

THE LOCAL PARAMETERS SENSITIVITY OF URBAN HYDROLOGICAL RESPONSE UNIT OF CONCEPTUAL HYDROLOGICAL MODEL METQ

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The urbanised areas have a significant impact on hydrological processes of the catchment. The average annual urbanisation temp in EU is 0.6%. The existing version of conceptual hydrological model METQ is developed for natural hydrological response units such as forests, swamps and agricultural land. The growing urbanisation level force to add to the model urban hydrological response unit. This study aims to analyse local parameter sensitivity of urban hydrological response unit of conceptual hydrological model METQ. The local sensitivity was made using Monte-Carlo simulations. To evaluate local sensitivity Nash–Sutcliffe efficiency index (NSE), determination coefficient R^2 , percent bias (PBIAS), ratios the root mean square error to the standard deviation of measured data (RSR) in addition to the graphical method were used.

The results show seven parameters to be calibrated the other 16 parameters have to stay as constant values for urban hydrological response unit.

Keywords: conceptual hydrological model METQ; parameter sensitivity; run-off component.

INTRODUCTION

The conceptual hydrological model METQ is developed to the model discharge of modelled catchment area according to climate data such as temperature, precipitation and humidity (Krams and Ziverts, 1993; Ziverts and Jauja, 1999). The additional hydrological response unit describing urban areas were integrated into the model (Grinfelde and Bakute 2017). The adaption of new hydrological response unit requires sensitivity analysis of all parameters to identify each parameter sensitivity and response to the model performance. There are developed several methods to evaluate model performance (Donigian et al., 1983; Gupta et al., 1999; Saleh et al., 2000; Santhi et al., 2001; Van Liew et al., 2007) however they are very specific and developed for particular project or specific.

In the previous studies of METQ, there was Nash-Sutcliffe efficiency (NSE) (Nash and Sutcliffe, 1970) and coefficient of determination (R^2) used. The NSE is commonly used end (Sevat and Dezetter 1991) recognise NSE as the best objective function for reflecting the overall fit of modelled and measured hydrograph. However, Legates and McCabe, 1999 identify oversensitivity of extreme values because of squared differences. The R^2 is commonly used to evaluate model performance. However, risks are overestimating extreme values such as spring floods and underestimate proportional differences between measured and modelled data (Legates and McCabe, 1999).

To provide accuracy in hydrological modelling Moriasi et al. 2007 proposes to use several model performance evaluation approaches. For runoff, there are recommended acceptable NSE is more significant than 0.75, PBIAS is $\pm 10\%$, and the ratio of the root mean square error to the standard deviation of measured data (RSR) is smaller than 0.50, and they recommend in addition to using the graphical techniques (Moriasi et al. 2007). R^2 typically with values greater than 0.75 are considered acceptable (Santhi et al., 2001, Van Liew et al., 2003).

This study aims to evaluate the sensitivity of parameters of conceptual hydrological model METQ.

MATERIALS AND METHODS

The Vienziemite catchment with 5.92 km² of total area and climate data from 1st of January 1993 until 31st of December 2015 were used to make sensitivity analysis of model METQ parameters. Totally 23 parameters were tested during the study. The sensitivity analysis can be divided into three steps (see Figure 1). The first step of analysis was the generation of reference hydrograph with default parameter values defined by Ziverts and Jauja 1999. Monte Carlo simulations of the parameter in amplitude $\pm 50\%$ of its value by keeping other parameters fixed.

