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## **Calibration of rainfall-runoff models**

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## INTRODUCTION

Hydrology is a science that deals with water on Earth, studying the chemical and physical characteristics, distribution in space and time, the dynamic behaviour and relationships with the environment during all phases of the complex cycle of exchanges between ocean, atmosphere and back to ocean, either directly or after surface runoff on land or water penetration and movement in the subsurface (water cycle or hydrologic cycle).

Hydrology is integrated with other disciplines working with the earth sciences as geology, meteorology, oceanography, geochemistry etc... ([The Columbia Electronic Encyclopedia, 2007](#)).

Strictly speaking the field of investigation concerns the study of the hydrology of the waters in their precipitation on land and runoff into the oceans, which deals with the waters, because the study of marine waters is the responsibility of oceanography, while that of the various aspects of water in the atmosphere (rain water) falls within the field of meteorology.

Hydrology deals with surface water (hydrography) and groundwater (geohydrology). The study of surface water not only concerns the waterways, but also the lakes (limnology), glaciers (glaciology) and also the drainage and irrigation. Among the fundamental tasks of the hydrology within the study of methods for ensuring effective and practical for quantitative determination of parameters relating to the water balance, data interpretation and formulation of principles and laws relating to the dynamic and the work of active water in the hydrological cycle. Applied hydrology sets itself the task of providing the necessary data to determine the intensity and distribution of rainfall, runoff values of the waterways on the basis of systematic and continuous sections in river characteristics and consequences of their regime, the rate of evaporation on lakes and reservoirs, underground water absorption etc.

Having relevant data is possible to reconstruct, with the use of mathematical models and computers, the flow of water and then predict the consequences of any actions undertaken by man. The results thus obtained can be compared with those derived from direct experimentation on physical models

appropriately reduced, but which need to be effective, required that all measured data are available and accurate.

The above considerations highlight the fundamental role of hydrology and hydrological modelling in water resources management and engineering. However, hydrological modelling is still imprecise and affected by limitations in general. The main reason is a result of the limitations of hydrological measurement techniques, since we are not able to measure everything about hydrological systems. Increasing demands on water resources throughout the world require improved decision-making and improved models.

The present study is focusing on rainfall-runoff modelling and in particular on techniques for parameter calibration. The objectives of the study is to assess the efficiency of currently used parameter estimation methods with respect to hypothetical and real world case studies. An established models is used for which calibration techniques are tested therefore deriving indications on their efficiency and suitability.

## CHAPTER 1

### WATERSHEDS

The watershed (Figure 1.1) is defined as that portion of land whose water runoff surface is directed towards a fixed section of a stream that is defined in section closure of the basin.

As the process of modelling the earth's surface that are formed due mainly just the erosive action of water flowing on the surface. Referring to collection only water catchment precipitation is talking about.

Watersheds can be large or small. Every stream, tributary, or river has an associated watershed, and small watersheds join to become larger watersheds.

Watersheds can also be called *basins* and *drainages*. Here is an example of what a watershed looks like:

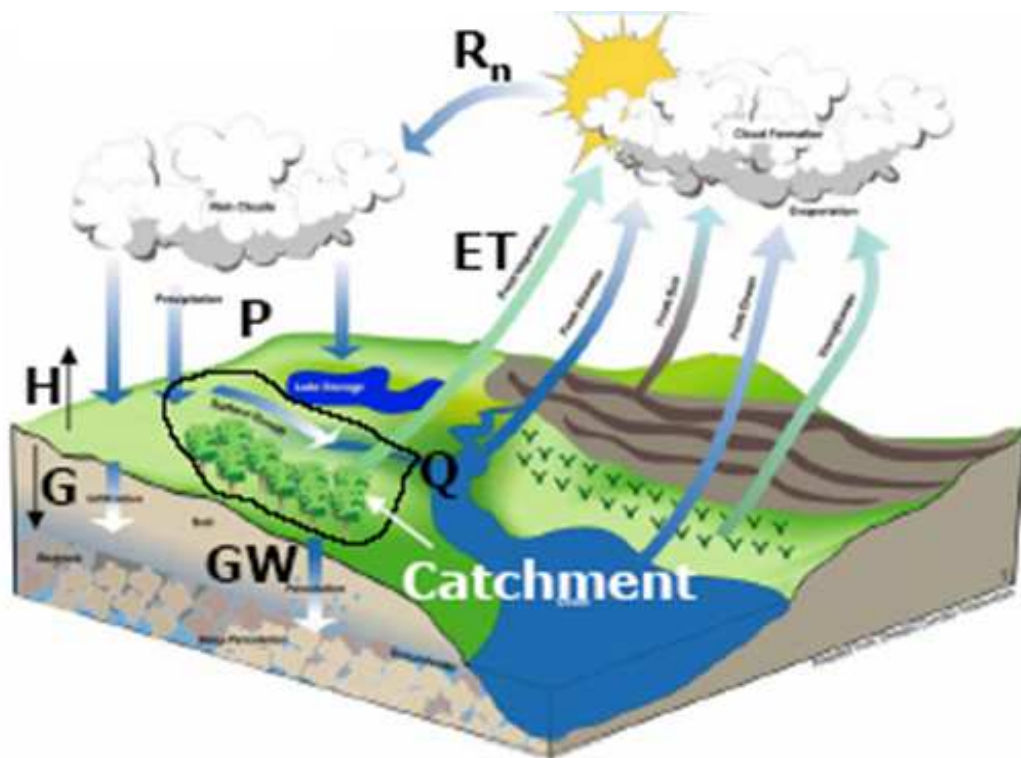


Figure 1.1: Example of watershed (North and south rivers watersheds association).

The catchment area is the fundamental physiographic units which refer to the study of phenomena of the river and hydro-geomorphological processes associated with them.

These dynamics are analyzed under the more general knowledge of hydrological cycle (water cycle changes on the Earth's surface and atmosphere) and the order to obtain the determination of elements essential for the proper sizing of the works hydraulic system interventions and river basins. For example, can affect estimate of the volume of water flowing through a section of a stream in a given period of time, the full extent of which can occur with a given return period, the amount of solid material eroded from the surface of the basin. The determination of these quantities is the subject of deterministic or statistical processing.

The hydrological response of a basin depends on rainfall that occur naturally on it (and thus indirectly from its position and altitude), from their interception and from the subsequent disposal (and thus the permeability determined by the texture and soil depth, the type of coverage etc.), by solar radiation and the orientation respect winds etc.

Watersheds are associated with creeks, streams, rivers, and lakes, but they are much more. A watershed is a highly evolved series of processes that convey, store, distribute, and filter water that, in turn, sustain terrestrial and aquatic life. Here we explore a cross-section of a natural, undeveloped river corridor to see how trees and wetlands, floodplains and uplands handle water as shown in Figure 1.2.

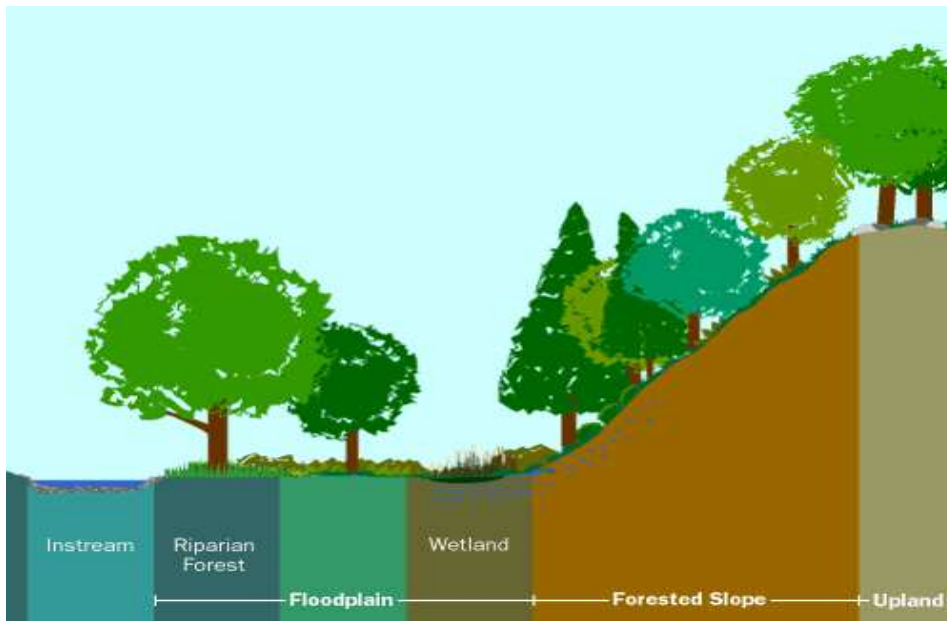


Figure 1.2: Natural systems (Watersheds Atlas).



It is estimated that 80 to 90 % of streams in our watershed are headwater streams starting in forested woodlands. Moving constantly downstream, a stream widens, its shape and structure changes, and so do its aquatic habitats, temperatures and food sources. Below are four factors involved with changes in complex stream dynamics:

- **Water temperatures vary:** Tree-covered *headwaters* are considered cold water streams because they are fed by cold groundwater and shaded overhead from the heat of the sun. Cold water streams enter larger rivers that have warmer temperatures because they have less shade and more sunlight hitting their mid-channels and sides.
- **Food sources change;**
- **Aquatic habitats vary within a stream reach:** high energy waters scour and erode stream channels. Deposition of soil sediments, silts, and sands happens in slower, low-energy river stretches, where benthic habitats tend to have more silts and sands and less gravel.
- **Water quality changes:** Streams tend to start out uncontaminated in headwaters and experience sediment and chemical loading as they traverse tilled, residential and industrialized landscapes. Headwaters are almost always cleaner than big river waters.

Riparian forests refer to forest vegetation occurring alongside streams and rivers and offer the last opportunity for runoff waters to have a lively exchange with vegetation and soils before entering streams and rivers.

Riparian forests have two main functions:

- **Filtering:** Runoff from rain or snow is intercepted by riparian vegetation, where it slows down and drops out sediments.
- **Stabilizing:** Interwoven root systems of streamside vegetation prevent erosion during high water events. Undisturbed riparian vegetation is usually made up of mature, native forest trees like red maples, sycamores, and willows, with a range of native shrubs and grasses that tolerate wetter soils.

After infiltrating natural systems, water evaporates from rivers and wetlands, soils and plants. It returns to the atmosphere to fall again as precipitation. Precipitation is water that falls from clouds in the sky as rain (liquid form of water) or as snow, sleet, or hail (solid forms of water). Runoff is water that flows

over the surface of the land. It usually occurs when the rate of precipitation (rain) exceeds infiltration, that is the soil becomes saturated with water and can absorb no more. In the built environment, runoff occurs on asphalt surfaces where the soil has been covered with an impervious material.

Water cycling cools the planet, cleans the air, and sustains life. This is the water cycle as shown in Figure 1.3:

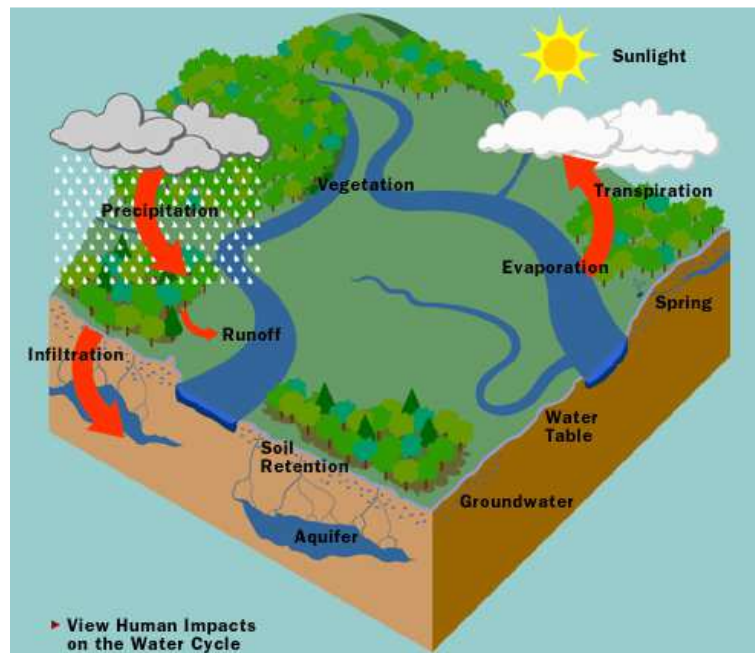


Figure 1.3: Water cycle (Watersheds Atlas).

Hydrological modelling of water balances or extremes (floods and droughts) is important for planning and water management. Unfortunately the small number (or even the lack) of observations of key variables that influence hydrological processes limits the applicability of rainfall-runoff models; so modelling is an important tool for assessing the data of the water cycle in the areas of interest. In principle, if the models are based on the basic principles of physics and so the estimation of model parameters should be an easy task.

Hydrological models describe the natural processes of the water cycle (see Figures 1.4 and 1.5).



Figure 1.4



Figure 1.5

Due to the large complexity of the corresponding natural phenomena, these models contain substantial simplifications. They consist of basic equations, often loosely based on physical premises, whose parameters are specific for the selected catchment and problem under study. In this project we will deal with watershed models and in particular, we will see an application of HBV model.

Understanding and modelling the water balance dynamics of catchments is important from both engineering and scientific perspectives. Hydrological rainfall runoff models may be used in managing the water resources of river basins. They can be employed for assessing anthropogenic effects on runoff regime, water quantity and quality, for estimating design flow values, and for river flow forecasting (e.g., [Beven, 2001](#)). In the past decades a large amount of rainfall runoff models water balance models were developed. These range from simple black box models, to conceptual models and complex physically based distributed models ([Singh and Frevert et al., 2001a, 2001b](#)).

In engineering application conceptual models are mostly used. In these, the basic processes such as interception, infiltration, evaporation, surface and subsurface runoff, etc., are reflected to some extent. In real life applications the algorithms that are used to describe the processes are essentially calibrated input-output relationships, formulated to mimic the functional behaviour of the process in question (e.g., [Beven et al., 2001](#)).

There is an important aspect in the calibration of catchment models, which is the time scale dependence of model performance ([Merz et al, 2009](#)).

During model calibration the user usually attempts to use a sufficiently long period of meteorological and runoff observations to make certain that the calibration can be regarded as a good fit to the data and it also properly represents the streamflow variability (Bergstrom et al., 1991).

The choice of record length is often determined by data availability in practice. So in many cases only short records (few years of data) can be used for calibration. In the literature it is recommended to choose the minimum calibration period as one that samples all different types of hydrological behaviours, including extreme events. This is usually checked by comparing model efficiencies for the calibration and verification periods (Refsgaard et al., 2000) rather than by varying the length of the calibration period. If the verification efficiency is not much poorer than the calibration efficiency, one concludes that the model genuinely represents the population of streamflow variability (Merz et al, 2009).

Both the estimation of model parameters and the issues of calibration and verification efficiencies are connected to problems of parameter uncertainty (Montanari, 2005, 2007; Refsgaard et al., 1996, 2006; Gotzinger and Bardossy, 2008; Freer et al., 1996). An analysis of the variability (uncertainty) of calibrated model parameters as a function of calibration time scale is therefore useful. The goal of such analysis would be to find out when the parameter uncertainty is smaller than possible time scale effects.

Many important scientific and practical questions can be risen in connection with the record length and calibration strategies of rainfall runoff models. It is important to learn for instance whether the model efficiency changes with the period of runoff data used for calibration and what is a sufficiently long period to acquire sufficient confidence in the performance of the model for future applications. The performance of optimisation algorithms with respect to the uncertainty (variability) of model parameters is also of interest.

This project therefore is organised as follows:

1. Calibration of the original data, using the HBV model, from the Hron catchment located in Slovak measured in a daily step in a period between 01/01/1980 and 31/12/2000 giving us 20 years of observed data. Obtaining parameters used to create generated data. Using of two

- optimization algorithms: genetic algorithm – GA and harmony search – HS and their comparison. Selecting better algorithm used in next calibrations.
2. Reproduction of the model by calibrating the generated data – use of the whole dataset.
  3. Reproduction of the model by calibrating the generated data – use of various calibration strategies.
  4. Results of the rainfall-runoff modelling in the Hron catchment.

## 1.1 Classification of watersheds models

Watersheds models are fundamental to integrated water management. The watershed models abound in hydrological literature and the state of art of modelling is reasonably advanced, especially when viewed in the context of practical application.

However, these models have yet to become common planning or decision-making tools. To that end, two milestones will have to be achieved. First, these models will have to be transformed and packaged at the level of a common user. Second these models will have to be integrated with social, economic and management models yielding information that is easily interpreted or understood by the user.

A majority of watershed models simulate watershed response either without consideration of water quality or inadequate consideration thereof.

A decision maker wants to know as much about a watershed as he can, not just water- quantity information. (Vijay P. Singh et al., 1995).

The models are of different types and can be developed for different purposes. Many of the models share structural similarities and some of the models are distinctly different.

The hydrological models can be broken down by classification of different kinds. The most famous and used are the following:

1. **Process based classification:** single process models, integrated models.
2. **Structure classification for black-box models:** conceptual and physically based. Stochastic models and deterministic models.

3. **Space-scale based classification:** lumped and spatially distributed models.
4. **Land-use based classification:** models of generation of synthetic variables and simulation models of real variables (observable).
5. **Model-use based classification:** continuous simulation models, scale models of events.

### 1.1.1 Process based classification

Many models are proposed to describe the dynamics of a single hydrologic process, representing a limited phase of the water cycle. Typical examples are the models of infiltration, interception models and many others.

Other models are proposed to describe larger portions of the hydrological cycle; an example is the rainfall-runoff model.

A model, as shown in Fig. 1.6 has five components:

1. System (watersheds) geometry
2. Input
3. Governing laws
4. Initial and boundary conditions
5. Output

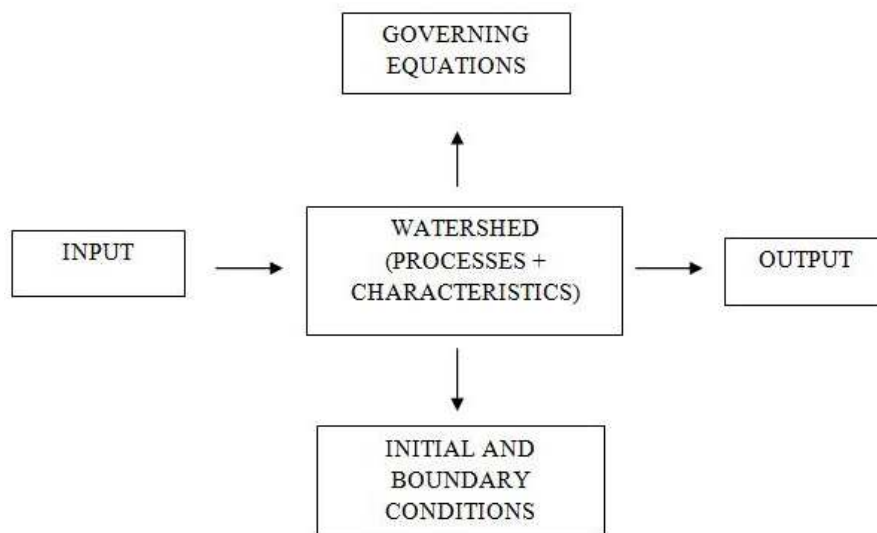


Figure 1.6: Model components (Vijay P. Singh, 1995).

