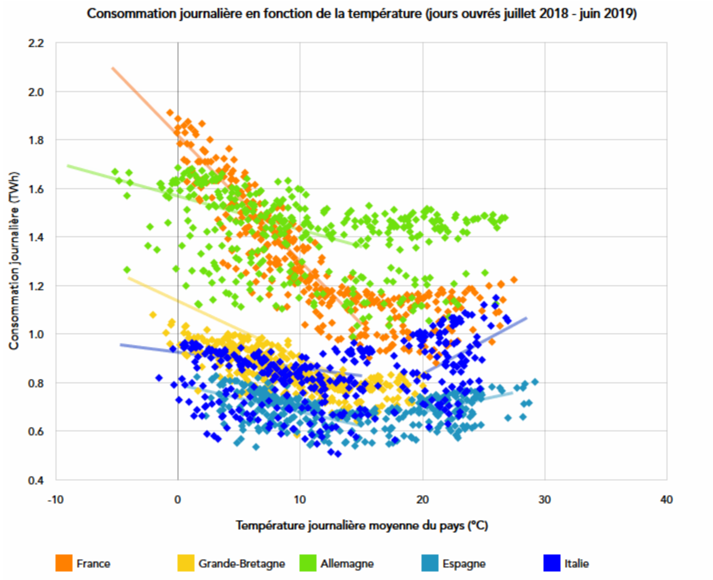
STOCHASTIC MODELLING AND EXTREMES OF CLIMATE VARIABLES IN AN INDUSTRIAL CONTEXT

EDF AND CLIMATE

Electricity generation, demand and transmission are linked to the meteorological conditions in many ways

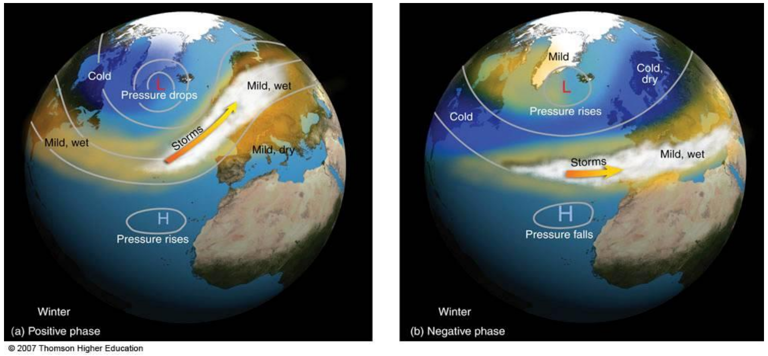
Daily electricity demand in Europe



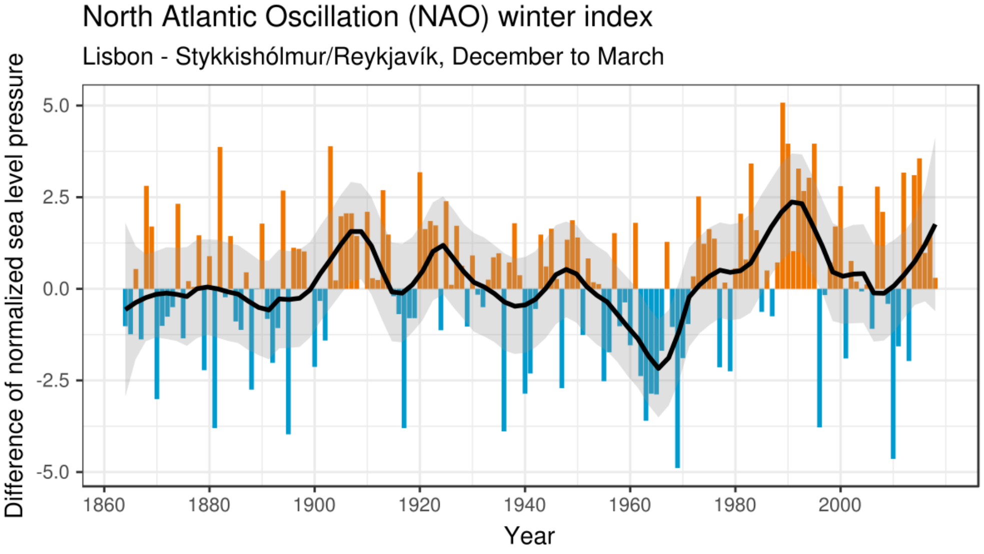
Electricity generation

EDF IS ADAPTED TO CURRENT CLIMATE VARIABILITY

NAO

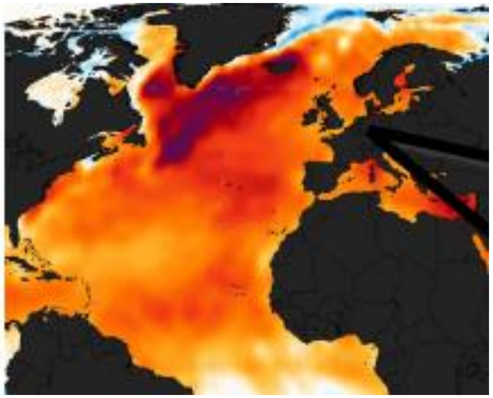


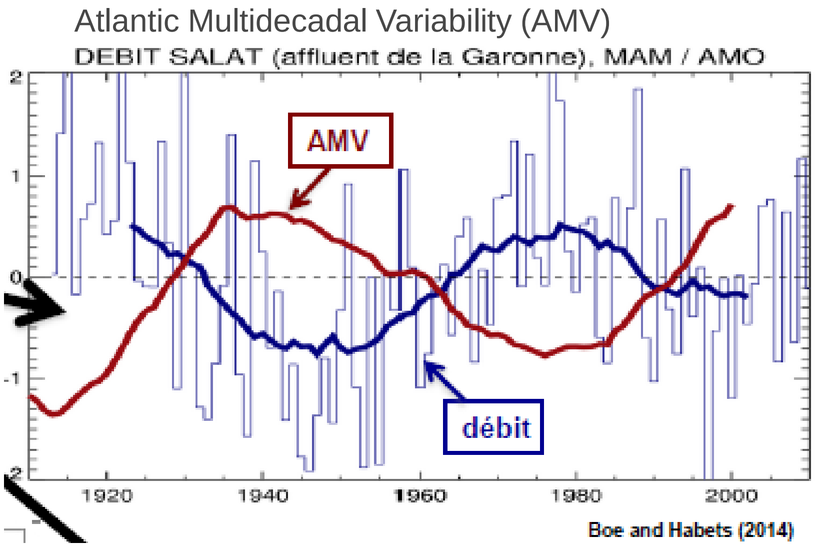
© 2007 Thomson Higher Education



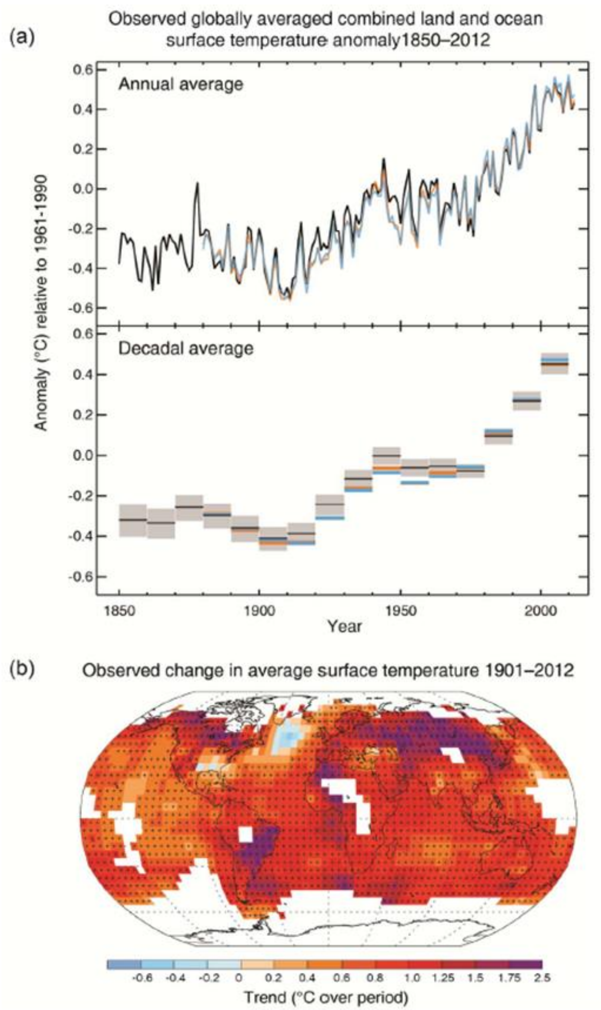
NAO Index Data provided by the Climate Analysis Section, NCAR, Boulder, USA, Hurrell (2003)
Updated regularly. Accessed 2018-10-21

