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# KINEROS2 calibration using particle swarm optimization in hydroPSO environment (Case study: Tamar watershed, Golestan, Iran)

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**Abstract**

Simulation of rainfall-runoff process for planning and management of water resources and watersheds, requires the use of a conceptual hydrological models, and play an important role in predicting the response to management scenarios in different climatic areas. In this study, the hydroPSO package was used to assess parameter identification and uncertainty for the KINEROS2 model applied in the Tamar watershed, Iran. Sixteen parameters were selected based on previous studies and parameter sensitivity analysis. According to validation metrics, results indicate better efficiency of K2 based on the event #۲. The coefficient of determination (R2) resulting by comparison of simulated flow and measured flow is equal to 0.9۰۸٤. The events #۳ and #4 with NSE equal to 0.۸۹ and 0.۸٦ had the excellent and very good fitness of simulated flow compared to observed flow, respectively. Sensitivity analysis shows that the parameters Ks_p, Ks_c, n_p, n_c, CV_p, and Sat were the most effective parameters in K2 calibration, respectively. The posterior distributions of some parameters such as Ks_p and n_c appear to be more sharply peaked than other parameters which establishes less uncertainty in hydrological modeling. Visual inspection of Boxplots shows that for 6 out of 16 parameters (Ks_c, n_c, G_c, Rock, Dist_c and Smax) the optimum value found during the optimization coincides with the median of all the sampled values confirming that most of the particles converged into a small region of the solution space. For In and Sat, sampled values were placed within the second quartile. Dotty plots show that the optimum values found for Ks_p, Ks_c, and n_c define a narrow range of the parameter space with high model performance. On the other hand, the model performance is more impacted by the interaction of Ks and n parameters. The parameters CV_p and n_p show a wider range of the optimized levels. Good model performance for a wide range of values of other parameters confirms that these parameters are not well identified.

**Keywords: KINEROS2, rainfall-runoff, simulation, particle swarm optimization (PSO)**

## 1. INTRODUCTION

This Simulation of rainfall-runoff process in the watershed is particularly important in order to have better understanding of hydrological issues, water resource management, river engineering, flood control's structures and flood storage [25; 27]. Models of different types provide a means of quantitative extrapolation or prediction that will hopefully be helpful in decision making [3].

In recent years, the application of models has become an essential tool for understanding the natural processes occurred in the watershed [36]. Rainfall and formation of surface runoff are the important phases of the hydrological cycle, and the basis of hydrological model is to examine the relationship between rainfall and runoff [15].

KINEROS2 (KINematic runoff and EROSion), or K2, originated at the USDA Agricultural Research Service (ARS) in the late 1960s as a model that routed runoff from hillslopes, represented by a cascade of overland-

flow planes using the stream path analogy proposed by Onstad and Brakensiek (1968), and then laterally into channels [40]. Conceptualization of the watershed in this form enables solution of the flow-routing partial differential equations in one dimension. Rovey (1974) coupled interactive infiltration to this model and released it as KINGEN. After substantial validation using experimental data, KINGEN was modified to include erosion and sediment transport as well as a number of additional enhancements, resulting in KINEROS, which was released in 1990 [34; 41]. Kalin & Hantush in 2003 evaluated the efficiency of GSSHA and Kineros2 models in simulating the movement of sediments and water. Based on the results, K2 model due to better formulation of the algorithm had better and stronger efficiency than GSSHA model in sediment routing. In another study by Smith et al (1999), the ability of Kineros2 to simulate sediment and runoff by selective rainfall events in the basin of Catsop in Netherlands has been investigated. According to simulation results due to lack of data, a detailed hydrologic simulation is needed to simulate erosion successfully. The application of the event based physical model, KINEROS2, on a developed tropical watershed in Malaysia was evaluated [18; 19]. Three storm events in different intensities and durations were applied for K2 calibration. K2 validation was done using two other rainfall events before and after the calibration year. Results established that K2 could simulate runoff well but, its capability in sediment load estimation was mostly limited to the accuracy of input data mainly land use maps.
Manual calibration of hydrological models have been concerned since the early 1960s, but due to its complexity and time consuming, automatic calibration has been concerned at the end of the mentioned decade. Auto-Calibration needs appropriate objective function, search algorithm and a criterion to complete the algorithm. At the moment, there are a few known issues that made some serious problems for researches related to optimum parameters set. These problems include several local optimum problem, numerical granularity, non-convex response level, nonlinear dependence of parameters, interaction of parameters on each other, creating a saddle point where the first derivative towards zero, unrelated and Perth data and deviation, autocorrelation, anisotropy and variance in the residual error.
In this context and in order to solve the problems mentioned above, advanced calibration and optimization algorithms and techniques have been proposed. These techniques include Simulated Annealing (SA), Genetic and Evolutionary Programming (GP and EP), Particle Swarm Optimization, Ant Colony Optimization (ACO), Differential Evolution, adaptive multi-method searching or AMALGAM.
Among the methods mentioned above, PSO algorithm due to the flexibility, easy implementation and high performance has been concerned by many researchers in the recent years. This method has a high rate of convergence and suitable computational cost [29]. R statistical package is the most important software which uses PSO algorithm to optimize hydrological models and to implement sensitivity analysis, models calibration and results analysis using hydroPSO tool as an independent tool. This package is able to connect with various hydrological models. Abdelaziz and Zambrano Bigiarini (2014) studied adaptability and capability of hydroPSO to optimize hydrological models in R software in watershed of Geneiss at Germany. Zambrano Bigiarini and Rojas (2013) used hydroPSO package as an independent package in R software to calibrate hydrological models and compared hydroPSO with standard algorithms using a series of specific functions.
This work aims to connect Kineros2 model to hydroPSO optimization package for optimizing main parameters of Kineros2 using PSO intelligent algorithm to overcome the problems resulting from the model calibration by common algorithms.

