



Article

A Hybrid Intelligence Model for the Prediction of the Peak Flow of Debris Floods

Mohammad Ebrahim Banihabib ^{1,*}, Lubos Jurik ^{2,*}, Mahsa Sheikh Kazemi ¹, Jaber Soltani ^{1,*} and Mitra Tanhapour ¹

¹ Department of Irrigation and Drainage Engineering, College of Aburaihan, University of Tehran, Tehran 3391653755, Iran; mah.sheikhkazemi@ut.ac.ir (M.S.K.); mitratanhapour@ut.ac.ir (M.T.)

² Department of Water Resources and Environmental Engineering (WREE), Slovak University of Agriculture in Nitra, 94901 Nitra, Slovakia

* Correspondence: banihabib@ut.ac.ir (M.E.B.); lubos.jurik.nr@gmail.com (L.J.); jsoltani@ut.ac.ir (J.S.)

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Abstract: Debris floods, as one of the most significant natural hazards, often threaten the lives and property of many people worldwide. Predicting models are essential for flood warning systems to minimize casualties of debris floods. Since HEC-HMS (Hydrologic Engineering Center's Hydrological Modelling System) cannot simulate debris flow, this study proposes a new hybrid model that uses artificial intelligence models to overcome HEC-HMS's insufficiency in reflecting the sediment concentration effect on the debris floods. A sediment concentration is an effective factor for evaluating debris flood peak flows. This led to the proposal of new hybrid models for predicting the debris flood peak flows on the basis of hybridization of the artificial intelligence models (Bayesian Network (BN) and Support Vector Regression–Particle Swarm Optimization (SVR-PSO)) and HEC-HMS. To estimate the sediment concentration of floods by using the proposed artificial intelligence models, we nominated an average basin elevation, an average basin slope, a basin area, the current day rainfall, the antecedent rainfall of the past 3 days, and the streamflow of the previous day the previous day as the effective variables. In the validation stage, the average of the Mean Absolute Relative Error (MARE) of the estimated values were 0.024, 0.038, and 0.024 for the typical floods that occurred in the Navrood, Kasilian, and the Amameh basins in the north of Iran, respectively. Similarly, we obtained values of 0.038, 0.073, and 0.040 for the debris flood events for the three respective locations. After predicting the debris flood peak flows by the proposed hybrid HMS-BN and HMS-SVR-PSO models, the average of the MAREs for all debris flood events was reduced to 0.013 and 0.014, respectively. The comparison of MAREs of the examined hybrid models shows that the HMS-BN model results in higher accuracy than the HMS-SVR-PSO model in the prediction of the debris flood peak flows. Generally, the absolute error of prediction by the proposed hybrid model is reduced to one-third of the HEC-HMS. The prediction of the debris flood peak flows using the proposed hybrid model can be examined in the debris flood warning systems to reduce the potential damages and casualties in similar basins.

Keywords: debris flood; HEC-HMS model; Bayesian Network model; Support Vector Regression model; sediment concentration

1. Introduction

Floods are natural phenomena that impact many countries, leading to destructive consequences. This natural disaster annually threatens the lives and property of people in urban areas all over the world. Flash floods generally move with high speed and extraordinary peak flow in short duration or are often triggered without warning in steep basins due to the severe rainfalls [1]. The high sediment

concentration in debris floods intensifies the peak flow and consequently enlarges the flooded areas. As a result, damages to facilities by debris floods are relatively bigger than typical floods in urban areas [2,3]. To mitigate these damages, it is necessary to develop predicting models for flood warning systems.

One of the most widely used hydrological models of the flood prediction is the Hydrologic Engineering Center's Hydrological Modelling System (HEC-HMS) [4]. Its distributive modelling capability, its possibility to be linked with other software, and its parameter calibration are the most significant advantages of this model [5–8]. Some studies have applied hydrological models to estimate the peak flow of typical floods (non-debris floods) and have determined the lead-time of the flood warning system [9–11]. Zelelew and Melesse [12] assessed the applicability of the HEC-HMS model to estimate the runoff in the Abbay river basin. They found that the flood peak and the total runoff depth values were well-matched with the observed values [12]. However, it is essential to develop models to predict the peak flow of the debris floods for the flood warning systems.

