Tailor-made spatial patterns for parameters through regionalization methods combination: improvement of predictions in ungauged basins

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Abstract

Calibration of spatially distributed models is a big issue given their over-parameterization. Three usual regionalization method can be distinguished which are transposition, prescription and constraint. This paper proposes a strategy where the three methods are combined to provide several spatial patterns according to the model parameters. On the one hand, insensitive and equifinal parameters are prescribed uniformly while "physical" parameters are prescribed at the mesh scale. On the other hand, parameters linked with a proxy runoff signature are constrained over each sub-basin and the remaining parameters are transposed with a physio-climatic pattern constructed over the calibration sub-basins.

The above tailor-made pattern regionalization is applied at the daily time step over two large French catchments, the Loire catchment at Gien covering 35,707 km^2 and the Durance catchment at Cadarache covering 11,738

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km^2. It is then evaluated and compared to a single regionalization method over dozens of validation stations, treated as ungauged during the parameter regionalization. For that purpose, simulated and observed streamflows are compared in light of four runoff signatures: daily runoff, daily regime, flood and low flow. The results show that the tailor-made patterns succeed to enhance significantly almost all the signatures. The enhancement appears for the least well-modelled stations which tends to guarantee a minimum performance in the ungauged context.
Keywords: parameter spatial variability, distributed hydrological modelling, regionalization, ungauged basins

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1. Introduction

Spatially distributed hydrological models allow for (i) spatially distributed climatic inputs, (ii) spatially distributed model parameters, (iii) ungauged simulations and (iv) upstream-downstream consistency. With the increasing availability of spatial data and the improvements in computational power, this type of model represents a real potential for hydrological modelling. The Distributed Model Intercomparison Project (Smith et al., 2004; Reed et al., 2004; Smith et al., 2012, 2013) investigated the capabilities of existing distributed hydrologic models. However, this project did not provide any recommandation about parameter estimation schemes. The strategy is not as well defined as for lumped models whose parameters usually follow from calibration over the observed outlet streamflow. Indeed, in distributed models, each spatial unit comprises one set of parameters while most of these units are ungauged (Sivapalan et al., 2003; Hrachowitz et al., 2013). Distributed models therefore suffer from overparameterization and equifinality (Beven and Hornberger, 1982; Beven, 2001). To overcome these difficulties, one can rests upon three regionalization methods: (i) transposition, (ii) prescription and (iii) constraint.

Transposition consists in grouping the N_u spatial units into N_r regions, each of them comprising one set of N_p parameters calibrated over gauged discharge stations. The region delineation can follows from physio-climatic similarity (Beldring et al., 2003; Kumar et al., 2013) or gauged network (Andersen et al., 2001; Feyen et al., 2008; Khakbaz et al., 2012; De Lavenne et al., 2016). This method reduces the dimensionality of the optimization problem from $N_u \times N_p$ to $N_r \times N_p$ free parameters.

Prescription is based on *a priori* or empirical relationships between catchment characteristics and model parameters (Koren et al., 2000; Twarakavi et al., 2009). That way, Andersen et al. (2001) and Khakbaz et al. (2012) tested an uncalibrated model with distributed parameters directly estimated from field data, literature and previous studies. However, within the framework of distributed modelling, prescription is pretty often enhanced with transposition to reduce the gap between the modelling and the physical expertise (Francés et al., 2007; Smith et al., 2013). Francés et al. (2007); Pokhrel and Gupta (2010); Samaniego et al. (2010) and Khakbaz et al. (2012) first prescribed spatial parameter fields from catchment characteristics and then adjusted them through transposition of uniform correction coefficients (*i.e.* calibration of one region) called superparameters or global parameters calibrated over the observed outlet streamflow. For instance, Pokhrel and Gupta (2010) defined three superparameters per model parameter: a multiplying, an additive and a power coefficients involving the calibration of 3 $\times N_p$ superparameters. The two steps can also be inverted by first calibrating the model parameters uniformly and then modifying them with spatial fields estimated from catchment characteristics without further calibration (Koren et al., 2004; Khakbaz et al., 2012). To a more limited extent, prescription can also be a tool to calibrate the model parameters to be transposed. As proposed by Ajami et al. (2004), each region of the catchment can be calibrated over its observed outlet streamflow by temporarily prescribing the downstream parameters with catchment characteristics.

Finally, constraint relies on proxy data, *i.e.* on hydrological signature estimated without any streamflow measure that can give a clue about the catchment hydrological behaviour. Constraint consists in using these proxy data instead of streamflow time series as a constraint in the calibration process. Madsen (2003) appraised a multi-objective calibration of a distributed model over observed outlet streamflow and groundwater levels measured at 17 interior wells. Instead of groundwater data, Khan et al. (2011) and Silvestro et al. (2015) proposed to calibrate the distributed model parameters with remote-sensing data. Along with streamflow observations, Khan et al. (2011) used satellite-derived flood maps to calibrate a module of a distributed model designed for flood, while Silvestro et al. (2015) proved the usefulness of land-surface temperature and surface soil moisture satellite observations to reduce parameter equifinality.

This paper aims to advance one step further and proposes to combine the three regionalization methods. The model parameters are spatialised with one of the three methods according to their characteristics and hydrological meaning. It follows from this multi-method, four parameter spatial patterns: a uniform, a hydrological mesh and two intermediate patterns. The method is applied over two French mesoscale catchments, the Loire at Gien and the Durance at Cadarache, for the 1980-2012 period. Thanks to a 50/50 spatial split-sample test, the performance of the tailor-made patterns is assessed over pseudo-ungauged stations and compared with that of a unique transposition scheme.

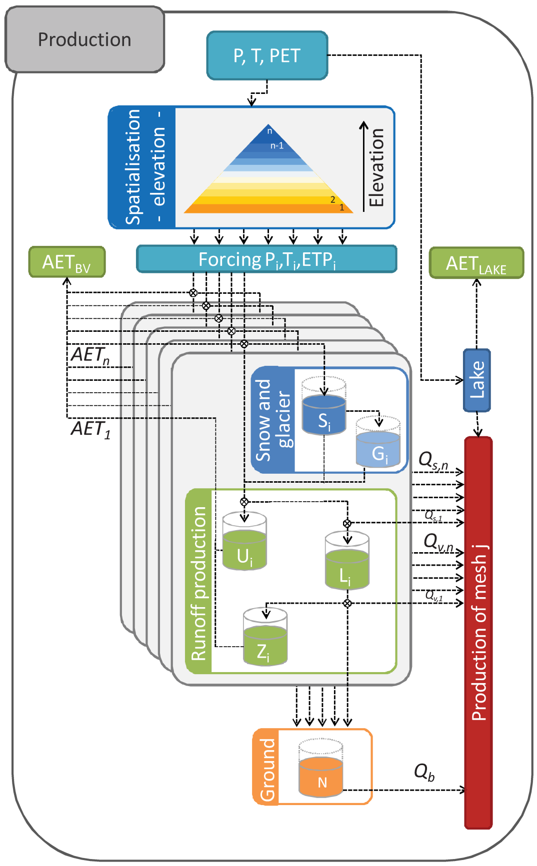
The paper is organised as follows. Section 2 presents the distributed rainfall-runoff model and the evaluation criteria. Section 3 introduces the data set. Section 4 details the parameter spatial patterns, Section 5 discusses the results and section 6 provides conclusions and perspectives.

