Uncertainty analysis of extreme flood daily discharges using a Weather Generator

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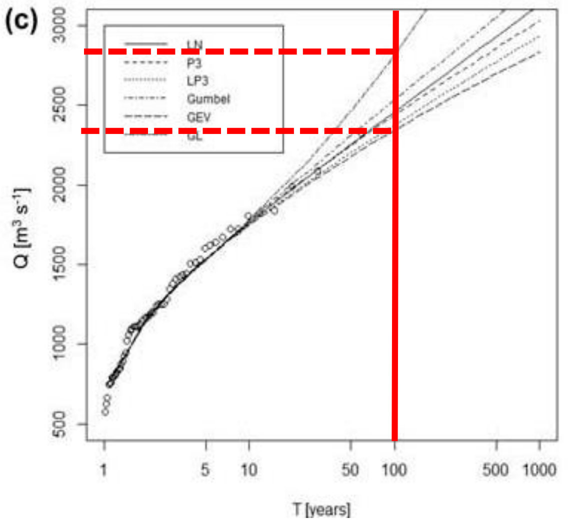
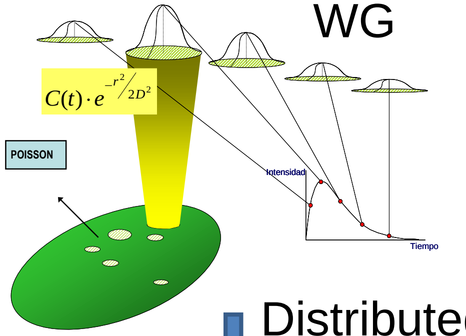
Introduction

Three main methods to estimate high return period flood quantiles. They can be roughly grouped into the following categories:

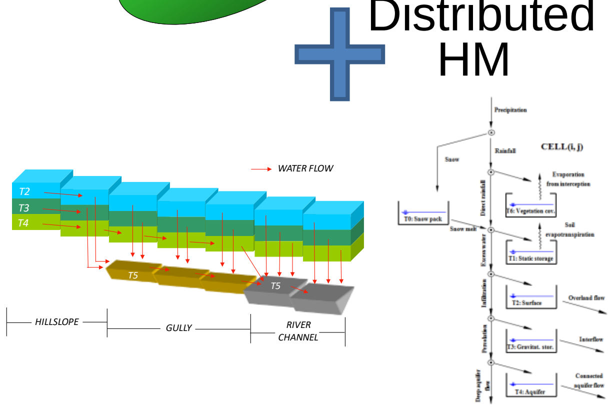
- Statistical (Q_{obs})
- Design Storm
- Synthetic Continuous Simulation



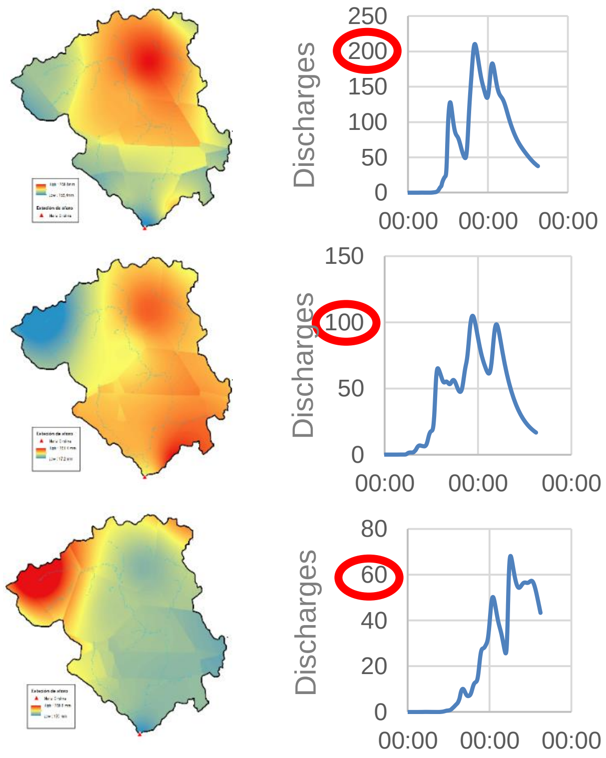
WG



Distributed HM



Duration: 78h, P_{med}=169,2mm



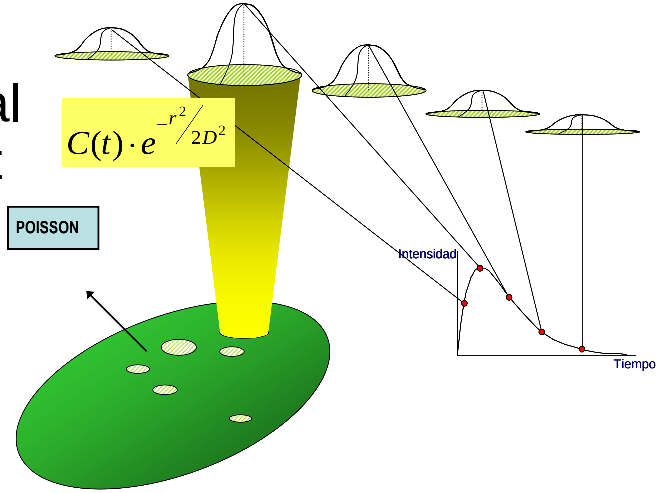
Synthetic Continuous Simulation:

Stochastic Weather Generator (WG) + Hydrological simulation

Stochastic generation of continuous synthetic precipitation series

❖Pros:

- Continuous long series of meteorological data with similar statistical properties as those of observed data → Initial soil moisture content
- Parametric WG → different weather scenarios can be simulated
- Multi-site WG (spatio-temporal variability)



❖Cons:

- Adequacy of the meteorological model (sub-daily → high computational requirements)
- Adequacy of hydrological model

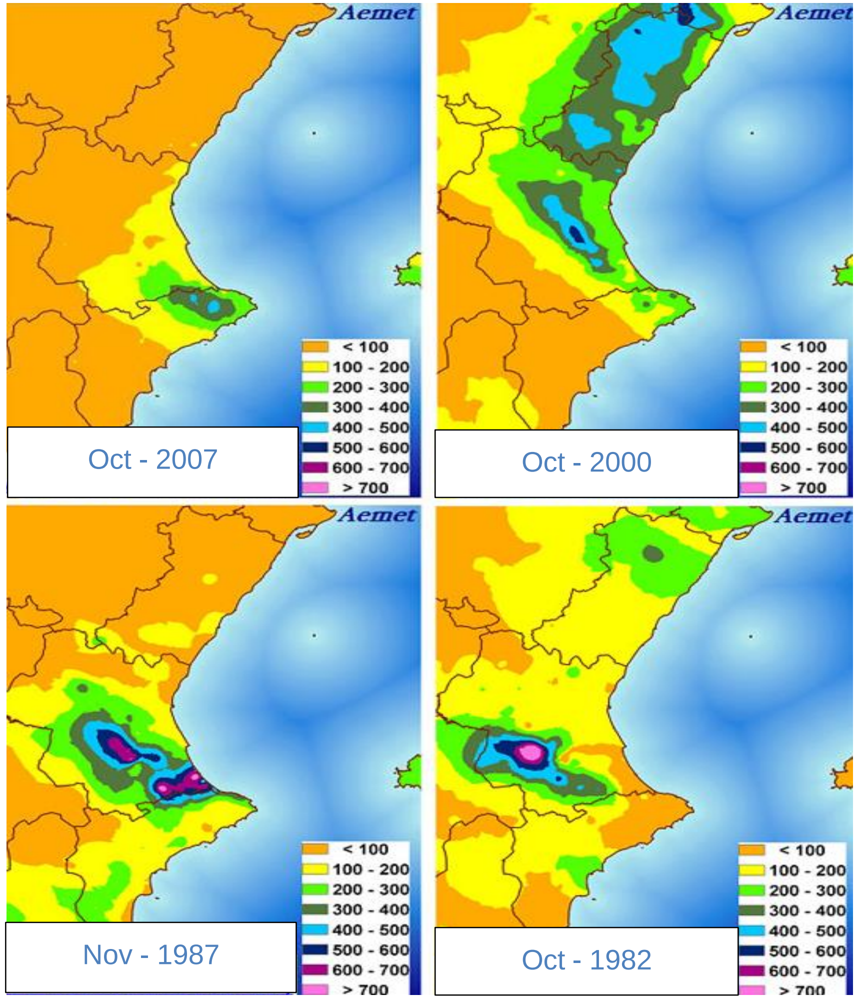
Still difficult to obtain reliable quantile estimates: HIGH UNCERTAINTY

Additional information is needed (e.g., regional precipitation studies)

Arid and semi-arid climates: extreme rainfall regime

Rainfall is concentrated in short periods of time, and these are followed by long drought conditions.

- High precipitation events every 7-8 years on average
- Huge amounts of precipitation (up to 900mm in 24h)
- Storm duration between 2-3 days
- Mainly in autumn months (SON)
- In the east of Spain: Mesoscale Convective Systems
- High spatial and temporal variability