## 2. Materials and Methods

### Study Area

Tamar is one of the subsidiary basins in Golestan province. The area of this basin is 1525.3 km2 and territorially is located in in the range of 37 ° 24' to 37 ° 49' north latitude and 55 ° 29'to 56 ° 04' east longitude (Figure 1). This area is located in the summering highest point with an altitude of 2168 meters in the south and the lowest point of Golestan 2 Dam with a height of 107 meters above sea level. The average height of this basin is 754.35 meters. There are limited number of evaporative and hydrometry stations in this basin. Most of these stations have short term inventory (up to 15 years for rain and 8 years for temperature), except Tamar stations that have 40-years old inventory including daily rainfall and temperature data [8].

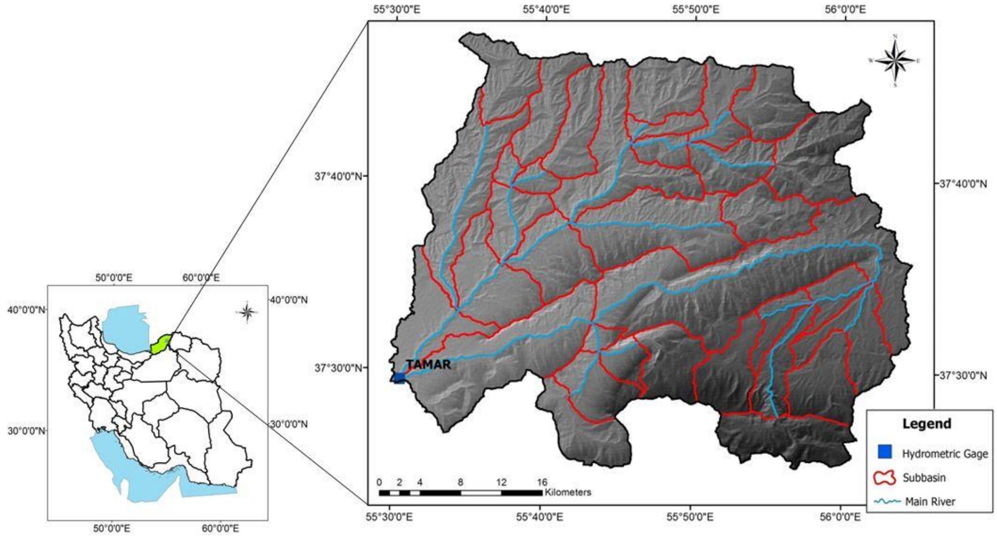


Figure۱ : Geographic location of the study area

**Data set**

A set of hydrological data of water flow and sediment load, rainfall data in four different storms such as September 2004, May 2005, October 2005 and August 2005 has been collected from Tamar hydrometric station in the studied area (Table1). Map of land use has been prepared based on field observation and visual interpretation of spot satellite images applied in Google Earth Software (Figure 2). The available data and FAO digital maps in form of Harmonized World Soil Database (HWSD)) FAO/IIASA/ISRIC/ISSCAS/JRC, 2012 have been used to prepare soil series. Digital elevation model was extracted by Aster satellite data sets with a resolution of 30 meters (Available online at http://gdex.cr.usgs.gov/gdex).

Table 1: Properties of selected storm events

| **Event #** | **Date** | **Duration (h)** | **Rainfall depth (mm)** | **Rainfall volume (MCM)** | **$I_{60}$_max (mm/h)** |
|---|---|---|---|---|---|
| 1 | 19 SEP 2004 | 17 | 50.28 | 76.7 | **13.13** |
| 2 | 06 MAY 2005 | 34 | 57.43 | 87.6 | **8.14** |
| 3 | 08 OCT 2005 | 14 | 41.17 | 62.8 | **7.67** |
| 4 | 09 AUG 2005 | 20 | 59.6 | 90.9 | **9.93** |

I60_max: Maximum 60 min. intensity

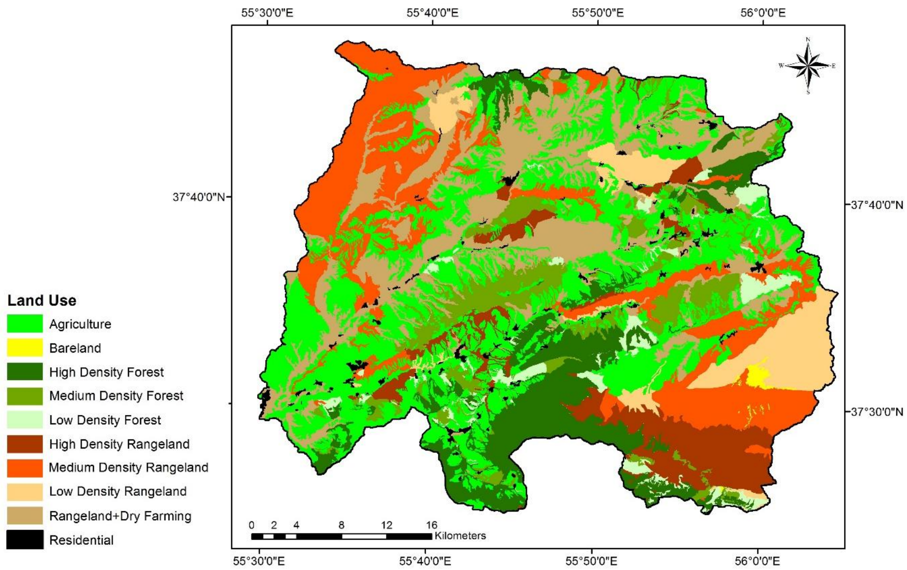


Figure 2: Land use map of Tamar watershed

**KINEROS2**

Kineros 2 (K2) is updated version of Kineros model [41] implemented under a graphical user interface (AGWA[1]) in ArcGIS software. K2 as a dynamic and distribution model based on rainfall events predicts surface runoff, erosion loss, amount of penetration and depth of basin preserve and model each watershed basin by a set of pages consisting of upstream, channel flow and potholes. In this model, the pages consisting of upstream can be divided in some parts with different slope, topography, soils and users [32; 35]. In the conceptual model of upstream flow, small scale changes of parameterized infiltration and micro topography are concerned in the simulation [20].

