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مدل هوشمند مبتنی بر ژئومورفولوژی و مقایسه با مدل GIUH برای برآورد رواناب مستقیم

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چکیده

درمدل هیدروگراف واحد لحظه ای ژئومورفولوژی از شبکه زهکشی حوضه آبریز و قوانین هورتون استفاده می‌گردد. این مدل یک رهیافت ساده مدل‌سازی رواناب–بارندگی برای حوضه‌های فاقد آمار می‌باشد. کارشناسان هیدرولوژی همواره سعی کرده اند رابطه‌ای بین پاسخ هیدرولوژیکی حوضه و مشخصات توپوگرافی حوضه ها بر قرار نمایند. در این تحقیق از سه مدل بارندگی– رواناب شامل مدل جعبه سیاه مبتنی بر مشخصات ژئومورفولوژی (GANN) و مدل مفهومی دو پارامتری ناش و مدل هیدروگراف واحد لحظه‌ای ژئومورفولوژیکی (GIUH) که برای حوضه‌های فاقد آمار پیشنهاد گردیده است برای یک حوضه متوسط استفاده شد. از این مدل‌ها برای مطالعه ده واقعه بارش–رواناب در حوضه معرف کسیلیان واقع در ناحیه شمالی ایران استفاده شد. نتایج حاصل از مدل ژئومورفولوژی با داده‌های مشاهده‌ای و دو مدل دیگر مقایسه گردیده است. نتایج این تحقیق نشان می دهد که مدل شبکه عصبی مصنوعی بر پایه ژئومورفولوژی (GANN) از مدل کاملاً تجربی شبکه عصبی مصنوعی می‌باشند، برتر است. علاوه بر این می‌توان چنین نتیجه‌گیری کرد که لحاظ مشخصات ژئومورفولوژی در مدل ANN بر توانایی این مدل برای شبیه‌سازی رابطه بارندگی– رواناب می‌افزاید.

کلمات کلیدی: GIUH، شبکه عصبی مصنوعی، حوضه معرف کسیلیان، مدل‌سازی، بارندگی– رواناب

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A Comparative Study of Geomorphologic Artificial Intelligent Model And GIUH For Direct Runoff Computations

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Abstract

The Geomorphologic Instantaneous Unit Hydrograph utilizes Horton's law and the drainage characteristics of the watershed. This is a simple approach to direct runoff computations in ungaged watersheds. Hydrologists have increasingly attempted to relate the watershed’s hydrological responses to watershed topographical characteristics. In this study three different categories of rainfall-runoff models proposed for ungaged watersheds, including a black-box model equipped with Geomorphologic characteristics called: the Geomorphologic 1-Artificial Neural Network (GANN) model, 2-a conceptual two parameter model (Nash model), and 3-Geomorphology Instantaneous Unit Hydrograph (GIUH) were evaluated in a middle size watershed. The applicability of these models were studied for ten rainfall-runoff events of the Kassilian representative watershed located in the north of Iran. The results indicated that GANN model in runoff estimation is more powerful than the other two models. It can also be concluded that adopting the geomorphologic characteristics of watershed in the ANN model can promote this model from a pure black-box model to a model with more capabilities in simulation of a rainfall-runoff relationship.

Keywords: Rainfall-runoff, Geomorphology, Artificial Neural Network, Kassilian

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1-Introduction

The estimation of watershed response has always been a controversial subject among hydrologists because of the importance in water resources system management. Recently approaches based on unit hydrograph theory introduced by Sherman (1932) are being used. These techniques require recorded data of rainfall-runoff events. Sometimes the watersheds are ungaged and consequently, such data are not available for flood estimation. Many researches attempted to develop the watershed response relation to the watershed geomorphology to be compensated for the lack of rainfall-runoff data. To extend the applicability of the unit hydrograph theory to the ungaged watersheds, several attempts have been made for relating the unit hydrograph parameters to watershed characteristics, based on the observed data. Nevertheless, these attempts have rarely been successful because of the complexities of rainfall-runoff relation. An important progress in the unit hydrograph approach is the Geomorphology Instantaneous Unit Hydrograph (GIUH) which has been introduced by Rodriguez-Iturbe and Valdes (1979). In this approach it is assumed that the excess rainfall flows in different channel paths with different orders and finally reaches the outlet according to the drainage network. It is also assumed that the the traveling time for this excess-rainfall follows exponential, uniform, and/or gamma probability distributions. The difference in GIUH models is due to the kind of the adopted density function distribution.

