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Accounting for spatial variability: a way to improve lumped modelling approaches? An assessment on 3300 chimera catchments

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Abstract Recent progress in collecting spatialized data with remote sensing techniques should allow the accounting for: (i) the spatial variability of rainfall and (ii) the basins' physical characteristics in rainfall–runoff models. To benefit from this spatial information, lumped approaches can quite easily be replaced by semi-distributed approaches. However, two questions need to be investigated. Does integrating additional information into a semi-distributed approach successfully improve the performance of flow simulations at the basin outlet? Which type of heterogeneity should first be taken into account to yield the most significant improvements? This paper presents a method to account for basin heterogeneity in lumped and semi-distributed models through the use of indices. Given the requirement for a large database to produce statistically significant results, "chimera" basins (virtual aggregation of two real basins) were used. We characterized 212 French basins using approximately 50 indices of pedology, geology, morphology and land use. Lumped and semi-distributed versions of a rainfall–runoff were compared on 3300 chimera basins. Results indicate that integrating "useful" spatial data in a lumped model can improve its performance without altering its parsimonious structure. Some indices correlated with rainfall confirm that the semi-distributed approach is more advantageous than the lumped approach for basins with high spatial variability of precipitation. The possible relations between physical characteristics and model parameters are investigated to help regionalization attempts and hence improve modelling abilities in ungauged basins.

Key words basin heterogeneities; disaggregation; rainfall–runoff modelling

INTRODUCTION

For water resources management and flood forecasting lumped rainfall–runoff models are well adapted to the requirements of operational applications. Simple models can efficiently represent the rainfall–runoff transformation while using a limited number of parameters (Perrin *et al.*, 2001).

However, estimating even a small number of parameters remains a major problem in the case of ungauged basins. Estimating parameters based on the basin physical characteristics is even more difficult when these characteristics are variable in space and time (Beven *et al.*, 1988; Diermanse, 1998; McDonnell, 2004). In addition, the spatial and temporal variability of the rainfall distribution can affect the runoff distribution (Wilson, 1979; Arnaud *et al.*, 2002). Taking this variability into account should be easier today, thanks to the high availability of spatialized data.

Many studies have attempted to take these variabilities into account through different lumped and distributed approaches. (Ambroise, 1995; Refsgaard & Knudsen, 1996; Krysanova *et al.*, 1999). However, most results are based on a limited number of basins, which leaves several questions open on the advantages of taking variability into account in rainfall–runoff modelling:

(a) Starting with a lumped approach, does taking spatial heterogeneities into account by dividing the basin into sub-basins effectively improve performance of flow simulations on a wide range of basins and climates?
(b) To improve runoff simulation, do we need to take the spatial variability into account by treating it in a distributed way?

The objective of this paper is first to compare the efficiency of different lumped and semi-distributed modelling strategies. Then the relationships between the temporal and spatial variations observed within a basin are analysed to investigate how model efficiency can be improved by semi-distribution of the inputs and the basin characteristics.

To meet these objectives, a database of French basins was built. Physical attributes (morphology, geology, vegetation and pedology) were collected for all basins.

For semi-distributed approaches, we used a methodology that uses virtual basins called chimeras (Andreassian *et al.*, 2004), which are the combination of two real, similarly sized basins that are located in different geographical areas. The exaggerated heterogeneity of these basins should allow us to understand which basin characteristics are interesting to use for the semi-distribution. To evaluate the amount of heterogeneity of each virtual basin, we used some global indices computable on each basin.

