Hydrol. Earth Syst. Sci. Discuss., 5, S1848–S1859, 2008
www.hydrol-earth-syst-sci-discuss.net/5/S1848/2008/

Hydrology and Earth System Sciences Discussions

Interactive comment on "Uncertainties on mean areal precipitation: assessment and impact on streamflow simulations" *by* L. Moulin et al.

L. Moulin et al.

Received and published: 17 November 2008

1 Detailed answers to the comments of referee 2

Thank you to referee 2 for the accurate and helpfull review of our manuscript. In this author comment, we list how each of the remarks provided by the referee was adressed. The comments made by the referee will be refered as RC and printed in bold ; the authors comments and answers as AC.

In a general authors comment, we summarise the main changes that were applied in the paper with respect to the main criticisms.

1.1 Concerning the rainfall interpolation errors

1.1.1 Concerning the use of a climatological variogram

RC : **The first point concerns the use of climatological variogram for rainfall data at daily and finer time scales. Kriging interpolation is often used for rainfall data aggregated to coarser time scale, such as monthly (e.g., Chen et al., 2008) or for mean of the annual rainfall averages (e.g., Pardo-Iguzquiza, 1998). For rainfall series at daily or finer time scales, Wood et al. (2000) and Villarini and Krajewski (2008) show that areal rainfall error depends on rainfall intensity. Adopting a climatological variogram such dependence is neglected, since the error standard deviation is ”constant over the whole period in case of stationary network” (pp. 2075-2076). This aspect could be not much important in the interpolation process (the usual application of kriging), but it could be in simulation.**

AC : Please, see also section 1.1 in the general comments. In case of a stationary network, the standard deviation of theoretical normalised error (standard deviation of interpolation error divided by the standard deviation SD of rainfall field, see Eqs. 7 and 8 of original manuscript) is constant but not the theoretical ”non normalised” standard deviation of the error which depends on the standard deviation of the rainfall field. Hence, there may be a relationship between the intensity and standard deviation of the error in the selected interpolation model. This relationship is nevertheless complex since it is a consequence of the dependency between the point rainfall intensity at a given location and standard deviation of the rainfall field. Fig 5 and 8 illustrate that the resulting simulated errors (or confidence intervals) depend on the point or MAP intensity value, as suggested by the referee. This question revealed that the hypotheses of ”climatological kriging” were not perfectly clearly presented in the initial version of the manuscript. The presentation in pages 2075-2076 has been improved to clarify the no-

HESSD
5, S1848–S1859, 2008
Interactive Comment

tion of normalised variogram and normalised standard deviation). The references cited by the referee (Wood et al (2000) and Villarini and Krajewski (2008)) are not exploring the same type of areal rainfall estimation errors. They are based on under-sampling of a dense network. Their results can not be directly compared to the errors estimated through a kriging approach.

RC : **In fact, as shown by Figs. 5 and 8, climatological assumption results in constant errors associated to interpolated values, since oscillations are only due to failures on data collection, and on the number of surrounding gauges used to interpolate (p. 2076).**

AC : We disagree with the referee on this point. The tendency to widen of the confidence intervals on Fig. 5 and 8 is clear despite the oscillations which are due to the variations of the number of available rain gauges but also and mainly to the fluctuation of the standard deviation of the rainfall field for a given value of rainfall intensity. This oscillation illustrates again the complexity of the link between the interpolation error distribution and the rainfall intensity mentioned above. A comment has been added in the text to stress this dependency.

RC : **This fact could be more evident if y-axis of Figs. 5 and 8 is extended to negative values, highlighting the symmetry of errors around the interpolated values.**

AC : There seems to be here a misunderstanding about the interpretation of Figures 5 and 8. The x–axis and y–axis represent intensity values either measured or simulated. Note that in some cases, negative intensity values have nevertheless been produced either by the kriging interpolation method or by the error model. The intensities were then set equal to zero (see answer 1.1.2 to the next comment of the referee).

