Rainfall Generator for the Rhine Basin

First results of simulations including a memory term in the feature vector

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Contents

1. Introduction

Since the mid 1990s rainfall generators for the Rhine and Meuse basins have been developed. These rainfall generators form part of the GRADE instrument for the Generation of Rainfall and Discharge Extremes (de Wit and Buishand, 2007). This report describes work on the Rainfall generator for the Rhine basin performed during the period September 2011 to November 2011 as part of the KNMI contribution to the Waterdienst-Deltares-KNMI collaboration regarding GRADE. Only one subject was studied, namely the inclusion of a memory term in the feature vector and its effect on long (50K years) simulations. This work is motivated by similar simulations for the Meuse basin in which the use of a memory term resulted in a significant reduction of the standard deviation of monthly precipitation sums in winter. Although the underestimation of the standard deviation of monthly precipitation sums in winter in simulations (without a memory term) for the Rhine basin is smaller (and statistically not significant) than for the Meuse basin, it is still interesting to see if any improvement is possible by including one, especially because the Rainfall generator for the Rhine basin will be ‘updated’ in 2012 by using a longer historical base period (i.e. 1951 to 2006 in stead of 1961 to 1995). For the Rainfall generator for the Meuse basin a 4-day memory turned out to be most successful (Leander et al, 2005), in this paper it is investigated whether a memory term is also beneficial for the Rainfall generator for the Rhine basin and what the optimal memory length is.

2. Sensitivity to the length of the memory term

Leander and Buishand (2004) and Leander et al. (2005) included a 4-day memory term in simulations with the Rainfall generator for the Meuse to improve the reproduction of the autocorrelation of daily precipitation and the standard deviation of monthly totals. Here memory terms with different lengths (4, 10 and 30 days) are considered. The feature vector for day *t* of these simulations is based on the composition of the feature vector of the earlier ue241 type simulations (see e.g. Beersma, 2011), i.e. the average (standardized) precipitation of the 34 stations used for the Rhine basin $\tilde{P}_t^*$, the fraction of stations with precipitation F_t^*, and the average (standardized) temperature $\tilde{T}_t^*$ with constant weights 2, 4 and 1 and hence “241” in the simulation type. The star denotes here a simulated value for day *t*, and the tilde refers to a standardized value. For the additional memory term: $(\tilde{P}_{t-1}^* + \tilde{P}_{t-2}^* + \tilde{P}_{t-3}^* + ... + \tilde{P}_{t-n}^*)/n$ with *n*=4, 10 or 30, the weights are set automatically, and are inversely proportional to the variance of this memory term. Since the variance of these memory terms varies considerably throughout the year (strong seasonal cycle) the weights are determined and applied separately for each calendar day (so called ‘local weights’).

