

# Un Tétris pour générer des précipitations

Rainfall modelling with compound discrete EGPD

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Statistiques au sommet de Rochebrune



# Motivation



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*“Fin janvier 2025, la tempête Eowyn, suivie des dépressions Herminia puis Ivo ont apporté des pluies continues. Ces pluies sont tombées sur des sols déjà saturés en eau par un antécédent pluvieux sur l'ensemble du mois, limitant l'infiltration dans le sol, provoquant des débordements de cours d'eau inédits et ralentissant la décrue.”*

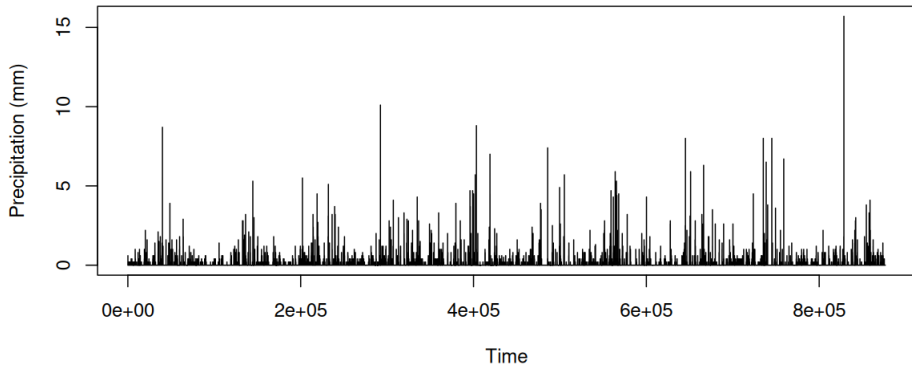
<https://www.ille-et-vilaine.gouv.fr>

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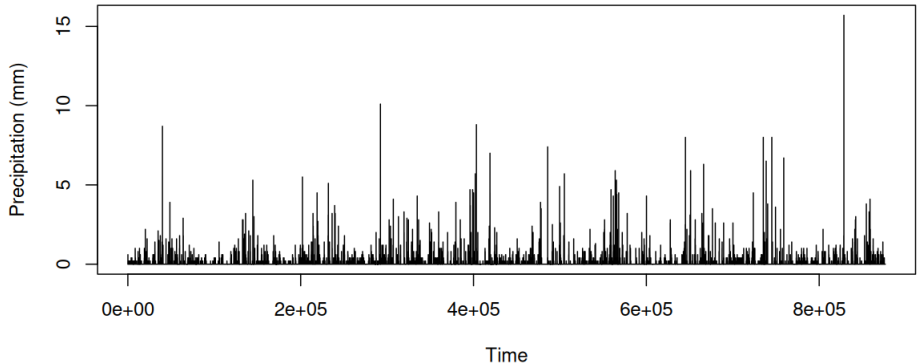


<https://www.aspas-nature.org>

## Goals of this project



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- ▶ Model precipitation time series by taking into account **time dependence** and **non-stationarities**
- ▶ Characterize the **whole distribution** of rainfall, including non-extreme values
- ▶ Develop a stochastic precipitation generator for **high-resolution** time series (6 minutes)

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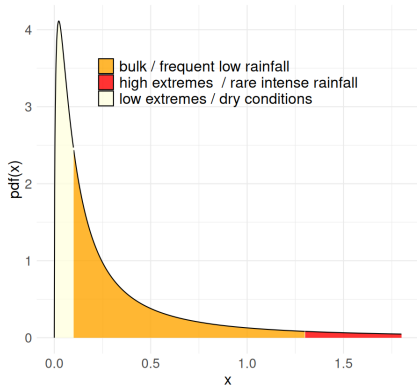
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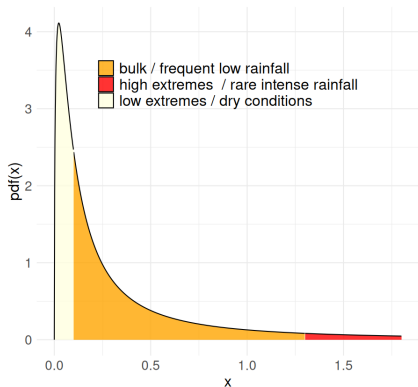
Ex: if  $E_i \sim \text{Gamma}$ ,  $Z$  is a Poisson-Gamma r.v. (Fisher et al., 1960)

