# Model appropriateness for simulation climate change and river flooding

M.J.Booij
*Department of Civil Engineering, University of Twente, Enschede, Netherlands.*

ABSTRACT: An important question in water resources and related subjects is how an appropriate model should look given a specific research area and objective. This question is dealt with by developing a model appropriateness procedure based on model uncertainties. The procedure has been applied to a river basin model meant to assess the impact of climate change on flooding in a large river basin to illustrate the approach. This application indicated that the procedure gives a nice indication in which direction most profit can be gained when an appropriate model should be obtained. Moreover, the results showed that a decrease of input uncertainties and uncertainties associated with the transformation of rainfall to effective rainfall were of particular importance. However, these latter results should be interpreted with caution given the uncertainties in the procedure.

## 1 INTRODUCTION

In water resources and related subjects, a broad palette of models is employed for several purposes. Models used range from simple, lumped black-box models to complex, distributed models including lots of physics and mathematics. More complex models increase data requirements and computational costs, but on the other hand uncertainties in model outcomes and associated costs generally decrease. So, it appears there exists an optimum model complexity associated with minimum total costs. This raises the question how such an appropriate model should look given a specific modeling objective and research area. Thus which physical processes and extra data should be incorporated and which more elaborate mathematical process descriptions should be used at which spatial and temporal scale to obtain an appropriate model level?

Different approaches with respect to model appropriateness have been suggested. For example an appropriateness criterion can be defined and compared with one of the common methods for model evaluation, e.g. the model efficiency coefficient (Nash & Sutcliffe 1970), root mean square error and sample correlation coefficient. Smith (1996) describes a qualitative procedure to incorporate additional processes or omit redundant ones dependent on e.g. the scale at which data are available and results are needed. Jakeman & Hornberger (1993) used time series techniques to determine how many parameters are appropriate to describe the rainfall-runoff relationship in the case that only rainfall, temperature and streamflow data are available. They found that after modulating the measured rainfall using a nonlinear loss function, the rainfall-runoff response of a variety of catchments is well represented using a two-component linear model with four parameters. This is in agreement with other investigations on this subject (e.g. Loague & Freeze 1985, Beven 1989). These approaches consider some specific part(s) of the appropriateness problem. There is a need for an integrated approach to determine an appropriate model for a specific modeling objective and research area.

The objective of this paper is to develop and preliminarily apply a framework for the analysis and improvement of model appropriateness. The framework has been applied to a river basin model meant to assess the impact of climate change on flooding in a large river basin. This is to illustrate the above-mentioned approach, rather than to obtain an appropriate model for the specific modeling objective. The chosen research area is the river Meuse basin in Northwest Europe. The objective is achieved by developing a stochastic rainfall model for rainfall generation and using a simple, water balance based river basin model (see Booij 1999) as a ‘starting model’ in the appropriateness framework. The rainfall model is developed, because for the climate change situation only rainfall on a coarse grid is available and thus changed statistics should be used in a stochastic model. The river basin model outputs of particular interest are the extreme discharges, here extrapolated to the design discharge. This is the discharge with a probability of occurrence once in a very long period (for river management in The Netherlands 1250 years). The direction of model appropriateness improvement is determined by a cost function dependent on model output uncertainty. This model output uncertainty is assessed by means of sensitivity and uncertainty analysis with respect to the main inputs, parameters and process descriptions. Finally, the point of minimum costs should be approached to a certain extent sufficient for the user or it turns out that this point will not be reached at all. This final stage is not the main objective and is beyond the scope of this paper.

In this paper, first an outline of the model appropriateness procedure is given, then descriptions of the stochastic rainfall model and the river basin model are presented and finally results are discussed and conclusions are drawn.

## 2 MODEL APPROPRIATENESS PROCEDURE

The procedure for the analysis and improvement of model appropriateness will be presented here. The way of analyzing model appropriateness is shown and the method of model appropriateness improvement is presented.

### 2.1 *Analysis of model appropriateness*

In the procedure, a cost function dependent on model output uncertainty $C(\sigma_y^2)$ is assumed. This cost function consists of two components, the costs necessary to obtain a specific uncertainty level for the input, parameters or model (e.g. model development, data exploration) $C_x$ and the expected costs as a result of the output uncertainty (in water management e.g. damage, dikes) $C_y$. A model is assumed to be appropriate for a specific research objective when the output uncertainty results in more or less minimal total costs. This is illustrated in Figure 1 (situation *A*). For simplicity it is assumed that $C_x$ is a block function instead of a declining one (situation *B* in Fig. 1). This reduces the appropriateness criterion to $C(\sigma_y^2) = C((\sigma_y^2)_B)$ or, when only uncertainties are considered, $\sigma_y^2 = (\sigma_y^2)_B = G$ (constant value). Then model appropriateness can be evaluated by comparing model output uncertainty $\sigma_y^2$ with a specific *G*.

