



HAL
open science

On evaluating the robustness of spatial-proximity-based regionalization methods

Laure Lebecherel, Vazken Andréassian, Charles Perrin

► **To cite this version:**

Laure Lebecherel, Vazken Andréassian, Charles Perrin. On evaluating the robustness of spatial-proximity-based regionalization methods. *Journal of Hydrology*, 2016, 539, pp.196-203. <10.1016/j.jhydrol.2016.05.031>. <hal-01709762>

HAL Id: hal-01709762

<https://hal.science/hal-01709762v1>

Submitted on 15 Feb 2018

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



HAL Authorization

Technical note

On evaluating the robustness of spatial-proximity-based regionalization methods

Laure Lebecherel, Vazken Andréassian* and Charles Perrin
Irstea, Antony, France

* *Corresponding author, vazken.andreassian@irstea.fr*

Abstract

This technical note deals with a question of importance for regionalization methods based on spatial proximity. These methods transfer hydrological information (typically calibrated parameter sets) from neighbor gaged stations to the target ungaged stations. The robustness of these regionalization methods (i.e., how their performance degrades when the hydrometric network becomes sparser) must be assessed. Here, we evaluate and compare two options for assessing this robustness: the random hydrometrical reduction (HRand) method, which consists in sub-sampling the existing gaging network around the target ungaged station, and the hydrometrical desert method (HDes), which consists in ignoring the closest gaged stations. Our tests show that the HDes method is a more conservative testing method than the HRand method.

Keywords

Rainfall-runoff modeling; ungaged basins; regionalization; spatial-proximity; robustness assessment;

26 **1. Why is it important to assess the sensitivity of regionalization** 27 **methods to the density of the hydrometric network?**

28 Hydrological models with parameters that cannot be directly derived from physical catchment
29 characteristics require calibration for parameter identification. Calibration is mostly based on observed
30 flow series. Therefore, ungauged catchments, where no observed runoff data are available, require
31 specific treatment. Much work has been done since the 1970s to handle the absence of runoff data
32 (see e.g. James (1972); Magette et al. (1976)), and the corresponding approaches are usually referred
33 to as regionalization approaches (Gottschalk et al., 1979). Recent advances on regionalization within
34 the framework of the IAHS Prediction on Ungauged Basin (PUB) decade have been reviewed by
35 Hrachowitz et al. (2013), showing how information can be transferred from gaged to ungauged
36 catchments.

37 Among the commonly used regionalization approaches, some use the principle of physical similarity,
38 based on the hypothesis that basins with similar physical characteristics have hydrologically similar
39 responses (see Oudin et al. (2010)). Other approaches use information from the catchment's spatial
40 neighborhood, based on the hypothesis that surrounding physical conditions are similar. In this paper,
41 we will specifically focus on this second type of approach, the efficiency of which strongly depends on
42 the density of the hydrometric network.

43 One of the important expected properties for a regionalization method is robustness. Two
44 regionalization methods could perform very similarly in a data-rich environment and perform much
45 differently under conditions of more limited data availability: assessing the sensitivity of any
46 regionalization method to the level of information availability (typically the density of the surrounding
47 hydrometric network in case of proximity-based approaches) is a good way to avoid disappointments
48 when comparing academic methods to real-world data (Andréassian et al., 2010). Operational
49 networks are rarely as dense as we hydrologists wish they were...

50 Surprisingly, the impact of hydrometric data density on regionalization efficiency does not seem to be
51 a matter of concern in the literature. We addressed this issue in a previous study on the regionalization
52 of the Turc-Mezentsev regionalization formula (Lebecherel et al., 2013). Here we would like to defend
53 the point of view that this sensitivity test is not a mere matter of "hydrological comfort" but rather a
54 scientific necessity, a kind of essential "crash test" to ensure credibility before practical use
55 (Andréassian et al., 2009).

56 This note explores spatial-proximity-based regionalization methods. It proposes and compares two
57 methods to evaluate the impact of hydrometric network density on regionalization performance. We
58 start with a description of the material in section 2: a data set of 609 French catchments, a rainfall-
59 runoff model and a spatial proximity-based regionalization method. Section 3 presents the two
60 alternative methods to evaluate the robustness of a regionalization method: the hydrometrical random
61 reduction (HRand) method and the hydrometrical desert method (HDes). Finally, the two methods are
62 compared.

63 **2. Material**

64 **2.1 Catchment set**

65 The two evaluation methods of regionalization robustness were tested on a data set consisting of 609
66 French catchments (Figure 1), where daily streamflow, rainfall and potential evaporation time series
67 were available over the 1997–2006 period. These catchments are spread over France and
68 encompass a variety of climatic conditions (oceanic, Mediterranean, continental).

69 Potential evaporation (PE) was computed using the Oudin formula (Oudin et al., 2005) and
70 precipitation data come from a countrywide interpolation(SAFRAN reanalysis) of rain-gage data
71 (Quintana-Segui et al., 2008; Vidal et al., 2010).

72



73

74

Figure 1. Location of the 609 French catchments used in this study.

75

76 Table 1 gives the main characteristics of the data set in terms of catchment area, mean annual
77 streamflow, precipitation and potential evaporation.

