Improving Precipitation Interpolation Using Anisotropic Variograms Derived from Convection - Permitting Regional Climate Model Simulations

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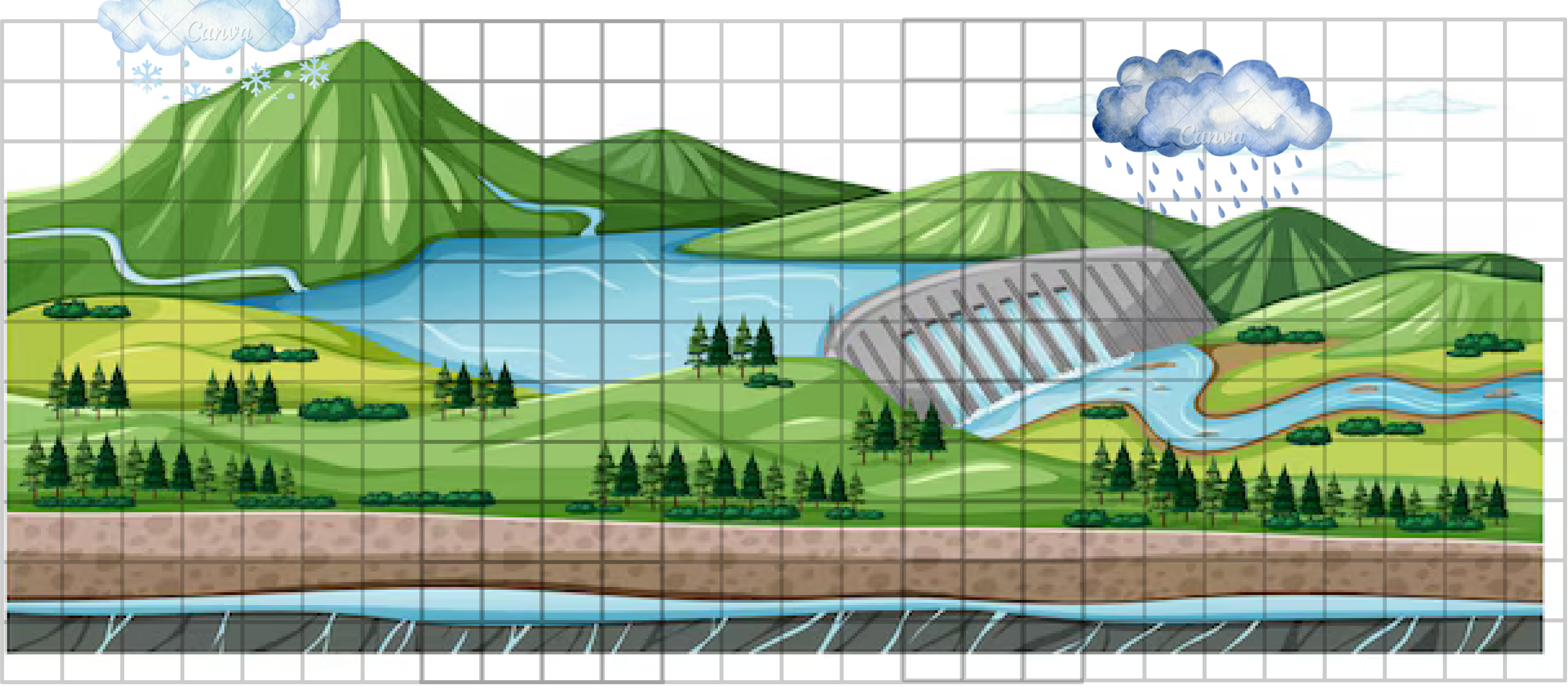
Data science pour les Risques Hydro-Climatiques et Côtiers , Roscoff

Monday 31th March, 2025

CONTEXT

Illustration of a catchment



Need **gridded daily precipitation** for**:**

- assessing flood risks,
- modeling glacier mass balance,
- evaluating climate models.

CONTEXT

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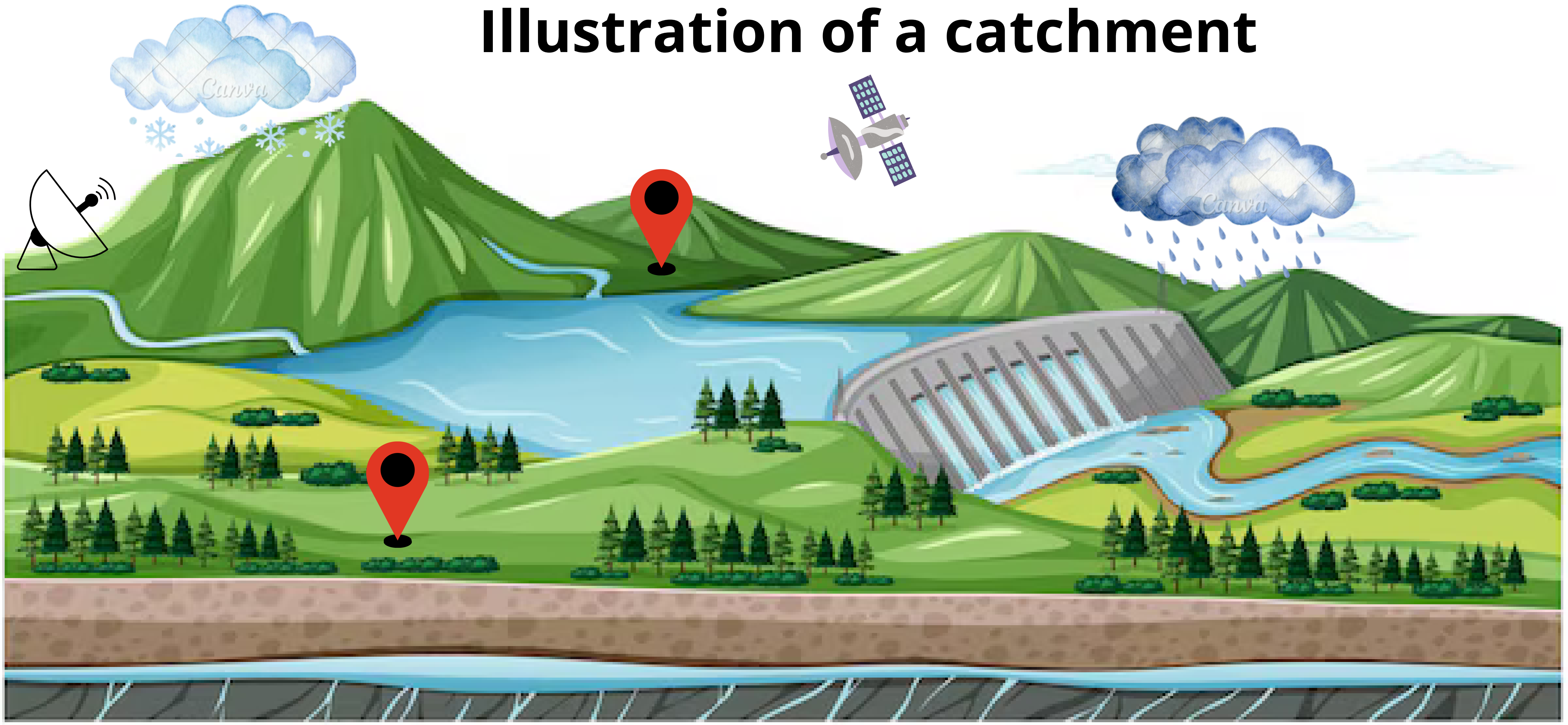


Rain gauges Radar Satellite

Rain gauges are sparse and only located at low altitude
Radars are subjected to beam blocking
Satelittes have too coarse resolutions

Spatial interpolation is required

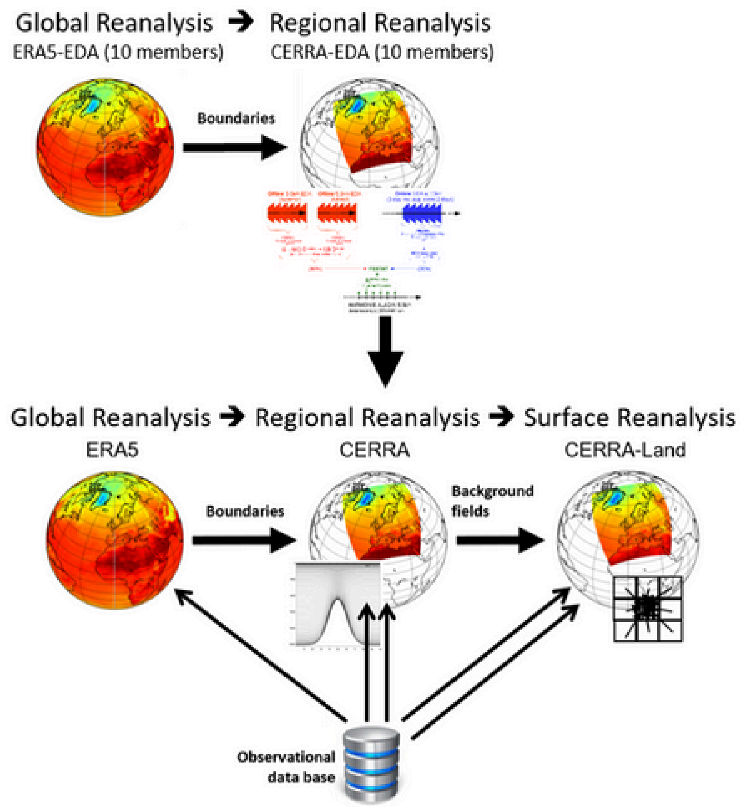
CONTEXT

Existing precipitation products

Reanalysis

<u>CERRA-Land</u> : daily 5.5 km, reanalysis associated to ERA5, Copernicus, (*Le Moigne, 2021*)

<u>SAFRAN, ARRA</u>: first guess from meteorological model + rain gauges, CNRM, (*Vidal et al., 2010*)



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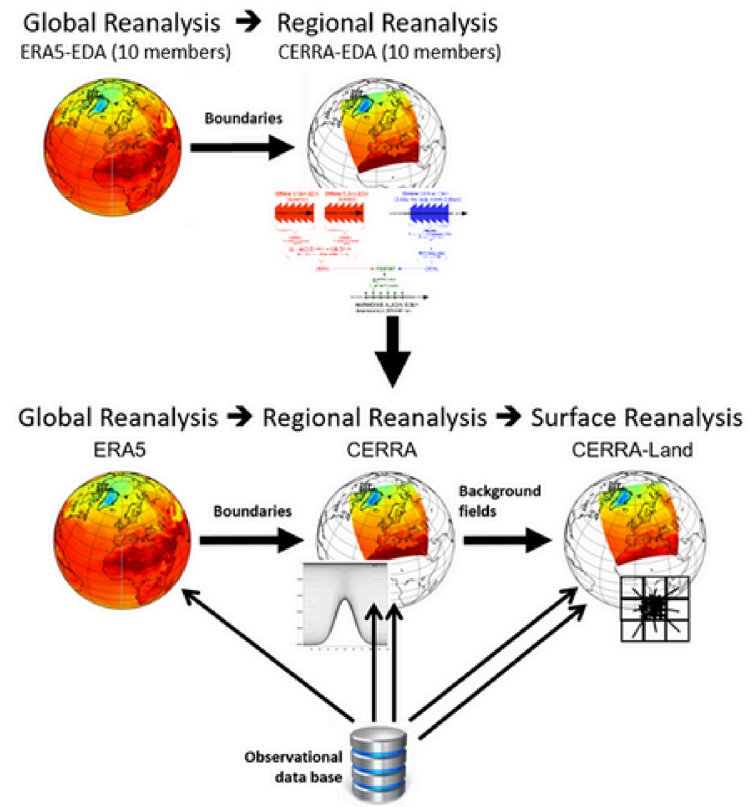

