ANN-based parameter regionalization for distributed hydrological models used for low-flow simulation over ungauged French catchments

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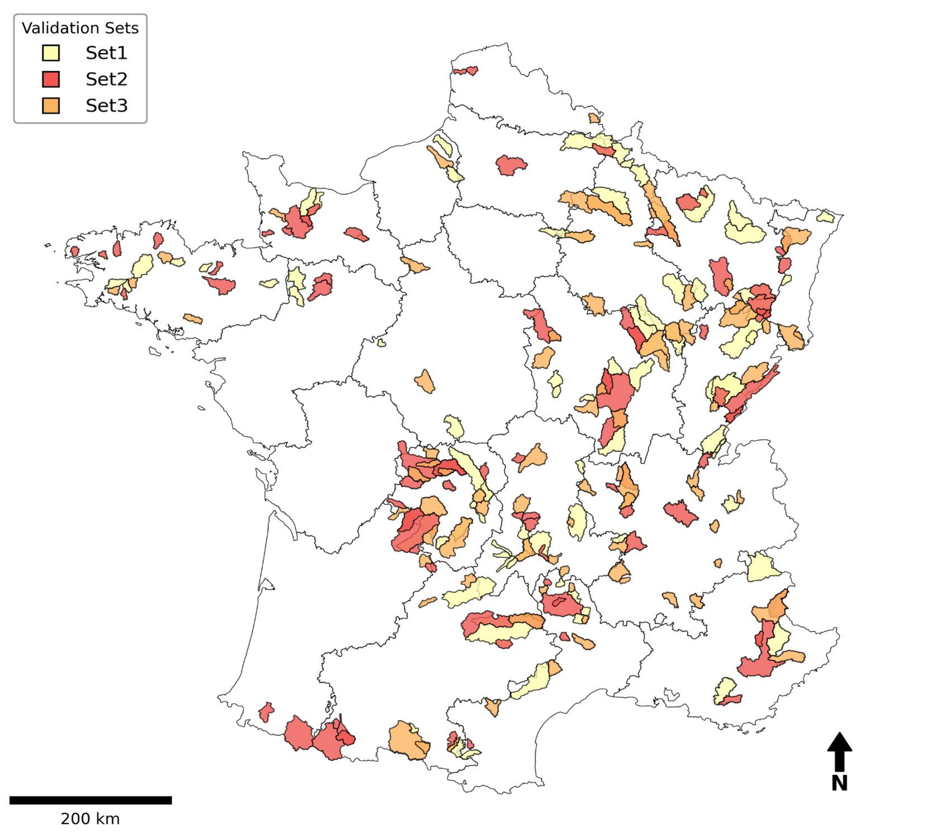
1 Our objectives

- Evaluate hydrological models for low-flow river basins using the **SMASH** platform, which incorporates models inspired by the **GR model family**.
- Evaluate the performance of these models in reproducing low flows, seasonality, and water balance across a series of basins covering France, using uniform calibration techniques and regionalization approaches.
- Incorporate an Artificial Neural Network (ANN) to process basin descriptors specific to France, enhancing regionalization exploration and establishing meaningful correspondence between these descriptors and model parameters.

2 Dataset

- Set of **248** catchments (split into 3 sets of validations) throughout French territory :
  - data available for at least 40 years between 1975 and 2018,
  - Naturals with limited human influence and surfaces < 2 000 km²,
  - Various hydro meteorological regimes
- Daily meteorological data come from the distributed mesoscale atmospheric analysis system SAFRAN[1] : estimations of daily solid and liquid precipitations temperatures and evapotranspiration on a regular square grid at the spatial resolution of 8*8 km²
- Daily streamflow data from the French database HYDRO
- Corine Land Cover and the International Hydrogeological Map of Europe[2](Lithology) maps to create descriptor maps for the ANN.

