



HAL
open science

GRAFFAS: A Stochastic Space-Time Model for High-Resolution Hourly Rainfall Fields

Philippe Cantet, Patrick Arnaud, Benjamin Renard

► **To cite this version:**

Philippe Cantet, Patrick Arnaud, Benjamin Renard. GRAFFAS: A Stochastic Space-Time Model for High-Resolution Hourly Rainfall Fields. SWGEN 2025, Dec 2025, Grenoble, France. <hal-05404973>

HAL Id: hal-05404973

<https://hal.science/hal-05404973v1>

Submitted on 8 Dec 2025

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



HAL Authorization

GRAFFAS: A Stochastic Space-Time Model for High-Resolution Hourly Rainfall Fields



Philippe Cantet^{1,2*}, Patrick Arnaud³, Benjamin Renard³

¹DCSC-EMA, Météo-France, Toulouse, France *Corresponding author: philippe.cantet@meteo.fr

²Hydris-Hydrologie, Montpellier, France ³RECOVER, Inrae, Aix-Marseille University, Aix en Provence, France



Abstract

We propose GRAFFAS (Generator of Rainfall Fields From Areal Statistics), a stochastic space-time model designed to simulate hourly rainfall fields at fine spatial resolution (down to km²), from areal statistics time series. The spatial disaggregation approach used in GRAFFAS enables the representation of spatial heterogeneity and anisotropy, which are essential features in many regions.

A multivariate auto-regressive Gaussian process is used to model the space-time dependencies of fields, including anisotropy. Then, a meta-model combines the simulated Gaussian fields and the areal rainfall statistics to provide synthetic rainfall fields. Local parameters are introduced within this meta-model to account for spatial heterogeneity. The model is calibrated and evaluated using kilometric hourly rainfall data across six climatically contrasting regions. The evaluation framework assesses the model's ability to reproduce key statistical properties of rainfall across temporal and spatial scales. Results highlight the importance of spatial heterogeneity in reproducing at-site rainfall distributions (including extremes) and the co-occurrence of extreme events across a region at different aggregation timescales.

Keywords: Stochastic Space-Time Model; Rainfall Fields; Meta-Gaussian Model; Spatial Disaggregation

Principle : transforming three areal statistics into a rainfall field $R_t(\mathbf{x})$

$\mathbf{x} = (x_1, \dots, x_N)$ denotes the N pixels included in the studied domain.

Considering three areal statistics available at each time t :

1. IMF_t the mean areal rainfall at time t ,
 2. WAR_t the wet area fraction at time t ,
 3. CV_t the coefficient of variation of the non-zero rainfall at time t ,
- and a MAR(1) process, noted G_t , defined as follows :

$$G_t(\mathbf{x}) = A.G_{t-1}(\mathbf{x}) + E_t(\mathbf{x}) \text{ with } E_t(x) \sim \mathcal{N}(0, \Sigma)$$

Then $R_t(x_i)$ giving the rainfall depth (mm/h) at pixel x_i and time t is defined by

$$R_t(x_i) = \begin{cases} 0 & \text{if } \Phi(G_t(x_i)) < 1 - WAR_t \\ F^{-1}\left(\frac{\Phi(G_t(x_i)) - 1 + WAR_t}{WAR_t}, \mu_t, \sigma_t\right) & \text{otherwise.} \end{cases}$$

where $F(\cdot, \mu, \sigma)$ (F^{-1}) denote the (inverse) cumulative distribution function (CDF) of the Log-Normal distribution with parameters μ and σ ,

$$\text{with } \sigma_t = \sqrt{\log(1 + CV_t^2)}; \mu_t = \log(IMF_t / WAR_t) - 0.5 \cdot \sigma_t^2$$

With this formulation from [2], all pixels are realizations from the same distribution in terms of both occurrence and intensity.

How to incorporate spatial heterogeneity?