In our case,  $E_i \sim \text{EGPD}$  (Naveau et al., 2016)

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### Low extremes

$\kappa$  the GPD parameter of  $1/E$

### Bulk

$B$  a CDF function on  $[0, 1]$

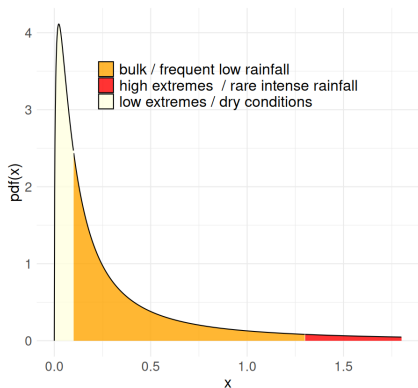
### High extremes

$\xi$  the GPD parameter of  $E$

$$E = \sigma H_{\xi}^{-1} \left( (B^{-1}(U))^{1/\kappa} \right) \sim E\text{GPD}(\sigma, \kappa, \xi, B)$$

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Sums of *iid* EGPD variables remain EGPD, with same  $\xi$  but different  $B$

## Adding some temporal dependence: **Trawl processes**<sup>1</sup>

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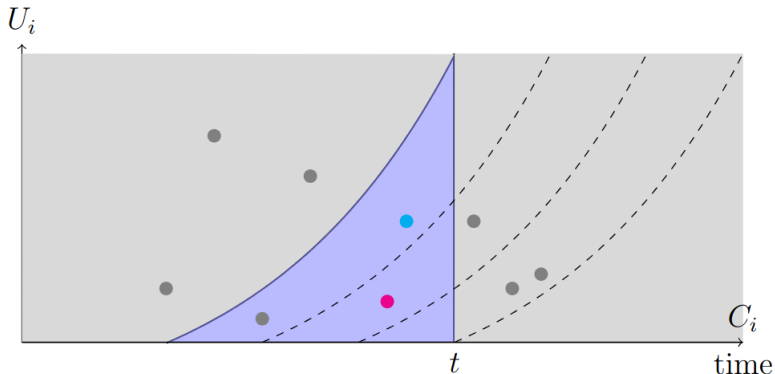


**Trawl  $\neq$  Troll !!**

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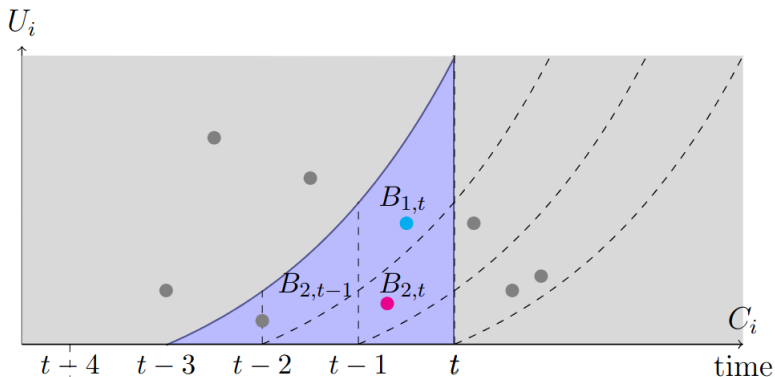
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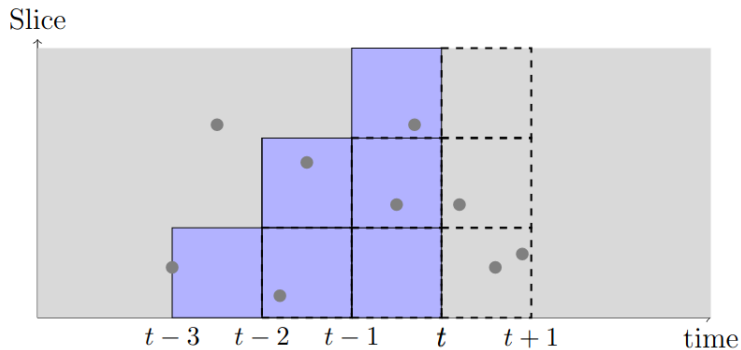
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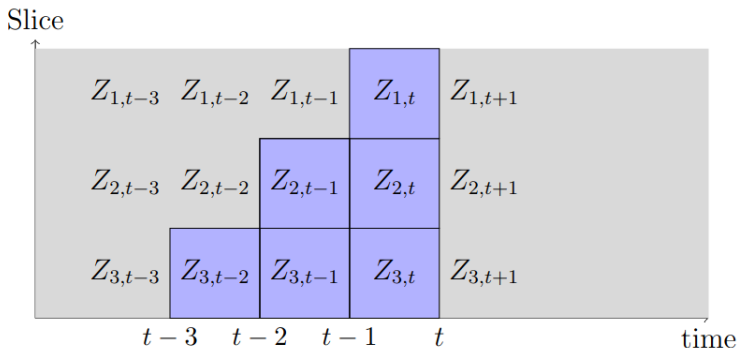
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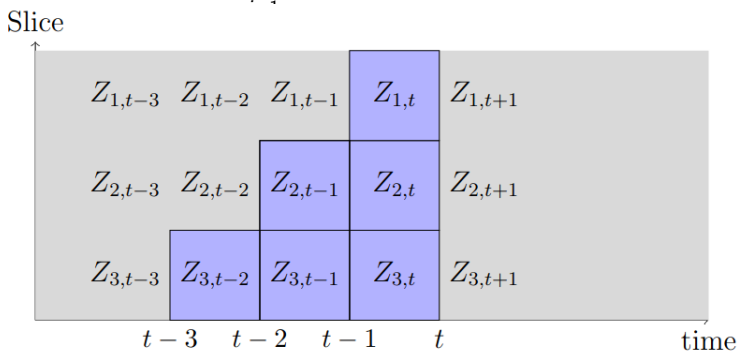
$$Z_{j,t} = \sum_{i=1}^{N_{j,t}} E_i^{j,t}, \quad j = 1, \dots, q, \quad t \in \mathbb{Z}$$