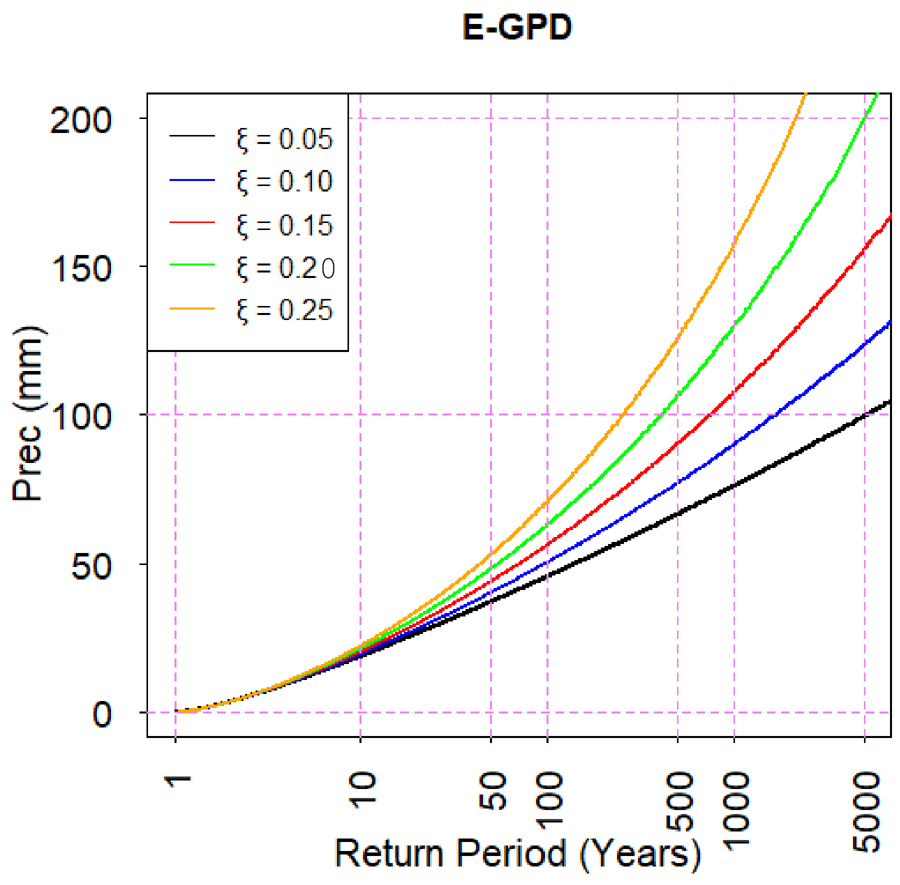
Complicates even more
Flood Frequency Estimation of
high return period flood quantiles

GWEX *(Evin et al., 2018)*

- Multi-site Weather Generator of daily P and max and min Temp, focused on extreme events
- Precipitation amounts: Extended Generalized Pareto Distribution (E-GPD) (*Papastathopoulos and Tawn, 2013*)

$$F(x;\lambda) = \left[1 - \left(1 + \frac{\xi x}{\sigma}\right)^{-1/\xi}\right]^{\kappa}$$

σ → Scale Parameter
κ → Transf. Parameter
ξ → Shape Parameter
(ξ directly affecting the upper tail)



Previous studies

Exploring the uncertainty of Weather Generators' extreme estimates in different practical available information scenarios (*Beneyto et al., 2022, under review*)

Information Scenarios

- With no additional information

  0. The ξ parameter value is set to 0.05 (default) as proposed in Evin et al. (2018)

  1. The value of the parameter ξ is estimated by fitting an E-GPD to the X_{100} estimated from the available observation

- With an additional regional study of maximum daily precipitation

  2. Parameter ξ is estimated with the regional X_{100} (if not regional E-GPD)

  3. The parameter ξ is set to the regional value (if regional E-GPD)

For simplicity, we will assume that the regional study is "perfect" – no uncertainty

Objectives

Quantify the uncertainty of the higher discharge quantile estimates generated by synthetic continuous simulation (Weather Generator + Hydrological Model) in different scenarios

Different climate extremality	→	Variation of shape parameter ξ
Different precipitation regimes	→	Different synthetic populations
Different hydrological characteristics of the basin	→	Different parameters in the Hydrological Model

Monte Carlo simulation over a synthetic population, measuring uncertainty through:

- Relative Root Mean Squared Error (RRMSE)
- Relative bias (RB)
- Coefficient of Variation (CV)

