UNCERTAINTY INTERVAL ESTIMATION OF WETSPA MODEL FOR FLOOD SIMULATION: A CASE STUDY OF VE WATERSHED, QUANG NGAI PROVICE, VIETNAM

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ABSTRACT: This paper presents the results of a research on uncertainty interval estimation of WetSpa model for flood simulation in Ve watershed. The method applied to uncertainty estimation is the GLUE methodology. The initial results show that uncertainty intervals obtained are reasonably capture the observations with the use of Nash-Sutcliff as likelihood measure. Over-estimation often occur with the low flow, which is acceptable in case of flood simulation. To estimate the prediction interval, the model should be run in prediction mode.

Keywords: WetSpa model, GLUE methodology, Ve watershed

INTRODUCTION

Recent advances in the field of hydrological modelling have brought the great benefits to the human lives and one of these is the application of hydrological simulation models to flood forecasting. A hydrological simulation model is defined by Klemes (1986) as a mathematical model aimed at synthesizing a (continuous) record of some hydrological variable Y, for a period T, from available concurrent records of other variables X, Z, ... In contrast, a hydrological forecasting model is aimed at synthesizing a record of a variable Y (or estimating some of its states) in an interval ΔT, from available records of the same variable Y and/or other variables X, Z, ... , in an immediately preceding period T.

A notable approach to enhance the quality of flood simulation and flood forecasting is to estimate the uncertainty interval or prediction interval. Wagener, T. and Gupta, H.V. (2005) discussed in detail about the uncertainty in input data, parameters, initial and boundary conditions, structural uncertainty and raised the need for incorporating these uncertainty into the simulation and prediction results. Numerical experiments have proven that there are many parameter sets of a model which may give similar results (Uhlenbrook et al., 1999). This author as well as others emphasised that predictions should be given in the form of uncertainty intervals instead of single values.

Generalized Likelihood Uncertainty Estimation (GLUE) methodology is one of efforts to estimate and present the uncertainty interval using Monte Carlo analysis and Bayesian/Fuzzy logic estimation. The starting point for the GLUE concepts is the rejection of the idea of an optimum parameter set in favour of the concept of equifinality of model structures and parameter sets (Beven K. J., 1998). Recent researches have been focusing on the improvement of sampling methods in Monte Carlo simulation to reduce computational efforts in uncertainty estimation under GLUE methodology (Uhlenbrook. S. and Sieber A. , 2005; Roberta-Serena Blasone et al., 2008). Beven, K. J. (2007) gave a detailed discussion on the use of uncertainty interval in flow and flood forecasting.

A flood forecasting project for the Ve river basin, an area in central Vietnam was stated in 2009 at Hanoi University of Science, funded by Vietnam National University - Hanoi. The main goal of the project is to develop a procedure which takes the uncertainty of input and model parameters into prediction results in order to raise the degree of reliability in flood forecasting. To this aim a sensitivity and an uncertainty analysis of the WetSpa model are made. This paper describes the uncertainty estimation applied to the Ve river using WetSpa model and GLUE methodology in the simulation mode. The application of this procedure in prediction mode will be presented in latter papers.

This paper is divided into 4 sections. Section 1 is involved with the problem overview. Section 2 is devoted to the description of the study area and the applied model. Section 3 describes methods for calibration of WetSpa model with the two flood events in Ve watershed when uncertainty estimation using GLUE was taken into consideration. Finally, section 4 presents the results and discussions.

STUDY AREA AND HYDROLOGICAL SIMULATION MODEL

Brief description of the study area

The Quang Ngai province is in the south central coast region of Vietnam. It is located 883 km south from Hanoi and 838 km north of Ho Chi Minh City. The Ve river is located south in the Quang Ngai province, which is shown in Figure 1. The total Ve river basin has a surface area of 1300 km^2; the main stream is 91 km long. Within this project only the upstream part from An Chi is taken into account, which has a surface area of 757,32 km^2. The Ve River rises from the mountainous region Truong Son in the south and leaves the study area at An Chi. The study area is shown in the right part of Figure 1.

