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Hydrological Modeling Using Chicken Swarm Optimization Algorithm – Oued El Melah Case Study (NE of Algeria)

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ABSTRACT

The aim of this article was hydrological modeling using chicken swarm optimization algorithm. Interactions between meteorological and hydrometric data been identified as a major conducting factor stationarity in rainfall-runoff relationships. The methodology employed in this work is rainfall-runoff modeling using chicken swarm optimization algorithm. This approach based on randomly selection and chicken society behavior. For the efficiency evaluation of chicken swarm optimization algorithm, a variety of statistical parameters have been used with acceptable values of Nash–Sutcliffe Efficiency (NSE) with 0.38% and index of agreement (IA) with 0.91%. The important and new results are the hydrological models (empirical models) adaptation to Algerian conditions especially in ungagged basins. Therefore, the proposal of the present modeling is a technique using the CSO method to model the rainfall-runoff relationship and discharge forecasting in the Oued El Melah basin located in Guelma city. CSO proves to be a valuable model for studies of the rainfall and flood runoff response to protection of agglomerations against flooding risks projections.

Keywords: water resources management, rainfall-runoff, Oued El Melah basin, flood forecasting, machine learning.

INTRODUCTION

Natural resources in the form of fresh surface water represent a tiny part of all water resources existing on planet Earth. However, their social significance is particular because the management and protection of these resources are of vital importance for human activities. To this end, the risks linked to fresh surface water, such as flooding or drought, cause serious damage, presenting an unavoidable economic issue reflecting the extent of the means implemented for the contained improvement of methods for quantifying and managing these resources (Arrigan et al., 2018; Chang et al., 2018; Dariane et al., 2018; Kumar et al., 2019). On the other hand, surface hydrology contributes to the prediction of river flows (Tasir et al., 2023). Despite the development noted in this field, hydrologists are continually confronted with the complexity of the multiple phenomena which occur during the formation and propagation of flows, in particular the increase in flooding (Surinaidu et al., 2014; Tian et al., 2015; Kiem et al., 2016). At this stage, hydrological modeling has enabled hydrologists to overcome some of these difficulties by simplifying the physical concepts used to represent the terrestrial water cycle. However, in this case, certain variables are often neglected or simply taken into account implicitly. This is the case for the water status of the soil (Saft et al., 2016; Pignotti et al., 2017; Saiki et al., 2017). In addition, the research questions raised by rainfall-runoff modeling in watersheds, as well as transposing the results to ungauged basins present very important scientific and operational challenges (Savenijem, 2010; Seibert and Van Meerveld, 2016). In the case of quantiles of maximum flood flows for the sizing of hydraulic structures, the transfer of information from a gauged site to an ungauged site used statistical classification methods by defining, for example, homogeneous hydrological regions (Wagener et al., 2010). Analysis of the classification results suggests that the controlling parameters are the physical and hydro-climatic characteristics of the watersheds, including rainfall and the ratio of potential evapotranspiration to rainfall. The shape characteristics (geology, pedology, topography), and the hydro-climatic characteristics make it possible to define measures of hydrological similarity between watersheds (Savenije, 2010). For the simulation of the spatiotemporal variability of flows in response to precipitation (Fakhri et al., 2021). The modeled phenomena must take into account the fact that the modeled biomes obey a well-determined spatial distribution. Their zoning is indeed largely dependent on climatic factors (Santos, 2018). In terms of performance, the comparison of global and semi-distributed approaches in rainfall-runoff modeling is a problem that has been strongly developed for a long time (Uhlenbrook et al., 2010; Tapiador 2012; Worqlul et al., 2014). All the scientific research in this direction gives a relatively complex picture (Radcliffe et al., 2017; Samadi et al., 2017; Tan and Duan, 2017). For its part, Algeria has recorded a significant increase in demand for water resources for more than two decades as well as the growth of the sinister effects of drought and pollution. The latter presented a major socio-economic challenge for the government and a scientific issue for Algerian hydrologists. Under these conditions, and for practical and optimal management of these water resources, Algeria has resorted to computer development through the modeling of the hydrological behavior of watersheds in order to reduce the complicity of the various phenomena linked with it. This is illustrated by the large number of studies conducted in this framework. Regarding optimization of the rainfall-runoff relationship, a bio-inspired algorithm was proposed that mimics the behavior of chickens named Chicken Swarm Optimization to model the rainfall-runoff relationship of the Oued El Melah basin located in Guelma city. The objective of this article was to highlight the effect of model parameters on estimated discharge in ungauged basin in the first way, and to adapt some empirical models to Algerian conditions in the second way, based on the observed data covering the study area.

MATERIALS AND METHODS

Study area

In this work, the hydro-meteorological data from the Oued El Melah basin were downloaded from global runoff data center. It is necessary to acquire the knowledge about the natural environment of the aquarium in various fields (topography, geology, climatology, hydrology, etc.) for effective study. A brief description of all these areas was included in the study in this section. Including the compression of the terrain and the large geological formations allows highlighting and classifying different groups of stones in order to better understand how they affect the infiltration conditions. On the other hand, it helps understand climate data, including the study of precipitation and temperature, which have a direct impact on the water system and cycle in the basin. Flows as well as their spatial and temporal fluctuations were addressed through a series of data to understand the hydrological system.

