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A simulation of the rainfall-runoff process using artificial neural network and HEC-HMS model in forest lands

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Abstract: Simulation of the runoff-rainfall process in forest lands is essential for forest land management. In this research, a hydrologic modelling system (HEC-HMS) and artificial neural network (ANN) were applied to simulate the rainfall-runoff process (RRP) in forest lands of Kasilian watershed with an area of 68 square kilometres. The HMS model was performed using the secondary data of rainfall and discharge at the climatology and hydrometric stations, the Soil Conservation Service (SCS) for simulating a flow hydrograph, the curve number (CN) method for runoff estimation, and lag time method for flow routing. Further, a multilayer perceptron (MLP) network was used for simulating the rainfall-runoff process. HEC-HMS model was used to optimize the initial loss (IL) values in the rainfall-runoff process as an input. IL reflects the conditions of vegetation, soil infiltration, and antecedent moisture condition (AMC) in soil. Then, IL values and also incremental rainfall were applied as inputs into ANN to simulate the runoff values. The comparison of the results of simulating the RRP in two scenarios, using IL and without IL, showed that the IL parameter has a high effect in increasing the simulation performance of the rainfall-runoff process. Moreover, ANN predictions were more precise in comparison with those of the HMS model. Further, forest lands can significantly increase IL values and decrease runoff generation.

Keywords: initial loss; flood; optimization; forest lands; Kasilian watershed

It is important to predict the behaviour of floods and runoff generation in forest lands, due to their complex nature and the great damage they cause (Khaleghi 2017, 2018). Many factors affect the rainfall-runoff process (RRP) and also the runoff phenomenon. Simulation of these phenomena is important and difficult. Therefore, different methods have been developed to analyse this process. Further, lack of vegetation or soil impermeability can lead to several outcomes, including an increase in surface flow and consequently annual runoff, increase of the watershed instantaneous peak discharge, increase in hydrograph slope, and finally reduction of the groundwater discharge (Burns et al. 2005; Khaleghi, Varvani 2018; Varvani 2019; Farajzadeh, Khaleghi 2020).

Recently, various hydrologic models have been used to simulate the quantitative dimensions of the RRP (Kim, Barros 2001). To manage natural disasters and to design and to build the water structures, it is necessary to estimate the peak discharge value and the runoff volume of a watershed (Khaleghi et al. 2011). Therefore, different methods have been presented for simulating the rainfall-runoff modelling. Sapountzis and Stathis (2014) quantified the hydrologic response of the torrents that originate in the forest area of Stratoni using the synthetic unit hydrograph method. Based on previous research, the hydrologic modelling system (HEC-HMS) has had effective results in this regard. For example, the results of Amengual et al. (2008) which were used for presenting a rainfall-runoff model (RRM) in the

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Emilia-Romagna Region, confirm it well. Hogue et al. (2006) proposed the Sacramento model. Hellweger and Maidment (1999) combined a geographic information system (GIS) directly with HEC-HMS to access an RRM. Also, Stone (2001) combined GIS and HEC-HMS model to achieve an RRM. Their results were favourable and desirable because of the high speed and capacity of the resultant model in simulation of a flood hydrograph and also in the estimation of flood quantitative characteristics such as runoff volume and peak discharge. Also based on the research results of Dibike and Solomatine (2001) the HEC-HMS model has sufficient reliability in the estimation of the infiltration parameters and for simulating daily streamflow.

Today, the use of the artificial neural network (ANN) method in simulating processes has increased (Abrahart, See 2007). This method has been inspired by the human brain and nervous system patterns (Maier, Dandy 2000; Tokar, Markus 2000; Tesch, Randeu 2006; Lee et al. 2008; Gholami et al. 2015, 2019; Varvani et al. 2019). Using this method has had very appropriate results. ANN has a high potential and ability to establish the relationship between different factors and also in the simulation of a parameter. The use of ANN causes a reliable and flexible learning ability in creating models and due to this property, converts the ANN to an attractive inductive approach in hydrological response forecasting (Manson et al. 1996; Luk et al. 2001; Kisi, Kerem Cigizoglu 2007; Pan et al. 2011; Sahour et al. 2020). The research results of Minns and Hall (1996) in implementing an ANN to present an RRM and simulate a flood hydrograph are satisfactory. Also, Dunjó et al. (2004) implemented an RRM to assess the spatiotemporal effects of land-use changes in runoff generation and access to good results. Zimmermann et al. (2006) and also Descheemaeker et al. (2006) revealed a significant and positive correlation between the total vegetation cover and the runoff generating threshold.