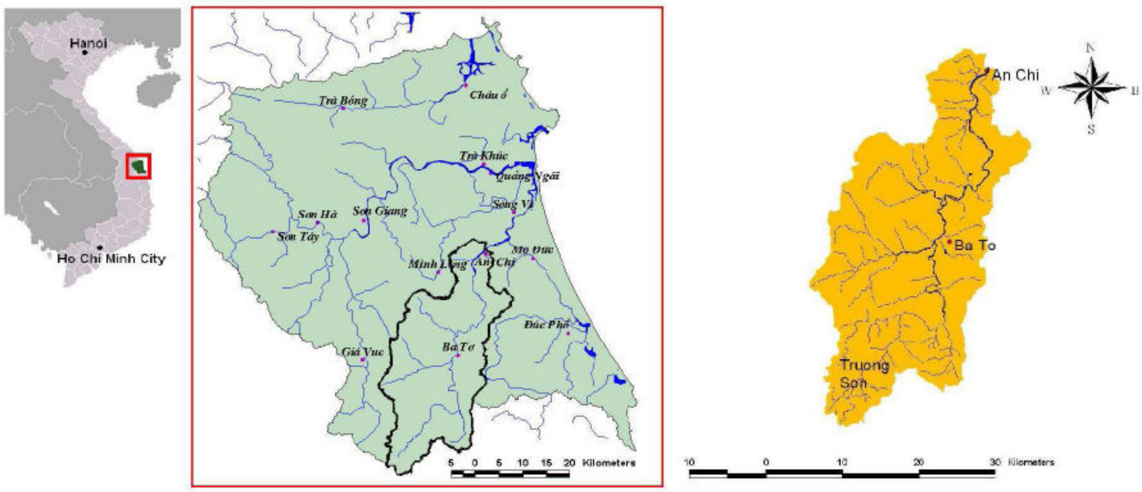

Figure 1 Location of the Quang Ngai Province in Vietnam (Wikipedia), and the Ve river upstream of An Chi inside Quang Ngai Province (Son, 2008)

- *Topographical and Lithological Characteristics*

The study area consists of many different lithological structures. The most conspicuous lithological characteristic of Ve river basin is a rapid change in topographical gradient in profile from the south to the north, shown in the DEM (Digital Elevation Model) in Figure 2. Figure 3 shows the soil of the river basin. There are six different types of soil. In the mountainous region, sandy loam is the most common soil type and in the plain, sandy clay loam is the most common soil type (Son, 2008).

- *Landuse*

The dominant landuse of the study is deciduous shrub. In the mountainous regions in the south evergreen broad leaf tree covers the surface. There is also a substantial amount of irrigated crop in the study area. An overview of the landuse is shown in Figure 4.

- *Climatic Conditions*

The Ve river basin is situated to the south of the Hai Van pass, which separates the two main climate regions of Vietnam. South of the Van Hai pass, there is a moderate tropical climate. In this region of Vietnam the average annual temperature is about 26^0C.

The precipitation in the plain is about 2000-2200 mm yearly, upstream it exceeds 3000 mm. During the year there are approximately 140 rainy days. The rainy season starts in September and ends in December. The amount of rainfall during this rainy season is 65-85% of the total amount of annual precipitation. So during the eight dry months there is only 15-35% precipitation of the total amount.

