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RESEARCH ARTICLE - HYDROLOGY

Study on the applicability of the SCS-CN-based models to simulate floods in the semi-arid watersheds of northern Algeria

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Abstract
Algeria has experienced catastrophic floods over the second half of the twentieth century, causing many deaths and extensive material damage. This study was conducted to find a suitable event-based rainfall-runoff (RR) model for semi-arid conditions, where continuous data are not available in all regional basins. The study compared, based on data availability, the SCS-CN model based on the antecedent moisture conditions (AMC) and four modified SCS-CN models incorporating antecedent moisture amounts (AMA) in order to find the best model to reproduce the flood hydrographs in two catchments. The modified models were predominant over the SCS-CN method. Nonetheless, the Singh et al. (Water Resour Manag 29:4111–4127, 2015. https://doi.org/10.1007/s11269-015-1048-1) model (M4) and the Verma et al. (Environ Earth Sci 76:736, 2017a. https://doi.org/10.1007/s12665-017-7062-2) model (M5) were superior and demonstrated more stable structures. Coupled with the Hayami routing model, the models showed promising results and were able to reproduce the observed hydrographs' shape. However, it was impossible to choose the preferred model since they each excelled as to a criterion. Therefore, the corresponding outputs were combined using the simple average (SA) method and the weighted average (WA) method. We found that the WA method showed better results in the two catchments and allowed a more accurate prediction according to the performance criteria.

Keywords AMC · AMA · Event-based · Flood prediction · RR model · SCS-CN

Introduction

Recurring floods are the most devastating natural hazards in many regions of the world. Therefore, many regional authorities increased awareness of flood and inundation hazards (Pilon 2002; WMO 2004). Particular focus has been placed on climate change, urbanization growth, and land-use change (Hdeib et al. 2018). Mediterranean regions are prone to flood risk due to their local climate (Gaume et al. 2009; Llasat et al. 2010), also the case for Algeria, which experienced catastrophic floods during the second half of the twentieth century. These floods caused many deaths and extensive material damage. The November 10–11, 2001 flood in Bab El Oued, Algiers and the flood on April 18–19, 2007, in Ghardaïa, remain the most devastating floods in recent years. They led to thousands of casualties and traumatized public opinion. As a result, protective measures have become a necessity, by using structural or non-structural strategies based on a solid understanding of the phenomenon of runoff and the many factors that can influence it (Brocca et al. 2011). Accordingly, the interest in rainfall-runoff (RR) models as an essential tool for flash flood prediction and real-time forecasting has increased (Todini 1988).

Many studies in Algeria have focused on analyzing flood frequency (e.g., Hebal and Remini 2011; Meddi et al. 2017). However, only a few studies have been conducted using RR models to understand flood processes and characterize their hydrological behavior over small time-steps. In scientific literature, several RR models are available, which differ by their structure and complexity. Continuous models can assess the soil moisture at the beginning of a rainfall event (Perrin et al. 2003; Tramblay et al. 2010; Massari et al. 2014), but the major limitation using these models is their

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requirement for a long-term and uninterrupted time series to collect the input data. However, long records of rainfall and runoff data in short time-steps are rarely available in Algeria or even in North Africa (Hughes 2011; El Khalki et al. 2018). Therefore, in flood modeling, event-based models represent an alternative to continuous ones (Tramblay et al. 2012). The event-based approach is a widely used alternative that requires data on the event's time scale (Chahinian et al. 2005; Brocca et al. 2011; Hossain et al. 2019). However, it involves additional parameters to assess the initial moisture conditions (Chang et al. 2017).

Several studies have highlighted the contribution of incorporating the initial moisture component before the storm to reproduce the corresponding flood hydrograph (e.g., Brocca et al. 2009; Tramblay et al. 2010; Massari et al. 2014; El Khalki et al. 2018). Therefore, the modeler must choose a RR model that can accurately simulate a wide variety of complex data from flood events (Chang et al. 2017), with a reduced number of parameters to avoid the over-parameterization which increases the complexity of the models (Perrin et al. 2003; Todini 2011).

Among the existing event-based RR models, the SCS-CN method (SCS 1972) is frequently used in the Mediterranean region (e.g., Soulis et al. 2009; Brocca et al. 2011; Abdi and Meddi 2015; Zema et al. 2017; El Khalki et al. 2018; Maref and Seddini 2018). The advantage of the SCS-CN method is its simplicity, predictability, stability, and applicability for ungauged basins (Ponce and Hawkins 1996; Verma et al. 2017b; Mishra et al. 2018). It relies on two parameters—the curve number (*CN*), which is linked to three levels of antecedent moisture conditions (AMC), and the initial losses (I_a). However, the original method has had critical reviews about its limitations (e.g., Ponce and Hawkins 1996; Singh 1999; Mishra et al. 2003, 2006; Garen and Moore 2005), especially for the sudden jump in *CN* that occurs with the variation of AMC (Mishra and Singh 2002b; Soulis et al. 2009; Verma et al. 2017b; Mishra et al. 2018). To overcome the limitations of the SCS-CN method, many authors suggested, with different degrees of success, modifications to the soil moisture accounting (SMA) procedure by incorporating the antecedent moisture amounts (AMA) (Michel et al. 2005; Geetha et al. 2007; Sahu et al. 2010; Singh et al. 2015; Verma et al. 2017a).

In this study, The SCS-CN method and four such modified methods will be tested and compared. The four modified methods are the: Mishra et al. (2006) model, Sahu et al. (2012) model, Singh et al. (2015) model, and Verma et al. (2017a) model. Thereby, the best performing models will be coupled with a transfer function to reproduce the flood hydrographs' shape. In comparing these models, we hope to find an efficient RR model that can estimate floods in a semi-arid region in northern Algeria. Indeed, an efficient RR model is necessary for dam managers to simulate the inflow of dams in these areas, which have been filled by floods in recent years. Furthermore, it is expected that an efficient RR model will be used for wadis development and flood control (Zeroual et al. 2016; Meddi et al. 2017).

The manuscript is organized as follows: First, the methods section details the model structures employed in the study and the performance criteria used to compare the models. Next, the study area section presents the study area and the data used for this study. Finally, the results and discussion section presents the comparison results of the different models.

The main objective of this paper is to (1) compare the performance of five SCS-CN-based models on flood events measured in two semi-arid catchments of northern Algeria; (2) evaluate the structural stability and the reliability of the models for the estimation of the initial soil moisture and runoff computation; and (3) choose the most suitable RR models for the regional context.

Methods

SCS-CN method

The Soil Conservation Service Curve Number (SCS-CN) method (SCS 1972) shows an empirical relation between the precipitation excess and direct runoff based on *CN*. The SCS-CN model is an event-based lumped RR model (Chow et al. 1988; Ponce and Hawkins 1996; Mishra and Singh 2002b).

$$P = I_a + F + R \tag{1}$$

$$I_a = \lambda S \tag{2}$$

$$R = \frac{(P - I_a)^2}{P + S - I_a} \quad \text{For } P \geq I_a, \quad R = 0 \text{ otherwise} \tag{3}$$

$$S = \frac{25,400}{CN} - 254 \tag{4}$$

where P is total precipitation, I_a is the initial losses, R is the direct runoff, S is the potential maximum retention capacity of the soil, and λ is the initial abstraction coefficient, F is the cumulative infiltration excluding I_a and CN is the curve number.

Many studies set *CN* ranges from 1 to 100, while the coefficient λ is assumed constant and equal to 0.2 to reduce parameters for the calibration process (Ponce and Hawkins 1996). Recent studies, however, have shown that λ take a value of approximately 0.05 (e.g., Shi et al. 2009; Soulis et al. 2009).

AMC are customarily considered the most significant factor in runoff computation. They are categorized into three levels: AMC I (dry conditions), AMC II (normal or average conditions), and AMC III (wet conditions), depending on 5 days of antecedent rainfall (SCS 1972). A median value of CN (CN_2) is assigned to AMC II, and for any change in AMC, CN_2 is converted to CN_1 for AMC I or to CN_3 for AMC III. Several analytical formula were developed to express CN conversion (e.g., Sobhani 1976; Hawkins et al. 1985; Chow et al. 1988; Mishra et al. 2008). Mishra et al. (2008) developed AMC-dependent conversion formulae compared with the existing formulas, using field data taken from the USDA-ARS database. The results showed that their formulae provided the best performance (Ajmal et al. 2015) and was accordingly used in this case. The conversion is expressed as:

$$CN_1 = \frac{CN_2}{2.2754 - 0.012754CN_2} \tag{5}$$

$$CN_3 = \frac{CN_2}{0.430 + 0.0057CN_2} \tag{6}$$

SCS-CN modifications

The original method was subject to many modifications to improve its efficiency and bypass its limitations. We detail the proposed methods that apply to our study area. These methods will be tested for the study context with a short duration storm at an hourly time scale; these models' governing equations are provided in Table 1.