One of the critical issues for the assessment of the debris flood peak flow is the estimation of sediment concentration. Banihabib and Forghani [13] proposed a framework for estimating the peak flow of debris floods using observed sediment concentration of the floods [13]. The estimation of the debris concentration of floods is a key factor in determining the peak flow of debris floods when the observed sediment concentration of debris floods is not available. Moreover, it is essential to predict the sediment concentration of debris floods to assess, in advance, the debris flood peak flow for flood warning systems. Thus, in this research, by upgrading the framework proposed by Banihabib and Forghani [13] and using the artificial intelligence models and HEC-HMS, we developed new hybrid models predict debris flow peak flow in this study.

Several studies have focused on appraising the risks of debris flood occurrences using various artificial intelligence methods [14,15]. Hirano et al. (1995) applied an artificial neural network (ANN) model to predict debris flood occurrence. Their research results revealed that the ANN model has a good performance to estimate runoff of these floods [16]. Kern, et al. [17] used machine learning techniques such as logistic regression, variance analysis, a decision tree, a neural network, a K-nearest neighbor algorithm, and a support vector machine to predict debris floods in the western part of the United States. The research results proved the superiority of the artificial intelligence methods over statistical methods [17]. These reported studies illustrate the artificial intelligence models' capability for the prediction of floods.

Some scientists applied conceptual models or the artificial intelligence models to predict the typical floods and the debris floods. Wang, et al. [18] indicated the random forest model's ability to predict the typical flood and the debris flood processes in Beijing's mountainous area. Banihabib [10] compared the efficiency of Dynamic Artificial Neural Network and HEC-HMS model to determine Flood Warning Lead Time (FWLT). The comparison showed that DANN can estimate FWLT longer than the HEC-HMS model [10]. The previous research did not link the results of the conceptual model with the artificial intelligence models, while this research highlights the significance of hybridization of HEC-HMS and the artificial intelligence models to improve HEC-HMS's deficiency in reflecting sediment concentration impact on the debris flood prediction.

Taking into consideration the above literature review, to reflect the impact of sediment concentration on the peak flow of debris floods, we proposed a new hybrid model by developing the artificial intelligence models (Bayesian Network (BN) and Support Vector Regression–Particle Swarm Optimization (SVR-PSO)) to overcome the insufficiency of HEC-HMS in predicting the peak flows of debris floods. The proposed model can be used to mitigate the hazards and risks of both typical and debris floods.

2. Material and Methods

2.1. Research Method

Figure 1 illustrates the steps of the research process and its sub-models. First, the recorded data of hydrometric stations and meteorological stations of the basins were collected to simulate the

flood hydrograph by the HEC-HMS model. Then, basins were divided into the sub-basins using a topographic map of 1:25,000 and the Arc Hydro tool of ArcGIS software, and the basin model was prepared using the HEC-Geo-HMS program. To validate the HEC-HMS model, we selected 13 flood events from the Navrood basin, 12 flood events from the Kasilian basin, and 11 flood events from the Amameh basin for the calibration and the test stages. The predicted flood hydrographs were compared with the observed flood. Then, the BN and SVR-PSO models were developed to predict the sediment concentration of debris flow in this study. After recognizing debris flow using the artificial intelligence models, we modified the simulated peak flows of floods by the HEC-HMS model using the sediment concentration predicted by the BN and SVR-PSO models to forecast the debris flood flows. The details of the hybridization of the artificial intelligence models and the HEC-HMS model are explained in Section 2.5 (the hybrid model for determining the debris flood peak flow). Moreover, details of artificial intelligence models (BN and SVR-PSO) are explained in Sections 2.3 and 2.4.