### 1.1.2 Structure classification for black-box models

In connection with hydrological models of their structure rainfall-runoff transformation can be classified as:

- **Hydraulic or detailed simulation models:** based on experimental observations and analytical models attempt to simulate the individual hydrological processes that are then connected by appropriate mathematical relationships.
- **Conceptual models:** assimilate the real transformation of rainfall to bring in another, referred to a physical system, even different, but can provide a similar response. In this category, you can frame models with very different structures: one can identify both models is complex, similar to hydraulic models, and models such as linear parameters, simple structure, similar to that of synthetic models.
- **Synthetic model (or empirical or black box):** are not intended to represent the processes hydrological and physical phenomena involved in rainfall-runoff transformation or physically or mathematically. They see the system as a closed box (black box) on which there is no specific hypotheses. Modelling, therefore, end with the search for a mathematical operator that links between them, in the best possible way, and incoming out of the system, or the meteor influx with flow flowing out to the closing section river basin.

Furthermore the models can be described as deterministic or stochastic.

A **deterministic model** is a physical-mathematical model that tries to predict numerically the evolution of the climate system in space-time, through the approximate solution (not analytical) of the system of mathematical equations that describe the physical laws (the classical mechanics and of thermodynamics) that govern the system atmosphere.

Once the initialization process is terminated the system of equations, that make up the deterministic model, evolves towards a unique solution. In this way we have achieved something unique number for each point in space and at every point in time future.

A **stochastic model** is a model consisting of a finite set of random variables that depend on a parameter "t", with which we generally mean time, and the values that the individual random variables have undertaken in the past, namely with respect to a statistical basis of departure.

The initialization of the random variables is done through the identification of the probability distribution that characterizes each variable, through statistical analysis of a database collected in the past, which represents the probability space of the values that the random variable can assume.

Once rebuilt, the probability distribution of individual random variables can be simulated via the stochastic model, the variation in time of the probability distribution of random variables, resulting in a new probability space of values for each random variable.

### **1.1.3 Space-scale based classification**

This classification is extremely important from a practical point of view. The hydrological model is said concentrate when the volume control reference for the application of constitutive equations is extended to large spatial scales, typically entire river basin. In this case, the model has no spatial dimensions. The model is, instead, said spatially distributed if the volume control is extended to very small spatial scale, so that within it is plausible the assumption of homogeneity of hydrological processes. Typically, the watersheds with area of 100 km<sup>2</sup> or less can be called small, those with area of 100 to 1000 km<sup>2</sup> medium, and those with area of larger than 1000 km<sup>2</sup> large.

### **1.1.4 Land-use based classification**

Hydrological models divided into two major categories. We talk about patterns of generation of synthetic series when the aim of work is to reproduce artificial hydrological variables, or variables that do not occur in reality. An example are the models for estimating flood flow.

The simulation models of observable variable, however, are designed to reproduce the variables that have occurred or will occur in the real world, independently from the availability or otherwise of the corresponding observed value. For instance, forecasting models and reconstruction models of observed events.



### 1.1.5 Model-use based classification

Many hydrological models are designed to produce simulations that are carried out over short time periods. This approach is justified by the necessity, which occurs when applying rainfall-runoff models, to have extended simulations to a single flood event, because we do not consider the simulation in periods of lean and tender. In this case we say that the model works at scale event. We speak instead of a continuous simulation model over time if the model is designed to produce simulations of long time span.

Nowadays, continuous simulation models receive attention from the scientific community, because are gaining interest the problems of the management of water resources during low flows.

## CHAPTER 2

# MODEL CALIBRATION

The practice application of a hydrological model is divided into the following stages:

1. Operational problems identification;
2. Model identification;
3. Calibration procedure selection;
4. Calibration;
5. Model verification.

Operational problems identification is a very delicate phase for the operator that must clarify what is the purpose of applying the model, in all its facets. Availability of data and technical requirements should be analyzed with great precision.

Model identification is made on the basis of technical requirements, and also according to the models available in the literature, hydrologist chooses the most appropriate model but the superiority of one approach than another is influenced from the scope.

For the selection of the calibration procedure we can make similar considerations. The calibration can be performed by two different alternatives: the manual calibration and automatic calibration which will be discussed in the next paragraph. In general, the automatic calibration requires more time and more availability of observed data. The manual calibration instead requires great sensitivity of the engineer who must understand how to change the parameters for improving the model performance. The parameters, that most influence on the results of the simulation, will be subject to more study in the calibration phase.

Model verification is a very important step because it gives information about the real functioning of the model unlike the calibration. After testing the model, it is appropriate to repeat the calibration using the full range of available data, in order to maximize the consistency of the database used to estimate parameter values.

## 2.1 Introduction to model calibration

The hydrological models are characterized by the presence of parameters to be set by the user. Obviously, different values of parameters correspond to different responses of the model and thus parameters variability allows the model to interpret the different characteristics of different river basins.

The procedure for assigning parameter values, which must precede so any practical application, is called parameters (or models) calibration, model parameterization, parameters (or model) optimization.

Usually the calibration is carried out by searching the parameter values that maximize the reliability of the simulation made by the model.

For modelling the rainfall–runoff process, models, that have been developed, are based on conceptual representations of the physical processes of the water flow lumped over the entire catchment area (lumped conceptual type of models). Examples of this type of model are the Sacramento model (Burnash et al., 1995), the Tank model (Sugawara et al., 1995), the HBV model (Bergstrom et al., 1995), and the MIKE 11/NAM model (Nielsen and Hansen, 1973; Havnø et al., 1995).

All rainfall-runoff models are so a simplifications of the real-world systems under investigation. The model components are aggregated descriptions of real world hydrologic processes. One consequence of this is that the model parameters often do not represent directly measurable entities, but must be estimated using measurements of the system response through a process known as model calibration. In fact all rainfall-runoff models are to some degree lumped, so that their equations and parameters describe the processes as aggregated in space and time. As a consequence, the model parameters are typically not directly measurable, and have to be specified through an indirect process of parameter estimation, that is called calibration.

To calibrate a model, values of the model parameters are selected so that the model simulates the hydrological behaviour of the catchment as closely as possible.

## 2.2 Model parameters

Such models typically have two types of parameters: “physical” parameters and “process” parameters.

- Physical parameters: represent measurable properties of the watershed like the area of the watershed, the fraction of the watershed area that is impervious, and so on.
- Process parameters: represent watersheds properties that are not directly measurable like the depth of surface soil moisture storage, the effective lateral interflow rate, and so on.

Due to the fact that in the range of possible (or already observed) input data, different model parameters lead to a similar performance, the identification of a unique dataset is practically impossible (Beven and Freer, 2001).

## 2.3 Manual calibration

In manual calibration, a trial-and-error parameter adjustment is made. In this case, the goodness-of-fit of the calibrated model is basically based on a visual judgment by comparing the simulated and the observed hydrographs. For an experienced hydrologist it is possible to obtain a very good and hydrologically sound model using manual calibration.

However, since there is no generally accepted objective measure of comparison, and because of the subjective judgment involved, it is difficult to assess explicitly the confidence of the model simulations. Furthermore, manual calibration may be a very time consuming task, especially for an inexperienced hydrologist.

## 2.4 Automatic calibration

In automatic calibration, parameters are adjusted automatically according to a specified search scheme and numerical measures of the goodness-of-fit. As compared to manual calibration, automatic calibration is fast, and the confidence of the model simulations can be explicitly stated. The development of automatic calibration procedures has focused mainly on using a single overall objective

function (e.g. the root mean square error between the observed and simulated runoff) to measure the goodness-of-fit of the calibrated model.

For automatic calibration is therefore necessary to establish a criterion for automatically and quantitatively compare the goodness of the simulation. For doing this, it use an objective function which is then minimized (or maximized) using the algorithms. The need for an objective function makes the automatic calibration using the shell is mainly when there are observed values of the data to be simulated, which are automatically compared with the corresponding simulated values. In this case, the objective functions can also be used in case of manual calibration, if you want the comparison between observed and simulated values occur quantitatively.

### 2.4.1 Objective functions

An objective function is an equation that is used to compute a numerical measure of the difference between the model-simulated output and the observed (measured) watersheds output.

The aim is so to find those values of the model parameters that optimize the numerical value of the objective function.

The objective functions mostly used are:

1. **Weighted Least Squares:** it is one of the most common used objective function. The weights  $w_t$  indicate the importance to be given to fitting a particular hydrograph value

$$F(\theta) = \sum_{t=1}^n w_t \cdot [q_t^{obs} - q_t(\theta)]^2 \quad [2.1]$$

where:

- $q_t^{obs}$  = observed (measured) streamflow value at time t;
- $q_t(\theta)$  = model simulated streamflow value at time t;
- $\theta$  = vector of model parameters;
- $w_t$  = weight at time t;
- $n$  = the number of data points to be matched.

2. **Daily root-mean square (DRMS):** The daily root-mean square (DRMS) computes the standard deviation of the model prediction error (difference between measured and simulated values). The smaller the DRMS value, the better the model performance (Gupta et al., 1999). Gupta et al. (1999) determined that DRMS increased with wetness of the year, indicating that the forecast error variance is larger for higher flows. According to Gupta et al. (1999), DRMS had limited ability to clearly indicate poor model performance. The function is:

$$F(\theta) = \sqrt{\frac{1}{n} \sum_{t=1}^n (d_t - o_t(\theta))^2} \quad [2.2]$$

3. **Nash-Sutcliffe measure (NS):** used to assess the predictive power of hydrological models. It is defined as:

$$E(\theta) = 1 - \frac{\frac{1}{n} \sum_{t=1}^n [d_t - o_t(\theta)]^2}{\frac{1}{n} \sum_{t=1}^n (d_t - \bar{d})^2} \quad [2.3]$$

Where  $d$  is observed discharge,  $o_t$  is modelled discharge and  $d_t$  is observed discharge at time  $t$ . Nash–Sutcliffe efficiencies can range from  $-\infty$  to 1. An efficiency of 1 ( $E = 1$ ) corresponds to a perfect match of modelled discharge to the observed data. An efficiency of 0 ( $E = 0$ ) indicates that the model predictions are as accurate as the mean of the observed data, whereas an efficiency less than zero ( $E < 0$ ) occurs when the observed mean is a better predictor than the model or, in other words, when the residual variance (described by the numerator in the expression above), is larger than the data variance (described by the denominator).

Essentially, the closer the model efficiency is to 1, the more accurate the model is. It should be noted that Nash–Sutcliffe efficiencies can also be used to quantitatively describe the accuracy of model outputs other than discharge. This method can be used to describe the predictive accuracy of other models as long as there are observed data to compare the model results. (Nash, J. E. and J. V. Sutcliffe et al.1970).

#### 4. Bias (mean daily error):

$$E(\theta) = \frac{1}{n} \sum_{t=1}^n (d_t - o_t(\theta)) \quad [2.4]$$

In statistics, bias (or bias function) of an estimator is the difference between this estimator's expected value and the true value of the parameter being estimated. An estimator or decision rule with zero bias is called unbiased. Otherwise the estimator is said to be biased.

5. **ABSERR (mean absolute error):** is a quantity used to measure how close forecasts or predictions are to the eventual outcomes. The mean absolute error is given by:

$$F(\theta) = \frac{1}{n} \sum_{t=1}^n |d_t - o_t(\theta)| \quad [2.5]$$

The mean absolute error is a common measure of forecast error in time series analysis, where the terms "mean absolute deviation" is sometimes used in confusion with the more standard definition of mean absolute deviation.

The mean absolute error is one of a number of ways of comparing forecasts with their eventual outcomes. Well-established alternatives are the mean absolute scaled error and the mean squared error.

Where a prediction model is to be fitted using a selected performance measure, in the sense that the least squares approach is related to the mean squared error, the equivalent for mean absolute error is least absolute deviations. (Hyndman, R. and Koehler A. et al.,2005).

#### 6. ABSMAX (maximum absolute error):

$$F(\theta) = \max |d_t - o_t(\theta)| \quad [2.6]$$

Where  $o_t$  is modelled discharge and  $d_t$  is observed discharge at time  $t$ .

## 2.5 Optimization methods

An optimization algorithm is a logical procedure that is used to search the response surface, constrained to the allowable ranges on the parameters, for the parameter values that optimize (maximize or minimize, as appropriate) the numerical value of the objective function. The procedure is typically implemented on a digital computer to enable a very rapid search. There are a lot of methods for automatic calibration but we will describe just two that we will see in the application with HBV model, Genetic Algorithm (GA) and Harmony Search (HS).

### 2.5.1 Genetic algorithm (GA)

A genetic algorithm (GA) is a search heuristic that mimics the process of natural evolution. This heuristic is routinely used to generate useful solutions to optimization and search problems. Genetic algorithms belong to the larger class of evolutionary algorithms (EA), which generate solutions to optimization problems using techniques inspired by natural evolution, such as inheritance, mutation, selection, and crossover (Eiben, A. E. et al, 1994).

With a genetic algorithm calibration algorithm, optimized parameter sets are found by an evolution of parameter sets using selection and recombination. An initial population of  $n$  parameter sets is generated randomly in the parameter space and “fitness” of each set was evaluated by the value of the objective function. From this population (generation) is generated by  $n$  times combining of two parameter sets. The two sets were chosen randomly but the chance of being picked is related to the fitness of the parameter set giving the highest probability to the set with the highest fitness. A new parameter set was generated from the two parent sets (set A and B) by applying one of the following four rules for each parameter randomly with certain probabilities,  $p$ :

- Value of set A
- Value of set B
- Random between the values of set A and set B
- Random value within the limits given for the parameter



The fitness of each set in the new population is evaluated and the new generation replaced the old one. This evolution is repeated for a number of generations (Jan Seibert et al.2000).

### 2.5.2 Harmony Search (HS)

A new heuristic algorithm has been developed and named Harmony Search (HS). Harmony search (HS) is a phenomenon-mimicking algorithm (also known as metheuristic algorithm, soft computing algorithm or evolutionary algorithm) inspired by the improvisation process of musicians. In the HS algorithm, each musician (= decision variable) plays (= generates) a note (= a value) for finding a best harmony (= global optimum) all together.

The goal of the process is to reach a perfect state of harmony. The different steps of the HS algorithm are described below:

#### Step 1:

The 1<sup>st</sup> step is to specify the problem and initialize the parameter values. The optimization problem is defined as minimize (or maximize)  $f(x)$  such that  $Lx_i < x_i < Ux_i$ , where  $f(x)$  is the objective function,  $x$  is a solution vector consisting of  $N$  decision variables ( $x_i$ ) and  $Lx_i$  and  $Ux_i$  are the lower and upper bounds of each decision variable, respectively. The parameters of the HS algorithm i.e. the harmony memory size ( $HMS$ ), or the number of solution vectors in the harmony memory; harmony memory considering rate ( $HMCR$ ); pitch adjusting rate ( $PAR$ ); distance bandwidth parameter ( $bw$ ); and the number of improvisations ( $NI$ ) or stopping criterion are also specified in this step.

#### Step 2:

The 2<sup>nd</sup> step is to initialize the Harmony Memory. The initial harmony memory is generated from a uniform distribution in the ranges  $[Lx_i, Ux_i]$ , where  $1 < i < N$ . This is done as follows:

$$x_i^j = Lx_i + r \times (Ux_i - Lx_i) \quad [2.7]$$

where  $j = 1, 2, 3, \dots, HMS$  and  $r \sim U(0, 1)$ .

#### Step 3:

The third step is known as the “improvisation” step. Generating a new harmony is called “improvisation”. The New Harmony vector is generated using

the following rules: memory consideration, pitch adjustment, and random selection.

Step 4:

In this step the harmony memory is updated. The generated harmony vector replaces the worst harmony in the HM (harmony memory), only if its fitness (measured in terms of the objective function) is better than the worst harmony.

Step 5:

The stopping criterion (generally the number of iterations) is checked. If it is satisfied, computation is terminated. Otherwise, Steps 3 and 4 are repeated.

## 2.6 Calibration strategies

There are different calibration strategies to meet two objectives: good discharge simulations in terms of least mean square errors and the ability to reproduce one functional characteristic of the system and the autocorrelation function of the discharge, which quantifies the linear dependency of successive values over time.

### 2.6.1 Split sample-test

The available record should be split into two segments one of which should be used for calibration and the other for validation. If the available record is sufficiently long so that one half of it may suffice for adequate calibration, it should be split into two equal parts, each of them should be used in turn for calibration and validation, and results from both arrangements compared. The model should be judged acceptable only if the two results are similar and the errors in both validations are acceptable. If the available record is not long enough for a 50/50 splitting, it should be split in such a way that the calibration segment is long enough for a meaningful calibration, the remainder serving for validation. In such a case, the splitting should be done in two different ways, e.g. (a) the first 70% of the record for calibration and the last 30% for validation; (b) the last 70% for calibration and the first 30% for validation. The model should qualify only if validation results from both cases are acceptable and similar. If the available record cannot be meaningfully split, then only a model which has passed a higher level test should be used. (Klemeš, V. et al., 1986).

### 2.6.2 Proxy-basin test

This test should be required as a basic test for geographical transposability of a model, i.e. transposability within a region, such as for instance, the European Alps, the prairie region of Canada and the USA, etc. If streamflow in an ungauged basin C is to be simulated, two gauged basins A and B within the region should be selected. The model should be calibrated on basin A and validated on basin B and vice versa. Only if the two validation results are acceptable and similar can the model command a basic level of credibility with regard to its ability to simulate the streamflow in basin C adequately.

This kind of test should also be required when an available streamflow record in basin C is to be extended and is not adequate for a split-sample test as described above. In other words, the inadequate record in basin C would not be used for model development and the extension would be treated as simulation in an ungauged basin (the record in C would be used only for additional validation, i.e. for comparison with a record simulated on the basis of calibrations in A and B).