Ghahraman (1996) applied the GIUH model with geomorphoclimatic instantaneous unit hydrograph (GCIUH) model to two representative watersheds, Ammameh and Kassilian, located respectively in South and North of Alborz mountains in Iran. He reported that GCIUH could produce better results than GIUH in estimation of the two main characteristics of hydrograph, i.e. the time to peak and the peak discharge. GIUH and GCIUH models were also used by other researchers, such as Mojaddadi et al., (2008), in Navrud watershed and Ghahraman, (1995) in Emameh watershed.

The nonlinear nature of the rainfall-runoff process in one hand and the temporal and spatial variation of effective parameters in this process on the other hand, led the research to the Artificial Neural Networks during the past 15 years for the estimation of watershed runoff (Anmala et al., 2000; Fernando and Jayawardena, 1998).

Hjelmfelt and Wang (1993) developed a three layer perception Artificial Neural Network based on the unit hydrograph theory. They adopted rainfall intensity as input, and found out the relative weights between the hidden layer according to the unit hydrograph characteristics.

Zhang and Govindaraju (2003) introduced the GANN model for the surface flow estimation based on GIUH theory, and they applied this model to two Indian watersheds.

The aim of this study is to apply and evaluate the GANN model proposed by Zhang and Govindaraju (2003) in rainfall-runoff simulation in comparison to both Nash conceptual model and GIUH model. A medium size watershed located in the northern part of Iran is selected for this purpose. The three different categories of rainfall-runoff models; a black-box model equipped with Geomorphologic characteristics called 1- Geomorphologic Artificial Neural Network (GANN) model, 2- a conceptual two parameter model, and 3- a geomorphologic instantaneous unit hydrograph were adopted and evaluated in Kassilian watershed.

2- Geomorphologic Instantaneous Unit Hydrograph

Geomorphologic Instantaneous Unit Hydrograph was introduced by Rodriguez-Iturbe and Valdes (1979) based on Shereve's theory and Hortonian ordering ratios using Strahler's proposed design order ratio which is expressed as,

$$N_i / N_{i+1} = R_B \qquad (1)$$

where N_i and N_{i+1} are the number of streams in order i and i+1, respectively, and R_B is bifurcation ratio. In addition, the law of stream lengths states that,

$$\overline{L}_{i+1} / \overline{L}_i = R_L \qquad (2)$$

where $\overline{L}_{i+1}$ and $\overline{L}_i$ are the average of lengths of channels of orders i+1 and i, respectively, and R_L is the length ratio. Schumm (1956) proposed the overland flow law as,

$$\overline{A}_{i+1} / \overline{A}_i = R_A \qquad (3)$$

where $\overline{A}_{i+1}$ and $\overline{A}_i$ are the mean area of the contributing subwatershed to streams of orders i+1 and i, respectively, and R_A is the area ratio. It can be observed that these ratios are constant for each watershed. In the GIUH theory, it is assumed that a watershed is a time variant but linear system. Therefore, its runoff can be estimated by the convolution integral,

$$Q(t) = \int_0^t I(\tau)\, h(t-\tau)\, d\tau \qquad (4)$$

where $Q(t)$ is direct runoff at time t (cm/hr), $I(t)$ is excess rainfall (cm), and $h(t)$ is the Instantaneous Unit Hydrograph (hr^{-1}). IUH can be defined as the probability density function of the traveling time of a raindrop in a certain path to the outlet as a random variable. If the stream order of a watershed is denoted by Ω, the probability of a rain drop to be in path s can be defined as,

$$P(s)=\Pi_{x_i}.P_{x_1,x_2}\ldots P_{x_{j-1},x_j} \qquad (5)$$

where Π_{x_i} is the ratio of the overland plane area of order i to total area of watershed, P_{x_i,x_j} is the ratio representing the number of channels of order i which join the channels of order j. This ratio is expressed as (Gupta et al., 1980)

$$P_{xi,xj} = \frac{(N_i - 2N_{i+1})E[j,\Omega]}{\sum_{k=j}^{\Omega} E[k,\Omega]N_i} + \frac{2N_{i+1}}{N_i}\delta_{i+1,j} \qquad (6)$$