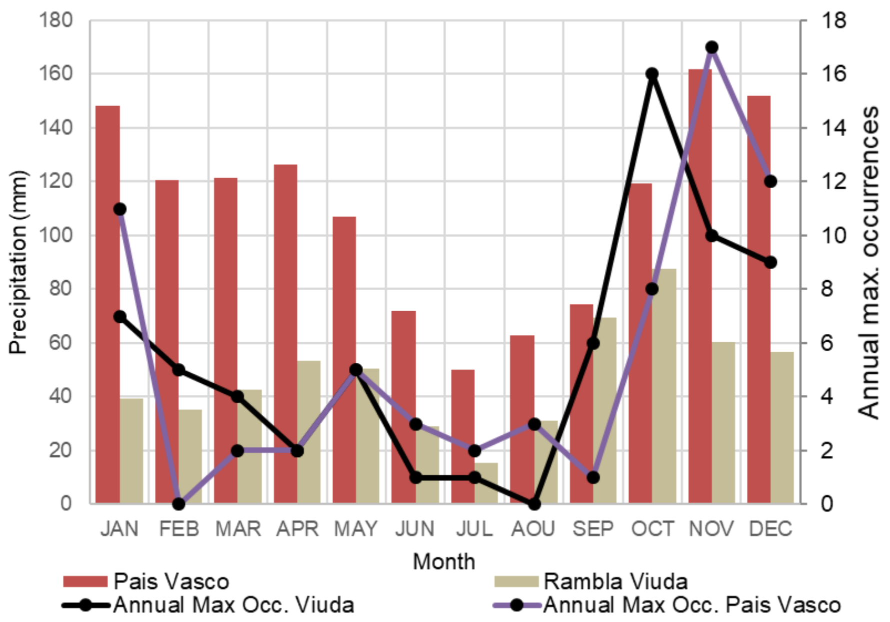
Synthetic case of study

Synthetic population

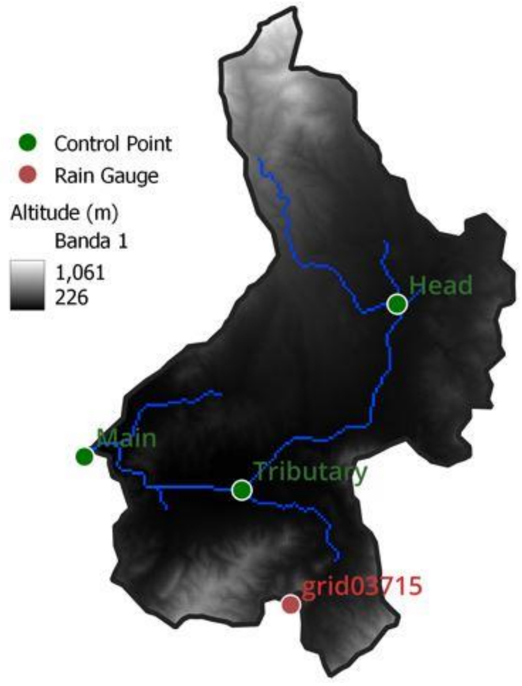
66 years sample length of one raingauge station in:

- Semi-arid climate -> Rambla de la Viuda (east coast of Spain)
- Humid climate -> Deba (north of Spain)

Variable	Statistic	Value		Units
		Semi-arid	Humid	
Daily Prec (P_d)	Mean	1.56	3.60	mm
	Mean > 0.1	6.28	6.19	mm
	Sd	6.81	7.23	mm
	Sd > 0.1	12.55	8.60	mm
	Days with Prec > 0.1	24.77	58.17	%
	Max.	206.94	110.12	mm
Annual Prec. (P_a)	Mean	569.86	1315.69	mm
Annual max. Prec (P_{am})	Mean	73.35	55.30	mm
	CV	0.56	0.28	-
	Coeff. Skewness	1.43	1.02	-
	Coeff. Kurtosis	1.66	4.38	-



All simulations were carried out at 3 different control points



Catchment areas: 180, 113 and 58 km^2

Methodology

POPULATION:
Very long daily synthetic discharges

Monte Carlo Simulation

- Typical sample length: 60 years P
- Perfect P_{100}
  - Different extremality: ξ (0.05; 0.11 ; 0.25)
  - Different precipitation regimes: arid/semi-arid and humid
  - Different hydrological characteristics of the basin

15,000 years

T	Population Q (mm)
T = 2 yrs	55.7
T = 5 yrs	81.3
T = 10 yrs	100.7
T = 25 yrs	125.8
T = 50 yrs	146.7
T = 75 yrs	158.8
T = 100 yrs	168.4
T = 200 yrs	192.0
T = 500 yrs	238.1
T = 1,000 yrs	262.8

50 realizations

$$RRMSE(\hat{X}_T) = \frac{\sqrt{1/n\sum(\hat{X}_{T,i} - X_T)^2}}{X_T}$$

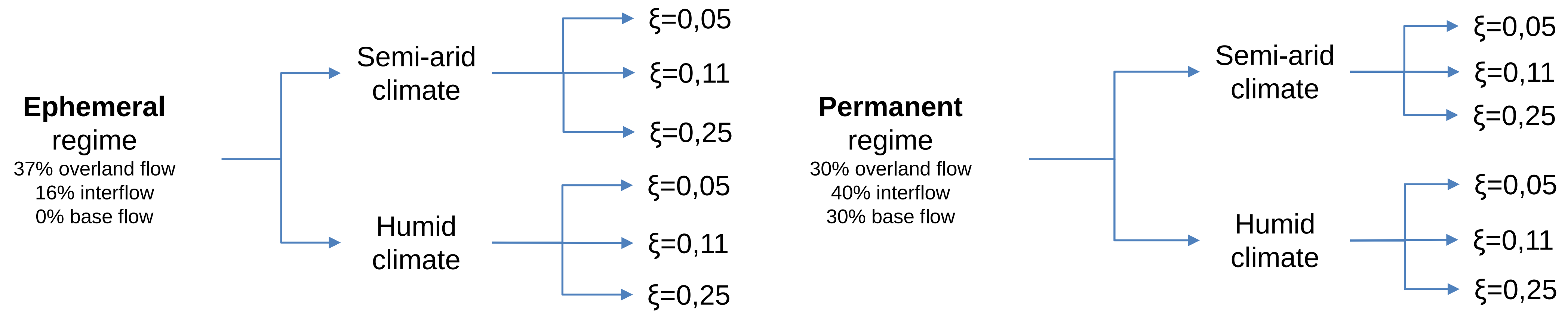
$$RB(\hat{X}_T) = \frac{1/n\sum(\hat{X}_{T,i} - X_T)}{X_T}$$

$$Cv(\hat{X}_T) = \frac{\sqrt{1/n\sum(\hat{X}_{T,i} - \overline{X_T})^2}}{\overline{X_T}}$$

