Czech University of Life Sciences Prague
Faculty of Environmental Sciences

Department of Water Resources and Environmental Modeling

Master thesis

THE EXTENSION OF OPTIMIZATION ALGORITHM OF BILAN MODEL

BSc. Hoang Trung Son

Supervisor: doc. Ing. Petr Máca, Ph.D.

Prague, 2017

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AUTHOR'S DECLARATION

I hereby declare that this submitted thesis "Building KGE coefficient calculation tool - implication for improving BILAN model" is my own work, all co-authors of the manuscripts are properly named, and only sources listed in the Bibliography were used.

Prague, 6th April 2017

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Hoàng Trung Sơn

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ABSTRACT

The Bilan model is a famous Czech hydrological model developed by the T. G. Masaryka Water Research Institute (WRI) in 15 years. Water balance model that can be used to simulate impacts of environmental change on hydrology. The structure of the model is formed by a system of relationships describing the principle of water balance on the land surface, the zone of aeration, including the effect of vegetation cover and groundwater (Kašpárek & Novický, 1997; Vizina et al., 2010). The model has eight free model parameters and uses four optimization algorithms for their calibration using gauged streamflow.

The model can be optimized which find the best suitable between the observed and simulated runoff series by using five optimization criteria. The Bilan model continues to evolve, with developers focused primarily on increasing the speed of computation and model accuracy, but optimization algorithms are unlikely to change. The model still uses five optimization criteria: "MSE" (mean squared error), "MAE" (mean absolute error), "NS" (Nash-Sutcliffe efficiency), "LNNS" (Nash-Sutcliffe of log-transformed data), "MAPE" (mean absolute percentage error).

This thesis discusses a new developmental trend for the Bilan model, which is to build a new optimization function based on the Kling-Gupta coefficient (Gupta H.V., 2009). For testing the accuracy of the new Bilan model, I used the KGE optimization function to simulate the total runoff of 57 catchments across the Czech Republic.

The results are then compared to the default optimization functions of the previous Bilan model, and are evaluated using the reference as results of the WRI center provided for each catchment. This paper demonstrates the feasibility of extending the optimization algorithm for the Bilan model using the Kling-Gupta coefficient for calibration.

CHAPTER 1. LITERATURE REVIEW

1.1. CONCEPTUAL HYDROLOGICAL MODELING

A model is a simplified representation of real world system. A model consists of different parameters that define the characteristics of the model. The model give result close to reality with the use of least parameters and model complexity is the best model (Sorooshian et al. 2008). Hydrologic models are simplified, conceptual representations of a part of the hydrologic cycle (Freeze and Harlan 1969, Kollet and Maxwell 2006). They are primarily used for hydrologic prediction and for understanding hydrologic processes.

A runoff model can be defined as a set of equations that helps in the estimation of runoff as a function of various parameters used for describing watershed characteristics. The two important inputs required for all models are rainfall data and drainage area. Along with these, watershed characteristics like soil properties, watershed topography, soil moisture content, vegetation cover, characteristics of groundwater aquifer are also considered. Hydrological models are considered as an important and necessary tool for water and environment resource management (Gayathri K. Devia 2015).

Conceptual model describes all of the component hydrological processes. It consists of a number of interconnected reservoirs which represents the physical elements in a catchment in which they are recharged by rainfall, infiltration and percolation and are emptied by evaporation, runoff, drainage etc. The hydrologic models have been divided to two main types, there are Stochastic models and Process-Based models (Xiaoxiang Zhang, 2012).

Stochastic Models are black box systems, based on data and using mathematical and statistical concepts to link a certain input (for instance rainfall) to the model output (for instance runoff). The random hydrodynamic models are models used some techniques, such as transfer functions, neural networks, regression and system identification. These models are known as stochastic hydrology models (S. K. Gupta, 2011).

Process-Based Models try to represent the physical processes observed in the real world. Typically, such models contain representations of channel flow, evapotranspiration, subsurface flow, and surface runoff, but they can be far more complicated (S. K. Gupta, 2011). These models are known as deterministic hydrology models. Deterministic hydrology models can be subdivided into single-event models and continuous simulation models (Rushton K.R., 2003).

1.2. PARAMETER ESTIMATES

Hydrologic models, no matter how sophisticated and spatially explicit, aggregate at some level of detail complex, spatially distributed vegetation and subsurface properties into much simpler homogeneous storages with transfer functions that describe the flow of water within and between these different compartments. These conceptual storages correspond to physically identifiable control volumes in real space, even though the boundaries of these control volumes are generally not known (J.A. Vrugt, 2008). The consequence of this synthesis is that most of the parameters in these models cannot be inferred from direct observations in the field, but only be meaningfully derived by calibration against an input-output record of the catchment response.

In this process, the parameters are adjusted in such a way that the model (e.g. simulated runoff) approximates as closely and consistently as possible the response of the catchment over some historical period of time (e.g. observed runoff). The parameters estimated in this manner represent effective conceptual representations of spatially and temporally heterogeneous watershed properties (J.A. Vrugt, 2008).

For a model to be useful in prediction, the values of the parameters need to accurately reflect the invariant properties of the components of the underlying system they represent.

Unfortunately, in watershed hydrology, many of the parameters cannot be measured directly, but can only be meaningfully derived through calibration against a historical record of streamflow data (J.A. Vrugt, 2008).

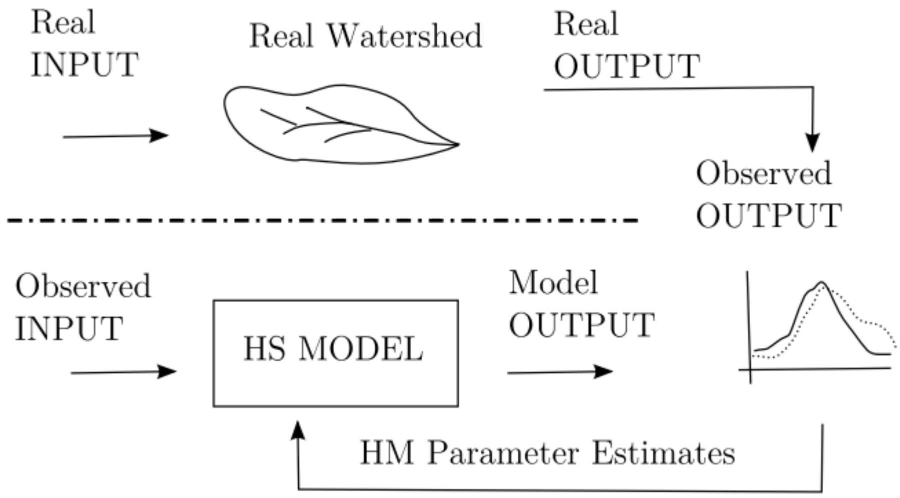

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Figure 1. Schematic overview of the parameter estimate

Figure 1 shows an overview of parameter estimation. Using the priority values of the parameters obtained through the regionalization relationships, human transfer functions or some remote (or on-site sensing data), the predictions of the model (indicated with black line) are behaviorally consistent with the observations (dotted line). But demonstrate a significant bias toward lower streamflow values.

The common approach is to ascribe this mismatch between model and data to parameter uncertainty, without considering forcing and structural model uncertainty as potential sources of error.

The goal of model calibration then becomes one of finding those values of the parameters that provide the best possible fit to the observed behavior using either manual or computerized methods.

A model calibrated by such means can be used for the simulation or prediction of hydrologic events outside of the historical record used for model calibration, provided that it can be reasonably assumed that the physical characteristics of the watershed and the hydrologic/climate conditions remain similar (J.A. Vrugt, 2008).

1.3. AIM OF MY THESIS

The main purpose of this thesis is to extend the optimization algorithms used in the typical Bilan hydrological model. The final version of the Bilan Model, released in 2015, has significant improvements in the computational approach, which makes it possible to analyze meteorological data more precisely and to process more quickly. However, the optimization functions used in the program remain the same from the first version (2011) to date, supported criteria: "MSE" (mean squared error), "MAE" (mean absolute error), " NS "(Nash-Sutcliffe efficiency)," LNNS "(Nash-Sutcliffe of log-transformed data)," MAPE "(mean absolute percentage error). The extension focuses on providing new optimization functions. In this thesis, I have developed a new optimization tool, based on the Kling-Gupta coefficient, to calibrate eight parameters of the Bilan model, resulting in a more accurate run-off simulation.

CHAPTER 2. MATERATURES AND METHOS

2.1. DATASET

For evaluation of the optimization ability of the proposed KGE modifications, Bilan model was calibrated using datasets from 57 Czech Republic catchments. The meteorological and hydrological data were obtained from Water Research Institute, which serves for benchmarking of hydrological models and calibration approaches.

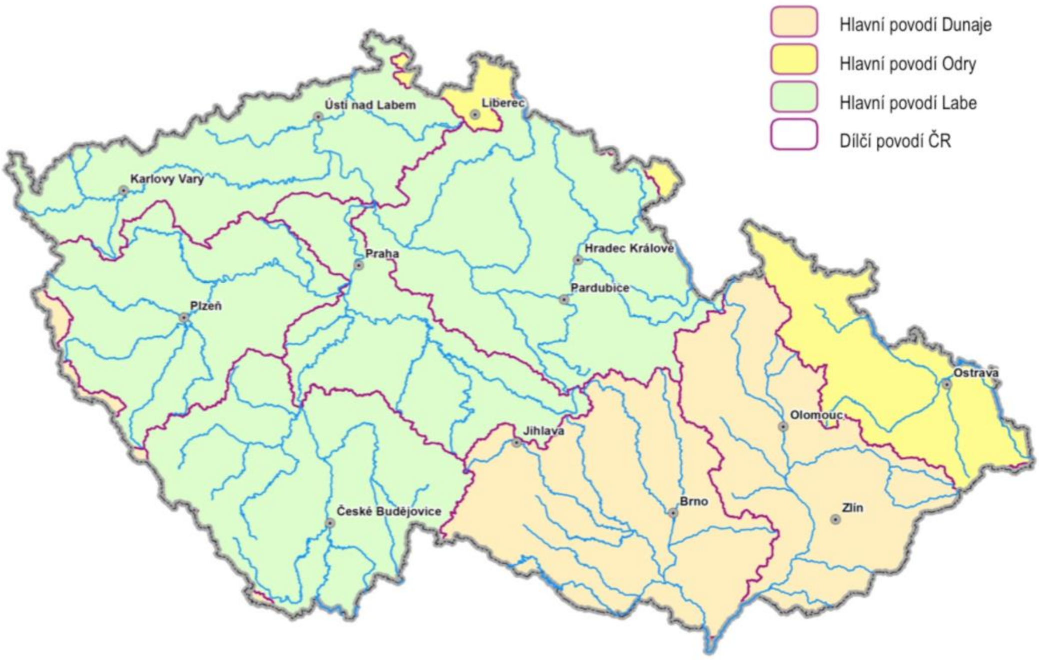

Figure 2. Sub-basins of the Czech Republic

For the analysis, the daily records from 1924 to 2003 were used. The main meteorological forcing of Bilan model were mean areal precipitation, mean air temperature and humidity.

2.2. THE HYDROLOGICAL MODEL BILAN

2.2.1. Introduction

Bilan is a lumped physically-based water balance model developed in T. G. Masaryk Water Research Institute in the Czech Republic (WRI) to simulate components of the water balance of the catchment. It is primarily used for assessing the impacts of climate change on the water regime and on supplies of surface and groundwater (Horáček et al. 2008; Šimková 2012; Vizina et al. 2010). A detailed description of the model is provided by the Bilan model manual, compiled by WRI (WRI 2015). It is a standard tool commonly used for assessment of water balance in the catchment.

The Bilan model has been developed to simulate components of the water balance in a catchment. The structure of the model is formed by a system of relationships describing basic principles of water balance on ground, in the zone of aeration, including the effect of vegetation cover, and in groundwater. Air temperature is used as an indicator of energy conditions, which affect significantly the water balance components. Its time resolution is one day or one month.

Input data used for water balance computation is daily or monthly series of basin precipitation P (mm), air temperature T (°C) and relative air humidity H (%)(optional). To calibrate the parameters of the model (applying the optimization algorithm), simulated and observed daily or monthly runoff series at the outlet from the basin are used.

The model simulates time series of daily or monthly potential evapotranspiration, actual evapotranspiration, infiltration to the soil and recharge from the soil to the aquifer. The amount of water that is stored in the snow pack, the soil and aquifer is also simulated for each time step. All these hydrological variables apply to the whole catchment. The total runoff consists of two or three components, that is direct runoff, interflow (monthly time step only) and base flow (WRI 2015).

The model has six (daily time step) or eight (monthly time step) free parameters and uses an optimization algorithm for their calibration at gauged basins (for a detailed list, see the manual – WRI 2015). The optimization is aimed at attaining the best fit between the observed and simulated runoff series, for which several optimization criteria are available.

The temperature and eventually the relative humidity are used for the calculation of the potential evapotranspiration. The temperature is also used for the distinction between winter and summer conditions (regime type). If a snow pack occurs, a snow storage algorithm and melting algorithm are applied. Melting snow and rainfall infiltrate into the soil. In the soil the infiltrated water is stored that can be extracted by agricultural crops or natural vegetation later. The crops or vegetation extract soil moisture at a potential rate (potential evapotranspiration) as long as there is sufficient water in the soil. If there is insufficient water in the soil the actual evapotranspiration will drop below the potential rate. During wet periods, when the precipitation exceeds the potential evapotranspiration, the surplus is used to replenish soil water storage.

Subsequently, percolation from the soil occurs if the soil moisture storage reaches maximum soil capacity. The percolation from the soil can follow a quick path towards the stream through interflow (monthly type only) or as recharge, a slow path through the aquifer. A third (second) streamflow component, i.e. surface runoff, may also occur if the rainfall amount is high.

Catchment system is schematized on vertical tanks are distinguished three levels - the surface area of soil and groundwater zone (see Figure 3). Sizes flows between basins are determined by algorithms model that are controlled by six free parameters (two less than the monthly version), considered to be time-invariant. Common to both versions of the three types of modulation schemes depending on the temperature (cold, melting snow, summer) (Vizina, 2009).

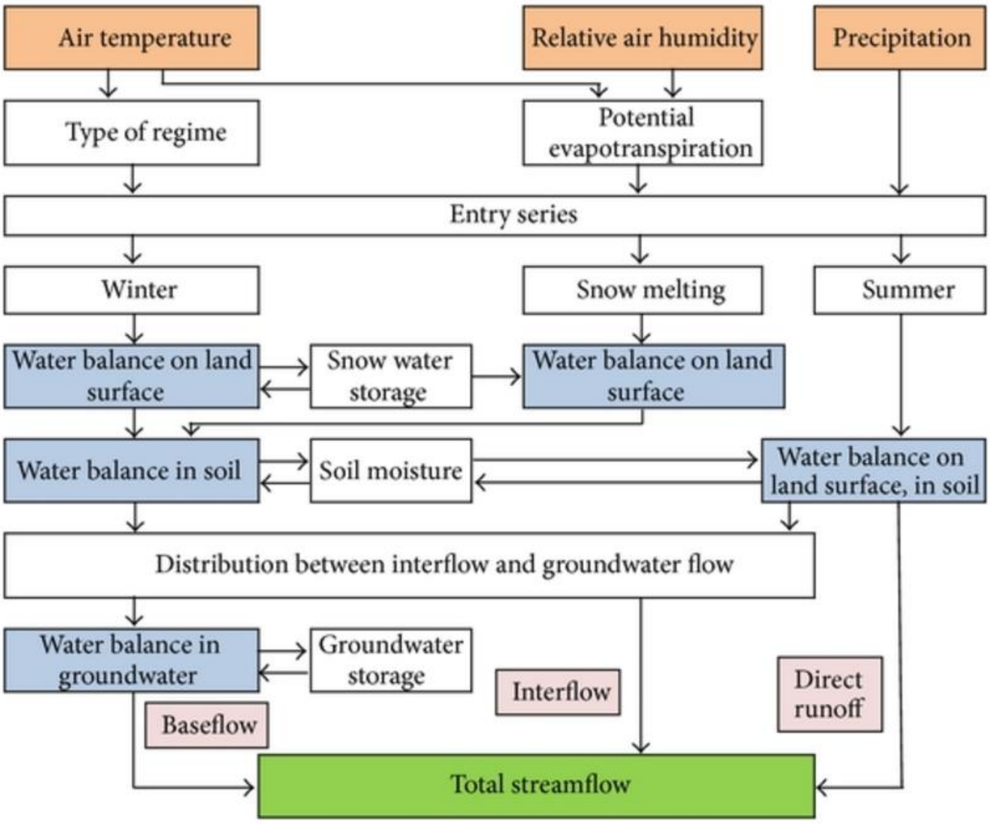

Figure 3. Scheme of Rainfall-Runoff Bilan model

2.2.2. Objective functions

The Bilan model is calibrated against the observed streamflow data, so the model time series of observed streamflow are used for calibrating of the model. Therefore, different calibration indices based on information obtained from model residuals are used for estimation of Bilan parameters. The solution of related inverse problem, which minimizes the analyzed hydrological index - objective function, was used. This approach is a standard way of calibration of lumped hydrological models.

