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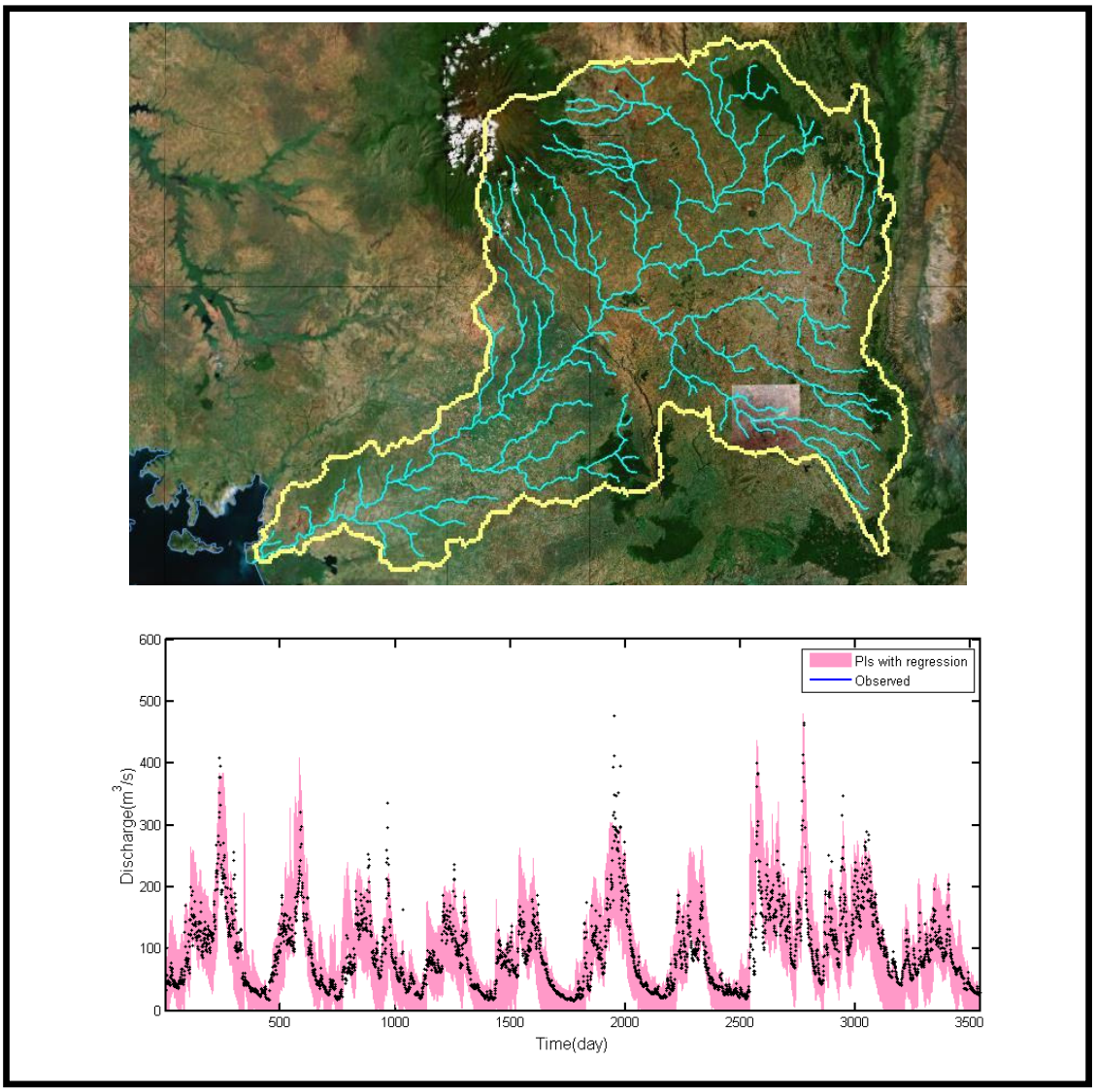

UNCERTAINTY ANALYSIS OF HYDROLOGICAL MODELS: NZOIA RIVER CASE STUDY

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Master of Science Thesis

by

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Abstract

Engineering decision making could range from simple problems to selecting the site for a major dam. In the same time, hydrological models became essential tool in every hydrological study or decision support system. These models by definition are simplifications of reality. Nevertheless, in most of the cases models' parameters and input data cannot be obtained directly and accurately enough in the field. Therefore, uncertainty analysis becomes unavoidable in any hydrological models.

The aim of this study was to explore different calibration and uncertainty analysis methods of hydrologic models. And develop necessary codes to link standard modeling software with external calibration and uncertainty systems. And apply new uncertainty analysis tool based on novel method to estimate the uncertainty using machine learning techniques. Finally, compare performances of these calibration and uncertainty analysis techniques on selected case study.

The procedures plan through this study starts by building a distributed hydrological model of the Nzoia River in Kenya on SWAT software. Then, calibration process starts which include apply many calibration systems and link them with SWAT. After that the uncertainty analysis of that model will be applied using different methods. Last step should be comparing the applied methods and these results.

Acknowledgements

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1 Introduction

Decision makers in water sectors depend a lot on hydrological models. So the more we are certain in our hydrological models' results the more we make good decisions. However, most of hydrological models available today focus on models construction and calibration but the efforts that directed to uncertainty analysis are very limited. Therefore, the research question of this study is "How far we are certain in our hydrological models results?" Therefore, this study compares different uncertainty analysis techniques and applies a novel technique in uncertainty analysis.

This thesis consists of seven chapters. The first chapter is a brief overview to some important definitions; also it contains the research objectives and methodology of the work. Then the second chapter is a literature review to different calibration and uncertainty analysis techniques. After that in chapter three, there are some descriptions for hydrological modeling software and different optimization and uncertainty analysis tools. The model setup comes in fourth chapter; in this chapter detailed description for the available data and steps to build the case study model. The applications of calibration methods are described in fifth chapter. While analyzing the uncertainty results are in chapter six. Conclusions and recommendations came in chapter eight. After that, there are two appendices, the first one is a manual describing how to link external analysis codes with watershed modeling tool. Appendix 2 contains Matlab codes, which used through the thesis.

1.1 Background on hydrological models

Hydrological models became essential tool in every hydrological study nowadays. These models by definition are simplifications of reality and it provides a clear understand to the complex real situations because any hydrological system whatever it is small, is very complicated with the objective of explanation or prediction, see (Figure 1-1). Nevertheless, in most of the cases models parameters cannot be obtained directly in the watershed. Therefore, parameters assumption is necessary and it becomes impossible to have a model free of errors.

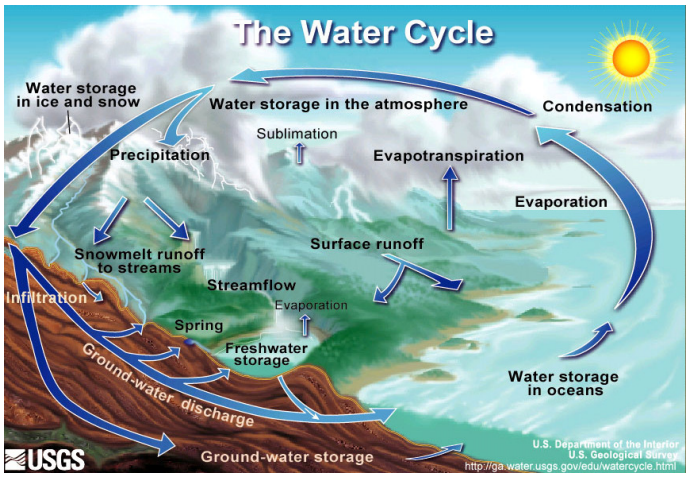


Figure 1-1 The water cucle

Modeling includes studying the system, formulating its behavior, collecting and preparing data, building the model, testing it, using it, interpreting the results, and, possibly, iterating the entire procedure. It is very important when applying models to keep in mind that there is no perfect hydrological model which we could expect output as the same as the natural. Therefore, in the hydrological modeling progresses the modelers are looking for appropriate models. This means the development or selection of a model with a degree of sophistication that reflects the actual needs for modeling results. It means a parameter parsimonious model with a discrimination in space and time that ensures a realistic simulation or prediction of the requested variables.

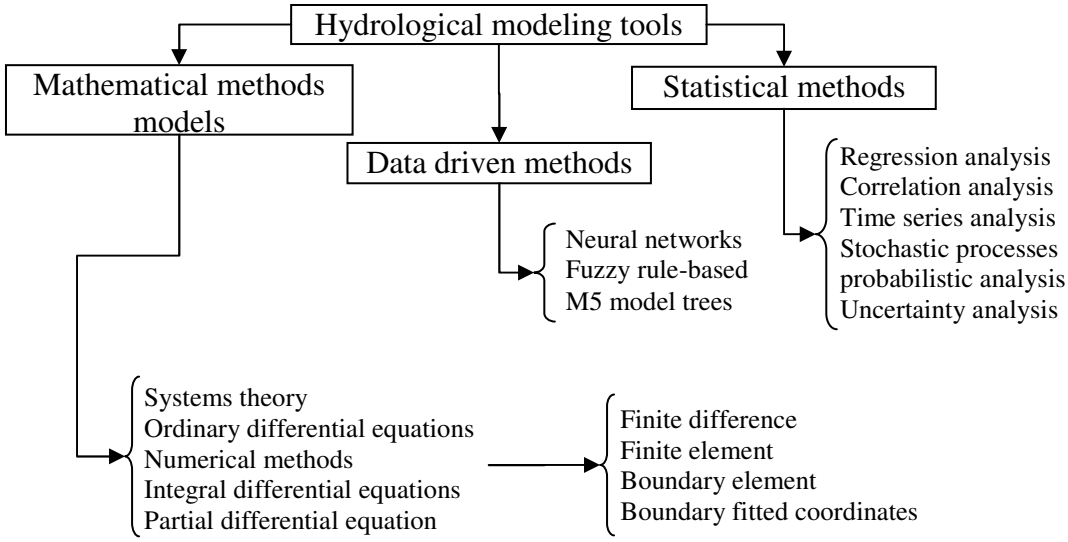


Figure 1-2 Hydrological models classification

There is a variety of classification methods of the hydrological models. One classification divides the hydrological models into lumped models and distributed models. Where lumped models (easy, fast and few data needed) deal with a catchment as a single unit without any consideration of the spatial patterns of the processes and characteristics within the catchment while the distributed models (difficult, slow and many data needed) attempt to take account of the spatial patterns of hydrological response within a catchment area. Another classification divides the models into deterministic and stochastic models. Where the deterministic models are these models, which take input sequence, produce a single prediction of all its output variables. Figure 1-3 displays hydrological model classifications (Beven, 2005).

Deterministic hydrological models occupy majority of model applications in hydrology until now. More attention should direct to the stochastic models that represents the model inputs in probability. This principle allows study uncertainty in the inputs or parameterizations or outputs, such that a given input sequence will produce an uncertain prediction of the output variables. Even though the uncertainties associated with such predictions are now widely appreciated, while another

classification method based on processes described based on physical laws (physically based models) conversely collected data approach (data-driven models).

1.1.1 Knowledge-driven modeling

Knowledge-driven modeling or physically-based modeling approach is based on our understanding (knowledge) of the physical behavior of the hydrological processes which control watershed response and use physically based equations to describe these processes. SWAT, HSPF, MIKE-SHE, AGNPS etc. are examples of Knowledge-driven modeling(Abbott and Refsgaard, 1996). SWAT will be described in details in section 3.1.

1.1.2 Data-driven modeling (DDM)

In contrast to Knowledge-driven modeling, Data-driven approaches needs limited knowledge of the physical characteristics of the watershed hydrological processes. It based on mathematical equations assessed not from our understanding of the physical process basin but from analysis of relationship between input and output discharges, the simplest example is linear regression analysis. There are many benefits of using data-driven models like, it allow for solving numerical prediction problems, reconstructing highly nonlinear functions, performing classification, grouping of data and building rule-based systems. Therefore, during the last decade the data-driven models became more and more common(Solomatine and Ostfeld, 2008).

In (Solomatine, 2002) he mentioned that machine learning is the main source of methods of data driven models. In fact machine learning is a subarea of Artificial intelligence (AI). (AI) is both the intelligence of machines and the branch of computer science which aims to write computer programs that can solve problems creatively; " hopefully to imitate intelligence of human brain".

1.1.2.1 Machine learning

Machine learning means giving computers ability to understand or to learn. It can be also defined as an area of artificial intelligence concerned with the study of computer algorithms that improve automatically through experience.

Due to data driven models usually applied when there is no clean understandable relation between (system input and output). Machine learning uses the available data to discover the dependency between these input/outputs. Then it will be able to predict the future systems outputs from known input data (Solomatine, 2002)

Learning process could be classification, clustering, regression and association methods. This process tries to minimize the difference between system observed data and its simulations.

1.1.2.2 Artificial neural networks (ANNs)

ANN is a very common application of machine learning to model complex hydrological watersheds. It is becoming more and more popular in the water resources community. ANN can be defined as a mathematical structure that identifies nonlinear

relationships between input and output model variables. The traditional way of implementing a neural network is to train it on measured input and output data for the system under studying, and then verified the ANN in terms of its ability to reproduce another set of data for the same system (Lobbrecht, et al., 2005).

ANN consists of a large number of measured data (samples) that are called neurons. These artificial neurons are devices which can receive many inputs and produce one output. The neuron in the training modem, it can be trained to fire (or not), for particular input patterns. While in testing mode, when a taught input pattern is detected at the input, its associated output becomes the current output. If the input sample does not belong to any of the trained inputs, ANN should follow some procedure to decide to fire or not (Price, et al., 1998).

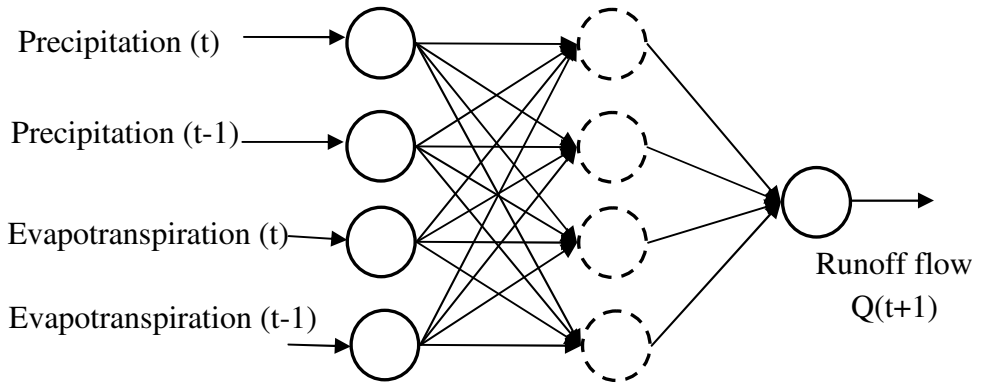


Figure 1-3 Simple example of ANN

1.2 Background on uncertainty of hydrological models

Decision support systems are used extensively in water management. Since the decision is made under uncertainty, it is also necessary to taking uncertainty of hydrological models into account.

The uncertainty in hydrological models may come from simplifications in the conceptual model. Processes occur in the watershed but not included in the model (wind erosion). Processes that are included in the model but their occurrences in the watershed are unknown to the modeler or unaccountable like irrigation systems. Process not known to the modeler and not included in the model either like constructions of roads. Errors in the input variables like rainfall and temperature or errors in the very measurements we use to calibrate the model.

Uncertainty analysis methods can be classified according to different approaches. One of the most important classifications is according to the reason of uncertainty. For example if it caused by inherently random (stochastic) behavior, the uncertainty called aleatoric uncertainty and this type is described with the stochastic models. On the

other side, if the uncertainty is a result by a lack of knowledge then it referred as epistemic uncertainty, which include fuzziness and intervals.

Well uncertainty analysis provides many benefits like; It is more honest to express the degree of certitude in hydrological models output. It enables to set risk-based criteria for flood warnings and emergency response. It provides the necessary information for making rational decisions, which enables the users to take risk explicitly into account. It provides additional economic benefits because of the forecasts to every rational decision maker and thereby to society as a whole. It helps decision-makers to use their own judgment more appropriately for decision making through the information that regarded by uncertainty (for example the confidence intervals, the probability of exceedance of certain levels, etc.)(Blasone and Rosbjerg).

1.3 Research questions

1. How can we asses the uncertainty of hydrological models?
2. How applicable are the known uncertainty methods in hydrological modeling?
3. How do these methods compare?

1.4 Research objectives

1. Understand different techniques for sensitivity and uncertainty analysis, of hydrological models and their calubration.
2. Identify and analyze uncertainty through of a model using different techniques including a novel method based on machine learning (UNEEC)
3. Develop necessary computer codes to link uncertainty analysis tools with a distributed hydrological model and to validate them by application to real-world problems.
4. Compare the performances of uncertainty analysis techniques in the case study at Nzoia River.

1.5 Methodology

Througt this study many software used for modelling or the uncertainty analysis or even to link the different used software. First of all, ArcGis used for catchment characteristics discovering, mapping and preseniting. Soil and Water Assessment Tool (SWAT) used for Nzoia catchment modelling. Matlab and mocrosoft excel also esed in data discribtive statistics and model results analysis.

The research methodology will follow the following major steps to achieve the objectives of the research:

1. Reviewing of literature
2. Build distributed hydrological model (SWAT)
3. develop necessary codes to link the case study model with external calibration and uncertainty systems

4. Sensitivity analysis for model parameters
5. Model calibration with different techniques
6. Model validation
7. Apply different uncertainly analysis techniques
8. Compare and analysis the results from the applied calibration and uncertainty analysis techniques
9. Apply new non-parametric methods UNEEC (Uncertainty Estimation based on local Errors and Clustering) for total uncertainty analysis
10. Reporting writing.

2 Model calibration and uncertainty analysis techniques

Parameters that used in hydrological models are not measurable in the field in most of the cases. Therefore, parameters estimation is essential step in almost every hydrological model. Process of adjusting the model parameters estimation to match the model behavior to the observed behavior of the watershed is called model calibration. Getting more experience in hydrological model calibration is main objective of this study as mentioned in Research objectives. Therefore, different calibration techniques studied in this thesis and applied on the case study. In the next paragraphs, there are brief descriptions to objective functions.

2.1 Introduction

Aim of calibration process is to find the model parameters values that minimize the difference between model and the reality. Therefore, researchers developed based on statistical equations some different statistical regression and model fitting techniques to measure how the simulated outputs fit the observed data. These equations are called objective function. Moreover, it has different values according to the selected set of parameters. Figure 2-2displays surfaces describe the objective function in parameter space, which is called “response surface”. Therefore, parameter optimization could be defined as the process of searching within response surface inside the allowable parameter ranges to achieve the minimum or maximum -as appropriate- objective function value(Singh and Frevert, 2002).

Figure 2-2 shows response surface complexity increasing when function's complexity raise from one variable (A) into two variables (B). Therefore, selecting calibration technique depends on the complexity of model, which depends on number of parameters to be optimized. Optimizing response surface that have single minima/maxima are much easier than those surfaces that have multi minima/maxima.

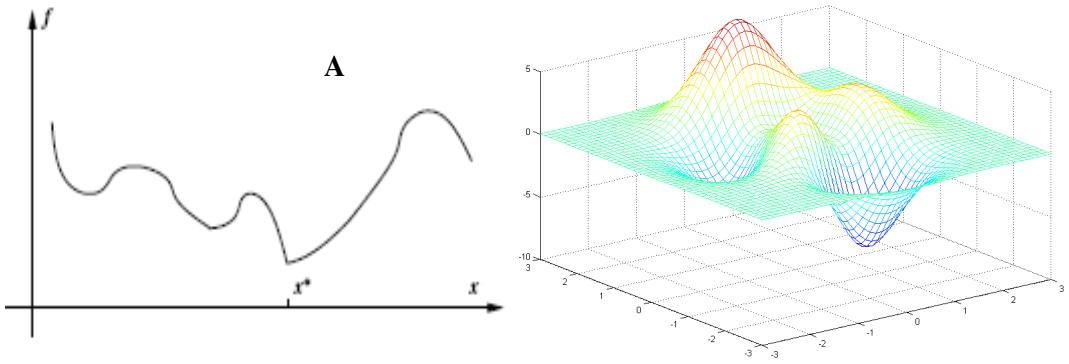


Figure 2-1 Single & Multi objective functions

In addition, rainfall runoff models may have ten parameters (response surface of ten dimensions) which give an idea of how the calibration process become very complicated with distributed hydrological models.

Optimization methods have three main classes (McCuen and Snyder, 1986). First class is the analytical optimization techniques, this type utilizing analytical calculus to derive parameters values. It provides direct solutions and gives exact solution if exist but it is practical only in case of simple models. The Second technique is the numerical optimization, which evaluate the parameters numerically as by using finite difference scheme. This type is more suitable in models that are more complex and adding parameters ranges constrains is quite easy. However, it needs a considerable number of iteration so it is considered time-consuming technique furthermore, the answers are usually not exact and it is necessary to estimate initial values for the parameters. Third one is subjective optimization techniques. This type is a trial and error process that depends mainly on the user experience. In addition, it is most often used with very complex models that involve many unknown.

2.2 Sensitivity analysis

Sensitivity analysis means a method to determine how the hydrological models outcomes are sensitive to its parameters. Furthermore, most of hydrological models now a day became very complex and over parameterised. Therefore, the sensitivity analysis is essential in most of hydrological models. In regards to reduce the number of parameters that calibrated and hence it reduces a lot the modelling time.

2.2.1 Manual sampling

It is the most simple sensitivity analysis method. It starts to change parameters values and check the effect on the model results. Then mark the parameters that cause significant changes to the total results with small variation in its values are sensitive. This method is applicable for the simple models that have few parameters like simple lumped models. But the sensitivity analysis processes become too complex to done manually. Because of that, there are now many automatic techniques impeded in the hydrological models packages to do study the hydrological models. In fact, those techniques uses the same idea by running the model several times with different sets of parameters values then the program calculates the degree of final results changing. Then the analysis sorts the used parameters according to that sensitivity.

2.2.2 Latin hypercube sampling

The statistical method of Latin hypercube sampling (LHS) was developed to generate sets of model parameter values with specific distribution. And it is often applied in uncertainty analysis. Figure 2-7 is an example of two parameters Latin square and it shows LHS principle which starts by determine each parameter domain and divide it into reasonable number then generate only one sample in each row and each column (van Griensven, 2005).

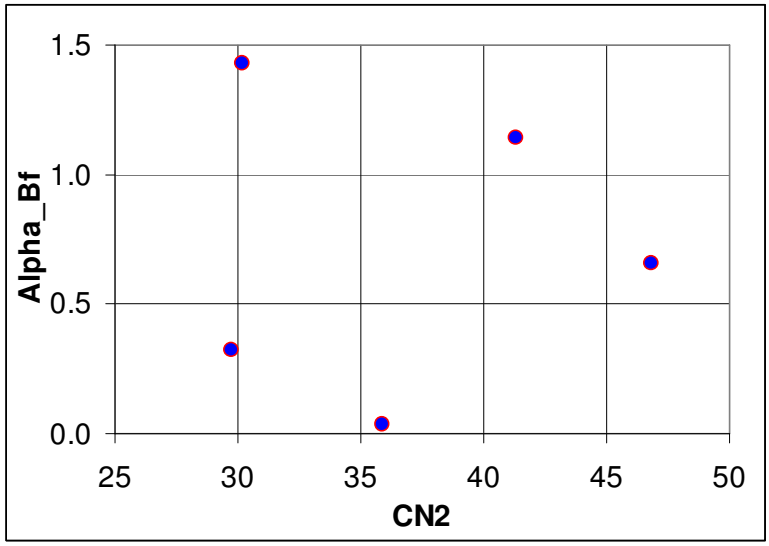


Figure 2-2 Latin square

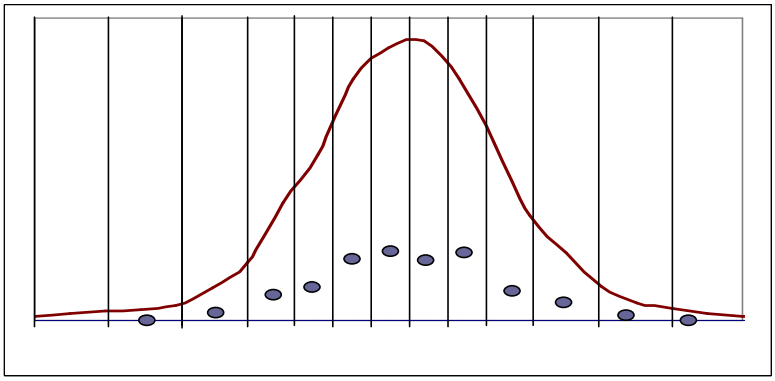


Figure 2-3 Latin hypercube sampling intervals in case of parameters values that follow normal probability distribution

2.2.3 One factor at a time algorithm

The sensitivity analysis method that implemented in SWAT depends on joining Latin hypercube sampling with One-factor-At-a-Time approach to form what known by (LH-OAT). LH sampling depends on the principals of Mont Carlo (MC) sampling but it eliminates the most deficit thing in MC by stratifying the parameters ranges into a reasonable number of sub-ranges. That allows efficient and full parameters representing without need to big number of runs as MC. that is because the statistical origin of LH depends on Latin square, which is a square grids that contains one and only one sample in each row and each column.

The LH technique main steps could be summarizing as the following. First, we assume the probabilistic distribution for studied parameters and its expected range of values. Then we stratified this range into N sub ranges with equal probability of occurrence (1/N) where N equals to the number of analysis runs. In figure 17, for example, the parameter probabilistic distribution assumed as normal distribution and it stratified into 12-sub range. Therefore, when the program will run to analysis model sensitivity to each parameter it will run 12 times with different generated values for

this parameter. The second part of (LH-OAT) technique is the One-factor-At-a-Time sampling approach. When this approach makes samples it changes only one parameter each time, so it gains information about one parameter in each run. Therefore, the model sensitivity to different parameters can unambiguously attribute to the input parameter changes. However, this method has disadvantage that it is not easy to study the interaction parameters. The two techniques (LH & OAT) are joining by taking the LH samples as initial values to QAT sampling technique.

In Table 2-1, there is an example to how OAT technique works. It starts by assuming initial values for all the parameters – from LH – and calculate the model response according to these values. Then it starts to change all the parameter values one each time – as in row 2 it only changed cn2 value - and calculate the model response according to each trial. In each trial, it compares the model response with the one that got from the previous trial. If the model response or the objective function developed after a change that means it was a right step and the model is sensitive to this parameter.

Table 2-1 OAT explanation example

Trial	**Sample parameters**				**Model**
	CN2	**sol_alb**	**gwqmn**	**Sol_k**	**output**
1	A1	B1	C1	D1	50
2	A2	B1	C1	D1	80
3	A2	B2	C1	D1	60
4	A2	B1	C2	D1	70
5	A2	B1	C1	D2	90
Most sensitive parameters are (CN2 and Sol _k)					

2.3 Objective functions and goodness of fit estimation

Objective function is a function that measures how model output fits with the observed flow data. Goodness-of-fit statistics studies these functions; it also provides some measures of the agreement between a set of sample observations and the corresponding values predicted from some model of interest. Some of these equations are listed in the following table.

Where in all previous equations:

Q_{obs} observed flow time series

Q_{sim} simulated flow time series

N number of flow data in the time series

Table 2-2 Some common objective functions

Objective function	**Method Equation**	**notes**
Mean square error (MSE)	$\frac{1}{n}\sum_{1}^{n}(Q_{obs}-Q_{sim})^2$	Zero means perfect model
Root mean square error (RMSE)	$\sqrt{\frac{1}{n}\sum_{1}^{n}(Q_{obs}-Q_{sim})^2}$	Zero means perfect model
mean absolute error (MAE)	$\frac{1}{n}\sum_{1}^{n}\lvert Q_{obs}-Q_{sim}\rvert$	Zero means perfect model
Sum of the squares of the residuals (SSQ)	$\sum_{1}^{n}(Q_{obs}-Q_{sim})^2$	The smaller is, the better.
sum of the squares of the residuals after ranking (SSQR)	$\sum_{1}^{n}(Q_{obs}-Q_{sim})^2$	the time of occurrence of observation of simulation is not accounted
Correlation Coefficient (r)	$\frac{\sum Q_{obs}\cdot Q_{sim}-n\overline{Q}_{obs}\cdot\overline{Q}_{sim}}{\sqrt{\sum {Q_{obs}}^2-n\overline{Q}_{obs}^{\,2}}\sqrt{\sum Q_{sim}^2-n\overline{Q}_{sim}^{\,2}}}$	R indicates the degree of linear relationship between observed and simulated flow. It lies between -1 and +1. +1 indicates perfect linear relationship
Coefficient of determination (r2)	$\left(\frac{\sum Q_{obs}\cdot Q_{sim}-n\overline{Q}_{obs}\cdot\overline{Q}_{sim}}{\sqrt{\sum {Q_{obs}}^2-n\overline{Q}_{obs}^{\,2}}\sqrt{\sum Q_{sim}^2-n\overline{Q}_{sim}^{\,2}}}\right)^2$	it is simply the square of the correlation coefficient, r.

The selected objective functions in modeling software used in this study are, Sum of the squares of the residuals (SSQ) and the sum of the squares of the difference of the measured and simulated values after ranking (SSQR).

to measure the goodness-of-fit between observed and simulated stream discharge, SWAT uses the Nash-Sutcliffe coefficient(Nash and Sutcliffe, 1970). The following equation summarize this method

$$E = 1 - \frac{\sum_{t=1}^{T} \left(Q_o^t - Q_m^t\right)^2}{\sum_{t=1}^{T} \left(Q_o^t - \overline{Q}_o\right)^2} \qquad \text{Equation 2-1}$$

Where

Q_o^t Observed discharge at time t

Q_m^t Modeled discharge at time t, *and*

$\overline{Q}_o$ Average observed discharge.

Nash-Sutcliffe efficiencies E ranges from -∞ to one, E=one corresponds to a perfect match of modeled discharge to the observed data. An efficiency of zero (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.

2.4 Searching methods

Model calibration is typically a form of optimization searching process. It starts by assuming an initial set pf variables and calculate its corresponding objective function value. Then repeat this processes many times after changing parameters values assumption tell get the most proper parameter value. Optimization strategies are distinguished based on its way of changing parameter values from iteration to the next.

Model optimization is to search within the allowed ranges of parameters values in order to determine the best solution. Best solution is the parameters combination that optimizes the selected objective function. Optimization searching strategy is changing according to model level of complexity. These strategies are classified into local search methods and global search methods. The following paragraphs have some detailed information about these methods.

2.4.1 Local search method

Local search methods are used for unimodal functions (functions that have only one maximum or minimum within allowable parameters ranges). The searching process starts by initial guess of a set of parameters and calculate the corresponding objective

function to stand at an initial on the response surface. Then change parameters values slightly to move on the response surface from point to its neighbor. Then, repeat these searching steps tell find a set of parameters that produce optimum value in the response surface.

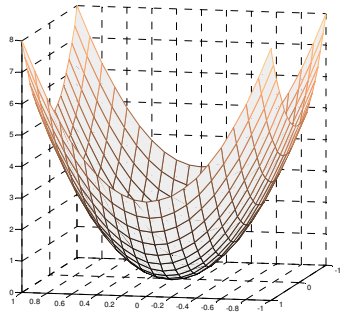


Figure 2-4

The main questions while moving on the response surface are a) which direction should we move. b) How far should move in that direction. c) How to decide that no more better points on the response surface .based on answers of these questions strategies, local search methods can be classified. Direct search methods and gradient search methods are the main classes of local search optimization. The difference between these two methods that the first one takes decision based on objective function values only while the second method uses both of objective function values and gradient.

2.4.1.1 Direct search methods

The general strategy of direct search methods is to start at initial point and calculate the objective function values at different direction and step sizes, then selesct one which has best optimization then repeat it tell achieve point where searching process will not be able to find better points any more.

Examples of direct search methods are the Nelder-Mead Simplex method, Hooke and Jeeves' pattern search, the box method, and Dennis and Torczon's parallel direct search algorithm. In next section, there is a description to the first method (simplex method) where it is the theoretical base of Parasol technique, which implemented in SWAT and applied in this thesis.

2.4.1.1.1 Simplex method

Simplex method also called Nelder-Mead method or downhill simplex method. It uses only function values, without calculate the derivatives. Simplex is the geometrical figure that consists of N+1 vertices in N dimensions. For example, in one dimension simplex is line, in two dimensions it is a triangle and in three dimensions simplex is a tetrahedron.

First step in this method is to calculate function values at random **(N+1)** points or vertex. Then it identifies vertices, and ranks them according to its objective function values. Next step is to calculate simplex centroid after excluding the worst vertex. After that, it moves the worst vertex to the opposite side through simplex centoid, the distance between old vertex point and the reflected point may be equally on both sides of centroid , expanded or even shrinkage, shows some of these alternatives, where at vertex (W) the worst function value. R = reflection, E = expansion, C+ = positive contraction and C- = negative contraction (Figure 2-6).

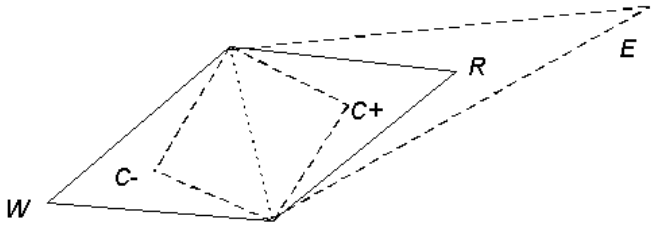
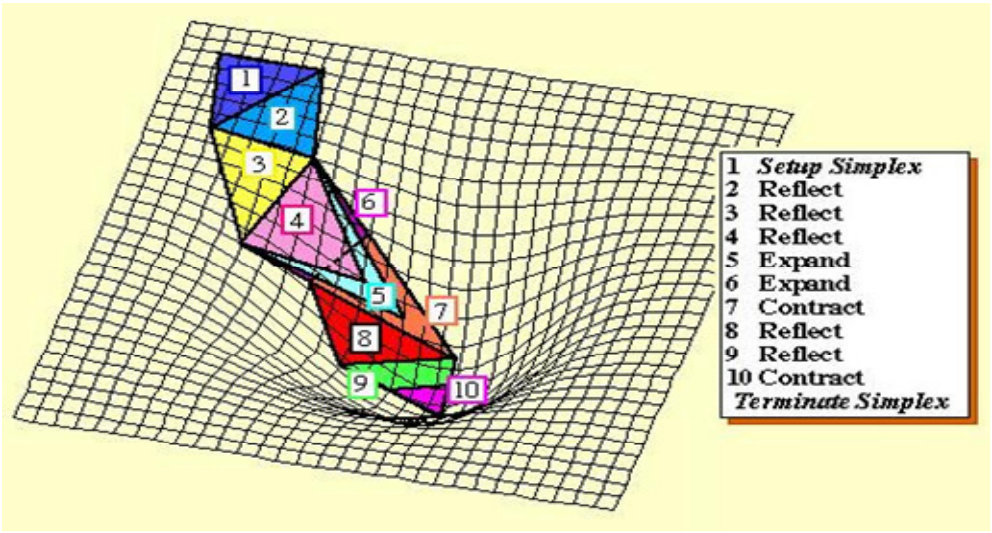


Figure 2-5 Worst vertex movements options in simplex method

Furthermore (Figure 2-7) shows a method for finding the optimum values of 3-D function, where a 2-D simplex proceeds by reflection, contraction, expansion or shrinking along the surface. Calculating how much the function developed each iteration determine when iterations should be stopped. (Gershenfeld, 1999)



2.4.1.2 Gradient search methods

Gradient search methods don't use only function values but it also use function gradients to find the optimal direction of search.. Steepest descent, continuous descent, Newton raphson and polack ribiere are all types of gradient search methods. The next equation is the base of most gradient methods.

$$\Theta_{I+1} = \Theta_I - \rho \cdot \mathrm{A} \cdot \nabla\Theta_I \qquad \text{Equation 2-2}$$

Where

Θ_{I+1} Initial parameter vector
Θ_I New parameter vector
ρ Step size parameter
A Square matrix
$\nabla\Theta_I$ Function gradient matrix

2.4.2 Global search methods

Global optimization methods are those algorithms, which tries to optimize multi-modal functions. These optimization methods are classified into deterministic and probabilistic approaches; In addition, there is a combination of them. The first approach is used when there is a clear relation between model parameters and model output, which is very rare case in real problems, therefore, most of the applicable methods are stochastic or a combination of deterministic and stochastic methods.

