# Sample Uncertainty Analysis of Daily Flood Quantiles Using a Weather Generator

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## 1. INTRODUCTION

The problem: short length of available observations.

### Synthetic Continuous Simulation:

Stochastic **Weather Generator (WG)** + **Hydrological model (HM)**: Stochastic generation of continuous synthetic precipitation (P) series and stochastic generation of continuous synthetic discharges (Q).

❖ 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
- If sub-daily → complexity and high computational requirements
- Adequacy of hydrological model

**Extreme rainfall regime complicates** even more Flood Frequency Estimation of high Return Period flood quantiles $X_T$

Still difficult to obtain reliable quantile estimates: **HIGH UNCERTAINTY**

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

## 2. SYNTHETIC CASE STUDY

**Nine Synthetic populations:** Mediterranean Semi-arid, Humid and Extremely Humid climate according to De Martonne Aridity Index ($I_a$)[1], each one with three different climate extremality ($\xi = 0.05$; $\xi = 0.11$; $\xi = 0.25$).

| Variable | Statistic | MEDITERRANEAN SEMI-ARID ($I_a$=21,6) | | | HUMID ($I_a$=33,8) | | | EXTREMELY HUMID ($I_a$=59,4) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | ξ = 0.05 | ξ = 0.11 | ξ = 0.25 | ξ = 0.05 | ξ = 0.11 | ξ = 0.25 | ξ = 0.05 | ξ = 0.11 | ξ = 0.25 | Units |
| Daily P | % $D_p$ > 0 | 24.79 | 24.79 | 24.79 | 31.11 | 31.34 | 31.91 | 57.95 | 57.95 | 57.95 | % |
| Annual P | Mean | 572.46 | 572.62 | 569.76 | 748.94 | 748.91 | 748.23 | 1313.27 | 1315.27 | 1313.08 | mm |
| Annual max Daily P | Mean | 59.56 | 62.96 | 70.77 | 47.61 | 50.88 | 60.88 | 53.51 | 58.07 | 72.18 | mm |
| | CV | 0.43 | 0.48 | 0.67 | 0.33 | 0.39 | 0.60 | 0.31 | 0.36 | 0.57 | - |
| | Coeff. Skewness | 1.55 | 2.02 | 3.53 | 1.36 | 1.75 | 4.53 | 1.41 | 1.81 | 3.63 | - |
| | Coeff. Kurtosis | 7.25 | 10.68 | 27.61 | 6.25 | 8.62 | 52.26 | 6.91 | 9.54 | 30.82 | - |

For the sake of simplicity, basin characteristics are obtained from an existing study. Drainage area: 180 $km^2$ approx.

Two different hydrological characteristics of the basin were analyzed, reproducing an ephemeral and a permanent regime.

- **Ephemeral** regime (70% overland flow, 30% interflow, **0% base flow**)
- **Permanent** regime(30% overland flow, 40% interflow, **30% base flow**)

Results for permanent regime are not shown since non-significant changes were detected.

## 3. METHODOLOGY

### GWEX [2]

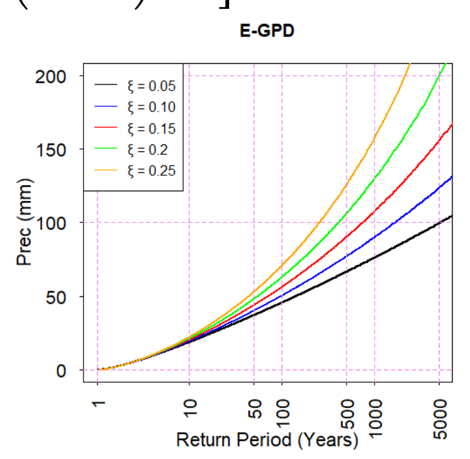
- **Multi-site** WG of **daily** P and max and min Temp, **focused on extreme events**
- Precipitation amounts: Extended Generalized Pareto Distribution (**E-GPD**)[3]

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

$\sigma$ → Scale Parameter

$\kappa$ → Transf. Parameter

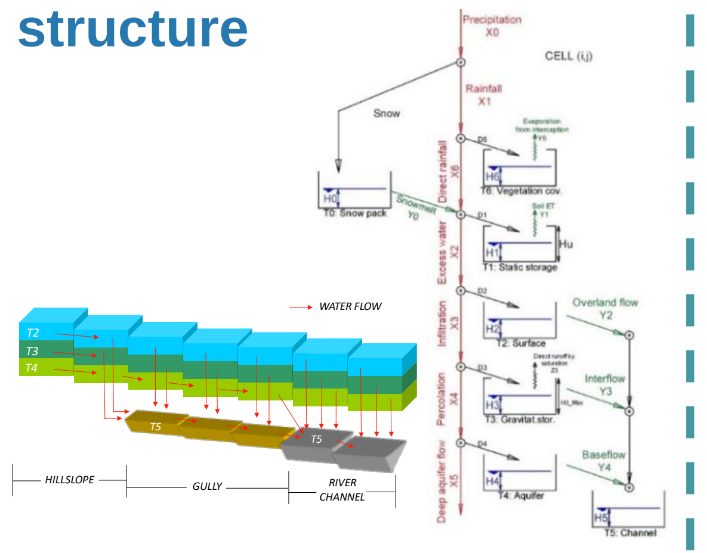
**$\xi$ → Shape Parameter (directly affecting the upper tail)**

