

This section introduces the rainfall intensity classification adopted throughout the study. The categories are based on the Mediterranean daily rainfall classification proposed by Alpert and are used to define rainfall magnitude classes in the subsequent analyses.

Table S. 1- Mediterranean daily rainfall rate classifications by Alpert

Category	Symbol	Rainfall Range (mm day ⁻¹)
Light	A	0–4
Light-Moderate	B	4–16
Moderate-Heavy	C1	16–32
Heavy	C2	32–64
Heavy-Torrential	D1	64–128
Torrential	D2	>128

Rainfall events were grouped according to both occurrence extent and rainfall magnitude to construct the event classes used throughout the modeling framework. The frequency distribution of these combined classes is summarized below.

Table S. 2- Frequency-based alignment of occurrence and magnitude classes

Magnitude / Occurrence	Light	Moderate	Heavy	Total (Days)
Widespread	A-B	A-C1, A-C2, B-C1	B-D1, B-D2, C1-C2, C1-D2, C2-D1, C2-D2	157 (14%)
Intermediate	A-A, A-B	A-C1, A-C2, A-D1, B-C1	B-C2, B-D1	251 (23%)
Localized	A-A, A-B	A-C1, A-C2, A-D1	B-D1, B-D2	688 (63%)
Total (Days)	739 (67%)	233 (21%)	124 (11%)	1096

Several empirical semivariogram estimators were evaluated to identify the most appropriate approach for estimating spatial dependence under the highly skewed rainfall distributions encountered in this study. Their main characteristics are summarized below.

Table S. 3- Comparison of empirical semivariogram estimators

Estimator	Calculation	Key Strength	Key Weakness
Matheron	$\hat{\gamma}(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [Z(s_i) - Z(s_i + h)]^2$	Standard, widely implemented – Unbiased under stationarity	– Highly sensitive to outliers – Can be erratic with skewed data
Cressie-Hawkins	$\tilde{\gamma}(h) = \frac{\left(\frac{1}{N(h)} \sum_{i=1}^{N(h)} Z(s_i) - Z(s_i + h) ^{1/2} \right)^4}{0.914 + \frac{0.988}{N(h)}}$	Down-weights outliers via 4th-root transformation – More robust than Matheron	– Still uses the mean, so not fully robust against extreme outliers
Dowd	$\gamma(h) = \frac{1}{2} \text{median}([Z(s_i) - Z(s_i + h)]^2)$	Highly robust due to median summarization – Resistant to isolated extreme pairs	– May be inefficient if many bins have few pairs
Genton	$\widehat{\gamma}_G(h) = \frac{1}{2} \left[c_n \cdot Q_n \left(Z(s_i) - Z(s_j) _{h_{ij} \approx h} \right) \right]^2$	Very high breakdown point – Asymptotically efficient under normality	– Computationally more intensive – Implementation less widespread and less comparative

Building on the comparison of candidate estimators, the final semivariance estimation procedure adopted in the workflow is summarized here, including the pairwise measure, bin aggregation method, and lag binning strategy.

Table S. 4- Summary of semivariance estimators and the final implementation choices.

Estimator	Pairwise Measure	Bin Summarization	Binning Strategy
Matheron	Squared difference $(z_i - z_j)^2$	Weighted mean (distance-based weights)	Uniform Log-spaced bins
Cressie-Hawkins	Fourth root of absolute difference $\sqrt[4]{\ z_i - z_j\ }$	Weighted mean, then back-transform	Uniform Log-spaced bins
Dowd	Absolute difference $\ z_i - z_j\ $	Median	Uniform Log-spaced

Supplementary Materials

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Multiple theoretical variogram models were considered to represent different types of spatial dependence and rainfall variability. The candidate models, their parameters, and the rationale for their inclusion are summarized below.

Table S. 5- Summary and Justification of Candidate Variogram Models.