(Solomatine, 1995) grouped the global optimization methods into five groups, first one contains the space covering techniques; second contains the random search methods; third group is for the multistart methods which based on multiple local searches; genetic algorithms are the fourth group; all the other methods are considered in the fifth group.

2.4.2.1 Space covering technique

The search space is divided into number of subsets and the objective function is evaluated in each sunset. Then the parameter value which corresponding to the best objective function will be selected. in case of use the previously selected parameters values and its corresponding objective functions values to choose the next parameter value the algorithm is called a sequential covering algorithm (Solomatine, 1995).

2.4.2.2 Random search methods

(Solomatine, 1995) mentioned three searching subgroups under random search techniques. These are pure random search methods, adaptive random search and controlled random search.

The pure random search (also called Monte Carlo search) is the simplest stochastic global optimization method. It generates model parameters sets assuming it have uniform distribution and calculates its objective functions, after net a stopping criteria it assumes the best objective function as the global optimum value. The main disadvantage of pure random search is that it needs large number of function evaluations; this number also grows exponentially with number of parameter increase. so, it was improved to use the known objective function values into consideration which gives parameters generation a sequential manner, this developed method called (adaptive random search) (Solomatine, et al., 1999).

2.4.2.3 Multistart local search methods

These methods came from develop the pure random search methods. It uses each generated point as a start point of a local optimization procedure. Then it applies local search procedure several times. The best found points of local search are most probable to have the global optimizer.

Multistart searching is repetition of two main steps tell achieving a stopping criterion. The first step is to generate a random points within a given accepted parameter ranges then use these points as a start points for local search process. After achieving the stopping criterion, the best local search is taken as a global optimum. Multistart is also

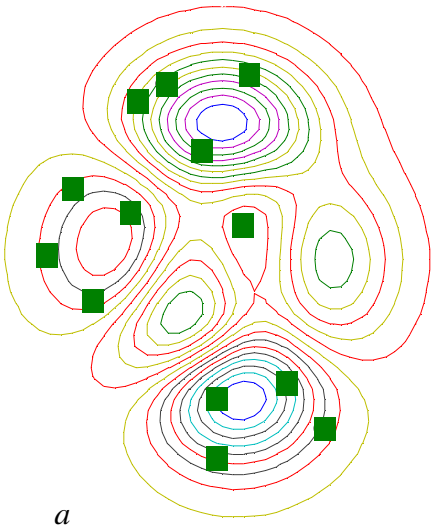
not efficient where many start points can lead to the same local optimum. (Arora, 2004)

2.4.2.4 The shuffled complex evolution algorithm (SCE-UA)

It is a global optimization method based on the use of multiple simplexes. SCE-UA developed originally as part of a doctoral dissertation in University of Arizona (Duan). SCE-UA is as an effective, robust, flexible and efficient algorithm because (a) it is a combination of deterministic and probabilistic approaches. (b) It evolutes model parameters values in direction of global optimization. (c) It is a Competitive evolution algorithm. (d) It shuffled the complexes(Singh, 1995).

SCE-UA uses two methods to select good simulations. First method is $\chi 2$ statistics, it looks for model simulations that make objective functions lies around the optimum value within selected confidence interval. Bayesian statistics is the second method, which defines high probability regions.

First step of SCE-UA, after user define parameters probability distributions or assume it uniform, is to sample points randomly within the parameter space and compute the function value or criterion at each point. Second step, is to sort sampled points according to criterion value from best to worst. Third step is partitioning into complexes, if user wants to have N complexes, ranked data should partition into N parts and each complex should has points from every part to be a mix of good/bad points as the work idea of simplex method. Fourth step is to evolve each complex independently to get the best points in each complex. Fifth step is to shuffle the complexes, in order to get the global optimum and to eliminate falling into local optimum it remix the complexes by shuffling some points from each complex to the others. Last step is to check if the searching process satisfied the convergence criteria, if not, a new random population will be generated and SCE-UA will repeat the whole steps (Duan, et al., 1992).



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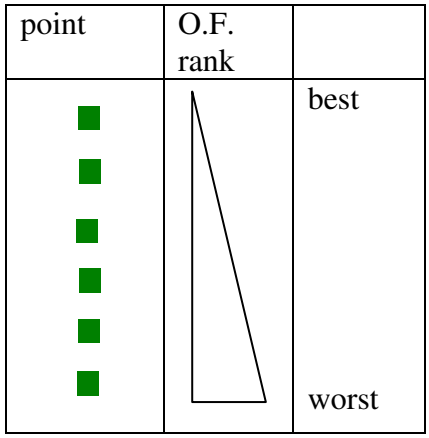

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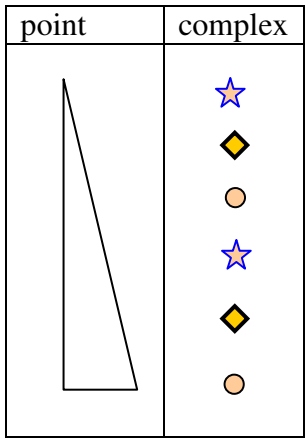

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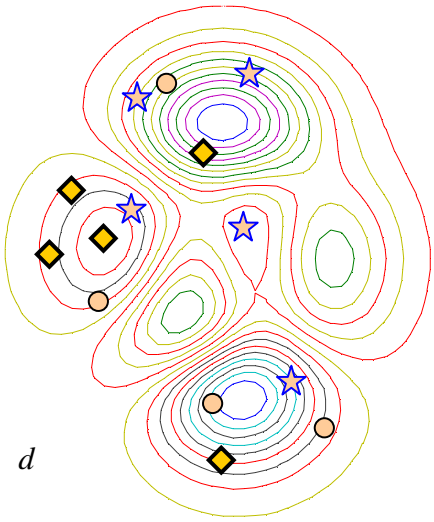

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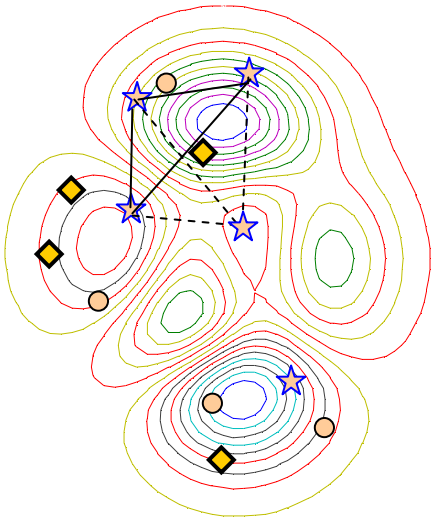

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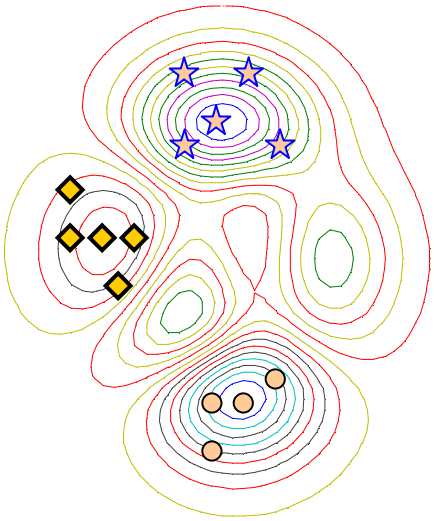

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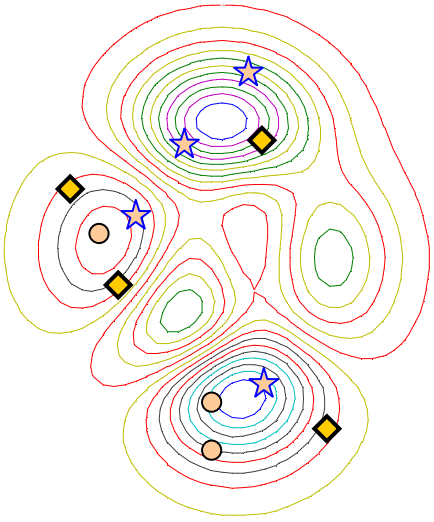

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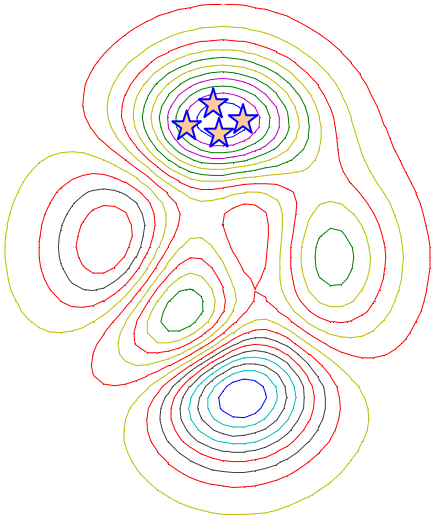


h

Figure 2-7

2.5 Calibration techniques

For real case studies calibration should done using global searching algorithms. Four global searching algorithms will discuss in the following sections in addition to quick look at manual calibration. The well-calibrated model has similar overall water balance as the observed flow. In addition, it should have similar shape of the hydrograph, peak flows and low flows. In addition, model prediction should have low uncertainty and negligible bias.

2.5.1 Manual calibration

For the manual calibration, it is very difficult in this case because the model as a SWAT models has over three hundreds of parameters and the watershed subdivided into 164 hydrological response units.

2.5.2 Parameter solution (PARASOL)

PARASOL is an acronym for (Parameter Solutions method), it is a model calibration and uncertainty analysis method. It is a multi-objective calibration based on adapting the shuffled complex evolution algorithm SCE-UA (described in section 2.4.2.4) for multi-objectives problems and for large number of parameters; it minimizes the global optimization criterion (described in section 2.3.2.32.5.2.1below). PARASOL starts by model calibration then it uses the behavioral simulations for uncertainty analysis.

2.5.2.1 Multi-objective optimization

Most realistic optimization problems, particularly distributed hydrological models, which may need to optimize water discharge, sediment transport, nutrient and pesticide movement. Therefore, it requires simultaneously optimization of more than one objective function. Therefore, instead of using SSQ's or SSQR's (section 0) SWAT utilizes a method based on the Bayesian theory, which assumes normal distribution of the residuals. It combines several SSQ's or SSQR's into Global Optimization Criterion (GOC). In this method, the sum of the squares of the residuals gets weights that are equal to the number of observations divided by the minimum. The following equation explain this method.

$$GOC = \sum_{i=1}^{n} \frac{SSQ_i * nobs_i}{SSQ_{i,\min}}$$

Equation 2 5

Where:

SSQ_i the sum of the squares of the residuals for optimized object i.

$nobs_i$ the number of observations for optimized object i.

$SSQ_{i,MIN}$ the sum of the squares at the optimum for optimized object i.

The probability of given parameter set to be the optimum solution is related to the GOC according to Equation 2-6

$$P(\theta \mid Y_{obs}) \propto \exp[-GOC]$$

Equation 2 6

2.5.3 Adaptive cluster covering (ACCO)

ACCO approach clusters a set of points into subregions with reduction of samples. It applies clustering only once, and then it covers the subregions. ACCO strategy is based on four principles Clustering, Covering shrinking subdomains, Adaptation, Periodic randomization (Solomatine, 1999). These four principles are described here.

2.5.3.1 Principals of ACCO strategy

- Clustering

Clustering is a process of dividing big group of things into groups (clusters); each one contains things which have similar characteristics and different than other cluster. For hydrological models calibration, after generating sets of parameters randomly or with any distribution and calculate its corresponding objective function values, clustering is used to split parameters population points into regions according to its fit with observed flow. So, ACCO can identify the most promise parameter values to make more searching around it which saves too much time. These promised cluster will considered as subdomains for more global optimization.

- Covering

Covering is to cover the clusters with generated sets of points and calculate the objective function values at these points to determine its characteristics. The covering type could be randomly or have grids shape. ACCO uses the pure random approach. Covering procedure will repeated many times in the clusters that are progressively reduced in size.

- Adaptation

Adaptation procedures shifts and shrink the search subregions, also it changes the number of points of each covering. This process updates its algorithmic behavior based on new information came with model running.

- Periodic randomization

Due to generating parameters in probabilistically there is a possibility to miss the global optimum, so, ACCO re-randomize the initial populations to solve the problem several times or use re-randomization at intermediate steps.

2.5.3.2 Strategy of ACCO

In this section, the main steps of optimization using ACCO are described for two parameters (CN2 and ALPHA_BF) calibration model.

First step is the initial sampling, it generates randomly with uniform distribution an initial population of N points from the practical parameters ranges. In the second step, the objective function values at each point of the population is calculated, after identify the best values the number of population will be reduces, so, this step called (initial reduction). Third step (initial clustering) is an application to "clustering principle"; it splits the population into number of clusters, and keeps dimensions of these clusters. Fourth step, for each cluster, it generates more points inside cluster

under studying, evaluate the objective function at every point then it removes the worst points, these processes what we called before "Covering ". After covering, there is population adaptation, where ACCO identifies the center of attraction of the cluster (it could be the best point) then it shifts the whole cluster so its center coincide with the center of attraction. Next step tries to reduce the size of the region by use smaller cluster dimensions surrounding the same center of attraction. All these steps should be repeated many times for each cluster tell meet stopping criteria.

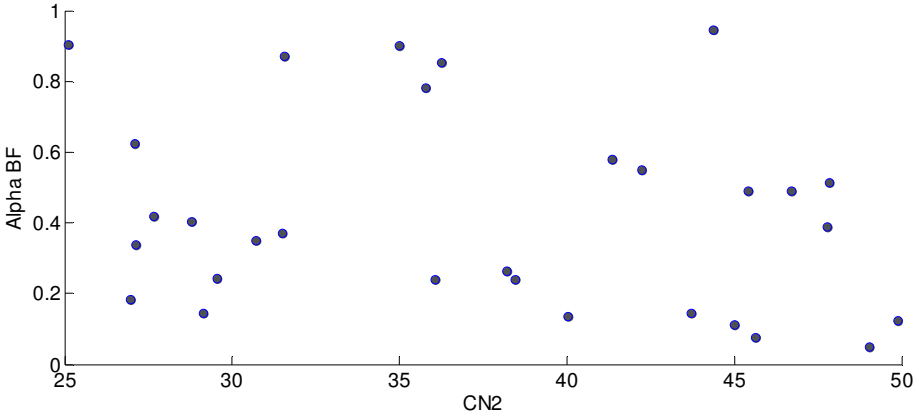


Figure 2-8

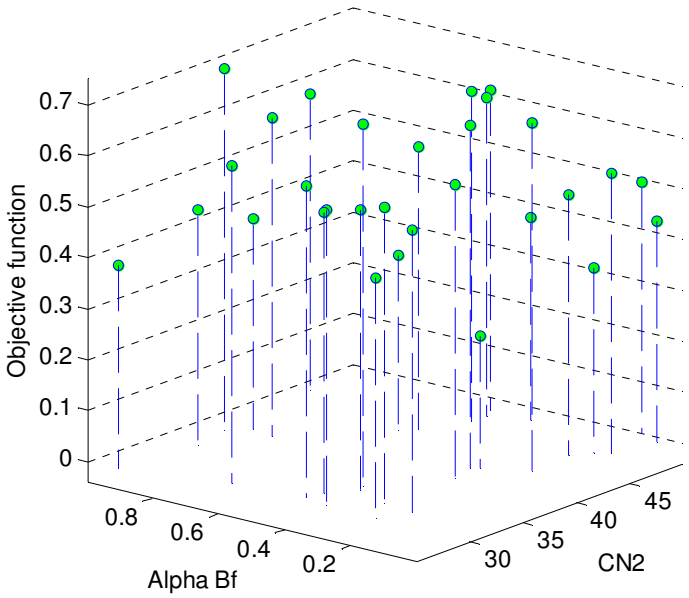


Figure 2-9

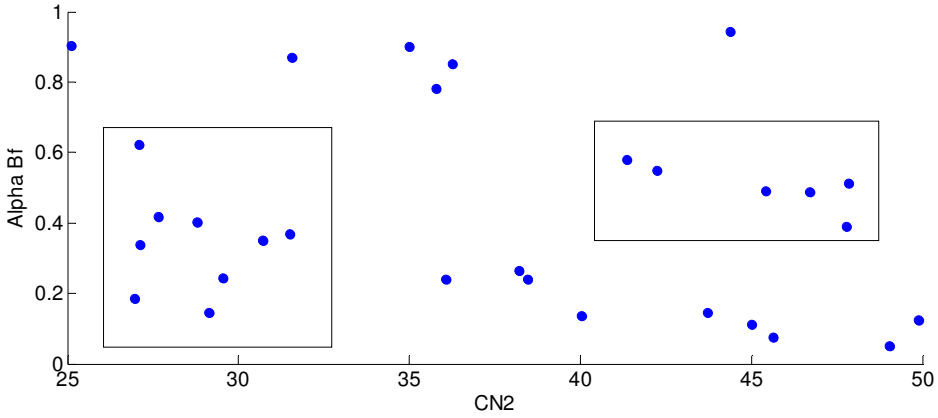


Figure 2-12

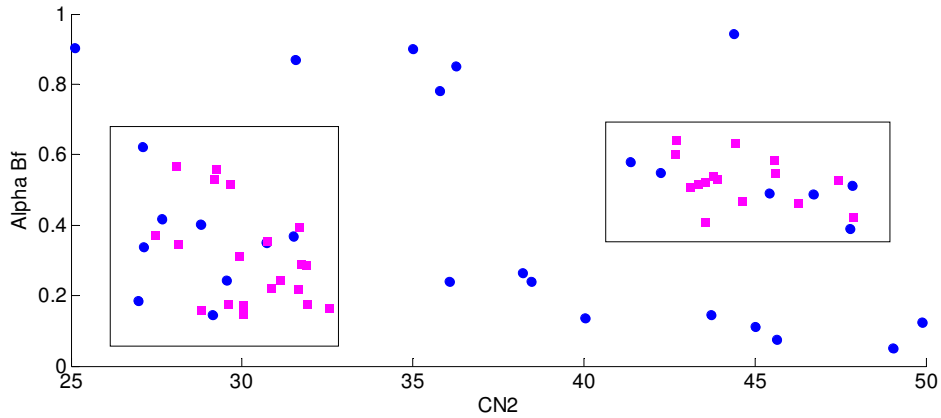


Figure 2-10

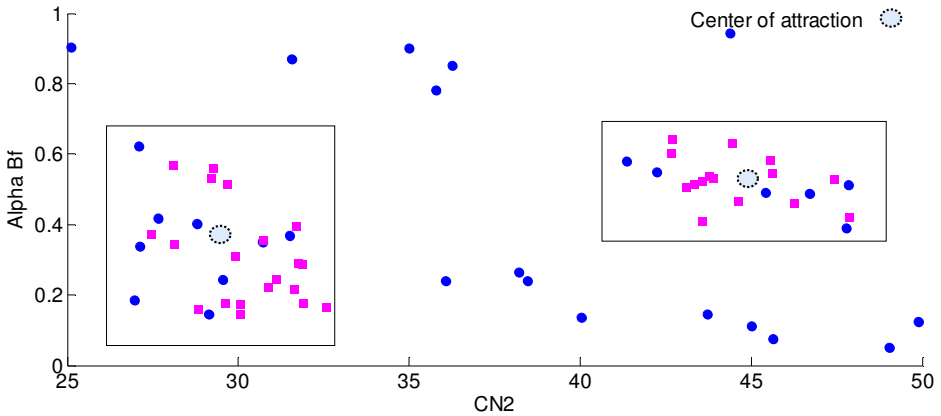


Figure 2-11

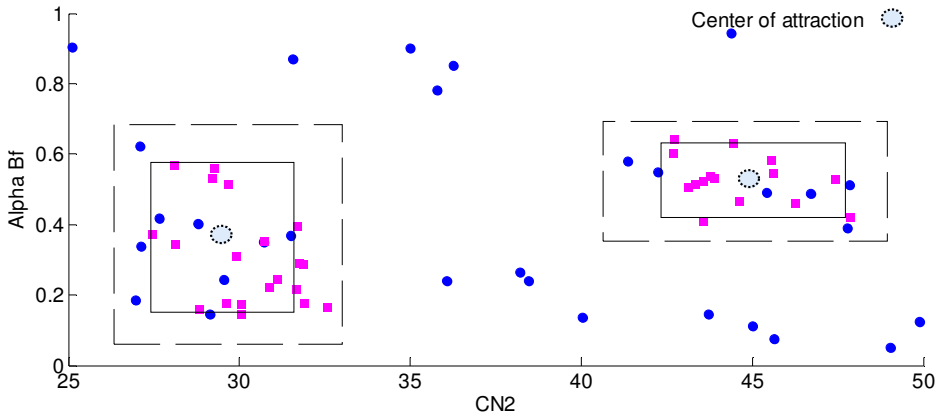


Figure 2-13

2.5.4 Adaptive cluster covering with local search (ACCOL)

ACCOL have are two phases: in the first one it applies ACCO to find several regions of attraction within parameters space. For the second phase (local search) it uses the points that generated from the ACCO phase and apply Powell-Brent search to find accurately the minimum.

2.5.5 Genetic algorithm (GA)

This algorithm became one of the most successful optimisation techniques that apply in hydrological models which based on fuzzy-logic and artificial neural networks. it tries to emulate a biological process that each child is a copy of its parents plus a variation. so, GA try to use the generated set of parameters of each model run (parents) to generate a new set of parameter (child)(Kamp and Savenije, 2006).

(Holland, 1975)wrote that GA is based on the principle of the survival of the fittest which tries to retain genetic information from generation to generation. furthermore he mentioned that the major advantages of GA algorithms are their broad applicability, flexibility and their ability to find optimal or near optimal solutions with relatively modest computational requirements(Gupta, et al., 1999).

Genetic algorithm starts by generate a random population from parameters to be calibrated, and calculate the objective function values according to these parameters guess. Secondly, select a group of the population which have better objective function values, these selected population points (parents) will have more probability to generate next generation (childs). Third step called crossover, it is a process of exchange information between selected population points to generate new childs. Mutation is the fourth step; it is used to randomly change the value of single point within the population. Selection, crossover and mutation should be repeated tell elapse predefined number or met a stopping criterion.

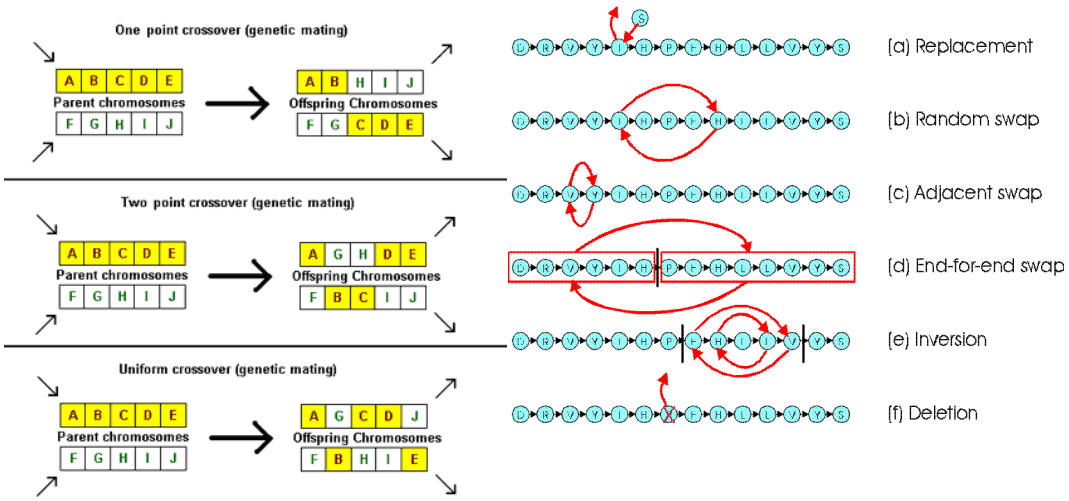


Figure 2-14 Crossoverand mutation of parameters

2.5.6 M-simplex calibration algorithm

M-simplex is one of the multistart local search methods (see section 2.4.2.3). So, it consists mainly of three steps. Firs one is to generate a set of random points and evaluate the objective function at each of these points. Second step called reduction; it reduces the initial set by choosing some points which have lowest value of objective function. Last step is the local search; it launches the local search procedures starting from each of the selected points. In M-simplex, local search process depends on the downhill simplex method (see section 2.4.1.1.1). The global optimum point is the best point results from local search.

2.6 Conditions of good calibration

Well-calibrated model should have (a) water balance close to measured one (b) simulated hydrograph shape similar to observed hydrograph (c) similarity with observed peak flows with respect to timing, rate and volume (d) similarity with observed low flows.

(Madsen, 2000) presents the following four equations to test if model achieved these goals. The first equation tests the condition (a) by measuring the overall volume error. Second one tests the shape of the simulated hydrograph. Third equation is a test of model goodness of fit with the peaks flow events. Last equation tests model goodness of fit with low flow events.

$$F(\theta) = \left[\frac{\sum_{i=1}^{N} w_i \left[Q_{obs,j} - Q_{sim,j}(\theta) \right]}{\sum_{i=1}^{N} w_i} \right] \qquad \text{Equation 2-3}$$

$$F(\theta)=\left[\frac{\sum_{i=1}^{N} w_i^2\left[Q_{obs,j}-Q_{sim,j}(\theta)\right]^2}{\sum_{i=1}^{N} w_i^2}\right]^{\frac{1}{2}}$$ Equation 2-4

$$F(\theta)=\frac{1}{M_p}\sum_{j=1}^{M_p}\left[\frac{\sum_{i=1}^{n_j} w_i^2\left[Q_{obs,j}-Q_{sim,j}(\theta)\right]^2}{\sum_{i=1}^{n_j} w_i^2}\right]^{\frac{1}{2}}$$ Equation 2-5

$$F(\theta)=\frac{1}{M_1}\sum_{j=1}^{M_1}\left[\frac{\sum_{i=1}^{n_j} w_i^2\left[Q_{obs,j}-Q_{sim,j}(\theta)\right]^2}{\sum_{i=1}^{n_j} w_i^2}\right]^{\frac{1}{2}}$$ Equation 2-6

Where:

Qobs,i	the observed discharge at time i,
Qsim,i	the simulated discharge,
N	the total number of time steps in the calibration period,
Mp	the number of peak flow events,
Ml	the number of low flow events,
nj	the number of time steps in peak/low flow event no. j,
u	the set of model parameters to be calibrated, and
wi	a weighting function. Peak flow events are defined as periods where the observed discharge is above a given threshold level.

2.7 Uncertainty analysis techniques

With increasing of interest of analysis the uncertainty in watersheds hydrological models many methods have been developed to estimate model uncertainty. Choice between these methods is according to the level of models complexity. In (Shrestha and Solomatine, 2008) these methods was classified into six main classes. Analytical methods, approximation methods, sampling based methods, Bayesian methods, and methods based on analysis of the model errors.

The next section is a brief explaining to the uncertainty analysis classifications. After that, there are some descriptions to some common methods to estimate uncertainty in hydrological models, most of these methods applied on a case study.

2.7.1 Classifications of Uncertainty analysis methods

Analytical methods compute probability distribution function of model outputs. And, it is applicable for simple models where the propagation of uncertainty through

the model is straightforward. Although of its easiness, its applicability is limited to models with linear summation of independent inputs.

Approximation methods provide only the moments of the distribution of the uncertainty output variable. Some of approximation based methods depend on the use of the Taylor series expansions for propagate the uncertainty through model. Furthermore, the main advantage of approximation methods, that it is enough to propagate the moments of each probability distribution of the model inputs instead of the entire probability distributions. On the other side, the main disadvantages of these methods are, firstly, it cannot be applied to problems with discrete or discontinuous behaviors because the model function should be differentiable. Secondly, it is computationally intensive as they typically require the evaluation of second order (may be higher) derivatives of the model. Thirdly, although these techniques are capable of propagating central moment of input distributions, information regarding the tails of the input distributions cannot be propagated.

Sampling based methods are the most common techniques to study the propagation of uncertainty. These methods involve running a set of model simulations at a set of sampled points from probability distributions of inputs and establishing a relationship between inputs and outputs using the model results. There are two types of sampling, the first one is simple random sampling that depends on the entire population and second is stratified random samples, which separate the population elements into non-overlapping groups called strata.

Furthermore Sampling based methods involve complex and nonlinear model and capable of solving a great verity of problems. do not require access to the model equations. Monte Carlo Methods and Latin Hypercube Sampling methods are the most common sampling based uncertainty analysis methods.

Bayesian methods utilize Bayes' theorem to estimate or update the probability distribution function of the parameters of the model and consequently estimate the uncertainty of model results. Generalized likelihood uncertainty estimation (GLUE) is based on Bayesian methods; it will be discussed in section (2.7.6).

Methods based on analysis of the model errors; its idea is to analyses model residuals that occurred in reproducing the observed historical data. UNEEC uncertainty analysis methods which described in details in section (2.7.9) and applied in section 6.4.

2.7.2 Measuring Uncertainty

Two methods to measure the uncertainty amount are used in this study. The first one is percentage of points that fall between upper and lower prediction interval. And the second one is the average width of uncertainty region between those two prediction interval boundaries.

First of all the prediction interval is different than the confidence interval, the first expresses the accuracy of model with respect to observed value. But confidence interval measures the accuracy of our estimate of the true regression. In real problems,

the prediction interval is more practical. If we need to have 90% predictive uncertainty, we have to calculate 5% and 95% quantiles of probability distributions of all possible flows values at each time step. After calculating upper and lower prediction limits, account number of flow observations that fall between those two limits, The higher this percentage the higher certain model, Figure 2-15.

On the other hand, the mean width of the prediction interval expresses the rapidity of searching tool to become close to the optimum value.

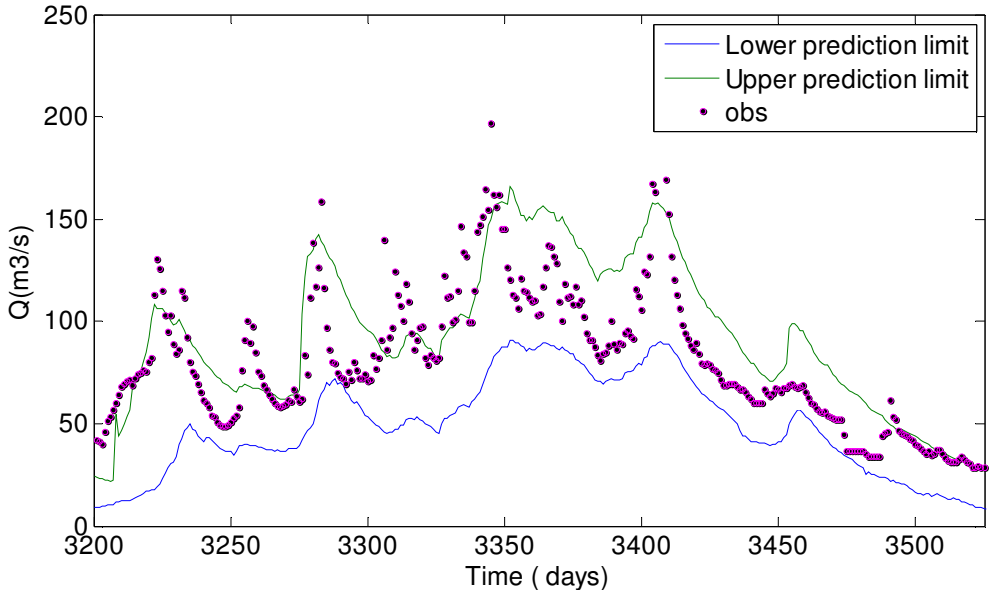


Figure 2-15

2.7.3 The probability theory description

It is the most complete description and the best understood method to solve uncertainty problems. The chief five approaches in probability theory are described briefly here. The classical approach assumes in case of finite number of independent outcomes the probability of an event is the proportion of occur this event to the total possible outcomes. The frequency approach used in case of an experiment that can be repeated under essentially identical conditions but the observed outcomes is random. The Propensity interpretation applied in cases of long recorded events repeated under essentially identical conditions that are difficult to release in practice. The Subjective approach measures our belief in probability of an event to occur. The Logical approach used when the outcomes are not independent and there is some implication between them so it uses the conditional probability as the degree of logical approximations. However, in most practical problems such a probability function cannot derive or found precisely.

2.7.4 PARASOL

Parasol is an optimization and uncertainty analysis it is based on (SCE_UA) as explained in section 2.4.2.4.

For uncertainty analysis, ParaSol divides the outputs of SCE-UA optimization method into ‘good’ simulations and ‘not good’ simulations. This process could be done using two separation techniques. The first method based on $\chi 2$-statistics to delineate the confidence regions around the optimum. The second method uses Bayesian statistics to define high probability regions.

2.7.5 Monte Carlo technique description

The most known sampling method is the Monte Carlo technique. The idea behind this method is to generate repeatedly a large number of realizations of model parameters according to (subjective) probability distributions and uncertainty bounds for each parameter. But to come up with these (subjective) probability distributions and uncertainty bounds, one must apply professional judgment after extensively reviewing the available literature and data. The Monte Carlo errors decreases as the sample size increases, but increase in computational time, which is not practical in many cases. There is Variance reduction techniques aim at obtaining high precision for MCS results without having to substantially increase the sample size. Among them Simple Random Sampling (SRS), generalized likelihood uncertainty estimation (GLUE), Latin hypercube sampling (LHS), and Monte Carlo Markov chain MCMC are widely used.

In SRS, Simple random sampling is the basic sampling technique. Each individual is chosen entirely by chance and each member of the population has an equal chance of being included in the sample. In standard LHS, the distribution for each parameter is divided into sections of equal probability; where the number of sections equals the number of samples or iterations to be made in the Monte Carlo simulation. During the sampling, the random numbers are selected by chance within each section, but only one random number is chosen from each section; then once a random number has been selected from a section, that section is excluded from the rest of the analysis.

The Monte Carlo application steps schematization is explained in Figure 2-17 and Figure 2-18 Now the model can be start running by sampling a group of parameters and try to give weight to each one. Repeat the previous steps many times then we will have a matrix of outputs according to the different values of input data and the generated parameters. When this matrix drawn it will form a region of expected output values through the whole inputs and parameters values.