HESSD

5, S1848–S1859, 2008

Interactive Comment

1.1.2 Concerning the negative values

RC : **From the text, the simulation algorithm seems to consist in adding a simulated AR(1) signal to interpolated rainfall. However, this procedure can easily generate negative rainfall values corresponding to interpolated values below about 10 mm/h, where many observations are clustered. If the above generation algorithm is correct (please, clarify in the text), it is important to point out how eventual negative values are managed. A simple removal can strongly affect both intermittency and event volumes, resulting in a bias and/or delay of hydrograms. Other correction procedures (if used) should be described and tested. We notice that the above problems do not arise when kriging is used for interpolation and one deals with data that exhibit values far from zero and/or allowing negative values.**

AC : Usually when we standardise the rainfall field, we bring the raw values Z^k of the k^{th} field considered to z^k by bringing its mean and its variance to 1, so as to make every field comparable (climatological kriging) and to allow the pooling of all the values of the different fields into a single variogram, as if we had a multirealisation data set of a single process. If we now consider the kriging of one standardised realisation z^k at the current point z^{k^0}, from the observed (standardised) values z^{k^i}. Then the standardised estimation error at z^{k^0} is at the most the variance of the field (here equal to one), when the point (x_0, y_0) is far from (out of range from) all observed points. If we further assume the estimation residual as Gaussian, we know that there is about 17% chance to have value lower than minus one standard deviation, here -1, and in that case, since the field average is also equal to one, then the kriged estimation z^{*^0} is 1 but adding a negative residual, the real (or simulated) realisation can be negative (with 14% probability at the most). Fortunately, if the network is sufficiently dense, the residual variance of e^0 will be smaller than 1, therefore reducing strongly the probability for a residual e^0 to drop below -1. This is why we only observe some few percents of our values to become slightly

HESSD

5, S1848–S1859, 2008

Interactive Comment

negative, much less than 17%! We also know that kriged estimates can, but in rather rare conditions, get higher than the highest observed value or lower than the lowest. In the case of rainfall, which is an intermittent non gaussian process, negative kriged values scarcely happen on the edges of the precipitation zone or when there is a small dry zone embedded into it. These negative values are slightly more numerous when we add on top of the kriged value a simulated residual (which may be negative). They are simply censored to 0 and this never concerns a large percentage of point value nor does it affect significantly our target which is the basin mean areal precipitation.

It is important to note that the AR(1) temporal correlation model does not modify the distribution of the normalised errors on hourly rainfall intensity estimates (Eq. 15). It does therefore not modify the probability of generating negative intensity values when adding a randomly drawn Gaussian error to the interpolated intensity values. It is clear on Fig. 5 and 8 that the confidence intervals may reach zero especially for low intensity values: i.e. the error model has produced negative intensity. When considering generated errors on MAP, it appears that roughly 20% of errors are negative (around 80% are positive or equal to zero). When additionated with computed MAP, around 6 to 7% of the total number of resulting simulated MAP values for the 100 scenarios are negative depending on the rain gauge or the catchment. They concern mostly low intensity values and are generally slightly negative. Their removal (considering that they are equal to zero) leads to increase the yearly total rainfall amount by 2 to 3% depending on the raingauge. A test was made on mean annual balance over all scenarios : an error ranging from 1.7 to 2.8% is made on the annual balance (for instance 15.4 mm/year for Bas-en-Basset compared with a mean annual precipitation of 900 mm; 40 mm for Rieutord compared with a mean annual precipitation of 1530 mm). The effect on high intensity rainfall events is negligible as illustrated by two hyetographs at the end of this discussion paper (80 and 95% confidence intervals for the MAPs estimated on the Rieutord catchment, Fig. in the final response file).

HESSD

5, S1848–S1859, 2008

Interactive Comment

1.2 On the use and validation of AR(1)

RC : **The second issue concerns the use and validation of AR(1) hypothesis. The assumption of autocorrelated errors can be reasonable, but the validation procedure in Section 4.2 can be questionable. Authors simulate using autocorrelated errors and show (Fig. 6) that the inflated errors are closer to the observed ones than uncorrelated errors. Then, they conclude that observed errors are autocorrelated. However, the variance inflation is an analytical property of AR(1) process, as pointed out in Eq. (15). Thus, AR(1) correction accomplishes the task of inflating variance, but it does not prove that inflation is due to autocorrelation.**

AC : As reminded in the 1.1.2, the AR(1) temporal correlation model does not modify the distribution of the normalised errors on hourly rainfall intensity estimates (Eq. 15).

