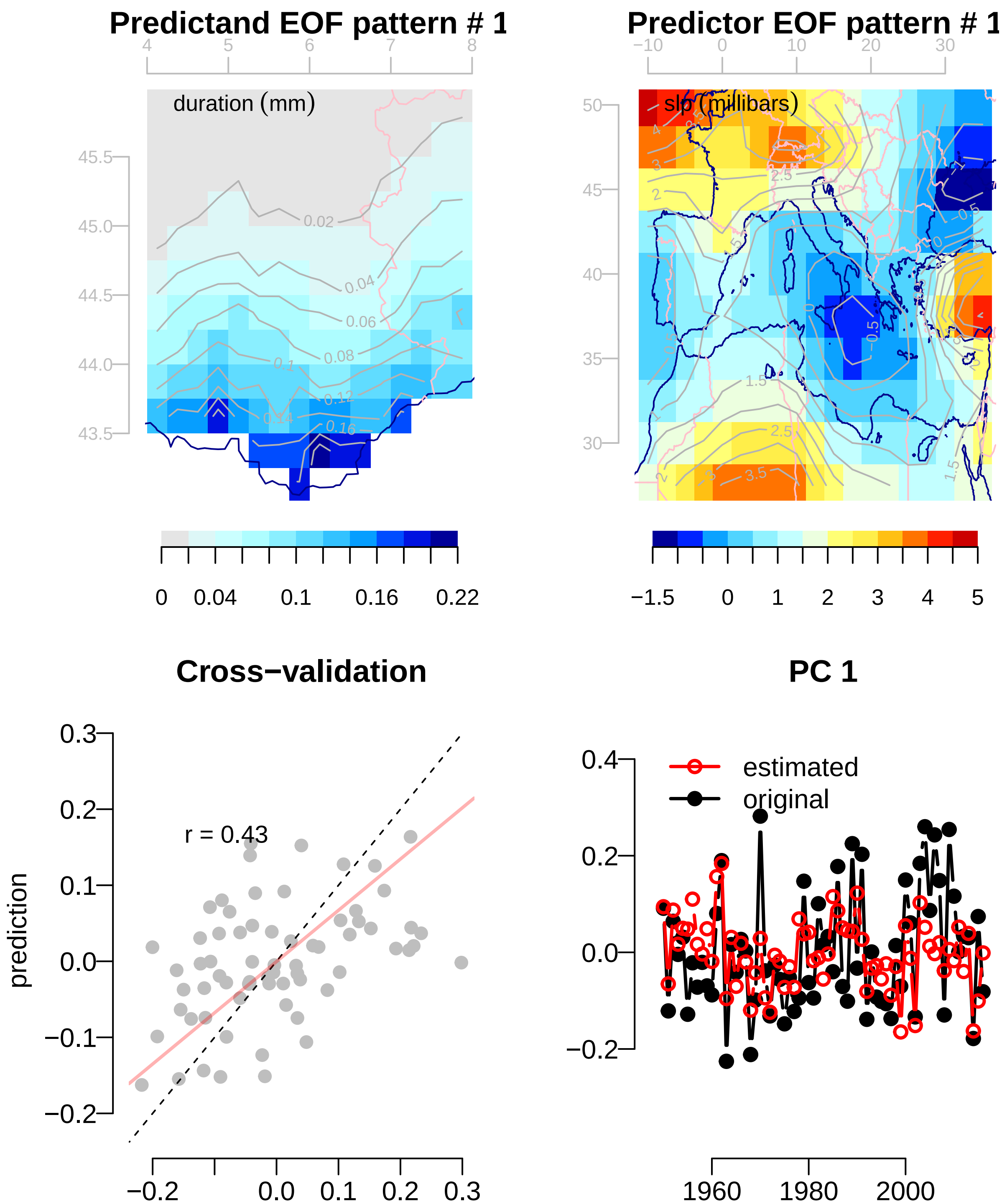
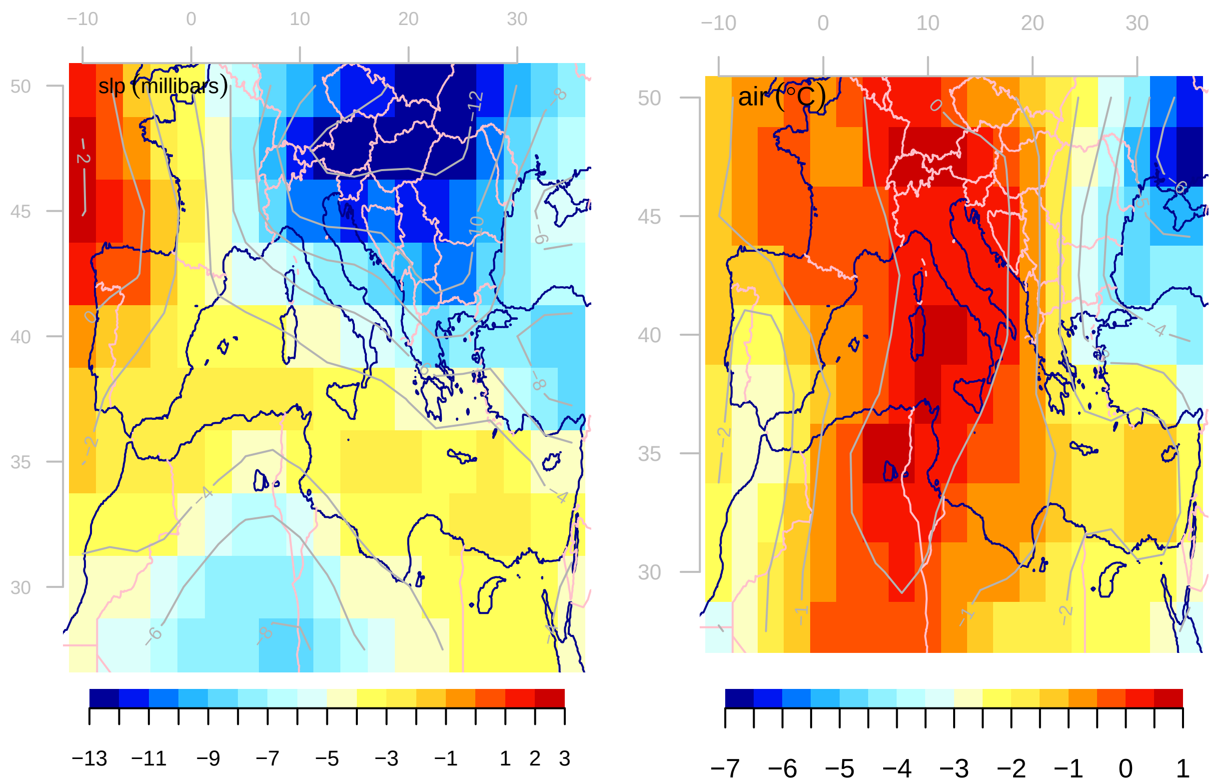

```r
plot(ds.slp,new=FALSE)
```