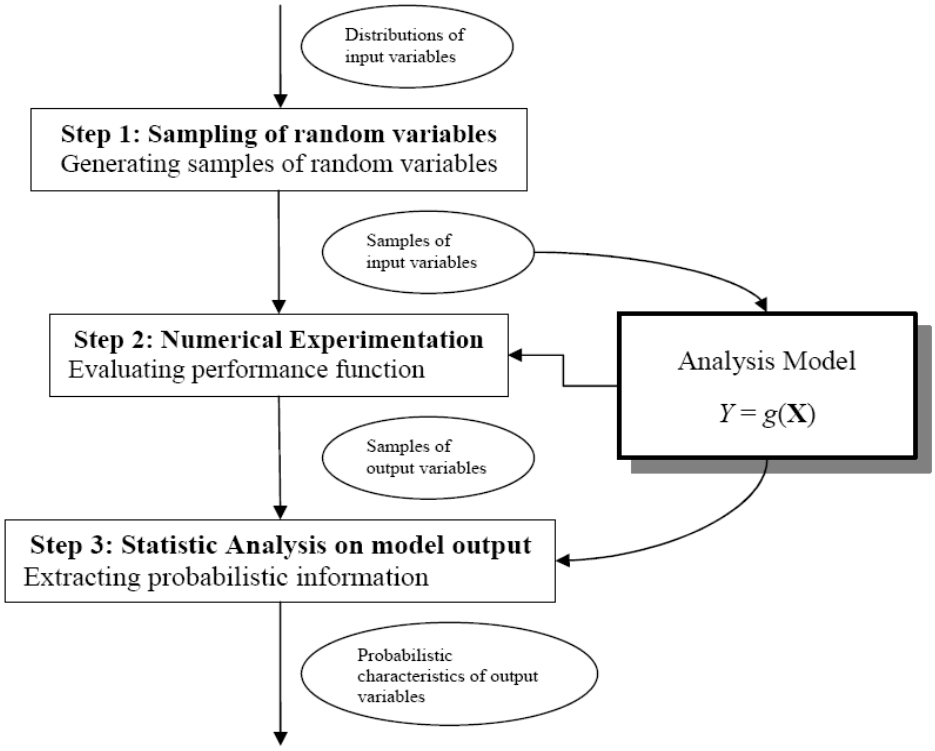


Figure 2-16 Monte Carlo main steps

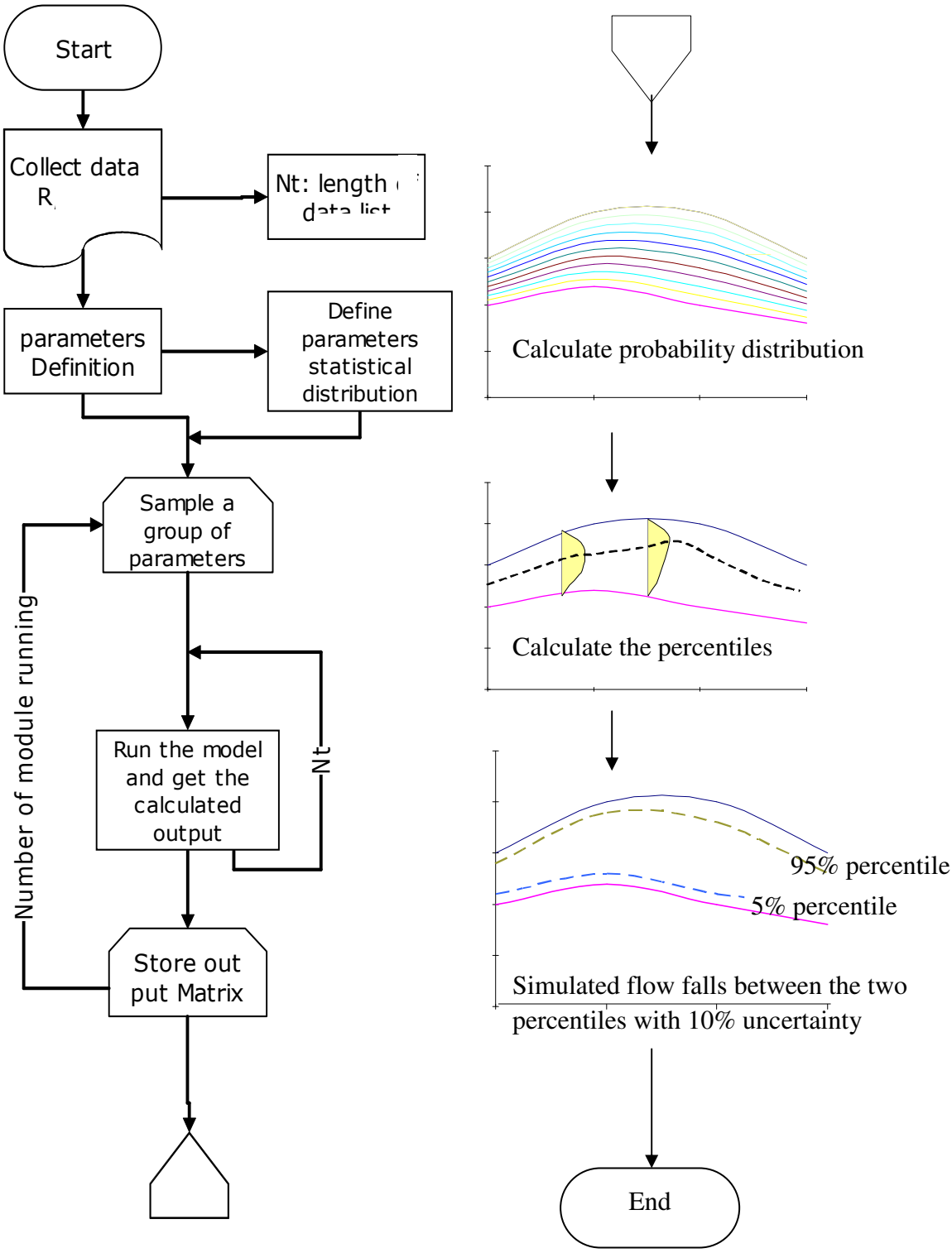

Start
Collect data
R
Nt: length
parameters
Definition
Define
parameters
statistical
distribution
Sample a
group of
parameters
Run the model
and get the
calculated
output
Nt
Number of module running
Store out
put Matrix
Calculate probability distribution
Calculate the percentiles
95% percentile
5% percentile
Simulated flow falls between the two
percentiles with 10% uncertainty
End

Figure 2-17

2.7.6 Generalized likelihood uncertainty estimation (GLUE)

The fourth technique that will discuss here is the Generalized Likelihood Uncertainty Estimation (GLUE). This method developed by (Beven and Binley, 1992) as a general strategy for model calibration and uncertainty estimation in such complex models. It became one of the most widely used methods for simultaneous calibration and uncertainty estimation in the water resources and environmental modeling. But the main drawback of this technique is the huge number required of model simulations(Blasone, et al., 2006).

Due to it is not possible to estimate that any particular set of parameter values will represent a true paradigm, GLUE measure of how well the model conforms to the observed flows by assessment the likelihood of parameter sets, where likelihood is the probability of achieve an observed flow given a set of parameters, then it assigns a likelihood weight for each parameters sets.

GLUE generates a combination of flow hydrographs given generated sets of parameters values. Then it chooses the set of parameters that gives the best fit with the observed data and estimates the uncertainty bounds around the optimum solution.

It runs models with a large number of Monte Carlo procedure simulations with different parameter sets, sampled from proposed (prior) distributions, and inferring the outputs and parameter (posterior) distributions based on the set of simulations showing the closest fit to the observations.

A GLUE analysis consists of the following three steps:

1. select a function to represent the model goodness of fit with the observations.
2. A large number of parameter sets are randomly sampled from the prior distribution and each parameter set is assessed as either “behavioral” or “non-behavioral” through a comparison of the “likelihood measure” with the given threshold value.

2) Each behavioral parameter is given a “likelihood weight” according to: where N is the number of behavioral parameter sets.

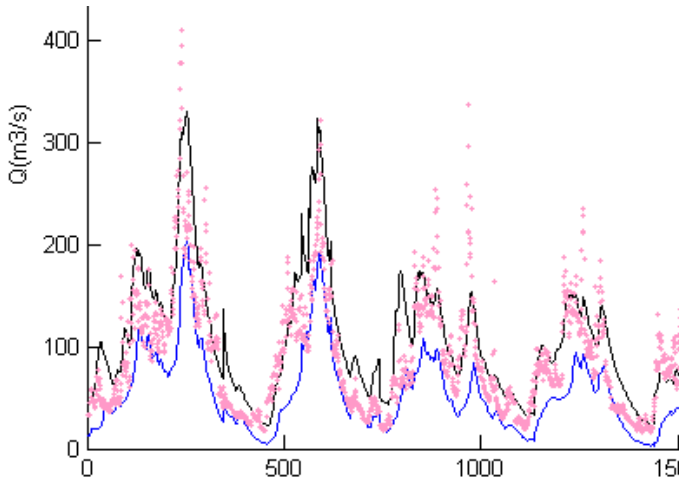
$$w_i = \frac{L(\theta_i)}{\sum_{k=1}^{N} L(\theta_k)}$$

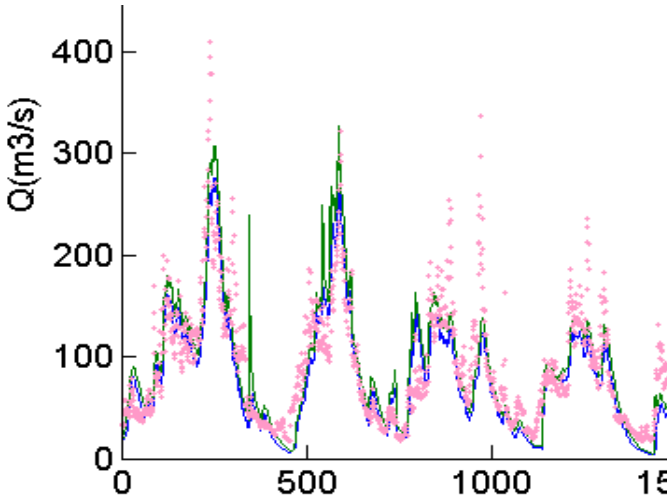
3) Finally, the prediction uncertainty is described as prediction quantile from the cumulative distribution realized from the weighted behavioral parameter sets.

In literature, the most frequently used likelihood measure for GLUE is the Nash-Sutcliffe coefficient (NS), which is also used in the GLUE06 program:

Where n is the number of the observed data points, and yti and yti (.) represents the observation and model simulation with parameter at time ti, respectively, and y is the average value of the bservations.

$$NS = 1 - \frac{\sum_{t_i=1}^{n} (y_{t_i}^{M}(\boldsymbol{\theta}) - y_{t_i})^2}{\sum_{t_i=1}^{n} (y_{t_i} - \bar{y})^2}$$





2.7.7 Sequential Uncertainty Fitting (SUFI-2)

Sequential uncertainty fitting procedure (SUFI-2) is a stochastic procedure; it performs calibration and uncertainty analysis. Parameter uncertainty is expressed as ranges and is sampled using a Latin Hypercube procedure. Two factors quantify the goodness of calibration and uncertainty analysis. The first one is the P-factor, quantified the percentage of data captured by the 95% prediction uncertainty (95PPU), and the other one is the R-factor, which quantifies the average thickness of the 95PPU.it is good to notice that the ideal values for p-factor and d-factor are 1 and 0, respectively. However, this is usually unattainable. But reasonable values are more likely to be around p-factor > 70% and d-factor < 1.2.

We do the SUFI2 analysis by being sure that "most" of the measured data is "respected" or "bracketed" by the 95% prediction uncertainty (95PPU). The percentage of the measured data that is bracketed by the 95PPU as well as the thickness of the 95PPU quantifies the strength of the calibration. In SUFI-2, parameter uncertainty accounts for all sources of uncertainties such as uncertainty in driving variables (e.g., rainfall), conceptual model, parameters, and measured data. The degree to which all uncertainties are accounted for is quantified by a measure referred to as the P-factor, which is the percentage of measured data bracketed by the 95% prediction uncertainty (95PPU). The 95PPU is calculated at the 2.5% and 97.5% levels of the cumulative distribution of an output variable obtained through Latin hypercube sampling. Breaking down the total uncertainty into its various components is of some interest, but quite difficult to do, and as far as the authors are aware, no reliable procedure yet exists.

Another measure quantifying the strength of a calibration/uncertainty analysis is the so called R-factor, which is the average thickness of the 95PPU band divided by the standard deviation of the measured data SUFI-2, hence seeks to bracket most of the measured data with the smallest possible R-factor. SUFI-2 starts by assuming a large parameter uncertainty (within a physically meaningful range), so that the measured data initially falls within the 95PPU, then decreases this uncertainty in steps while monitoring the P-factor and the R-factor. In each step, previous parameter ranges are updated by calculating the sensitivity matrix (equivalent to Jacobean), and equivalent of a Hessian matrix, followed by the calculation of covariance matrix, 95% confidence intervals of the parameters, and correlation matrix. Parameters are then updated in such a way that the new ranges are always smaller than the previous ranges, and are centered on the best simulation. The goodness of fit and the degree to which the calibrated model accounts for the uncertainties are assessed by the above two measures. An ideal situation would lead to a Pfactor of about 100% and an R-factor near zero. When acceptable values of R-factor and P-factor are reached, then the parameter uncertainties are the desired parameter ranges. Further goodness of fit can be quantified by the R2 and/or Nash-Sutcliffe (NS) coefficient between the observations and the final best simulation.

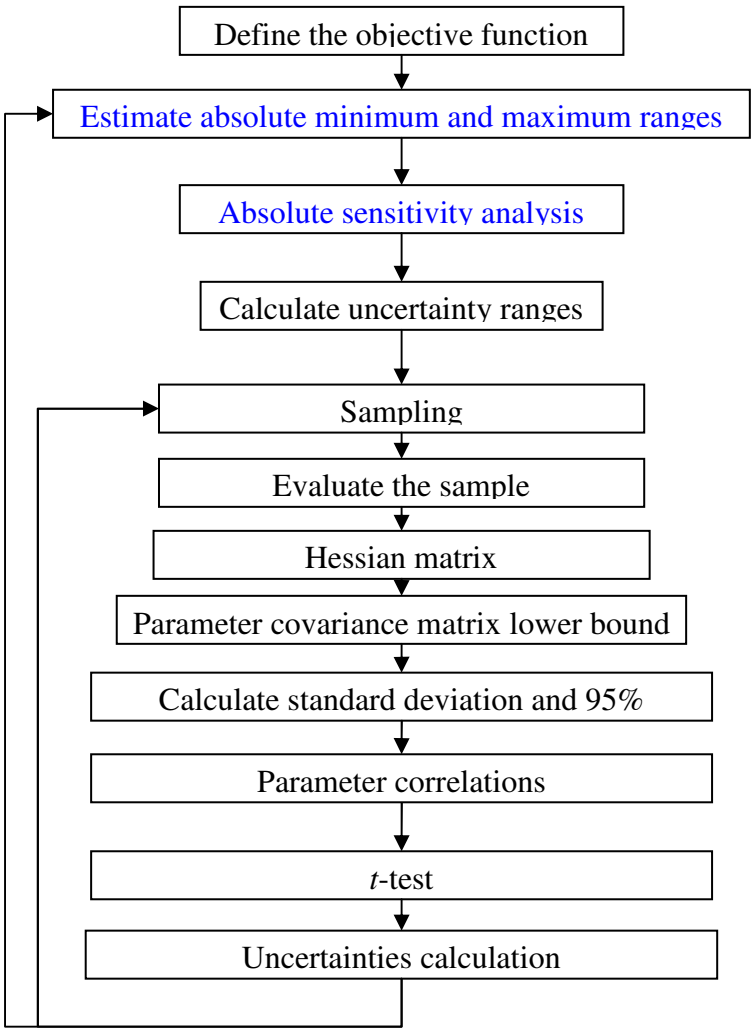


Figure 2-18 Schematic presentation of SUFI-2 uncertainty analysis routine main steps

2.7.8 First-order second moment (FOSM)

The first-order second moment (FOSM) method is one of the uncertainty assessment methods that are based on probability theory. Owing to its simplicity, the FOSM method is one of the most widely used techniques in civil engineering applications for uncertainty assessment. This method uses a linearization of the function that relates the input variables and parameters to the output variables. It takes its name from the fact that it uses the first-order terms of the Taylor series expansion about the mean value of each input variable and requires up to the second moments of the uncertain variables (Maskey, 2004).

In the following paragraph, there is a general idea about this method. The mean (also called the first moment) and variance (or second moment) information on the probability density function of studied variables is needed. In many cases the available information is limited to the mean and variance of X. Furthermore, even if the probability density function is known, the computation of the integrals of the mean and variance may be time consuming. The FOSM method provides faster

approximations that allow approximate values of the mean and variance to be computed.

For example, consider a function of several random $X_1,...,X_n$.

$Y = y(X_1,...,X_n)$

Expanding the function in a Taylor series about the mean values $\overline{X}_1,...,\overline{X}_n$ yields the following expressions

$$E(Y) = y(\overline{X}_1,...,\overline{X}_n)$$ Equation 2-7

Equation 2-8

$$\text{var(Y)} = \text{E}\left[\left(\sum_{i=1}^{n}\left(X_i - \overline{X}_i\right)\frac{\partial y}{\partial X_i}\right)^2\right]$$

$$= \sum_{\text{i=1}}^{\text{n}}\left(\frac{\partial y}{\partial X_i}\right)^2 \text{var}\left(X_i\right) + 2\sum_{i=1}^{n-1}\sum_{j=i+1}^{n}\left(\frac{\partial y}{\partial X_i}\right)\left(\frac{\partial y}{\partial X_j}\right)\text{cov}\left(X_i, X_j\right)$$

$$\text{cov}\left(X_i, X_j\right) \equiv E\left[\left(X_i - \overline{X}_i\right)\left(X_j - \overline{X}_j\right)\right]$$

Where *Cov* (X_i, X_j) is the covariance between X_i and X_j, defined as

All derivatives are evaluated at the mean values $\overline{X}_i$, The quantity $\frac{\partial y}{\partial X_i}$ is called the sensitivity of *Y* to the input variable X_i. The first term on the right-hand side of Equation (2) represents the contribution of the variances of the input variables to the total variance of the output. The second term denotes the influence of a possible correlation among the various possible pairs of input variables. If the input variables are statistically independent, i.e. $\text{cov}\left(X_i, X_j\right) = 0$ this second term vanishes and the variance of *Y* becomes

$$\text{var(Y)} = \sum_{i=1}^{\text{n}}\left(\frac{\partial y}{\partial X_i}\right)^2 \text{var}(\text{X}_\text{i}) = \sum_{i=1}^{\text{n}} Var(Y)_i$$ *Equation 2-9*

Where $Var(Y)_i$ is the variance in *Y* due to the variance (uncertainty) in the input variable X_i.

Although the method is simple and widely used, it suffers from some disadvantages, which will be discussed din more details in the Literature review chapter.

Furthermore, there are also the different applications of artificial neural networks (A.N.N.). The fuzzy set theory that the representation of uncertainty by a non-probabilistic approach began to increase in pace rapidly

2.7.9 Uncertainty estimation based on local errors and clustering (UNEEC)

This section presents a novel method to estimate models total uncertainty using machine learning approach. This method is called "uncertainty estimation based on local errors and clustering" and it was originally developed by (Durga and Dimitri, 2006). It assumes that the model error (mismatch between the observed and simulated river flow) is the best indicator of the total model uncertainty.

UNEEC considers model as in Equation 2-10

$$y = M(X, \theta) + \varepsilon_1 = \hat{y} + \varepsilon_2$$ *Equation 2-10*

Where:

X	the input data
θ	the parameter values,
ŷ	the model output,
ε	the additive error,

UNEEC consists of three main parts, clustering, compute empirical error distribution and build uncertainty processor.

Cluster analysis here is the partition of the input data into clusters. There are three types of clustering (excluding, overlapping and hierarchical). In excluding clustering (like K-means clustering) each data point belongs to only one cluster. Overlapping clustering (like fuzzy C-means clustering) each data point belongs to several classes with some degree ranges from zero to one. Last clustering type, hierarchical clustering, it begin with each data point as a separate cluster then it merge them into larger clusters(Durga and Dimitri, 2006) .

compute empirical error distribution, in this step UNNEC calculates prediction interval for any cluster by fitting the error distribution to each cluster independently without pre-assumptions about model errors are not required.

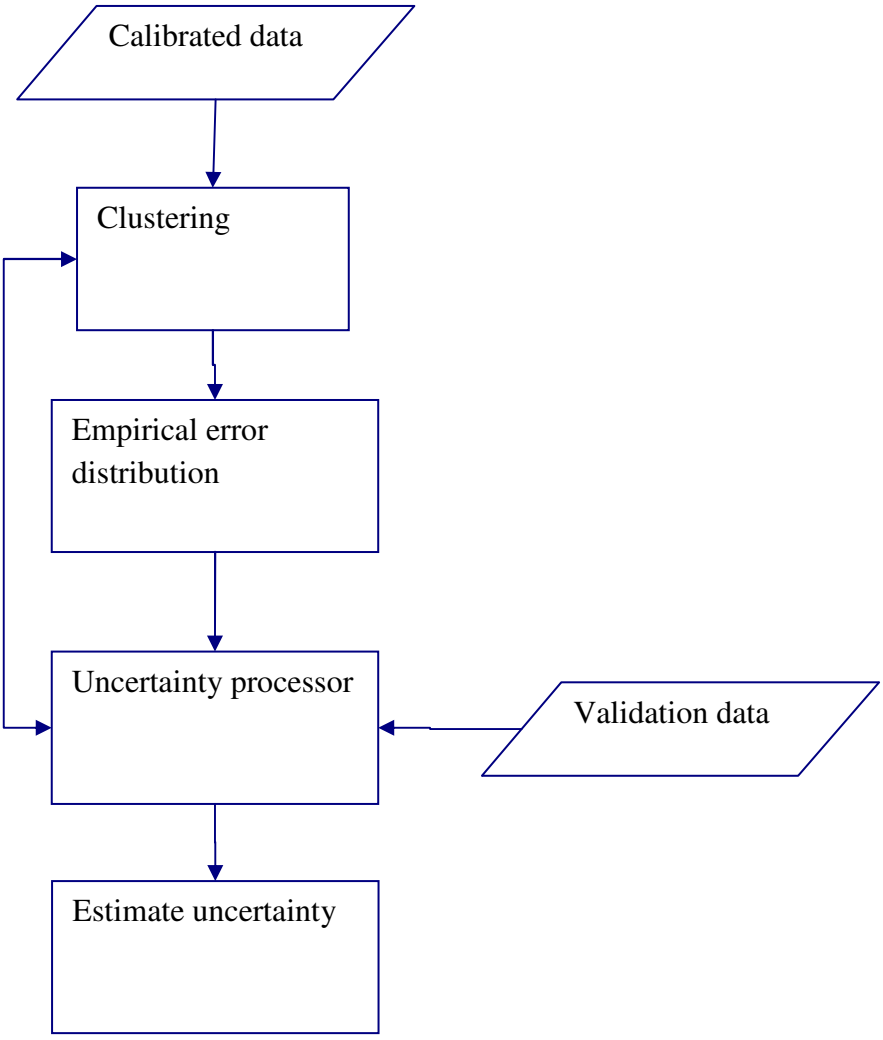


Figure 2-19 Main steps of uncertainty estimation using UNEEC

3 Tools used in watershed modeling and optimization

3.1 Soil and water assessment tool (SWAT)

3.1.1 Introduction

Selecting the appropriate tool is the first step in hydrological watershed modelling and it has great affect on the final results. For this model Soil and Water Assessment Tool (SWAT) was selected as a hydrological modelling tool. Because it is accepted by most of the hydrologiest as a powerfull hydrological modeling tool. And it simulates very large basins or a variety of management strategies without excessive investment of time or money. Also it is a continuous time modelling tool that enables its users to study long-term impacts. Furthermore, it is easy to use it and it's documents are very detailed and clear. Lastly it is a free software and public domian which make it easy to use it even in the limited budget projects.

As a quick overview on SWAT, this software developed by the United State Department of Agriculture (USDA), to predict the impact of land management practices on water, sediment and agricultural chemical yields in large complex watersheds with varying soils, land use and management conditions over long periods. SWAT can deal with large watersheds without high costs of money or computer time. Moreover, it is valid for the biological issues, and to study long-term hydrological processes and its impacts.

SWAT devides the watershed subcatchments into number of hydrologic units(HRUs) in regards to increase model accurasy. These units are the areas that have the unique compination of landuse, management system and soil attrinutes so it will be modelled in the same method and have the same parameters. HRUs became a general role that every subbasin shouls has (1-10) HRUs. SWAT groups the input parameters into cateegories like (subbasin, wetland, wateruse, managent, etc) inputfiles. The total number of parameters to model watersheds it may be needs over 300 parameters to discribr it very accuratly.

In the following, a short overview, on the mathematical equations that control hydrological process in SWAT models, more details are given in . First of all, water balance is the driving force behind everything that happens in the watershed, where the laws for conservations of mass and momentum are used to describe the water balance in the hydrological system. Also, SWAT deparates hydrological process into two main parts, these parts are land and routing phases. Figure 3-2 and Figure 3-3 displays the whole hydrological process in SWAT.

3.1.2 SWAT Mathematical equations

A complete description of SWAT equations can be found in (Neitsch, et al., 2002).

3.1.2.1 Main phases in SWAT hydrological processes

land phase of the hydrologic cycle controls the amount of water, sediment, nutrient and pesticide loadings to the main channel in each subbasin. While routing phase

defines as the movement of water, sediments, etc through the channel network of the watershed to the outlet.

land phase consists of precipitation interception, surface runoff, soil and root zone infiltration, evapotranspiration and ground water flow . And SWAT solves this phase using the following water balance equation:

$$SW_t = SW_o + \sum_{i=1}^{t} (R_{day} - Q_{surf} - E_a - \omega_{sweep} - Q_{gw}) \qquad \text{Equation 3-1}$$

Where SW_t is the final soil water content (mm).
SW_o is the initial soil water content (mm).
t is the time (days).
R_{day} is the amount of precipitation on day i (mm).
Q_{surf} is the amount of surface runoff on day i (mm).
E_a is the amount of evapotranspiration on day i (mm).
w_{seep} is the amount of water entering the vadose zone from the soil profile on day i (mm). and
Q_{gw} is the amount of return flow on day i (mm).

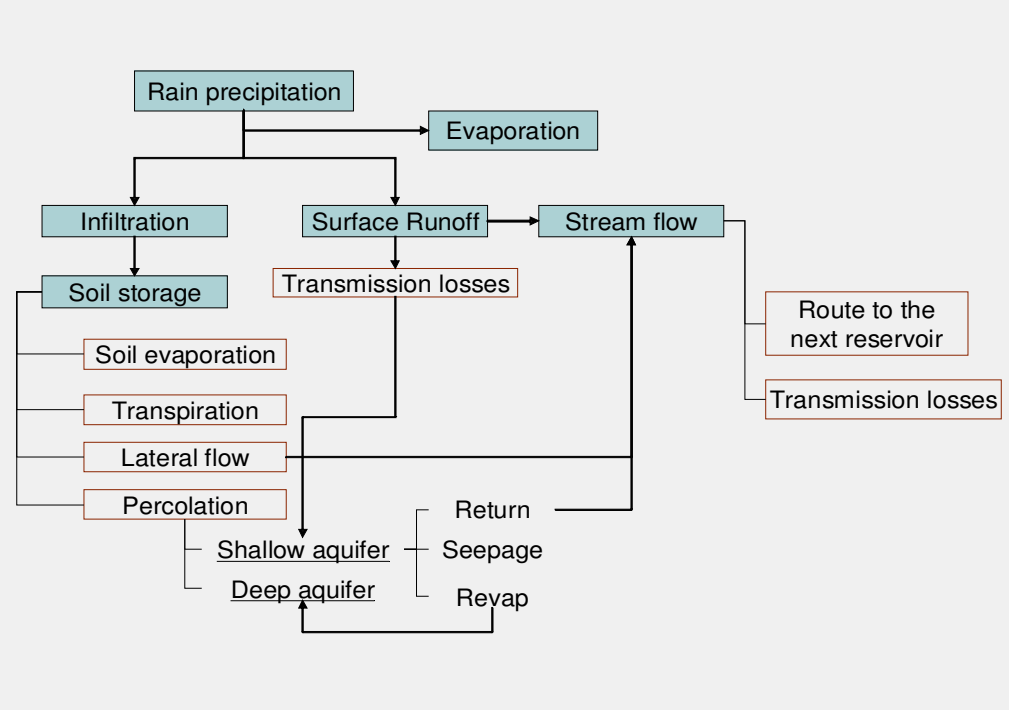


Figure 3-1 Schematic of pathways available in SWAT

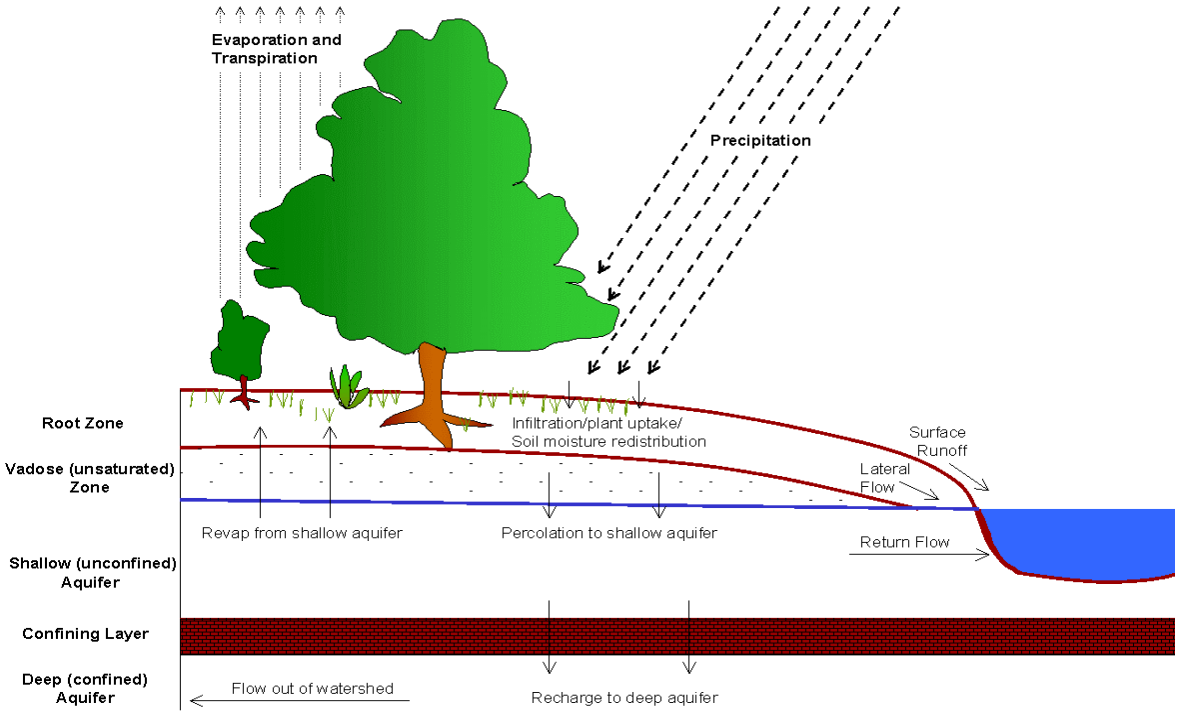


Figure 3-2 Schematic representation of the hydrologic cycle in SWAT

3.1.2.2 Surface runoff calculations

For the surface runoff process, it occures whenever the rate of water application to the ground surface exceeds the rate of infiltration. SWAT provides two methods for estimating surface runoff: the SCS curve number procedure and the Green & Ampt infiltration method. here is a brief discription to both methods.

1. The SCS curve number procedure is a function of the soil's permeability, land use and antecedent soil water conditions. where the SCS runoff equation is an empirical model that came into common use in the 1950s.

this equation is : $$Q_{surf} = \frac{(R_{day} - I_a)^2}{(R_{day} - I_a + S)}$$ Equation 3-2

Where Q_{surf} :the accumulated runoff or rainfall excess (mm),
R_{day} :the rainfall depth for the day (mm),
I_a :the initial abstractions (surface storage, canopy interception, infiltration prior to runoff) (mm), and
S :the retention parameter.

theredore, Runoff will only occur only when $R_{day} > I_a$. and That retention parameter S is defined as:

$$S = 25.4\left(\frac{1000}{CN} - 10\right)$$ Equation **3-3**

Where *CN* is the curve number for the day. and the initial abstractions, I_a, is commonly approximated as 0.2*S* and $Q_{surf} = \frac{(R_{day} - I_a)^2}{(R_{day} - I_a + S)}$ Equation 3-2 becomes

$$Q_{surf} = \frac{(R_{day} - 0.2S)^2}{(R_{day} + 0.8S)}$$ Equation 3-4

SWAT calculates CN using soil classes and land uses classifications data. Moreover, it makes three classes of CN. The first one CN1 is the lowest; it is corresponding to dry condition. The third type CN3 is corresponding to wet condition. While the second type CN2 is the curve number in the average moisture case. The moisture condition CN2 is assumed to appropriate for 5% slopes.

2. The Green & Ampt equation was developed to predict infiltration assuming excess water at the surface at all times. The equation assumes that the soil profile is homogenous and antecedent moisture is uniformly distributed in the profile. The Green-Ampt Mein-Larson infiltration rate is defined as:

$$f_{\inf,t} = K_e \cdot \left(1 + \frac{\Psi_{wf} \cdot \Delta\theta_v}{F_{\inf,t}}\right)$$ Equation 3-5

where f_{inf} :the infiltration rate at time *t* (mm/hr),
K_e :the effective hydraulic conductivity (mm/hr), is approximately equivalent to one-half the saturated hydraulic conductivity of the soil, K_{sat}
Ψ_{wf} :the wetting front matric potential (mm), where matric potential is A force between water and soil surfaces
$\Delta\theta_v$:the change in volumetric moisture content across the wetting front (mm/mm) and
F_{inf} :the cumulative infiltration at time *t* (mm H_2O).

3.1.2.3 Peak runoff rate assessment

The peak runoff rate is the maximum runoff flow rate that occurs with a given rainfall event. The peak runoff rate is an indicator of the erosive power of a storm and is used to predict sediment loss. SWAT calculates the peak runoff rate with a modified rational method.

$$q_{peak} = \frac{\alpha_{tc} \cdot Q_{surf} \cdot Area}{3.6 \cdot t_{conc}}$$

Where q_{peak} is the peak runoff rate (m^3/s),
α_{tc} is the fraction of daily rainfall that occurs during the time of concentration,
Q_{surf} is the surface runoff (mm),
Area is the subbasin area (km^2),
t_{conc} is the time of concentration for the subbasin (hr) and
3.6 is a unit conversion factor.

3.1.2.4 Evapotranspiration assessment

Evapotranspiration is a collective term that includes all processes by which water at the earth. surface is converted to water vapor. It includes evaporation from the plant canopy, transpiration, sublimation and evaporation from the soil. The difference between precipitation and evapotranspiration is the water available for human use and management. Assessment of watershed evapotranspiration is critical in the assessment of water resource. SWAT calculates potential and actual evapotranspiration.

SWAT incorporated three numerical methods to estimate potential evapotranspiration PET. The Penman-Monteith method, the Priestley-Taylor method and the Hargreaves method, also user can enter PET manually. On the other side, SWAT calculates actual evapotranspiration ET after determine PET. SWAT first evaporates any rainfall intercepted by the plant canopy. Next, SWAT calculates the maximum amount of transpiration and the maximum amount of sublimation/soil evaporation. When PET is less than amount of free water held in the canopy, it assumes that ET = PET. However, when PET less than amount of free water held in the canopy, so no water will remains in the canopy after initial evapotranspiration.

3.1.2.5 Percolation assessment

Percolation is calculated for each soil layer in the profile. Water is allowed to percolate if the water content exceeds the field capacity water content for that layer. The volume of water available for percolation in the soil layer is calculated:

$$SW_{ly,excess} = SW_{ly} - FC_{ly} \quad \text{if } SW_{ly} > FC_{ly} \qquad \text{Equation 3-6}$$

$$SW_{ly,excess} = 0 \quad \text{if } SW_{ly} \le FC_{ly} \qquad \text{Equation 3-7}$$

Where:

$SW_{ly,excess}$ is the drainable volume of water in the soil layer on a given day (mm)
SW_{ly} is the water content of the soil layer on a given day (mm) and
FC_{ly} is the water content of the soil layer at field capacity (mm).

The amount of water that moves from one layer to the underlying layer is calculated using storage routing methodology. The equation used to calculate the amount of water that percolates to the next layer is:

$$w_{perc,ly} = SW_{ly,excess} \cdot \left(1 - \exp\left[\frac{-\Delta t}{TT_{perc}}\right]\right) \qquad \text{Equation 3-8}$$

where

$w_{perc,ly}$ is the amount of water percolating to the underlying soil layer on a given day (mm),
$SW_{ly,excess}$ is the drainable volume of water in the soil layer on a given day (mm),
Δt is the length of the time step (hrs), and
TT_{perc} is the travel time for percolation (hrs).

The travel time for percolation is unique for each layer. It is calculate by

$$TT_{perc} = \frac{SAT_{ly} - FC_{ly}}{K_{sat}}$$ Equation 3-9

Where

TT_{perc} is the travel time for percolation (hrs),
SAT_{ly} is the amount of water in the soil layer when completely saturated (mm),
FC_{ly} is the water content of the soil layer at field capacity (mm), and
K_{sat} is the saturated hydraulic conductivity for the layer (mm/h).