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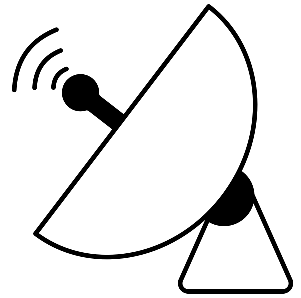
Precipitation Interpolators

COMEPHORE: hourly 1km , rain gauges + radar, beam masking due to mountains, (*Champeaux, 2009*)



SPAZM: daily 1km, rain gauges using local altitude - precipitation relationships stratified by weather patterns , EDF, (*Gottardi et al., 2012*)

CONTEXT

Main challenges in precipitation interpolation for hydrological applications

- Accurate precipitation amounts in mountainous areas

- Accurate estimation of intense precipitation

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- Accurate estimation of intense precipitation

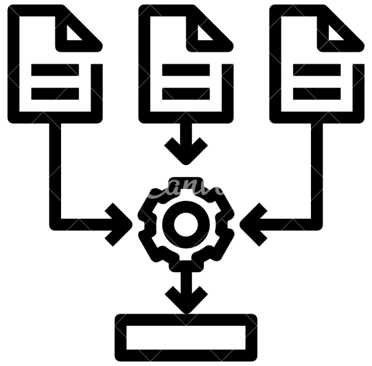
Present work

Comparison of covariance estimation for the spatial interpolation of intense precipitation

PLAN OF THE PRESENTATION

(1) Study domain and data

(2) Precipitation interpolation

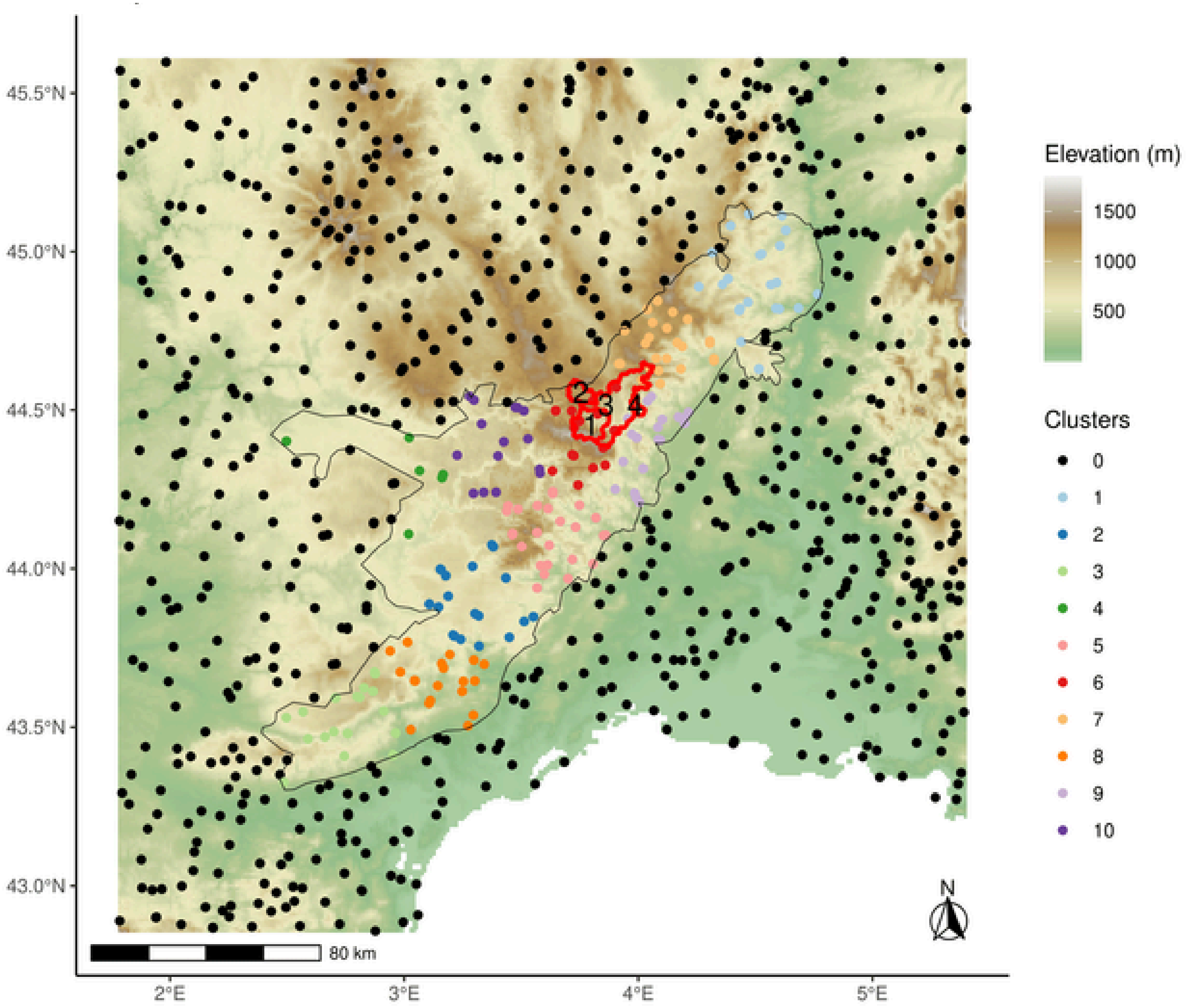


(3) Precipitation evaluation

(4) Hydrological evaluation

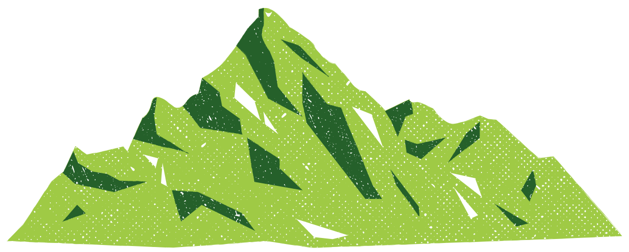
1

STUDY DOMAIN AND DATA



1000 rain gauges

1,700 m



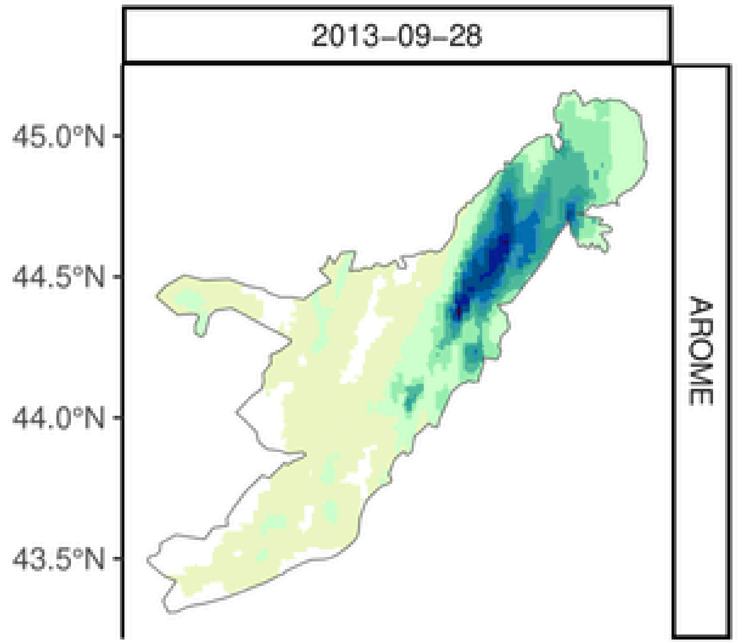
Focus on the **Cevennes** region over the 1982 - 2018 period, intense precipitations

STUDY DOMAIN AND DATA

1

Additional datasets

Daily **AROME** precipitation grids
Simulations of the Convective - Permitting Regional Climate Model (CP-RCM) AROME= weather model driven by large-scale reanalysis
Used to help spatial interpolation



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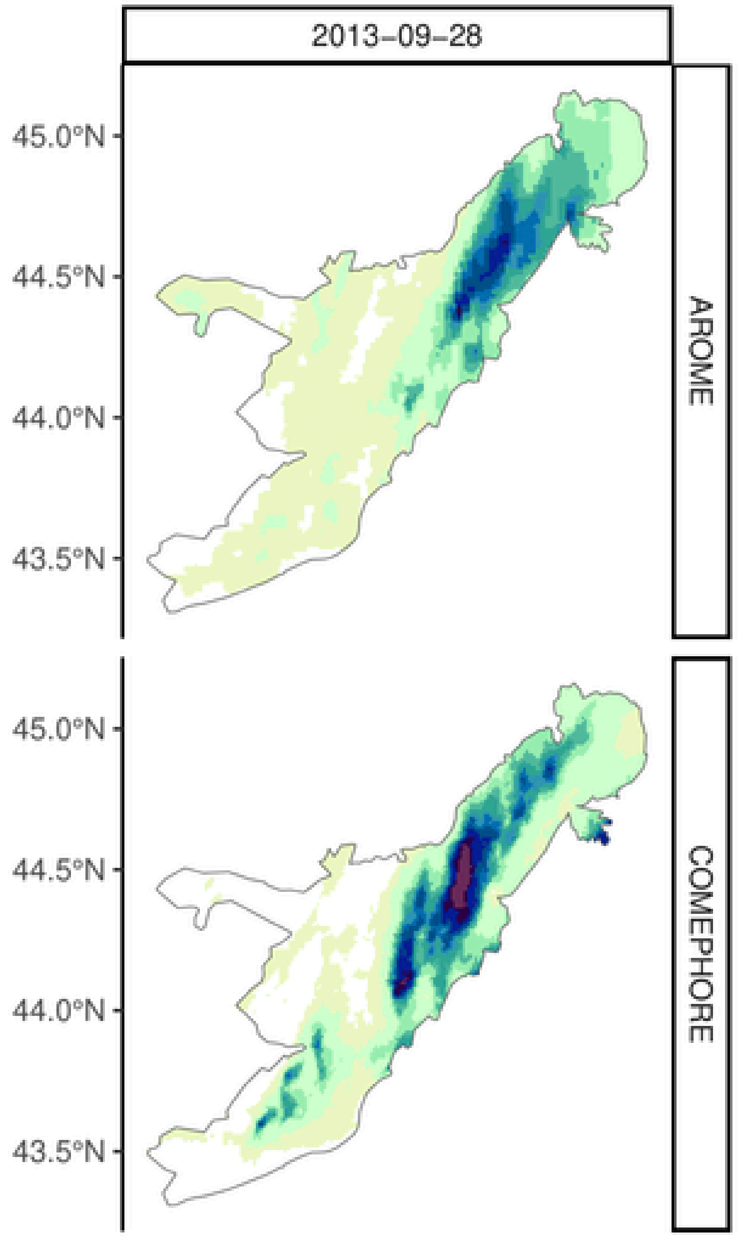
Radar- rain gauges merging
Used for evaluation