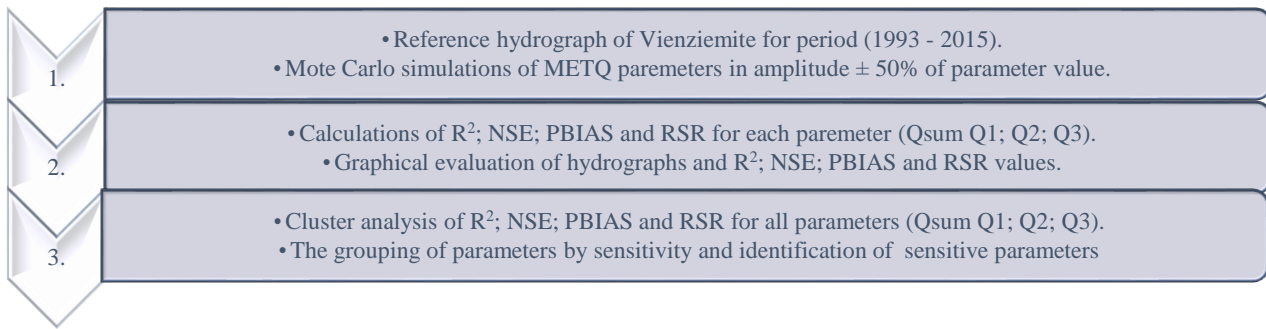


Figure 1. The steps of sensitivity analysis

The second step is to calculate model performance characteristic values of total run off (Qsum) and separately run-off components: surface run-off (Q1); upper layer subsurface run-off (Q2) and base layer run-off (Q3).

The NSE were calculated using following formula:

$$NSE = 1 - \left[\frac{\sum_{i=1}^n (Q_i^{obs} - Q_i^{sim})^2}{\sum_{i=1}^n (Q_i^{obs} - Q_{mean})^2} \right]$$

where Qobs – measured runoff; Qsim – simulated runoff; Qmean – average measured runoff (Nash and Sutcliffe, 1970).

The RSR were calculated using following formula:

$$RSR = \frac{RMSE}{STDEV_{obs}} = \frac{\left[\sqrt{\sum_{i=1}^n (Q_i^{obs} - Q_i^{sim})^2} \right]}{\left[\sqrt{\sum_{i=1}^n (Q_i^{obs} - Q_{mean})^2} \right]}$$

where Qobs – measured runoff; Qsim – simulated runoff; Qmean – average measured runoff.

The PBIAS were calculated using formula:

$$PBIAS = \left[\frac{\sqrt{\sum_{i=1}^n (Q_i^{obs} - Q_i^{sim}) * (100)}}{\sum_{i=1}^n (Q_i^{obs})} \right]$$

where Qobs – measured runoff; Qsim – simulated runoff (Gupta et al., 1999);

The R² were calculated using formula:

$$R^2 = \left(\frac{n(\sum_{i=1}^n (Q_i^{obs} * Q_i^{sim}) - \sum_{i=1}^n (Q_i^{obs}) * \sum_{i=1}^n (Q_i^{sim}))}{\sqrt{[n(\sum_{i=1}^n (Q_i^{obs})^2 - (\sum_{i=1}^n (Q_i^{obs}))^2)] - [n(\sum_{i=1}^n (Q_i^{sim})^2 - (\sum_{i=1}^n (Q_i^{sim}))^2]}} \right)^2$$

where Qobs – measured runoff; Qsim – simulated runoff (Anderson-Sprecher, 1994).

The graphical analysis of hydrograph was made using hydrograph of spring floods in 2013 and hydrograph of summer floods after long period of droughts in 1999. The third step is to use hierarchical agglomerate cluster analysis to classify parameters in groups by their similarities (Al-Odaini et al. 2012; Farmaki et al. 2012; Zhang et al. 2013). The classification of conceptual hydrological model METQ parameters can be illustrated using a dendrogram measuring the degree of homogeneity using the Ward method and Euclidean distance calculation (Lau et al 2009).

RESULTS

The Monte Carlo simulations were made for all 23 parameters (A2; A3; CFR; KS; PZ; RROB; RROB2; RROB2Z; T1; WHC; WMAX; ALFA; AMCOR; ROBK; RROBZ; BETA; CMELT; DPREC; KL; ZCAP; DZ; KU; T2) of conceptual hydrological model METQ. The example of Monte Carlo simulation of parameter BETA is presented in figure 2. The parameter BETA show high sensitivity to parameter value change. Any change of parameter BETA has to be carefully evaluated during conceptual hydrological model calibration process.