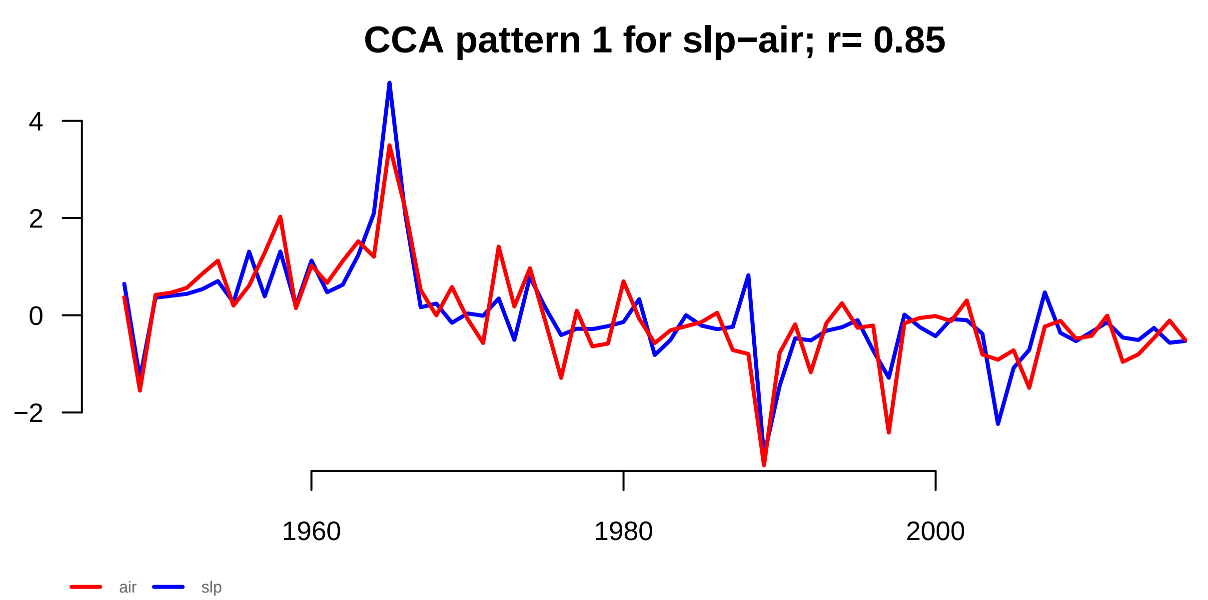



```
## NULL
```

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,new=FALSE)
```





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)
```

```r
coredata(eof.res) <- coredata(eof.res) - coredata(ds.slp)
```

Check to see if the residual contains covariance with the temperature

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

```
##
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  |
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  |
  |=================================================================| 100%
```
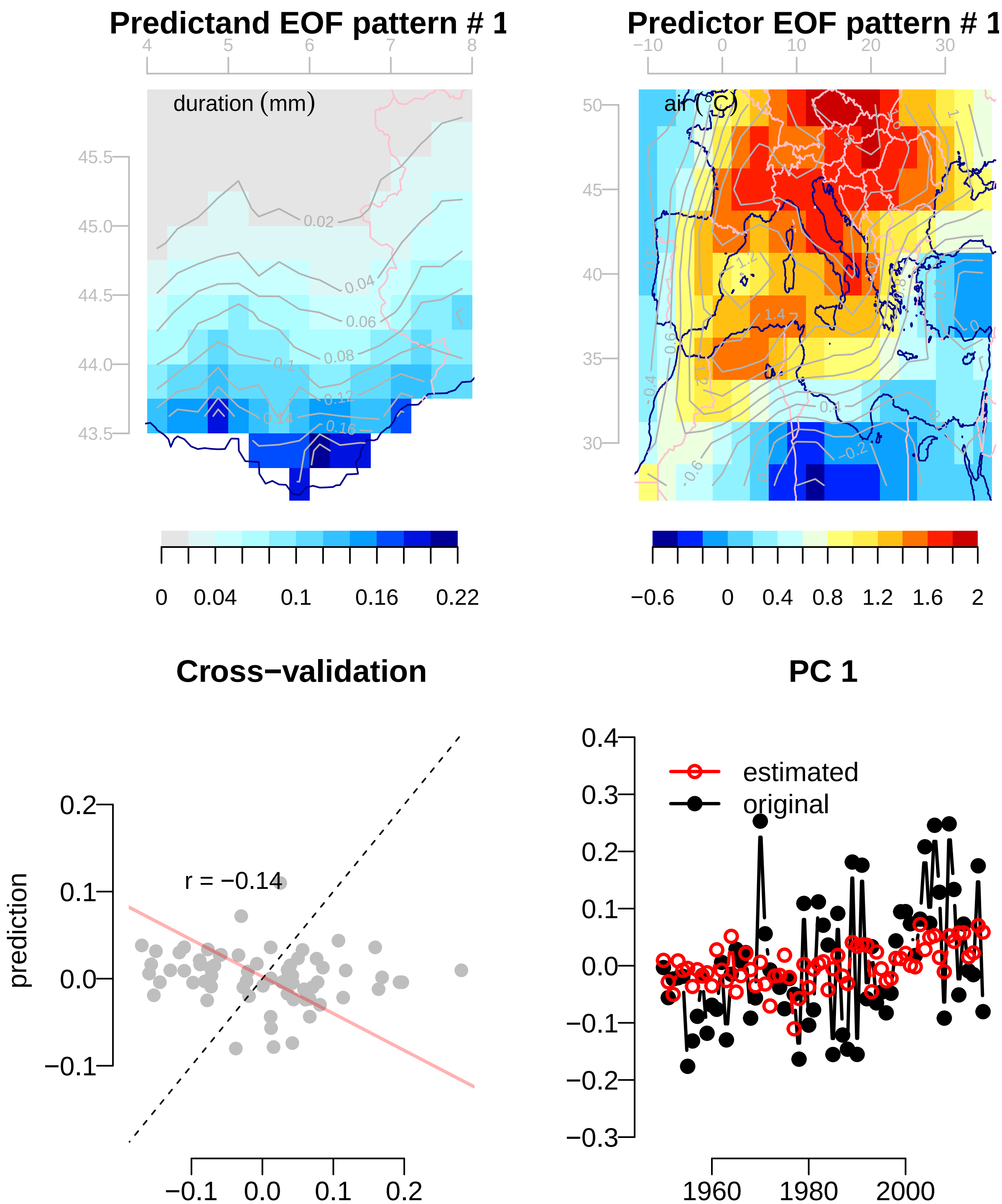

```r
plot(ds.res,new=FALSE)
```



NULL

The downscaling exercise applied to the residual suggests that there is little to gain from using both SLP and temperature for downscaling the statistics of duration of dry days. Hence, a projection using SLP from GCMs as predictor may capture most of the future change. The temperature will nevertheless still be important for fires, as hotter temperatures are more favouralbe for fires.

Projections for the future

Need to read the predictors again to get all months

```
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.
```

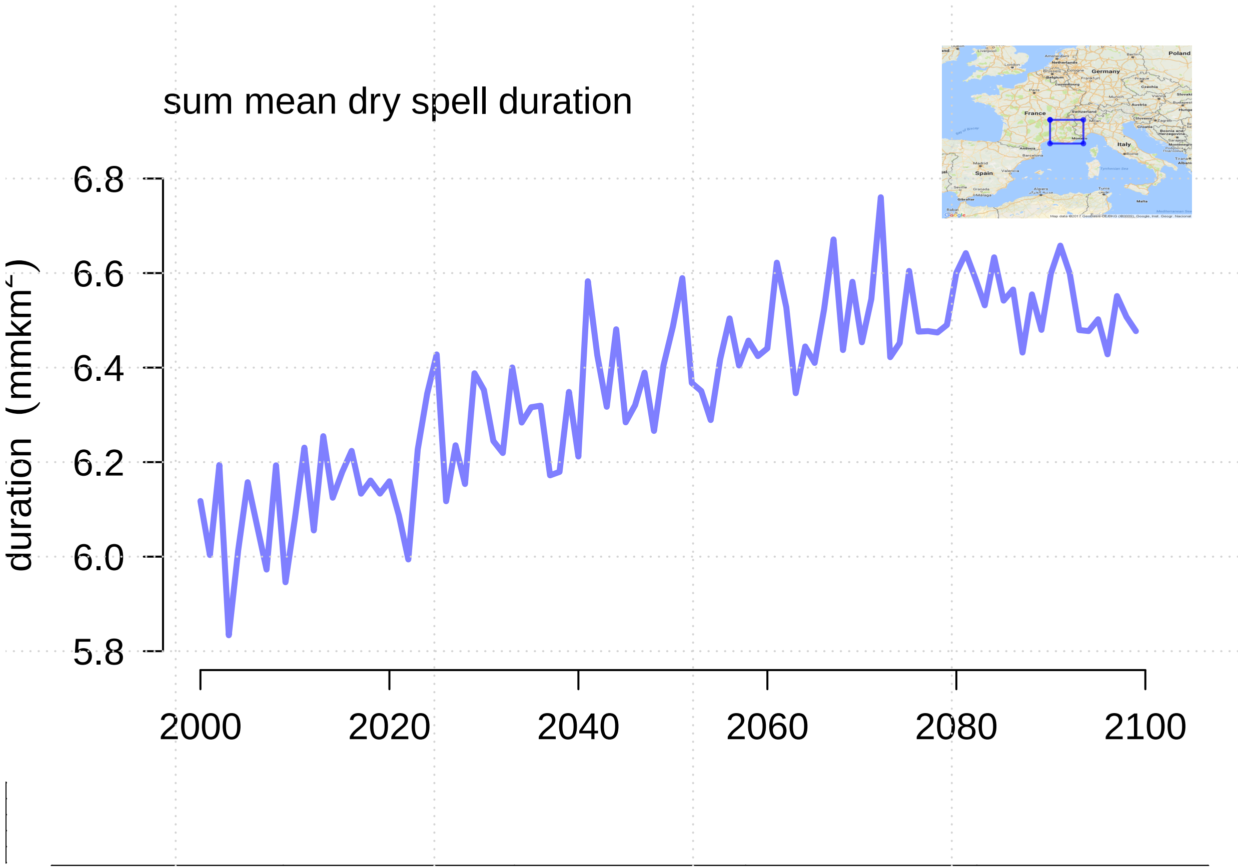
```
SLP <- retrieve('~/Downloads/slp.mon.mean.nc',lon=c(-12,35),lat=c(27,50))
```

