

Quantification of devastating climate events under climate change through novel multivariate bias correction methods

Séminaire Géolearning

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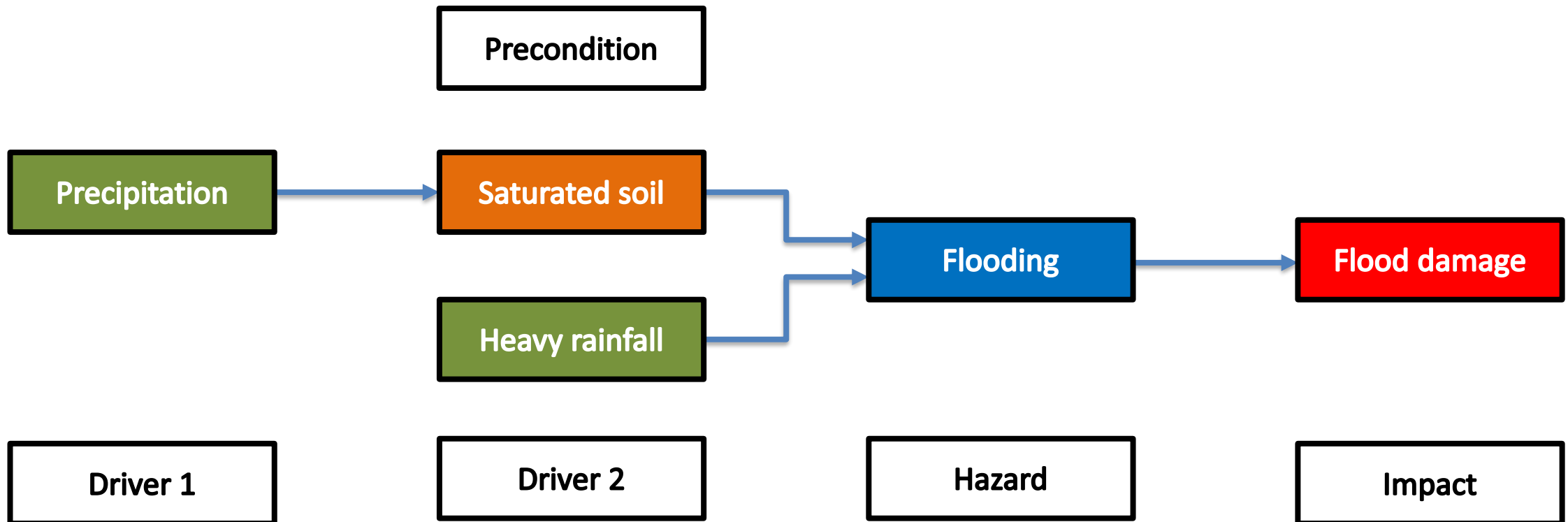
GEOLEARNING
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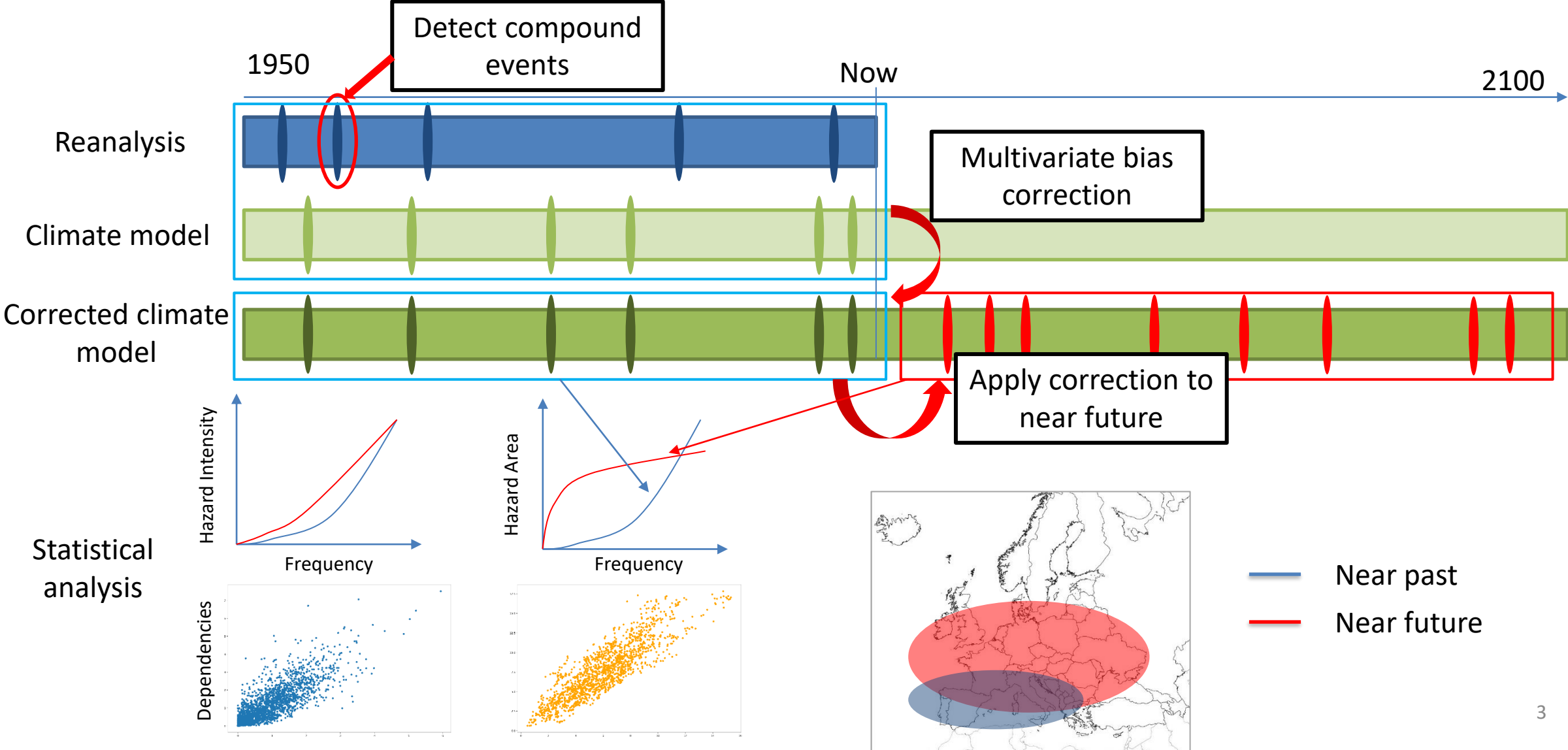
PSL

Compound events

A combination of multiple drivers and/or hazards that contributes to societal or environmental risk (Zscheischler et al., 2020)



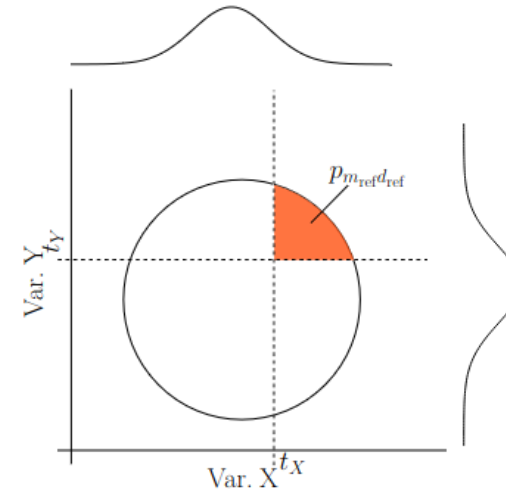
PHD Objective



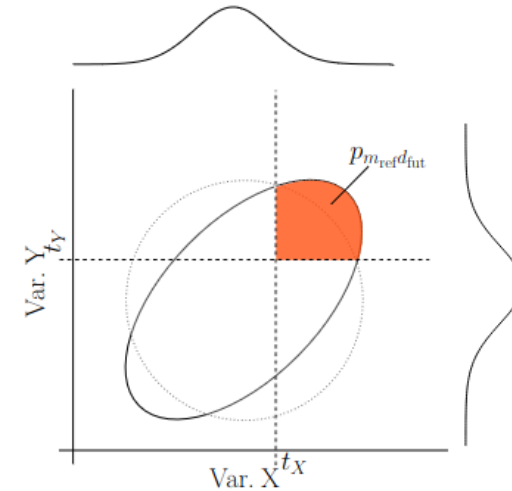
Modelling the dependence

- With climate change, or in the simulations, the marginals and the dependence structure can change.
- Multivariate bias correction is probably necessary to affect both the marginals and the dependence.