RC : **The reasoning should be opposite: after proving the existence of autocorrelation by computing e.g. the autocorrelation function (ACF) and assessing its significance at lag 1, then, lag-1 ACF value can be used to build AR(1) model. On the contrary, authors fix the lag-1 ACF value (= 0.6) that allows obtaining the desired variance inflation without showing the actual existence of temporal linear dependence.**

AC : During our research work, we first looked at the autocorrelation function ACF of the errors (normalised errors (see Fig. in the final response file, where the lag-1 ACF appears to be close to 0.6 for 3 test raingauges)). This figure shows also long range correlations (non-exponential decrease of the ACF function with the lag), that can not be reproduced by simple AR models. A more complex time-dependency model could have been proposed for the normalised errors but it must be also considered that the

HESSD

5, S1848–S1859, 2008

Interactive Comment

final interpolation errors are the result of the product of these normalised errors and of the standard deviation of the rainfall field. Both random variables may not be independent as hypothesised in the proposed error model. Hence, even a perfect error model for the normalised errors does not guaranty an accurate simulation of the interpolation errors and their temporal structure if this last dependency is neglected. These reasons led us to select a relatively simple time dependency model for the normalised errors and to test the adequacy of the resulting error model on the final interpolation errors and their temporal statistical structure (Table 3, Fig 6). We did not want to get too deep into the subtleties of the choice of the error model and of its validation method in the manuscript to keep it concise and to the point. A sentence has been added to mention that the parameter 0.6 corresponds to the average value of the lag-1 autocorrelation coefficient of the normalised errors obtained through the cross-validation approach. This discussion will be attached to the published paper. We didn't change the presentation of the error model and its results as it is to keep it simple. The interested readers will have the possibility to read this discussion if necessary.

1.3 On the relationship between errors and size of catchments

RC : **Another point relates to conclusions reported in Section 5.1.2. Authors show distributions of the highest simulated MAP errors in Fig.7, and state that small errors for large catchments depend on averaging effects of the catchment area. Actually, differences between small and large catchments should be only due to rain gauge network configuration. If a dense network is available in a small basin, we could have averaging effects in spite of catchment area. Furthermore, 90% simulated confidence intervals of maximum computed MAPs at the three stations are close to each other (about 20, 14, 18 mm/h at Rieutord, Chambon-sur-Lignon and Bas-en-Basset, respectively) and do not exhibit the behaviour of maxima. Thus, conclusions could be that: (i) maxima of absolute errors decrease when the number of**

interpolation points increase (dependence on the area is indirect); (ii) 90% confidence bands are theoretically constant for each quantile (differences must be ascribed to lack of measurements in some site); (iii) 90% confidence bands seem rather constant for all catchments (straight lines interpolating the peaks of 90% confidence bands in Fig. 8 show rather constant width).

AC : We do not completely share the interpretation of the referee.

(i) Referee comment must be true for a given catchment. The interpolation error decreases of course if the number measurement points increases or better said if the density of the measurement points increases. If various catchment areas are considered and compared, the density of measurement points (rather than their number) is still an explanatory factor, but since the MAP is an average value on the area, the area has also a direct impact on the absolute value of computed intensities and errors. This relation to the area and gauge network density implicitly appears in Eq. 14 (σ depends on n but also on $\gamma_{i,s}$ and $\gamma_{S,S}$). This is also illustrated in Table 1 in the present discussion paper : the Rieutord catchment has got from far the greatest rain gauge density either within the catchment or at a distance smaller than the variogram range from the catchment but has got the highest theoretical normalised standard deviation.

(ii) The 90% confidence bands are not theoretically constant for each quantile (see previous discussion). They depend on the rainfall field standard deviation which is not independent on the intensity value (Fig 5).

(iii) Fig 8 does not show constant widths, this is particularly clear on Fig 8.c (see also the figures given on p. 2085 of original manuscript).

HESSD

5, S1848–S1859, 2008

Interactive Comment

1.4 On the conclusions related to propagation of MAP errors to streamflow

RC : **At lines 15-25 of page 2087 (Section 5.2.2), authors comment Table 5 and write that ”For the smallest catchments (Rieutord, Chambon-sur-Lignon), the simulated 90% confidence interval contains almost 90% of the measured streamflow values when a tolerance factor of 20% is considered (Table 5)8221;. From Table 5, this conclusion seem to be correct for the smallest and the largest basins when Qobs $>$ Q10. In the other cases, percentages are 68.7, 53.6, 50.6, 65.0%, rather far from 90.0%.**

AC : That is true. Please, see the response in general comments (Section 1.5). The text had been written based on preliminary results which were slightly different from the results presented in Table 5 (with other confidence intervals). In the revised manuscript the discussion has been reformulated and nuances have been introduced in the text.

1.5 On the choice of Gaussian model

RC : **Authors recognize that the model is far from being perfect, but some properties and aspects have to be accounted for in order to obtain reliable results. In particular, rainfall observations at daily or finer time scale represent an intermittent process difficult to be modelled with Gaussian-based tools. Perhaps, the approach proposed by authors can be more suitable for rainfall at coarser time scales.**

AC : The results obtained appear consistent as indicated by the various cross-validation tests. The short time step was imposed by the objective : produce rainfall scenarios to be used as input to rainfall-runoff models in the context of flood forecasting. We agree that other more sophisticated models could have been used but the proposed model,

HESSD

5, S1848–S1859, 2008

Interactive Comment

Full Screen / Esc

Printer-friendly Version

Interactive Discussion

Discussion Paper

though simple, get satisfying results. Thus, we believe that those results justify the use of such a model.