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

```
## 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

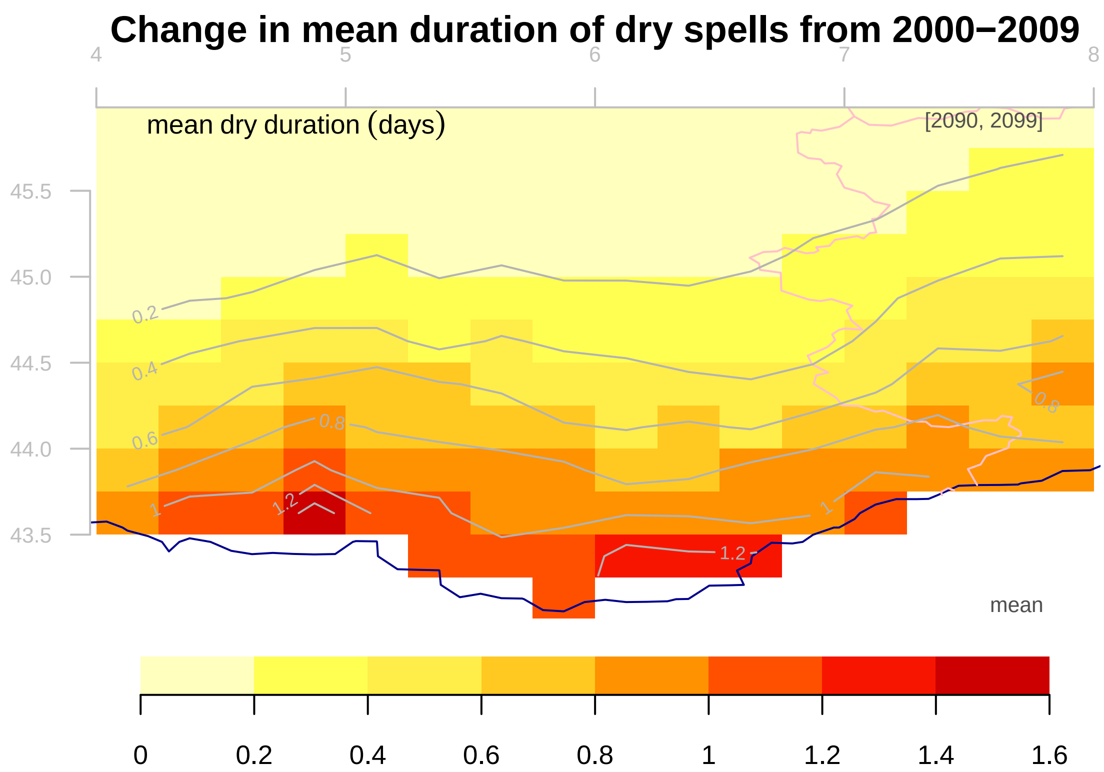
```
if (!file.exists('dse.mld.slp.rda')) {
  dse.mld.slp <- DSensemble.eof(eof.dry,predictor=SLP,it='mjjas',ip=1:10,path="~/data/CMIP5.monthly",pa
  save(dse.mld.slp,file = 'dse.mld.slp.rda')
} else load('dse.mld.slp.rda')
plot(dse.mld.slp,new=FALSE)
grid()
```



Plot maps of changes in the mean dry spell duration

```
zmap1 <- map(dse.mld.slp,FUN="mean",FUNX='mean',it=c(2000,2009),plot=FALSE)
zmap2 <- map(dse.mld.slp,FUN="mean",FUNX='mean',it=c(2090,2099),plot=FALSE)
zmap <- zoo(coredata(zmap2) - coredata(zmap1),order.by=index(zmap2))
```

