Parametric uncertainty analysis of Darang catchment

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ABSTRACT: This report estimates the influence of uncertainty of the parameters on the simulated outflow at the outlet of Darang. HEC-HMS will be applied to build the catchment model, and Monte Carlo simulation will be used to calibration the uncertainty. Last, we need to judge the impact of parametric uncertainty on the model output.
KEY WORDS: Parametric uncertainty, HEC-HMS, Monte Carlo, Curve number

1 INTRODUCTION

This case studies the Darang catchment in Indonesia (Figure 1) to predict the outflow at the outlet. To model this area, we need to finish two steps: catchment delineation in ArdGIS environment and Event-based modelling of Darang. In the catchment delineation part, we need to compute the weights by Thiessen polygons. Note that we change the rain gauge locations to the Part A's data. In the modelling part, we should create the basin model and the meteorological model. There are three important processes in a basin considered: loss, transform and baseflow respectively. After that, we utilize the Monte Carlo simulation to test the parametric uncertainty. Normally, uncertainty reflects our lack of sureness about the outcome of the sub-basin model. Then, we give rise to potential difference between assessments of the outcome and its 'true' value, evaluating whether the model is flexible and robust.

Table 1. The coordinates of rain gages

Rain gauge locations	X coordinate	Y coordinate
Gage 1	-3837524	10725653
Gage 2	-3856952	10731882
Gage 3	-3816773	10721315

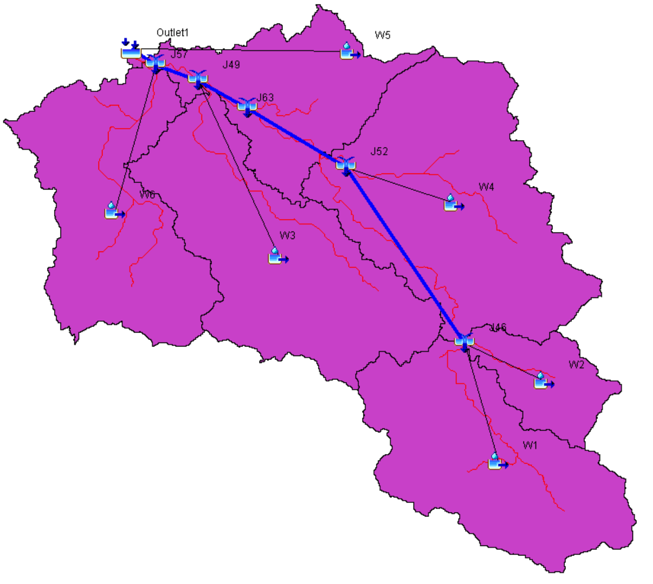

Figure 1. The modelling area

2 Experimental setup

First, this case calibrates the sub-basin model to search the optimized parameters. And then we choose curve number as the aim to study the parametric uncertainty. Next, we utilize the Monte Carlo to calculate the uncertainty until it satisfy the requirements.

2.1 Quantification of uncertainty

The parametric uncertainty belongs to aleatoric connected with the randomness observed in nature. In the model we characterize it by the simple uniform distribution. For the curve number, it not only depends upon the land use but also upon the soil type. Normally expert judgment is often subjective, and process of calibration involves the measured model outputs that are inaccurate as well.
Next we need to determine the range of each parameter. Add and subtract 10 to each optimized value, getting the distribution in the following table.

Table 2. The range of each parameter

Element	W1	W2	W3	W4	W5	W6
Optimized value	66.99	62.59	53.05	49.68	54.43	38.87
Lower	56.99	52.59	43.05	39.68	44.43	28.87
Upper	76.99	72.59	63.05	59.68	64.43	48.87

