

Uncertainty analysis of hydrological modeling in a tropical area using different algorithms

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Abstract Hydrological modeling outputs are subject to uncertainty resulting from different sources of errors (e.g., error in input data, model structure, and model parameters), making quantification of uncertainty in hydrological modeling imperative and meant to improve reliability of modeling results. The uncertainty analysis must solve difficulties in calibration of hydrological models, which further increase in areas with data scarcity. The purpose of this study is to apply four uncertainty analysis algorithms to a semi-distributed hydrological model, quantifying different source of uncertainties (especially parameter uncertainty) and evaluate their performance. In this study, the Soil and Water Assessment Tools (SWAT) eco-hydrological model was implemented for the watershed in the center of Vietnam. The sensitivity of parameters was analyzed, and the model was calibrated. The uncertainty analysis for the hydrological model was conducted based on four algorithms: Generalized Likelihood Uncertainty Estimation (GLUE), Sequential Uncertainty Fitting (SUFI), Parameter Solution method (ParaSol) and Particle Swarm Optimization (PSO). The performance of the algorithms was compared using P-factor and R-factor, coefficient of determination (R^2), the Nash Sutcliffe coefficient of efficiency (NSE) and Percent Bias (PBIAS). The results showed the high performance of SUFI and PSO with P-factor > 0.83, R-factor < 0.56 and R^2 > 0.91, NSE > 0.89, and $0.18 < \text{PBIAS} < 0.32$. Hence, we would suggest to use SUFI-2 initially to set the parameter ranges, and further use PSO for final analysis. Indeed, the uncertainty analysis must be accounted when the outcomes of the model use for policy or management decisions.

Keywords SWAT-CUP, GLUE, SUFI2, ParaSol, PSO, Vietnam

1 Introduction

Hydrological models are simplified characteristics of the real world system, which are useful for simulation of water balance and for water resources planning and management. A large number of hydrological models have been developed ranged from simple conceptual models to comprehensive physically based distributed models (Singh, 1989; Khoi and Thom, 2015; Wu and Chen, 2015). Conceptual lumped models (e.g., WASMOD (Xu, 2002), AWBM (Boughton, 2004), IHACRES (Croke et al., 2006)) assume a basin as a single-homogeneous unit requiring a small number of parameters, whereas Semi-distributed (e.g., SWAT (Arnold et al., 1998)) and distributed models (e.g., MIKE SHE (Refsgaard and Storm, 1995)) are able to account for the spatial variability of the watershed and requires a large number of parameters (Refsgaard, 1997; Carpenter and Georgakakos, 2006; Wu and Chen, 2015).

Regardless of the context in which hydrological models are designed, various sources of uncertainty occur in hydrological models. The principal errors lie particularly in the model structure, the input data or the parameter set, due to model simplifications and unknown or non-ascertainable relations within the model (Jin et al., 2010; Setegn et al., 2010). Thereby the properties of the errors depend on the source of uncertainty, hence different techniques are often necessary to treat the uncertainty (Liu and Gupta, 2007). Due to difference sources of uncertainties the calibration of hydrological models is a challenging task. However, among various sources of uncertainty, parameter uncertainty is easy to control through various calibration procedures (Vrugt et al., 2003; Yang et al., 2007, 2008; Wu and Chen, 2015).

In recent years diverse methods have been developed to account for the uncertainties of the hydrological models, such as, Particle Swarm Optimization (PSO) (Eberhart and Kennedy, 1995), generalized likelihood uncertainty estimation (GLUE) (Freer et al., 1996), Markov Chain Monte Carlo (MCMC) (Vrugt et al., 2003), parameter solution method (ParaSol) (van Griensven and Meixner, 2006), and sequential uncertainty fitting (SUFI-2) (Abbaspour et al., 2007). Shen et al. (2012) used GLUE method to evaluate the uncertainty of the SWAT model for the Daning River Watershed, China. They reported that only a few parameters were sensitive and had influence on streamflow and sediment simulation. van Griensven et al. (2008) used the ParaSol method to analyse the parameter uncertainty of the SWAT model in Honey Creek, USA. They revealed that the ParaSol showed clear bias for the sediment load predictions during the calibration and validation periods. Zhang et al. (2009) used five global optimization algorithms for parameter calibration of a complex hydrologic model and they found that PSO method can obtain better parameter solutions than other algorithms. Rafiei Emam et al. (2017) used SUFI-2 method for calibration and uncertainty assessment of a SWAT model in Central Vietnam. They used a multi-approach techniques through the calibration of river discharge, actual evapotranspiration and crop yield. They indicated that the model was calibrated with high NSE and R^2 through the multi-calibration approaches.

Due to the large uncertainty methods and hydrological models, the application of uncertainty methods should be evaluated in different areas from arid and semi-arid (Rafiei Emam et al., 2015) to tropical climates (Khoi and Thom, 2015). The aim of this study is to apply four uncertainty

algorithms to a semi-distributed hydrological model to quantify the impacts of uncertainties, and to compare the performance of different uncertainty methods. Selecting an objective function, and reasonable parameter ranges is the first procedure of algorithms. Different parameter combinations should be evaluated and the best set of parameters should be used as the parameter inputs of hydrological model. SWAT semi-distributed hydrological model was implemented in the Nam Dong district of Vietnam as a case study to simulate the surface runoff.