```r
zmap <- attrcp(zmap1,zmap)
class(zmap) <- class(zmap1)
attr(zmap,'variable') <- 'mean dry duration'
attr(zmap,'unit') <- 'days'
rm('zmap1','zmap2')
map(zmap,colbar=list(pal='warm'),main='Change in mean duration of dry spells from 2000-2009',new=FALSE)
```



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.

Wildfire risk

The fire season: May-October (allowing for longer season in the future).

Hazards: Smoke (Area/density) and burned area. Use historic data or model results (RCM)? Damage functions - has not been used and need to come up with some sensible choices (e.g. mean/minimum density of assets?). The assets are distributed unevenly (roads and power lines). Model risk in a conditioned Monte-Carlo type of fashion?

Data: number of events n_f, burned area A_f, area of smoke A_s, location of event (x, y), the day of the event, number of multiple events n_i $i = [2, 3, ..]$.

Fire indices

Gridded data which can be downscaled.

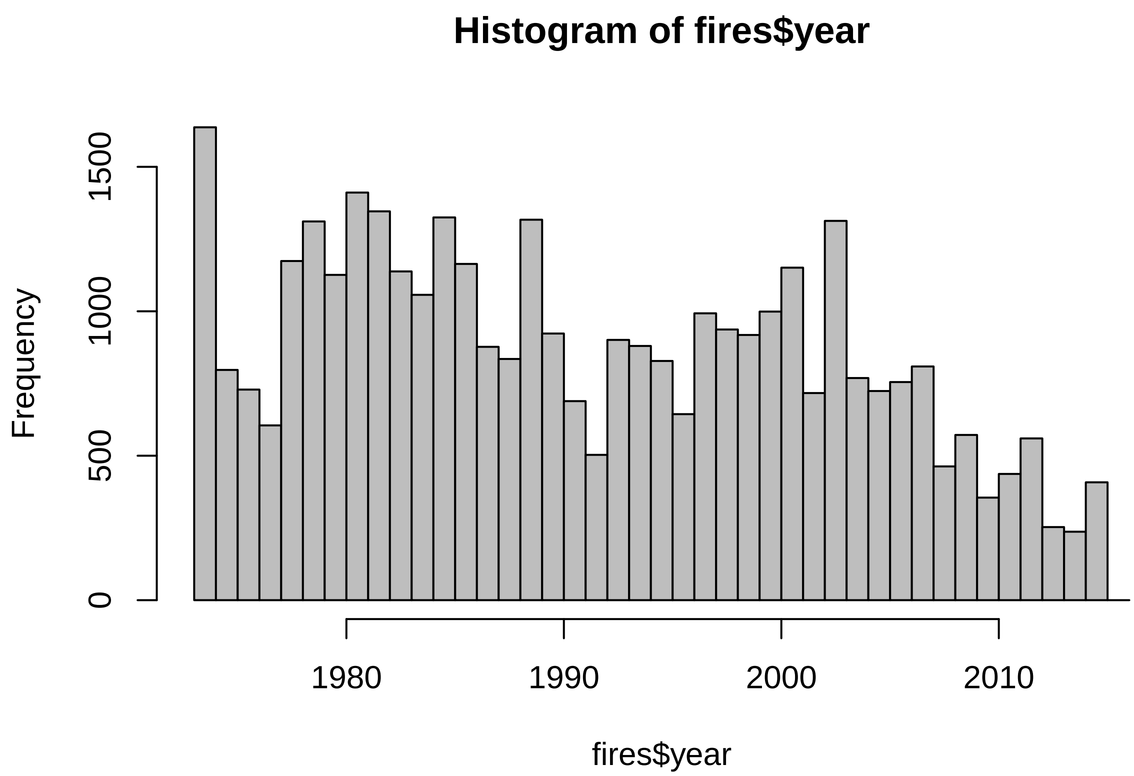
Events

Model number of evens n_f and their area A_f seperately, a little like precipitation (μ and f_w). When it comes to number of events, we can look at the total number or the number of events associated with a threshold area - the number of sevre fires.

The area has an impact on the risk of affecting the number of assets. Base this on historic data and relate to large-scale conditions (predictors). Model as a partly stochastic process where the likelihood depends on an external variable. Poisson model (`GLM`) of n_f and the nature of the A_f distribution dictates the model strategy for the area.

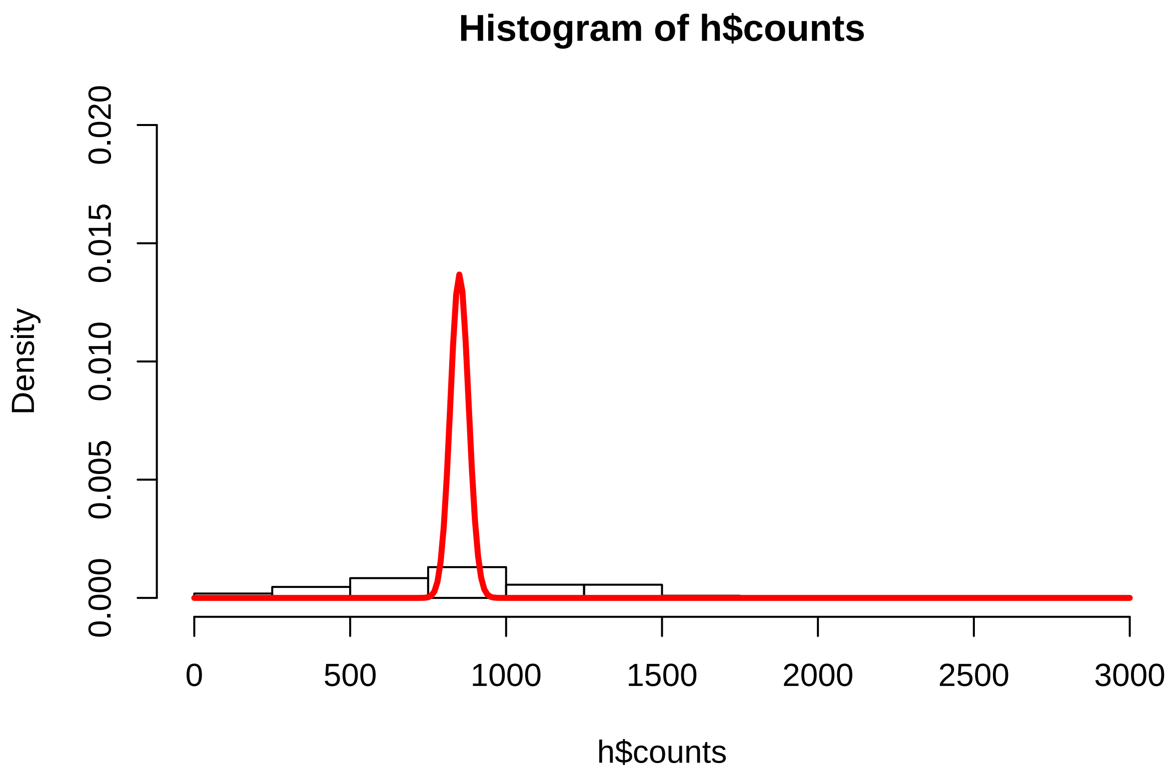
Also model number of simultaneous events, which strain the fire fighters, as they need to split/divert resources. Based on historic data and the assumption of a Poisson process dependent on external condition.

```
## Read wild fire data
colnames <- c('year','number','type','department','code-INSEE','municipality','something','DFCI.code','
fires <- read.table('~/Downloads/liste_incendies_ du_09_05_2017.csv',sep=';',col.names=colnames,header=
h <- hist(fires$year,col='grey',breaks=1973:2016)
```



Examine the fire event statistics: is it Poisson distributed?

```
breaks <- seq(0,3000,by=250)
lambda <- mean(h$counts)
hist(h$counts,breaks=breaks,freq = FALSE,ylim=c(0,0.02))
lines(seq(0,3000,by=10),dpois(seq(0,3000,by=10),lambda=lambda),lwd=3,col='red')
```

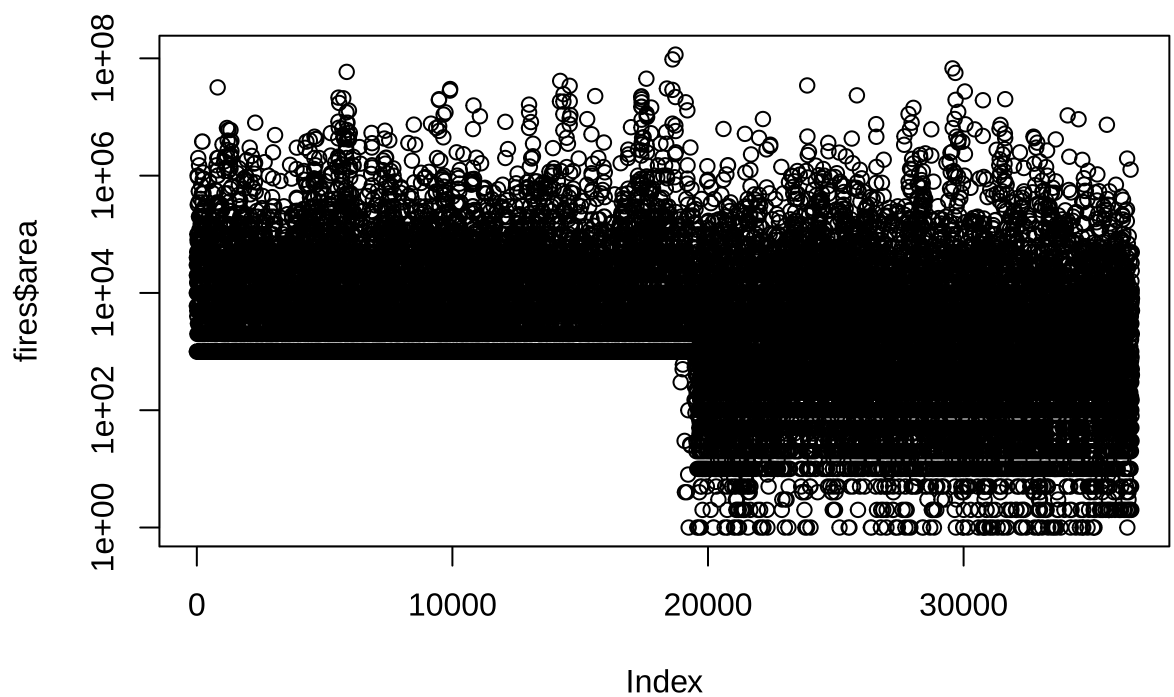


The annual number is not Poisson distributed. Examine the statistics of the area.