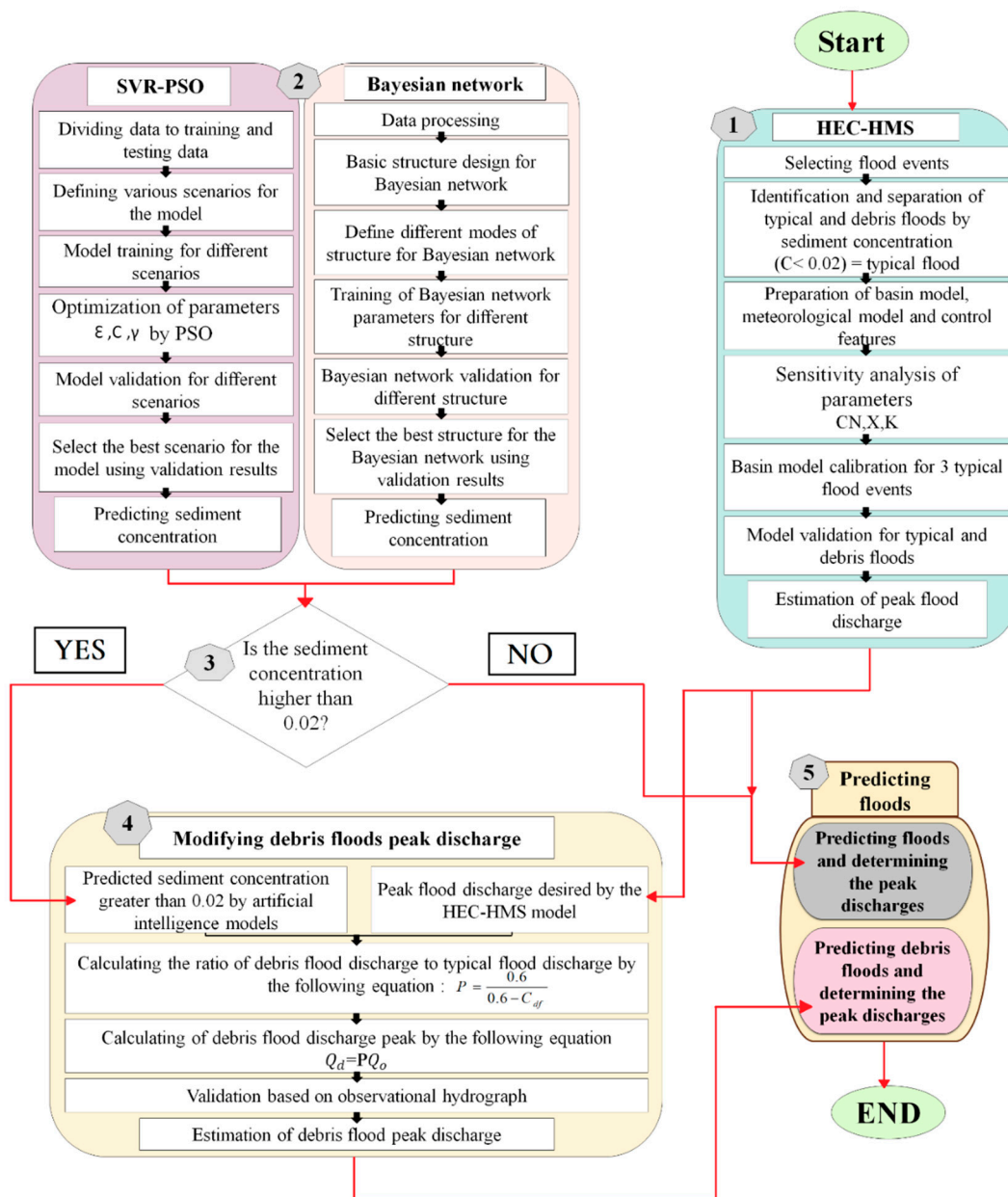


Figure 1. The research process flowchart for determining the typical and debris flood peak flows.

2.2. HEC-HMS Model

In this study, according to the type of available information in the studied basins, we used the Curve Number (CN) of the US Soil Conservation Service (SCS, Washington, DC, USA) to estimate the losses in the basins. Moreover, the SCS unit hydrograph was applied to convert the runoff to flood hydrograph, and the constant monthly method was utilized to estimate the base flow. Since the other river routing methods require a river cross-section and the roughness coefficient that were not available, we employed the Muskingum method in this research. However, the accuracy of river flood routing was improved by the calibration of X and K .

CN is a hydrologic parameter to describe the flood runoff potential in basins, which depends on geological characterizes of the basin, vegetation, land use, soil type and the antecedent soil moisture [9,19–21]. Its value can be changed from 1 to 100 for various land uses. In the Muskingum method, coefficient X is the weight coefficient of discharge, which varies from 0 to 0.5. K is flow travel time in river reach length. This coefficient can be initially obtained using observed inflow and outflow hydrographs. After estimating parameter K , the initial value of X can be estimated using suggested values by previous studies [11,21,22]. The Muskingum model is expressed on the basis of Equations (1) and (2):

$$\frac{dw}{dt} = I - Q \quad (1)$$

$$w = K [XI + (1 - X)Q] \quad (2)$$

$$K = \frac{L}{V} \quad (3)$$

where w is the flow storage, t is time, I is the inflow, L is the reach length, V is the average velocity of flow, and Q is the outflow. Equation (1) demonstrates the mass balance, and Equation (2) represents the river storage volume, which is the linear combination of inflow of the upstream section and outflow of the downstream section [22].