2 Materials and methods

2.1 Study area

The study area is the “Thuong Nhat basin”, which is located in central Vietnam in the province Thua Thien Hue (between $16^{\circ}0'N$ and $16^{\circ}10'N$ and $107^{\circ}35'E$ and $107^{\circ}46'E$) (Fig. 1). The basin has an area of approximately 200 km². The main river called “Ta Trach” flows toward the “Hai lagoon”. The average annual temperature of the entire Basin based on Nam Dong climate station is 25°C (Hue University of Agriculture and Forestry (HUAF)). The annual precipitation is estimated 3800 mm. The lowest and highest amount of precipitation is in February (41 mm) and October (1005 mm), respectively. Acrisols is the dominating soil class (95%), followed by Fluvisols (approximately 5% of the area). The main land cover/use in the basin is natural forest (e.g., Pine, Acacia, Rubber) with more than 90% followed by shrubs and grassland, unused land in a hilly area, and residential areas.

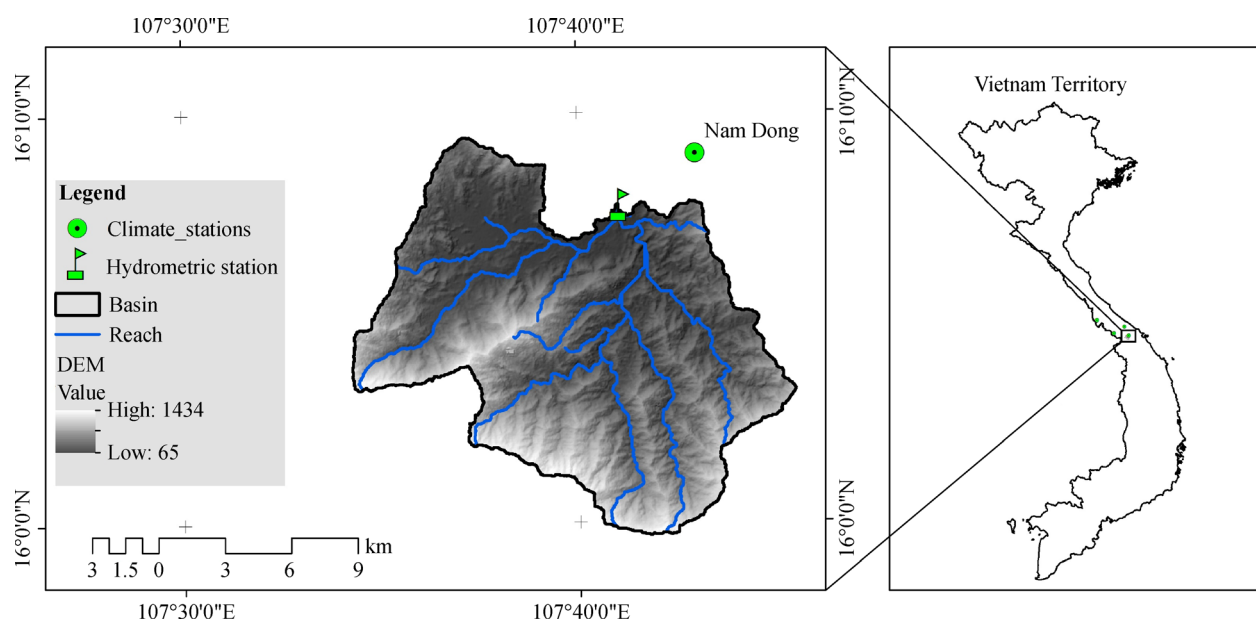


Fig. 1 Location map of the study area, including climate and hydrometric stations. The altitude in watershed changes from 65 m above sea level from the north to 1294 m above sea level in the south of the watershed.

2.2 Hydrological modeling

We used the Soil and Water Assessment Tools (SWAT) hydrological model. SWAT is a semi-distributed and physically based model developed by Arnold et al. (1998), which is able to estimate the impact of land management practices on water and sediment in large, complex watersheds with varying soil, land use and management conditions (Neitsch et al., 2011). In SWAT, water balance calculations are computed for homogeneous units called hydrological response units (HRUs). The hydrologic cycle in SWAT includes two processes: land process and routing process. Land process of model controls the quantity of water, sediment, nutrient and pesticide loading to the main stream in each subbasin. The routing process of the model defined as the movement of water, sediment, nutrients through the stream network of the watershed to the outlet of the watershed. The model predicts the water balance at the land process as follows:

$$SW_n = SW_0 + \sum_{i=1}^n (R_{\text{day}} - Q_{\text{surf}} - ET - W_{\text{seep}} - Q_{\text{gw}}),$$

where SW_n is the final soil water content, SW_0 is the initial soil water content, R_{day} is the precipitation on day i , Q_{surf} is the surface runoff on day i , ET refers to evapotranspiration on day i , W_{seep} is infiltration on day i , and Q_{gw} is return flow on day i .

To estimate surface runoff SWAT uses two methods, SCS-CN procedure (USDA, 1986) and the Green and Ampt infiltration method (Green and Ampt, 1911). The SCS-CN method was used in this study to estimate surface runoff. SWAT uses the modified rational method to calculate the Peak runoff rate. Potential evapotranspiration is calculated in SWAT using the Penman–Monteith method (Monteith, 1965), the Priestley–Taylor method (Priestley and Taylor, 1972) and the Hargreaves method (Hargreaves et al., 1985). Hargreaves method was used in this study to estimate the potential evapotranspiration. SWAT partitioned the Aquifer in each subbasin into shallow (unconfined) and deep (confined) aquifers in order to simulate the groundwater. Water that reaches the deep aquifer is assumed to contribute to streamflow outside the watershed (Arnold et al., 1998). Water is routed in SWAT through the channel network using variable storage routing and Muskingum routing method. We used variable storage in our simulation.

The input data require setting up the SWAT includes Digital Elevation Model (DEM), soil data provided by HUAF, land use, climate data (daily data), and river discharge data. We used the monthly discharge data (2005–2010) at the Nam Dong station to calibrate and validate the model during 2005 and 2010.