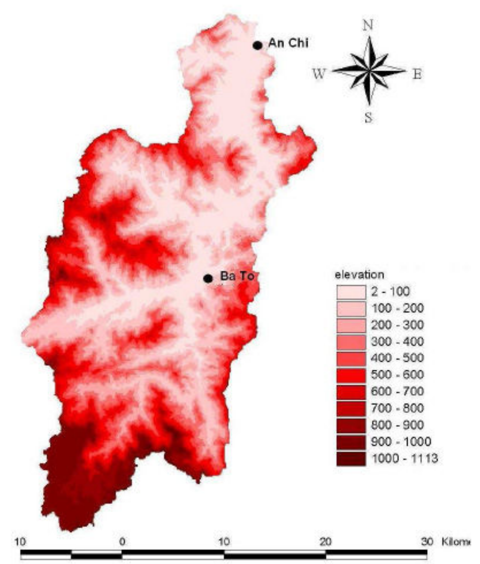

Figure 2 DEM of the study area

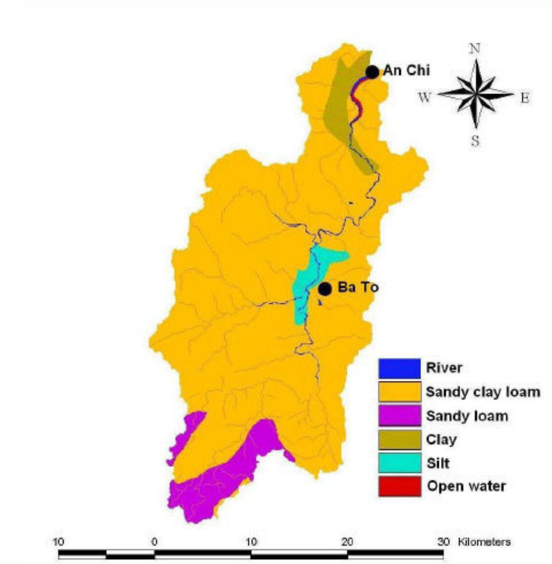

Figure 3 Soil type map of the study area

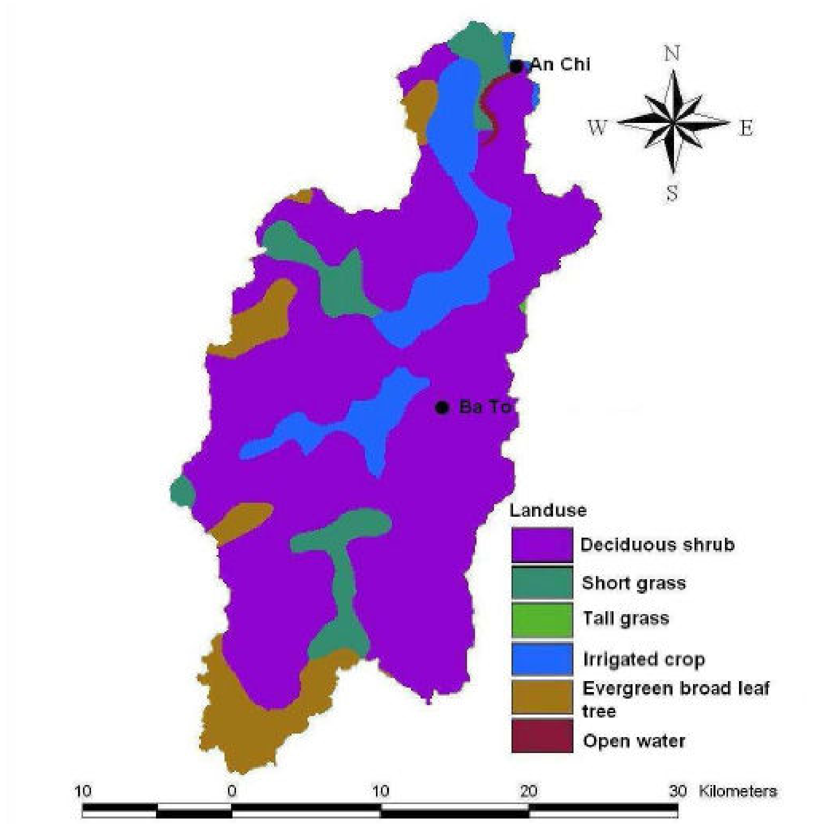

Figure 4 Landuse map of the study area

Simulation Model

For detailed information about the WetSpa model, the user manual of Liu & De Smedt (2004) and Giang & Thuy (2009) are referred to. Only brief description of the model is given here for purpose of illustration.

- *WetSpa model*

The WetSpa (extension) model is a GIS based distributed hydrological model for flood prediction and water balance simulation on catchment scale (Bahremand and De Smedt, 2008). WetSpa is an acronym for "Water and Energy Transfer between Soil, Plants and Atmosphere". It is a physically based model, and the hydrological processes considered in the WetSpa model are precipitation, depression storage, snowmelt, surface runoff, infiltration, evapotranspiration, percolation, interflow, groundwater flow, and water balance. WetSpa consists of two models: a semi-distributed model, and a fully-distributed model. The fully-distributed model has a large processing time. This complex fully-distributed model is used here in this paper.