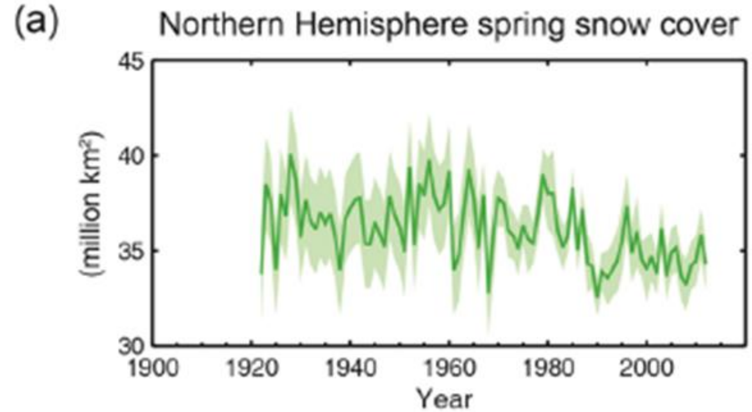
AMV

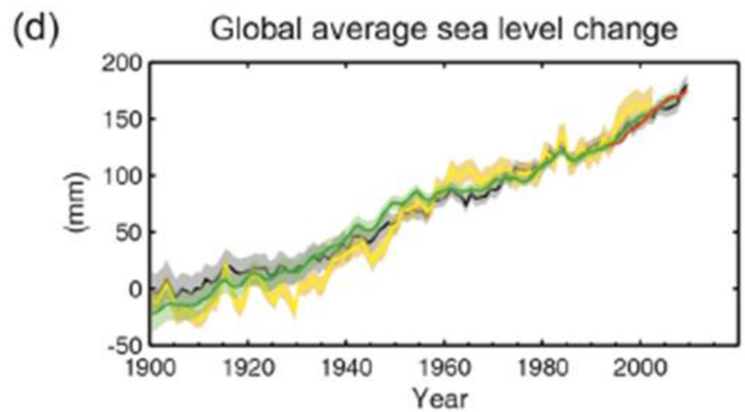


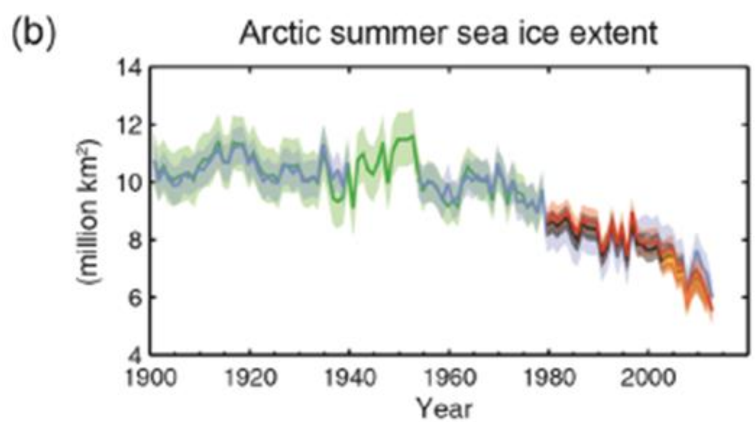


AND IS ADAPTING TO CLIMATE CHANGE



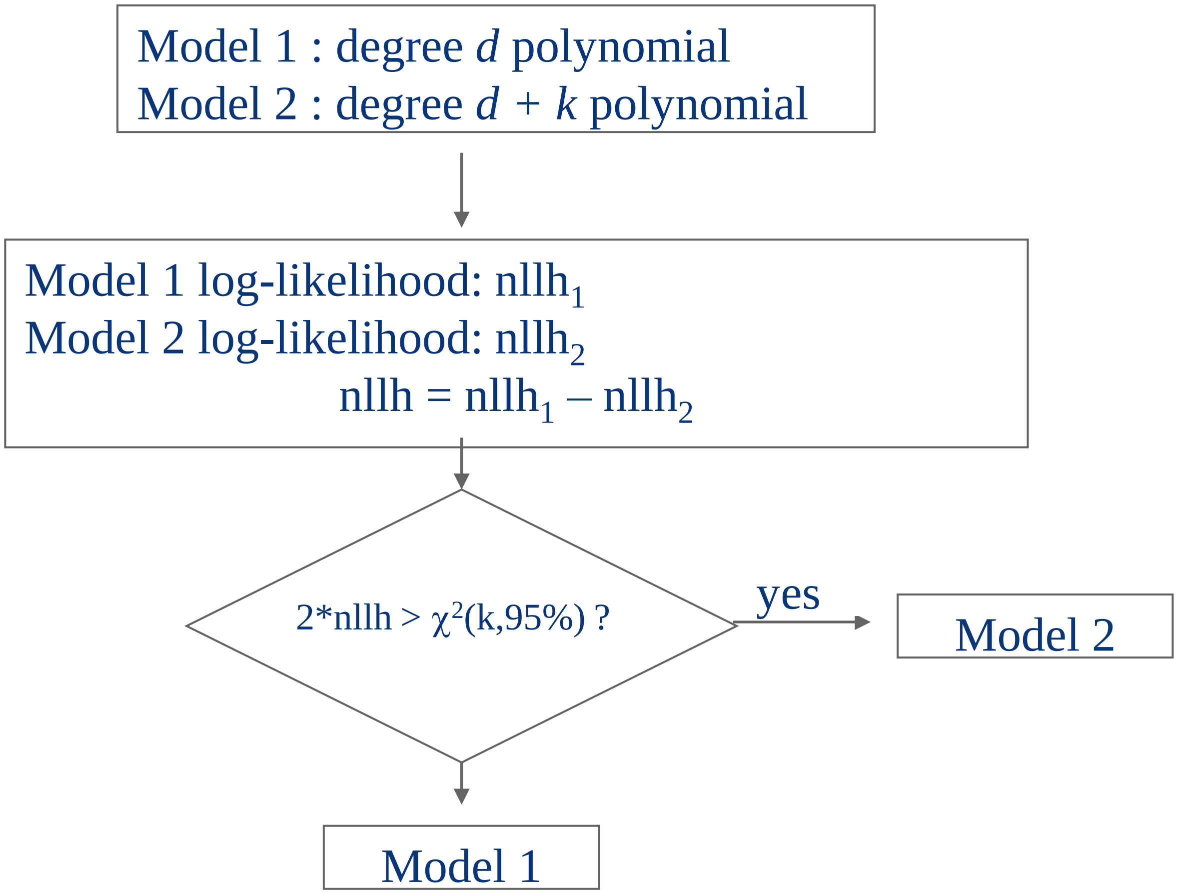






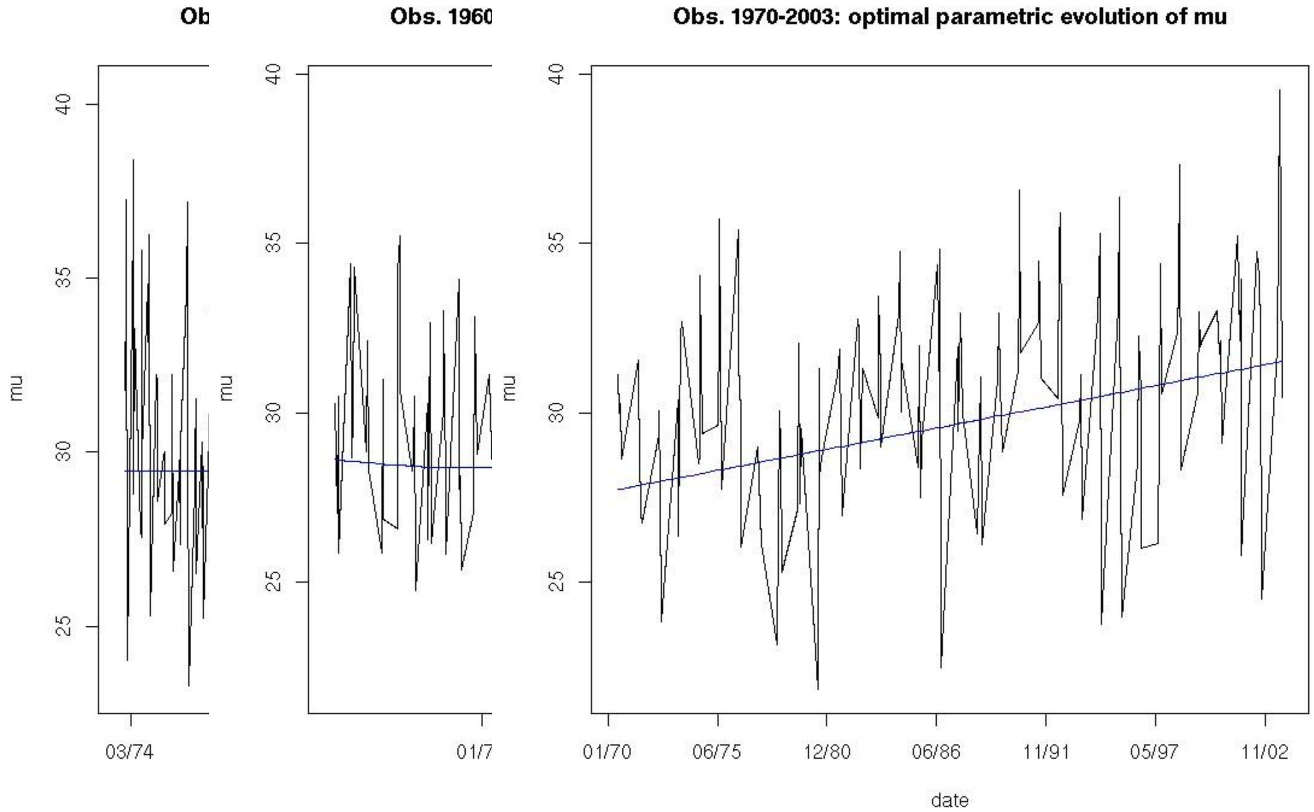
EXAMPLE: EXTREME LEVEL ESTIMATION

- **First studies in 2002 in collaboration with Professor Dacunha-Castelle (Paris 11 university)**



S. Parey, F. Malek, C. Laurent, D. Dacunha-Castelle: Trends and climatic evolution: Statistical approach for very high temperatures in France, Climatic Change (2007) 81:331 - 352