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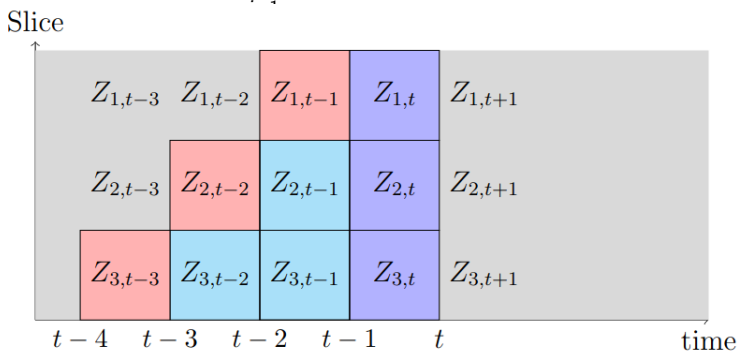


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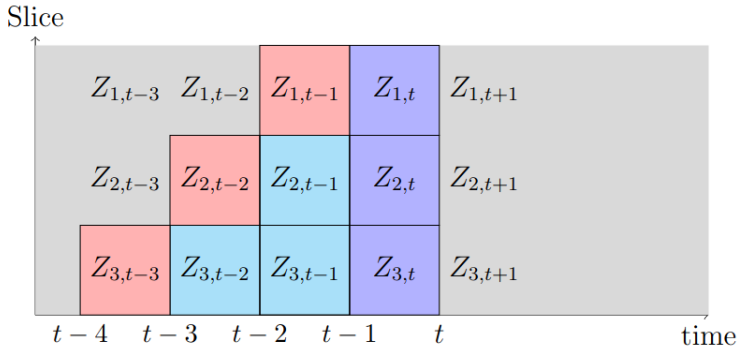


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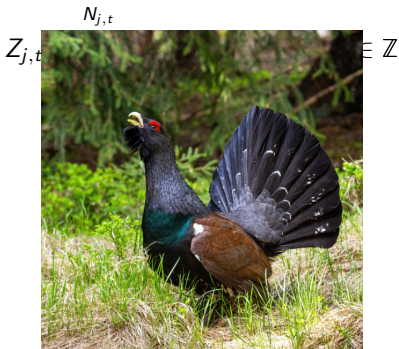


