Modelling the intermittence of watercourses in the small French Mediterranean catchments of the Maures massif (Réal Collobrier) with the SMASH platform : « Spatially distributed Modelling and ASsimilation for Hydrology »

Nathalie Folton[1], Thomas de Fournas[1], François Colleoni[1], Pierre André Garambois[1;] (1) INRAE, Aix-Marseille Université, RECOVER, 3275 Route de Cézanne, 13182Aix-en-Provene, France

1 . Objective

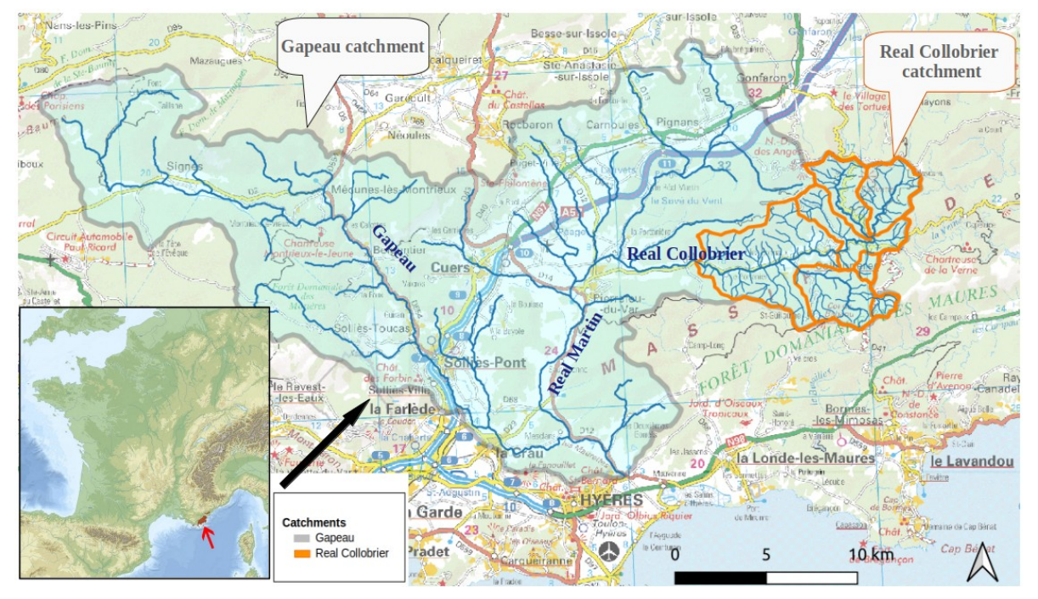
- To represent the spatio-temporal dynamics of flow intermittence at the reach level in river of the seven sub-catchments (between 1.5 and 70 km²) of the Real Collobrier, a French Mediterranean catchment of the Maures massif.

➔ The daily and spatially distributed hydrological model (SMASH) is used and compared to the benchmark model GR6J, a global conceptual model.

➔ Flow condition observed from multiple data sources (water level measurements, photo traps, conductivity measurements) are used to evaluate the ability of the regional model to simulate flow intermittence (prediction of dry events) at river section level of the sub-catchments of the Real Collobrier.

2 . Dataset

- The Real Collobrier, a French Mediterranean catchment is located in South-East France, at the western end of the Maures mountain range on the Mediterranean coast. The sub-catchments have surface area between 1.5 to 70 km².



Name	Area (km²)	Mean Elevation (m)	Mean annual Rain (mm)	Mean Annual Runoff (mm)	Runoff coefficient
Pont de Fer	70.4	335	993	271	0.27
Maliere	12.4	386	999	334	0.33
Valescure	8.5	466	1164	420	0.36
Maurets	9.2	453	1059	314	0.3
Vaubarnier	1.49	466	1164	420	0.36
Desteou	1.53	391	1039	392	0.38

