

Year 2019 was very dry in several regions of northern France and year 2020 is following the same trend. Hydrological forecasting tools are crucial to design adaptative policies for many economic sectors and surface water users. More than floods, droughts are generally following long-term dynamics over several hydrological years; piezometric data, broadly available over French territory, are likely to be good indicators of these dynamics, which represent the memory of a catchment. How can an assessment of the hydrological memory help build a better low-flow forecasting model?

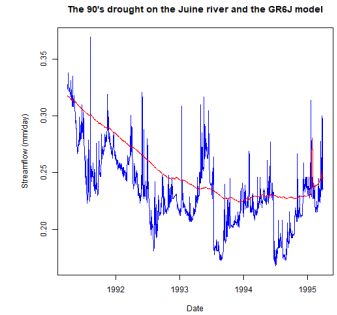
## 1 Introduction: the memory of catchments in low-flow modelling

In temperate regions, severe droughts are often caused by a cumulated rainfall deficit over several years. This is a consequence of the memory of catchments: the past meteorological conditions have an influence on the current hydrological behaviour of the river.

Aquifers carry most of this hydroclimatic memory; indeed, a catchment beginning summer with empty aquifers will not have the same trajectory as the same catchment with higher than average piezometric level. Most hydrological models struggle in reproducing this multiyear dynamics [Fowler et al., 2019] – see Figure 1 as an example – and adding piezometry as a new data is a way to improve them, but a prior analysis is necessary.

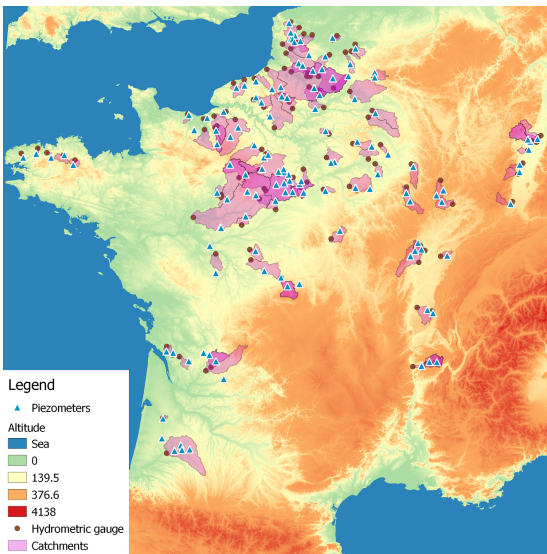
In this work, we value the temporal memory of streamflow and piezometry on a selection of catchments and relevant aquifers, to assess the benefit of adding piezometry as input data in a hydrological model.

Figure 1: example



The 1991-1995 drought on the Juine river. Observed streamflow is in blue ; in red, streamflow is simulated by the GR6J model.

Figure 2: map of the selected catchments



Map of the 107 selected catchments and 130 piezometers.