It is assumed that the model to be used is approximately smooth and linear and the inputs are independent. Then, model output uncertainty is expressed as (e.g. Morgan & Henrion 1990):

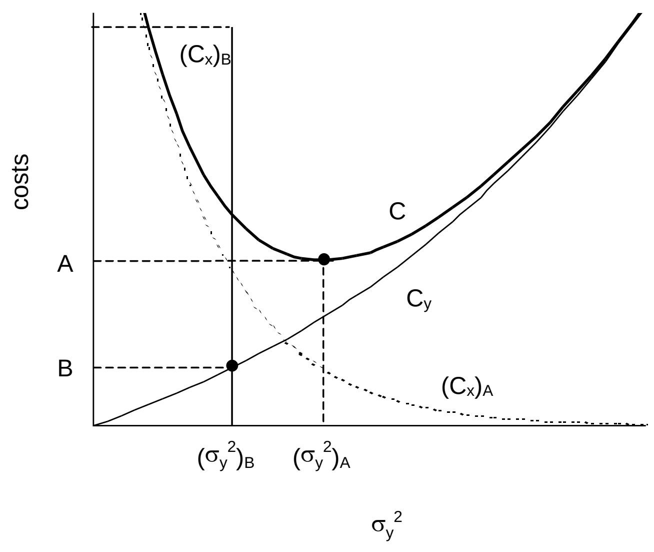


Figure 1. Costs as a function of output uncertainty $\sigma_y^2$ for situation A and B.

$$\sigma_y^2 = \sum_{i=1}^{N} \left( \frac{\partial y}{\partial x_i} \right)_{X_0}^2 \sigma_{x_i}^2 \tag{1}$$

where $X = (x_1, x_2, \ldots\ldots, x_N)$ are the relevant inputs, parameters and processes in the model, $X_0$ are the expected values of $X$ and $\sigma_X^2 = (\sigma_{x1}^2, \sigma_{x2}^2, \ldots.., \sigma_{xN}^2)$ are the variances of $X$. These variances are described by a spatio-temporal semivariogram. The spherical model proposed by Hoosbeek (1998) was used here:

$$\sigma_{x_i}^2(h,\tau) = c_0 + c_1 H(h) + c_2 S(\tau) \tag{2}$$

where:

$$\begin{aligned} H(h) &= 1.5\left(\frac{h}{L}\right) - 0.5\left(\frac{h}{L}\right)^3 \qquad & h \le a \\ H(h) &= 1 & h > a \end{aligned} \tag{3}$$

$$\begin{aligned} S(\tau) &= 1.5\left(\frac{\tau}{T}\right) - 0.5\left(\frac{\tau}{T}\right)^3 \qquad & \tau \le b \\ S(\tau) &= 1 & \tau > b \end{aligned} \tag{4}$$

Here, $h$ is the lag distance or model scale in space, $\tau$ is the lag distance or model scale in time, $c_0$ is the nugget variance, $c_1$ is the spatial variance contribution, $c_2$ is the temporal variance contribution, $L$ is the spatial range and $T$ is the temporal range. All these parameters are dependent on input, parameter and process $x_i$. An example of a spatio-temporal semivariogram showing $\sigma_{xi}^2(h,\tau)$ for arbitrary $c_0$, $c_1$, $c_2$, $L$ and $T$ is given in Figure 2.