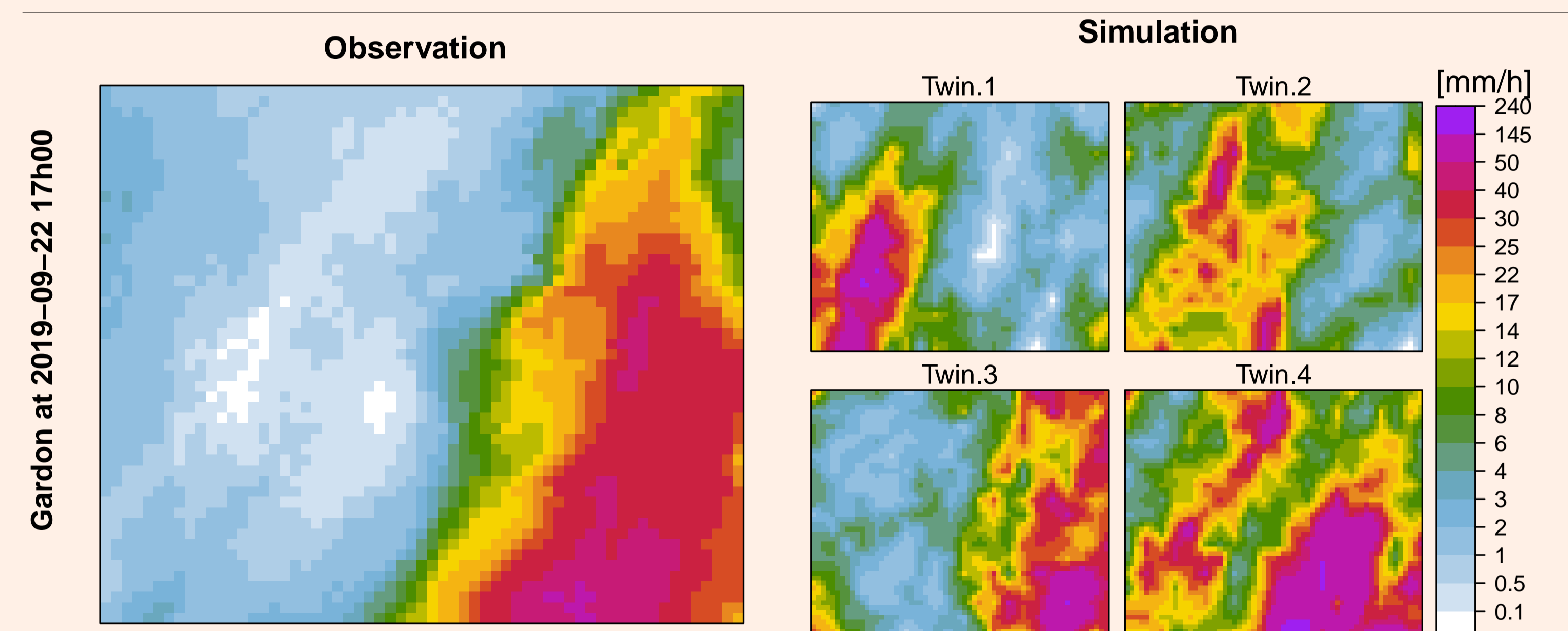
$$\bullet P_{wet}(x_i, w_t) = \Pr(R_t(x_i) > 0 | WAR_t = w_t) = F_{Beta}(w_t, 1 - k_i^{WAR}, 1 + k_i^{WAR})$$

$$\bullet \widehat{IMF}_t(x_i) = k_i^{IMF} * IMF_t$$

$$\rightarrow \Pr(R_t(x_i) \leq y | WAR_t = w_t) = (1 - P_{wet}(x_i, w_t)) + P_{wet}(x_i, w_t) \cdot F(y, \mu_t(x_i), \sigma_t)$$

How to incorporate anisotropy?

$$\Sigma_{ij} = \exp(-\tau_{ij}/\lambda) \text{ with } \tau_{i,j} = Mahalanobis_{b,\psi}(x_i, x_j)$$



Observed and simulated rainfall fields with $WAR_t = 0.99, IMF_t = 11, CV_t = 0.2$

Calibration : using hourly gridded COMEPHORE dataset

One set of parameters per season (DJF, MAM, JJA, SON)

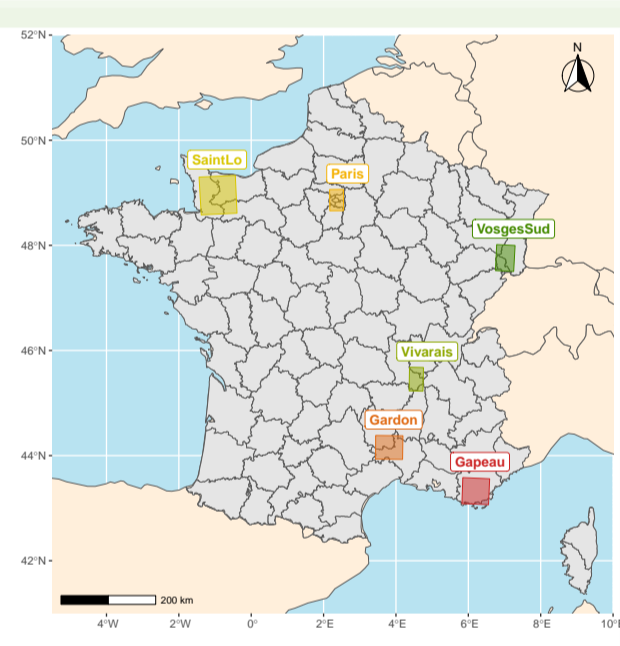
Notation	Description	Objective
$\{k_i^{WAR}\}_{i=1..N}$	Corrective factor for rainfall occurrence	Spatial heterogeneity
$\{k_i^{IMF}\}_{i=1..N}$	Corrective factor for rainfall intensity	Spatial heterogeneity
$\{a_{i,i}\}_{i=1..N}$	Components of the auto-regression matrix A	Temporal dependence
$\{\lambda, b, \psi\}$	Parameters of the anisotropic covariance function	Spatial dependence