The performance of model was evaluated using R^2 , NSE and PBIAS. R^2 is the coefficient of determination, indicates

the proportion of the variance in the observed data. R^2 ranged from 0 to 1, high value shows less error variance. According to Santhi et al. (2001) values greater than 0.5 are considered acceptable. NSE determines the relative magnitude of the residual variance (Moriassi et al., 2007). NSE ranges between $-\infty$ to 1. However, values greater than 0.5 are considered acceptable. PBIAS shows the tendency of the simulated data compare to the observed data. The ideal value of PBIAS is 0.0. Positive values show model underestimation bias, and negative values indicate overestimation bias. The model performance is acceptable if $-15\% < \text{PBIAS} < 15\%$.

2.3 Uncertainty analysis

Four uncertainty methods (GLUE, SUFI, ParaSol, and MCMC), which are part of SWAT-CUP (Abbaspour, 2011), were used in this research to evaluate the uncertainty of SWAT model in a tropical area of Vietnam. A brief introduction of the four uncertainty analysis methods is provided as follows.

2.3.1 Sequential Uncertainty Fitting (SUFI-2)

SUFI-2 can be applied to all sources of uncertainty (Yang et al., 2008). According to Abbaspour et al. (2004) the objective of SUFI-2 is a combined optimization and uncertainty analysis using a global search method and deal with model parameters through Latin hypercube sampling (LH). LH is a statistical method to generate controlled random samples (Abbaspour, 2011).

To measure the degree of uncertainty two factors were used in SUFI-2. The P-factor refers to the percentage of observed data bracketed by the 95% prediction uncertainty (95PPU) while the R-factor describes the average width of 95PPU band divided by the standard deviation of the data. The 95PPU was calculated at the 2.5% and 97.5% levels of the cumulative distribution of the output variables. A large R-factor shows the large uncertainty of parameters. A balance between these two factors is needed when decreasing parameter uncertainty (Abbaspour, 2011). If the results show a relatively large P-factor as well as a relatively small R-factor, the calibration is acceptable (Setegn et al., 2010; Wu and Chen, 2015).

To apply this algorithm within our hydrological model, we chose the objective function first; here NSE was selected as the objective function. The parameter ranges were pre-defined based on the literature (Khoi and Thom, 2015; Rafiei Emam et al., 2017). Further, the Latin Hypercube (McKay et al., 1979) sampling was applied for “ n ” iterations, yielding “ n ” parameter combinations (in our case we chose “ $n = 500$ ”). These sampled parameter sets were used as the parameter input of the hydrological model.

2.3.2 Generalized Likelihood Uncertainty Estimation (GLUE)

GLUE was developed by Beven and Binley (1992), is used for all kinds of uncertainty and suitable for distributed hydrological models. GLUE is easy to implement, which is the reason why GLUE is widely applied for the estimation of uncertainty in hydrological models (Blasone et al., 2008b; Shen et al., 2012). The algorithm involves the uncertainty of various modelling elements such as input data, model structure and parameter error (Blasone et al., 2008a). In GLUE, the parameter uncertainty is described as a set of discrete behavioural parameter sets with corresponding likelihood weight by:

$$w_i = \frac{L(Q_i)}{\sum_{k=1}^n L(Q_k)}$$

where n is the number of behavioural parameter sets, and $L(Q_i)$ is generalized likelihood measure.

To apply this algorithm in our SWAT model, the parameter ranges were assigned based on the physically meaning of the parameters and further Monte Carlo random sampling was applied. The random sampled parameter sets were used as the base parameter inputs of the hydrological model to simulate the surface runoff in the watershed. The parameter uncertainty was analyzed according to behavioral simulation using NSE, and the model uncertainty was analysed using P-factor, R-factor and 95 percent prediction uncertainty (95PPU) (Abbaspour, 2011).

2.3.3 Parameter Solution Method (ParaSol)

The ParaSol method (van Griensven and Meixner, 2006) is a statistical uncertainty method that estimates parameter uncertainty in complex distributed models by using a modified Shuffled Complex Evolution algorithm (SCE-UA), which is a “global search algorithm for the minimization of a single function” (van Griensven and Meixner, 2006; Setegn et al., 2010). In the ParaSol method, the determined objective functions (OF) are linked to a global optimization criterion (GOC) to minimize the OF or a GOC using the SCE-UA algorithm and the uncertainty analysis is realized with the statistical concepts (Setegn et al., 2010; Khoi and Thom, 2015)).

To apply the ParaSol method in the SWAT model, the modified SCE-UA algorithm was conducted. To apply the algorithm, the “ n ” sample points were randomly sampled in the parameter ranges and the likelihood values were computed at each point. Further, the samples were partitioned into p groups containing m points and each group was evolved according to the competitive complex evolution (CCE) algorithm. The points in the last steps were combined into a single value and further the process will stop if any of the pre-specified convergence criteria are

satisfied. More information on this method is found in van Griensven and Meixner (2006) and Wu and Chen (2015).

2.3.4 Particle Swarm Optimization (PSO)

The PSO method is a population based stochastic optimization technique developed by Eberhart and Kennedy (1995). PSO has many similarities with evolutionary computation techniques such as genetic algorithms. Compared to the genetic algorithm, PSO algorithm is easier to implement, and there are only a few parameters to adjust.

PSO is initialized with a population of random solutions and search for optima by updating generation. In each iteration, every particle is updated by following two ideal values. The first value is the best solution obtained so far, called individual optimal value ($pbest$). The second ideal value that is tracked by the particle swarm optimizer is the best solution which has achieved so far by any particle in the population, called $gbest$. After achieving the two ideal values, the particles renew its velocity and positions with the following equation:

$$v [] = v [] + b1 \times rand [] \times (pbest [] - present [])$$

$$+ b2 \times rand () \times (gbest [] - present []),$$

And

$$Present [] = present [] + v [],$$

where $v []$ is the velocity of particle, $present []$ is the current particle, $rand ()$ is a random number between (0, 1), $b1$ and $b2$ are learning factors.