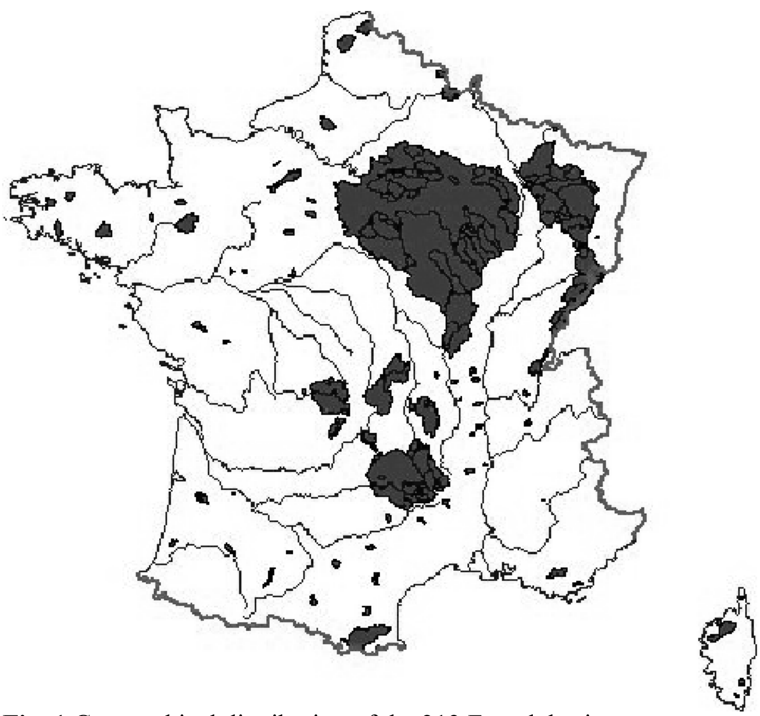


Fig. 1 Geographical distribution of the 212 French basins.

MATERIAL AND METHODS

Database

The streamflow data was taken from a sample of 212 basins in France representing a wide range of area, geomorphology and climatic conditions. Mean daily rainfall, streamflow and mean potential evapotranspiration data were available at a daily time-step. The distribution of the basins is illustrated in Fig. 1 and the main hydrological characteristics are shown in Table 1. This database has a good geographical diversity to guarantee the generality of our results. For every basin we used a GIS database and a digital terrain model (DTM) to calculate a number of geological, pedological and geomorphological characteristics that could be potentially useful to explain the hydrological features of the basin. The databases and the distribution of each type of information are summarized in Table 2. For each basin, approximately 30 indices, representing a majority of the invariant physical characteristics that could influence runoff formation, were calculated.

Table 1 Annual hydro-climatic characteristics of the real sample.

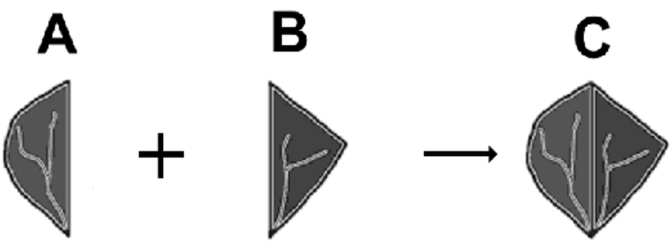
	Min.	Median	Max.
Mean annual rainfall (mm)	620	940	2300
Mean annual ETP (mm)	640	720	1250
Mean annual runoff (mm)	20	420	1960
Basin area (km^2)	7	136	43800
Time series length (years)	5	13	36

Table 2 Type, origin and scale of data bases used to establish the physiographical characteristics of the basins and classes of attributes chosen for each type.

Genre	Origin of the data bases and scale	Defined types et represented classes	
Pedology	SGBDE The Soil Geographical Database of Europe at Scale 1:1000 000, 1996	SOIL TYPE (5 CLASSES) [Cambisol], [Podzoluvisol], [Rendzina], [Lithosol], [Fluvisol]	TEXTURE (4 classes) [Coarse], [Medium], [Medium fine], [Fine]
Geology	BRGM Numerical geological map at 1:100 000 000 (6' edition,1996) + diverses geologicals maps	LITHOLOGY (6 CLASSES) [Alluvial deposits, Ice deposits and Sends], [Massives limestones], [Chalks, Molasses], [Marls], [Basaltic crystalline magmatic rocks], [Shists and metamorphous,détrital rocks]	BED ROCK PERMEABILITY (4 classes) [Impermeables], [Permeables with cracks], [Permeables with interstice], [Few permeables]
Land Use	Corine Land Cover (Source IFEN, 2000) at scale 1:500 000	7 CLASSES [Urban areas], [Arable and irrigated lands and permanent crops], [Heterogeneous agricultural zones], [Prairies], [Forests], [Végétation arbusive], [Natural areas without vegetation]	
Morphology	Logiciel River Tools cuple with a DTM at mesh of 75 meters	5 CLASSES [saturability], [slope and form], [arborescence of hydrological network], [hydrological response]	