5,000 years

T	Estimated Q (mm)
T = 2 yrs	53.2
T = 5 yrs	78.2
T = 10 yrs	105.2
T = 25 yrs	126.4
T = 50 yrs	151.3
T = 75 yrs	160.8
T = 100 yrs	165.6
T = 200 yrs	198.9
T = 500 yrs	235.1
T = 1,000 yrs	254.6

Methodology



Variable	Statistic	Semi-arid climate				Humid climate				Units
		Sample	ξ = 0.05	ξ = 0.11	ξ = 0.25	Sample	ξ = 0.05	ξ = 0.11	ξ = 0.25	
Daily Prec. (P_d)	Mean	1.56	1.57	1.57	1.56	3.60	3.60	3.60	3.60	mm
	Mean > 0.1	6.28	7.74	7.65	7.37	6.19	6.75	6.70	6.53	mm
	SD	6.81	6.19	6.35	6.90	7.23	7.15	7.34	8.05	mm
	SD > 0.1	12.55	11.90	12.27	13.47	8.60	8.65	8.92	9.93	mm
	Days with Prec > 0.1	24.77	20.22	20.49	21.25	58.17	53.25	53.75	55.03	%
	Max	206.94	249.51	373.15	846.69	110.12	208.37	263.20	677.65	mm
Annual Prec. (P_a)	Mean	569.86	572.46	572.62	569.76	1315.69	1313.27	1315.27	1313.08	mm
Annual max Prec. (P_{am})	Mean	73.35	59.56	62.96	70.77	55.30	53.51	58.07	72.18	mm
	CV	0.56	0.43	0.48	0.67	0.28	0.31	0.36	0.57	-
	Coeff. Skewness	1.43	1.55	2.02	3.53	1.02	1.41	1.81	3.63	-
	Coeff. Kurtosis	1.66	7.25	10.68	27.61	4.38	6.91	9.54	30.82	-

TETIS eco-hydrological model

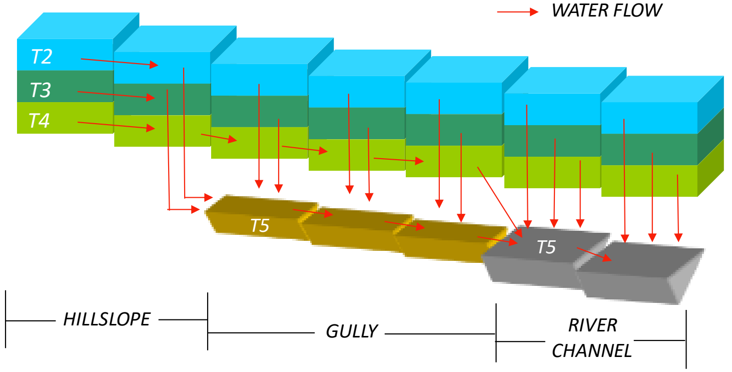
Developed by our group since 1994

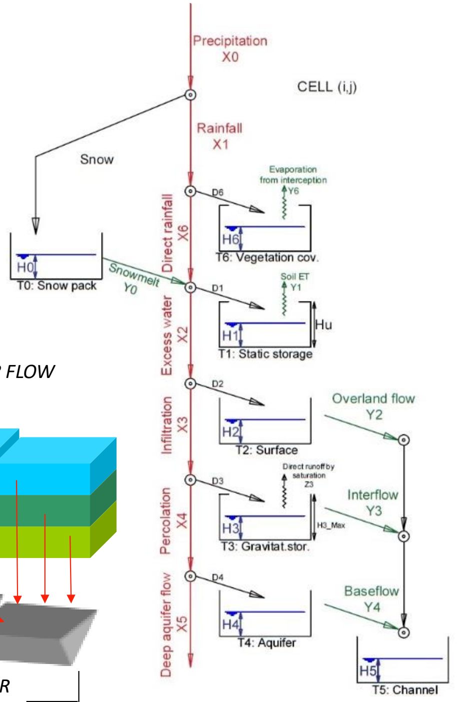
Integral model: water resources, floods, erosion, sediments, dynamic vegetation, crop production, N-C cycle,…with different temporal discretization

Conceptual (tank structure) model
with **physically based parameters**

Distributed in space:

- Reproduces the spatial variability of hydrological cycle
- Uses all spatial information available
- Gives results at any point





Incorporates a **split effective parameter structure**
(Francés et al., 2007)