Modeling in urban sector is based on runoff estimation of permeable and impermeable sections. In K2 model, infiltration is dynamic and is associated with rainfall and runoff. The conceptual model is able to insert a double layer in the soil profile and redistribution of soil moisture in time steps [32].

In this work, local minimum method was applied on flow data to separate the base flow [17]. 58 planes with the average area of 27.65 $km^2$ and 22 channels with the average length of 10 km were discretized using the AGWA interface.

**Optimization Algorithm**

The optimization algorithm used in this study to determine the optimum values of K2 model parameters is PSO algorithm. Initially, this algorithm is started by a swarm of random answers. Each member of this swarm is particles. Particles conducting are done in a way that all particles store the best position during the searching process in the memory. On other hand, the best position obtained in each stage by all particles is stored [14, 30]. In this algorithm, all particles move towards better solutions based on a weighted average with random components to eventually converge to a single point.

hydroPSO package in R software environment was used to implement PSO optimization algorithm. The possibility to develop R capabilities by adding the created packages by the users is one of the most important specifications of this software [5].

hydroPSO package includes below key functions [42]:

1. Lhoat function: This function implements sensitivity analysis based on LH-OATI[2] technique [9]. In this technique, the most effective parameter on output is model of rating 1 and the parameter with lowest efficiency is a rating equal to number of parameters (D) [42].
2. Hydromod function: role of this model depending on hydroPSO is to control on model implementation. Initially, this function reads a set of parameter's value written by user in a file named Paramfiles.txt. Then, hydromod function recalls the administered file of model to produce some outputs. These outputs are read through out.FUN function. Finally, simulated outputs are compared to actual outputs (observed) through gof.FUN function (fitness function). In this study, the objective function of Nash-Sutcliffe Efficiency (NSE) has been used.
3. hydroPSO function: this main driver of calibrating hydrologic model. In the first iteration of algorithm, the parameters are sampled in a domain may be defined by a user in ParamRanges.txt file. Then, hydromod is recalled to estimate the fitness for each particle and location and speed of each particle is improved and evolved based on the setting defined by user to estimate the final standard of fitness and optimization. Finally, hydroPSO collects and save optimum parameter, sampled parameters, fitness of parameters, speed of particles and convergence measures.
4. Plot-results function: this function implements post-processing of results and give the plots with high quality to the user to evaluate the results of calibration.
5. Verification function: to validate a set of defined parameters by used using fitness estimation.

## Model Evaluation

The statistical criteria used in this study are Model Bias (MB), Modified Correlation Coefficient ($r_{mod}$), and Nash-Sutcliffe Efficiency (NSE). Ability of the model in water balance estimation can be evaluated by MB, while $r_{mod}$ represents the differences both in hydrograph size and shape [20; 22]. In addition ability of the model for reproducing the hydrograph can be investigated using the NSE [20; 26]. The perfect value for Model Bias is 0 and for other evaluators is 1. NSE is a normalized statistic, ranging between $-\infty$ and 1, which

[1] Automated Geospatial Watershed Assessment
[2] Latin Hypercube One factor At a Time

determines the relative magnitude of the residual variance compared to the measured data variance. NSE values between 0.75 and 0.36 are considered satisfactory while values ≥ 0.75 are considered excellent [7; 24]. For assessing the size, shape and volume of simulated hydrographs, an Aggregated Measure (AM) can be calculated as below:

$$AM = \frac{r_{mod} + NSE + (1 - |MB'|)}{3} \qquad (12)$$

AM value of 1 reflects a perfect fit. Table 2 presents classes of fit goodness based on AM value.

Table 2: Model performance categories

| Goodness of fit | Aggregated Measure (AM) |
|---|---|
| Excellent | >0.85 |
| Very good | 0.70-0.85 |
| Good | 0.55-0.70 |
| Poor | 0.40-0.55 |
| Very poor | <0.4 |

**K2 Parameters in Optimization Process**

The main objective of this study is to calibrate the parameters of K2 model using hydroPSO tool that has been developed in R environment and a few cases of using this tool has been reported in modeling of water resource [1; 42]. Due to higher speed of implementing of PSO algorithm in R environment compared to MATLAB Software environment and also easy access and apply in the parallel processing, hydroPSO was used as an optimum relation of parameters of K2 model. 16 parameters listed in Table3 have been introduced as parameters affecting flood hydrography in the model.

The common parameters in the calibration used in the main code of software include Ks, n, CV, G and In. in this study, by changing some of codes in K2 model in In Fortran language, number of calibration parameters have been increased to 17 parameters (Table 3). Therefore, the response of basin to the changing of these parameters separated for channel and domain can be evaluated well. As clear in the Table, changing the amount of each parameter due to semi-distribution simulation model has been done through "relative changes" in the initial amount with the default value using Multiplier method.