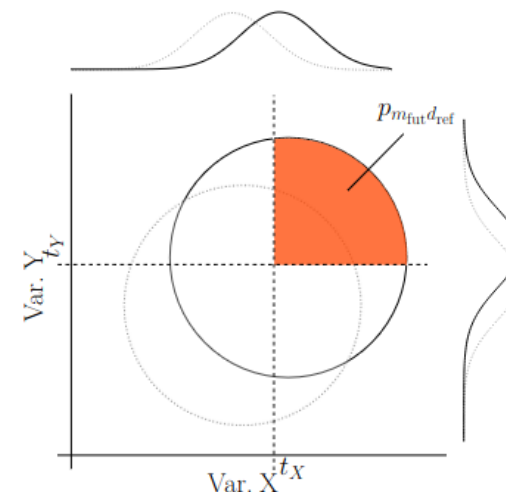
(a) Marg. and dep. for reference period



(b) Marg. from reference, dep. from future period



(c) Marg. from future, dep. from reference period



(d) Marg. and dep. for future period

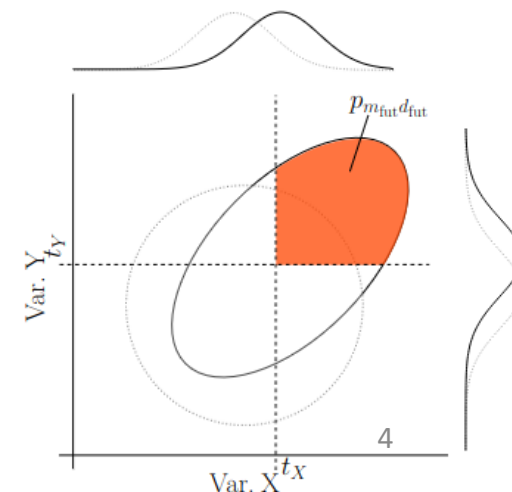


Figure from B. François and M. Vrac, *Time of emergence of compound events: contribution of univariate and dependence properties*

Multivariate extreme value theory

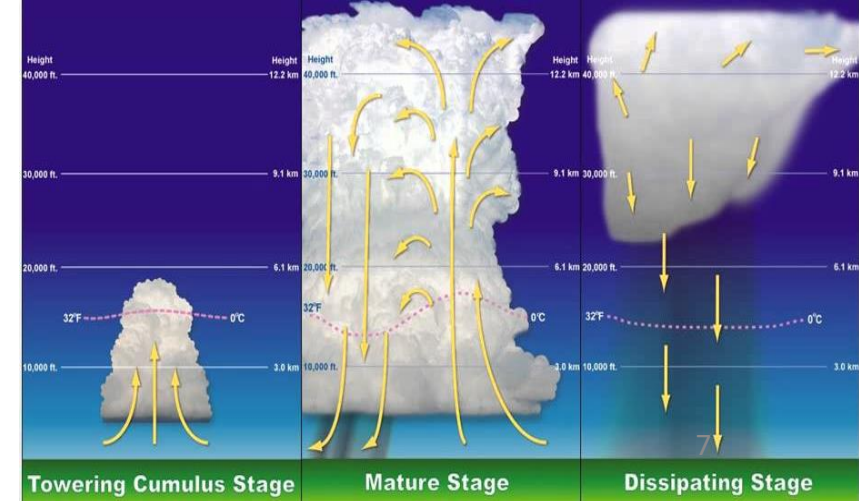
- X_N and Y_N are two samples with bivariate cumulative distribution function \mathbf{F} , supposedly in the domain of attraction of a bivariate extreme value cumulative distribution function \mathbf{G} .
- Sklar's theorem (1959) : Any multivariate cumulative distribution function \mathbf{F} can be expressed in terms of its margins F_i and a copula \mathbf{C} :
$$\mathbf{F}(x_1, \dots, x_d) = \mathbf{C}(F_1(x_1), \dots, F_d(x_d))$$
 with $\mathbf{C} : [0,1]^d \rightarrow [0,1]$
- Therefore, we get weak convergence of the marginal distribution functions and the copula function

Copulas and uniform margins

- This allows us to propose the following approach :
 1. Propose a univariate extreme model for the marginals
 2. Reduce to uniform margins
 3. Determine the copula
- X_N and Y_N must be i.i.d. and extreme, and (X_N, Y_N) must be extreme in some sense

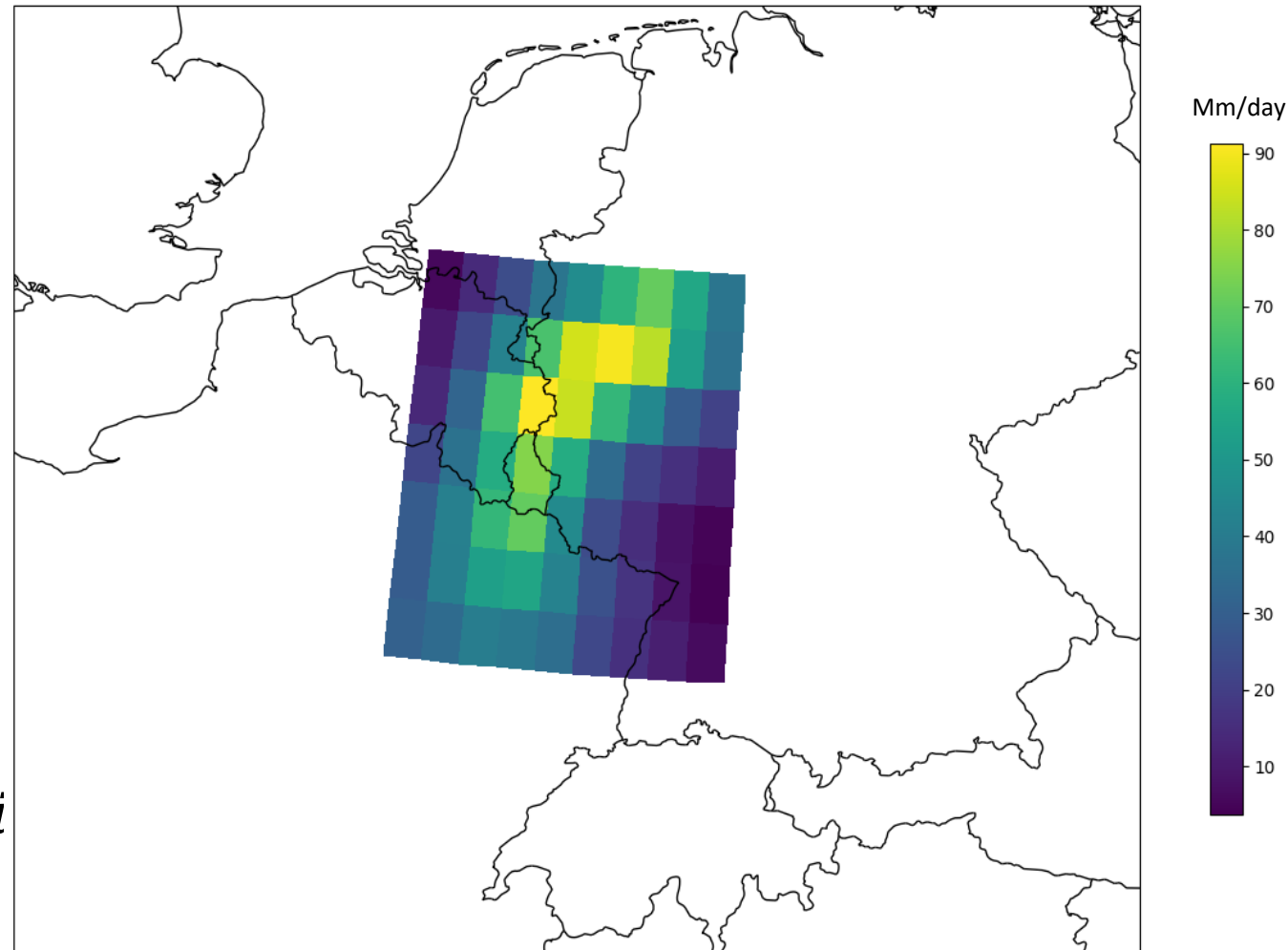
Three potential events

- July 2021 Belgian/German flooding
(Preconditioned event)
- May/June 2016 French flooding
(Spatially compound event)
- Convective cells
(Multivariate compound event)



14th July 2021 flooding

- Data from ERA5 reanalyzes
- Total Precipitation (TP) : daily precipitation (mm/day)
- Antecedent Precipitation Index (API) : $API_j = \sum_{i=1}^{i=N} k^{i-1} * TP_{j-i}$ with $k=0.9$ and $N=30$



Data Selection

Data must be i.i.d. and extreme

Data selection for 1D

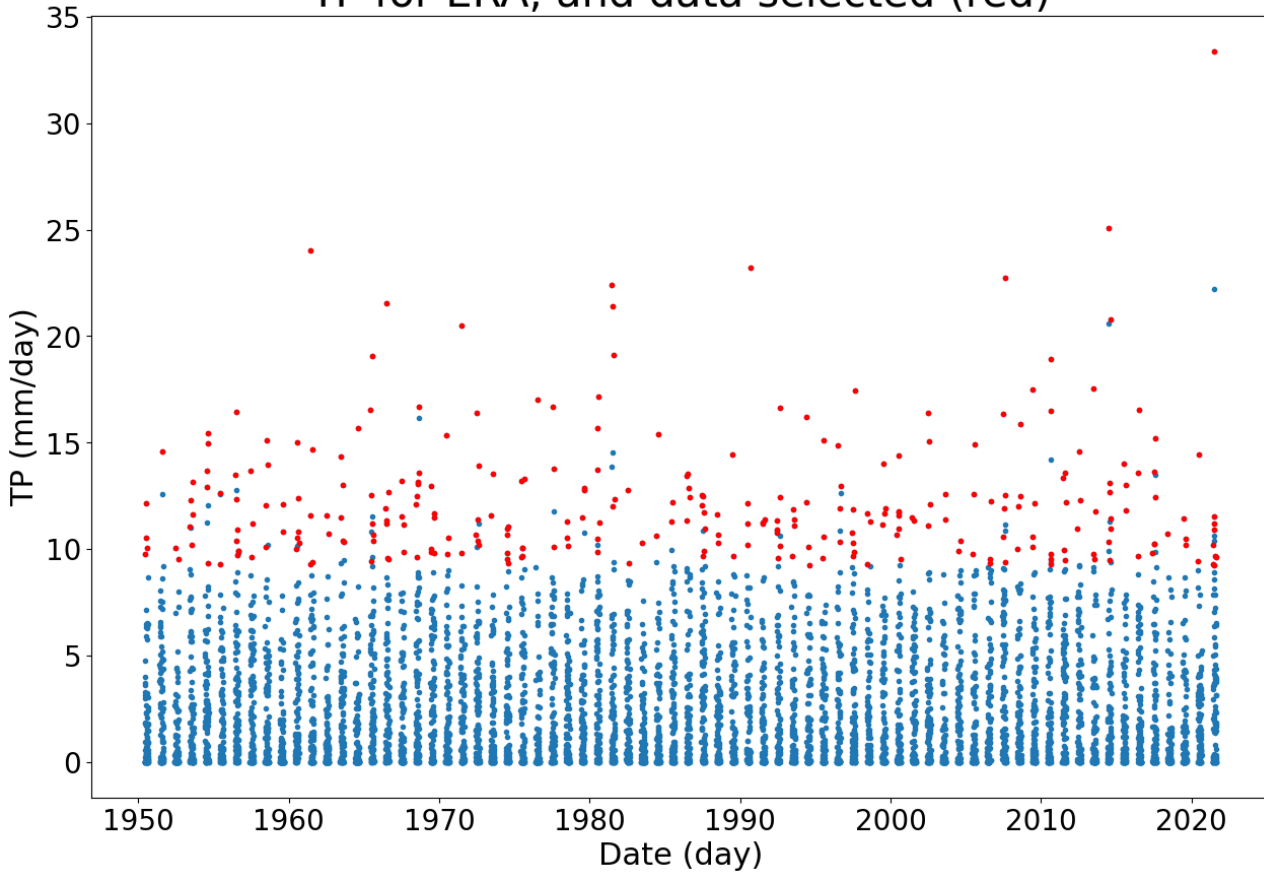
- For TP : select points above the 95th quantile, separated by at least 2 days
- For API : select points above the 95th quantile, separated by at least D days, with :
$$\rho(API_j, API_{j+D}) < 0,1 \quad (D = 20)$$