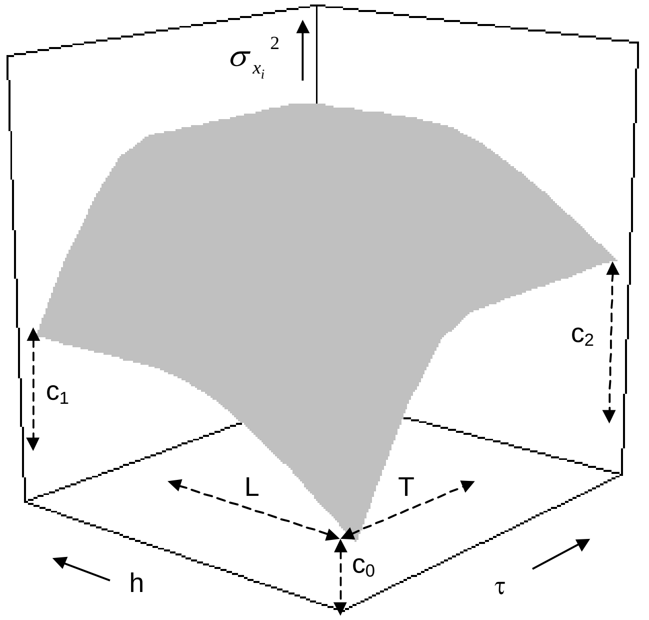


Figure 2. Spatio-temporal semivariogram showing $\sigma_{xi}^2(h,\tau)$ for arbitrary $c_0$, $c_1$, $c_2$, $L$ and $T$.

## 2.2 *Improvement of model appropriateness*

Model output uncertainty usually will be much larger than $G$ and consequently, reduction of uncertainties is required. This reduction can be obtained through a variety of techniques. The here applied procedure of model uncertainty reduction and accompanying model appropriateness increase will briefly be described. Starting-point is a simple river basin model, which transforms rainfall to runoff. The processes, accompanying parameters and inputs to be incorporated in the model are determined by comparing simulations from model versions with varying numbers of processes with observations through the model efficiency coefficient and the discharge regime. These processes remain incorporated throughout the entire procedure, however process descriptions can be adapted as will be shown below. The squared sensitivities $(\partial y/\partial x_i)_{X0}^2$ for these relevant processes, parameters and inputs $x_i$ are determined by varying their values within a specific range and simulating the effect on the output $y$. Then uncertainties $\sigma_{xi}^2$ according to (2) are determined and multiplied with the squared sensitivities to obtain the partial contributions to the output uncertainty $\sigma_y^2$. Sensitivities are assumed to be only dependent on research area and process description and not on data availability and model scales. On the other hand, uncertainties are assumed to be dependent on all these aspects, resulting from (2), (3) and (4) as well. The dependence of the sensitivity and the uncertainty on the mentioned aspects is shown in Table 1.

Table 1. Presence of dependence of sensitivity ($\partial y/\partial x_i$) and uncertainty (parameters/ variables from (2), (3) and (4) $L$, $T$, $c_0$, $c_1$, $c_2$, $h$, $\tau$) on aspects (research area, process description, data availability, model scale) indicated with X.

| Aspect | Sensitivity | Uncertainty | | |
|---|---|---|---|---|
| | $\partial y/\partial x_i$ | $L$, $T$ | $c_0$, $c_1$, $c_2$ | $h$, $\tau$ |
| Research area | X | X | X | X |
| Process description | X | | X | X |
| Data availability | | | X | X |
| Model scales | | | | X |

The largest partial contributions to the output uncertainty should be reduced taking into account Table 1. This means for a fixed research area that uncertainties associated with large sensitivities should be reduced through adapting process descriptions, increasing data availability and changing model scales. Which adaptations take place depend for a specific process, parameter or input on the uncertainty contributions of the nugget part $c_0$, spatial part $c_1 H(h)$ and temporal part $c_2 S(\tau)$ of (2). When process descriptions are adapted sensitivities should be recalculated. Uncertainty reduction should proceed until uncertainty level $G$ associated with an appropriate model for a specific situation is reached. Obviously, it may be possible that this appropriate uncertainty level will not be reached at all.

In this paper, this procedure will be applied to a simple river basin model. This application is meant to illustrate the procedure, rather than to derive an appropriate river basin model to assess the effect of climate change on flooding in the river Meuse.