78

79 **Table 1. Main characteristics of the data set**

Quantiles	0.05	0.25	0.5	0.75	0.95
Area (km ²)	33	109	270	833	4515
Mean annual precipitation, P (mm/yr)	714	863	1003	1209	1688
Mean annual runoff, Q (mm/yr)	159	272	411	643	1308
Mean annual potential evaporation, PE (mm/yr)	533	616	655	687	782

80

81 **2.2 Rainfall-runoff model and calibration procedure**

82 The GR4J hydrological model (Perrin et al., 2003), a daily lumped continuous model with four free
83 parameters, was used. The GR4J model parameters need to be calibrated (on gaged catchments) or
84 transferred from neighbors (on ungaged catchments). The model has two stores: a production store,
85 which computes effective rainfall, and a routing store combined with a unit hydrograph for water
86 transfer. The input model data are rainfall (P) and potential evaporation (PE) data. We use on top of
87 GR4J, an altitude-distributed snow accounting routine, Cemaneige (Valéry et al., 2014). Here, the two
88 parameters of the routine are not calibrated and we use regionalized values.

89 The objective function used for GR4J optimization is a transformation of the Nash and Sutcliffe (1970)
90 criterion (NS) computed on root square-transformed flows. The transformation proposed by Mathevet
91 et al. (2006) (C2M) is chosen to compute meaningful mean model performance values over the entire
92 catchment set and to avoid the bias introduced by highly negative NS values:

$$C2M = \frac{NS}{2 - NS} \quad \text{Eq. 1}$$

93 Note that this criterion keeps the same zero reference as the Nash-Sutcliffe criterion ($C2M = 0$ when
94 $NS = 0$), has the same optimum (1 means perfect simulation for both criteria), but yields lower positive
95 values compared to the NS criterion (e.g., $C2M = 0.67$ when $NS = 0.80$).

96 The model was calibrated on each catchment over the available data using a steepest descent search
97 algorithm that proved efficient for this model (Edijatno et al., 1999). Hence, for each catchment

98 considered unaged, 608 parameter sets were available as possible donors. Model performance in
99 calibration will be later used as a reference to evaluate efficiency loss due to regionalization.
100 Obviously, the evaluation methods could be applied with other rainfall-runoff models, calibration
101 procedures and objective functions.

102 **2.3 Spatial-proximity-based regionalization method**

103 Since the aim here is not to develop new regionalization methods but only to evaluate them, we used
104 the existing method proposed by Oudin et al. (2008b). This spatial-proximity approach with the output
105 averaging pooling option consists in transferring the GR4J parameter sets calibrated at the n closest
106 neighbor catchments to the target unaged catchment. Then n daily runoff series are simulated on the
107 unaged catchment successively using rainfall and PE data available for this catchment and each
108 parameter set from the neighboring catchments. The final simulated runoff time series for the unaged
109 catchment is computed as the weighted average of the n runoff time series. Here, weights consist in
110 the inverse squared distance between the unaged catchment and the gaged catchment:

$$Q_{unaged\ catchment} = \frac{\sum_{i=1}^n \left(Q_{\theta_i} \times \frac{1}{d_i^2} \right)}{\sum_{i=1}^n \frac{1}{d_i^2}} \quad \text{Eq. 2}$$

111 with Q_{θ_i} the runoff of the unaged catchment simulated with the parameter set θ_i of the neighboring
112 catchment i and d_i the distance between the unaged and the neighboring catchment i .
113 McIntyre et al. (2005) and Oudin et al. (2008b) showed that this method is more coherent than the
114 parameter averaging method since it transfers whole parameter sets from the gaged to the unaged
115 catchments.

116
117 Based on preliminary tests, we chose the following modalities of the regionalization method:

- 118 • $n=10$: we limit the parameter transfer to the 10 closest neighbors;
- 119 • the distance between catchments combines the distance to the outlet and the distance to the
120 centroid (necessary to transfer information between catchments of different sizes), the
121 distance considered in Eq. 2 is thus defined as:

$$d = 0.2 \times d_{\text{outlet}} + 0.8 \times d_{\text{centroid}} \quad \text{Eq. 3}$$

- 122 • inverse distance weighting based on a squared distance.