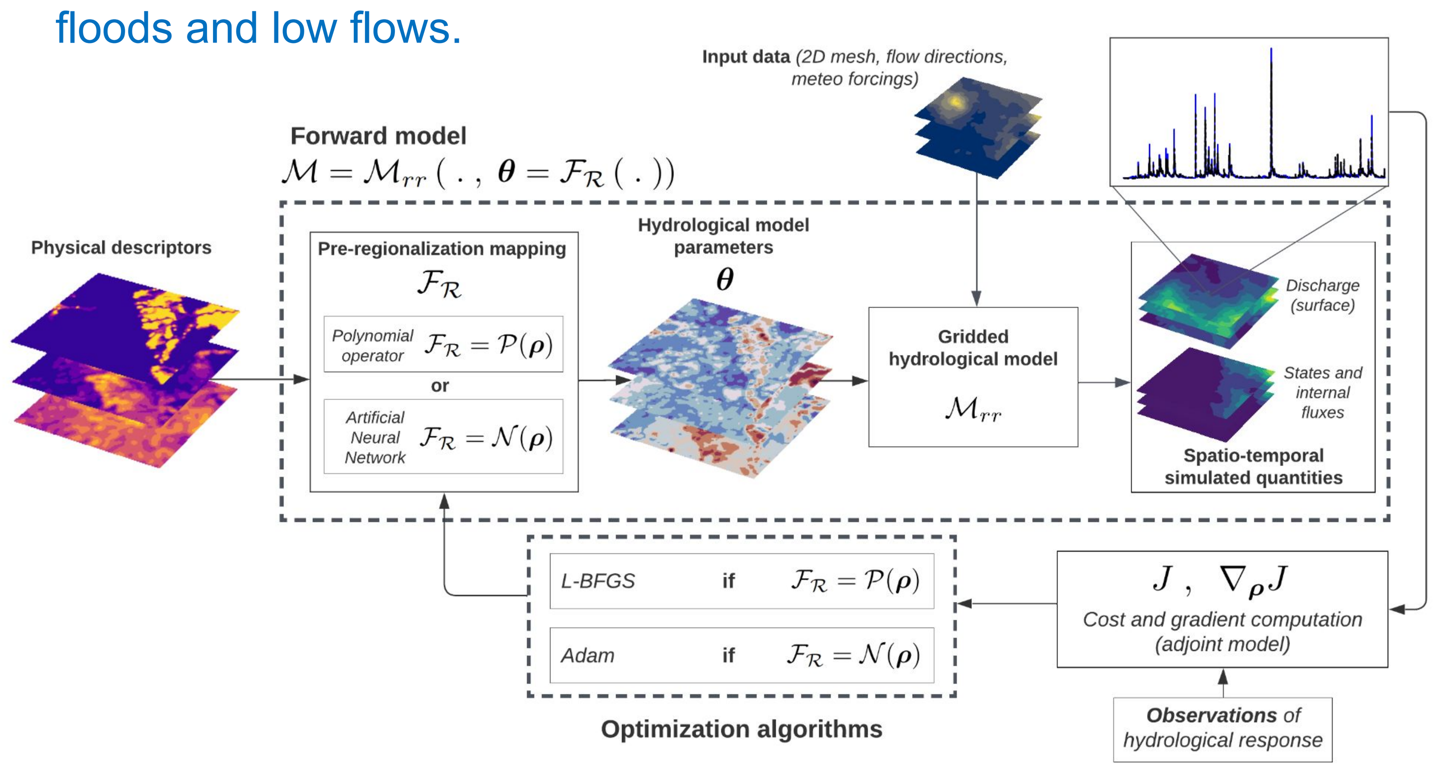


Hydrological regime	Uniform	Oceanic	Nivo-pluvial	Mediterranean
Count (%)	11 (4.4%)	189 (76.2%)	40 (16.1%)	8 (3.2%)

3 Methodology

❖ SMASH[3] Platform (Spatially-distributed Modelling and ASsimilation for Hydrology)