# 3 MODEL DESCRIPTIONS

## 3.1 *Stochastic rainfall model*

Sophisticated stochastic rainfall models have been developed (e.g. Bras & Rodriguez-Iturbe 1976, Waymire et al. 1984, Shah et al. 1996). A simple stochastic rainfall model has been used in this project before (Booij 1999). This slightly modified version of a random phase model turned out to be computationally inefficient and moreover, statistical rainfall characteristics appeared to be difficult to preserve. The stochastic rainfall model used here is a multivariate autoregressive lag-one model AR(1). This model incorporates main statistical characteristics of observed precipitation to generate spatially and temporally varying rainfall series. The model assumptions are:

1. The rainfall process is a stationary one, i.e. its statistics do not change with time.

2. The rainfall process has a uniform character, i.e. its statistics do not vary in space.

3. There is correlation in time and space between rainfall amounts.

The multivariate AR(1) model is described by:

$$\mathbf{P}(t) = \mathbf{A}\mathbf{P}(t-1) + \mathbf{B}\varepsilon(t) \tag{5}$$

where the vector $\mathbf{P}(t)$ is composed of $n$ different but interdependent rainfall time series, $\mathbf{A}$ and $\mathbf{B}$ are $n \times n$ parameter matrices and the vector $\varepsilon(t)$ consists of $n$ uncorrelated shocks originating from a symmetrical three-parameter gamma distribution (reflected with respect to the y-axis). It is assumed that $\mathbf{A}$ is a diagonal matrix with uniform non-zero elements equal to $a$ determining the temporal correlation $\rho_t$ and transition probabilities from wet to wet days *WW*, dry to dry *DD* etc.. Elements $b_{ij}$ of $\mathbf{B}$ are obtained through the following relation with distance between two locations $|(x, y)_i-(x, y)_j|$ and parameter $b$ determining the spatial correlation $\rho_s$, see e.g. Stol (1972):

$$b_{ij} = e^{-b\left|(x,y)_i-(x,y)_j\right|} \tag{6}$$

The shape parameter $\lambda$, scale parameter $\beta$ and horizontal displacement $c$ of the gamma distribution determine respectively the peakness of the rainfall (represented by the kurtosis $K$), the average rainfall $\mu$ and the ratio wet to dry days $W/D$:

$$f(x) = \frac{1}{\beta^{\lambda}\Gamma(\lambda)}\left|x-c\right|^{\lambda-1} e^{-\frac{|x-c|}{\beta}} \tag{7}$$

with $-\infty < x < \infty$. The five parameters ($a$, $b$, $c$, $\lambda$ and $\beta$) have been determined in such a way that the statistical characteristics of observed rainfall are approximated in a right way.

The rainfall model is applied to the river Meuse basin upstream of Borgharen (near the Belgian-Dutch border) which has a surface area of about 21 $10^3$ km$^2$. Its parameter values have been obtained by means of observed rainfall (Stol 1972, Berger 1992, NOAA 1999). Daily rainfall series for $n$ = 64 points in a regular square grid (distance between points is approximately 20 km) for a 30-year period have been generated.

## 3.2 *River basin model*

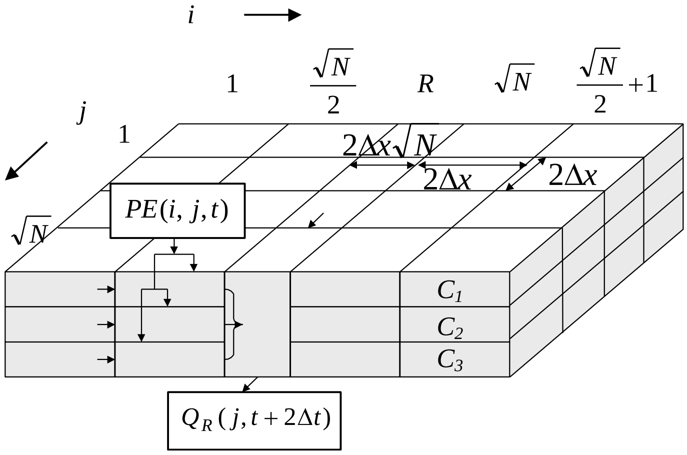


Figure 3. River basin model with catchment cell position expressed in $i$ and $j$, river cell position ($R$) expressed in $j$, cell dimensions expressed in $\Delta x$, input $PE$ ($i$, $j$, $t$) and output $Q_R$ ($j$, $t$+2$\Delta t$) and water flow directions illustrated for an arbitrary catchment and river cell (the figure has not been drawn to scale).

A simple river basin model with variable spatial and temporal resolution has been used as the ‘starting model’ in the appropriateness procedure. This model will briefly be described here, for a more comprehensive description reference is made to Booij (1999).