The investigated objective functions are in hydrological modelling commonly used accuracy criteria: mean squared error (MSE), mean absolute error (MAE), mean absolute percentage error (MAPE) and Nash-Sutcliffe efficiency (NS).

The analyzed objective functions are defined as:

The mean square error (MSE) is the mean of squared deviations between the observed and the simulated runoff series:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(R[i] - RM[i])^2 \tag{2.1}$$

The mean absolute error (MAE) is calculated as the mean of absolute deviations between the observed and the simulated runoff series, where “absolute” means that negative deviations are converted to positive values:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|R[i] - RM[i]| \tag{2.2}$$

The mean absolute percentage error (MAPE) represents the mean of relative deviations where “relative” means that each deviation is divided by the observed value:

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{|R[i] - RM[i]|}{R[i]} \tag{2.3}$$

The definition implies that MAPE cannot cope with zero values of runoff Nash-Sutcliffe efficiency (NS) or logarithmic Nash-Sutcliffe (LNNS) can be also used:

$$NS = 1 - \frac{\sum_{i=1}^{N}(R[i] - RM[i])^2}{\sum_{i=1}^{N}(R[i] - \bar{R})^2} \tag{2.4}$$

$$LNNS = 1 - \frac{\sum_{i=1}^{N}(lnR[i] - RM[i])^2}{\sum_{i=1}^{N}(lnR[i] - \overline{lnR})^2} \tag{2.5}$$

Where $\bar{R}$ is the mean observed runoff and $\overline{lnR}$ is the mean of the logarithmized runoff time series:

$$\overline{lnR} = \frac{1}{n}\sum_{i=1}^{n} lnR[i] \qquad (2.6)$$

2.2.3. Model calculations

In this paper, I focus on the use of the monthly Bilan model because of the large amount of data input (57 catchments and data collected do not have the same duration, over a long period of time). The choice of model by date or by month will affect the calculation method and calculation results. The results needed for use in comparing the optimization functions listed below are "observed total runoff" and "simulation total runoff."

2.2.3.1. Simulation total runoff

The model simulated the total runoff RM[i] by three components:

$$RM[i] = DR[i] + I[i] + BF[i] \qquad (2.7)$$

Where DR[i] = direct runoff, I[i] = interflow, BF[i] = base flow

The DR[i] component of the total runoff includes summer surface runoff and that part of interflow which, together with the surface runoff, flows so rapidly that it neither affects water balance in the soil nor is significantly available for evaporation. The summertime direct runoff is caused by heavy rainfall.

The interflow I[i] results from water balance as excess water in the zone of aeration irrespective of the season. This runoff component is assumed also to include surface runoff if it occurs in winter or during the period of snow melting (WRI 2015).

The base flow BF[i], whose retention time in the basin is longer than that of the other runoff components, is constituted by the outflow from groundwater storage.

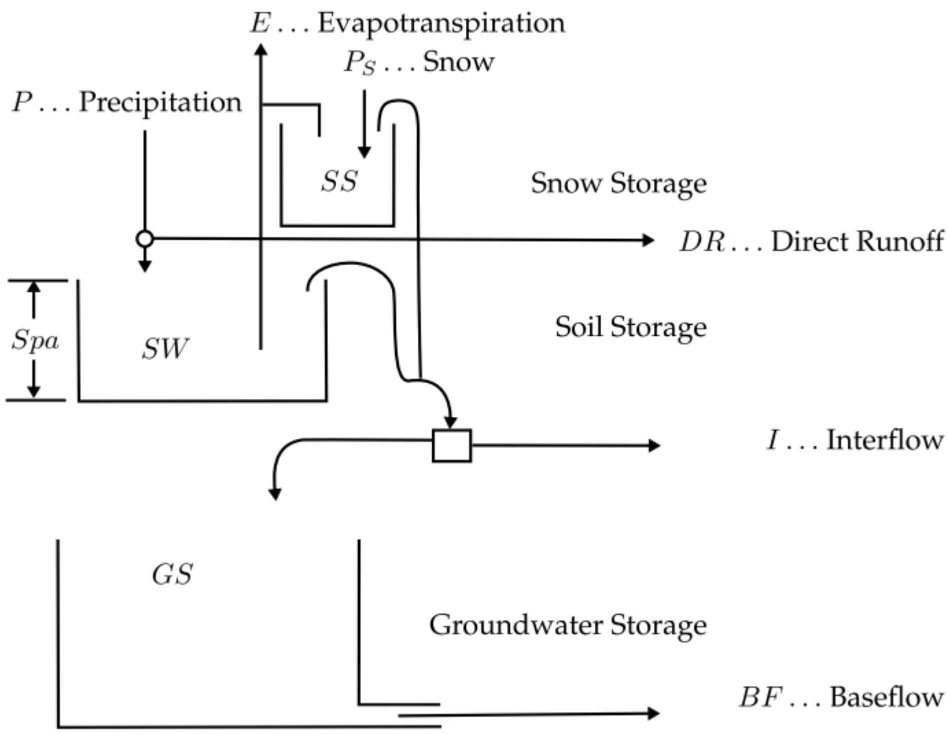

Figure 4. Scheme about total runoff in Bilan model

2.2.3.2. Problem of potential evapotranspiration

Method based on vegetation zones:

The potential evapotranspiration is estimated from the saturation deficit by using functions (in the form of tables) derived for individual months and for different bioclimatic zones from empirical graphs (Gidrometeoizdat, 1976). The saturation deficit is calculated from air temperature and relative air humidity data. For extreme, improbable or erroneous combinations of these variables, the resulting saturation deficit can either be less than zero or it can exceed the upper calculation limits of the method (nomogram) used to derive the potential evapotranspiration (WRI 2015).

If the saturation deficit is less than zero, the execution will stop and a correction of the data will be required. If the saturation deficit exceeds the upper calculation limit, the maximum admissible value is substituted.

The bioclimatic zones are as follows: tundra, coniferous forest, mixed forest, deciduous forest and steppe. Each bioclimatic zone is characterized by its characteristic mean air temperature. The model makes use of an interpolation algorithm using the long-term average air temperature in the catchment for reasons of interpolation between the bioclimatic zones, i.e. between the respective tables (WRI 2015).

Method based on temperature and latitudinal solar radiation:

The potential evapotranspiration is estimated by using a relationship derived by Oudin et al. (2010), employing solar radiation and air temperature and requiring air temperature as the sole input. The catchment latitude (in degrees) has to be specified since the value of extraterrestrial solar radiation is calculated for each time step. By using the algorithm relies on the sunset hour angle, which is not defined for polar day conditions, the latitude entered has to be between the Arctic and the Antarctic Circles (i.e. from -66.5 to 66.5 degrees) (WRI 2015).

2.2.3.3. Parameters of model

The free model parameters, which have to be identified for the model to be able to simulate the streamflow generation, are listed in Table 1 for both the daily and the monthly model types. The optimization procedure requires initial values of the parameters (relevant for the gradient method only) and their lower and upper limits to be set by the user. The program uses default values, which normally do not have to be changed; however, the values in the table of parameters can be changed to attain an alternative solution. The search space was constrained with physically meaningful ranges of parameters (see column Parameter Constraints in Table 1). The parameter constraints were estimated by an expert knowledge.

Table 1: Description of the model parameters of the BILAN model

Parameter	Description	Parameter Constraints
Spa	capacity of soil moisture storage (mm)	[0,200]
Dgm	snow melting factor	[0,200]
Dgw	factor for calculating the quantity of liquid water available on the land surface under winter conditions	[0,20]
Alf	parameter for rainfall- surface runoff equation (direct runoff)	[0,1]
Soc	parameter controlling distribution of percolation into interflow and groundwater recharge under summer conditions	[0,1]
Mec	parameter controlling distribution of percolation into interflow and groundwater recharge under conditions of snow melting	[0,1]
Wic	parameter controlling distribution of percolation into interflow and groundwater recharge under winter conditions	[0,1]
Grd	parameter controlling outflow from groundwater storage (base flow)	[0,1]

2.2.3.4. Calibration of the parameters

The parameters of the model are identified (calibrated) by using an optimization algorithm. The optimization is aimed at attaining the best fit between the observed and the simulated runoff series.

Two optimization algorithms (the local and global one) are available.

Local gradient algorithm (binary search)

The calibration of the parameters by using the gradient method is executed in two steps. The procedure under the default settings is described below, however the optimization criterion can be set for each step independently. Apart from the criteria mentioned below, Nash-Sutcliffe efficiency or its logarithmic version can be used.

In the "classical" optimization procedure, the mean square error (MSE) would normally be used as the optimization criterion. This criterion suffers from the drawback that its application does not ensure a good fit between the observed and the simulated runoff series in the low-flow parts of the hydrograph. This can substantially be improved by using the sum of relative deviations between the observed and the simulated runoff series (represented by the mean absolute percentage error, MAPE) instead of MSE. However, this criterion frequently deteriorates the fit in terms of the mean runoff and, therefore, an optimization procedure combining both these criteria has been developed (WRI 2015).

In the first step, MSE or the mean absolute error (MAE) is used as the optimization criterion to calibrate the *Dgw* (monthly type only), *Dgm*, *Spa* and *Alf* parameters (See description in table 1) which significantly influence the mean runoff.

The remaining parameters *Wic* (monthly type only), *Mec*, *Soc* and *Grd* parameters (See description in table 1) impacting the runoff distribution to its individual components are then calibrated using MAPE. This calibration procedure mostly ensures an acceptable fit in terms of both mean runoff and low-flow runoff including predominantly of base flow. The resulting value of the optimization criterion for the second part appears in the output of the model (WRI 2015).

Number of iterations

The values of the model parameters resulting from the optimization algorithm can also be influenced by setting the number of iterations to be performed under this algorithm. The default value, derived from practical experience, is 500. Normally, this value need not be changed.

The program can be run also without optimization of parameters, just by using their initial values. This option can be activated by setting the number of iterations of the optimization procedure to zero.

Global shuffled complex evolution/differential evolution algorithm

The global algorithm employs shuffled complex evolution (SCE-UA) combined with differential evolution for complex evolution. The user-defined settings of the algorithm are as follows:

- Type of differential evolution (BEST_1_BIN, BEST_2_BIN or RAND_2_BIN)
- Number of complexes NC
- Complex size M
- Number of shuffles
- Number of generations
- Crossover parameter CR
- Mutation parameter F
- Mutation parameter K
- Size of ensemble – an ensemble of optimization runs will be calculated.

<u>*) Description of the SCE-UA optimization algorithm:</u>

The global algorithm employed combines the SCE-UA (shuffled complex evolution – The University of Arizona) method (Duan et al. 1994) and the differential evolution (DE) method (Storn and Price 1997) which is used for complex evolution.

The algorithm steps are as follows:

1. A population of a given number NP of parameter sets (points) is generated by using Latin Hypercube sampling with specified upper and lower limits for the parameters.
2. The parameter sets are sorted by their criterion values.
3. The parameter sets are divided into NC complexes, each complex containing M sets. The best criterion value set p1 is assigned to the first complex C1, the second criterion value p2 to the complex c2 and so on, i.e. the complex C1 contains sets p1, pnc+1 up to p(M-1).NC+1.
4. The differential evolution method used to evolve complexes.
5. A new population is created from the evolved complexes.

6. The algorithm stops on reaching the maximum number of iterations. Otherwise, it continues to step 2.

The differential evolution algorithm for complex evolution (step 4) is described as follows:

1. Mutation is performed on the best parameter set of the whole population pB or a random parameter set pr5 by using differences between parameter sets randomly chosen from the complex. Three types of mutation are available:

$$mp_{i,G+1} = p_{B,G} + F\,(p_{r1,G} - p_{r2,G}) \tag{2.8}$$

$$mp_{i,G+1} = p_{B,G} + F\left(p_{r1,G} - p_{r2,G}\right) + K\,(p_{r3,G} - p_{r4,G}) \tag{2.9}$$

$$mp_{i,G+1} = p_{r5,G} + F\left(p_{r1,G} - p_{r2,G}\right) + K\,(p_{r3,G} - p_{r4,G}) \tag{2.10}$$

where G and G + 1 denote a generation of parents and offsprings, F and K are mutation control parameters and r1, r2 ... r5 are random indexes of parameter set within the complex.

2. If the probability of crossover for a given parameter par exceeds the value of the crossover control parameter CR, then the parameter value of the mutated set is assigned to offspring:

$$p_{i,G+1}[par] = mp_{i,G+1}[par] \tag{2.11}$$

Apart from the probabilistic crossover depending on CR, the mutated value for one parameter of random index i is always assigned to offspring (WRI 2015).

Otherwise, or if the mutated parameter has exceeded its limits and if such values are bound to be rejected, the parent parameter value is assigned to offspring:

$$p_{i,G+1}[par] = p_{i,G}[par] \tag{2.12}$$

3. Selection: If the criterion value for the set of offspring parameters is better than that for parent, the new parameter set is assigned to offspring, else the old parental parameters are retained for the offspring.

The algorithm can be allocated a name composed of the type of parameter set to be mutated (best/rand), the number of differences between parameters used for mutation (1/2) and the type of crossover (binomial). Therefore, Equation (2.8) represents the BEST_1_BIN type, while Equation (2.9) is BEST_2_BIN and Equation (2.10) is RAND_2_BIN.

Weight of baseflow

By default, the optimization criterion is calculated from series of observed and simulated runoff. Value of weight for baseflow wBF (between 0 and 1) sets optimization with respect to difference between observed and simulated baseflow series. The combined criterion is calculated as:

$$crit = (1 - w_{BF}) * crit(R, RM) + w_{BF} * crit(B, BF) \qquad (2.13)$$

2.3. KLING – GUPTA EFFICIENCY (KGE)

2.3.1. Introduction

Kling-Gupta efficiency between *sim* and *obs*, with treatment of missing values. This goodness-of-fit measure was developed by Gupta et al. (2009) to provide a diagnostically interesting decomposition of the Nash-Sutcliffe efficiency (and hence MSE), which facilitates the analysis of the relative importance of its different components (correlation, bias and variability) in the context of hydrological modelling.

Kling et al. (2012), proposed a revised version of this index, to ensure that the bias and variability ratios are not cross-correlated:

$$KGE = 1 - \sqrt{(r-1)^2 + (\beta - 1)^2 + (vr - 1)^2} \qquad (2.14)$$

In the computation of this index, there are three main components involved:

1) r : the Pearson product-moment correlation coefficient. Ideal value is r=1

Correlation – often measured as a correlation coefficient – indicates the strength and direction of a linear relationship between two variables (for example model output and observed values).

$$r = \frac{\sum_{i=1}^{n}(R[i] - \bar{R}).(RM[i] - \overline{RM})}{\sqrt{\sum_{i=1}^{n}(R[i] - \bar{R})^2.\sum_{i=1}^{n}(RM[i] - \overline{RM})^2}} \quad (2.15)$$

2) β : the ratio between the mean of the simulated values and the mean of the observed ones. Ideal value is Beta=1

$$\beta = \frac{Mean\ (sim)}{Mean\ (obs)} \quad (2.16)$$

3) vr : variability ratio, which could be computed using the standard deviation (α) or the coefficient of variation (γ) of sim and obs, depending on the value of method.