2. Modelling

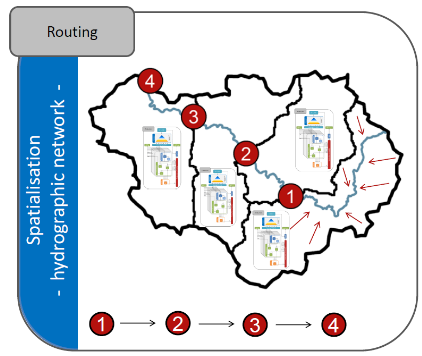
2.1. Distributed rainfall-runoff model

The spatially distributed rainfall-runoff model used for this study is the conceptual MORDOR-TS model presented in Rouhier et al. (2017). The catchment is divided into hydrological meshes, each of them attributed to one set of parameters and connected to each other according to the hydrographic network. At each daily time step, the continuous model (i) calculates the water production of each mesh independently and (ii) routes all production to the simulation points, which can be any mesh outlet.

The production module aims at quantifying the exchanges between different components of the hydrologic cycle. Based on precipitation and air temperature data, six conceptual interconnected storage components evolve and supply the hydrographic network as described by Figure 1a. The ver-



(a) Production structure



(b) Routing scheme

Figure 1: Overview of the MORDOR-TS distributed model in its entire formulation: (a) production module used for each hydrological mesh and (b) routing scheme with intra-mesh and inter-meshes propagation.

tical spatialisation of the hydrological meshes into elevation zones, designed for mountainous regions, is only activated for the Durance catchment. A complete description of the production module can be found in Garavaglia et al. (2017).

Since the production module is applied to every hydrological mesh, as many runoff contributions are estimated. They are propagated to the simulation points through the hydrographic network as described in Figure 1b. The routing module combines the intra-mesh and inter-mesh transfers by means of a formulation based on the 1D diffusive wave model, with celerity and diffusion independent of runoff (Hayami, 1951; Litrico and Georges, 1999).

In its entire formulation, MORDOR-TS has 22 free parameters. In this study, a simplified version is adopted with only 12 and 16 free parameters for the Loire and the Durance catchments, respectively. Details about the parameters are given in Appendix A.

2.2. Calibration and validation criteria

We expect the model to provide a reliable hydrological behaviour for the catchment. Therefore, it has to reproduce faithfully the various runoff signatures, which reflect the different dynamics of its hydrology. The observed and simulated streamflows are then compared on the basis of four numerical criteria. The Kling-Gupta Efficiency (KGE, Gupta et al. (2009)) is calculated over four streamflow signatures: (i) the entire time-series (KGE daily runoff), which is the result of all the processes, (ii) the inter-annual daily regime (KGE daily regime), which reflects the interaction between water and energy availability as well as catchment storage, (iii) the average of the monthly empirical cumulative distributions weighted by monthly runoff (KGE flood), which focuses on floods produced by highly dynamic interactions and (iv) flow recessions during low flow period (KGE low flow), which result from long-term processes (Blöschl et al., 2013; Garavaglia et al., 2017). These four KGE criteria are used both for calibration and spatial validation.

For parameter calibration, the four criteria are implemented in the multi-objective genetic algorithm caRamel[1] (Rouhier et al., 2017). Systematically, a first 1-year period is used for model spin-up. After 5000 runs, the algorithm provides a 4D Pareto frontier (Yapo et al., 1998) in which we select the set which minimises the Euclidian distance calculated on ranks.

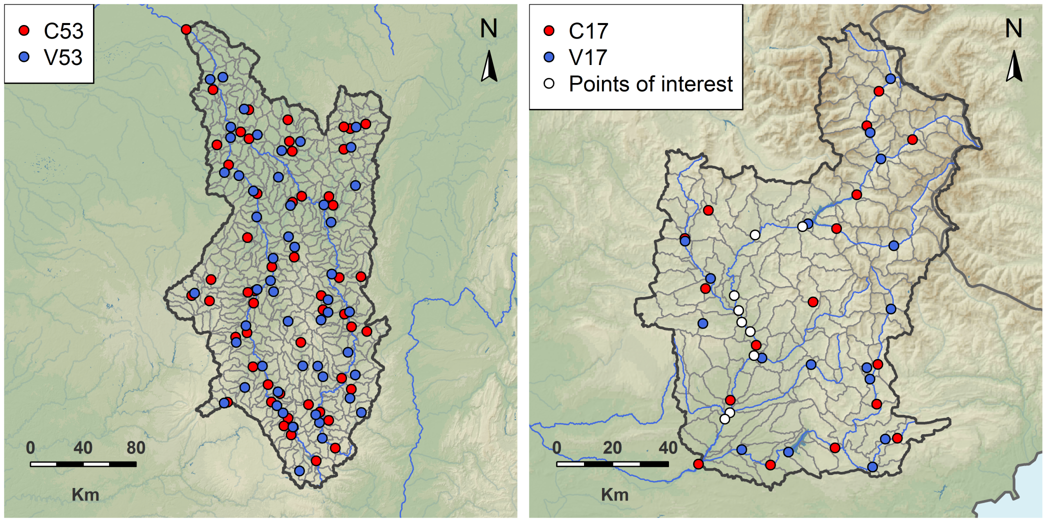
3. Data set

3.1. Study area

The tailor-made method is assessed over two large French catchments: the Loire basin at Gien (2a) and the Durance basin at Cadarache (2b). The Loire catchment at Gien extending over 35,707 km^2 is located in the central part of France. Its elevation ranges from 118 to 1838 m.a.s.l. at which the summits of the Massif Central peak. It is a mainly pluvial catchment with a median elevation of 417 m.a.s.l. The Durance catchment at Cadarache extending over 11,738 km^2 is located in the Alps in south-east part of France. Its elevation ranges from 247 to 4102 m.a.s.l. at which the Barre des Écrins peaks. With 60% of the basin above 1000 m.a.s.l., the upper part is nival while the lower part is nivo-pluvial. On top of that, the Durance catchment is subject to karstic systems. In the south-west, a karstic formation supplies the Fontaine de Vaucluse. Likewise, in the south-east of the catchment, very permeable limestone rocks supply the Siagne basin.

To apply the distributed MORDOR-TS model, the Loire and the Durance catchments are discretised into 387 and 133 hydrological meshes, respectively.