- *ArcView and WetSpa*

The WetSpa model is a GIS-based model, and consists of two parts. The first part, ArcView, is used to read the geo-information data. This must be done before the second part of the model, the calculation with the WetSpa model, can be used. The process of loading the data in ArcView is time-consuming, because the model has to save all the data of the study area. The maps loaded are used to calculate the values for new maps that are built in ArcView. This process is also time-consuming, because all steps must be taken manually. During this loading process a few input values have to be set.

- *Grid cell*

The model calculates the different types of discharges and the evapotranspiration for every grid cell separately. In Figure 5 the structure is presented at grid cell level.

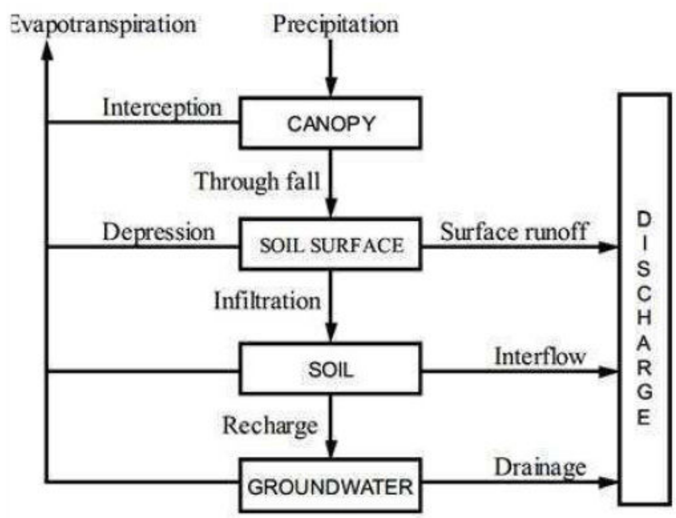

Figure 5 Structure of WetSpa Extension at a pixel cell level (Liu & De Smedt, 2004)

METHODS AND DATA

Methods

The GLUE methodology, Generalized Likelihood Uncertainty Estimation, is a way to calibrate and estimate the uncertainty of models based on generalized likelihood measures, proposed by Beven and Binley (1992). They came up with this method originally to provide a strategy to calibrate and estimate uncertainty for physically-based distributed modelling. But as stated by Blasone et al (2008), the GLUE framework has found widespread application for uncertainty assessment in environmental modelling, including rainfall-runoff modelling, soil erosion modelling, groundwater modelling, flood inundation modelling and distributed hydrological modelling. As concluded by Beven and Freer (2001) the GLUE methodology implicitly takes into account all sources of uncertainty, i.e., input uncertainty, structural uncertainty, parameter uncertainty and response uncertainty.

The basis of the GLUE-method is the premise that all model structures must, to some extent, be in error, and all observations and model calibration must also be subject to error. So there is no reason to expect that any one set of parameter values within a model will represent the true parameter set. When applying the GLUE-method one does not look for the optimum parameter set, but one makes an assessment of the likelihood of many parameter sets in a Monte Carlo analysis (Beven and Binley, 1992).

These likelihoods are used in a GLUE-procedure to determine the uncertainty. It is also possible to update these likelihood values when new data sets become available, and determine the value of these new data sets.

The GLUE methodology requires five steps, which are:

i) Specify a formal definition of a likelihood measure or a set of likelihood measures.

ii) Make an appropriate definition of the initial range or distribution of parameter values.

iii) A procedure for using likelihood weights in uncertainty estimation.

iv) A procedure for updating likelihood weights as new data become available.

v) A procedure for evaluating uncertainty in such a way that the value of additional data can be assessed.

These steps are explained in detail in Putten (2009) and Giang et al.(2009). This paper only briefly describes a part of these steps, which would facilitate reader to follow the contents.