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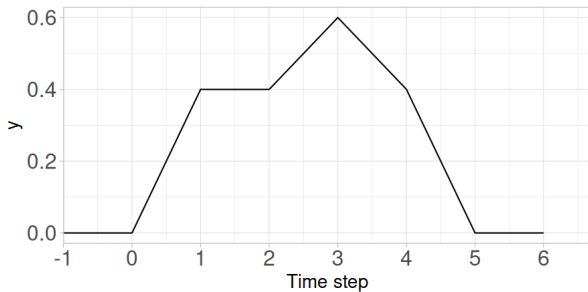
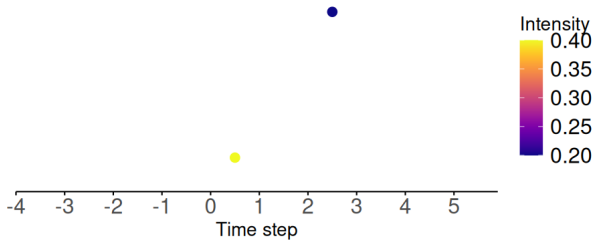
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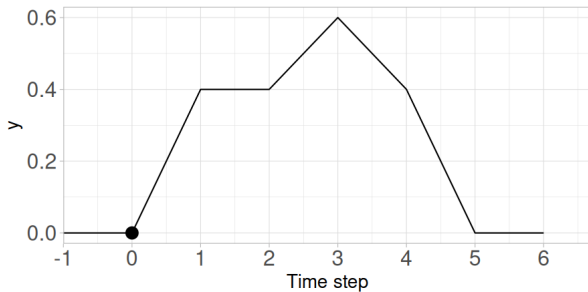
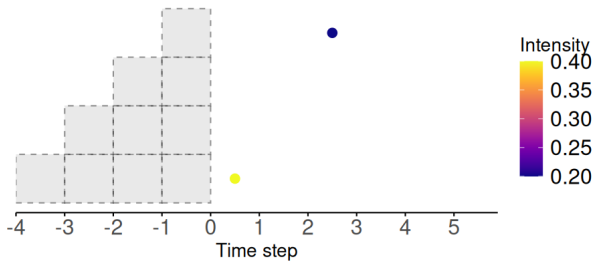
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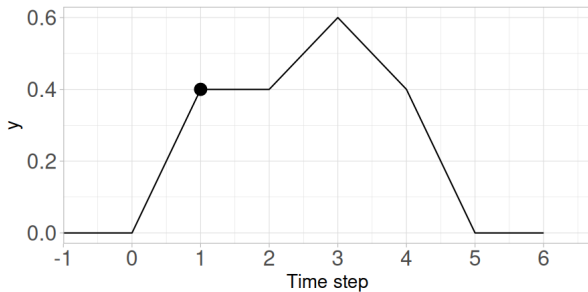
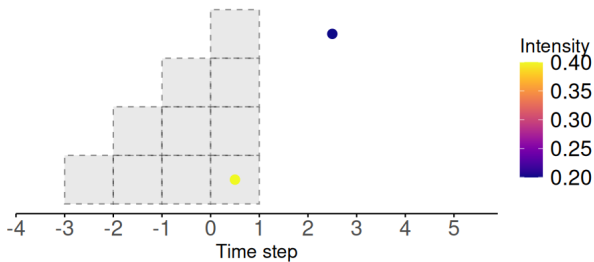
## Simulation example of the Tetris process with $q = 4$