Model and methodology

The lumped model used for this study is the GR4J model (Perrin *et al.*, 2003). It is a daily four-parameter model. It was tested on more than 400 basins in several countries. The methodology adopted here to create chimera basin was developed by Andreassian *et al.* (2004). The chimera construction and the model parameterization strategies are illustrated in Fig. 2. Based on 212 real basins, this technique provided nearly 3300 highly heterogeneous virtual basins with known intermediate flows.



$$Q_C = Q_A + Q_B \quad , \quad P_C = \frac{S_A P_A + S_B P_B}{S_A + S_B} \quad , \quad E_C = \frac{S_A E_A + S_B E_B}{S_A + S_B}$$

Fig. 2 Construction of the chimera basin C from sub-basins A and B with a surface area of S_A and S_B, respectively. Computation of data input for the sub-basin C from P_A and P_B precipitations Q_A ,Q_B streamflows, and E_a E_b potential evapotranspiration.

Our goal here was to evaluate the efficiency of three modelling approaches differentiated by their disaggregation level: a classical initial lumped approach (IL), an intermediate semi-distributed approach (rainfall SD) where only the mean rainfall of each sub-basin is distributed and finally a true semi-distributed approach (true or total SD).

For the lumped approach, a single parameter vector is optimized with a single rainfall P_c and a single evapotranspiration E_c variable as input data. For the intermediate approach, we used two sub-models for sub-basins A and B, each one having as input data P_a, E_a and P_b, E_b, respectively. However, the same parameter vector was used in calibration for the two sub-models. Consequently, this approach is also defined as semi-lumped. The simulated flow Q_c was obtained by the sum of two simulated intermediary flows Q_b and Q_a. For the last approach, called the true semi-distributed approach, we had two models running in parallel, each one fed by rainfall and the potential evapotranspiration of sub-basins A and B. Two parameter vectors, for each sub-basin, were optimized. This gave a semi-distribution of the input data and the parameters.

Optimization and performance evaluation The optimization algorithm is the step by step method (Edijatno *et al.*, 1999). We used the split-sample test framework. (Klemeš, 1986) to assess models. The objective function chosen is the *C2M* criterion (Mathevet, 2005) defined by:

$$C2M(\%) = \frac{Nash}{(200 - Nash)} * 100 \tag{1}$$

in which Nash (%) is the Nash & Sutcliffe (1970) criterion. The $C2M$ is bounded in the [–100; 100] domain.

The performance of the three approaches was compared in validation mode on periods different from those used in calibration mode. The $C2M_Q$ criterion used in validation mode, is a criterion based on the quadratic error between flows as the evaluation criterion, whereas in calibration mode we used this criterion based on the errors between the $\sqrt{Q}$. We will compare the average values of $C2M_Q$ obtained for the three approaches in validation for the whole sample of chimera basins.

Quantifying the heterogeneities of the chimeras To evaluate the level of heterogeneity of the different physical characteristics observed within each chimera, we developed a simple heterogeneity index. We found it necessary to choose a heterogeneity index that can be calculated on each basin and for physical each characteristic. We used the following index, applied to each physical characteristic described and each chimera. We define the distance d_x between basins by**:**

$$d_X = \frac{|I_A - I_B|}{I_{\max} - I_{\min}} \tag{2}$$

where I_A and I_B are the values of the physical descriptor X for sub-basins A and B, and $I_{\max}$ and $I_{\min}$ the maximum and minimum values, respectively, of descriptor X on the initial sample of 212 basins. This heterogeneity index varies between 0 for the homogeneous chimera basins and 1 for the most heterogeneous basins of the sample.