Mishra et al. (2006) model

Mishra and Singh (2002b) modified the original equation by introducing the AMA parameter M instead of the AMC. The AMC are quite challenging to evaluate because of the discrete relationship between the CN and AMC classes, which results in a sudden jump in calculated runoff (Mishra and Singh 2002a, b; Mishra et al. 2018). Runoff is calculated using Eq. (7). Mishra et al. (2006) also modified the I_a–S relationship by highlighting the high dependency of initial abstraction I_a on antecedent soil moisture M as shown in Eq. (8), and also proposed an empirical relationship linking antecedent moisture M to antecedent 5-day rainfall (P_5), as shown in Eq. (9).

Sahu et al. (2010) model

Sahu et al. (2010) proposed a more hydrological representative procedure for I_a and M computation to improve the performance of the model introduced by Mishra and Singh (2002b). The runoff is calculated using Eq. (10) by employing the potential maximum retention in an arid condition (S_0) (i.e., AMC I) which is independent of the antecedent moisture and depends entirely on watershed characteristics. I_a and M are calculated using Eqs. (11) and (12), respectively.

Table 1 Equations used in SCS-CN-based hydrological simulation models

Model name	Empirical equation			Accounting of antecedent moisture		
Mishra et al. (2006)	$R = \frac{(P-I_a)(P-I_a+M)}{P+S-I_a+M}$	For $P \geq I_a$ $R=0$ otherwise	(7)	$M = \alpha\sqrt{P_5 \times S}$		(9)
	$I_a = \frac{\lambda S^2}{S+M}$		(8)	where M is the AMA, α is a coefficient, and P_5 is the antecedent 5-day rainfall		
Sahu et al. (2010)	$R = \frac{(P-I_a)(P-I_a+M)}{P-I_a+S_0}$	For $P \geq I_a$ $R=0$ otherwise	(10)	$M = \beta\left[\frac{(P_5-\lambda S_0)S_0}{(P_5-\lambda S_0)+S_0}\right]$	For $P_5 > \lambda S_0$ $M=0$ otherwise	(12)
	$I_a = \lambda(S_0 - M)$		(11)	where β is proportionally coefficient		
Singh et al. (2015)	$R = 0$	If $V_0 \leq S_a - P$	(13)	$V_0 = \alpha\sqrt{P_5 \times S}$		(16)
	$R = \frac{(P+V_0)(P+V_0-S_a)}{P+S+V_0}$	If $S_a - P \leq V_0 \leq S_a$	(14)	$S_a = \beta \times S$		(17)
	$R = P\left(1 - \frac{(S_b-V_0)^2}{SS_b+P(S_b-V_0)}\right)$	If $S_a \leq V_0 \leq S_b$	(15)	$S_b = S_a + S$		(18)
				where S_a is the threshold soil moisture, S_b is the absolute potential maximum retention, and α and β are coefficients		
Verma et al. (2017a)	$R = 0$	If $V_0 \leq S_a - P$	(19)	V_0 is calculated using Eq. (16)		
	$R = \frac{(P-S_a+V_0)(P-S_a+2V_0)}{P-S_a+2V_0+S}$	If $S_a - P \leq V_0 \leq S_a$	(20)	S_a is calculated using Eq. (17)		
	$R = P\left[1 - \frac{(S_a+S-V_0)^2}{P(S_a+S-V_0)+S(S+V_0)}\right]$	If $S_a \leq V_0 \leq S_a + S$	(21)			

Singh et al. (2015) model

Singh et al. (2015) proposed an improved SMA procedure using the concept introduced by Mishra and Singh (2002b). The procedure incorporates initial moisture (V_0), threshold soil moisture (S_a), and the absolute potential maximum retention (S_b). V_0 is the initial soil moisture, which is calculated using Eq. (16), and S_a and S_b are calculated using Eqs. (17) and (18). The runoff is computed using Eqs. (13)–(15).

Verma et al. (2017a) model

More recently, Verma et al. (2017a) proposed an improved SMA based on the concept introduced by Mishra and Singh (2002b) and inspired by the work of Singh et al. (2015). However, they were critical that the initial abstraction was included in the proportionality hypothesis, and therefore they proposed a different formulation. The runoff is computed using Eqs. (19)–(21). The SMA parameters are calculated similarly to the model introduced by Singh et al. (2015) using Eqs. (16)–(17).

For convenience, the original SCS-CN model, Mishra et al. (2006) model, Sahu et al. (2010) model, Singh et al. (2015) model, and Verma et al. (2017a) model are referred to as M1, M2, M3, M4, and M5, respectively, in the forthcoming text. Table 2 summarizes the formulation of all these models.

Routing model

For routing the rainfall excess R to the catchment's outlet, the Hayami (1951) kernel transfer function is used. This function is an approximation of the diffusive wave method that has been used mainly for flood routing problems (Moussa and Bocquillon 1996; Chahinian et al. 2005; Wang et al. 2014). The discharge at the outlet $Q(t)$ is calculated as:

$$Q(t) = \int_0^t R(\tau)\, H(t-\tau)\, \mathrm{d}\tau \tag{22}$$

where $H(t)$ is the Hayami kernel function defined as:

$$H(t) = \left(\frac{\omega\, z}{\pi}\right)^{\frac{1}{2}} \frac{\exp^{z\left(2-\frac{t}{\omega}-\frac{\omega}{t}\right)}}{(t)^{\frac{3}{2}}} \text{ with } \int_0^\infty H(t)\, \mathrm{d}t = 1 \tag{23}$$

where t is the time-step, and ω and z are parameters representing both translation and diffusivity of the unit hydrograph (Moussa and Chahinian 2009).

Base flow separation

For the identification of runoff components (i.e., direct flow and a base flow), hydrographs separation is essential (Tallaksen 1995; Eckhardt 2005), which is an essential step for the runoff model's calibration (Arnold and Allen 1999).

In this study, we use the digital filter method proposed by Lyne and Hollick (1979), which is a commonly used method (Mei and Anagnostou 2015) expressed as:

$$q_t = a_f \times q_{t-1} + \frac{1+a_f}{2}(Q_t - Q_{t-1}) \tag{24}$$

where q_t is the direct runoff at time-step t, Q_t is the total discharge at time-step t, and a_f is the digital filter parameter depending on the catchment geological conditions.

Table 2 Models' parameters description and ranges

Model	Parameters				
	Number	Equations used	Symbol	Description	Range
M1	2	(1)–(6)	CN_2	Median Curve Number (–)	0–100
			λ	Initial abstraction coefficient (–)	0–0.2
M2	3	(7)–(9)	S	Maximum storage capacity (mm)	0–500
			λ	Initial abstraction coefficient	0–0.2
			α	Coefficient relating P_5 and S to initial soil moisture	0–1
M3	3	(10)–(12)	S_0	Maximum storage capacity (mm)	0–500
			λ	Initial abstraction coefficient (–)	0–0.2
			β	Coefficient relating P_5 and S_0 to initial soil moisture (–)	0–1
M4	3	(13)–(18)	S	Maximum storage capacity (mm)	0–500
			α	Coefficient relating P_5 and S to initial soil moisture (–)	0–1
			β	Coefficient of threshold soil moisture (–)	0–0.2
M5	3	(19)–(21) and (16)–(17)	S	Maximum storage capacity (mm)	0–500
			α	Coefficient relating P_5 and S to initial soil moisture (–)	0–1
			β	Coefficient of threshold soil moisture (–)	0–0.2

Performance criteria

To evaluate the models' performances, we use the following numerical criteria presented in Table 3, which are commonly used in hydrological modeling.

Where N is the number of events, R_{sim} and R_{obs} are the simulated and the observed runoff, respectively, $Q_{\text{sim}}^{\text{peak}}$ and $Q_{\text{obs}}^{\text{peak}}$ are the simulated and the observed peak flow, respectively, r is the Pearson correlation coefficient between the simulated and observed flow, B is the ratio between the mean simulated and mean observed flow, and C is the ratio between the simulated and observed flow variance.