Geographical transposability between regions I and II (e.g. the Inland Waters Directorate of Environment Canada has identified a need to develop models for simulating streamflow in ungauged basins of northern Ontario; such models would have to be developed on the basis of data from gauged basins in southern Ontario or Quebec which have different physical conditions). If streamflow needs to be simulated in an as yet unspecified ungauged basin C (or on a number of such basins) in region II the procedure should be as follows. First, the model is calibrated on the historic record of a gauged basin D in region I. Streamflow measurements are started on at least two different substitute basins, A and B, in region II and maintained for at least three years. Then the model is validated on these three-year records of both A and B and judged adequate for simulation in a basin C if errors in both validation runs, A and B, are acceptable and not significantly different. After longer records in A and B become available, these two basins can be used for model development and subjected to the simpler test for transposability within a region as described above, using A and B as proxy basins for C. Of course, the substitute basins A and B, would not be chosen randomly but would be selected so as to be

representative of the conditions in region II, and, as far as possible, with due consideration of future streamgauging needs (Klemeš, V. et al.1986).

### 2.6.3 Differential split-simple test

This test should be required whenever a model is to be used to simulate flows in a given gauged basin under conditions different from those corresponding to the available flow record. The test may have several variants depending on the specific nature of the change for which the flow is to be simulated.

For a simulation of the effect of a change in climate, the test should have the following form. Two periods with different values of the climate parameters of interest should be identified in the historic record, e.g. one with high average precipitation, the other with low. If the model is intended to simulate streamflow for a wet climate scenario then it should be calibrated on a dry segment of the historic record and validated on a wet segment. If it is intended to simulate flows for a dry climate scenario, the opposite should be done. In general, the model should demonstrate its ability to perform under the transition required: from drier to wetter conditions or the opposite.

If segments with significantly different climatic parameters cannot be identified in the given record, the model should be tested in a substitute basin in which the differential split-sample test can be done. This will always be the case when the effect of a change in land use, rather than in climate, is to be simulated. The requirement should be as follows: to find a gauged basin where a similar land-use change has taken place during the period covered by the historic record, to calibrate the model on a segment corresponding to the original land use and validate it on the segment corresponding to the changed land use.

Where the use of substitute basins is required for the testing, two substitute basins should be used, the model fitted to both and the results for the two validation runs compared. Only if the results are similar can the model be judged adequate. Note that in this case (two substitute basins) the differential split-sample test is done on each basin independently which is different from the proxy-basin test where a model is calibrated on one basin and validated on the other (Klemeš, V. et al, 1986).

#### 2.6.4 Proxy-basin differential split-sample test

This test should be applied in cases where the model is supposed to be both geographically and climatically (or land-use-wise) transposable.

Such universal transposability is the ultimate goal of hydrological modelling, a goal which may not be attained in decades to come. However, models with this capability are in high demand (e.g. in Canada for assessing the climate-change impact in northern regions where most basins are not gauged) and hydrologists are being encouraged to develop them despite the fact that thus far even the much easier problem of simple geographical transposability within a region has not been satisfactorily solved. (Klemeš, V. et al, 1986).

## CHAPTER 3

# HBV MODEL - HYDROLOGISKA BYRÅNS VATTENBALANSAVDELNING

The HBV hydrology model, or Hydrologiska Byråns Vattenbalansavdelning model, is a computer simulation used to analyze river discharge and water pollution. Developed originally for use in Scandinavia, this hydrological transport model has also been applied in a large number of catchments on most continents.

The HBV model is a conceptual hydrological model capable of simulating outflow from a river catchment, given meteorological input data and set of parameters.

### 3.1 Introduction

The HBV model (Bergstrom et al., 1976; 1992) is a conceptual model that simulates daily discharge using daily rainfall and temperature, and monthly estimates of potential evaporation as input. The model consists of different routines representing snow by a degree-day method, soil water and evaporation, groundwater by three linear reservoir equations and channel routing by a triangular weighting function.

The first successful run with an early version of the HBV hydrological model was carried out in the spring of 1972 (Bergstrom et al., 1972) (Figure 3.1):

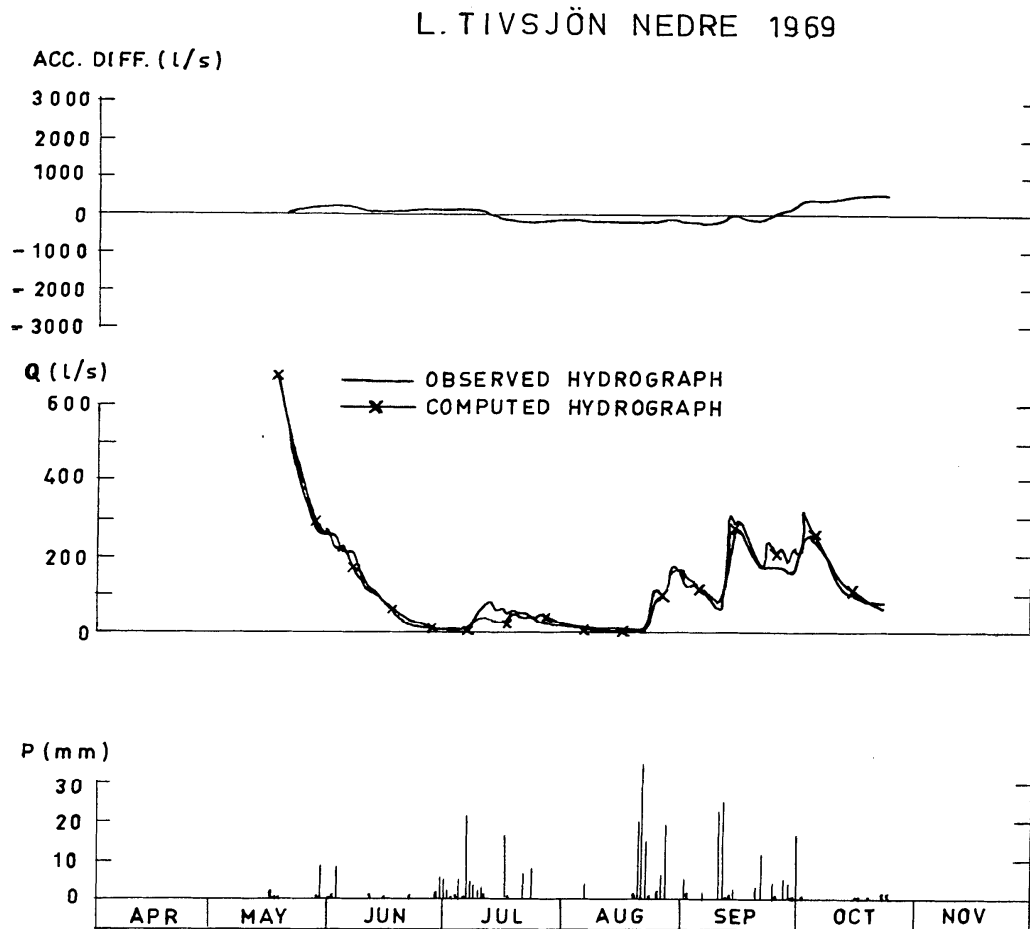


Figure 3.1: The first successful application of the HBV model (Sten Bergstrom et al., 1972).

After twenty years the HBV model has become a standard tool for runoff simulations in the Nordic countries, and the number of applications in other countries is growing. Some of applications abroad are carried out by the Swedish Meteorological and Hydrological Institute using a standard computer code.

Its successor, the PULSE model, is used for hydrochemical simulations and simulations in ungauged catchments.

Work with HBV model has been reported on numerous occasions and in a large number of scientific papers.

The general structure of HBV model is shown in a Figure 3.2:

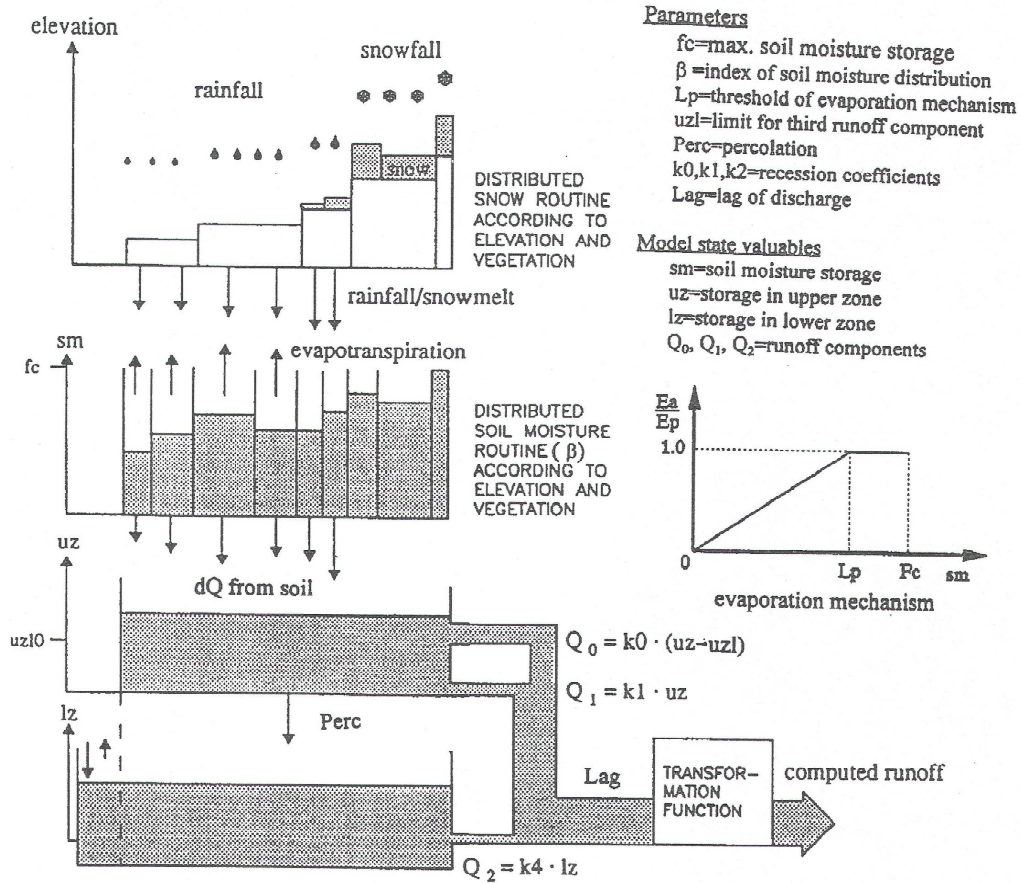


Figure 3.2: Scheme of the HBV model.

Symbols:

- $S_{sf}$  is the snow storage in forest;
- $S_{so}$  is the snow storage in open areas;
- $S_{sm}$  is the soil moisture storage;
- $Fc$  is the Max. soil moisture storage;
- $Wp$  is the Min. soil moisture storage;
- $S_{uz}$  is the storage in upper zone;
- $L_{uz}$  is the limit for third runoff component;
- $S_{lz}$  is the storage in lower zone;
- $Q_0, Q_1, Q_2$  are the runoff components;
- $K_0, K_1, K_2$  are the recession coefficients.



Below is a summary of the input data required and output data produced by the HBV model. The model requires little geographical input data, only the size of the modeled catchments is needed.

Input data (daily values):

- Size of modeled catchments (km<sup>2</sup>);
- Lake surface height (m) – lake surface area (km<sup>2</sup>) curve;
- Precipitation (mm/d), one station, or weighted sum of several stations;
- Potential evaporation computed from one of the following:
  - Pan evaporation (mm/d);
  - Min and max temperature);
  - Average temperature (°C), cloudiness (%);
  - Average temperature (°C), short wave radiation (MJ/d), wind speed (m/s) and relative humidity (%);
- Average outflow (m<sup>3</sup>/s), one station;

Computed result (daily values):

- Average outflow (m<sup>3</sup>/s);
- Optionally model state variables (mm), evaporation (mm/d), corrected precipitation (mm), lake surface height (m) and lake area (km<sup>2</sup>);

### 3.2 The HBV model and its parameters

The HBV model is a rainfall-runoff model, which includes conceptual numerical descriptions of hydrological processes at the catchment scale. The general water balance can be described as:

$$P - E - Q = \frac{d}{dt} [SP + SM + UZ + LZ + lakes] \quad [3.1]$$

Where:

- $P$  is the precipitation;
- $E$  is the evapotranspiration;
- $Q$  is the runoff;
- $SP$  is the snow pack;
- $SM$  is the soil moisture;
- $UZ$  is the upper groundwater zone ;
- $LZ$  is the lower groundwater zone;
- $lakes$  is the lake volume.

In different model versions HBV has been applied in more than 40 countries all over the world. It has been applied to countries with such different climatic conditions as for example Sweden, Zimbabwe, India and Colombia. The model has been applied for scales ranging from lysimeter plots (Lindström and Rodhe et al., 1992) to the entire Baltic Sea drainage basin (Bergström and Carlson et al., 1994; Graham et al., 1999). HBV can be used as a semi-distributed model by dividing the catchment into subbasins. Each subbasin is then divided into zones according to altitude, lake area and vegetation. The model is normally run on daily values of rainfall and air temperature, and daily or monthly estimates of potential evaporation. The model is used for flood forecasting in the Nordic countries, and many other purposes, such as spillway design floods simulation (Bergström et al., 1992), water resources evaluation (for example Jutman et al., 1992; Brandt et al., 1994), nutrient load estimates (Arheimer et al., 1998).

### 3.2.1 Parameters

In summary the model parameters of the HBV model are sixteen and the following definitions give basic information about the meaning of particular parameter, about their possible names and also some information about the interval from which it should be taken.

The parameters that we have to calibrate are:

- **Fc**, *field capacity* – maximum amount of water the soil can hold [mm];
- **Rc** (BETA), *recharge coefficient* – determines the contribution of precipitation and melted snow to the soil and upper zone;
- **Emp** (C), *empirical parameter* – used only when calculating daily PET from monthly values of PET;
- **Uzl** (luz), *upper zone limit* – determines the threshold in upper zone when the discharge  $q_0$  occurs [mm];
- **tempRain** – temperature threshold above which all precipitation is liquid [°];
- **tempMelt** (TT) – temperature threshold determining the melting of snow cover [°];
- **tempSnow** – temperature threshold below which all precipitation is solid (snow) [°];
- **ddf** (CMELT), *degree day factor* – determines the speed of snow melting [mm];
- **perc**, *percolation* – amount of water from upper to lower zone [mm];
- **lpe** (LP), *limit of potential evapotranspiration* – used to estimate actual evapotranspiration [-];
- **k<sub>0</sub>,k<sub>1</sub>,k<sub>2</sub>**, empirical parameters influencing the discharge from upper and lower zones;
- **croute**- parameter affecting the distribution of flow into several days;
- **scf**,  $C_{SF}$ , *snow correction factor* – Snow accumulation is adjusted by a free parameter; it should remain 1;
- **maxbas**, number of days into which the flow from particular storages is distributed.

The HBV model can best be classified as a semi-distributed conceptual model. It uses subbasins as primary hydrological units, and within these an area-elevation distribution and a crude classification of land use (forest, open, lakes) are made.

The HBV model consists of three main components:

1. Subroutines for snow accumulation and melt;
2. Subroutines for soil moisture accounting;
3. Response and river routing subroutines.

The model has a number of free parameters, values of which are found by calibration. There are also parameters describing the characteristics of the basin and its climate which remain untouched during model calibration. ( [Bergstrom et al., 1992](#)).

Input data are precipitation and, in areas with snow, air temperature. The soil moisture accounting procedure requires data on the potential evapotranspiration.

Areal averages of the climatological data are computed separately for each subbasin.

### 1. Snow submodel

The snow routine of the model controls snow accumulation and melt. The precipitation accumulates as snow when the air temperature drops below a threshold value (TT). Snow accumulation is adjusted by a free parameter,  $C_{SF}$ , the snowfall correction factor.

Melt starts with temperatures above the threshold, TT; according to a simple degree-day expression:

$$MELT = C_{MELT} \cdot (T - TT) \quad [3.2.]$$

Where:

- MELT is a snowmelt (mm/day);
- $C_{MELT}$  is degree-day factor (mm/°C);
- TT is the threshold temperature (°C).

Thus the snow routine of the HBV model has primarily three free parameters that have to be estimated by calibration: TT,  $C_{SF}$  and  $C_{MELT}$ .

## 2. *Soil moisture submodel*

The soil moisture accounting routine computes an index of the wetness of the entire basin. It is controlled by three free parameters, FC, BETA and LP which will be discussed later.

Recently a modification of the evapotranspiration routine has been introduced in order to improve the model performance when the spring and summer is much colder or warmer than normal (Lindstrom and Bergstrom et al., 1992). This routine accounts for temperature anomalies by a correction which is based on mean daily air temperatures and long term averages according to this equation:

$$PE_A = (1 + C \cdot (T - T_M)) \cdot PE_M \quad [3.3]$$

Where:

- $PE_A$  is a adjusted potential evapotranspiration;
- $C$  is a empirical model parameter;
- $T$  is the daily mean air temperature;
- $T_M$  is the monthly long term average temperature;
- $PE_M$  is the monthly long term average potential transpiration.

The three free parameters are:

- $FC$  is a maximum soil moisture storage in the basin;
- $BETA$  determines the relative contribution to runoff from a millimeter of rain or snowmelt at a given soil moisture deficit;
- $LP$  controls the shape of the reduction curve for potential evaporation.

## 3. *Runoff response submodel*

The runoff response routine transforms excess water ( $\Delta Q$ ) from the soil moisture routine, to discharge for each subbasin. The routine consist of two reservoirs with the following free parameters:

- $K_0, K_1, K_2$  are three recession coefficients;
- $U_ZL$  is the threshold;
- $PERC$  is the constant percolation rate.

Finally there is a filter for smoothing of the generated flow. This filter consists of a triangular weighting function with one free parameter, MAXBAS. It is a model parameter affecting the distribution of flow into several days.

### 3.3 Model calibration

The agreement between observed and computed runoff is evaluated by Nash and Sutcliffe efficiency criterion (Nash and Sutcliffe et al., 1970) which is commonly used in hydrological modeling:

$$R^2 = \frac{\sum(\bar{Q}_0 - Q_0)^2 - \sum(Q_c - Q_0)^2}{\sum(\bar{Q}_0 - Q_0)^2} \quad [3.4]$$

Where:

- $Q_0$  is a observed runoff
- $\bar{Q}_0$  is the mean of observed runoff
- $Q_c$  is the computed runoff

A perfect fit would give a value of  $R^2 = 1$ , but in practice the value above 0.8 means good fit and measured hydrographs (IHMS, 1999).