3.1) α: the ratio between the standard deviation of the simulated values and the standard deviation of the observed ones. Ideal value is Alpha=1.

$$\alpha = \frac{\sigma\ (sim)}{\sigma\ (obs)} = \frac{\sqrt{\frac{\sum_{i=1}^{n}(RM[i] - \overline{RM})^2}{N}}}{\sqrt{\frac{\sum_{i=1}^{n}(R - \bar{R})^2}{N}}} \quad (2.17)$$

3.2) γ: the ratio between the coefficient of variation (CV) of the simulated values to the coefficient of variation of the observed ones. Ideal value is Gamma=1.

$$\gamma = \frac{cv\ (sim)}{cv\ (obs)} = \frac{\sigma\ (sim)/Mean\ (sim)}{\sigma\ (obs)/Mean\ (obs)} \quad (2.18)$$

For a full discussion about the Kling-Gupta index, and its advantages over the Nash-Sutcliffe efficiency (Gupta et al., 2009).

2.3.2. Result to make a KGE tool

I used the C ++ programming language to write a tool to calculate the KGE coefficients, as shown in Figure 5 below, in order to test the accuracy of the formulas for calculating the KGE coefficient before inclusion in the Bilan model for calibration.

```
//****Calculate Pearson correlation coefficient******
    cxy=(n*sxy-sx*sy);
    sdx=sqrt(n*sxx-sx*sx);
    sdy=sqrt(n*syy-sy*sy);
    r=cxy/(sdx*sdy);
    cout<<"\n Pearsons correlation coefficient : r = "<<r;

//*****Calculate bias ratio**************************
    mx=sx/n;
    my=sy/n;
    beta=my/mx;
    cout<<"\n Bias ratio : beta = "<<beta;

//*****variability ratio***************************
    varx = 0; vary = 0;
    i = 0;
    while (i<n){
        varx = varx + ((a[i][0] - mx) * (a[i][0] - mx));
        vary = vary + ((a[i][1] - my) * (a[i][1] - my));
        i++;
    }
    varx /= n;
    vary /= n;
    gramma = ((sqrt(vary))/my)/((sqrt(varx))/mx);
    alpha = (sqrt(vary))/(sqrt(varx));
    cout<<"\n variability ratio : gramma = "<<gramma;

//************KGE**************************
    kge1 = 1 - sqrt((r-1)*(r-1)+(beta-1)*(beta-1)+(alpha-1)*(alpha-1));
    kge2 = 1 - sqrt((r-1)*(r-1)+(beta-1)*(beta-1)+(gramma-1)*(gramma-1));
    cout<<"\n";
    cout<<"\n Kling-Gupta Efficiency (method 2009) : KGE = "<<kge1;
    cout<<"\n Kling-Gupta Efficiency (method 2012) : KGE = "<<kge2;
```

Figure 5. KGE criteria on C++

2.4. HYDROGOF PACKAGE

HydroGOF is an R package that provides S3 functions implementing both statistical and graphical goodness-of-fit measures between observed and simulated values, mainly oriented to be used during the calibration, validation, and application of hydrological models. Missing values in observed and/or simulated values can removed before the computations (Mauricio Zambrano-Bigiarini, 2011).

In this thesis, I used 5 criterions of hydroGOF package to evaluate optimization functions, including MAE, RMSE, NS, KGE1, and KGE2.

CHAPTER 3: RESULTS AND DISCUSSION

3.1. BUILDING KGE OPTIMIZATION FUNCTION FOR BILAN MODEL

3.1.1. Structure of Bilan model project

All algorithms of the Bilan models were written in C++ programming language, and the code ran under 64-bit Linux operating system. All post-processing calculations were made in R statistical software environment.

3.1.2. KGE optimization function

The KGE optimization tool is added to the source code of the Bilan model (model.cpp, model.h, optim.h and optim_de.h files). The calculation mechanism of KGE is similar to previous optimization functions (MSE, MAE, MAPE, NS, LNNS).

For the Binary Search algorithm, we can select the specific KGE coefficient in the two criteria (crit_part1 and crit_part2) to calibrate each set of 4 parameters in the 8 parameters of the Bilan model (Spa, Dgm, Dgw, Alf Soc, Mec, Wic, Grd). Other program parameters such as maximum number of iterations (max_iter) or initial groundwater storage (init_GS) are also tested with different values to recognize their effect on model accuracy. In the following comparison results, I use the default values recommended by the original Bilan program (max_iter = 500 and init_GS = 50) to easily compare with other criteria (WRI 2015).

For the Differential Evolution algorithm, we will select KGE as the primary type criteria for all eight parameters of the Bilan model. All 3 types of differential evolution are used in my research, DE1 = BEST_ONE_BIN, DE2 = BEST_TWO_BIN, and DE3 = RAND_TWO_BIN, respectively, used in comparing model performance with the Binary Search method.

3.2. CALIBRATION BILAN MODEL

For the purpose of checking the accuracy of the Bilan model when calibrated with the KGE optimization tool, I ran a test of all 5 optimization functions (MSE, MAE, NS, KGE1, KGE2) for each of the 4 optimization algorithms (BS, DE1, DE2, DE3). For 57 different input file catchments, I collected a total of 1140 Bilan output files respectively.

The table 2 below is an example of the simulation runoff total obtained by running the model (one month of 0044.dat catchment, BS method, KGE1 optimization function):

Table 2. Example result output file from Bilan model

MDY	P	R	RM	BF	B	I	DR
12/1/1952	21.93	**29.92**	**65.1283**	8.29356	NA	56.8348	0
1/1/1953	21.93	**40.71**	**56.546**	16.7566	NA	39.7894	0
2/1/1953	53.34	**40.94**	**23.04**	16.8683	NA	0	6.17166
3/1/1953	94.17	**18.21**	**16.5394**	7.91362	NA	0	8.62579
4/1/1953	123.19	**50.85**	**12.8498**	3.7126	NA	0	9.13725
5/1/1953	46.5	**21.61**	**5.80075**	1.74173	NA	0	4.05902
6/1/1953	39.81	**20.35**	**1.68005**	0.817116	NA	0	0.862939
7/1/1953	18.24	**34.37**	**0.497607**	0.383342	NA	0	0.114266
8/1/1953	101.07	**27.87**	**14.8964**	0.179841	NA	11.8683	2.84818
9/1/1953	64.18	**68.34**	**44.3317**	25.4465	NA	9.95015	8.93502
10/1/1953	61.35	**51.97**	**39.6845**	33.2011	NA	6.48339	0
11/1/1953	18.46	**33.76**	**29.1447**	21.5928	NA	7.55182	0
12/1/1953	25.58	**55.68**	**31.4894**	17.1385	NA	14.3509	0
1/1/1954	99.61	**84.98**	**81.3487**	21.3586	NA	59.9901	0
2/1/1954	56.86	**82.47**	**30.6133**	23.6002	NA	0	7.0131
3/1/1954	76.18	**32.47**	**18.5684**	11.0718	NA	0	7.49663
4/1/1954	196.01	**34.75**	**40.1063**	5.19423	NA	7.88374	27.0284
5/1/1954	53.95	**21.58**	**25.5977**	19.2841	NA	0	6.31363
6/1/1954	121.34	**39.99**	**26.5923**	9.04693	NA	6.69465	10.8507
7/1/1954	61.59	**21.2**	**32.6963**	18.5505	NA	5.91736	8.22842
8/1/1954	16.61	**17.46**	**23.5115**	21.3479	NA	1.56507	0.59846
9/1/1954	50.72	**56.7**	**30.2715**	13.3597	NA	16.9118	0
10/1/1954	72.39	**42.2**	**34.1523**	21.9625	NA	12.1898	0
11/1/1954	69.51	**19.16**	**21.6161**	21.6161	NA	0	0

12/1/1954	37.17	**61.19**	**27.2601**	10.141	NA	17.1191	0
1/1/1955	61.32	**109.86**	**99.5056**	20.6448	NA	78.8608	0
2/1/1955	83.74	**67.66**	**42.7483**	27.5371	NA	0	15.2112
3/1/1955	60.17	**42.65**	**19.3785**	12.9188	NA	0	6.45973
4/1/1955	138.13	**26.21**	**19.0065**	6.06071	NA	0	12.9458
5/1/1955	97.83	**19.16**	**22.0742**	2.84332	NA	0	19.2309
6/1/1955	91.12	**20.49**	**21.3051**	1.33392	NA	3.67061	16.3006

To be able to judge whether a model is correct or not, scientists give a number of different views. "It is argued that many difficulties in the current model are due to unrealistic expectations based on a lack of appreciation of the nature of a model, and finally, some criteria used to evaluate Hydro-meteorological models. The focus is on quantitative watershed models, but most of the arguments involve any kind of model in current use, at least in environmental science". In this thesis, I use 5 main criteria: MAE, RMSE, NS, KGE1 and KGE2. These criteria are used through hydroGOF package in R-Studio. Input data is 2 columns highlighted above (R = Qobs = observed total runoff, Rm = Qsim = simulated total runoff). The results obtained after running Rscript are 25 tables (detailed in the appendix). Each table corresponds to one criterion of a different optimization function. In each of these tables, five columns, are the result of the Water Research Institute and four optimization algorithms (BS, DE1, DE2, DE3).

Example: KGE1 optimization function use to calibrate parameters of Bilan model. The five tables below correspond to five different criteria:

Table 3. Result of 57 catchment simulated by KGE1 optimization function and criterion by MAE

Catchments	MAE_WRI	MAE_BS	MAE_DE1	MAE_DE2	MAE_DE3
1	14.79985	15.62511	15.4882	15.45505	15.27718
2	8.701771	9.282111	9.26176	9.27948	9.500078
3	5.768665	6.047948	6.019375	6.051642	6.207182
4	6.40763	6.851721	6.837867	7.106812	7.064918
5	8.009667	8.370021	8.235165	8.285949	8.243924
6	9.875146	10.64216	10.56064	10.70254	11.11708
7	7.908323	8.196057	8.220772	8.311923	8.319005

8	14.73514	16.00865	16.07685	16.05736	15.837
9	9.481499	10.06699	10.15439	10.25979	10.23437
10	5.383439	5.470344	5.451931	5.549378	5.504075
11	4.593428	4.7497	4.739319	4.848162	4.848467
12	22.30288	23.43576	25.51886	25.12568	25.69231
13	4.890502	5.267704	5.263481	5.366359	5.414947
14	9.928447	11.13892	11.14895	11.26903	11.26705
15	6.504339	6.8675	6.78438	7.01226	7.020002
16	6.787659	7.015723	6.933081	7.001515	7.251047
17	7.967396	9.070097	9.038794	9.217079	8.976486
18	5.786598	6.099797	6.096029	6.233359	6.215508
19	5.867597	5.690838	5.688628	5.636517	5.698023
20	12.14355	12.91469	13.04455	12.62114	12.41677
21	5.740209	5.796844	5.795311	5.748431	5.848526
22	2.586289	2.699283	2.694847	2.67945	2.757449
23	13.09462	14.10531	14.01018	14.0027	14.33258
24	4.784961	5.092995	4.963209	4.926561	5.401054
25	9.694001	9.109915	9.12472	9.282148	9.416034
26	19.62452	20.58208	20.61454	20.63754	21.06791
27	11.44525	12.50285	12.50468	12.48877	12.62076
28	2.721778	3.001672	3.009995	2.988544	2.880091
29	9.560573	9.059976	9.041171	9.041952	9.06927
30	22.36878	25.54016	25.23482	24.50556	26.60027
31	20.24002	19.88523	19.88986	20.14398	20.39508
32	13.68282	14.05865	14.10281	14.51465	15.17491
33	13.23029	14.55383	14.47475	14.72675	16.00654
34	21.78774	24.32332	24.96254	25.33877	24.842
35	6.32414	6.988796	6.975126	7.198624	7.038391
36	10.9682	12.68657	12.66616	12.86864	13.46754
37	10.72371	10.80246	10.80231	10.88795	10.77006
38	12.95613	12.71479	12.64423	12.67005	12.82036
39	9.338666	9.403384	9.415837	9.555243	9.550662
40	6.680253	6.753105	6.73617	6.625795	6.662495
41	5.728456	5.834983	5.827682	5.799136	6.022556
42	5.876072	5.936231	5.965029	6.192488	5.775345
43	5.39025	5.514156	5.492958	5.445942	5.571461
44	3.912731	3.911708	3.924318	3.981553	4.075359
45	11.6324	12.21118	12.28985	12.48546	12.31358
46	2.968732	3.063943	3.049669	3.161439	3.066122
47	13.31496	13.88476	13.9702	13.71024	13.84592
48	7.261508	7.694219	7.907193	7.663469	7.978905
49	2.2855	2.503412	2.197621	2.324142	2.352162
50	6.276659	6.345564	6.336372	6.136231	6.201613

51	3.871867	4.091493	4.102721	4.293035	4.337005
52	1.970807	1.655093	1.659841	1.661182	1.786228
53	9.623665	9.639381	9.591277	9.626827	9.612004
54	15.96901	17.88732	17.98206	17.9993	18.91209
55	5.436058	5.578791	5.604159	5.660538	5.623421
56	13.53478	12.90813	12.90788	12.96218	13.13508
57	7.723161	7.968459	7.971297	8.162712	8.149874
Median	7.967396	8.370021	8.235165	8.311923	8.319005
Standard deviation	5.136783	5.575754	5.701418	5.661247	5.836335

Table 4. Result of 57 catchment simulated by KGE1 optimization function and criterion by RMSE

Catchments	RMSE_WRI	RMSE_BS	RMSE_DE1	RMSE_DE2	RMSE_DE3
1	22.33188	21.85961	21.71072	22.12135	21.50016
2	12.24718	12.70355	12.65945	12.86844	13.08102
3	9.459082	9.33046	9.250408	9.530809	9.554507
4	11.19926	11.11332	11.15931	11.24303	11.09405
5	12.27701	11.99701	12.03102	12.04891	12.10603
6	15.22916	14.89377	15.10041	14.96297	15.2216
7	11.66908	11.6009	11.59489	11.83235	11.85443
8	23.26557	22.676	22.66395	22.68407	22.66047
9	14.86268	14.98814	15.07763	15.1047	15.32005
10	8.839227	7.857607	7.847481	7.998754	7.984147
11	6.51257	6.651961	6.644502	6.800368	6.716211
12	32.36814	33.93634	34.58413	34.38501	34.54032
13	6.971114	7.517801	7.51146	7.590671	7.616893
14	15.1271	15.63469	15.65158	15.77284	15.99411
15	9.840711	9.792442	9.769667	9.944383	9.997477
16	9.721	9.65405	9.606678	9.654095	9.830477
17	11.13237	11.99071	11.87625	11.99202	11.94697
18	8.64201	8.980951	8.966815	9.191932	9.063157
19	10.90119	10.00646	9.99575	9.902062	10.02209
20	21.93146	20.43688	19.31436	20.00177	20.64993
21	9.850658	8.803561	8.803599	8.812636	8.820135
22	3.994777	3.914926	3.911833	3.813367	4.058382
23	21.11719	22.08664	21.91215	22.16247	22.19523
24	6.909676	6.858582	6.76021	6.78355	7.185476
25	12.8432	11.89941	11.89703	12.03343	12.34704
26	30.78008	29.87164	29.74148	30.33236	29.95273
27	18.32182	18.76328	18.71794	18.78785	18.92038
28	5.199407	4.925023	4.935488	4.985204	4.867826
29	14.91227	13.3537	13.33221	13.46914	13.45089