A standard gradient-based automatic optimization method ('fmincon' function in MATLAB®) was used for the models' calibration. Indeed, Brocca et al. (2011) applied this method for the calibration of the MISDc model and found that, for a low number of involved parameters, it furnished similar results to the more efficient but slower methods, such as the Shuffled Complex Evolution algorithm (Duan et al. 1993). Moreover, the parameters of both the production functions and the transfer function are strictly linked to different components; hence, the infiltrations models' calibration was made separately from the transfer functions to avoid possible parameter dependence. The multi-objective calibration method was adopted (Moussa and Chahinian 2009) by applying the balanced aggregated objective concept proposed by Madsen (2000), which transforms the multi-objective problem into a single objective optimization problem by defining a scalar that aggregates the various objective functions. Therefore, it was applied for both the production function and the transfer function. As such, there are two balanced aggregated objectives functions (Madsen 2003; Hundecha and Bárdossy 2004), which are expressed as:

$$F_{\text{agg}}^{\text{production}} = \frac{1}{2}(\text{MAE} + \text{MARE}) \tag{30}$$

$$F_{\text{agg}}^{\text{routing}} = \frac{1}{2}\left[(1 - \text{KGE}) + \left(\frac{1}{N}\sum_{i=1}^{N} |\text{PPEAK}|_i\right)\right] \tag{31}$$

Study area

Two of Algeria's northern region catchments were selected for this study due to their hydro-climatic, geomorphological difference, and data availability. These catchments are Boubhir, in the province of Tizi-Ouzou, and Allalah, in the province of Chlef. The region is characterized by a Mediterranean humid climate and an annual rainfall of 1000 mm (Meddi et al. 2017). The main characteristics of these catchments are illustrated in Fig. 1 and summarized in Table 4.

The catchments' delineations (Fig. 1) were made with GIS software. The software used digital elevation map data with a resolution of 30 m, obtained using an advanced spaceborne thermal emission and reflection radiometer (ASTER) and global digital elevation model (NASA/METI/AIST/Japan Spacesystems and U.S./Japan ASTER Science Team 2009).

The land cover map used in this study (Fig. 1) was extracted from the European Space Agency Climate Change Initiative (CCI) product: CCI Land Cover, particularly the S2 prototype Land Cover 20 m map of Africa 2016 (CCI Land Cover team 2017). Data were extracted using GIS software.

A total of forty-eight events were available, thirty for Allalah catchment and eighteen for Boubhir catchment. The split-sample approach (Klemeš 1986) was used for calibration and validation. The events were divided into two sections. Sixty per cent of the available data were used for calibration, and the remainder was used for validation. The Duplex algorithm (Snee 1977; Daszykowski et al. 2002) was used to divide the datasets, which allowed a representative subset selection by maximizing the Euclidean distances

Table 3 Performance criteria used

Criterion	Equation		Optimal value
The mean absolute error (MAE)	$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N}\left(\lvert R_{\text{obs}} - R_{\text{sim}}\rvert\right)_i$	(25)	0
The mean absolute relative error (MARE)	$\text{MARE} = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{\lvert R_{\text{obs}} - R_{\text{sim}}\rvert}{R_{\text{obs}}}\right)_i$	(26)	0
The percent bias (PBIAS) at the event scale	$\text{PBIAS} = 100 \times \left(\frac{R_{\text{obs}} - R_{\text{sim}}}{R_{\text{obs}}}\right)$	(27)	0
The mean relative peak flow error (PPEAK) at the event scale	$\text{PPEAK} = 100 \times \left(\frac{Q_{\text{obs}}^{\text{peak}} - Q_{\text{sim}}^{\text{peak}}}{Q_{\text{obs}}^{\text{peak}}}\right)$	(28)	0
The criterion Kling-Gupta efficiency (KGE) (Gupta et al. 2009)	$\text{KGE} = 1 - \sqrt{(r-1)^2 + (B-1)^2 + (C-1)^2}$	(29)	1

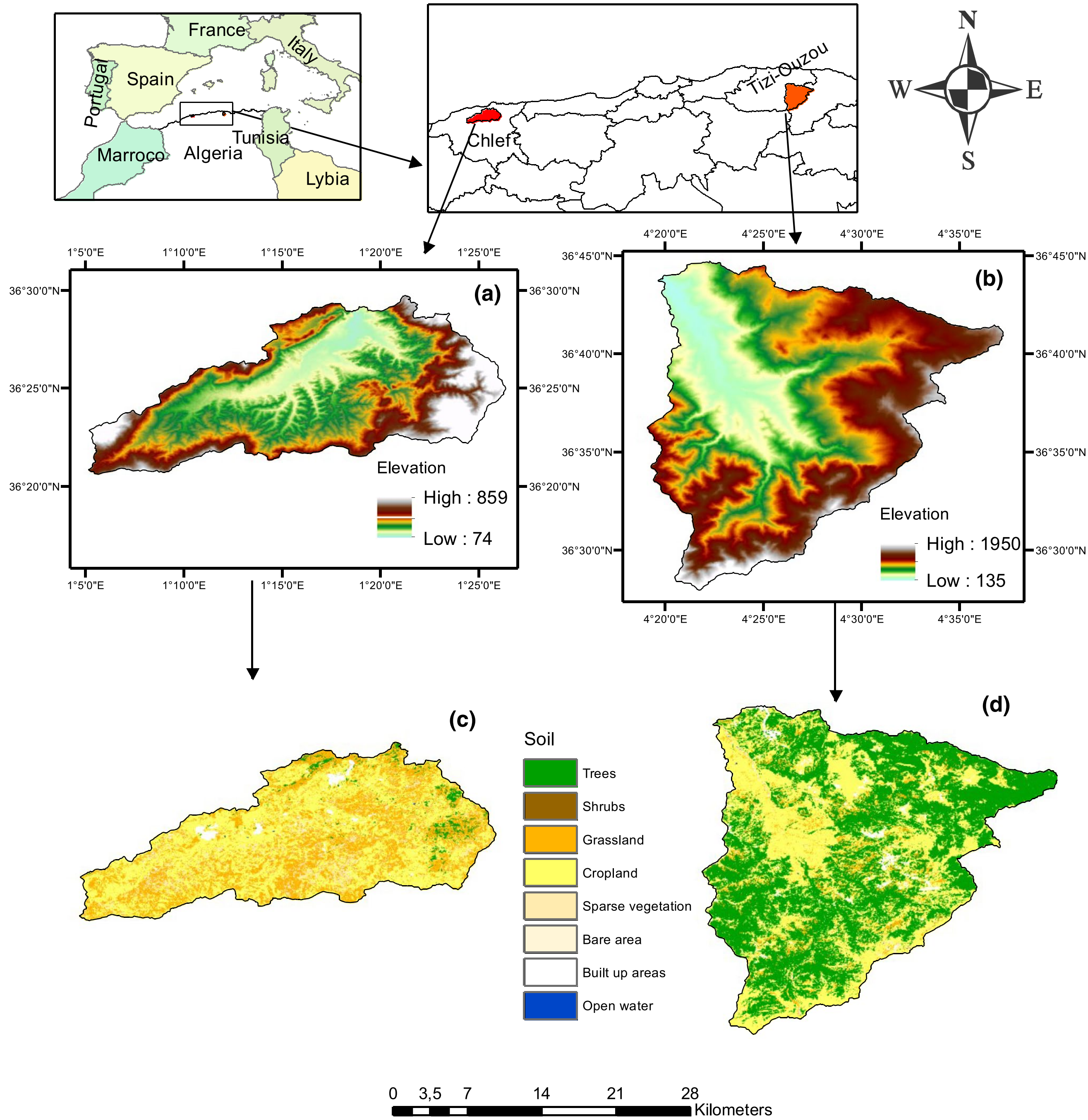


Fig. 1 Study area, catchments delineation: **a** Allalah, **b** Boubhir, and Land Cover: **c** Allalah, **d** Boubhir

Table 4 The main characteristics of the study catchments

Catchment	Area (Km^2)	Mean slope (%)	Channel length (Km)	Land use (%)			
				Woods	Crops	Pasture	Urban
Allalah	295	20.5	28.5	2.7	51.2	44.3	1.8
Boubhir	475	30.1	28.7	51.3	39.1	7.4	2.2

between the subsets (Daszykowski et al. 2002; Mora and Schimleck 2008; Puzyn et al. 2011). The used RR events' main characteristics are illustrated in Fig. 2, which shows the relations between the total rainfall, the mean rainfall intensity, initial condition, and runoff coefficient (RC).