There are also examples where the two approaches are combined to improve forecasting performance (Alvisi et al. 2006). If the flow data (discharge-stage data) is not available or the purpose is to study the hydrological and climatic conditions and land use, applying an RRM is a satisfactory alternative (Haberlandt et al. 2008). Some of the researchers such as Wilby et al. (2003) and Jain et al. (2004) emphasized the effectiveness of ANN in the simulation of RRP. Therefore based on recent reviews, one can say that ANN has a high ability and potential in hydrological process modelling. Therefore, the incorporation of HEC-HMS model (optimizing a simulated hydrograph) and ANN (the high performance in the simulation) will result in much more effective results. For example, Verma et al. (2010) used remote sensing (RS) and GIS to investigate the performance of HEC-HMS and WEPP models in simulating the runoff generation in watersheds. Peters et al. (2006) incorporated the HEC-RAS capacities and ANN to perform flood routing in a stream. One of the features of this method is that if there is no observational data, synthetic precipitation can be used repeatedly (Cameron et al. 1999; Blazkova, Beven 2004; Aronica, Candela 2007; Moretti, Montanari 2008). The goal of this study is to evaluate the performance of ANN coupled with HEC-HMS in simulating the RRP in forest lands. This study presents a methodology with high performance for simulating the RRP and the runoff values through coupling the HEC-HMS model and an ANN in the Kasillian forested watershed.

MATERIAL AND METHODS

Study area. The Kasilian watershed, a forested area, is divided into three sub-basins of Velikh-Chal, Sangheh, and Sarband in Mazandaran province. Also, this watershed is one of the few watersheds in Iran which is less influenced by human activities and has long-term statistics. Therefore, this area is considered as a representative of mountainous and forest areas and has a total area of about 68 square kilometres, which is located between 53°8'44"E to 53°15'42"E and 35°58'30"N to 36°07'15"N in Mazandaran province (Northern Iran). Figure 1 shows the location of Kasilian watershed. The elevation ranges from 204 to 2 995 m a.s.l. in the Kasilian watershed. The study area has a semi-humid and cold climate (Gholami et al. 2008). The region has the mean annual precipitation of 791 mm and the mean temperature is 11 °C. There is a hydrometric station in the outlet of the watershed and a rainfall recorder station upstream of it. The most important land uses of the study area in terms of hectares are forests (4 222.6), farming (2 143.6), rangelands (346.8), and residential areas (87) (Khaleghi 2017). Table 1 presents the characteristics of the Kasilian watershed. In the studied watershed, different types of tree species are observed such as *Carpinus betulus*, *Buxus hyrcana*, *Fagus orientalis*, and

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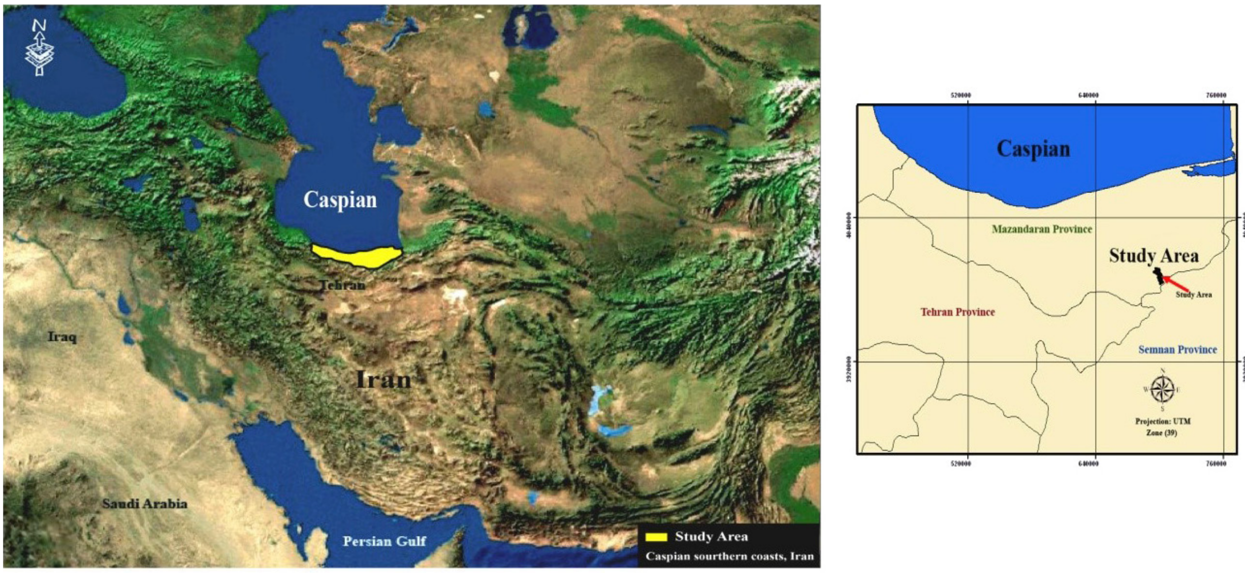