STUDY DOMAIN AND DATA

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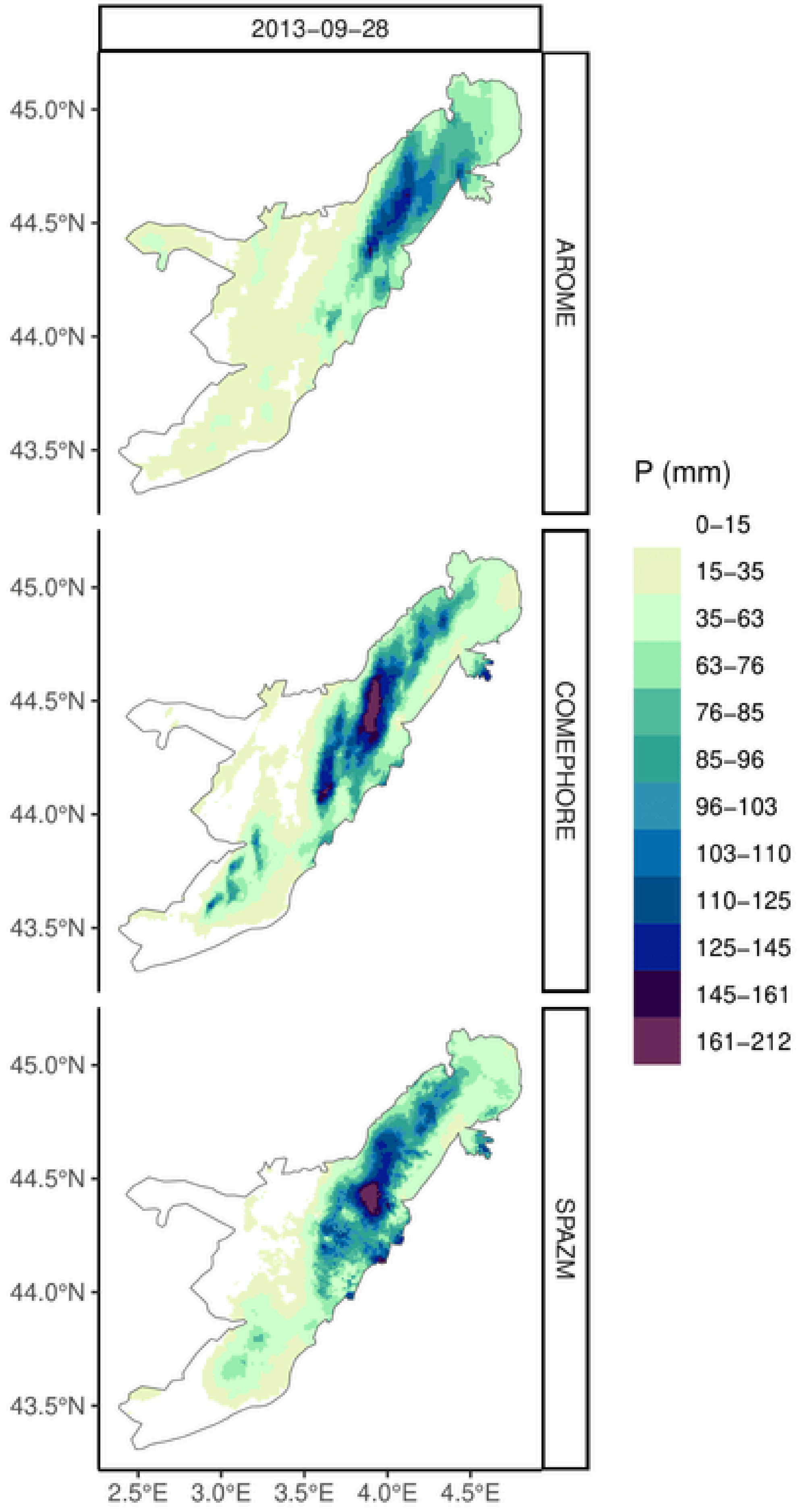
Daily **SPAZM** precipitation grids
Precipitation analyses used at EDF
Used in comparison



1

STUDY DOMAIN AND DATA

Study domain and data → **Precipitation interpolation**

2

PRECIPITATION INTERPOLATION

Trans-Gaussian Random Fields framework (*Diggle et al., 2003*)

Main steps

(1) Normalisation of daily rain gauge observations

(2) Modeling of the mean and the covariance of daily precipitation

(3) Generation of 100 realisations (conditional simulations)

2

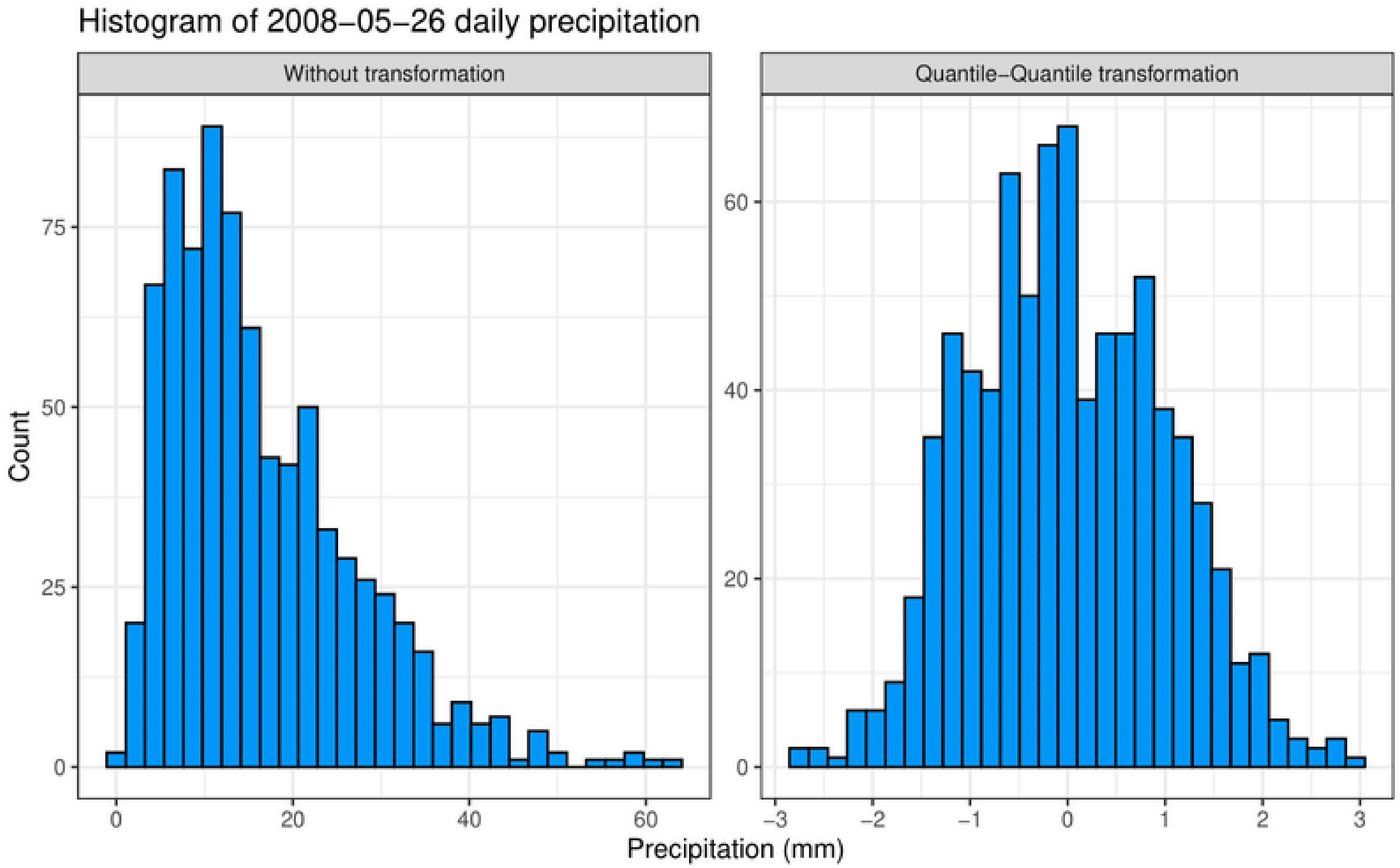
PRECIPITATION INTERPOLATION

Normalisation

Lots of zeros and highly-skewed distribution

→ Quantile-Quantile transformation, maintain the skewness of observations

fitdistrplus R package (Delignette-Muller and Dutang, 2015) to fit the gamma distributions using maximum likelihood



Transformation step

$$w_s = \begin{cases} \Phi^{-1}\left[F_R\left(Y_s\right)\right], & Y_s > 0 \\ \Phi^{-1}\left[p_0\right], & Y_s = 0 \end{cases}$$

Back- Transformation step

$$Y_s = \begin{cases} F_R^{-1}\left[\Phi\left(w_s\right)\right], & \Phi\left(w_s\right) \geqslant p_0 \\ 0, & \Phi\left(w_s\right) < p_0 \end{cases}$$

Φ : Gaussian CDF

F_R : Gamma CDF

p_0 : proportion of dry observations

2

PRECIPITATION INTERPOLATION

Geostatistics model

Precipitation at location $\boldsymbol{s}$

$$w(\boldsymbol{s}) = \mu(\boldsymbol{s}) + Z(\boldsymbol{s}), \quad \mu(\boldsymbol{s}) = \beta_0 + \sum_{k=1}^{K} \beta_k \cdot x_k(\boldsymbol{s}), \quad Z(\boldsymbol{s}) \sim \mathcal{N}(0, Cov_{n\times n})$$