3 Results and discussion

After setting up the SWAT model in the study area, we selected model parameters for calibration and uncertainty analysis by referring the relevant study in central Vietnam and based on the sensitivity analysis (Rafiei Emam et al., 2017). Table 1 shows the 16 sets of selected parameters used in the model uncertainty analysis. After the calibration processes, the model was validated with the same parameters ranges but in different period.

3.1 SUFI-2

The SUFI-2 method was conducted in three iterations with 500 runs in each iteration through the SWAT model. NSE was selected as an objective function. The behavioral threshold value of 0.5 was chosen. According to Moriasi et al. (2007), if NSE is greater than 0.5, the performance of the model is good and the parameter uncertainty ranges are acceptable. The initial parameter ranges were set based on the physical meaning of parameters. The range of

Table 1 Model parameters and their initial and final ranges for surface runoff simulation

Parameters	Code	Change type	SUFI-2	
			Initial range	Final range
Curve number	CN2	Relative change	-0.2 – 0.2	-0.90 – 0.30
Base flow Alpha factor	ALPHA BF	Absolute change	0 – 1	0.33 – 0.90
Groundwater delay time	GW DELAY	Absolute change	30 – 450	335 – 500
Threshold water level in shallow aquifer for base flow	GWQMN	Absolute change	0 – 5000	3000 – 5000
Threshold depth of water in the shallow aquifer for “revap” to occur (mm)	REVAPMN	Absolute change	0 – 500	0 – 50
Deep aquifer percolation fraction	RCHRG DP	Absolute change	0 – 1	0.5 – 0.9
Revap coefficient	GW REVAP	Absolute change	0.02 – 0.2	0.13 – 0.2
Soil bulk density	SOL-BD	Relative change	-0.5 – 0.5	-0.27 – 0.20
Soil conductivity	SOL_K	Relative change	-0.5 – 0.5	-0.02 – 0.02
Soil available water storage capacity	SOL_AWS	Relative change	-0.5 – 0.5	-0.4 – 0.2
Manning’s value for main channel	CH_N2	Absolute change	0.01 – 0.3	0.01 – 0.1
Effective hydraulic conductivity in main channel	CH_K2	Absolute change	50 – 500	480 – 500
Base flow alpha factor for bank storage	ALPHA BNK	Absolute change	0 – 1	0.18 – 0.29
Manning’s value for overland flow	OV_N	Relative change	-0.5 – 0.5	0.24 – 0.72
Average slope length	SLSUBBSN	Relative change	-0.5 – 0.5	0.35 – 0.65
Lateral flow travel time	LAT_TTIME	Relative change	-0.5 – 0.5	-0.68 – 0.1

parameters are decrease in each iteration based on the evaluation of model performance. The new ranges of the parameters are much closer to the optimum range leading to reduce the uncertainty in steps while monitoring the P-factor and R-factor. The final parameter set values with high NSE and acceptable P-factor and R-factor were selected to implement in the SWAT model in order to simulate surface runoff. The parameter ranges of the first and last iterations are shown in Table 1.

Figure 2 shows the behavior of the parameters against the objective function in SUFI-2 method. (Ranged from the minimum to the maximum values of the parameter range) The graphs shows the sensitivity of the parameters. The parameters are sensitive when there is a trend between parameters and the objective function. The highest objective function value for each parameter would be desirable. Further, the measure of sensitivity and the

significance of sensitive parameters were computed by t-Stat and P-Value, respectively. The larger t-Stat value are more sensitive, and the smaller P-Value are, the less chance of a parameter being by chance assigned as sensitive (Fig. 3) (Abbaspour et al., 2007). As Fig. 2 shows by increasing the Curve number (CN2) and Soil bulk density (SOL_BD) values, the objective function value decreased. However, the objective function value increased by raising of Threshold water level in shallow aquifer for base flow (GWQMN) value. The results showed that in the last iteration, there is no non-behavioral simulations. Figure 3(a) showed that CN2 is the most sensitive parameter with t-Stat = 7.1 and P-Value = 0. The same results reported by Rafiei Emam et al. (2017) in a study in Aluoi watershed of central Vietnam. The second sensitive parameter is GWQMN with t-Stat = [-6.8] and P-Value = 0, it followed by SOL_BD with t-Stat = 5.6 and P-Value = 0.

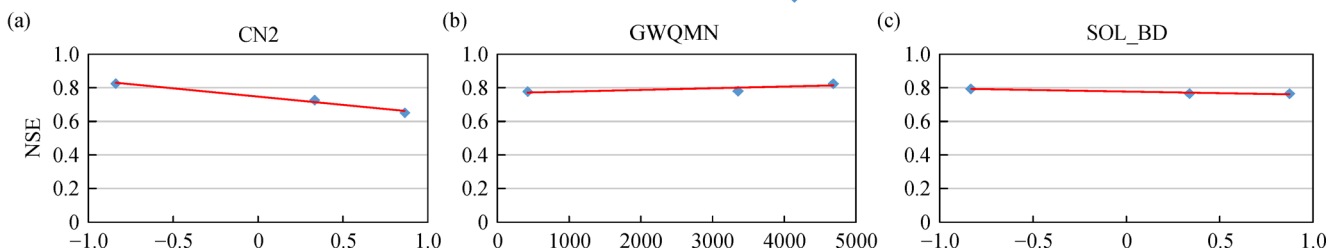


Fig. 2 Behavior of parameters against the objective function (i.e., NSE) showing the sensitivity of parameters. The x-axis shows the value of parameters, or relative changes, and the y-axis shows the objective function value. The higher the value of the objective function, the better the value for parameters. (a) Shows the best fitting values for curve number (CN2) against NSE in relative change, meaning that the initial value should decrease more than 50% to achieve the ideal objective function value. (b) Shows the best fitting values for threshold water level in shallow aquifer for base flow (GWQMN), meaning the higher the GWQMN value, the better the value for objective function. (c) Shows the behavior of soil bulk density (SOL_BD) against NSE in relative changes.