Figure 1. Location of the study area, Kasilian watershed in northern Iran

Alnus subcordata. Moreover, species of spruces, *Populus*, and *Cupressus* trees can be seen in reforested lands.

Methods. In this study, an HEC-HMS and an ANN model were applied to simulate RRP in the Kasilian watershed. The HMS model was performed using the SCS and curve number (CN) methods.

SCS and CN methods were used for hydrograph simulating and estimating runoff values, respectively.

Table 1. The characteristics of the Kasilian watershed

Watershed properties	Kasilian
The main river	Talar
Location	53°18'00"E 53°60'30"E 35°58'30"N 36°07'00"N
Dominant geological formation	shale – sandstone
Pedology	very deep clay
Dominant vegetation	forests, rangelands, and villages
Climate	semi-humid
Watershed area (km^2)	67.8
Watershed perimeter (km)	44.5
Circular ratio	0.43
The mean elevation (m)	1 672
The mean slope (%)	15.8
The mean slope of main river (%)	13
Drainage density (km·km^{-2})	2.282

The SCS-CN method was applied for the determination of the initial loss and determination of the runoff-rainfall relation (runoff values). Therefore, initial loss is a parameter that involves those factors for simulation of the RRP, which was selected as an input in the rainfall-runoff model. The initial loss values were calculated by the following formula:

$$S = \frac{25\,400}{\mathrm{CN}} - 254 \tag{1}$$

where:
S – total loss (mm);
CN – curve number.

S is obtained through the above formula and the initial loss is equal to $0.2 \times S$. The average value of CN was estimated as equal to 70.71 in the study area. The maximum and minimum values of CN were observed in the dense forest and the dry farming (deforested lands), respectively. Due to some contradictory cases in which the IL values of some rainfall events were more than the total rainfall (Table 1), it was necessary to use a model to optimize this parameter. HEC-HMS model was selected for this purpose due to its high capability in optimization. In the first step, to a simulation of the flood hydrograph and also to optimizing the initial loss parameter, the HEC-HMS model was used. To do this, the extension of HEC-GeoHMS in the ArcGIS medium and also the digital elevation model (DEM) were implemented to simulate the physical model of the watershed. This process was done by

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importing the watershed physical model into the HEC-HMS model and implementing rainfall data (Sangdeh station) and flood hydrograph data (Valikben station). Moreover, the lag time method was used for flood routing in the main channel. IL and the SCS lag time were selected as the optimization parameters. In this study, a total of nine events were considered: 6 events for data training in ANN and 3 events for data testing. To simulate the flood hydrograph in the ANN, both IL and rainfall values were used. Table 2 presents the input data of the incremental rainfall and IL during a rainfall event.

Rainfall-runoff process modelling using an ANN. To execute this research, a single-layer perceptron with a backpropagation algorithm was run in the environment of MATLAB software (Version 7.5.0, 2007). To attain the best results in an accurate simulation of RRP, HEC-HMS and ANN capabilities were combined. To determine the optimized structure of an ANN network in rainfall-runoff modelling, the trial-error method was used. To do optimization, different structures of the MLP network were used. To pattern mapping problems, the MLP network was selected with the backpropagation rule and the learning techniques of GDX (Gradient Descent), LM (Levenberg-Marquardt), and CG (Conjugate Gradient) and with (2–20) neurons (Hung et al. 2009). To select the desired optimal network model, statistical criteria were used. The selection procedure is based on the following statistics: correlation (R), coefficient of determination (R-squared), and root mean squared error (RMSE). The performance of the network was evaluated through different parameters, for example:

$$\mathrm{RMSE}=\sqrt{\frac{\sum_{i=1}^{n}\left(Q_{\mathrm{obs}}-Q_{\mathrm{cal}}\right)^{2}}{n}} \tag{2}$$

Table 2. The values of rainfall and initial loss (based on formula 1) for the used events in rainfall-runoff modelling

Date	Rainfall (mm)	Initial loss (mm)	Optimized initial loss
24 May 1991	26.32	21	11.32
22 Oct 1994	25.53	21	9.8
4 May 1993	10.5	21	10.1
2 Sep 1990	18.2	21	8.8
26 Sep 1991	15.6	21	11
20 Jun 1992	20	21	11.03

where:
Q_{obs} – observed values;
Q_{cal} – values calculated by network and model;
n – number of data in each step.