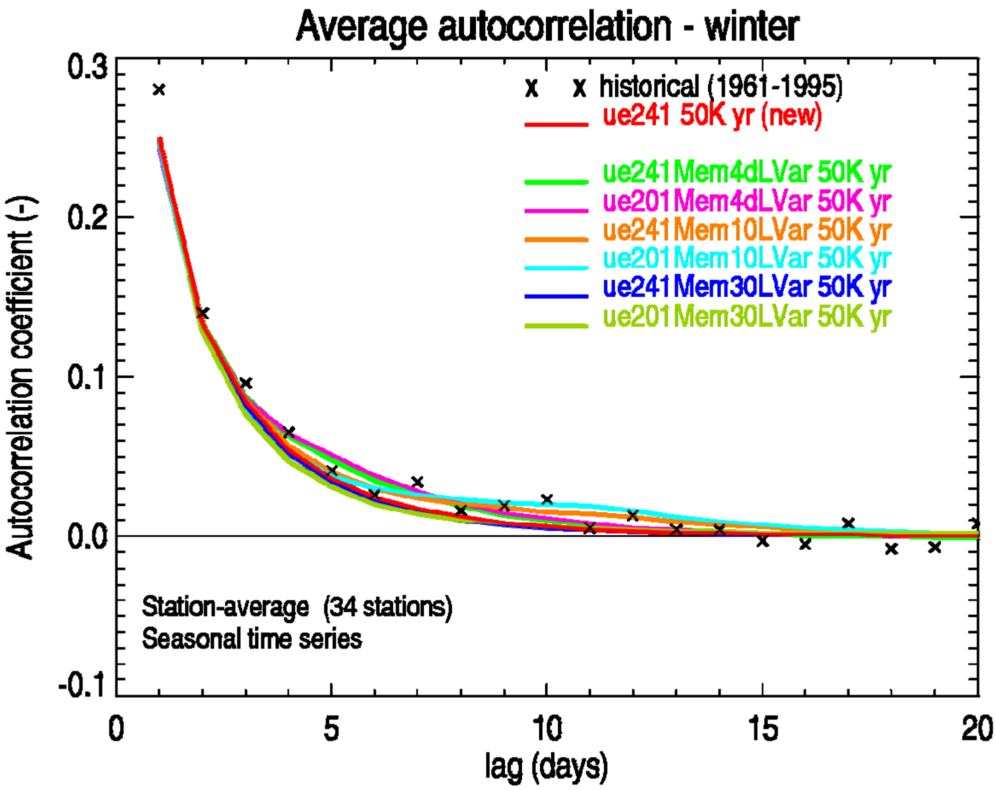
Also note that the Rainfall generator for the Meuse basin in Leander et al. (2005) does not contain F_t^* as a feature vector element. Therefore to make the comparison between the rainfall generators with an additional memory as fair as possible simulations for the Rhine basin were also performed with the weight for F^* set to zero. These simulations are denoted as ‘ue201’ type simulations. So in total 6 different simulations with a memory term are compared with the reference simulation (ue241) without a memory term. Table 2.1 presents the results of these 7 simulations for the standard deviation of the monthly precipitation totals and the lag 1 and 2 autocorrelation coefficients of daily precipitation both for the winter and summer halves of the year. The first observation is that for the reference simulation without memory (ue241) the standard deviation differs significantly from the historical one in the summer half-year but not in the winter half-year. For the simulations with a 4- and 10-day memory term the underestimation of the standard deviation is reduced in particular for the summer season. A 30-day memory gives only a slight improvement in summer and a deterioration in winter. As for the lag 1 and lag 2 autocorrelation coefficients there is little difference between the simulations with and without memory. In all cases (both winter and summer) the lag 1 autocorrelation is significantly underestimated. The lag 2 autocorrelation in winter is in all cases slightly underestimated and in summer slightly overestimated but none of these differences is significant. This may not be a surprise since Leander et al. (2005) already showed that differences in autocorrelation between simulations with and without memory become more apparent for higher order autocorrelation coefficients (lag 3 and higher). Figure 2.1 presents for the same 7 simulations the autocorrelation function in comparison with the one obtained for the historical series both for the winter and summer halves of the year. Compared with the reference simulation (ue241) the influence of the 4- and 10-day memory on the autocorrelation for the higher lags is clear both for winter and summer. A 4-day memory has a visible effect around lag 4 while a 10-day memory has a noticeable effect around lag 10. A 30-day memory seems to have only a marginal effect in summer for lags

Table 2.1. Differences between statistical properties of the simulated time series (50K years) and the historical records (1961–1995) for winter (October – March) and summer (April – September) precipitation. For the mean standard deviation of monthly values ($\bar{s}_{\mathrm{M}}$) the percentage differences are given and for the mean lag 1 and 2 autocorrelation coefficients ($\bar{r}$) the absolute differences. Values between 〈〉 denote averages over the 34 stations (details in Beersma, 2002). Bottom lines: average historical estimates (standard deviation in mm) and their standard error *se* (standard errors for the standard deviation in % and for the auto-correlation coefficients dimensionless). Values in bold refer to differences more than 2 × *se* from the historical estimate.