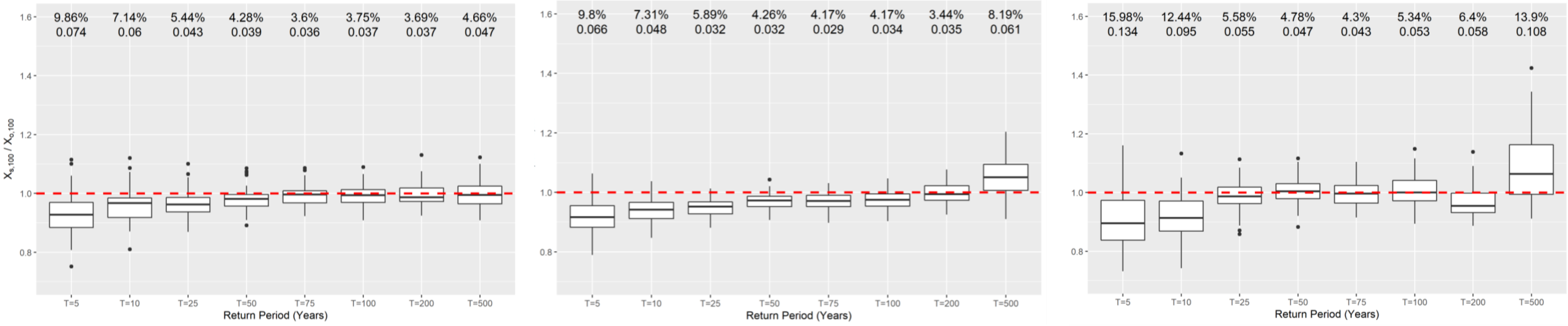
- **Parsimonious**: Significant reduction of the number of the variables to be calibrated => facilitates model calibration stage
- Maintains the spatial pattern of the parameter maps

Results – Climate Extremality

Rain generated from **semi-arid climate** and **ephemeral regime**

+ Climate Extremality

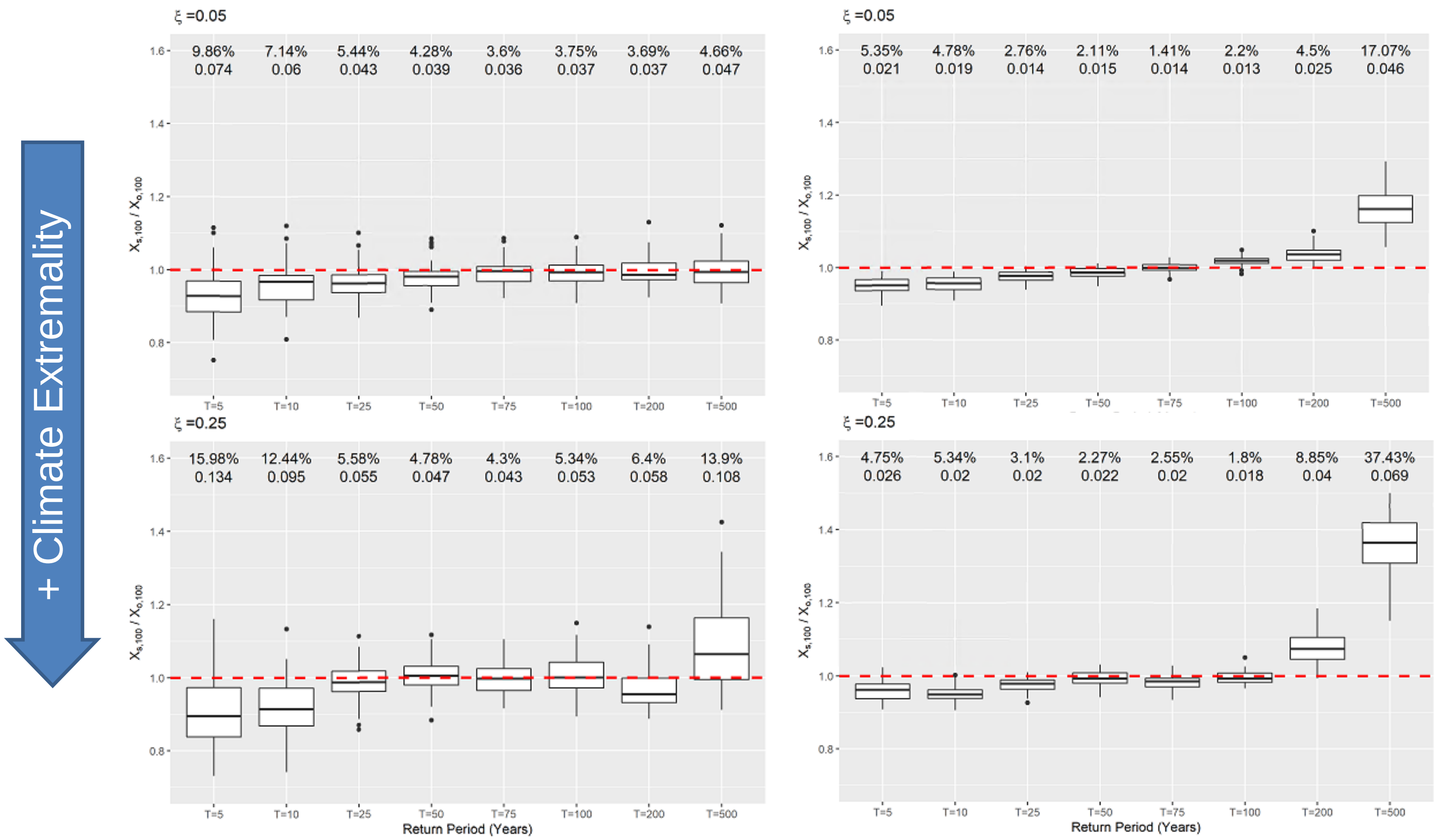
ξ=0.05 ξ=0.11 ξ=0.25



- As climate extremality increases, both RRMSE and CV increase
- Underestimation of lower quantiles, overestimation of higher quantiles
- As expected, quantiles around X_{100} are less uncertain