```
summary(fires$area)
```

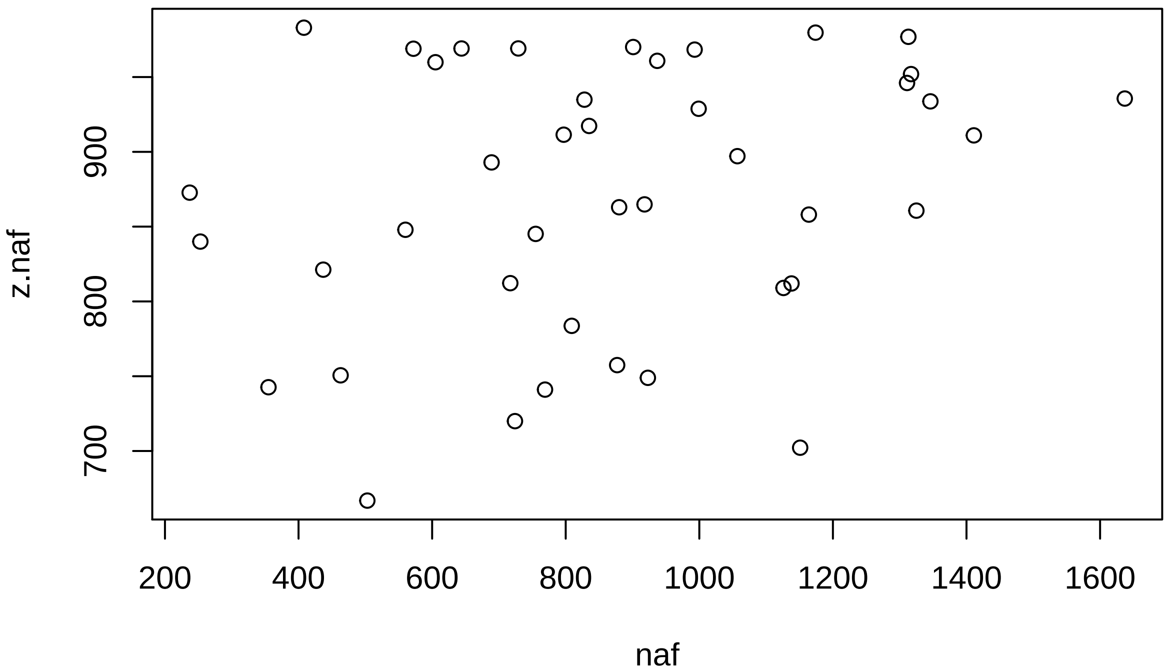
```
##      Min.   1st Qu.    Median      Mean   3rd Qu.      Max.
##         1      1000      1000     82140     10000 115800000
```

```
plot(fires$area,log='y')
```



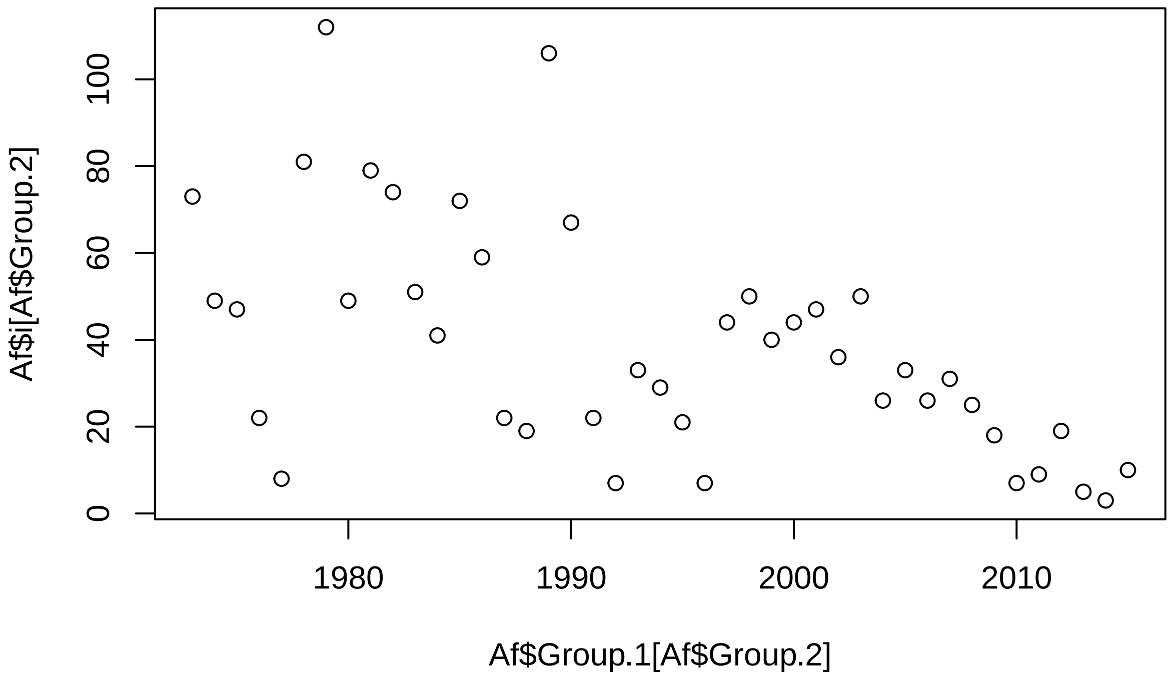
Compare the fire statistics with the mean duration of dry intervals from ECAD (eof.dry), the temperature and SLP.

```
## Number of annual fires
naf <- zoo(h$counts,order.by=trunc(h$mids))
naf[naf==0] <- NA
index(naf) <- year(naf)
xy <- merge(naf,zoo(eof.dry),all=FALSE)
cal.naf <- data.frame(y = coredata(xy$naf), x1=coredata(xy$x.1), x2=coredata(xy$x.2),
                      x3= coredata(xy$x.3), x4=coredata(xy$x.4))
naf.model <- lm(y ~ x1 + x2 + x3 + x4, data=cal.naf)
z.naf <- zoo(predict(naf.model),order.by=trunc(h$mids))
plot(naf,z.naf)
```

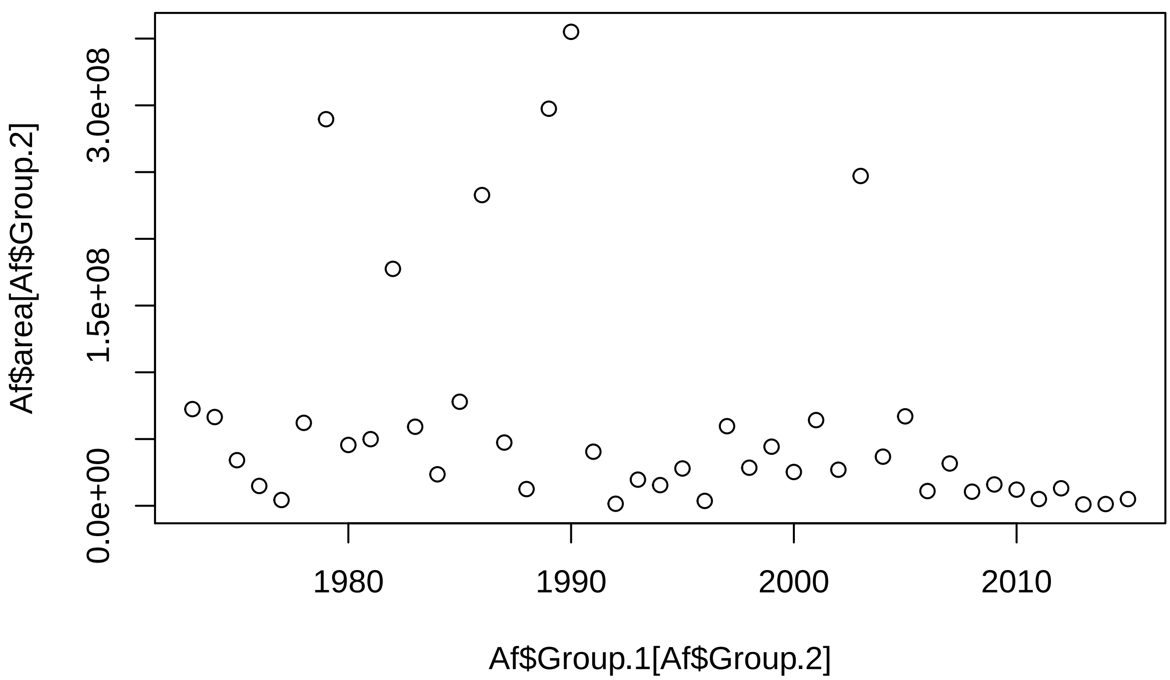


Burned area

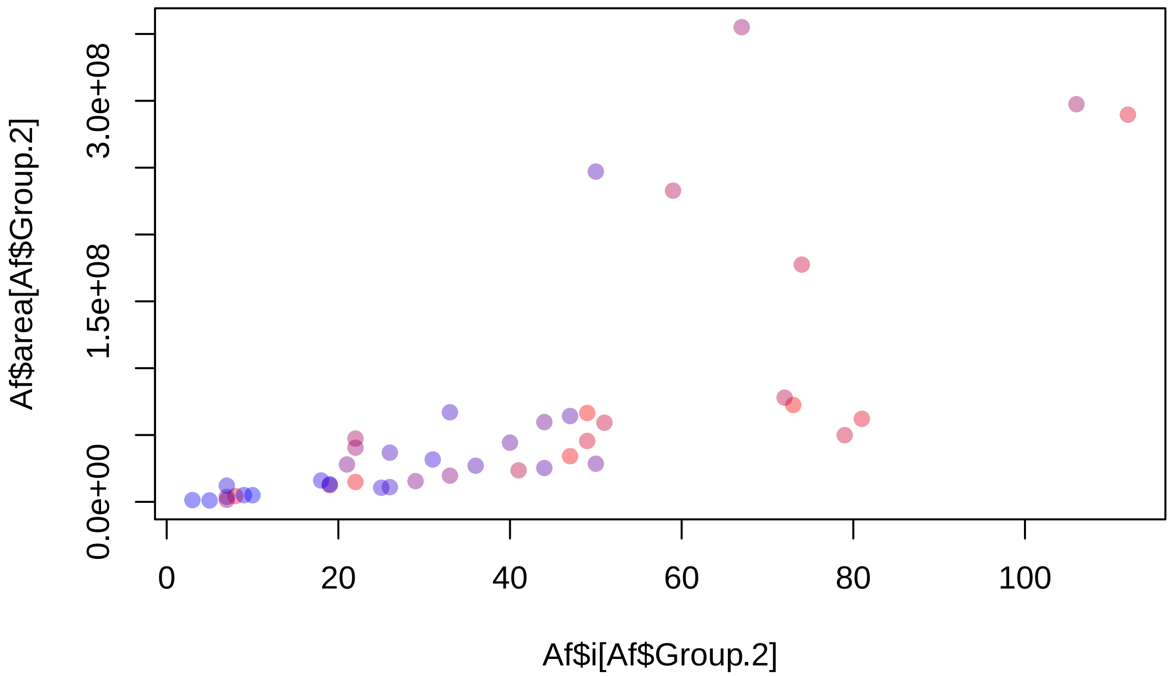
```
firearea <- data.frame(i=rep(1,length(fires$year)),area=as.numeric(as.character(fires$area)),year=fires
## Only include fires where more than 1 km^2 has burned down
Af <- aggregate(firearea,by=list(firearea$year,firearea$area > 100000),FUN=sum)