Since CN, X , and K are lumped parameters of HEC-HMS, the final values of these parameters should be determined using calibration. The main reason of sensitivity analysis is to examine the impact of these parameters in calibration. For this purpose, we examined the effect of variations of CN, and Muskingum X and K coefficients on the simulated flood from -20% to 20% + at 2% intervals from the initial values. In this study, a simple split-sample test method was employed for dividing the calibration and validation data [23]. To minimize the error of the calibration, we selected a peak-weighted root-mean-square error as the objective function of calibration. In this research, to minimize the value of an objective function and to find the optimum values of the parameters, we used the Nelder and Mead method by which all parameters were evaluated and corrected simultaneously and automatically in the HEC-HMS model [24]. Sensitivity analysis was performed on the simulation parameters. On the basis of the results of sensitivity analysis, we applied calibration on all sensitive parameters using the Nelder and Mead method.

For modelling rainfall runoff, we selected 36 flood events at the hydrometric stations of the Navrood, Kasilian, and Amameh basins. Of these, 13 events, 12 events, and 11 events were used for the Navrood, Kasilian, and Amameh basins, respectively. On the basis of the sediment concentration of these floods, we identified 5 events from 13 events in the Navrood basin as debris floods. Similarly, four events of the debris floods occurred in each of the Kasilian and Amameh basins. Since HEC-HMS is often applied for the typical flood model, we utilized the typical flood events for the calibration of flood simulation in the basins (in the Navrood basin on 11 July 2004, the Kasilian basin on 2 December 2008, and the Amameh basin on 18 November 2009).

2.3. Bayesian Network (BN) Model

Hugin 8.4 [25] was utilized for the BN model [26] in this research. The BN model predicts the sediment concentration of the flood events on the basis of the input variables and the interactions

between the variables. The learning methods of the BN model are classified into two categories: parametric learning and structure learning. The structural training means to identify the dependent and independent variables and finding the possible relations between the variables in the modelling. In structural learning, the main purpose is to find the best structure for the BN model. Parametric learning means to determine the conditional probabilities between two nodes of the network using the trained structure as well as the observed data. In this study, the Estimation–Maximization (EM) algorithm was used for the parameter learning. This algorithm estimates the conditional probability of distribution in each node on the basis of the observed data. The EM algorithm calculates the value of the probability logarithm of the data according to the joint probability distribution by performing the repetitive process in each iteration [27]. On the other hand, if the relations between the variables and the network structure are known, there is no need to use the structural learning algorithms, and relations are determined by an expert [28]. Therefore, the structural learning algorithms were not used in this study.

Figure 2 demonstrates the graphical structure of the Basic Scenario (BS), which shows all variables in the structure. This network structure illustrates that the basin area (A) and the average basin elevation (EL) are parent nodes. The parent nodes are the nodes that none of the variables impact. Moreover, as all variables affect the flood occurrence status (C), it is an output node. Other variables that affect other variables and are influenced by some other variables are the dependent variables. It is clear that EL affects the basin slope (S), and rainfall (current days' rainfall (RA, RB, RC, RD, RE) and antecedent rainfall from the previous 3 days (PRA1, PRA2, PRA3, PRB1, PRB2, . . .) for the stations A, B, C, D, E, respectively. Similarly, the basin slope (S), the basin area (A), and antecedent rainfall (PR) affect the streamflow of the previous day (PQ).