Results – Precipitation Regime

Semi-arid climate / Humid climate



Rain generated for **ephemeral regime**

Semi-arid climate more uncertain respect to humid climate, except for T=500 quantile

Lower sensitivity to climate extremality changes in humid climates

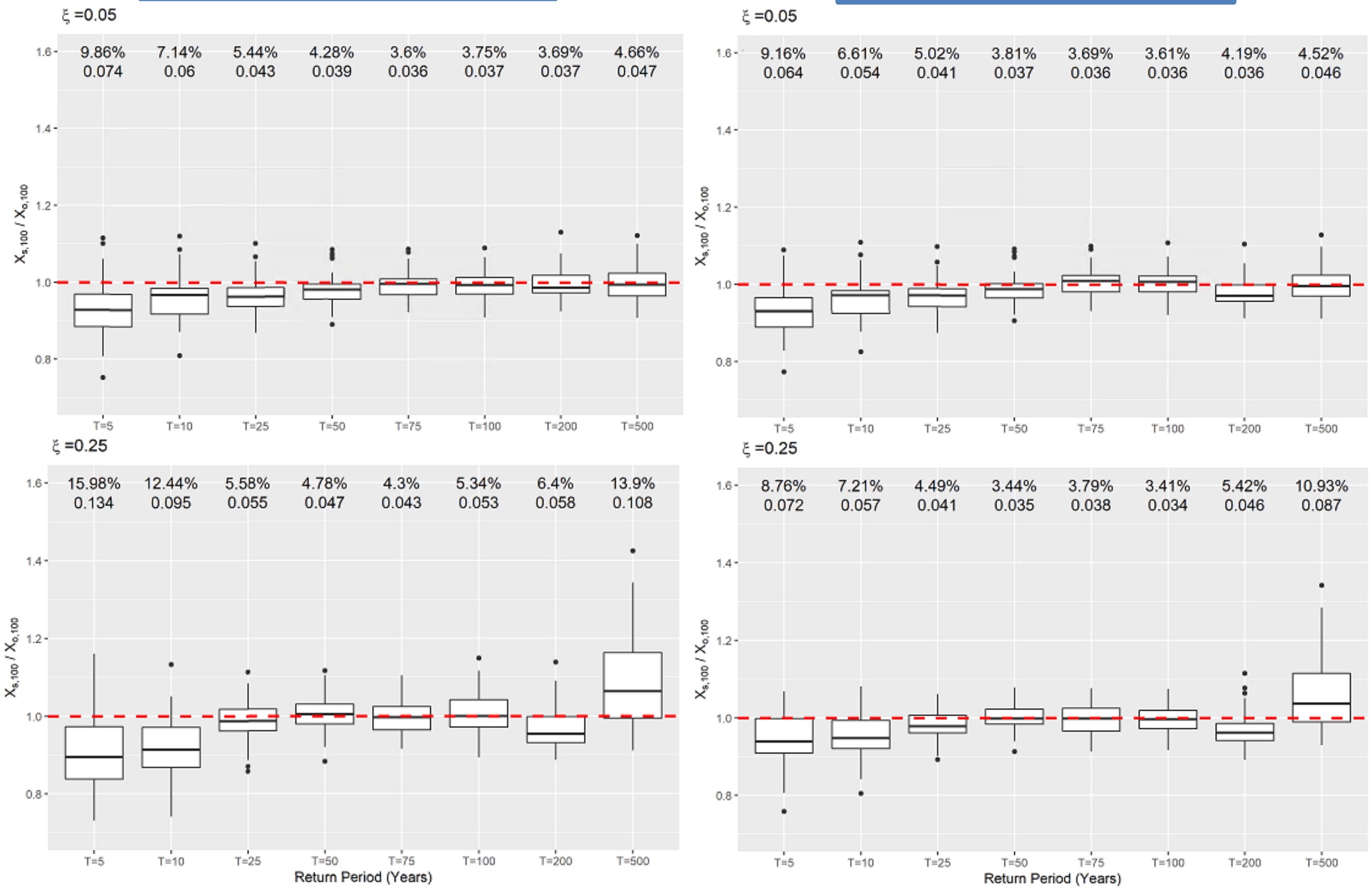
Results - Hydrological Characteristics of the Basin

Ephemeral regime

Permanent regime

Rain generated from **semi-arid climate**

+ Climate Extremality



Non-significant changes but less uncertainty in permanent regime, more evident for high quantiles and more extreme climates