- *Formal definition of likelihood*

A likelihood measure calculates the likelihood of a simulation, which is a way to evaluate how well the simulation simulates the study area. A likelihood measure is also named a goodness-of-fit index. In the past several goodness-of-fit indices are used within the context of GLUE. They mostly exist of two parts. The first is a goodness-of-fit formula; the second is a cut-off threshold.

Goodness-of-fit formula: Within the context of GLUE several goodness-of-fit indices were used in the past. The Nash-Sutcliffe coefficient (NS), the model efficiency (ME), the variance of the residuals or called error variance (EV) are used within this research.

Cut-off threshold: A cut-off threshold is used to separate behavioural from non-behavioural simulations. The likelihood values of non-behavioural simulations are set to zero, which means that they are not used in the procedure to estimate uncertainty. In literature the most common cut-off thresholds are a certain likelihood value (for example: NS > 0,8) or a certain percentage of the observations (for example: best 10% of all simulations). For this research, NS value of 0.7 ; ME value of 10%; EV value of zero are used following Andersen, Refsgaard, and Jensen (2001), Beven and Myrabo (1998), Beven and Binley (1992), respectively.

- *Initial parameter range and distribution*

Parameter selection: The parameters in the WetSpa model are divided into two parts: parameters during set-up time in ArcView and global parameters. The parameters in ArcView could not be taken into account within the uncertainty estimation, because ArcView cannot run automatically. From the twelve global parameters seven are taken into account. The time step is the first parameter that is not taken into account. Three parameters, T0, K_snow and K_rain, are only used when snow melting occurs, therefore omitted. The fifth parameter not taken into account is K_ep, a correction factor for evapotranspiration since evapotranspiration is very small during the whole flood period.

Ranges and distributions: Defining the prior ranges and distributions of parameters is done by prior knowledge about realistic parameter values. These are often defined purely subjectively. In case of little prior knowledge, a uniform distribution function over a chosen wide range will be appropriate (Beven and Binley, 1992). Therefore the distributions of the parameters are chosen uniform within this research. The range of parameters are determined from literature and sensitivity analysis as shown in Table 1 (Doldersum, 2009).

Table 1 Ranges for the global parameters

Parameter	Range	Description
Ki	0 - 10	Scaling factor for interflow computation (-)
Kg	0 - 0.07	Groundwater recession coefficient (-)
K_ss	0- 1.5	Initial soil moisture (-)
G0	0 - 50	Initial groundwater storage in water depth(mm)
Gmax	50 - 100	Maximum groundwater storage in water depth (mm)
K_run	0 - 12	Surface runoff exponent when the rainfall intensity is very small
P_max	0 - 500	The threshold rainfall intensity (mm/d or mm/hour; depending on the time step)

- *Sampling method*

For determining the parameter ranges, Latin Hypercube Sampling (LHS) is used with the fully-distributed model. LHS is a stratified sampling approach which efficiently estimates the statistics of an output. The probability distribution of each parameter is subdivided into N ranges with an equal probability of occurrence (1/N). Random values of the parameters are simulated such that each range is sampled just once. The order of selecting the ranges is randomized and the model is executed N times with a random combination of parameter values from each prior defined range. (Yu, Yang, and Chen, 2001). Within this research N is set to five, and 200 parameter sets were evaluated for defining the parameter ranges. The processing time of the fully-distributed model for 200 model simulations took approximately two hours (mesh size is equal to 90x90 m).

- *The procedure of using likelihoods for uncertainty estimation*

After determining the formal definition of the likelihood measure and the initial range and distribution of parameters, a Monte Carlo analysis is done to evaluate many parameter sets. For this aim LHS is used, because the uncertainty analysis is done in the fully-distributed model. For every parameter set created by LHS, the WetSpa model calculates the discharges. This output of the model gets a likelihood value from the likelihood measure used. Within this research three likelihood measures are used, so every output gets three (different) likelihoods. However, in this paper only NS is used as the likelihood measure. After the calculation of the likelihoods, the behavioural and nonbehavioural simulations are separated by the cut-off threshold. Only the behavioural simulations are taken into account in the assessment of the uncertainty. For the non-behavioural simulations the likelihood is set to zero, so they are not taken into account in the uncertainty analysis. The likelihoods of the behavioural simulations are rescaled so their sum is one, calculated as