## 2 Material and methods

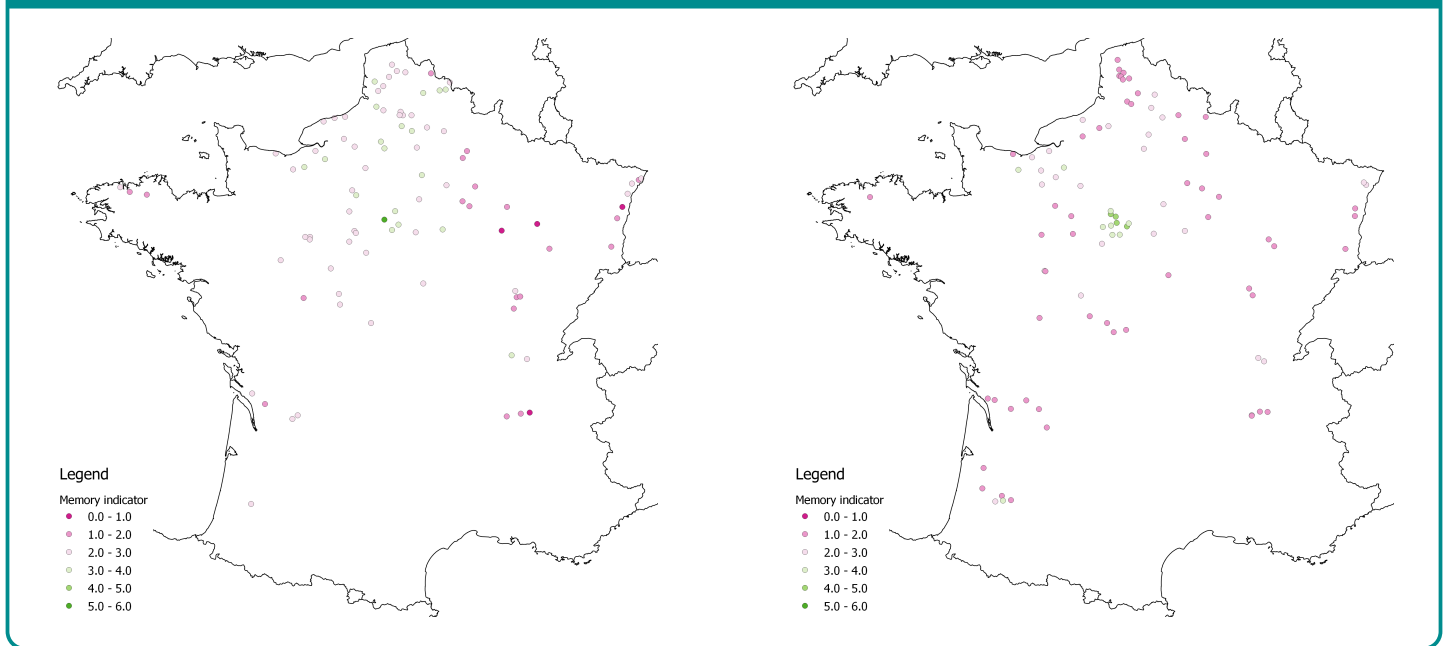
The analysis is performed on a set of 107 catchments in mainland France; for each one, a selection of relevant piezometers was made, for each aquifer connected to the river to be represented. Data was then aggregated as monthly means and for each hydrological year – taken here from April to March – the minimum of monthly means was isolated as an annual drought statistics; it is called  $QMNA$  for streamflow and  $zMNA$  for piezometry. The memory effect is then valued through a simple linear convolution:  $P_i$  being annual rainfall of the  $i$ -th year before the current one and  $E_i$  being annual potential evaporation of the same  $i$ -th year, the following model is used:

$$QMNA/P = \sum w_i P_i / E_i$$

$$zMNA = \sum w_i P_i / E_i$$

Weights  $w_i$  follow a gamma distribution, whose median is taken as a memory indicator.

Figure 3 : results for streamflow (left) and piezometry (right)



### 3 Results

The memory indicator can be regarded as a response time, expressed in years. Values range from 0.5 to 6 years for streamflow and from 1 to 11 years for piezometry, while mean values are 2.5 years for streamflow and 2.4 years for piezometry, which is quite surprising, since aquifers are supposed to have a slower memory than surface water. Long-memory piezometers generally correspond to long-memory catchments, with a correlation of 0.47 between the two sets of indicators.

Figure shows the geographic distribution of the results. For streamflow, it is not surprising that catchments connected to large aquifers – like the Chalk and the Beauce limestone in the Paris basin – have longer memory than catchments in alluvial plains – like Bièvre, Bresse or Alsace. For piezometry, results highlight the long memory effect of the Beauce catchment, but they fail to do so for the Chalk aquifer, known to have a predominant multiyear dynamics [Janyani et al., 2012].

### 4 Conclusion and perspective

This convolution regression method shows good performance to assess the memory effect of a catchment, using streamflow and climatic data. The results for streamflow memory are consistent with the known hydroclimatic and geological context. For piezometry, the results are less consistent with the local context and the method needs to be improved, for instance by using other terms in the regression or through a more precise pre-processing of piezometric data.

In order to improve the performance of a hydrological model, the same analysis can be applied to its states – for instance the reservoir levels in a conceptual lumped model – to identify which part of the structure could be perfected to get a better low-flow forecasting tool.

### References

- [Fowler et al., 2019] Fowler, K., Knoben, W., Peel, M., Peterson, T., Ryu, D., Saft, M., Seo, K.-W., and Western, A. (2019). Many commonly used rainfall-runoff models lack long, slow dynamics: implications for runoff projections. *Water Resources Research*. Under press.
- [Janyani et al., 2012] Janyani, S. E., Massei, N., Dupont, J.-P., Fournier, M., and Dörfliger, N. (2012). Hydrological responses of the chalk aquifer to the regional climatic signal. *Journal of Hydrology*, 464-465:485 – 493.