Hydrography

The two wadis SFA and RANEM make up the main watercourse, these wadis received the waters through the wadi Rirane formed in turn by the meeting of the wadi El hammam, draining the waters of the region of the wadis dhan, and of the R'biba wadi where the region crossed by these wadis is characterized by deep and very steep hilly slopes. Oued Melah is formed in the north-east by the Bourdine and el Meza wadis (Figure 1).

Chicken swarm optimization algorithm

Chicken swarm optimization (CSO) is stochastic method based on chicken daily life (Li et al., 2017). In hydrological modeling, CSO started by swapping chicken swarm group (Roslina et al., 2016; Liu et al., 2018) (dominant rooster, a couple of hens, and chicks) with hydro-meteorological data (ex: observed runoff, rainfall, and evaporation) (Fouad et al., 2019; Deng et al., 2020; Deng et al.,2020). In the

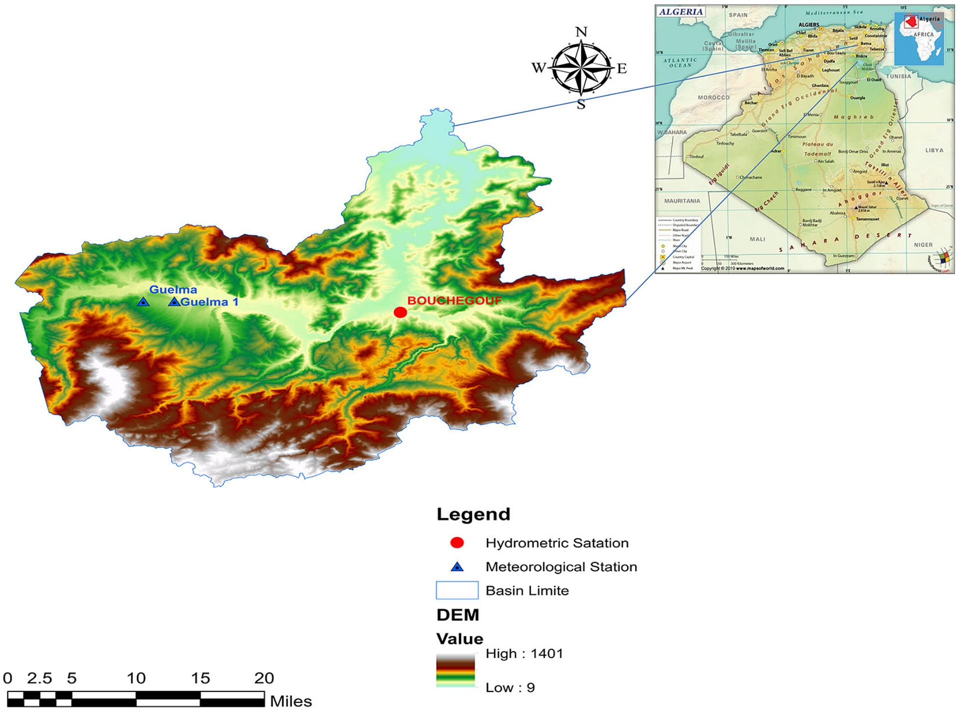

Figure 1. The Oued El Melah basin and its location

second stage, chicken swarm algorithm divides into several classes and determine the placement of the variable (variables are modeled as roosters, hens or chicks) when any individual or variable depend on the objective function (health conditions of the chickens themselves) (Wang et al., 2019; Fu et al., 2019). The last stages are repeated in various time steps, where hierarchal structure, superiority and mother-child relationship will be unchanged. An individual in CSO follows their group mate rooster (modeled runoff) to find optimum local (food), they may not be the optimum global. In food competition, superior individuals have chance