Results and discussion

According to the results presented in Table 5, the modified models (i.e., M2, M3, M4, and M5) were more efficient than the SCS-CN AMC-based model (M1), which was the poorest performing in terms of quality. This is especially true for the Boubhir catchment, for which the MAE and the MARE in the validation were, respectively, 3.01 and 0.36 mm. Furthermore, according to Fig. 3, most events' PBIAS values were in the unacceptable range.

The modified models showed better results, which implies that the AMA has improved runoff prediction results. However, although different results were recorded, there was no precise classification between M2, M3, M4, and M5 models based on their ability to predict runoff. Indeed, according to Table 5, the lowest MAE value recorded was for the M4 model for the Allalah catchment. In contrast, the lowest

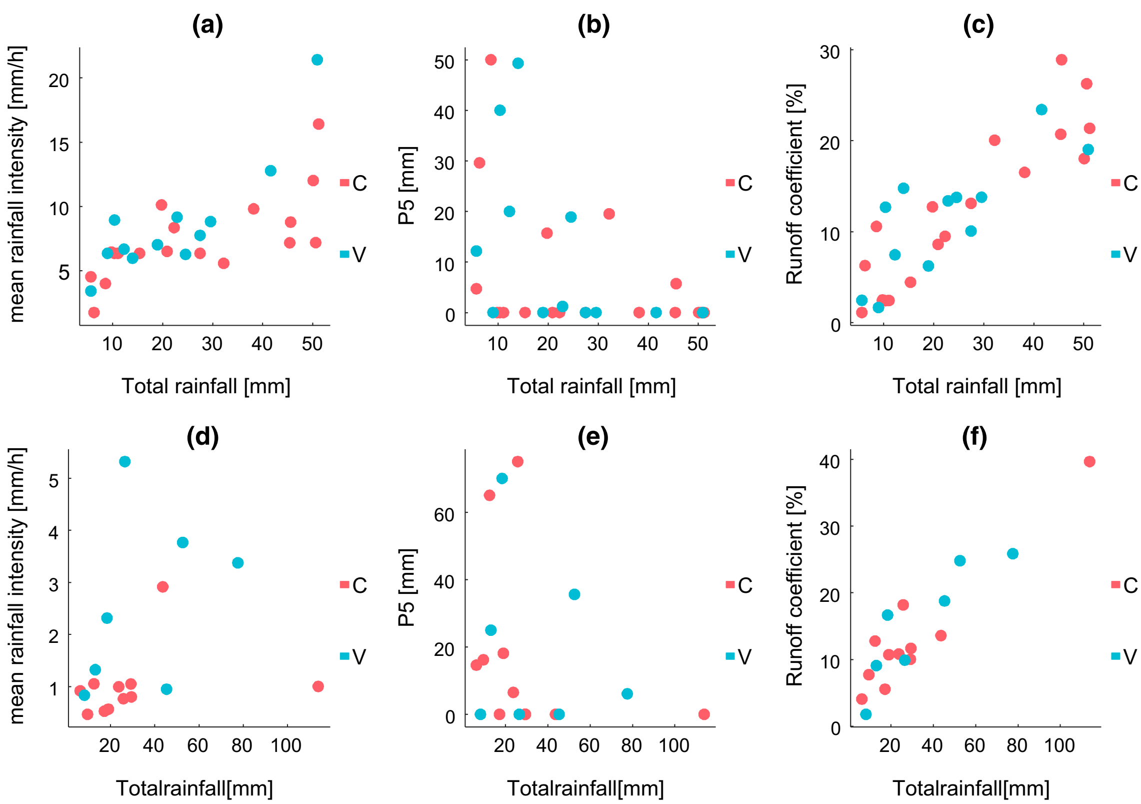


Fig. 2 Main characteristics of the selected RR events (*C* calibration and *V* validation); **a**, **b**, and **c** for Allalah catchment, **d**, **e**, and **f** for Boubhir catchment

Table 5 Runoff models results

Catchment		Models									
		M1		M2		M3		M4		M5	
		MAE	MARE	MAE	MARE	MAE	MARE	MAE	MARE	MAE	MARE
		mm	(–)	mm	(–)	Mm	(–)	mm	(–)	mm	(–)
Allalah	C	0.87	0.29	0.49	0.12	0.54	0.13	0.49	0.08	0.49	0.10
	V	0.96	0.43	0.55	0.14	0.58	0.18	0.53	0.16	0.54	0.16
Boubhir	C	1.42	0.29	0.50	0.10	0.52	0.15	0.49	0.08	0.46	0.07
	V	3.01	0.36	0.79	0.07	0.67	0.13	0.63	0.09	0.61	0.08

C calibration, *V* validation

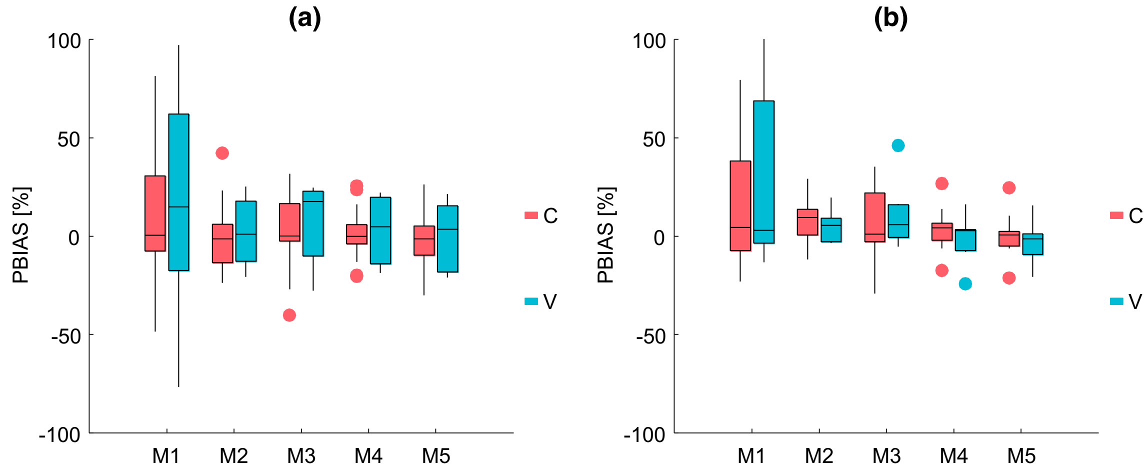


Fig. 3 RR models comparison statistics based on PBIAS: (*C* calibration and *V* validation); **a** for Allalah catchment, and **b** for Boubhir catchment

value recorded in both calibration and validation was for the M5 model for the Boubhir catchment. Furthermore, the lowest MARE values were recorded for the M2 model for the two basins, which were close to the MARE values of the M4 and M5 models. However, the PBIAS values of some events of the M2 model were within the acceptable range of ± 25% (Moriasi et al. 2007) in the case of Allalah catchment (Fig. 3a). Also, the maximum PBIAS values were recorded for the M3 model in both catchments as well as the MARE criterion. Furthermore, since the models have the same number of parameters, the models' selection criteria, such as the Akaike information criterion and the Bayesian information criterion, are not applicable (Bennett et al. 2013). Therefore, further analysis of the behavior and results of the models will be conducted.

The optimal parameters of the models are provided in Table 6. We found no significant difference between the models' maximum storage capacity parameters in the two catchments. In contrast, the main difference lies in the initial moisture parameters and the losses process parameters (i.e., initial abstraction and threshold moisture).

Therefore, Figs. 4 and 5 are designed to emphasize the parameterization effect on the models' behavior. Indeed, Fig. 4 shows the computed initial moisture using the models' optimal parameters for different P_5 values. We noticed that the M2 model overestimated the small P_5 values' initial humidity to adapt to the different events. However, it was not the case for M3, M4, and M5 models where the initial moisture corresponding values were below P_5.

Figure 5 shows the models' behavior in terms of the RC for the two watersheds. Indeed, the optimal parameters given in Table 6 were used to simulate the RCs for different cases of P_5: dry case, moderately wet, wet, and extremely wet (i.e., $P_5 = 0$, 10, 50, and 100 mm).