Trend component

Residual component

Covariance between the observations represented by a valid variogram function

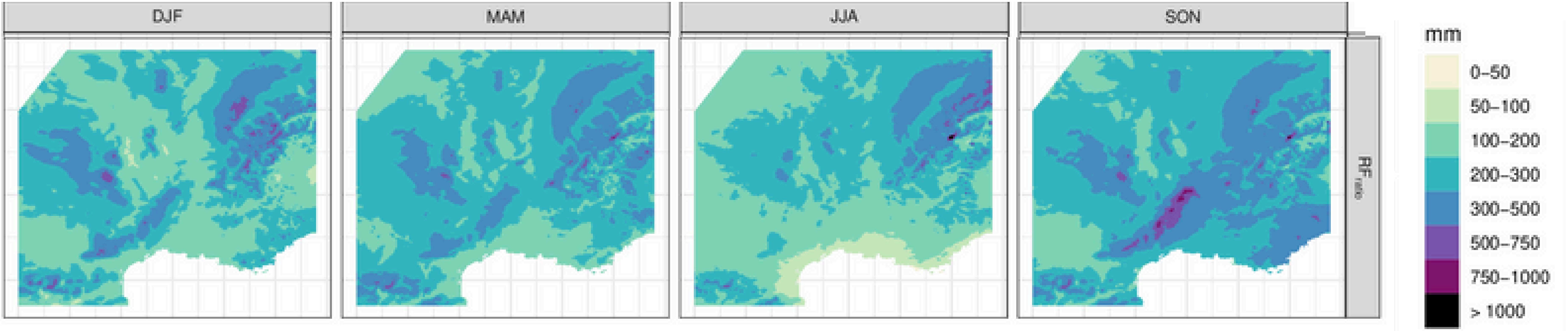
PRECIPITATION INTERPOLATION

2

Modeling of the mean

$$\begin{aligned}\mu(\boldsymbol{s}) = \quad & \beta_0 + \\ & \beta_1 \cdot Longitude(\boldsymbol{s}) + \\ & \beta_2 \cdot Latitude(\boldsymbol{s}) + \\ & \beta_3 \cdot Altitude(\boldsymbol{s}) + \\ & \beta_4 \cdot SeasonalClimatology(\boldsymbol{s})\end{aligned}$$

Seasonal climatological background fields (*Dura et al., 2024*)



2

PRECIPITATION INTERPOLATION

Modeling of the covariance

second-order stationary variogram describes the dependance of semi-variance on the distance between the observations

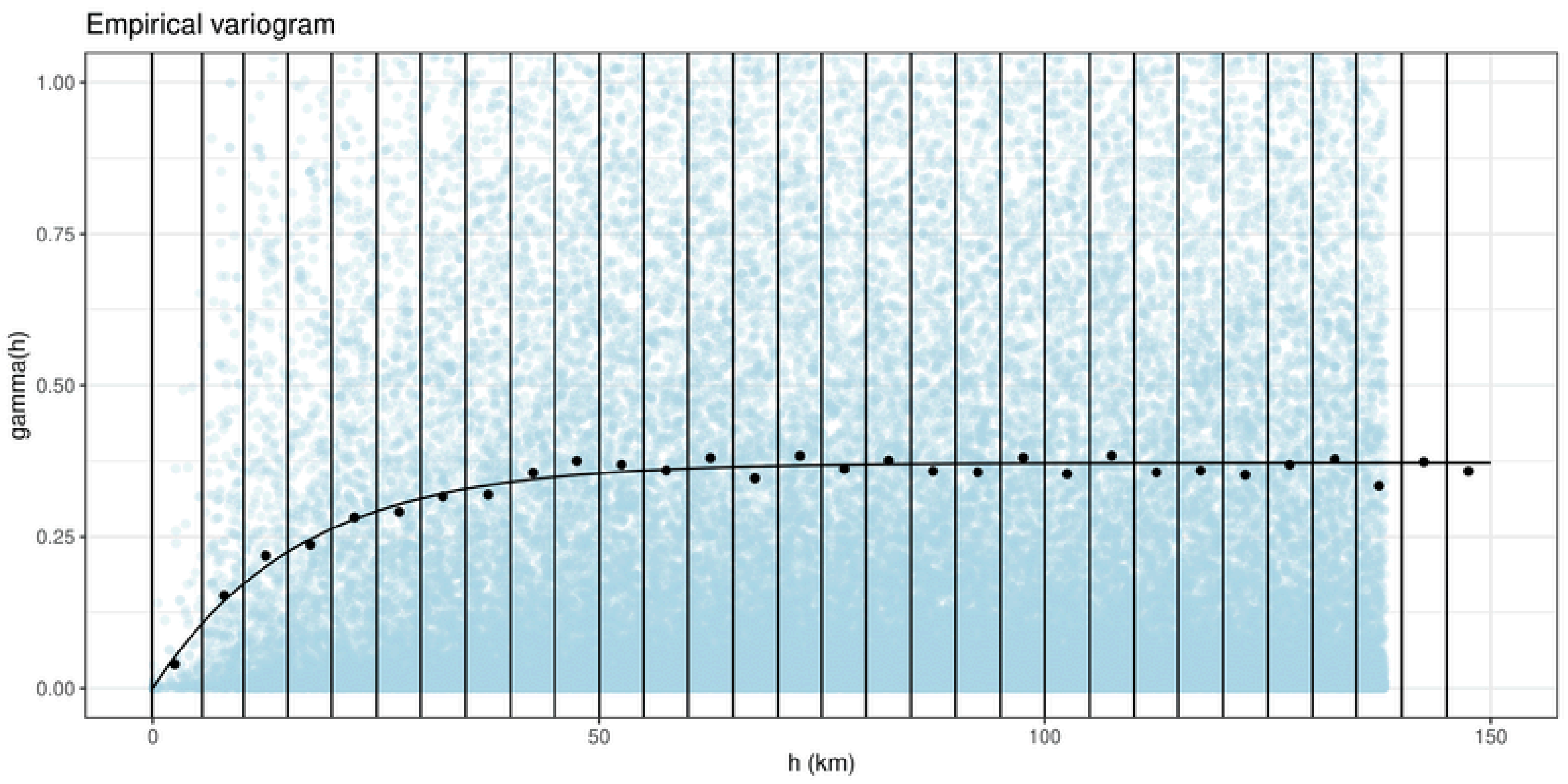
Fitting of an exponential variogram with a nugget effect

$$\gamma(h) = c_0 + c_s \left(1 - e^{-\frac{h}{r}}\right)$$

c_0 : nugget

c_s : partial sill

r : range



Weighted Least Square $\sum_{j=1}^{p} \omega_j(\gamma(h) - \hat{\gamma}(h))^2$

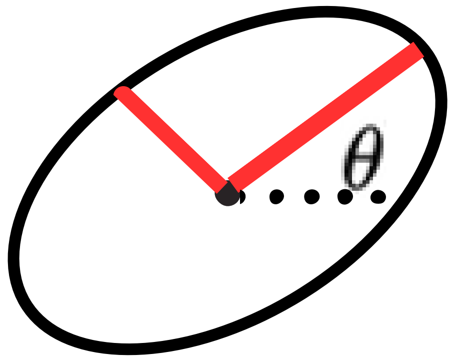
PRECIPITATION INTERPOLATION

Modeling of the covariance

$$h = \begin{cases} \sqrt{x^2 + y^2} & \text{isotropic} \\ \sqrt{x'^2 + y'^2} & \text{anisotropic} \end{cases}$$

$$x' = x \cdot \cos(\theta) + y \cdot \sin(\theta)$$

$$y' = -x \cdot \sin(\theta) + y \cdot \cos(\theta)$$



θ : anisotropy angle

η : anisotropy angle

2

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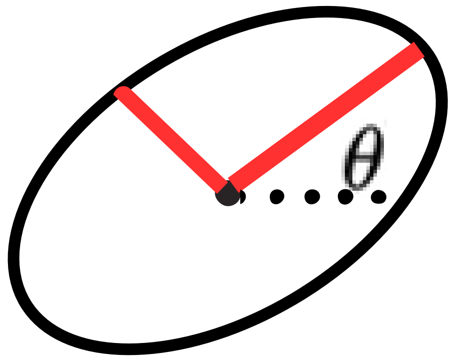

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Data/Structure	isotropic	anisotropic
rain gauges	rgISO	rgANISO
arome	arISO	arANISO

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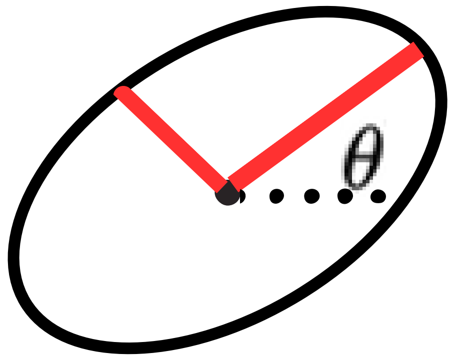

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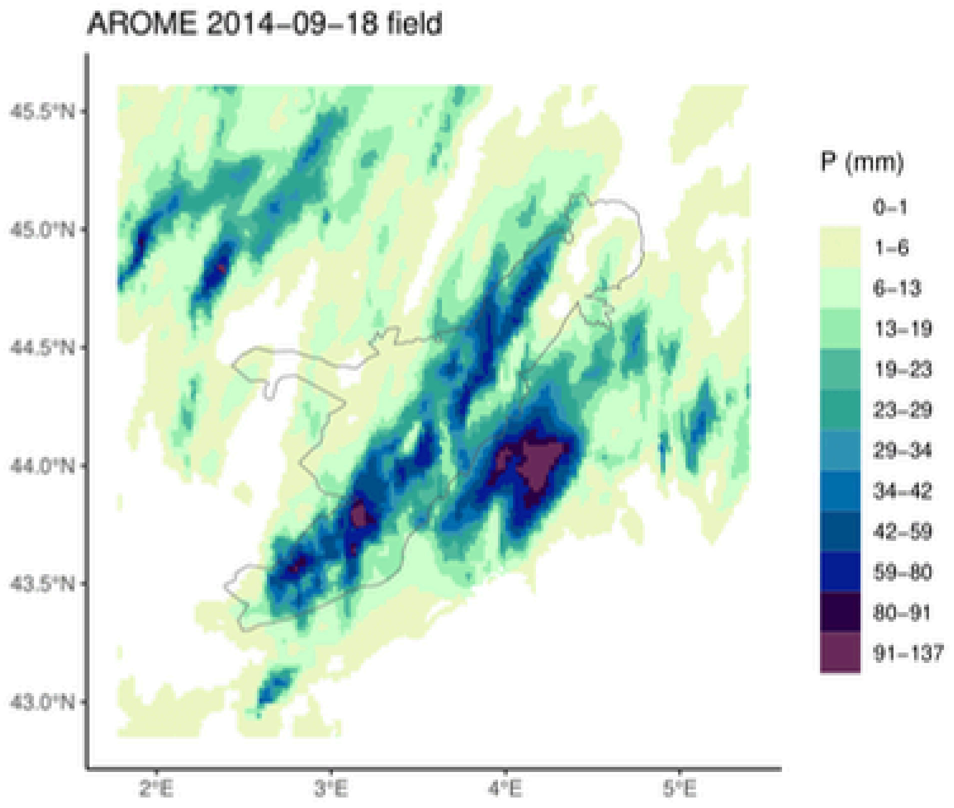