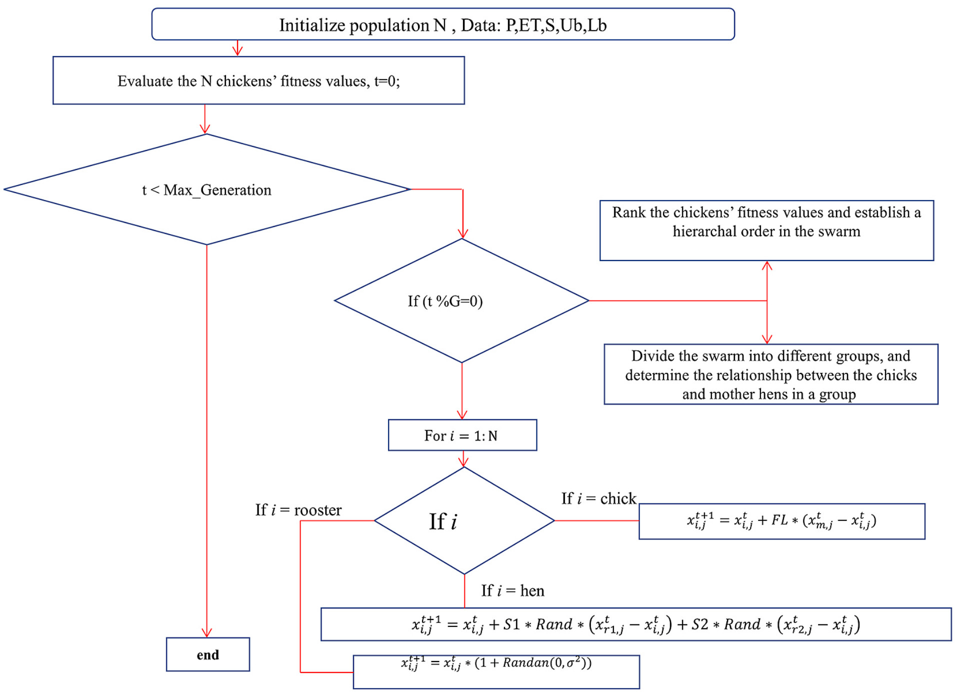

Figure 2. Chicken swarm optimization algorithm

where this phenomenon is modeled as the minimum of error in rainfall-runoff relationship (Li et al., 2002; Meng et al., 2014; Chen et al., 2015). The individuals with minimum values have priority for local or global optimum access over the ones with worse values (Wu et al., 2016; Han and Liu 2017; Deb et al., 2020).

For food accessing, roosters are split for two kinds: roosters with better fitness and others with worse fitness values. This phenomenon can be modeled by the range of searching food for the two kinds, greater or smaller as formulated mathematically as follow:

$$q_{ij}^{t+1} = q_{ij}^{t} * (1 + randn\,(0, \sigma^2) \tag{1}$$

Regarding the hens, they can follow their swarm to obtain food. Also, sometimes hens steal some food in case they are curbed by others. In food competition, more dominant chickens have greater chance than the submissive ones (Eq. 2).

$$\begin{aligned} q_{ij}^{t+1} = q_{ij}^{t} + C1 \cdot rand \cdot \left(q_{r1,j}^{t} - q_{i,j}^{t}\right) + \\ + C2 \cdot rand \cdot \left(q_{r2,j}^{t} - q_{i,j}^{t}\right) \end{aligned} \tag{2}$$

Objective function

Hydrological model calculates a modeled discharge value for a monthly time series. The performance of chicken swarm optimization Algorithm is validated by the statistical parameter MSE to obtain the minimum value of error (Eq. 3).

$$MSE = \frac{\sum(Q_{obs} - Q_{est})^2}{\mathrm{N}} \tag{3}$$

RESULTS AND DISCUSSIONS

Objective function

As the name suggest, in this work, the objective function basically sets the optimization of CSO parameters. On the basis of upper and lower values of GR2M parameters, the objective function focuses on the minimized the real values of statistical parameter (Fig. 3).

Runoff simulation by the linked SCO algorithm

The modeled and observed runoff comparison is displayed in Fig.4 when mean monthly values are used in calibration stage. In this stage, the SCO algorithm reproduces the runoff values when relatively better modeling by the SCO algorithm is noted for validation period if these values are compared by the GR2M model. The results from this section show that the SCO algorithm performs better in the Oued El Melah basin compared to the GR2M model. Figure 5 show the scatter plot of observed and modeled runoff values for the SCO model. An ideal line during the scenario is shown as well spread in