$1 \le i \le j \le \Omega$

$\delta_{i+1,j}$ equals 1 if $j = i+1$ and equals 0 otherwise. The probabilities Π_{x_i} can be expressed as (Smart, 1972)

$$\Pi_{x_1} = \frac{N_1\overline{A_1}}{A_\Omega} \qquad (7)$$

$$\Pi_{x_i} = \frac{N_i}{A_\Omega}\left[\overline{A_i} - \sum_{j=1}^{i-1}\overline{A_j}\frac{N_jP_{ji}}{N_i}\right] \quad i=2,\ldots,\Omega \qquad (8)$$

where A_Ω is the total area of watershed and $E[i,\Omega]$ is the average number of upstream channel orders joining streams of the ith order. This is defined as

$$E[i,\Omega] = N\prod_{j=2}^{i}\frac{(N_{j-1}-1)}{2N_j - 1} \quad \text{i=2,…,}\Omega \qquad (9)$$

Geomorphologic Instantaneous Unit Hydrograph for discrete time is defined as

$$Q_n = \sum_{i=n-m}^{n}P_i\sum_{s\in S}P(s)(f_{x_1} * f_{x_2} * \ldots * f_{x_j}) \qquad (10)$$

where n is the time step (hour), P_i is depth of excess rainfall at step i, f_{xi} is the probability density function of traveling time at path x_i , and * denotes convolution integral. Rodriguez-Iturbe and Valdes (1979) used an exponential probability density function with parameter K_{x_i} for the distribution of water holding time for each of the watershed components as follows:

$$h(t) = \sum_{s\in S}\sum_{i=1}^{j}C_{ij}\exp(-K_{x_i}t)p(s) \qquad (11)$$

where $1/K_{x_i}$ is the average of holding time of component x_i and C_{ij} are coefficients related to K_{xi} represented as,

$$C_{ij} = K_{x_1}.K_{x_2}\ldots.K_{x_j} \qquad (12)$$

$$\left[(K_{x1}-K_{x_i})\ldots(K_{x_{i-1}}-K_{x_i})(K_{x_{i+1}}-K_{x_i})\ldots(K_{x_j}-K_{x_i})\right]^{-1}$$

The average holding time for an i_{th} order channel, C_i, and overland plane can be represented as (Gupta et al., 1980)

$$\frac{1}{K_{c_i}} = \gamma(\overline{L_i})^{1/3} \qquad 1\le i \le \Omega \qquad (13)$$

$$\frac{1}{K_{O_i}} = \gamma\left[\frac{\Pi_{O_i}A}{2N_i\overline{L_i}}\right]^{1/3} \qquad (14)$$

where γ is an empirical constant. This constant can be estimated from an empirical relationship, which relates traveling time parameter to the watershed area (A), as follows (Mitchell, 1948):

$$\gamma=1.05\times A^{0.6} \quad \text{(unit of } A \text{ is square mile)} \qquad (15)$$

3- Nash Conceptual Model

In the Nash model an instantaneous unit depth of effective rainfall is considered as input only into the farthest (n_{th}) reservoir in a series. It is then routed through the remaining reservoirs. The outflow of each reservoir serves as the inflow into the next reservoir in the series as the flow moves toward the outlet of the watershed. The outflow of the last reservoir of the series, at the outlet of the watershed, is considered to be the IUH, $u(t)$ for the watershed. Presented as a gamma probability density function (Nash, 1957) as,

$$u(t) = \frac{1}{\kappa\Gamma(n)}\left(\frac{t}{\kappa}\right)^{n-1}e^{-\frac{t}{\kappa}} \qquad (16)$$

where n is the number of linear reservoirs, κ is the storage coefficient, and $\Gamma(.)$ is the gamma function. To determine parameters κ and n, the following set of equations are used.

$$\begin{cases} M_{Q1} - M_{I2} = n\kappa \\ M_{Q2} - M_{I2} = n(n+1)\kappa^2 + 2n\kappa M_{I1} \end{cases} \qquad (17)$$

where M_{Q1} and M_{Q2} are the first and the second moment of direct runoff hydrograph about the origin (zero) divided by total direct runoff, respectively; M_{I1} and M_{I2} are the first and the second moment of effective rainfall hyetograph about the origin (zero) divided by total effective rainfall. Two parameters of κ and n must be estimated during the calibration mode. More details about equation 17 can be found in standard references in hydrology such as (Chow et al., 1988).