$$RL_i = L_i / \left(L_1 + L_2 + ... + L_n \right) \qquad (1)$$

where RLi is the rescaled likelihood of the ith simulation, Li is the original likelihood of the ith simulation, L_1 and L_2 are the likelihoods of the 1st and 2nd behavioural simulation respectively, and *Ln* the likelihood of the last simulation qualified as behavioural. At every time step, the discharges of the behavioural simulations are sorted from low to high. The likelihoods, associated with the simulations, are also sorted per time step, in the same way as simulated discharges per time step. Notice that for every time step the sequence of likelihoods, and therefore the distribution of likelihoods, can be different. For every time step, the discharge value of the 5% and 95% of the cumulative likelihood distribution are the uncertainty bounds of the prediction. (Beven and Binley, 1992).

The n% cumulative likelihood is found by the weighted average of the cumulative likelihoods of the nearest neighbours (of behavioural simulations) above and below the n% cumulative likelihood, calculated as

$$Q_{n\%} = Q_{nnb} + \frac{CL_{n\%} - CL_{nnb}}{CL_{nna} - CL_{nnb}} \left(Q_{nna} - Q_{nnb} \right) \qquad (2)$$

where Qn% is the discharge calculated belonging to the n% cumulative likelihood, CLn% is the n% step of the cumulative likelihood distribution, CLnnb and CLnna respectively are the cumulative likelihood of the simulation just below and above the n% cumulative likelihood, and Qnnb and Qnna respectively the discharge simulated, belonging to CLnnb and CLnna respectively. The uncertainty bound are then plotted in resulting figures.

Data

- *Streamflow data*

The streamflow data are provided by the Hydro Meteorological Service. The data are measured at An Chi, where the Ve River leaves the study area. The discharge was measured hourly in November 1999 and December 1999. During the October 2003 flood not hourly discharges were measured, but only hourly water level data. For fifteen measurements discharges were also available. To convert water level data to discharges, a trend line was added. This power-function had a R^2 of 0,9569, which indicates a good fit. The formula of the trend line was used to create discharges from the water level data.

- *Rainfall data*

The rainfall data are provided by the Hydro Meteorological Service, and also from the Hydro Meteorological Forecasting Centre. For the rainfall five stations should be taken into account, because they cover the study area. However, one station lacks data, so it is not taken into account. The covering of this station is very small, about 0,02 % of the study area. So the effect of eliminating this station on the model output is very small. Figure 6 shows how the other four stations cover the study area.

At three stations (An Chi, Son Giang and Gia Vuc) the rainfall was measured with a six-hourly time step, at one station (Ba To) it was measured one-hourly. The data must be in accordance with the other ones, and therefore the data of the three six-hourly stations are changed into one-hourly data. The temporal (one-hourly) rainfall pattern of Ba To is used as a format for the temporal pattern of the three other rainfall stations. In reality the temporal patterns of rainfall at the four stations are probably not exactly the same. To compensate this, a random factor could be implemented. However, the result of this can model reality better or worse. Therefore no random factor is implemented within this research

- *Temperature*

Temperature data in the WetSpa model are used only for the snowmelt and snow accumulation process (Liu and De Smedt, 2004). Within the study area snow melting does not occur, so the temperature values are irrelevant.