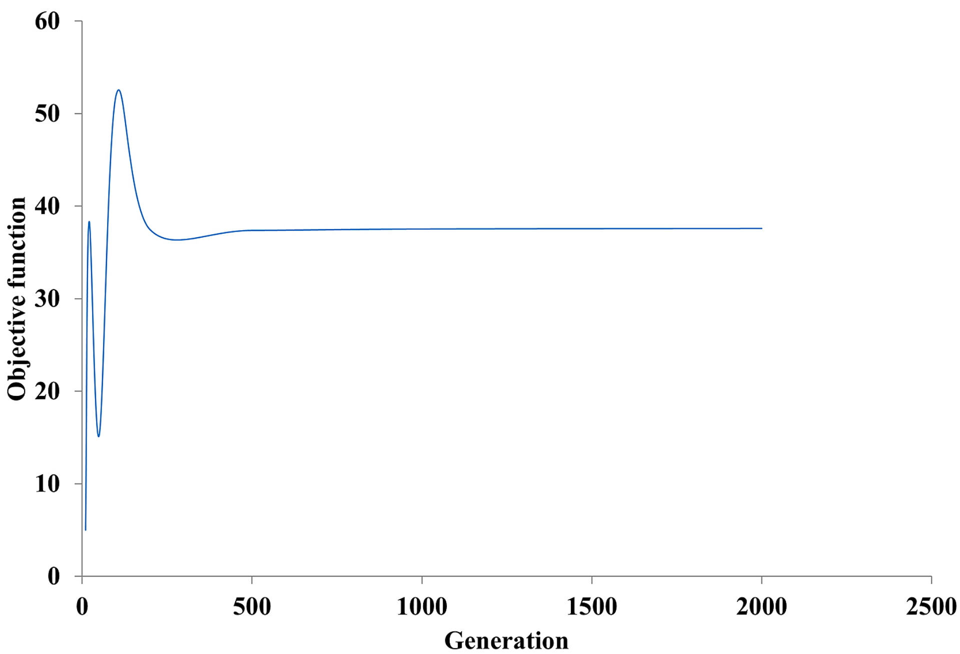

Figure 3. Objective function along the generations and its fluctuation

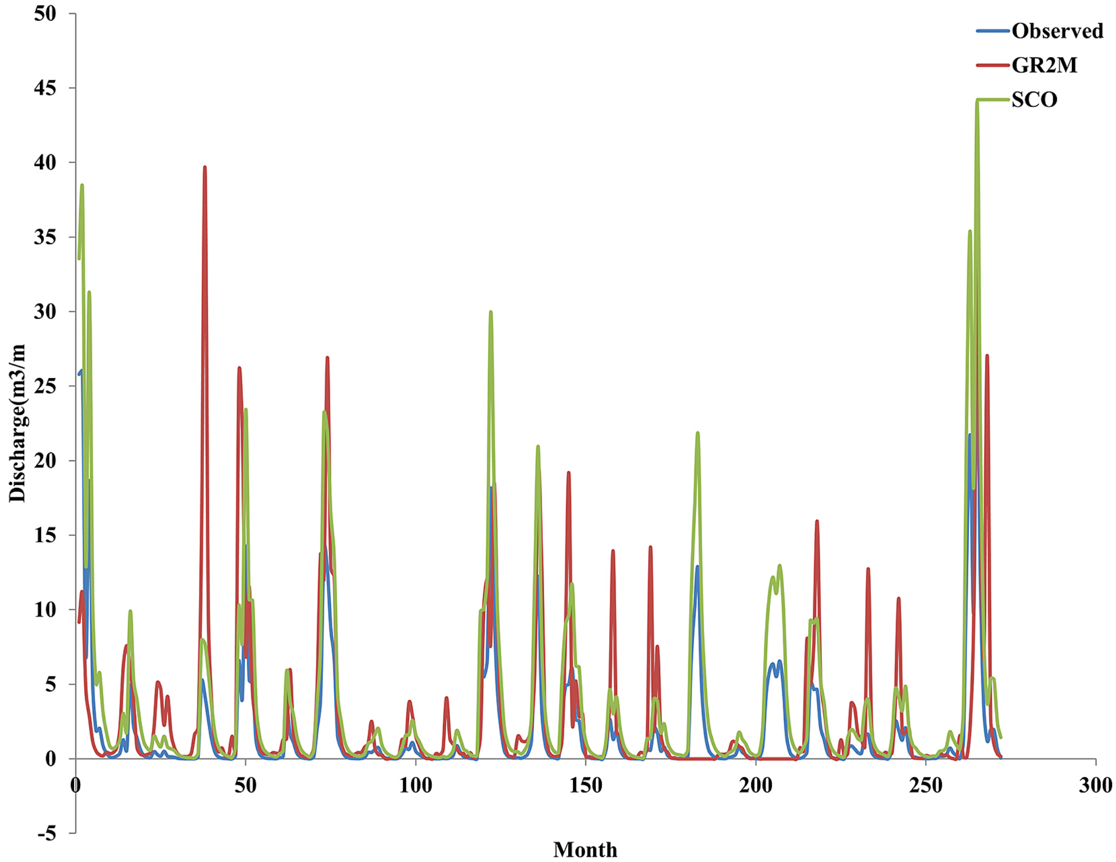

Figure 4. Hydrograph of modeled and observed hydrometric values

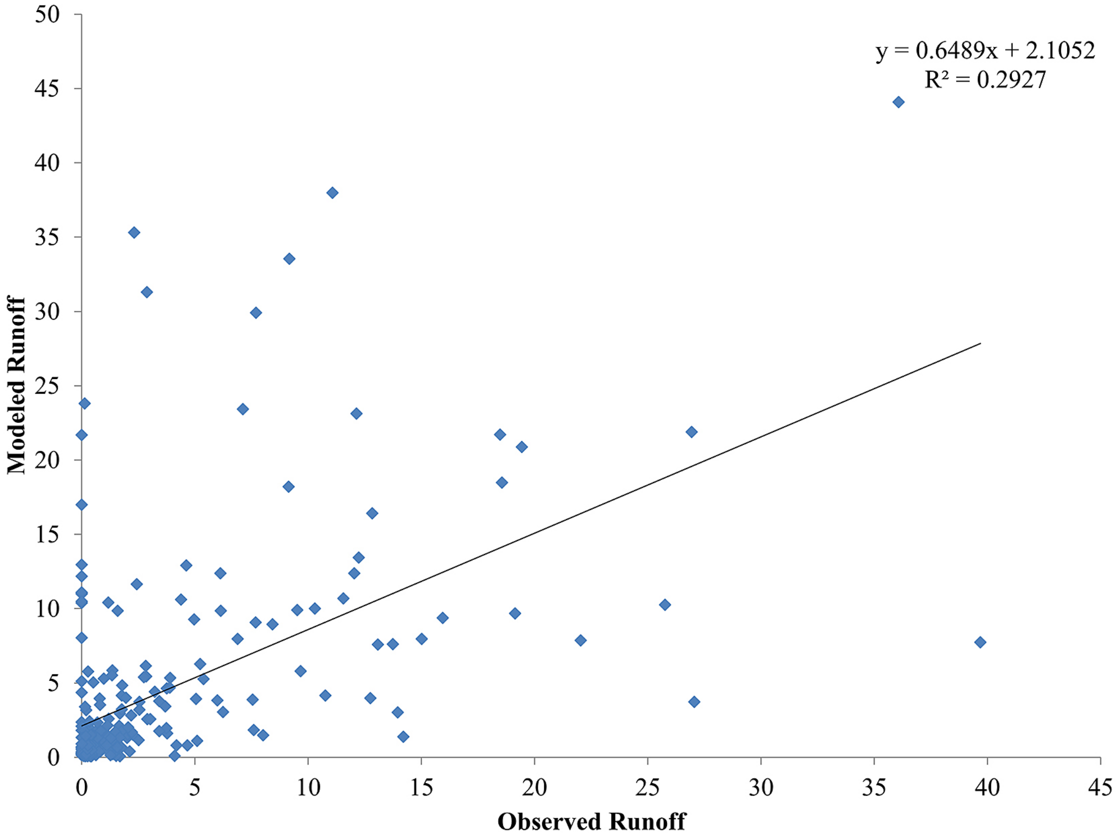

Figure 5. Scatter plots for the SCO model

this scatterplot. In this case, both time variance in the error and persistence exist because of a large scatter and shift from the ideal line.

Runoff modeling based on Statistical-Stochastic coupling

The observed discharge adjustment rates will be made by the Gumbel distribution method, which makes it possible to adjust a large number of statistical distributions to a series of data which verify the hypotheses of independence, homogeneity and stationary (Alzaatreh et al., 2013; Tahir and Nadarajah 2015; Aisha et al., 2022). To better understand this monthly irregularity of discharge which has an essential and decisive role on the flow and in order to characterize the monthly flooding regime, an adjustment law for the distribution of monthly discharge was sought in order to arrive at a determination of the adjustment parameters for the proposed return periods (Table 1).

Empirical models

To calculate the estimated discharge at a given return period, values are used at the input of the observed annual rainfall values (mm), intensity and geomorphological characteristics and monthly discharge (expressed in sheets of water discharged) observed at the level of the watershed station (Guelma outlet). Estimated discharge values are evaluated using several empirical models (Fig. 6, 7) that are written mathematically as follows (Eq. 4, 5, 6 and 7):