Name	Type	Equation	Parameters	Potential Capability & Motivation
Spherical	Stationary	$\gamma(h) = C_0 + C_1 \left[\frac{3h}{2a} - \frac{1}{2} \left(\frac{h}{a} \right)^3 \right]$ for $h \leq a$	Nugget, Sill, Range	Most common geostatistical model, Baseline for comparison • Linear near origin – suitable for many natural processes
Exponential	Stationary	$\gamma(h) = C_0 + C_1 \left[1 - \exp \left(-\frac{h}{a} \right) \right]$	Nugget, Sill, Range	Approaches sill asymptotically Models rougher fields with higher short-distance variability than spherical • Suitable for highly intermittent processes.
Gaussian	Stationary	$\gamma(h) = C_0 + C_1 \left[1 - \exp \left(-\left(\frac{h}{a} \right)^2 \right) \right]$	Nugget, Sill, Range	Parabolic near origin – very smooth continuity Use only when process is genuinely smooth • May cause kriging instability if misapplied
Matern	Stationary	$\gamma(h) = C_0 + C_1 \left[1 - \frac{2^{1-\kappa}}{\Gamma(\kappa)} \left(\frac{h}{a} \right)^\kappa K_\kappa \left(\frac{h}{a} \right) \right]$	Nugget, Sill, Range, Smoothness κ	Highly flexible – controls smoothness continuously Replicates Exponential ($\nu=0.5$) and Gaussian ($\nu \rightarrow \infty$) • Robust general-purpose choice
Power Law	Unbounded	$\gamma(h) = C_0 + b \cdot h^\alpha$	Nugget, Slope b, Power α	Models fractal processes Variance increases indefinitely with distance • Captures strong unmodeled trends
Linear	Unbounded	$\gamma(h) = C_0$	Nugget, Slope	• Simplest unbounded model, Suitable for linear spatial drift
Rational Quadratic	Stationary	$\gamma(h) = C_0 + C_1 \left(1 - \frac{1}{(1 + (h/a)^2)^\alpha} \right)$	Nugget, Sill, Range, Shape α	Multi-scale behavior – sum of exponentials with different ranges Accommodates different decay rates • Captures variation at multiple scales
J-Bessel	Stationary	$\gamma(h) = C_0 + C_1 \left[1 - \frac{2^\nu \Gamma(\nu + 1)}{(h/a)^\nu} J_\nu(h/a) \right]$	Nugget, Sill Range, Order ν	Can model oscillatory / hole-effect patterns • Flexible for complex empirical variograms
Cubic	Stationary	$\gamma(h) = C_0 + C_1 \left[7 \left(\frac{h}{a} \right)^2 - \frac{35}{4} \left(\frac{h}{a} \right)^3 + \frac{7}{2} \left(\frac{h}{a} \right)^5 - \frac{3}{4} \left(\frac{h}{a} \right)^7 \right]$ for $h \leq a$.	Nugget, Sill, Range	Polynomial-based valid model and high spatial continuity • Alternative when common models are not optimal
Wave (Hole effect)	Stationary	$\gamma(h) = C_0 + C_1 \left[1 - \frac{\sin(ah)}{ah} \right]$	Nugget, Sill Wavelength	Explicit periodic / quasi-periodic patterns Models negative correlation at certain distances • Suitable for cyclical spatial structures

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Circular	Stationary	$\gamma(h) = C_0 + C_1 \left[1 - \frac{2}{\pi} \arccos \left(\frac{h}{a} \right) + \frac{2h}{\pi a} \sqrt{1 - \left(\frac{h}{a} \right)^2} \right]$ for $h \leq a$.	Nugget, Sill, Range	Derived from geometric overlap of circles Valid transition model • Represents patchy spatial structures
Stable	Stationary	$\gamma(h) = C_0 + C_1 \left[1 - \exp \left(- \left(\frac{h}{a} \right)^\alpha \right) \right]$ for $0 < \alpha \leq 2$.	Nugget, Sill, Range, Power α	Continuous spectrum between Exponential ($\alpha=1$) and Gaussian ($\alpha=2$) Fine control over smoothness at origin • Flexible for intermediate continuity
Super-Spherical	Stationary	$\gamma(h) = C_0 + C_1 \left[1 - s \cdot \frac{r}{1} \cdot \frac{{}_2F_1\left(\frac{1}{2}, -\nu, \frac{3}{2}, \left(\frac{s \cdot r}{1}\right)^2\right)}{{}_2F_1\left(\frac{1}{2}, -\nu, \frac{3}{2}, 1\right)} \right]$	Nugget, Sill, Range Shape	Generalization of spherical with extra shape parameter Allows non-uniform decay of correlation • Provides flexibility near origin
Nested	Special Structure	$\gamma(h) = C_0 + \gamma_{\text{short}}(h) + \gamma_{\text{long}}(h)$	Parameters of combined models	Captures variability at multiple distinct spatial scales E.g., local convective cells within larger synoptic system • Combines simple structures additively
Hybrid	Special Structure	<Equation variable>	Parameters of combined models	Merges properties of standard models • Tests combination of general decay with periodic component for complex rainfall fields