BUT THE TREND MAY DEPEND ON THE PERIOD



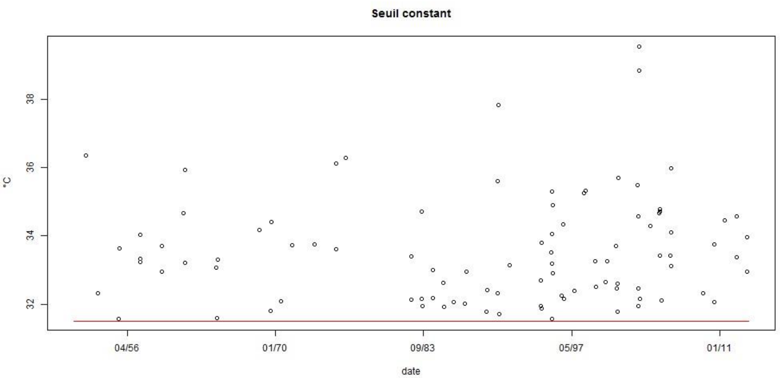
GEV

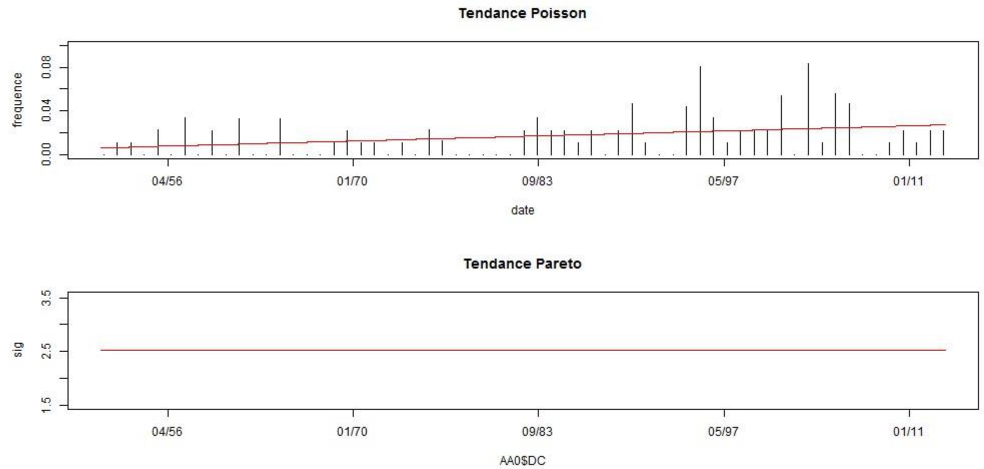
POT

Period	P10	P21	P22	P31	P32	P33
l(t) degree	5	0	2	0	0	2
σ(t) degree	1	0	0	0	4	0

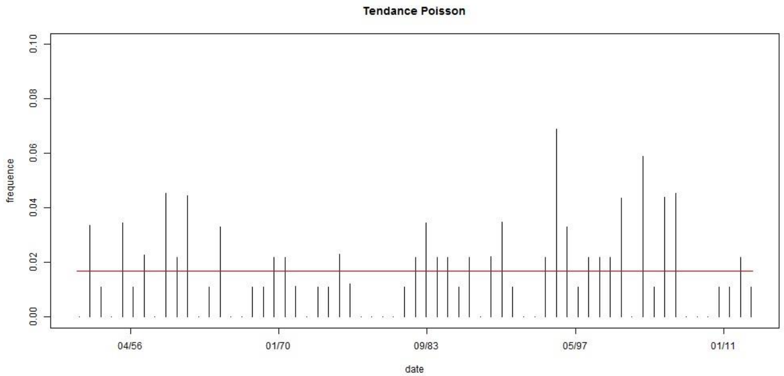
DIFFERENT CHOICES FOR THE TREND DETECTION

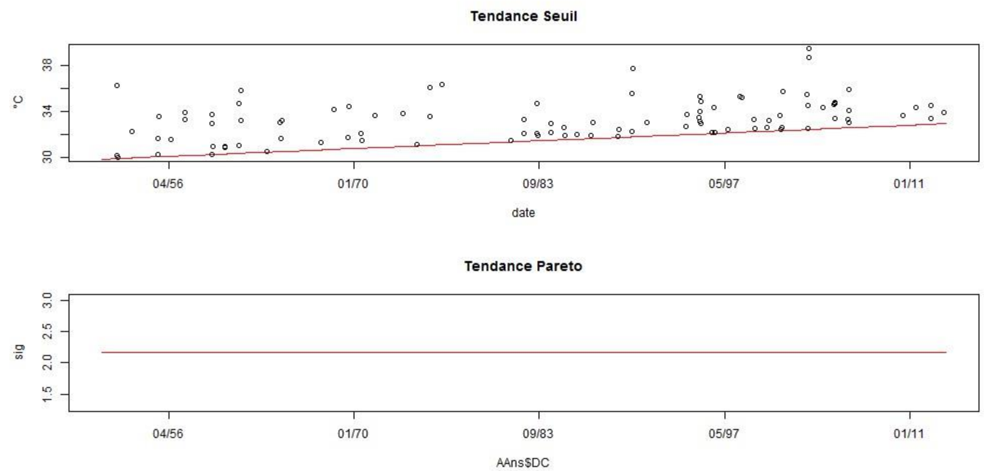
Constant threshold





Time varying threshold





THEN THE RETURN LEVEL MUST BE RE-DEFINED

- **Value exceeded *1* every *N* years on average => value whose exceedance expectation in the next *N* years is *1***

$$\frac{1}{nb}\sum_{t=t_0}^{t_0+365a}\left\{1-\exp\left[-\left(1+\frac{\xi}{\sigma(t)}(z_a-\mu(t))\right)^{-1/\xi}\right]\right\}=1 \qquad \text{GEV}$$

$$\text{POT} \qquad \sum_{t\in D(t_0,a)}\left(1+\frac{\xi}{\sigma(t)}(z_a-u)\right)^{-\frac{1}{\xi}} I(t)=1$$

- **depends on the identified trend**

- **implies the need to take the trend uncertainty into account in the confidence interval: bootstrap**

- **Other definitions in the literature:**
  - ENE: $\sum_{t=T_1}^{T_1+m-1}\{1-G_Z(z^{ENE}(m)|\theta_t)\}=1$
  - RE: $RE_{T_1-T_2}^{ns}=\prod_{t=T_1}^{T_2}(1-p_t)=\prod_{t=T_1}^{T_2}G_Z(z_q\,|\,\theta_t)$
  - DLL: $z_{T_1-T_2}^{DLL}(m)=F_{T_1-T_2}^{-1}(1-1/m)$ with $F_{T_1-T_2}(z)=\prod_{t=T_1}^{T_2}G_{Z,t}(z)=\prod_{t=T_1}^{T_2}G_Z(z|\theta_t)$
  - ADLL: $\frac{1}{T_2-T_1+1}\sum_{t=T_1}^{T_2}G_Z(z_{T_1-T_2}^{ADLL}(m)|\theta_t)=1-1/m$

  and $z^{ENE}(m)=z_{T_1-(T_1+m-1)}^{ADLL}(m)=H_{T_1-(T_1+m-1)}^{-1}(1-1/m)$

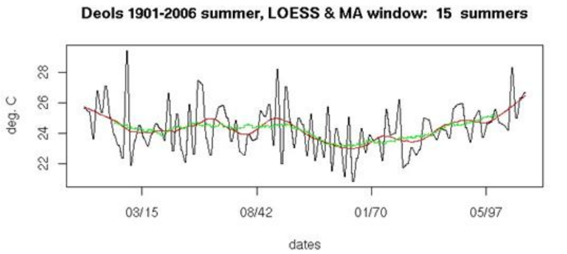
LIMITATIONS OF THE APPROACH -> FURTHER RESEARCH

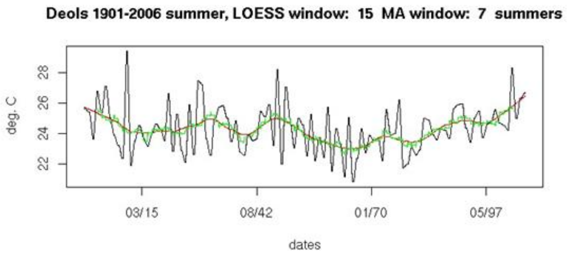
- **Careful study of the links between mean, variance and extremes : Thi Thu Huong Hoang PhD (2010)**

- **Nonparametric trends**
  - Cubic splines

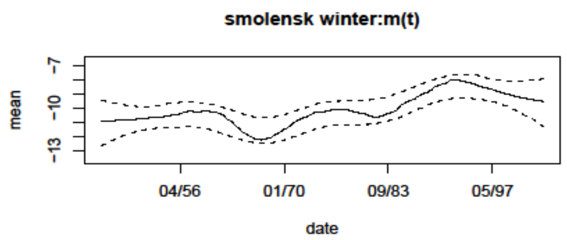
$$l - \frac{1}{2}\lambda \int \left(f''(t) \right)^2 dt$$

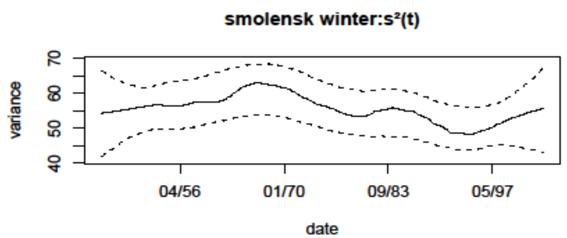
  - Loess: local regression



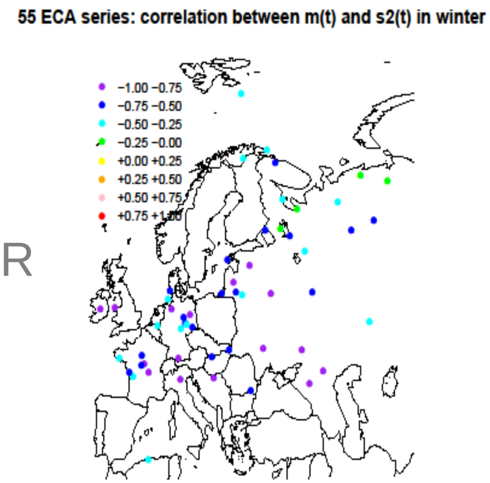


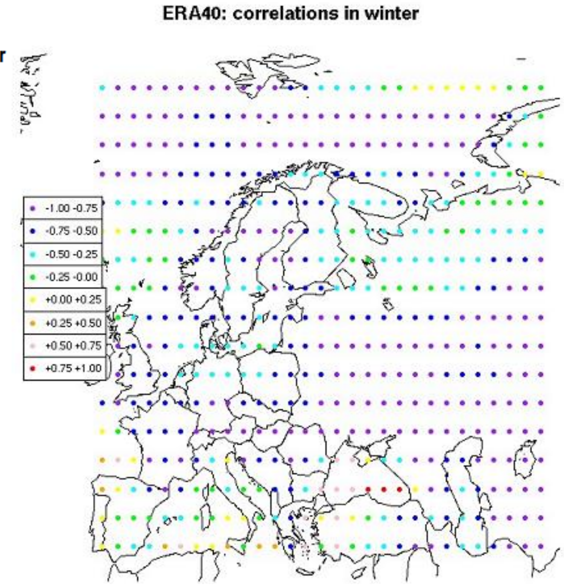
TEMPERATURE MEAN AND VARIANCE TRENDS ARE LINKED

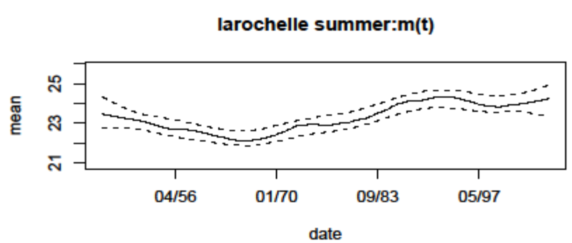


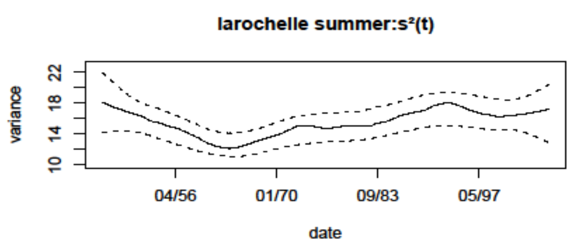


WINTER

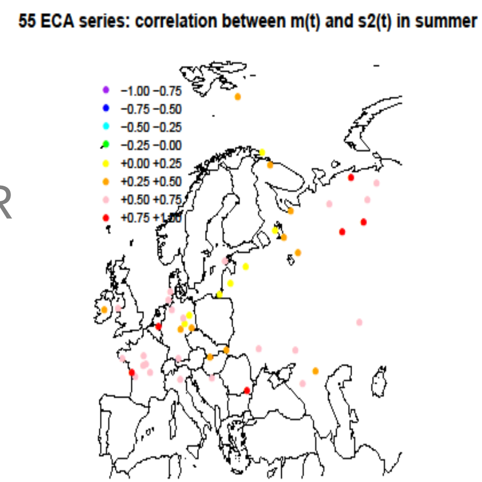


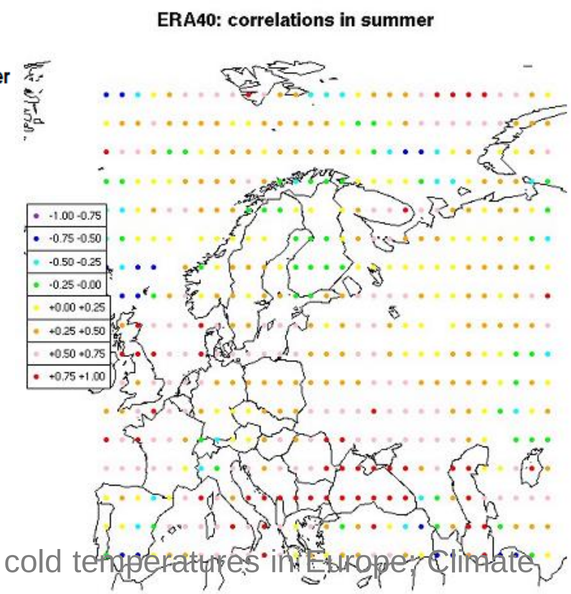






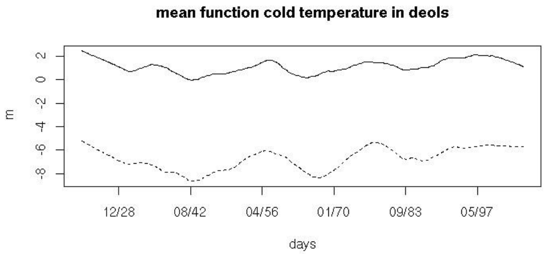
SUMMER

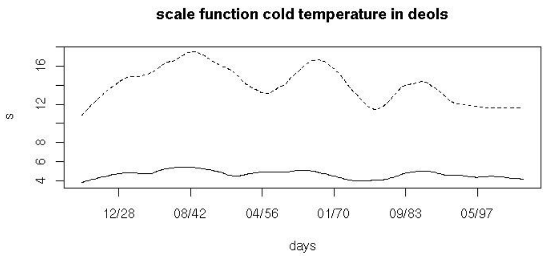




Parey S., Dacunha-Castelle D., Hoang T.T.H.: Mean and variance evolutions of the hot and cold temperatures in Europe, Climate Dynamics, 34, 345-369, DOI 10.1007/s00382-009-0557, 2010