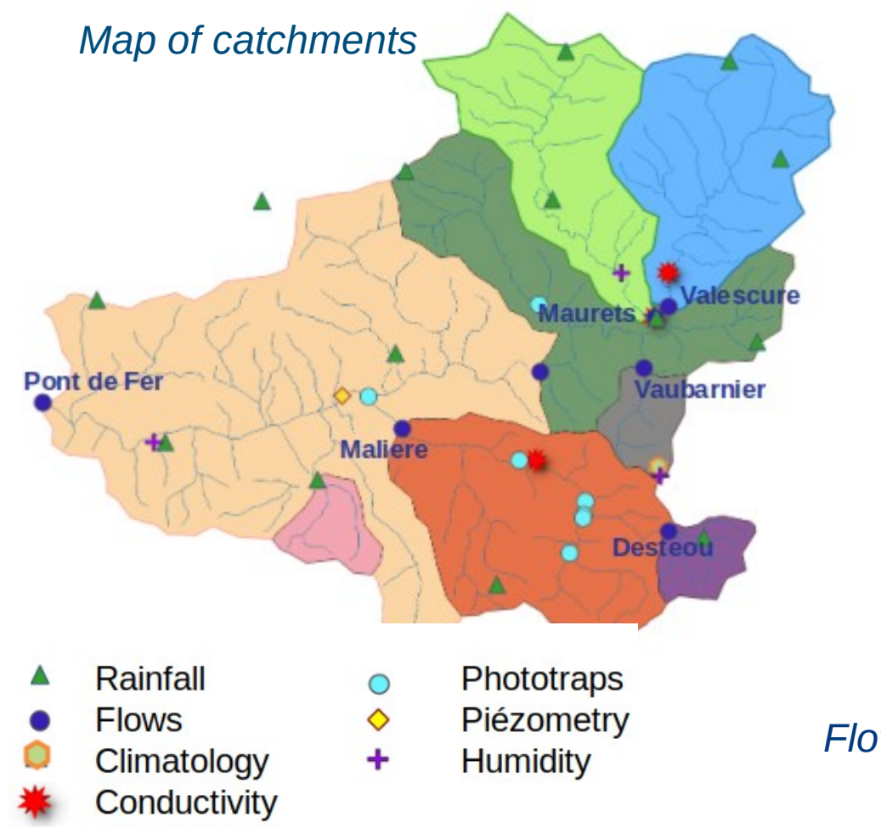
The catchment area is representative of the geological formations of the crystalline Provence of the Maures, made up of metamorphic and granitic massifs.

The catchment is characterized by a typical Mediterranean climate with dry summers and high precipitation events, mainly during autumn (September to December). Due to the orography, the mean precipitation (1055 mm year-1) is higher than in the surrounding areas.

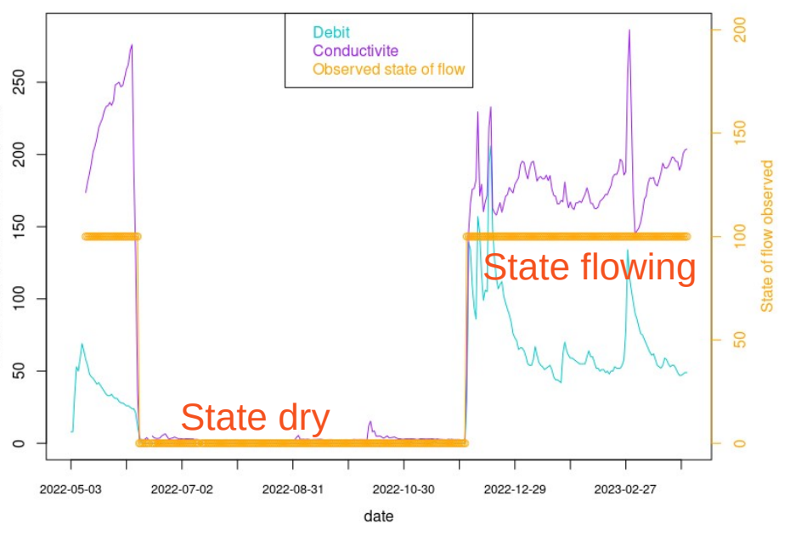
Observations:

- Daily rainfall and discharges time series from 01/1970 to 12/2023
- Phototraps installed along rivers take daily pictures from 21/04/2021 to 31/12/2022
- Daily conductivity measurements series from 05/2022 to 04/2023