To assess the effectiveness of the normal-score transformation required by the geostatistical framework, Q–Q plots were examined for representative rainfall classes.

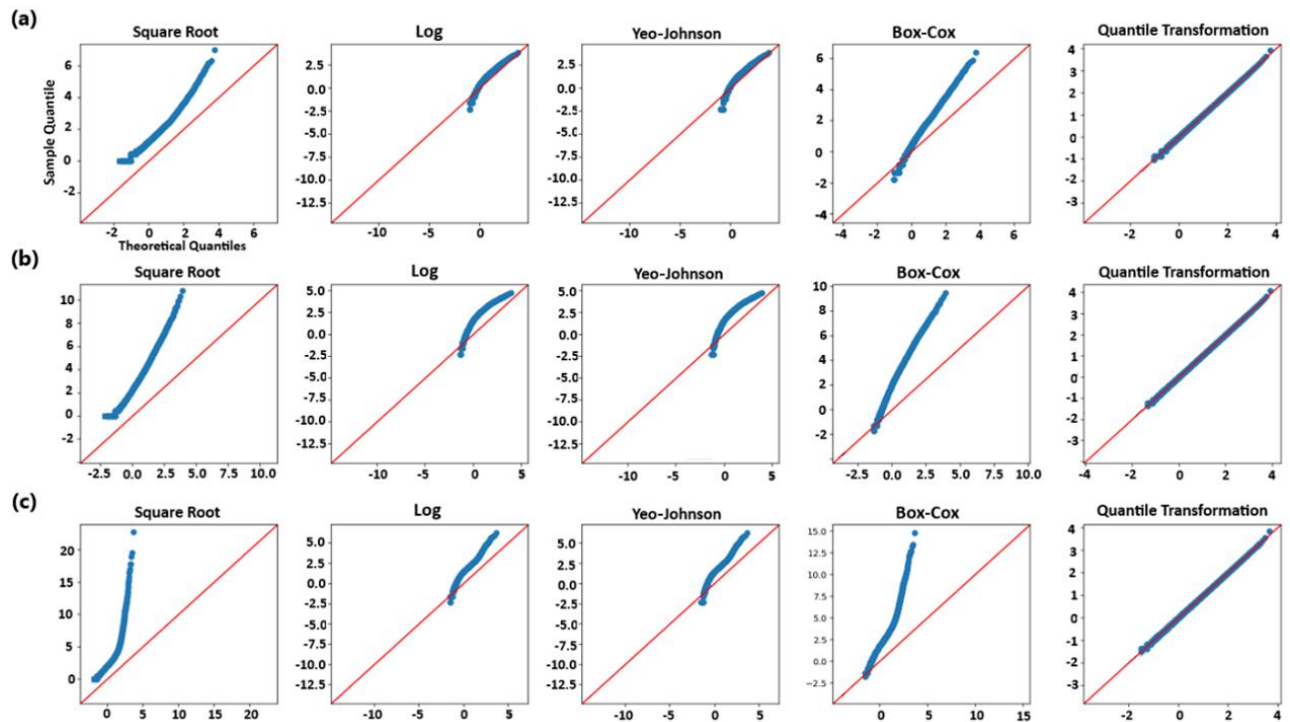


Figure S. 1 - Q-Q plots comparing the empirical distribution of transformed daily rainfall amounts against the theoretical standard normal distribution for (a) Widespread-Light, (b) Widespread-Moderate, (c) Widespread-Heavy.