Maximum Likelihood Estimation (See [1] for more details and Equations)

- Local parameters (corrective factors) : Bernoulli distribution (k_i^{WAR}) and interval-censored likelihood formulation of the log-normal distribution (k_i^{IMF})
- MAR(1) parameters : distribution of a censored-Gaussian process [3]

Calibration performed on six contrasted regions

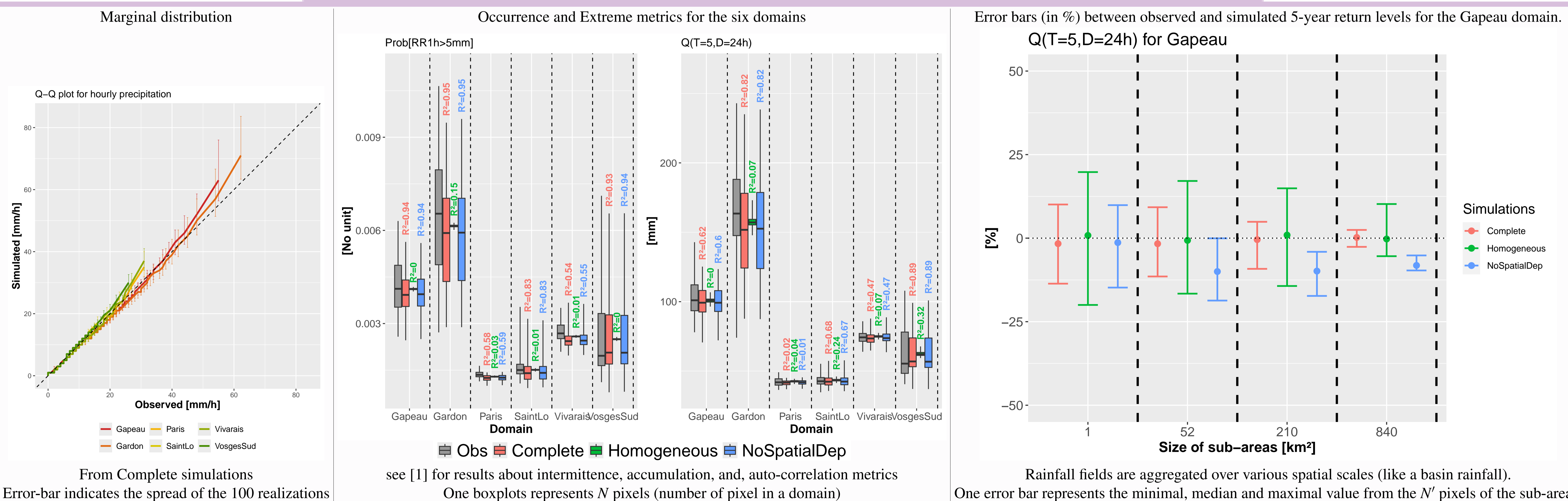
Mediterranean, (Altered-)Oceanic, and (Semi-)Continental Climates



Results : marginal and spatial properties of simulated rainfall

100 independent time series of rainfall fields are generated by the GRAFFAS model from the observed areal statistics time series (1997-2022).

Three different simulations : Complete - Homogeneous (similar to [2]) - NoSpatialDep (without spatial dependence)



Conclusions

GRAFFAS can generate realistic realizations of hourly rainfall field time series from given areal rainfall statistics time series. Its performance was analyzed in terms of the marginal and areal properties of the simulated rainfall fields at different time scales.

Simulated rainfall fields may be used as **inputs by a distributed hydrological model**, which opens the way for several important applications such as estimating flood quantiles everywhere on the hydrologic network by continuous simulation, or estimating hydrological impacts of climate change by **disaggregating coarse climate model outputs**.

A key perspective is to introduce advection; a challenging approach would be to add non-diagonal coefficients to the A matrix of the MAR(1) process.

This work benefited from a fund from the French National Research Agency (ANR, France2030) under the reference ANR-24-EXMA-0008.

References

- [1] Cantet, P., Renard, B., Fine, J. A., Arnaud, P. (2025). Space-time simulation of hourly rainfall from areal statistics accounting for spatial heterogeneity and anisotropy. *Water Resources Research*, 61, e2024WR038562 (QRcode at the top).
- [2] Paschalis, A., Molnar, P., Fatchi, S., Burlando, P. (2013). A stochastic model for high-resolution space-time precipitation simulation. *Water Resources Research*, 49(12), 8400–8417. <https://doi.org/10.1002/2013WR014437>.
- [3] Vaittinada Ayar, P., Blanchet, J., Paquet, E., Penot, D. (2020). Space-time simulation of precipitation based on weather pattern sub-sampling and meta-Gaussian model. *Journal of Hydrology*, 581, 124451. <https://doi.org/10.1016/j.jhydrol.2019.124451>.

Codes (in R) for calibrating and running the GRAFFAS model are freely available at Zenodo : QR code \Rightarrow