The nearer the RMSE to zero, the nearer are the observed and calculated values to each other and the more accurate is the simulation in each stage. Pearson's R-Squared statistics (RSqr) and efficiency index (R^2):

$$\mathrm{RSqr}=\left[\frac{\sum_{i=1}^{n}(Qi-\overline{Qi})\times(\hat{O}i-\tilde{O}i)}{\sqrt{\sum_{i=1}^{n}(Qi-\overline{Qi})^{2}\times\sum_{i=1}^{n}(\hat{O}i-\tilde{O}i)^{2}}}\right]^{2} \tag{3}$$

where:
Qi – observed value;
$\hat{O}i$ – simulated value;
$\bar{O}i$ – mean of the observed data;
$\tilde{O}i$ – mean of the simulated data.

The purpose of the network terrain is to obtain a network that can improve the relationship between the inputs and output of the model.

Finally, an MLP network was trained by using secondary rainfall data and the optimized IL values in the HMS model. The model was optimized by using the trial-error method and the changes in the inputs, transfer function, learning technique, epoch number, and neuron number. Network performance was evaluated by comparison between the observed runoff values and the simulated values and the statistical criteria. Runoff values were estimated by subtracting the baseflow from the recorded streamflow hydrograph. Baseflow is the discharge value before flood or rainfall started. The optimized network was selected based on the minimum error and the maximum conformity between the observed and simulated hydrographs. In the test stage, the optimized network was used for simulating runoff and flood hydrograph of the three validation events (rainfall-runoff). Finally, the optimized MLP network was validated by a comparison between the observed and simulated runoff values.

RESULTS

To optimize the IL parameter, an RRM was used in the HEC-HMS model. Table 1 illustrates the IL values of the used rainfall events. The HEC-HMS model was implemented to simulate and optimize flood hydrograph events (Figures 2 and 3). Table 2

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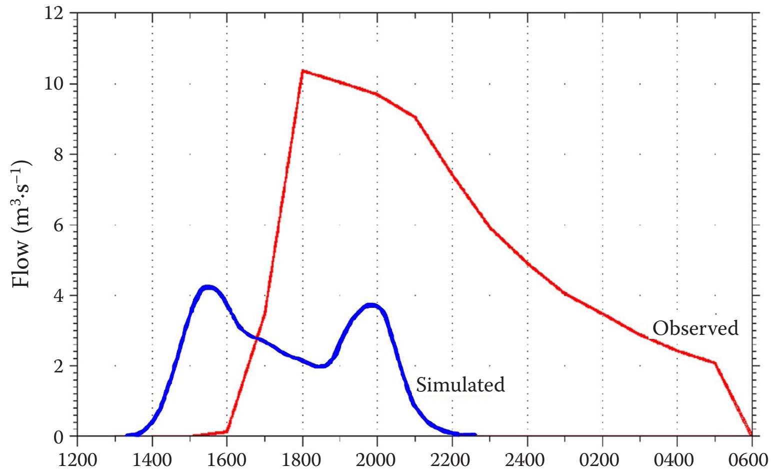

Figure 2. The comparison of the observed and simulated hydrographs by HEC-HMS model (May 24, 1991)

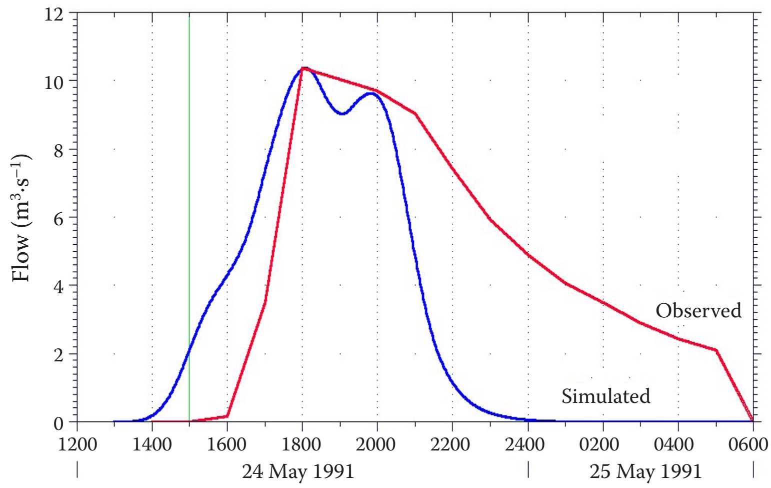

Figure 3. The comparison of the observed and optimized hydrographs by HEC-HMS model (May 24, 1991)