Map of catchments



Flow intermittence captured by phototraps



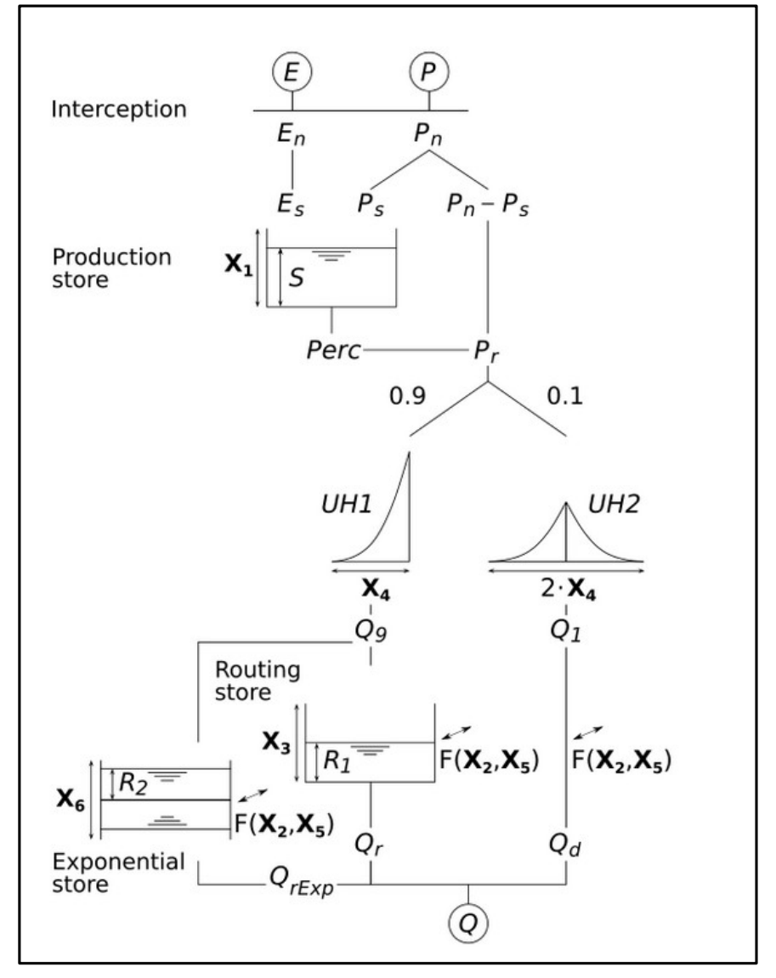
Flow intermittence deducted from conductivity time serie on Maurets catchment.

When daily conductivity is lower 10 , then observed state flow is dry otherwise is flowing.

3 . Methodology

❖ 3.1 Models

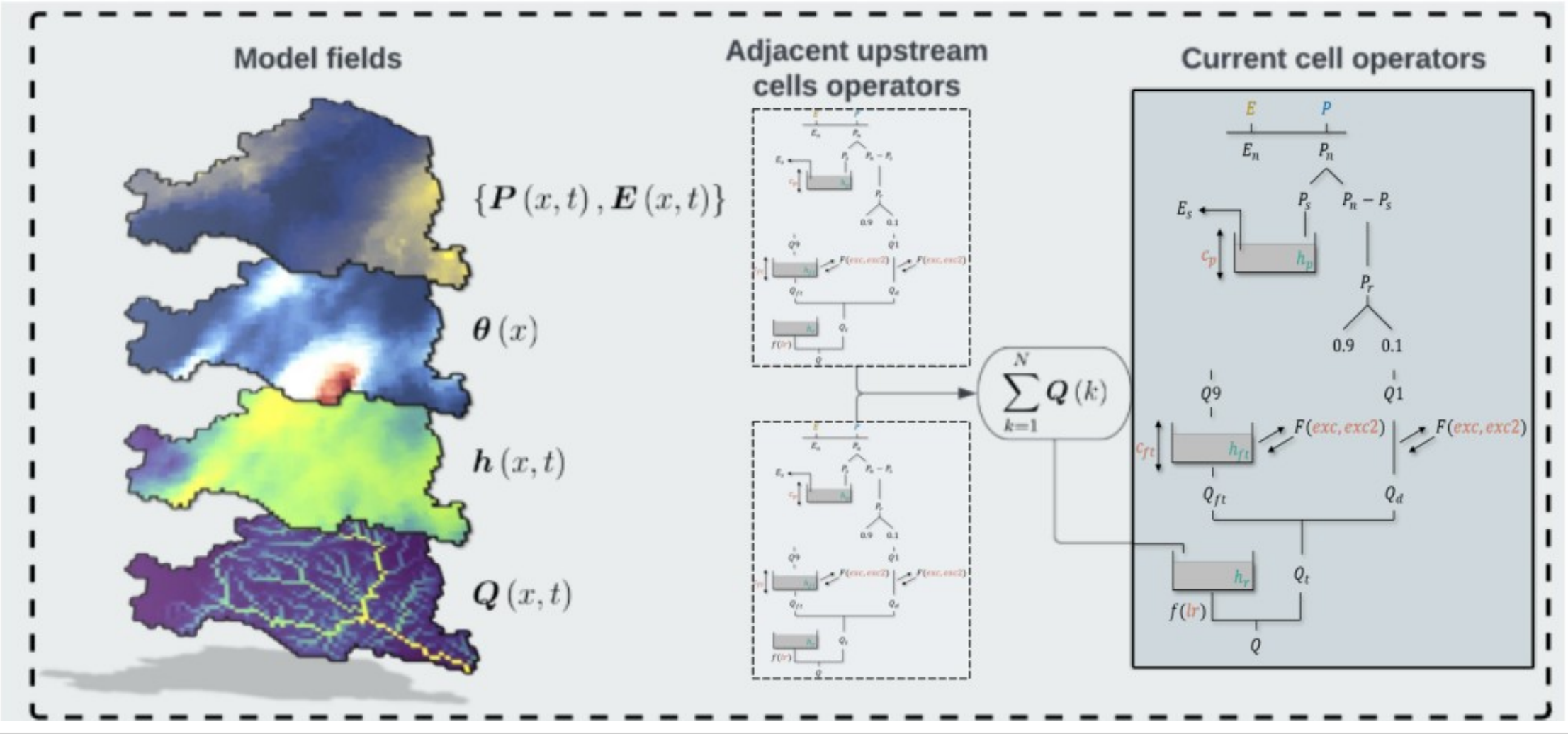
GR6J a conceptual daily lumped rainfall-runoff model with 6 parameters. Two unit hydrographs and two parallel nonlinear routing stores.