The model consists of a number of catchment cells $N$ and river cells $\sqrt{N}$. Different resolutions are obtained by multiplying $N$ with $4^n$ depending on the actual $N$. These varying resolutions do not change model output for uniform and stationary input and parameters. The model structure for $N$ = 16 is illustrated in Figure 3. This structure shows that each catchment cell in strip $j$ receives effective precipitation (*PE*) and discharges this precipitation to the adjacent cell in strip $j$ in the river direction. The catchment cell that borders a river cell discharges into this river cell in strip $j$, from this river cell the water is transported further to the river cell in strip $j$+1 and finally to the outflow point.

The water movement is described by means of a water balance for the catchment cells and the river cells in a dimensionless form in order to reduce the number of parameters:

$$\begin{aligned} h_{C_m}(i,j,t) - h_{C_m}(i,j,t-\Delta t) &= -K_m k_R h_{C_m}(i,j,t-\Delta t) \\ &+ p_{C_m}(i,j,t)\,PE(i,j,t)\Delta t \\ &+ K_m k_R h_{C_m}(i-1,j,t-\Delta t) \end{aligned} \tag{8}$$

$$Q_C(j,t) = \sum_{m=1}^{3} \frac{K_m k_R}{\Delta t} \left[ h_{C_m}(\sqrt{N}/2, j, t-\Delta t) + h_{C_m}(\sqrt{N}, j, t-\Delta t) \right] \quad (9)$$

$$h_R(j,t) - h_R(j,t-\Delta t) = -k_R h_R(j,t-\Delta t) + Q_C(j,t)\Delta t + k_R h_R(j-1,t-\Delta t) \quad (10)$$

$$Q_R(\sqrt{N},t) = \frac{k_R}{\Delta t} h_R(\sqrt{N}, t-\Delta t) \quad (11)$$

where $h_{Cm}$ is the water depth for reservoir $C_m$ in a catchment cell, $\Delta t$ is the time step, $K_m$ is the ratio of the lag constant of reservoir $C_m$ to the lag constant of reservoir $R$, $k_R$ is the lag constant of reservoir $R$ in the river cell, $p_{Cm}$ is a distribution function for the rainfall, $PE$ is the effective rainfall, $Q_c$ is the total discharge from the adjacent catchment cells into a river cell, $h_R$ is the water depth for reservoir $R$ and $Q_R$ is the discharge of the river basin. All terms are dimensionless which have been achieved through using a spatial correlation length, a temporal correlation length, the surface area of the basin and the mean effective rainfall.

Equations (8) and (9) applies to one of the reservoirs in a catchment cell and equations (10) and (11) applies to the reservoir in a river cell. The left-hand side of (8) represents the storage change, the first term on the right-hand side is the discharge out of the reservoir ($Q_m$)*, the second term reflects the rainfall distribution ($p_m$)* and the third term represents input from the same reservoir of the cell upstream of the considered catchment cell (see Fig. 3). The left-hand side of (10) represents the storage change, the first term on the right-hand side is the discharge out of the reservoir ($Q_R$)*, the second term reflects input from the adjacent catchment cells and the third term represents input from the river cell upstream of the considered river cell. It is assumed that effective rainfall ($PE$)* is only received by the catchment cells. Only water balance terms indicated with an asterisk are assumed to be process descriptions subject to uncertainty.

The initial state of the system is assumed to be equal to the equilibrium state, implying uniform (independent of $i$ and $j$) and stationary (independent of $t$) initial conditions. The main assumption done when defining the water distribution functions $p_{Cm}(i, j, t)$ is that the more water is stored in reservoir $C_2$ and $C_3$ the more water will flow into reservoir $C_1$ respectively $C_2$. It appears (see Booij 1999) that for parameters $p_{Cm}(i, j, 0)$, $K_m$ and $k_R$ values have to be determined. Effective rainfall is obtained by multiplying observed rainfall or simulated rainfall **P** from (5) with a time-dependent runoff coefficient **rc** = ($rc_1$, $rc_2$,…., $rc_k$). It is made dimensionless to obtain $PE(i, j, t)$ from (8) by scaling it with its mean value.