Data selection for 2D

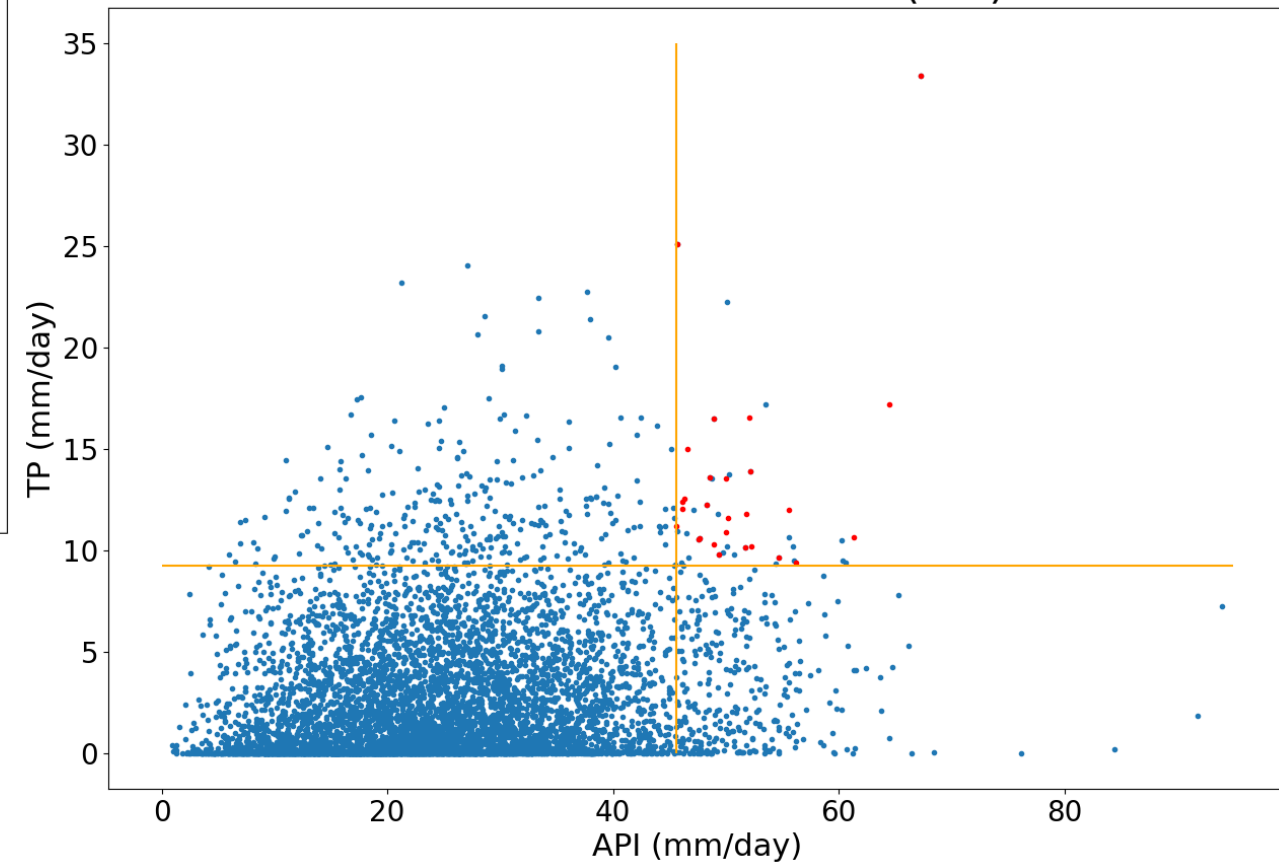
- Select (TP_i, API_j) with $TP_i > Q95_{TP}$, $API_j > Q95_{API}$ and $i - 5 \leq j \leq i$
- Then select couples separated by at least D days, according to the highest TP value

Data selection

TP for ERA, and data selected (red)



Bivariate data selection (red)



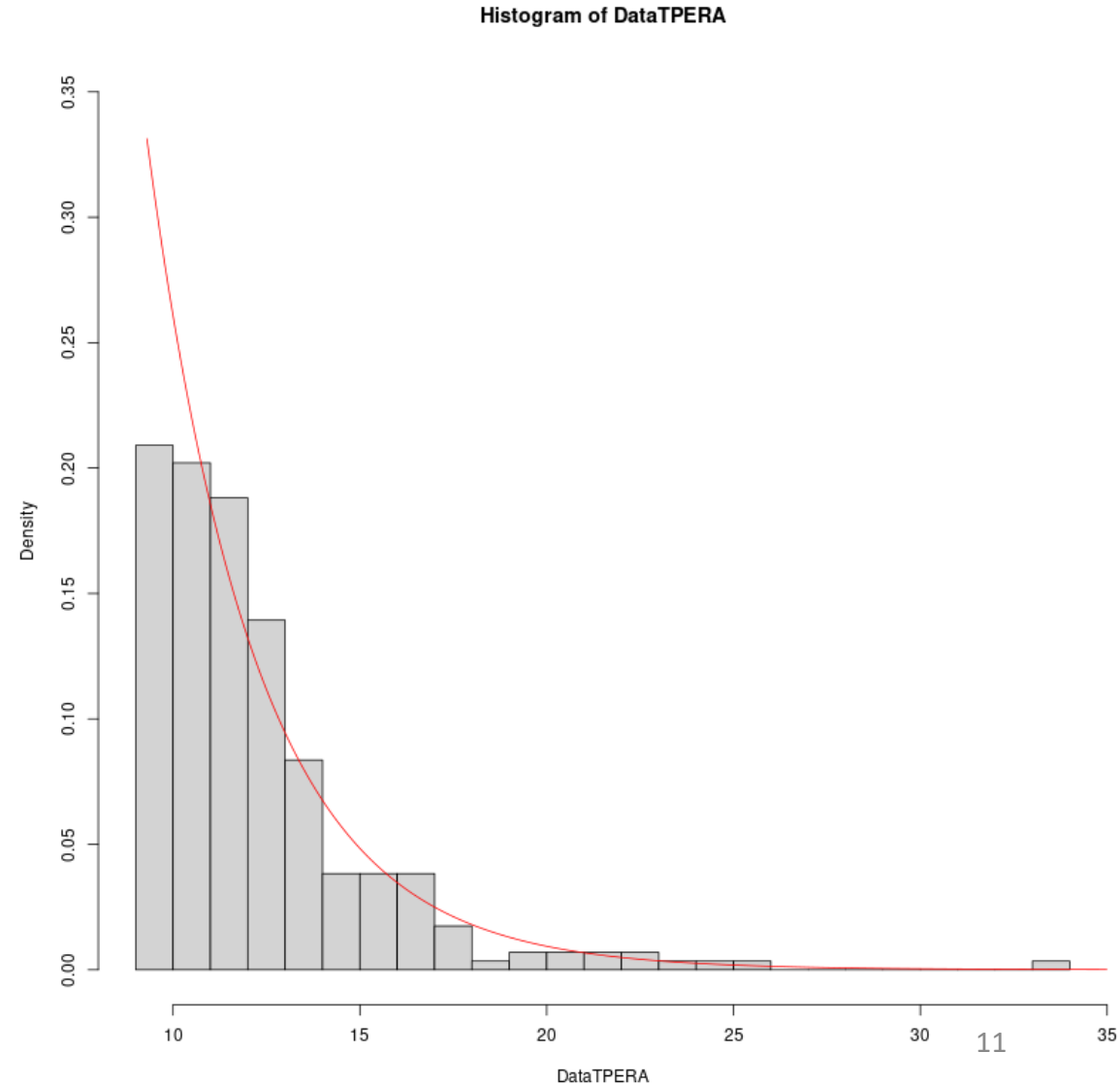
Generalized Pareto Distribution model

With the univariate data selection, we can use a Generalized Pareto Distribution (GPD) model :