4- Geomorphologic Artificial Neural Network Model

In this study, the perceptive three layer artificial neural network model was adopted. The input layer nodes consist of excess rainfall and direct runoff at previous (one hour) time step. The output layer is presented as a node for direct runoff at the next (one hour) time step. Back propagation algorithm based on error modification learning law was used for network training. Based on the network output type, the transfer function was selected as log sigmoid (0, 1) type.

GIUH theory states that the effect of traveling time is taken into consideration in relative weights between middle and input layers. These weights have been trained during the learning process. Path probability also constitutes relative weights between middle and output layers, therefore, the number of nodes in the middle layer should be equal with the number of probable paths (Zhang and Govindaraju, 2003). Thus, 8 nodes were taken into consideration in the middle layer (based on the results shown in Table 3). Figure 1 represents the adopted GANN structure.

The events which are selected for training process in the GANN model are the same events chosen for calibration of γ constant in the GIUH model. These events were also used for calibration of κ and n in Nash model. In designed artificial neural network, the amount of output direct runoff is calculated as (Zhang and Govindaraju, 2003)

$$Q_t = \sum_{j \in S} P_j(s)\varphi\left(\sum_{i=1}^{m} p_i f_{ij}\right) \tag{18}$$

where p_i is the ith input variable, f_{ij} is connection weights between the ith node in the input layer and the jth node in the middle layer, m is number of nodes in the middle layer, $P_j(s)$ is the j_{th} path probability and φ is the sigmoid function which is expressed as,

$$\varphi(x) = \frac{1}{1+e^{-x}} \tag{19}$$

where x denoted the input to middle layer. Hence, in the training step, it is attempted to minimize MSE between the computed direct runoff (q_{ij}) and the corresponding observed values of the hydrograph (Q_{ij}):

$$MSE = \sum_{i=1}^{NE}\sum_{j=1}^{N_i}(Q_{ij} - q_{ij})^2 \tag{20}$$

Where N_i = number of ordinates of i_{th} event and NE = number of events that are used in the training process.

5- Data and the Study Watershed

Kassilian representative watershed is located in the northern part of Iran with an area of 67.2 km^2 and average slope of 16.4 percent. This watershed is one of the sub-basins of Talar river in Mazandaran province. Kassilian is a mountainous watershed with 43% of its total area covered with forests. Considering the climatology and vegetations of this watershed, it has been known as a representative of mountainous and forest regions in the middle Alborz. The vegetation cover of Kassilian watershed is indicated in Table 1. This watershed has a discharge gaging station at the outlet and a raingage station in its centroid. The drainage network and the location of these stations are presented in Figure 2. The values of geomorphologic parameters were obtained from a map with a scale of 1:50000. These values are given in Table 2. The probabilities of a rain drop to fall on an upstream surface of order i and the probabilities of the transition between channels of different orders are represented in Table 3. The path probabilities are shown in Table 4.

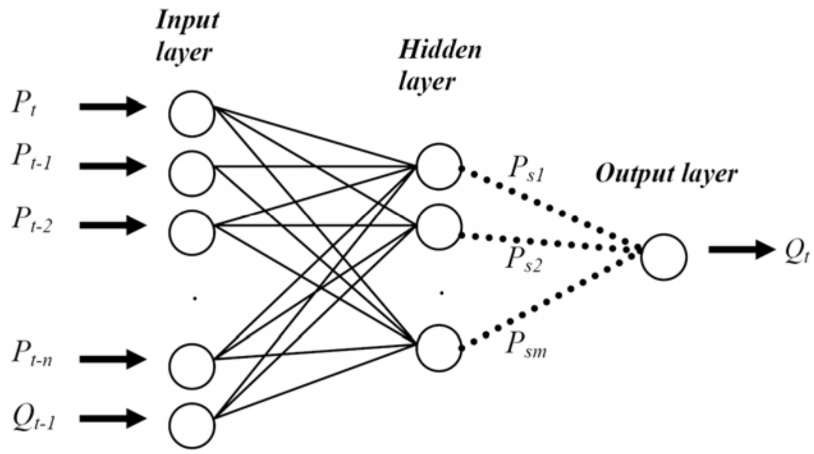


Figure 1- Architecture of GANN model

Table 1- Vegetation state for Kassilian watershed

Type of vegetation	Covered area (km^2)	Percentage of covered area (%)
Agronomy Lands	18.4	27.5
Pasture	3.1	4.6
Forest	43	64.2
Dry Lands (without vegetation)	2.5	3.7