30	38.85464	40.48042	39.36625	38.48444	40.40607
31	29.23497	28.58664	28.59108	28.99929	29.52822
32	20.82627	19.75142	19.68345	20.11888	20.47271
33	20.22068	21.60935	21.37041	21.83875	22.36484
34	32.89078	35.05709	36.08899	36.23841	35.68752
35	10.27171	10.45697	10.35989	10.55615	10.52394
36	18.07038	19.40192	19.4218	19.66208	20.15813
37	17.22432	16.44004	16.44998	16.55069	16.57975
38	20.13556	18.9629	18.98285	19.10681	19.04237
39	14.55492	13.53174	13.48667	13.72887	13.89959
40	9.393154	9.925309	9.872693	9.736912	9.647509
41	8.46146	8.614751	8.73431	8.82106	8.906044
42	8.820895	8.620221	8.685043	8.875147	8.624242
43	8.120655	7.904961	7.899595	7.931484	8.116341
44	6.648048	5.524611	5.527879	5.622039	5.77226
45	17.41678	18.32578	18.43889	18.4411	18.33769
46	4.396574	4.522741	4.513351	4.638255	4.520134
47	21.28192	21.51942	21.52799	21.43232	22.08514
48	12.4498	12.01425	11.98455	11.85586	12.08196
49	3.238565	3.533308	3.2212	3.490119	3.40979
50	9.804517	9.734905	9.723452	9.652445	9.597925
51	5.937853	6.19146	6.224608	6.44732	6.535996
52	3.680822	2.630486	2.62002	2.709342	2.712009
53	16.37885	14.11569	14.07929	14.3926	14.33387
54	26.62169	26.87223	27.05835	27.43856	27.89548
55	7.993558	7.73173	7.789473	7.890735	7.835392
56	20.96975	19.78253	19.78546	19.92321	20.1321
57	11.48001	11.58034	11.56885	11.8369	11.93477
Median	12.24718	11.99071	11.89703	11.99202	12.08196
Standard deviation	8.082222	8.316723	8.319414	8.311747	8.431122

Table 5. Result of 57 catchment simulated by KGE1 optimization function and criterion by NS

Catchments	NS_WRI	NS_BS	NS_DE1	NS_DE2	NS_DE3
1	0.536422	0.608712	0.607321	0.607587	0.582285
2	0.536001	0.54521	0.548871	0.532341	0.549827
3	0.559229	0.530852	0.547251	0.530865	0.495729
4	0.105436	0.174575	0.169061	0.188196	0.157349
5	0.231145	0.573299	0.576886	0.57177	0.572523
6	0.298604	0.608813	0.604858	0.594574	0.603676
7	0.340441	0.4512	0.452918	0.469727	0.461359

8	-0.04328	0.173511	0.180067	0.168306	0.144908
9	-0.02877	0.170709	0.189512	0.177665	0.189818
10	0.440137	0.569504	0.569647	0.57008	0.573061
11	0.424822	0.48882	0.486535	0.507032	0.468977
12	0.364691	0.434451	0.42421	0.386604	0.406466
13	0.473881	0.540254	0.539754	0.537738	0.534904
14	0.048126	0.445998	0.446542	0.44033	0.437622
15	0.30788	0.422033	0.417752	0.40554	0.430607
16	0.402292	0.52924	0.529983	0.503825	0.507034
17	0.234339	0.46678	0.476578	0.467242	0.45617
18	0.282451	0.571493	0.569865	0.574978	0.540194
19	0.328391	0.483846	0.490625	0.461334	0.468786
20	-0.25708	0.240001	0.315125	0.275768	0.206895
21	0.320238	0.459345	0.463502	0.443887	0.442316
22	-0.24464	0.320907	0.317131	0.329478	0.330794
23	0.652921	0.720297	0.724699	0.7145	0.718391
24	0.536068	0.676714	0.683575	0.662187	0.652329
25	0.576565	0.681943	0.682667	0.658243	0.629586
26	0.357694	0.453615	0.45996	0.458815	0.461919
27	-0.18164	0.268578	0.278068	0.265951	0.282667
28	-0.08888	0.111544	0.117166	0.108805	0.018325
29	0.600104	0.677737	0.67742	0.67265	0.661074
30	-1.29653	0.057988	0.10595	0.03903	0.019338
31	0.571382	0.603843	0.603331	0.605279	0.610077
32	0.593895	0.70243	0.708522	0.706091	0.681107
33	0.415043	0.506997	0.519016	0.494452	0.493046
34	0.503625	0.469092	0.45674	0.449849	0.436901
35	0.248615	0.483401	0.494091	0.501415	0.48216
36	0.283719	0.527077	0.526797	0.527841	0.510136
37	0.424501	0.575408	0.575625	0.56189	0.555896
38	0.5742	0.613567	0.616613	0.618048	0.601251
39	0.552605	0.658397	0.660166	0.653646	0.641213
40	0.495412	0.526346	0.524246	0.500342	0.493889
41	0.486148	0.620301	0.614736	0.607606	0.602519
42	0.71138	0.729305	0.725245	0.717281	0.707527
43	0.563444	0.614971	0.619041	0.600581	0.597395
44	0.45651	0.559758	0.560473	0.561191	0.568785
45	0.500302	0.599121	0.593943	0.592345	0.588286
46	0.436786	0.548837	0.54754	0.550735	0.518071
47	0.258847	0.246664	0.246218	0.210162	0.246263
48	0.304362	0.368982	0.374464	0.336828	0.349289
49	0.379047	0.466697	0.535117	0.531521	0.497664
50	0.209566	0.275021	0.273522	0.26367	0.226701

51	0.342951	0.465152	0.464645	0.459943	0.472762
52	0.323764	0.312029	0.332076	0.317095	0.275366
53	0.51523	0.634988	0.63649	0.622792	0.623637
54	0.023559	0.165631	0.164047	0.1358	0.141851
55	0.165566	0.492721	0.485619	0.475058	0.481339
56	-0.02663	0.080667	0.079786	0.084724	0.085618
57	0.497334	0.50032	0.502477	0.487142	0.477087
Median	0.364691	0.50032	0.519016	0.501415	0.493046
Standard deviation	0.314945	0.171634	0.167646	0.171472	0.17499

Table 6. Result of 57 catchment simulated by KGE1 optimization function and criterion by KGE1

Catchments	KGE1_WRI	KGE1_BS	KGE1_DE1	KGE1_DE2	KGE1_DE3
1	0.766021	0.797961	0.798265	0.790246	0.78252
2	0.773538	0.771276	0.772595	0.763753	0.764511
3	0.764446	0.760487	0.763997	0.752264	0.745835
4	0.569582	0.592009	0.589061	0.588802	0.584647
5	0.599541	0.785524	0.785574	0.784141	0.783114
6	0.604738	0.804938	0.801763	0.799411	0.799402
7	0.687035	0.721874	0.722533	0.718708	0.713597
8	0.52967	0.597478	0.599155	0.595725	0.589691
9	0.539052	0.598173	0.60109	0.597307	0.594956
10	0.721218	0.784585	0.784834	0.780227	0.780942
11	0.719659	0.738999	0.738945	0.734459	0.732487
12	0.695974	0.701922	0.686841	0.682861	0.681973
13	0.729814	0.771789	0.771786	0.768998	0.763287
14	0.529604	0.722687	0.722925	0.719758	0.715339
15	0.671408	0.705744	0.705592	0.69699	0.699936
16	0.713995	0.76246	0.763604	0.754846	0.746096
17	0.600508	0.734484	0.739277	0.735538	0.730527
18	0.589779	0.784932	0.785242	0.7801	0.772176
19	0.673932	0.742519	0.744331	0.737788	0.737639
20	0.458007	0.62839	0.666283	0.64515	0.614512
21	0.650751	0.726846	0.727752	0.722816	0.721196
22	0.454571	0.655313	0.655717	0.657108	0.649268
23	0.770272	0.86081	0.863443	0.858617	0.858356
24	0.742721	0.837031	0.841208	0.83313	0.822047
25	0.785635	0.83524	0.835456	0.824456	0.812095
26	0.686989	0.727802	0.728042	0.723578	0.723558
27	0.455202	0.648949	0.653244	0.646093	0.646599
28	0.485265	0.560731	0.560803	0.553345	0.540504

29	0.800694	0.839343	0.839359	0.836787	0.833043
30	-0.0409	0.507611	0.520599	0.506349	0.49957
31	0.778886	0.794437	0.794304	0.792498	0.785632
32	0.766157	0.846419	0.848809	0.838793	0.828247
33	0.680424	0.744168	0.756633	0.731948	0.737993
34	0.754912	0.674701	0.690399	0.685919	0.676221
35	0.601343	0.74266	0.747869	0.743833	0.742058
36	0.569378	0.758178	0.758143	0.753627	0.752119
37	0.708461	0.78185	0.782345	0.777942	0.771012
38	0.780903	0.803894	0.803507	0.798556	0.799806
39	0.761971	0.83092	0.831326	0.827263	0.823385
40	0.751713	0.767009	0.767144	0.756256	0.75318
41	0.719827	0.812013	0.808277	0.804413	0.80013
42	0.851781	0.863867	0.861816	0.856914	0.852812
43	0.786677	0.806861	0.807911	0.802265	0.794796
44	0.684177	0.777285	0.777397	0.772761	0.762051
45	0.719667	0.797383	0.794726	0.793806	0.793298
46	0.713097	0.770509	0.770726	0.761832	0.762403
47	0.631966	0.607063	0.607356	0.600625	0.598147
48	0.653344	0.681325	0.682777	0.675046	0.67451
49	0.696072	0.730738	0.770227	0.745597	0.747912
50	0.610691	0.629158	0.629083	0.61981	0.613978
51	0.68371	0.732409	0.731069	0.718795	0.715494
52	0.491345	0.656228	0.662511	0.646332	0.635794
53	0.764107	0.819166	0.819838	0.812625	0.81325
54	0.547938	0.580032	0.577179	0.565279	0.560942
55	0.60403	0.745565	0.742281	0.737398	0.737582
56	0.522443	0.567991	0.568372	0.568024	0.564771
57	0.747744	0.728231	0.728512	0.719703	0.714567
Median	0.686989	0.744168	0.756633	0.743833	0.742058
Standard deviation	0.137404	0.084823	0.083624	0.084151	0.085068

Table 7. Result of 57 catchment simulated by KGE1 optimization function and criterion by KGE2

Catchments	KGE2_WRI	KGE2_BS	KGE2_DE1	KGE2_DE2	KGE2_DE3
1	0.774957	0.790539	0.792496	0.774993	0.7855
2	0.778768	0.768761	0.769592	0.759993	0.756214
3	0.768281	0.753941	0.756808	0.748365	0.736192
4	0.571991	0.592188	0.58922	0.585208	0.583503
5	0.57695	0.785485	0.785281	0.784007	0.782986
6	0.577322	0.801198	0.799729	0.793218	0.797618

7	0.687002	0.72016	0.720998	0.715197	0.702268
8	0.529432	0.596833	0.5975	0.595468	0.59285
9	0.531235	0.59866	0.60112	0.597372	0.594943
10	0.715779	0.784513	0.784718	0.779698	0.779218
11	0.727574	0.736234	0.736675	0.729249	0.732473
12	0.712172	0.680783	0.655565	0.66694	0.65474
13	0.737017	0.771942	0.772012	0.76867	0.758456
14	0.556117	0.721469	0.72198	0.719276	0.715275
15	0.673015	0.705171	0.705723	0.697146	0.69871
16	0.720095	0.76226	0.762849	0.755344	0.736919
17	0.595752	0.73282	0.737572	0.735077	0.729471
18	0.609736	0.784079	0.785055	0.779483	0.773367
19	0.65878	0.742117	0.744013	0.735309	0.738115
20	0.434925	0.628974	0.666836	0.645083	0.608226
21	0.641354	0.726641	0.727375	0.722835	0.720335
22	0.261054	0.647816	0.650012	0.648303	0.640632
23	0.809993	0.861572	0.864062	0.859651	0.858398
24	0.756057	0.837148	0.841192	0.834814	0.822835
25	0.747239	0.823577	0.824114	0.800899	0.786205
26	0.692678	0.726584	0.723665	0.717434	0.713525
27	0.555787	0.653872	0.657355	0.651123	0.646522
28	0.480331	0.558062	0.557326	0.547771	0.536614
29	0.799607	0.839397	0.839601	0.836788	0.833951
30	0.362455	0.515461	0.528658	0.551859	0.520252
31	0.772609	0.785909	0.785922	0.781481	0.766895
32	0.797931	0.841996	0.842633	0.82146	0.816639
33	0.735248	0.735144	0.752886	0.718625	0.728308
34	0.76044	0.63512	0.656872	0.652127	0.648181
35	0.67601	0.742118	0.74736	0.739479	0.74206
36	0.69037	0.75338	0.753319	0.743357	0.749298
37	0.735098	0.776512	0.777205	0.775839	0.76727
38	0.775726	0.800856	0.798611	0.787298	0.798323
39	0.781674	0.833175	0.833866	0.828419	0.824549
40	0.747381	0.767755	0.768195	0.764028	0.762695
41	0.721704	0.812193	0.808318	0.804394	0.798792
42	0.848542	0.863207	0.861142	0.856908	0.857025
43	0.786612	0.806844	0.80789	0.802561	0.790939
44	0.695779	0.777489	0.777666	0.77306	0.76838
45	0.72998	0.797422	0.79468	0.794079	0.796791
46	0.644333	0.770947	0.770978	0.756457	0.763174
47	0.631288	0.586232	0.586972	0.589175	0.57169
48	0.653016	0.680313	0.68046	0.676187	0.673865
49	0.693958	0.730844	0.768632	0.745505	0.747911

50	0.61102	0.626886	0.626535	0.607192	0.60942
51	0.663131	0.731947	0.730995	0.717333	0.717658
52	0.487069	0.656105	0.662657	0.646854	0.634906
53	0.76502	0.823814	0.824568	0.817278	0.818309
54	0.558847	0.571593	0.567919	0.557586	0.551775
55	0.580857	0.743407	0.740582	0.737229	0.732553
56	0.53009	0.578134	0.578543	0.576061	0.570323
57	0.747617	0.705708	0.705885	0.702162	0.695184
Median	0.692678	0.742118	0.752886	0.739479	0.736919
Standard deviation	0.117371	0.08539	0.084343	0.082536	0.085541

Evaluation:

The problem now is that with so many tables, what is the best way to evaluate them? The solution I use is to reduce the amount of work to be done as little as possible. For each of these results, I used the Excel program to calculate the Median and Standard Deviation values for each Simulation total runoff column.

1. KGE1 optimization function use to calibrate parameters of Bilan model:

Table 8. Median values of methods/criteria for KGE1 optimization function

	WRI	BS	DE1	DE2	DE3	Good if near	Number of WRI better	Best method
MAE	7.967396	8.370021	8.235165	8.311923	8.319005	0	44/57	WRI
RMSE	12.24718	11.99071	11.89703	11.99202	12.08196	0	22/57	DE1
NS	0.364691	0.50032	0.519016	0.501415	0.493046	1	3/57	DE1
KGE1	0.686989	0.744168	0.756633	0.743833	0.742058	1	5/57	DE1
KGE2	0.692678	0.742118	0.752886	0.739479	0.736919	1	6/57	DE1

Looking at the table 8 above, we can see that, based on the median value of the criteria coefficients of the simulation total runoff, using the KGE optimization function, the Bilan model yields better results than the reference value of the WRI (Water Research

Institute) center. The difference between the methods is small (highest index – lowest index = less than 0.2). The difference was only in MAE criteria when the WRI result was the lowest, but not too different from all 4 methods run by KGE optimization function. The DE1 (BEST_ONE_BIN differential evolution) method achieves the best results in all four criteria RMSE, NS, KGE1 and KGE2, so that we can deduce that the DE1 method is the best fit for the KGE1 optimization function.

The "Number of WRI better" column shows the number of catchments when we use criteria for estimation the good model (MAE ≈ 0, RMSE ≈ 0, NS ≈ 1, KGE ≈ 1), the result from WRI center is the best. We find that the results of the NS, KGE criteria from the WRI account for only a small fraction of the 57 research catchments (less than 10%). This is analogous to the median values obtained. I can say that when using the KGE1 optimization function we obtain the best Bilan model output files.