Structure of the rainfall-runoff model GR6J [1]

- **SMASH** structure GR-like, a daily distributed hydrology model.

The distributed model with 5 parameters is based on a gridded mesh. On each cell, the model features different hydrological components. Each component offers different modeling options such as snow modules, surface interception, production, transfer and percolation functions. At the grid scale, different routing models are implemented via a cell-to-cell numerical routing scheme [2].



Forward model *dt = 1 day and dx = 250 m*

The classical forward model M is a dynamic operator projecting the input fields P (x,t') and E (x,t') onto the discharge field Q (x,t) and states fields h (x,t) written as:

$$Q(x,t) = M[P(x,t'), E(x,t'), h(x,0), \theta(x), t] \; \forall x \in \Omega, \; t' \in [0,t]$$

where $\theta(x)$ is the N_θ-dimensional vector of model parameters 2D fields to be estimated.

SMASH comes with its numerical adjoint model which is obtained by automatic differentiation with Tapenade. A variational data assimilation algorithm is implemented and helps to calibrate the distributed parameters or evaluate the model states. This algorithm uses the quasi-Newton lbfgs-b descent algorithm and the gradient of the cost function relative to the model parameters and states. This gradient is computed by a run of the adjoint model.

Calibration function [3]

$[\, KGE_Q + KGE_{(1/Q)}] / 2$

- **Cost function**

$$[\theta, \hat{h_0}](x) = \underset{[\theta, h_0](x)}{\operatorname{argmin}} J(\theta) \quad \begin{cases} J(\theta) = J_{obs}(\theta) + \alpha J_{reg}(\theta) \\ J_{obs} = 1 - ([\, KGE_Q + KGE_{(1/Q)}] / 2) \end{cases}$$

❖ 3.2 Evaluation criteria

- **on daily flows**

Temporal robustness assessment

using the split sample test on 4 sub periods:

- P1/P2 : 2 temporal sub periods
- D/W : Driest years and Wettest years according to annual aridity index

Spatio-Temporal robustness assessment using **Leave One Out cross validation**

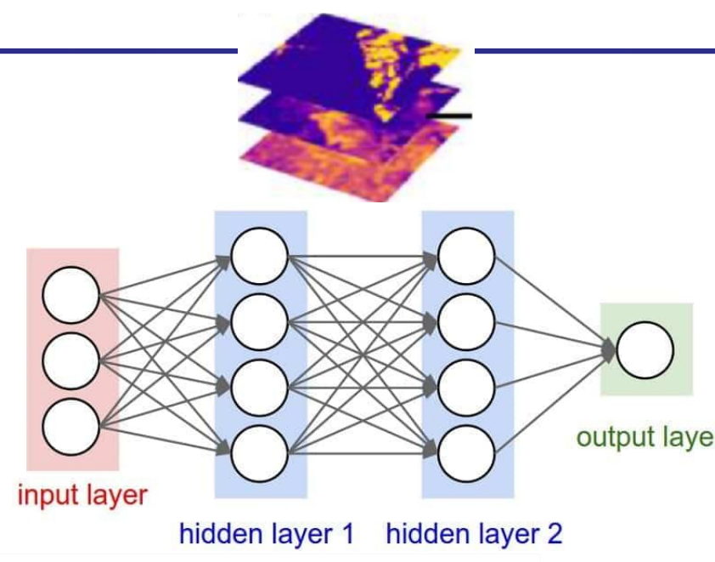
Name	Description	Formula bounded in]0,1]
	Efficiency criteria used for model evaluation in simulation mode	
	Quadratic criteria	
$C2M_i$	Nash-Sutcliffe efficiency bounded in]-1;1] calculated with Q and $Q^{0.5}$	
	Low flow quadratic criteria	
$C2M_i$	Nash-Sutcliffe efficiency bounded in]-1;1] calculated with 1/Q	
	Volume based and temporal criteria for low flow considering the Q_{85} threshold	
Vdef	Ratio of observed and simulated cumulative annual volume deficit	1- | 1-Vdef |
LFD	Ratio of observed and simulated cumulative low-flow duration	1- | 1-LFD |
DateSt	Relative difference between observed and simulated start of annual low-flow period	$1 - \frac{DateSt}{max(DateSt)}$
DateEn	Relative difference between observed and simulated end of annual low-flow period	$1 - \frac{DateRn}{max(DateEn)}$