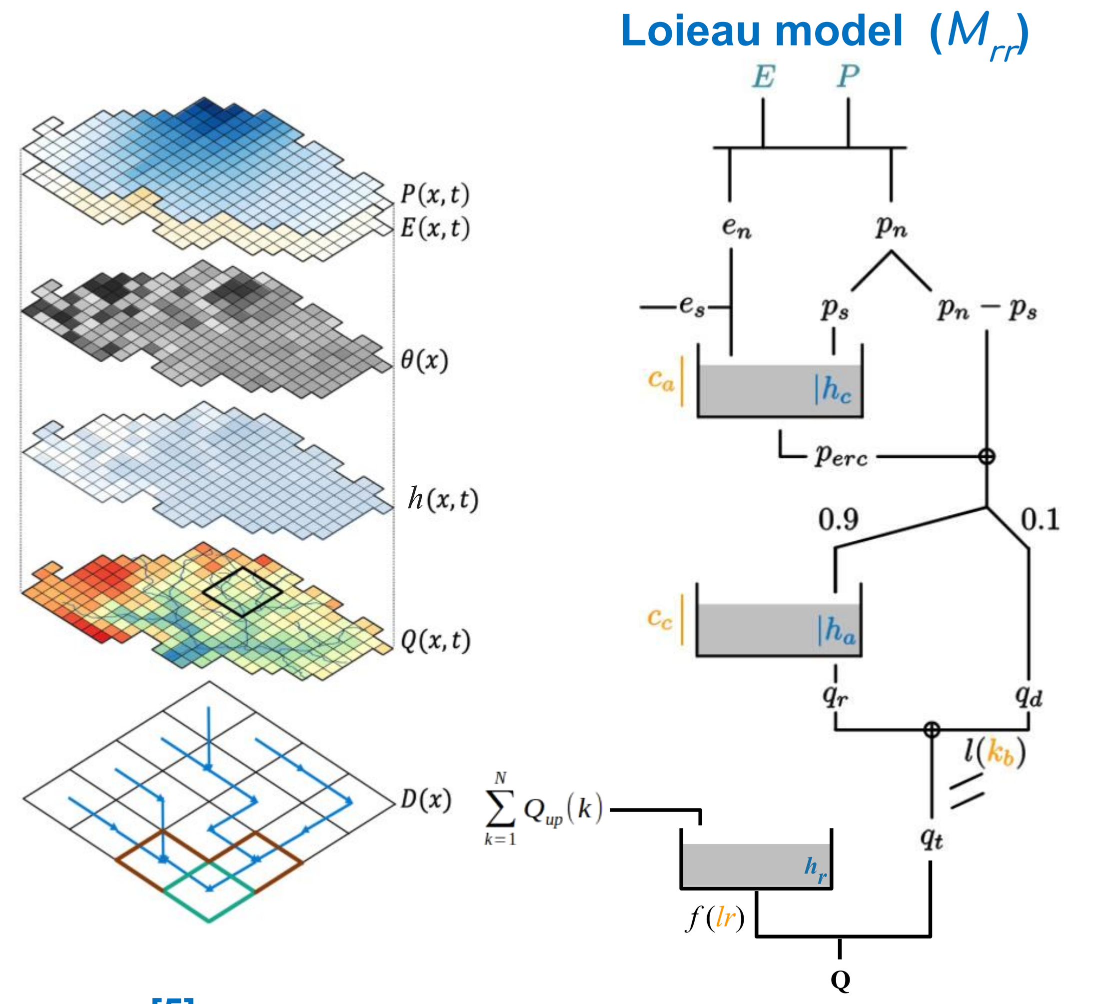
- SMASH is a computational software framework enabling to tackle spatially distributed differentiable hydrological modeling, with learnable parameterization-regionalization.
- It is designed to simulate discharge hydrographs and hydrological states at any spatial location within a basin, enabling the hydrological response of contrasted catchments, both for operational forecasting of floods and low flows.



- Physical descriptors (e.g., land cover, hydrogeology) are linked to model parameters using either multiple linear regression (ML) or multilayer perceptron (MLP) artificial neural networks (ANN)[4], where coefficients or weights are optimized and iteratively updated at each step of the optimization algorithm in order to minimize the cost function.

❖ Modeling Setup and Evaluation Metric

Loieau model (M_{rr})



LoiEau$_J$[5]: a conceptual daily model associated with 3 hydrological parameters and 1 routing parameter.