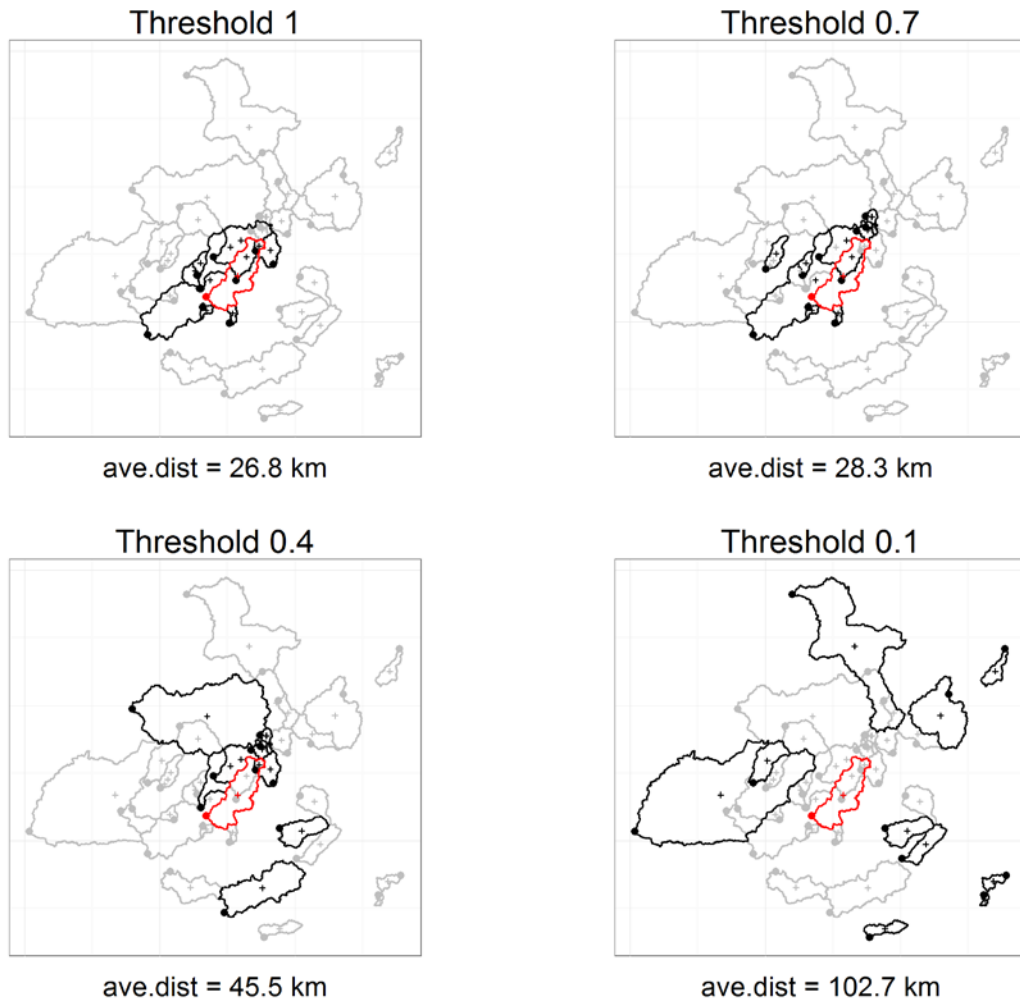
123 **3. Two alternatives for sensitivity analysis of a spatial-proximity-** 124 **based regionalization method**

125 **3.1 Sensitivity analysis based on a random thinning of the hydrometrical** 126 **network (HRand)**

127 The random hydrometrical reduction (HRand) method consists in randomly removing 10%, 20%,
128 30%,..., 90% of the available hydrological network. The number of donor catchments remains the
129 same (10), but they are located on average further from the receiver catchment (though the sampling
130 may keep close neighbors).

131 The thinning procedure proceeds as follows: for each receiver catchment, the neighboring catchments
132 are ranked from the closest to the most distant. For each neighboring catchment, a number x between
133 0 and 1 is drawn randomly and a threshold of acceptance x_{thresh} is considered: if x is larger than the
134 threshold, the neighboring catchment is not used for regionalization. The sensitivity analysis starts with
135 the full network ($x_{thresh}=1$) and moves progressively to a reduced network corresponding to 90%
136 ($x_{thresh}=0.9$), 80%, ... and 10% ($x_{thresh}=0.1$) of the initial network. The selection always yields the 10
137 closest catchments among the remaining donors, but for the reduced network, these donors are
138 located farther on average than for the complete network. The random drawing was done once per
139 catchment. Since the number of catchments is large, we believe that this does not preclude obtaining
140 robust results.

141 This method aims at randomly thinning the network of donor catchments. Figure 2 illustrates an
142 example of the impact of network thinning on the selection of neighboring catchments. It shows that
143 although the neighboring catchments are located farther away on average as the thinning becomes
144 stronger, some close neighbors can still remain in the selection, even at high thinning rates.