LINK WITH THE TRENDS IN EXTREMES





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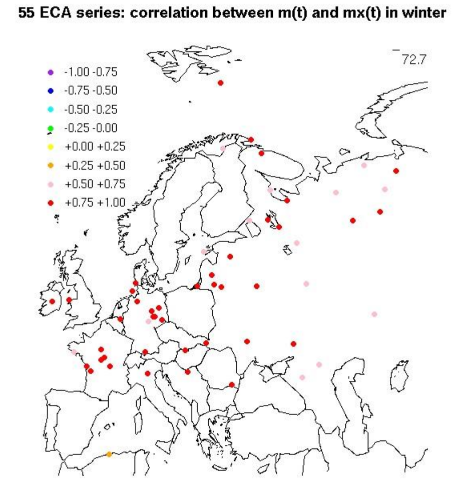
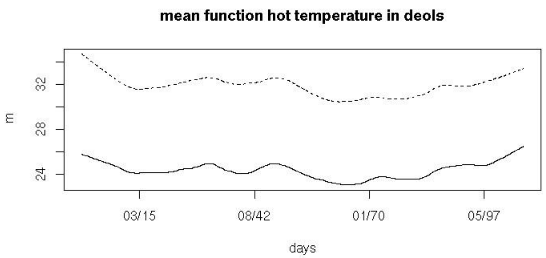
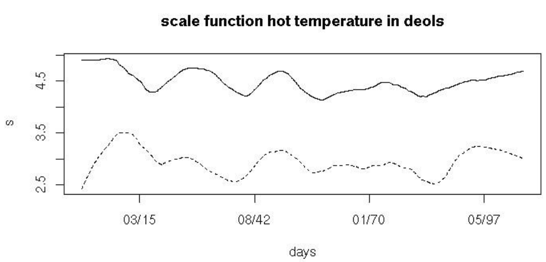
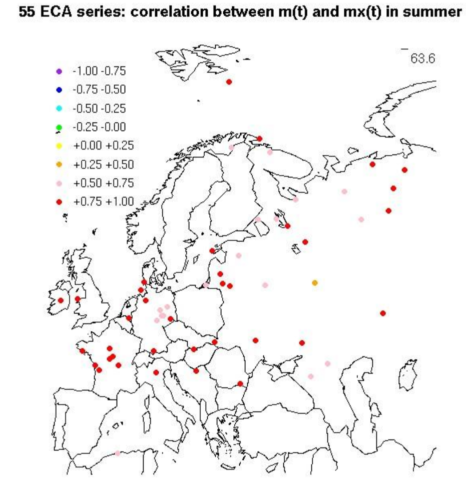






SUMMER



BUILD A VARIABLE WITH STATIONARY EXTREMES?

$$Y_t = \frac{X_t - m_t}{s_t}$$

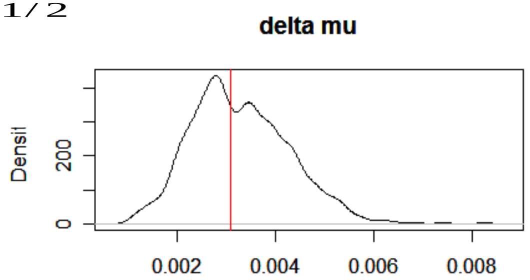
Assumption :

the extremes of Y_t are stationary

Test

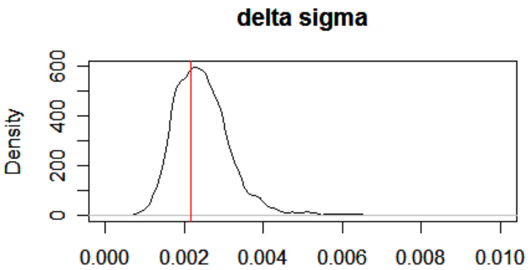
1) Define a distance between two functions:

$$\Delta(f,g) = \frac{1}{T}\left(\int (f(t) - g(t))^2 dt\right)^{1/2}$$



2) Compute a statistical table of these distances for a stationary distribution

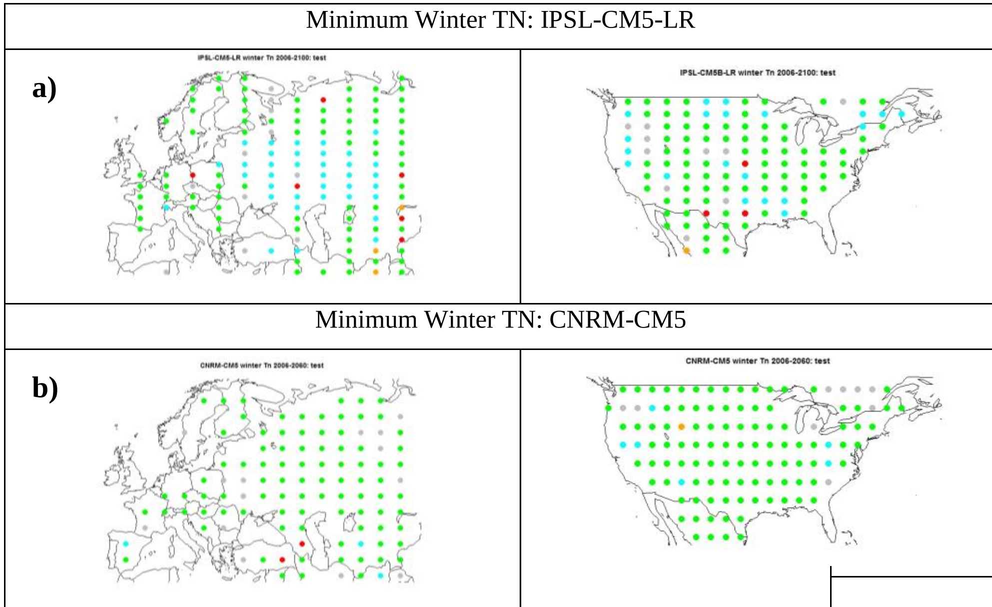
- 1000 samples of a stationary GEV (ξ_Y, μ_Y, σ_Y)
- Estimate the parameters:
  1) As constants
  2) As time varying
- Compute the distance Δ

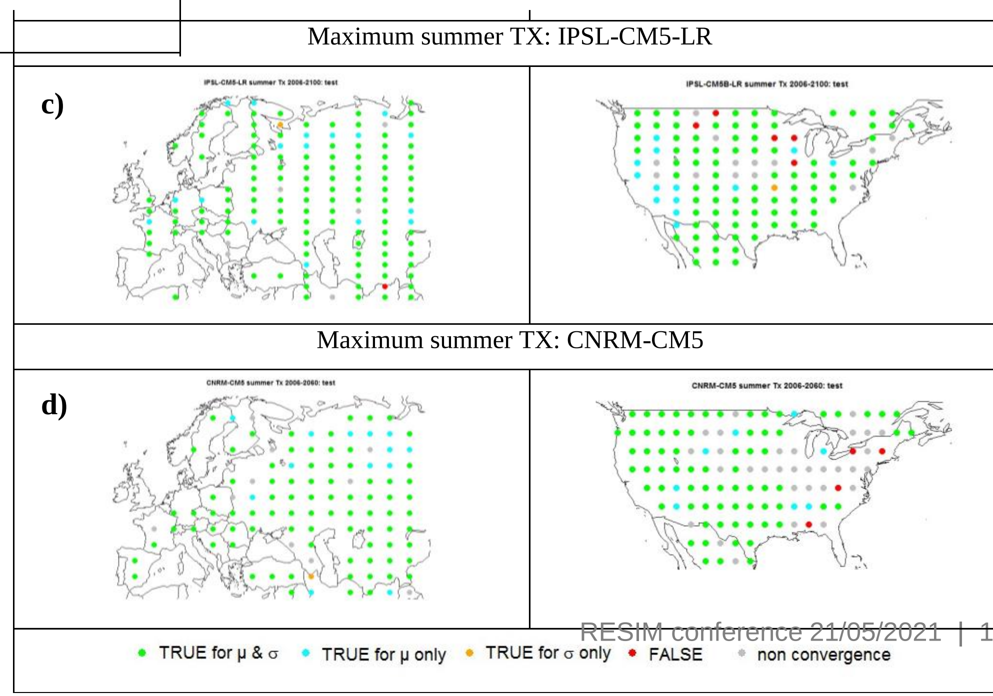


RESULTS FOR DIFFERENT LOCATIONS

Parey S., Hoang TTH, Dacunha-Castelle D.: The importance of mean and variance in predicting changes in temperature extremes, Journal of Geophysical Research: Atmospheres, Vol 118, 1-12, 2013, doi:10.1002/jgrd.50629

AND FOR FUTURE CLIMATE





FUTURE RETURN LEVEL

- **Hot extremes**
  - **Estimation:** $\boldsymbol{Z_X} = m_f + s_f Z_Y$, with m_f and s_f **in the desired future period obtained from climate simulations**