1.6 Technical notes

Typos and minor changes suggested by the referee 2 for pages 2076, 2080, 2098, 2109 were integrated into the revised manuscript. The other ones are detailed below.

RC : **Pag. 2098, Table 4: Please, add a sentence in the caption explaining that column "50%"refers to NSE (as mentioned in the text).**

AC : The sentence "As a complement, the standard Nash and Sutcliffe criterion between 50 percentile and measured values (Eq. 16) gives an estimation of accuracy of the estimates." has been deleted because these results were not presented in the original manuscript. To make it easier to understand, notation RMSR(80%) was changed for RMSR_{10-90} in the Eq.17. The same notation has been used in the Table 4.

RC : **Pag. 2103, Fig. 4: Histograms are not suitable to point out goodness of fit. Please, consider qq-plots or pp-plots for visual assessing the agreement of normal distribution and empirical one. Furthermore, it should be better to use formal goodness-of-fit tests (Kolmogorov-Smirnov, Lilliefor, Shapiro-Wilk for normality, among others).**

AC : Distribution of empirical errors is not normal. Results of normality tests would be negative. We wanted to approximate it with a normal distribution. During this process, global agreement of both distributions was tested with various graphical representations. Among these representations, histograms were one possibility.

HESSD

5, S1848–S1859, 2008

Interactive Comment

RC : **Pag. 2104, Fig. 5: Please, extend y-axis to negative values to point out the symmetry of the errors around the interpolated values.**

AC : See author comment in 1.1.2.

RC : **Pag. 2105, Fig. 6: This figure is difficult to be read. Please, increase dimensions of characters and symbols.**

AC : Fig. 6 has been modified.

RC : **Pag. 2106, Fig. 7: Consider to invert axes, and to change ”scenario” label with ”probability of (non-) exceedance”. ”...higher errors...”, ”...the highest errors...”**

AC: This figure has been modified following the referees'suggestion.

RC : **Pag. 2107, Fig. 8: Please, extend y-axis to negative values (see comment to Fig. 5).**

AC : See author comment in 1.1.2.

RC : **Pag. 2110, Fig. 11: This plot is not mentioned in the text. Consider to remove it, since related information is already described in Table 5.**

AC : This figure has been removed.

HESSD

5, S1848–S1859, 2008

Interactive Comment

Table 1. For each one of the three studied catchments, number of raingauges contained in the catchment area (col. 3) and the corresponding density (col. 4) are computed. The same computations (col. 5 & 6) are made for the total number of raingauges contained in the catchment or whose the distance to the catchment is less than the range of variogram (25 km). In the last column the normalised theoretical error standard deviation computed with all the available network is indicated.

	Area (km^2)	Nb rain gauges in	Density ($1/km^2$)	Nb raingauges in range	Density ($1/km^2$)	Normalised error St Dev (mm/h)
Rieutord	62	2	1/31	17	1/4	0.283
Chambon	139	3	1/46	21	1/7	0.209
Bas-en-B	3234	32	1/101	40	1/81	0.130

References

Datin, R. : Outils operationnels pour la prevision des crues rapides : traitements des incertitudes et integration des previsions meteorologiques. Developpements de TOPMODEL pour la prise en compte de la variabilite spatiale de la pluie. Application au bassin versant de l'Ardeche. PhD Thesis, Institut National Polytechnique de Grenoble, Grenoble, 369 pp., 1998.

Kirstetter, P.E., Delrieu, G., Boudevillain, B. and Obled, C. : Towards an error model for radar quantitative precipitation estimation in the Cévennes-Vivarais region, France, Adv. Water Resour., submitted, 2008.

Villarini, G. and Krajewski, W. F.: Empirically-based modeling of spatial sampling uncertainties associated with rainfall measurement by rain gauges, Adv. Water Resour., 31, 1015–1023, 2008.

Wood, S. J., Jones, D. A. and Moore, R. J.: Accuracy of rainfall measurement for scales of hydrological interest, Hydrol. Earth Syst. Sc., 4(4), 531–543, 2000.

Interactive comment on Hydrol. Earth Syst. Sci. Discuss., 5, 2067, 2008.