[1]https://cran.r-project.org/web/packages/caRamel/index.html



(a) Loire catchment at Gien (b) Durance catchment at Cadarache

Figure 2: The two catchments selected for the present study : (a) the Loire catchment at Gien with its 106 stream gauges and (b) the Durance catchment at Cadarache with its 34 stream gauges and its 9 points of interest. The stream gauges belonging to the calibration sample are indicated in red while those belonging to the validation sample are in blue. The hydrological meshes are represented by the grey units.

They are represented by the grey units in Figure 2. These hydrological mesh patterns arise from a 100-m DEM with a mesh target area of 100-km^2.

3.2. Climatic inputs data

Climate data follow from a method inspired by SPAZM (Gottardi et al., 2012). They are obtained by a statistical reanalysis based on ground network data, reliefs and weather patterns (Garavaglia et al., 2010). Over the Loire catchment at Gien (resp. Durance catchment at Cadarache), the precipitation and air temperature fields are built from 146 (resp. 115) rain gauges and more than 100 (resp. more than 70) temperature gauges. They are available for the 1948-2012 period at 1-day and 1-km^2 resolution. For this study, we only used the data from 1 September 1980 to 31 August 2012. This recent 32-year period was chosen in order to maximize the number of streamflow data and the reliability.

3.3. Streamflow data

Daily streamflow time series are collected from the databases of EDF and French national environmental agencies. They are selected according to observation time availability over the 1948-2012 period, drainage area, quality and temporal homogeneity (Bois, 1987). Within the Loire catchment, the 106 time series selected have an average observation period of about 22 hydrologic years per station with a minimum of 7 and a maximum of 32 years. The stations' location is given in Figure 2a (red and blue points). Their drainage areas range from 100 to 35 707 km^2 with an average of 2844 km^2. With regards to runoff, it ranges from 136 to 1057 mm/year. Among these 106 catchments, the inter-annual precipitation varies between 729 and 1495 mm/year. As for the humidity index, defined as the inter-annual ratio between precipitation and potential evapotranspiration $\frac{P}{PET}$ (Andréassian and Perrin, 2012), it ranges from 1 to 2,7 with an average of 1,5.

Within the Durance catchment, 34 time series are selected besides 9 ungauged points of interest for EDF. In Figure 2b, the gauged stations' location are represented by the red and blue points, while the 9 ungauged points are the white points. The 34 time series have an average observation period of about 22 hydrologic years per station with a minimum of 6 and a maximum of 32 years. Their drainage areas range from 94 to 11 738 km^2 with an average of 1275 km^2. The inter-annual runoff and precipitation are of the same order of magnitude as over the Loire. Among the 34 catchments, runoff ranges from 162 to 881 mm/year and precipitation from 898 to 1321 mm/year. The Durance catchment is more humid than the Loire with mean humidity index of 2, ranging from 1,2 to 3.

As the model deals with natural hydrology, the influence of the dams within the two catchments was accounted for by adding their storage variation to the discharge data.

3.4. Spatial split-sample test

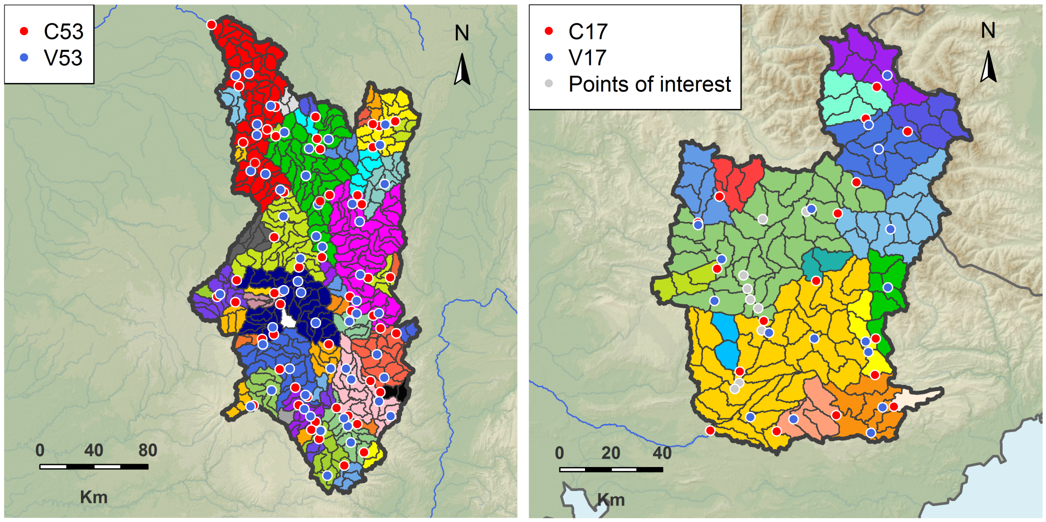
The model parameterisation is assessed over pseudo-ungauged stations through a 50/50 spatial split-sample test introduced in Rouhier et al. (2017). Over each catchment, the streamflow data are split into two similar parts: a calibration and a validation station sample. The two samples are equal in number of stations, spatially homogeneous and as similar as possible in terms of temporal, climatic and physiographic characteristics. Hereafter, the calibration and the validation samples of the Loire catchment of 53 gauges each are referred to as « C53 » and « V53 ». Similarly, those of the Durance catchment of 17 gauges each are referred to as « C17 » and « V17 ». The 9 ungauged stations are not included in any sample since no streamflow data are available. They are only used to define the sub-basin patterns. In Figure 2, the calibration stream gauges are represented by the red points and the validation stream gauges by the blue points. The calibration stations are the gauged stations whose streamflows are used to calibrate the model parameters. On the contrary, the validation stations are pseudo-ungauged stations : their streamflow time series are never used to calibrate or even estimate the model parameters but are used *a posteriori* to evaluate the parameter regionalization.

It should be noted that the validation scheme is not purely spatial. Given that the streamflow observation periods of the calibration and validation stations are not systematically identical, the validation scheme lies between spatial and spatiotemporal depending on the periods' intersection (Patil and Stieglitz, 2015).

4. Parameter spatial patterns

4.1. From a unique transposition pattern...

In a first time, the model parameters were all spatialised at the same resolution: a spatial pattern based on the calibration sub-basins. This pattern, introduced in Rouhier et al. (2017), consists in defining a new sub-basin every time we meet a calibration station while continuing down the hydrographic network. Every sub-basin, whose outlet is therefore a calibration station, corresponds with one set of parameters, similar to the work of Feyen et al. (2008) and De Lavenne et al. (2016). For a given sub-basin, the parameters are calibrated on the outlet by injecting the streamflow of its upstream nested calibration stations. For reasons of upstream-downstream streamflow availability, two sub-basins of the Loire catchment are merged with the downstream sub-basins. Thus, the Loire catchment is divided into 51 sub-basins while the Durance catchment comprises 17 sub-basins. Figure 3 presents these patterns. Each colour stands for one calibration sub-basin, *i.e.* one set of parameters.