- **on daily state of flow (dry or flowing) in model prediction**

Name	Description	Formula bounded in]0,1]
	Efficiency criteria used for model evaluation in simulation mode on ungauged station (phototraps, conductivity data) based on the contingency table for low flows considering the zero flow	
	a is the number of dry observations correctly simulated by the model , b is the number of flowing observations that were simulated as dry and c is the number of dry observations that were simulating as flowing	
	Threshold criteria: no flow	
POD	Probability of correctly detection drying events	a/(a+c)
FAR	False alarm rate: probability of wrongly predicting a drying events	b/(a+b)

❖ 3.3 Regionalization Method [4]

- **Spatially Uniform (SU) with multi gauged catchments**

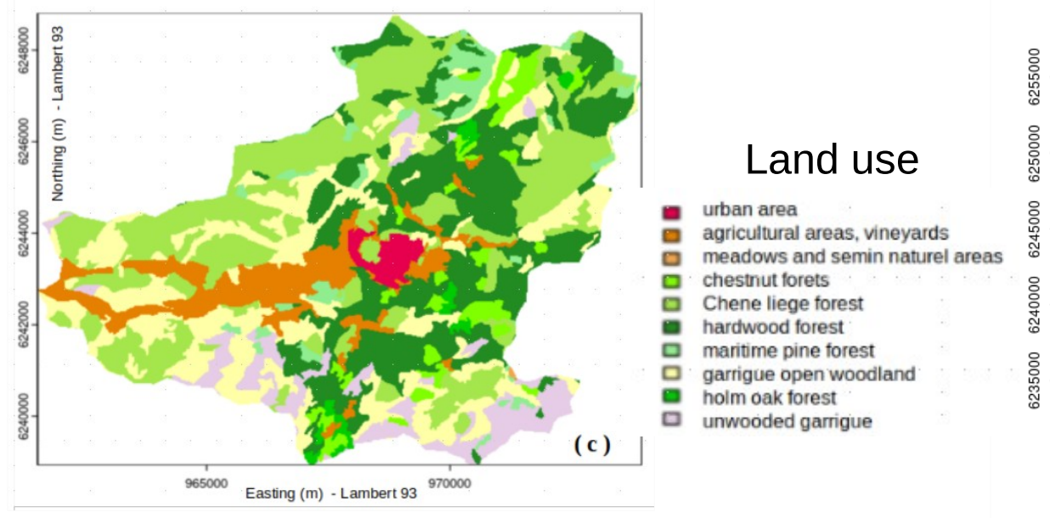


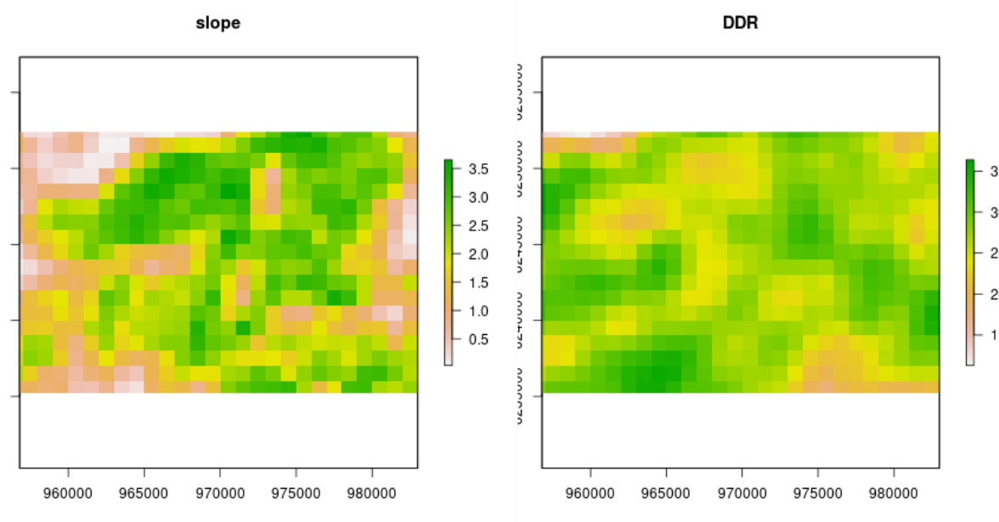
- **ANN: An artificial neural network (ANN) is used to map physical descriptors D onto conceptual parameters θ and initial states *h0* of the model**