- **Cross validation:**

  Observation period splitted in 2 sub-periods

  Estimation of Y over 1951-1986

  Estimation of the RL over 1987-2016

model	Bourges	Perpignan	Caen	Clermont-Ferrand	Tarbes	Mont de Marsan	Belle Ile
Bcc-csm1-1-m	**40.2** **[38.3 ; 42.1]**	**40.3** **[38.8 ; 41.9]**	**38.8** **[36.5 ; 41.1]**	**40.7** **[39.1 ; 42.4]**	**39.2** **[37.8 ; 40.6]**	**41.1** **[40.1 ; 42.1]**	35.2 [33.8 ; 36.6]
BNU-ESM	**39.7** **[37.8 ; 41.5]**	**40.2** **[38.6 ; 41.7]**	**38.4** **[36.2 ; 40.7]**	**40.4** **[38.7 ; 42.0]**	**39.3** **[37.9 ; 40.7]**	**40.9** **[39.9 ; 41.9]**	**34.0** **[32.7 ; 35.3]**
CNRM-CM5	38.2 [36.4 ; 40.0]	**39.2** **[37.6 ; 40.7]**	**37.5** **[35.3 ; 39.8]**	38.7 [37.1 ; 40.2]	38.1 [36.7 ; 39.5]	39.5 [38.5 ; 40.5]	**33.3** **[32.1 ; 34.6]**
EC-EARTH	**39.4** **[37.5 ; 41.4]**	**39.9** **[38.3 ; 41.4]**	**38.6** **[36.3 ; 41.0]**	**40.1** **[38.4 ; 41.7]**	**38.8** **[37.4 ; 40.2]**	**40.7** **[39.7 ; 41.7]**	**34.5** **[33.2 ; 35.9]**
IPSL-CM5A-MR	**39** **[37.1 ; 40.9]**	40.6 [38.9 ; 42.2]	**37.5** **[35.3 ; 39.8]**	**40.0** **[38.3 ; 41.7]**	**38.8** **[37.4 ; 40.3]**	**40.4** **[39.4 ; 41.4]**	**33.4** **[32.1 ; 34.6]**
MIROC5	38.6 [36.7 ; 40.4]	**40** **[38.4 ; 41.5]**	36.1 [34.0 ; 38.2]	39.3 [37.7 ; 40.9]	38.1 [36.7 ; 39.5]	39.6 [38.6 ; 40.6]	**33.1** **[31.9 ; 34.4]**
MIROC-ESM-CHEM	37.4 [35.5 ; 39.2]	38.0 [36.5 ; 39.5]	35.7 [33.6 ; 37.9]	38.0 [36.5 ; 39.6]	37.3 [35.9 ; 38.7]	39.0 [38.0 ; 39.9]	**33.5** **[32.2 ; 34.8]**
MIROC-ESM	**40.5** **[38.5 ; 42.6]**	**40.2** **[38.5 ; 41.9]**	**37.5** **[35.2 ; 39.9]**	**41.3** **[39.5 ; 43.1]**	**39.3** **[37.7 ; 40.8]**	**40.8** **[39.7 ; 41.9]**	**33.7** **[32.3 ; 35.0]**
MPI-ESM-MR	**38.9** **[37.0 ; 40.8]**	**39.8** **[38.2 ; 41.4]**	**37.2** **[35.0 ; 39.4]**	**39.5** **[37.9 ; 41.2]**	38.4 [37.0 ; 39.8]	**40.1** **[39.1 ; 41.1]**	**33.5** **[32.2 ; 34.8]**
CCSM4	**39.9** **[37.9 ; 41.9]**	**40.0** **[38.4 ; 41.6]**	**38.1** **[35.8 ; 40.4]**	**40.8** **[39.1 ; 42.6]**	**39.0** **[37.6 ; 40.5]**	**41.1** **[40.0 ; 42.2]**	**34.3** **[32.9 ; 35.6]**
NorESM1-M	**40.7** **[38.6 ; 42.7]**	40.7 [39.0 ; 42.4]	**40** **[37.4 ; 42.5]**	**41.4** **[39.6 ; 43.2]**	**39.8** **[38.2 ; 41.3]**	**41.4** **[40.3 ; 42.5]**	35.1 [33.7 ; 36.5]
GFDL-CM3	**40.0** **[38.0 ; 42.0]**	40.8 [39.1 ; 42.5]	**38.5** **[36.2 ; 40.9]**	**40.7** **[38.9 ; 42.4]**	**39.2** **[37.7 ; 40.7]**	**40.8** **[39.8 ; 41.9]**	35.2 [33.8 ; 36.6]
CESM1-CAM5	**39.7** **[37.7 ; 41.6]**	**40.2** **[38.7 ; 41.8]**	**38.9** **[36.5 ; 41.3]**	**40.3** **[38.6 ; 41.9]**	**39.1** **[37.6 ; 40.5]**	**40.3** **[39.3 ; 41.3]**	**34.2** **[32.9 ; 35.5]**
observations	40.2 [38.8;41.5]	39.5 [38.7;40.3]	38.4 [36.8;40.0]	40.9 [39.7;42.0]	39.5 [38.5;40.5]	41.2 [40.1;42.3]	33.9 [32.8;34.9]

Parey S., Hoang T.T.H., Dacunha-Castelle D. (2018): Future high temperature extremes and stationarity, Natural Hazards, https://doi.org/10.1007/s11069-018-3499-1

STOCHASTIC MODELLING OF AIR TEMPERATURE

Hoang, T. T. H. (2010), Modélisation de séries chronologiques non stationnaires, non linéaires: application à la définition des tendances sur la moyenne, la variabilité et les extrêmes de la température de l'air en Europe http://www.tel.archivesouvertes.fr/tel-00531549/fr/

Dacunha-Castelle D., Hoang T.T.H., Parey S.: Modeling of air temperatures: preprocessing and trends, reduced stationary process, extremes, simulation, Journal de la Société Française de Statistique, 2013

Parey S., Hoang T.T.H., Dacunha-Castelle D. (2013): Validation of a stochastic temperature generator focusing on extremes and an example of use for climate change, Climate Research

PRE-PROCESSING

- Remove deterministic parts to obtain a stationary process
- Based on both parametric and nonparametric estimations

$$X(t) = m(t) + S(t) + s(t)S_V(t)Z(t)$$

– $m(t), s(t)$: trends in mean and standard deviation, $S(t), S_V(t)$: seasonality

– **Estimation :**

» estimate $m(t)$ using loess, $S(t)$ as a trigonometric function from $X(t)$, then $s(t)$ using loess and $S_V^2(t)$ as a trigonometric function from $[X(t) - \hat{m}(t) - \hat{S}(t)]^2$

» For $m(t), s(t)$, modified partitioned cross-validation[(1)] is used, while for $S(t), S_V^2(t)$ an Akaike criterion is considered

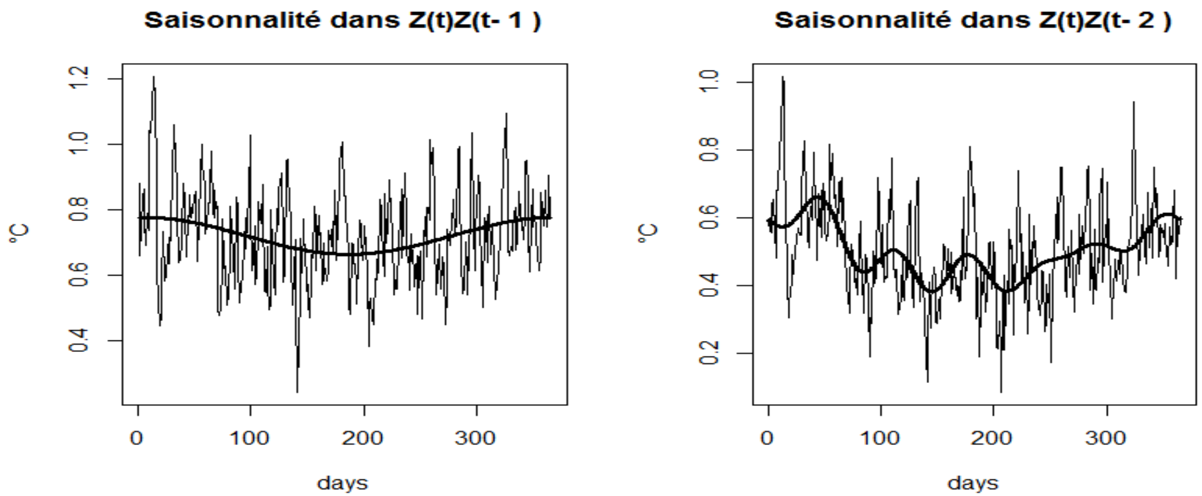
» Standardized timeseries:

$$Z_t = \left(X_t - \hat{m}_t - \hat{S}_t\right)/(\hat{s}_t \hat{S}_{Vt})$$

[(1)] ***Modified partitioned CV: new algorithm for correlated data (thesis of Hoang, 2010)***

CHARACTERISTICS OF THE REDUCED VARIABLE

- short memory
- seasonality remains in higher moments and autocorrelations
- cyclo-stationary
- tails are bounded
- nonlinear
- volatility depends on the state
- studies:
  - Trend tests[(2)] for basic statistics (mean, variance, skewness, kurtosis)
  - Cyclo-stationarity test[(3)] for the extremes
  - Analysis of trends and seasonality in $Z_t Z_{t-k}$



(2), (3) : A new test proposed in Hoang (2010), the principle of test is described in the next slide

PRINCIPLE OF THE STATIONARITY TESTS

- Considered model: ***X(t)= θ(t)+ ε(t)***, the distribution of ε is known or not

- **Hypotheses of the test**: *θ is constant / θ is not constant*

- If:
  - $\hat{c}_n$ is a constant estimator of θ (through mlh if the distribution of ε is known, through least squares otherwise)
  - $\hat{\theta}_n$ is a nonparametric estimator of θ (through splines if the distribution of ε is known, through loess otherwise)

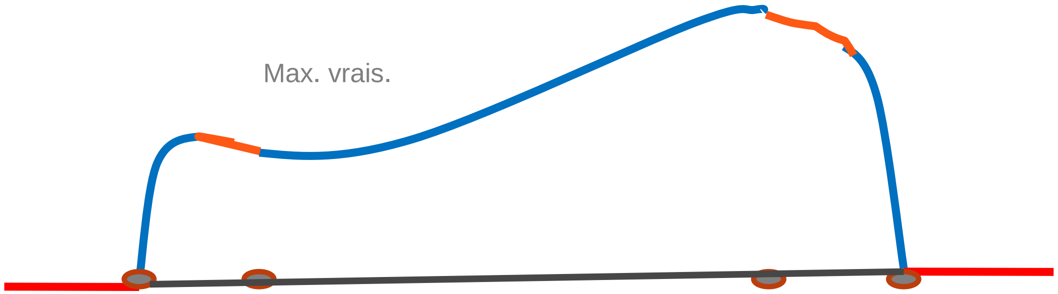
- **goal** : compare those 2 estimators using an *L^2 distance*:

$$\Delta = \left\| \hat{\theta}_n - \hat{c}_n \right\|$$

- *In practice*: test using Δ (build an **empirical distribution of Δ under H0** by simulation if the distribution of θ is known or by permutation (or block bootstrap) otherwise)
- **Trend tests for the moments**: mean, variance, skewness, kurtosis, correlation, and for the **extremes**

MODEL TYPE

Conditional variance form



FARCH Model **(Functional AutoRegressive conditional Heteroscedastic)**

Approximation (order 1 Euler scheme) of the discrete Markov chain given by the discrete observations of a continuous diffusion with the same coefficients

THE SFHAR MODEL (SEASONAL FUNCTIONAL HETEROSCEDASTIC AUTOREGRESSIVE)

- $Z_t = b(Z_{t-1}) + a(Z_{t-1})\varepsilon_t, \quad \varepsilon_t \propto N(0,1)$

- Extension: SFHAR model

$$Z(t) = \left[\theta_{0,k} + \sum_{j=1}^{p_1}\left(\theta_{1,k}^{j}\cos\frac{2j\pi t}{365} + \theta_{2,k}^{j}\sin\frac{2j\pi t}{365}\right)\right]Z(t-1) + a(t, Z_{t-1})\varepsilon_t$$

$$\varepsilon_t \propto N(0,1)$$

- Estimate $a^2(t, Z_{t-1})$ with constraints:
  - Zero outside the boundaries
  - positive
  - constraints *C* for the 1st derivatives of the continuous time process

$$(a^2)\ '(r_1) = \frac{2b(r_1,t)}{1-1/\xi_1} \quad and \quad (a^2)\ '(r_2) = \frac{2b(r_2,t)}{1-1/\xi_2}$$