The accuracy of the KGE1 optimization function is again confirmed when calculating the standard deviation of the criteria. “In statistics, the standard deviation is a measure that is used to quantify the amount of variation or dispersion of a set of data values. A low standard deviation indicates that the data points tend to be close to the mean (also called the expected value) of the set, while a high standard deviation indicates that the data points are spread out over a wider range of values”. Because standard deviation of MAE and RMSE are higher than 1, we can ignore them in evaluating models. When comparing the coefficients of the remaining 3 criteria, we can see that the coefficients of the KGE1 optimization function are much lower than the WRI center reference data. And re-affirming, DE1 method is the most suitable method when running Bilan model for KGE1 optimization method.

Table 9. Standard Deviation of methods/criteria for KGE1 optimization function

	WRI	BS	DE1	DE2	DE3	Good if	Best method
MAE	5.136783	5.575754	5.701418	5.661247	5.836335	0	null
RMSE	8.082222	8.316723	8.319414	8.311747	8.431122	0	null
NS	0.314945	0.171634	0.167646	0.171472	0.17499	0	DE1

KGE1	0.137404	0.084823	0.083624	0.084151	0.085068	0	DE1
KGE2	0.117371	0.08539	0.084343	0.082536	0.085541	0	DE2

Similar to the table 9 above comparison, we obtain the evaluation result for the KGE2 optimization function on table 10 and table 11. Like KGE1, BEST_ONE_BIN differential evolution method is the most suitable method for calibrating a Bilan model using the KGE2 optimization function. We have the following tables:

Table 10. Median of methods/criteria for KGE2 optimization function

	WRI	BS	DE1	DE2	DE3	Good if	Number of WRI better	Best method
MAE	7.967396	8.379652	8.262397	8.445639	8.534201	0	38/57	WRI
RMSE	12.24718	12.02988	12.07265	12.12361	12.12366	0	21/57	BS
NS	0.364691	0.478194	0.497015	0.487565	0.489214	1	4/57	DE1
KGE1	0.686989	0.741036	0.747505	0.737145	0.736073	1	6/57	DE1
KGE2	0.692678	0.745027	0.758679	0.744686	0.737376	1	6/57	DE1

Table 11. Standard Deviation of methods/criteria for KGE2 optimization function

	WRI	BS	DE1	DE2	DE3	Good if	Best method
MAE	5.136783	5.238879	5.232682	5.346945	5.363933	0	null
RMSE	8.082222	7.836804	7.770378	7.974467	7.931564	0	null
NS	0.314945	0.22083	0.190167	0.222032	0.196544	0	DE1

KGE1	0.137404	0.108104	0.090542	0.107589	0.092177	0	DE1
KGE2	0.117371	0.087636	0.080391	0.087776	0.081652	0	DE1

<u>Results of median values and standard deviation of other optimization functions:</u>

From the below results, we can see that when calibrating the parameters of the Bilan model by other optimization functions such as MSE, MAE, NS the results are not as good as the reference data of the WRI center. The reason for this problem is that the selection of other model support parameters like init_GS, max_iter, etc. are not optimal. It can be deduced that KGE optimization function is consistent with global optimization.

1. MSE optimization function use to calibrate parameters of Bilan model:

Table 12. Median values of methods/criteria for MSE optimization function

	WRI	BS	DE1	DE2	DE3	Good if	Number of WRI better	Best method
MAE	7.967396	8.001612	7.988591	8.057369	8.033909	0	7/57	WRI
RMSE	12.24718	11.21246	11.36487	11.38387	11.39657	0	2/57	BS
NS	0.364691	0.312637	0.310999	0.276958	0.338507	1	32/57	WRI
KGE1	0.686989	0.627268	0.628426	0.63659	0.648165	1	37/57	WRI
KGE2	0.692678	0.652228	0.65203	0.643838	0.671908	1	32/57	WRI

Table 13. Standard Deviation of methods/criteria for MSE optimization function

	WRI	BS	DE1	DE2	DE3	Good if	Best method

MAE	5.136783	5.056761	5.046577	5.040411	5.087424	0	Null
RMSE	8.082222	7.712448	7.66169	7.673153	7.682337	0	Null
NS	0.314945	0.408764	0.41348	0.395023	0.429118	0	WRI
KGE1	0.137404	0.163968	0.166226	0.159472	0.169546	0	WRI
KGE2	0.117371	0.147487	0.147261	0.136602	0.156727	0	WRI

2. MAE optimization function use to calibrate parameters of Bilan model:

Table 14. Median values of methods/criteria for MAE optimization function

	WRI	BS	DE1	DE2	DE3	Good if	Number of WRI better	Best method
MAE	7.967396	7.744555	7.745841	7.83743	7.839638	0	2/57	BS
RMSE	12.24718	11.47294	11.4514	11.68489	11.62175	0	11/57	DE1
NS	0.364691	0.107878	0.153216	0.122065	0.097342	1	43/57	WRI
KGE1	0.686989	0.509341	0.531024	0.552086	0.510758	1	45/57	WRI
KGE2	0.692678	0.639543	0.640725	0.634369	0.611325	1	38/57	WRI

Table 15. Standard Deviation of methods/criteria for MAE optimization function

	WRI	BS	DE1	DE2	DE3	Good if	Best method
MAE	5.136783	4.937068	4.894156	4.952817	5.025648	0	null
RMSE	8.082222	7.863471	7.596234	7.671155	7.757995	0	null

NS	0.314945	0.636733	0.592411	0.663059	0.648769	0	WRI
KGE1	0.137404	0.231295	0.217041	0.231698	0.244952	0	WRI
KGE2	0.117371	0.165862	0.158366	0.167257	0.165989	0	WRI

3. NS optimization function use to calibrate parameters of Bilan model:

Table 16. Median values of methods/criteria for NS optimization function

	WRI	BS	DE1	DE2	DE3	Good if	Number of WRI better	Best method
MAE	7.967396	8.001612	7.977613	7.972568	7.991999	0	6/57	WRI
RMSE	12.24718	11.21246	11.25889	11.38282	11.34439	0	2/57	BS
NS	0.364691	0.312637	0.327675	0.309097	0.306579	1	32/57	WRI
KGE1	0.686989	0.627268	0.629841	0.624228	0.6196	1	35/57	WRI
KGE2	0.692678	0.652228	0.650503	0.671182	0.668649	1	30/57	WRI

Table 17. Standard Deviation of methods/criteria for NS optimization function

	WRI	BS	DE1	DE2	DE3	Good if	Best method
MAE	5.136783	5.056761	4.928002	5.104186	5.041057	0	null
RMSE	8.082222	7.712448	7.529648	7.80787	7.731471	0	null
NS	0.314945	0.408764	0.396031	0.414275	0.384423	0	WRI
KGE1	0.137404	0.163968	0.156544	0.168841	0.155316	0	WRI

KGE2	0.117371	0.147487	0.145167	0.147403	0.134912	0	WRI

When using the NS and KGE criteria to evaluate models using the MAE, MSE, NS optimization functions, the criteria of the catchments obtained from the WRI center results are mostly higher than the criteria of the catchments when calculate for results of the models run by other optimization functions, this shows that the result of WRI center is better than the result of the models where I use the MAE, MSE, NS optimization function to calibrate.

BOXPLOT FOR 5 CRITERIA:

Boxplot is used to evaluate aggregate model performance. All five columns in each table above are grouped into one matrix. Each chart below consists of 5 blocks representing 5 different optimization functions. The chart helps us to compare the effectiveness of the model between optimization functions. In sum, we have five charts that represent the five criteria (KGE1, KGE2, NS, MAE and RMSE).

- KGE1 criteria

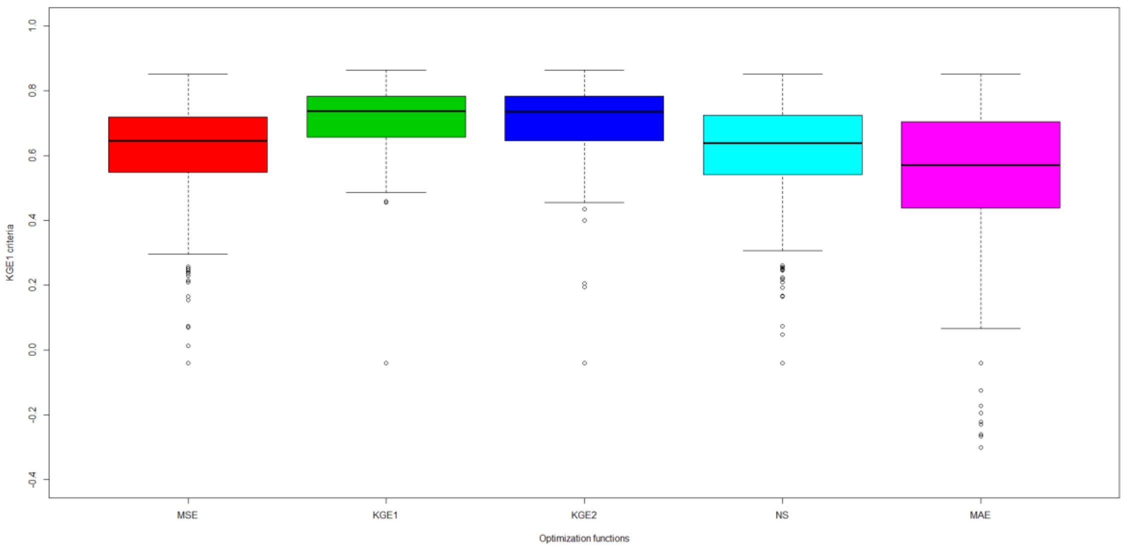

Figure 6. Boxplot of KGE1 criteria for 5 optimization functions

- KGE2 criteria

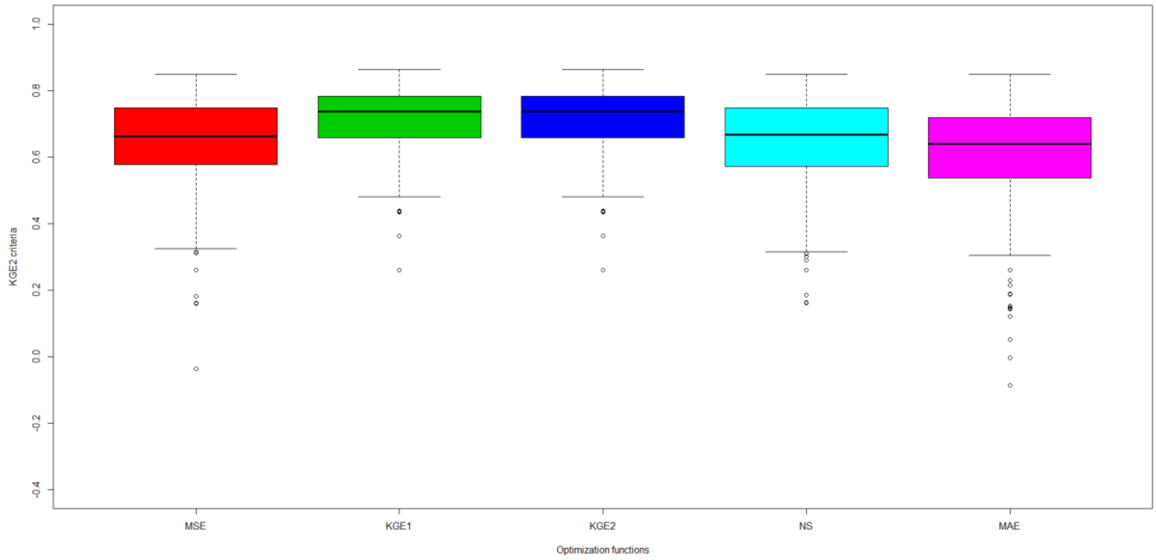

Figure 7. Boxplot of KGE2 criteria for 5 optimization functions

It can be seen from Figures 3 and 4 that the optimization functions KGE1 and KGE2 both have a higher criterion coefficient and are closer to 1 than the remaining 3 optimization functions. This is satisfactory for evaluating a model as good or not when using KGE1 and KGE2 criteria as the comparative value (as close to 1 as possible).

This is reasserted using the NS criteria as shown in 5th boxplot below. The median values of the two optimization functions (KGE1 and KGE2) are both higher and closer to 1 than the MSE, MAE, or NS optimization function (Black lines in the box blocks).

- NS criteria

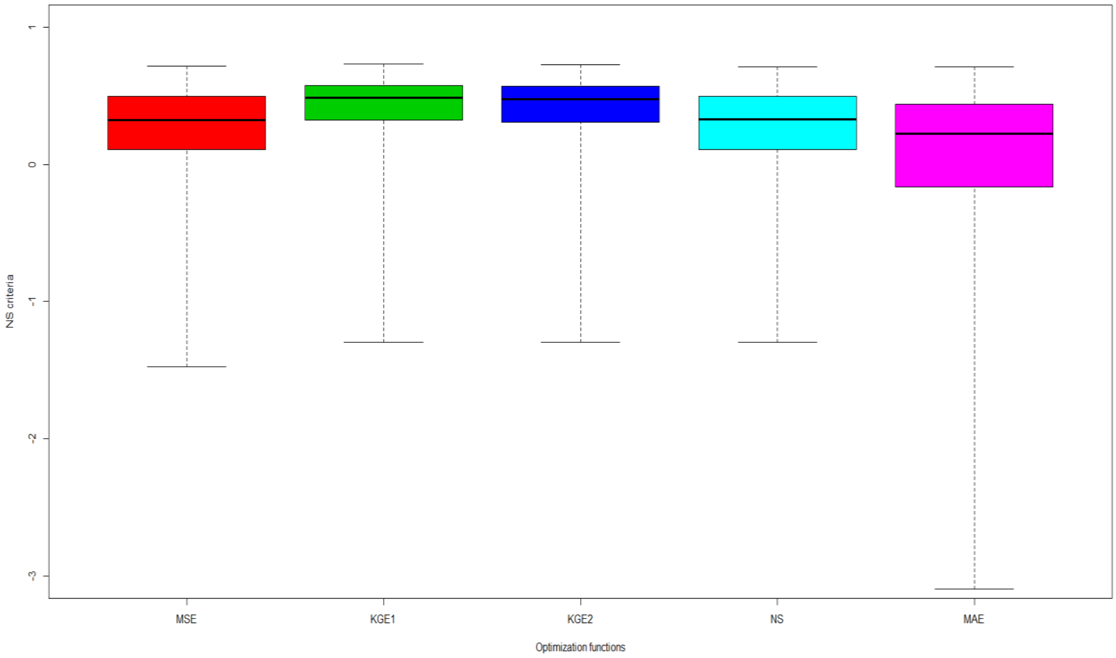

Figure 8. Boxplot of NS criteria for 5 optimization functions

When using the MAE and RMSE coefficients to evaluate model performance, the results were not clear. Boxes are about the same size; the horizontal lines are nearly equal. The MAE criteria and RMSE criteria of the KGE optimization function, though slightly higher than those of the remaining 3 optimization functions, are negligible.