Physical descriptors D :

Corine Land Cover (8 classes)

slope and drainage density calculated from digital terrain model



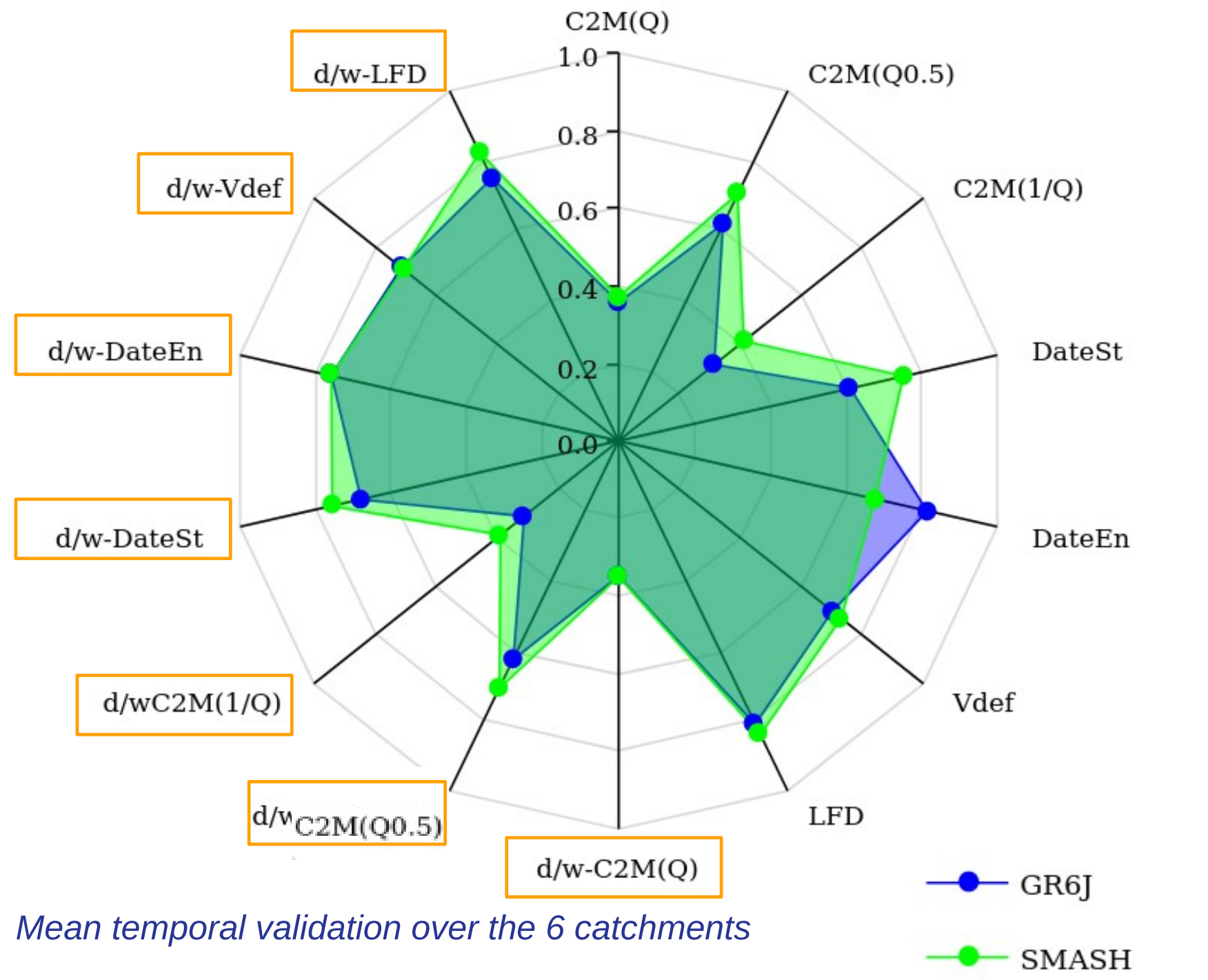


4 . Results

❖ 4.1 Temporal robustness

The simulated flows optimized are evaluated with the previous criteria on the four sub-periods over the 6 catchments.