Table 3: Optimization parameters used in hydroPSO

| No | Symbol | Parameter | Values suggested or used in the reference | Reference | Initial values | Multiplier range used in this work | |
|---|---|---|---|---|---|---|---|
| | | | | | | Lower | Upper |
| 1 | Ks_p | Saturated hydraulic conductivity ($mm.h^{-1}$)_planes | 0.6–210.<br>0.22–266.3<br>0.3–73.3<br>17.2-48.3<br>0–10<br>1.46-63.27 | Woolhiser et al. (1990)<br>Meyer et al. (1997)<br>Guber et al. (2009)<br>Guber et al. (2011)<br>Al-Qurashi et al. (2008)<br>Memarian et al. (2012) | 5-24.21 | 0.2 | 2 |
| 2 | Ks_c | Saturated hydraulic conductivity ($mm.h^{-1}$)_channels | | | 210 | 0.2 | 2 |
| 3 | n_p | Manning's roughness coefficient_planes | 0.1–0.63<br>0.053–0.8<br>0.01–0.1<br>0.09-0.64 | Woolhiser et al. (1990)<br>MacArthur and DeVries (1993)<br>Al-Qurashi et al. (2008)<br>Memarian et al. (2012) | 0.102-0.149 | 0.3 | 4 |
| 4 | n_c | Manning's roughness coefficient_channels | | | 0.035 | 0.5 | 5 |
| 5 | CV_p | Coefficient of variations of Ks_planes | 0.1–2.0<br>0.02–27.3<br>1.6-7.6<br>0.57-0.95 | http://www.tucson.ars.ag.gov/kineros/<br>Guber et al. (2011)<br>Memarian et al. (2012)<br>Wagener and Franks (2005) | 0.75-1.4 | 0 | 2 |
| 6 | G_p | Mean capillary drive (mm)_ planes | 50.0–410<br>46.0–407<br>1.0–263<br>100–306<br>1.0-10.0 | http://www.tucson.ars.ag.gov/kineros/<br>Woolhiser et al. (1990)<br>Guber et al. (2009)<br>Guber et al. (2011)<br>Memarian et al. (2012) | 120.67-240.87 | 0.3 | 3 |
| 7 | G_c | Mean capillary drive (mm)_ channels | | | 101 | 0.3 | 3 |
| 8 | In | Interception depth (mm) | 0.5–4.1<br>4.77–101.3 | Woolhiser et al. (1990)<br>Wagener and Franks (2005) | 0.5-1.27 | 0.1 | 2 |
| 9 | Cov | Percent of surface covered by intercepting cover | 1.0<br>34.5-46.5<br>5.0-90 | Kasmaei et al. (2015)<br>Vatseva et al. (2008)<br>Koster (2013) | 0.229-0.66 | 0.5 | 2 |
| 10 | Rock | Volumetric rock fraction | 0.57-0.62<br>0.1 | Wagener and Franks (2005)<br>Kennedy et al. (2012) | 0-0.32 | 0.5 | 2 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | | 0.011-0.193 | Koster (2013) | | | |
| 11 | Por_p | Porosity_planes | 0.44–0.46<br>0.25-0.35 | Wagener and Franks (2005)<br>Kasmaei et al. (2015) | 0.456-0.468 | 0.5 | 2 |
| 12 | Por_c | Porosity_channels | 0.42-0.56 | Koster (2013) | 0.44 | 0.5 | 2 |
| 13 | Dist_p | Pore size distribution index_planes | 0.15–0.694<br>0.14–1.43 | Rawls et al. (1982)<br>Meyer et al. (1997) | 0.26-0.34 | 0.5 | 2 |
| 14 | Dist_c | Pore size distribution index_channels | 0.25–0.54<br>0.16-0.40 | Wagener and Franks (2005)<br>Koster (2013) | 0.545 | 0.5 | 2 |
| 15 | Smax | Maximum soil saturation | 0-10<br>0.85<br>0.4-0.58 | Al-Qurashi et al. (2008)<br>Memarian et al. (2012)<br>Koster (2013) | 0.88-0.92 | 0.1 | 1 |
| 16 | Sat | Initial soil saturation | 0-0.5<br>0.4<br>0.19-0.32 | Al-Qurashi et al. (2008)<br>Wagener and Franks (2005)<br>Koster (2013) | 0.2 | 0.5 | 5 |

## 3. Results and Discussion

According to R2 metric, results (Figure 3) indicate better efficiency of K2 based on the event #3. The coefficient of determination (R2) resulting by comparison of simulated flow and measured flow is equal to 0.9114. This indicates that a large part of variable variance of response means water flow is explained and justified by the model. After this event, the best coefficient of determination (R2=0.9084) has been obtained for event #2. Event #4 with coefficient of determination of 0.8946 is placed after events number 2 and 3. But, the weakest result of model optimization using hydroPSO was observed for event #1 with coefficient of determination of 0.6368. Due to larger R2 in all simulated events than threshold of 0.5, the result of hydroPSO simulation for all events was acceptable in collinearity term [23; 24]. As shown in Figure 3, the estimated peak flow compared to simulated peak flow is different for various events. This difference in the first event is 9% and this indicates that the estimated peak is larger than actual peak for 9%. In second, third and fourth events, simulated peak were lower than observed hydrograph peak as 17%, 16% and 30%. Therefore, the highest difference was observed in second and fourth events and lowest difference was observed in first event. Totally, the model to adopt simulated hydrography compared to observed hydrograph has more intension toward underestimation of peak flow. As shown in Table 4, events number 2 and 4 with NSE equal to 0.92 and 0.85 have the best fitness of simulated flow compared to observed flow. Event number 3 with NSE of 0.83 is placed in the next priority. While, in event number 1 with NSE of 0.39 had lowest fitness among the simulated events. According to AM measure, the best fitness was observed in event number 2 (AM = 0.92). Then, events number 4, 3 and 1 are placed (with AM = 0.85, 0.83 and 0.56). According to MB measure, optimization model of hydroPSO has been overestimated for flood simulation in events number 2 to 4. But, underestimation of flood is observed in event number 1.

Some diversions are observed in rising and recession limbs of the simulated hydrographs than the real data which are higher for the event #1 than those for other events.