$$Q_{MG} = 2K.\log\left(1 + 20P_{moy}\right).$$

$$.\frac{S}{\sqrt{L}}\sqrt{1 + \log(T) - \log(TS)} \tag{4}$$

$$Q_{Sok} = \frac{0.28.(P_t - H_0)\alpha p\%.F.S}{T_c} \tag{5}$$

$$Q_{Gia} = \frac{C.S\left(H_{moy} - H_{min}\right)}{4\sqrt{s} + 1.5L} \tag{6}$$

$$Q_{po} = \frac{\mu.Pj_{max}.S}{L_p} \tag{7}$$

Table 1. Discharge values for return periods

100	50	20	5
0.99	0.98	0.95	0.8
4.6	3.9	3.0	1.5
15.2	**12.9**	**9.9**	**5.0**

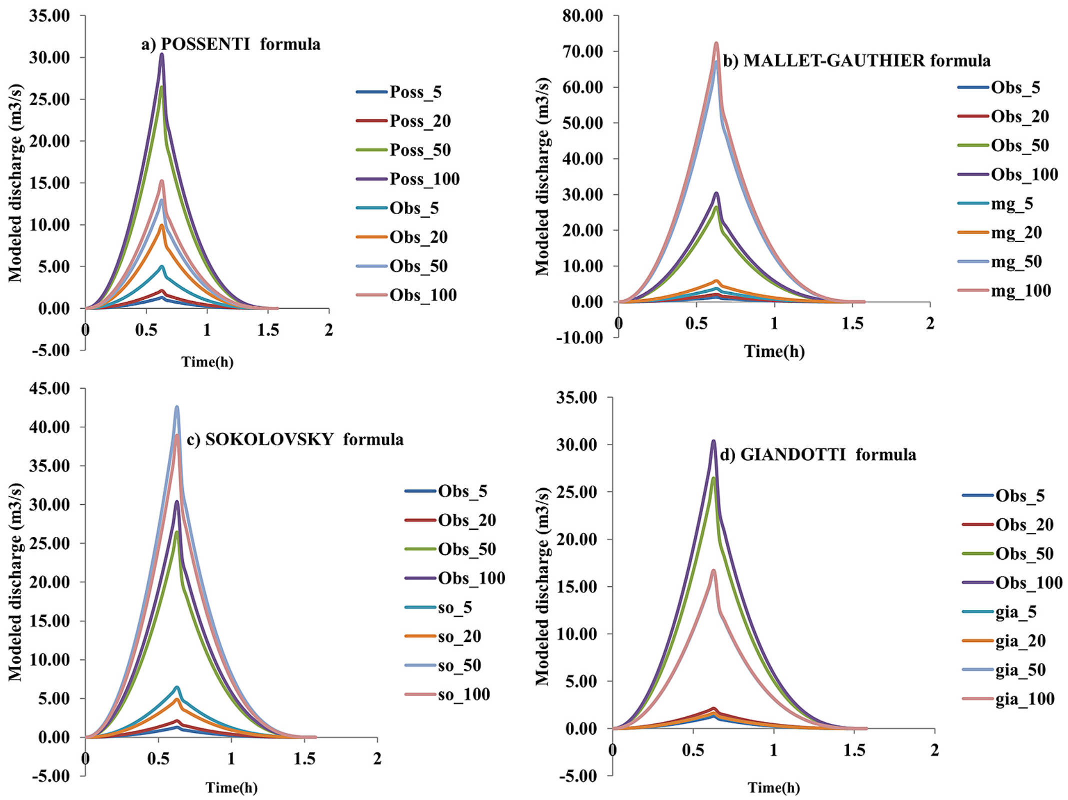

Figure 6. Estimated discharge values using empirical models

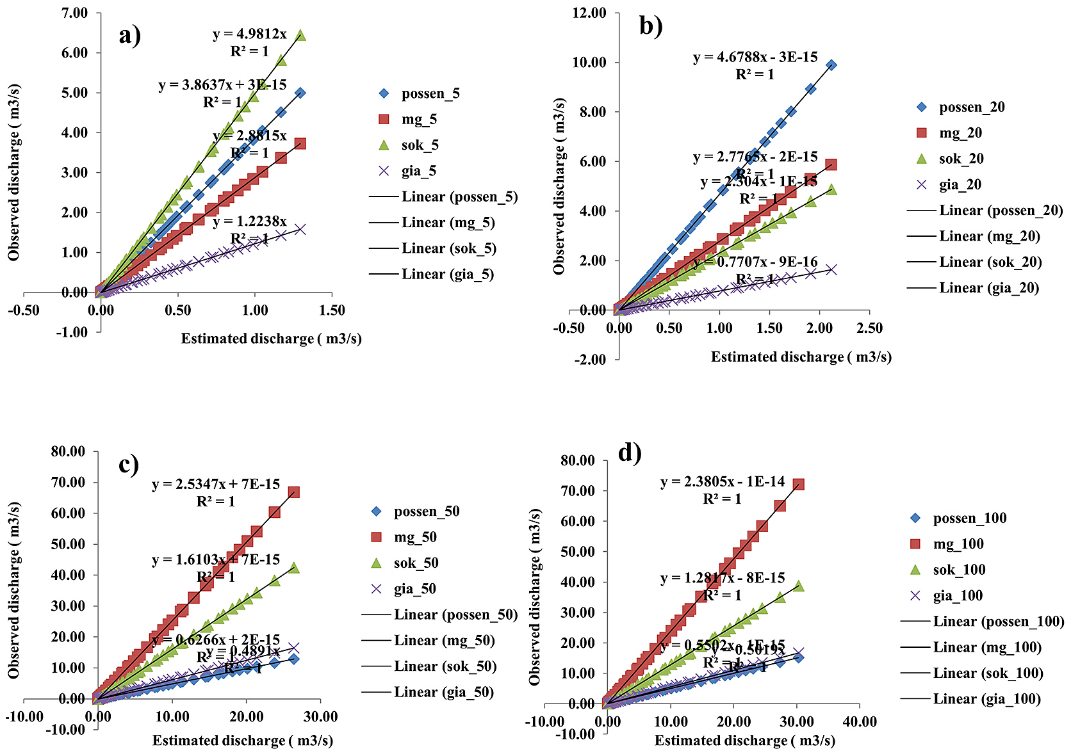

Figure 7. Estimated and observed discharge relationship

where: Q_{MG} – the estimated discharge using Mallet-Gauthier formula; Q_{Sok} – the estimated discharge using Sokolovsky formula; Q_{Gia} – the estimated discharge using Giandotti formula; Q_{po} – the estimated discharge using Possenti formula.