The (dimensionless) design discharge $Q_p$ for a specific return period $T_R$ is (Shaw 1983):

$$Q_p = \mu_{QA} + K(T_R)\sigma_{QA} \quad (12)$$

where $\mu_{QA}$ and $\sigma_{QA}$ are respectively the mean and the standard deviation of the annual maximum discharge and $K(T_R)$ is the frequency factor:

$$K(T_R) = -\frac{\sqrt{6}}{\pi}\left[\gamma + \ln\ln\left(\frac{T_R}{T_R - 1}\right)\right] \quad (13)$$

where $\gamma \approx 0.5772$. The relative error $E_{Qp}$ in determining $Q_p$ with specific $T_R$ is (Shaw 1983):

$$E_{Qp} = \frac{\sqrt{\frac{\sigma_{QA}^{\;2}}{n_d}\left(1 + K(T_R)S_{QA} + \frac{K(T_R)^2}{4}(K_{QA} - 1)\right)}}{Q_p} \quad (14)$$

where $n_d$ is the number of annual maximum discharges and $S_{QA}$ and $K_{QA}$ are respectively the skewness and the kurtosis of the annual maximum discharge.

The 'starting model' of the Meuse basin is the most simple one, namely when $N = 1$. With a spatial correlation length of 140 km and a temporal correlation length of 1 day this gives for the model scales $\Delta x$ =0.52 and $\Delta t$ = 1. Processes to be incorporated in this 'starting model' and parameter values to be used have been determined by using an observed daily rainfall-runoff series. The observed rainfall series is from a station near the center of the Meuse basin (Charleville-Mézières) from the period 1994 through 1997 (NOAA 1999). The observed discharge series is from the station Borgharen at the outflow point of the river basin model from the period 1994 through 1997 (Rijkswaterstaat 1998). Runoff coefficients are assumed to be monthly means ($k$ = 12) and have been obtained from observed rainfall in the Meuse basin during the period 1951 through 1980 (Berger 1992).

The design discharge is obtained by simulating a daily Borgharen discharge series $Q_R(\sqrt{N}, t)$ for a 30-year period and by using one or more of the generated daily rainfall series from the regular square grid for a 30-year period. The discharge series for a 30-year period results in a relative error in determining the design discharge $E_{Qp}$ due to extrapolation of about 5 %.

## 4 RESULTS AND DISCUSSION

### 4.1 *Stochastic rainfall model*

Parameter values for the rainfall model and related observed and simulated statistics are summarized in Table 2.

Table 2. Parameter values for the rainfall model and related observed and simulated rainfall statistics.

| Parameter | Value | Statistic | Unit | Value Observed | Simulated |
|---|---|---|---|---|---|
| $a$ | 0.45 | $\rho_t$(1 day) | - | 0.24* | 0.38 |
| | | $WW$ | - | 0.69* | 0.66 |
| | | $DD$ | - | 0.71* | 0.66 |
| $b$ | 1.5 | $\rho_s$(25 km) | - | 0.84** | 0.93 |
| | | $\rho_s$(50 km) | - | 0.75** | 0.85 |
| | | $\rho_s$(100 km) | - | 0.64*** | 0.63 |
| $c$ | 0 | $W/D$ | - | 0.92* | 0.99 |
| $\lambda$ | 0.15 | $K$ | $(mm/d)^4$ | 19* | 11 |
| $\beta$ | 100 | $\mu$ | mm/d | 2.56*** | 2.55 |

* From daily observed rainfall of 3 stations in and around the Meuse basin (Charleville-Mézières, Metz and St. Dizier) during the period 1994 through 1998 (NOAA 1999).
** From spatial correlations between daily observed rainfall in the eastern part of the Netherlands (Stol 1972).
*** From observed rainfall in the Meuse basin during the period 1951 through 1980 (Berger 1992).

It appears from Table 2 that observed and simulated statistics correspond quite well. Only the differences between observed and simulated temporal correlation $\rho_t$ and kurtosis $K$ are substantial. This first difference is due to the fact that parameter $a$ determines besides this temporal correlation also the transition probabilities from wet to wet days $WW$ and dry to dry $DD$. Therefore $a$ had to be chosen in such a way that the three statistics are jointly simulated as good as possible. The second difference ($K$) is due to the gamma distribution used. This distribution simulated the rainfall extremes quite well, however it was not able to reproduce the extremes of the extremes. These are small disadvantages of the rainfall model and should be kept in mind when interpreting the results.

### 4.2 *River basin model appropriateness procedure*

First the processes to be incorporated throughout the whole procedure were determined. Models with a different number of processes were obtained by varying the number of reservoirs in a catchment cell from $m$ = 1 through $m$ = 3. Simulations with these models (with calibrated parameters) resulted in model efficiency coefficients of respectively 0.81, 0.84 and 0.85. A value of 1 would have implied perfect correspondence between observed and simulated discharge. On the basis of these coefficients no decision can be made. However, when comparing the discharge regimes associated with the three simulations, the one for $m$ = 1 showed a very extreme behavior. Therefore two reservoirs were incorporated in the river basin model. The incorporated input, processes and parameters are summarized in Table 3.