(a) Loire catchment at Gien (b) Durance catchment at Cadarache

Figure 3: Calibration sub-basin patterns used initially to transpose the

4.2. ... to tailor-made patterns

The objective was then to improve the spatialisation by adapting the spatial pattern and the regionalization method to the several parameters. To do so, we conducted an incremental experimental framework based on trial and error. This framework which does not pretend to be exhaustive, rely on a large feedback of the model and on an exhaustive sensitivity analysis of the model parameters (Michon and Castaings, 2017b,a). After dozens of experiments we propose four spatial patterns combined with the three regionalization methods, as shown in Figure 4. The details about these four spatial patterns are presented in the following sections.

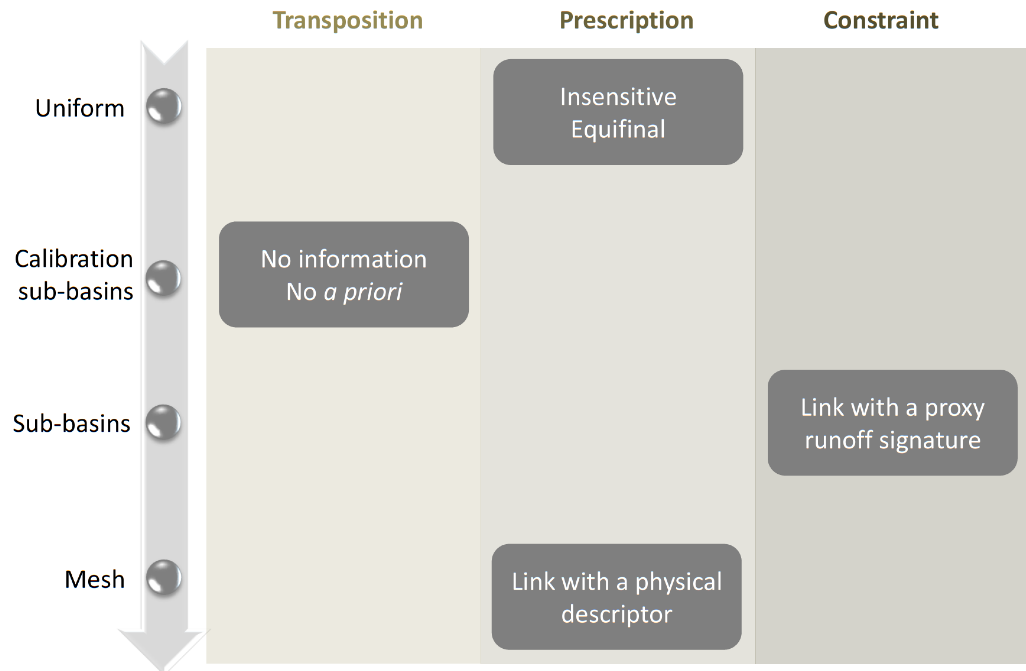


Figure 4: Overview of the tailor-made method which combines three regionalization methods to provide four spatial patterns according to the characteristics of the model parameters.

4.2.1. The uniform prescription pattern for insensitive and equifinal parameters

A sensitivity analysis of the MORDOR model has been conducted over several catchments with a uniform set of parameters (Michon and Castaings, 2017a,b). Figure 5 shows the results obtained for the discharge station of Gien in our 12-parameter configuration as regards KGE daily runoff. This graphical representation is inspired by the FANOVA graphs of Muehlenstaedt et al. (2012). The radius of the red disc reprensents the value of the first-order sensitivity S_i of the parameter (Sobol, 1993), while the radius of the blue disc gives the total sensitivity S_{Ti} of the parameter (Homma and Saltelli, 1996), *i.e.* first-order sensitivity plus its sensitivity in interaction with the other parameters. The red disc is superimposed on the blue disc since the first-order sensitivity is always lower than the total sensitivity. The larger the red disc, the greater the first-order sensitivity. The larger the differences between the blue and the red discs, the greater the interactions with the other parameters. The distribution of these interactions are represented by the blue lines between the parameters. The greater the thickness of the line, the greater the interaction TII_{ij} between the two parameters (Liu and Owen, 2006). Figure 5 therefore informs us that five parameters are not sensitive at all: the snow parameters (kf and lts), the parameter generating the delayed flows (evl), the diffusivity (Dif) and the celerity (Cel). This outcome is confirmed by the sensitivities distributions over the 106 discharge stations of the Loire catchment shown in Figure 6. The same outcome is obtained for the other three signatures : KGE daily regime, KGE flood and KGE low flow. Consequently, these insensitive parameters are prescribed uniformly at their default value, except for celerity whose low sensitivity was due to irrelevant bounds, corrected thereafter. This uniform prescription does not concern the snow parameters of the Durance catchment whose nival to nivo-pluvial regime requires their spatialisation, neither the parameter generating the delayed flows which is sensitive over this catchment.

On top of that, the sensitivity analysis pointed out the equifinality between the two parameters governing the groundwater reservoir draining (evn and lkn). One of the two is thus prescribed uniformly at its default value while the other is left free.