Cost Function : Criteria combined[6]:

$$\boxed{J = \tfrac{1}{2} * KGE(Q) + \tfrac{1}{2} * KGE(\tfrac{1}{Q})}$$

$$KGE = 1 - \sqrt{(r-1)^2 + (\alpha - 1)^2 + (\beta - 1)^2}$$

$$r = \frac{1}{n}\sum \frac{(Q_i^{obs} - \mu_{obs})(Q_i^{sim} - \mu_{sim})}{\sigma_{obs}\,\sigma_{sim}} \qquad \alpha = \frac{\alpha_{sim}}{\alpha_{obs}} \qquad \beta = \frac{\mu_{sim}}{\mu_{obs}}$$

Temporal validation :

- P1 (1976–1996, +1 yr warm-up) → Calibration
- P2 (1998–2018, +1 yr warm-up) → Validation

Spatio-temporal cross-validation :

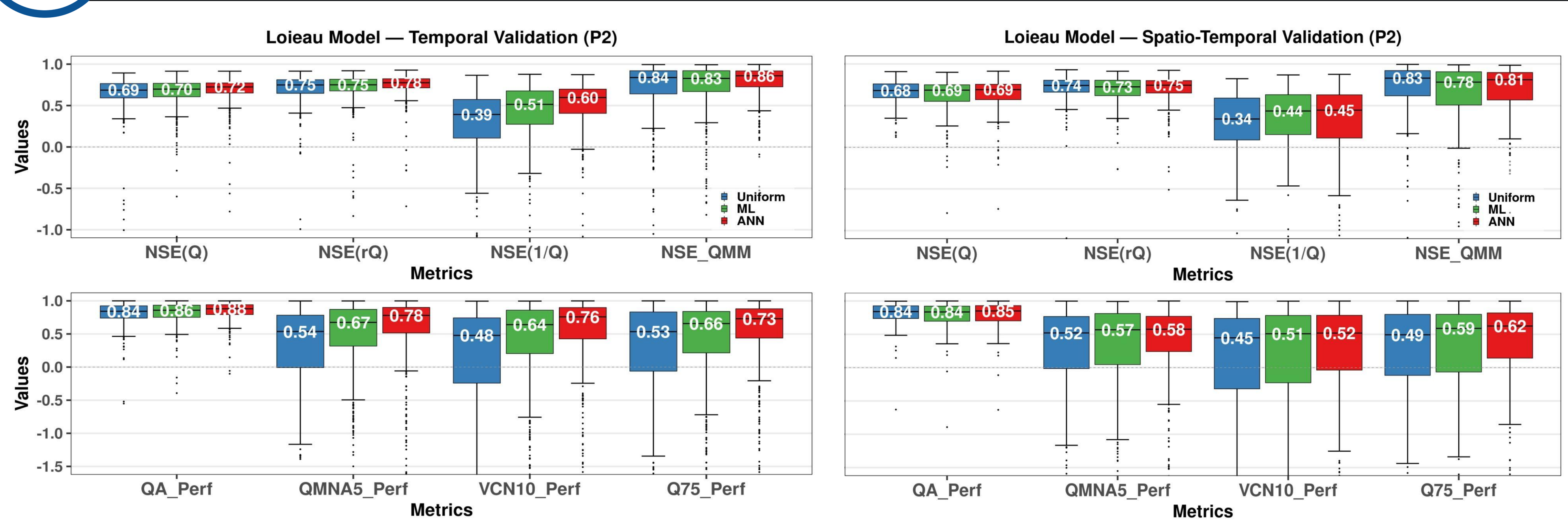
- 3 randomized basin splits
- Per split:
  - -Calibration (⅔ catchments)
  - -Validation (⅓ catchments)
- Ensures robustness & tests spatial transferability of regionalized parameters to ungauged basins

