Extreme low flow estimation: added value of piezometry to constrain the asymptotic behavior of a lumped rainfall-runoff model

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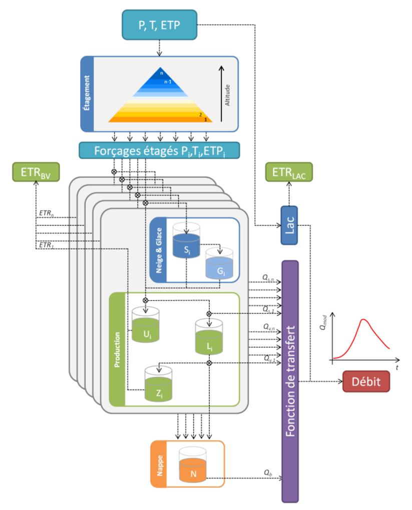
1. Research motivation

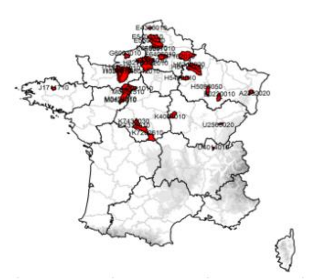
- Thermal power plants adaptation to climate change necessitates the characterization of high impact hazards, among which extremely low river flow. Estimation methods traditionally used rely on extreme value theory, but recent developments now make it possible to consider another approach coupling a climate generator and a hydrological model. [1]
- The first study was carried out on a single basin. The purpose of this work is then (i) to extend this proof of concept to a larger number of basins and (ii) to quantify the sensitivity of the simulation chain to the parameters of the hydrological model.
- In particular, we explore the added value of piezometry *(used or not during the calibration process)* to constrain the asymptotic behavior of the model.

2. Hydrological model and data



A. The MORDOR-SD semi-distributed model [2]

- A spatial discretization based on orographic zones
- 1 to 24 hours time resolution
- 6 interconnected stores (water storage, snow, ice)
- 8 to 15 free parameters
- Detailed degree-day schemes for snow and ice modelling
- Evapotranspiration as a function of potential evapotranspiration (PET), crop coefficient and soil wetness

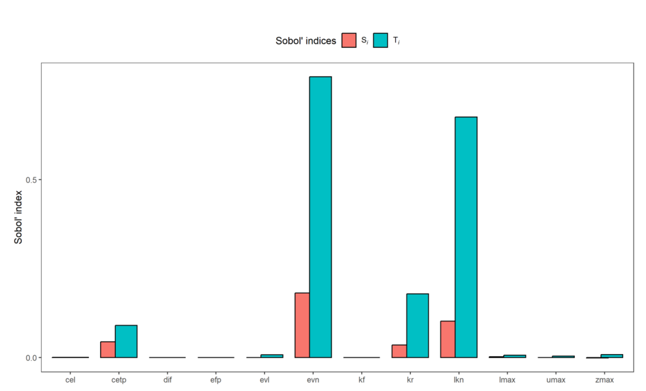


B. Hydro-climatic data

- Meuse@Chooz catchment (10 173 km²) *(EDF power plant)*
- 33 other catchments, from ~80 to 2000 km²
- Precipitation, Temperature: SAFRAN [3] reanalysis
- Potential evapotranspiration: Oudin temperature-based formula [4]
- Discharge: French national hydrometric data *(https://hydro.eaufrance.fr/)*
- Piezometry: French national piezometric data *(https://ades.eaufrance.fr/)*

3. Sensitivity analysis

Use case: Meuse@Chooz watershed (10 173 km²) 1953-2020 period
Method: Exploration of MORDOR parameters + calculation of the empirical ten-year annual minimum (Q10)
Results: Calculation of sobol indices (R *sensobol* package)