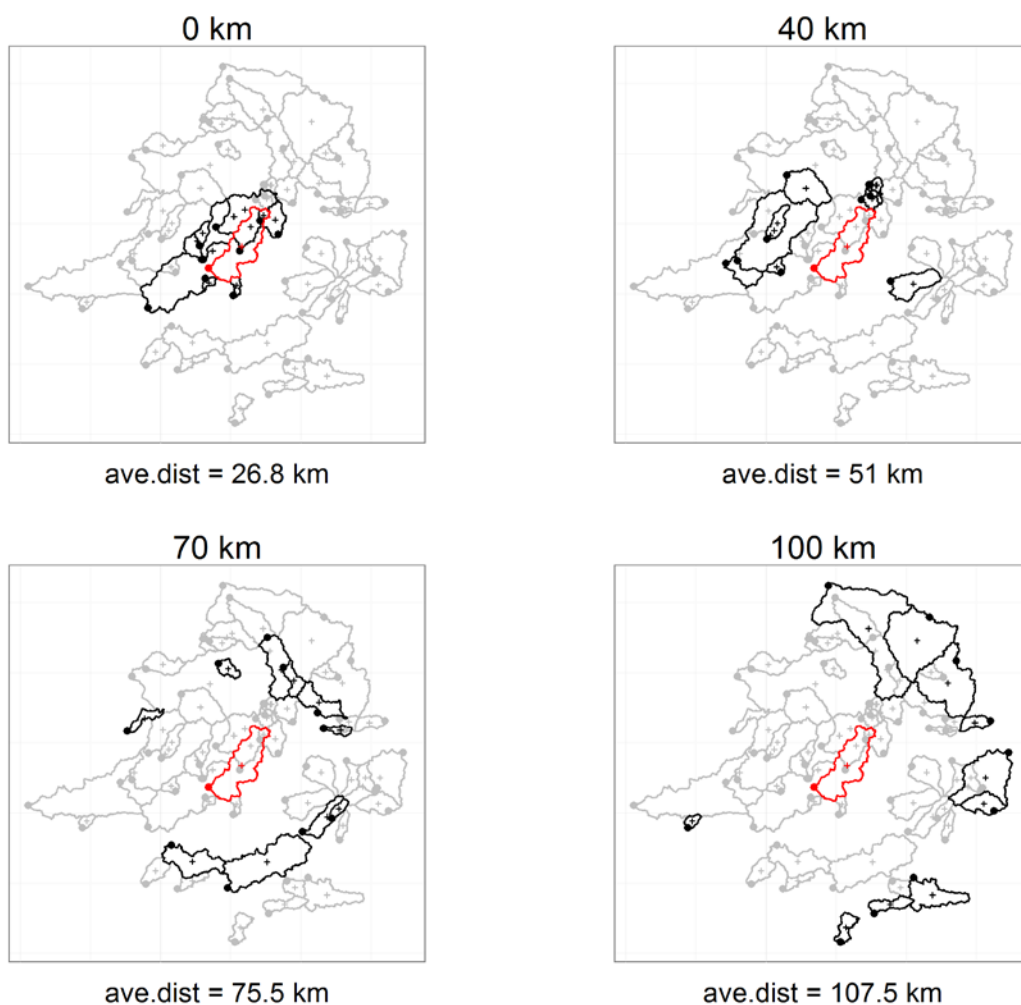
145

146 **Figure 2. Illustration of the selection of neighboring catchments with the full network**
147 **(Threshold = 1) and when applying the procedure of random reduction of the hydrometric**
148 **network (HRand) for different thinning levels (Thresholds = 0.7, 0.4 and 0.1). In red, the**
149 **ungaged (receiver) catchment, in black the selected neighboring (donor) catchments, and in**
150 **grey the complete set of neighboring catchments. *ave.dist* is the average distance of the 10**
151 **donor catchments.**

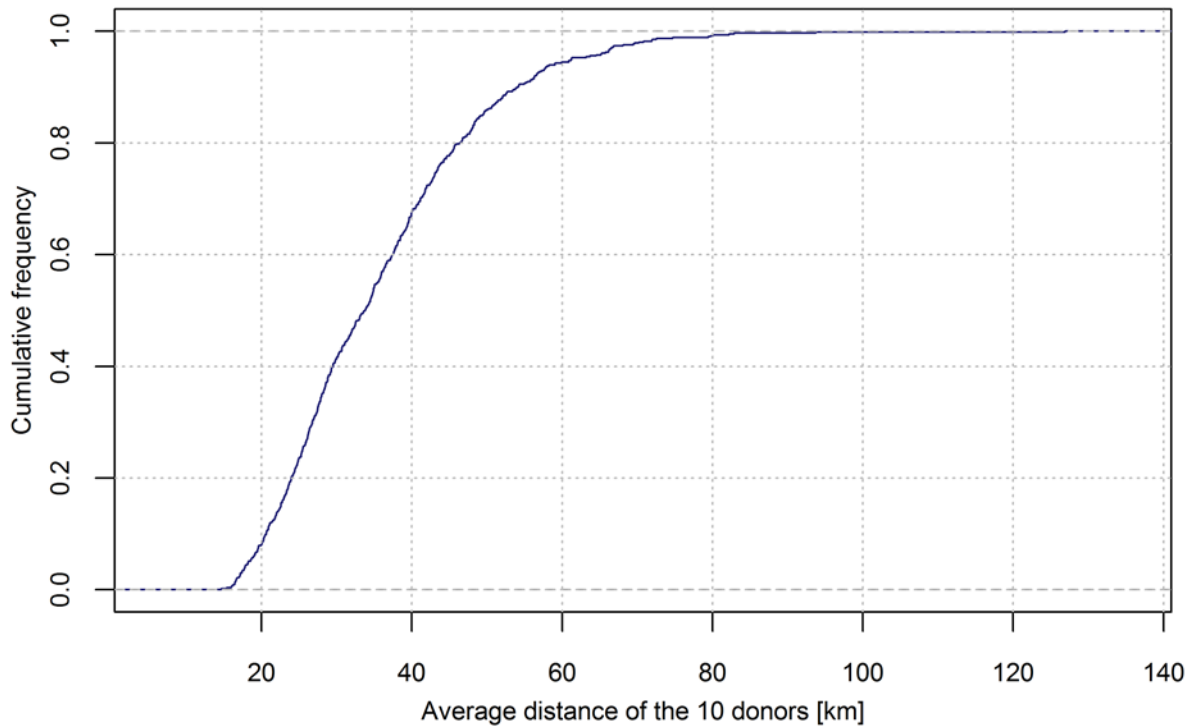
152 **3.2 Sensitivity analysis based on the hydrometrical desert (HDes) method**

153 The hydrometrical desert method (HDes) first proposed by Boldetti (2012) consists in progressively
154 excluding the closest donor catchments: the parameters are transferred from neighbors that are
155 increasingly distant from the ungaged target catchment by setting a lower limit below which neighbors
156 are ignored (Figure 3). Here, we propose a test to analyze the sensitivity of the regionalization method

157 when information has to be transferred from progressively farther distances: we tested the following
158 threshold distances: 0 (no distance limit), 10, 20, 30, ..., 100, 150 and 200 km.
159 To measure the potential impact of such exclusion thresholds, we can compare them to the
160 distribution of distances of the ten closest catchments for the 609 catchments of the dataset. Figure 4
161 shows that quantiles 10% and 90% of this distribution are of the order of 20 and 50 km, and the
162 minimum value is around 15 km. It confirms the relatively high density of the French hydrometrical
163 network. Then, the choice of the threshold distances for the nearest neighbor will clearly impact the
164 choice of donor catchments.