The performance of the occurrence model was evaluated by comparing observed and simulated occurrence characteristics across the three intermittency classes and rainfall intensity regimes.

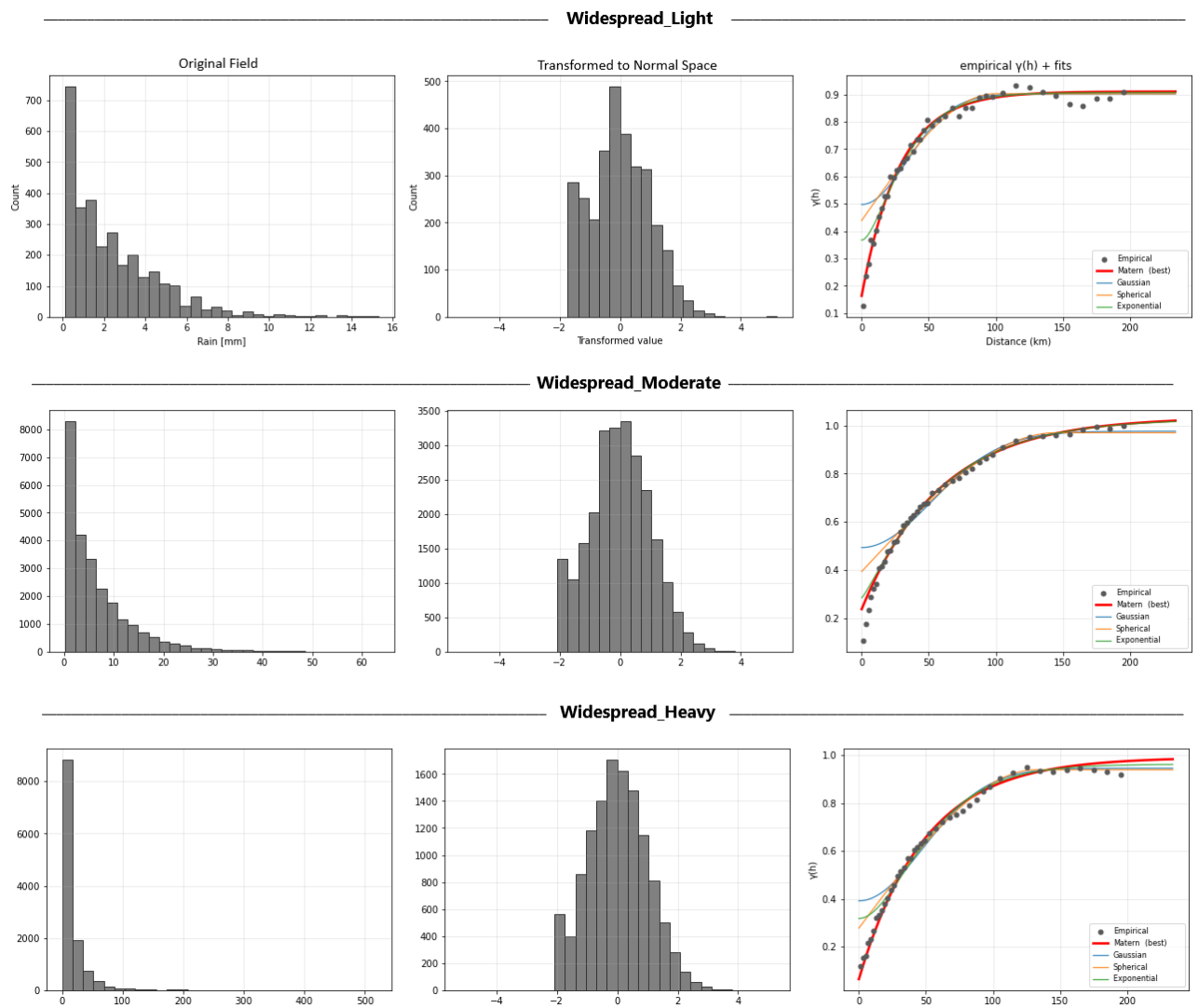


Figure S. 2- Comparison of observed and predicted occurrence characteristics across the intermittency class of Widespread and for three intensity regimes, correspond to (a) Light, (b) Moderate, and (c) Heavy.