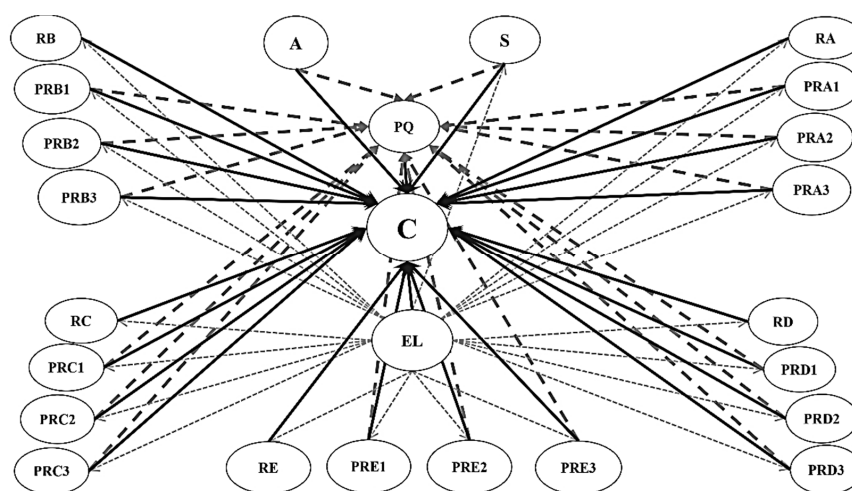


Figure 2. The graph structure of the basic scenario.

Generally, the elevation factor affects the rainfall (both current days' rainfall and antecedent rainfall). The amount of rainfall is enhanced by increasing elevation, and appropriate conditions are created for the occurrence of debris floods due to the erosion of loose materials. The effect of elevation on rainfall has been certified by other researchers [27,29]. Furthermore, the BN model creates a probabilistic relationship between variables.

Antecedent rainfall supplies the soil with moisture, and it is employed because it addresses the influence of antecedent soil moisture on the initiation of debris floods. Most previous studies considered the impact of antecedent rainfall on triggering debris floods [30,31].

In current study, daily rainfall was used to estimate sediment concentration by the BN model, and rainfall mass curve (hourly) was applied to determine peak flow by the HEC-HMS model. Then, hybrid model (linking the BN model and HEC-HMS model) was proposed to predict debris flood peak flows.

2.4. Support Vector Machine Regression Model

The Support Vector Machine (SVM) is a supervised learning method that can be employed for classification and regression problems. This method was first developed on the basis of the theory of statistical learning. The support vectors are a set of points in the n-dimensional space of data that determine the boundary of categories. They determine the closest training data to the separator plates. The SVM model conducts data processing as a vector. Among all separator plates, it chooses the plate that specifies the best classification among data [32]. The SVM model is divided into two main groups, including the SVM classification model and the Support Vector Regression (SVR) model.

Vapnik proposed the usage of the SVM in 1995 [33]. In this method, the objective function of modelling is to maximize the ability of the model to generalize and to minimize its complexity, simultaneously [34]. In this study, Support Vector Regression (SVR) was utilized. Most of the regression problems depicted by the SVM method are nonlinear. In general, nonlinear problems require hypothesis space (input) more complex than linear functions. When it is impossible to fit the linear functions to the training functions, researchers can transfer data to a space using the kernel functions in which the training function can be fitted to the data [35,36]. The kernel function is defined as follows:

$$K(x_i, x) = \langle \varphi(x_i), \varphi(x) \rangle \quad (4)$$

where φ is transformation function to transfer data to the high-dimensional space. Using the kernel functions, the standard form of the estimation function in the SVR problems can be obtained as follows:

$$f(x) = \sum_{i=1}^m (\alpha_i - \alpha_i^*) K(x_i, x) + b \quad (5)$$

where α_i is the Lagrange coefficient, $K(x_i, x)$ is the desired kernel function, and b is the constant coefficient. Since the parameters can be determined using Radial Basis Function (RBF) with higher speed and lower error than the other kernel functions [37], we employed the RBF kernel function in this research to predict the flood sediment concentration by the SVR model.

The optimal values of the SVR model's parameters (ϵ , C_{PSO} , and γ) must be determined. Parameter C_{PSO} creates a balance between an experimental error and the generalization error. Another parameter affecting the SVR is the error interval width (ϵ), which affects the flexibility of the SVM responses, and following that, it can be effective on the complexity and capability of network generalization. Furthermore, γ is the kernel parameter that plays an important role in the prediction by the SVR model [34]. The SVR model's performance is highly affected by determining the correct value of the model parameters (ϵ , C_{PSO} , and γ). Thus, the proper determination of the parameters is significant to increase the accuracy of the model. To find the optimum value of these parameters, we utilized the Particle Swarm Optimization (PSO) method in this research.

