Identification of the parameters of rainfall-runoff models at ungauged locations: can we benefit from the regionalization of flow statistics?

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Context

- A four-parameter lumped RR model (GR4J)

- An ungauged catchment for which only the streamflow record is unknown

- Many gauged catchments

- Our objective here is to identify one suitable parameter set.

- The efficiency criterion used here is NSE, calculated on square-rooted flows
Different regionalization approaches...

**DIRECT METHODS**

- **regression**
- **catchment-similarity measures**
- **spatial proximity**

**INDIRECT METHODS**

- One regionalizes flow statistics first
- On this basis, candidate (“behavioural”) parameter set(s) can be identified
- Several recent studies (Yadav et al., 2007; Bardossy, 2007; etc...)
Different approaches...

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- Several recent studies (Yadav et al., 2007; Bardossy, 2007; etc...)
“Behavioural” parameter set

In our case we are looking for the (single) parameter set that best reproduces some previously regionalized statistics...which (we hope!) will also be a NS-efficient set

- What is the impact of the statistics’ regionalization efficiency?

- Where do we look for candidate parameter sets?
  - Do we want a broad “library” or a more constrained one?

- Is such a method robust?
Our Data

• We worked on 794 catchments, all located in France.

• For each catchment, we had at least 80% of streamflow data between 1986 and 2005 (we only used data from this 20 year period).

• Daily time step

• For each catchment, several physiographic descriptors were available.
Flow statistics used

- Average runoff
- $Q_0, Q_{10}...Q_{100}$ fdc quantiles, normalized by the average daily flow
- “Slopes” of the FDC
- LAG: time shift for which the correlation between rainfall and runoff records is the highest
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Regionalization of statistics

Two steps:

1. **Stepwise regression between statistics and physiographic descriptors** (log-transformed worked best)

   \[
   \ln(\hat{Q}) = a + b_1 \ln(x_1) + \ldots + b_n \ln(x_n)
   \]

2. **IDW interpolation of the residuals** (ratios between empirical and regression-generated statistic)

   \[
   \vartheta = Q / \hat{Q}
   \]

   (jack-knife)
Evaluation of parameter sets, step one

• we work with a library constituted by the calibrated parameter sets of all our catchments (other than the single catchment we treat as ungauged)

• For each parameter set, our model is run with the rainfall record of the “ungauged” catchment

• Flow statistics are calculated on the simulated streamflow record
Evaluation of parameter sets, step two

- For each statistic, we calculate the difference between simulation-generated and regionalized values. (This “error” is normalized by the variation range of each statistic)

\[ err = |\hat{Q}_{sim} - \hat{Q}_{reg}| \]

- A penalty score is calculated, as a weighted sum of all errors (the weights are calibrated to maximize the median NSE)

\[ p = \sum w_i err_i^\alpha \]

- In the end, we keep the parameter set with the lowest score
What is the impact of regionalization efficiency?

• We would like to do better than just borrowing the closest neighbour’s parameters.

• In any way, we could not do better than the black line (this method cheats, and chooses the best possible parameter set in the library)
What is the impact of regionalization efficiency?

- With regression-estimated flow statistics, we don’t satisfy our objective of beating the “first neighbour” case.
What is the impact of regionalization efficiency?

- Using the regression+IDW estimates yields a small (but noticeable) improvement
- Still, the “first neighbour” isn’t beaten…
What is the impact of regionalization efficiency?

- We cheated, using the flow statistics we had calculated on the actual runoff record (forgetting our catchment is “ungauged”)

- In this case, the result would be satisfying!
where do we look for parameter sets?

Do we want a broad parameter set “library” or is it worth to constrain it?

- As our network is very dense, we tested a constraint based on spatial proximity (of course not the only possibility)
where do we look for parameter sets?

- We tried limiting the available parameter sets to those of the closest 7 gauged catchments.

- It seems easier to identify efficient parameter sets, we’re finally doing better than the “first neighbour” method.
where do we look for parameter sets?

- The impact of flow statistics’ estimation efficiency is slightly less dramatic than without constraints.

- Even when “cheating” we get better results here than without constraint.
where do we look for parameter sets?

- However, there is a drawback: the potential of an “ideal case”, where we always pick the best possible parameter set, is diminished (smaller margin for improvement).
Is such a method robust?

794 catchments over France: a very spatially-dense gauging network...
Is such a method robust?

The red-circled catchments sit in the middle of an “hydrological desert”.

We can artificially put other catchments of our dataset in the same situation, by preventing them to “see” their closest neighbours.
Is such a method robust?

- This is what happened without simulating the “hydrological desert” situation

- For this case and the following two, we used regression-estimated flow statistics (no IDW)
Is such a method robust?

- In this case, we only accepted parameter sets from catchments being at least 20 km away.

- While pure spatial proximity loses interest, the two options using flow statistics keep almost unchanged performances.
Is such a method robust?

- 50 km “hydrological desert
- constraining the choice of parameter sets on a spatial-proximity base starts to be less interesting, even if not yet detrimental.
Conclusions

• There is a strong dependence on the signature’s regionalization efficiency

• There’s a clear advantage in combining this method with at least another way of selecting candidate sets (in this case, spatial proximity)

• This method seems a good choice for spatially sparse networks, provided that flow signatures can still be satisfactorily estimated at ungauged locations
Developments

• testing more signatures

• Will our conclusions hold on a different country? (possibly one with a less-dense gauging network)

• Application with a different model

• Discussing the weights that statistics get:
  – dependence on the objective function
  – dependence on the statistic’s estimation efficiency
  – dependence on the model?
Thank You!

(and blame him!)
en plus…

• confrontation avec une bibliothèque plus riche (10 random sets par bassis, ça ne change rien du tout!!)

• distance 1,2,3…,7° voisin
Which statistics? Which weights?

• At first, we tested the possibility of giving each statistic the same weight

• Then, we tested calibrating the weights so that the median efficiency was maximized
What happens when we change our criterion?

- peut être ajouter ici une figure qui montre la performance en régionalisation de chaque statistic : on pourraient ainsi discuter l’influence de la performance et l’influence de la “pertinence au critère” sur le poids de chaque sig.
- Bassin  P(mm) ETP(mm) T(°C) Vent(m/s) Hum(g/kg)  S
  Zmin  Zmoy  Zmax  Z_0.1  Z_0.2  Z_0.3  Z_0.4  Z_0.5
  Z_0.6  Z_0.7  Z_0.8  Z_0.9  PenteMin  PenteMoy
  PenteMax  P_0.1  P_0.2  P_0.3  P_0.4  P_0.5  P_0.6
  P_0.7  P_0.8  P_0.9  URBAN  AGRICOLE  FRUIT
  HYBRIDE  FOREST  OTHER