Relation between heterogeneities and improvement We originally hypothesized that the semi-distributed approach would benefit more to the basins with the highest variability indices. To test the validity of this hypothesis, we sought to relate the performance improvement from lumped to semi-distributed approaches to the level of heterogeneity for different physical characteristics. Exaggerating the natural heterogeneity of the basins using the chimera method allowed us to highlight the physical characteristics that, in the case of high variability, made semi-distribution advantageous. Relations between the model performance considering only the semi-distribution of the parameters (parameter SD) called here $\Delta C2M$ (equation (3)) and the heterogeneity index of the different physical characteristics evaluated have thus been established:

$$\Delta C2M = [C2M_Q\,(SDtotally) - C2M_Q\,(SDrain)] \tag{3}$$

RESULTS AND DISCUSSION

The difference in performance provided by the criterion $C2M_Q$ between the lumped approach and the totally semi-distributed (SD) approach on the 3300 chimera basins is presented in Fig. 3. The points above the (1:1) line represent the basins whose performance was improved by semi-distribution. It should be noted that approximately 70% of the basins had significantly improved (greater than 1% of $C2M_Q$) and approximately 14% were degraded (greater than –1%). However, there was enormous variability in the performance improvements. For the group of basins whose

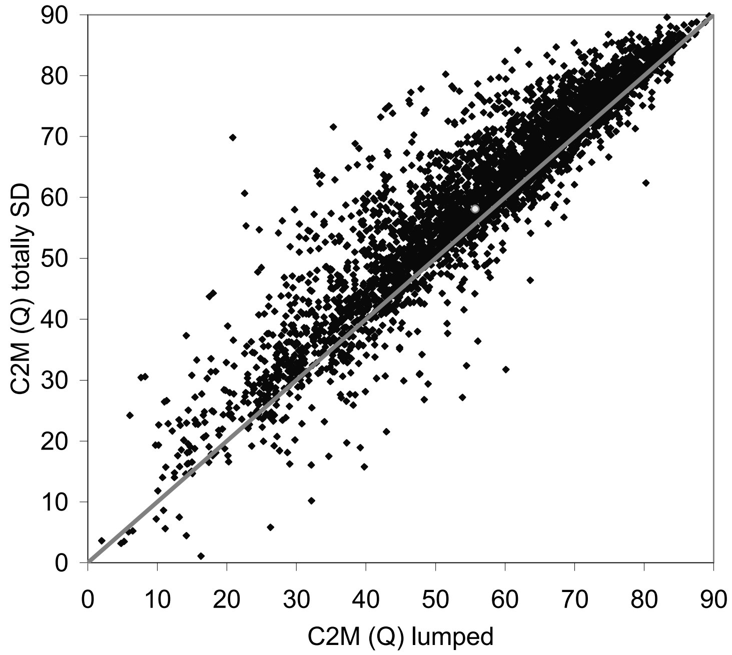


Fig. 3 Model mean efficiency ($C2M_Q$) in validation mode on the whole sample: IL *vs* totally SD approach.