- Globally, the two models perform well and SMASH model allows a better perform on low flow crietria except for « DateEn » in P1/P2 validation period.
- In dry/wet periods, the results shows also good performs.



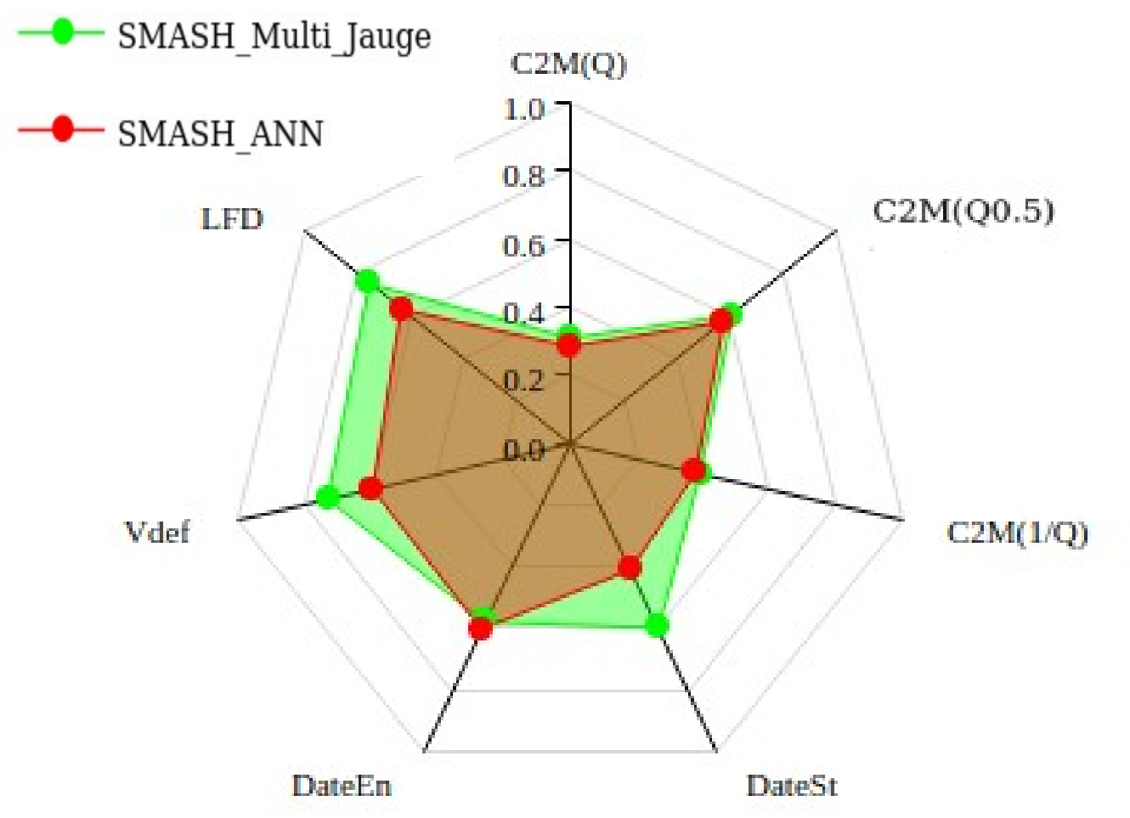
Mean temporal validation over the 6 catchments

❖ 4.2 Spatio-temporal robustness

Two regionalization methods are compared using distributed SMASH model: **Spatially Uniform** and the use of **ANN** with topography and land cover descriptors.

Globally, the performance of **Spatially Uniform** method is better than ANN, specially on 3 criteria (LFD, Vdef and DateSt).

For criteria based on the hydrogram (C2M), the results of both methods are similar and comparable to those obtained throught temporal validation.