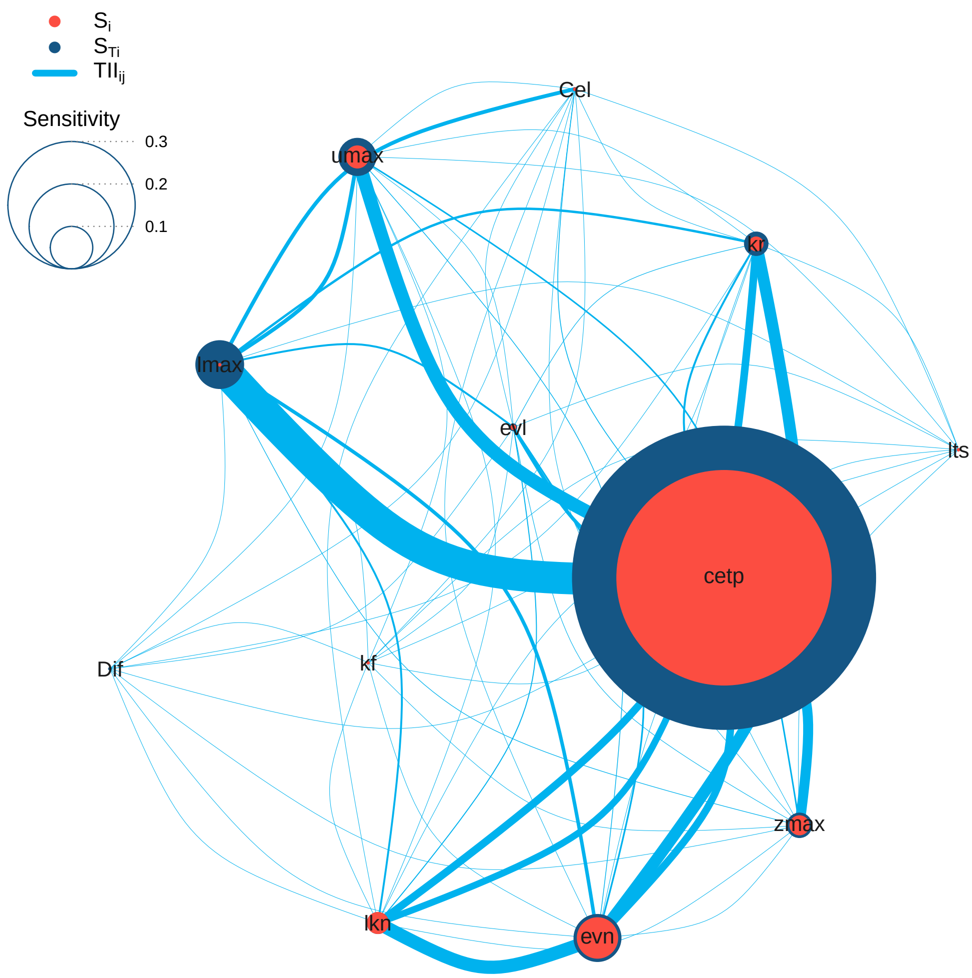


Figure 5: FANOVA graph of parameter sensitivity as regards the KGE daily runoff of Gien

4.2.2. The hydrological mesh prescription pattern for "physical" parameters

The potential evapotranspiration (PET), or atmospheric evaporative demand, is affected by vegetation and crop type, variety and development stage.

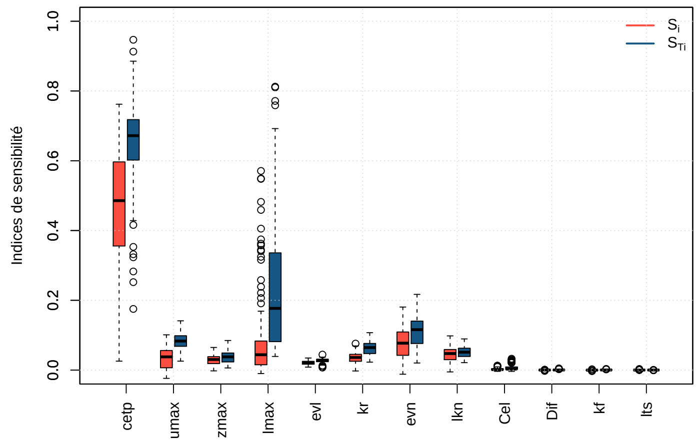
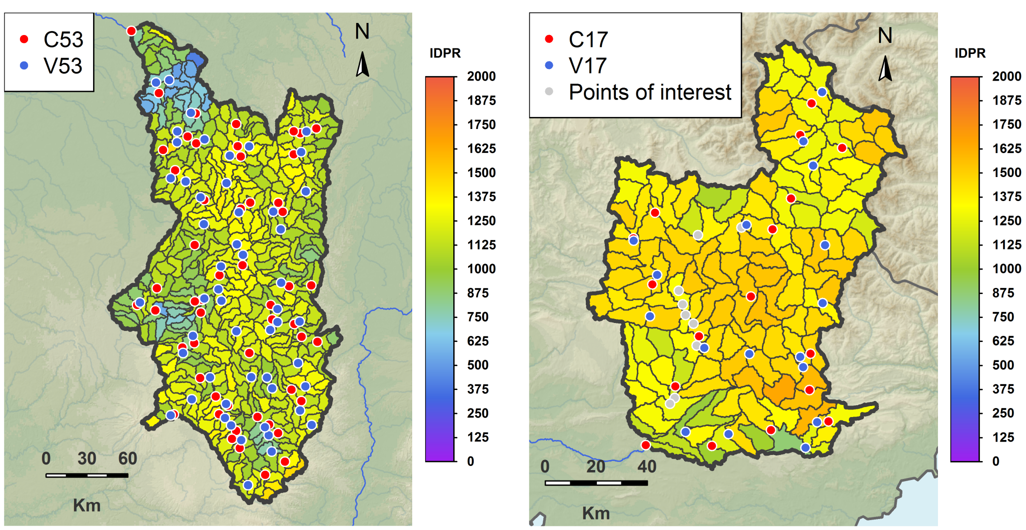


Figure 6: Boxplot of parameter sensitivity over the 106 streamflow stations of the Loire catchment as regards the KGE daily runoff

Allen et al. (1998) and Allen (2003) lumped the impacts of these variables into a single parameter, termed the crop coefficient K_C, to predict crop evapotranspiration (CET) as CET = PET $\times$ K_C. Duchemin et al. (2006) and van der Slik (2013) then highlighted the link between this crop coefficient and a vegetation index based on satellite observations. Since 2000, a satellite instrumentation named MODIS provides a Normalized Difference Vegetation Index (NDVI) at 16-day and 1-km^2 resolution (Solano et al., 2010). Since the K_C formulation is adopted in MORDOR-TS, we can therefore implement this observed NDVI as an appraisal of the crop coefficient time series. This one was previously defined through one parameter set as a constant controlling the amplitude of the potential radiation cycle. To do so, the interannual time series of NDVI is calculated at the mesh scale and then used to prescribe K_C at the same scale.

The BRGM, a French national geological agency, proposes an index of development and persistence of the river networks, termed IDPR (Mardhel et al., 2004). This index compares a theorical network of surface water drainage with the natural hydrological network. Thus, the IDPR quantifies the capacity of soils and underlying rocks to encourage rainfall infiltration or diversion to natural stream channels. Figure 7 shows the spatial variability of the IDPR at the mesh scale over the Loire and the Durance catchments. The index, which ranges from 0 to 2000, has values that are all the lower as water infiltration increases. In MORDOR-TS, the parameter kr, ranging from 0 to 1, stands for the runoff coefficient. It drives precipitations towards the groundwater reservoir for values close to 0, and towards the river for values close to 1. Then, the concepts of IDPR and kr are quite similar which makes it possible to prescribe at the mesh scale the model parameter as $kr = \frac{IDPR}{2000}$.