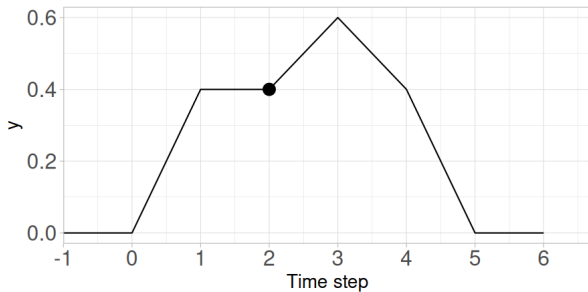
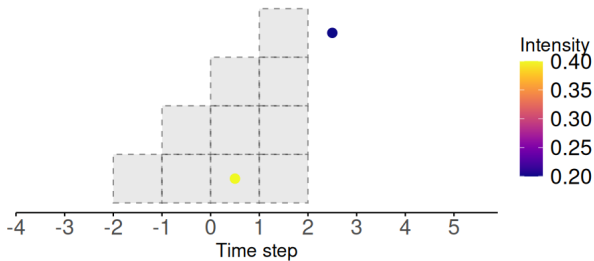
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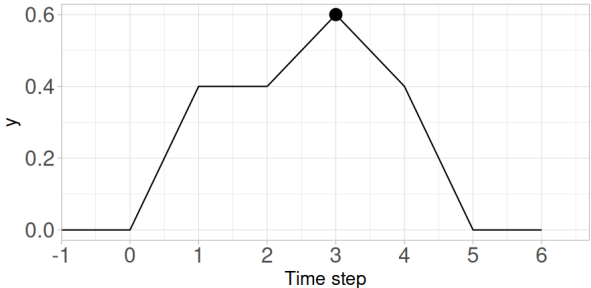
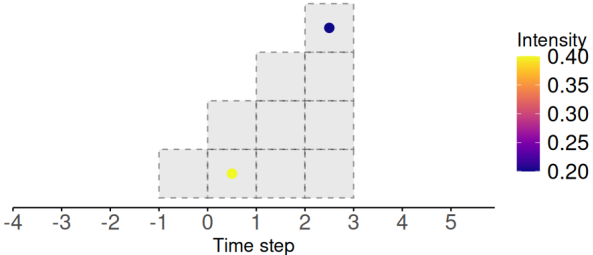
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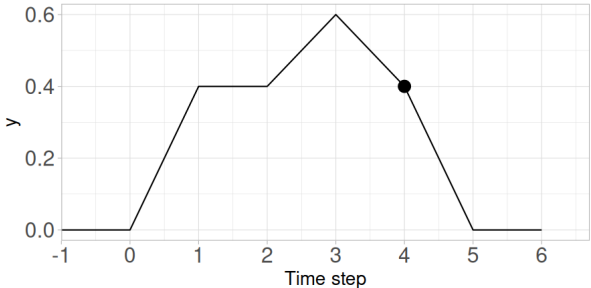
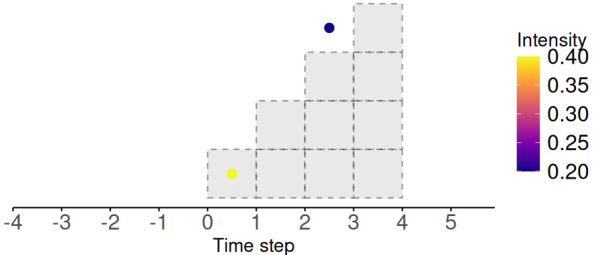
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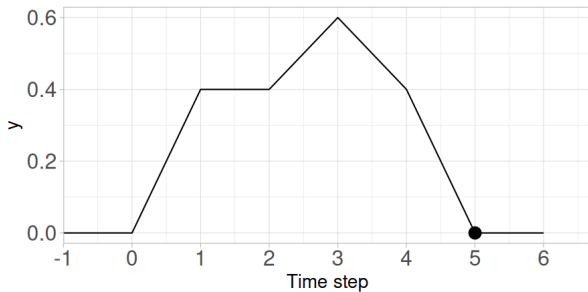
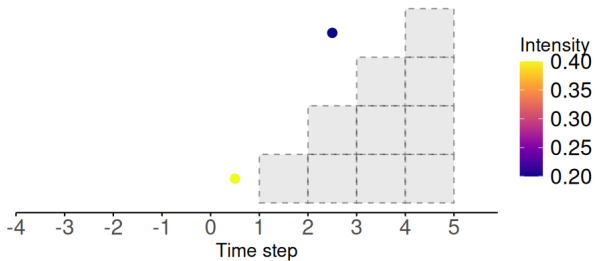
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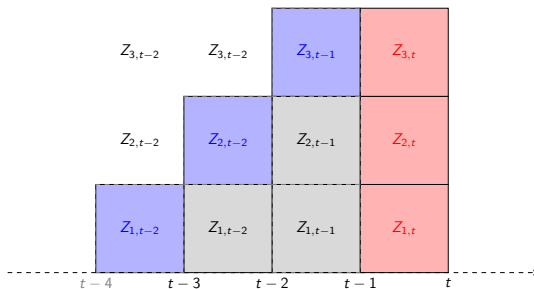
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## Inference scheme

$$Y_t = \sum_{i \in I_t \setminus I_s} Z_i + \sum_{i \in I_t \cap I_s} Z_i = Y_{(t \setminus s)} + Y_{(t,s)}$$

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Bivariate probability function given by

$$\mathbb{P}(Y_t = y_t, Y_s = y_s) = \sum_{k=0}^{\min(y_t, y_s)} \mathbb{P}(Y_{t \setminus s} = y_t - k) \mathbb{P}(Y_{t,s} = k) \mathbb{P}(Y_{s \setminus t} = y_s - k)$$