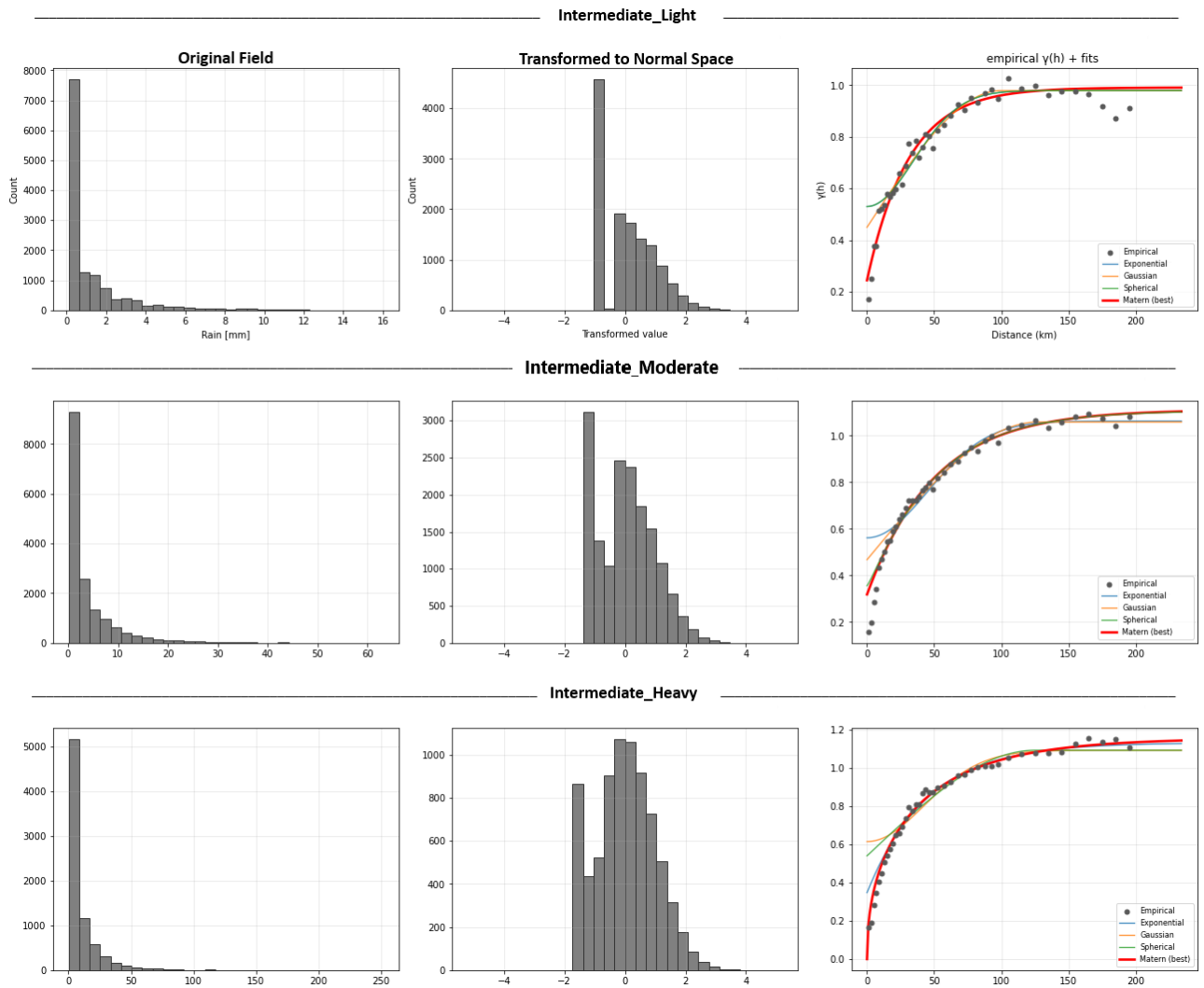


Figure S. 3- Comparison of observed and predicted occurrence characteristics across the intermittency class of Intermediate and for three intensity regimes, correspond to (a) Light, (b) Moderate, and (c) Heavy.