$$F(x) = 1 - (1 + \xi x)^{\frac{-1}{\xi}}$$

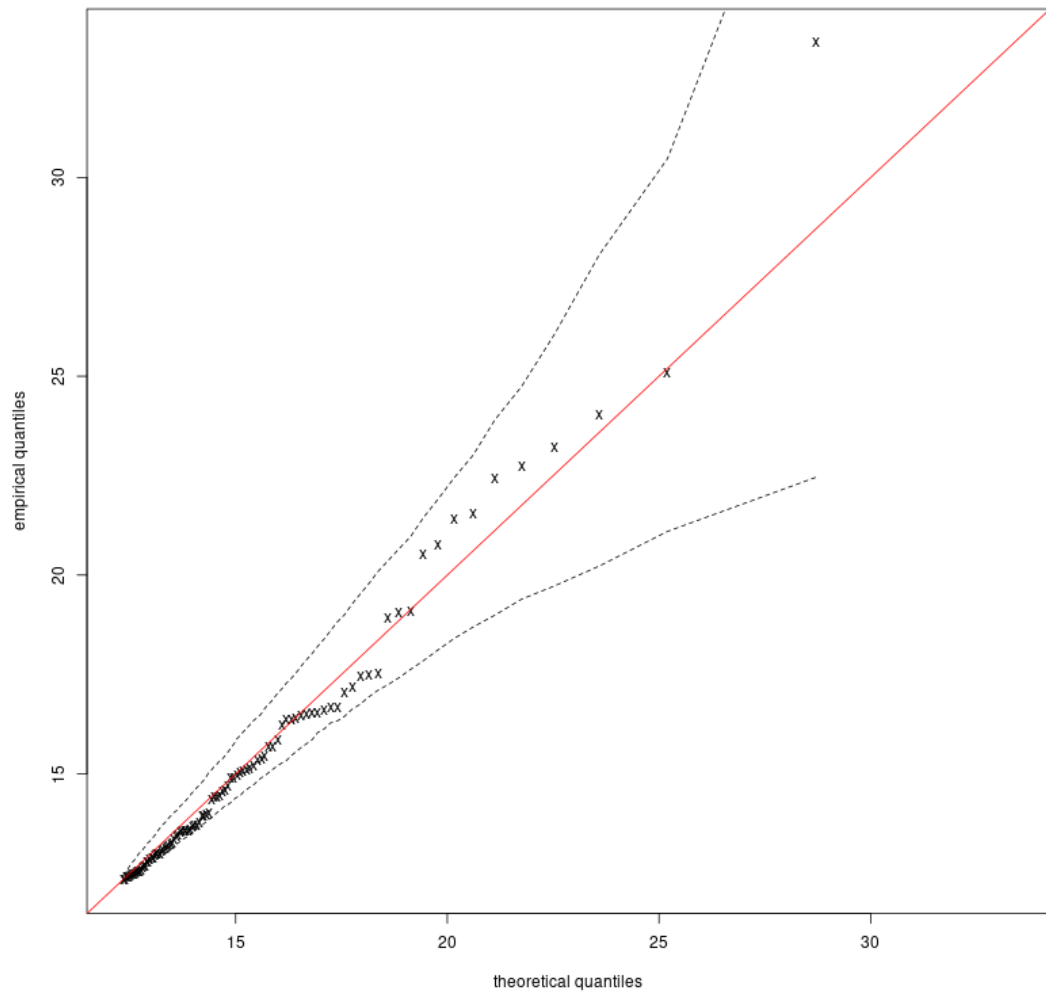
with $x \geq 0$ and $\xi \neq 0$

Parameters are estimated through maximum likelihood method



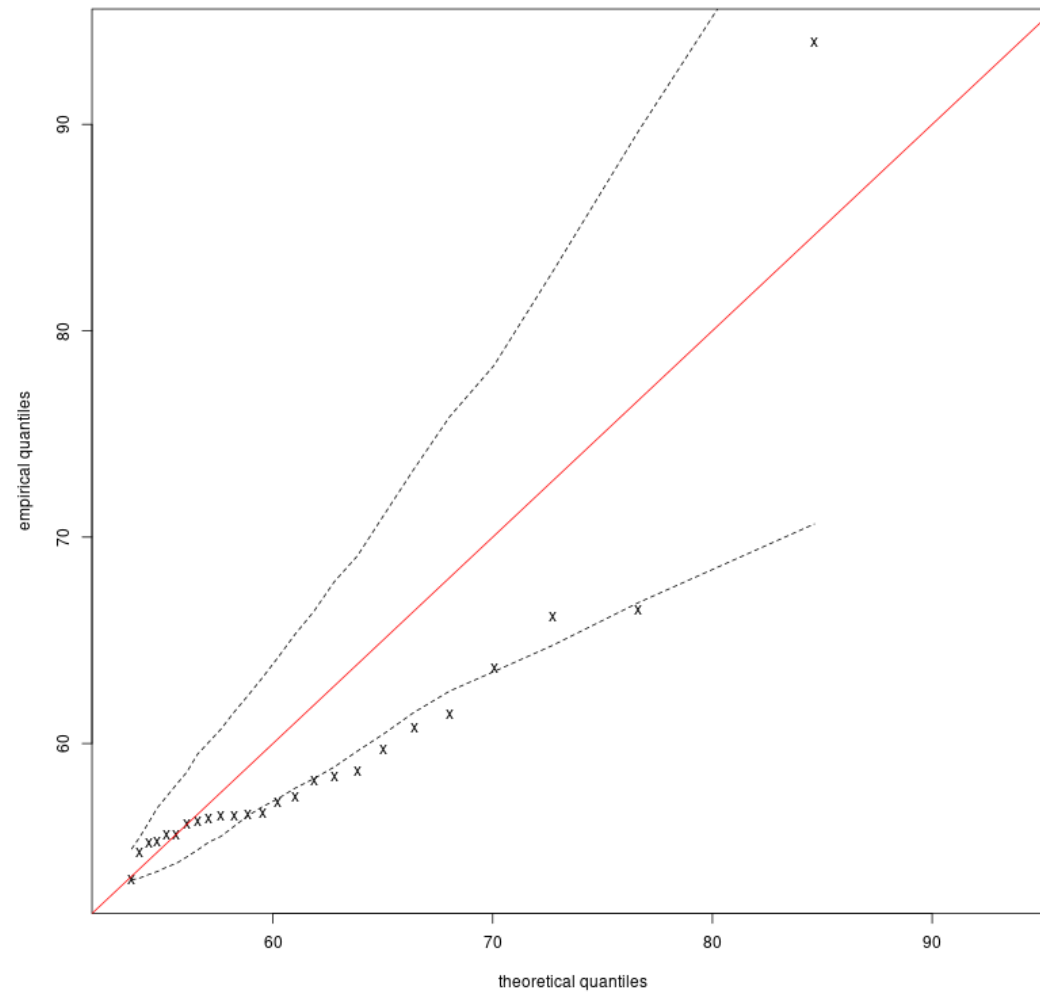
Quantile plots of GPD adjustment

QQplot TP (ERA)



$$\hat{\xi} = 0,016 (0,060)$$

QQplot API (ERA)

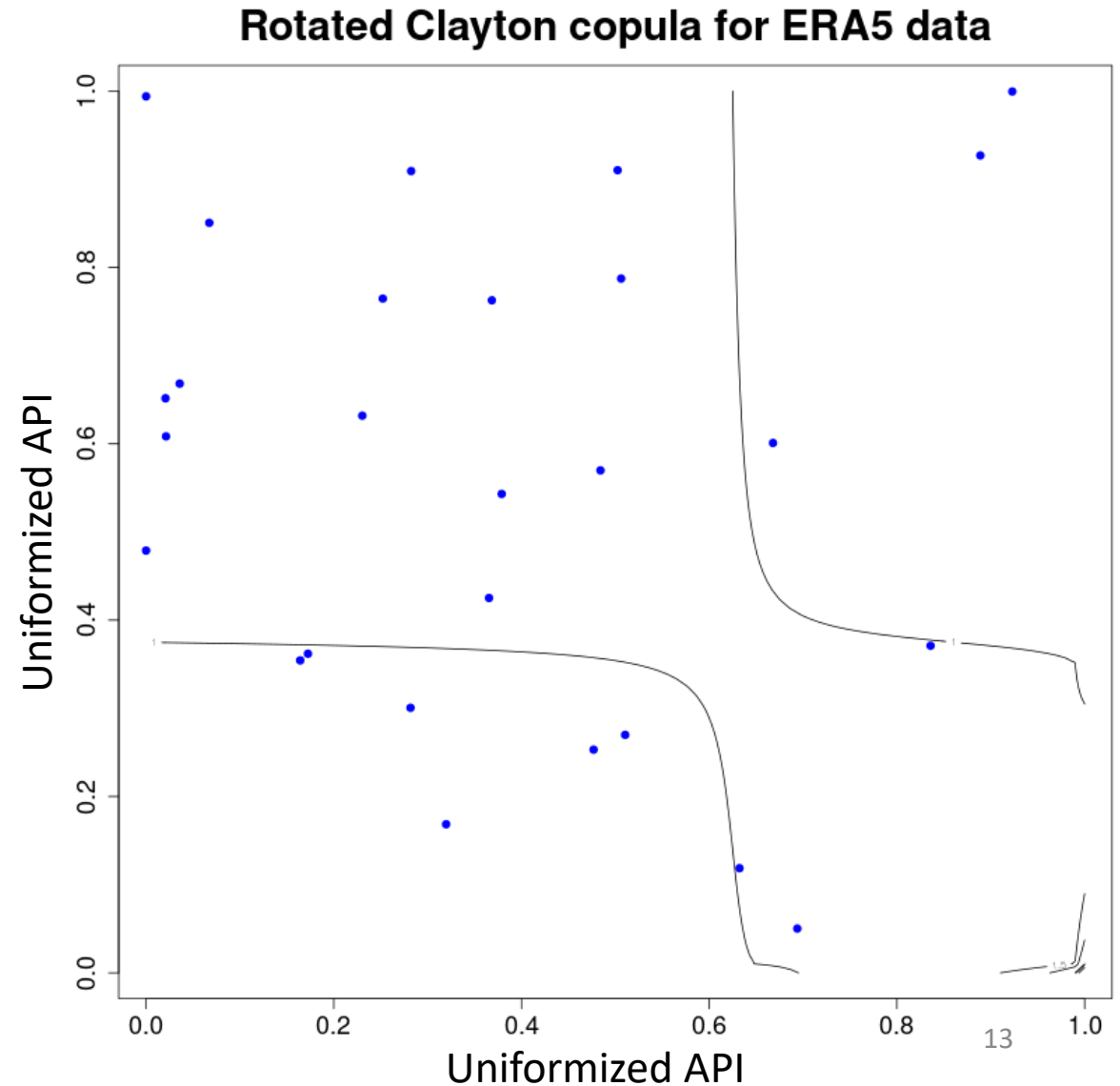


$$\hat{\xi} = -0,063 (0,130)$$

Copula model estimation

Use maximum likelihood to estimate the parameters of all the copulas from the selection : Gaussian, student, Archimedean