## CHAPTER 4

# STUDY CATCHMENT: THE HRON RIVER BASIN

One catchment was used in this study, the Hron river basin, located in Slovakia. The Hron River is a left-side tributary of the Danube River; its basin is located in Central Slovakia. The catchment is feather-shaped, located along the long main river with numerous shorter tributaries. It covers an area of 5465 km<sup>2</sup>; its upper and middle parts are situated in the area of Inner Carpathian Mountains, while the lower part of the basin belongs to the Danubian Lowlands. The spring of the Hron River is at an altitude of 934 m a.s.l. near the village of Telgárt and it flows into the Danube near Štúrovo at an altitude of 103 m a.s.l. The total length of the Hron River is 284 km. The mean slope of the river varies from about 7.6 ‰ in the upper part to 0.9 ‰ in the lowlands. The Hron River drains 11.2 % of Slovakia. After the Váh and Bodrog catchments, the Hron is the third largest river in Slovakia. The most important tributaries in the upper part of the basin are Hronec, Čierny Hron and Rohožná from the left, Bystrá, Vajskovský and Jasenský potok from the right side. In the middle part of the basin the Slatina is the largest tributary; other important tributaries are Bystrica, Kremnický and Žarnovický potok.

With regards to the availability of hydro-meteorological data and also according to the character of the hydrologic processes in the catchment the alluvial part of the river has not sufficient data suitable for hydrologic modelling (short series and less a dense network). However, due to its lowland character and very low specific discharge (mostly less than 1.5 l s<sup>-1</sup> km<sup>-2</sup>), modelling approaches have to be applied which better account for the physically based description of processes in the unsaturated zone than conceptual rainfall-runoff models. Therefore the discharge gauging station Banská Bystrica was selected as the closing cross section for this study (the term “Hron River basin” refers mainly to the Hron catchment to Banská Bystrica hereafter). This upper Hron River basin up to the Banská Bystrica gauging station has an area of 1766 km<sup>2</sup>, the minimum elevation of the basin is 340 m a.s.l.; the maximum elevation is

2004 m a.s.l.; and the mean elevation is 850 m a.s.l. The location of the basin in Slovakia is shown in Figure 4.1:

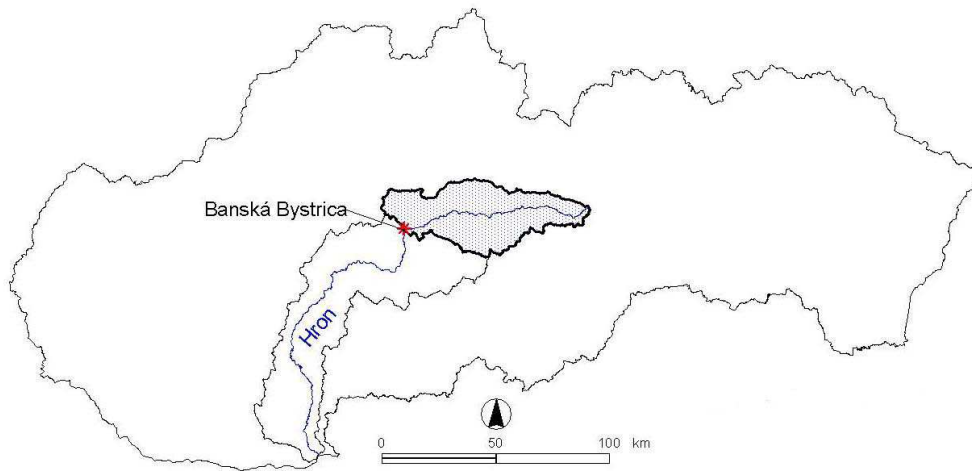


Figure 4.1: Location of the Hron River in Slovakia.

The climatic conditions of the Hron River basin correspond to the European-continental climatic region of the mild zone, with oceanic air masses transforming into continental ones. The annual precipitation in the basin varies from 570 to 700 mm year<sup>-1</sup> in the lowlands to about 700 - 1400 mm year<sup>-1</sup> in the valleys and upper mountainous areas. The overall average is approximately 800 mm year<sup>-1</sup>. Evaporation amounts to approximately 300 to 600 mm year<sup>-1</sup>.

Three regional subdivisions of the catchment can be made according to relief and elevation: the warm region (lowlands), which is spreading out in the Danube lowland, the Žiar and Zvolen Valleys, the mild-warm region (valleys), which covers the mountain slopes up to 800 m a.s.l., and the whole Upper Hron Valley. The third, the cold region (mountainous slopes), is located above 800 m a.s.l. in all mountains surrounding the upper part of the basin. The basic climatic characteristics of these sub-regions are given in Table 4.1.

The Hron River has a snow-rain combined runoff regime type. The precipitation in the upper part of the Hron basin reaches 1600 mm, while in lower flat areas it is only 600 mm. The runoff represents in the upper part up to 60 % of the precipitation, while in the flatlands only 10 %, the mean value for the whole basin being 37 %. The long-term mean annual discharge for the Hron in Brezno is 8.12 m<sup>3</sup> s<sup>-1</sup>, in Banská Bystrica 28.0 m<sup>3</sup> s<sup>-1</sup>, and at the confluence with the Danube it increases to 55.2 m<sup>3</sup> s<sup>-1</sup> (Table 4.2).



The specific runoff in the Hron River basin varies between 1.6 in the lowlands to  $28 \text{ l s}^{-1} \text{ km}^{-2}$  in the mountains. The richest tributaries are Bystrianka, Jasenienský potok, Vajskovský potok and Bystrica, where these values reach 22 -  $25 \text{ l s}^{-1} \text{ km}^{-2}$ . In the flatland areas the specific yield is only  $1.5 \text{ l s}^{-1} \text{ km}^{-2}$ . The mean values for the whole basin is  $10.1 \text{ l s}^{-1} \text{ km}^{-2}$  which is 20 % more than that for the whole territory of Slovakia.

The flood generation problem in the basin is complex. In the alpine high mountain regions floods from snowmelt, mixed events and flash floods represent a threat to local villages build in narrow valleys all over the year. Due to runoff concentration snowmelt floods and floods of cyclonic origin represent danger to major cities and industrial areas with heavy and chemical industry, electric and atomic power plants in the middle of the catchments.

**Table 4.1: Climatic characteristics of the Hron Basin (based on data provided by the Slovak Hydrometeorological Institute).**

Climatic characteristics	Lowlands	Valleys	Mountainous slopes
Mean temperature in January [°C]	-1.5 to -2.5	-2.5 to -6.5	-2.5 to -8.0
Mean temperature in July [°C]	20.3 to 19.5	19.5 to 14.5	19.5 to 9.5
Days with temperature above 0 [°C]	320 - 300	300 - 245	300 - 195
Number of summer days	75 - 60	60 - 20	60 - 0
Number of ice days	25 - 35	35 - 50	35 - 75
Days with precipitation above 1 mm	85 - 100	100 - 120	100 - 150
Annual precipitation [mm]	580 - 700	700 - 900	700 - 1400
Precipitation in the warm season [mm]	330 - 400	400 - 500	400 - 750
Precipitation in the cold season [mm]	250 - 300	300 - 400	300 - 650
Number of days with snow cover	35 - 50	50 - 100	50 - 220
Evapotranspiration [mm]	600 - 500	500 - 400	500 - 300

**Table 4.2: Discharge characteristics in selected profiles in the Hron basin (based on data provided by the Slovak Hydrometeorological Institute).**

River Profile	Basin area	Mean discharges	Mean annual runoff	Mean monthly discharges for period 1931 – 1980 [ $\text{m}^3 \text{s}^{-1}$ ]					
				11	12	1	2	3	4
	[ $\text{km}^2$ ]	[ $\text{m}^3 \text{s}^{-1}$ ]	[ $10^6 \text{m}^3 \text{y}^{-1}$ ]	5	6	7	8	9	10
Hron				26.690	24.440	17.490	20.020	37.050	57.230
Banská Bystrica	1766.48	27.990	883.3	42.850	31.080	23.850	18.960	16.450	19.760

**Table 4.3: Water balance characteristics of the Hron River and its tributaries in the period of 1931 – 1980 (based on data provided by the Slovak Hydrometeorological Institute).**

	Hron River mouth	Bystrianka	Vajskovský potok	Jaseniansky potok	Bystrica
Precipitation [mm]	869	1414	1466	1407	1194
Runoff [mm]	319	755	820	704	722
Losses [mm]	550	659	646	703	472
Runoff coefficient	0.37	0.53	0.56	0.50	0.60
Specific runoff [ $\text{l s}^{-1} \text{km}^{-2}$ ]	10.10	23.92	25.98	22.31	22.89

Extensive studies conducted by the Slovak Hydrometeorological Institute have shown that hydrological time series from the periods 1931 to 1960 and from 1931 to 1980 can be considered stationary. When comparing statistical data from the period 1961 – 2000 with the long term behaviour of the catchments as described by data from the period 1931 – 1980, occasionally a slight decrease in runoff can be shown. The decrease in runoff is approximately the same for the Hron as for the whole country (about 10 %), precipitation decrease is less significant (about 1 to 4 %). In consequence there was a slight increase in evapotranspiration in the water balance. As for long-term mean monthly discharges for the same two periods, both increase and decrease can be detected in

the Hron river basin; the mean monthly discharges do not necessarily decrease in all months in all catchments. An increasing tendency can be detected in some catchments in the spring and early winter.

#### 4.1 Description of the pilot basins

For the estimation of climate change impact on the annual, monthly and flood runoff one gauging station was selected in this study: Banská Bystrica. Table 4.4 contains the characteristics of the upper Hron basin and of the nested subcatchment: the mean basin values of air temperature, precipitation and runoff represent the mean annual averages from the period 1981 – 1990.

Table 4.5 shows the basin averages of long-term mean annual potential evapotranspiration (*EP*) and long-term mean annual actual evapotranspiration (*ET*) period 1981 – 1990 computed by the Turc model, which is used in this study. The spatial estimates of the long-term mean annual air temperature (1981 – 1990) from the six climatic stations, where the daily measurements of air temperature, air humidity, sunshine duration, vapour pressure and wind speed were carried out, are shown in Figure 4.2. Figure 4.3 shows the map of spatial estimates of the long-term mean annual precipitation (1981 – 1990) and precipitation stations (as points) used in interpolation of the map. The grid maps of the long-term mean annual potential and actual evapotranspiration (1981 – 1990) as estimated by the Turc empirical model from the precipitation, air temperature and runoff maps are shown in Figures 4.4 and 4.5.

**Table 4.4: Basic characteristics of Banská Bystrica sub-basins from the period 1981 – 1990.**

Basin	Banská Bystrica
Area [km <sup>2</sup> ]	1763.2
Elevation mean/range [m a.s.l.]	847/1672
Air temperature [°C]	5.4
Precipitation [mm]	828
Runoff [mm]	394

Table 4.5: Basin averages of long-term mean annual potential evapotranspiration (EP) and long-term mean annual actual evapotranspiration (ET) for the period 1981 – 1990 computed by the Turc model.

Basin	Banská Bystrica
<i>EP</i> Turc [mm]	475
<i>ET</i> Turc [mm]	445

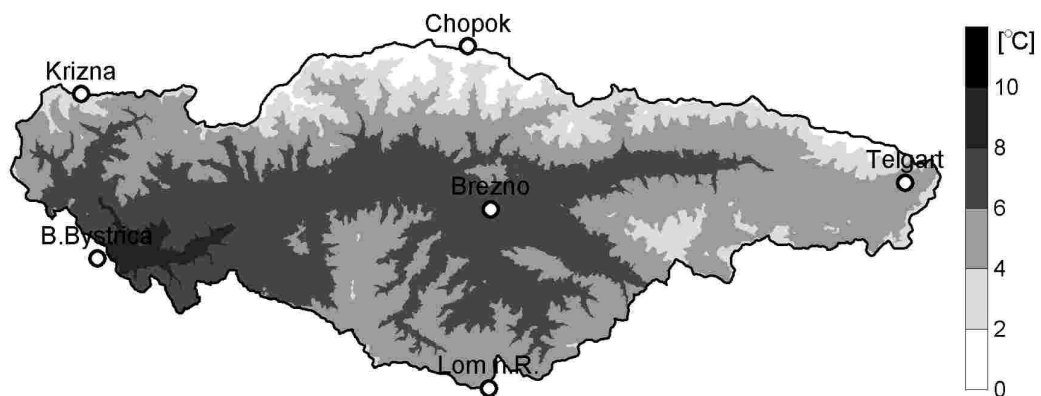


Figure 4.2: Spatial estimates of the long-term mean annual air temperature (1981 – 1990) and the six climatic stations.

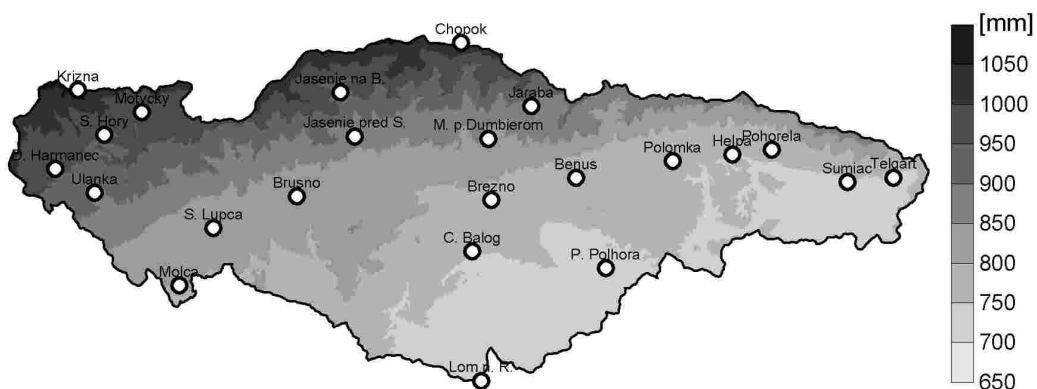


Figure 4.3: Map of the long-term mean annual precipitation (1981 – 1990) and precipitation stations (points) used in interpolation.

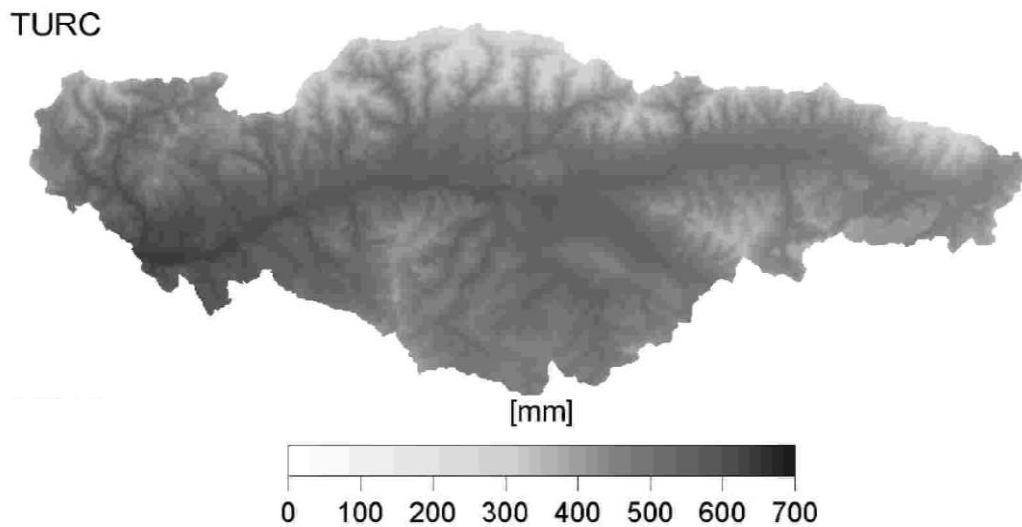


Figure 4.4: Grid map of the long-term mean annual potential evapotranspiration (1981 – 1990) as estimated by the Turc empirical model.

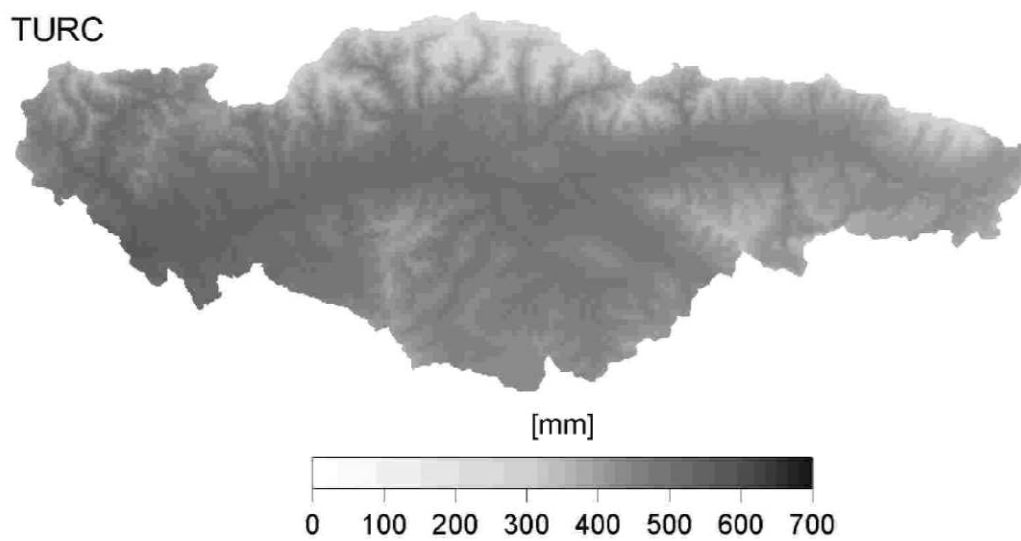


Figure 4.5: Grid map of the long-term mean annual actual evapotranspiration (1981 – 1990) as estimated by the Turc empirical model.

The time of concentration to the basin's outlet in Banská Bystrica is around one day. The largest travel time of 28 hours was estimated by hydraulic routing, considering the overland and subsurface flow from the basin's cells on the catchment's boundary to the basin with the physically-based distributed rainfall-runoff model of WetSpa (Liu and De Smedt et al., 2004) (taking into account the flow length, the slope, the soil properties and surface roughness as a function of

the land-use). This estimate is supported by travel times computed from the commonly used Kirpich and Nash formula, which yielded values of 19 and 23 hours respectively.