Table 2- Geomorphology parameters of watershed

Order No.	N	$\overline{L_i}$ (km)	$\overline{A}$ (km^2)
1	53	0.767	0.6187
2	17	1.689	2.4801
3	14	5.118	16.8070
4	1	4.666	67.10

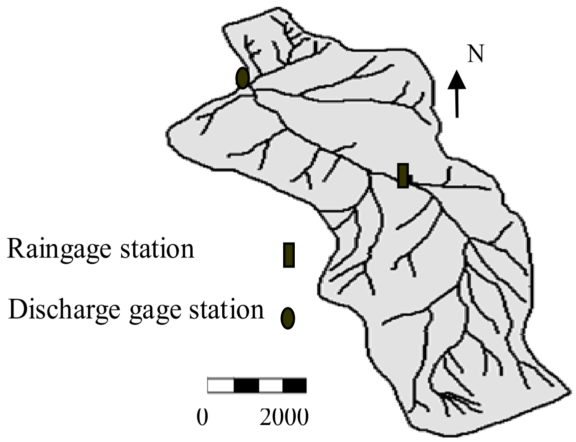


Figure 2- The Kassilian watershed drainage map

Table 3- The probabilities of water falling on an overland plane of order i, (Π_{x_i}) and transition probability, P_{x_i,x_j} for the study watershed

Π_{x_i} or P_{x_i,x_j}	P_{c_3,c_4}	P_{c_2,c_4}	P_{c_2,c_3}	P_{c_1,c_4}	P_{c_1,c_3}	P_{c_1,c_2}	Π_{o_4}	Π_{o_3}	Π_{o_2}	Π_{o_1}
value	1.0	0.235	0.773	0.037	0.204	0.826	0.08	0.12	0.30	0.49

Table 4- Path probabilities P(s) for the Kassilian watershed

Path number	Path	P(s)
1	$O_1 \rightarrow C_1 \rightarrow C_2 \rightarrow C_3 \rightarrow C_4$	0.3125
2	$O_1 \rightarrow C_1 \rightarrow C_2 \rightarrow C_4$	0.0951
3	$O_1 \rightarrow C_1 \rightarrow C_3 \rightarrow C_4$	0.1002
4	$O_1 \rightarrow C_1 \rightarrow C_4$	0.0184
5	$O_2 \rightarrow C_2 \rightarrow C_3 \rightarrow C_4$	0.2325
6	$O_2 \rightarrow C_2 \rightarrow C_4$	0.0707
7	$O_3 \rightarrow C_3 \rightarrow C_4$	0.1192
8	$O_4 \rightarrow C_4$	0.0838

In order to evaluate the capabilities of the models, the data of 10 rainfall–runoff events from 1976 to 2000 were adopted for both model calibration and model validation such that seven events are selected randomly for calibration mode and three remaining events for validation mode. The characteristics of these events are presented in Table 5. For each event direct runoff was separated from base-flow by a constant slope line. The excess rainfall was calculated by assuming constant loss rate of abstractions ϕ-index during the rainfall period.

Table 5- The Characteristics of rainfall-runoff events

Mode	Event date	Direct runoff			Excess rain	
		Duration (hr)	Time to peak $t_p(hr)$	Peak discharge $Q_p(m^3/s)$	Duration (hr)	Depth $P_i(mm)$
Calibration	28/10/1974	36	6	0.91	1.0	0.48
	04/09/2000	28	6	6.54	2.0	2.28
	25/11/1994	45	8	8.60	1.0	5.31
	15/04/1990	57	8	4.15	1.2	2.95
	30/05/1987	23	5	1.33	0.5	0.60
	28/05/1987	27	3	2.06	0.5	0.72
	11/04/1986	29	5	0.84	0.7	0.46
Validation	09/01/1990	36	18	12.60	3.0	6.10
	05/13/2000	34	12	1.10	2.0	1.70
	26/03/1994	57	6	13.28	3.0	9.00

6- Results & Discussion

Calibration mode of the models: The average value of Nash model parameters n and κ for the seven events were estimated to be 2.725 and 2.495, respectively, where n is an integer; therefore, the value of this parameter was set equal to 3 and the corresponding value of κ was recalculated as 2.235. Using equation (15) in the GIUH model, the value of the constant γ was estimated as 0.78.