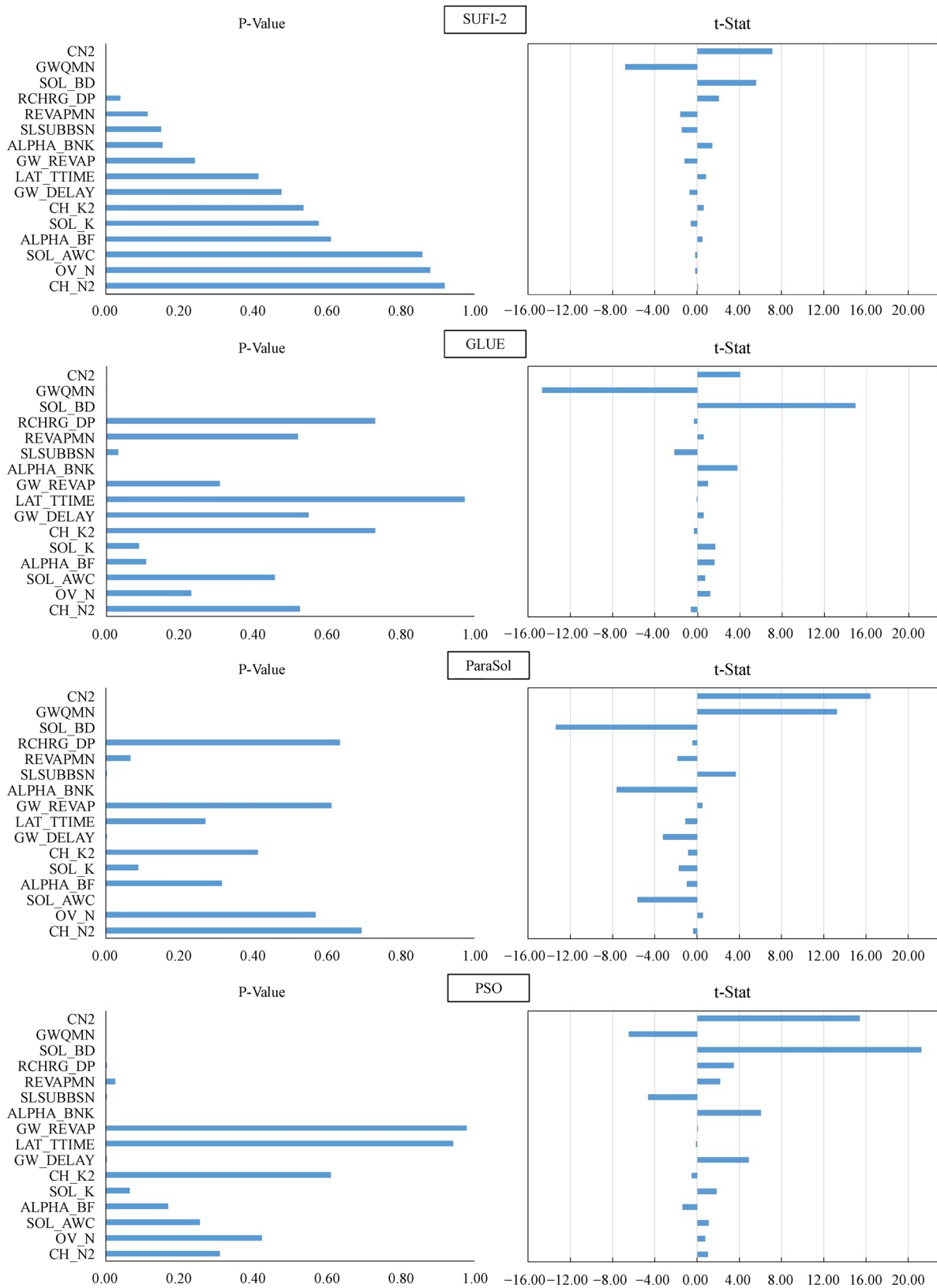


Fig. 3 Sensitivity of parameters by using P-Value and t-Stat in different algorithms. (a) SUFI2; (b) GLUE; (c) ParaSol; (d) PSO. P-Value is the probability of observing a test statistic and t-Stat refers to T-test which measures the size of the difference relative to the variation in the data set. T-test trying to find evidence of a significant difference between population means.

Figure 4(a) shows the predicted uncertainty of simulated surface runoff with 95PPU against the observed discharge using SUFI-2 algorithm. The results showed that all simulations are in the behavioral range. The gray band in this figure shows the 95PPU, which depicted the uncertainty of the model. As the figure shows the 95 PPU band can capture most of the peak flow and base flow periods, however, the model overestimated both peak flow and base flow from October 2007 to September 2008. That is probably due to high precipitation in this physical year compare to the other periods of simulation. The performance of model was satisfactory with $R^2=0.91$, $NSE=0.89$ and $PBIAS=0.32\%$. The P-factor and R-factor are 0.9 and 0.56, respectively.