(a) Loire catchment at Gien (b) Durance catchment at Cadarache

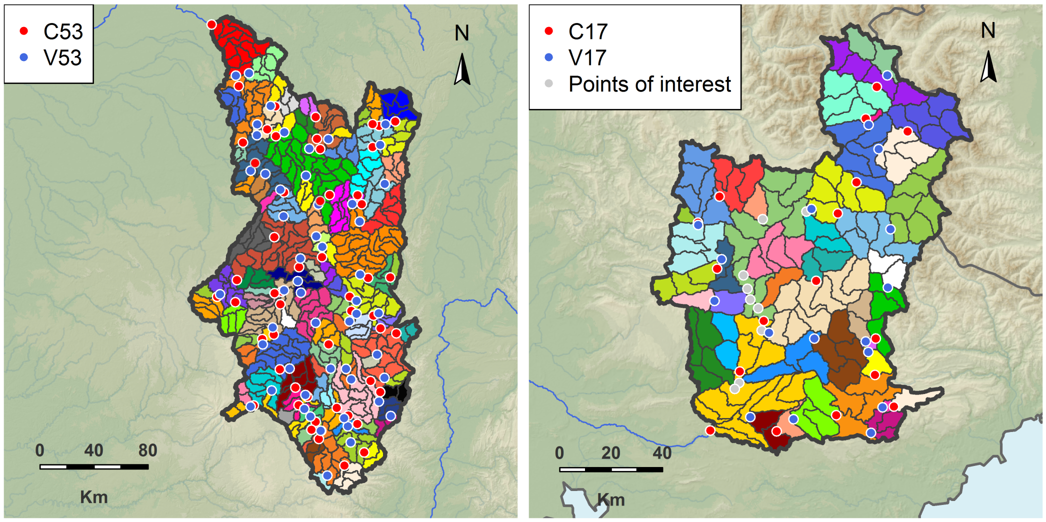
Figure 7

4.2.3. The sub-basin constraint pattern for parameters linked with a proxy runoff signature

Over the Loire and the Durance catchments, we estimated the interannual runoff and the monthly regime for each validation station with a mathematical method. For the interannual runoff, we used the generalised Turc-Pike formula (Turc, 1954; Mezentsev, 1955; Budyko, 1974; Pike, 1964) :

$$\frac{Q}{P} = 1 - \frac{1}{\left[1 + (\frac{P}{PET})^n\right]^{\frac{1}{n}}} \tag{1}$$

where Q is the interannual runoff, P the interannual precipitation, PET the interannual potential evapotranspiration and n the shape factor. This shape factor was calibrated for each catchment over the calibration sample and then used to estimate the interannual runoff over the validation sample. In a second time, a multi-linear regression was established over the calibration sample between the residuals $\frac{Q_{est}-Q_{obs}}{Q_{obs}}$ and the principal components of around fourty physio-climatic catchment descriptors. The values estimated for the Loire's validation stations V53 after residuals correction do not out-perform the initial regionalization of the MORDOR-TS model (cf. 4.1). However, those of the Durance's validation stations V17 proved to be more accurate. This finding may be explained by a water balance much more uncertain in nival catchments whose estimation benefits from the knowledge of the physio-climatic descriptors. Over the Durance catchment, the interannual runoff estimations are then used as a constraint to calibrate the water balance correction parameter at the validation stations V17, on top of its calibration at the calibration stations C17 over the observed streamflows. This model parameter is therefore spatialised at the sub-basin scale of all the stations. The nine points of interest are also integrated in this pattern. The resulting 43-sub-basin pattern is presented in Figure 8b.



(a) Loire catchment at Gien (b) Durance catchment at Cadarache

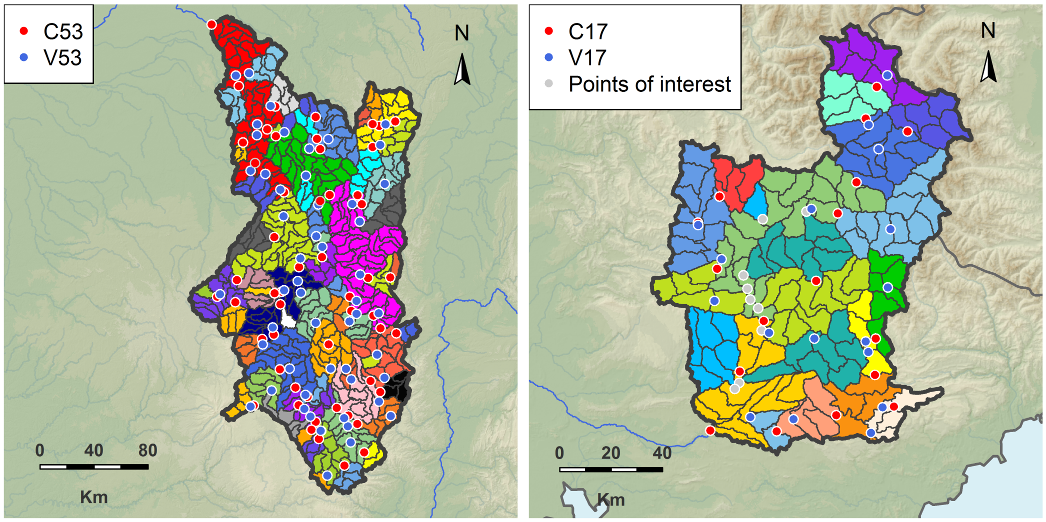
Figure 8: Sub-basin patterns used to constrain the parameters linked with a proxy runoff signature

For the monthly regime, we conducted the method proposed by Sauquet et al. (2008) over each of the two catchments. To do so, (i) we applied a Principal Component Analysis (PCA) over the physio-climatic catchment descriptors, (ii) we carried out a PCA over the Pardé coefficients (Pardé, 1933), (iii) we established relationships over the calibration sample between these principal components and (iv) we used these relationships to estimate the monthly regime at the validation stations. Over the Loire catchment, this method better estimates the regime than the initial regionalization of the MORDOR-TS model. This is not the case for the Durance catchment whose regimes are very well constrained by its nival character. As for the Durance's interannual runoff, the Loire's monthly regime estimated at each validation sample is therefore used as a constraint. The groundwater reservoir draining parameter (lkn) which governs the period of low flows and the capacity of the evaporating storage ($Zmax$) are calibrated over the estimated regime at the validation stations V53 and over the observed streamflow at the calibration stations C53. The resulting sub-basin pattern is presented in Figure 8a.

4.2.4. The physio-climatic sub-basin transposition pattern for the remaining parameters

The initial calibration sub-basin pattern (cf. 4.1) can be improved to avoid small validation basins to inherit parameters from huge calibration basins. To do so, the calibration sub-basin pattern is rearranged with physio-climatic information to become a physio-climatic calibration sub-basin pattern. The validation stations whose drainage area ratio with the downstream calibration station is lower than 20% no longer inherits parameters from this one but inherits those of the most similar calibration station in terms of physio-climatic descriptors. The selection of the new donor calibration station is carried out through an Euclidian distance calculated over the principal components of the physio-climatic descriptors. The new transposition pattern is presented in Figure 9. It is intended for all the remaining parameters about which we have no information or *a priori*.