Calibration and validation

The calibration methodology consists in determining the optimized parameters from the various quality criteria; therefore, the authors sought to calibrate the parameter of the empirical model. By modifying this parameter automatically by using the stochastic method SCO until an optimum statistical criterion is obtained (the objective function) with an acceptable value and a very good correlation. The results obtained are grouped in and represented in the Figures below (Fig. 8, 9). The validation of the empirical models-SCO coupling focuses on the application of the models on a series of data that were not used during the calibration. The simulated correlation coefficient Q observed Q related to the use of the optimized parameters. The coupling validation obtained by the use of the optimizable parameters, gives a perfect correlation (R). It can be seen that the rain-flow modeling elaborated by the use of empirical models-SCO coupling to give very acceptable results. (Fig. 9)

Efficiency criteria

In this work, statistical parameters were used to determine the performance of the hydrological model based on SCO method for forecasting runoff time series and test it in both validation and training parts. This is also stayed by statistical parameters for the observed and modeled runoff for stand-alone SCO algorithm (Table 2). These parameters are mathematically defined as follow:

$$PBIAS = \frac{\sum(Q_{obs} - Q_{est})}{\sum Q_{obs}} \times 100 \quad (8)$$

$$NSE = 1 - \frac{\sum(Q_{obs} - Q_{est})^2}{\sum(Q_{obs} - Q_{obs}^{mean})^2} \quad (9)$$

$$A = 1 - \frac{\sum(Q_{obs} - Q_{est})^2}{\sum(|Q_{est} - mean_{obs}| + |Q_{obs} - mean_{obs}|)^2} \quad (10)$$

The NSE parameter indicates that (NSE-GR2M) occurs when the observed discharge

Table 2. Values of statistical parameters

Parameter	GR2M	SCO
NSE	-0.44	0.38
PBIAS	-42.92	97.09
IA	0.67	0.91
MES	25.55	10.91
RMES	5.05	3.3