165
166 **Figure 3. Illustration of the selection of neighboring catchments with the full network (distance**
167 **= 0 km) and when applying the procedure of the hydrometrical desert (HDes) method for**
168 **different limit distances (40, 70, 100 km). In red, the ungaged (receiver) catchment, in black the**
169 **selected neighboring (donor) catchments, and in grey the complete set of neighboring**
170 **catchments. ave.dist is the average distance of the 10 donor catchments.**



171
172 **Figure 4. Distribution of the average distance of the 10 closest donors, for the 609 catchments.**

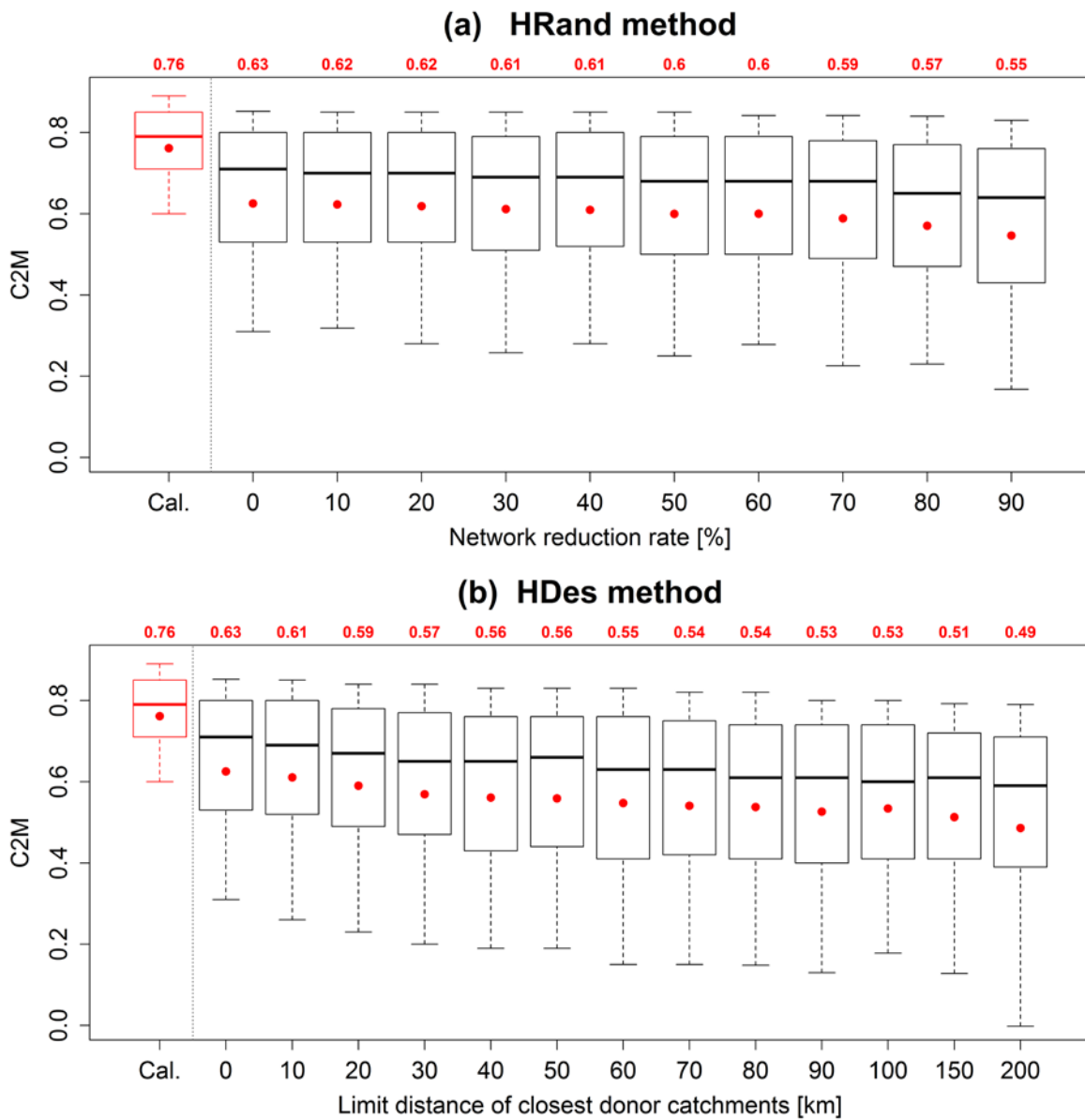
173 **3.3 Comparison of the two sensitivity analysis methods**

174 The two sensitivity approaches HRand and HDes were applied to the regionalization of the GR4J
175 model on the 609 catchments. Each catchment was successively considered ungauged. The
176 regionalization approach was applied in each case, and model performance was evaluated using the
177 C2M criterion. Figure 5 shows the performance distributions over the full catchment sample. As
178 expected, the performance of the regionalized model, even with the full donor catchment set, is much
179 lower than the calibrated model (see Oudin et al., 2008a).

180 The most obvious effect of applying the two sensitivity analysis methods is a clear decreasing trend in
181 the efficiency of regionalization. The second important result is that the hydrometrical desert method
182 (HDes) provides a more abrupt decrease than the random thinning (HRand) method.