3.1.2.6 Lateral Flow assessment

Lateral flow will be significant in areas with soils having high hydraulic conductivities in surface layers and an impermeable or semipermeable layer at a shallow depth. In such a system, rainfall will percolate vertically until it encounters the impermeable layer. The water then ponds above the impermeable layer forming a saturated zone of water, i.e. a perched water table. This saturated zone is the source of water for lateral subsurface flow.

the drainable volume of water stored in the saturated zone of the hillslope segment per unit area, $SW_{ly,excess}$, is

$$SW_{ly,excess} = \frac{1000 \cdot H_o \cdot \phi_d \cdot L_{hill}}{2}$$ Equation 3-10

where

$SW_{ly,excess}$ is the drainable volume of water stored in the saturated zone of the hillslope per unit area (mm),
H_o is the saturated thickness normal to the hillslope at the outlet expressed as a fraction of the total thickness (mm/mm),
Φ_d is the drainable porosity of the soil (mm/mm),
L_{hill} is the hillslope length (m), and
1000 is a factor needed to convert meters to millimeters.

3.1.2.7 Groundwater assessment

Groundwater is water in the saturated zone of earth materials under pressure greater than atmospheric. Water enters groundwater storage primarily by infiltration or percolation. Water leaves groundwater storage primarily by discharge into rivers or lakes, but it is also possible for water to move upward from the water table into the capillary fringe. Furthermore SWAT simulates two aquifers in each subbasin. The shallow aquifer is an unconfined aquifer that contributes to flow in the main channel or reach of the subbasin. The deep aquifer is a confined aquifer. Water that enters the deep aquifer is assumed to contribute to streamflow somewhere outside of the Watershed .

The water balance for the shallow aquifer is:

$$aq_{sh,i} = aq_{sh,i-1} + w_{rchrg} - Q_{gw} - w_{revap} - w_{deep} - w_{pump,sh}$$ Equation 3-11

where

$aq_{sh,i}$ the amount of water stored in the shallow aquifer on day i (mm),
$aq_{sh,i-1}$ the amount of water stored in the shallow aquifer on day i-1 (mm),
w_{rchrg} the amount of recharge entering the aquifer on day i (mm),

Q_{gw} the groundwater flow, or base flow, into the main channel on day i (mm),

w_{revap} the amount of water moving into the soil zone in response to water deficiencies on day i (mm),

w_{deep} the amount of water percolating from the shallow aquifer into the deep aquifer on day i (mm), and

$w_{pump,sh}$ the amount of water removed from the shallow aquifer by pumping on day i (mm).

The water balance for the deep aquifer is:

$$aq_{dp,i} = aq_{dp,i-1} + w_{deep} - w_{pump,dp}$$

Where

$aq_{dp,I}$ the amount of water stored in the deep aquifer on day i (mm)

$aq_{dp,i\text{-}1}$ the amount of water stored in the deep aquifer on day i-1 (mm)

w_{deep} the amount of water percolating from the shallow aquifer into the deep aquifer on day i (mm), and

$w_{pump,dp}$ the amount of water removed from the deep aquifer by pumping on day i (mm).

3.1.3 Important input files for SWAT

There are some important files control model operations in SWAT. SWAT user is able to read / edit these files to control model operation and its printouts. The following sections review some of those.

Watershed configuration file is called (fig.fig). It defines the routing network in the watershed. Controlling SWAT inputs/outputs is done mainly by (file.cio) file. It contains names of input files for all watershed level variables, controlling model variables and output printing variables. Management input files are those files with (mgt) extension. It contains management scenarios and specifies the land cover simulated. Files with (sol) extension are soil input files. It contains information about the physical characteristics of the soil. Groundwater input files have extension (gw). It contains information about the shallow and deep aquifers.

Some of the privious files are editable by user to give him more flixability to control modeling process in case of using SWAT out of the graphical interface. or when linking SWAT model with external systems. te most inportant ones will discuss in the next paragraph.

(fig.fig). This file has thirteen different commands may be used in the watershed configuration file. The commands that used in this study with their numeric codes are reviewed here. First command in the list is finish command is the last command line in the .fig file. The finish command notifies the model that the end of the command lines in the watershed configuration file has been reached. Second one is the subbasin command simulates all processes involved in the land phase of the hydrologic cycle and computes runoff, sediment, and chemical loadings from each HRU within the subbasin. Third command is the route command, it routes the water, sediment, and chemical loadings through a main channel or reach. Fourth command is the add command, it is used to sum the water, sediment, and chemical loadings of any two flows. Last command is the saveconc command, it saves flow, sediment and water

quality indicator information from a specified point on the reach network to a file. The water quality information is reported as concentrations. This command is useful for isolating reach information at a particular point on the channel network.

(File.cio) SWAT user can select between different types of calculations that provided by SWAT by selecting values of factor called ICLB. ICLB values ranges from 0 to 8. Zero means run the model and calculate the outflow. One is for calculating the sensitivity analysis and write the most sensitive parameters I file called (sensresult.out). Two could be used to calibrate model parameters by ParaSol and calculate accepted set of parameters in (goodpar.out) and the best parameters in(bestpar.out). While ICLB = four directs SWAT to validate the model by rerun the model using the beast parameters values that calculated from calibration before but the moduler should change the simulation period to the validation period. Fifth choice, is to make ICLB = 5 which means run the uncertainty analysis using ParaSol technique and write the maximum and minimum flows according to the accepted range of parameters.

3.2 SWAT Arc-View interface

Due to the huge amount of requred input data into SWAT. It uses one of ArcView extensions called AVSWAT as a graphical user interface to define input data and other characteristics with easly and quick way. AVSWAT requires the designation of land use, soil, weather, groundwater, water use, management, soil chemistry, pond, and stream water quality data, as well as the simulation period, to ensure a successful simulation. And it creates SWAT input data files. Furthermore, it controls and calibrates SWAT simulations. Finally, it extracts and organizes SWAT model output data for charting and displaying.

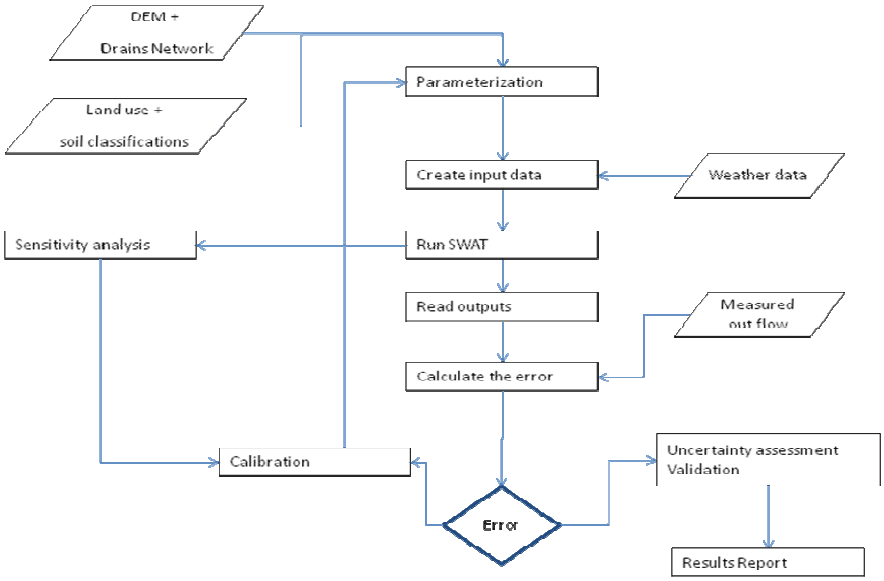


Figure 3-3AVSWAT model main steps

It is a complete preprocessor, interface and post processor of the hydrological model SWAT and the SWAT interface, which depends on manual editing on the input files. The Arcview interface used for Watershed Delineation; Land Use and Soil Definition; Editing of the model Data Bases; Definition of the Weather Stations; Input Parameterization and Editing; Model Run; Read and Map-Chart Results and Calibration tool.

Model building procedures using AVSWAT startes after Collecting the data in appropriate format. these data contains detailed information about Spatial data, Climate/weather data, Rainfall data and temperature data. Then, firstly define the spatial data by delineate the study area digital elevation model, catchment shape file and delineated streams files. secondly, define the Land Use and Soil classifications, so the hydrological response units could be defined. Thirdly; load the weather data which is rain fall data, temperature data and weather simulation data. last main step is to build the input data files to create ArcView tables (.dbf) that store values for SWAT input parameters also to generate the Initial SWAT ASCII input files. After these steps the model is ready to run. these steps could be summarized in eight modules: (1) Watershed Delineation; (2) HRU Definition; (3) Definition of the Weather Stations; (4) AVSWAT Databases; (5) Input Parameterization, Editing and Scenario Management; (6) Model Execution; (7) Read and Map-Chart Results; (8) Calibration tool. these steps

3.3 Optimization and uncertainty analysis development tools

Many software integrated through this study into applying the study objectives. To link SWAT model with calibration or uncertainty analysis programs two software packages used. GLOBE used to link SWAT model with three calibration techniques, and iSWAT used to change edit input files link. The following parts there are description to these programs.

3.3.1 SWAT interface (iSWAT)

(Yang, 2004) developed this interface to link SWAT text-file-based projects with external system analysis programs, this interface consist of two executive files (sw_edit2005.exe, sw_extract2005.exe) and some library files.

First file is editing executable file, it changes SWAT project parameters according to a given parameters names and values specified in (model.in) text file. So it is very useful for manual calibration. This file has the following format

x__<parname>.<ext>__<hydrogrp>__<soltext>__<landuse>__<subbsn>

Equation 3-12

The parameter name means that the parameter name will be changed according to method x for the combinations of given items <hydrogrp>, <soltexture>, <landuse> and <subbasin>, and the missing item(s) mean(s) this change method applies to this entire item. The sections in parameter name are separated by two underlines, as single

underlines are contained in some SWAT parameter names. Here is an example shows the model.in file.

Table 3-1

v__Rchrg_Dp.gw	0.08
v__Canmx.hru	5.13
v__Esco.hru	0.60
v__Ch_K2.rte	56.43
r__Cn2.mgt	-0.08
v__Gw_Revap.gw	0.15
v__Gwqmn.gw	63.48
v__Alpha_Bf.gw	0.72
v__Surlag.bsn	5.70

This means that all Deep aquifer percolation fraction (Rchrg_Dp) had to be replaced by 0.08, all curve numbers (CN2) had to be multiplying a factor of (1- 0.08 = 0.92), In <model.in>, a line beginning with "//" means this line is comment.

Second file is to extract the SWAT outputs into file model.out after running SWAT. the format of output definition file (swExtract.def) as the following

Comments	
rch	//data source type, reserved (only rch file is supported at present). The program will extract data from basins.rch
Output file	//output filename
Simulation type	//simulation type of SWAT project. It can be 0---monthly, 1—daliy, 2—yearly simulation, -1 lets the program get the type of swat simulation
Starting year	//start simulating year of the SWAT project.
Reach number	output option outputVariable1 outputVariable2 Remark

Here is an exampled of (swExtract.def)

// this is an example	
rch	
model.out	//output filename
-1	lets the program get the type of swat simulation
-1	means let the program get the start year of the simulation
47	FLOW_OUT

This file means that sw_extract.exe will extract the discharge for reach 47 from basins.rch to model.out. and here is an example of the outputs

FLOW_OUT47_1970.1	33.69
FLOW_OUT47_1970.2	33.69
FLOW_OUT47_1970.3	33.26
FLOW_OUT47_1970.4	33.26
FLOW_OUT47_1970.5	32.83

A schematic of iSWAT working is illustrated in Figure 3-5. First, sw_edit.exe reads the parameter information from model.in and change the parameter value of the swat

text-file-based project, and then swat runs, and in the last step sw_extract.exe extracts the specific results defined in file model.out .

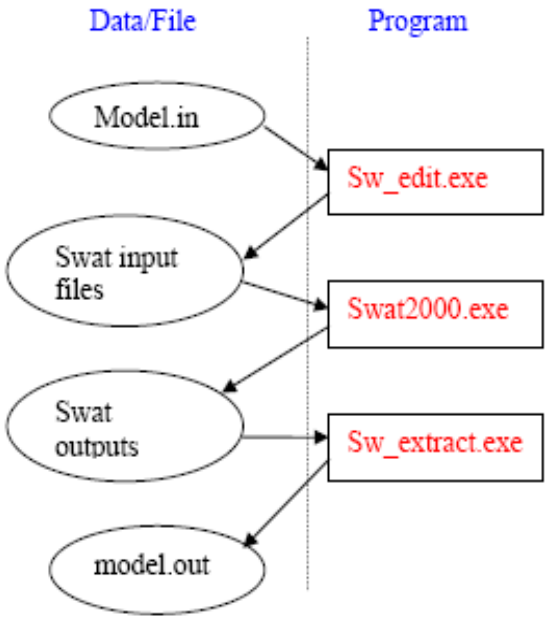


Figure 3-4 ***iSWAT working stratigy***

3.3.2 GLOBE

GLOBE: global and evolutionary optimization tool developed by D. P. Solomatine. GLOBE is a global optimization tool that search for minimum of a function of multiple variables.

GLOBE configured to use an external program to supply the objective function values. The output file of program is used directly by GLOBE. The number of independent variables and its constraints values are supplied by the user in the form of a simple text file.

GLOBE applies the following seven global optimization techniques to calibration problems:

- Controlled random search (CRS)
- Genetic Algorithm (GA)
- Adaptive cluster covering (ACCO/ACCOL)
- Multis (a version of Powell-Brent non-derivative algorithm, with multiple randomized starts)
- M-Simplex (a version of the simplex decent algorithm with randomized multiple starts)
- Improved Controlled random search (CRS4a)
- Adaptive cluster descent (ACD)

GLOBE iteratively generate values of the model's variables (input vector) and supply it to the external program via the file G.PIN. Then GLOBE runs the external program (written by the user). This program must read G.PIN file (This file contains real

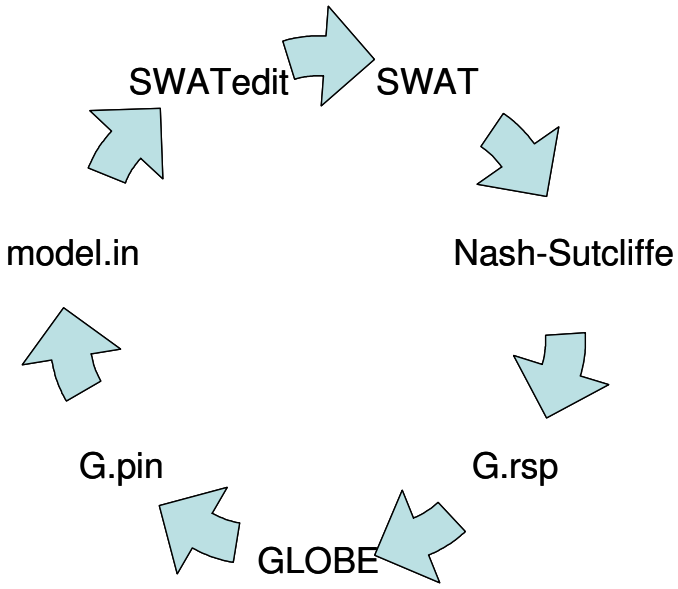


Figure 3-5 Main steps of GLOBE program

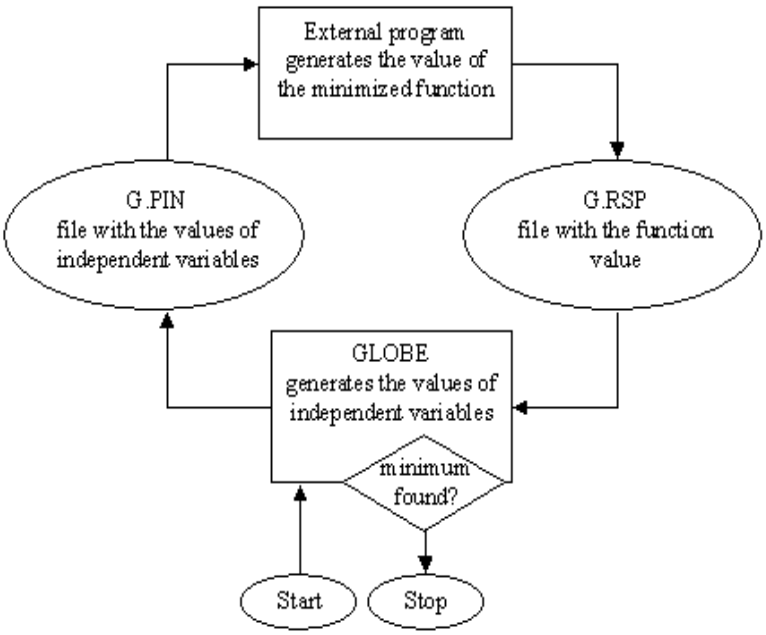


Figure 3-6 Exchanging information between SWAT and GLOBE

numbers either on one line separated by spaces or on separate lines; example follows). Then this program calculates the function value and places the calculated value (one real number in any format) to the file G.RSP. This file is then read and analyzed by GLOBE; the new G.PIN file is generated, etc. The results are reported on

screen and in a number of report files. These results files have extensions HIS, RST and OUT. (Project name).his (file with the history of algorithms runs; (Project name).rst (similar to the previous one but gives more details); (Project name).out (file to be used in spreadsheet programs to for visualize the comparative performance of algorithms).

3.3.3 UNEEC TOOL for uncertainty estimation

This is a Matlab graphical user interface developed by (D. L. Shrestha,). Figure 3-7 displays the main window of this tool, it shows switching buttons between different windows, also it displays the controlling buttons. UNEEC TOOL uses different alternative data driven modeling approaches to estimate hydrological models uncertainty, these alternatives are found in main module window, from this window also, UNEEC TOOL reads the necessary data for the selected model (Figure 3-9). After that, user should select clustering method, UNEEC TOOL provides four clustering methods and it also gives user ability to add his own clustering method Figure 3-10. All uncertainty analysis options, by means, select uncertainty analysis tool, define confidence level, select validation parameters and some other options are found in window of uncertainty module, as can see in Figure 3-11. After completing all these steps, user now can click on run buttons, the results will be as

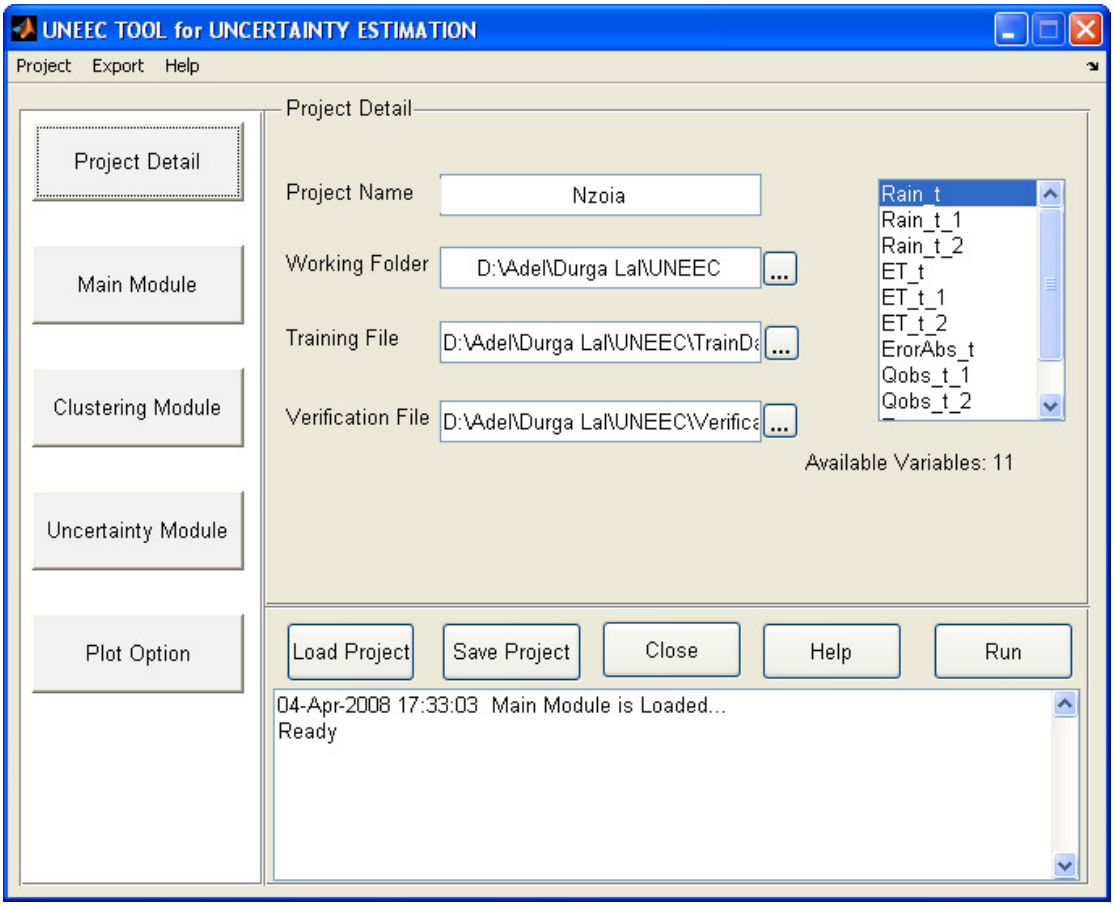


Figure 3-7 UNEEC TOOL main interface

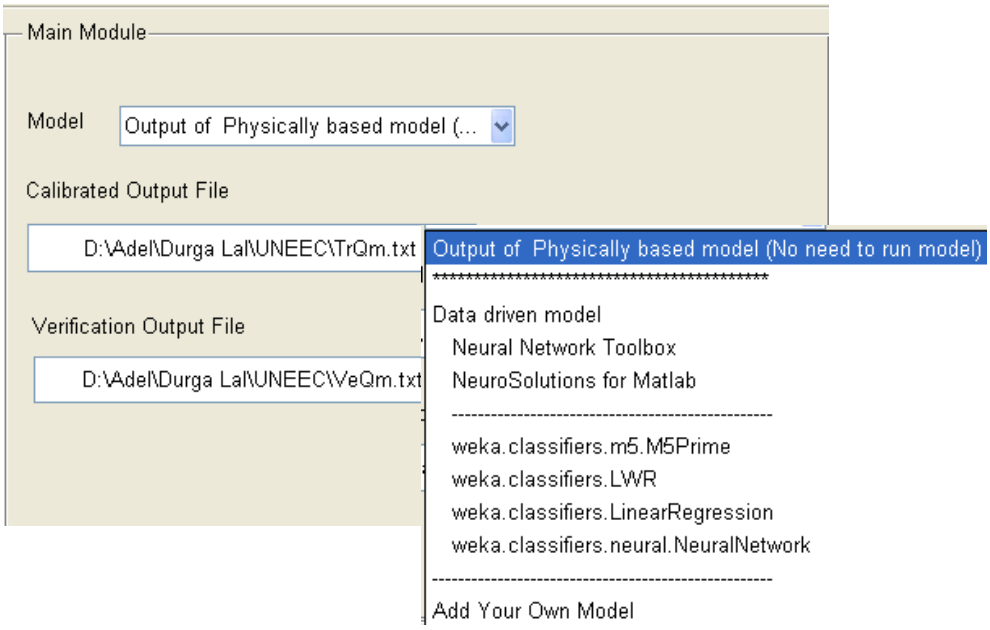


Figure 3-8 Selecting the uncertainty analysis method in UNEEC TOOL

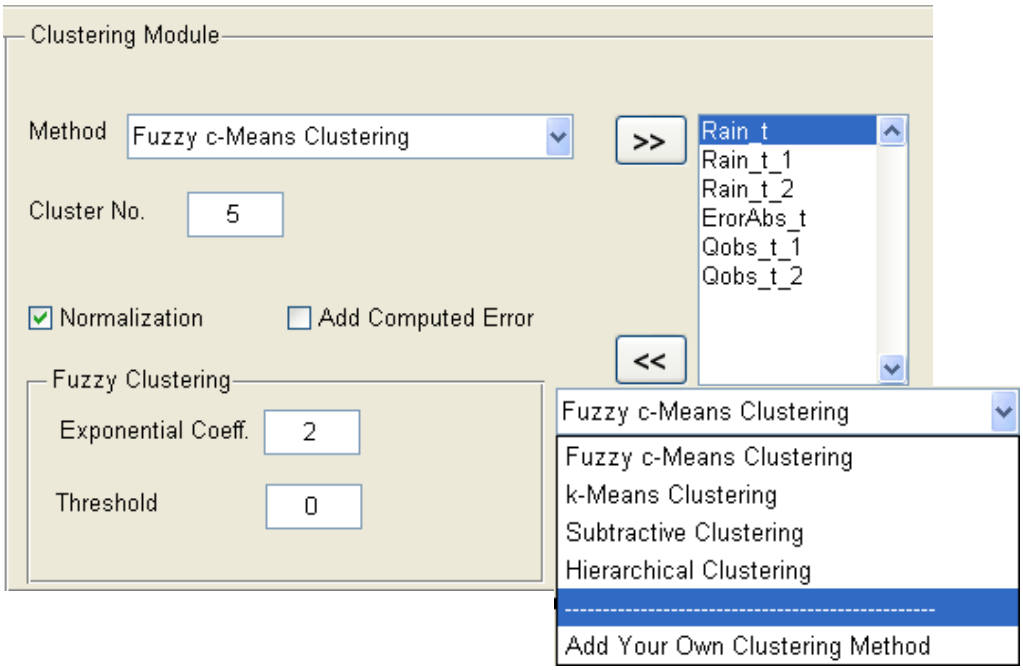


Figure 3-9Clustering options in UNEEC TOOL

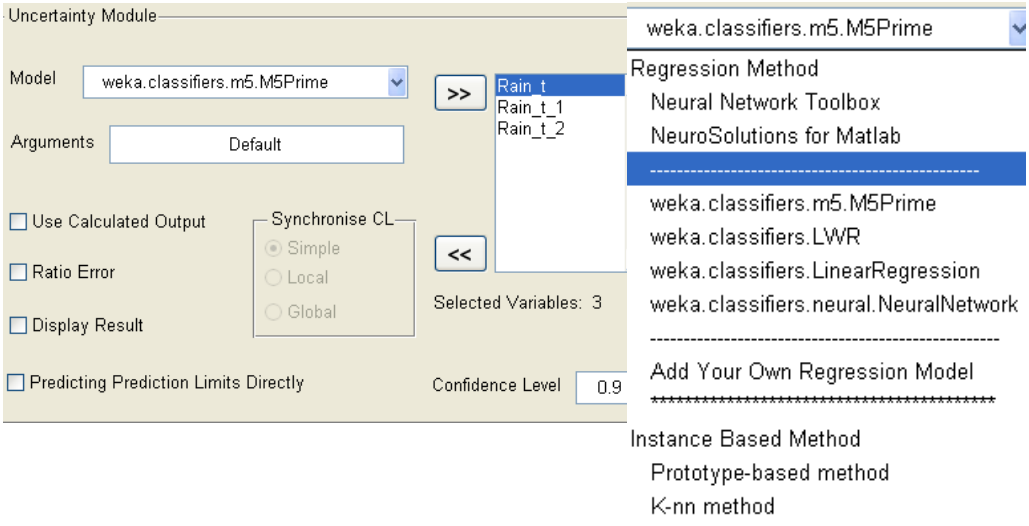


Figure 3-10 Uncertainty options in UNEEC TOOL

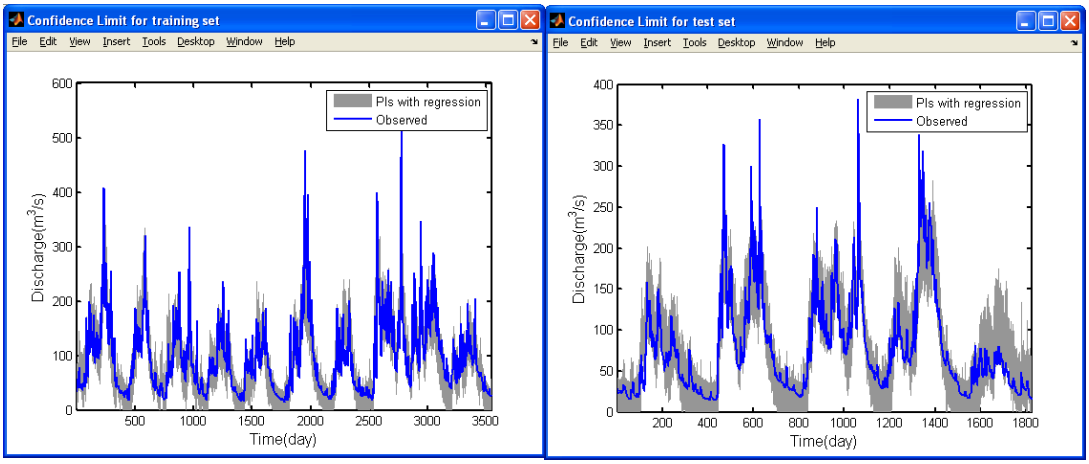


Figure 3-11 Hydrograph and prediction interval in training and validation periods

3.3.4 Matlab

MATLAB stands for 'MATrix LABoratory'. It is a numerical computing environment and programming language. MATLAB is a high performance interactive software package for scientific and engineering computation. It integrates numerical analysis, matrix computation and graphics in an easy-to-use environment where problems and solutions are expressed just as they are written mathematically. In addition, MATLAB functionality can be extended by application specific toolboxes, like, partial differential equation, genetic algorithm and direct search, statistics, neural network, and matlab compiler toolbox.

MATLAB was used to link operate GLOBE with SWAT as an external application, ad for generate sets of parameters to use Monte Carlo and GLUE calibration methods.

4 Nzoia case study

4.1 Introduction

The study catchment is in the western part of Kenya. This country is about as large as France is and situated in East Africa between 5°N and 5°S. It has a very diverse relief with a low coastal plain on the Indian Ocean shore, extensive inland plateau regions between 915 m and 1,500 m and several mountain ranges and isolated peaks such as Mount Kenya, which rises to 5,200 m and has a permanent snowcap. It is bordered on the west by Uganda and the shores of Lake Victoria.

The catchment under studying as written before is in the western region of Kenya where most of this region is highlands on side of the eastern Rift valley, extending to the Ugandan border. It is the most densely populated part of the country and contains the most productive agricultural land. So, Nzoia River has been selected to study the uncertainty of hydrological models results. This river is also of international importance as it contributes enormously to the shared waters of Lake Victoria. It lies within the south-Eastern part of Mt Elgon and the western slopes of the Cherangani hills.

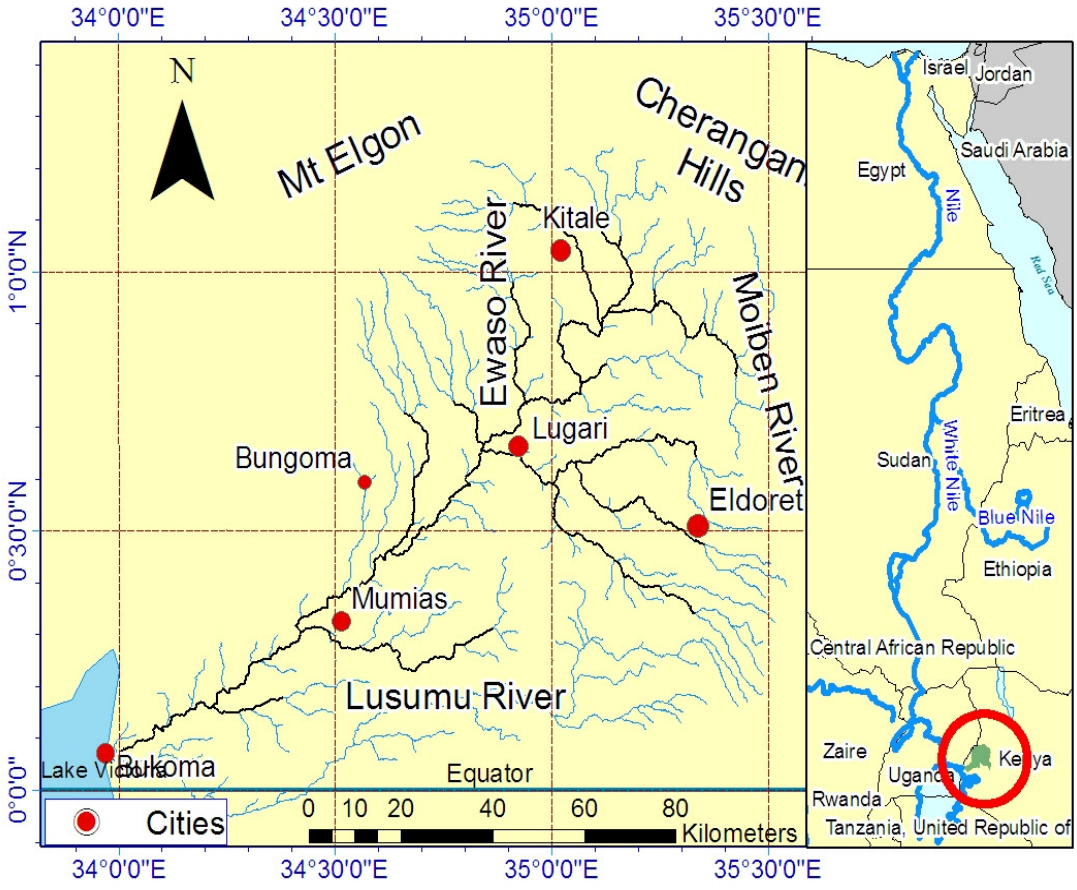


Figure 4-1 Nzoia catchment

Many other rivers feed the Nzoia before it discharges into Lake Victoria. The major ones are Koitogos (Sabwani), Moiben, Little Nzoia, Ewaso Rongai, Kibisi, Kipkaren and Kuywa. Other tributaries are Chwele, Khalaba, Lusumu and Viratsi .