## CHAPTER 5

### RESULTS

In this chapter we are going to present the results of the rainfall-runoff modelling in the Hron catchment using the HBV model. The model calculates discharge from the catchment using various meteorological and climatic data such as precipitation, temperature and daily potential evapotranspiration. In this study we have been working with data from the Hron catchment measured in a daily step in a period between 01/01/1980 and 31/12/2000 giving us 20 years of observed data.

Since the main objective of this study was to compare various calibration strategies and optimization algorithms we have decided that the best way how to evaluate their performance is to eliminate the measurements errors. By doing this we have achieved that the goodness of fit of a particular model was given only by the different parameters obtained from various calibration strategies. In order to eliminate the effect of the data errors we have created a new time series of flows calculated with the HBV model with parameters that were calibrated on the whole period of the original data.

The whole process of the calculations can be divided into these steps.

**Step 1:** calibration of the original data and obtaining parameters used to create generated data. Using of two optimization algorithms: genetic algorithm – GA and harmony search – HS and their comparison. Selecting better algorithm used in next calibrations.

**Step 2:** reproduction of the model by calibrating the generated data – use of the whole dataset.

**Step 3:** reproduction of the model by calibrating the generated data – use of various calibration strategies.

## 5.1 Calibration of the original data

In order to create the generated flows, further used in the study, we had to calibrate the original dataset to obtain the best set of parameters. We have used two types of optimization algorithms: genetic algorithm and harmony search. To compare these algorithms we have decided to do 50 calibrations for both algorithms. Their comparison is depicted in Figure 5.1 showing that both algorithms gave similar values of the Nash-Sutcliffe coefficient (NS) used as an objective function. Since the highest value of NS was achieved by the GA we have decided to use only the GA in further calibrations. The distribution of the parameters for both GA and HS is shown in Figures 5.3 and 5.4 after 50 calibration using GA and HS and triangle transformation.

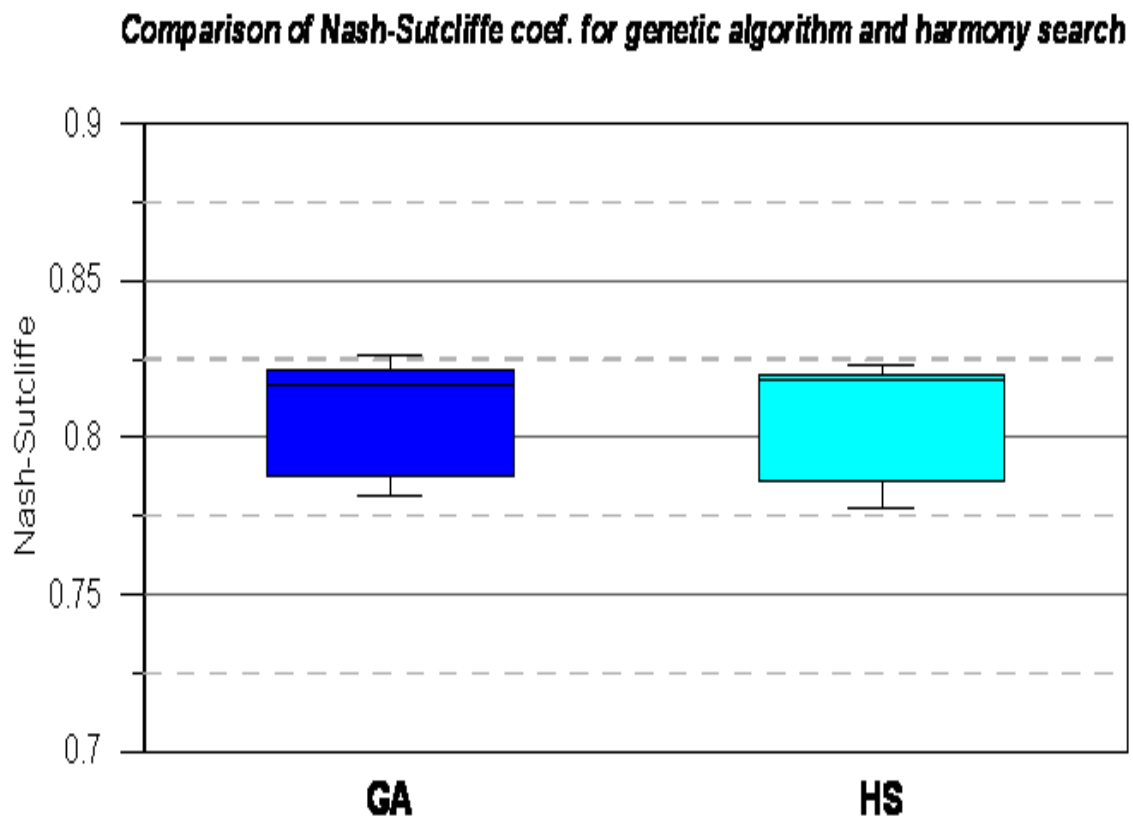


Figure 5.1: Comparison between GA and HS.



Using the best set of parameters we have achieved a value of NS of 0.826.

Furthermore we have two graphics about:

- snow water equivalent (swe),
- upper zone storage (suz),
- lower zone storage (slz),
- soil moisture (sm),
- daily potential evapotranspiration (DPET),
- actual evapotranspiration (aet),
- temperature,
- precipitation,
- runoff components  $q_0$ ,  $q_1$ ,  $q_2$ .

Which can be compared. The values of a particular parameters are shown in Table 5.1. These parameters were then used to create simulated flows, which together with observed flows, are depicted in Figure 5.2.

**Table 5.1: Parameters used to create generated data.**

Parameter	Value
fc	162.61369
rc	1.00315
emp	1.0000
uzl	10.171452
tempRain	7.42226
tempMelt	-1.52136
tempSnow	-8.97445
ddf	0.75727
perc	2.67033
lpe	0.50453
k0	48.56770
k1	4.19195
k2	22.79866
scf	1.0000
maxbas	3.36842

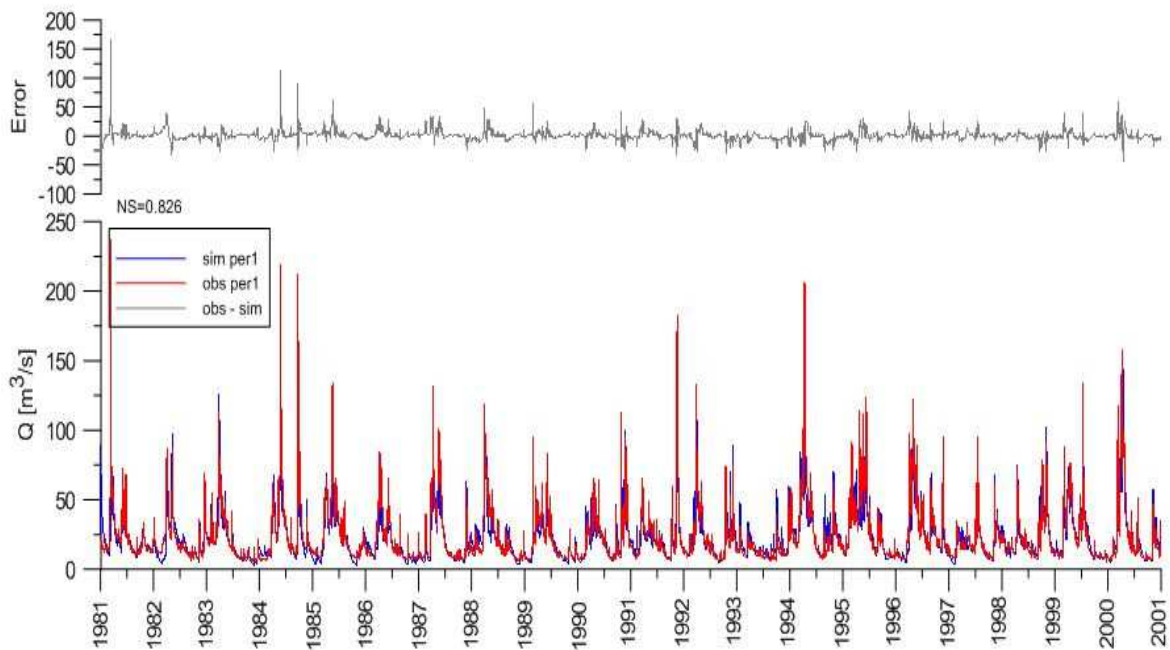
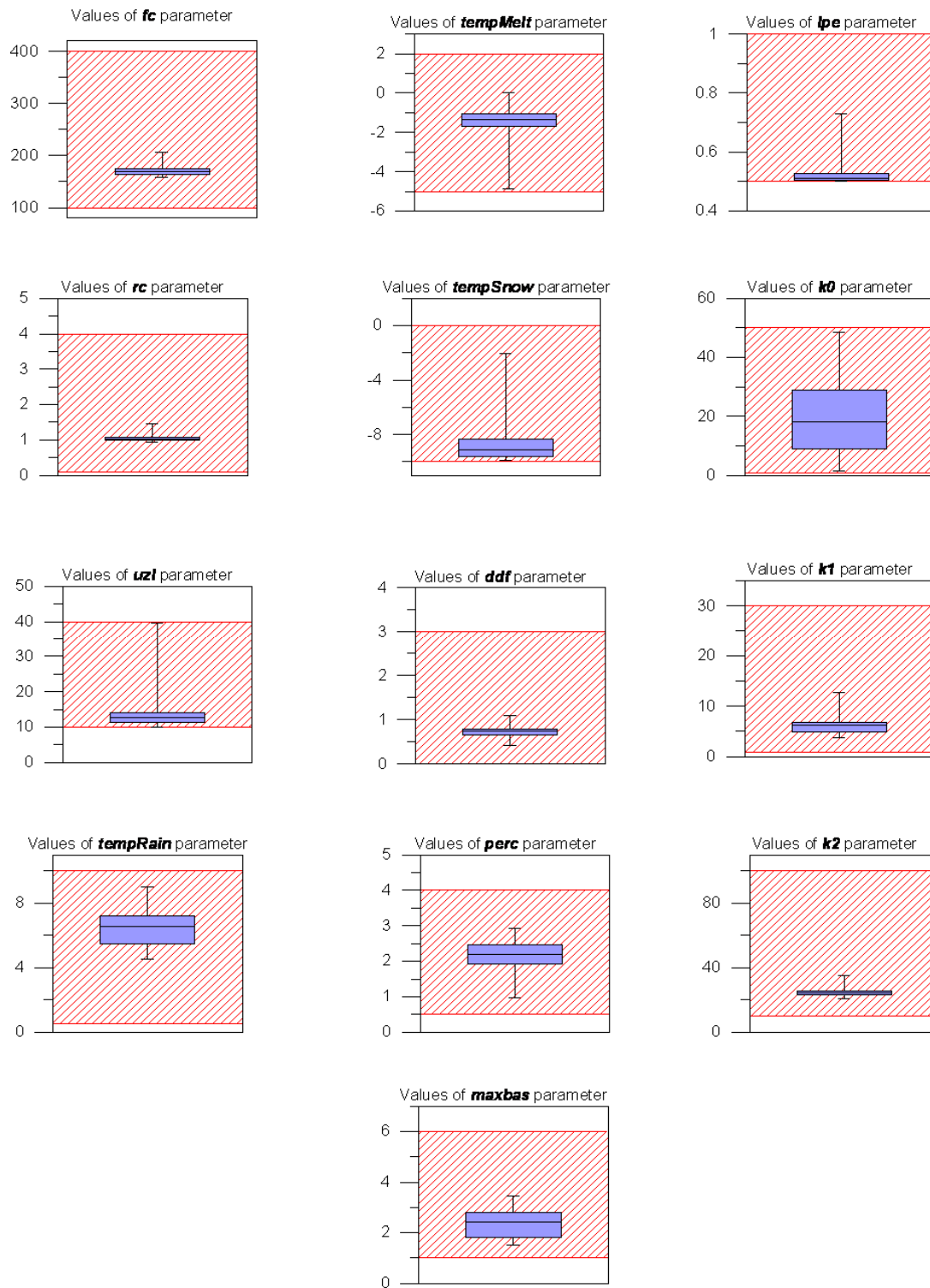


Figure 5.2: Simulated (blue) and observed (red) flows plotted together with their errors (observed – simulated).

As we can see, the blue line shows the simulated flows, meanwhile the red line the observed flows. We can observe a good result of the calibration as well as for the errors. In fact the maximum value is 150 in the first year and we have another two peaks between 1984 and 1986, but in general we can conclude the first step is good and from these new parameters we can obtain, subsequently, the new generated data.

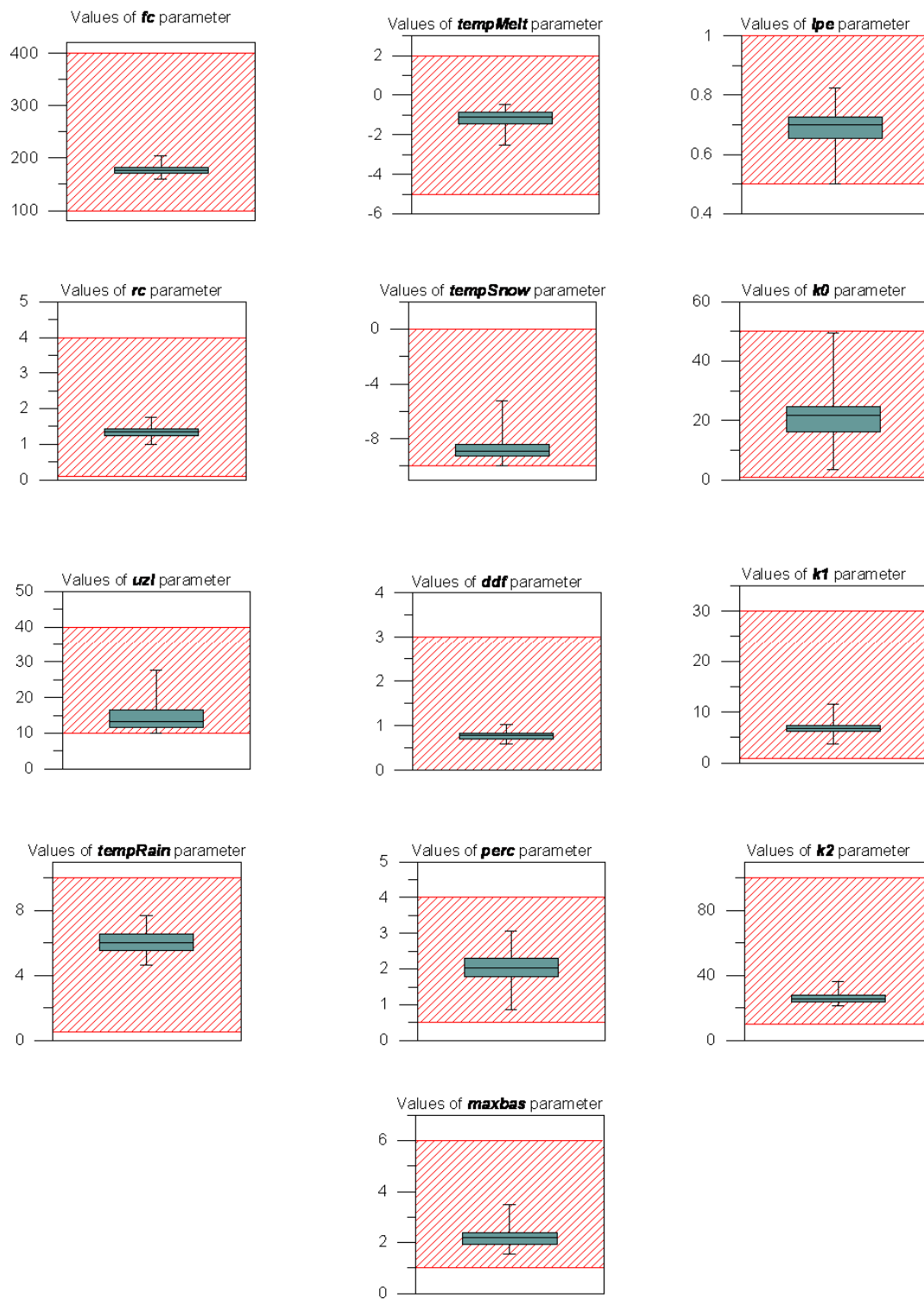
Hereinafter the distribution of the parameters after 50 calibrations for both GA and HS is shown:

**Parameter variation after 50 calibrations using GA and triangle transformation**



**Figure 5.3: Parameter variation after 50 calibrations using GA. Red hatched area represents the interval from which particular parameter was selected.**

**Parameter variation after 50 calibrations using HS and triangle transformation**



**Figure 5.4: Parameter variation after 50 calibrations using HS. Red hatched area represents the interval from which particular parameter was selected.**

As we can see in the Figure 5.3 the parameter distribution is almost stable for each sixteen parameters. We can observe, for instance, that the values of the field capacity (**fc**) are very stable around the value of 160 and the same we can say about the recharge coefficient (**rc**) that is stable around 1.

Instead we can note how the values distribution of the recession coefficient (**k<sub>0</sub>**) are not so much distributed, in fact we have a range between 10-30 and so we can say that the distribution is not stable.

We got almost the same parameter distribution using Harmony Search (HS) as we can see in the Figure 5.4. We can observe the most significant difference for the values of limit of potential evapotranspiration (**lpe**). In fact, the parameter variation using GA is stable around the value 0.5, instead, using HS, is not so stable and we have a range between 0.65-0.75. That for further analysis the parameters estimated using GA were selected.