The PSO method was extracted from the collective performance of the animal groups such as fish and birds. In this algorithm, some of the creatures that are called particles are scattered in the search space. Each particle selects the direction for the next movement, combining the information of its current location, the best previous location, and information about the best particles in the group. After performing the collective movement, one step of the algorithm ends. These steps are repeated several times to obtain the desirable result [38,39]. The simple concepts, an acceptable computation volume, and simplicity of implementation of the PSO algorithm are the most important advantages of the mentioned algorithm [40].

In this research, the input variables of the SVR-PSO model are the same as the BN model for the prediction of the sediment concentration.

2.5. Validation of the Models

The model validation, as an important stage of model development, represents the rate of model reliability [41]. From this point of view, the database is divided into two parts, including the training

and the test data. In total, 80% and 20% of the data were devoted to the training and the test stages, respectively. For such purposes, we used a determination coefficient (R^2), the Root Mean Square Error (RMSE), and the Mean Absolute Relative Error (MARE) for the validation of BN and the SVR models, which are presented in Equations (6)–(8).

$$R^2 = \left(\frac{\sum (X - \bar{X})(Y - \bar{Y})}{\sqrt{\sum (X - \bar{X})^2 \sum (Y - \bar{Y})^2}} \right)^2, \quad (6)$$

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^n (X_i - Y_i)^2}{n}}, \quad (7)$$

$$\text{MARE} = \frac{1}{n} \sum_{i=1}^n \left| \frac{(X_i - Y_i)}{Y_i} \right|, \quad (8)$$

where, X_i is the predicted values by model, Y_i is observed values, \bar{X} is the mean of predicted values, and \bar{Y} is the mean of observed values.

2.6. Hybrid Model for Determining Debris Flood Peak Flow

Banihabib and Forghani [13] proposed a practical framework for estimating the sediment volume of the debris floods. In this framework, the debris flood peak flow can be estimated through using observed sediment concentration and simulated flood by the HEC-HMS model. The sediment concentration of the debris flow in this framework is the value observed or determined on the basis of the observed factors [13]. This framework can be used to assess the occurred events of the debris flood, but not to forecast the future events before the occurrence of the debris flood. It cannot be used for the prediction of a debris flood and in a flood warning system since it requires the observed sediment concentration. To upgrade this framework for the flood warning systems, in this research, we developed the artificial intelligence models to predict the sediment concentrations of the debris flood. Therefore, in this study, a hybrid model combined the HEC-HMS model to predict the rainfall runoff and the intelligent model to predict the sediment concentration. The debris flood peak flow was as follows:

$$Q_d = PQ_o, \quad (9)$$

where Q_d is the debris flood discharge, and Q_o is the typical flood discharge that is predicted by the HEC-HMS model and comprises only the fluid part of debris flood. P can be determined as follows [13]:

$$P = \frac{0.6}{0.6 - C} \quad (10)$$

where C is the observed average sediment concentration, which is replaced by the predicted sediment concentrations (C) of the developed BN and SVR-PSO models. Then, the peak flow of the debris flood is predicted using Equation (9) by substituting the predicted peak flow by using HEC-HMS (Q_o) and P value from Equation (10). Since the prediction of both C (predicted using the artificial intelligence models) and Q_o (by HEC-HMS) is based on the geometric, land use of the basin, and rainfall data, we can apply the proposed hybrid model to predict the debris flood before the event. This can promote the current flood warning systems for warning debris floods also. If the sediment concentration is more than 0.6, it is not a debris flood. These flows mostly consist of solid materials, and they are called debris avalanches.

2.7. Case Study

In this study, data of three basins (the Kasilian basin in Mazandaran Province, the Navrood basin in Gilan Province, and the Amameh basin in Tehran Province) in Iran were employed for the

examination of the proposed hybrid model. Since the intensive rainfall often happens in the study areas, these areas are more prone to flash floods, especially debris floods. Figure 3 shows the location of the hydrometric and rain gauge stations in the basins, and Table 1 represents the information of the case study.