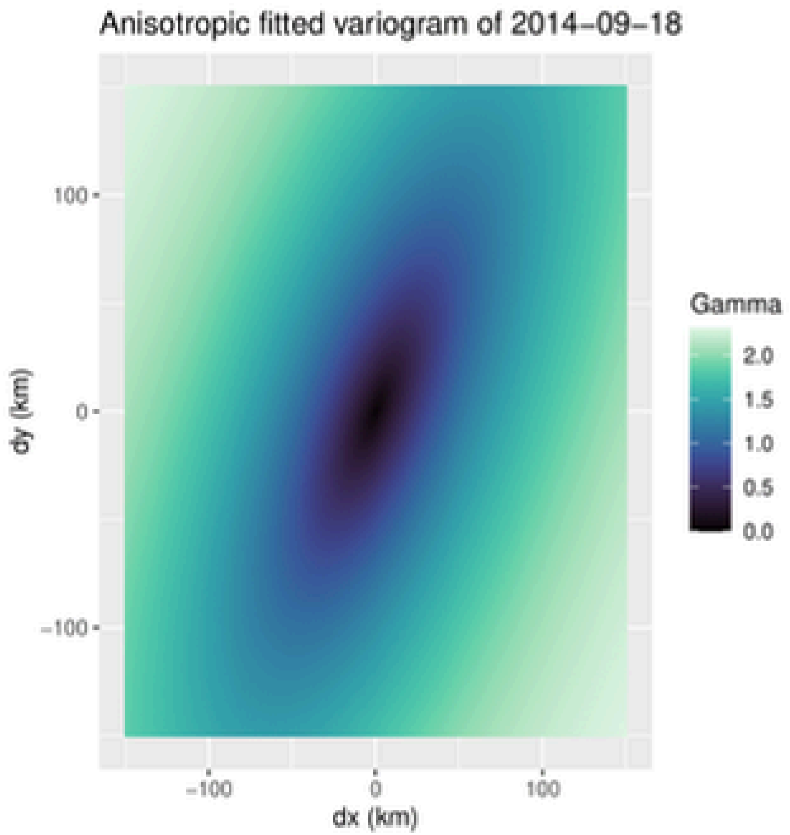

Anisotropy estimated southwest to northeast

PRECIPITATION INTERPOLATION

Conditional simulations

Sequential Gaussian Simulation (Gyasi-Agyei, 2018)

(1) Choose a random prediction location $\mathbf{s}_0$

PRECIPITATION INTERPOLATION

2

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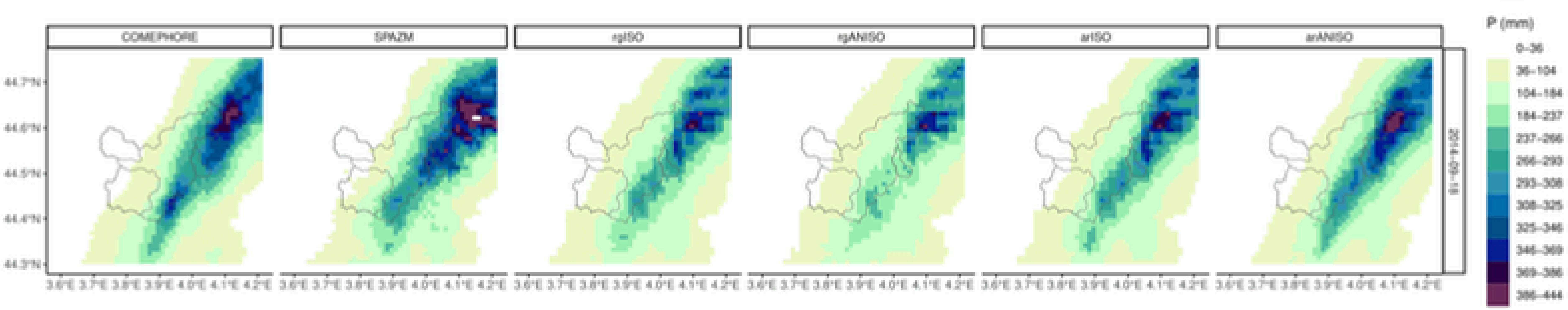
(4) Repeat steps (1), (2) and (3) until all prediction locations are simulated.

gstat R package (Pebesma, 2004) to produce the conditional simulations

2

PRECIPITATION INTERPOLATION

Mean of conditional simulations



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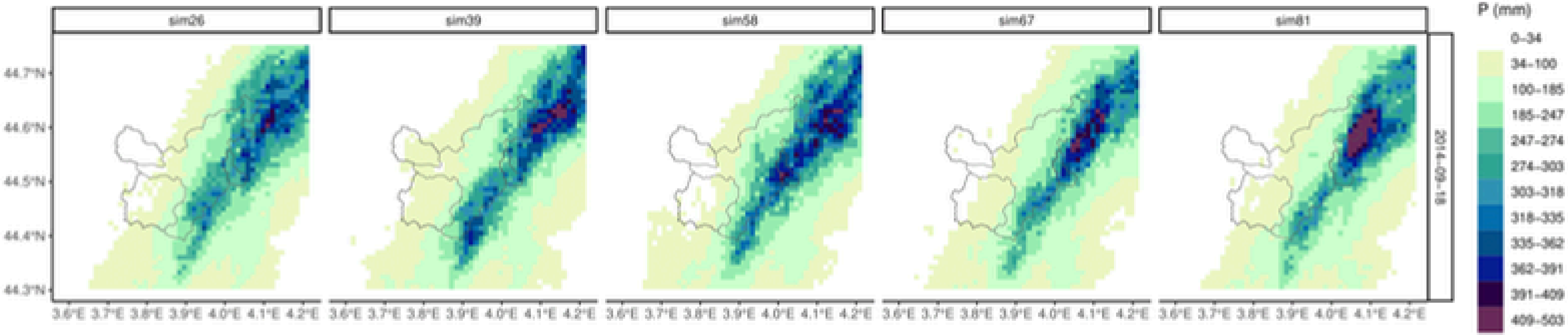
PRECIPITATION INTERPOLATION