Then select the best copula according to the Akaike Information Criteria (AIC)



Coefficients of extremal dependence

For (U, V) uniform r.v., we define χ : $\chi = \lim_{u \rightarrow 1} P(V > u | U > u)$

and $P(V > u | U > u) \approx 2 - \frac{\log C(u, u)}{\log u}$

Similarly, we can define $\bar{\chi}$: $\bar{\chi} = \lim_{u \rightarrow 1} \frac{2 \log(1-u)}{\log \bar{C}(u, u)} - 1$

With $\bar{C}(u, v) = 1 - u - v + C(u, v)$

Here, we have : $(\chi, \bar{\chi}) = (0, -0.019)$ ---> asymptotic independence, close to total independence

Return periods

- Univariate return period = inverse of the probability to exceed a determined threshold :

$$T(x_{14.07}) = \frac{1/n}{1 - P(X \leq x_{14.07})}$$

- When describing a bivariate event by a joint exceedance (AND), the return period is defined by :

$$T_B(TP_{14.07}, API_{14.07}) = \frac{1/n}{1 - U_{TP} - U_{API} + C(U_{TP}, U_{API})}$$

with $U_X = F(x_{14.07})$ and C the copula

CDF-t correction

- We apply the same statistical treatment to CMIP-6 Historic data (1950-2021) and CMIP-6 Projection data (2022-2100)
- For the moment, we have considered only the IPSL model, low resolution (ssp585)

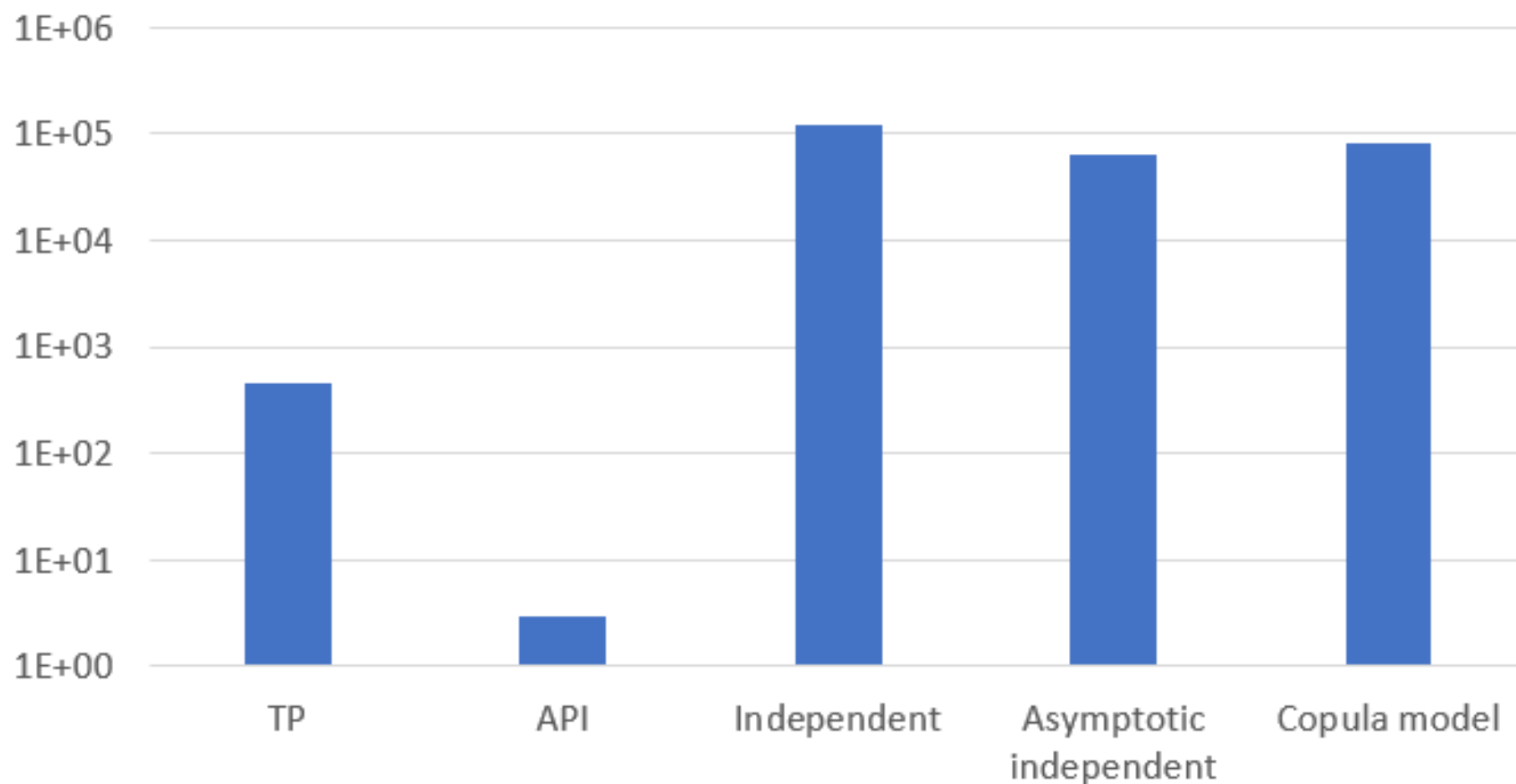
CDF-t	Historic	Projection
Model (CMIP-6)	$F_{CMIPHist}$ \downarrow T	$F_{CMIPProj}$ \downarrow T
Reference (ERA5)	F_{ERA}	$F_{Corrected}$

$$F_{Corrected}(x) = F_{ERA}(F^{-1}_{CMIPHist}(F_{CMIPProj}(x)))$$

- We get the corrected CDF, and then we perform a quantile-quantile correction between the corrected CDF and the projection data

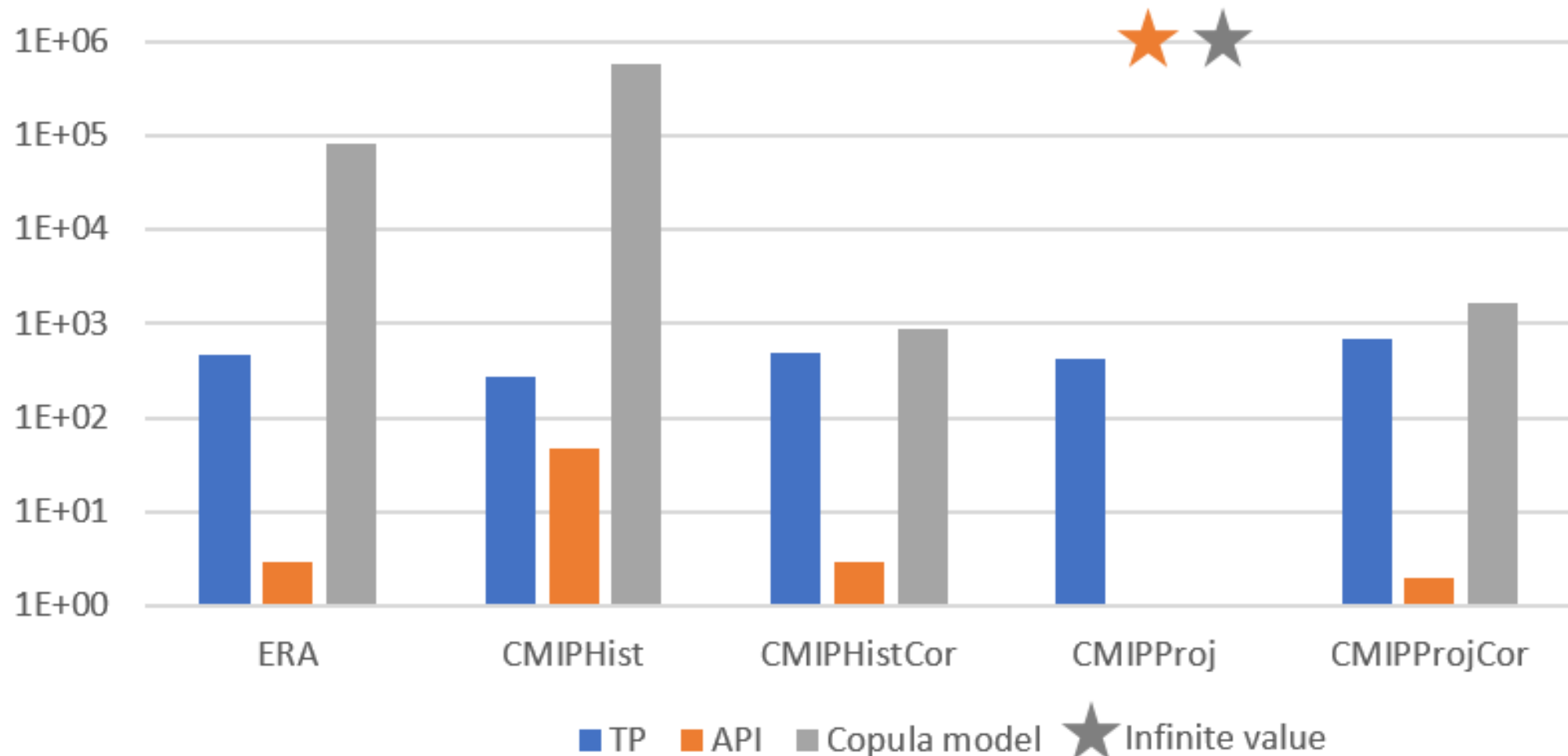
Return periods results

Return periods of the 14th July 2021 (ERA)