183 The reason seems to lie in the fact that the HRand method allows situations where the first donor is
184 quite close to the receiver (and potentially more similar and a better donor), as we can see in Figure 6.
185 Because it forces the exclusion of the closest donors, the hydrological desert appears more

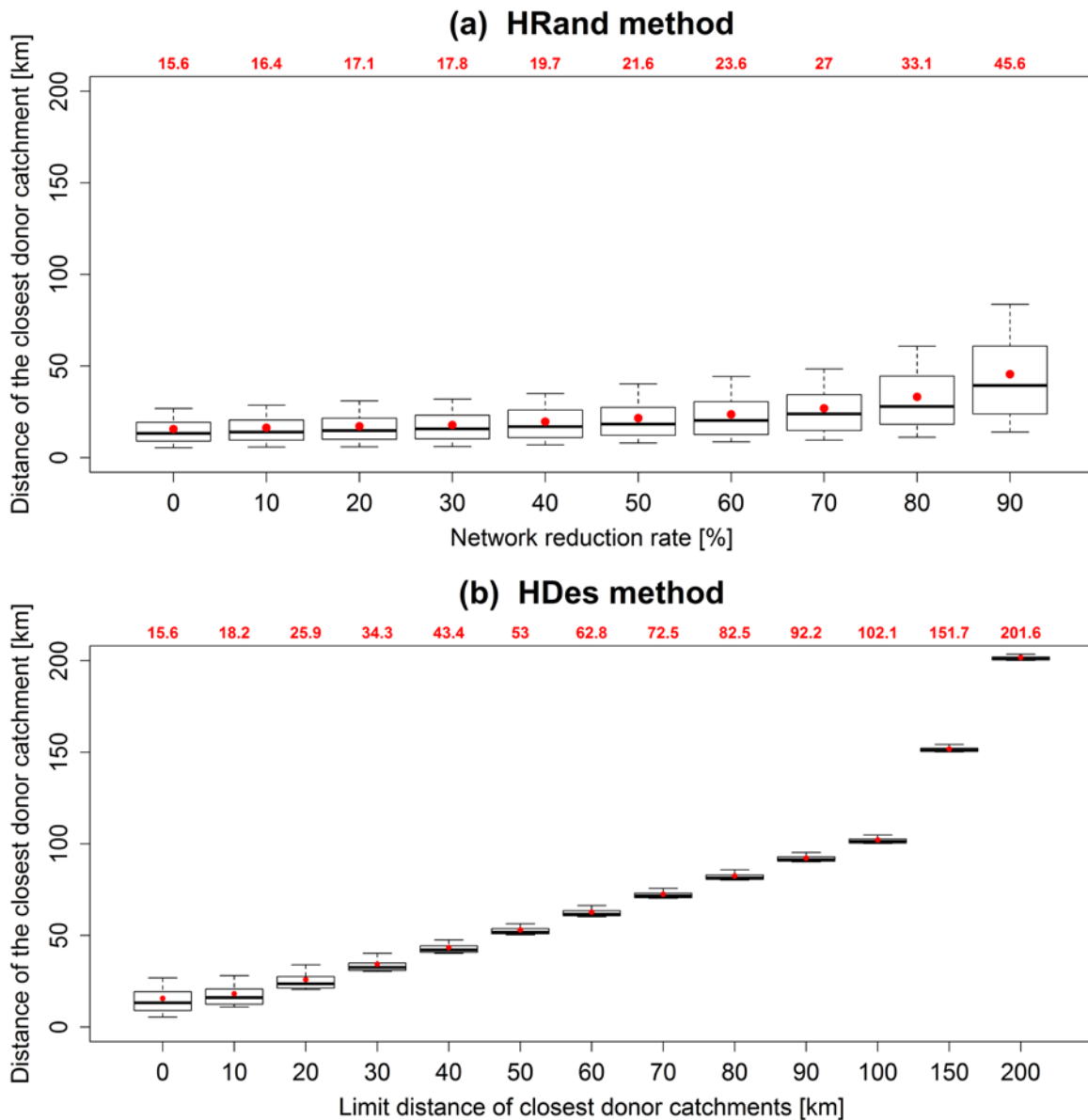
186 conservative.



187

188 **Figure 5. Distributions of performance of the calibrated and regionalized GR4J model on the**
189 **609 catchments, showing the impact of the two methods of robustness evaluation (a: random**
190 **hydrometrical reduction method - HRand; b: the hydrometrical desert method - HDes).**
191 **Calibration results (left) are used as a reference. Boxplots show the 10, 25, 50, 75 and 90**
192 **percentiles of the distribution from bottom to top. Mean performance is indicated by a dot and**
193 **the corresponding value is shown on top of the graph.**