- MAE criteria

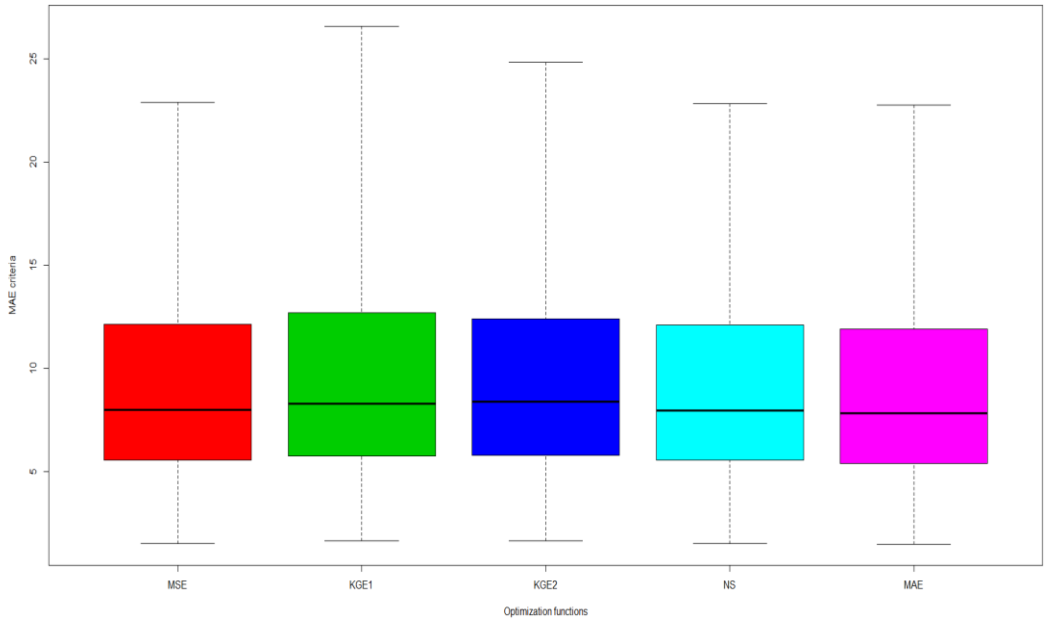

Figure 9. Boxplot of MAE criteria for 5 optimization functions

- RMSE criteria

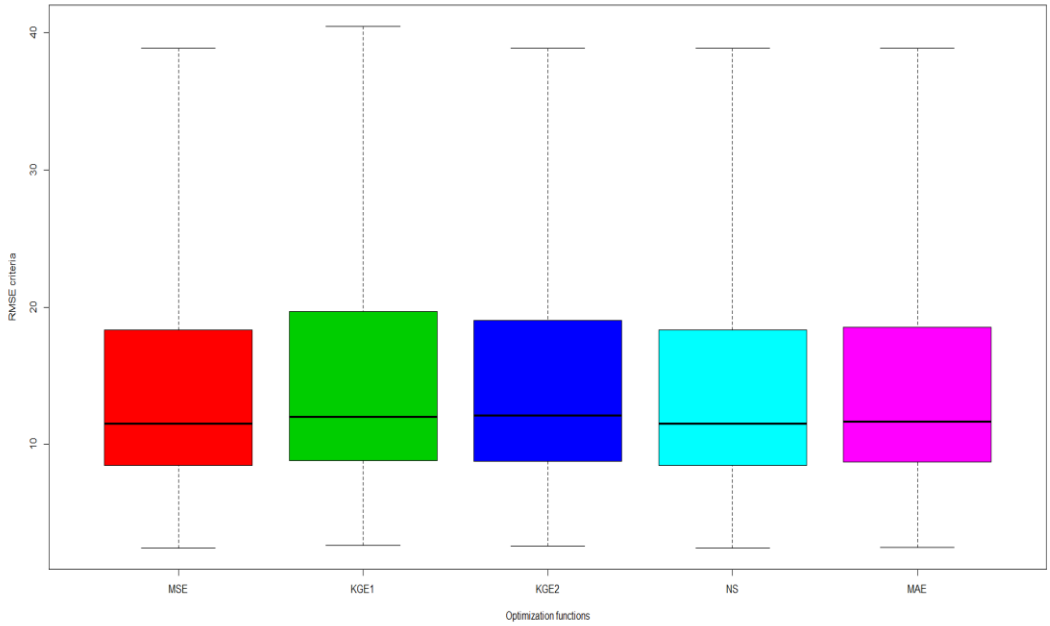

Figure 10. Boxplot of RMSE criteria for 5 optimization functions

Thus, we can conclude that for all four methods of the Bilan model used in this study (BS, DE1, DE2, DE3), we all have better model results for KGE optimization functions. Compared to the old optimization functions used previously, such as MSE, MAE, NS, they were used to calibrate the parameters of the Bilan model.

3.3. BUILDING NEW VERSION OF BILAN PACKAGE

The R 3.3.2 or higher with the Rcpp package installed (version 0.12.10 or higher) is required for the Bilan package.

The package bilan.tar.gz (for Linux) or bilan.zip (for Windows) can be installed into the R environment in a standard way routinely used to install local packages (e.g. using the install.packages command). In manual part of Bilan model in Rstudio, only function names are referred (highlighted in blue); the detailed description is contained in R-help associated with each individual function.

Example results of 0040.dat (first catchment) in 100 months:

I. BS method:

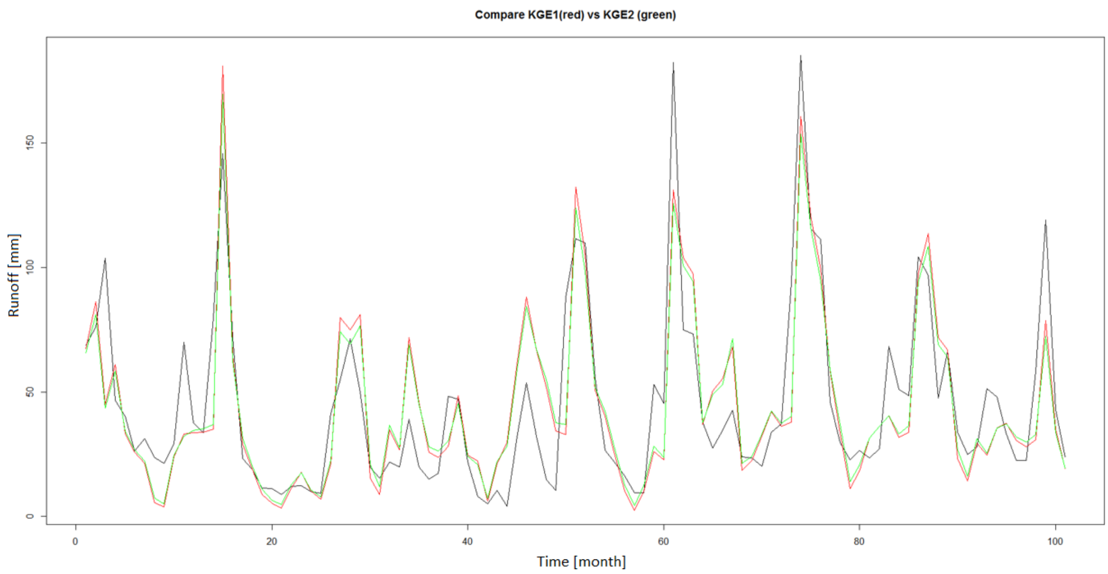

Figure 11. Runoff hydrograph for KGE optimization function of BS method

Figure 11 below shows the hydrograph for the total runoff of the Bilan model using the Binary Search method and the KGE optimization function for all eight parameters of the model. The red line shows the results of the simulated runoff using the KGE1 criteria function, the green line is the result of a simulated runoff using the KGE2 criteria function and the black line is the observed total runoff. In general, there is not much difference between red and blue lines. The peak discharge of KGE1 simulated waves was approximately 1% higher than the KGE2 discharge waves. In this 100 months' example, the runoff reached the highest value (approximately 200mm) at 15th, 63rd, 75th month, the simulated runoff lines of the KGE optimization function were similar in shape to the observed data.

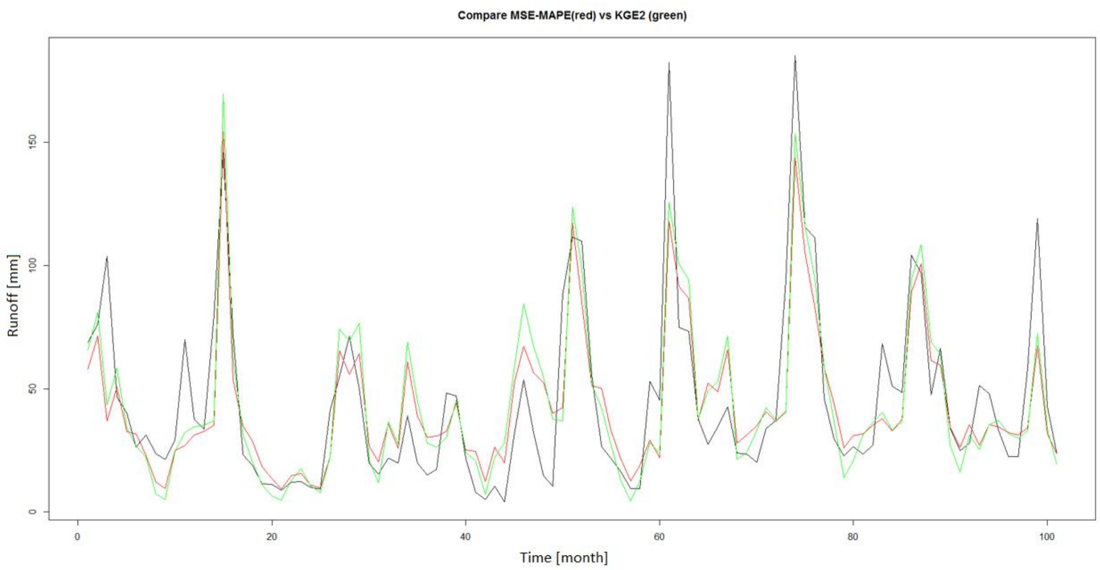

Figure 12. Runoff hydrograph for MSE-MAPE and KGE optimization functions of BS method

Figure 12 shows the hydrograph results of two different optimizations functions when using the Bilan model in the new package with the Binary Search method. The red line is the simulated total runoff using MSE coefficient as the first criteria and MAPE coefficient as the second criteria for modifying the parameters of the model. Blue lines are simulated total runoff using KGE optimization function (with KGE2 coefficient for both criteria). The blue line of the KGE coefficient is almost always greater than the red line of the MSE-MAPE at the top of the graph, and closer to the black line of the observed data.

II. DE method:

Figure13 shows the results of the Bilan model using Differential Evolution. The red line is the simulated runoff of the Bilan model using the MSE coefficient for the calibrate model and the green line is the simulated runoff of the KGE optimization function.

In general, blue lines have higher peaks than red ones. At 15th month, the results of the MSE criteria model seemed to be better than the KGE as the red lines almost coincided with the blacked line (observed data). At other months, the results of the KGE optimization function are almost always better than the MSE. Repeat results are similar to figure 14 and figure 15 when using two other methods, BEST_TWO_BIN and RAND_TWO_BIN, respectively.

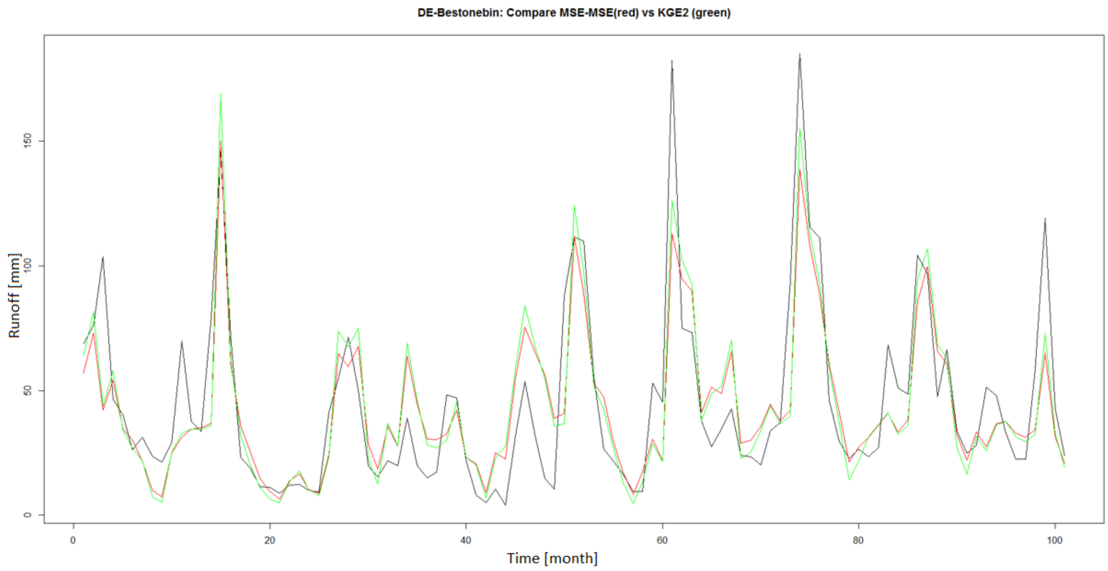

Figure 13. Runoff hydrograph for MSE and KGE optimization functions of DE-BEST_ONE_BIN method

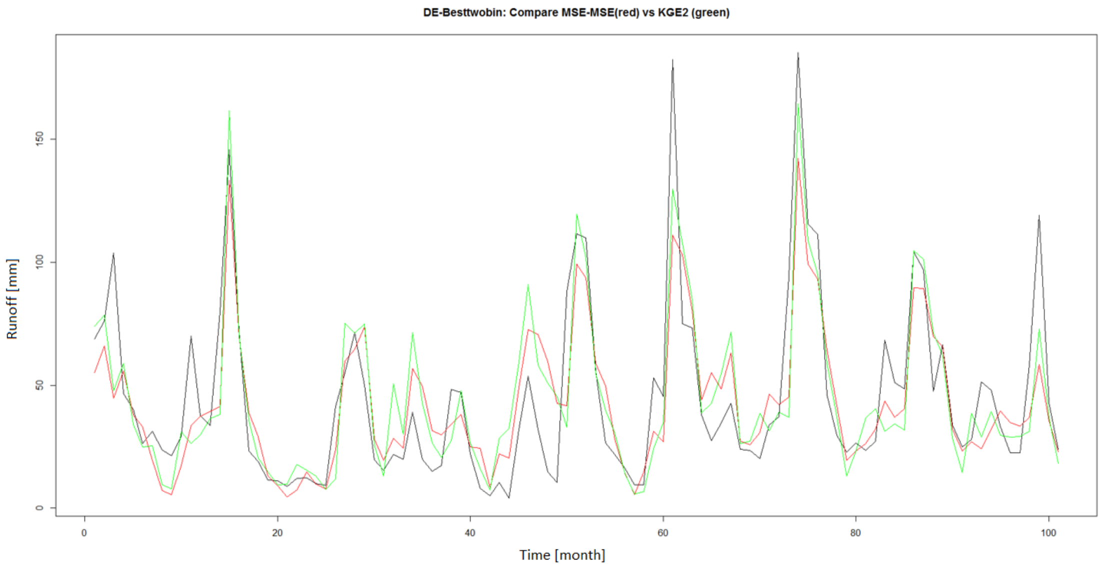

Figure 14. Runoff hydrograph for MSE and KGE optimization functions of DE-BEST_TWO_BIN method

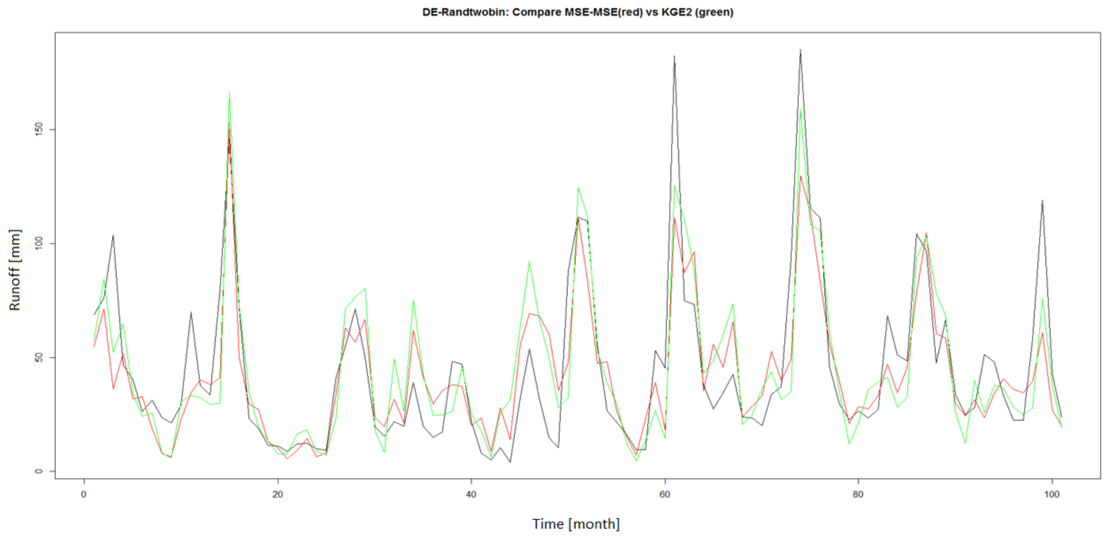

Figure 15. Runoff hydrograph for MSE and KGE optimization functions of DE-RAND_TWO_BIN method