## Number of events with Af > 1km^2 per year
plot(Af$Group.1[Af$Group.2],Af$i[Af$Group.2])
```



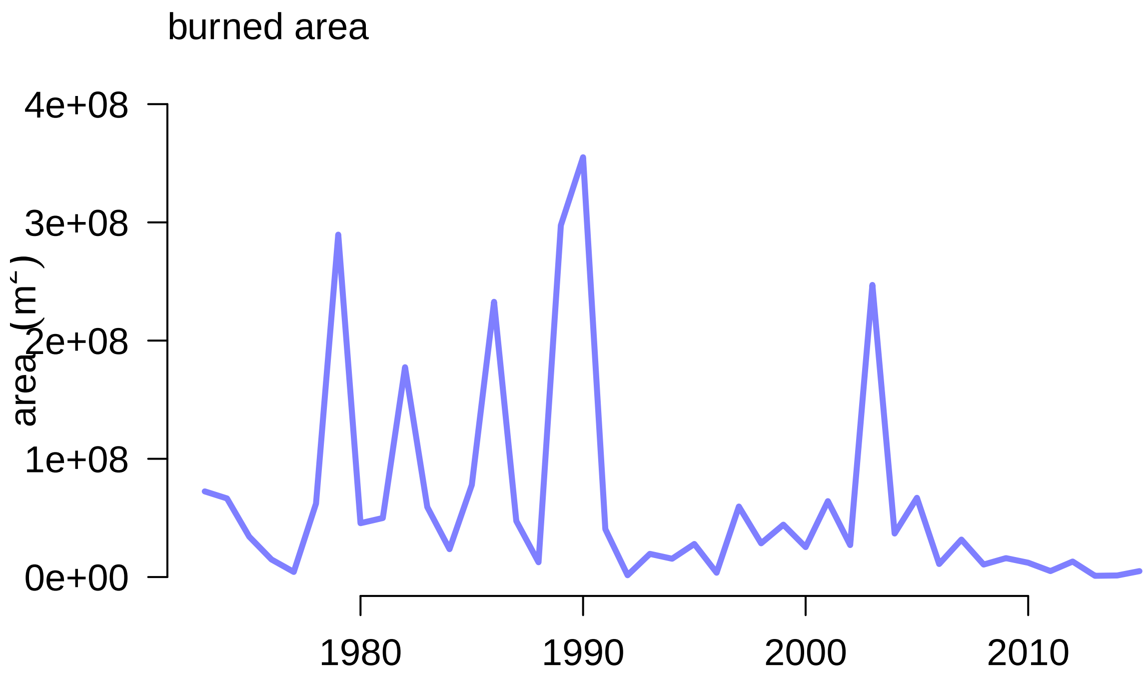

```
## Number of events with Af > 1km^2 per year
plot(Af$Group.1[Af$Group.2],Af$area[Af$Group.2])
```




```
## Relationship between the number of events and total area.
col <- rgb((2015 - Af$Group.1[Af$Group.2])/42,0,1- (2015 - Af$Group.1[Af$Group.2])/42,0.4)
plot(Af$i[Af$Group.2],Af$area[Af$Group.2],col=col,pch=19)
```




```
## annual total area of fires
ataf <- as.station(zoo(Af$area[Af$Group.2],order.by=Af$Group.1[Af$Group.2]),loc='Southern France',param=
                   longname='burned area')
plot(ataf,new=FALSE)
```



The number of wild fire events appears to have decreased over time and there burned area is characterised by a weak decline in years with moderate fire activity. There are also some exceptional years with large burned area, but the sample of these extreme cases is too small for a proper trend analysis. The peak years in fire activity may suggest that the fire hazard is sensitive to certain factors or that increases abruptly when some factors exceed a critical threshold state.

The high sensitivity in the wild fire activity can be compared with the predictors if we take ln(Af) rather than using a linear relationship:

```
index(ataf) <- year(ataf)
index(eof.dry) <- year(eof.dry)
eof.dry <- subset(eof.dry,ip=1:4)
ds.ataf.dry <- DS(log(ataf),eof.dry)
ds.ataf.t2m <- DS(log(ataf),eof.t2m)
```

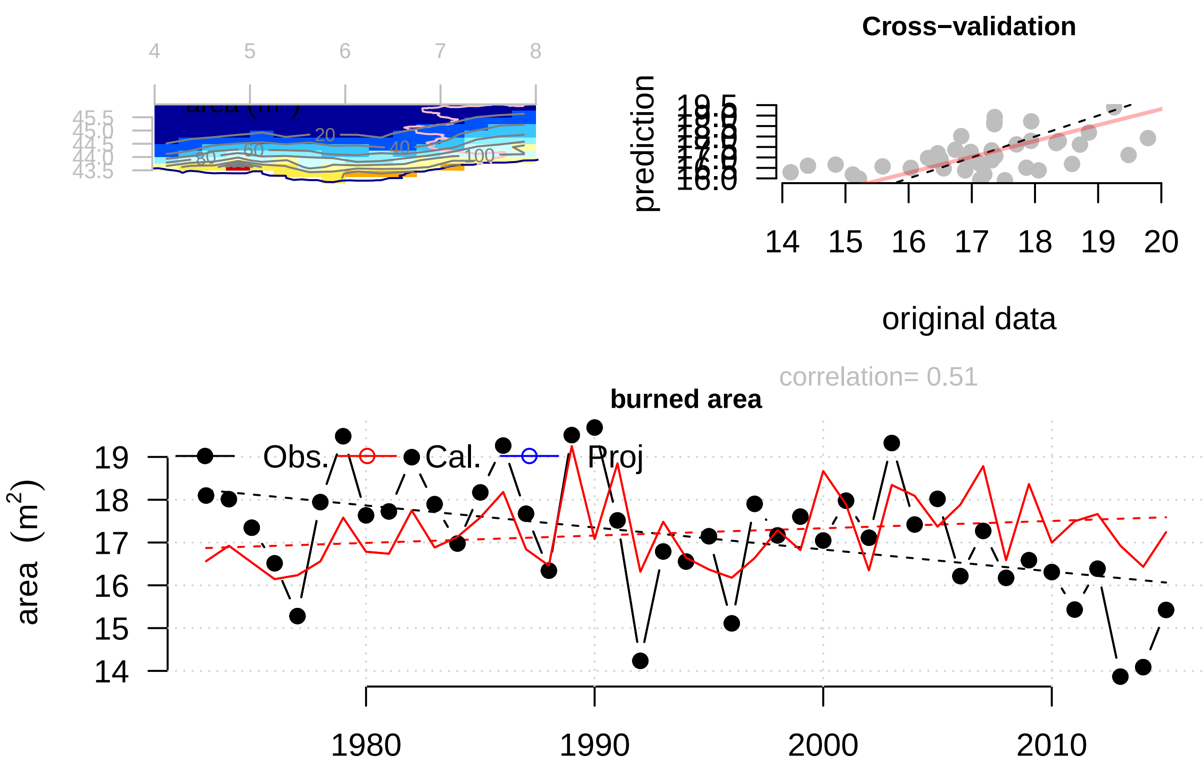
```
## Warning in DS.station(log(ataf), eof.t2m): DS.station: different indices:
## numeric Date
```

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