194



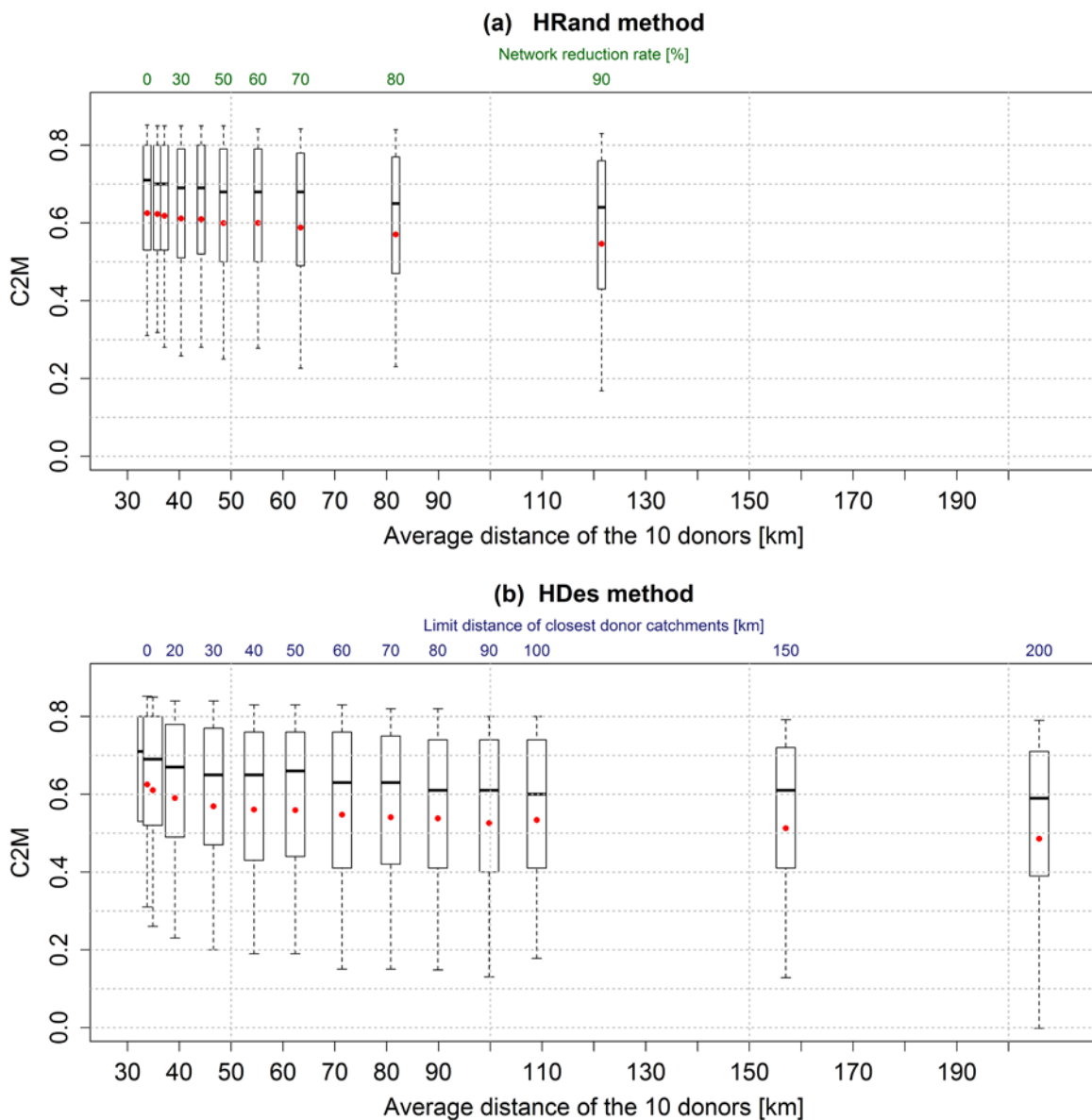
195

196 **Figure 6. Distributions of the distance of the closest donor catchments for the two methods**
197 **used to evaluate robustness of the regionalization method (a: random hydrometrical reduction**
198 **method - HRand; b: the hydrometrical desert method - HDes). Boxplots show the 10, 25, 50, 75**
199 **and 90 percentiles of the distribution from bottom to top. Mean performance or mean distance**
200 **is indicated by a dot and the corresponding value is shown on top of graphs a and b**
201 **respectively.**

202

203 However, the comparison between the two methods seems is not straightforward due to different x-
204 axis. To make HRand and HDes methods comparable despite the different units (network reduction
205 rate for HRand and limit distance of closest neighbors for HDes), we had to find a common x-axis for

206 both methods. We chose to take as common denominator the evolution of the average distance of the
207 10 donor catchments, which can be obtained for both methods. Then, we can take as a new x-axis
208 (common to both methods) the average distance of 10 donor catchments. This will be associated with
209 the values of the network reduction rate for HRand, and the limit distance of donor catchments for
210 HDes. These results are presented in Figure 7. Thus, we can confirm with these graphics what was
211 noted above. Actually, we observe a loss of performance, a little more abrupt for HDes method than
212 for HRand method, particularly for the lowest average distances of the ten donors.



213
214 **Figure 7. Distributions of performance of the regionalized GR4J model on the 609 catchments,**
215 **according to the average distance of the 10 donor catchments for the two methods of**
216 **robustness evaluation (a: random hydrometrical reduction method - HRand; b: the**
217 **hydrometrical desert method - HDes). Corresponding values of network reduction rate for**

218 **HRand method and corresponding values of limit distance for HDes method are indicated on**
219 **top of the graphs. Boxplots show the 10, 25, 50, 75 and 90 percentiles of the distribution from**
220 **bottom to top.**

221 **4. Conclusion**

222 In this note, we proposed and compared two robustness evaluation methods: the random thinning
223 method (HRand) and the hydrometrical desert method (HDes). Although both methods allow analyzing
224 the sensitivity of regionalization methods to decreasing hydrometric data availability, we observe that
225 the HDes method is the most conservative, since it produces the fastest decrease in model efficiency.
226 From a hydrological "crash test" perspective, as discussed by Andréassian et al. (2009), we would
227 recommend using the HDes method, which will provide a more realistic (although a more pessimistic
228 view) of spatial-proximity-based regionalization efficiency. A further reason for this is that, for a
229 practical application on a given ungauged catchment, it is always easier to compute the distance
230 between this catchment and its closest neighbor than to assess the regional density of catchments.
231 Once this distance is known, Figure 5-b can be used to give an indication of the expected value of
232 GR4J regionalized efficiency, with an uncertainty interval on this expected value.