In these other five graphics we can compare the simulated flow with a observed flow and we can observe lines of simulated and observed flow almost overlapping, that means, very good results:

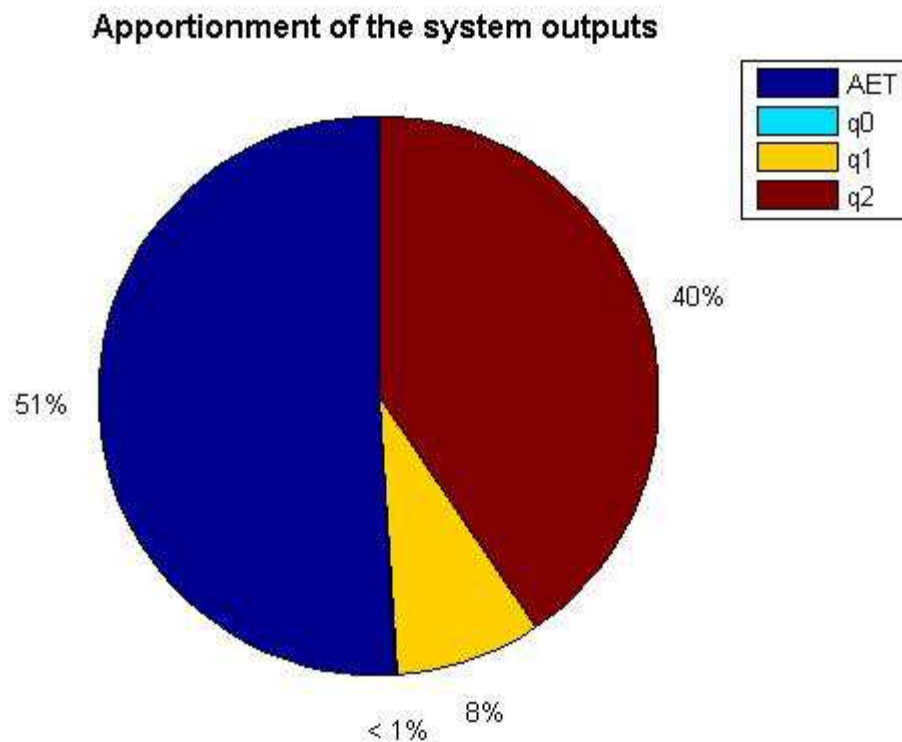


Figure 5.5: Apportionment of the system outputs.

As we can see in the Figure 5.5 the actual evapotranspiration (AET) is just a little bit more than 50 % (precisely 51%) of the system outputs. The runoff components  $q_0$ ,  $q_1$ ,  $q_2$  represent the remaining 49 % are distributed in this way:

- $q_0 < 1\%$
- $q_1 = 8\%$
- $q_2 = 40\%$

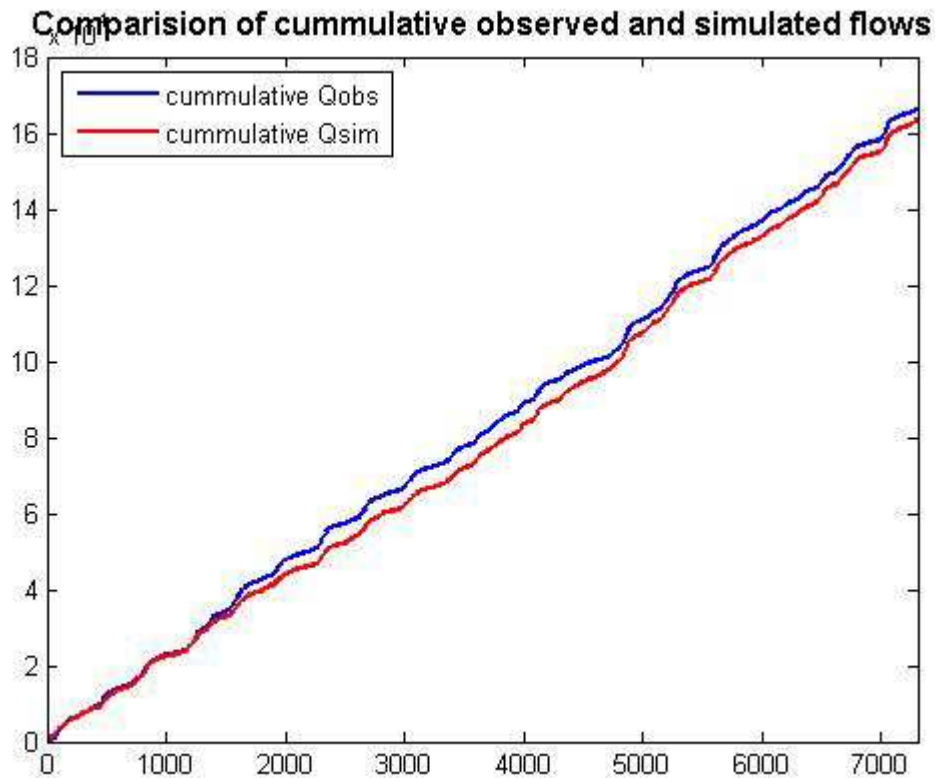


Figure 5.6: Comparison of cummulative observed and simulated flow.

In this Figure 5.6 instead we can observe that the lines of cumulative observed flow ( $Q_{OBS}$ ) and cumulative simulated flow ( $Q_{SIM}$ ) are almost the same. We can note as after the first 1300 steps the two lines start to deviate but with a difference that is always irrelevant.

In this Figure 5.7 is shown the comparison of discharge simulated flow and discharge observed:

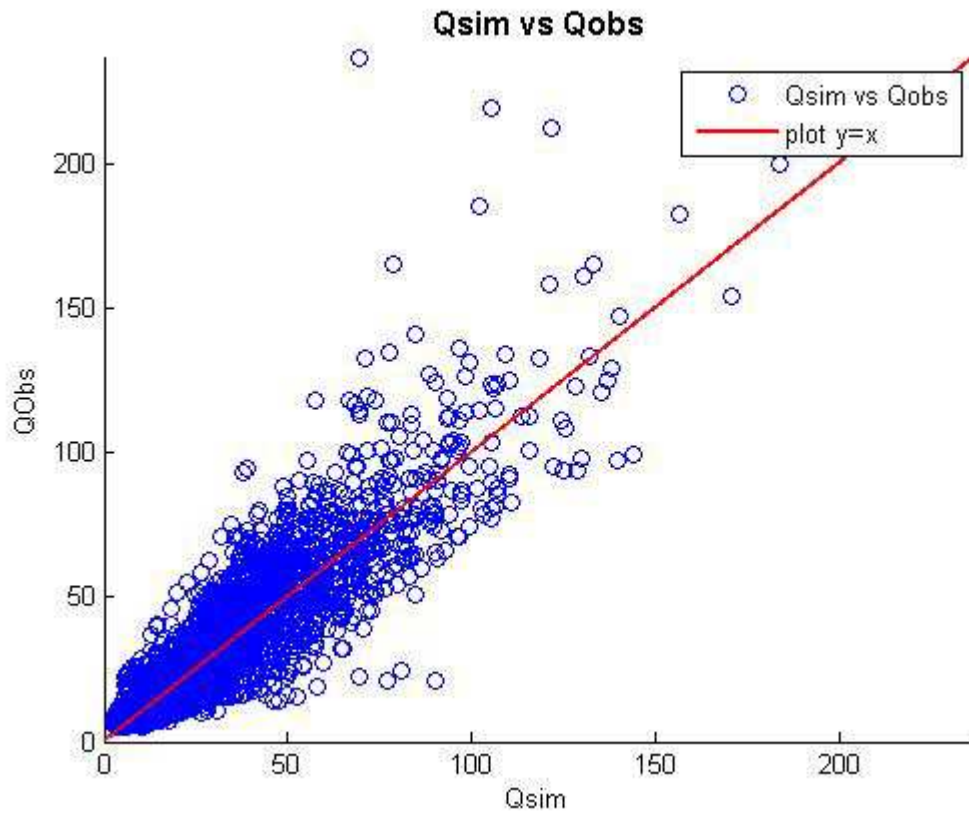


Figure 5.7: Comparison of discharge simulated and discharge observed.

We can note that, if we put the simulated flow in the abscissa axis and the observed flow in ordinate axis, below the value 100, there is a strong distribution around the line  $y = x$ , that is perfect comparison, and we can say that the values are not properly similar and very close, but however the results are very good. We can say the same about the Figure 5.8, where is shown empirical distribution function, or empirical cdf, that is the cumulative distribution function associated with the empirical measure of the sample:

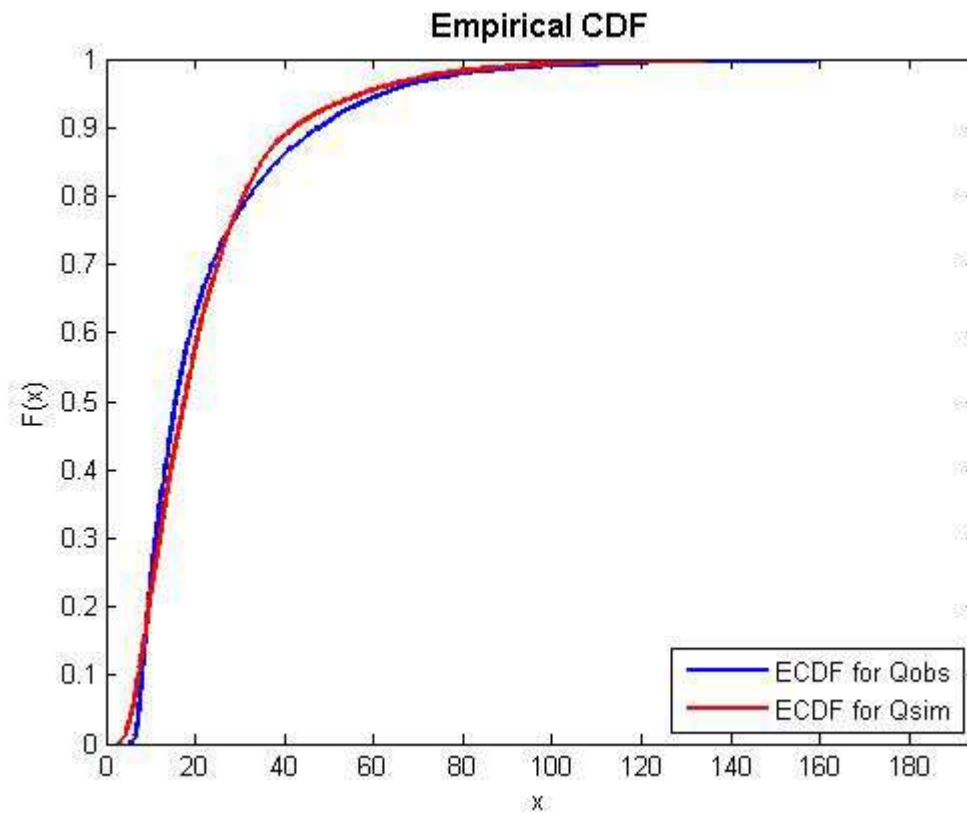


Figure 5.8: Comparison of simulated and observed flow.

As we can see the two lines deviate slightly and we can say that ECDF for Qobs and ECDF for Qsim are almost the same.



Hereinafter (Figure 5.9) is shown the comparison between the input data and output data.

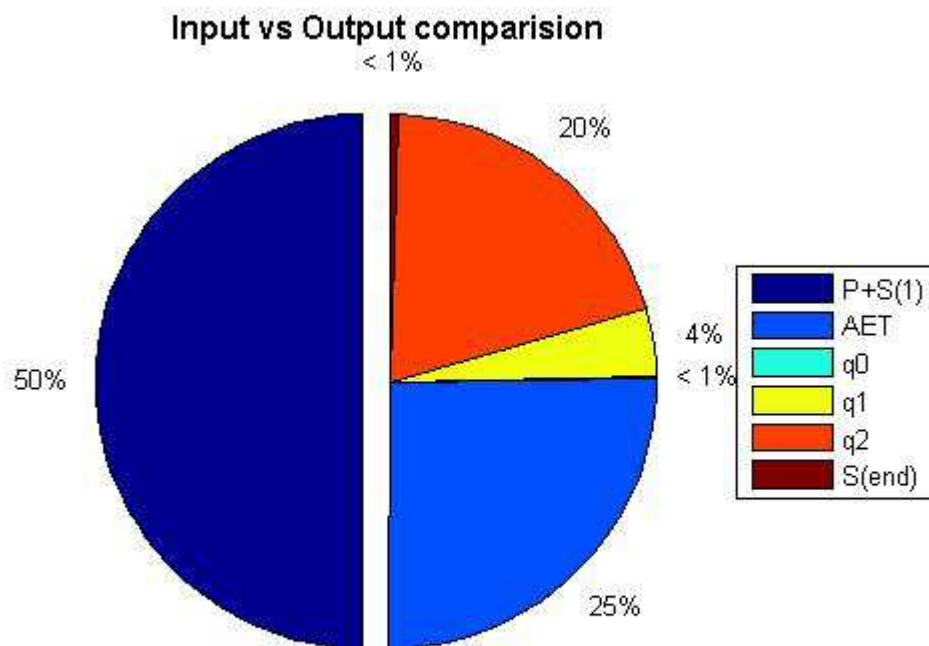


Figure 5.9: Comparison of input and output data.

As we can see precipitation (P) + snow (S) constitute the 50 %. The actual evapotranspiration (AET) 25%, the remaining 25% is done by runoff components  $q_0, q_1, q_2$  distributed in this way:

- $q_0 < 1\%$
- $q_1 = 4\%$
- $q_2 = 20\%$

Furthermore there is another very small (less 1%) percentage of S.

In order to analyze the correlation dependence among the parameters we have performed correlation analysis to identify relations among the parameters. After we analyzed the parameters and we calculated Pearson coefficient. The most familiar measure of dependence between two quantities is the Pearson correlation coefficient. 'Pearson correlation index, also called Pearson's correlation coefficient (or Bravais-Pearson), between two random variables is a coefficient that expresses the linearity between their covariance and the product of their standard deviations.

In fact it is obtained by dividing the covariance of the two variables by their standard deviations.

The correlation coefficient  $\rho_{X,Y}$  between two random variables X and Y with expected values  $\mu_X$  and  $\mu_Y$  and standard deviations  $\sigma_X$  and  $\sigma_Y$  is defined as:

$$\rho_{x,y} = \text{corr}(X, Y) = \frac{\text{cov}(X, Y)}{\sigma_x \sigma_y} = E[(X - \mu_X)(Y - \mu_Y)] \quad [5.1]$$

where E is the expected value operator, cov means covariance, and, corr a widely used alternative notation for Pearson's correlation.

The Pearson correlation is +1 in the case of a perfect positive (increasing) linear relationship (correlation), -1 in the case of a perfect decreasing (negative) linear relationship and some value between -1 and 1 in all other cases, indicating the degree of linear dependence between the variables. As it approaches zero there is less of a relationship. The closer the coefficient is to either -1 or 1, the stronger the correlation between the variables.

In the following Figure 5.10 is shown “Scatter” plot with the correlations between model parameters:

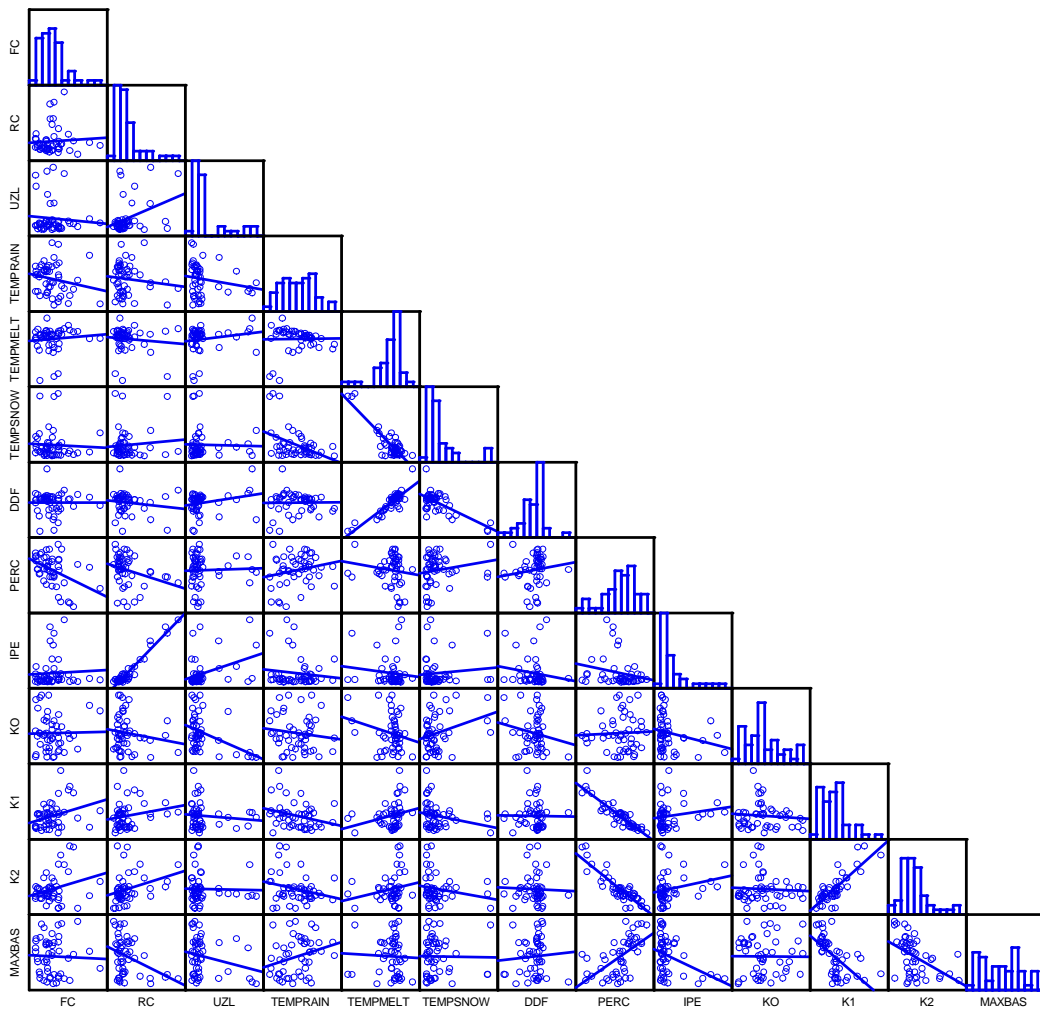


Figure 5.10: Scatter plot with the correlations between model parameters.

The scatter plot represents the relationship between the set of 50 calibrated model parameters. The histograms represent graphical interpretation of the frequency distribution of the selected parameters.

Linear smoothing was used to see the relationship. We can observe a high correlation between degree day factor (**ddf**) and **tempmelt** or between recession coefficients **k<sub>0</sub>** and **k<sub>1</sub>**. The same we can say for limit of potential evapotranspiration (**ipe**) and recharge coefficient (**rc**). Instead we can note a high inverse correlation between **tempsnow** and **tempmelt** as well as **k<sub>1</sub>** and **perc**.