```
## Warning in DS.station(ataf, eof.slp): DS.station: different indices:
## numeric Date
```

Examine the connection between the mean dry spell duration and the area of burned forest

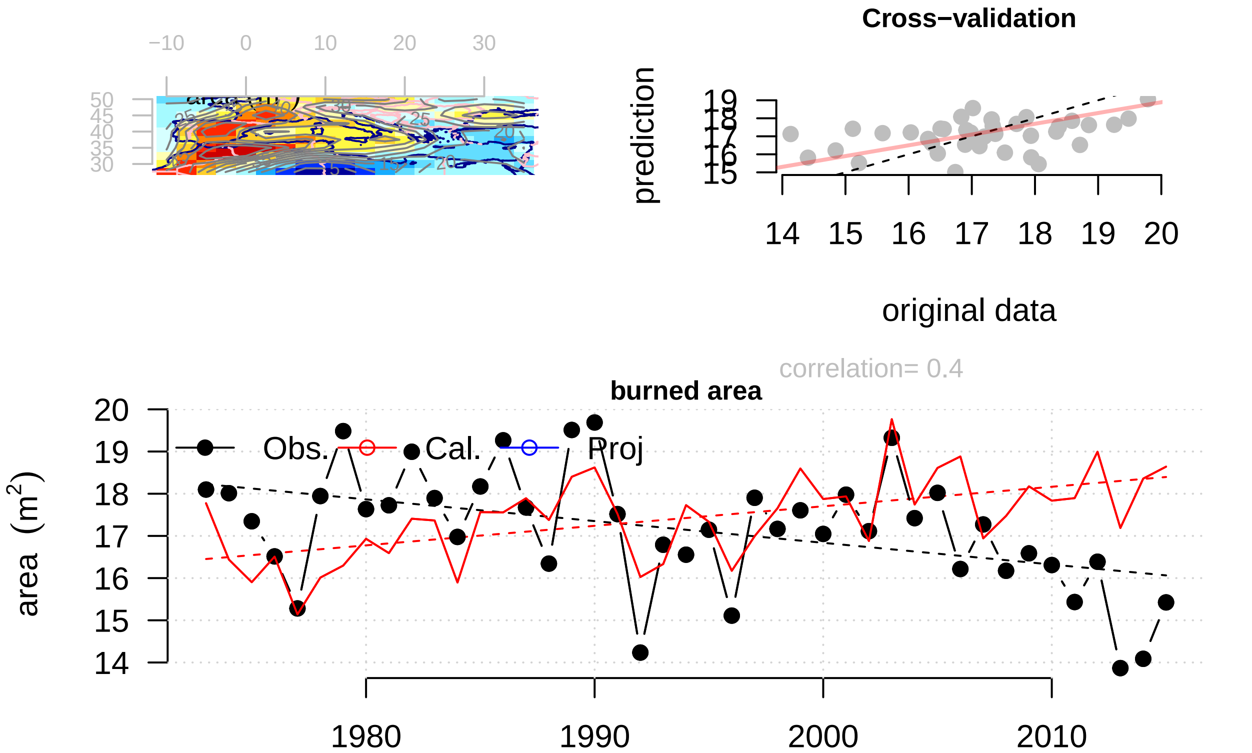
```
plot(ds.ataf.dry,new=FALSE)
```



The regression results suggest a connection between the mean duration of the dry intervals and ln(Af) as the cross-validation correlation is 0.49.

Also examine the connection between high summer temperature and the burned area:

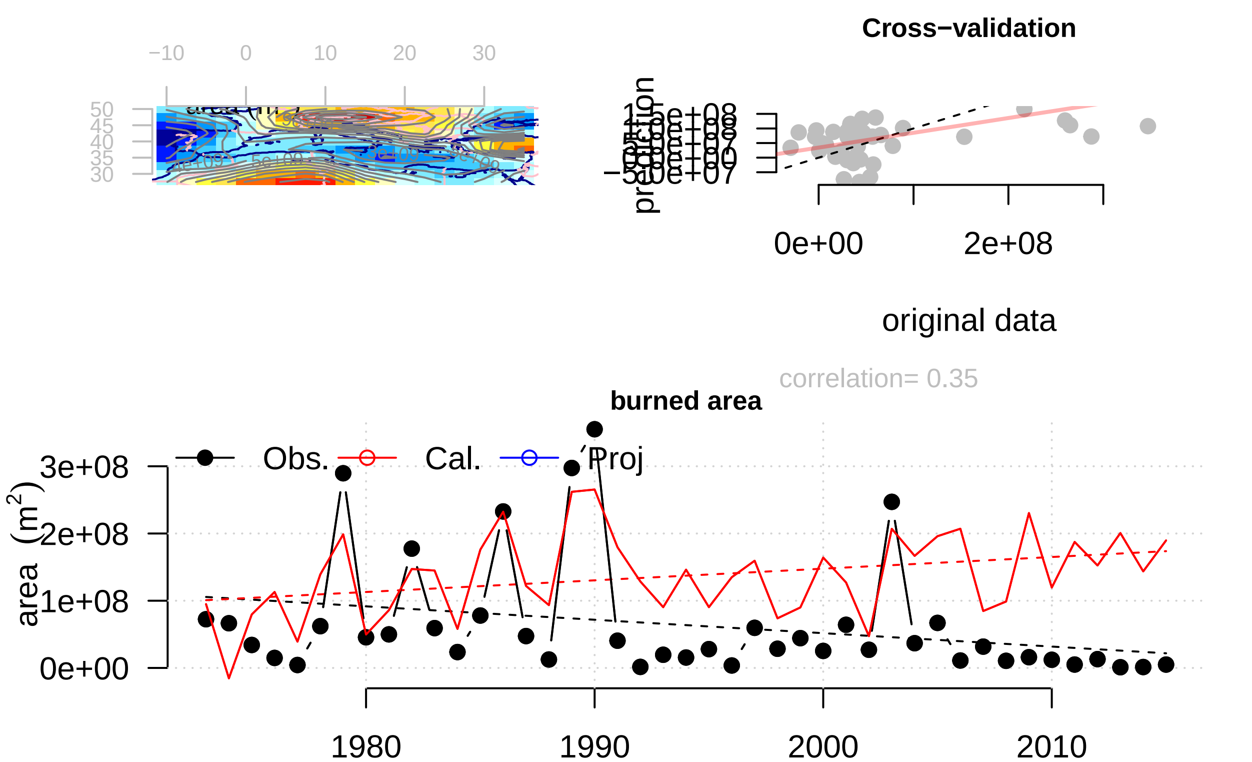
```
plot(ds.ataf.t2m,new=FALSE)
```



There is also a connection between ln(Af) and the summer temperature, and the cross-validation correlation is 0.4.

The same analysis repeated for the SLP fails to find a connection for ln(Af), but the linear relationship between SLP and Af captures a dependency