233 **5. Acknowledgements**

234 The authors wish to thank the different institutions that allowed us to build the large catchment sets on
235 which this paper is based: MétéoFrance for meteorological data and SCHAPI for hydrometrical data.
236 ONEMA provided financial support for the first author.

237 **6. References**

- 238 Andréassian, V. et al., 2009. HESS Opinions 'Crash tests for a standardized
239 evaluation of hydrological models'. *Hydrology and Earth System Sciences*,
240 13(10): 1757-1764.
- 241 Andréassian, V., Perrin, C., Parent, E., Bardossy, A., 2010. The Court of Miracles of
242 Hydrology: can failure stories contribute to hydrological science? *Hydrological
243 Sciences Journal-Journal Des Sciences Hydrologiques*, 55(6): 849-856.
- 244 Boldetti, G., 2012. Estimation of the parameters of hydrological models on ungauged
245 basins: a comparison of direct and indirect approaches. PhD Thesis,
246 AgroParisTech - Irstea (Antony), 207 pp.
- 247 Edijatno, Nascimento, N.D., Yang, X.L., Makhlof, Z., Michel, C., 1999. GR3J: a daily
248 watershed model with three free parameters. *Hydrological Sciences Journal-
249 Journal Des Sciences Hydrologiques*, 44(2): 263-277.

- 250 Gottschalk, L., Jensen, J.L., Lundquist, D., Solantie, R., Tollan, A., 1979. Hydrologic
251 regions in the Nordic countries. *Nordic Hydrology*, 10(5): 273-286.
- 252 Hrachowitz, M. et al., 2013. A decade of Predictions in Ungauged Basins (PUB)a
253 review. *Hydrological Sciences Journal-Journal Des Sciences Hydrologiques*,
254 58(6): 1198-1255.
- 255 James, L.D., 1972. Hydrologic modeling, parameter estimation, and watershed
256 characteristics. *Journal of Hydrology*, 17(4): 283-307.
- 257 Lebecherel, L., Andreassian, V., Perrin, C., 2013. On regionalizing the Turc-
258 Mezentsev water balance formula. *Water Resources Research*, 49(11): 7508-
259 7517.
- 260 Magette, W.L., Shanholtz, V.O., Carr, J.C., 1976. Estimating selected parameters for
261 Kentucky watershed model from waterched characteristics. *Water Resources*
262 *Research*, 12(3): 472-476.
- 263 Mathevet, T., Michel, C., Andréassian, V., Perrin, C., 2006. A bounded version of the
264 Nash-Sutcliffe criterion for better model assessment on large sets of basins.
265 *IAHS-AISH Publication(307)*: 211-219.
- 266 McIntyre, N., Lee, H., Wheeler, H., Young, A., Wagener, T., 2005. Ensemble
267 predictions of runoff in ungauged catchments. *Water Resour. Res.*, 41:
268 W12434, doi:10.1029/2005WR004289.
- 269 Nash, J.E., Sutcliffe, J.V., 1970. River flow forecasting through conceptual models
270 part I - A discussion of principles. *Journal of Hydrology*, 10(3): 282-290.
- 271 Oudin, L., Andreassian, V., Perrin, C., Michel, C., Le Moine, N., 2008a. Spatial
272 proximity, physical similarity, regression and unged catchments: A
273 comparison of regionalization approaches based on 913 French catchments.
274 *Water Resources Research*, 44(3).
- 275 Oudin, L., Andréassian, V., Perrin, C., Michel, C., Le Moine, N., 2008b. Spatial
276 proximity, physical similarity, regression and unged catchments: a
277 comparison of regionalization approaches based on 913 French catchments.
278 *Water Resources Research*, 44: W03413, doi:10.1029/2007WR006240.
- 279 Oudin, L., Kay, A., Andréassian, V., Perrin, C., 2010. Are seemingly physically similar
280 catchments truly hydrologically similar? *Water Resources Research*, 46(11):
281 W11558.
- 282 Perrin, C., Michel, C., Andréassian, V., 2003. Improvement of a parsimonious model
283 for streamflow simulation. *Journal of Hydrology*, 279(1-4): 275-289.
- 284 Quintana-Segui, P. et al., 2008. Analysis of near-surface atmospheric variables:
285 Validation of the SAFRAN analysis over France. *Journal of Applied*
286 *Meteorology and Climatology*, 47(1): 92-107.
- 287 Valéry, A., Andréassian, V., Perrin, C., 2014. 'As simple as possible but not simpler':
288 What is useful in a temperature-based snow-accounting routine? Part 2 –
289 Sensitivity analysis of the Cemaneige snow accounting routine on 380
290 catchments. *Journal of Hydrology*, 517: 1176-1187.
- 291 Vidal, J.P., Martin, E., Franchisteguy, L., Baillon, M., Soubeyroux, J.M., 2010. A 50-
292 year high-resolution atmospheric reanalysis over France with the Safran
293 system. *International Journal of Climatology*, 30(11): 1627-1644.
- 294
295