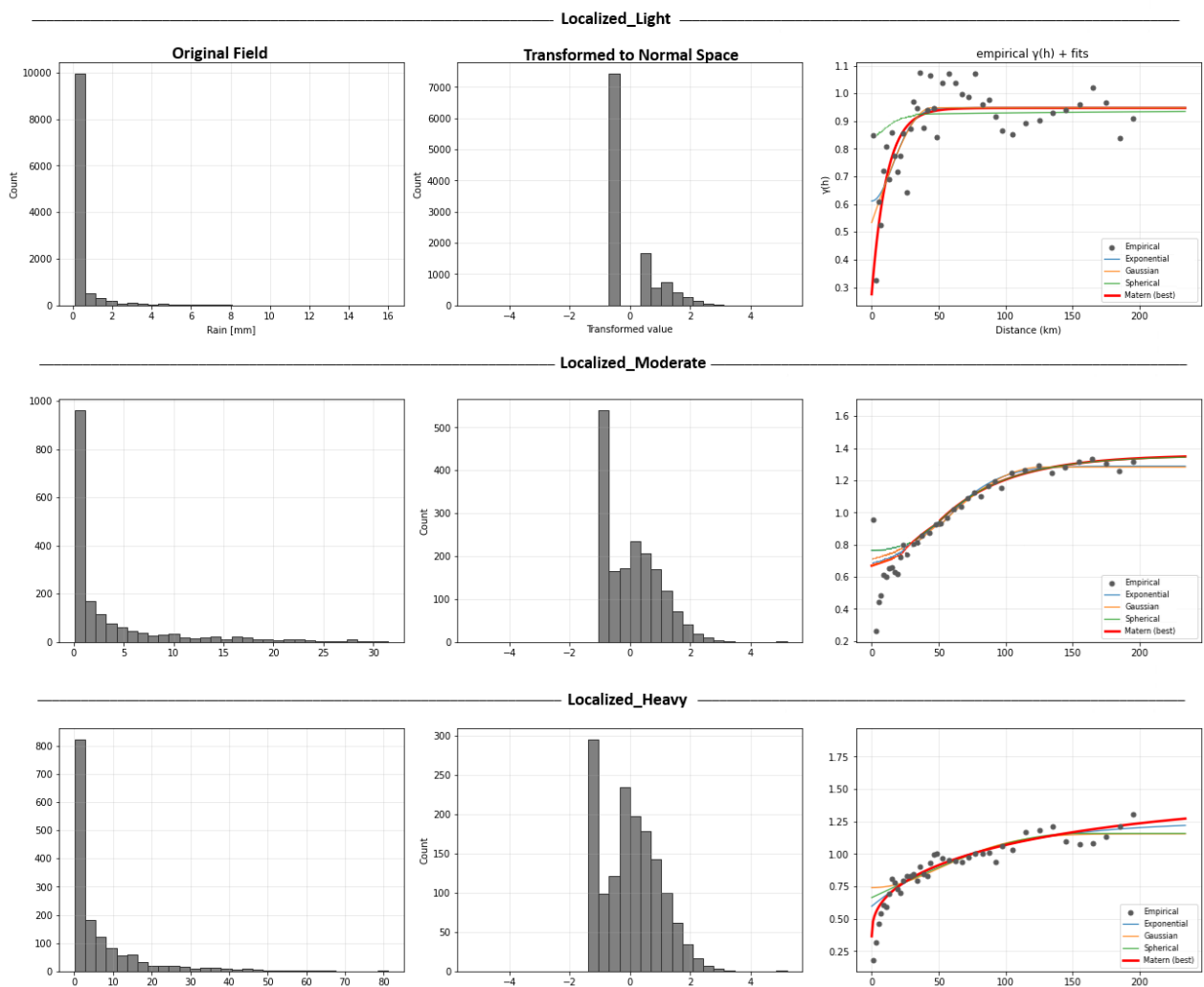


Figure S. 4- Comparison of observed and predicted occurrence characteristics across the intermittency class of Localized and for three intensity regimes, correspond to (a) Light, (b) Moderate, and (c) Heavy.