Conditional simulations with arANISO model



2

PRECIPITATION INTERPOLATION

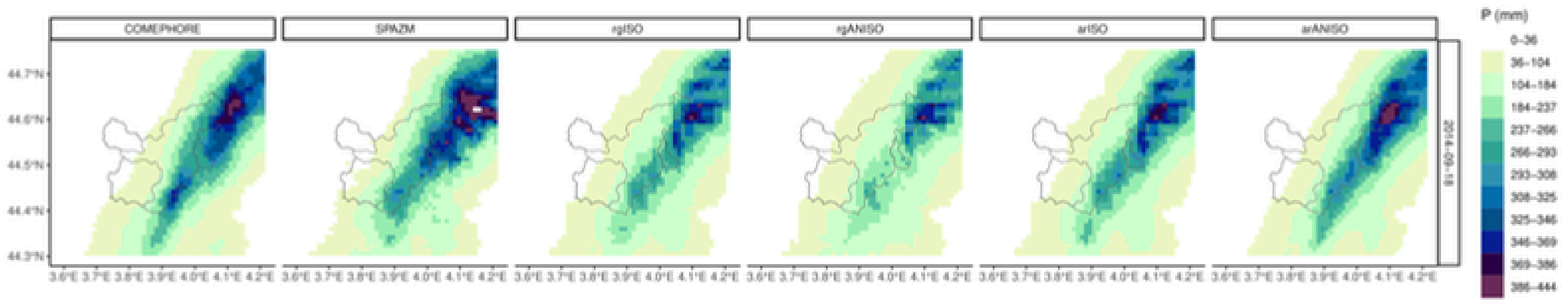
Precipitation interpolation

Precipitation evaluation

3

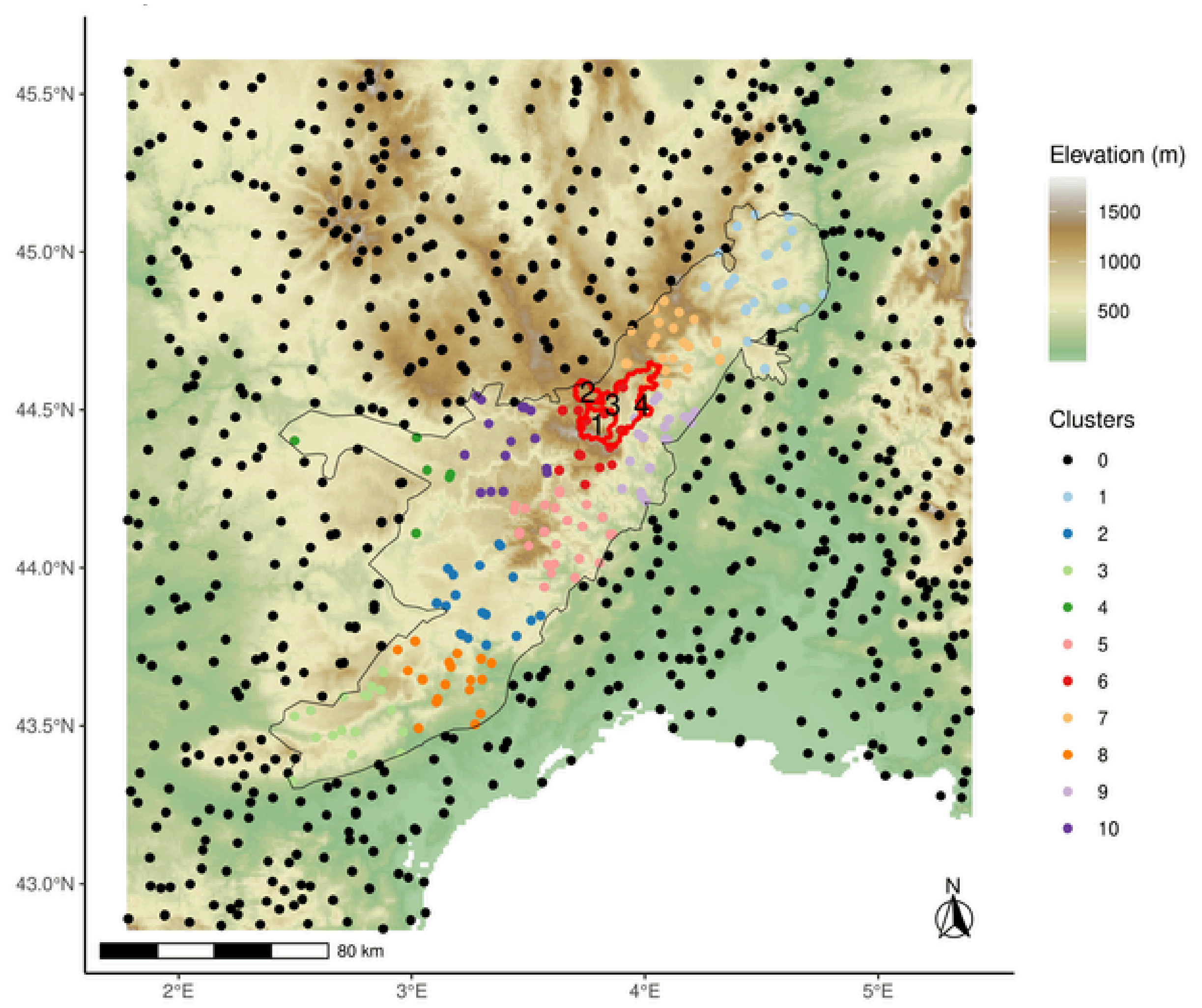
PRECIPITATION EVALUATION

(1) Spatial evaluation on gradient image similarities, COMEPHORE as reference



(2) Cross-validation CRPS: leave-one-cluster-out

(3) Comparison of mean catchment precipitation, COMEPHORE as reference



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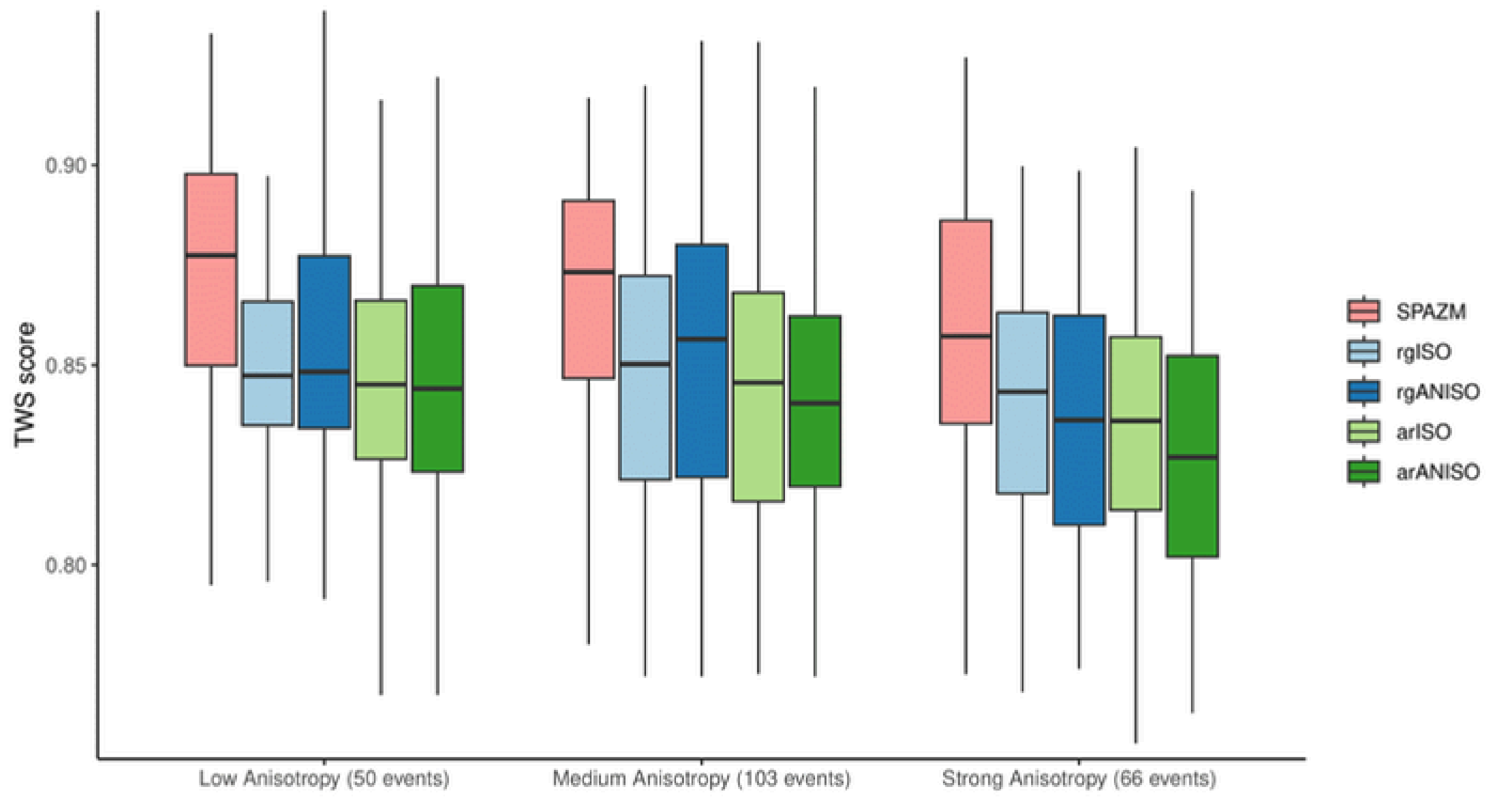
PRECIPITATION EVALUATION



Spatial structure evaluation

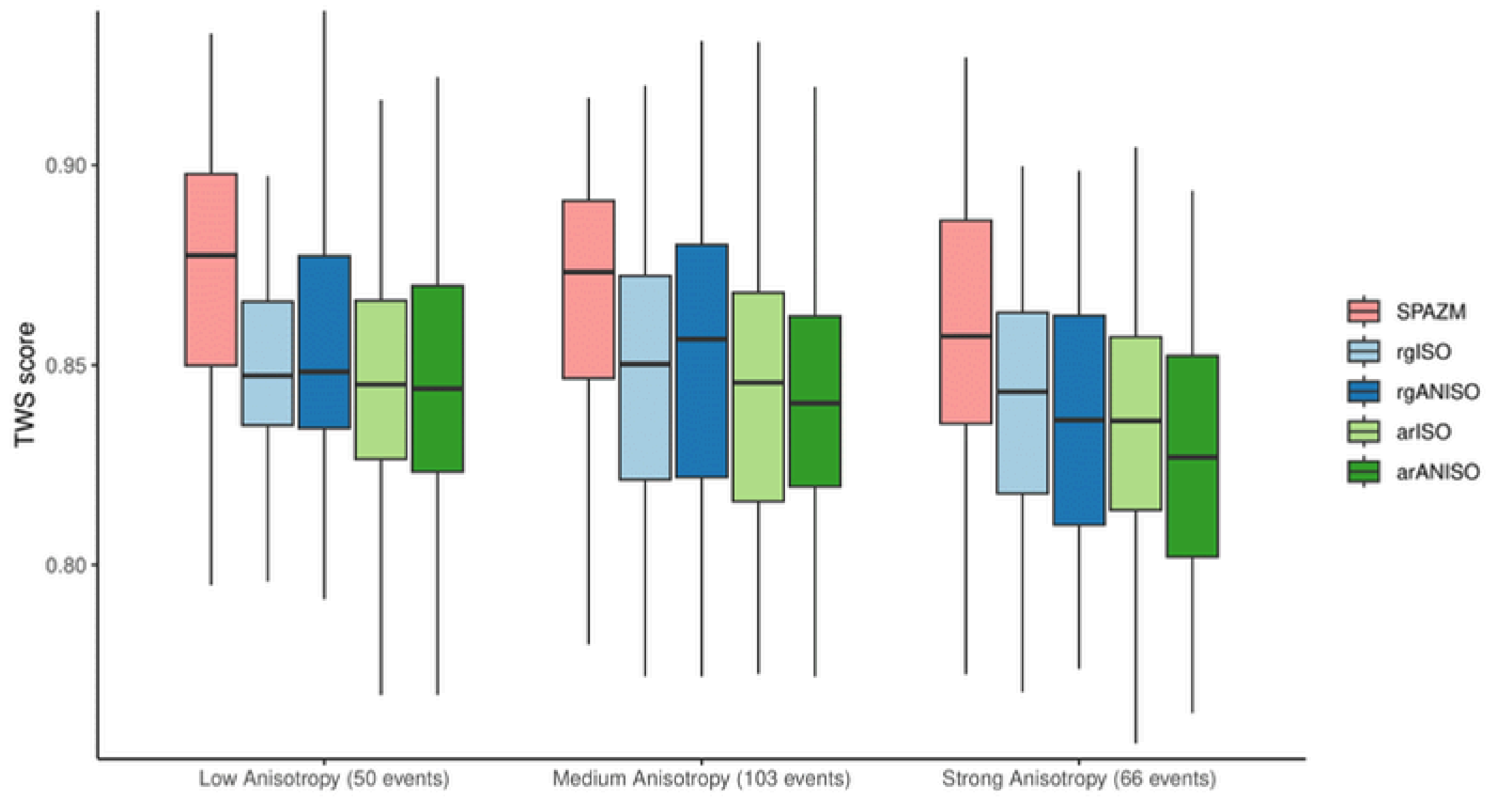
SPAZM shows poor resemblance to COMEPHORE