shows the estimated IL (based on a formula) and the optimized IL (based on the HMS model) in the study area. Then, a series of inputs includes the IL values, incremental rainfall, and runoff values that were entered into the ANN model for simulating the rainfall-runoff process. The mean of the optimized IL values was used as IL for the modelling process. Also, three rainfall events were implemented to validate or test the network results. Table 3 shows a sample of input and output data (a rainfall-runoff event) for modelling in the ANN.

ANN was used to simulate the runoff in two different scenarios with IL input and without IL input. The results of this comparison are given in Figures 4 to 9. Based on the quantitative comparison of hydrographs (Figures 8 and 9), implementing the IL increases the simulation performance. Comparison of the ANN and HEC-HMS models based on the goodness of fit test showed that compared to the ANN model, the HEC-HMS model gave much higher MSE and MRE. Also, compared to the HEC-HMS model, the ANN model provides more accurate streamflow prediction at both high and low streamflow conditions. Therefore, the higher the number of independent variables, the better is the performance of both ANN and empirical models. But due to the limitation of this process in the number of independent variables, we do not see a significant improvement in the performance of the model. This is because of a data error, so the more the independent variables, the higher is the precipitation data error.

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Table 3. Artificial neural network (ANN) input parameters for rainfall-runoff modelling in one-hour intervals (May 4, 1993)

Time (h)	Discharge ($m^3 \cdot s^{-1}$)	Rainfall (mm)	Initial loss (mm)
7	0.475	0	0
8	0.475	0.7	0.7
9	0.525	0.4	0.4
10	0.6	1.5	1.5
11	0.675	1.6	1.6
12	0.833	0.9	0.9
13	0.998	2	2
14	1.163	1.4	1.4
15	1.615	0.8	0.8
16	1.895	0.5	0.5
17	2.043	0.5	0.3
18	2.043	0.2	0
19	1.965	0	0
20	1.895	0	0
21	1.825	0	0
22	1.685	0	0
23	1.615	0	0
24	1.475	0	0
1	1.335	0	0
2	1.273	0	0
3	1.218	0	0
4	1.108	0	0
5	1.053	0	0
6	0.998	0	0
7	0.97	0	0
8	0.943	0	0
9	0.888	0	0
10	0.833	0	0
11	0.833	0	0
12	0.778	0	0
13	0.75	0	0
14	0.725	0	0
15	0.7	0	0
16	0.675	0	0
17	0.65	0	0
18	0.625	0	0
19	0.625	0	0
20	0.6	0	0
21	0.575	0	0
22	0.575	0	0
23	0.525	0	0
24	0.525	0	0

DISCUSSION

HMS model was used for exact or optimized IL values. According to Table 2, a significant difference was observed between the primary IL and the optimized IL. IL is an important parameter in a rainfall-runoff model because it reflects a complex of vegetation, soil texture, and AMC. The optimized IL is lower than the primary IL values. Tree species, tree height and density, vegetation canopy, and initial lost values are the most important determinative factors of IL and runoff generation. Runoff is produced when rainfall exceeds the IL values (Table 3). Therefore, incremental IL values the same as in Table 3 can be used as an efficient input in a rainfall-runoff model. The optimized hydrographs in the HMS model showed that the HMS model has high capabilities in the optimization process. The optimization process will be more efficient for estimating peak discharge values or runoff volumes. ANN can optimize its structure and it is not suitable for IL optimization. Therefore, a coupling of HMS (hydrologic model) and ANN can improve the modelling process. In Figures 4 to 9, we can observe the effect of the optimized IL in the rainfall-runoff modelling. It is important to simulate IL values from similar rainfall. There are two significant advantages of mastering IL values. One is that the conditions of forest cover, soil, and even AMC are somehow applied in the model. Second, it will increase the performance of the rainfall-runoff model, especially in the peak discharge index. Finally, an optimized MLP network was tested or validated. The results showed that the MLP network can simulate runoff values with acceptable accuracy (Abrahart, See 2007; Kisi, Kerem Cigizoglu 2007; Gholami et al. 2015). Further, that can be used for simulating a flood hydrograph. The optimized network was an MLP network with a tangent hyperbolic transfer function, LM learning technique, 1 000 training epochs, and one neuron. Further, an important point in the application of the rainfall-runoff model in forest lands is runoff estimation at a specific area. Moreover, a validated model can be used to evaluate the effect of forestry, tree cover type, or deforestation on runoff generation. On the other hand, it can be used in the design of forest engineering structures in connection with the design of forest roads or drains.