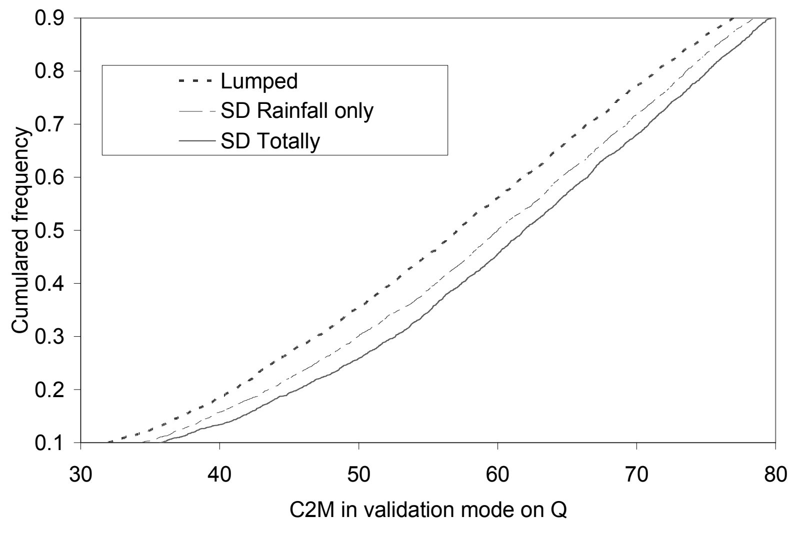


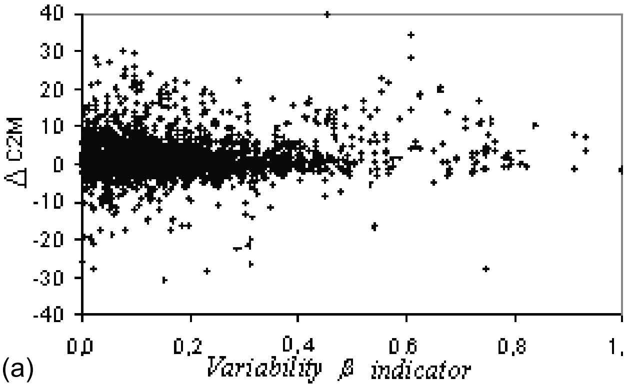
Fig. 4 Cumulative frequency curves of the mean efficiency ($C2M_Q$) in validation mode for the 3300 chimera with IL and the two SD approaches.

performance in lumped mode was already high (over 75%), no major improvement was observed. In fact a high criterion may indicate that the lumped approach is already well suited to these basins. Thus, it will be more difficult to improve results. For the group of basins whose criterion was lower, clear improvements due to semi-distribution were observed, as well as a greater number of degradations.

In terms of cumulative frequency of the mean efficiency, both semi-distributed versions significantly overtouch the initial lumped version (Fig. 4). Table 3 indicates the average performances for the whole sample obtained by the three approaches. The true SD version was the best, with a mean difference of 4% in validation. The rainfall SD approach provided a mean gain over the lumped approach of approximately 2.4%. The improvement attributable only to the distribution of the parameters, independent from the improvement caused by the semi-distribution of rainfall, was (4–2.4%) thus 1.6%. Semi-distribution of rainfall alone was responsible in average of 60% of the improvement. Moreover, the greatest improvements can be explained by the non-correlation of rainfall.

Table 3 Average *C2M*(*Q*) for the whole sample of chimera for the three different approaches.

C2M(*Q*)	Lumped approach	SD Rainfall only	SD totally
Average	55.8	58.1	59.8
Median	57.1	60.0	61.9
Percentile 10%	31.9	34.3	35.8
Percentile 90%	79.9	78.6	79.17



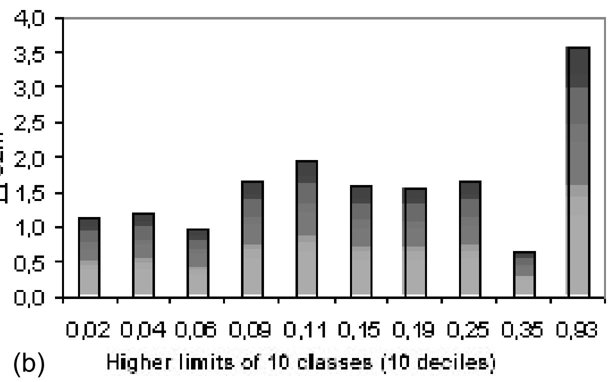


Fig. 5 (a) Mean efficiency gain obtained with parameters SD approach in function of heterogeneity level of β indicator on the whole sample; (b) same result but presented in function of increasing classes of the distribution of β heterogeneity indicator.