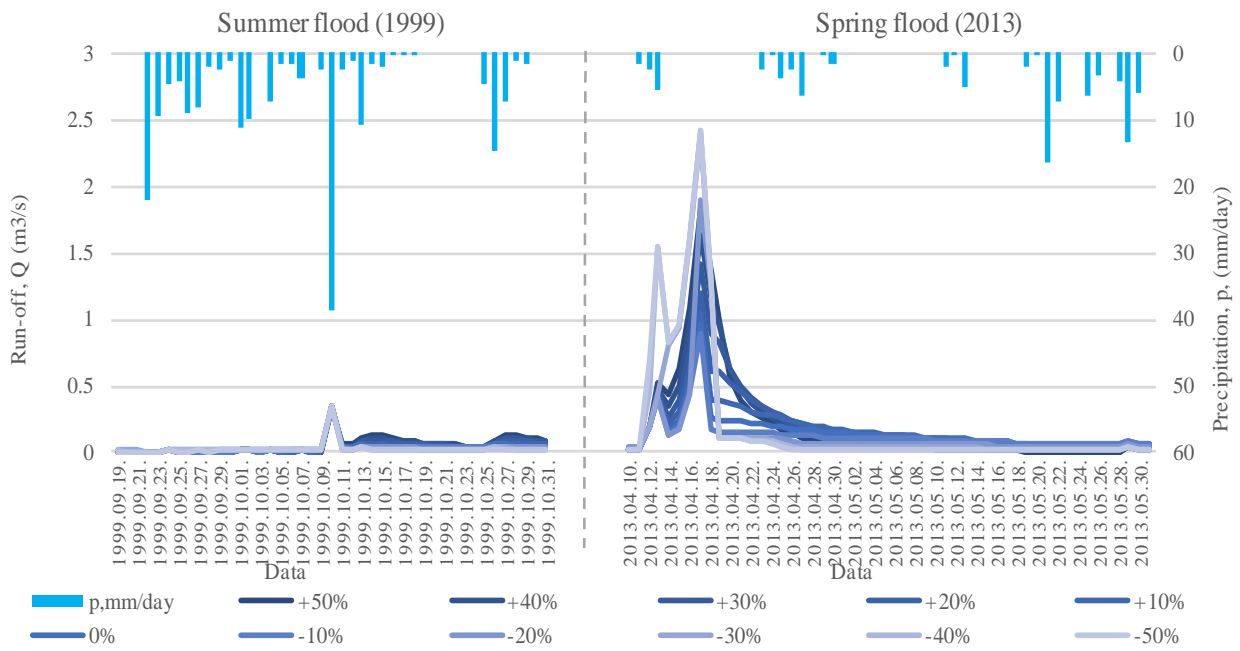


Figure 2 The graphical analysis of parameter BETA sensitivity

The graphical analysis of parameter KU sensitivity is presented in figure 3. The parameter KU is one of root zone parameters and show high impact on long term run-off.