3.2 GLUE method

The final parameter ranges of SUFI-2 were used as initial inputs for the GLUE method. Regardless SUFI2, GLUE requires one iteration with a large number of simulation runs (e.g., 5000 runs) (Wu and Chen, 2015). In the GLUE analysis, we selected the same objective function (i.e., NSE) as SUFI2 to better comparison of the results. The sensitivity analysis (Fig. 3(b)) showed that with the same objective function and parameter ranges as SUFI-2, the SOL_BD (t-Stat = 14.9) is the most sensitive parameter followed by GWMN (t-Stat = -14.6) and CN2 (t-Stat = 4). The prediction uncertainty of hydrological model using GLUE method is presented in Fig. 4(b). Similar to SUFI results, all simulations are in the behavioral ranges, therefore the 95PPU was obtained at the 2.5% and 97.5% of the accumulated distribution of prediction uncertainty from all parameter sets. As it is shown in the figure the gray band (95PPU) shows the uncertainty of the model with P-factor and R-factor 0.81 and 0.58, respectively. The performance of the model is quite satisfactory by $R^2=0.91$ and $NSE=0.90$.

3.3 ParaSol

ParaSol method was conducted to quantify the uncertainty analysis of the SWAT model. Same as GLUE, the final parameter ranges of SUFI method were used as initial input for ParaSol, and the model was run with large number of simulations (i.e., 3000 runs for an iteration). The results of sensitivity analysis (Fig. 3(c)) showed that CN2 (t-Stat = 16.4) followed by SOL_BD (t-Stat = -13.4) and GWQMN (t-Stat = 13.2) are the most sensitive parameters in the model using ParaSol method. The results of the uncertainty analysis by 95PPU are shown in Fig. 4(c). As it is shown in the figure, the 95PPU band is narrower than that of the SUFI-2 and GLUE methods, which is corresponding to the low R-factor (R-factor = 0.42). Compare to SUFI-2 and GLUE, the P-factor is also small with the value of 0.6. The same results presented by Wu

and Chen (2015). The results showed the ParaSol failed to catch the reasonable prediction uncertainty, probably because this method does not consider the uncertainty in the model structure (van Griensven and Meixner, 2006). The same results reported by Khoi and Thom (2015). They also mentioned that the statistical assumption of ParaSol could be another reason for this discrepancy.

3.4 PSO

Same as GLUE and ParaSol, the final parameter ranges of SUFI method were fed into the PSO as initial input. The model was run with 1000 simulation runs and 5 number of iterations. To better comparison by the other methods we used the same objective function (i.e., NSE) with the behavioral threshold of 0.5. The results of sensitivity analysis (Fig. 3(d)) showed that SOL_BD (t-Stat = 21.3) followed by CN2 (t-Stat = 15.4) and GWQMN (t-Stat = [-6.5]) are the most sensitive parameters in the model using PSO method. The uncertainty analysis (Fig. 4(d)) by 95PPU showed that in compare to the other methods the uncertainty band in PSO is narrow corresponding to the low R-factor (R-factor = 0.49), whereas the P-factor is quite high (P-factor = 0.83) showing the 95PPU band could capture most of the observed data using this uncertainty method.

To compare the algorithms, the monthly simulated and observed data were platted against each other in different algorithms in a double-mass plot (Fig. 5). Although the results showed that the R^2 of all methods are very close to each other, the PSO indicated higher R^2 ($R^2=0.9389$) compare to the other algorithms.

Comparing of performance and capability of algorithms in quantifying parameter uncertainties indicated that PSO and SUFI-2 are the most accurate methods to analysis the uncertainty of the SWAT model to simulate surface runoff, while having a good balance between R-factors and P-factor, corresponding to small uncertainty impacts, and high coverage of measurement. The accuracy of the model is also high, both for PSO and SUFI-2, due to high NSE and R^2 . Zhang et al. (2015) found that SUFI-2 has the best estimation of uncertainty analysis among different uncertainty analysis methods. The same results mentioned by Khoi and Thom (2015) and Wu and Chen (2015). However, based on our results, we suggest to use SUFI-2 initially to find the final parameter bound, and further to use PSO to analyze the uncertainty of the model in SWAT hydrological modelling.

3.5 Validation of the model

After the calibration processes, the model further was validated during 2009–2010 by SUFI-2 and PSO algorithms using monthly discharge data. The simulated hydrograph is shown in Fig. 6(a) and Fig. 6(b). The