Table 3. Incorporated input, processes and parameters and associated parameter values in river basin model.

| Input | Process | Parameter | Value |
|---|---|---|---|
| **P** | | | |
| | $PE$ | **rc** | monthly mean |
| | $p_1$ | $p_{C1}(i, j, 0)$ | 0.5 |
| | | $p_{C2}(i, j, 0)$ | 0.5 |
| | | $K_2$ | 0.05 |
| | $p_2$ | $p_{C1}(i, j, 0)$ | idem |
| | | $p_{C2}(i, j, 0)$ | idem |
| | | $K_2$ | idem |
| | $Q_1$ | $K_1$ | 0.5 |
| | $Q_2$ | $K_2$ | idem |
| | $Q_R$ | $k_R$ | 0.5 |

The above described model ($N$ =1 and 2 reservoirs) is the 'starting model' for the model appropriateness procedure. The input is a daily rainfall series of one point (near the basin center) for a 30-year period. The parameter values of the spatio-temporal semivariogram described by (2), (3) and (4) for each input, process and parameter for this model have been roughly estimated and are given in Table 4. It has been tried to estimate the right ratios between the different parameter values for the different variables partly on the basis of literature (e.g. Blöschl & Sivapalan 1995, Kitanidis 1997, Hoosbeek 1998). The parameters $L$, $h$, $T$ and $\tau$ are scaled with respect to their correlation lengths and the (root of) parameters $c_0$, $c_1$ and $c_2$ are relative to their corresponding input, process or parameter value.

Table 4. Parameter values $\sqrt{c_0}$, $\sqrt{c_1}$, $L$, $h$, $\sqrt{c_2}$, $T$, $\tau$ for input, process descriptions and parameters used in start simulation (dimensionless).

| Input/ process/ parameter | Nugget | Spatial | | | Temporal | | |
|---|---|---|---|---|---|---|---|
| | $\sqrt{c_0}$ | $\sqrt{c_1}$ | $L$ | $h$ | $\sqrt{c_2}$ | $T$ | $\tau$ |
| **P** | 0.2 | 0.2 | 1.43 | 1.04 | 0.3 | 4 | 1 |
| $PE$ | 0.2 | 0 | 0.36 | 1.04 | 0.2 | 90 | 1 |
| $p_1$ | 0.3 | 0.025 | 0.036 | 1.04 | 0.4 | 8 | 1 |
| $p_2$ | 0.3 | 0.025 | 0.036 | 1.04 | 0.4 | 8 | 1 |
| $Q_1$ | 0.2 | 0.05 | 0.036 | 1.04 | 0.4 | 4 | 1 |
| $Q_2$ | 0.1 | 0.05 | 0.36 | 1.04 | 0.3 | 50 | 1 |
| $Q_R$ | 0.1 | 0.05 | 2.14 | 1.04 | 0.4 | 15 | 1 |
| **rc** | 0.1 | 0.1 | 0.36 | 1.04 | 0.3 | 90 | 30 |
| $p_{C1}(i, j, 0)$ | 0.2 | 0.3 | 0.036 | 1.04 | 0.1 | 8 | 100 |
| $p_{C2}(i, j, 0)$ | 0.2 | 0.3 | 0.036 | 1.04 | 0.1 | 8 | 100 |
| $K_1$ | 0.2 | 0.3 | 0.036 | 1.04 | 0.1 | 4 | 100 |
| $K_2$ | 0.1 | 0.1 | 0.36 | 1.04 | 0 | 50 | 100 |
| $k_{R0}$ | 0.05 | 0.1 | 2.14 | 1.04 | 0.1 | 15 | 100 |

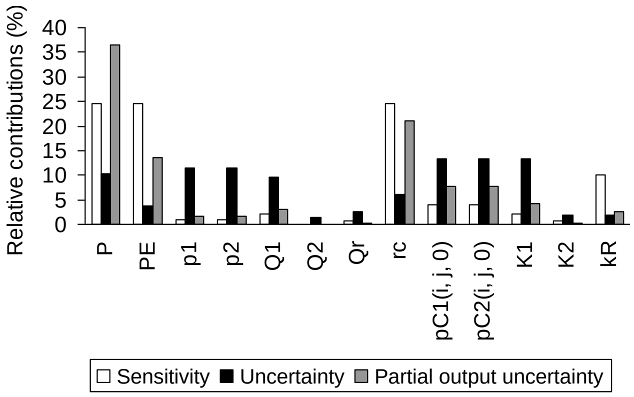


Figure 4. Relative contributions of input, process descriptions and parameters to sensitivity, uncertainty and output uncertainty.