Then we compared the different types of heterogeneity and the gains obtained by the SD parameter approach (Δ*C2M*). In some cases, "positive" trends were observed, i.e. the higher the heterogeneity, the higher the gain obtained by the SD parameter approach.

For the indexes on the geomorphology and the hydrographic network, the types of heterogeneity presenting a "positive" relation were β form factor (Moussa & Bocquillon, 1993), the drainage network density (DD) (Horton, 1945) and the hypsometric integral (HI) (Chow, 1964).

Figure 5(a) shows the relationship obtained for the heterogeneity indicator of the β form index for all the chimeras of the sample. It can be observed that even though virtual basins were used, the majority of these indicators had values lower than 0.5, and, although improvements for the criterion are present, substantial degradations also exist. On the other hand, the basins whose heterogeneity was greater than 0.5 were systematically improved. Figure 5(b) summarizes these results through the means of the gains obtained on ten crescent classes of this index. These classes represent the ten crescent deciles of the index's distribution. This leads to the conclusion that on average for this index, a "positive" relationship is obtained between the improvement using the SD parameter approach and the basin heterogeneity index. The same types of observation were made for the indexes representing the heterogeneity of the drainage network density (Fig. 6) and the hypsometric integral (Fig. 7). The other indicators involving the basin morphology showed no significant relationships.

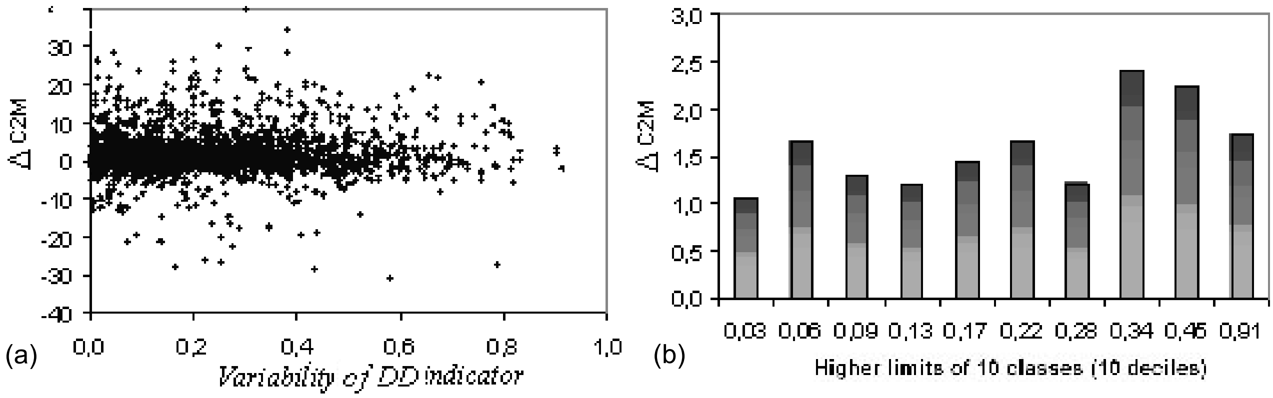


Fig. 6 (a) Mean efficiency improvement obtained with the SD parameters approach as a function of the heterogeneity level of the DD indicator on the whole sample; (b) Same result but presented as a function of increasing classes of the distribution of DD heterogeneity indicator.