  - Which gives *a*

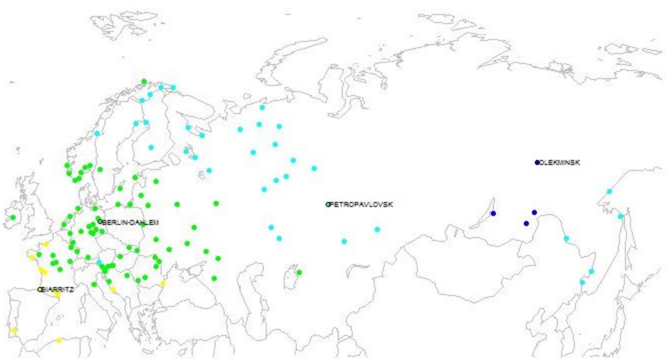
$$\begin{cases} \hat{a}^2(t, Z_{t-1}) = (\hat{r}_2 - t)(t - \hat{r}_1)\sum_{k=0}^{5}\sum_{j=1}^{p_2}\left(\alpha_{1,k}^{j}\cos\frac{2j\pi t}{365} + \alpha_{2,k}^{j}\cos\frac{2j\pi t}{365}\right)Z_{t-1}^{k} \\ C(\hat{r}_1, t), C(\hat{r}_2, t) \\ \hat{a}^2(t) > 0\ \forall t \end{cases}$$

ESTIMATION PROCEDURE

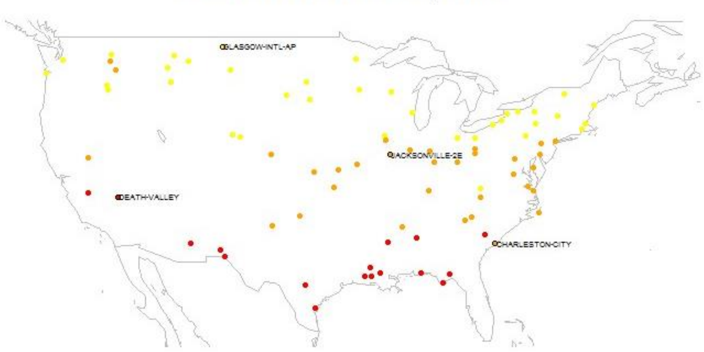
- **Estimation of the autoregressive part (AR(1))**
- **Choice of the number of sines and cosines using Akaike criterion**
- **Volatility estimation by maximum likelihood with constraints**
  - **Initial values obtained by least squares**
  - **Maximum likelihood: estimation with constraints**
- **Simulation of *Z(t)***
- **Computation of *X(t)* by reintroducing trends and seasonality**

VALIDATION: CHOICE OF DIFFERENT CLIMATES

1950-2009 ECA series TN: annual mean temperature



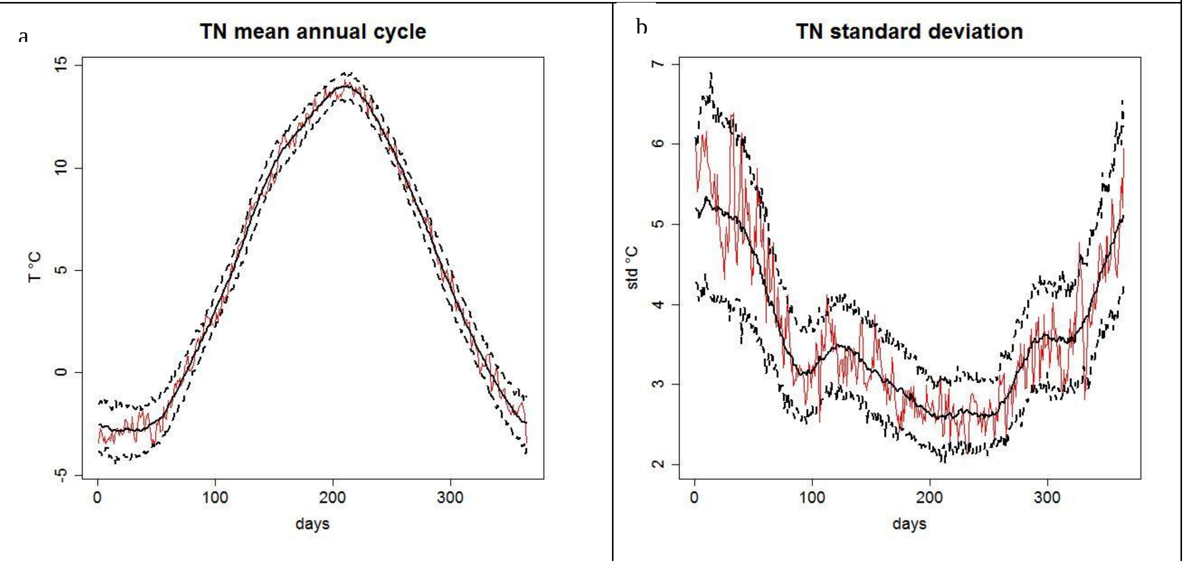
NOAA series TX annual mean temperature



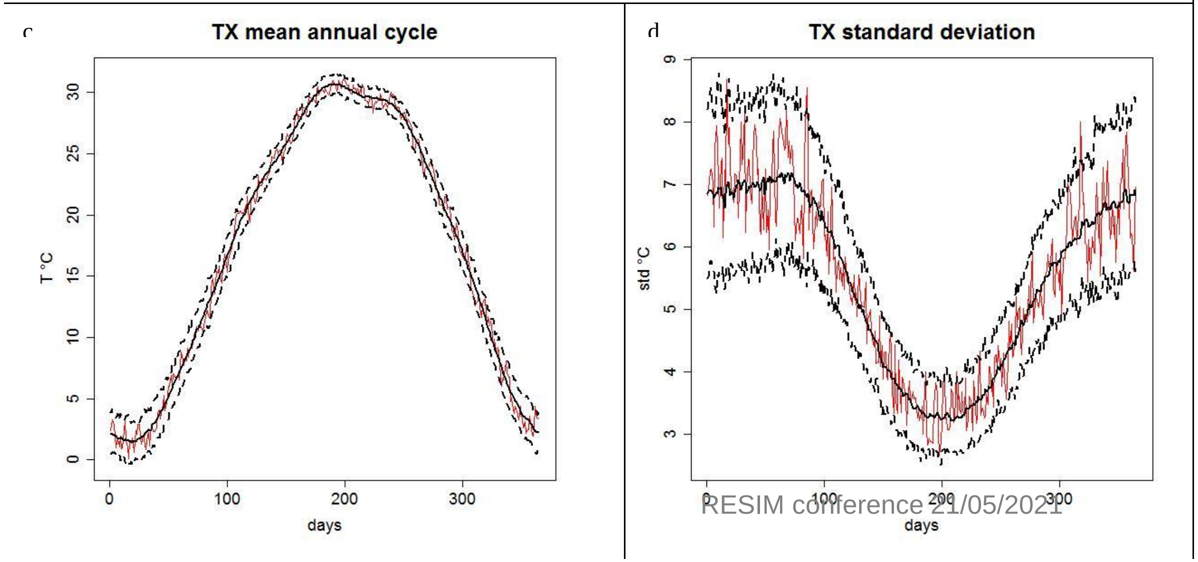
Weather station	Daily minimum temperature TN		Daily maximum temperature TX	
	period	Mean annual mean (°C)	period	Mean annual mean (°C)
Biarritz	1956-2009	10.1	1956-2009	17.7
Berlin	1950-2009	5.1	1950-2009	13.4
Petropavlovsk	1950-2009	-3.3	1950-2009	6.9
Olekminsk	1950-2009	-11.3	-	-
Death Valley	1962-2009	17.0	1962-2009	32.8
Charleston	1950-2009	15.4	1950-2009	23.0
Jacksonville	1950-2009	5.2	1950-2009	17.5
Glasgow	1950-2009	-0.7	1950-2009	12.5

MEAN ANNUAL CYCLES

BERLIN: daily minimum temperature TN



JACKSONVILLE: daily maximum temperature TX

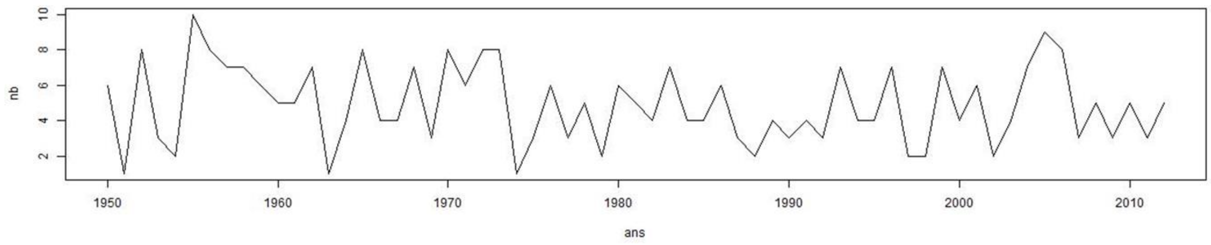


EXTREMES

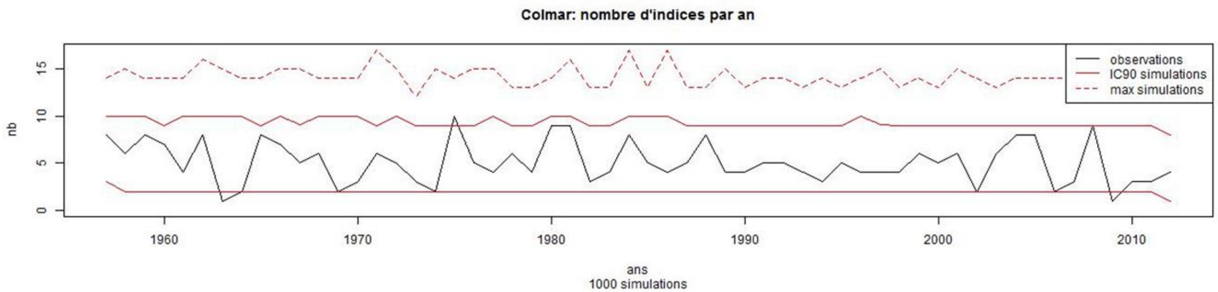
	TX		TN	
	observations	simulations	observations	simulations
Berlin	38.2 [37.1;39.2]	39.8 [38.8;41.0]	-23.4 [-25.5;-21.0]	-26.5 [-31.5;-22.9]
Biarritz	39.6 [38.8;40.4]	41.0 [39.0;43.5]	-9.4 [-12.2;-6.6]	-11.0 [-12.6;-9.7]
Petropavlovsk	38.5 [37.6;39.5]	41.5 [39.3;44.8]	-43.7 [-45.2;-42.1]	-48.7 [-52.5;-45.3]
Olekminsk	-	-	-56.3 [-57.8;-54.8]	-58.8 [-61.4;-56.2]
Death Valley	54.3 [53.5;55.1]	55.2 [54.3;56.1]	-6.4 [-7.5;-5.3]	-7.4 [-8.8;-6.0]
Jacksonville	41.8 [40.3;43.3]	43.1 [41.5;44.5]	-29.5 [-31.3;-27.7]	-33.8 [-38.5;-30.6]
Glasgow	42.0 [41.1;42.8]	45.5 [44.3;46.9]	-42.9 [-44.4;-41.4]	-46.9 [-50.4;-44.0]
Charleston	39.5 [38.6;40.4]	40.3 [39.5;41.2]	-11.3 [-13.7;-9.0]	-8.8 [-10.0;-7.5]