This Basin lies between latitudes 1°30'N and 0°05'S and longitudes 34° and 35° 45'E see Figure 4-2 . It originates from Cherangani Hills at a mean elevation of 2300 m above sea level (asl) and drains into Lake Victoria at an altitude of 1000 m (asl). It runs approximately South-West and measures about 334 km with a catchment area of about 12,900 km^2, with a mean annual discharge of 1800 x 10^6 m^3 see

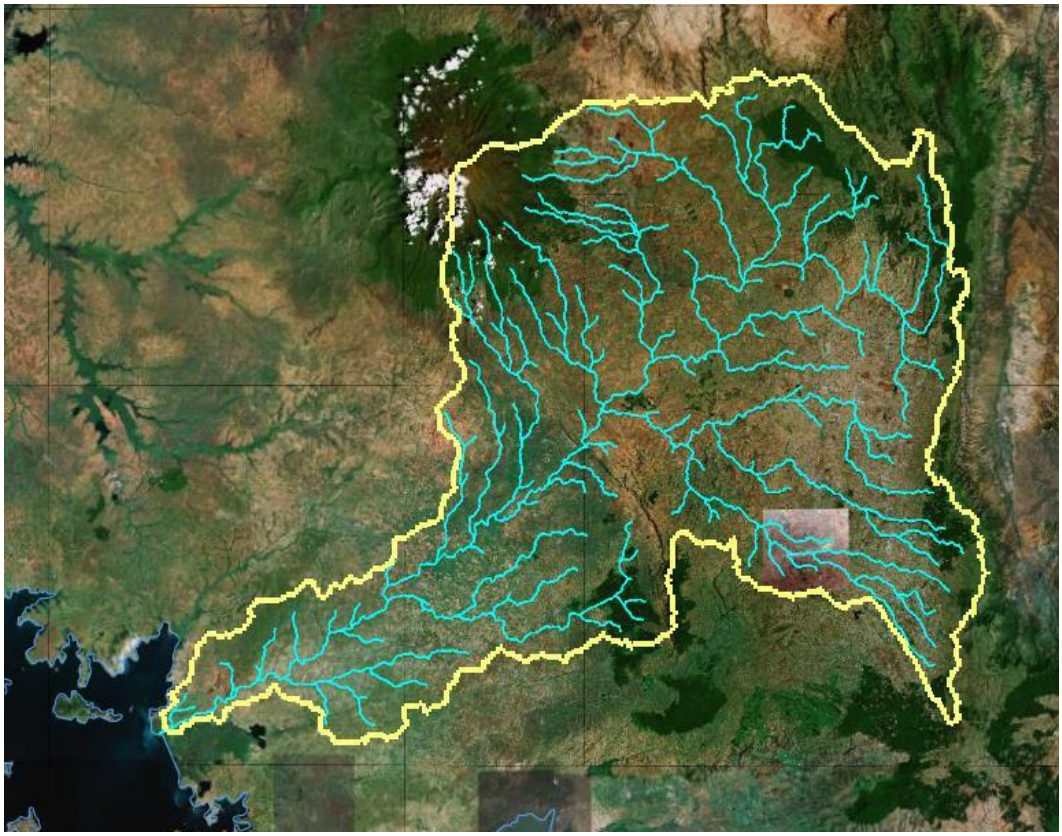


Figure 4-2 Satellite image for Nzoia River

From the geology point of view, Nzoia area like most of western Kenya, characterized by Archean granite/greenstone terrain in along Lake Victoria (Schlüter, 1997). See

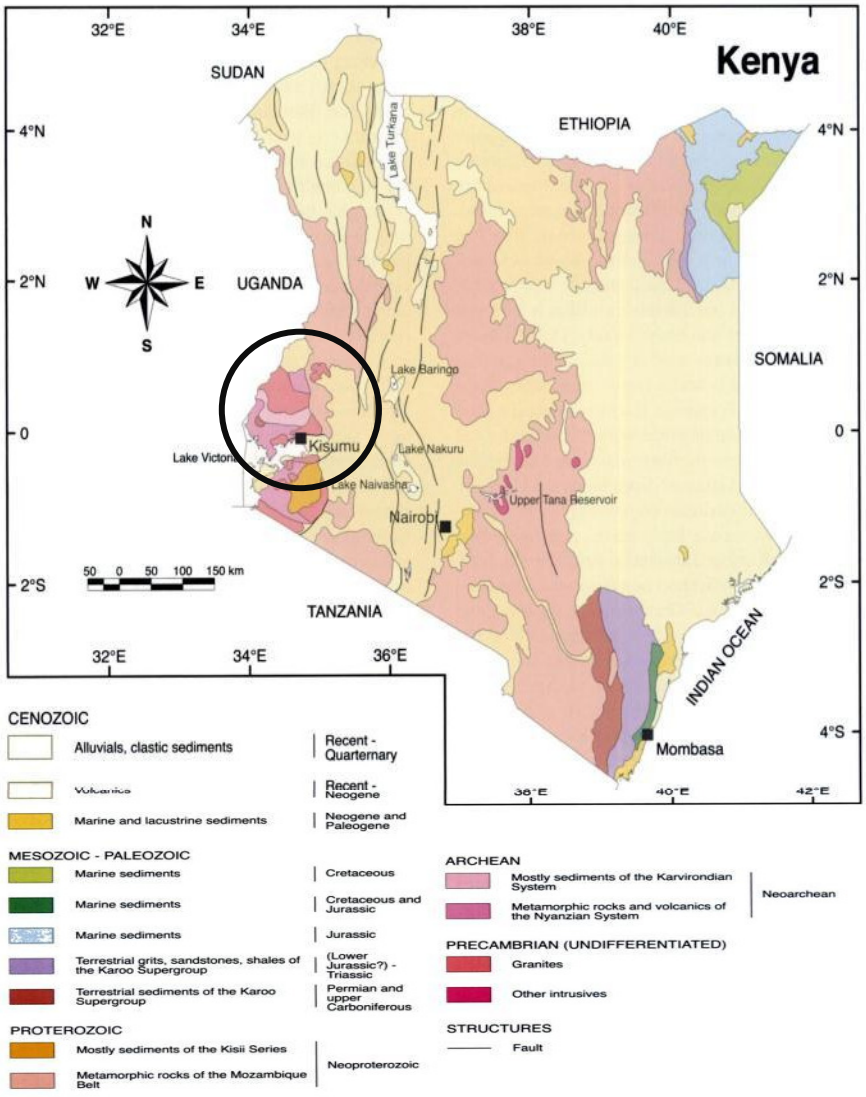


Figure 4-3 Geological map of Kenya(Schlβter and Trauth, 2006)

The population within the Basin is more than 3 million comprising of Bantu and Nilotes see Figure 4-5.

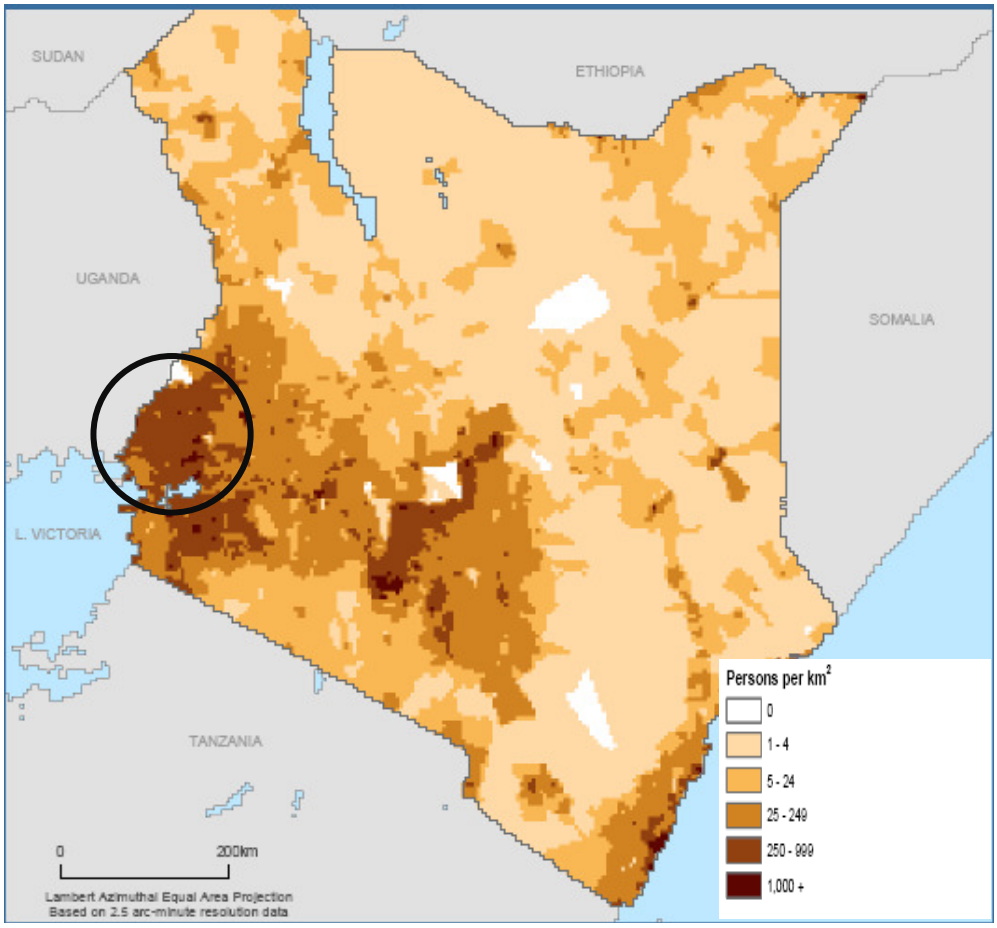


Figure 4-4 Population density in Kenya

On the climate side, Although Kenya lies athwart the equator; annual rainfall over most of the country is surprisingly low and rather variable from year to year. This is because the inter-tropical belt of cloud and rain passes rather quickly across Kenya in April and October and because the predominant seasonal winds, the north and south monsoons as they are called in East Africa, have a track parallel to the coast and have already passed over large areas of land before reaching Kenya.

So, The climate of the Basin is mainly tropical humid characterized by day temperatures varying between 16℃ in the highland areas of Cherangani and Mt. Elgon to 28° C in the lower semi-arid areas on annual basis. The mean annual night temperatures vary between 4° C in the highland areas to 16° C in the semi-arid areas. Mean annual rainfall varies from a maximum of 1100 to 2700 mm and a minimum of 600 to 1100 mm. The catchment experiences four seasons in a year as a result of the inter-tropical convergence zone. There are two rainy seasons and two dry seasons, namely, short rains (October to December) and the long rains (March to May). The dry seasons occur in the months of January to February and June to September.

4.2 Data preparation

Because SWAT is a distributed physically based model, it needs a huge amount of information about weather, soil properties, topography, vegetation, and land management practices occurring in the watershed. In the following part, there is a catchment's data description and some descriptive statistics about it.

Input data for SWAT assembled with the SWAT Arc View Interface. SWAT model input data for topography were extracted from a digital elevation model (DEM) and Figure 4 displays the elevation information for the watershed after delineating the watershed, contouring the surface and predicting the stream flow paths.

4.2.1 Topographic data

For the soil properties, a shape file with all the available soil characteristics loaded into SWAT. In addition, the land use added to the model, there are two figures (7,8) displays the land use classes distributions and it distribution map.

For the weather data there are 32 Rainfall stations with available recorded data from 1960 until 2004, also there are four temperature stations with temperature data for years. Finally there is a recorded out flow discharge at the out let of sub-basin 29 as shown in figure 5.

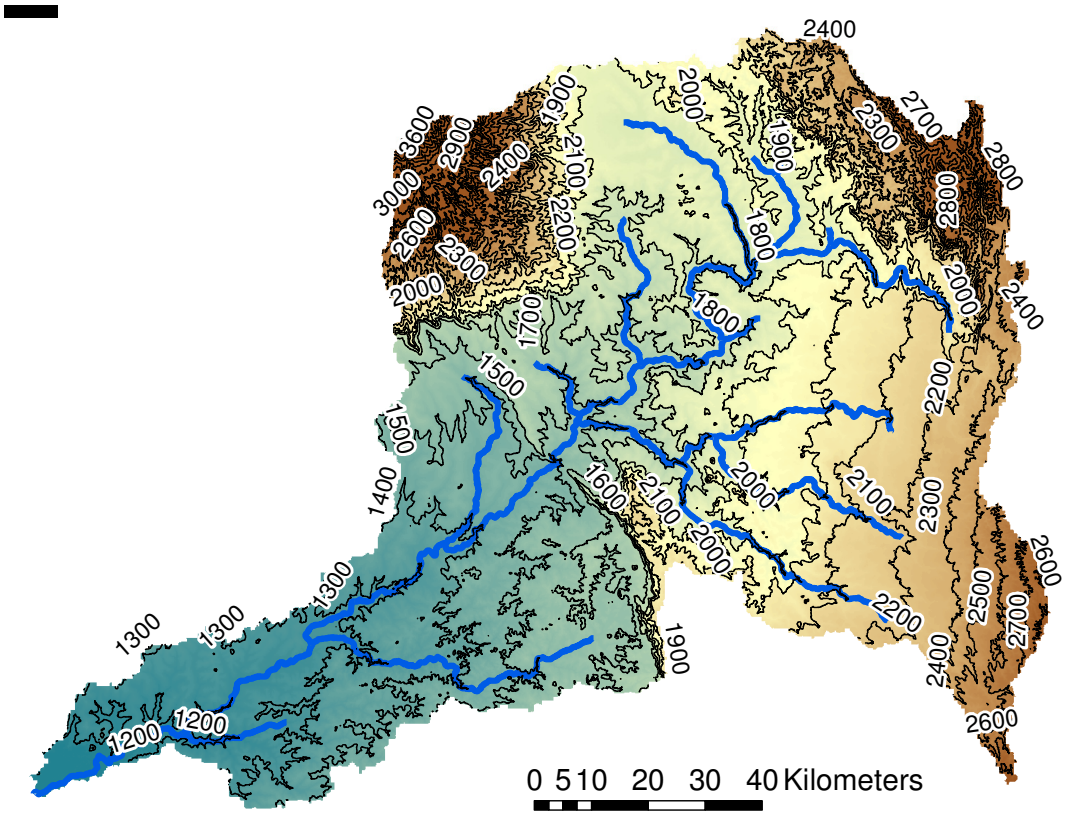


Figure 4-5 Nzoia Catchment topographic map

4.2.2 Soil types data

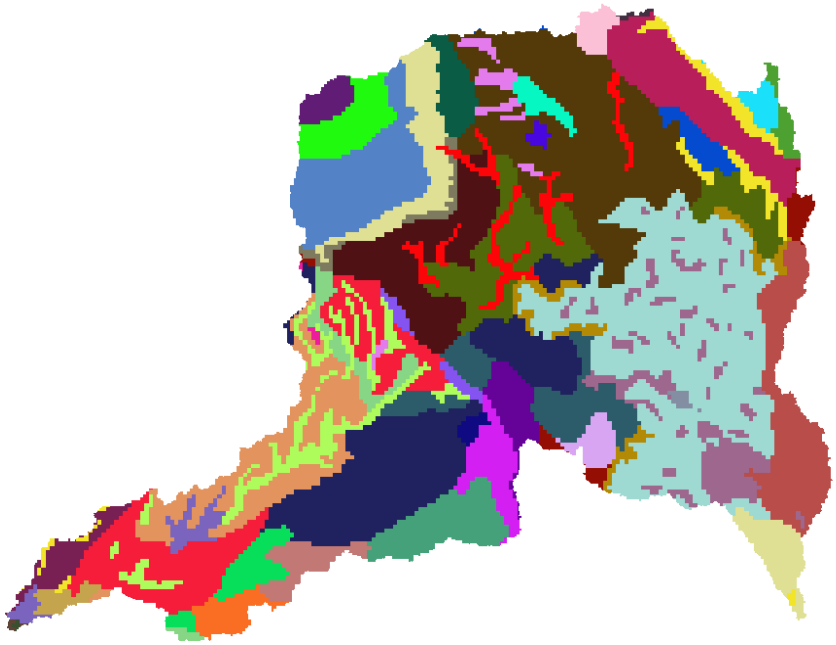


Table 4-1 Soil classifications map

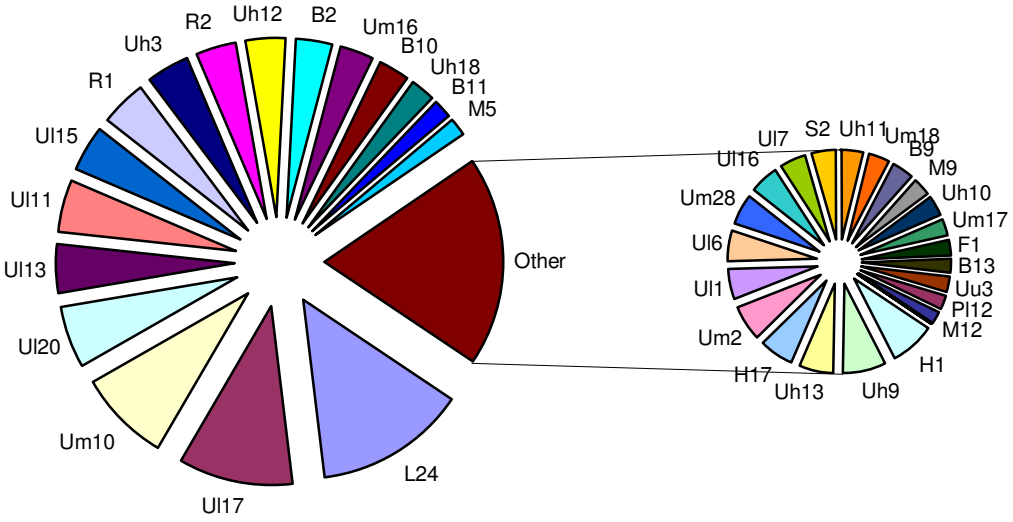
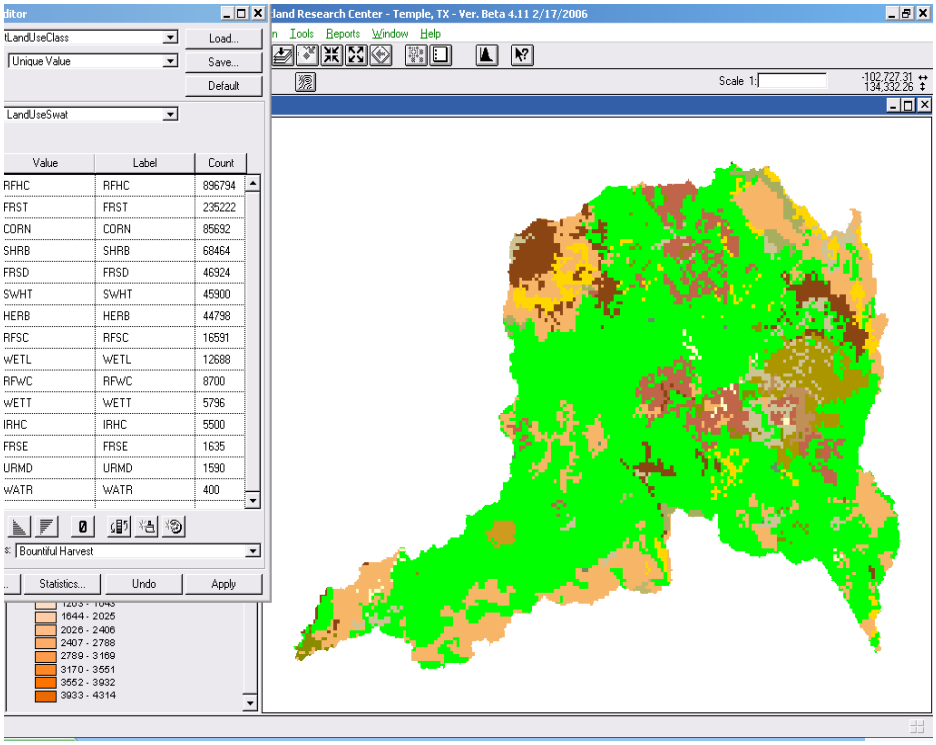


Figure 4-6 Soil classes percentiles in Nzoia watershed

4.2.3 Land use data



\model folder\watershed\text\landusesoilrepswat.txt

Table 4-2 Land cover and plant codes

Class	Land use	% Area
RFHC	Rainfed herbaceous crop	60.73
FRST	Forest-Mixed	15.93
CORN	Corn	5.81
SHRB	Closed and open shrubs	4.63
FRSD	Forest-Deciduous	3.18
SWHT	Spring Wheat	3.11
HERB	Closed and open herbaceous	3.03
RFSC	Rainfed shrub crop	1.12
WETL	Wetlands-Mixed	0.86
RFWC	Wheat	0.59
WETT	Woody and shrub temporary	0.39
IRHC	Irrigated herbaceous crop	0.37
FRSE	Forest-Evergreen	0.11
URMD	Urban	0.11
WATR	Water	0.03

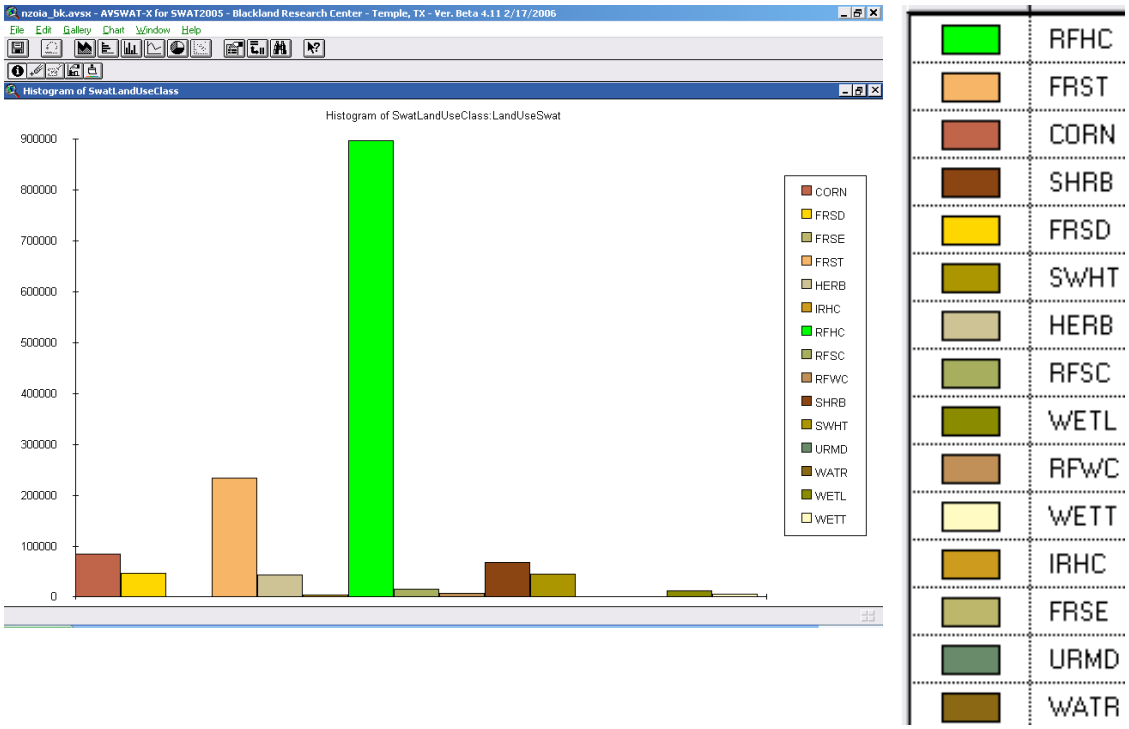


Table 4-3 Land use classes percentiles in Nzoia watershed

4.2.4 Temperature data

Temperatures over much of Kenya are subtropical or temperate, because of the reduction of temperature with altitude, and are similar to those in California rather than those elsewhere in equatorial Africa. Only the coastal lowlands experience the constant high temperatures and humidity associated with equatorial latitudes. Within the study area, there are four-temperature gauge stations have been used to the temperature data, but unfortunately, many data are missing. These stations are kakamega (average 27°c), kisumu (average 23.3°c), Kitale (average 25.9°c), Eldoret (average 18.4°c).

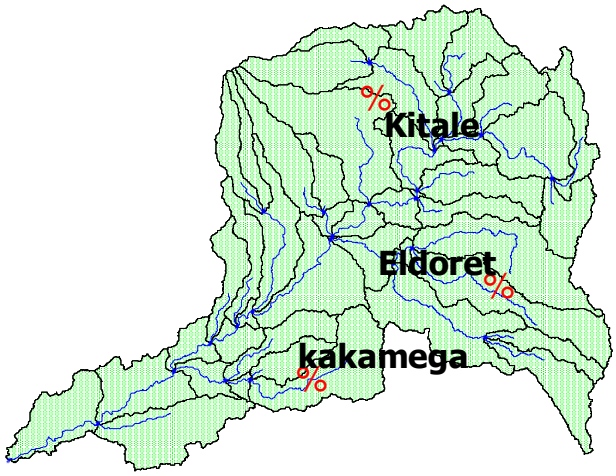


Table 4-4 Temperature data records

4.2.5 Rainfall data

There are data collected from 32 rainfall stations in the area of the Nzoia. Only 15 of those fall inside the watershed. Therefore, those 15 stations' data are the only used in rainfall analysis. Because SWAT calculate the rainfall on the subcatchments according to the shortest distance between rain gage station and the center of the subcatchment. Those station provide daily rainfall data from (1960 to 2004) In the following table, there are some descriptive statistics on the rainfall data all over the recorded years.

Table 4-6 rainfall data description

Station#		Jan	Feb	Mar	Apr	Ma	Jun	Jul	Aug	Sep	Oct	Nov	Dec
k8835039	Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Mx	15.0	42.0	65.0	65.0	48.0	40.0	29.0	46.0	42.0	50.0	72.0	50.0
	μ	0.37	0.92	2.07	3.85	4.28	3.31	3.98	3.92	2.29	3.04	2.24	0.56
	σ	1.08	2.64	4.96	6.77	6.78	6.23	5.41	6.43	5.00	4.99	4.99	2.09
k8834013	Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Mx	20.0	60.0	41.0	92.0	53.0	33.0	55.0	45.0	38.0	47.0	41.0	28.0
	μ	0.56	1.13	1.34	4.07	4.40	2.68	3.98	4.41	2.45	2.45	1.56	0.33
	σ	1.71	3.82	3.35	7.89	7.95	5.04	6.36	6.80	4.94	4.80	3.25	1.27
k8935158	Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Mx	66.3	48.4	60.1	45.0	58.0	37.7	49.9	52.7	60.4	100.	77.1	28.0
	μ	0.62	1.06	2.16	3.97	3.85	2.48	4.52	3.96	2.51	1.42	2.14	0.33
	σ	2.29	3.22	5.30	6.40	7.09	5.08	7.02	6.49	6.68	4.13	5.16	1.27
Kitale	Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Mx	23.2	54.1	75.9	60.1	57.3	50.2	41.1	58.2	52.5	44.7	53.0	42.3
	μ	0.77	1.59	3.28	5.86	7.31	4.15	3.91	5.09	4.06	3.75	3.46	1.26
	σ	2.02	4.33	6.47	9.36	10.9	7.53	6.47	8.61	6.55	6.04	6.37	4.12
k8935133	Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Mx	33.0	53.0	47.0	95.0	44.0	46.0	54.0	42.0	78.0	41.0	52.0	26.0
	μ	0.81	1.47	2.54	4.98	4.17	3.34	5.65	5.08	2.59	1.73	2.34	0.48
	σ	2.57	3.87	5.62	9.84	7.17	6.04	8.65	8.36	6.94	3.67	4.83	1.64
k8934008	Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Mx	41.0	61.0	58.0	68.0	75.0	43.0	41.0	51.0	81.0	79.0	58.0	21.0
	μ	1.28	1.88	3.62	5.90	6.46	4.42	3.66	5.68	5.09	3.66	3.08	0.84
	σ	3.99	4.46	7.41	9.36	9.85	7.14	5.67	8.59	8.74	6.69	5.79	2.37
k8935170	Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Mx	94.4	49.0	62.8	85.8	58.7	55.9	84.2	51.5	58.4	51.4	35.8	37.2
	μ	1.08	1.68	2.56	5.04	5.91	5.06	5.48	6.77	3.98	2.20	2.01	0.85
	σ	3.92	4.13	5.75	8.21	9.29	8.19	9.00	9.99	7.60	5.13	3.94	2.64
k8934060	Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Mx	31.8	49.8	55.1	48.1	48.1	56.0	48.0	69.0	44.8	76.5	72.2	55.5
	μ	1.39	2.55	3.33	6.20	7.61	3.74	5.57	6.18	5.17	4.15	3.55	1.33
	σ	3.80	5.75	7.09	8.87	9.82	7.27	7.53	10.1	7.56	7.69	7.01	4.08
Eldoret	Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

	Mx	28.0	55.0	51.0	81.0	49.0	56.0	48.0	69.0	30.0	38.0	63.0	24.0
	μ	0.82	1.52	2.42	5.32	4.21	3.74	5.57	6.18	2.13	1.69	2.51	0.62
	σ	2.22	3.89	5.71	10.2	7.64	7.27	7.53	10.1	5.17	3.45	5.18	2.08
k8934130	Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Mx	82.0	80.0	80.0	100.	73.0	73.0	60.0	120.	80.0	74.0	37.0	45.0
	μ	2.48	2.93	4.99	8.93	8.75	7.25	6.29	8.58	5.84	4.16	3.57	1.64
	σ	6.87	6.69	10.5	13.9	11.3	10.4	9.37	11.3	9.10	7.41	6.59	5.01
K8935010	Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Mx	29.3	81.3	46.9	55.4	42.5	51.6	50.5	40.0	45.1	30.6	53.5	24.5
	μ	0.89	1.66	2.82	6.88	4.59	2.61	3.49	4.53	1.92	2.14	3.05	1.13
	σ	2.46	4.54	5.47	9.14	6.66	5.05	5.17	6.95	4.04	3.95	5.84	3.06
kakamega	Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Mx	67.0	42.0	80.0	74.0	52.0	73.0	84.0	74.0	62.0	52.0	65.0	57.0
	μ	2.89	3.58	4.91	8.46	8.03	6.12	5.96	6.97	5.90	4.41	4.46	2.36
	σ	7.76	7.61	9.73	12.6	9.86	10.1	9.06	10.3	9.22	7.24	8.11	6.15
k8934059	Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Mx	50.0	54.0	90.0	85.0	58.0	60.0	82.0	63.0	75.0	76.0	74.0	67.0
	μ	2.00	2.15	4.93	8.96	8.11	3.41	5.37	4.82	5.00	4.99	4.70	2.44
	σ	5.17	5.31	10.3	13.2	11.2	7.56	8.48	10.2	9.29	9.29	9.55	6.72
K8934139	Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Mx	59.5	58.1	90.0	98.5	60.0	38.8	56.2	68.0	49.7	72.0	60.9	139.
	μ	1.14	1.72	4.14	5.45	4.34	1.75	3.77	2.42	2.68	2.93	3.05	2.68
	σ	3.36	5.19	9.62	9.60	7.88	4.34	4.44	5.55	5.64	6.24	6.81	7.24
k8934134	Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Mx	41.0	90.0	75.0	72.0	73.0	42.0	58.0	54.0	108.	37.0	57.0	71.0
	μ	1.30	3.15	4.79	8.16	8.88	4.33	3.81	4.33	4.42	3.85	5.14	1.92
	σ	3.65	7.91	9.19	12.1	12.0	7.07	6.55	7.41	7.91	6.52	9.68	5.68
k8934119	Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Mx	40.0	48.0	61.5	89.0	58.4	95.5	54.5	61.7	66.0	52.8	69.0	130.
	μ	1.51	2.84	4.04	6.76	8.24	5.45	5.11	5.75	5.36	3.80	3.94	1.89
	σ	4.34	6.54	8.46	11.7	12.3	9.37	9.28	9.40	9.44	8.80	8.24	6.11

The following figure displays that there is a double rainy peaks in the summer in months April and August with minimum rain in winter season.

In the figures Figure 4-8 and Figure 4-9, the spatial distribution of the rainfall average monthly data over Nzoia watershed.

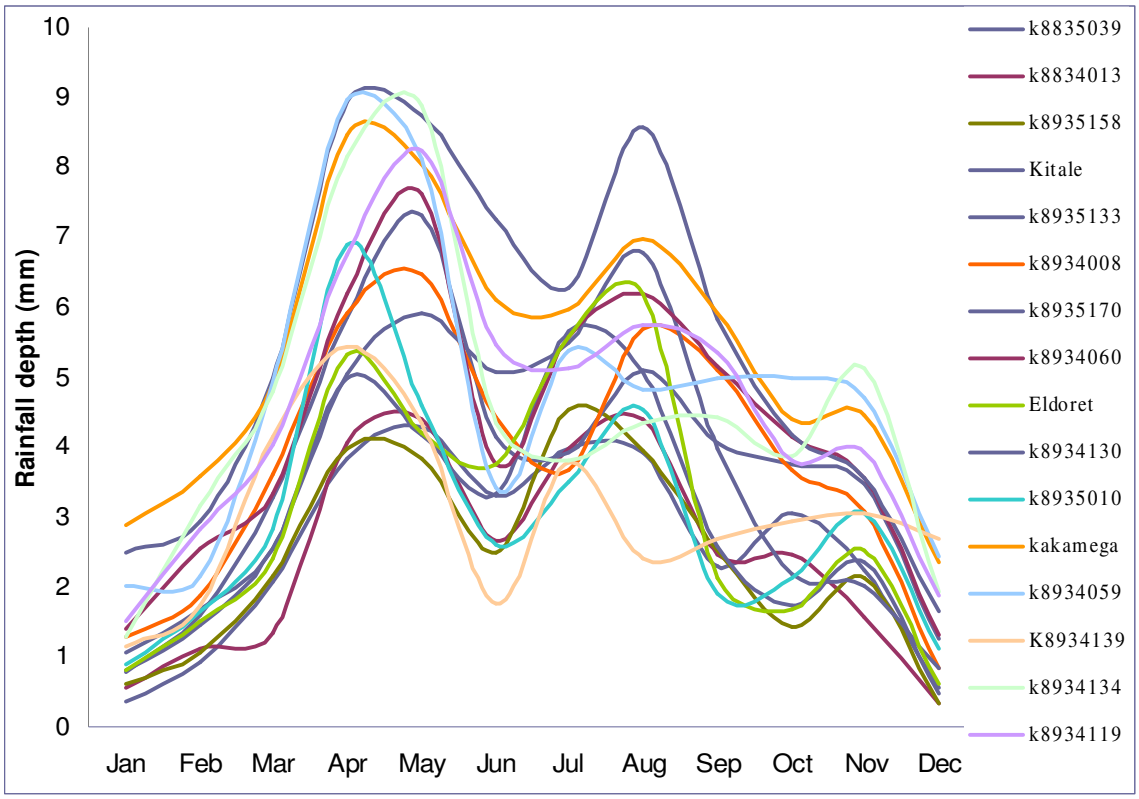


Table 4-7 Average yearly rainfall

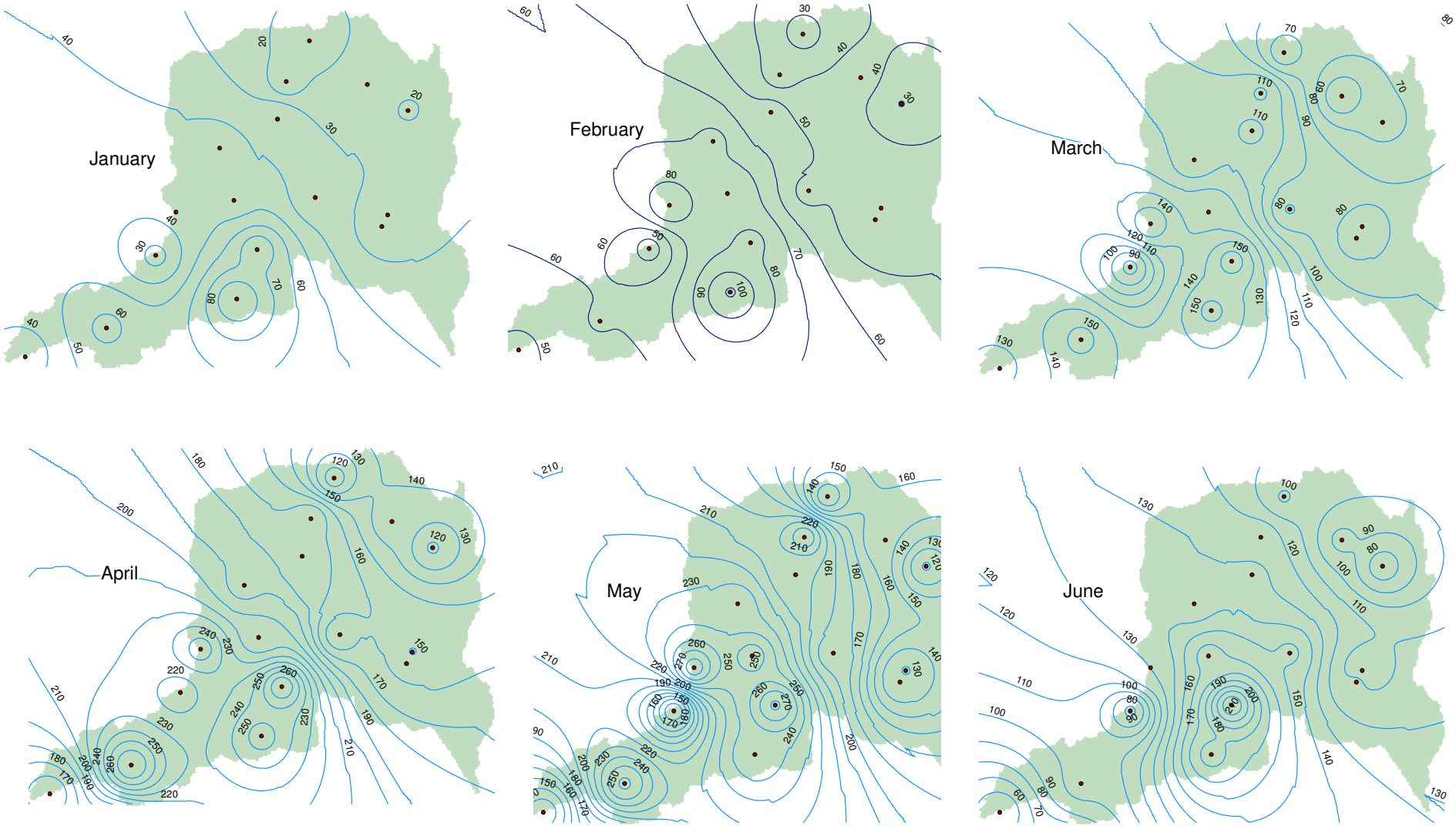


Figure 4-7 Monthly rainfall spatial distribution (Jan.-Jun.)