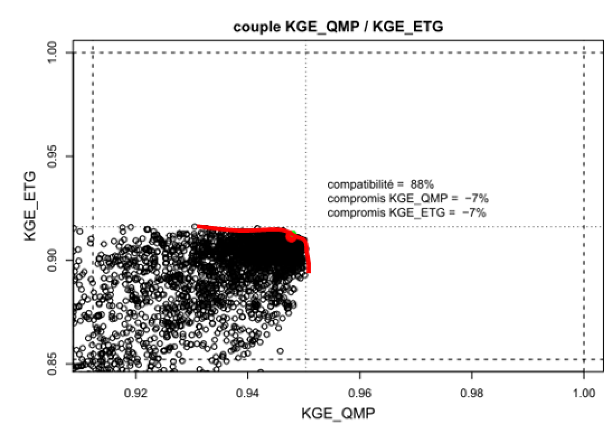


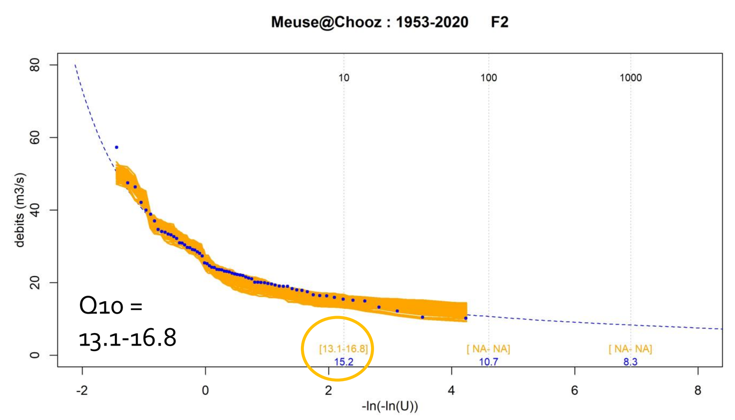
Most sensitive parameters:
lkn and evn: controls the dynamics of the deep store N
kr (1-kr ~BFI): controls the percentage of flows going to the deep store
cetp: multiplicative coefficient of evapotranspiration
Some strong interactions between parameter, notably between *lkn* and *evn*

4. Added value of piezometry – Meuse@Chooz catchment

- A multi-objective calibration is implemented, optimizing both (i) flow simulation with 4 criterions focusing on different streamflow signatures [2] and (ii) eventually one supplementary criterion base on the affine correspondence between the deep storage level of the model and piezometry

Use case: Meuse@Chooz watershed
Method: Extraction of the "Pareto Front" during calibration (R *mco* package)
Result: n sets of parameters selected at each calibration, i.e. n empirical Q10 estimation to be compared to the empirical Q10 reference based on observations *(ln3 fit + bootstrap)*

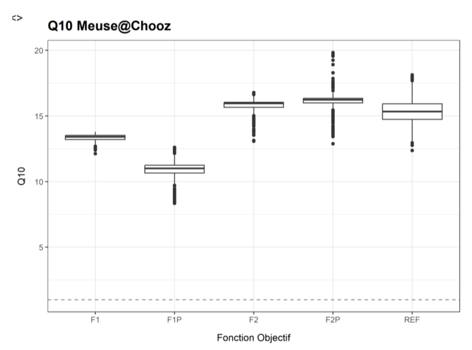




("Pareto Front": here illustrated in 2 dimensions, in reality 4 or 5 dimensions)

4 different objective functions, with *(F1P,F2P)* or without *(F1,F2)* piezometric information
Rext: correlation between piezometric data and the model deep store level
KGEetg: KGE on recession subsets *(used to constrain the model to fit low flows)*
KGEi: KGE on 1/Q *(an alternative to constrain the model to fit low flows)*

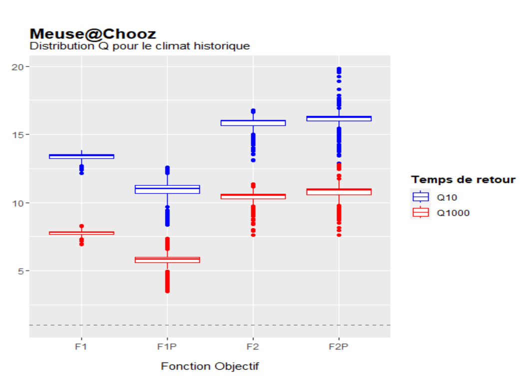
$$F1: KGEq + KGEqmp + NSHreg + KGEetg$$
$$F1P: KGEq + KGEqmp + NSHreg + KGEetg + Rext$$
$$F2: KGEq + KGEqmp + NSHreg + KGEi$$
$$F2P: KGEq + KGEqmp + NSHreg + KGEi + Rext$$

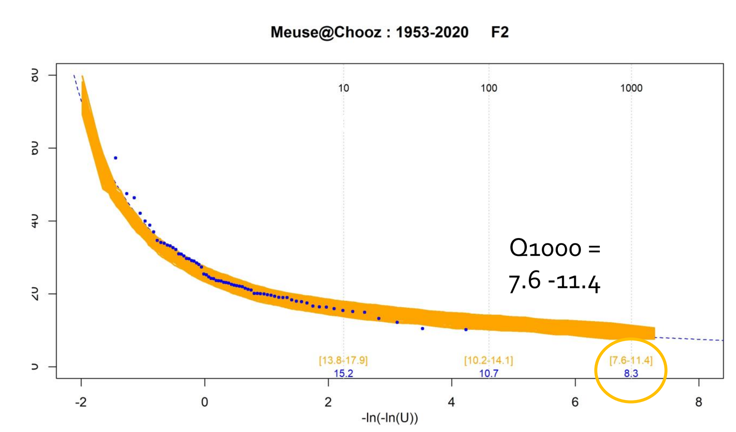


Partial conclusions :
F2 > F1: i.e. criterion KGEi > KGEetg to constrain the model to fit low flows ?
No real improvement while using the "piezometric information" ?
Fragile results on a single case: extension of experiments to the 33 watersheds *(cf. section 6)*