Additional validation results are provided at the monthly scale to illustrate the spatial distribution of performance metrics after bias correction for the two best-performing methods.

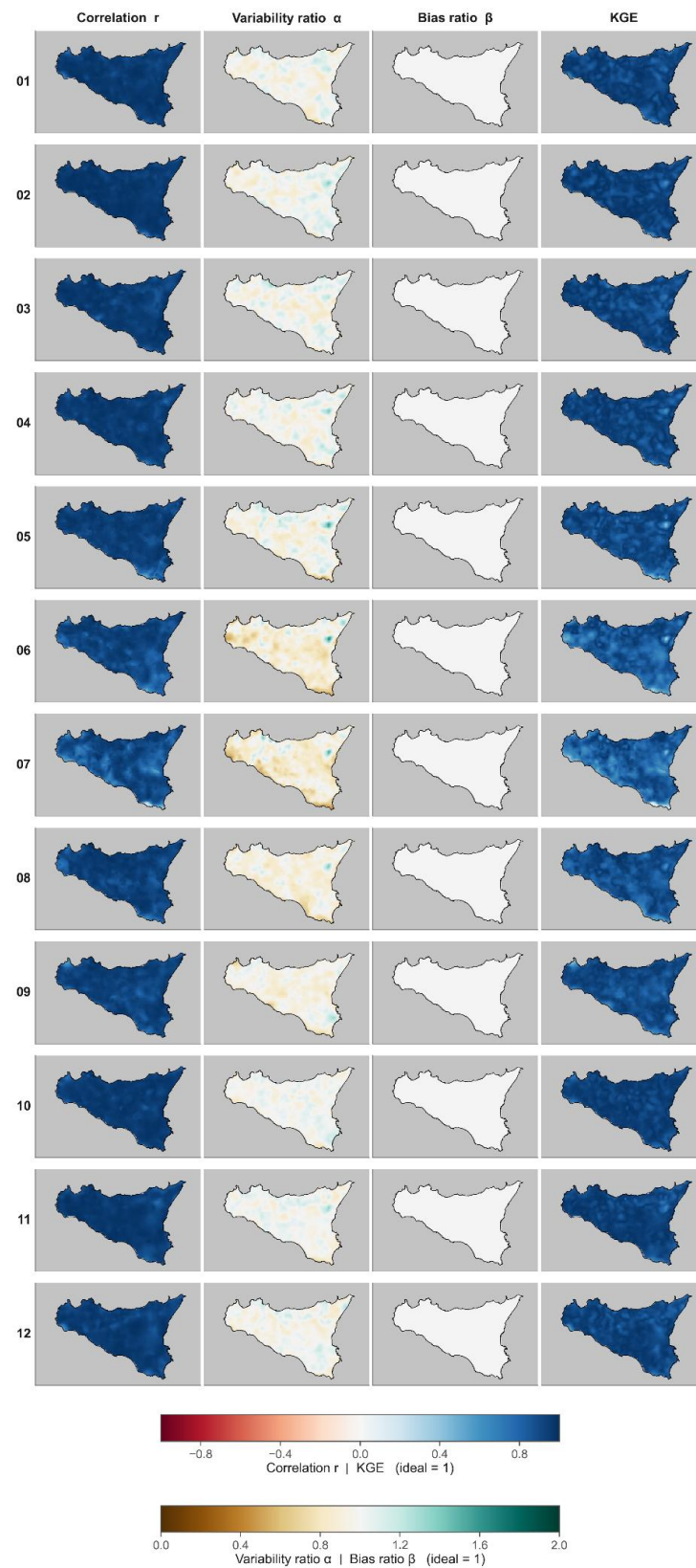


Figure S. 5- Per-grid-cell monthly interannual validation of the corrected I2-IIA product against the benchmark. Rows: the twelve calendar months (January–December). Columns: the KGE decomposition into temporal correlation r , variability ratio α and bias ratio β , the composite KGE, and the interannual RMSE (mm).