Kassilian watershed is a 4th order watershed and has 8-path probabilities (Table 3). Thus, 8 nodes in the middle layer of the model were taken into consideration. Connective weights between output and hidden layers formed path probabilities in the initial steps. This was further updated during the training process. During the training process, the ordinates of the seven rainfall-runoff events were adopted and the Mean Square of Errors (MSE) were minimized between the calculated and the observed values subsequently. The final minimum error was obtained 0.00749 with 500 epochs.

Validation (testing) mode of the models: Taking the isolated storm events into consideration, the instantaneous unit hydrograph for each was derived. These hydrographs are averaged to arrive at an average instantaneous unit hydrograph of the watershed.

In the GANN model, by applying a unit excess rainfall in the input layer, the unit hydrograph model is obtained. This unit hydrograph along with the hydrographs obtained from Nash and GIUH models and the derived UH are plotted and presented against the observed unit hydrograph in Figure 3. These UH's are derived after dividing the direct runoff ordinates by the corresponding direct runoff depths. To get a single UH, the derived UH's are averaged which is demonstrated in Figure 3 (Singh, 1988).

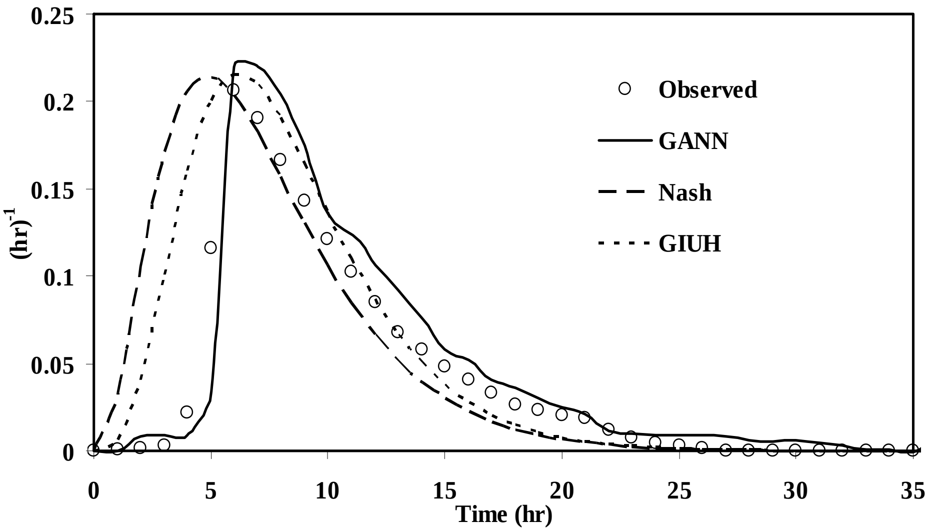
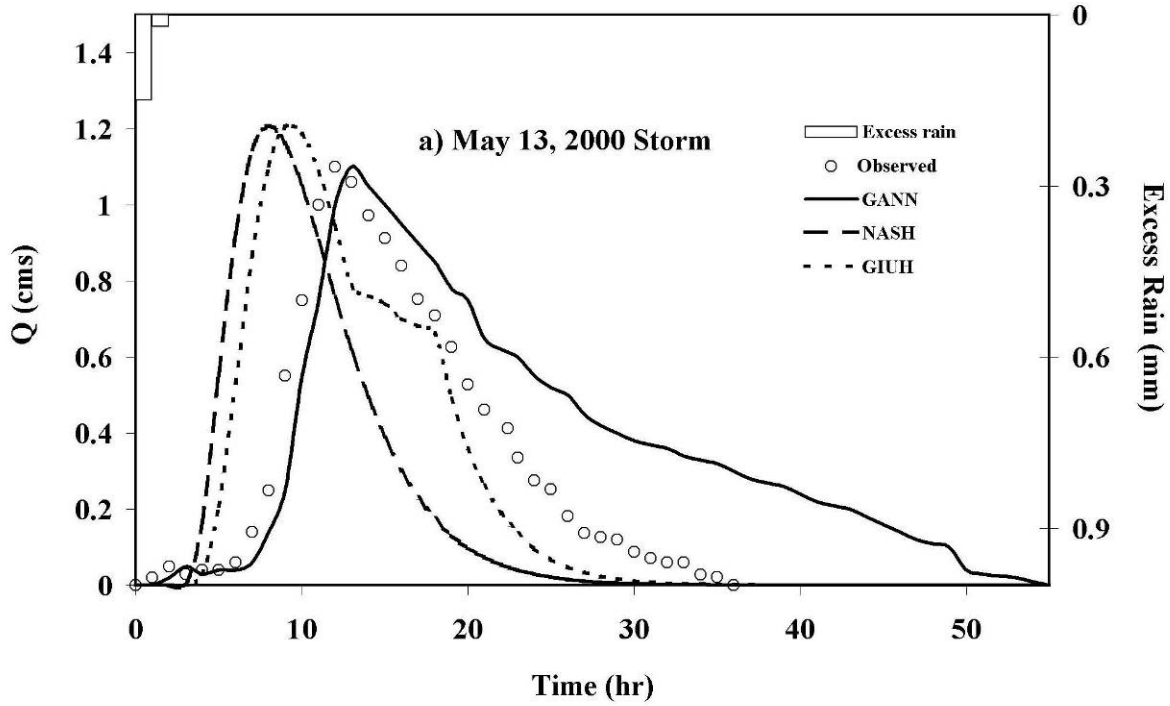