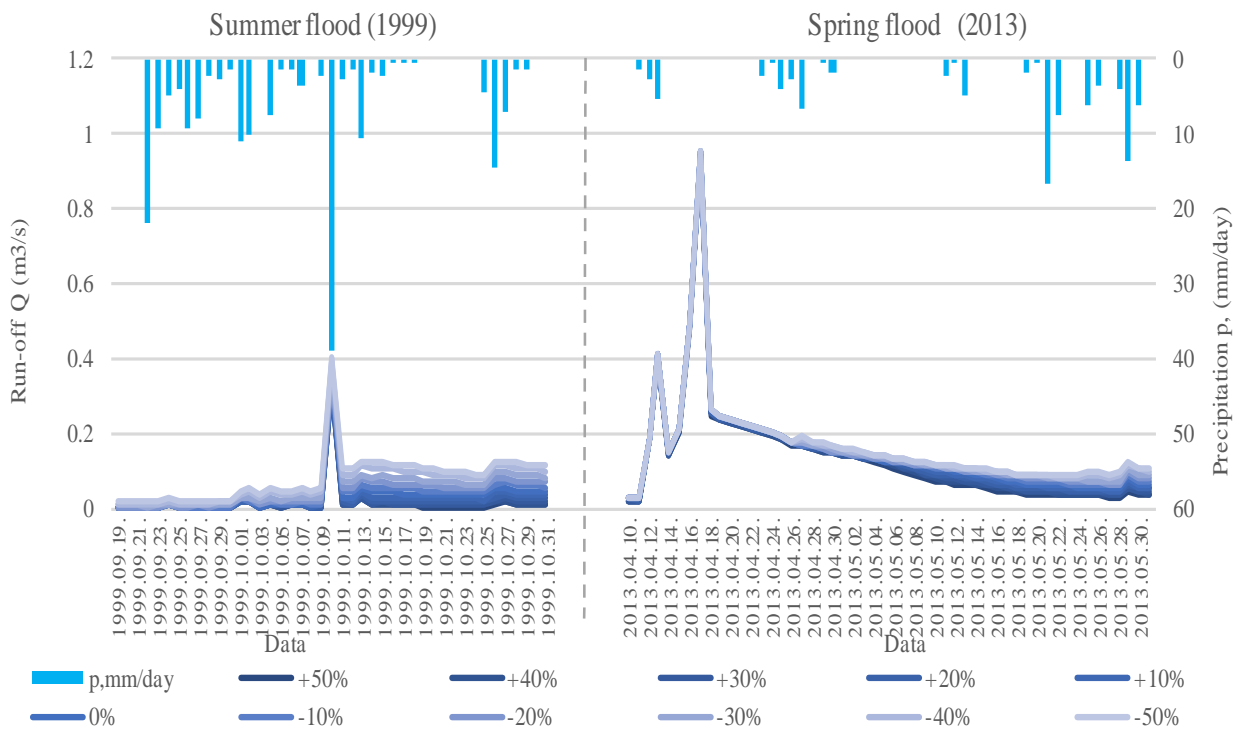


Figure 3 The graphical analysis of parameter KU sensitivity

The clusters of sensitivity analysis results of 23 parameters are presented in table 1. The change of parameters A2; A3; CFR; KS; PZ; RROB; RROB2; RROB2Z; T1; WHC; WMAX; ALFA; AMCOR; ROBK; RROBZ; CMELT; DPREC; KL; ZCAP; DZ and T2 value by +50% the conceptual hydrological model METQ performance is very good. However, the change of parameters BETA and KU by +50% impact the performance of the conceptual hydrological model METQ (Moriassi et al. 2007).

The change of parameters A2; AMCOR; RROB; RROBZ; T2; A3; CFR; KL; KS; PZ; RROB2; RROB2Z; T1; WHC and WMAX value by -50% the conceptual hydrological model METQ performance is very good (see Table 2). However, the change of parameters ALFA; CMELT; ROBK; BETA; DPREC; DZ; KU and ZCAP by -50% impact the performance of the conceptual hydrological model METQ (Moriassi et al. 2007).

Table 1 The results of cluster analysis of runoff (Qsum) deviation at parameter change by + 50%

Class	Objects	Within-class variance	R2	PBIAS	RSR	NSE	Parameters
1	11	0.065	0.993	0.014	0.075	0.992	A2; A3; CFR; KS; PZ; RROB; RROB2; RROB2Z; T1; WHC; WMAX
2	4	0.020	0.966	0.409	0.207	0.957	ALFA; AMCOR; ROBK; RROBZ
3	1	0.000	0.630	-4.440	1.262	-0.591	BETA
4	1	0.000	0.828	1.075	0.431	0.814	CMELT
5	3	0.251	0.997	6.644	0.096	0.990	DPREC; KL; ZCAP
6	1	0.000	0.984	-8.498	0.159	0.975	DZ
7	1	0.000	0.907	33.507	0.478	0.771	KU
8	1	0.000	0.901	-2.972	0.327	0.893	T2