The sensitivity analysis conducted over the MORDOR model highlighted the benefit of a reparameterisation of the production module. Michon and Castaings (2017a,b) suggested to no longer calibrate independently the capacities of the superficial ($Umax$) and the evaporating ($Zmax$) storages and even proposed to make them equal in order to notably increase the produc-



(a) Loire catchment at Gien

(b) Durance catchment at Cadarache

Figure 9: Physio-climatic calibration sub-basin patterns used to transpose the remaining parameters

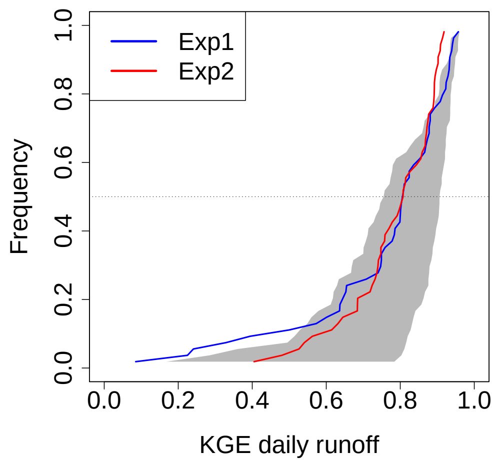
tion module sensitivity. Similarly to Eckhardt et al. (2005), we therefore define an equality relationship between the two model parameters, allowing to now calibrate only one of the two according to the the physio-climatic calibration sub-basin pattern.

5. Results

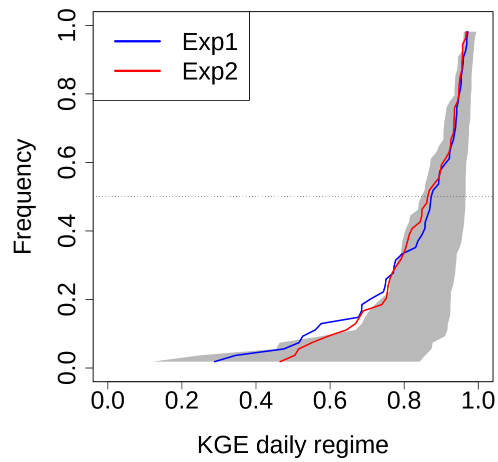
The unique transposition pattern presented in section 4.1 constitutes the initial reference in terms of distributed parameters. It is referred to as *Exp1*. The tailor-made pattern method developed in this paper consists in the four parameter patterns presented in section 4.2, namely a uniform, a hydrological mesh, a sub-basin and a physio-climatic calibration sub-basin patterns. This parameter scheme is referred to as *Exp2*. The two experiments are compared according to their performance in terms of daily runoff, daily regime, flood and low flow in an ungauged context. The experiments' performance is then analysed with the cumulative KGE distribution functions over the validation sample. Figure 10 presents these results over the validation sample of the Loire catchment (V53) while figure 11 presents those obtained over the validation sample of the Durance catchment (V17). The closer the distribution is to the vertical line equal to 1, the better the performance. To get hindsight on the results, a grey area indicates the gap between a uniform set of parameters and a gauged modelling of all the validation stations. For more details, interested readers may refer to Rouhier et al. (2017).

Over the Loire catchment, the multi-pattern method allows to significantly decrease the number of model parameters to be calibrated. From 12 parameters for *Exp1*, only 5 parameters still require to be calibrated for *Exp2*. Despite this drastic simplification, the modelling of the four runoff signatures is improved. If the head of the KGE daily runoff and KGE low flow distributions is slightly degraded, this loss of performance is largely compensated by a significant enhancement of the 50% of the least well-modelled stations. Daily regime suffer from a little performance decrease in the middle of its distribution but, as for the two other signatures, the least well-simulated stations are better modelled. For flood, the tailor-made pattern method is even more efficient: regionalizing the parameters differently improves the whole KGE flood distribution.

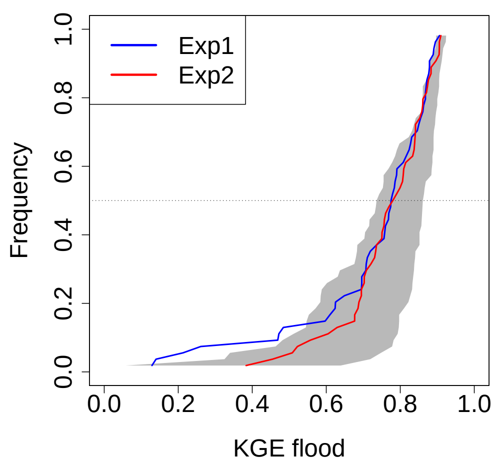
To quantify this performance improvement brought by the multi-pattern regionalization compared to the single regionalization, we propose the enhancement index EI defined by equation 2. The index is based on the area



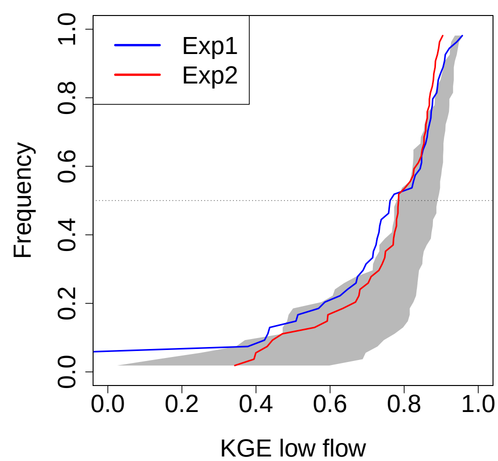
(a) impact on daily runoff



(b) impact on daily regime



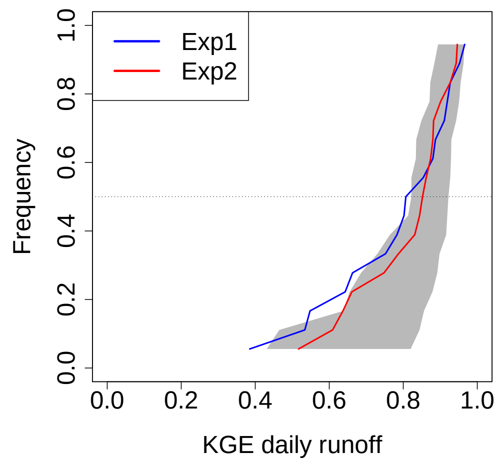
(c) impact on floods



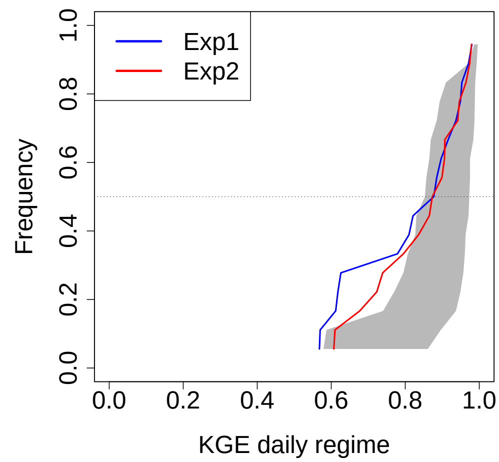
(d) impact on low flows

Figure 10: Distributions of performance over the validation sample V53 of the Loire catchment