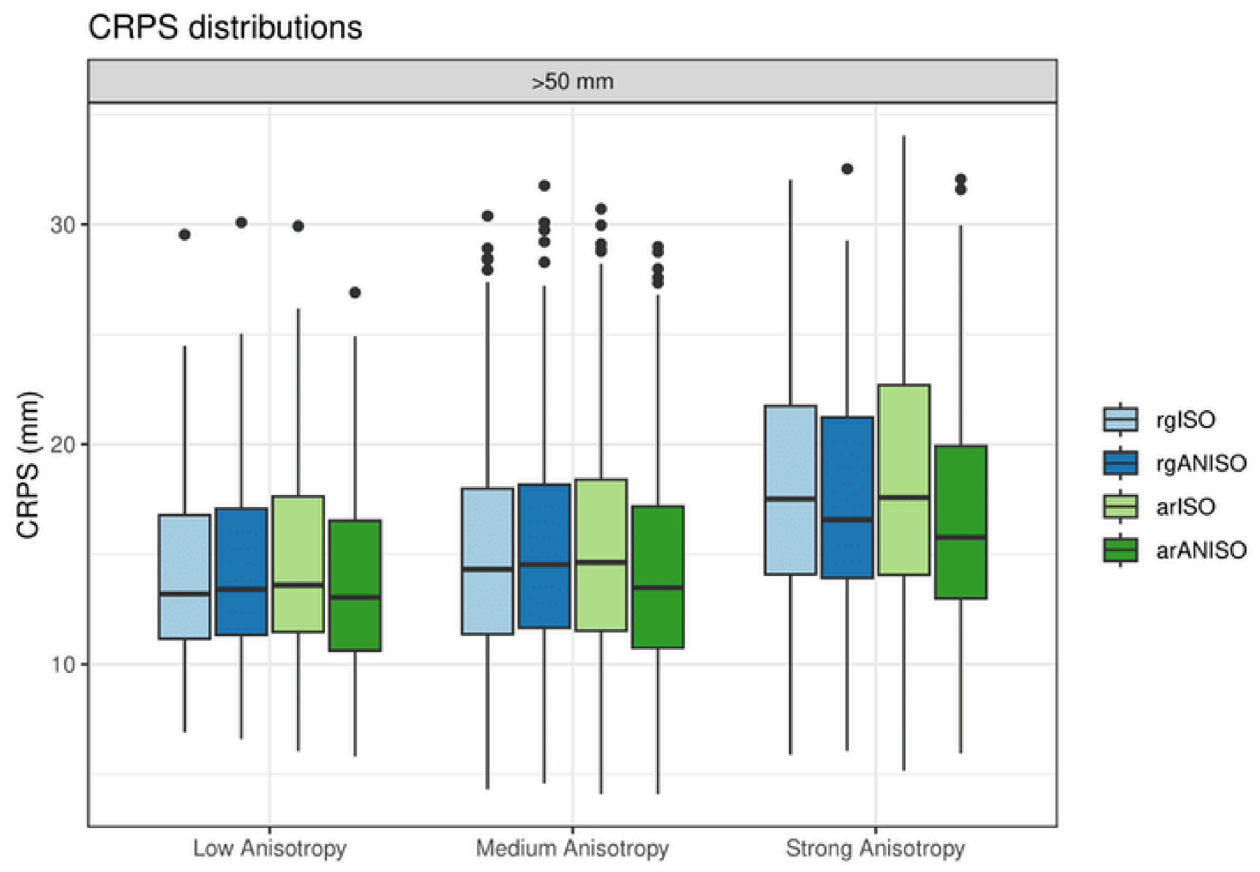
rgANISO lacks robustness

arANISO is the most similar to COMEPHORE

3

PRECIPITATION EVALUATION





Spatial structure evaluation

SPAZM shows poor resemblance to COMEPHORE

rgANISO lacks robustness

arANISO is the most similar to COMEPHORE

Cross-validation results

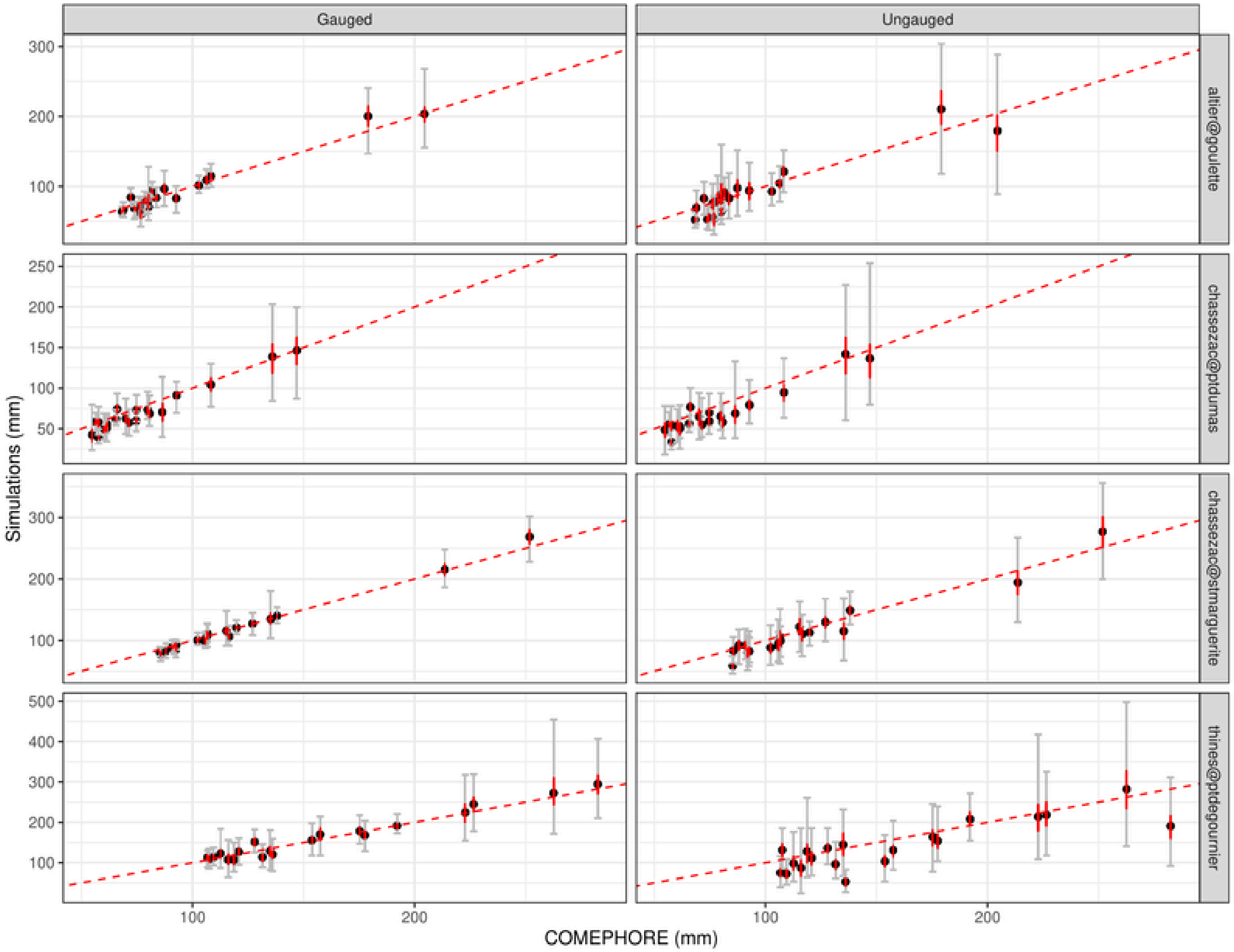
arANISO has the best mean CRPS score

SPAZM lacks robustness (not shown)

3

PRECIPITATION EVALUATION

Mean catchment precipitation with arANISO model



3

PRECIPITATION EVALUATION

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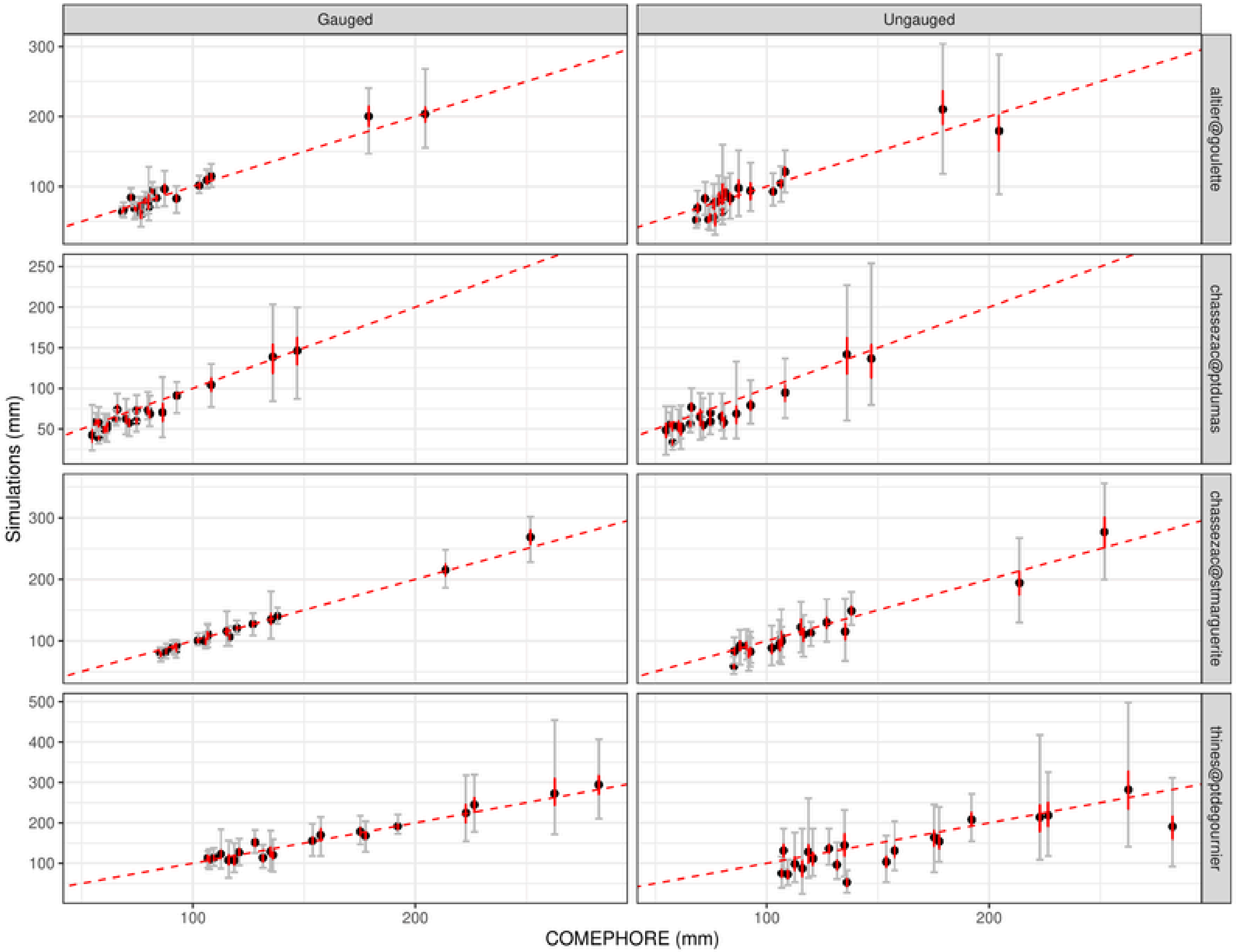


Ensemble spreads contain COMEPHORE precipitation

Uncertainty
- ↗ Precipitation intensity
- ↘ Rain gauge density
- ↘ Catchment size

Uncertainty can be asymetrical

3

PRECIPITATION EVALUATION

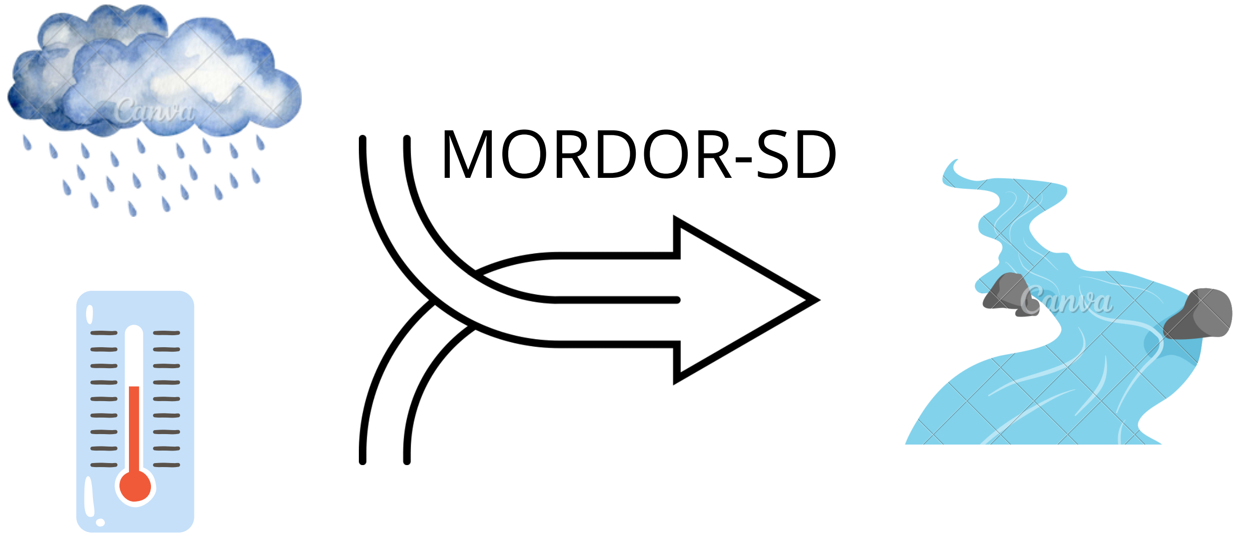
Precipitation evaluation → **Hydrological evaluation**