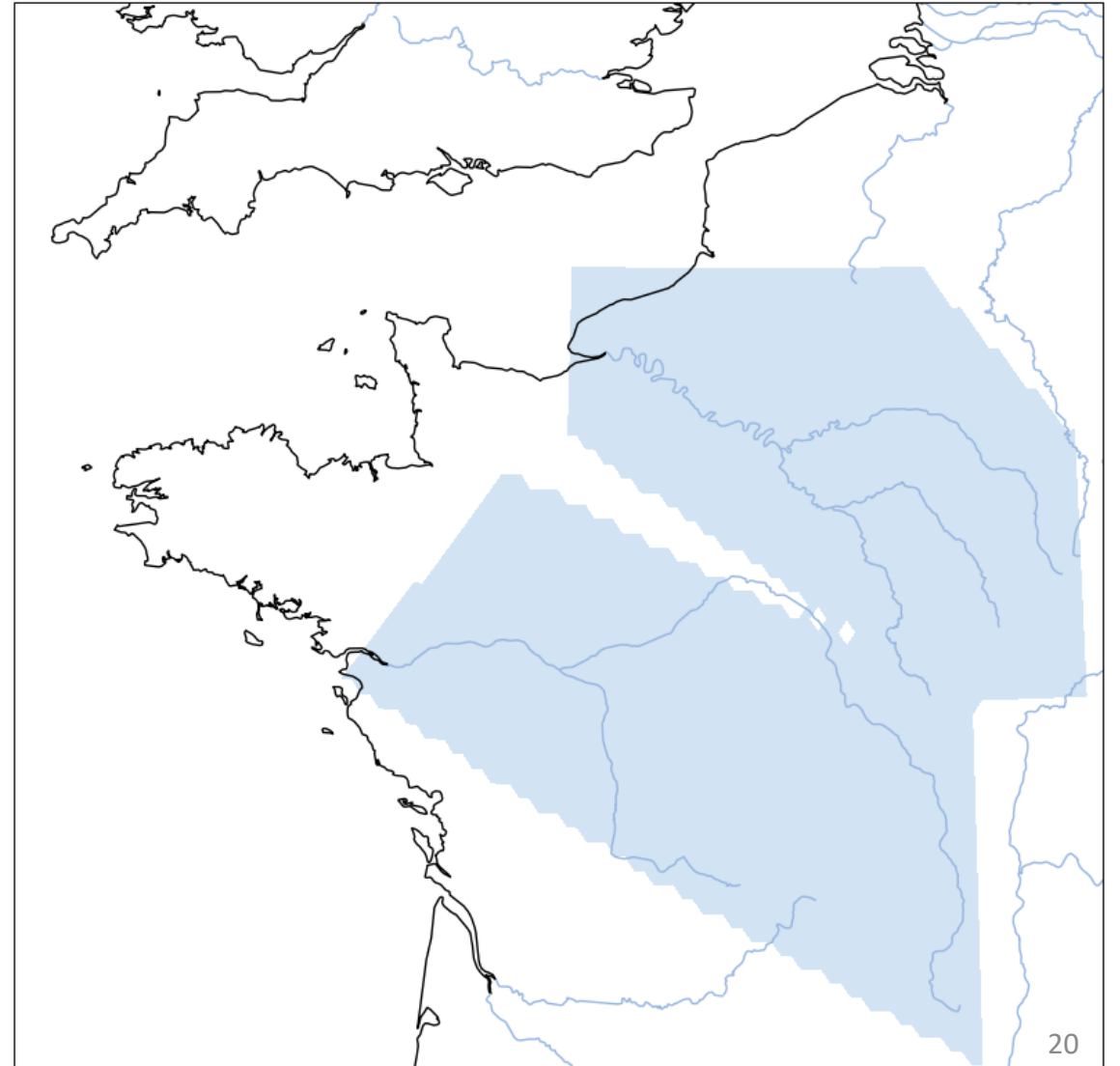
Return periods results

Return periods of the 14th July 2021 (comparison)



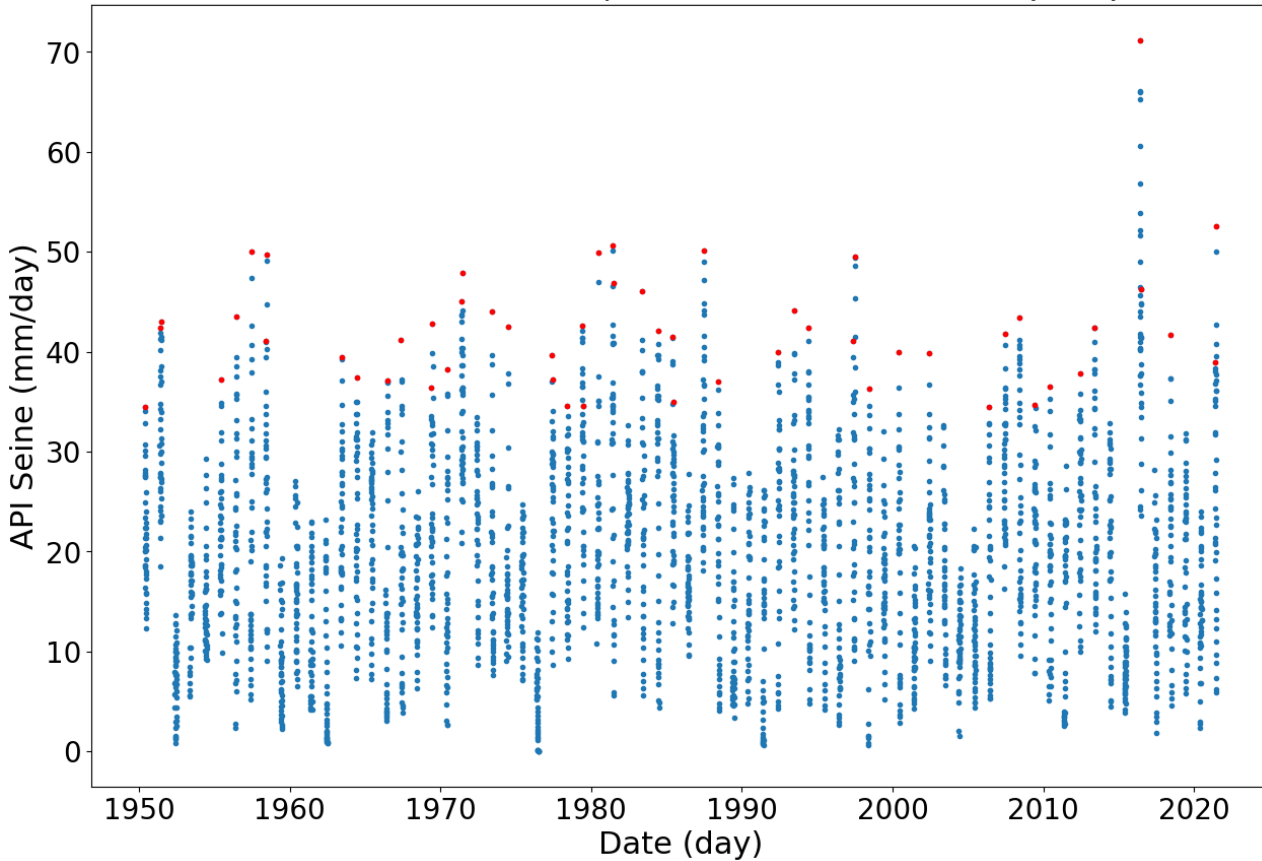
May/June French flooding

- Spatial daily precipitation means over the Seine and the Loire watersheds
- API : $API_j = \sum_{i=1}^{i=N} k^{i-1} * TP_{j-i}$
with $k=0.9$ and $N=20$
- Same methodology (Data selection, GPD model, copula ...)

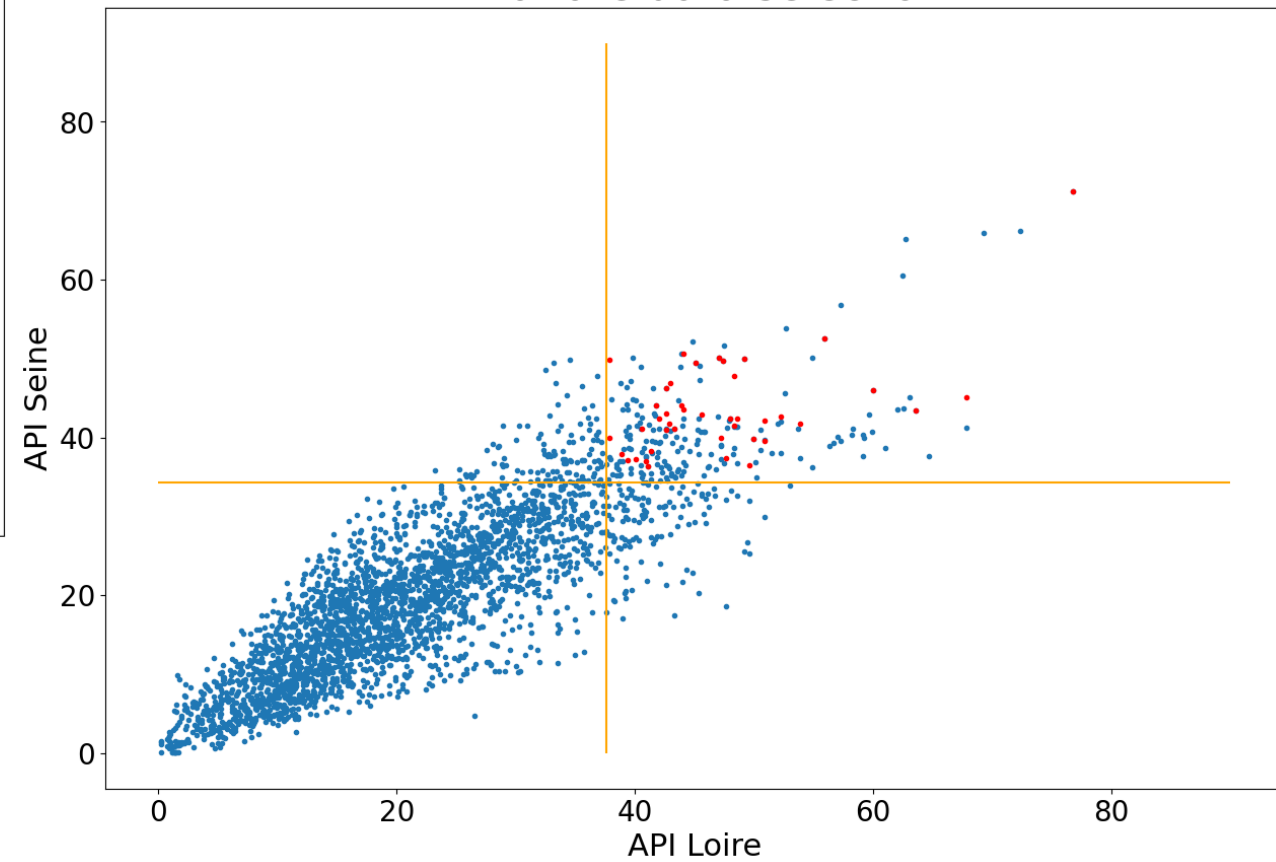


Data selection

API Seine for ERA, and data selected (red)