III. Compare 4 method with KGE2:

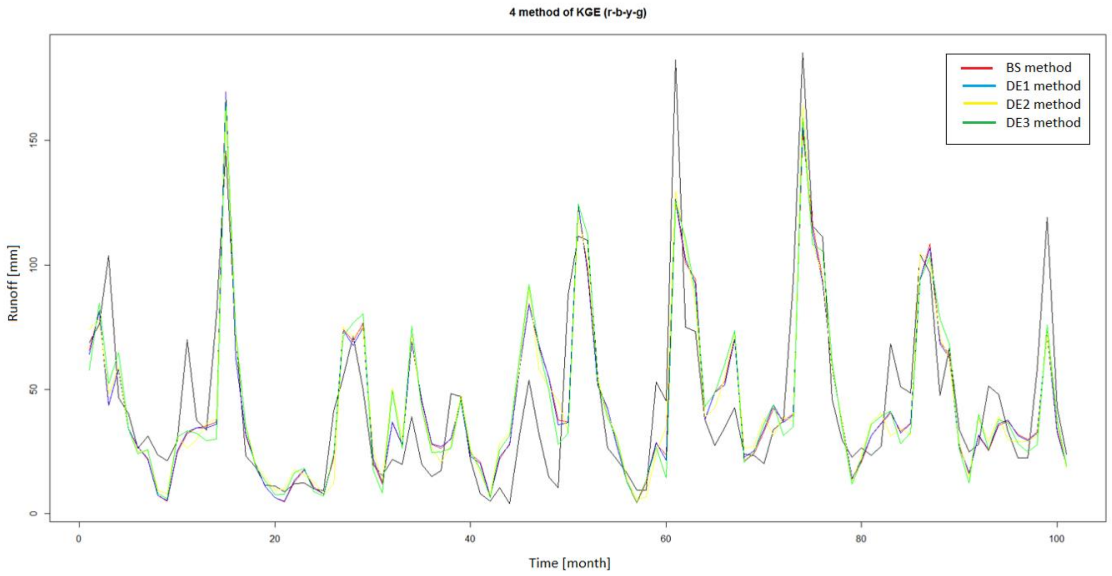

Figure 16. Runoff hydrograph for KGE optimization function of 4 methods

Figure16 is a hydrograph comparing the results of four methods using the same KGE coefficient as the optimization function. The red line is the simulated runoff of the Binary Search method, the blue line is the simulated runoff of the BEST_ONE_BIN Differential Evolution method, the yellow line is the simulated runoff of the Differential Evolution BEST_TWO_BIN method, the green line is the simulated runoff of Differential Evolution RAND_TWO_BIN method. In general, there is not much difference between these 4 lines.

CHAPTER 4: CONCLUSION

The main purpose of this thesis is to extend the optimization algorithms used in the typical Bilan hydrological model. The extension focuses on providing new optimization functions, based on the Kling-Gupta coefficient, to calibrate eight parameters of the Bilan model, resulting in a more accurate run-off simulation.

Bilan hydrological model developed by the T. G. Masaryka Water Research Institute (WRI) is main lumped hydrological model for the assessment of hydrological balance in Czech Republic. The entry data of the model are monthly series of catchment precipitation and air temperature. Monthly runoff series at the outset of the catheter are used to calibrate model parameters (Kašpárek & Novický, 1997; Vizina et al., 2010).

The results obtained in simulation and forecasting of the model show the advantages and disadvantages of the Bilan model. Optimizing the model and minimizing the level of error, is an essential requirement that is set in the present and in the future.

By using the following statistical tools; MAE, RMSE, NS and KGE as criteria in hydroGOF package of Rstudio, the results of the Bilan model using the KGE optimization function were compared to the default criteria functions of Bilan model such as MSE, MAE and NS.

My analysis of the modeling for 57 Czech catchments shows that the construction of a new optimization function for the Bilan model is feasible. The Kling-Gupta coefficient has several advantages over previous Bilan models for the calibration of eight free parameters. This new optimization function minimizes the difference between the simulated and observed runoff of catchments using the Bilan model. The results when run using the KGE optimization model are superior when we use criteria such as NS and KGE, indicating that the KGE optimization function is useful for calibrating the multidimensional model parameters.

However, setting of optimizers were not the main focus of this thesis so the results of running the model using the previous optimization functions such as MSE, MAE and

NS have not achieved the results as expected, there are few deviations from the WRI reference. I hope that there will be consultation with the WRI center to further development of the Bilan model for this study in the near future.

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APPENDIX

I. C++ code:

1. File bil_model.cpp:

```
/**
 * - calculates optimization criterion for observed and modelled runoff, optionally using weights
 * - NS and LNNS are residuals to 1 (to be minimized)
 * @param crit_type type of optimization criterion
 * @param var_obs observed variable
 * @param var_mod modelled variable
 * @param use_weights whether to use weights for time steps of runoff
 * @return value of the criterion
 */
long double bilan::calc_crit(unsigned crit_type, unsigned var_obs, unsigned var_mod, bool use_weights)
{
  long double cit, jmen;
  long double ok = 0, mean = 0; //TDD otestovat NS

  if ((crit_type == optimizer<bilan_fcd*>::NS) || (crit_type == optimizer<bilan_fcd*>::LNNS)) {
    cit = 0;
    jmen = 0;
    mean = 0;

    for (ts = 0; ts < time_steps; ts++) {
      if (crit_type == optimizer<bilan_fcd*>::NS)
        mean = mean + var[ts][var_obs];
      else
        mean = mean + log(var[ts][var_obs]); //natural logarithm
    }
```

```
    mean = mean / time_steps;
  }

  long double tmp_weight;
  for (ts = 0; ts < time_steps; ts++) {
    if (use_weights) {
      if (var[ts][WEI] < NUMERIC_EPS && var[ts][WEI] > -NUMERIC_EPS)
        continue;
      tmp_weight = var[ts][WEI] / (sum_weights / time_steps);
    }
    else
      tmp_weight = 1;

    switch (crit_type) {
      case optimizer<bilan_fcd*>::MSE:
        ok = ok + tmp_weight * pow((var[ts][var_obs] - var[ts][var_mod]), 2); //standard error
        break;
      case optimizer<bilan_fcd*>::MAE:
        ok = ok + tmp_weight * abs(var[ts][var_obs] - var[ts][var_mod]); //mean absolute error
        break;
      case optimizer<bilan_fcd*>::MAPE:
        ok = ok + tmp_weight * abs(var[ts][var_obs] - var[ts][var_mod]) / var[ts][var_obs]; //mean absolute percentage error
        break;
      case optimizer<bilan_fcd*>::NS: //Nash-Sutcliffe efficiency
        cit = cit + tmp_weight * pow(var[ts][var_obs] - var[ts][var_mod], 2);
        jmen = jmen + pow(var[ts][var_obs] - mean, 2);
        break;
      case optimizer<bilan_fcd*>::LNNS: //logarithmic Nash-Sutcliffe efficiency
```

```
      cit = cit + tmp_weight * pow(log(var[ts][var_obs]) - log(var[ts][var_mod]), 2);
      jmen = jmen + pow(log(var[ts][var_obs]) - mean, 2);
      break;
    default:
      break;
  }
 }

 if ((crit_type == optimizer<bilan_fcd*>::MSE) || (crit_type == optimizer<bilan_fcd*>::MAE) || (crit_type == optimizer<bilan_fcd*>::MAPE))
   ok = ok / time_steps;
 else if ((crit_type == optimizer<bilan_fcd*>::NS) || (crit_type == optimizer<bilan_fcd*>::LNNS))
   ok = cit / jmen;

 if (crit_type == optimizer<bilan_fcd*>::KGE1) //Kling-Gupta Efficeincy with st. dev.
      ok = ED(var_obs, var_mod,0);

 if (crit_type == optimizer<bilan_fcd*>::KGE2) //Kling-Gupta Efficeincy with st. dev.
      ok = ED(var_obs, var_mod,1);

 if (ok == numeric_limits<long double>::infinity()) //zero modelled value matters for LNNS
   throw bil_err("Optimization criterion value is infinity (probably due to zero observed or modelled value).");

 return ok;
}

/**
```

```
 * - calculates KGE
 */
long double bilan::ED(unsigned var_obs, unsigned var_mod,unsigned kge_type)
{
  long double ed = 0, mean_obs = 0, mean_sim = 0, sigma_obs = 0, sigma_sim = 0;
  long double sum_obs = 0, sum_sim = 0, sum_obs2 = 0, sum_sim2 = 0, obs_sim = 0;
  long double cv_obs = 0, cv_sim = 0, kgeGamma = 0;
  long double Alpha = 0, Beta = 0, rPearson = 0;

    for (ts = 0; ts < time_steps; ts++) {
      mean_obs = mean_obs + var[ts][var_obs];
      mean_sim = mean_sim + var[ts][var_mod];
      sum_obs = sum_obs + var[ts][var_obs];
      sum_sim = sum_sim + var[ts][var_mod];
      sum_obs2 = sum_obs2 + pow(var[ts][var_obs],2);
      sum_sim2 = sum_sim2 + pow(var[ts][var_mod],2);
      obs_sim = obs_sim + var[ts][var_obs] * var[ts][var_mod];
    }
    mean_obs = mean_obs / time_steps;
    mean_sim = mean_sim / time_steps;

    rPearson = (time_steps * obs_sim  - sum_obs*sum_sim) / pow((time_steps * sum_obs2 - pow(sum_obs,2)),0.5) / pow((time_steps * sum_sim2 - pow(sum_sim,2)),0.5);

    for (ts = 0; ts < time_steps; ts++) {
      sigma_obs = sigma_obs + pow((var[ts][var_obs] - mean_obs),2);
      sigma_sim = sigma_sim + pow((var[ts][var_mod] - mean_sim),2);
    }
```

```
    sigma_obs = pow((sigma_obs / (time_steps - 1)),0.5);
    sigma_sim = pow((sigma_sim / (time_steps - 1)),0.5);

    cv_obs = sigma_obs / mean_obs;
    cv_sim = sigma_sim / mean_sim;

    Alpha = sigma_sim / sigma_obs;
    Beta = mean_sim / mean_obs;
    kgeGamma = cv_sim / cv_obs;

//          cout << rPearson << "\t a\t" << (time_steps * obs_sim - sum_obs*sum_sim)<< << "\t a\t" << endl;

    if(kge_type == 0){
        ed = pow( (pow((rPearson-1),2)) + (pow((Alpha-1),2)) + (pow((Beta-1),2)) ,0.5);
    } else ed = pow( (pow((rPearson-1),2)) + (pow((kgeGamma-1),2)) + (pow((Beta-1),2)) ,0.5);

    return ed;
}
```

II. Table:

Table 18. Result of 57 catchment simulated by MSE optimization function and criterion by MAE

Catchments	MAE_WRI	MAE_BS	MAE_DE1	MAE_DE2	MAE_DE3
1	14.79985	14.33408	14.32213	14.80918	14.7293
2	8.701771	8.556719	8.511418	8.706312	8.754932
3	5.768665	6.067747	6.092636	6.358133	6.296089
4	6.40763	5.849105	5.844344	5.804885	5.812601
5	8.009667	8.001612	7.988596	8.112594	8.033909

6	9.875146	9.788805	9.781243	9.737043	9.831229
7	7.908323	7.65907	7.687675	7.818129	7.814277
8	14.73514	13.07029	13.05009	13.05645	13.33955
9	9.481499	9.035154	9.028657	9.028419	9.115501
10	5.383439	5.100225	5.095546	5.189395	5.227509
11	4.593428	4.47564	4.469911	4.542611	4.496014
12	22.30288	22.0619	22.16712	22.62701	22.7517
13	4.890502	4.803757	4.791192	4.797232	4.859302
14	9.928447	10.09815	10.04967	10.42423	10.17521
15	6.504339	6.352327	6.368212	6.346018	6.398977
16	6.787659	6.599444	6.465872	6.656875	6.646737
17	7.967396	7.832737	7.809158	7.904103	7.897732
18	5.786598	5.791803	5.801931	5.911266	6.03151
19	5.867597	5.541568	5.536995	5.575326	5.584542
20	12.14355	12.54213	10.43621	11.17724	10.83909
21	5.740209	5.542241	5.538563	5.529255	5.702736
22	2.586289	2.279288	2.256888	2.265568	2.435175
23	13.09462	12.85901	12.78386	13.28085	13.12415
24	4.784961	4.806296	4.904796	4.909972	4.934834
25	9.694001	8.80406	8.794675	9.97817	9.329237
26	19.62452	18.07558	18.08625	18.35454	18.36542
27	11.44525	11.2673	11.27088	11.25757	11.70765
28	2.721778	2.316895	2.323283	2.356886	2.295743
29	9.560573	8.719748	8.584845	8.714646	8.69757
30	22.36878	22.30404	22.37332	20.29755	21.01871
31	20.24002	19.55976	19.53353	19.7128	19.70491
32	13.68282	13.07901	13.04655	13.9584	13.96517
33	13.23029	13.06838	13.09737	13.33211	13.28223

34	21.78774	22.29552	22.27939	22.35433	22.9073
35	6.32414	6.282656	6.1891	6.160916	6.310394
36	10.9682	10.99201	11.03748	11.20048	11.02778
37	10.72371	9.818996	9.809812	9.994511	10.0895
38	12.95613	12.73808	12.72153	12.82221	12.71696
39	9.338666	8.688404	8.683373	8.740351	8.80467
40	6.680253	6.178723	6.206751	6.260928	6.227736
41	5.728456	5.55631	5.594645	5.638064	5.592563
42	5.876072	5.623465	5.628323	5.635875	5.808976
43	5.39025	5.291538	5.309205	5.278353	5.410553
44	3.912731	3.741296	3.744271	3.776084	3.809991
45	11.6324	11.4306	11.40798	11.30849	11.61899
46	2.968732	2.900735	2.902654	2.853933	2.927557
47	13.31496	12.72947	12.70427	12.71602	12.67463
48	7.261508	6.908531	6.974437	6.945355	7.231961
49	2.2855	2.278638	2.075908	2.112916	2.137005
50	6.276659	5.887605	5.554504	5.923353	5.906744
51	3.871867	3.712927	3.913406	3.843647	3.858632
52	1.970807	1.525491	1.53159	1.552842	1.526778
53	9.623665	8.827569	8.838316	8.915149	8.990594
54	15.96901	15.53071	15.5135	16.06734	16.08691
55	5.436058	4.993874	5.005534	5.043099	5.124908
56	13.53478	12.47553	12.49047	12.50689	12.68145
57	7.723161	8.054367	7.988591	8.057369	8.035411
Median	7.967396	8.001612	7.988591	8.057369	8.033909
Standard deviation	5.136783	5.056761	5.046577	5.040411	5.087424

Model is good if MAE value near to 0

➔ Value from WRI is the best.