Simulation	Winter half-year			Summer half-year		
	$\langle\Delta\bar{s}_{\mathrm{M}}\rangle$	$\langle\Delta\bar{r}(1)\rangle$	$\langle\Delta\bar{r}(2)\rangle$	$\langle\Delta\bar{s}_{\mathrm{M}}\rangle$	$\langle\Delta\bar{r}(1)\rangle$	$\langle\Delta\bar{r}(2)\rangle$
ue241	-4.0	**-0.035**	-0.012	**-8.0**	**-0.027**	0.008
ue241_4d	-2.3	**-0.040**	-0.011	-4.8	**-0.032**	0.010
ue201_4d	-2.9	**-0.041**	-0.012	-5.4	**-0.035**	0.006
ue241_10d	-2.0	**-0.039**	-0.012	-2.3	**-0.031**	0.012
ue201_10d	-2.6	**-0.039**	-0.014	-2.7	**-0.033**	0.007
ue241_30d	-5.1	**-0.036**	-0.013	-5.7	**-0.027**	0.012
ue201_30d	-6.3	**-0.035**	-0.016	-6.9	**-0.030**	0.006
Historical	35.8	0.285	0.144	36.7	0.178	0.044
se	4.53	0.008	0.009	3.91	0.009	0.010

larger than 10. For winter there is no evidence that the inclusion of a memory term really improves the higher order autocorrelation. For summer the situation is a bit different. The lag 4 to 7 autocorrelation is systematically underestimated in the simulation without memory and in the simulations with a 30-day memory. This result seems also consistent with the large underestimation of the monthly precipitation totals in these simulations in summer. In conclusion, for the summer half-year inclusion of a memory term is clearly beneficial both in terms of reproduction of monthly precipitation totals and higher order autocorrelation coefficients. Based on visual inspection of Figure 2.1 it is expected that the optimal memory length lies somewhere between 4 and 10 days. For winter the reduction of the underestimation of the standard deviation of monthly precipitation sums is small and the relation between this reduction and the reproduction of the autocorrelation function is not clear.

Finally, and for completeness, also the effect of the inclusion of a memory term on the reproduction of the quantiles of the distributions of extreme 4-day, 10-day and 20-day precipitation amounts is analyzed. Figure 2.2 presents Gumbel plots of the maxima of basin-average 4, 10 and 20-day precipitation in the historical 1961 – 1995 series and those in the seven 50K-year simulated series for the winter and summer halves of the year. In winter the most extreme quantiles of the 4, 10 and 20-day amounts are all reduced in the simulations with a memory term. The decrease is relatively large for the extreme 10-day quantiles and small for the extreme 4-day quantiles. For 20-day amounts the largest reduction is found for simulations with a 30-day memory and the smallest reduction for the 4-day memory simulations. These results can not be explained by differences in the standard deviation of the monthly precipitation amounts or the autocorrelation coefficients. For summer the effect of inclusion of a memory term is (relatively) also largest for the extreme quantiles of 10-day precipitation amounts. A 4-day memory leads to a reduction of the extreme quantiles, a 10-day memory has little influence and a 30-day memory results in larger extreme 10-day quantiles. For the 4-day and 20-day amounts these effects are much smaller but qualitatively they point in the same direction. Again, the difference in the extreme quantiles could not be related to the differences in the standard deviation of the monthly precipitation amounts and/or autocorrelation coefficients.