The resulting squared sensitivity from (1) of the model output $Q_p$ with respect to the input, process descriptions and parameters, relative to the output value and its input, process or parameter values and relative to each other, is given in Figure 4. When determining these sensitivities, it appeared that *Qp* behaved more or less linear with different values for input, processes and parameters. The uncertainty from (2) of the input, process descriptions and parameters relative to its input, process or parameter value and relative to each other is given in Figure 4 as well. Finally, the partial output uncertainty contributions from (1) of the input, process descriptions and parameters relative to each other, is given in Figure 4. The relative model output uncertainty $\sigma_y/Q_p$ (%) is in this case 69 % as could be expected from the very simple model. Again, it is emphasized that this application is only an illustration of the proposed procedure. Moreover, the parameters in Table 4 are roughly chosen and thus uncertain. The model output $Q_p$ = 11.9. In the following, 3 steps in the model appropriateness improvement procedure are presented.

Step 1. The largest partial contribution to the output uncertainty stems from **P**. The nugget, spatial and temporal uncertainty contributions are comparable (not shown here). It has been decided to decrease the spatial contribution by including rainfall series from all stations ($n$ = 64) in the simulations. An accompanying decrease in parameter $\sqrt{c_1}$ of **P** from 0.2 to 0.1 was assumed. The resulting $\sigma_y/Q_p$ is 65 % meaning a decrease of 'only' 4 % in output uncertainty. However, $Q_p$ has changed dramatically to 7.7 due to the averaging effect of the input (average of 64 points).

Step 2. The changed relative contributions according to Figure 4 (not shown here) are calculated. The partial contribution from **P** is still the largest one, but the partial contribution from **rc** is considerable as well. For this parameter the temporal uncertainty contribution is the largest one, therefore this contribution has been decreased by modeling **rc** day-dependent ($k$ = 365) instead of month-dependent ($k$ = 12) through a sinus function. This resulted in a decrease of parameter $\tau$ for **rc** from 30 to 1. The resulting $\sigma_y/Q_p$ is 60 % (5 % decrease) and $Q_p$ remains more or less unchanged.

Step 3. The undesirable averaging effect of the input on the output in step 1 was assumed to decrease when the model scales ($h$ and $\tau$) would be decreased. Parameter $h$ was changed from 1.04 to 0.26 for all processes and **P** and parameter $\tau$ was changed from 1 to 0.25 for all processes and **rc**. With this change in both parameters the same constant ratio between space and time in the model is preserved as was done by Booij (1999). The resulting $\sigma_y/Q_p$ is 58 %, only a 2 % decrease in output uncertainty. However, $Q_p$ has changed considerable (to 13.2) close to its original value, which seems to be more plausible.

## 5 CONCLUSIONS

The results of the stochastic rainfall model indicate that a relative simple model already is able to produce realistic rainfall statistics. The only substantial departure from observed statistics was found for the temporal correlation.

The application of the model appropriateness procedure showed that the procedure could give a nice indication in which direction (input, process descriptions or parameters as well as nugget, spatial or temporal part) most profit can be gained when an appropriate model should be obtained for a specific research area and objective. It appeared that for this or a similar research area and objective 2 reservoirs in the catchment cell already seems to be sufficient. Furthermore, the results indicated that a decrease of input uncertainty and uncertainties associated with the transformation of rainfall to effective rainfall were of particular importance.

These latter results should be interpreted with caution, in particular because of the substantial uncertainties in the parameters of the spatio-temporal semivariogram. Also, when including more noon-linear process descriptions to decrease output uncertainty, these process descriptions should be linearized to maintain linearity necessary for the determination of the output uncertainty. Otherwise this output uncertainty should be determined in a different, more complex manner. However, it is again emphasized that the application was meant to illustrate the procedure rather than to derive an appropriate model for the river Meuse basin designed to assess the impact of climate change on river flooding.

The framework will be extended and improved in order to apply it to a more sophisticated model to determine the appropriate model level for this research objective. Moreover, the framework could be applied to other areas and water resources problems in future.

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