Table 2 The results of cluster analysis of runoff (Qsum) deviation at parameter change by - 50% by (R2; PBIAS; RSR; NSE)

Class	Objects	Within-class variance	R2	PBIAS	RSR	NSE	Parameters
1	5	0.036	0.936	0.901	0.266	0.928	A2; AMCOR; RROB; RROBZ; T2
2	10	0.033	0.992	-0.729	0.079	0.991	A3; CFR; KL; KS; PZ; RROB2; RROB2Z; T1; WHC; WMAX
3	3	0.099	0.802	-2.443	0.525	0.717	ALFA; CMELT; ROBK
4	1	0.000	0.371	10.706	2.615	-5.841	BETA
5	1	0.000	0.995	-16.559	0.202	0.959	DPREC
6	1	0.000	0.536	7.992	1.375	-0.890	DZ
7	1	0.000	0.858	-47.038	0.656	0.570	KU
8	1	0.000	0.989	-10.105	0.153	0.977	ZCAP

The radar diagram of standardised cluster centroids of model performance indicators at parameter change by + 50% is presented in figure 4. The cluster 3 represented by BETA and cluster 7 represented by KU strongly differ from others.

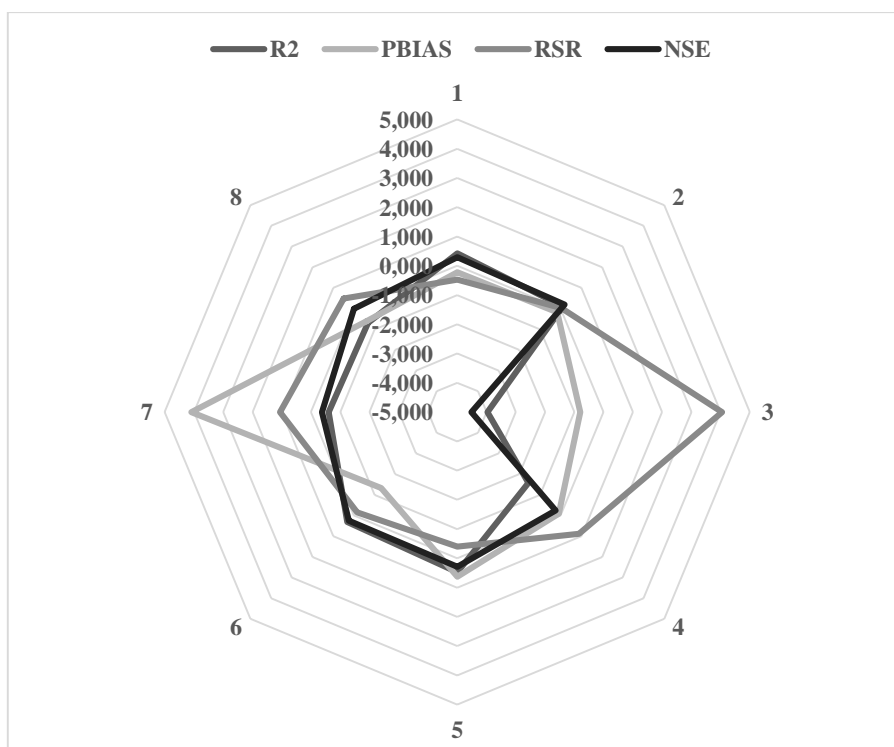


Figure 4. The radar diagram of standardised cluster centroids of model performance indicators at parameter change by + 50%

The radar diagram of standardised cluster centroids of model performance indicators at parameter change by - 50% is presented in figure 5. The cluster 3 represented by ALFA; CMELT; ROBK, the cluster 4 represented by BETA; the cluster 5 represented by DPREC, the cluster 6 represented by DZ, the cluster 7 represented by KU and the cluster 8 represented by ZCAP strongly differ from others.