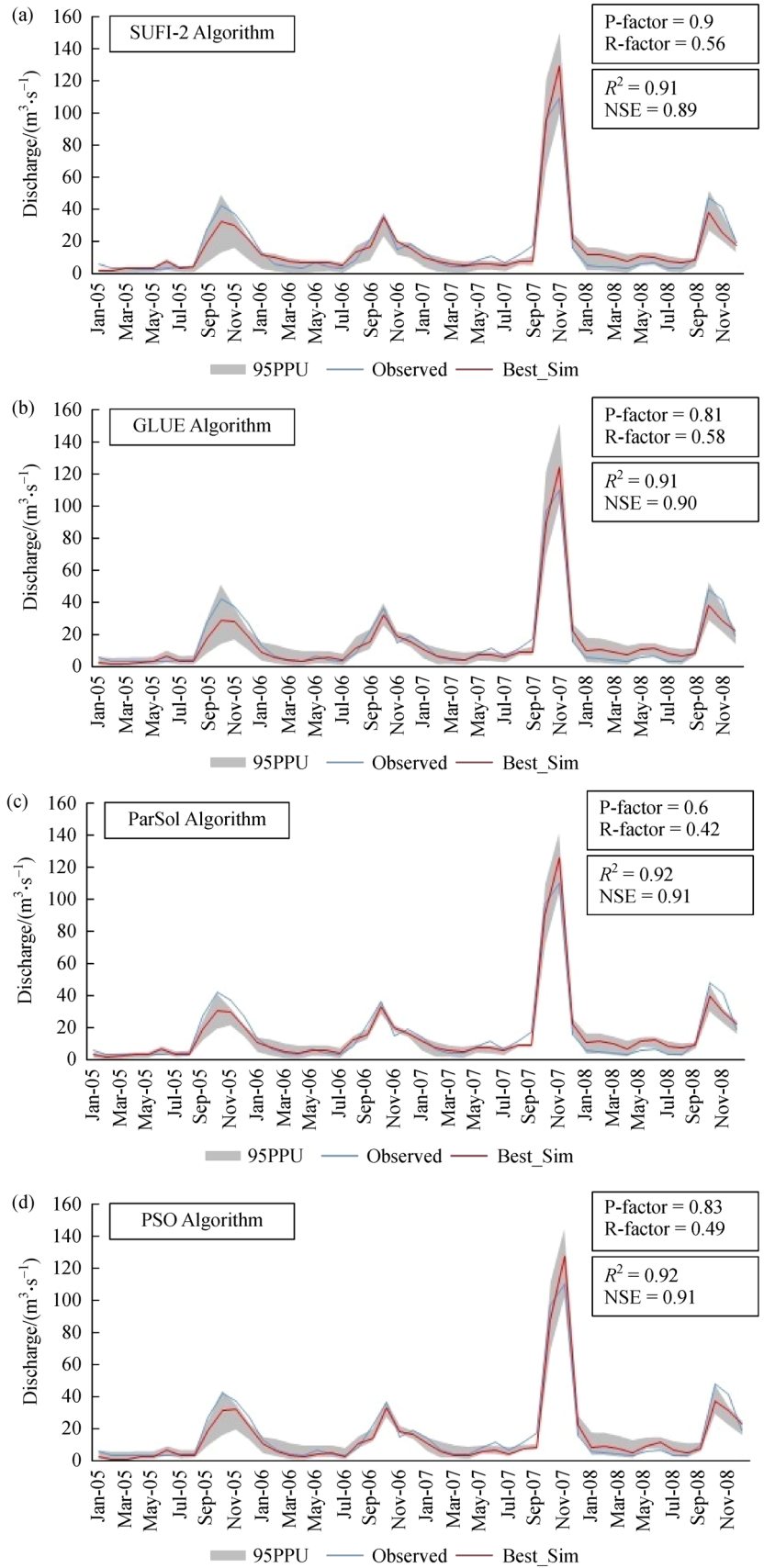


Fig. 4 Monthly runoff simulation by using (a) SUFI2; (b) GLUE; (c) ParaSol; (d) PSO methods.