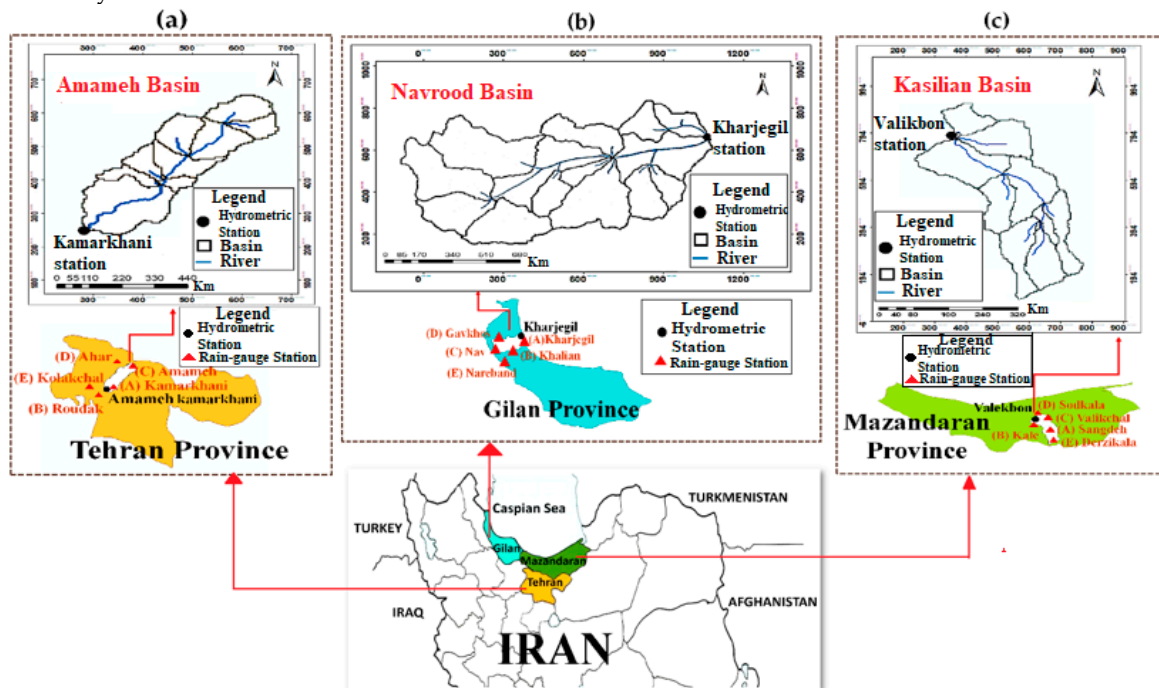


Figure 3. Location of the studied basins and the hydrometric rainfall stations in the basins (a) Amameh, (b) Navrood, and (c) Kasilian.

Table 1. The information of case study basins.

Basin	Area (km ²)	Average Length of Main Channel (km)	Mean Channel Slope (%)	Average Basin Elevation (m)	Average Lag Time (Minute)	Average Time of Concentration (Hour)
Navrood	265.23	32.5	5.1	1393.91	77.37	2.11
Kasilian	67.8	15.2	4.7	1569	95.36	2.6
Amameh	37.2	13.6	9.2	2650	81.6	2.25

2.8. Debris Flood Event Data Evaluation

To identify debris flood and the typical flood events in this research, we acquired the flow discharge (m³/s) and the sediment discharge (tons/day) from Iran Water Resources Management Organization for the basins in 1997–2016. The detail of the basins and the recorded floods can be found in Tables S1–S3 in Supplementary Materials. To determine the flood occurrence state, we calculated the sediment concentration according to Equation (11). If the dimensionless sediment concentration (the ratio of sediment volume q to flow volume q_w) exceeds from 0.02, it can be regarded as a debris flood [42].

$$C = \frac{q}{q_w} \tag{11}$$

On the basis of the recorded data, in this research, the minimum value of the volumetric sediment concentration for the debris flood is about 0.02 (dimensionless (cm³/cm³)), and the sediment concentration of the debris flood events varies from 0.02 to 0.041.

The criterion for diagnosing debris floods is based on performed experiments by Banihabib, Tanhapour and Roozbahani [27]. On the basis of these research results, the range of dimensionless sediment concentration of debris flows is 0.02–0.6 [26].