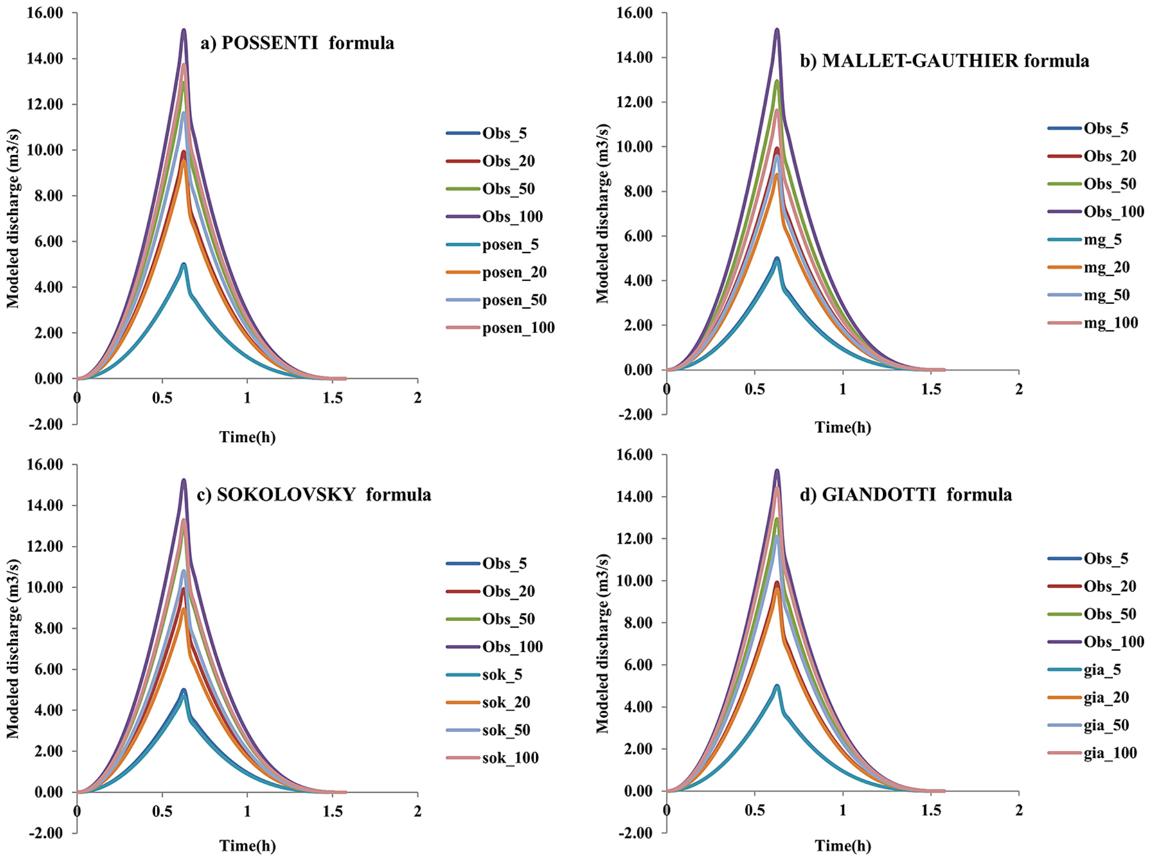

Figure 8. Corrected hydrographs of empirical models

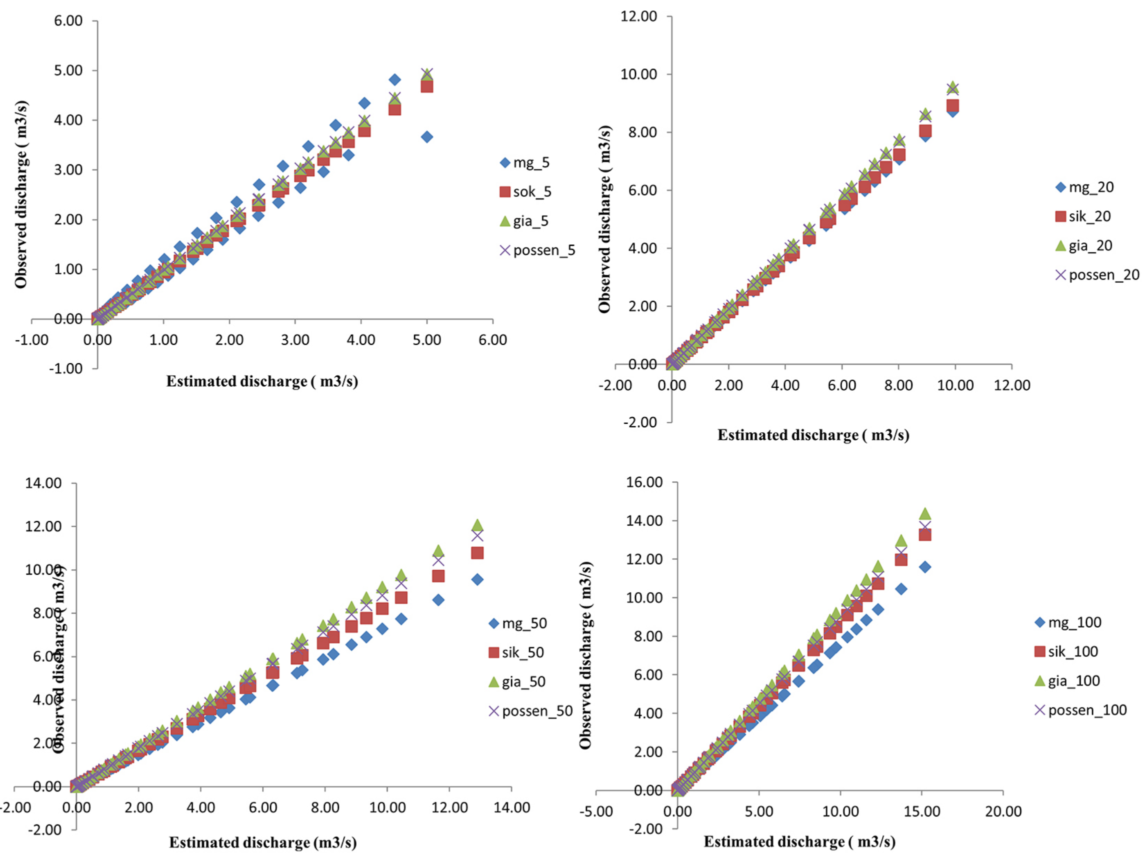

Figure 9. Corrected rain-flow modeling

mean is a better than the modeled discharge (McCuen et al., 2006; Moriasi et al., 2007; Criss and Winston 2008; Ritter and Muñoz-Carpena, 2013). Regarding PBIAS values, it can be seen that SCO overestimates while GR2M underestimates the modeled runoff (Gupta et al., 2002; Hugo et al., 2019).

CONCLUSIONS

Runoff simulation is a primary input for the hydrologist to understood both function and adaptation of hydraulic problems There are multiple applications of rainfall-flow models: short-term flood simulations, low flow forecasting, and predetermination of floods and sizing of structures, highlighting the non-stationary of hydrological behavior under the effect of climate change or changes in land use. This study consisted in optimizing the rainfall-runoff model GR2M in the Oued El Melah watershed using the Chicken Swarm Optimization Algorithm. This study focused on several parameters the main goal of which was to highlight the contribution of the SCO algorithm in improving hydrological models and their calibrations. Also, this work sought to characterize the most adequate method for hydrological modeling signatures relevant for hydrology management and making decision on flooding risks evaluation and protection. For this purpose, and above all, the different factors involved in the modeling of the considered watershed were studied, such as: the physical presentation of the study area (geographical location, type of relief, hydrographic network, etc.), the study of the climate (precipitation, temperature, etc.), as well as the hydrographic characteristics of the Oued El Melah basin.

The results obtained by the application of the GR model optimized by the SCO algorithm turn out to be interesting and give appreciable results despite the problem of lack of data relating to the study area. The validation gave more acceptable results for the hydrological model, confirming the performance of the SCO methodology and supported by the high stability of the objective function. Finally, the goal of this study was to highlight of model parameters effect on estimated discharge in Oued El Melah basin in the first way, and to adapt the Mallet-Gauthier, Sokolovsky, Giandotti, and Possenti formulas to Algerian conditions in the second way, based on the observed data covering the hydrometric stations.

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