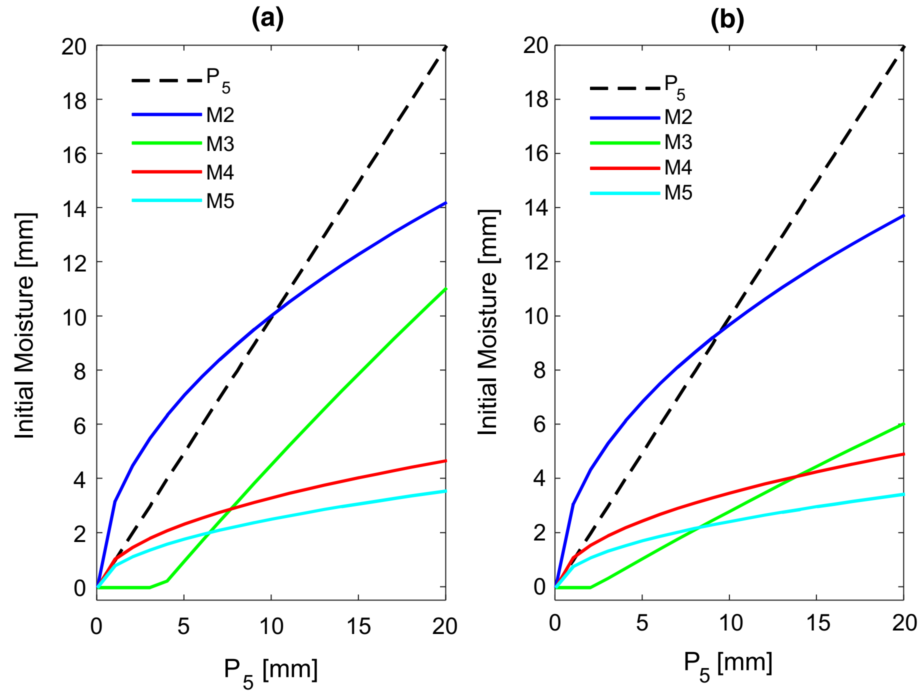
For the dry scenario, we found that the different models' curves were very close, indicating that the models behaved similarly. It was also true for the moderately wet case, where the curves were relatively close. Nevertheless, a disparity between the models' results was found once P_5 reached a certain threshold, particularly for model M3, where the curves of the simulated RC values (in green) diverged from the other models (Fig. 5c and g). This irregularity intensified as P_5 increased (Fig. 5d and h). Also, we found a break in the simulated RC curves (in blue) resulting from the M2 model for low precipitation (Fig. 5c, d, and h).

Consequently, we noted that the M2 and M3 models' structures were unstable and gave inconsistent results for high P_5 values, implying that a continuous SMA procedure (M4 and M5 models) ensured a more stable model structure under different P_5 values. Indeed, models M4 and M5 gave good results, and their SMA procedures ensured the structural reliability of the models. Consequently, based on these

Table 6 The models' optimal parameters

Catchment	Models										
	M2			M3			M4			M5		
	S	λ	α	S_0	λ	β	S	α	β	S	α	β
Allalah	143.0	0.03	0.27	147.4	0.03	0.75	141.5	0.09	0.05	133.6	0.07	0.04
Boubhir	172.7	0.02	0.23	173.9	0.01	0.37	176.5	0.08	0.03	176.5	0.06	0.02

Fig. 4 The models' initial moisture results: **a** for Allalah catchment, and **b** for Boubhir catchment



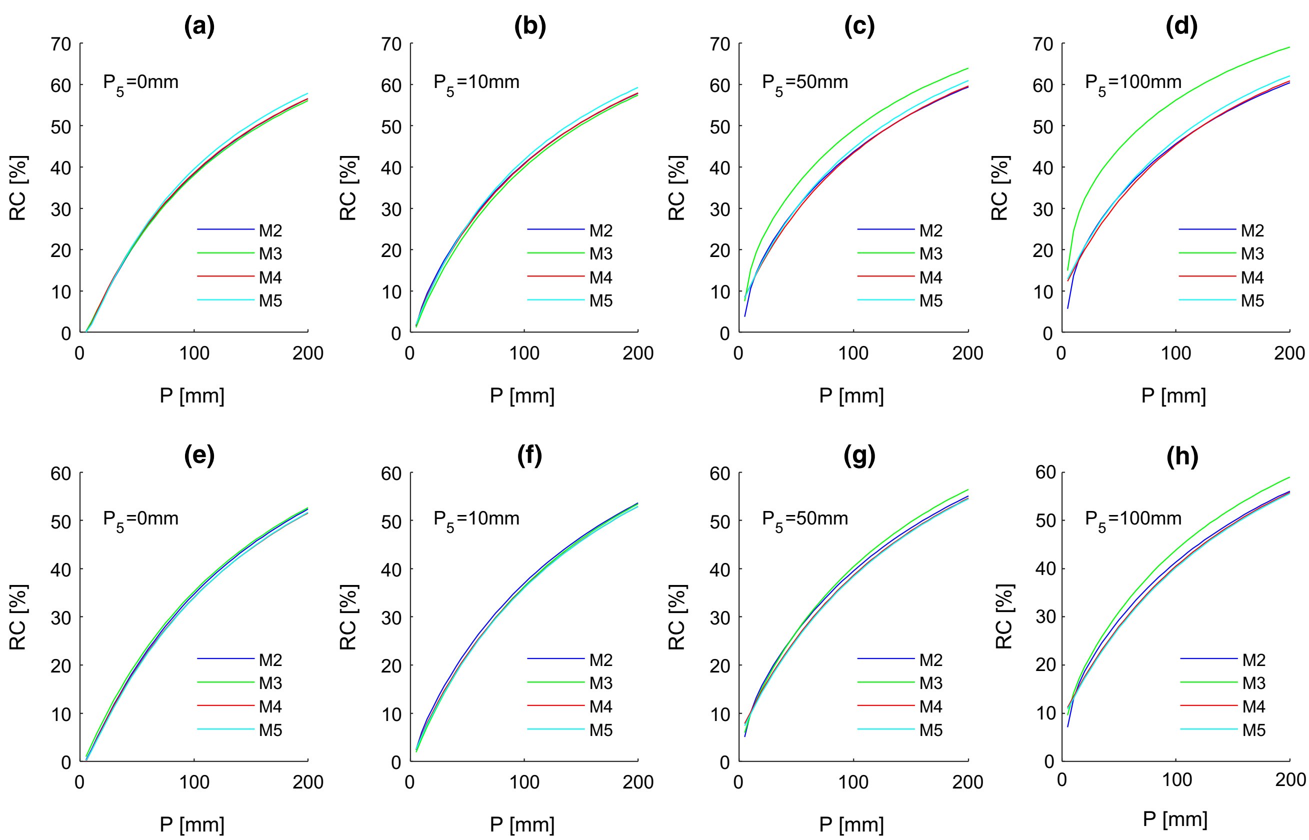


Fig. 5 Models' behaviors in terms of RC: **a**–**d** for Allalah catchment, **e**–**h** for Boubhir catchment

analyses and the results (Table 4 and Fig. 3), the M4 and M5 models were selected.

While the M4 and M5 models performed well, the respective simulated runoffs differed depending on events, which led us to test their ability to replicate the hydrographs observed by combining both models with the Hayami kernel transfer function. Indeed, although the models provided similar results, the distribution of runoff within the events can be different; this can impact the shape of the corresponding hydrographs and the routing model parameters.

As expected, different values of the routing model's optimal parameters were obtained for the respective coupled models (Table 7), where no significant difference was found between the parameters. Though these differences were not significant, however, the shape of the corresponding unit hydrographs will be different and, thus, the shape of the simulated hydrographs will differ.

Table 7 Optimal parameters of the transfer model

Catchment	Optimal parameters of the transfer model			
	Coupled to M4		Coupled to M5	
	ω	z	ω	z
Allalah	4.70	0.56	4.34	0.65
Boubhir	8.15	0.51	8.00	0.45

Figure 6 showed the simulated versus observed discharge using the coupling for both catchments. We noticed that both models performed well and produced comparable results concerning the determination coefficient (R^2). However, different results in terms of KGE and PPEAK were obtained according to the KGE and PPEAK. The M4 model was better with mean values of 0.83 and 0.82, respectively, for Allalah and Boubhir catchments. Also, the minimum KGE value was 0.68 for the Allalah catchment and 0.66 for the Boubhir catchment, while the minimum KGE values obtained using the M5 model were less than 0.6 (Fig. 7a and c). However, PPEAK values obtained using the M5 model were better than those of the M4 model (Fig. 7b and d). This implies that the model M4 coupled to the transfer function reproduced the shape of the observed hydrograph better, while the M5 model coupled to the transfer function reproduced better the peak flows.