```
plot(ds.ataf.slp,new=FALSE)
```



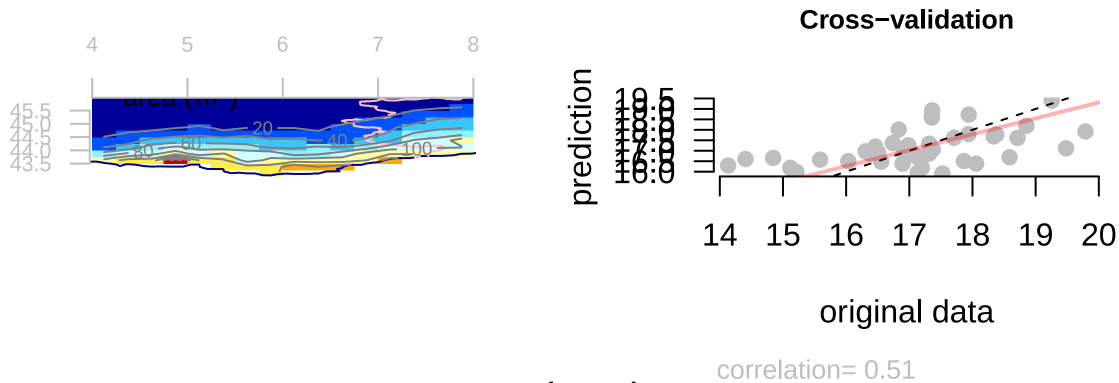
The connection between SLP and burned area is weaker than for the the mean dry interval duration and summer temperature if we use ln(Af), with a cross-validation correlation of 0.35. It is particularly the peak years which are associated with high-pressure systems (often associated with dry conditions and heatwaves).

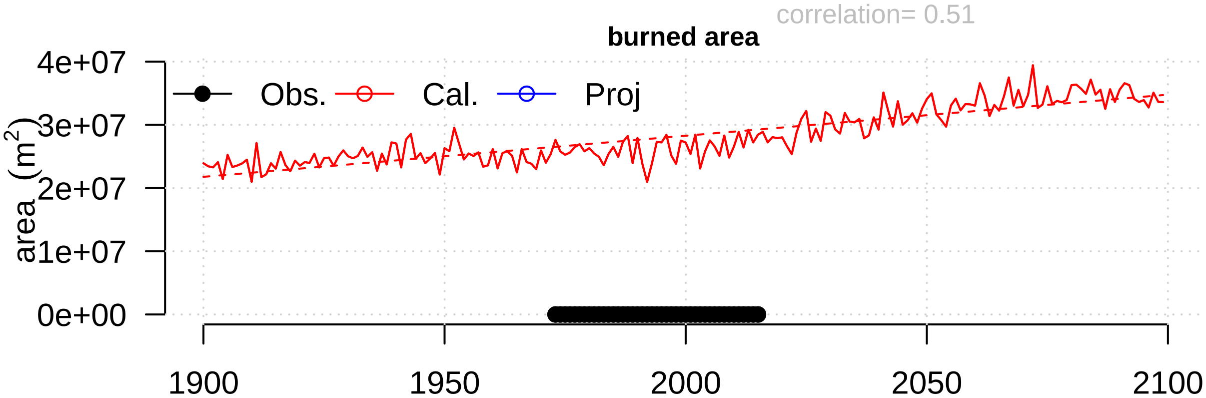
The time series suggest an increasing bias over time, which possibly can be explained by more efficient fire service since 1990. This can be checked to some extent by examining the budget of the fire services to see if there have been more efforts and resources devoted to firefighting over time. It is also possible that the vegetation has changed or that the landscape has been altered (e.g. more fields or more paved area) so that the potential for wild fires has been reduced. Also, once there has been a fire, the are is burned down and it takes time for it to recover so that new fires may occur.

Projections of future wild fire activity

We can combine the projections of the mean dry interval duration with the downscaling result using the same quantity as predictor. The dry duration statistics was downscaled using the SLP as predictor, so the SLP is in the equation.

```
## Convert the projected data into an EOF for the multi-model ensemble
eof.dry.z <- as.eof(dse.mld.slp)
## Use this EOF as input with the downscaling model calibrated with mean dry interval duration to make p
ds.Af <- exp(predict(ds.ataf.dry,newdata=eof.dry.z))
plot(ds.Af,new=FALSE)
```

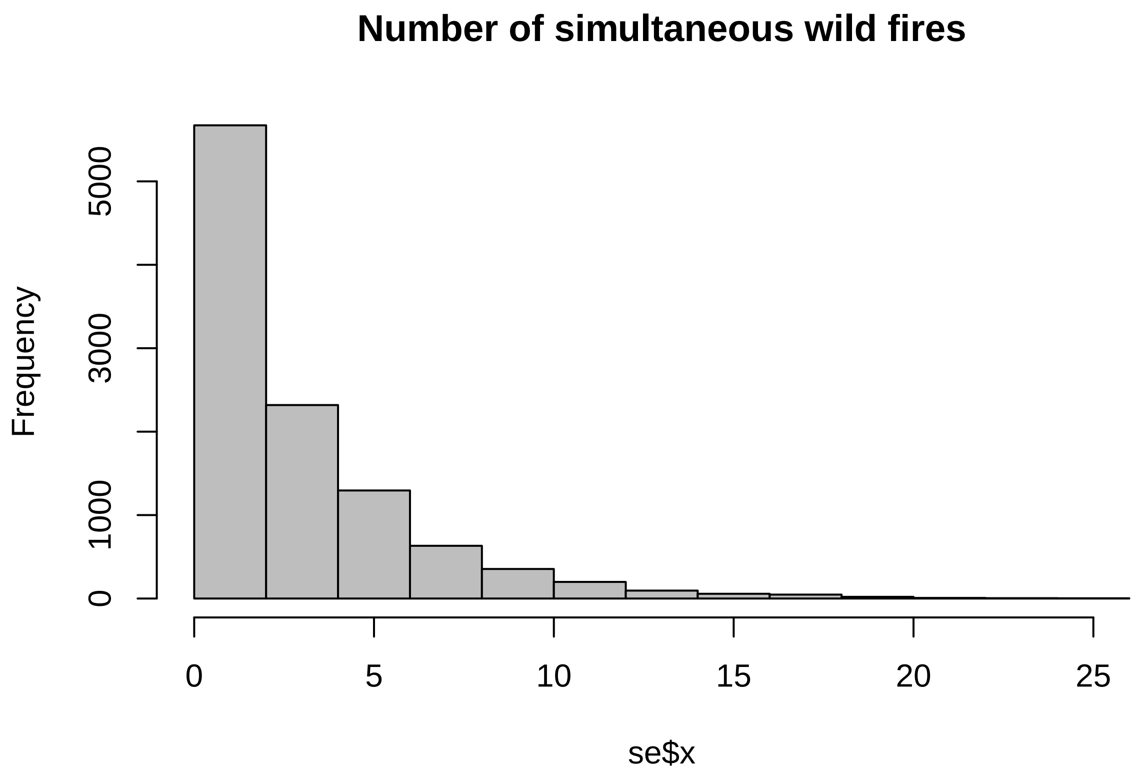




Simultaneos fires

```
fevents <- data.frame(i=rep(1,length(fires$year)),area=as.numeric(as.character(fires$area)),year=fires$y
## Only include fires where more than 1 km^2 has burned down
se <- aggregate(fevents$i,by=list(fevents$date,fevents$area > 100000),FUN=sum)
```

```
## Examine the statistical distribution of simultaneous events
hist(se$x, col='grey', main='Number of simultaneous wild fires')
```




```
plot(year(se$Group.1),se$x,pch=19,col=rgb(1,0,0,0.2),main='Number of simultaneous wild fires by year',yl
points(year(se$Group.1),se$x,pch=21,col=rgb(0.5,0.5,0.5))
grid()
```