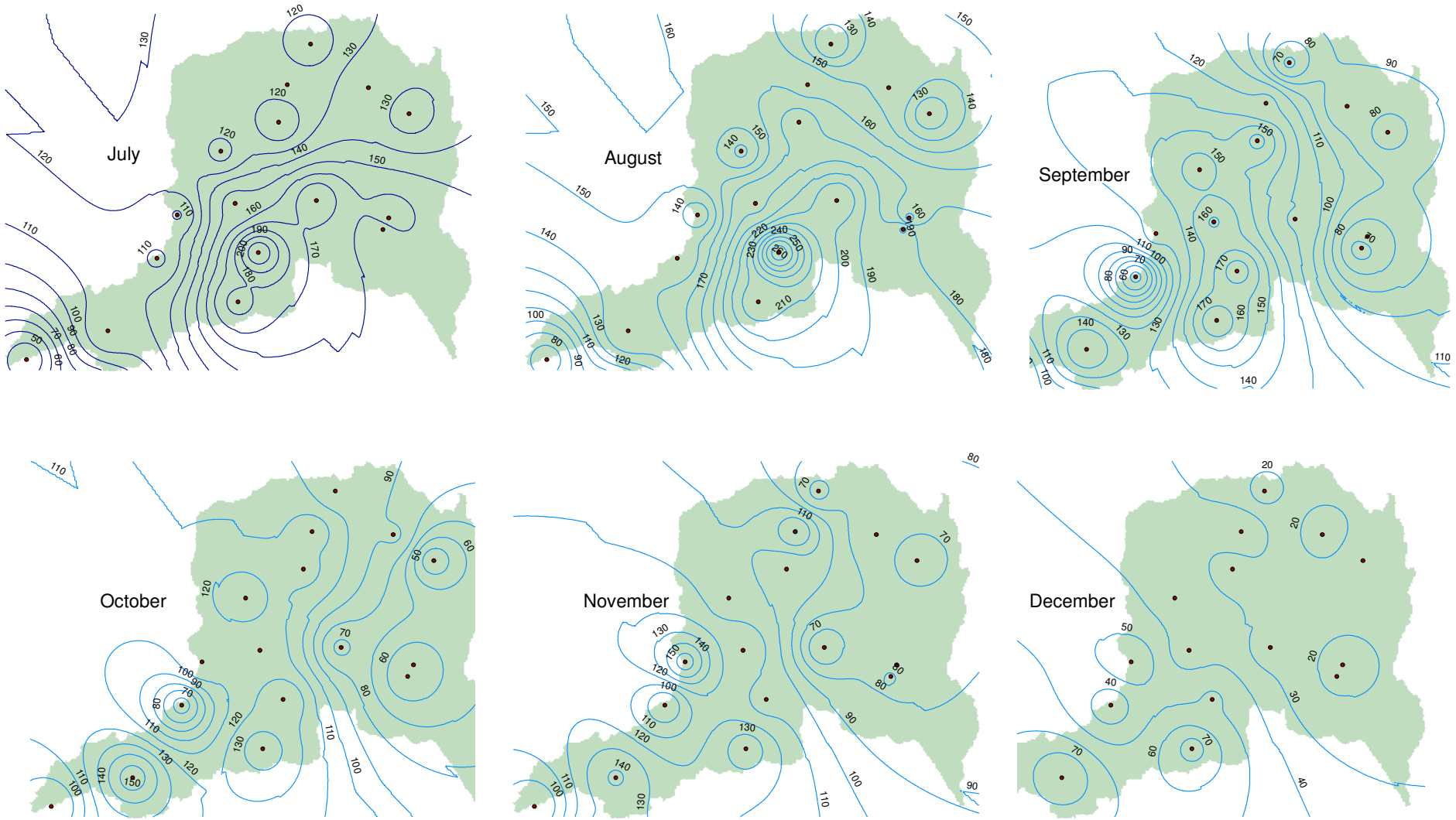


Figure 4-8 Monthly rainfall spatial distribution (July-Dec.)

4.2.6 Observed flow data

29 years of observed flow data was measured in a flow station at outlet of Nzoia river (Figure 4-10) these data are valid from 1970 to 1998. Unfortunately, flow data after mid 1985 have a lot of missing values. So, calibration periods selected to be from 1968 to 1979 with two years worming up. while the validation period selected from 1978 to 1984.

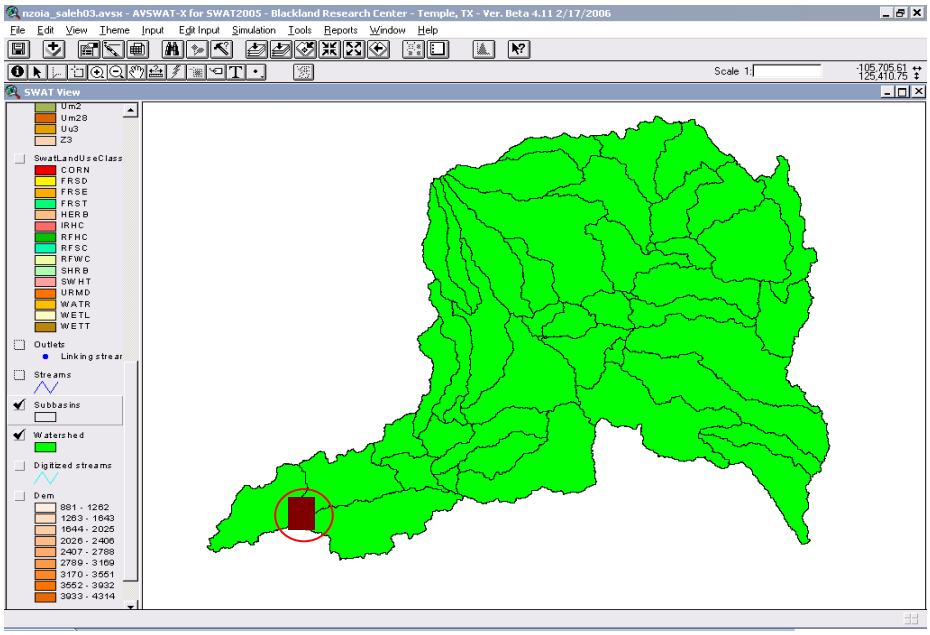


Figure 4-9 Flow gage station

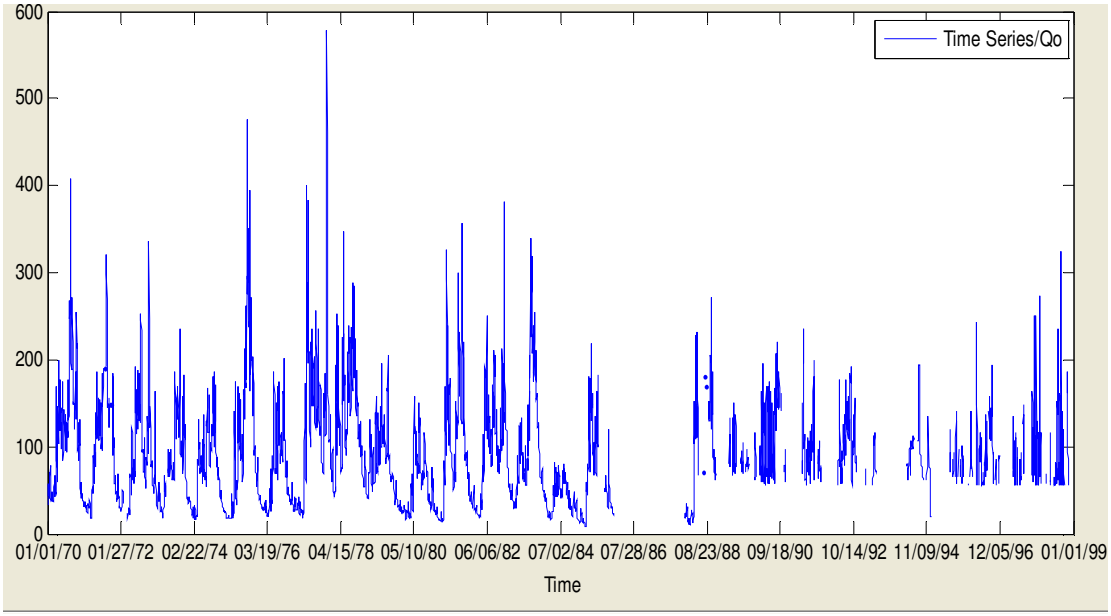


Figure 4-10Observed flowtime series

4.3 Model setup

4.3.1 Introduction

Building distributed hydrological models became more easy after the great development in data collection techniques like remote sensing and settelites which gives more accurate data. So, After prepare data, model setuped using SWAT graphical user interface called AVSWAT. This model setup process as in Figure 3-4can be classified into the following main steps. First step is watershed deliniation, which includes DEM setup, streams definition and outlet definition. Second step is land use/soil characterization. Thisrdly, import weather data. Fourth step is creation of inputs, which includes write all input files and modify any of them manually if needed. last step is to run SWAT and read the outputs. In the following paragraphs there are some discriptions to main steps of model setup.

4.3.2 Watershed delineation

This tool is an automatic procedure utilizes Digital Elevation Model (DEM) data to delineate subwatersheds, after define some parameters by the user. Figure 4-12shows defining DEM file, also definition of shapefile contains a digitization to study area streams, which makes delineation processes more easy and accurate. But before completing this procedure, user should check DEM properties Figure 4-12. This check means select DEM projection and DEM vertical and horizontal units.

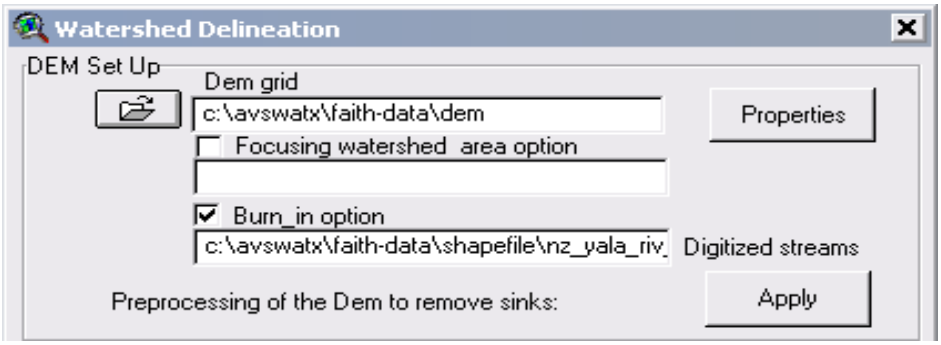


Figure 4-12 Define DEM file and digitized strams

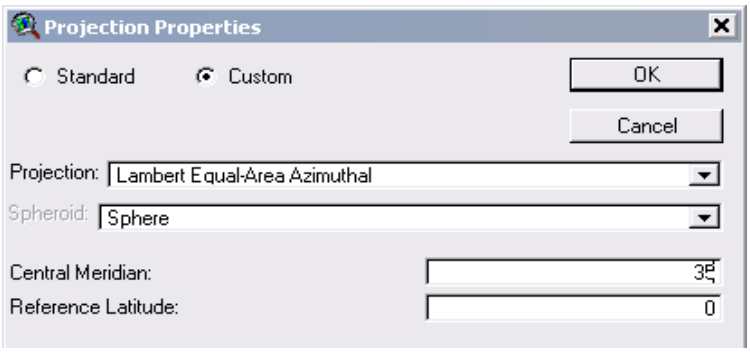


Figure 4-11 Projecting definition

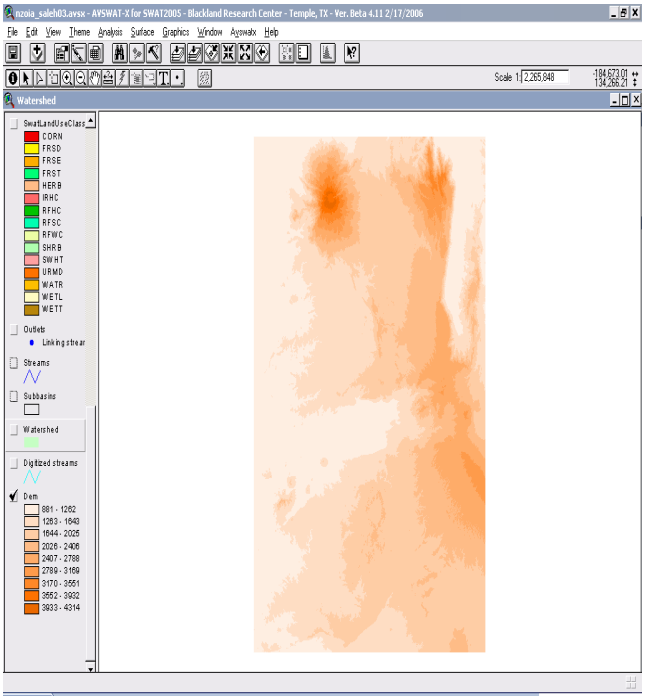


Figure 4-16 Open DEM file

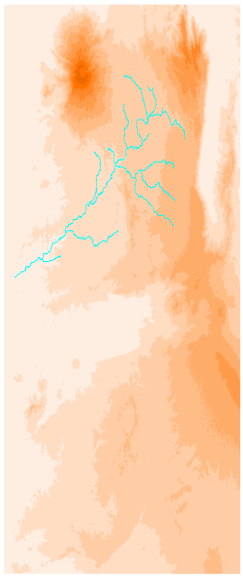


Figure 4-15Open manual digitized shapefile for Nzoia ruver

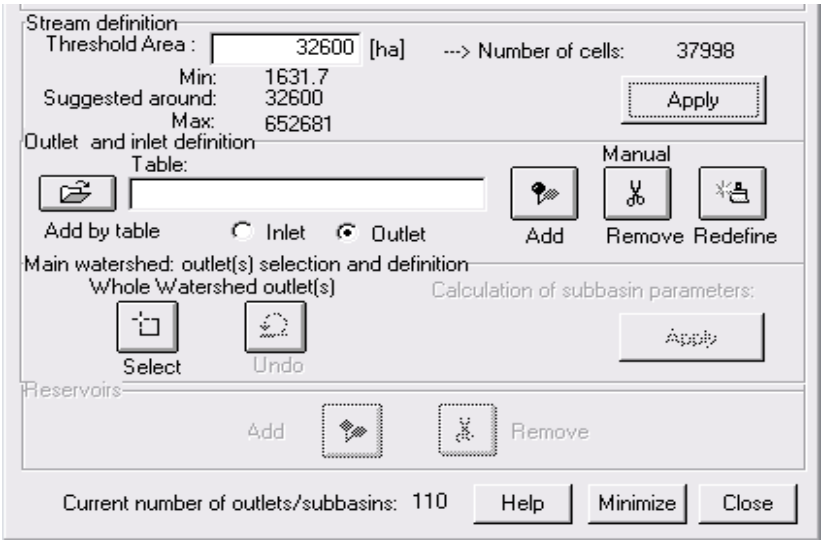


Figure 4-14 Select suncatchments areas

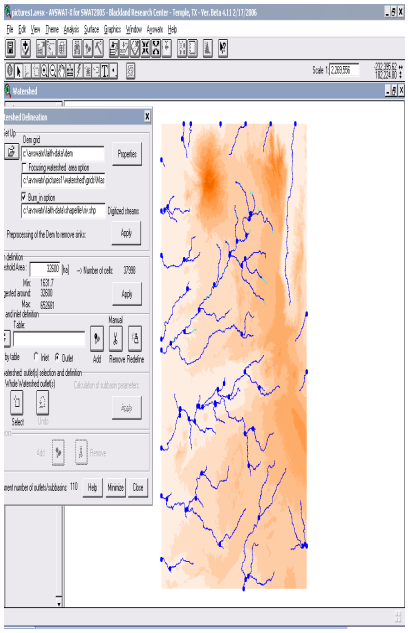


Figure 4-13Automatic streams defining

4.3.3 Land use and soil characterization

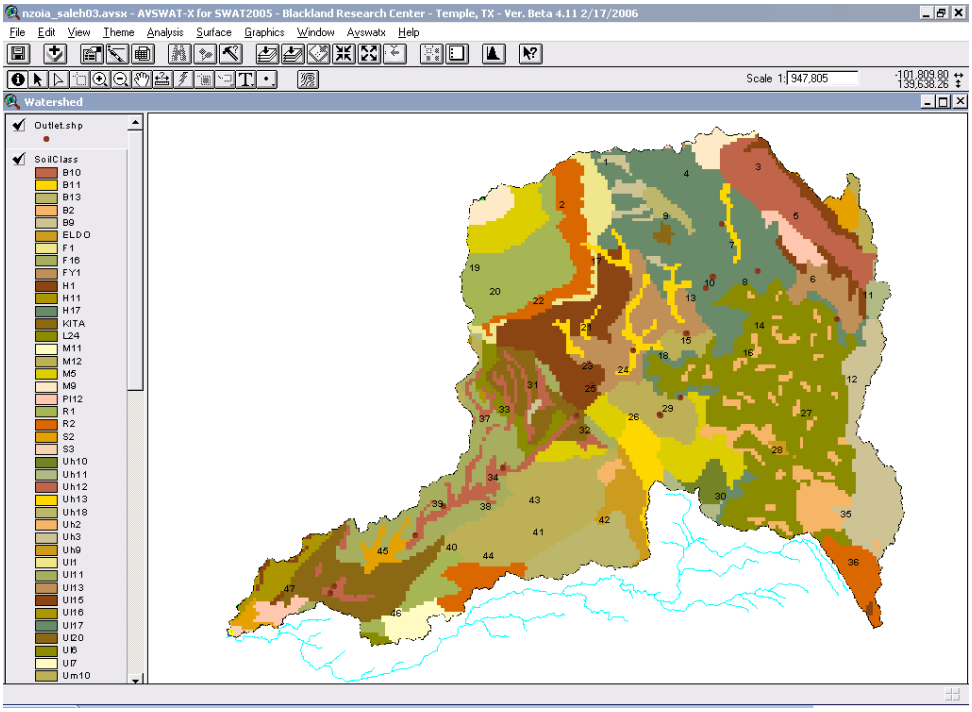


Figure 4-17 Landuse classes

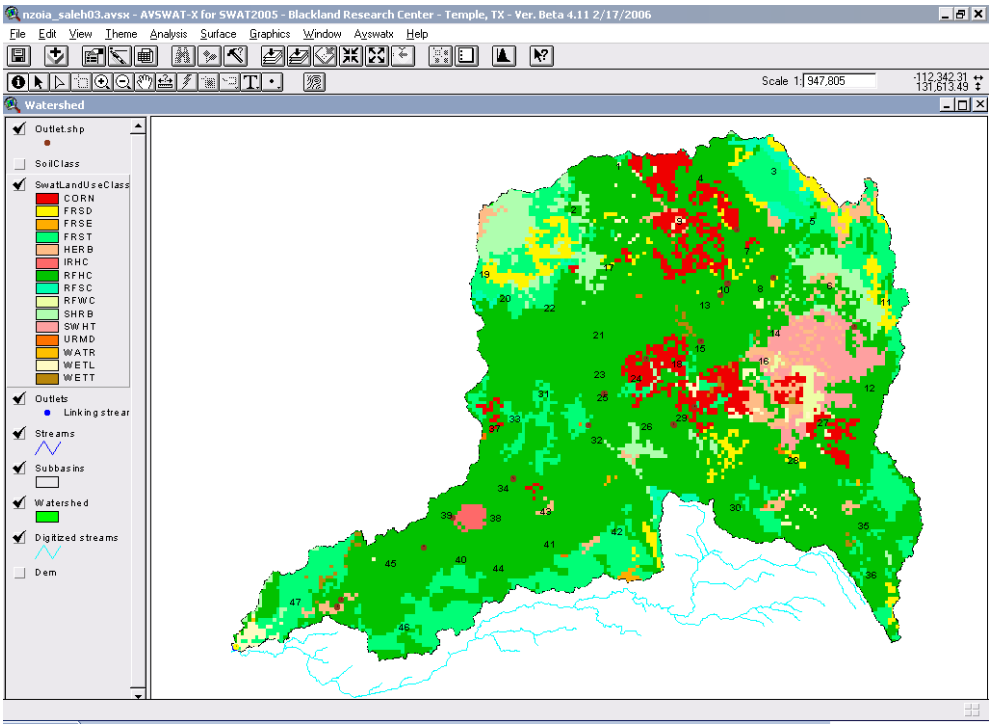


Figure 4-18 Soil classes

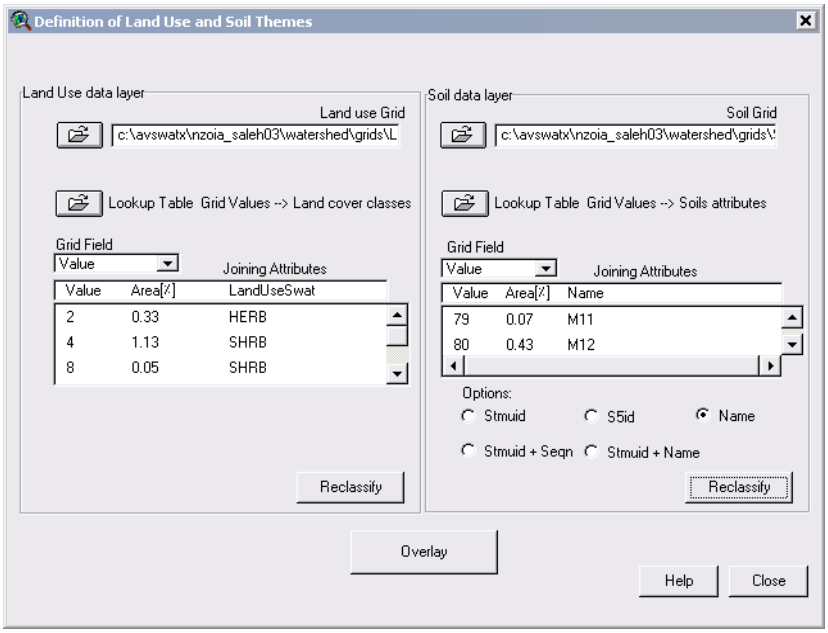


Figure 4-19 Define soil and landuse shape files

4.3.4 Import weather data

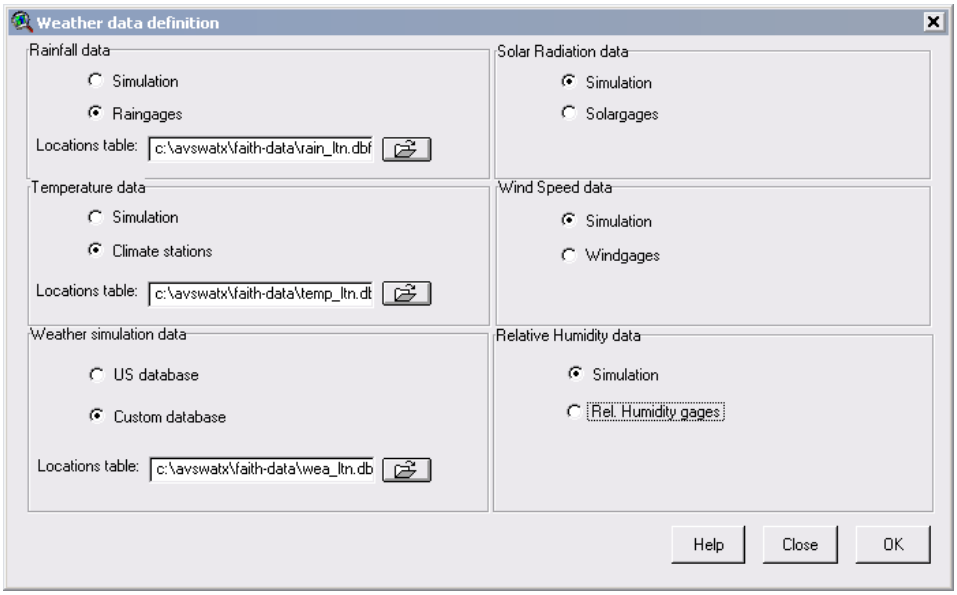


Figure 4-20 Weather data definition

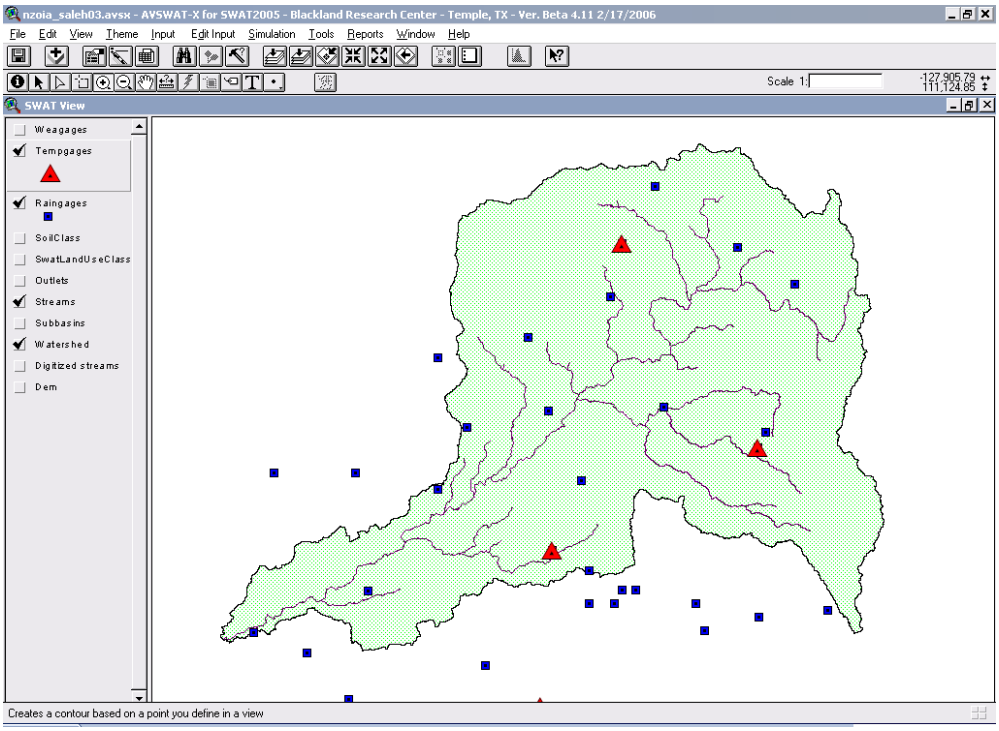


Figure 4-21 Weather stations

4.3.5 Creation of inputs

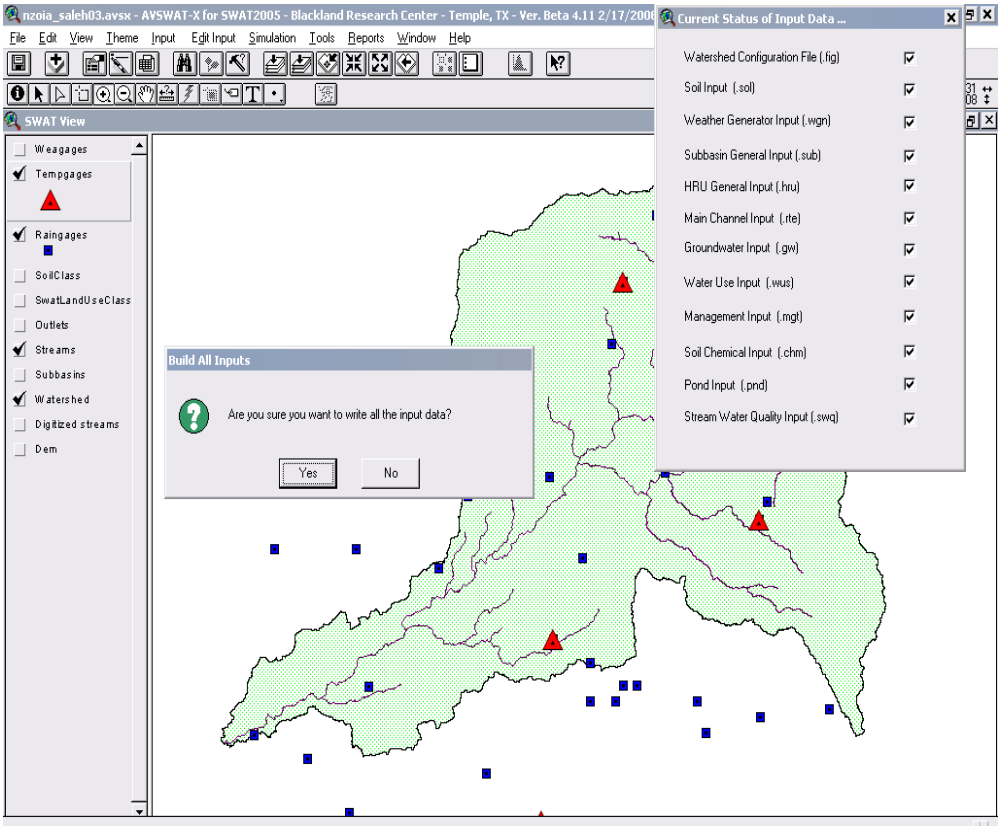


Figure 4-22 Build all input files

4.3.6 Running the model

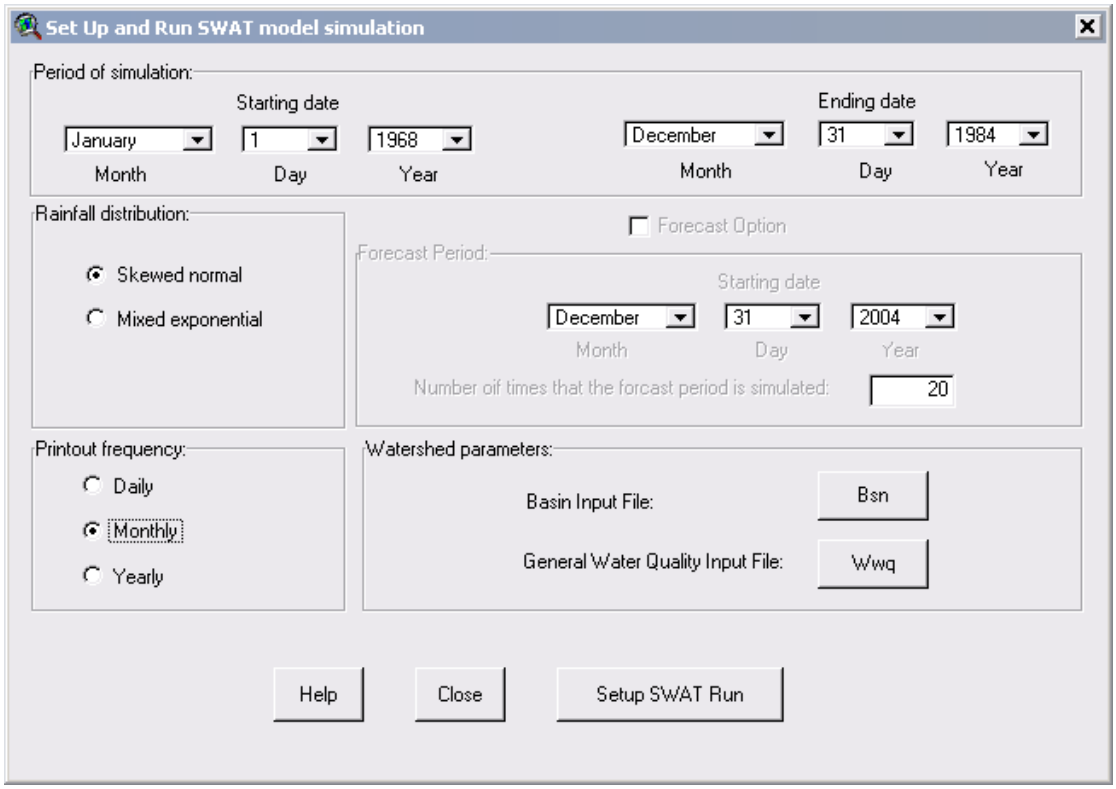


Figure 4-24 Model runing options

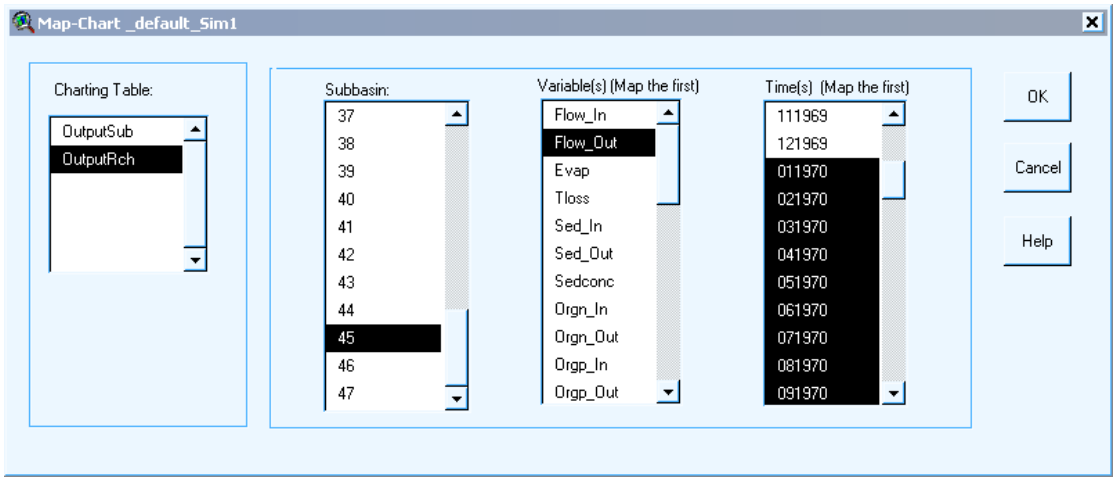


Figure 4-23

4.3.7 Read model outputs

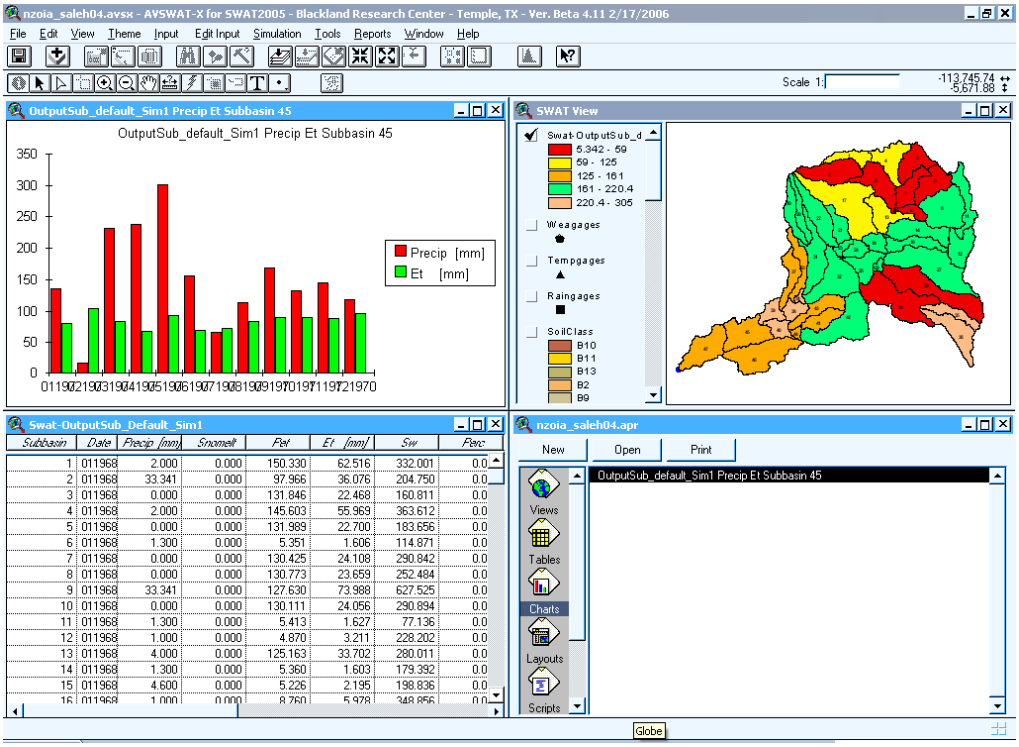


Figure 4-25 SWAT results window

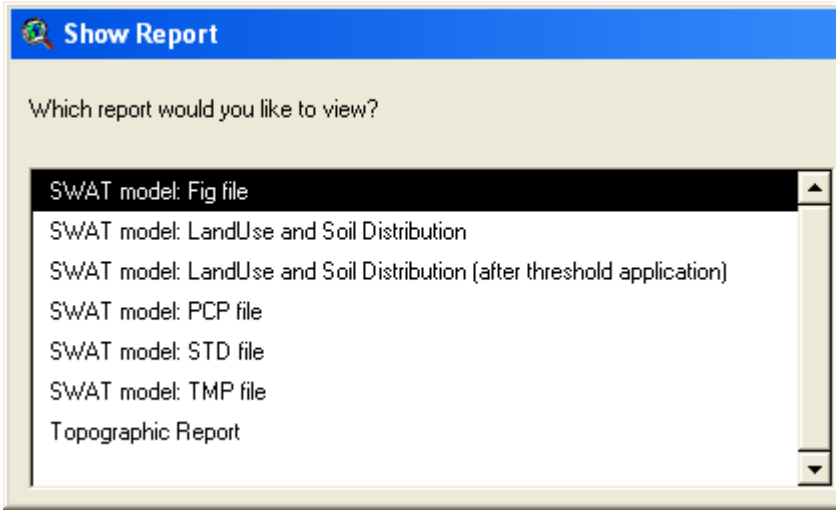
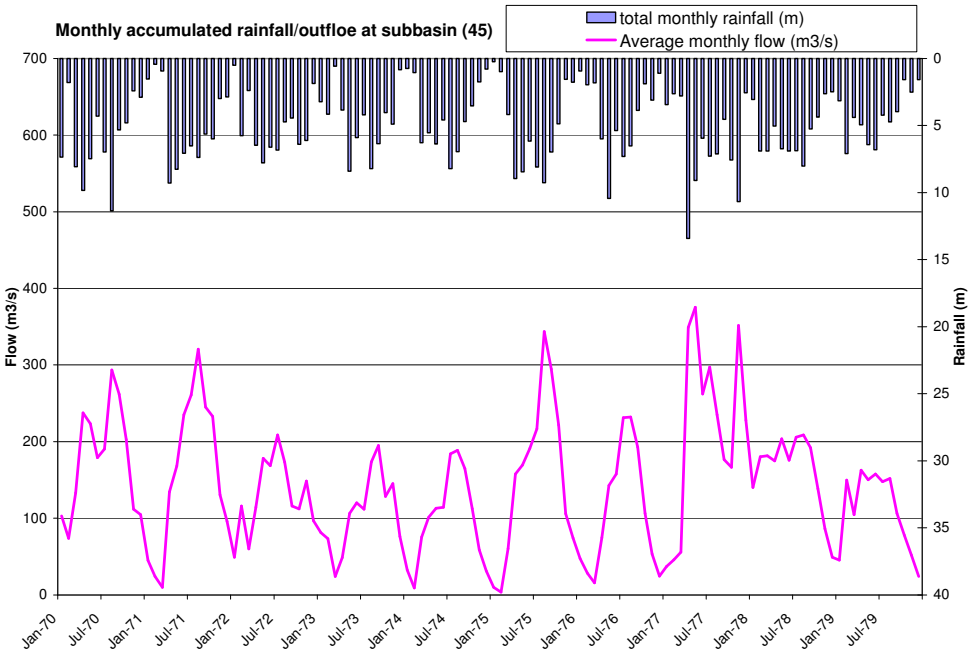


Figure 4-26 Available data reports in SWAT

Reports menu appears when select SWAT user can show model output reports after complete running the model, by selecting show list from,

4.4 Model results analysis

In case of text files model, user has ability to define number of years to skip output printing by changing NYSKIP value in (file.cio).Furthermore, user can select output details level to be daily, monthly or yearly by changing print code IPRINT value in (file.cio). Then After running SWAT, user can get the model outputs as map charts, reports or database files. The most important SWAT output files are (output.std) this file has a summary output. (output.rch) the main channel output file contains summary information for each routing reach in the watershed.