5. Impact on extreme low flow estimation

- For the Meuse@Chooz catchment we perform the framework describe in [1]: we feed our hydrological model with a large number of temperature and rainfall time series produced by a stochastic weather generator based on hidden Markov models. This allows us to calculate not only the ten-year annual minimum (Q10) but also the thousand-year annual minimum (Q1000)
- We find the same results as previously (same sensitivity to the objective function used to calibrate the model for the Q1000 value). The sensitivity analysis on the ten-year annual minimum (Q10) therefore seems sufficient at first approach.



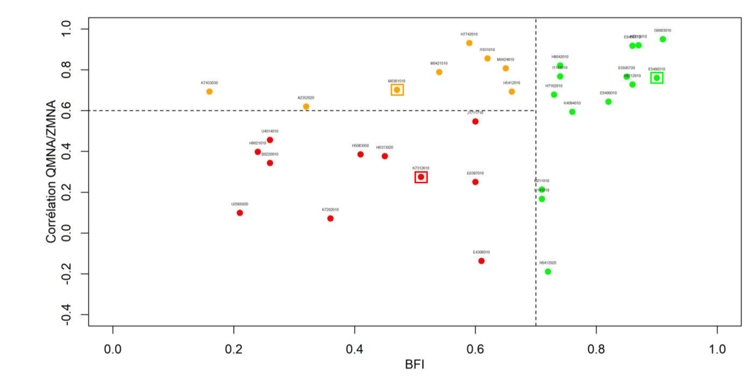


6. Added value of piezometry – other catchments

- We perform the same protocol as in section 4 but for the 33 other watersheds

The results led us to propose a classification of the 33 watersheds based on two indices.
The first index characterizes the importance of the baseflow in the streamflow *(BFI = baseflow index)*. The second index characterizes the a priori representativity of the piezometric time series during low flows *(cor QMNA/ZMNA, also used in [5])*
(nb: Meuse@Chooz watershed: BFI = 0.52 & cor QMNA/ZMNA = 0.8 i.e. in class 3)

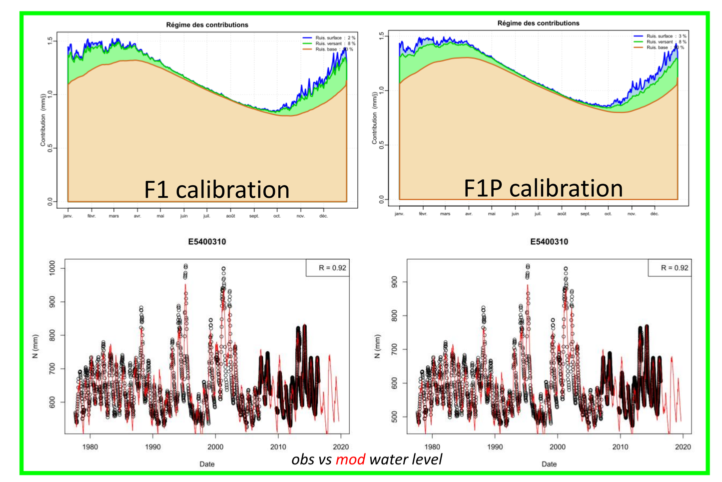
Class 1 *(green)*: BFI > 0.7: piezometric information is not necessary
Class 2 *(red)*: Cor QMNA/ZMNA < 0.6: piezometric information is not relevant / misleading
Class 3 *(orange)*: BFI < 0.7 & Cor QMNA/ZMNA > 0.6: piezometric information seems to be *(sometimes)* useful