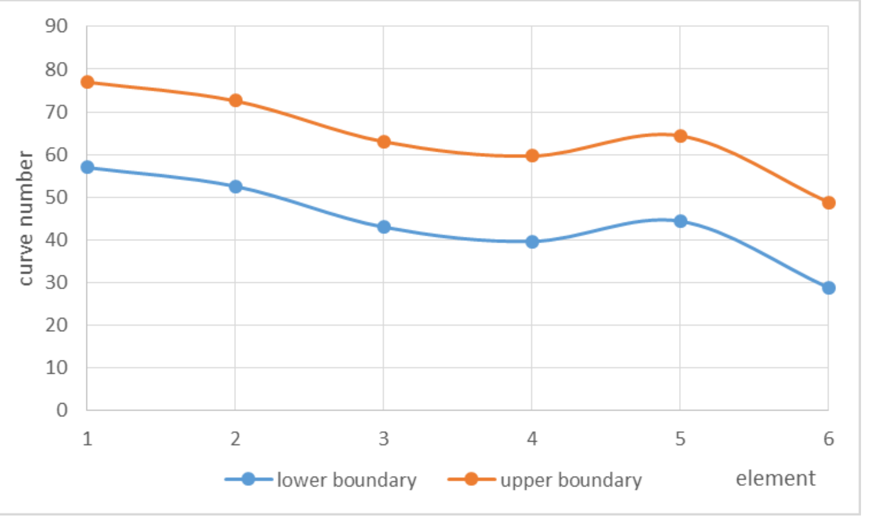

Figure 2. The range of each parameter

2.2 Monte Carlo simulation

The Monte Carlo method is one way to judge the uncertainty in the simulated model, which works by creating many alternative models using an automated sampling procedure. All of the response from all of the samples can be analyzed statistically to evaluate the uncertainty. Total samples are set to 500 times, which must be large enough to accurately estimate the uncertainty. The process of determine when testing finished is called convergence. Convergence is achieved when statistical measures do not change if more samples computed. In this case, convergence in the peak flow is achieved when increasing the number of samples does not result in a change in the computed mean. However, we should notice that automatic convergence criteria are not available in HEC-HMS software.

3 result and analysis

3.1 result presentation

Table 3. The range of each parameter

Variable	Ensemble	Optimized data	Minimum	Maximum	Standard deviation
Maximum outflow (m^3/s)	164.62	165.8	152.35	177.17	4.77
Outflow volume (mm)	5.88	6.05	5.43	6.36	0.19

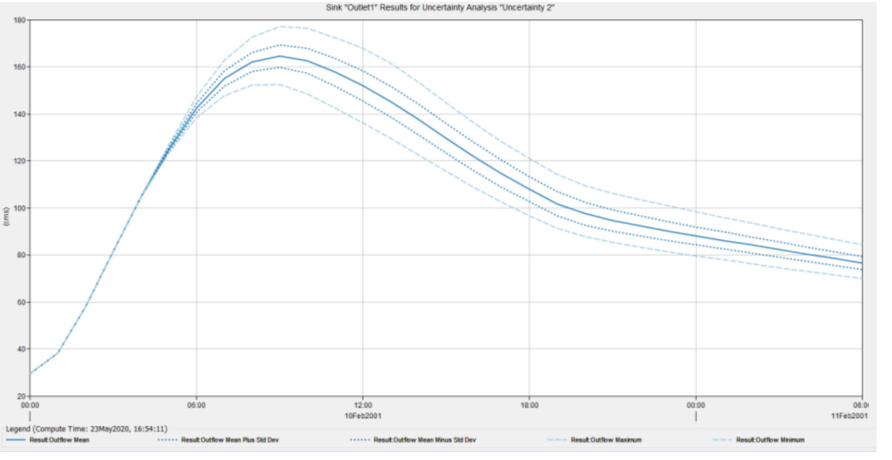

Figure 3. Outlet for uncertainty analysis

In this figure, we apply prediction intervals, which consist of the upper and lower limits between which a future certain value of the quantity is expected to lie with a prescribed probability. The endpoints of a prediction interval are known as the prediction limits. The width of the prediction interval gives us some idea about how uncertain we are about the uncertain entity. Thus, the prediction intervals start from 160 to 170m^3/s, and the extreme value are 152.35 and 177.17 m^3/s respectively. The difference between ensemble data and optimized data is small. That means the sub-basin is robust and flexible enough. Then, we calculate the uncertainty.

$$\text{uncertainty} = \frac{outflow\ range}{parameter\ range} = \frac{177.17 - 152.35}{20} = 1.24 \tag{1}$$

This means that the uncertainty of curve number increases by 1, then the uncertainty of outflow increases by 1.24m^3/s.

Overall, the prediction value appears between 160 to 170m^3/s considering the uncertainty existence.

Meanwhile, the model is enough insensitivity since the ensemble data (164.62) is close to the optimized data (165.8), which doesn't have clear change in model output values given modest changes in model input values.