Figure 3- Unit hydrograph obtained by the three models

Three events studied for validation mode are applied to evaluate the model performance. In brief, the results of the above models for two events are only shown in Figure (4a and b). In these events, GIUH and Nash model predict the hydrograph shape satisfactorily. In most of the events, the time to peak of the computed hydrographs are smaller compared to the observed hydrographs and the results obtained by applying the GANN model. However, the GANN model is almost more efficient and accurate in all events than the other models in predicting the hydrograph shape and other parameters.



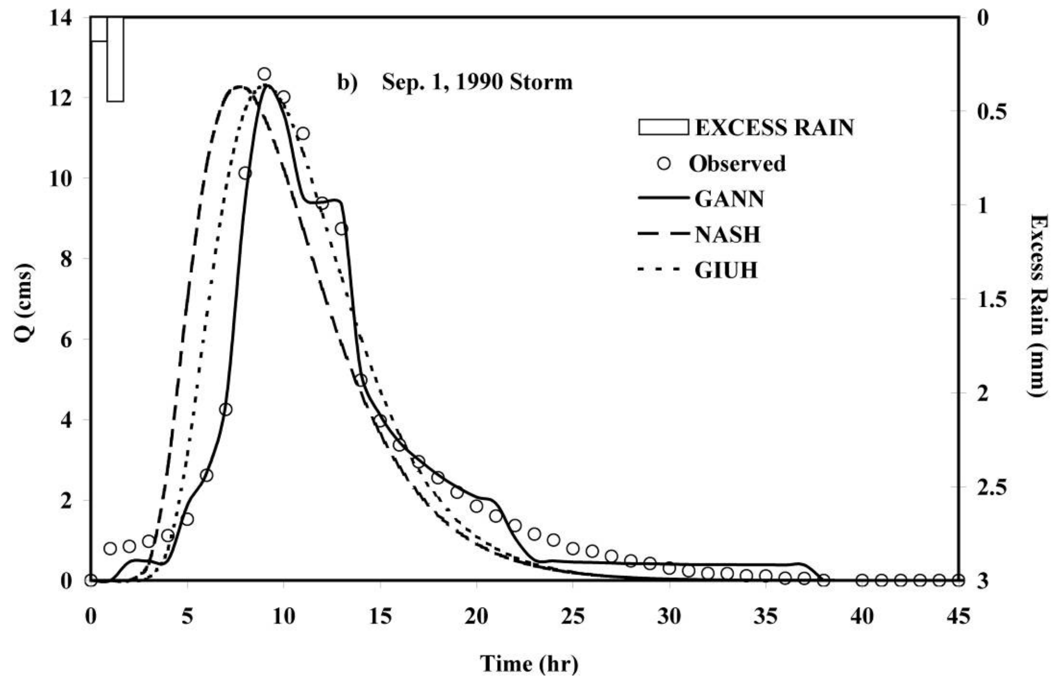


Figure 4(a), 4(b)- Comparison of obtained results from three models with observed direct runoff. (cms denotes cubic meter per second)

To evaluate the suitability of the model for the studied watershed, three criteria were chosen to analyze the goodness of fit in both training mode and validation mode. These criteria were:

(1) The coefficient of efficiency (Nash and Sutcliffe, 1970)

$$CE = 1 - \frac{\sum_{t=1}^{n}\left[Q_{obs}(t) - Q_{cal}(t)\right]^2}{\sum_{t=1}^{n}\left[Q_{obs}(t) - \overline{Q}_{obs}\right]^2} \tag{21}$$

where $Q_{obs}(t)$ is the recorded discharge at time t (hr), (m^3/sec), $Q_{cal}(t)$ is the simulated discharge at time t, (m^3/sec), $\overline{Q}$ is the average of recorded discharge values during the storm event, and n is the number of hydrograph ordinates.

(2) The error in peak discharge

$$EQ_p(\%) = \frac{(Q_p)_{cal} - (Q_p)_{obs}}{(Q_p)_{obs}} \times 100 \tag{22}$$

where $(Q_p)_{cal}$ is the peak discharge of the simulated hydrograph (m^3/sec) and $(Q_p)_{obs}$ is the recorded peak discharge (m^3/sec).

(3) The errors in time to peak of simulated hydrograph

$$ET_P = (T_p)_{cal} - (T_p)_{obs} \tag{23}$$

where $(T_p)_{cal}$ is the simulated time to peak discharge (hr) and $(T_p)_{obs}$ is the recorded time to peak (hr).

Equations (21) to (23) were applied to all events used in model training and validation modes. The corresponding computed values are present in Table 6. In terms of the *CE* coefficient, the GANN model has higher value for all events. The GANN model has a higher coefficient in terms of the magnitude of the predicted peak discharge and the time to peak compared to the other models.

The average values of the evaluation criteria (*CE*, EQ_p, ET_p) applied for the comparison of model performances are presented in the Table 7. These values reveal higher performance of the GANN model compared to the other two models.

Table 6- Simulation results of storm events

Mode	Event date	*CE* (-)			EQ_p(%)			ET_p (hr)		
		GANN	NASH	GIUH	GANN	NASH	GIUH	GANN	Nash	GIUH
Calibration	28/10/1974	0.91	0.72	0.28	-7.3	-11.25	-11.04	1	0	1
	04/09/2000	0.91	0.48	0.78	0	-25.53	-25	0	-1	0
	25/11/1994	0.94	0.56	0.83	-7	-4.9	5.54	0	0	2
	15/04/1990	0.60	0.36	0.20	-3.1	-25.4	-2	0	-3	-2
	30/05/1987	0.60	0.20	0.36	-14.5	0.65	0.65	0	0	1
	28/05/1987	0.90	0.38	0.76	-4.4	3.9	4.36	0	1	0
	11/04/1986	0.92	0.32	0.59	3.4	18	18	-1	-1	-2
Average	-	0.83	0.43	0.54	5.7*	12.8*	9.5*	0.29*	0.86*	1*
Validation	09/01/1990	0.96	0.45	0.37	-2.4	-2.85	-1.58	0	-1	0
	05/13/2000	0.95	0.46	0.36	9.10	8.20	9.10	1	-3	-2
	26/03/1994	0.78	0.74	0.71	-4.36	17.8	18.52	1	1	3
Average	-	0.90	0.55	0.48	5.3*	9.6*	9.75*	0.7*	1.7*	1.7*

* Average of absolute values.

Table 7- The improvement percentage of GANN model compared with two other models

Mode	*CE*		EQ_p*(%)*		ET_p	
	Nash	GIUH	Nash	GIUH	Nash	GIUH
Calibration	92	53	55	40	66	71
Verification	64	88	82	84	60	60

7- Conclusion

When applying the ANN model to estimation of watershed response, the definition of model structure and optimum number of nodes in the input and middle layers of the model are controversial components. It requires numerous trials to conclude, whereas, the GANN approach directly uses geomorphology characteristics of watershed in defining the model structure and the number of nodes. This characteristic reduces the computation cost and CPU time requirements. Furthermore, use of feedback loops as a node in input (and the same in output) layer in the proceeding time step in terms of runoff, is the reason why the GANN model has higher performance. Finally, the GANN model is a promising tool compared to the ANN model which is completely empirical and has promoted a black box model to a model based on watershed geomorphology. In the estimation of runoff, the GANN model is a more powerful tool compared to the GIUH and the Nash conceptual model which use recorded rainfall-runoff data.

8-References

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