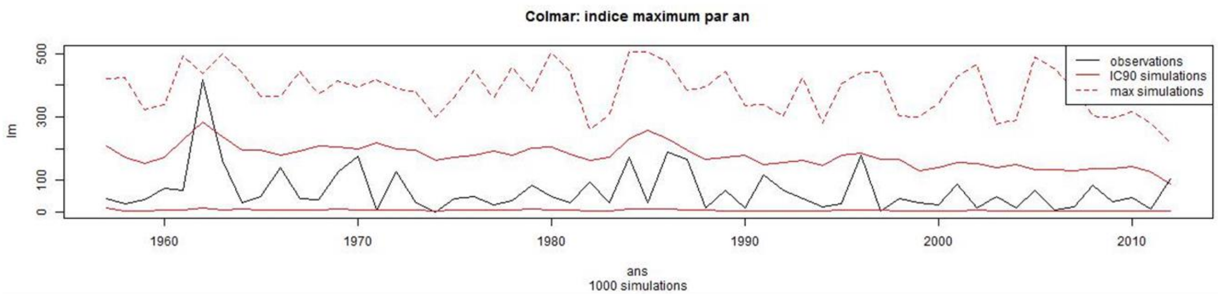
EXAMPLE: FROST INDICES

- **Frost index = cumulation of daily mean temperatures < 0°C ⇒ few events each year**



- **Simulation of a large number of temperature time series consistent with the observed one**





nb < nb5%: 2 nb>nb95%: 1

Im<Im5%: 3 IM>IM95%: 2

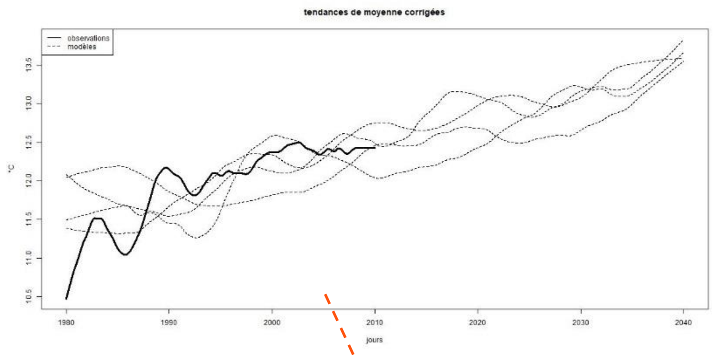
5% 56 years : 2,8

BUILDING TIMESERIES COVERING RECENT PAST AND NEAR FUTURE

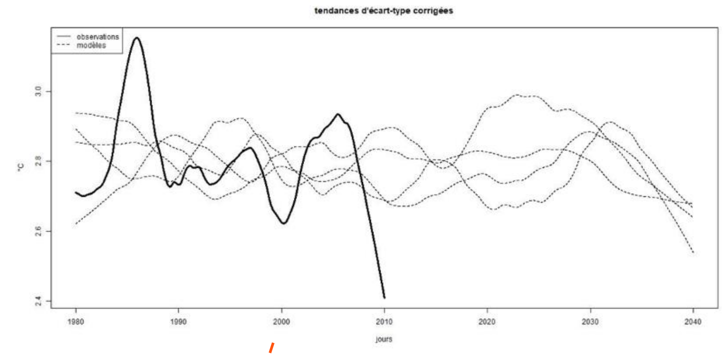
we use:

- The bias adjusted trends given by climate models

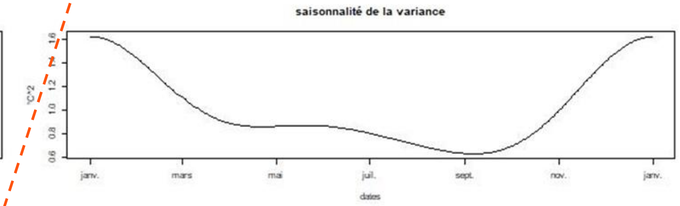
mean



variance



- The observed seasonality



- Residuals simulated with the stochastic model

$$X(t) = m(t) + S(t) + s(t)Sv(t)Z(t)$$

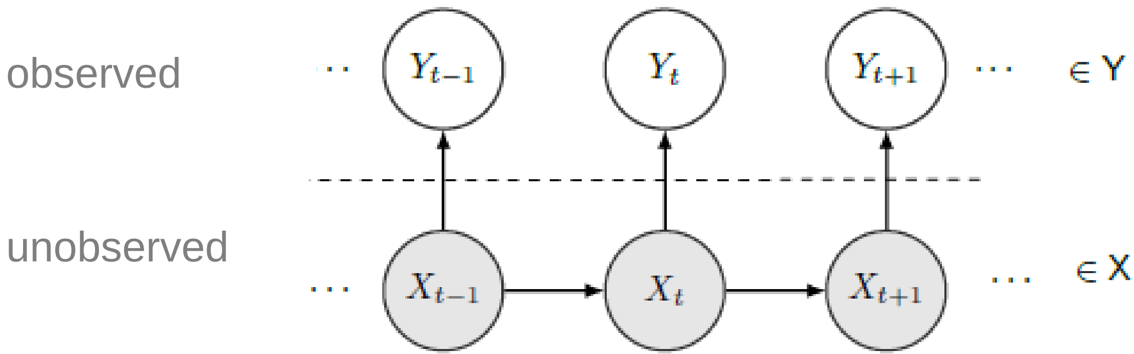
MULTIVARIATE STOCHASTIC MODEL

Touron A. (2019): Modélisation multivariée de variables météorologiques. Statistiques [math.ST]. Université Paris-Saclay. Français. ⟨NNT : 2019SACLS264⟩. ⟨tel-02319170⟩

Touron, A. (2019): Consistency of the maximum likelihood estimator in seasonal hidden Markov models. *Stat Comput* **29,** 1055–1075, https://doi.org/10.1007/s11222-019-09854-4

NON HOMOGENOUS HIDDEN MARKOV MODELS

- **Model principle**



Seasonality in the transition matrix

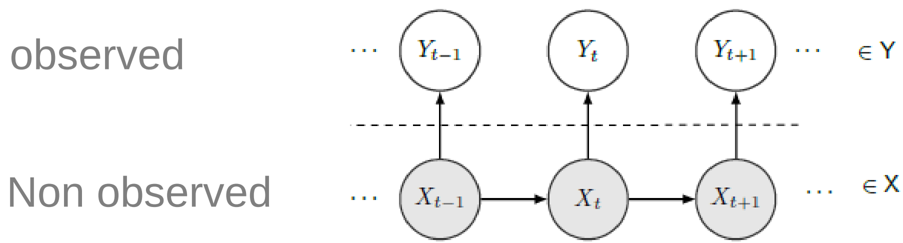
$$\mathbb{P}(X_{t+1} = j \mid X_t = i) =: Q_{ij}(t)$$

  - Trends and seasonality in the emission distributions

- **Different models proposed**
  - Univariate: temperature, precipitations, wind
  - Bivariate: temperature and precipitations
  - Tri-variate: temperature, precipitations, wind

EXAMPLE: BIVARIATE MODEL RAINFALL / TEMPERATURE

- **Bivariate weather generator: temperature and rainfall**
  - Non-Homogeneous Hidden Markov Model (NH HMM)



$$\mathbb{P}(X_{t+1} = j \mid X_t = i) =: Q_{ij}(t)$$ seasonal

  - Emission law for *Y(t)* given *X(t) = k*:

$$\nu_k(t) = \sum_{m=1}^{M_1} p_{km}\delta_0 \otimes \mathcal{N}(T_k(t) + S_k(t) + \mu_{km}, \sigma_{km}^2) + \sum_{m=M_1+1}^{M} p_{km}\mathcal{E}\left(\frac{\lambda_{km}}{1+\sigma_k(t)}\right) \otimes \mathcal{N}(T_k(t) + S_k(t) + \mu_{km}, \sigma_{km}^2)$$

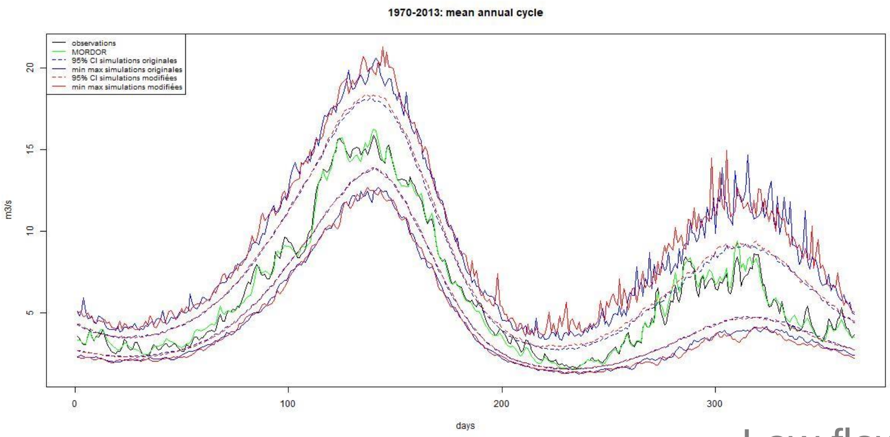
- **Choice of the “meta-parameters”: 7 states, M1 = 2, M = 4**

- **1000 simulations for T & Precipitation 1970-2013 => 44 000 years**

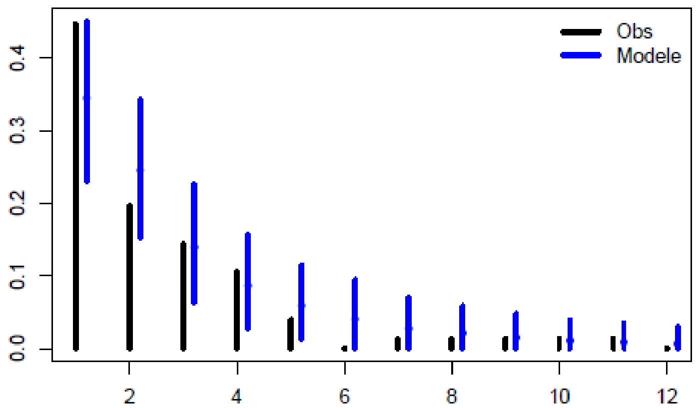
USE TO SIMULATE RIVER FLOW

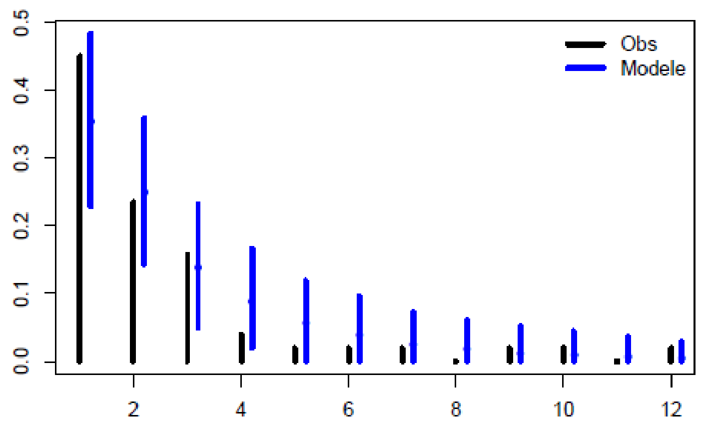
- **Temperature and rainfall are used as inputs of a physically based river flow model**
- **Validation**