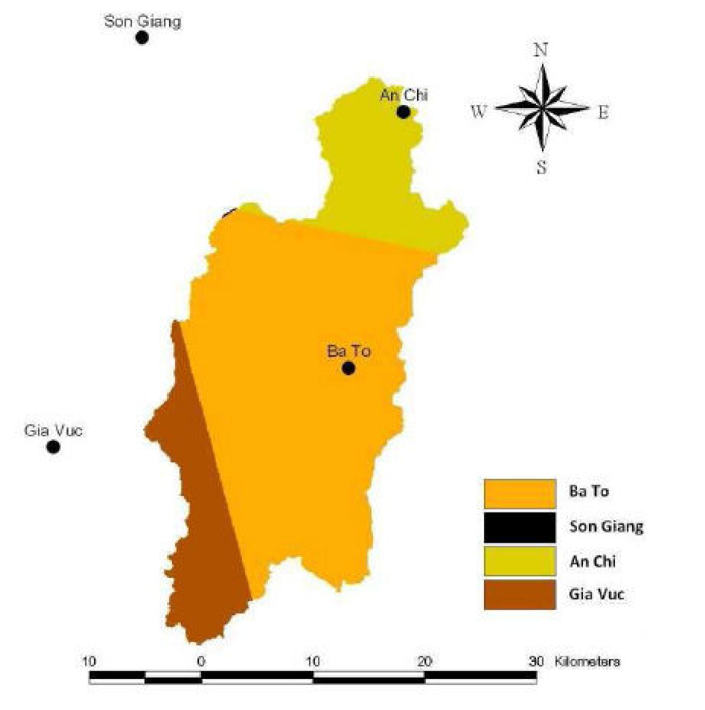

Figure 6 Meteorological stations surrounding the study area

- *PET*

PET-data (Potential EvapoTranspiration) were not available within this research. However, PET is so small during floods that it is almost negligible (Gash and Stewart, 1977). Therefore it is reasonable to use a PET of 0 during the flood period.

- *Maps*

There are five digital maps available for this project. These maps deal with DEM (Figure 2), soil type (Figure 3), landuse (Figure 4), measurement locations and the stream network. The DEM, landuse and soil type were available on a 90 m by 90 m grid cell size. Some improvements of the available data needed to be made, before using them in the model. The improvements made are described in the next part.

- *Boundaries*

The original files of DEM, landuse and soil type covered a square around the study area. But the WetSpa model does not work when an area bigger than the study area is implemented. Therefore the maps were initially clipped by a boundary. However, this boundary was drawn in straight lines. This does not correspond with reality, because a watershed is a natural phenomenon. Therefore a second option is used to calculate the boundary. This is done by a function in ArcView, to calculate the boundary of a watershed from a DEM-map. This boundary is used to clip every map.

RESULTS AND DISCUSSIONS

Figure 7 and 8 show the results of uncertainty estimation for the two flood events occurring in November 1999 and October 2003 respectively. Those figure shows that the uncertainty intervals are reasonably capture the observations with the use of Nash-Sutcliff as likelihood measure. Over-estimation often occur with the low flow, which is acceptable in the case of flood prediction.

Meaning of uncertainty intervals: the width of uncertainty interval is an indicator of precision of a model prediction. As the width increases the precision decreases. In the sense of model usefulness, if the model is used to inform the decision makers for their action, there are two situations would happen when the uncertainty interval are well surrounding observations: i) The width of interval is large enough to capture observations but small enough to give meaningful prediction (precise) – this is an ideal case; and ii) The width of the intervals are so large that the interval are meaningless – there is a need to improve the simulations to reduce the uncertainty interval.