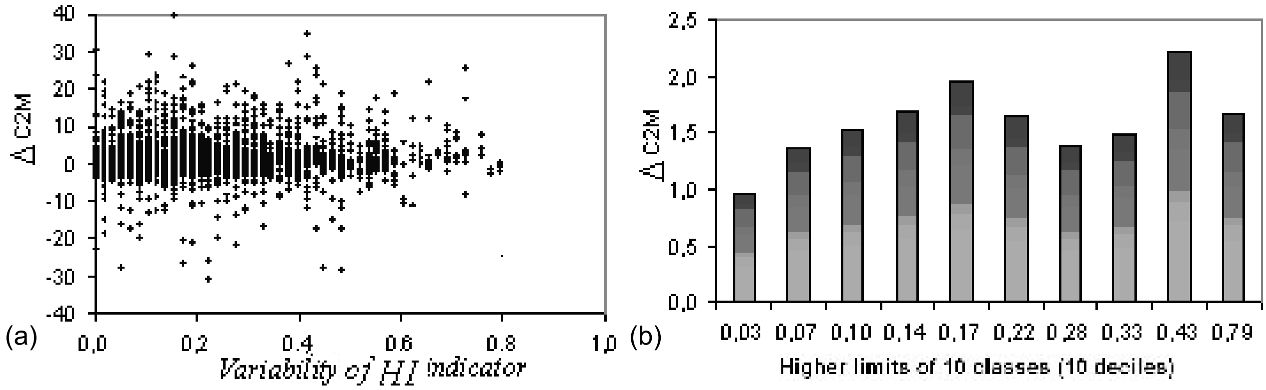


Fig. 7 (a) Mean efficiency improvement obtained with the SD approach as a function of the heterogeneity level of the HI indicator on the whole sample; (b) same result but presented as a function of increasing classes of this indicator.

For the geological indexes, the limestone indexes show a positive trend between the mean gains obtained and their heterogeneity rate within the chimeras (Fig. 8(a)), as for the permeable rock indicator (Fig. 8(b)). For land use, only the combined indicator of arable land and heterogeneous agricultural land described the same type of relation (Fig. 8(c)). For pedology, a positive trend is observed only on the amount of heterogeneity of Cambisol (Fig. 8(d)) and Podzoluvisol (Fig. 6(e)) type soils.