4.5 Sensitivity analysis in SWAT

Sensitivity analysis is described theoretically in section 2.2 and here is a brief description of using sensitivity analysis in SWAT model. SWAT will perform the analysis for a predefined set of 27 variables with 10 intervals in the LH sampling. This means that SWAT will make 280 runs to complete the sensitivity analysis.

Modeler can study sensitivity analysis using AVSWAT or manually in case of text files based model. In first case, user should first activate "Sensitivity Analysis-Autocalibration-Uncertainity" tools from tools menu. Then he has to select a specific scenario and simulation to analyses the sensitivity in it. After that, user should select if the sensitivity analysis will be for flow only, flow and sediment or flow, sediment and water quality. After defining the observed data file, user can click on start button to start sensitivity analysis.

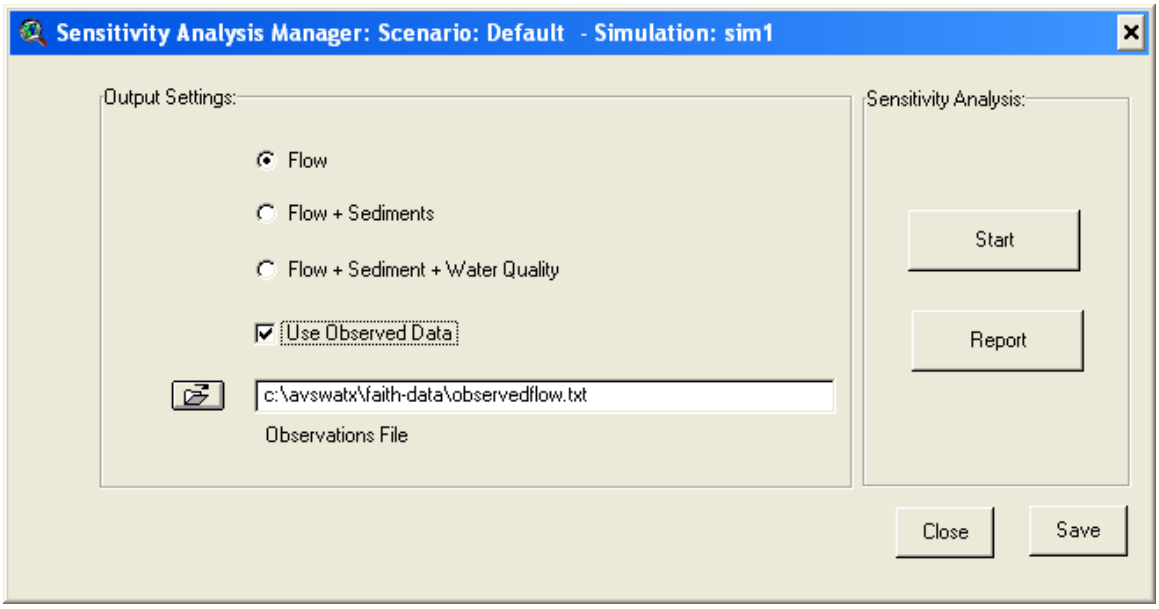


Figure 4-27 Sensitivity analysis options

In the other case, text files based model, to apply sensitivity analysis in SWAT it is necessary to prepare some files. The first necessary files for sensitivity analysis is (Sensin.dat), it specifies control variables of the LH-OAT. Second one is (changepar.dat), it specifies model parameters included in the sensitivity analysis, the upper / lower bounds and its variation method. Third file contains the observed flow after replacing the empty periods. Furthermore, ICLB value should be changed in file.cio file into one. Sensitivity analysis results are written in details in (sensout.out) and in summarized in (sensresult.out). In these files the parameters are sorted according to its affect on objective function values and model output values.

4.5.1 Sensitivity analysis results

After preparing those files, sensitivity analysis output of Nzoia watershed displays that 10 parameters out of 27 parameters are more sensitive in controlling the flow.

The results of analysis displayed more clearly in Figure 4-30. In addition, a detailed description of sensitivity analysis results is listed in Table 4-8.

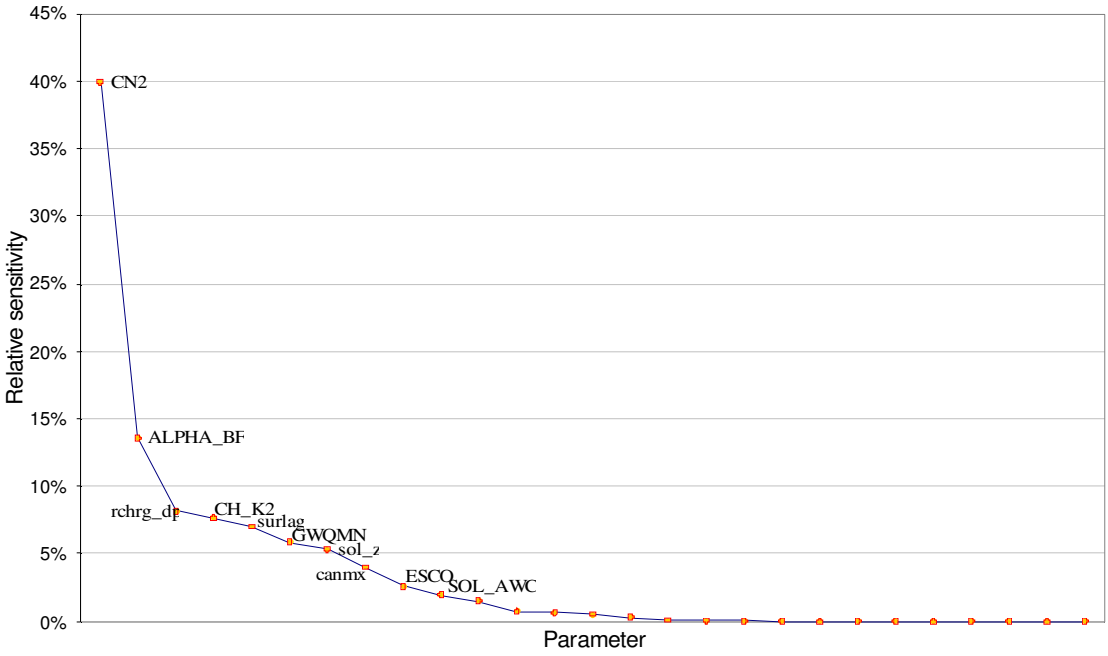


Figure 4-28 Relative sensitivity between model parameters

Table 4-8 Sensitivity analysis results

Parameter	*Rank*	***Description***
CN2	1	Initial SCS runoff curve number for moisture condition II. It is directly proportional to the surface runoff.
ALPHA_BF	2	Base flow alpha factor (days). It is directly proportional to speed of land response to recharge
rchrg_dp	3	Deep aquifer percolation fraction. It is directly proportional to lateral flow
CH_K2	4	Channel effective hydraulic conductivity (mm/hr). It is directly proportional to the movement of water from the streambed to the subsurface
surlag	5	Surface Runoff time lag (days)
GWQMN	6	Threshold depth of water in the shallow aquifer required to start the return flow (mm H2O). It is inversely proportion to amount of base flow.
sol_z	7	Depth from soil surface to bottom of layer (mm).
canmx	8	Maximum canopy storage (mm H2O).
ESCO	9	Soil Evaporation Compensation factor. It is inversely proportion to amount of evaporation.
SOL_AWC	10	Available Water Capacity (mm H2O/mm soil)
GW_REVAP	11	Groundwater "revap" coefficient. It inversely proportion to the amount of water transfer from shallow aquifer to root zone
sol_k	12	Saturated hydraulic conductivity (mm/hr).
GW_DELAY	13	Groundwater delay (days)
SLOPE	14	Average slope steepness (m/m).

SLSUBBSN	15	Average slope length (m).
epco	16	Plant uptake compensation factor.
REVAPMN	17	Threshold depth of water in the shallow aquifer for "revap" or percolation to the deep aquifer (mm H2O).
BIOMIX	18	Biological mixing efficiency
ch_n	19	Channel Manning coefficient
sol_alb	20	Moist soil albedo.
SMFMX	28	Melt factor for snow on Jun 21 (mm/ºC/day)
SMFMN	28	Melt factor for snow on December 21 (mm/ºC/day)
TLAPS	28	Temperature laps rate (ºC/km)
SFTMP	28	Snow Fall Temperature
SMTMP	28	Snow melt base temperature (^{o}C)
TIMP	28	Snow Pack Temperature Lag factor
blai	28	Leaf area index for crop

4.6 Auto-calibration

Selecting the "Auto-calibration and Uncertainty" from tools menu in AVSWAT opens a new dialog. This dialog allows selecting the scenario and the simulation target of the application. After that a new window will open, (Figure 4-31), in this window SWAT gives users ability to selecting a method of updating the parameters values, it has three alternatives (replacement by value, adding to initial value or multiplying the initial value).

In case of text files based model, ICLB value in (file.cio) file should changed to two. also, a new line should add to (fig.fig) file to define at which subcatchment's outlet we have the calibration observed flow, Figure 4-30shows this line, where (a45.aut) is file name for subcatchment 45 observed flows, it is important to replace all missing data in (a45.aut) with negative values. Furthermore, (Changepar) file should add, this file defines all parameters to be optimized, this file also contains these parameters max/min values, way of changing these parameters values within calibration process, Figure 4-31 is an example to this file.

```
autocal      16  136    1    0
       a45.aut
```

Figure 4-30define calibration data file in (fig.fig) file

low. bound	up. bound	par	imet	HRU numbers
0.000	1.000	4	1	2001 Rchrg_Dp
0.000	10.000	7	1	2001 Canmx
0.000	150.000	54	1	2001 Ch_K2
0.000	10.000	33	1	2001 Surlag
35.000	98.000	10	1	2001 Cn2
0.000	5000.000	6	1	2001 Gwqmn
0.000	1.000	1	1	2001 Alpha_Bf
0.000	1.000	17	1	2001 Sol_Awc

Figure 4-29 example of "changepar.dat" file

PARASOL tries to optimization Multi-objectives, so it calculates Global Optimization Criterion (GOC) In addition to objective function (see section 2.5.2 for more details). PARASOL writes GOC values in " sceparobj.out " file,

calculates Nash-Sutcliffe when calibrate a model, using the following equation

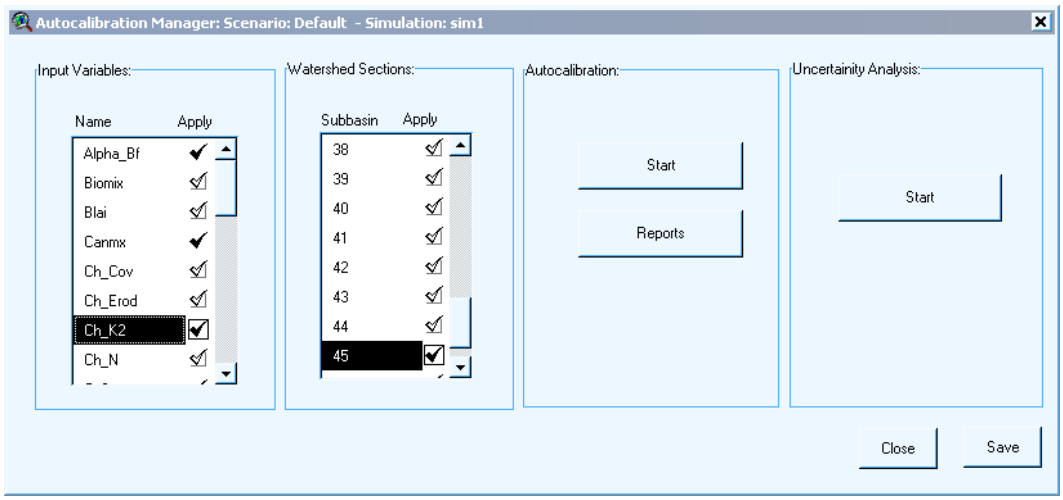


Figure 4-31 Autocalibration options in SWAT

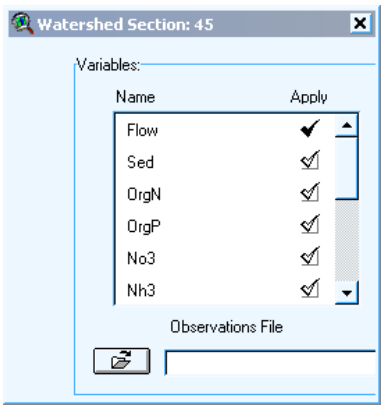


Figure 4-33 Select parameters to be autocalibrated

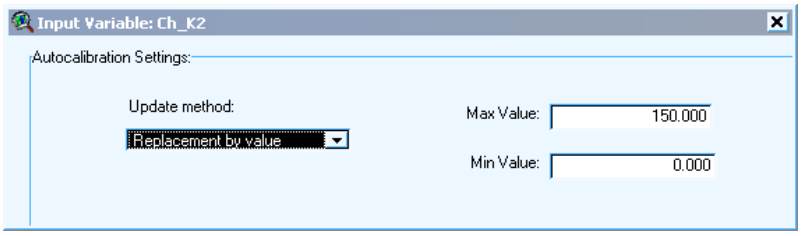


Figure 4-32 Select parameters updating methodand its boundaru values

5 Applications of model calibration techniques

This chapter contains applications to the calibration techniques which described in chapter 2 (except the manual calibration method due to its extremely difficult in this case study) followed by analysis for its results. These calibration analyses utilized the modeling tools which described in chapter 3.

Calibration period -after two years worming up- is 9 years from beginning of 1970 tell the end of 1979. Followed by five years for validation from beginning of 1980 tell the end of 1984.

Nash-Sutcliffe model efficiency coefficient is used to assess the calibration power of applied model. This coefficient as described before in section 2.3, it ranges from -∞ to one, and as it increase it is better.

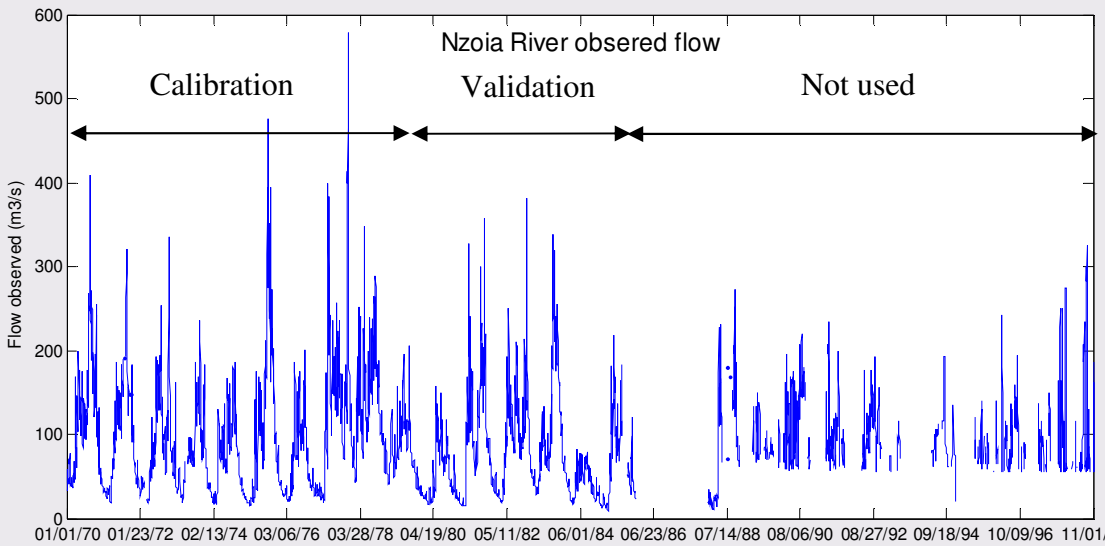


Figure 5-1

5.1 PARASOL

PARASOL method as described in sections (2.5.2 and 4.6) was applied firstly to calibration model parameters because it is complemented in SWAT and almost all of its input files are ready after completing the model and sensitivity analysis. From the output files, model's global optimization criterion (GOC) enhanced with every model run, Figure 5-2displays that more clearly.

Wide ranges of parameters boundaries were selected to calibrate the model initially, then parameters likelihoods to make good GOC were calculated and drawn in Figure 5-3. These likelihoods used to modify the parameters boundaries which will help in making faster and more accurate calibration process.

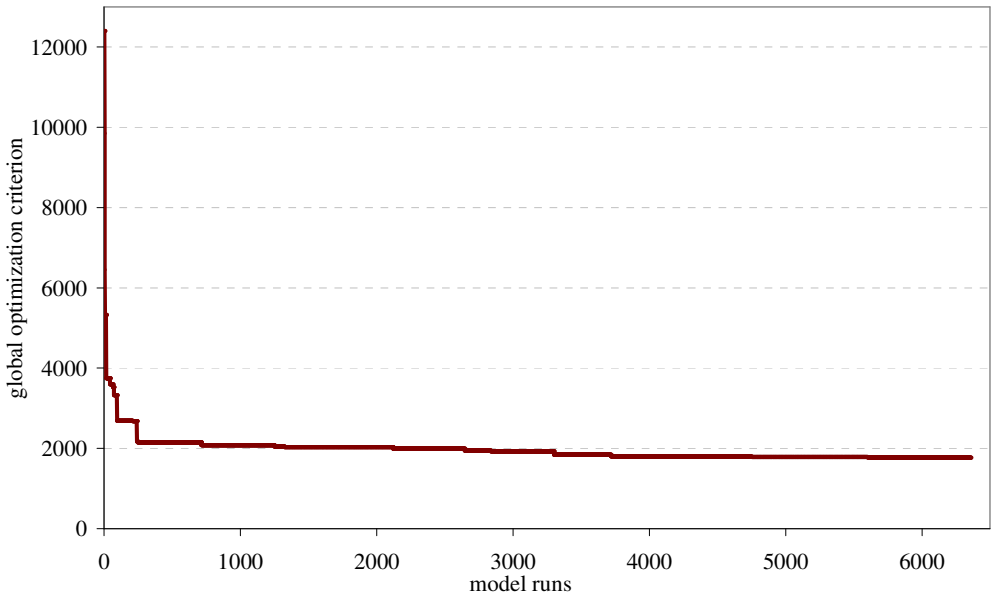


Figure 5-2 Global optimization criterion

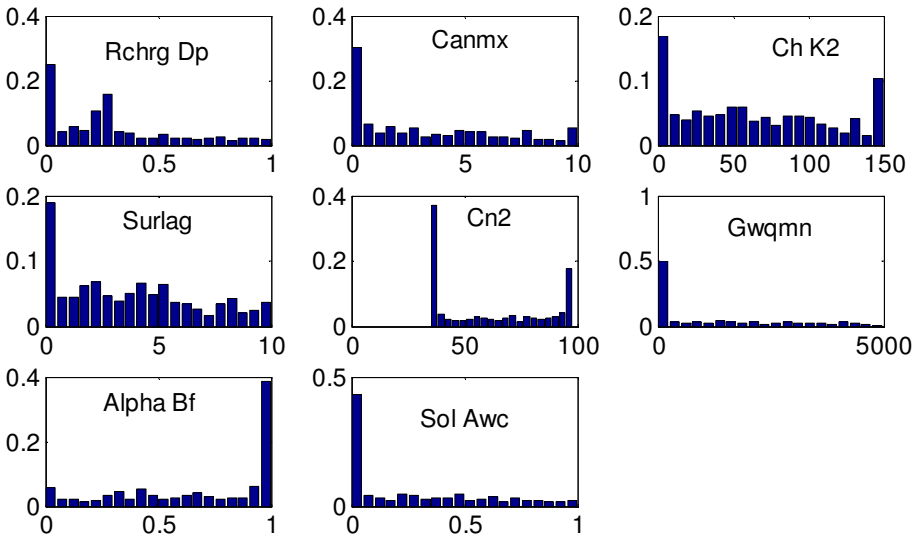


Figure 5-3 Parameters likelihood values

In previous figure, it contains of eight subfigures each one represent one of calibrated parameters. the horizontal axe is the parameters value and the virtical one is the liklihood value for each subrange (bin). We can understand from that figure that, for six parameters (Rchrg_Dp, Canmx, Ch_K2, Surlag, Gwqmn and Sol_Awc), it is beter to reduce the parameter boundaries and make it norrow. For the runoff curve number (cn2), it is better to make the lower boundary starts from (35 : 40). and may be 50 is good for the upper bound. Last parameter Alpha_Bf should rais the upper boundary and make it norrow.

Detailed output for each optimization loop is found in "parasolout.out" file. Notice that PARASOL wrote "Lowest Nash-Sutcliff" but it means "Highest Nash-Sutcliff". Parameter values which corresponding to the optimum solution can be found in "bestpar.out" file.

PARASOL applied two times for model calibration. First one it was searching in wide ranges of parameters, summary of this case results are in Table 5-1. The other case the searching ranges became narrower around the higher likelihood values, results of this case are presented in Figure 5-4 and summary of results is valid in Table 5-2

Table 5-1PARASOL calibration results (ordinary parameters ranges)

Parameter	Lower bound	Upper bound	Best Value	Notes
Rchrg_Dp	0.00	1.00	0.311	The model run 6356 times
Canmx	0.00	10.00	0.135	The highest Nash-Sutcliff is 0.748
Ch_K2	0.00	150.00	24.11	Found the best at the trial 6147
Surlag	0.00	10.00	0.58	
Cn2	35.00	98.00	35.13	
Gwqmn	0.00	5000.00	0.095	
Alpha_Bf	0.50	1.50	0.98	
Sol_Awc	0.00	0.50	0.266	

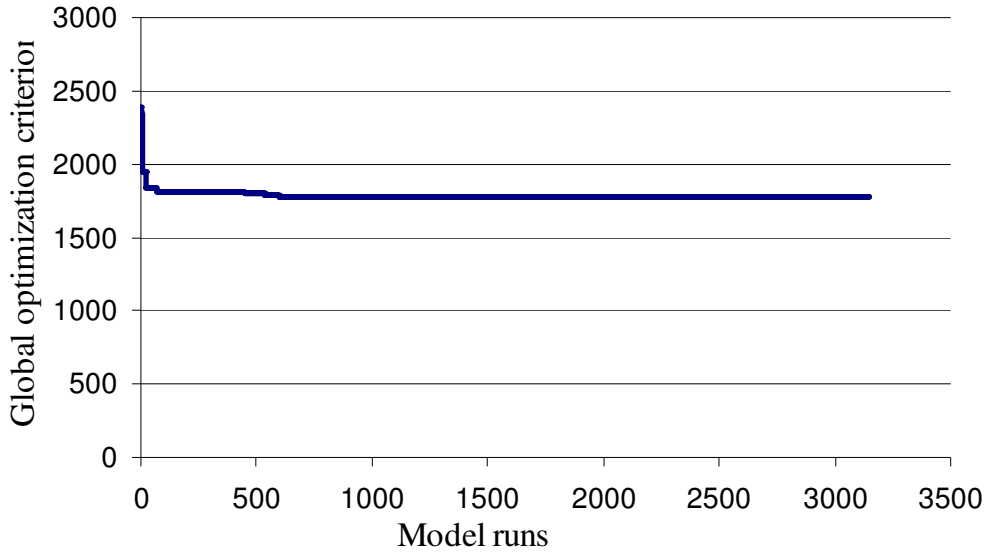


Figure 5-4 Global optimization criterion improvement (case two)

Table 5-2PARASOL calibration results (modified parameters ranges)

Parameter	Lower bound	Upper bound	Best Value	Notes
Rchrg_Dp	0.00	0.50	0.23	The model run 3146 times The highest Nash-Sutcliff is 0.713 Found the best at the trial 2854
Canmx	0.00	1.00	0.06	
Ch_K2	0.00	50.00	15.25	
Surlag	0.00	1.00	0.45	
Cn2	25.00	50.00	25.30	
Gwqmn	0.00	1.0	0.11	
Alpha_Bf	0.00	1.50	1.46	
Sol_Awc	0.00	8.00	8.0	

5.2 ACCO

Adaptive cluster covering (ACCO) was used in calibrating the case study model. It is working under GLOBE and linked with swat through some MATLAB codes, for more details please revise sections (2.5.3.1 and 3.3.2).
Based on the ACCO output files (ACCOL.gen, ACCOL.rst and ACCOL.his). The calibration process by ACCO made 125 model runs in a total running time about one hour, at the end it found that best parameter compination that make Nash-Sutcliff value equals to 0.72.
Figure 5-5displays the improvement in Nash-Sutcliff after removing the outlier values which came at the beginning of each searching loop.

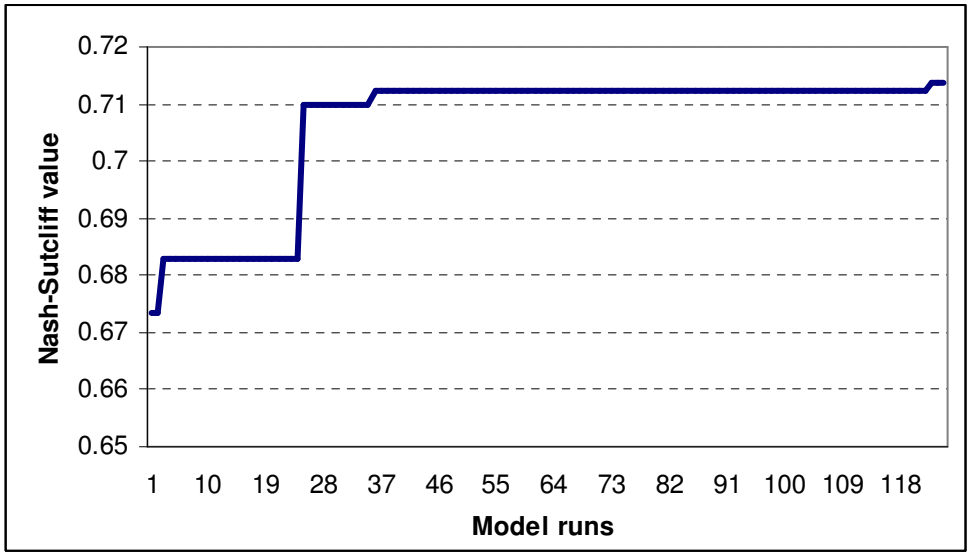


Figure 5-5 Model goodness of fit improvement through searching process

The optimum parameters values as estimated by ACCO in Table 5-3

Table 5-3 Best parameters values using ACCO

Parameter	Lower bound	Upper bound	Best Value	Notes
Rchrg_Dp	0.00	0.50	0.24	The model run 125 times The highest Nash-Sutcliff is 0.714
Canmx	0.00	1.00	0.23	
Ch_K2	0.00	50.00	38.24	
Surlag	0.00	1.00	0.73	
Cn2	25.00	50.00	41.00	
Gwqmn	0.00	1.0	0.64	
Alpha_Bf	0.00	1.50	1.41	
Sol_Awc	0.00	8.00	2.73	

5.3 ACCOL

Adaptive cluster covering with local searches described before in 2.5.4. For GLOBE user he has to select "with local search (Powell-Brent)" option under "local search in ACCO". Analysis of output gen file gives Figure 5-6 that displays the development of model goodness of fit through searching process.

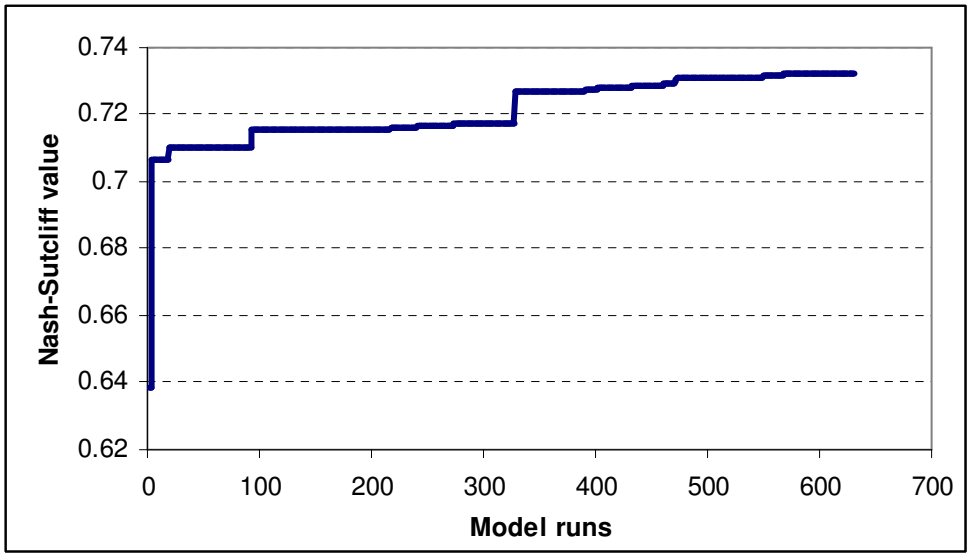


Figure 5-6 Model goodness of fit improvement through searching process

The optimum parameters values as estimated by ACCOL in Table 5-4

Table 5-4 Best parameters values using ACCOL

Parameter	Lower bound	Upper bound	Best Value	Notes
Rchrg_Dp	0.00	0.50	0.27	The model run 613 times The highest Nash-Sutcliff is 0.742
Canmx	0.00	1.00	0.05	
Ch_K2	0.00	50.00	22.22	
Surlag	0.00	1.00	0.70	
Cn2	25.00	50.00	34.20	
Gwqmn	0.00	1.0	0.02	
Alpha_Bf	0.00	1.50	1.74	
Sol_Awc	0.00	8.00	0.24	

5.4 GA

Genetic algorithm calibration was applied to calibrate this case study model, a brief explanation to theory of genetic algorithm optimization is found in 2.5.4. GLOBE was used to apply this algorithm; user can control the optimization process through number of characteristics (Figure 5-7). The population size and the maximum number of generations are two main characteristics of those.

In order to know the effect of these two parameters on the goodness of fit, Nzoia model was optimized using three different values of these parameters. Table 5-5 contains summary of these cases, also (Figure 5-9, Figure 5-10 and Figure 5-11) describes the rapidity of improving the goodness of model fit in three different cases. Figure 5-8 displays part of the "rsp' file that contains the calibration results. In Table 5-5 a summary of the results.