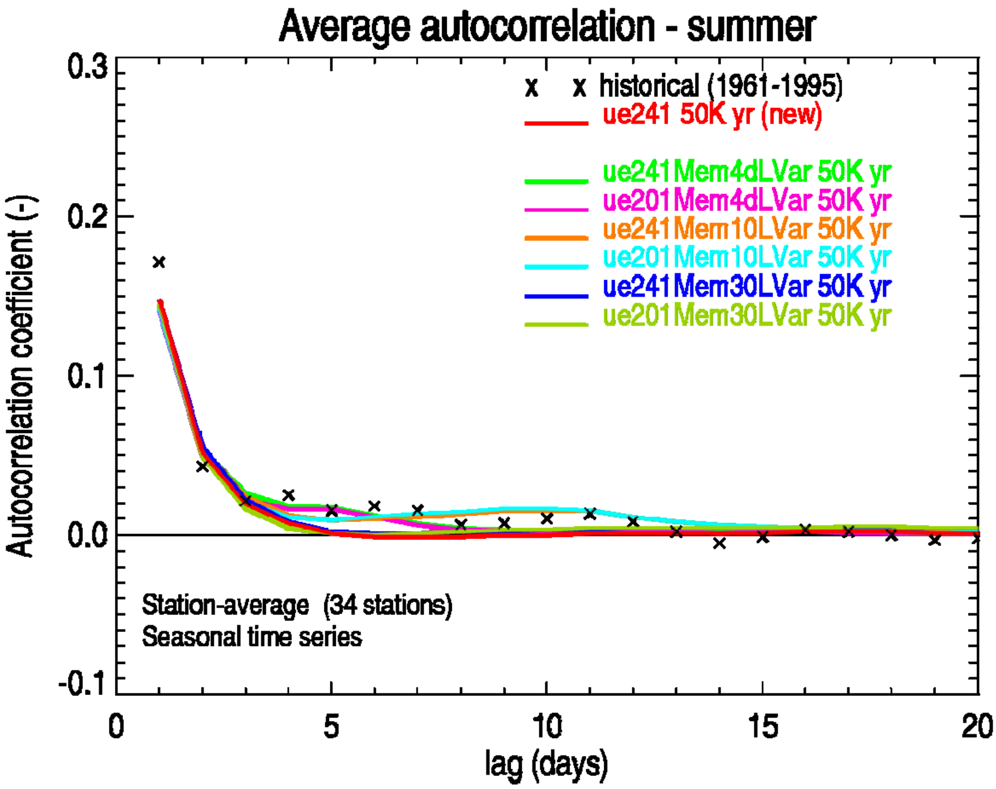


Figure 2.1. Average (34 stations) autocorrelation coefficients of daily precipitation in the historical 1961 – 1995 series and those in 50K-year simulated series for winter (October to March) and summer (April to September).