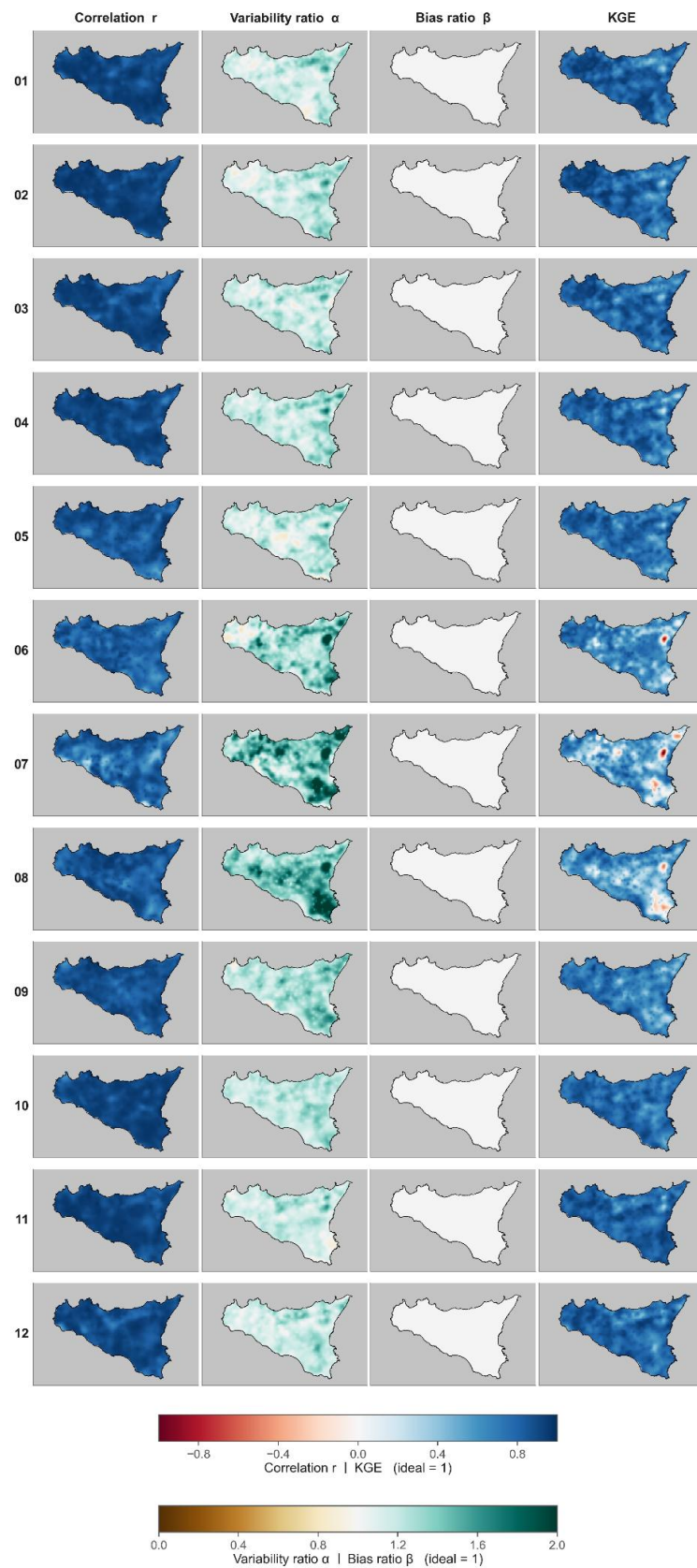


Figure S. 6- Same as Fig. S.6, for Method I3-IIA.