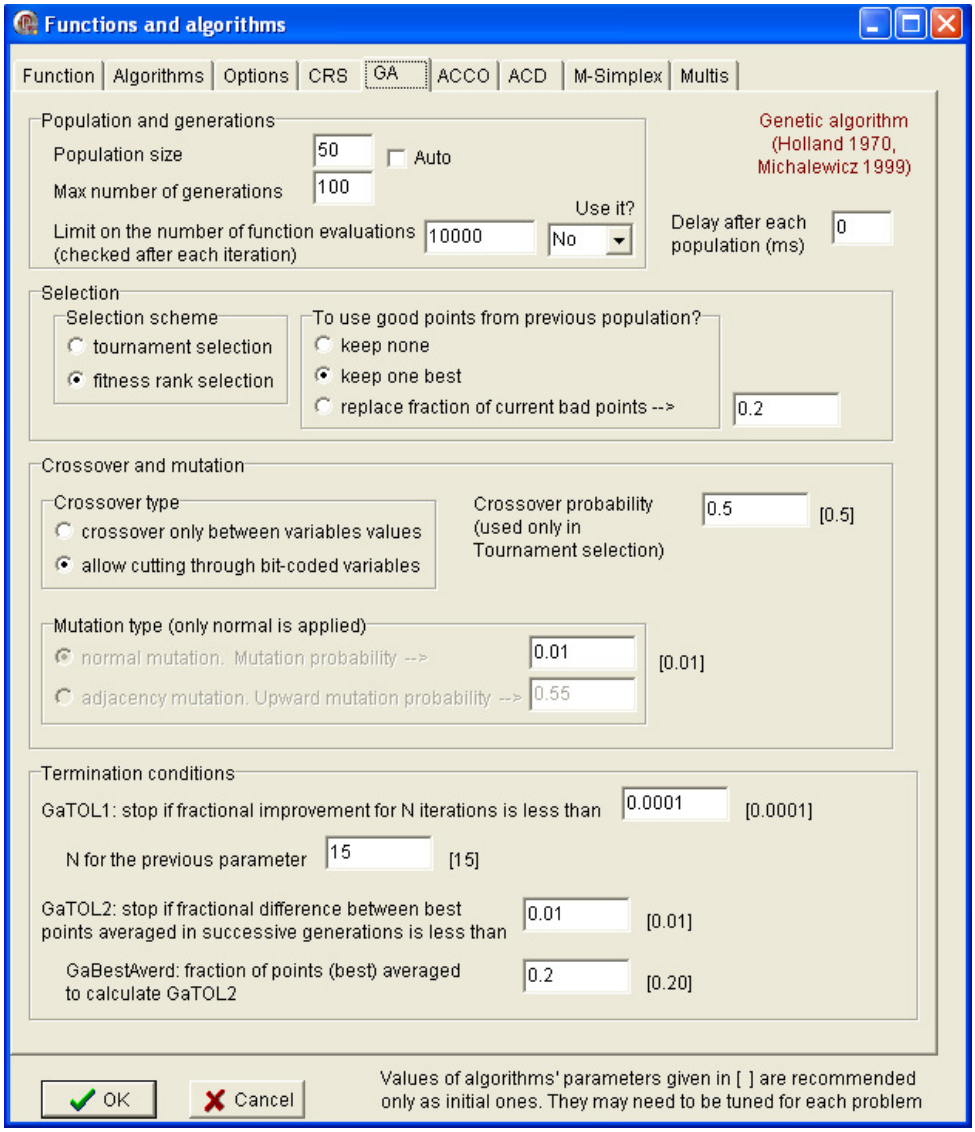


Figure 5-7 Genetic algorithm options in GLOBE

```
                GA final results
                ========================
Total number of function evaluations: 1899
The best point in G.PIN format (8 vars, F=-7.27837E-01
^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^
 2.32368E-01
 8.09656E-02
 9.41649E+00
 1.36722E-02
 4.97703E+01
 1.44841E-01
 1.49570E+00
 6.42866E+00
^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^^
------------ All    10 best points------------
        Func.            x1           x2           x3           x4           x5
F=-7.27837E-01 ( 2.32368E-01, 8.09656E-02, 9.41649E+00, 1.36722E-02, 4.97703E+01,
F=-7.27837E-01 ( 2.32368E-01, 8.04773E-02, 9.41649E+00, 1.36722E-02, 4.97703E+01,
F=-7.27750E-01 ( 2.32368E-01, 7.85241E-02, 1.05884E+01, 1.36722E-02, 4.97703E+01,
F=-7.27750E-01 ( 2.32368E-01, 8.09656E-02, 1.05884E+01, 1.36722E-02, 4.97703E+01,
F=-7.27717E-01 ( 2.31880E-01, 9.02432E-02, 1.21540E+01, 1.36722E-02, 4.97581E+01,
F=-7.27484E-01 ( 2.32368E-01, 8.09656E-02, 9.41649E+00, 1.36722E-02, 4.97703E+01,
F=-7.27443E-01 ( 2.32368E-01, 2.05969E-01, 9.41649E+00, 1.36722E-02, 4.97703E+01,
F=-7.27331E-01 ( 2.32368E-01, 2.05359E-01, 1.05884E+01, 1.36722E-02, 4.97703E+01,
F=-7.27224E-01 ( 2.32307E-01, 9.07315E-02, 6.29139E+00, 1.36722E-02, 4.95743E+01,
F=-7.26472E-01 ( 2.32368E-01, 3.38786E-01, 6.29139E+00, 1.36722E-02, 4.95743E+01,
--------------------------------------------------------------------------------
GA running time: 13 h 23 m 50.53 s
```

Figure 5-8 GA outputs

Table 5-5 GA outputs with diffrent controlling parameters values

	Case one	*Case two*	*Case three*
Population size	10	50	60
Maximum number of generations	20	100	100
Best objective function value	0.723	0. 727	0.748
Total number of function evaluations	180	1899	3835

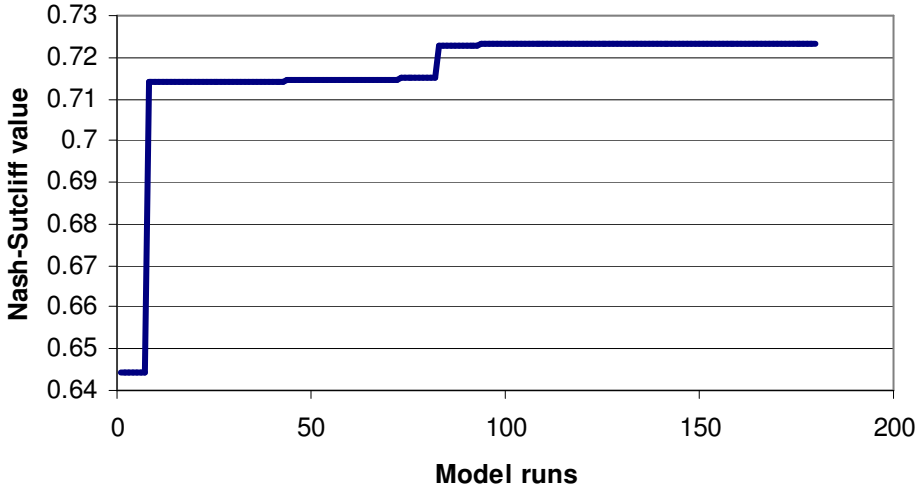


Figure 5-9 Model goodness of fit improvement (case one)

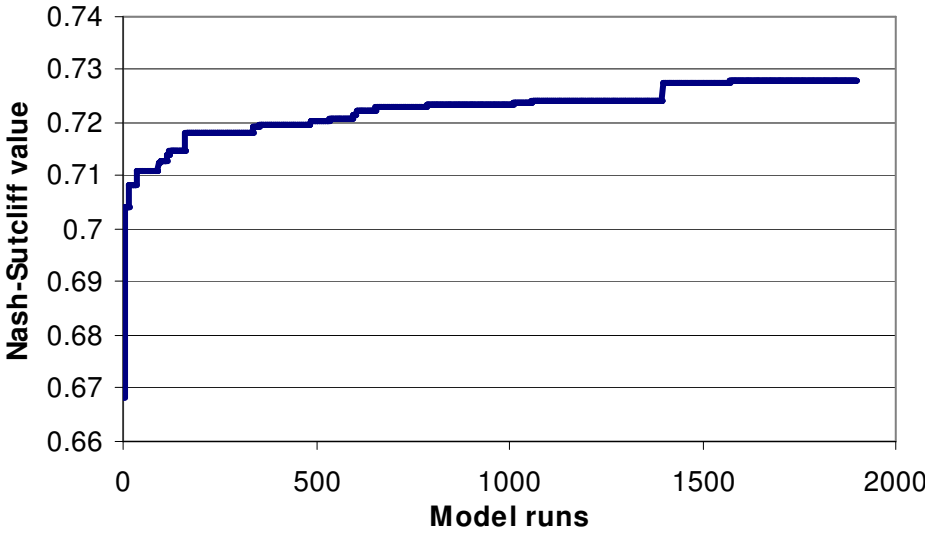


Figure 5-10 Model goodness of fit improvement (case two)

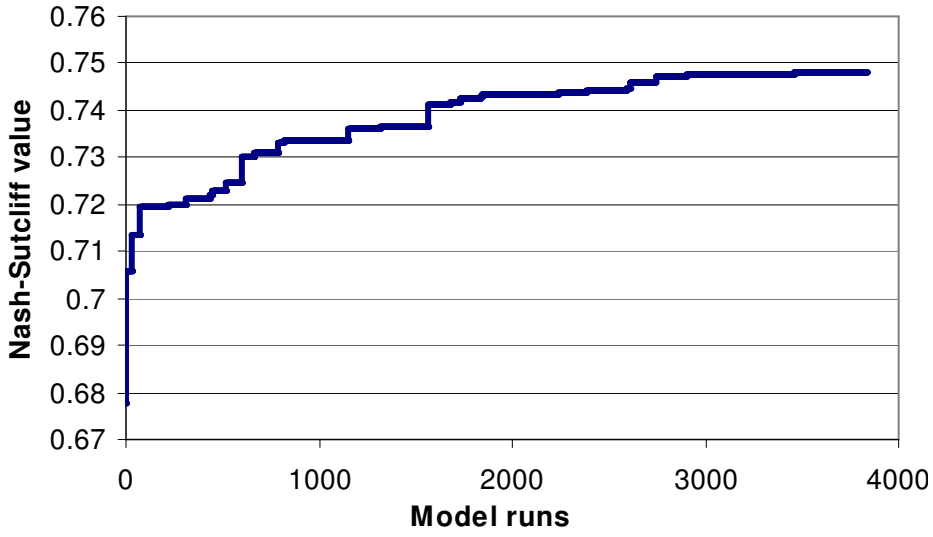


Figure 5-11 Model goodness of fit improvement (case three)

5.5 M-Simplex

Brief explanation to this algorithm can be found in section 2.5.6. M-simplex was applied using initial population size = 60, and 100 starts. Figure 5-12 displays M-Simplex main widow in GLOBE. M-Simplex achieved 0.717 Nash-Sutcliff objective function's value after 1414 model runs.

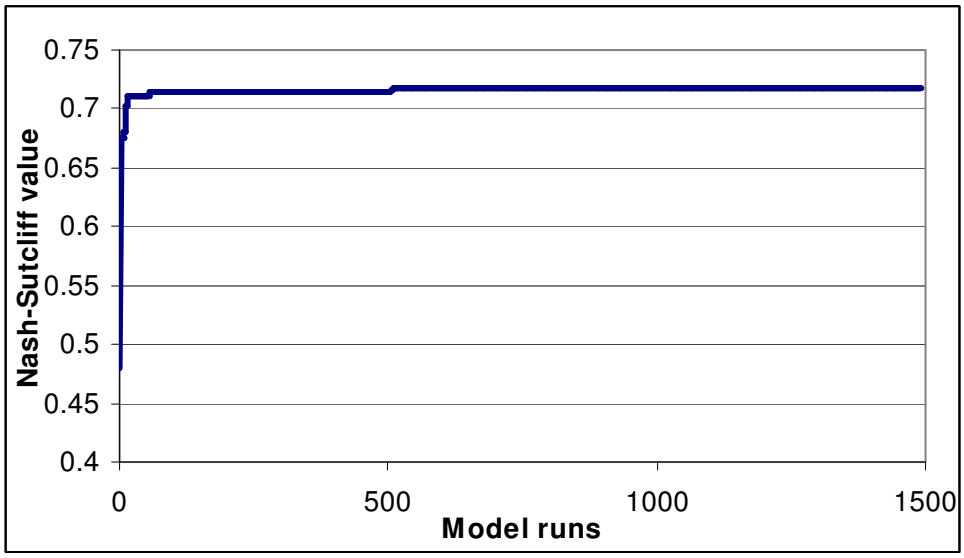


Figure 5-12 Model goodness of fit improvement (M-simplex)

5.6 Comparison between different calibration techniques results

In previous section, five alternatives calibration algorithms were applied in Nzoia watershed model. Some of them applied many times with different characteristics. Since PARASOL algorithm was applied first, it gave a guide about the boundary values of model sensitive parameters, so, these boundaries has been changed for calibration algorithms implemented in GLOBE.

Table 5-6Summary results of calibration algorithms

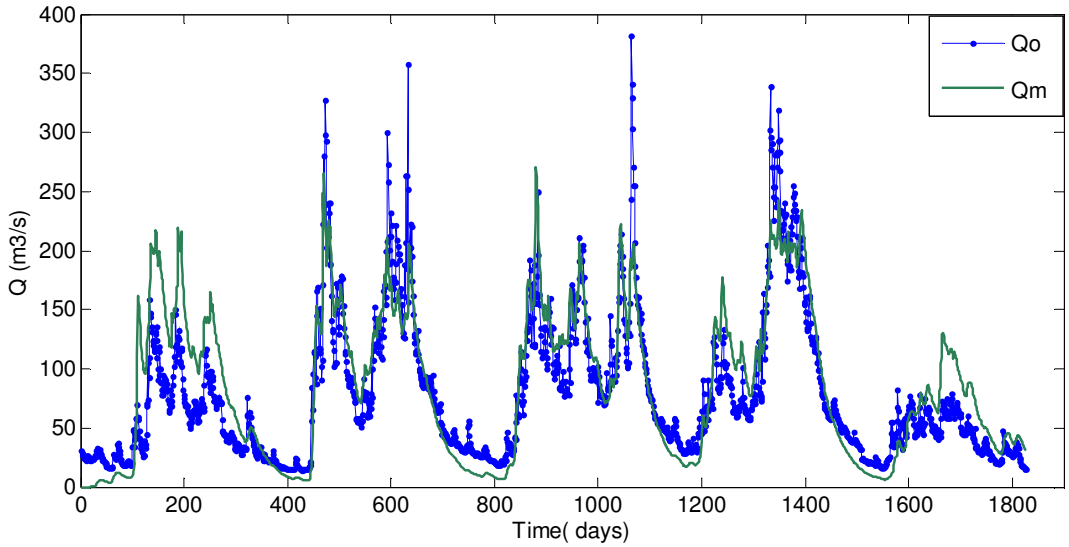
Calibration algorithm	*Best Nash-Sutcliff*	*Number of model runs*
PARASOL	0.748	6356
GLUE (random sampling)	0.717	605
GLUE (LHC sampling)	0.717	500
ACCO	0.714	125
ACCOL	0.732	613
GA (fastest)	0.723	180
GA (most accurate)	0.748	3835
M-Simplex	0.717	1414

5.7 Model validation

Model validation is an essential step in hydrological modeling; it aims to be sure that parameter values were estimated properly in calibration. In validation process the model out should be calculated using parameters values as estimated in calibration period and using observed inputs but it should be run in a time period not used in calibration, then we can compare model output with observed stream flow.

Validation period in this case study is 5 years from beginning of 1980 tell the end of 1984. PARASOL calibration gave good results so validation used its parameters estimation. For running validation, modeler should change ICLB value into 4 (see section 3.1.3). And define the selected validation period in "file.cio" file.

After rerun the model with calibration results, it gave Nash-Sutcliff value for validation = 0.714, which is good. So the model considered as well calibrated.



6 Applications of model uncertainty analysis techniques

In this section there is a description to four uncertainty analysis applications. The theoretical description for all used algorithms can be found in section 2.7.

6.1 PARASOL

PARASOL as mentioned before; it performs calibration and uncertainty analysis. It utilizes results of calibration results to study uncertainty analysis. Parasol divides the whole simulations done by SCE-UA calibration process into good solutions and not good solutions based on Bayesian method or $\chi 2$ method; User can select one of them by changing ISTAT value in "PARASOLIN.dat" file (1= $\chi 2$; 2=Bayesian), in this case ISTAT=1 that means the threshold here calculated by $\chi 2$ Statistical method. Also, "goodpar.out" file contains the parameter values that produce these good solutions.

Now after successfully completed the calibration, the input for the uncertainty analysis are ready. User can read Detailed or only upper and lower uncertainty boundaries. For the detailed uncertainty analysis results user can check "ParaSolout.out" file. Otherwise user can check "minval.out" and "maxval.out" for the minimum and maximum discharge uncertainty boundaries.

Improvement of objective function in the good simulations is presented in Figure 6-1.

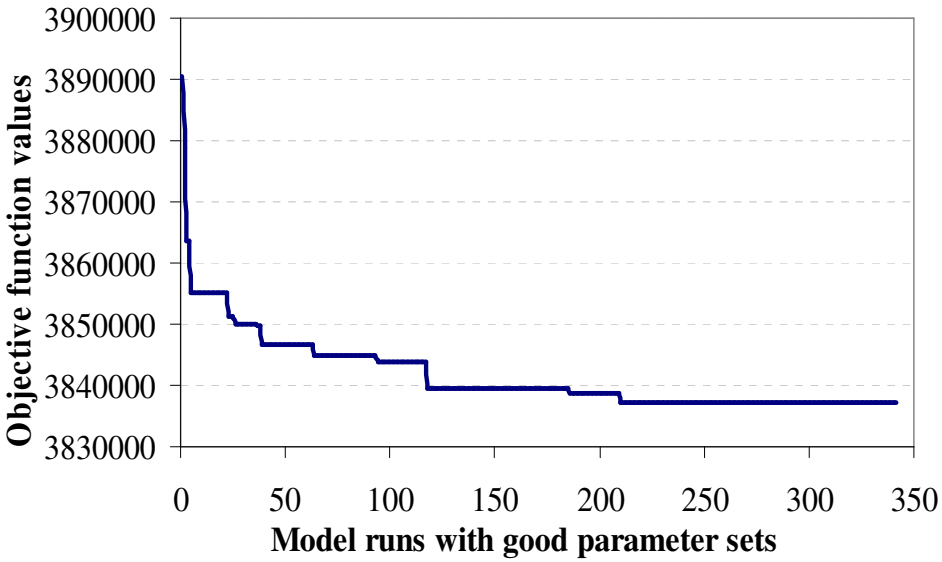


Figure 6-1 objective function development for the good parameter sets

Figure 6-2 displays the upper and lower boundary limits of uncertainty analysis, and the observed flow.

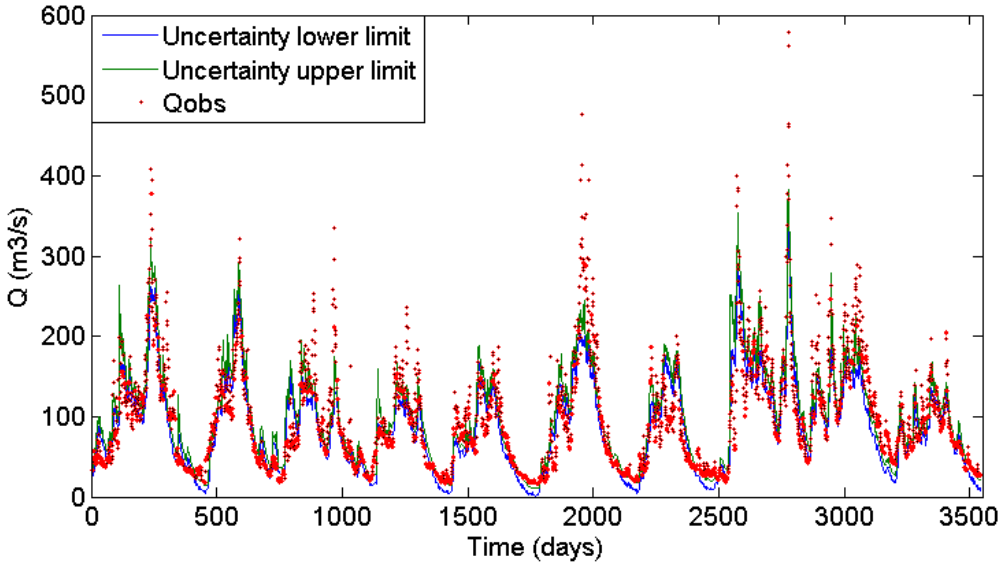


Figure 6-2 interval and observed flow (PARASOL)

Uncertainty estimation based on this method says that 23.5% of observed data falls inside the prediction intervals, and the average width of prediction intervals is 15.6m3/s.

6.2 GLUE

A MATLAB code was written to apply GLUE (described in section 2.7.6) to study uncertainty of Nzoia watershed. The following figure summarizes that code.

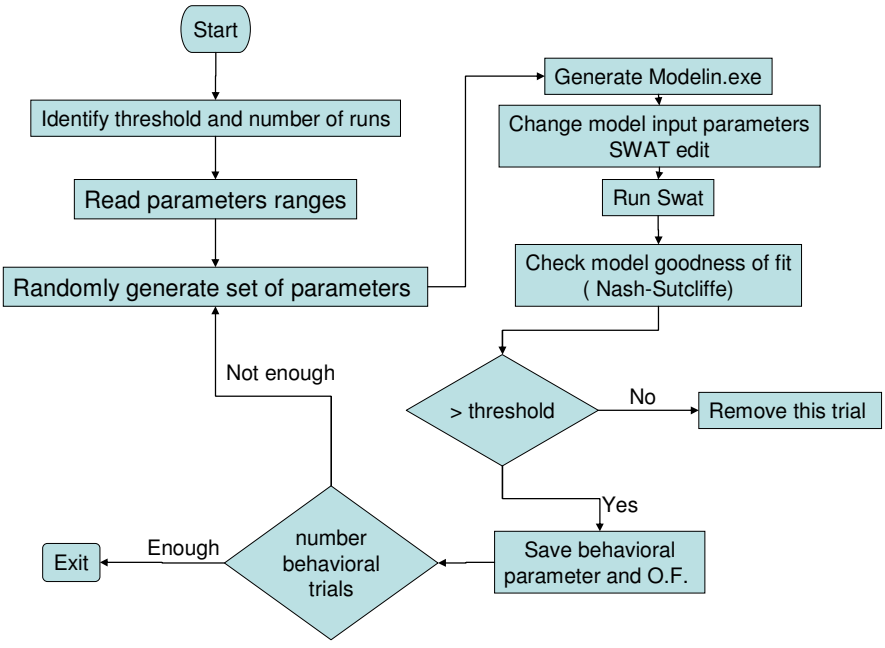


Figure 6-3Flowchart of MATLAB code to run GLUE

The uncertainty analysis of GLUE results indicates that 60.7% of observed flows fall inside the prediction intervals, and the average width of the prediction intervals is 50.8 m3/s.

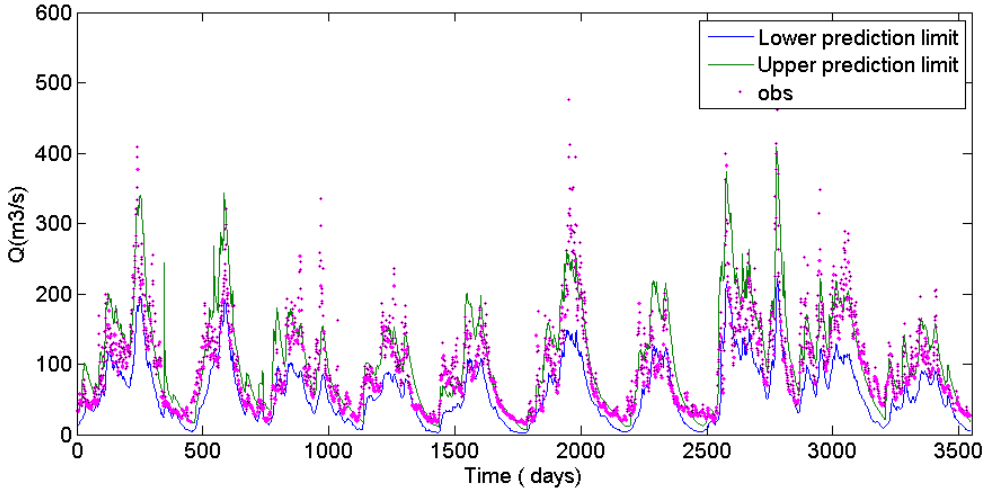


Figure 6-4 Prediction interval and observed flow (GLUE)

6.3 M-Simplex

M-simplex makes 79.25% of observed data flows fall inside the prediction intervals, and the average width of the prediction intervals is 70.5 m3/s.

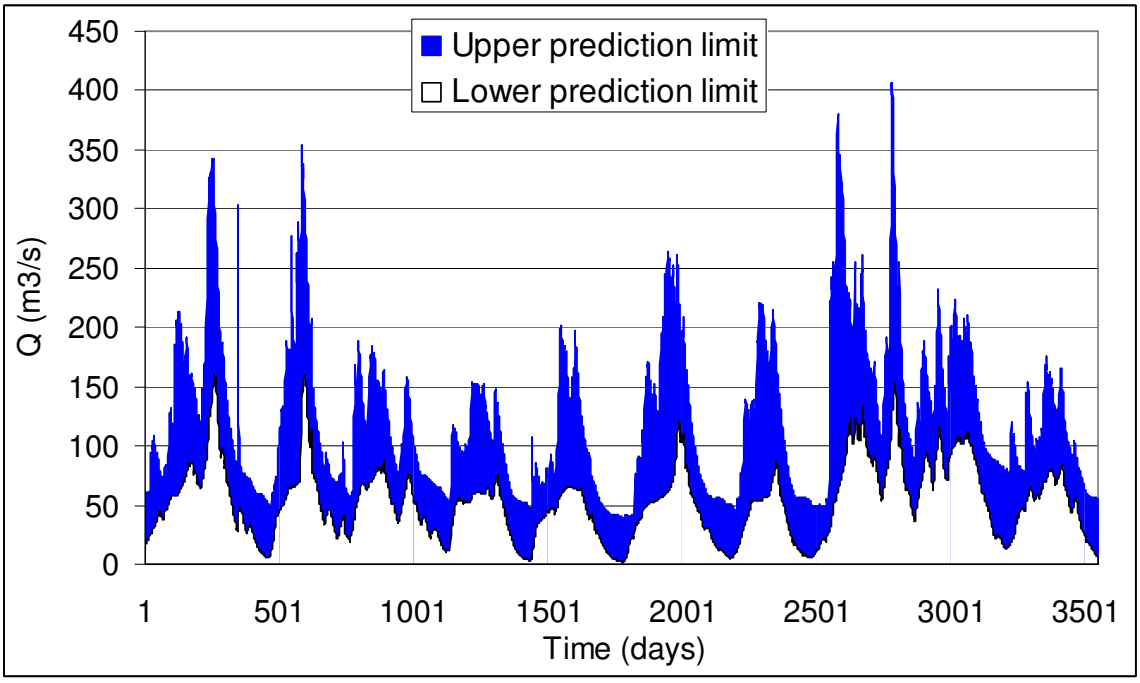


Figure 6-5 Prediction interval and observed flow (M-simplex)

6.4 UNEEC

This method as describes in section 2.7.9 depends on on the problem is to identify how many past flow values and past rainfalls it is reasonable to include to the model. AMI is a matlab code developed by (Shrestha, 2005), it computes and plots average mutual information (ami) and correlation of time series for different values of time lag.

The result of AMI (Figure 6-6) shows that the highest correlation between model input and output is at no lag days. This means that it may be better to take into consideration the input data only one day back. Q= f (R_t,R_{t-1}, R_{t-2}, Q_t,Q_{t-1}, Q_{t-2}, ET_t,ET_{t-1}, ET_{t-2}, ER, ER_{abs}). After that, the total available observed flow and its corresponding simulated flow should be spitted into training and verification data sets.

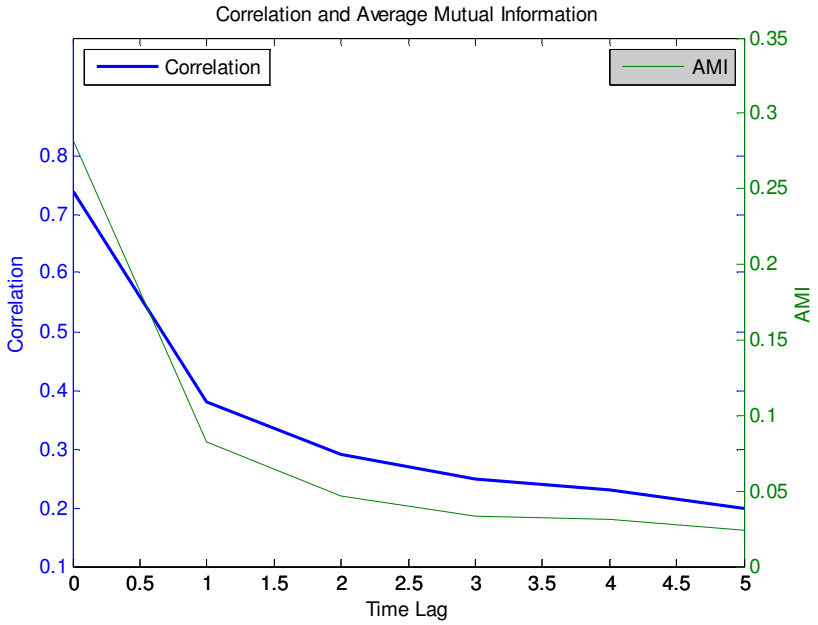


Figure 6-6 Correlation between rainfall and model reseduals in different lag time

After running UNEEC TOOL using Fuzzy c-mean clustering method with 6 clusters and weak classifiers M5 M5prime for analysis the uncertainty period of the data. 92% of observed data in training period and 94 in verification period were inside the prediction limits. Also the mean prediction intervals are 100 m3/s in training period and 88.66 m3/s in testing period. Furthermore UNEEC TOOL provides figures for prediction intervals and observed flow. These figures are presented in the following two figures.

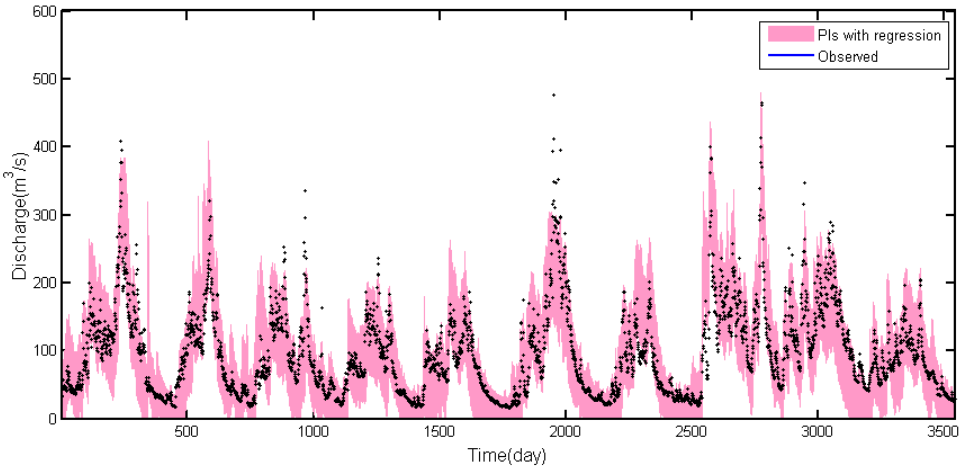


Figure 6-7 Prediction interval and observed data in training period

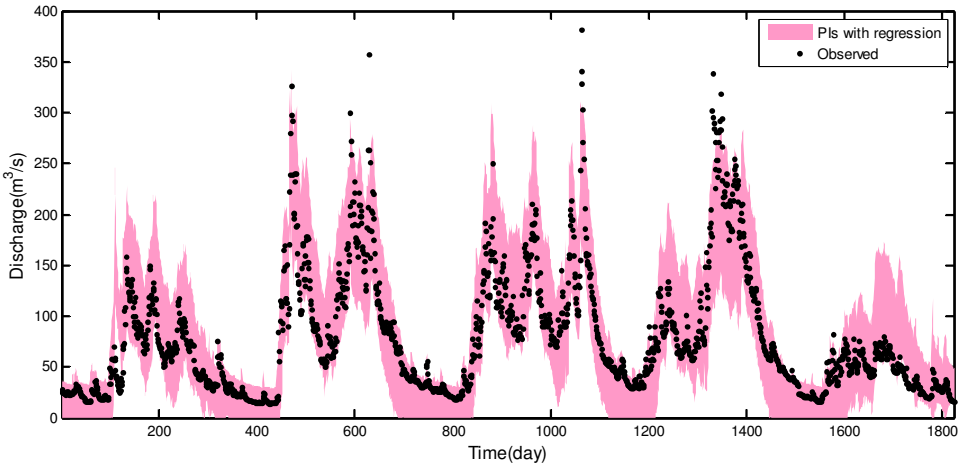
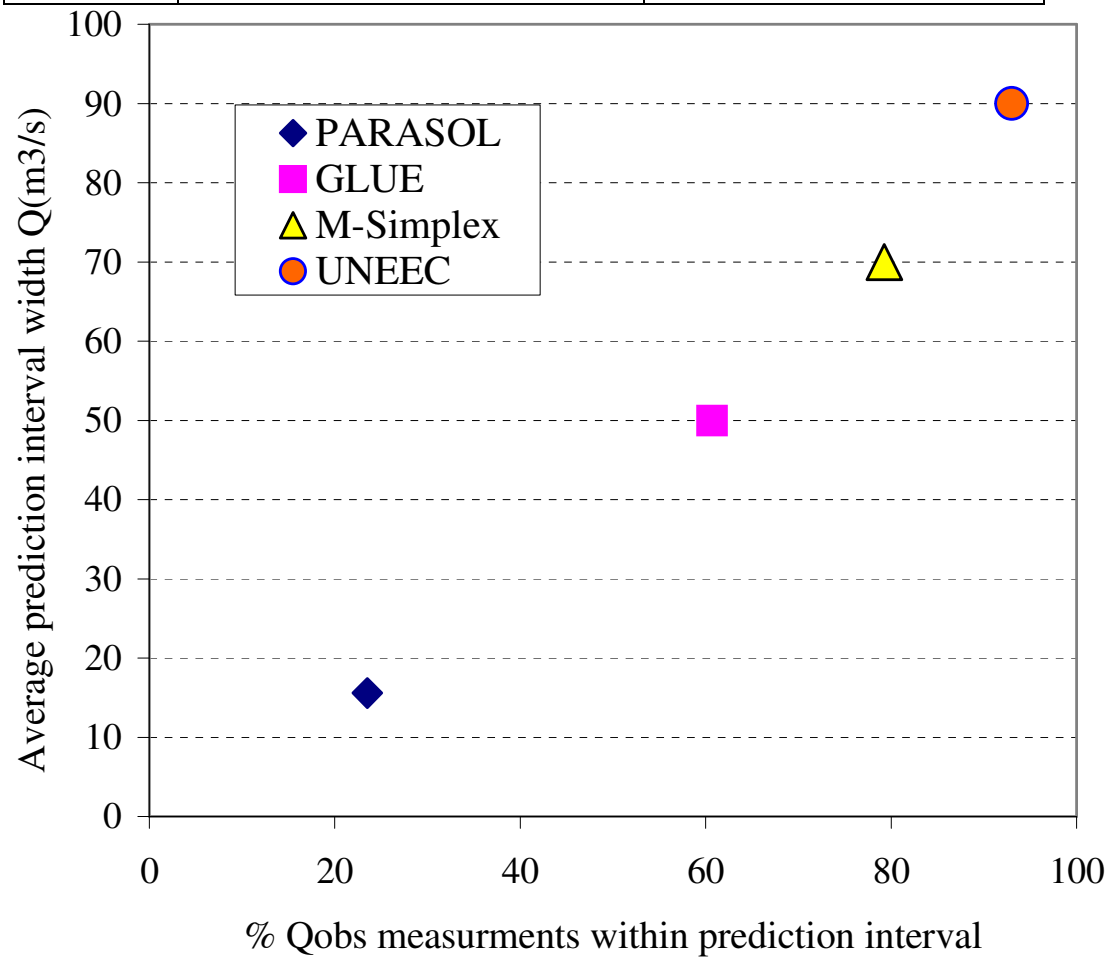


Figure 6-8 Prediction interval and observed data in testing period

6.5 Conclusion

By comparing results from different uncertainty analysis methods. And by knowing that the better uncertainty analysis the one which cover more observed data without making very wide prediction interval.

	% of observed flow within prediction interval	Average prediction interval width Q (m3/s)
PARASOL	23.5	15.6
GLUE	60.7	50
M-Simplex	79.25	70
UNEEC	93	90



7 Conclusions and recommendations

SWAT is an easy to use and accurate physically based distributed model. When it used under Arcview interface, user should take care when moving any project from machine to another one, he should be attention to put project files and data exactly in the same place, otherwise he will not be able to read or run the project.

After creating a project with SWAT, it is easy to run sensitivity analysis, calibration and uncertainty analysis using (iSWAT), this application is explained in 3.3.1 without the Arcview interface. But, this software is able to edit SWAT input files but it failed to change Sol_Z values, therefore this parameters didn't calibrate in this study.

When delineate watershed, flow gages positions should be at outlet of subcatchments.

However autocalibration is fast, but with complex models which have a lot of parameters, it is really time consuming. so sensitivity analysis give big help, it reduced the parameters to be calibrated in this case study from 27 parameters to only 8 parameters.

The more widely parameters searching ranges, the more time needed for calibration, to reduce this range, a likelihood distribution of the parameters with the initially calibrated model, it helped a lot to minimize that range.

Model parameters calibration using five different methods was applied in this study (PARASOL, ACCO, ACCOL, GA and M-Simplex). ACCO was the fastest one it was able to achieve good objective function value (not the best one compare to the other methods) in 125 times of model run. Also, it appeared that the difference in the final result is not so big, but the main affective factor is the time using to get the optimum parameter set.

Matlab provides great ability to link modeling tool (SWAT) with a powerful optimization and uncertainty analysis tools like (GLOBE). The only comment is that MATLAB compiler needs very big space on hard disk to compile any project to be sure that it will work in machines that haven't Matlab installed on it.

Searching surface near the optimum values seems flat. So after achieving reasonable objective function value, more searches will be waste of time, hence, modular should estimate reasonable number of model runs.

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