In the Table 5.2 the Pearson correlation matrix with the values of correlation coefficients between calibrated model parameters is shown:

Table 5.2: Correlation matrix with the values of correlation coefficients between calibrated model parameters.

	fc	rc	uzl	tempRain	tempMelt	tempSnow	ddf	perc	lpe	k <sub>0</sub>	k <sub>1</sub>	k <sub>2</sub>	maxbas/k
fc	1												
rc	0.066	1											
uzl	-0.079	0.368	1										
tempRain	-0.196	-0.121	-0.200	1									
tempMelt	0.097	-0.108	0.170	0.017	1								
tempSnow	-0.045	0.089	-0.028	-0.442	-0.871	1							
ddf	0.002	-0.144	0.253	0.011	0.892	-0.696	1						
perc	-0.435	-0.293	0.038	0.216	-0.145	0.174	0.135	1					
lpe	0.053	0.969	0.384	-0.122	-0.116	0.099	-0.138	-0.227	1				
k <sub>0</sub>	0.020	-0.155	-0.428	-0.132	-0.234	0.308	-0.179	0.043	-0.228	1			
k <sub>1</sub>	0.315	0.200	-0.111	-0.282	0.261	-0.237	-0.016	-0.911	0.178	-0.094	1		
k <sub>2</sub>	0.278	0.308	-0.022	-0.248	0.210	-0.188	-0.038	-0.887	0.233	-0.058	0.830	1	
maxbas/k	-0.034	-0.380	-0.243	0.276	-0.042	-0.015	0.068	0.597	-0.395	-0.004	-0.615	-0.460	1

Where the values of Pearson correlation coefficient between calibrated parameters are presented we can observe high correlations between the set of parameters in snow subroutine: **tempmelt** with **tempsnow** and **ddf**, **perc** with **k<sub>1</sub>** and **k<sub>2</sub>** and both parameters with **maxbas**. High correlation was observed between **lpe** and **rc**. Furthermore moderate correlation was observed between **Perc** with **fc** and between **maxbas** and **k<sub>2</sub>**.

In particular, the values marked in yellow are:

- **Tempsnow-temp melt** = -0.87132
- **ddf -tempMelt** = 0.892121
- **Ipe-rc** = 0.968776
- **perc-k<sub>1</sub>** = -0.91122
- **perc-k<sub>2</sub>** = -0.8868
- **perc-maxbas** = 0.596702
- **k<sub>1</sub>-k<sub>2</sub>** = 0.829575
- **k<sub>1</sub>-maxbas** = -0.61466

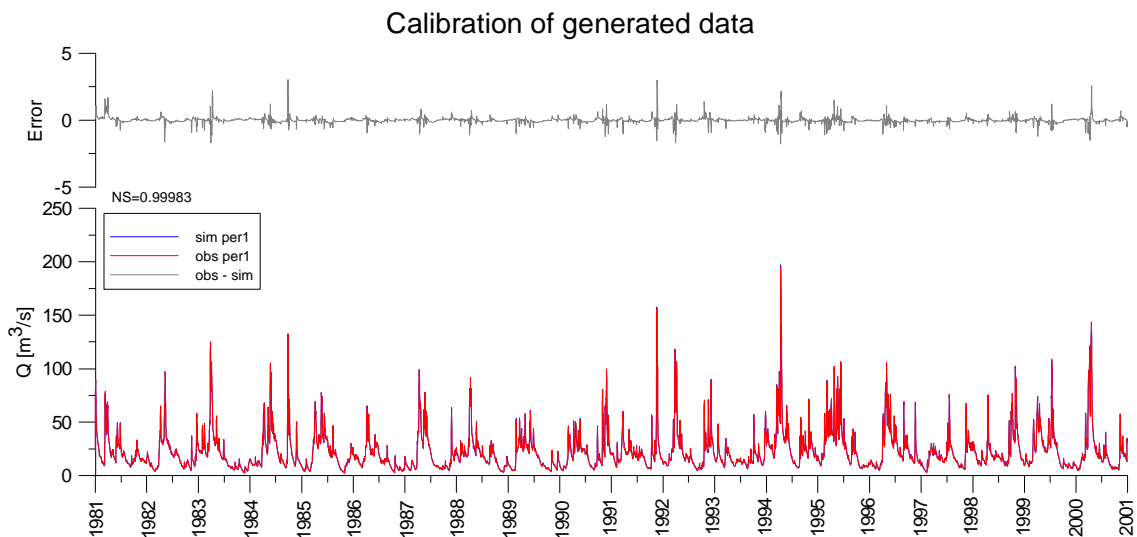
Instead, the values marked in red, that is with a moderate correlation, are:

- **Perc- fc** = -0.4350
- **Maxbas-k<sub>1</sub>** = -0.46007

## 5.2 Calibration of the generated data

After obtaining the best set of parameters calibrated on the observed data we have used the parameters and measured precipitations, temperatures and glare indexes to create simulated flows - hereinafter referred to as generated data.

These generated data were further used to calibrate another set of parameters which should show us whether we are able to reproduce the model itself (we are already calibrating simulated data). The result of the calibration shows (see Figure 5.11) that the fit of the model is very good with the Nash-Sutcliffe value equal to 0.99983. This means that with the use of genetic algorithm we have managed to reproduce the model itself.



**Figure 5.11: Generated (red) and simulated (blue) data plotted together with their errors (generated – simulated). The fit of the data is so good (NS=0.99983) that red line overlaps the blue one.**

Furthermore we got the same five graphics of the original data but with the little difference that here the results are just a little bit more excellent as we can see hereinafter. In fact we can compare the simulated flow with a observed flow and we can observe lines of simulated and observed flow overlapping, that means, excellent results:

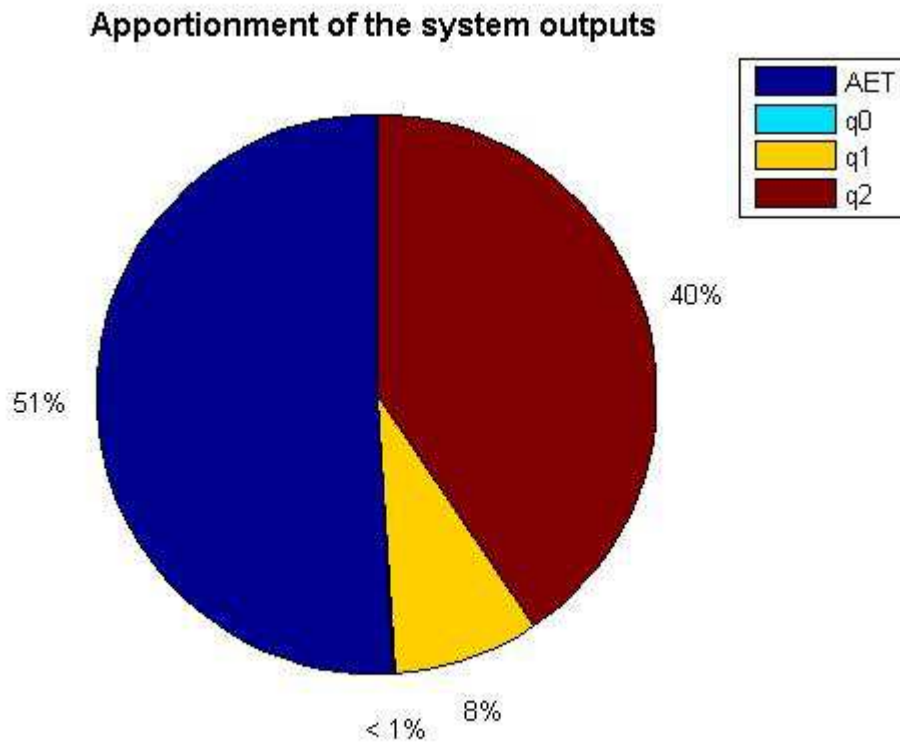


Figure 5.12: Apportionment of the system outputs.

As we can see in the Figure 5.12 the actual evapotranspiration (AET) is just a little bit more than 50 % (precisely 51%) of the system outputs. The runoff components  $q_0$ ,  $q_1$ ,  $q_2$  represent the remaining 49 % are distributed in this way:

- $q_0 < 1\%$
- $q_1 = 8\%$
- $q_2 = 40\%$

We can say that this graphic of generated data is practically equal to the same graphic of original data.

Better results we can observe in the Figure 5.13 where the two lines of cumulative observed flow ( $Q_{OBS}$ ) and cumulative simulated flow ( $Q_{SIM}$ ) are overlapping.

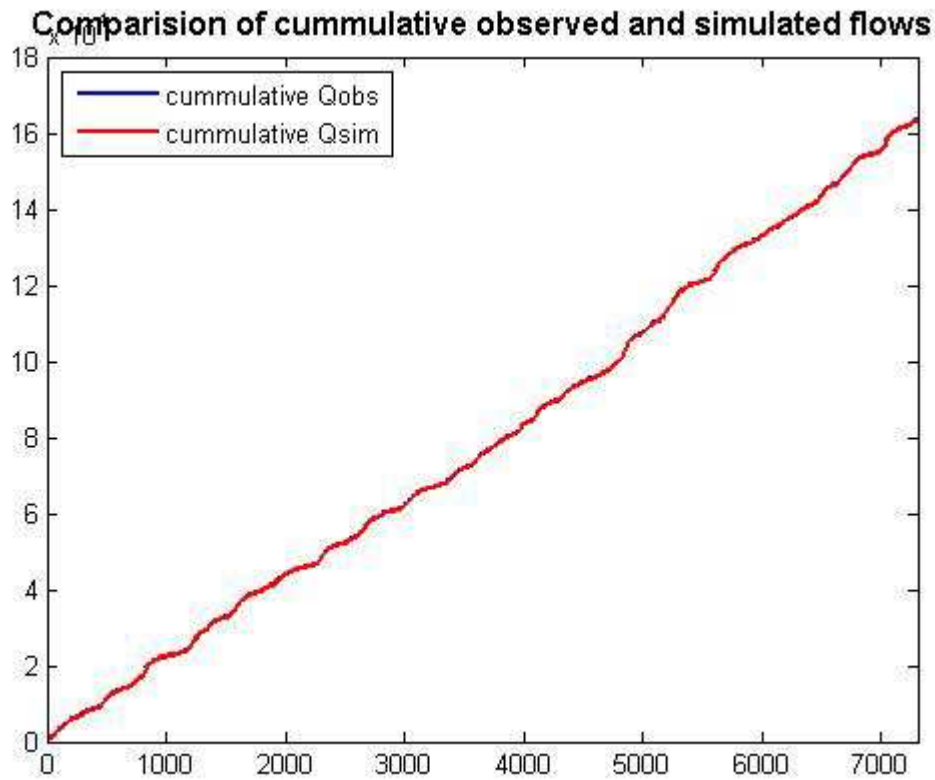


Figure 5.13: Comparison of cumulative observed and simulated flow.

In the Figure 5.14 hereafter is shown the distribution discharge simulated and discharge observed around the line  $y = x$ , that means  $Q_{sim} = Q_{obs}$ , that is perfect comparison. The results are of course better than original data because we have a perfect comparison between  $Q_{sim}$  and  $Q_{obs}$ :

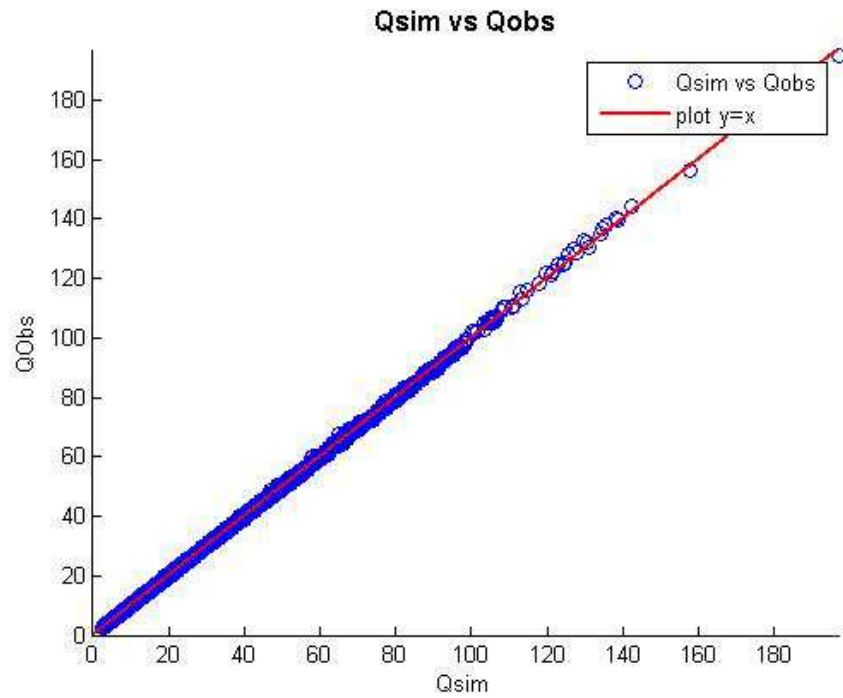


Figure 5.14: Comparison of discharge simulated and discharge observed.

We can say the same about the Figure 5.15, where is shown empirical distribution function, or empirical cdf. We can observe a perfect coincident of the two lines ECDF for Qobs and ECDF for Qsim:

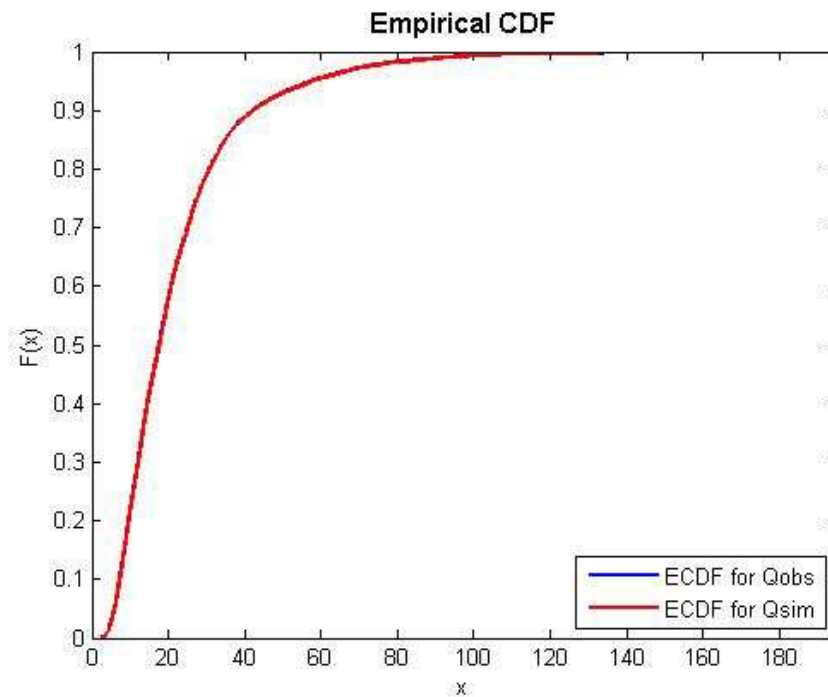
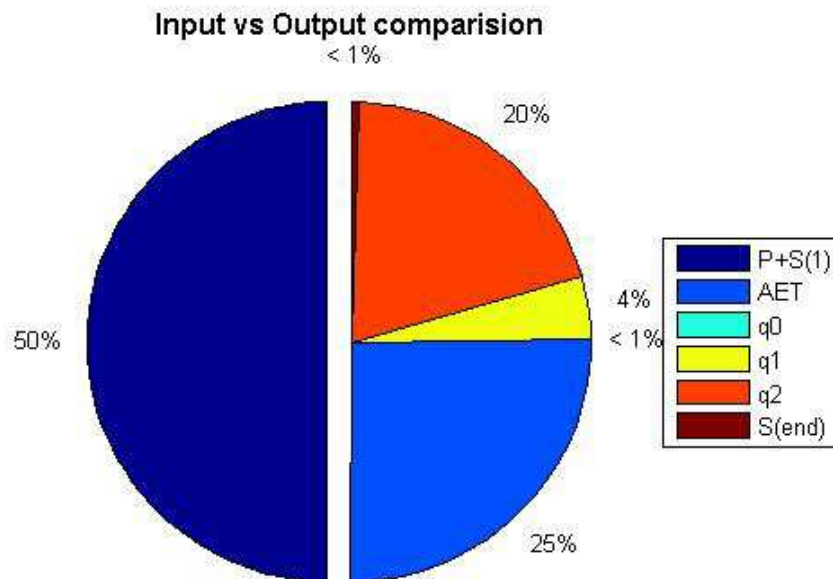


Figure 5.15: Comparison of simulated and observed flow.



The last graphic (see Figure 5.16) that we got from the generated data shows the comparison of input and output data.



**Figure 5.16: Comparison of input and output data.**

We can note the same things we have already seen in the same graphic of the original data. As we can see precipitation (P) + snow (S) constitute the 50 %. The actual evapotranspiration (AET) 25%, the remaining 25% is done by runoff components  $q_0, q_1, q_2$  distributed in this way:

- $q_0 < 1\%$
- $q_1 = 4\%$
- $q_2 = 20\%$

Furthermore there is another very small (less 1%) percentage of S.

### 5.3 Split-sample test

There are different calibration strategies to meet two objectives: good discharge simulations in terms of least mean square errors and the ability to reproduce one functional characteristic of the system and the autocorrelation function of the discharge. One of these calibration strategies is split-sample test.

The available record should be split into two segments one of which should be used for calibration and the other for validation. It should be split into two equal parts, each of them should be used in turn for calibration and validation, and results from both arrangements compared. The model should be judged acceptable only if the two results are similar and the errors in both validation runs acceptable.

So in the next step we have tried to calibrate model parameters with the use of only one half of the generated data. The second half was then used as a validation period used to verify that the calibrated parameters can also be used on different data. We have also used the second half of the data as a calibration period and the first half as a validation period. The generated data were split in the 31.12.1990 creating two periods spanning 1.1.1980 and 31.12.1990 and 1.1.1991 and 31.12.2000. When calibrating the model on the first period we have achieved the NS values of 0.999 for the calibration period and 0.998 for the validation period. Calibration on the second period brought similar results with the NS values of 0.999 and 0.999 for calibration and validation periods respectively.

Since both of these values are very close to 1 and the visual assessment of the models (see Figure 5.17 and 5.18) is also very good we can say that in both cases we have managed to reproduce the model itself.

All the calibrated parameters are listed in Table 5.3.