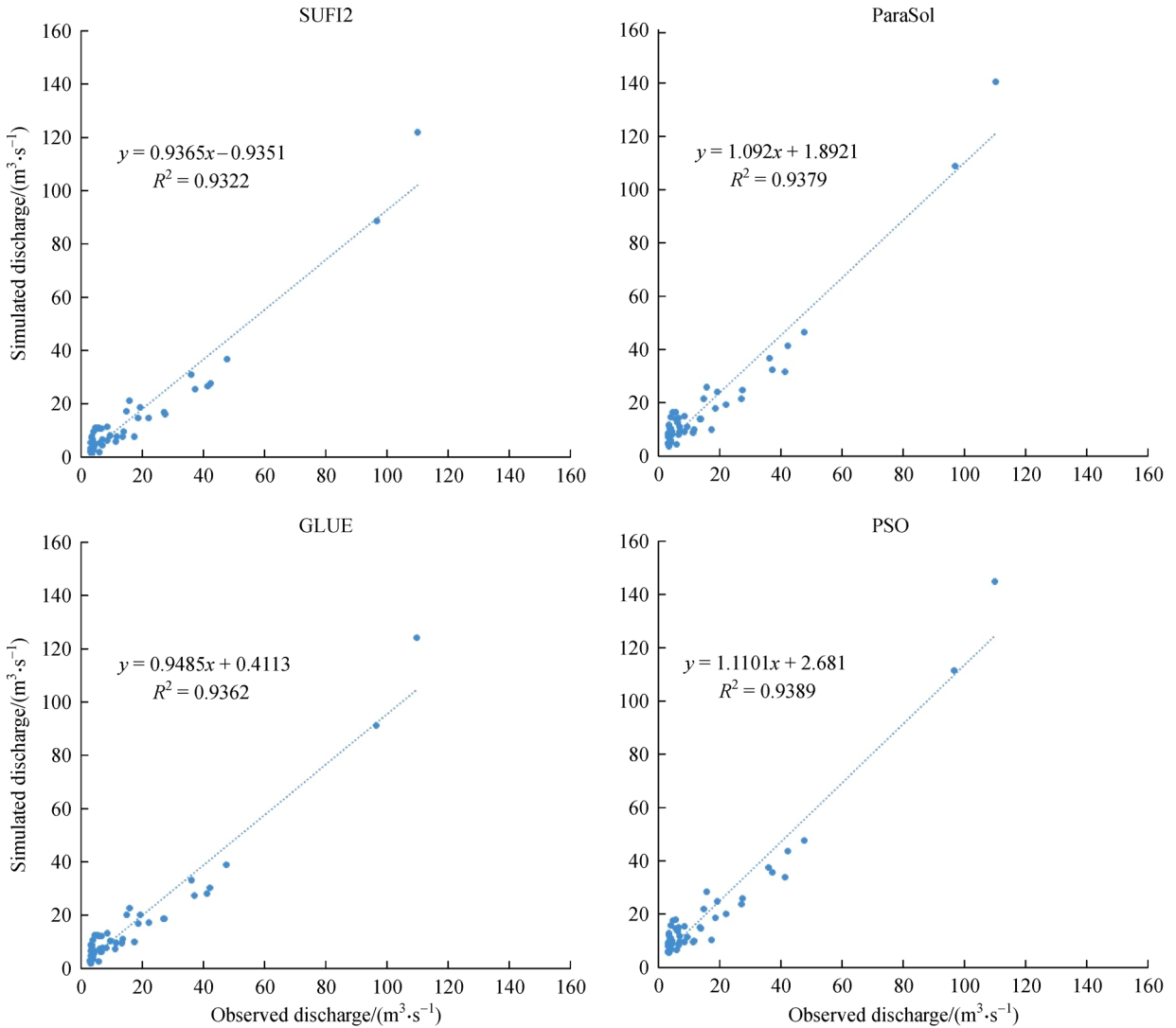


Fig. 5 Comparing of different uncertainty analysis algorithms, the figure indicated the high R^2 for PSO compare to the others.

results indicated the high NSE (0.94, 0.96), and R^2 (0.95, 0.96) for SUFI-2 and PSO algorithms, respectively, revealed a satisfactory result.

4 Conclusions

The results of hydrological modeling without uncertainty analysis are not reliable. Due to a large number of hydrological models and uncertainty analysis methods it is important to evaluate the performance of the uncertainty methods corresponding to the type of hydrological model in different area. We used SWAT hydrological model to simulate the surface runoff, and four uncertainty algorithms were used to evaluate the uncertainty of SWAT model and quantifying parameter uncertainty. The study area conducted in Thua Thien Hue province in central Vietnam.

Sixteen parameter set with initial parameter ranges were selected for parameter uncertainty analysis. The best ranges of parameter combination obtained by SUFI-2 algorithm were used as the input parameter of the other algorithms. NSE was selected the objective function of all algorithm, which make the comparison easier. In general, the results indicate the high performance of SUFI2. In comparing to the other algorithms, SUFI-2 and PSO provide more accurate simulation than the other methods by comparing P-factor and R-factor using 99PPU in 2.5 and 97.5 percent of the accumulated distribution of prediction uncertainty from all parameter sets in the behavioral ranges. The best balance between R-factor and P-factor which shows the uncertainty impacts indicated in SUFI-2 and PSO algorithms. Although the results showed SUFI-2 and PSO are able to support hydrological modeling with more reliable on their outputs, we would suggest to use SUFI-2 initially to set the

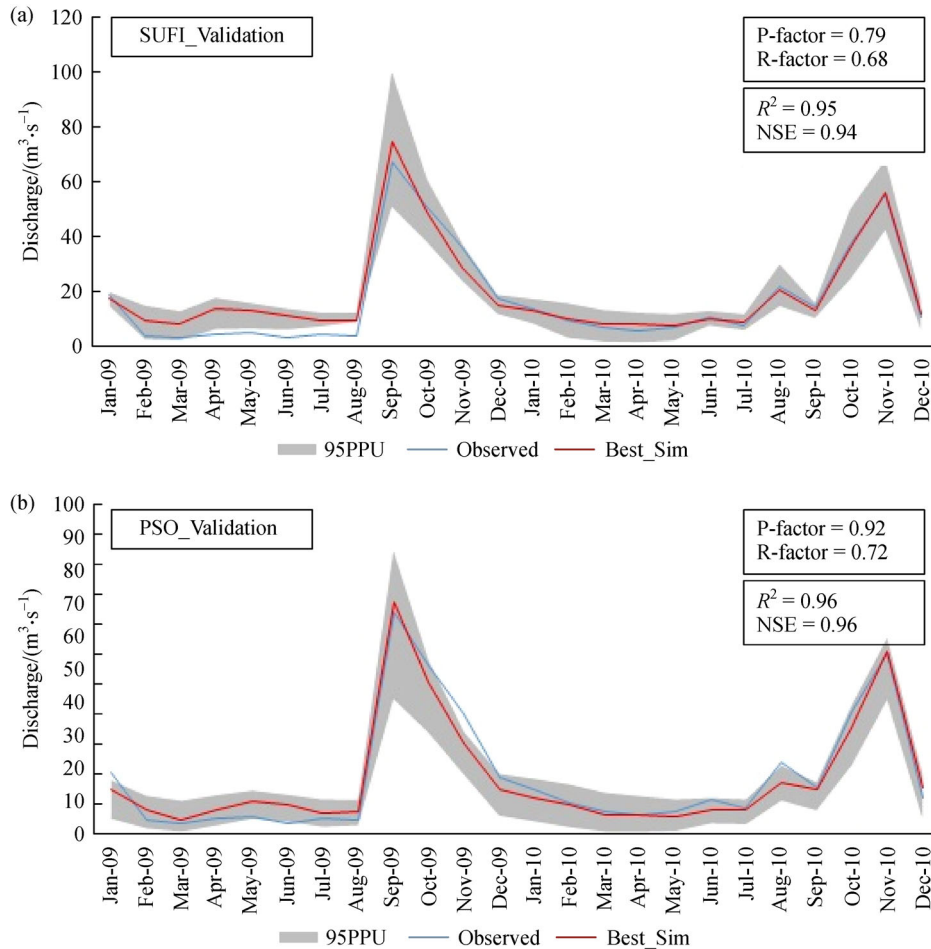


Fig. 6 The average monthly simulated discharge, and the uncertainty band (95PPU) in the validation period over 2009–2010 based on (a) SUFI-2 and (b) PSO.

parameter ranges, and further use PSO for final analysis. However, more uncertainty analysis application in different areas with different scenarios would be suggested for the further research.

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