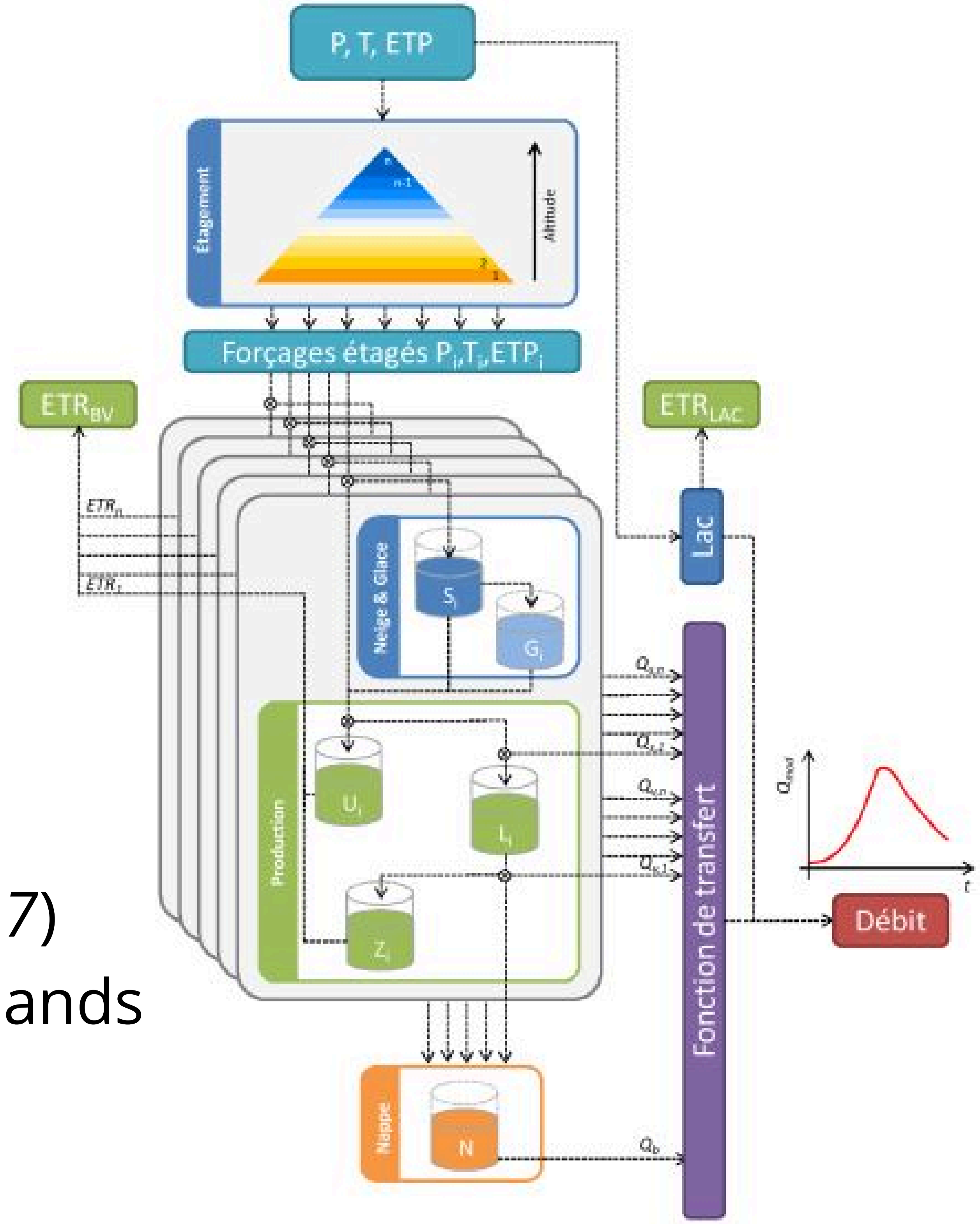
4

HYDROLOGICAL EVALUATION

Hydrological Modeling

Are the conditional simulations able to reproduce the highest observed streamflows ?





Use of the hydrological model MORDOR-SD (*Garavaglia et al., 2017*) precipitation and temperature inputs distributed by altitudinal bands

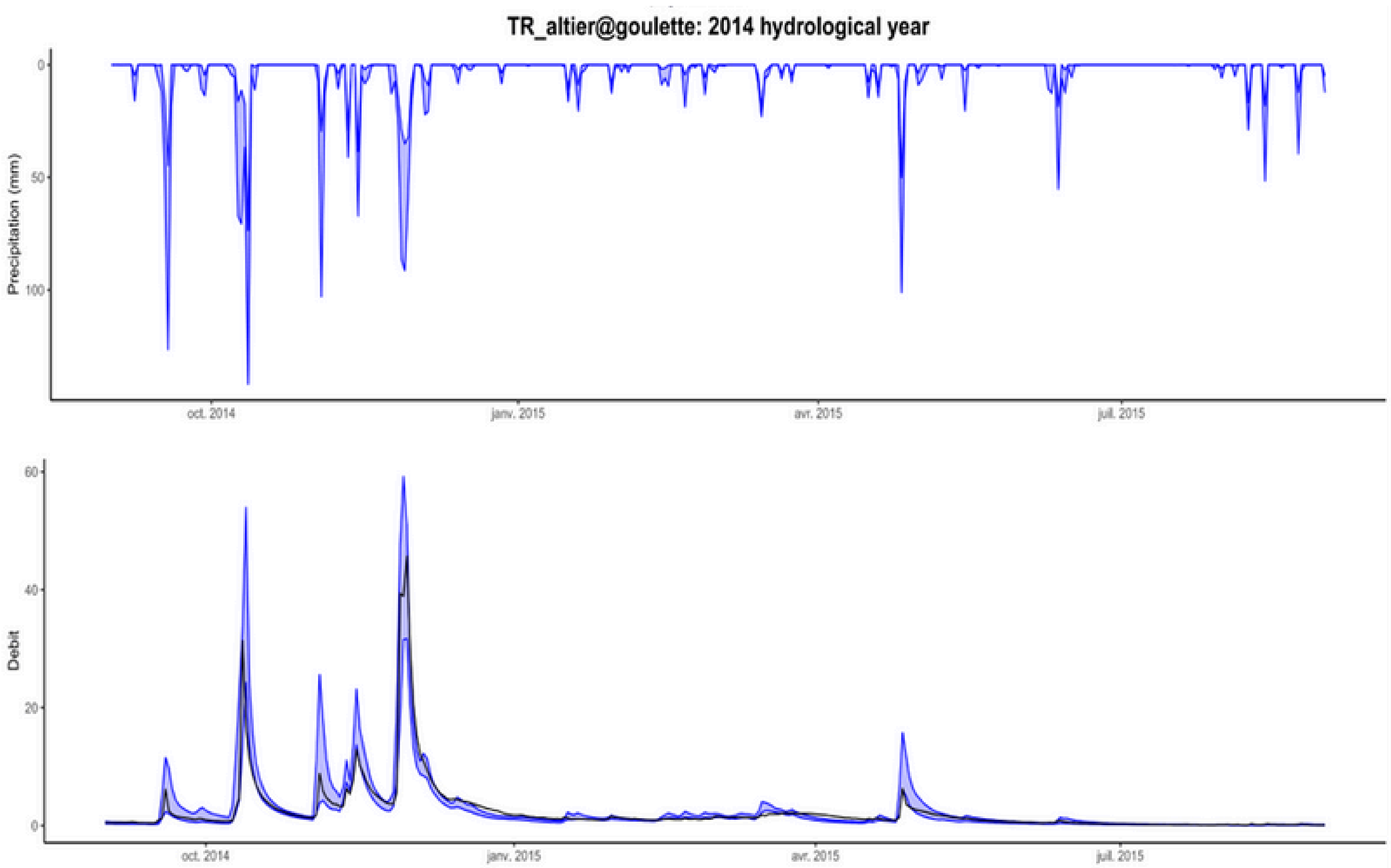
CRPS on high streamflow values

scoringRules R package to compute CRPS scores

4

HYDROLOGICAL EVALUATION

Illustration of hydrological modeling



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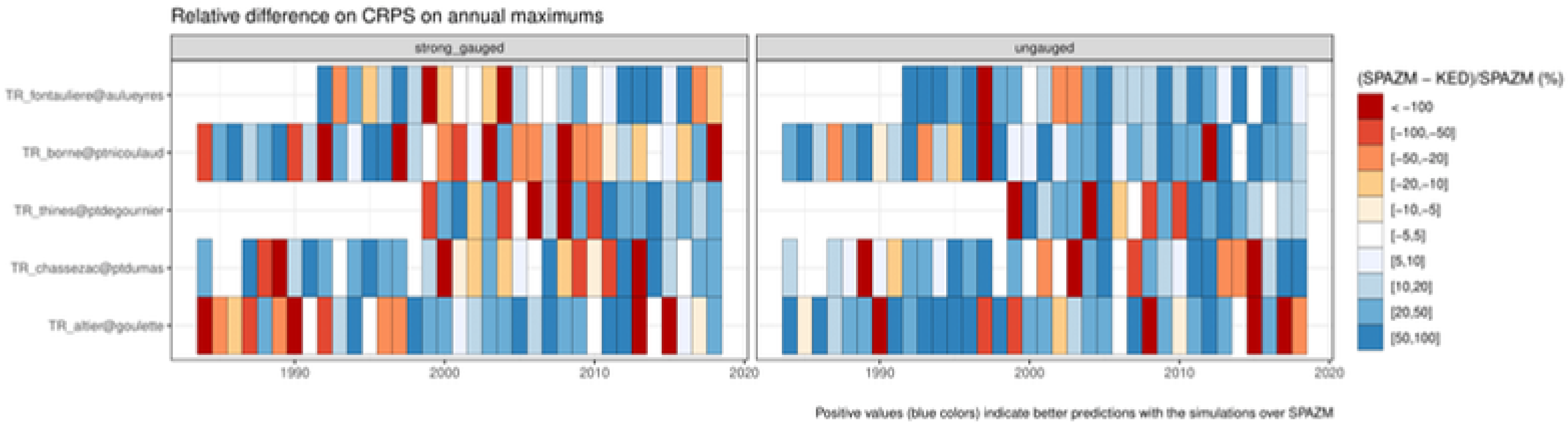
HYDROLOGICAL EVALUATION

Evaluation on annual streamflow maximums



No better models in the *strong_gauged case*

conditional simulations > SPAZM in the *ungauged case* ✓

Too wide condidence intervals for some events ✗

CONCLUSIONS - PERSPECTIVES

Use of CP-RCM simulations to derive anisotropic spatial structure

Conditional simulations to model intense streamflow

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Use of CP-RCM simulations to derive anisotropic spatial structure

Conditional simulations to model intense streamflow

How to improve the interpolation ?

- **Non-stationary** covariance: variable dependance or mixture of local stationnary covariance (*Risser and Calder, 2017*)
- Include additional **uncertainties**: wind-induced precipitation undercatch, variogram estimation (*Frei and Isotta, 2019*)

Bayesian hierarchical models present the ideal framework