Based on these findings, it was difficult to clearly define the best "single" model for both catchments, mainly because the two models produced good results. Indeed, the best model choice is the traditional objective of any predictive study, but rarely is a single model the best in all cases (Clemen et al. 1995). Instead, each model has its particular strengths and weaknesses (McLeod et al. 1987; Kim et al. 2006). Hence, rather than selecting a unique model, the most suitable alternative is to aggregate the results of the respective models' outputs by averaging the results to refine each model's weaknesses. Indeed, many authors have used the

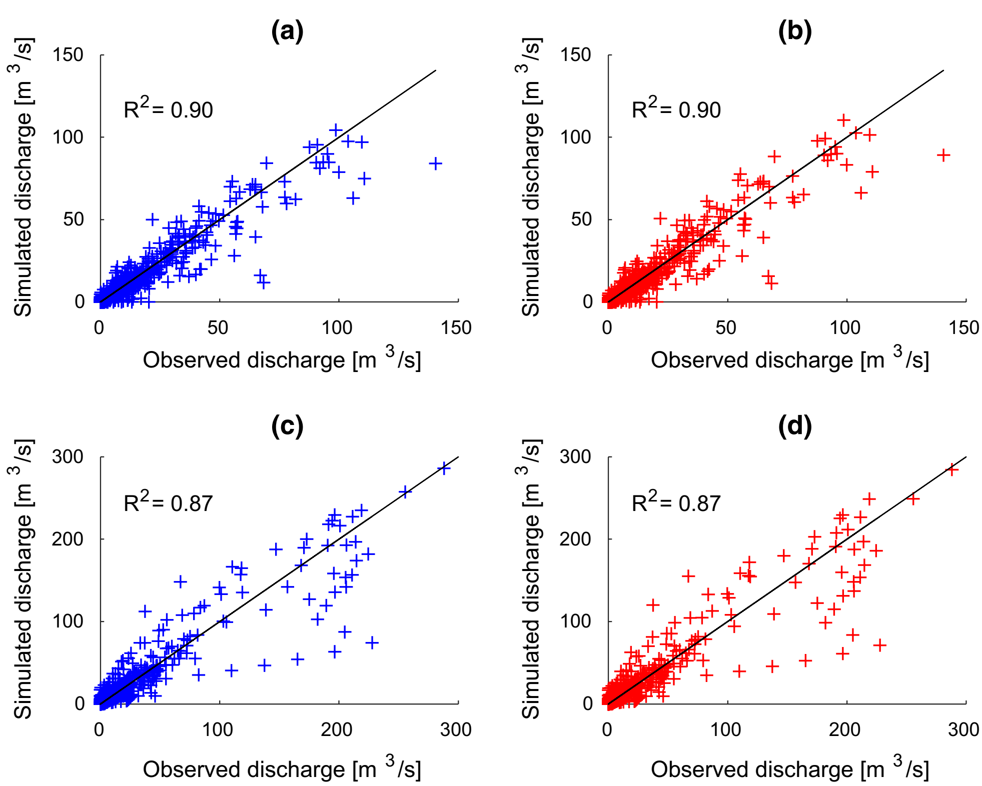


Fig. 6 Observed versus simulated discharges using M4 (blue) and M5 (red) models coupled to the routing function: **a** and **b** for Allalah catchment, **c** and **d** for Boubhir catchment

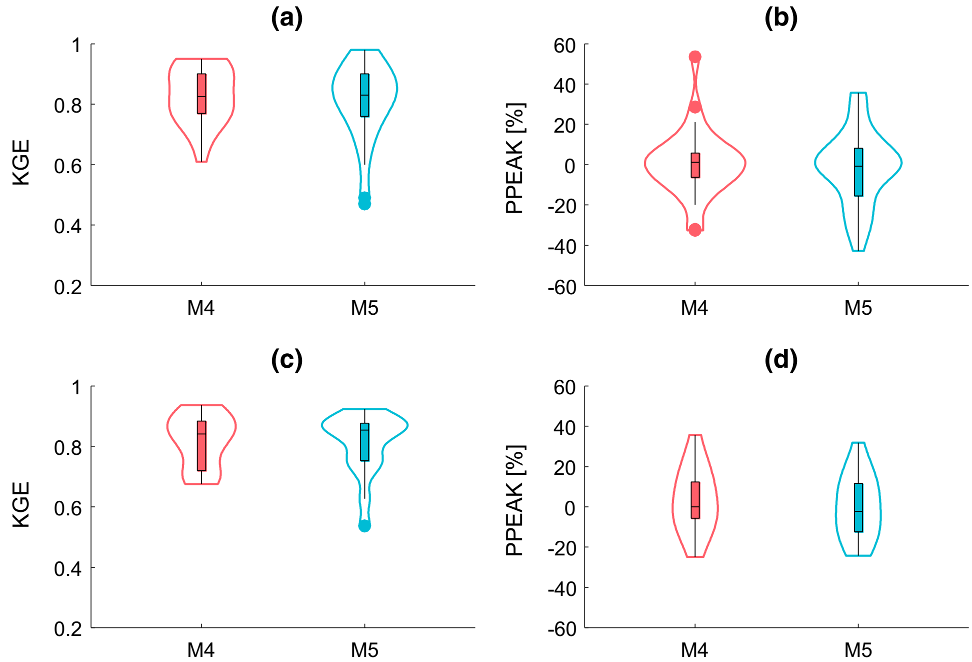


Fig. 7 Models' comparison based on KGE and PPEAK statistics: **a** and **b** for Allalah catchment, **c** and **d** for Boubhir catchment

combining concept (e.g., McLeod et al. 1987; McIntyre et al. 2005; Kim et al. 2006; Velázquez et al. 2010; Li et al. 2018). They found significant improvements when the predictions from different models were combined. Therefore, the combination concept was used by combining the flows resulting from models M4 and M5 using the simple average (SA) method and the weighted average (WA) method (Shamseldin and O'connor 1999; Ajami et al. 2006). The approaches used are expressed as:

$$\left(Q_c\right)_t = \sum_{i=1}^{N_m} x_i \left(Q_{\text{sim}}\right)_{i,t} \text{ with } \begin{cases} x_i > 0 \\ \sum x_i = 1 \end{cases} \tag{32}$$

where $(Q_c)_t$ is the combined model simulation at time t, $(Q_{\text{sim}})_{i,t}$ is the ith model flow simulation for time t, and x_i are the corresponding weights. In our case, two models were combined, so when using the SA method, the weights (x_i) were the same and equal to 0.5, while the weights were optimized for the WA method.

We found that the two methods of combining provided good performance, while the WA method was superior, where this approach minimized the dispersion of the criteria. Indeed, as shown in Fig. 8, the WA approach ensured a reasonable balance giving a satisfactory KGE and reduced the PPEAK range.

Conclusion

A comparative analysis was carried out using different models to determine the most efficient event-based RR model capable of reproducing the shapes of hydrographs in two watersheds located in northern Algeria. These models have different mathematical structures for both the incorporation

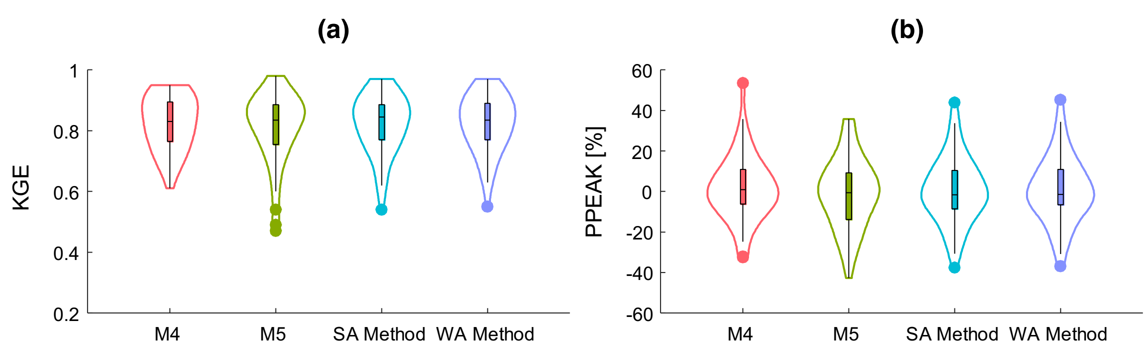


Fig. 8 Comparison of the combination methods based on KGE and PPEAK statistics

of antecedent moisture and the SMA procedure. The models that incorporate the AMA have proven to be more efficient than the SCS-CN method that is based on the AMC. Also, the analysis of model structures showed that the M4 and M5 models were more stable for different precipitation and P_5 scenarios and highlighted the value of continuous SMA procedures. The M4 and M5 models were therefore selected and combined with the Hayami transfer model. Both combinations gave good results in the two catchments studied. However, instead of using the best "unique" model, the M4 and M5 models' results were combined using two averaging approaches to reduce the weakness of each of the two models. The WA method improved the results by ensuring an acceptable balance between the performance criteria.