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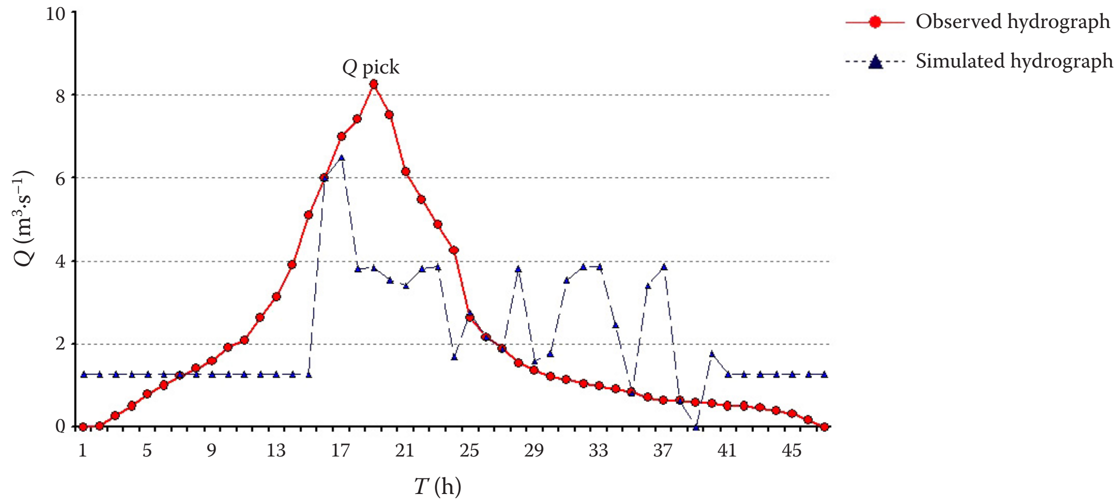

Figure 4. The comparison of the observed and simulated hydrographs by artificial neural network (ANN) in the case without the initial loss parameter (October 12, 1995)

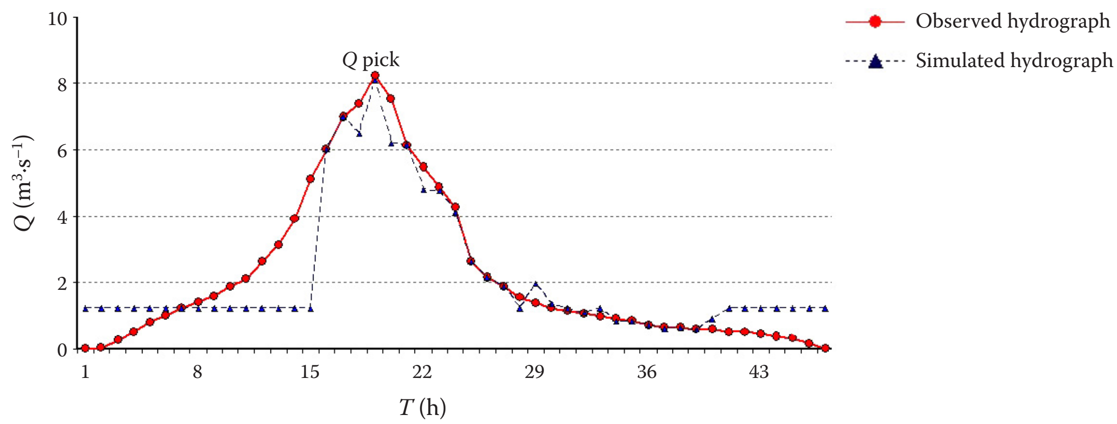

Figure 5. The comparison of the observed and simulated hydrographs by ANN in the case of using the optimized initial loss parameter (October 12, 1995)