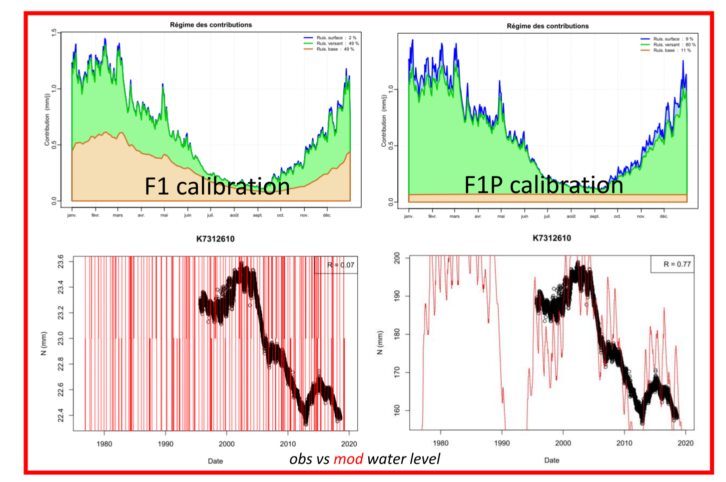


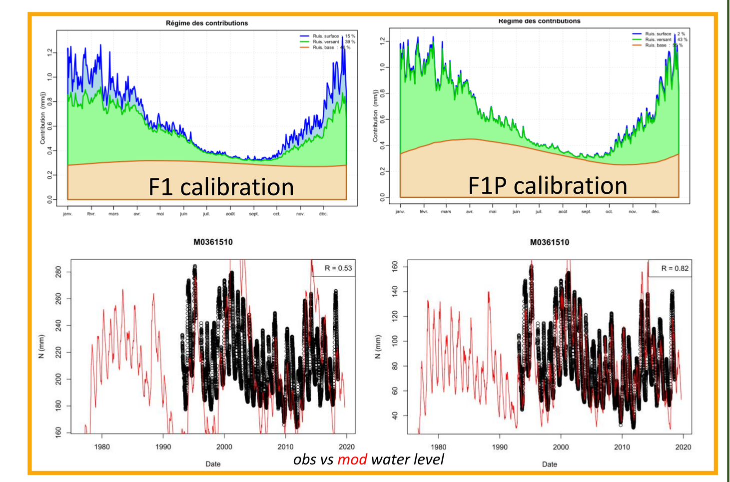
	F1	F1P	F2	F2P
Class 1	14.1 %	14.2 %	12.2 %	14.2 %
Class 2	55.3 %	120.2 %	36.7 %	52.9 %
Class 3	21.4 %	17.1%	20.1 %	20.9 %

MAE error between Q10_mod and Q10_ref

Illustration with examples from the 3 different classes

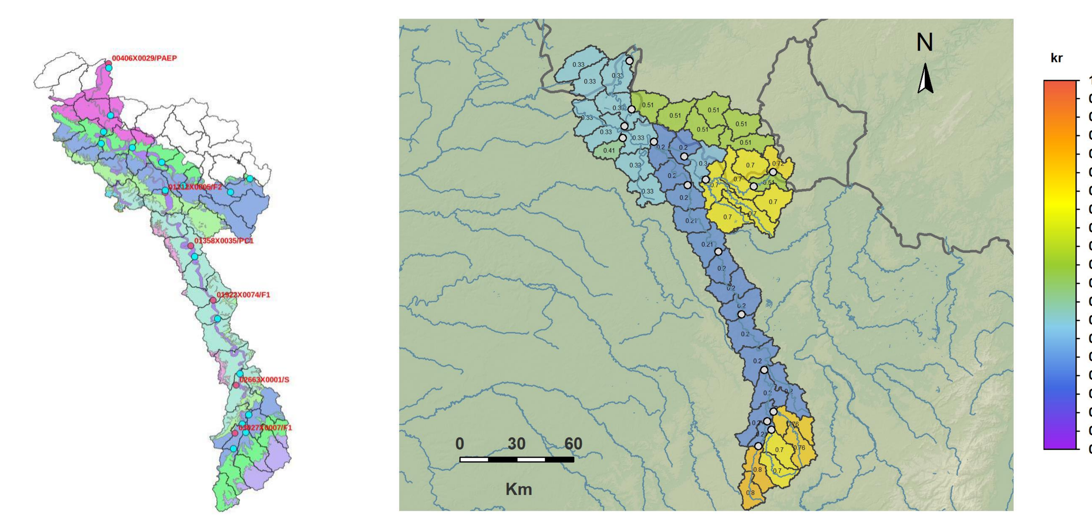






7. Conclusions and perspectives

- As already mentioned in previous works, using piezometric information during the calibration process to improve hydrological model behavior is far for being a straightforward task
- Anyway, this first insight allowed us to verify that our conceptual model was able to correctly represent piezometric information in some favorable cases.
- For further work, we intend to use a spatially distributed version of the MORDOR model, allowing perhaps an even better reconciliation between the piezometric data and the internal states of the model.



Meuse@Chooz watershed (10 173 km²)

References

[1] Parey , S et al., (2022). Extreme low flow estimation under Climate Change. Atmosphere, 13(2), 164.
[2] Garavaglia, F. et al. (2017). Impact of model structure on flow simulation and hydrological realism: from a lumped to a semi-distributed approach. Hydrology and Earth System Sciences, 21(8), 3937-3952.
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[5] Pelletier, A., & Andréassian, V. (2023). An underground view of surface hydrology: what can piezometers tell us about river floods and droughts?. *Comptes Rendus. Géoscience*, *355*(S1), 271-280.