These diversions or overestimation/underestimation of water discharge could be caused by the fact that only one rain gauge station was used, and only one isolated storm event on the watershed surface was considered [18; 20; 21].

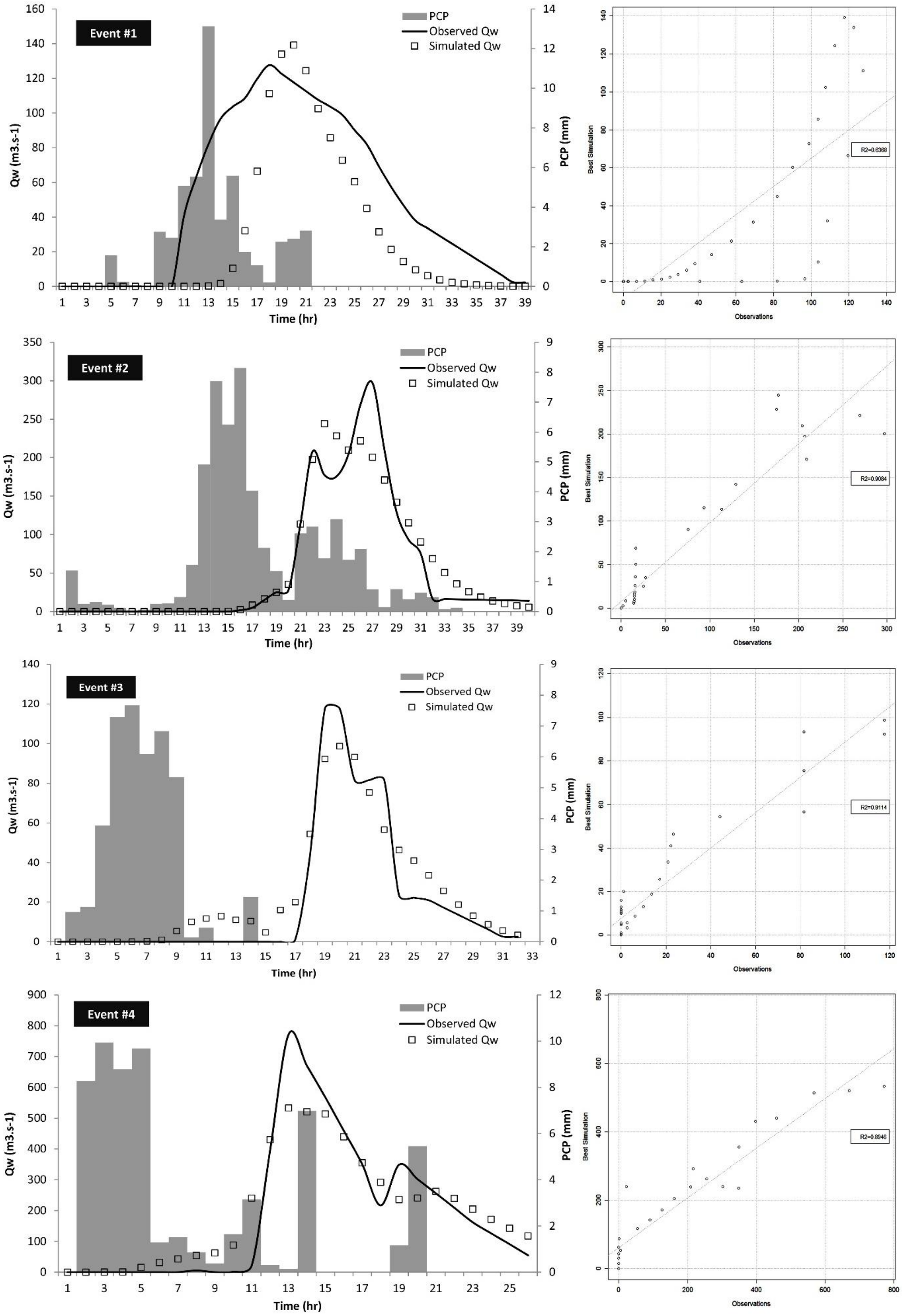


Figure 3: Observed vs. simulated water discharge of selected storm events

Table ۴: Fitting metrics of selected storm events for runoff modeling

| Fitting metrics | Event #1 | Event #2 | Event #3 | Event #4 |
|---|---|---|---|---|
| MB | -0.44 | 0.04 | 0.20 | 0.05 |
| $r_{mod}$ | 0.74 | 0.90 | 0.81 | 0.73 |
| NSE | 0.39 | 0.91 | 0.89 | 0.86 |
| AM | 0.56 | 0.92 | 0.83 | 0.85 |
| Goodness of fit | Good | Excellent | Very good | Excellent |

The identification of the sensitive parameters was analyzed to assess the effectiveness of the algorithm in K2 model calibration. This was achieved by tracking the evolution and convergence of parameter values, global optimum and the Normalized Swarm Radius (NSR). Figure 4 shows the evolution of the 16 parameters employed in K2 calibration. This shows that the parameters Ks_p, Ks_c, n_p, n_c, CV_p, and Sat were the most effective parameters in K2 calibration, respectively. This was also reported and confirmed in previous studies by Nearing et al. (2005), Canfield (2006), Martinez Carreras et al. (2007), Al-Qurashi et al. (2008), and Memarian et al. (2012).