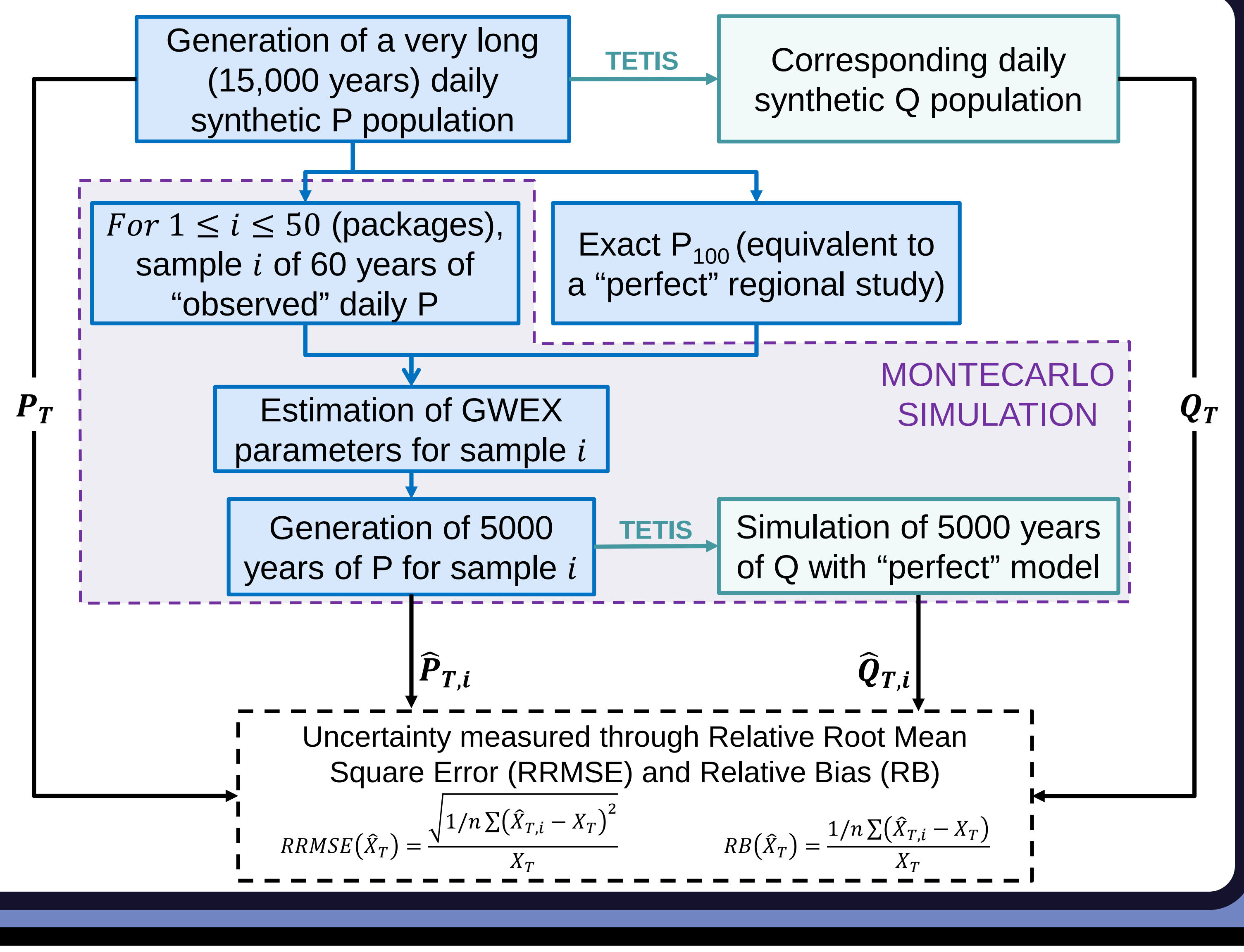


Parameter **ξ** is **estimated with the regional $P_{100}$**

### TETIS [4]

- **Integral** HM
- **Conceptual** (tank structure) model with **physically based parameters**
- **Distributed** in space
- Incorporates a **parsimonious split effective parameter structure**





Generation of a very long (15,000 years) daily synthetic P population

Corresponding daily synthetic Q population

*For* $1 \le i \le 50$ (packages), sample $i$ of 60 years of “observed” daily P

Exact $P_{100}$ (equivalent to a “perfect” regional study)