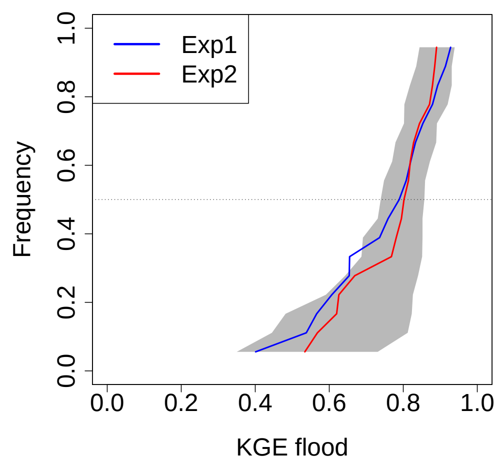
under a cumulative distribution function up to the 1 vertical line. It is all the closer to 100% as the improvement towards the gauged modeling (right



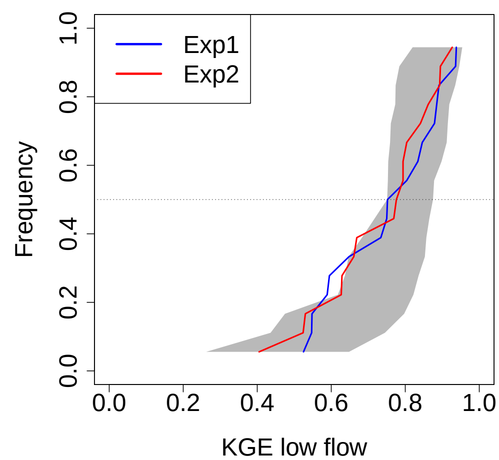
(a) impact on daily runoff



(b) impact on daily regime



(c) impact on floods



(d) impact on low flows

Figure 11: Distributions of performance over the validation sample V17 of the Durance catchment

border of the grey area) is important. The values of the enhancement index over the validation station sample are given in Table 1. Over the Loire catchment, the multi-pattern regionalization method proves to be really efficient. The improvement towards the gauged modelling is patent and even reaches 41% for low flow.

$$E = \frac{area\ KGE(Exp1) - area\ KGE(Exp2)}{area\ KGE(Exp1) - area\ KGE(Gauged)} \quad (2)$$

Over the Durance catchment, he number of degrees of freedom is also reduced. From 16 parameters for *Exp1*, only 11 parameters still need to be calibrated for *Exp2*. Over the runoff signatures, the first three are improved. The modelling of daily runoffs and daily regimes is particularly enhanced for the 50% of the least well-modelled stations. For flood, the 50% of the least well-modelled stations are also significantly improved to the detriment of slight performance degradation for the best modelled stations. Finally, the multi-pattern method is much more debatable for low flow. The degradation of the performance leads to deviate from the gauged modelling. Despite this significant loss of performance for low flow, the improvements brought by the tailor-made pattern method are substancial for daily runoff, daily regime and flood with a gain of about 20% towards the gauged modelling.

To get hindsight on parameter spatial variability, we here give the enhancement index in relation to a uniform set of parameters (left border of the grey area). Over the Loire catchment, the improvement of *Exp2* in terms of daily runoff, daily regime, flood and low flow represents 28, 19, 38 and 23% of the gap between uniform parameters and the gauged modelling, respectively. Similarly, the improvement represents 30, 10, 43 and 30% over the Durance catchment.

	Loire catchment	Durance catchment
Daily runoff	18 %	22 %
Daily regime	8 %	18 %
Flood	30 %	20 %
Low flow	41 %	-18 %

Table 1: Summary over the validation station sample of the enhancement index in relation to a single regionalization method for all parameters

6. Conclusion and perspectives

This paper aimed to present an unconventional regionalization scheme where several spatial patterns allowed by several regionalization methods are adopted according to the characteristics and the hydrological meaning of the model parameters. Firstly, the insensitive and the equifinal parameters are prescribed uniformly at their default values. Secondly, parameters linked with a physical characteristic are prescribed at the mesh scale. Thirdly, parameters linked with a proxy runoff signature are constrained at the sub-basins scale. Finally, parameters about which we have neither information nor *a priori* are transposed according to a physio-climatic pattern constructed over the calibration sub-basins.

This multi-pattern method is evaluated over four runoff signatures of pseudo-ungauged stations over the Loire and the Durance catchments. It not only greatly reduces the number of model parameters to be calibrated, but also proves to be significantly efficient for singular stations. Indeed, the modelling of the 50% least well-modelled stations is largely improved for all the runoff signatures, except the Durance's low flow. This outcome suggests that the tailor-made pattern method tends to guarantee a minimum performance in the ungauged context. Whatever the runoff signature and the catchment, the KGE is least of 0,4. The improvement of the tail stations sometimes goes along with the performance degradation of the best modelled stations. However, degradation remains very limited which does not question the strategy. If we put aside the Durance's low flow, our multi-pattern strategy achieves from 8% and up to 40% of the way towards the gauged modelling compared to a single regionalization method.

The loss of performance of the Durance's low flow would deserve further research. Understanding the reasons for this degradation could point to a new avenue for improving the regionalization method. Moreover, the constraint method was restricted to proxy runoff signatures while other types of proxy data such as snow satellite observations could give additional spatialized information. It would therefore be interesting to study wheather the integration of these data could bring further improvements in the distributed hydrological modelling.

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Appendix A. Details about the model parameters to be estimated in the study

Table A.1 details the symbol, the description and the unit of each parameter.

Module	Parameter	Description	Unit	Loire	Durance
Water balance	Cetp	Potential evapotranspiration correction factor	-	x	
	Cp	Precipitation correction factor	-		x
	gtz	Temperature gradient	$^\circ$/100m		x
Runoff production	Umax	Maximum capacity of the root zone U	mm	x	x
	Lmax	Maximum capacity of the hillslope zone L	mm	x	x
	Zmax	Maximum capacity of the capillarity storage Z	mm	x	x
	evl	Outflow exponent of storage L	-	x	x
	kr	Runoff coefficient	-	x	x
	evn	Outflow exponent of storage N	-	x	x
	lkn	Logarithm of the outflow coefficient of storage N	$mm.h^{-1}$	x	x
Simplified snow model	kf	Constant part of melting coefficient	$mm.^\circ C^{-1}.day^{-1}$	x	x
	kfp	Variable part of melting coefficient	$mm.^\circ C^{-1}.day^{-1}$		x
	lts	Smoothing parameter of snow pack temperature	-	x	x
	efp	Additive correction of rain/snow partition temperature	°C		x
	eft	Additive correction of melting temperature	°C		x
Routing scheme	Cel	Wave celerity	$m.s^{-1}$	x	x
	Dif	Wave diffusion	$m^2.s^{-1}$	x	x

Table A.1: Symbols, descriptions and units of the parameters used in the study.

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