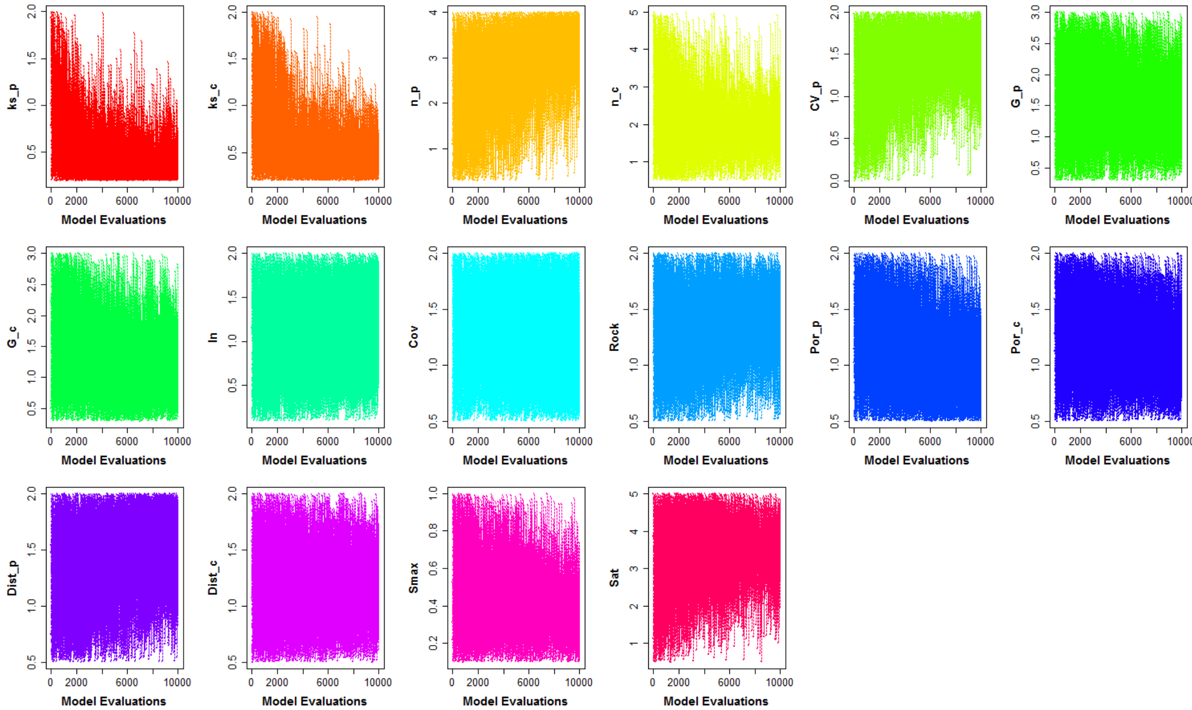


Figure 4: Parameters values per run in model calibration based on the event #2

Frequency histograms of posterior parameter values for eight parameters are shown in Fig. 4a. Irregular and flat shapes of the histograms signify the uncertainty on the most probable optimum values of the parameters [24]. In this work, the parameters are well defined as the peak of the posterior distribution is sharp around the best value in all parameters expect In, COV, Por_p, and Dist_p.

In addition, empirical cumulative distribution functions (ECDFs) in Fig. 5b are used to estimate the true underlying cumulative distribution function (CDF) of the sampled points. Both figures (Figure 5a and Figure 5b) confirm that parameters n_p, n_c, CV_p, G_c, Rock, Por_c, Dist_c, Smax and Sat follow normal and near-normal distributions, while Ks_p and Ks_c show a sampled distribution highly skewed towards the lower boundary used for calibration. Furthermore, the parameters In, COV and Dist_p show a uniform distribution of sampled values.

The posterior distributions of some parameters such as Ks_p and n_c appear to be more sharply peaked than other parameters which establishes less uncertainty in hydrological modeling. However, some other parameters such as In, Cov, Por_p and Dist_p did not significantly change from their prior uniform distributions. This behavior may represent two types of error which are whether the systematic errors of input (forcing) data or compensating for structural deficiencies in the model [33; 38].