Our work's interest lies in the practical concerns of risk and water resource management in the semi-arid region of Algeria, where most of the wadis require efficient models that can simulate the flows linked to rainy events. Indeed, the use of combined model methods as a decision support tool would be a useful approach for forecasting flows and estimating project floods to cope with the recurrent floods that have hit the country in recent years and the design and management of dams and hydraulic structures. Nevertheless, the primary deficiency lies in the lack of hourly data on flows and rainfall. Therefore, more watersheds in other regions of the country and the Maghreb should be studied further to validate the models' relevance.

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Compliance with ethical standards

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

References

Abdi I, Meddi M (2015) Modélisation pluie-débit distribuée dans deux bassins versants de l'est de l'Algérie. LARHYSS J P-ISSN 1112-3680/E-ISSN 2602-7828 7–22

Ajami NK, Duan Q, Gao X, Sorooshian S (2006) Multimodel combination techniques for analysis of hydrological simulations: application to distributed model intercomparison project results. J Hydrometeorol 7:755–768

Ajmal M, Waseem M, Ahn J-H, Kim T-W (2015) Improved runoff estimation using event-based rainfall-runoff models. Water Resour Manag 29:1995–2010. https://doi.org/10.1007/s11269-015-0924-z

Arnold JG, Allen PM (1999) Automated methods for estimating baseflow and ground water recharge from streamflow records. JAWRA J Am Water Resour Assoc 35:411–424. https://doi.org/10.1111/j.1752-1688.1999.tb03599.x

Bennett ND, Croke BFW, Guariso G et al (2013) Characterising performance of environmental models. Environ Model Softw 40:1–20

Brocca L, Melone F, Moramarco T, Morbidelli R (2009) Soil moisture temporal stability over experimental areas in Central Italy. Geoderma 148:364–374. https://doi.org/10.1016/j.geoderma.2008.11.004

Brocca L, Melone F, Moramarco T (2011) Distributed rainfall-runoff modelling for flood frequency estimation and flood forecasting. Hydrol Process 25:2801–2813. https://doi.org/10.1002/hyp.8042

CCI Land Cover team (2017) CCI LAND COVER-S2 prototype Land Cover 20 m map of Africa 2016

Chahinian N, Moussa R, Andrieux P, Voltz M (2005) Comparison of infiltration models to simulate flood events at the field scale. J Hydrol 306:191–214. https://doi.org/10.1016/j.jhydrol.2004.09.009

Chang TK, Talei A, Alaghmand S, Ooi MP-L (2017) Choice of rainfall inputs for event-based rainfall-runoff modeling in a catchment with multiple rainfall stations using data-driven techniques. J Hydrol 545:100–108. https://doi.org/10.1016/j.jhydrol.2016.12.024

Chow VT, Maidment DR, Mays LW (1988) Appl hydrol. McGraw-Hil, New York

Clemen RT, Murphy AH, Winkler RL (1995) Screening probability forecasts: contrasts between choosing and combining. Int J Forecast 11:133–145

Daszykowski M, Walczak B, Massart DL (2002) Representative subset selection. Anal Chim Acta 468:91–103

Duan QY, Gupta VK, Sorooshian S (1993) Shuffled complex evolution approach for effective and efficient global minimization. J Optim Theory Appl 76:501–521

Eckhardt K (2005) How to construct recursive digital filters for baseflow separation. Hydrol Process Int J 19:507–515. https://doi.org/10.1002/hyp.5675

El Khalki E, Tramblay Y, Saidi ME et al (2018) Comparison of modeling approaches for flood forecasting in the High Atlas Mountains of Morocco. Arab J Geosci 11:15. https://doi.org/10.1007/s12517-018-3752-7

Garen DC, Moore DS (2005) Curve number hydrology in water quality modeling: uses, abuses, and future directions 1. JAWRA J Am Water Resour Assoc 41:377–388

Gaume E, Bain V, Bernardara P et al (2009) A compilation of data on European flash floods. J Hydrol 367:70–78. https://doi.org/10.1016/j.jhydrol.2008.12.028

Geetha K, Mishra SK, Eldho TI et al (2007) Modifications to SCS-CN method for long-term hydrologic simulation. J Irrig Drain Eng 133:475–486. https://doi.org/10.1061/(ASCE)0733-9437(2007)133:5(475)

Gupta HV, Kling H, Yilmaz KK, Martinez GF (2009) Decomposition of the mean squared error and NSE performance criteria: Implications for improving hydrological modelling. J Hydrol 377:80–91. https://doi.org/10.1016/j.jhydrol.2009.08.003

Hawkins RH, Hjelmfelt AT, Zevenbergen AW (1985) Runoff probability, storm depth, and curve numbers. J Irrig Drain Eng 111:330–340. https://doi.org/10.1061/(ASCE)0733-9437(1985)111:4(330)

Hayami S (1951) On the propagation of flood waves. Bull Disaster Prev Res Inst Kyoto Univ 1(1):1–16

Hdeib R, Abdallah C, Colin F et al (2018) Constraining coupled hydrological-hydraulic flood model by past storm events and post-event measurements in data-sparse regions. J Hydrol 565:160–176. https://doi.org/10.1016/j.jhydrol.2018.08.008

Hebal A, Remini B (2011) Choix du modèle fréquentiel le plus adéquat à l'estimation des valeurs extrêmes de crues (cas du nord de L'Algérie). Can J Civ Eng 38:881–892

Hossain S, Hewa GA, Wella-Hewage S (2019) A comparison of continuous and event-based rainfall-runoff (RR) modelling using