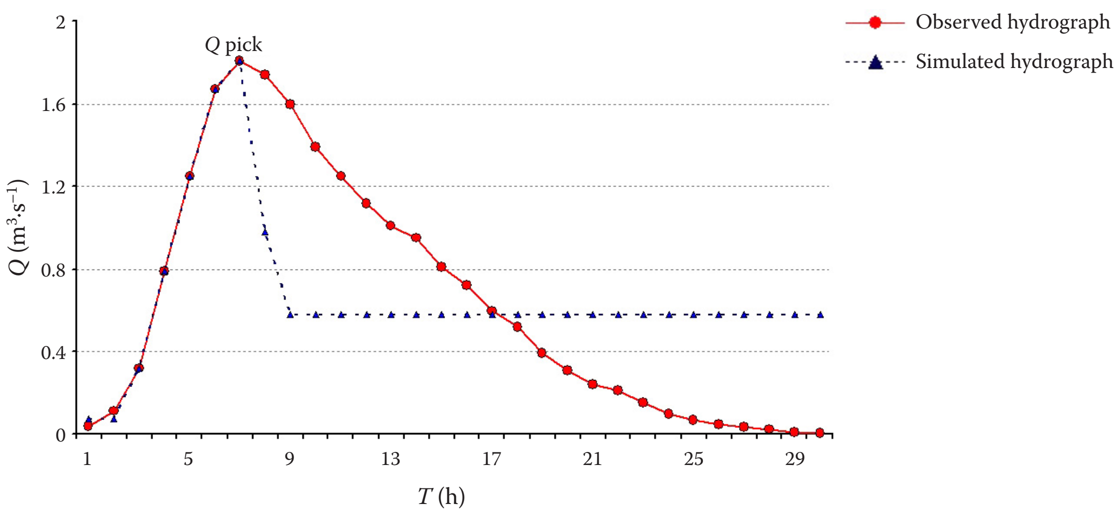

Figure 6. The comparison of the observed and simulated hydrographs ANN in the case without using the initial loss parameter (October 6, 1992 – the correlation between observed and simulated values equals 0.42)

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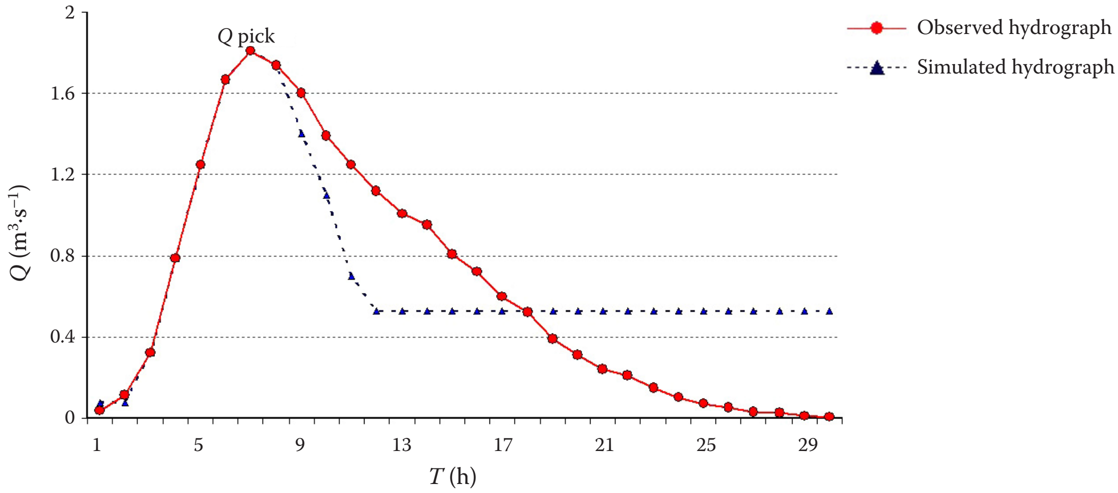

Figure 7. The comparison of the observed and simulated hydrographs by ANN in the case of using the optimized initial loss parameter (October 6, 1992 – the correlation between observed and simulated values equals 0.67)