Results – Uncertainty transmission

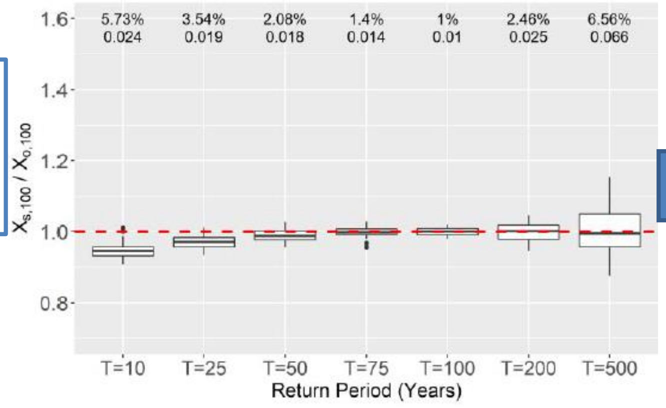
Precipitation

Discharge

Uncertainty trasmitted to the HM, which makes it increase, expecially in semi-ari climate

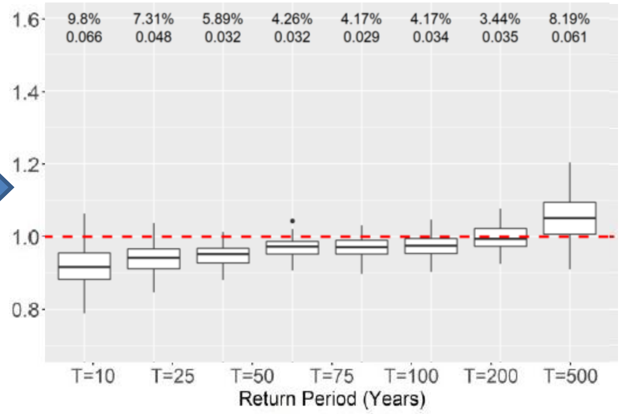
Uncertainty propagation is inferior in a permanent regime

Semi-arid climate ξ=0.11

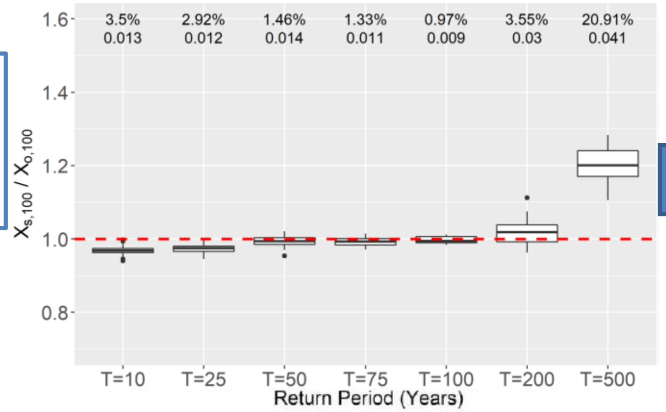


TETIS HM

Ephemeral regime

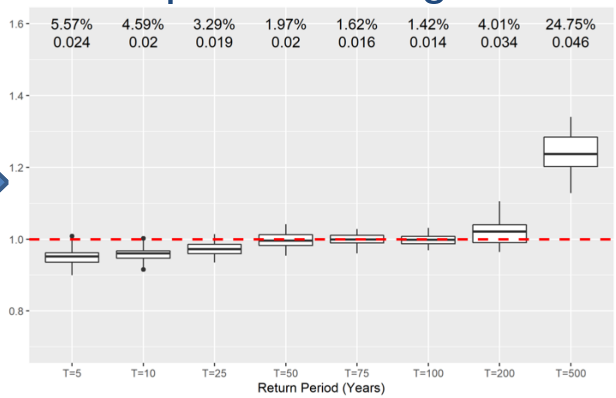


Humid climate ξ=0.11

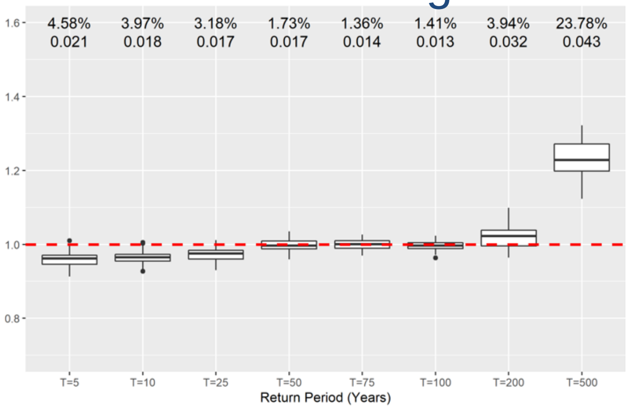


TETIS HM

Ephemeral regime



Permanent regime



Conclusions

- As obtained in the preliminary study (*Beneyto et al., 2022, under review*), additional information is needed to reduce the uncertainty of P and Q
- Climate extremality has been demonstrated to be a key factor for the weather generator performance. As climate extremality increases, there is more uncertainty on the quantile estimates, especially in those associated with high return period
- For arid and semi-arid climates, where the precipitation regime is less homogeneous, the uncertainty of the quantile estimations is clearly higher compared to humid precipitation regimes, where the weather generator has been proved to perform optimally
- No major differences can be found between ephemeral and permanent regimes, in terms of quantile uncertainty
- Climate extremality has been proved to be the most sensitive factor, affecting especially high return period quantile estimates, therefore, special attention must be paid when implementing continuous simulation in arid and semi-arid climates
- Uncertainty propagates through Hydrological Model, being this propagation lower in the case of humid climates and permanent regimes

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Thanks for your attention!

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