Table 19. Result of 57 catchment simulated by MSE optimization function and criterion by RMSE

Catchments	RMSE_WRI	RMSE_BS	RMSE_DE1	RMSE_DE2	RMSE_DE3
1	22.33188	20.52359	20.52016	20.90001	20.97657
2	12.24718	11.98887	11.92064	12.13696	12.28598
3	9.459082	8.80248	8.760173	8.994693	9.003696
4	11.19926	10.14219	10.14095	10.18277	10.26078
5	12.27701	11.75771	11.75686	11.83124	11.87871
6	15.22916	14.30415	14.29	14.42775	14.44102
7	11.66908	11.0518	11.0395	11.12207	11.16993
8	23.26557	20.49824	20.48955	20.57486	20.65163
9	14.86268	13.81982	13.83379	13.88039	13.92646
10	8.839227	7.48679	7.485733	7.588526	7.600451
11	6.51257	6.347226	6.345627	6.412234	6.430986
12	32.36814	31.97099	31.89096	32.65964	32.85407
13	6.971114	7.002879	7.002625	7.044226	7.16147
14	15.1271	14.99083	14.98785	15.1539	15.2151
15	9.840711	9.287854	9.316629	9.356514	9.386072
16	9.721	9.263165	9.185013	9.397695	9.3417
17	11.13237	11.10449	11.04436	11.13261	11.30365
18	8.64201	8.564109	8.563594	8.644894	8.83077
19	10.90119	9.555383	9.560521	9.589785	9.672102
20	21.93146	20.0336	15.29997	17.22353	16.2943
21	9.850658	8.423227	8.422019	8.501984	8.62493
22	3.994777	3.577326	3.533538	3.592068	3.601465
23	21.11719	20.71163	20.73558	21.23865	21.06786
24	6.909676	6.608927	6.699201	6.775332	6.684243
25	12.8432	11.58335	11.57405	12.86527	12.48574

26	30.78008	27.81489	27.81859	28.49607	28.09707
27	18.32182	17.45914	17.42437	17.46725	17.69159
28	5.199407	4.378793	4.377544	4.384539	4.434686
29	14.91227	12.74113	12.5614	12.6442	12.74646
30	38.85464	36.97516	36.90161	35.03502	35.50031
31	29.23497	27.57656	27.57774	27.8063	27.8486
32	20.82627	18.81563	18.76437	19.33015	19.67011
33	20.22068	19.92739	19.93686	20.35502	20.43676
34	32.89078	32.94315	32.93394	33.07941	33.37371
35	10.27171	9.699043	9.61661	9.733137	9.758136
36	18.07038	17.87372	17.9317	17.95699	17.96406
37	17.22432	15.51773	15.51441	15.63447	15.59986
38	20.13556	18.39047	18.39503	18.65752	18.64324
39	14.55492	12.56261	12.56089	12.69884	12.76774
40	9.393154	9.142483	9.133466	9.306145	9.336976
41	8.46146	8.314597	8.319137	8.463696	8.599601
42	8.820895	8.381532	8.380823	8.503506	8.587424
43	8.120655	7.668909	7.682143	7.847926	7.83396
44	6.648048	5.313656	5.317622	5.3641	5.37269
45	17.41678	17.16122	17.1433	17.31629	17.31452
46	4.396574	4.348338	4.347597	4.381535	4.405625
47	21.28192	19.64825	19.67118	19.93978	19.93978
48	12.4498	11.16414	11.26446	11.38387	11.39657
49	3.238565	3.291749	3.028201	3.087339	3.215881
50	9.804517	9.067083	8.903422	9.069531	9.128556
51	5.937853	5.807788	6.06551	5.946796	6.059225
52	3.680822	2.427888	2.435338	2.457645	2.489421
53	16.37885	13.18555	13.18108	13.35137	13.32829
54	26.62169	24.1406	24.12027	24.72668	24.49255
55	7.993558	7.313722	7.343994	7.357311	7.418265

56	20.96975	18.3313	18.34731	18.38093	18.45099
57	11.48001	11.21246	11.36487	11.31189	11.39569
Median	12.24718	11.21246	11.36487	11.38387	11.39657
Standard deviation	8.082222	7.712448	7.66169	7.673153	7.682337

Model is good if RMSE value near to 0

➔ Value from BS is the best.

Table 20. Result of 57 catchment simulated by MSE optimization function and criterion by NS

Catchments	NS_WRI	NS_BS	NS_DE1	NS_DE2	NS_DE3
1	0.536422	0.499862	0.492113	0.457209	0.468602
2	0.536001	0.387616	0.395948	0.371775	0.339113
3	0.559229	0.355396	0.38546	0.464935	0.30824
4	0.105436	-0.55989	-0.56191	-0.57137	-0.63598
5	0.231145	0.500929	0.497639	0.524259	0.498951
6	0.298604	0.502942	0.509271	0.449389	0.478921
7	0.340441	0.18522	0.20249	0.186089	0.33473
8	-0.04328	-0.54369	-0.56583	-0.50575	-0.45942
9	-0.02877	-0.42951	-0.44574	-0.48349	-0.29769
10	0.440137	0.414801	0.414331	0.409323	0.408703
11	0.424822	0.27071	0.263978	0.271789	0.300753
12	0.364691	0.110324	0.120838	-0.12217	0.074875
13	0.473881	0.33606	0.324126	0.276958	0.314811
14	0.048126	0.122761	0.09631	0.191219	-0.0288
15	0.30788	0.129767	0.118623	0.109582	0.205116
16	0.402292	0.344968	0.316955	0.253711	0.378793
17	0.234339	0.20158	0.21442	0.209411	0.143927
18	0.282451	0.414119	0.416518	0.414291	0.340408
19	0.328391	0.309522	0.308554	0.277224	0.344698
20	-0.25708	0.068244	0.261715	-0.27946	0.095717

21	0.320238	0.230143	0.232372	0.2512	0.385014
22	-0.24464	-0.12384	-0.09063	-0.21376	0.03438
23	0.652921	0.672253	0.663201	0.658671	0.681782
24	0.536068	0.61817	0.607002	0.615865	0.628501
25	0.576565	0.615049	0.612315	0.54781	0.512004
26	0.357694	0.173772	0.167463	0.145304	0.237661
27	-0.18164	-0.11682	-0.09505	-0.06944	-0.04635
28	-0.08888	-0.88488	-0.86766	-0.83133	-1.4733
29	0.600104	0.597789	0.617963	0.588584	0.552782
30	-1.29653	-0.85812	-0.8467	-0.63565	-0.69615
31	0.571382	0.493349	0.497051	0.48231	0.474934
32	0.593895	0.671745	0.672668	0.695188	0.659247
33	0.415043	0.342799	0.308026	0.128278	0.375238
34	0.503625	0.267798	0.262858	0.276279	0.162012
35	0.248615	0.247276	0.243384	0.142868	0.254882
36	0.283719	0.38107	0.414375	0.41701	0.363078
37	0.424501	0.447837	0.453973	0.439663	0.453007
38	0.5742	0.51259	0.528133	0.542552	0.530052
39	0.552605	0.607266	0.606385	0.558129	0.601462
40	0.495412	0.385929	0.374963	0.314478	0.277234
41	0.486148	0.51073	0.515325	0.514134	0.514689
42	0.71138	0.679064	0.679468	0.680124	0.716476
43	0.563444	0.514109	0.51931	0.460556	0.516364
44	0.45651	0.395471	0.394049	0.368811	0.396971
45	0.500302	0.506673	0.510713	0.431551	0.536911
46	0.436786	0.356332	0.361357	0.244653	0.338507
47	0.258847	-0.43416	-0.48051	-0.37188	-0.25044
48	0.304362	-0.11045	-0.0593	0.042982	0.103922
49	0.379047	0.105382	0.310999	0.400965	0.052284
50	0.209566	-0.29252	-0.43503	-0.3322	-0.44031

51	0.342951	0.176329	0.107773	0.181754	0.215561
52	0.323764	-0.11556	-0.12906	-0.12377	-0.15785
53	0.51523	0.568127	0.571513	0.559037	0.576893
54	0.023559	-0.74514	-0.76915	-0.62704	-0.82113
55	0.165566	0.263193	0.263708	0.290663	0.348523
56	-0.02663	-0.73896	-0.72497	-0.77062	-0.63893
57	0.497334	0.312637	0.325618	0.34856	0.424103
Median	0.364691	0.312637	0.310999	0.276958	0.338507
Standard deviation	0.314945	0.408764	0.41348	0.395023	0.429118

Mode good if NS value near to 1

➔ Value from WRI is the best

Table 21. Result of 57 catchment simulated by MSE optimization function and criterion by KGE1

Catchments	KGE1_WRI	KGE1_BS	KGE1_DE1	KGE1_DE2	KGE1_DE3
1	0.766021	0.712799	0.70691	0.685594	0.694291
2	0.773538	0.66654	0.669179	0.664099	0.64812
3	0.764446	0.655161	0.671854	0.718209	0.626822
4	0.569582	0.326627	0.325588	0.322266	0.303627
5	0.599541	0.756505	0.754621	0.769277	0.75673
6	0.604738	0.729508	0.73435	0.688623	0.71449
7	0.687035	0.603408	0.612899	0.607039	0.682406
8	0.52967	0.308137	0.298332	0.326443	0.349187
9	0.539052	0.374558	0.368481	0.355047	0.431969
10	0.721218	0.68749	0.687031	0.689688	0.689331
11	0.719659	0.638136	0.634315	0.640528	0.659624
12	0.695974	0.553731	0.557836	0.439223	0.545821
13	0.729814	0.625796	0.616436	0.582999	0.621283
14	0.529604	0.566514	0.551406	0.608046	0.490955
15	0.671408	0.585228	0.580655	0.57735	0.625561

16	0.713995	0.668218	0.645009	0.61578	0.69319
17	0.600508	0.576848	0.581598	0.58392	0.551676
18	0.589779	0.684506	0.686427	0.691417	0.648324
19	0.673932	0.654094	0.653246	0.63659	0.683015
20	0.458007	0.577237	0.579392	0.3419	0.513066
21	0.650751	0.627268	0.628426	0.64114	0.703696
22	0.454571	0.446702	0.453536	0.409368	0.468009
23	0.770272	0.78265	0.770229	0.773214	0.794587
24	0.742721	0.795031	0.791643	0.801556	0.809969
25	0.785635	0.785916	0.782991	0.765128	0.730607
26	0.686989	0.571534	0.567658	0.566288	0.617124
27	0.455202	0.470288	0.480033	0.492839	0.512733
28	0.485265	0.208624	0.214781	0.229615	0.012202
29	0.800694	0.747734	0.7594	0.728928	0.695219
30	-0.0409	0.073753	0.070347	0.164912	0.15417
31	0.778886	0.727415	0.730179	0.72256	0.71716
32	0.766157	0.79842	0.797142	0.809473	0.789415
33	0.680424	0.626313	0.602963	0.49356	0.648165
34	0.754912	0.56577	0.563792	0.572281	0.511881
35	0.601343	0.593593	0.586268	0.52316	0.60293
36	0.569378	0.616648	0.624511	0.644804	0.611712
37	0.708461	0.680551	0.684589	0.685257	0.694321
38	0.780903	0.737594	0.749577	0.767045	0.755235
39	0.761971	0.744162	0.743625	0.691575	0.742361
40	0.751713	0.653608	0.644555	0.595596	0.570018
41	0.719827	0.730913	0.734976	0.73425	0.744074
42	0.851781	0.813649	0.81517	0.82705	0.848306
43	0.786677	0.747256	0.75174	0.716184	0.756628
44	0.684177	0.686505	0.685987	0.674479	0.691072
45	0.719667	0.705692	0.707235	0.645101	0.731737

46	0.713097	0.666204	0.670302	0.596039	0.661387
47	0.631966	0.352021	0.332779	0.386406	0.428759
48	0.653344	0.468387	0.498918	0.542324	0.574345
49	0.696072	0.533863	0.613778	0.692308	0.472417
50	0.610691	0.428212	0.358362	0.412726	0.371874
51	0.68371	0.577238	0.561951	0.59255	0.586963
52	0.491345	0.481124	0.476572	0.483854	0.468674
53	0.764107	0.720893	0.724855	0.711655	0.737197
54	0.547938	0.246341	0.236219	0.307791	0.228886
55	0.60403	0.619815	0.622331	0.639918	0.679706
56	0.522443	0.250638	0.256744	0.23996	0.295081
57	0.747744	0.64966	0.658636	0.67498	0.695819
Median	0.686989	0.627268	0.628426	0.63659	0.648165
Standard deviation	0.137404	0.163968	0.166226	0.159472	0.169546

Model is good if KGE1 value near to 1

➔ Value from WRI is the best.

Table 22. Result of 57 catchment simulated by MSE optimization function and criterion by KGE2

Catchments	KGE2_WRI	KGE2_BS	KGE2_DE1	KGE2_DE2	KGE2_DE3
1	0.774957	0.768083	0.76229	0.751571	0.759936
2	0.778768	0.72437	0.727825	0.713005	0.697477
3	0.768281	0.573766	0.584345	0.626439	0.486342
4	0.571991	0.365889	0.370946	0.406883	0.353373
5	0.57695	0.758059	0.756277	0.769125	0.756825
6	0.577322	0.711019	0.716132	0.667307	0.695296
7	0.687002	0.626295	0.626585	0.60871	0.701333
8	0.529432	0.400806	0.396135	0.436663	0.43847

9	0.531235	0.353591	0.350989	0.356167	0.433327
10	0.715779	0.690589	0.691571	0.711138	0.655724
11	0.727574	0.675638	0.671317	0.683991	0.690336
12	0.712172	0.647818	0.65203	0.583625	0.643914
13	0.737017	0.652228	0.642582	0.632818	0.683587
14	0.556117	0.59005	0.573421	0.643838	0.512776
15	0.673015	0.588894	0.581807	0.594873	0.647293
16	0.720095	0.680519	0.664456	0.588779	0.694499
17	0.595752	0.602866	0.609534	0.60163	0.590056
18	0.609736	0.713618	0.714385	0.695122	0.671908
19	0.65878	0.597033	0.592732	0.578596	0.682512
20	0.434925	0.56593	0.640677	0.476955	0.597071
21	0.641354	0.627015	0.624256	0.657384	0.683048
22	0.261054	0.580974	0.591413	0.548349	0.565335
23	0.809993	0.818908	0.811194	0.826521	0.838393
24	0.756057	0.812475	0.803915	0.816414	0.811767
25	0.747239	0.745143	0.742415	0.700663	0.680698
26	0.692678	0.601371	0.596518	0.63395	0.64591
27	0.555787	0.510326	0.517628	0.548723	0.518589
28	0.480331	0.16179	0.158968	0.181764	-0.03688
29	0.799607	0.803812	0.812742	0.797082	0.776346
30	0.362455	0.426112	0.422298	0.470034	0.458174
31	0.772609	0.768034	0.769846	0.763962	0.761217
32	0.797931	0.832311	0.831804	0.799015	0.802
33	0.735248	0.716791	0.702444	0.624332	0.715751
34	0.76044	0.664212	0.6652	0.662781	0.650129
35	0.67601	0.66362	0.652947	0.621904	0.668581
36	0.69037	0.71465	0.698924	0.719879	0.714248
37	0.735098	0.750468	0.75282	0.744845	0.751106
38	0.775726	0.776813	0.782395	0.78674	0.781788

39	0.781674	0.805762	0.805094	0.778792	0.803812
40	0.747381	0.715445	0.708165	0.702238	0.688169
41	0.721704	0.739837	0.748253	0.7749	0.775125
42	0.848542	0.841271	0.840723	0.835916	0.846366
43	0.786612	0.748284	0.75986	0.72361	0.752771
44	0.695779	0.646367	0.646993	0.659385	0.64211
45	0.72998	0.768566	0.771634	0.719034	0.783847
46	0.644333	0.614408	0.625939	0.552506	0.616602
47	0.631288	0.453651	0.439959	0.494542	0.553412
48	0.653016	0.490062	0.532977	0.617434	0.631554
49	0.693958	0.501306	0.599238	0.694921	0.604261
50	0.61102	0.478085	0.418569	0.446366	0.393163
51	0.663131	0.580636	0.57387	0.627951	0.660118
52	0.487069	0.52384	0.511524	0.50373	0.558689
53	0.76502	0.784494	0.786258	0.786353	0.794497
54	0.558847	0.36774	0.361458	0.416381	0.336449
55	0.580857	0.654162	0.658092	0.678899	0.701222
56	0.53009	0.315944	0.324165	0.325715	0.312065
57	0.747617	0.521163	0.535269	0.585604	0.592832
Median	0.692678	0.652228	0.65203	0.643838	0.671908
Standard deviation	0.117371	0.147487	0.147261	0.136602	0.156727

Model is good if KGE2 value near to 1

➔ Value from WRI is the best.