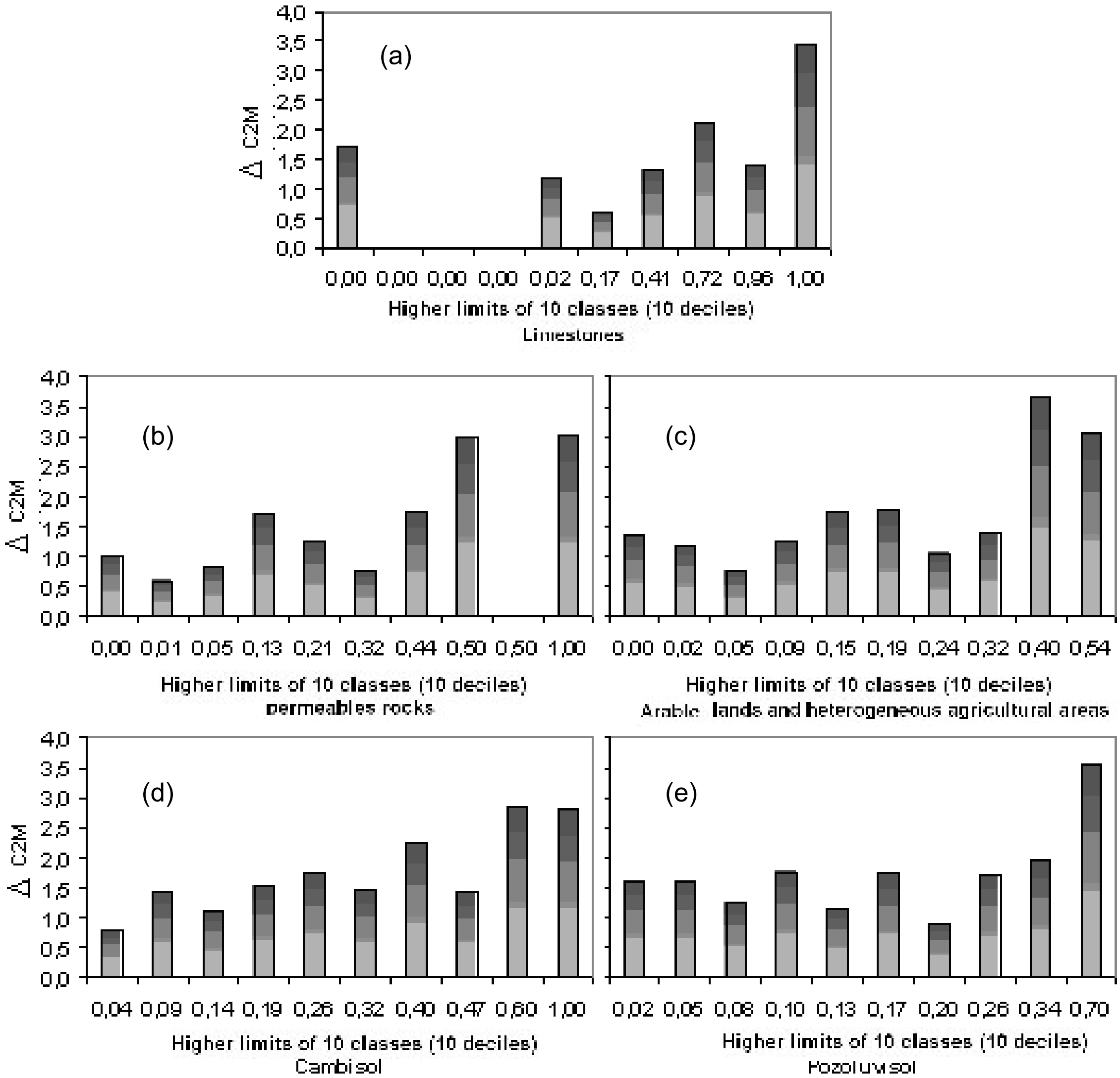


Fig 8 (a) Mean efficiency improvement obtained with the SD parameters approach as a function of increasing classes of the distribution obtained for the limestones indicator; (b) for permeable rocks; (c) for arable land added to heterogeneous agricultural area; (d) for Cambisol; (e) for Podzoluvisol.

The positive trends between the heterogeneity index of the basins and the gains obtained using the semi-distributed parameter approach only appeared for only a few types of the descriptors tested.

Nevertheless, the significance of this heterogeneity index is complex. It is difficult to physically interpret its value. For example, a value of 0.5 for the forest indicator means that the basin is covered 50% by forest and 50% by another land use type. But, there is no information on the composition of this other part.

These results are in line with those obtained by Merz & Blöschl (2004) who tried to regionalize the parameters of the HBV model (Bergström & Forsman, 1973) from basin attributes such as the percentage of various geological types, soil types, land uses and topographic indices on 308 Austrian catchments. This research shows the poor relationships between these attributes and the parameters, although the model parameters seem to represent the physics of the basins.

CONCLUSION

The objective of this study was to bring out the differences in performance between a lumped approach and semi-distributed approaches as well as to relate the basin variability to model performance improvements for artificially heterogeneous basins. This investigation has confirmed the relative superiority of the semi-distributed approaches. However, this result was not systematically observed on basins. The greater part of the improvement stems from taking the rainfall distribution into account. This is observed especially in the cases where the rainfall timeseries of each sub-basin are weakly correlated in time.

While analysing the impact of parameter semi-distribution for given indicators, relationships were found between the basin heterogeneities and the performance gains of the semi-distributed approach. This variation in performance is conditioned by the initial performance of the lumped approach: the basins with the weakest initial performance obtained the greatest gains. In fact it is easier to improve the modelling of the basins when a lumped approach is not suitable.

Similar tests at the hourly time-step should be interesting to study to continue this work. Indeed at this time step, the rainfall field is more decorrelated in time for a given distance. In addition, the relationships that emerged from the physical heterogeneities may be used in the definition of similar basins for the modelling of ungauged basins (Rojas Serna, 2005).

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