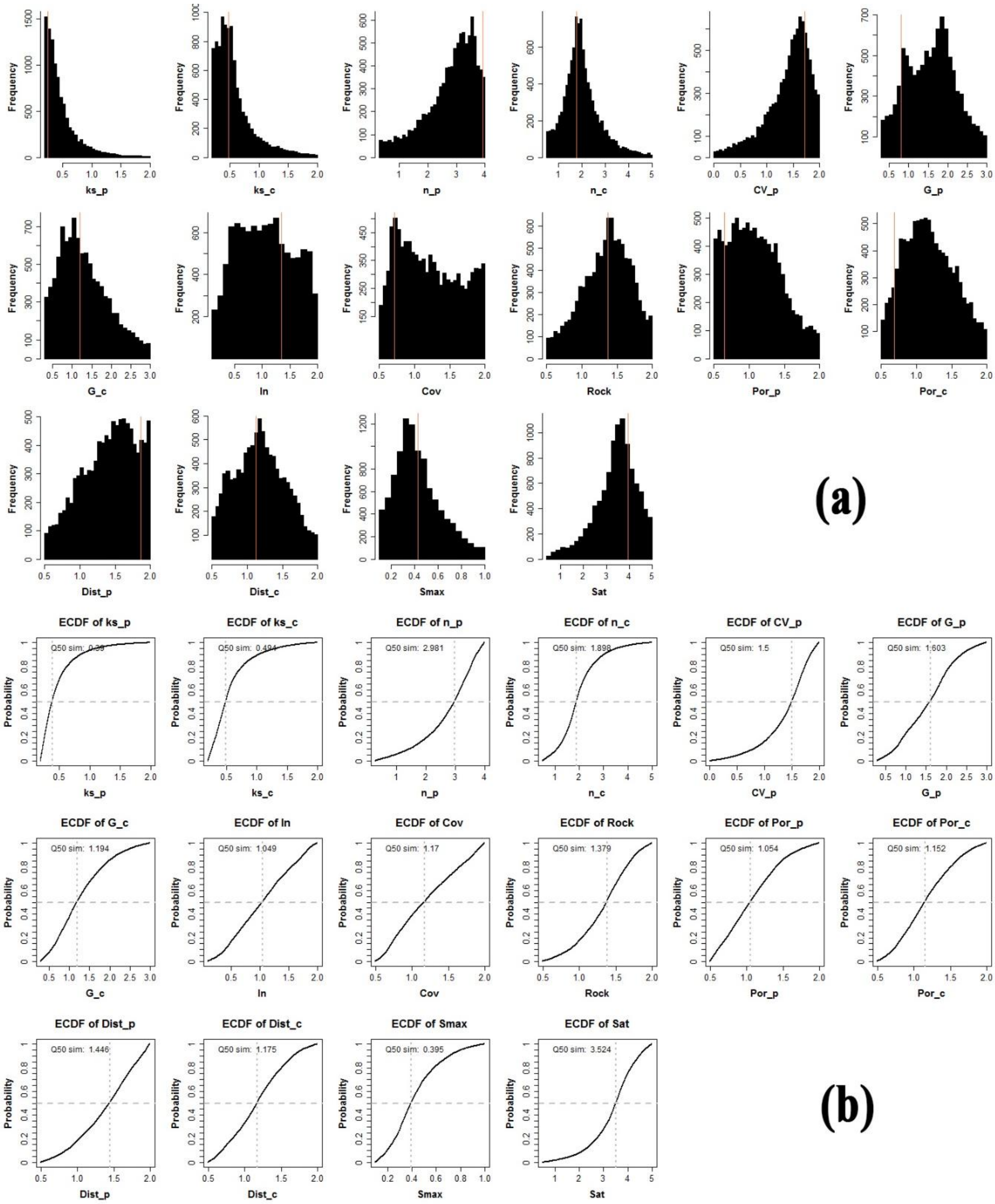


Figure. 5. Graphical summary of parameter values sampled during the optimization. (a) Histograms showing the frequencies of the parameter values. Vertical red line indicates the optimum value found for each parameter. (b) ECDFs of parameter values. Horizontal gray dotted lines represent a cumulative probability equal to 0.5 (median of the distribution). Vertical gray dotted lines represent a cumulative probability of 0.5 (its value is shown in the upper part of each figure).

Boxplots in Fig. 6a are useful non-parametric diagrams for summarizing the statistical distribution of the sampled values. The top and bottom of the box show the first and third quartiles, respectively, while the horizontal line inside the box represents the second quartile (the median). The notches extend to +/−1.58 · IQR/sqrt(n), where IQR is the interquartile range and n is the number of points.

Finally, points outside the notches are considered to be outliers. Dotty plots in Fig. 7b show the parameter values against its corresponding goodness of fit value (NSE) obtained during the optimization. They are useful for identifying parameter ranges that produce the best model performance or with roughly the same model performance [1; 4].
Visual inspection of Fig. 6a shows that for 6 out of 16 parameters (Ks_c, n_c, G_c, Rock, Dist_c and Smax) the optimum value found during the optimization coincides with the median of all the sampled values confirming that most of the particles converged into a small region of the solution space. For In and Sat, sampled values were placed within the second quartile. Fig. 6b shows that the optimum values found for parameters Ks_p, Ks_c, n_c, CV_p and Sat are relatively well defined, whereas other parameters show a wider region around their optimum.