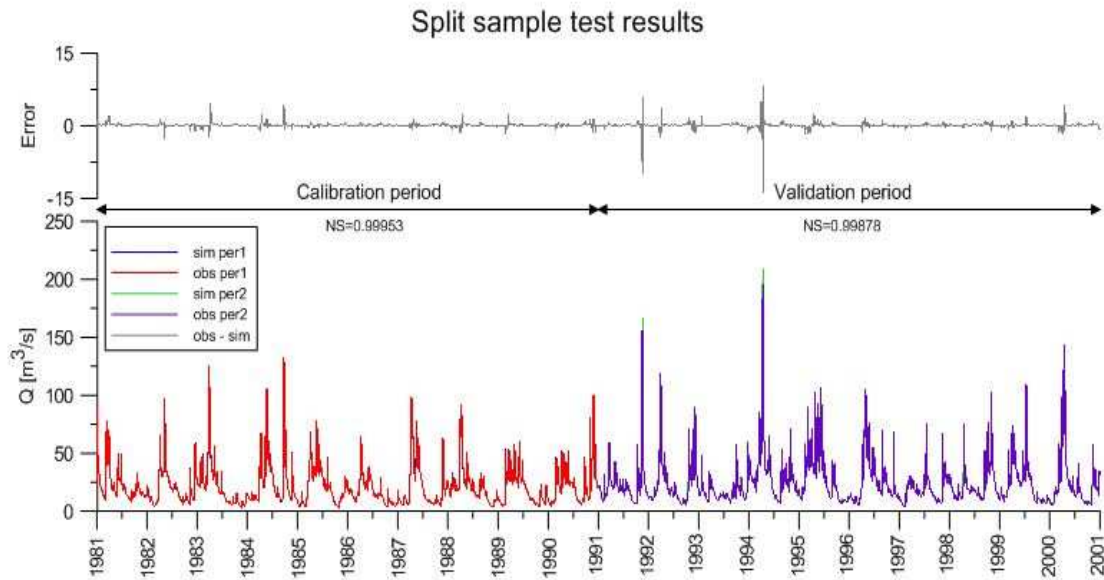


Figure 5.17: Comparison of generated and simulated data. Calibrated on the first period.

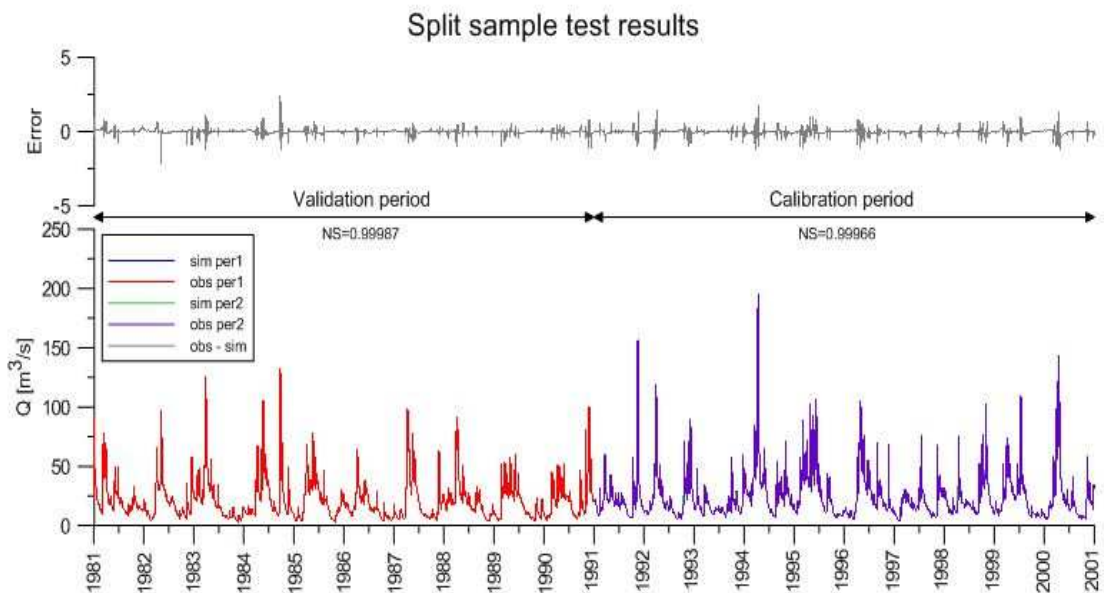


Figure 5.18: Comparison of generated and simulated data. Calibrated on the second period.

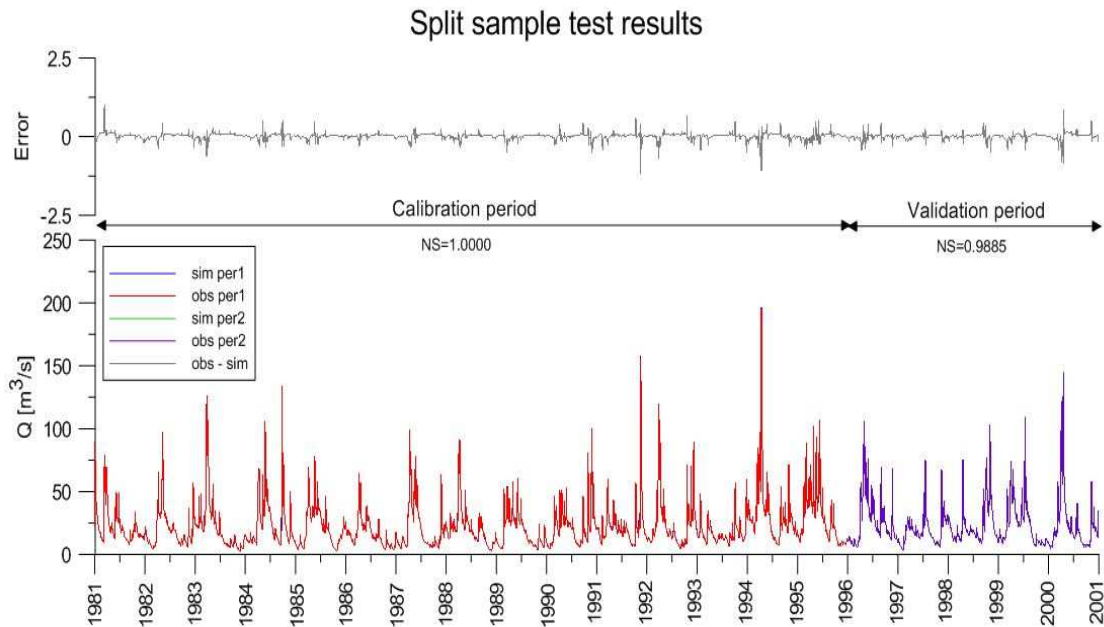
Table 5.3: Summary table showing all the calibrated periods and boundaries that were used in the calibration.

Parameter	Original	Gen all	Period 1	Period 2	lower bound	upper bound
fc	162.61	164.25	164.59	162.02	100	400
rc	1.00	1.04	1.03	1.02	0.1	4
emp	1.00	1.00	1.00	1.00	1	1
uzl	10.17	26.45	14.43	30.86	10	40
tempRain	7.42	7.09	7.20	7.20	0.5	10
tempMelt	-1.52	-1.48	-1.52	-1.53	-5	2
tempSnow	-8.97	-8.81	-8.77	-8.76	-10	0
ddf	0.76	0.76	0.76	0.76	0	3
perc	2.67	2.68	2.67	2.71	0.5	4
lpe	0.50	0.53	0.52	0.52	0.5	1
k0	48.57	20.75	27.92	18.68	1	50
k1	4.19	4.07	4.17	4.02	1	30
k2	22.80	23.05	22.81	22.90	10	100
scf	1.00	1.00	1.00	1.00	1	1
maxbas	3.37	3.16	3.02	3.05	1	6

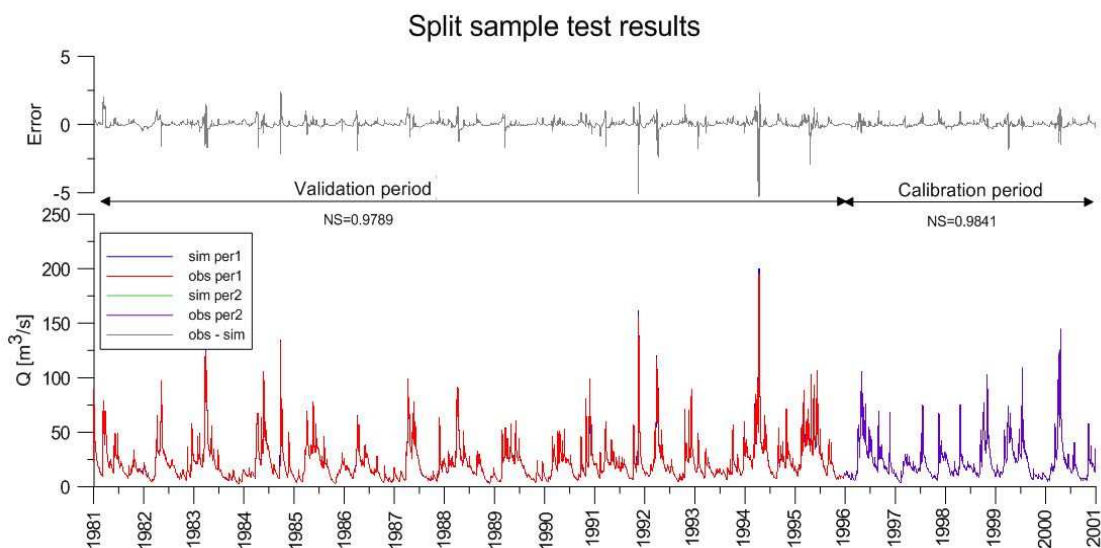
## 5.4 Additional split-sample test

In the next step we have done the same as described previously but with the difference that we have chosen two different periods: the first period of 15 years and the second of 5 years. The procedure is the same as described above: the generated data were split in the 31.12.1995 creating two periods spanning 1.1.1980 and 31.12.1995 and 1.1.1996 and 31.12.2000. When calibrating the model on the first period we have achieved the NS values of 1.000 for the calibration period and 0.9885 for the validation period. Also in this additional split-sample test calibration on the second period brought similar results with the NS values of 0.9841 and 0.9789 for calibration and validation periods respectively.

As we can see the values are very close to 1 and the visual assessment of the models (see Figure 5.19 and 5.20) is also very good we can say, also here, that in both cases we have managed to reproduce the model itself.



**Figure 5.19: Comparison of generated and simulated data. Calibrated on the first period.**



**Figure 5.20: Comparison of generated and simulated data. Calibrated on the second period.**

We have repeated this procedure, but changing again the periods: we have chosen for the last split-sample test the first period of 5 years and the second period of 15 years. And so the generated data were split in the 31.12.1985

creating two periods spanning 1.1.1980 and 31.12.1985 and 1.1.1986 and 31.12.2000. When calibrating the model on the first period we have achieved the NS values of 0.9999 for the calibration period and 0.9997 for the validation period. Also in this additional split-sample test calibration on the second period brought similar results with the NS values of 0.9997 and 0.9998 for calibration and validation periods respectively.

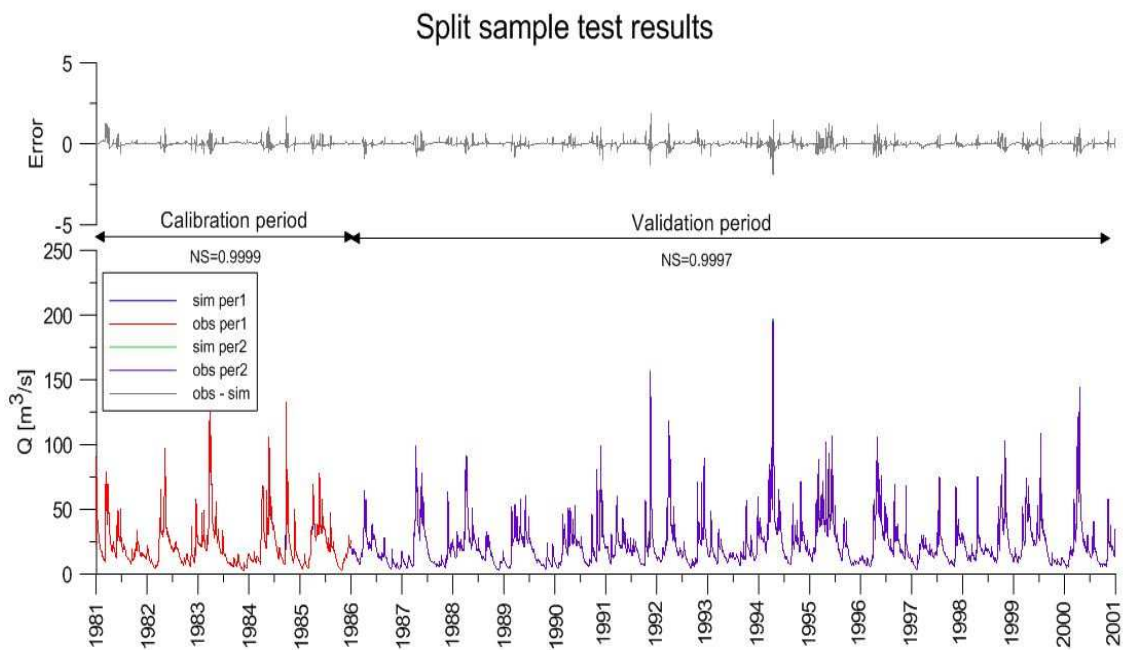


Figure 5.21: Comparison of generated and simulated data. Calibrated on the first period.

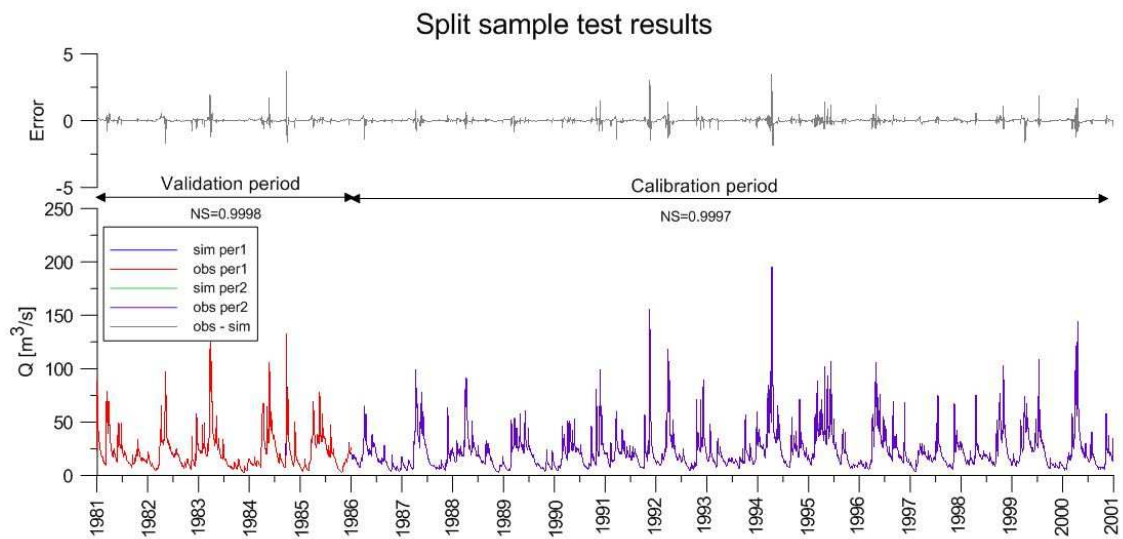


Figure 5.22: Comparison of generated and simulated data. Calibrated on the second period.

Even here we can conclude that since both of these values are very close to 1 and the visual assessment of the models (see Figure 5.21 and 5.22) is also very good. So we can say that in both cases we have managed to reproduce the model itself.

## CONCLUSIONS

The present study is focusing on rainfall-runoff modelling and in particular on techniques for parameter calibration. The objectives of the study is to assess the efficiency of currently used parameter estimation methods with respect to hypothetical and real world case studies. An established models is used for which calibration techniques are tested therefore deriving indications on their efficiency and suitability.

We got results of the rainfall-runoff modelling in the Hron catchment (in the middle of Slovack) using the HBV model. The model calculates discharge from the catchment using various meteorological and climatic data such as precipitation, temperature and daily potential evapotranspiration. In this study we have been working with data from the Hron catchment measured in a daily step in a period between 01/01/1980 and 31/12/2000 giving us 20 years of observed data.

Since the main objective of this study was to compare various calibration strategies and optimization algorithms we have decided that the best way to evaluate their performance is to put ourselves in an ideal conditions where measurements errors are not present. By doing this we have achieved that the goodness of fit of a particular model was given only by the different parameters obtained from various calibration strategies. In order to eliminate the effect of the data errors we have simulated a synthetic time series of flows calculated with the HBV model with parameters that were calibrated on the whole period of the original data.

We have used two types of optimization algorithms for the whole dataset: genetic algorithm and harmony search and we have used the Nash-Sutcliffe coefficient (NS) as an objective function.

After obtaining the best set of parameters calibrated on the observed data we have used the parameters and measured precipitations, temperatures and glare indexes to create simulated flows (generated data).

These generated data were further used to calibrate another set of parameters which have shown us whether we are able to reproduce the model itself. The result of the calibration shows that the fit of the model is very good



with the Nash-Sutcliffe value equal to 0.99983. This means that with the use of genetic algorithm we have managed to reproduce the model itself.

Then we have used various calibration strategies.

We have tried to calibrate model parameters with the use of only one half of the generated data. The second half was then used as a validation period used to verify that the calibrated parameters can also be used on different data. We have also used the second half of the data as a calibration period and the first half as a validation period. The generated data were split in the 31.12.1990 creating two periods spanning 1.1.1980 and 31.12.1990 and 1.1.1991 and 31.12.2000. When calibrating the model on the first period we have achieved the NS values of 0.999 for the calibration period and 0.998 for the validation period. Calibration on the second period brought similar results with the NS values of 0.999 and 0.999 for calibration and validation periods respectively. Since both of these values are very close to 1 and the visual assessment of the model is also very good we can say that in both cases we have managed to reproduce the model itself.

We have repeated this procedure, but changing again the periods: we have chosen for the last split-sample test the first period of 5 years and the second period of 15 years. And so the generated data were split in the 31.12.1985 creating two periods spanning 1.1.1980 and 31.12.1985 and 1.1.1986 and 31.12.2000. When calibrating the model on the first period we have achieved the NS values of 0.9999 for the calibration period and 0.9997 for the validation period. Also in this additional split-sample test calibration on the second period brought similar results with the NS values of 0.9997 and 0.9998 for calibration and validation periods respectively.

Even here we can conclude that since both of these values are very close to 1 and the visual assessment of the models is also very good. So we can say that in both cases we have managed to reproduce the model itself.

We can conclude that the HBV model is an efficient tool for runoff simulation. The model is simple and has been applied in some 40 countries, in all parts of the world and the number of applications in other countries is growing. It is also used for many other purposes, such as spillway design floods simulation, water resources evaluation, nutrient load estimates.

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