Estimation of GWEX parameters for sample $i$

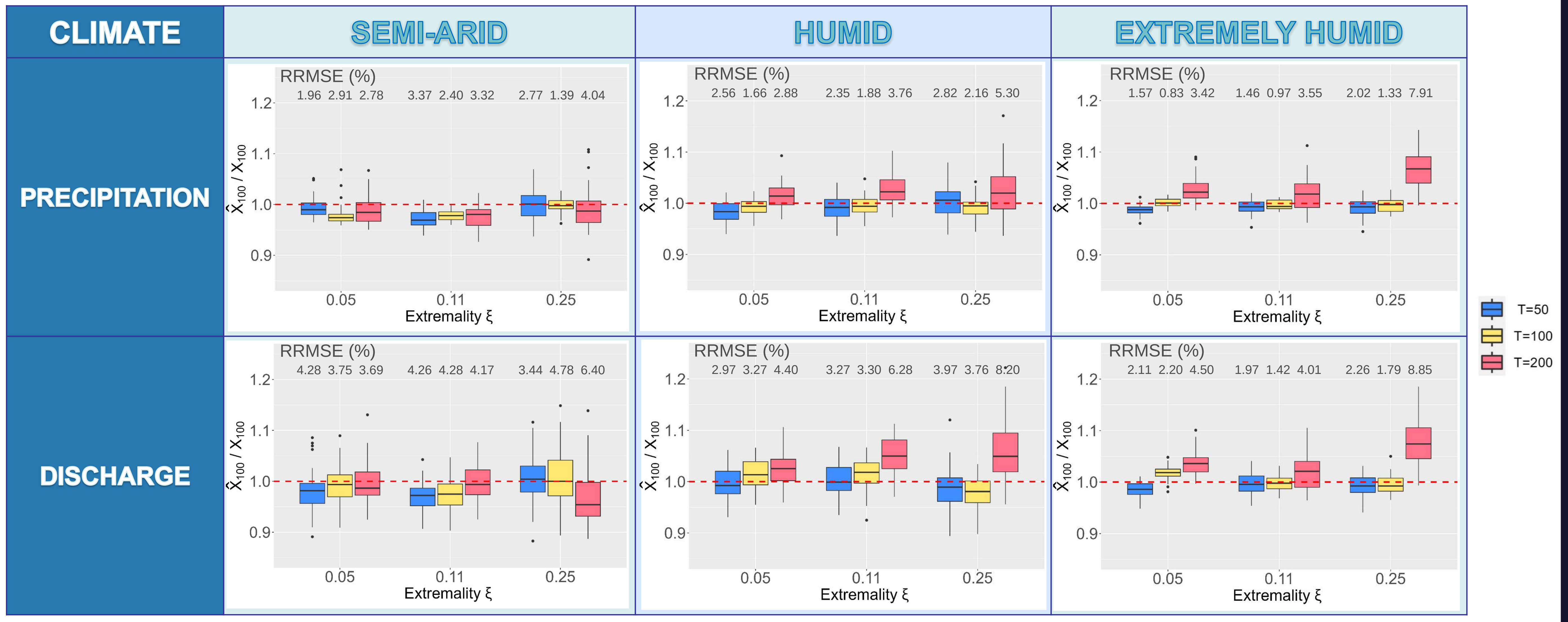
Generation of 5000 years of P for sample $i$

Simulation of 5000 years of Q with “perfect” model

Uncertainty measured through Relative Root Mean Square Error (RRMSE) and Relative Bias (RB)

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

## 4. RESULTS



| | |
|---|---|
| Different quantile estimates $X_T$ → | As expected, quantiles around $X_{100}$ are less uncertain.<br>Underestimation of lower $X_T$, overestimation of higher $X_T$, except for semi-arid climate |
| Different extremalities ξ → | As climate extremality increases, uncertainty increase.<br>Lower sensitivity to climate extremality changes in humid and very humid climates. |
| Different precipitation regimes (3 climates) → | Semi-arid climate more uncertain respect to humid and very humid climates in lower T, less uncertain for high T. |
| From WG to HM → | Uncertainty transmitted to the HM, which makes it increase, especially in semi-arid climate. |

## 5. CONCLUSIONS

- As obtained in preliminary studies [5-6], additional information is needed to reduce the uncertainty of P and Q.
- Climate extremality has been demonstrated to be a key factor for the WG performance. As $\xi$ increases, there is more uncertainty on the quantile estimates, especially in those associated with high T.
- For Mediterranean semi-arid climates, where the precipitation regime is less homogeneous, uncertainty of the quantile estimations is clearly higher compared to Humid and Very Humid climates. Quantile estimations in these climates present less uncertainty.
- Uncertainty propagates through Hydrological Model, being this propagation lower in the case of Very Humid climate.

## 6. REFERENCES

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