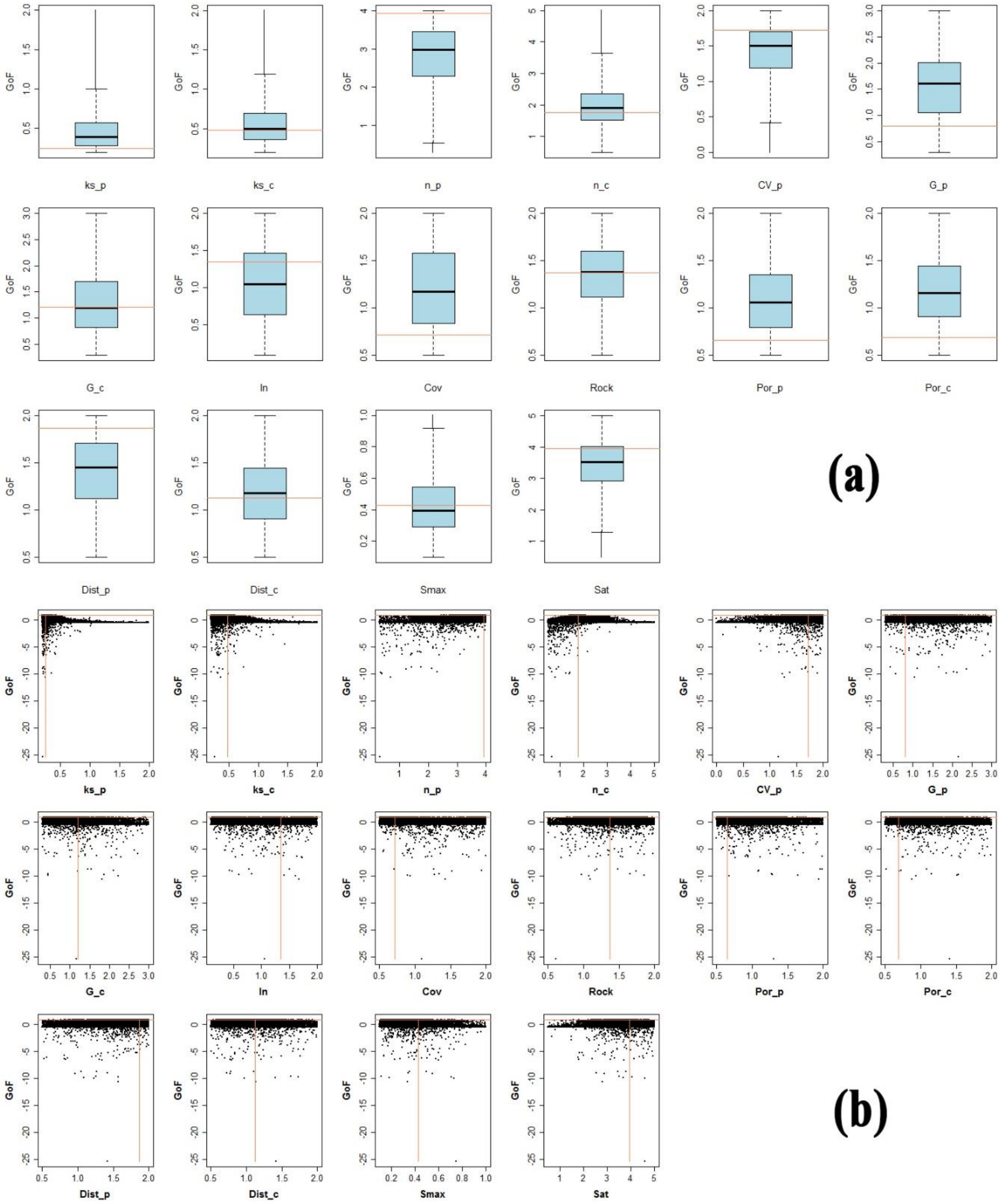

Figure. 8: shows (quasi)-three dimensional dotty plots, which summarize interactions among parameters by projecting the NSE response surface onto the parameter space (for different pairs of parameters). In this figure low model performance is represented with dark-red color while high model performance is shown with light-blue color. In general, it can be seen that particles are spread all over the parameter space, indicating a good exploratory capability of PSO. However, regions with bad model performance have a low density of points while regions with better model performance are more densely sampled, confirming the good ability to exploitation of PSO [42]. This figure shows that the optimum values found for Ks_p, Ks_c, and n_c define a narrow range of the parameter space with high model performance. On the other hand, the model performance is more impacted by the interaction of Ks and n parameters. The parameters CV_p and n_p show a wider range of the optimized levels. Good model performance for a wide range of values of other parameters confirms that these parameters are not well identified.

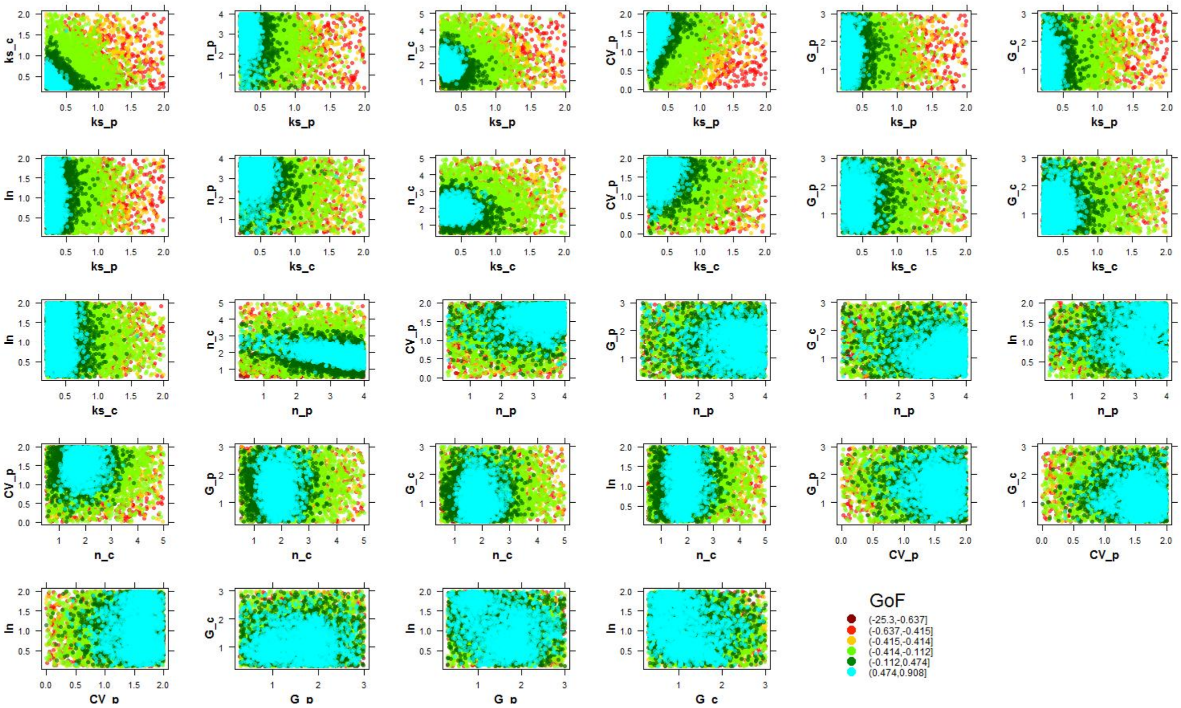


Figure 8: Model performance (NSE) projected onto the parameter space for different pairs of parameters

## 4. CONCLUSION

Comparing the results shown in this section, where PSO and multi-objective PSO was implemented for the same case using HEC-HMS, we found that the use of hydroPSO integrated with Kineros2 provided a significant improvement in the simulated water discharge based on the events #2, #3, and #4. However, HMS-PSO outperformed K2-PSO for hydrological modeling based on the event #1.

We should finally refer to the limitations regarding the lack of sufficient data, especially soil attributes and flood events, which seriously affects the results of this study. In this regard, the results and their generality are of course limited. However, any applications should benefit from the available data as much as possible, and lack of sufficient data for a basin does not mean that something partially helpful cannot be done. Nevertheless, the results obtained should be updated when new information and data become available. Moreover, combining hydroPSO and uncertainty analysis would be an important issue to which future works should refer.

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