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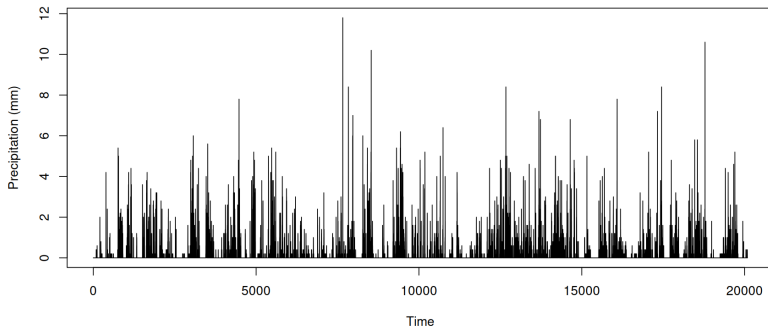
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► Inference based on pairwise likelihood and Panjer's algorithm <sup>2</sup>

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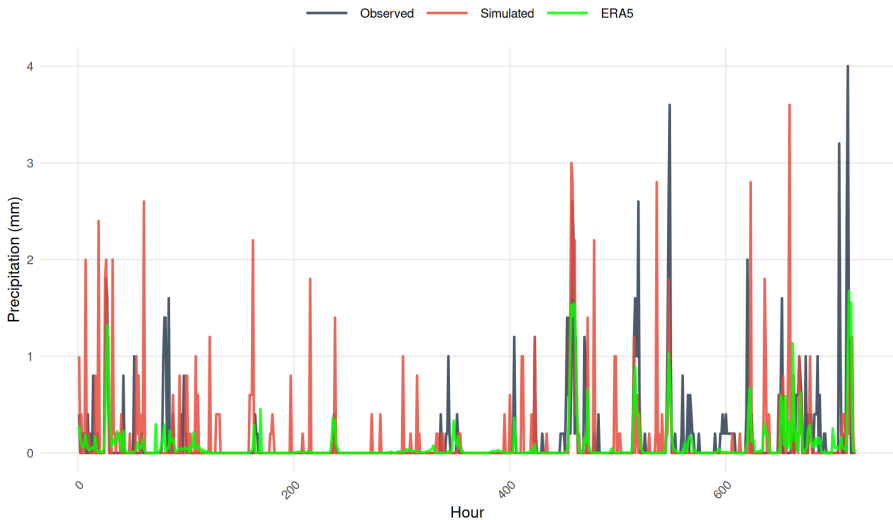
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## Simulation of “realistic” rainfall events

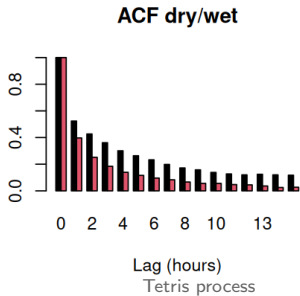
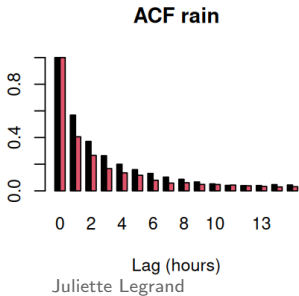
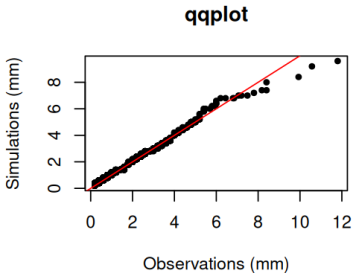
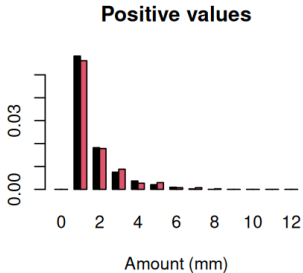


- Precipitation data from Brest-Guipavas station, France
- 1 hour time resolution
- Covariate: ERA5 precipitation at the nearest grid point
- Effect on the  $\lambda_t$  (Poisson parameters) and on the  $\sigma$  (EGPD scale parameter, by tetris-slice)

# Simulation of “realistic” rainfall events



# Simulation of “realistic” rainfall events ( $q = 4$ )



## Conclusion and perspectives

- ▶ Good reproduction of marginal properties and temporal dependence structure
- ▶ High flexibility:
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- ↪ Extension to spatial setting (upcoming PhD)