Mean annual cycle



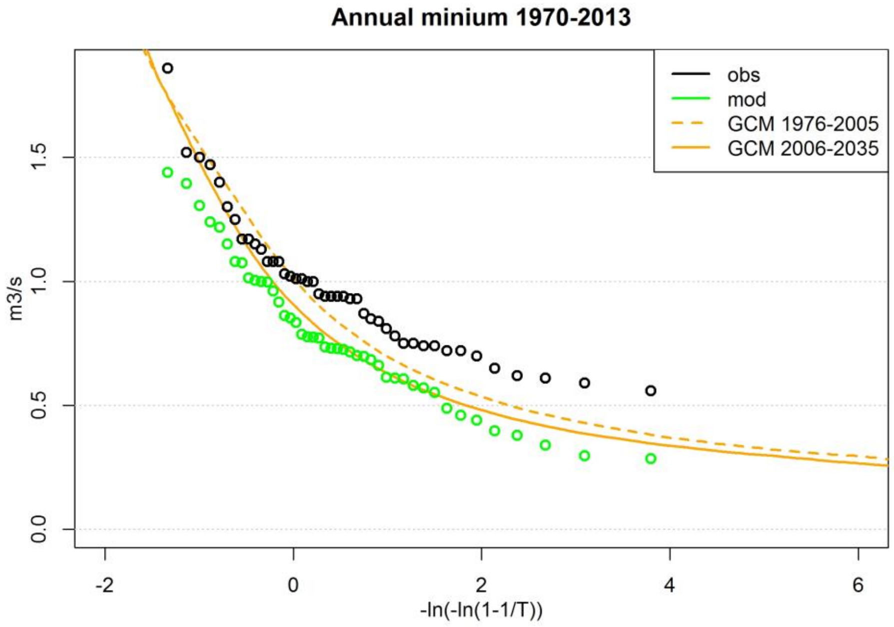
Low flows: streamflow < 5th and 3rd percentiles





AND ESTIMATE FUTURE EXTREMES

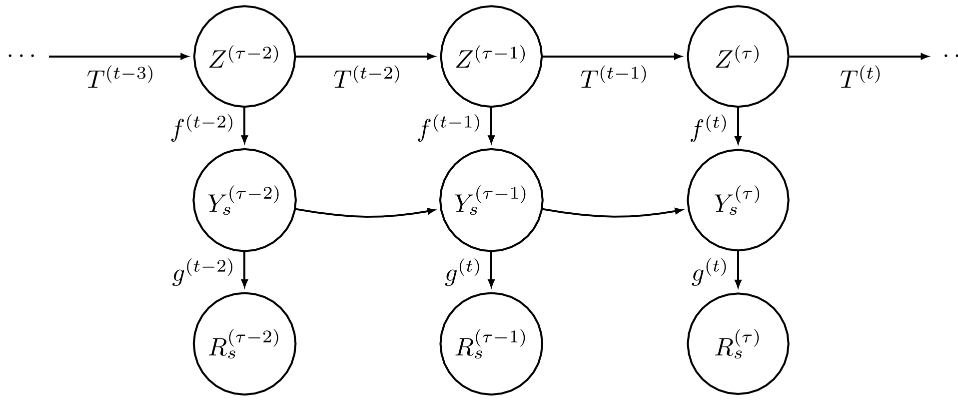
- **Calibration of the model using bias adjusted climate simulation**
- **Example: streamflow simulation over period 1976-2035**



- **Historical period 1976-2005**
  - 100-year RL: 0.342 [0.340;0.344]
- **Future period 2006-2035**
  - 100-year RL: 0.312 [0.309;0.314]

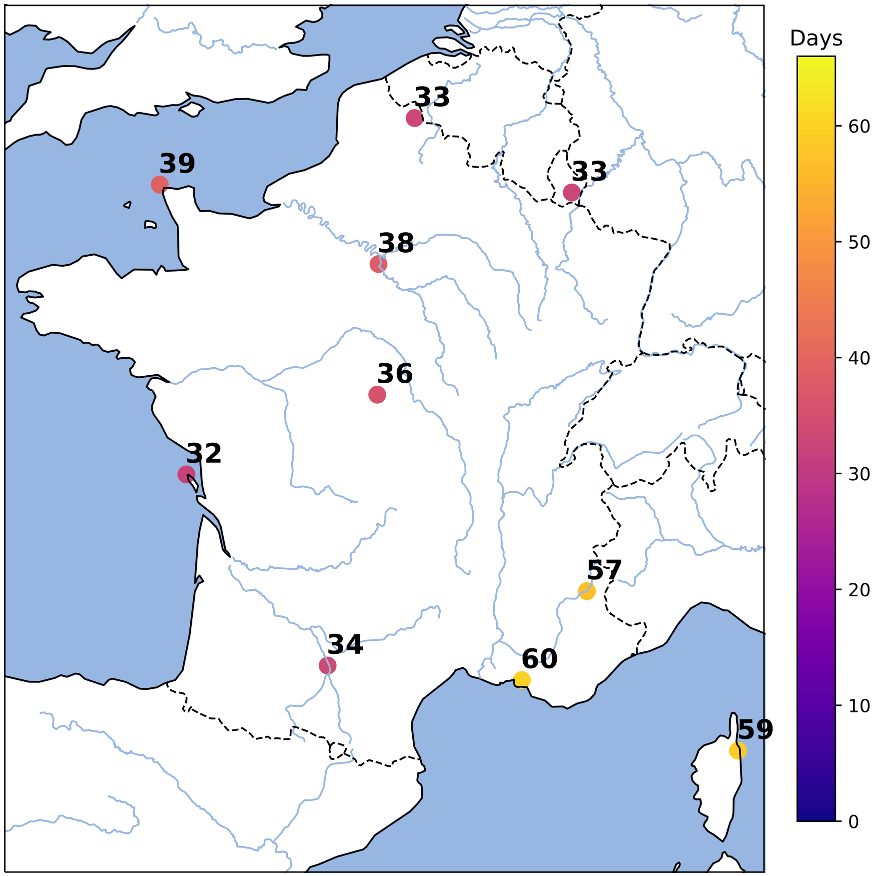
ADDITION OF THE SPATIAL DIMENSION

- **Work in progress in collaboration with Emmanuel Gobet and David Métivier (CMAP, école Polytechnique)**

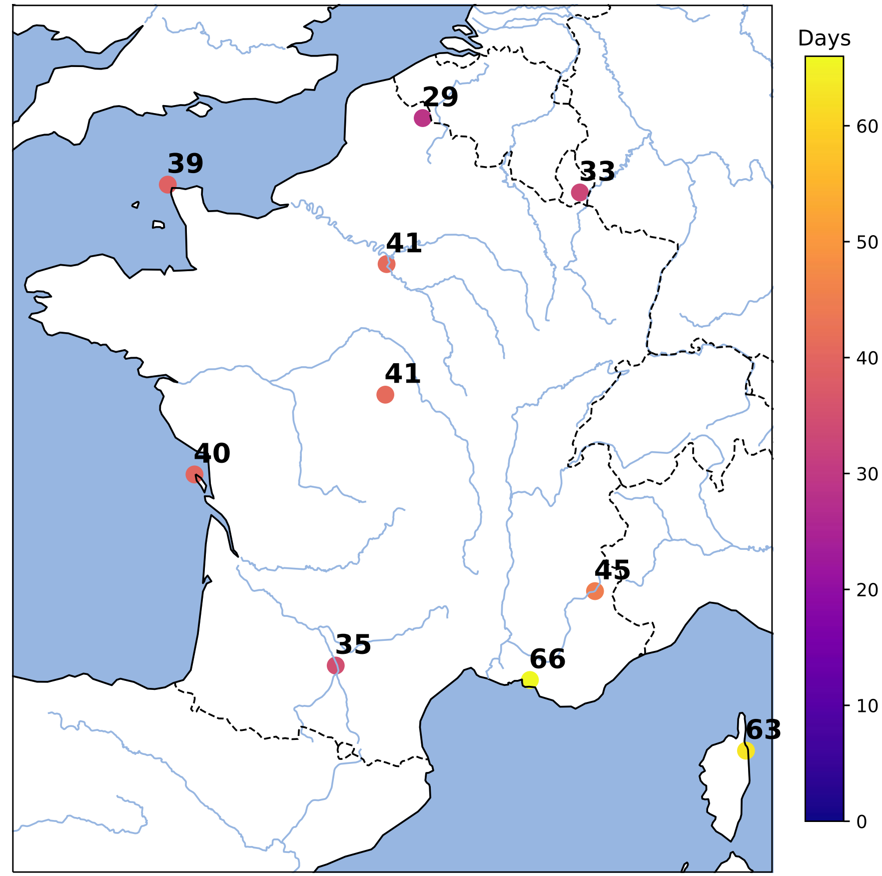


- **Spatial rainfall generator**
  - Based on Hidden Markov Models
  - First step : rainfall occurrence
    - 3 models tested and compared
      - $(H_1)_s^{(t)} = Y_s^{(t)} \in I_{C_1} = \{d, w\}$
      - $(H_2)_s^{(t)} = (Y_s^{(t-1)}, Y_s^{(t)}) \in I_{C_2} = \{dd, dw, wd, ww\}$
      - $(H_3)_s^{(t)} = (Y_s^{(t-2)}, Y_s^{(t-1)}, Y_s^{(t)}) \in I_{C_3} = \{ddd, wdd, dwd, ddw, wwd, wdw, dww, www\}$
    - Fit a mixture model as a probability product of each station: $f(H) = \sum_{k=1}^{K} \pi_k \prod_{s=1}^{S} f_{s|k}(H_s)$
    - One mixture per day, with smoothing a posteriori
    - K = 4 and model C_2 are found optimal
  - Rainfall amounts
    - For each station, each day and each state k: rainfall amount distribution = mixture of Gamma and exponential distributions
    - Station correlations introduced through Gaussian copula

RECORD OF THE NUMBER CONSECUTIVE DAYS WITHOUT RAIN



Historical data 1956-2019



One 64 year simulation

CONCLUSION AND PERSPECTIVES

- **EDF activities are sensitive to the meteorological conditions**

- **This implies the need to**
  - Estimate extreme weather conditions
  - Generate large samples of possible hydroclimatic variables evolutions to test the system

- **Development of:**
  - Methodologies to estimate extreme values in taking climate change into account
  - Different weather generators:
    - Local air temperature
    - Local multivariate timeseries: temperature, rainfall, wind
    - Spatial univariate generator

- **Future work**
  - Spatial (at least) bivariate generator: temperature and rainfall
  - Use to simulate streamflow and its possible changes with climate change to go further in the study of climate change impacts on nuclear generation

Thank you