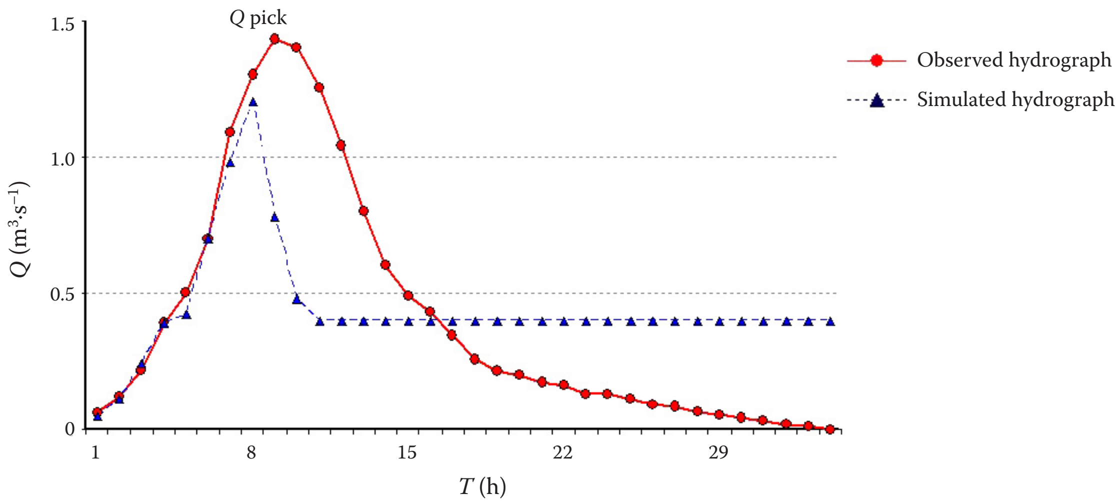

Figure 8. The comparison of the observed and simulated hydrographs by ANN in the case without using the initial loss parameter (June 15, 1995 – the correlation between observed and simulated values equals 0.39)

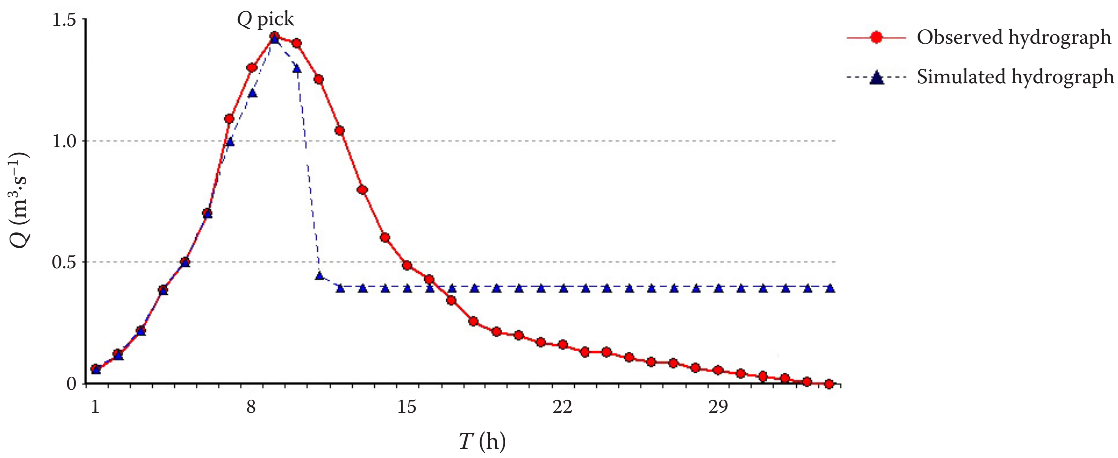

Figure 9. The comparison of the observed and simulated hydrographs by ANN in the case of using the optimized initial loss parameter (June 15, 1995 – the correlation between observed and simulated values equals 0.6)

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CONCLUSION

The goal of this research was to simulate flood hydrograph and runoff values by implementing the ANN model in forest lands. The results of this study certify the capability of the ANN model. The results of this study are in line with Abrahart and See (2007) and also Zimmermann et al. (2006). All of them find good results in their researches. It was also revealed that the performance of the model varies depending on the accuracy and number of input data. Therefore, the higher the number of real-time rainfall data, the forecasting of stream flows at incremental intervals will be more accurate. Further, vegetation is one of the main affecting factors in the runoff generation that should be considered. According to the results, IL can be used as an applied index for simulating the vegetation conditions in a rainfall-runoff model. Generally, based on the results of this study, implementing the IL parameter as a volume or quantity index increases the simulation accuracy of hydrograph dimensions as much as twice. In this regard, implementing historical rainfall and streamflow/gage height data increases the performance of the model (Dawson, Wilby 1998). Finally, compared to the HEC-HMS model, the ANN model has a better performance in simulating and solving phenomena and problems. Thus, one can say that ANN hydrologic models have high performance in real-time prediction of stream flows and watershed modelling. For future studies, we suggest that the other ANN structure and also field plot measurements be used for modelling the rainfall-runoff process and to estimate IL values in different types of forest cover in forest lands.

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