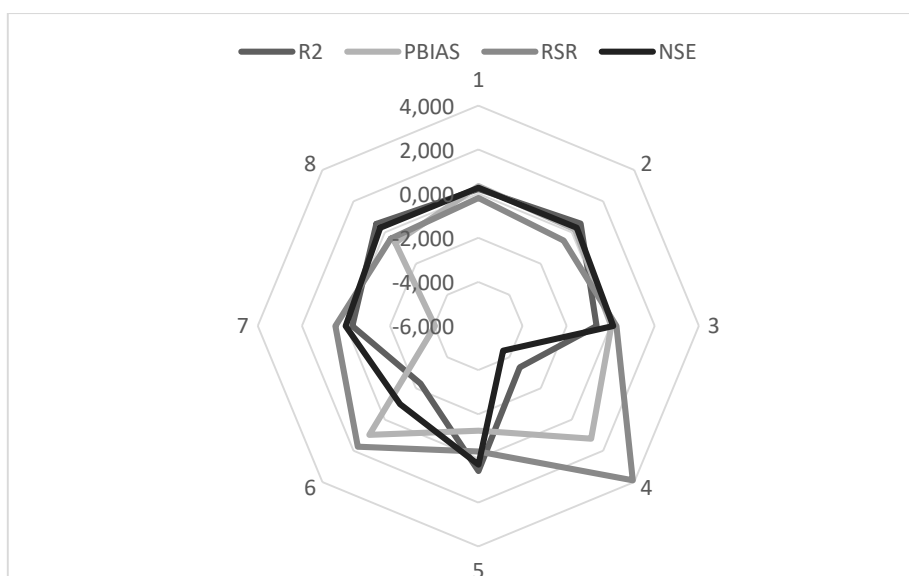


Figure 5. The radar diagram of standardised cluster centroids of model performance indicators at parameter change by - 50%

The analysis of run-off components Q1; Q2; Q3 and total run-off Qsum changes by changing parameter BETA in amplitude $\pm 50\%$ is presented in figure 6. The analysis of NSE; RSR; R2 and PBIAS show parameter BETA impact on run off component Q1.