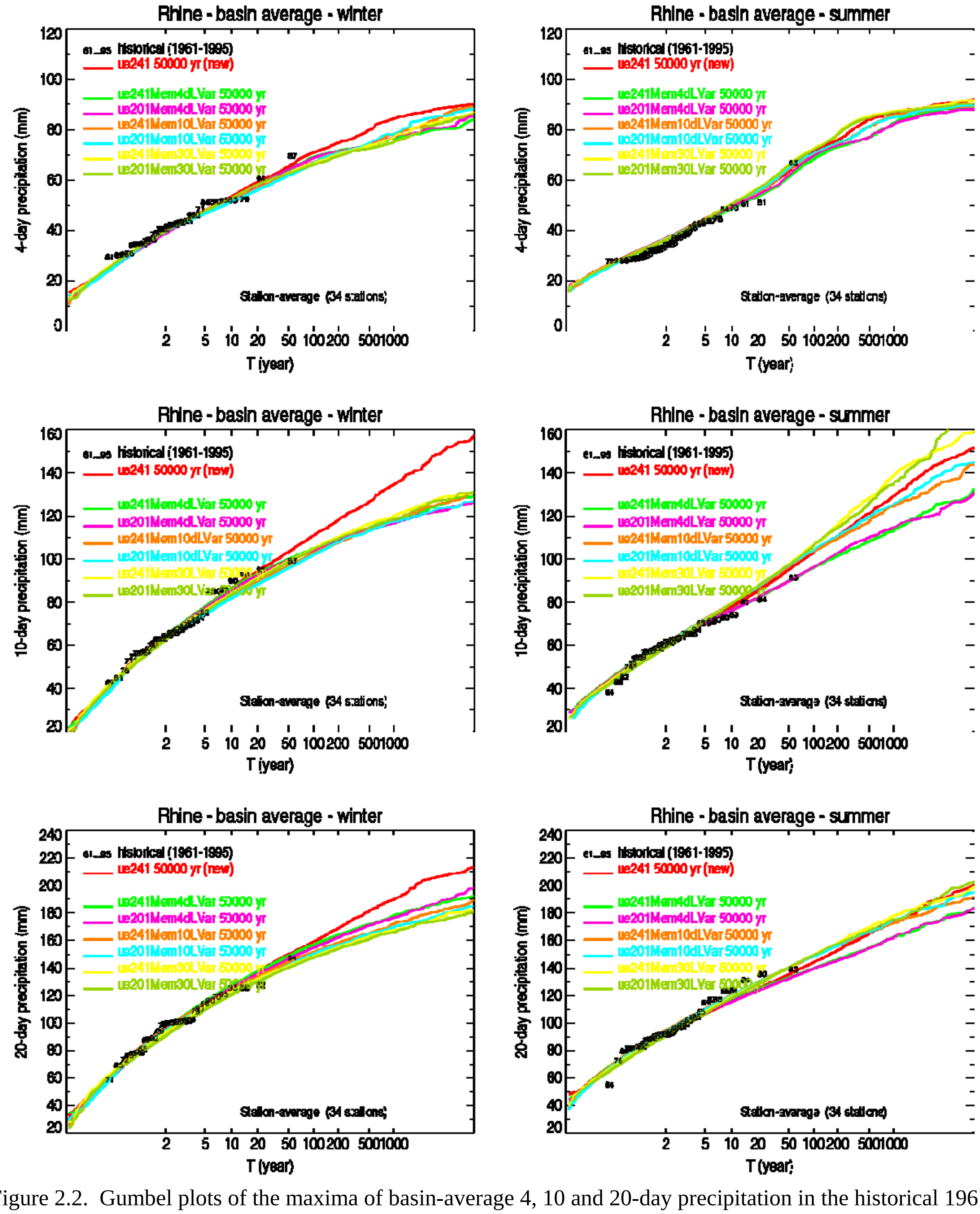


Figure 2.2. Gumbel plots of the maxima of basin-average 4, 10 and 20-day precipitation in the historical 1961 - 1995 series and those in 50K-year simulated series for winter (October to March) and summer (April to September). T refers to the return period (in years). Basin average precipitation is determined as the average of the 34 stations in the Rhine basin.

3. Conclusions

The simulations with the Rainfall generator for the Rhine with an additional memory term show that this term has an influence. Such a term seems beneficial for the summer half-year, both in terms of the reproduction of the standard deviation of monthly precipitation amounts and the higher order autocorrelation coefficients of daily precipitation. From the preliminary results it is expected that the optimal memory length for the summer half-year lies between 4 and 10 days. From the results in Figure 2.2 it can also be expected that this will lead to some reduction of the extreme quantiles of 10- and 20-day precipitation amounts compared with the simulation with no memory term. For the winter season, the influence of a memory term on the standard deviation of the monthly precipitation amounts is small and it also does not improve the reproduction of the autocorrelation function. The inclusion of such a term leads, however, to a reduction of the extreme quantiles of the 4-, 10- and 20-day precipitation amounts in winter, which is most pronounced for the 10-day precipitation. This effect can not be explained by the effects of the memory terms on the standard deviation of the monthly precipitation amounts and on the autocorrelation structure. Therefore, before any decisions are taken regarding the inclusion of a memory term, it is recommended to repeat part of this analysis with simulations based on the Hyras 1951 – 2006 precipitation data for the Rhine basin combined with the E-Obs temperature data for the same period (see also Buishand, 2011). Comparison with the results presented here could indicate whether the effects that we see are systematic or are related to ‘noise’ in the historical reference data. Thereby laying a better foundation for the definite decision to include a memory term for the ‘updated’ Rainfall generator for the Rhine basin.

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