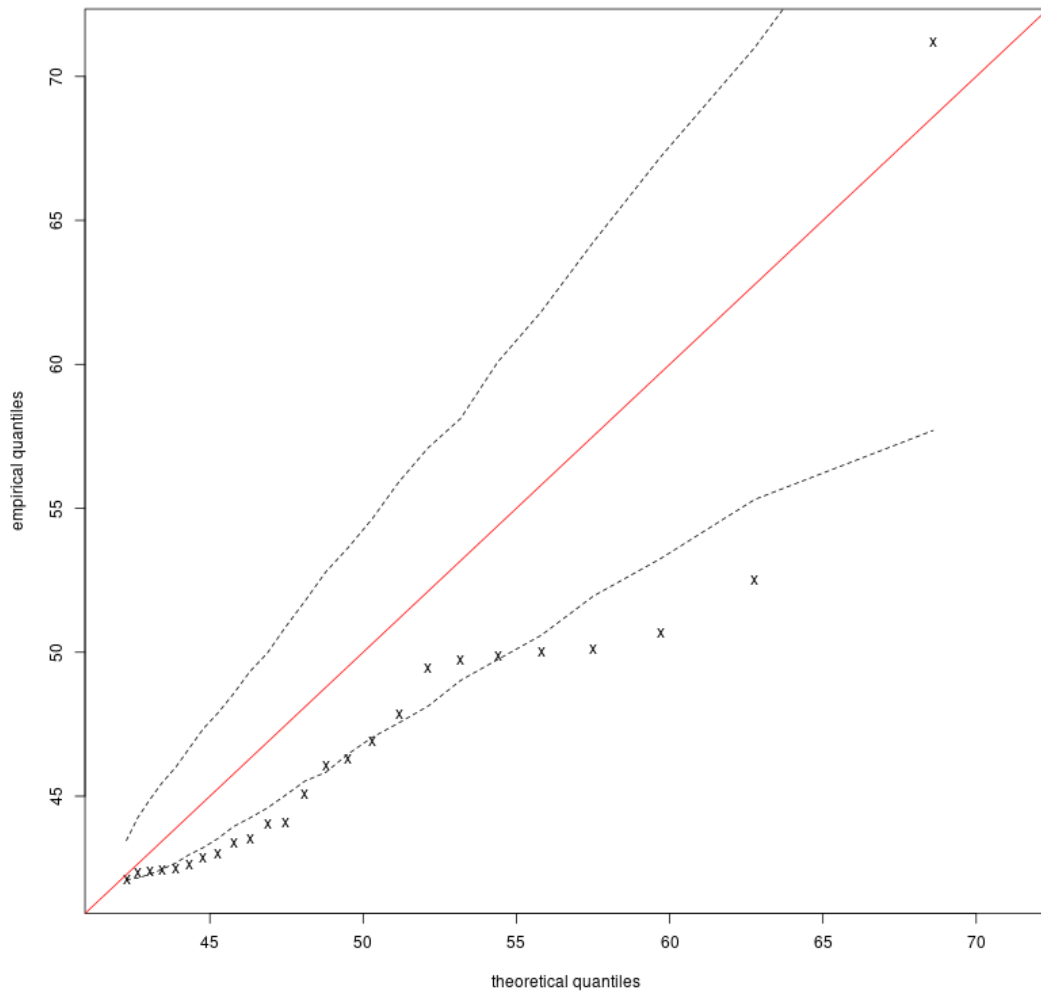


Bivariate data selection



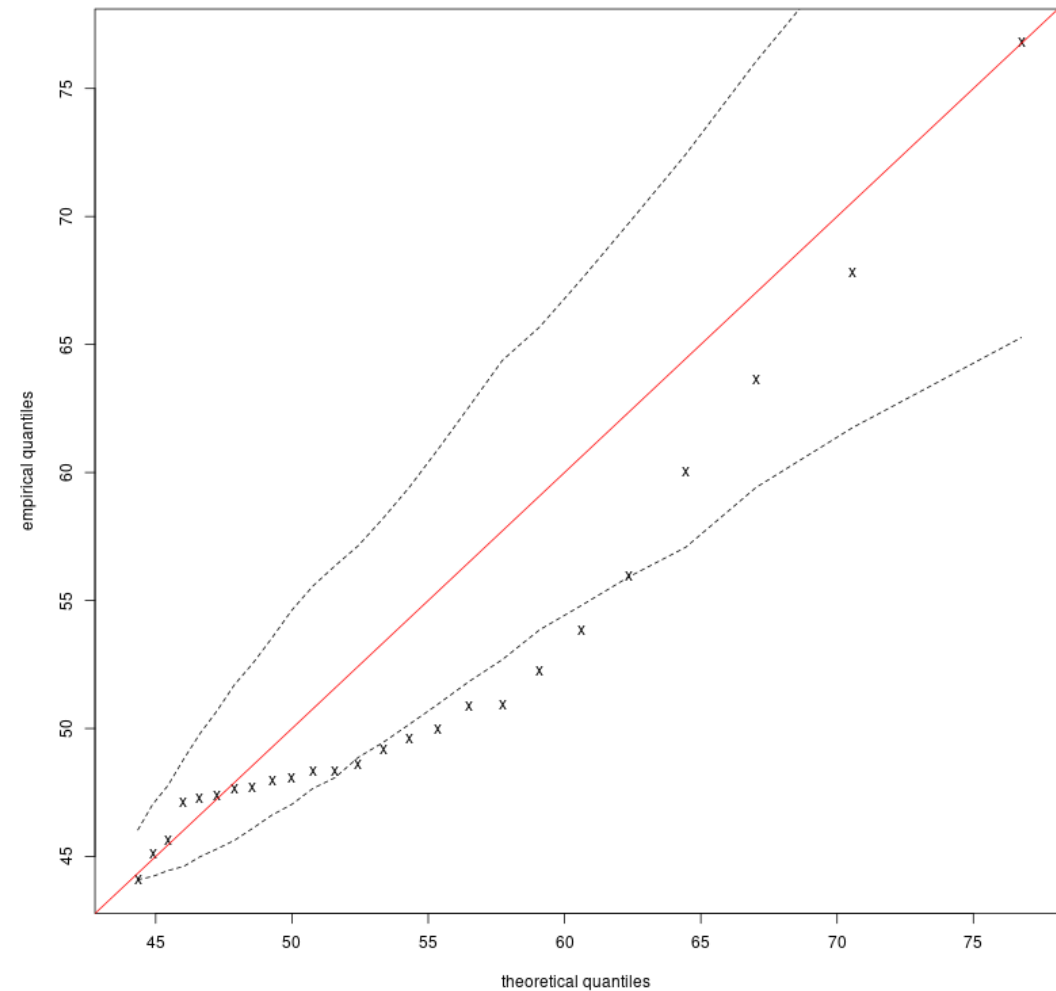
Quantile plots of GPD adjustment

QQplot Seine (ERA)



$$\hat{\xi} = -0,164 (0,116)$$

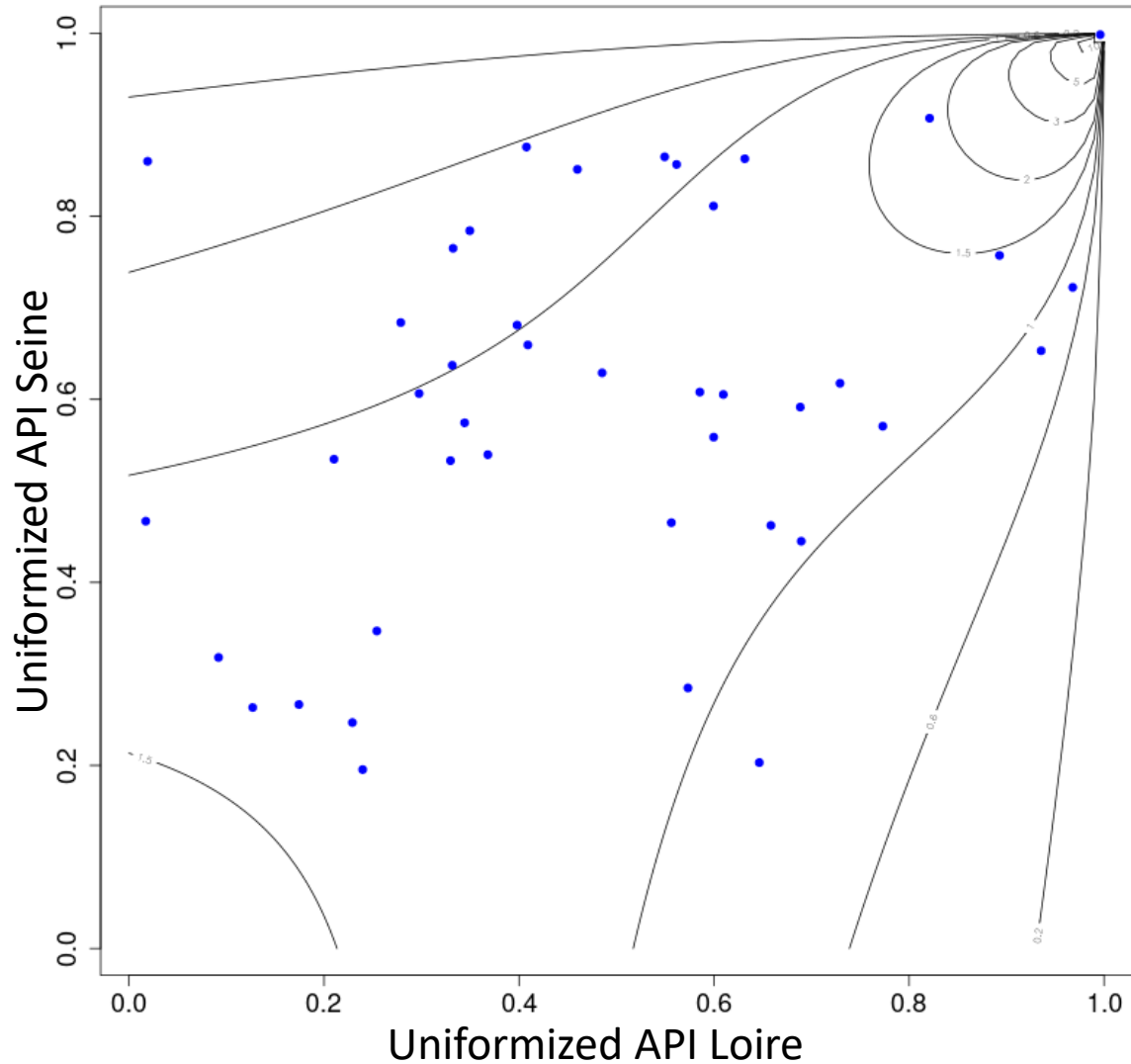
QQplot Loire (ERA)