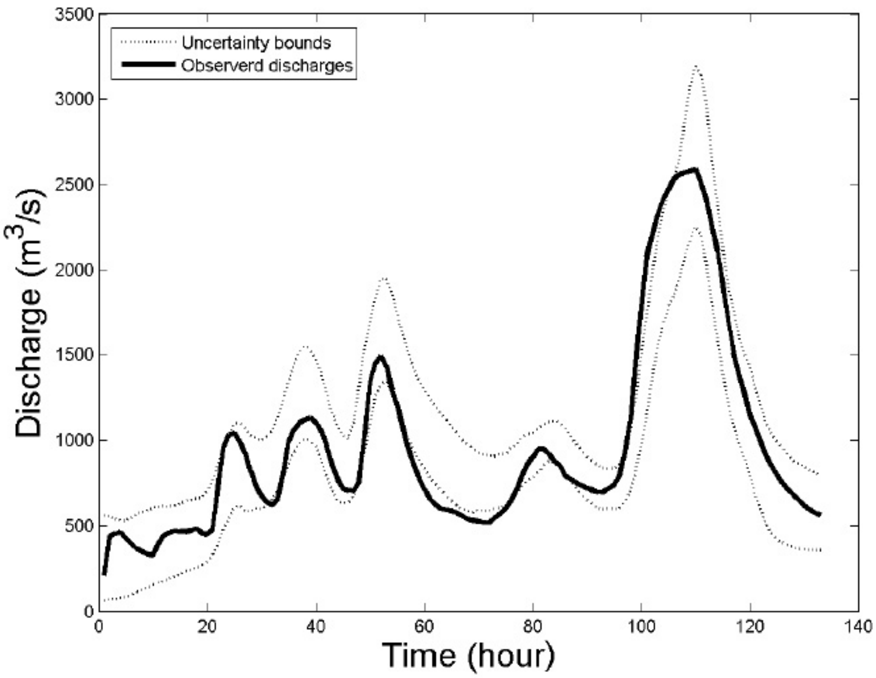

Figure 7 The uncertainty bounds for the November 1999 flood, calculated with NS

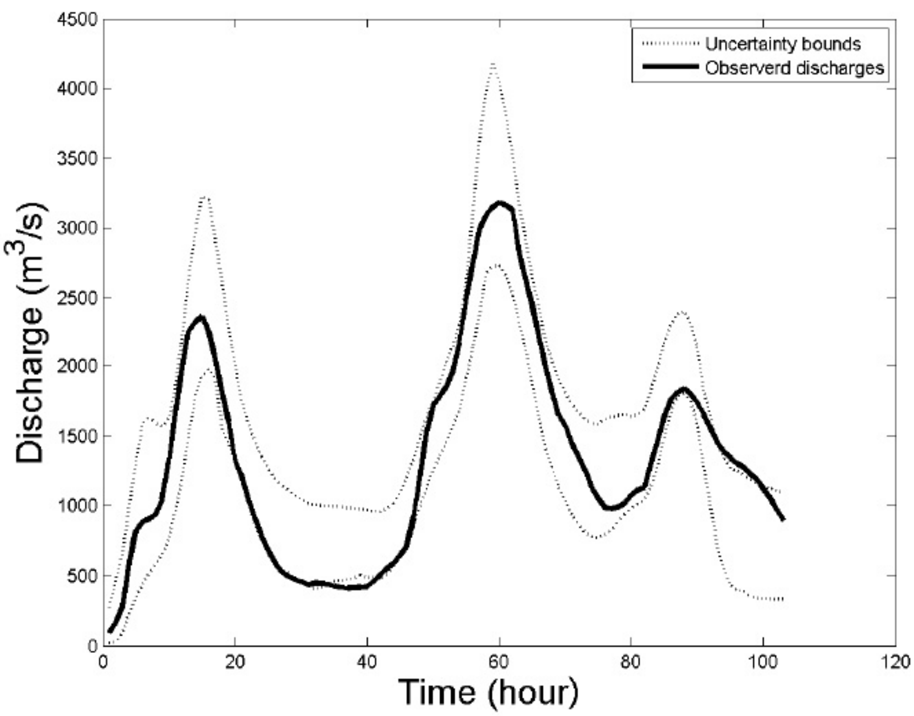

Figure 8 The uncertainty bounds for the October 2003 flood, calculated with NS

The width of uncertainty intervals are widely perceived to dependent on the choice of likelihood measure and shaping factor. We have tried with all three above-mentioned likelihood measures and see that NS is still the best measure among three. It is interesting to note that, NS has been claimed to be a bad measure used for GLUE methodology.

In conclusion, this paper presents a part of our research on the use of GLUE methodology for flood simulation and prediction in Ve watershed, Quang Ngai Province. The initial results shows that the method can give uncertainty interval which are in reasonable range and would be useful for decision making purposes. To estimate the prediction interval, the model should be run in prediction mode. This will be the next step of our research. The DEM model used in this research is 90x90 m in spatial resolution which was obtained from web. This resolution would be reduced by adopting more reliable DEM. As claimed by some authors, the choice of likelihood function is crucial to the success of GLUE methodology, more likelihood functions should be tested in the future.

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