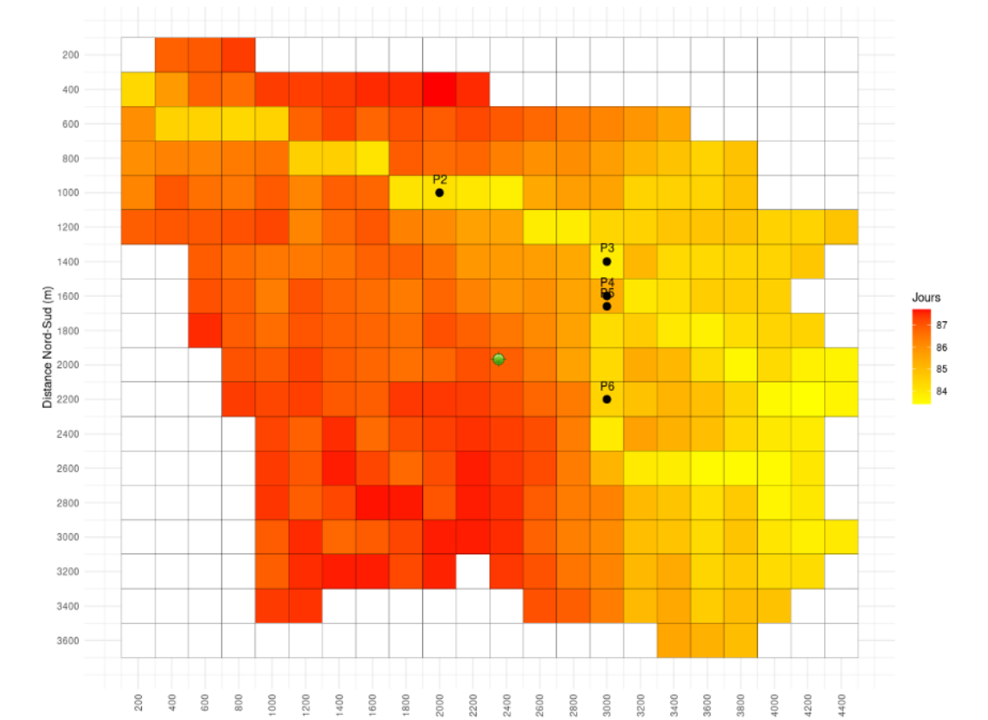
Mean spatio-temporal validation over the 6 catchments

❖ 4.3 Prediction of flow intermittence

Results of simulation of flow intermittence with SMASH (SU) multi-jauge at phototrap stations on Malière and Pont de Fer catchments.

Only gauging stations are used in spatially distributed model. The spatial outputs of the model enables to calculate the daily flow state (flowing or dry) to be predicted in each reach of catchments. From the daily flow state simulated, the number of dry days is calculated on each cell of the grid. The figure show an example of the state of flow predicting on the Maliere sub catchment.

Mean annual number of dry days for each cell of the Malière catchment on period from 1968 to 2022.



The daily flow states simulated (dry days) are compared with observations at photostrap station on Maliere and Pont de Fer catchments. Each photo is analyzed as: 0 = dry day and 1= flowing. day.

Catchments	Pont de Fer	Malière
Phototrap stations	P1 P7	P2 P3 P4 P5 P6
Number of observations	889 pictures	2145 pictures
POD	0.9	0.2
FAR	0.74	0.06

Analysis of phototrap stations from 21/04/2021 to 31/12/2022.

5 . Conclusion and perspectives

With a high POD score and a low FAR score, the performance of the model is promising for predicting flow conditions on the river reaches tested.

The results show that the spatial distributed model allows to predict the daily state of flow at the reach scale along river networks of a Mediterranean catchment.

In order to improve spatial distributed model on flow intermittence, further improvements could be made in descriptors used with ANN.

To improve the prediction of flow intermittence on river network, daily conductivity time-series can be used to collect various sources of observed flow state.

National Research Institute for Agriculture, Food and the Environmentational
CONTACT : Nathalie Folton - ***nathalie.folton@inrae.fr***
INRAE, Aix-Marseille Université, RECOVER
www.inrae.fr/en
https://recover.paca.hub.inrae.fr/nos-infrastructures/le-bvre-du-real-collobrier
https://www.ozcar-ri.org/fr/observatoire-real-collobrier/

References

[1] Pushpalatha, R., Perrin, C., Moine, N., Mathevet, T., & Andréassian, V. (2011). A downward structural sensitivity analysis of hydrological models to improve low-flow simulation.Journal of Hydrology ,411. https://doi.org/10.1016/j.jhydrol.2011.09.034
[2] Colleoni, F., Garambois, P.-A., Javelle, P., Jay-Allemand, M., & Arnaud, P. (2022). Adjoint-based spatially distributed calibration of a grid GR-based parsimonious hydrological model over 312 French catchments with SMASH platform . Catchment hydrology/Modelling approaches. https://doi.org/10.5194/egusphere-2022-506
[3] Garcia, F., Folton, N, Odin L., (2017) Which objective function to calibrate rainfall-runoff model for low-flow index simulations ? Hyd. Sciences Jour., 62(7), 1-18.
[4] Huynh, N. N. T., Garambois, P.-A., Colleoni, F., Renard, B., Roux, H., Demargne, J., & Javelle, P. (2023). Learning Regionalization within a Differentiable High-Resolution Hydrological Model using Accurate Spatial Cost Gradients.