$$\hat{\xi} = -0,252 (0,109)$$

Copula model

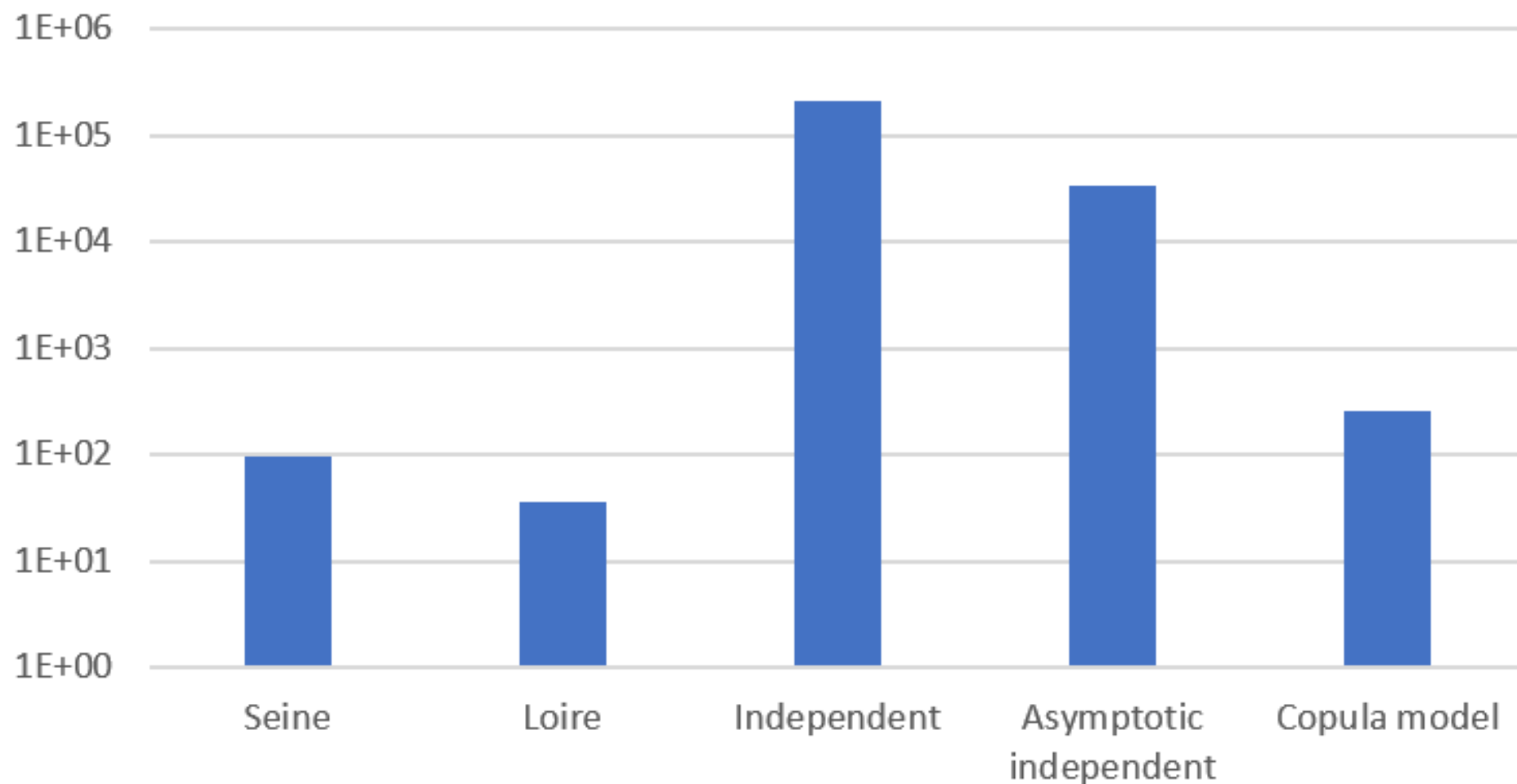
Survival Clayton copula for ERA5 data



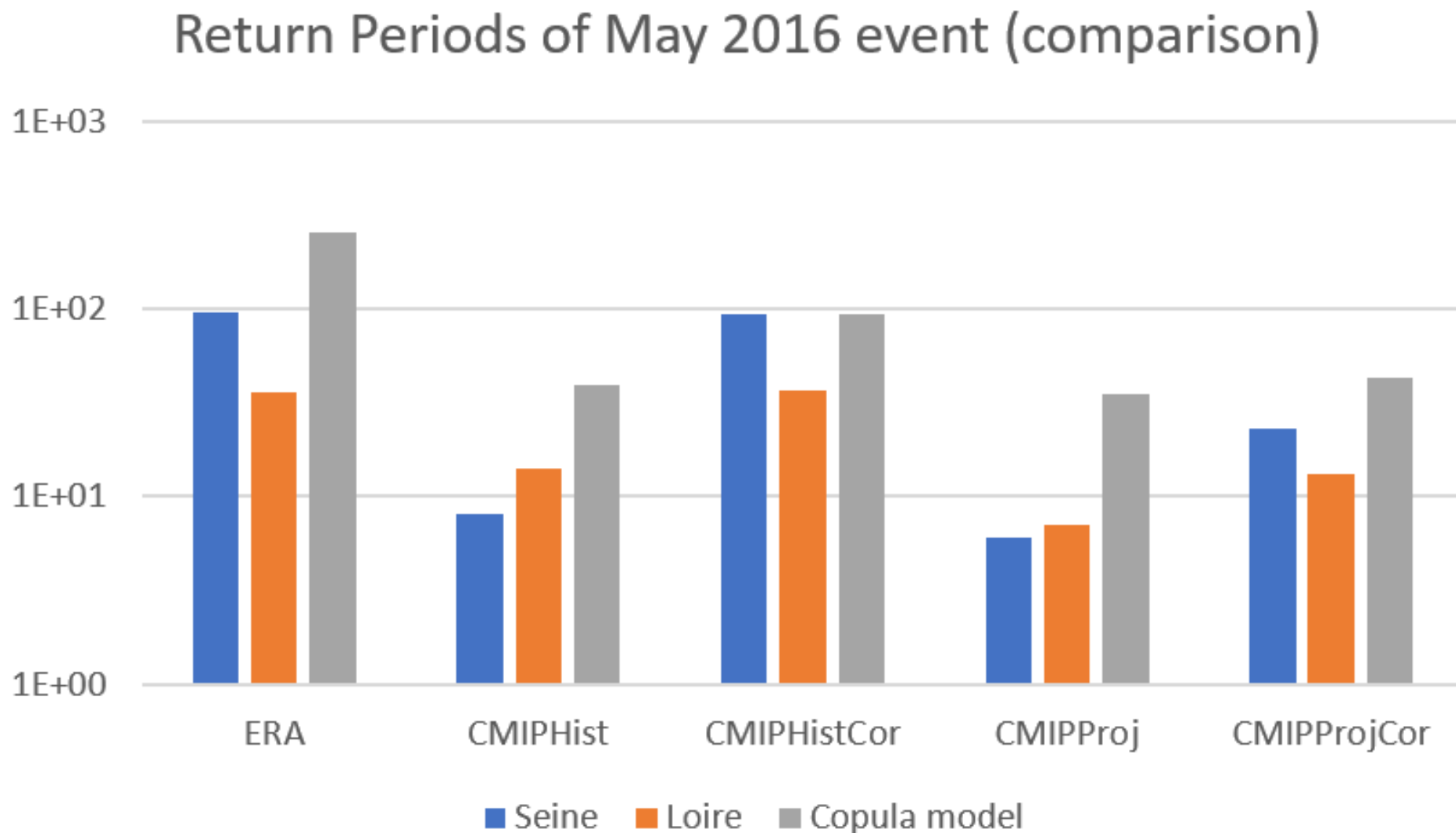
Data sets	Copula	χ	$\bar{\chi}$
ERA	Survival Clayton	0,43	1
Historic	Survival Clayton	0,295	1
Projection	Joe	0,425	1
Projection corrected	Student	0,441	1

Return periods results

Return Periods of May 2016 event (ERA)



Return periods results



Next steps

Next months :

- Multivariate bias correction
- Scale up framework to include more CMIP-6 simulations
- Paper

Next years :

- Apply treatment to convective cells