EPA-SWMM. Water 11:611. https://doi.org/10.3390/w11030611
Hughes DA (2011) Regionalization of models for operational purposes in developing countries: an introduction. Hydrol Res 42:331–337
Hundecha Y, Bárdossy A (2004) Modeling of the effect of land use changes on the runoff generation of a river basin through parameter regionalization of a watershed model. J Hydrol 292:281–295
Kim Y-O, Jeong D, Ko IH (2006) Combining rainfall-runoff model outputs for improving ensemble streamflow prediction. J Hydrol Eng 11:578–588
Klemeš V (1986) Operational testing of hydrological simulation models. Hydrol Sci J 31:13–24
Li Z, Yu J, Xu X et al (2018) Multi-model ensemble hydrological simulation using a BP Neural Network for the upper Yalongjiang River Basin, China. Proc Int Assoc Hydrol Sci 379:335
Llasat MC, Llasat-Botija M, Prat MA et al (2010) High-impact floods and flash floods in Mediterranean countries: the FLASH preliminary database. Adv Geosci 23:47–55. https://doi.org/10.5194/adgeo-23-47-2010
Lyne V, Hollick M (1979) Stochastic time-variable rainfall-runoff modelling. In: Institute of Engineers Australia National Conference, pp 89–93
Madsen H (2000) Automatic calibration of a conceptual rainfall–runoff model using multiple objectives. J Hydrol 235:276–288. https://doi.org/10.1016/S0022-1694(00)00279-1
Madsen H (2003) Parameter estimation in distributed hydrological catchment modelling using automatic calibration with multiple objectives. Adv Water Resour 26:205–216
Maref N, Seddini A (2018) Modeling of flood generation in semi-arid catchment using a spatially distributed model: case of study Wadi Mekerra catchment (Northwest Algeria). Arab J Geosci 11:116
Massari C, Brocca L, Barbetta S et al (2014) Using globally available soil moisture indicators for flood modelling in Mediterranean catchments. Hydrol Earth Syst Sci 18:839–853. https://doi.org/10.5194/hess-18-839-2014
McIntyre N, Lee H, Wheater H et al (2005) Ensemble predictions of runoff in ungauged catchments. Water Resour Res 41:W12434. https://doi.org/10.1029/2005WR004289
McLeod AI, Noakes DJ, Hipel KW, Thompstone RM (1987) Combining hydrologic forecasts. J Water Resour Plan Manag 113:29–41
Meddi M, Toumi S, Assani AA (2017) Application of the L-moments approach to the analysis of regional flood frequency in Northern Algeria. Int J Hydrol Sci Technol 7:77. https://doi.org/10.1504/IJHST.2017.080959
Mei Y, Anagnostou EN (2015) A hydrograph separation method based on information from rainfall and runoff records. J Hydrol 523:636–649. https://doi.org/10.1016/j.jhydrol.2015.01.083
Michel C, Andréassian V, Perrin C (2005) Soil conservation service curve number method: How to mend a wrong soil moisture accounting procedure? Water Resour Res. https://doi.org/10.1029/2004WR003191
Mishra SK, Singh VP (2002a) SCS-CN-based hydrologic simulation package. In: Singh VP, Frevert DK (eds) Math Model Small Watershed Hydrol Appl 2841:391–464
Mishra SK, Singh VP (2002b) SCS-CN method. Part I: derivation of SCS-CN-based models. Acta Geophys Polon 50(3):457–477
Mishra SK, Singh VP, Sansalone JJ, Aravamuthan V (2003) A modified SCS-CN method: characterization and testing. Water Resour Manag 17:37–68. https://doi.org/10.1023/A:1023099005944
Mishra SK, Sahu RK, Eldho TI, Jain MK (2006) An improved I_aS relation incorporating antecedent moisture in SCS-CN methodology. Water Resour Manag 20:643–660. https://doi.org/10.1007/s11269-005-9000-4
Mishra SK, Jain MK, Suresh Babu P et al (2008) Comparison of AMC-dependent CN-conversion formulae. Water Resour Manag 22:1409–1420. https://doi.org/10.1007/s11269-007-9233-5
Mishra SK, Singh VP, Singh PK (2018) Revisiting the soil conservation service curve number method. In: Hydrologic modeling. Springer, pp 667–693
Mora CR, Schimleck LR (2008) On the selection of samples for multivariate regression analysis: application to near-infrared (NIR) calibration models for the prediction of pulp yield in Eucalyptus nitens. Can J For Res 38:2626–2634
Moriasi DN, Arnold JG, Van Liew MW et al (2007) Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. Trans ASABE 50:885–900
Moussa R, Bocquillon C (1996) Algorithms for solving the diffusive wave flood routing equation. Hydrol Process 10:105–123. https://doi.org/10.1002/(SICI)1099-1085(199601)10:1%3c105:AID-HYP304%3e3.0.CO;2-P
Moussa R, Chahinian N (2009) Comparison of different multi-objective calibration criteria using a conceptual rainfall-runoff model of flood events. Hydrol Earth Syst Sci 13:519–535. https://doi.org/10.5194/hess-13-519-2009
NASA/METI/AIST/Japan Spacesystems, U.S./Japan ASTER Science Team (2009) ASTER global digital elevation model [Data set]. https://doi.org/10.5067/ASTER/ASTGTM.002
Perrin C, Michel C, Andréassian V (2003) Improvement of a parsimonious model for streamflow simulation. J Hydrol 279:275–289. https://doi.org/10.1016/S0022-1694(03)00225-7
Pilon PJ (2002) Guidelines for reducing flood losses. United Nations International Strategy for Disaster Reduction (UNISDR)
Ponce VM, Hawkins RH (1996) Runoff curve number: Has it reached maturity? J Hydrol Eng 1:11–19. https://doi.org/10.1061/(ASCE)1084-0699(1996)1:1(11)
Puzyn T, Mostrag-Szlichtyng A, Gajewicz A et al (2011) Investigating the influence of data splitting on the predictive ability of QSAR/QSPR models. Struct Chem 22:795–804. https://doi.org/10.1007/s11224-011-9757-4
Sahu RK, Mishra SK, Eldho TI (2010) An improved AMC-coupled runoff curve number model. Hydrol Process 24:2834–2839. https://doi.org/10.1002/hyp.7695
Sahu RK, Mishra SK, Eldho TI (2012) Performance evaluation of modified versions of SCS curve number method for two watersheds of Maharashtra, India. ISH J Hydraul Eng 18:27–36. https://doi.org/10.1080/09715010.2012.662425
SCS (1972) SCS national engineering handbook. Section 4, Hydrology. In: National engineering handbook
Shamseldin AY, O'connor KM (1999) A real-time combination method for the outputs of different rainfall-runoff models. Hydrol Sci J 44:895–912
Shi Z-H, Chen L-D, Fang N-F et al (2009) Research on the SCS-CN initial abstraction ratio using rainfall-runoff event analysis in the Three Gorges Area, China. Catena 77:1–7. https://doi.org/10.1016/j.catena.2008.11.006
Singh SKMVP (1999) Behaviour of SCS-CN method in C-l'a-x spectrum. In: Hydrologic modeling: proceedings of the international conference on water, environment, ecology, socio-economics, and health engineering (WEESHE): October 18–21, 1999, Seoul National University, Seoul, Korea. Water Resources Publication, p 112
Singh PK, Mishra SK, Berndtsson R et al (2015) Development of a modified SMA based MSCS-CN model for runoff estimation. Water Resour Manag 29:4111–4127. https://doi.org/10.1007/s11269-015-1048-1
Snee RD (1977) Validation of regression models: methods and examples. Technometrics 19:415–428
Sobhani G (1976) A review of selected small watershed design methods for possible adoption to Iranian conditions
Soulis KX, Valiantzas JD, Dercas N, Londra PA (2009) Investigation of the direct runoff generation mechanism for the analysis of the SCS-CN method applicability to a partial area experimental

watershed. Hydrol Earth Syst Sci 13:605–615. https://doi.org/10.5194/hess-13-605-2009

Tallaksen LM (1995) A review of baseflow recession analysis. J Hydrol 165:349–370. https://doi.org/10.1016/0022-1694(94)02540-R

Todini E (1988) Rainfall-runoff modeling: past, present and future. J Hydrol 100:341–352. https://doi.org/10.1016/0022-1694(88)90191-6

Todini E (2011) History and perspectives of hydrological catchment modelling. Hydrol Res 42:73–85. https://doi.org/10.2166/nh.2011.096

Tramblay Y, Bouvier C, Martin C et al (2010) Assessment of initial soil moisture conditions for event-based rainfall-runoff modelling. J Hydrol 387:176–187. https://doi.org/10.1016/j.jhydrol.2010.04.006

Tramblay Y, Bouaicha R, Brocca L et al (2012) Estimation of antecedent wetness conditions for flood modelling in northern Morocco. Hydrol Earth Syst Sci 16:4375. https://doi.org/10.5194/hess-16-4375-2012

Velázquez JA, Anctil F, Perrin C (2010) Performance and reliability of multimodel hydrological ensemble simulations based on seventeen lumped models and a thousand catchments. Hydrol Earth Syst Sci 14:2303–2317

Verma S, Mishra SK, Singh A et al (2017a) An enhanced SMA based SCS-CN inspired model for watershed runoff prediction. Environ Earth Sci 76:736. https://doi.org/10.1007/s12665-017-7062-2

Verma S, Verma RK, Mishra SK et al (2017b) A revisit of NRCS-CN inspired models coupled with RS and GIS for runoff estimation. Hydrol Sci J 62:1891–1930. https://doi.org/10.1080/02626667.2017.1334166

Wang L, Wu JQ, Elliot WJ et al (2014) Linear diffusion-wave channel routing using a discrete Hayami convolution method. J Hydrol 509:282–294. https://doi.org/10.1016/j.jhydrol.2013.11.046

WMO (2004) Associated program on flood management. Technical Support Unit (ed). Associated Programme on Flood Management Technical Document No. 1, 2nd edn

Zema DA, Labate A, Martino D, Zimbone SM (2017) Comparing different infiltration methods of the HEC-HMS model: the case study of the Mésima Torrent (Southern Italy). Land Degrad Dev 28:294–308

Zeroual A, Meddi M, Assani AA (2016) Artificial neural network rainfall-discharge model assessment under rating curve uncertainty and monthly discharge volume predictions. Water Resour Manag 30:3191–3205. https://doi.org/10.1007/s11269-016-1340-8