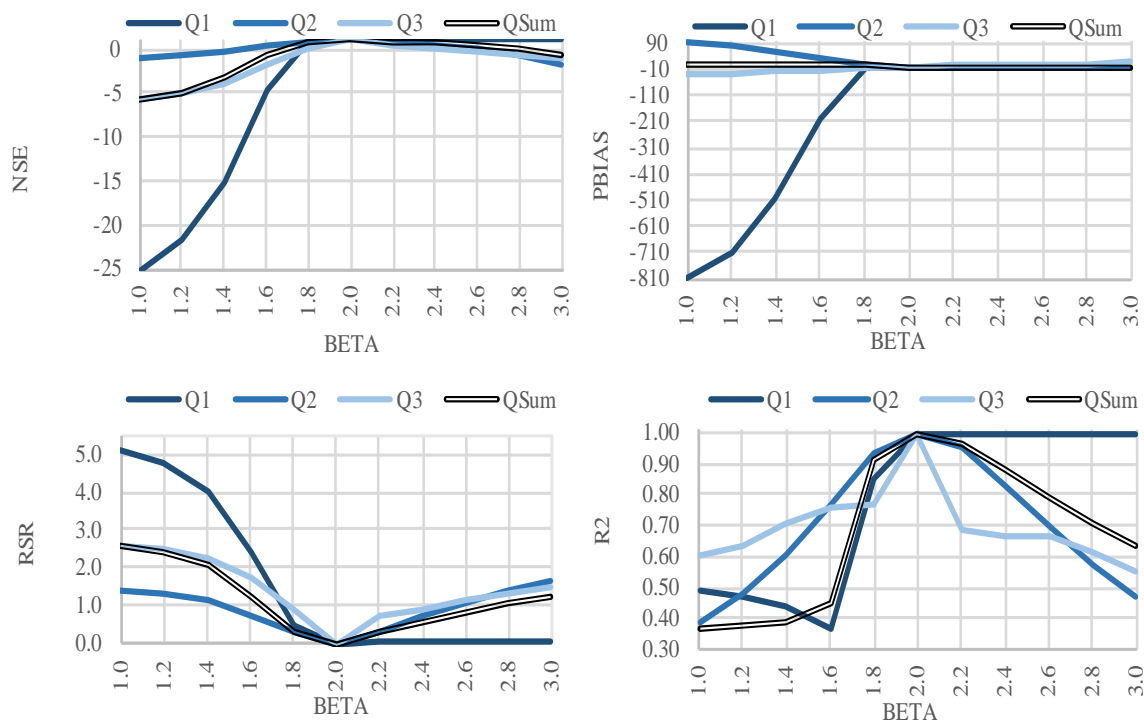


Figure 6. The graphical analysis of parameter BETA impact on conceptual hydrological model METQ performance

The analysis of run-off components Q1; Q2; Q3 and total run-off Qsum changes by changing parameter KU in amplitude $\pm 50\%$ is presented in figure 7. The analysis of NSE; RSR; R2 and PBIAS show parameter KU impact on run off component Q3.

CONCLUSION

The conceptual hydrological model parameters ALFA; CMELT; ROBK, BETA, DPREC, DZ, KU and ZCAP are very sensitive. During calibration of conceptual hydrological model METQ there is need for evaluation of parameter changes.

The analysis showed different impact of parameters on modelling results of different run-off components.

The future research has to be focused on sensitivity analysis of conceptual hydrological model parameters sensitivity for each run-off component.

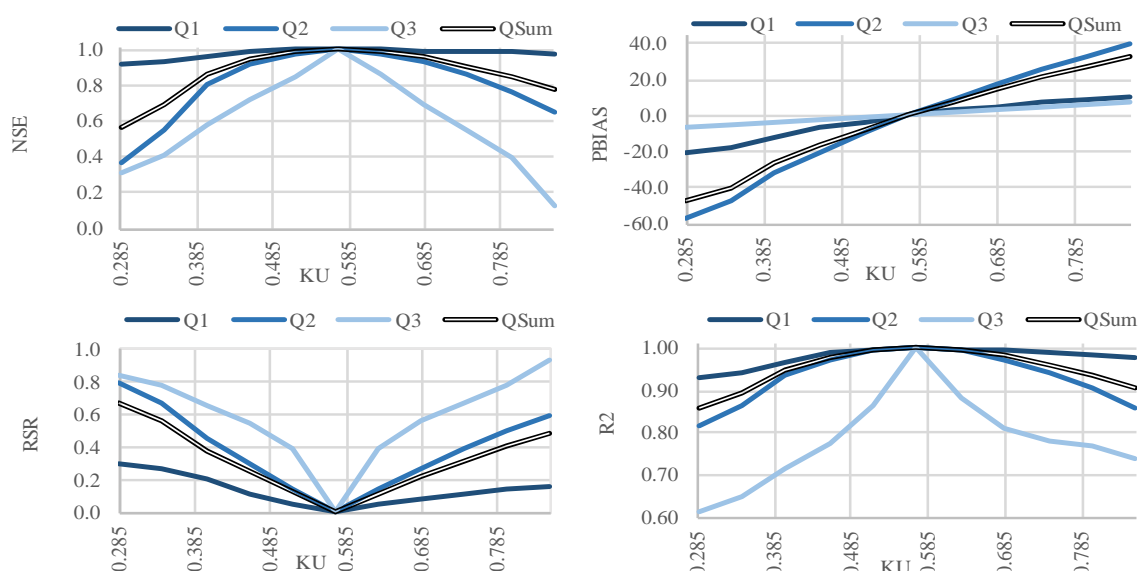


Figure 7. The graphical analysis of parameter KU impact on conceptual hydrological model METQ performance

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