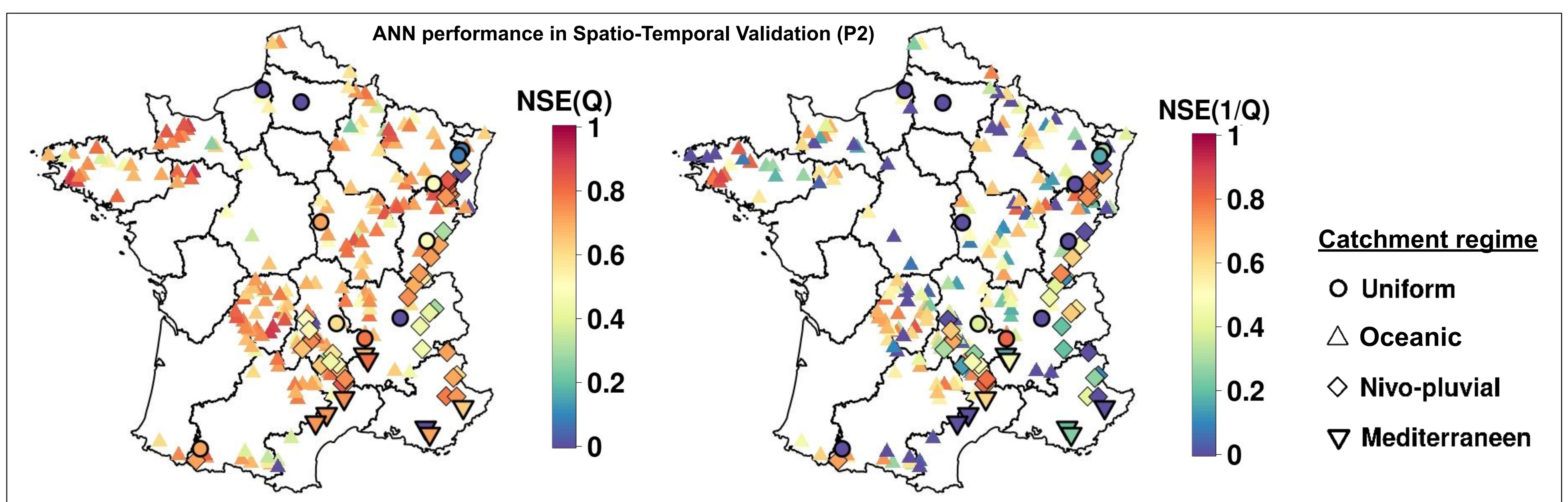
Evaluation Metric :

Metric	Definition
$NSE(Q)$	$NSE(Q_{\mathrm{sim}}, Q_{\mathrm{obs}})$
$NSE(rQ)$	$NSE(\sqrt{Q_{\mathrm{sim}}}, \sqrt{Q_{\mathrm{obs}}})$
$NSE(1/Q)$	$NSE\left(\frac{1}{Q_{\mathrm{sim}}}, \frac{1}{Q_{\mathrm{obs}}}\right)$
$NSE(QMM)$	$NSE(QMM_{\mathrm{sim}}, QMM_{\mathrm{obs}})$
QA Perf	$1 - \left\lvert 1 - \frac{QA_{\mathrm{sim}}}{QA_{\mathrm{obs}}} \right\rvert$
QMNA5 Perf	$1 - \left\lvert 1 - \frac{QMNA5_{\mathrm{sim}}}{QMNA5_{\mathrm{obs}}} \right\rvert$
VCN10 Perf	$1 - \left\lvert 1 - \frac{VCN10_{\mathrm{sim}}}{VCN10_{\mathrm{obs}}} \right\rvert$
Q75 Perf	$1 - \left\lvert 1 - \frac{Q75_{\mathrm{sim}}}{Q75_{\mathrm{obs}}} \right\rvert$

$$NSE = 1 - \frac{\Sigma(Q_{obs} - Q_{mod})^2}{\Sigma(Q_{obs} - Q_{mean})^2}$$

4 Results in Regionalization





- **ANN** consistently outperforms **ML** and **Uniform** optimization across most metrics.
- The largest gains appear on low-flow indicators (**QMNA5**, **VCN10**), underscoring ANN's strength for drought-prone regimes.
- **ML** also delivers clear improvements over **Uniform**, confirming the benefit of spatial regionalization.
- These performance gaps remain stable under both **temporal** and **spatio-temporal** validation, indicating good generalization to unseen periods and basins.

- **Oceanic** & **Nivo-pluvial:** consistently strong performance on NSE[Q] with robust flow-dynamics reproduction, though low-flow skill (NSE[1/Q]) still drops.
- **Mediterranean**: more variable performance, with clear weaknesses on low flows (NSE[1/Q]).
- **Uniform:** poorest performance overall, with difficulty reproducing both flow dynamics (NSE[Q]) and low flows (NSE[1/Q]).

CONCLUSION

The ANN emerges as the most robust and reliable calibration strategy in this study both in temporal and spatio-temporal validation. It provides a robust improvement in well-structured regimes but struggles in highly variable or poorly defined regimes. This highlights the need for further adaptations to enhance generalization in Mediterranean and Uniform catchments.

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