3. Results and Discussion

3.1. The Results of Sensitivity Analysis

The sensitivity analysis of HEC-HMS results for the variations of three factors (CN, and Muskingum coefficients X and K) are illustrated in Figure 4. According to Figure 4, it can be inferred that the flood peak flow is highly sensitive to the variation of CN. This signifies that the model is sensitive to this parameter. In other words, changing the values of the parameters (CN, K , and X), the variations range of the peak flow for the changing CN is more than K and X . This implies that the model is highly sensitive to the coefficient CN, but it is less sensitive to the X and K parameters. Moreover, according to the gradient of the X and K graphs in Figure 4, it can be concluded that parameter K is more effective than parameter X on the simulated floods by the HEC-HMS. As a result, regarding the sensitivity analysis performed on the parameters of HEC-HMS, the model is sensitive to CN, K and X . Thus, HEC-HMS was calibrated by changing CN, K , and X using the Nelder and Mead method. Generally, the sensitivity analysis of CN, K , and X parameters in the HEC-HMS model indicated that CN has the highest effect on the accuracy of the flood prediction, and K and then X follow in terms of rank. Previous studies also recommended that CN is one of the most effective factors in the simulation of flood flow [9,43,44].

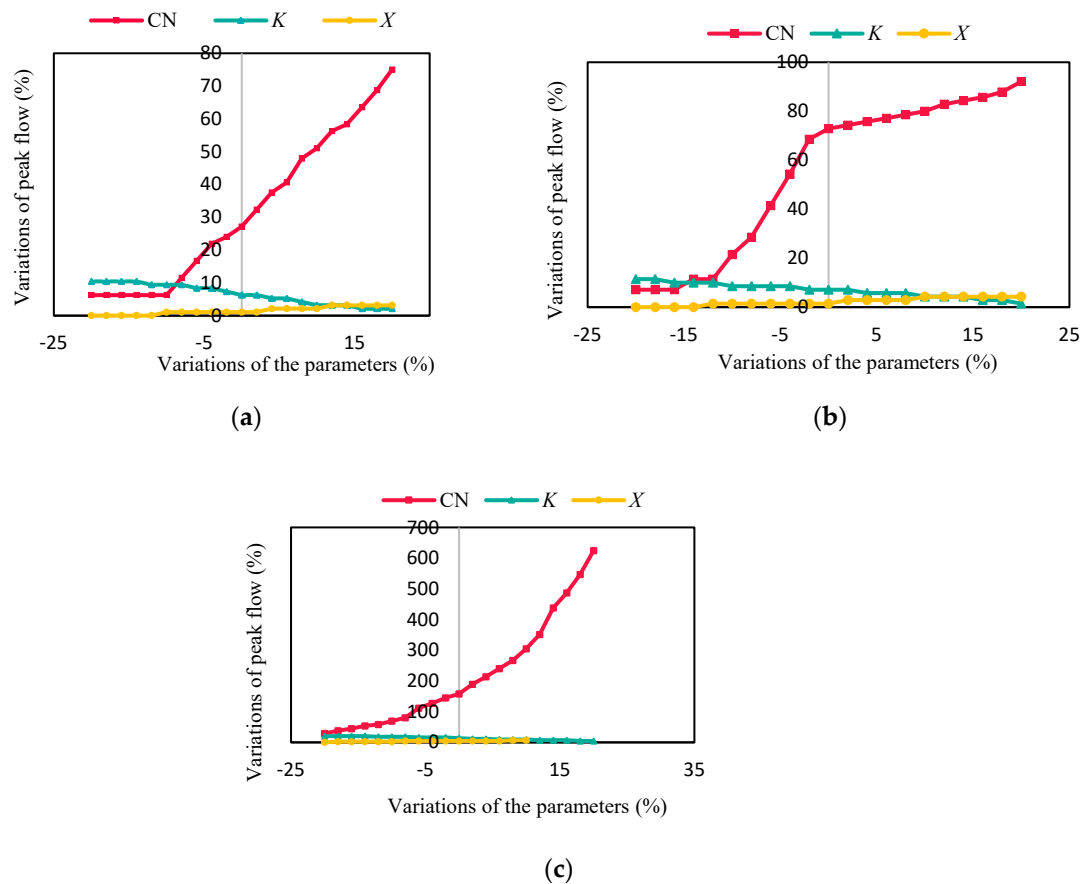


Figure 4. Sensitivity analysis of Hydrologic Engineering Center’s Hydrological Modelling System (HEC-HMS) model for variations of Curve Number (CN) and Muskingum coefficients (K and X) in (a) Navrood, (b) Kasilian, and (c) Amameh.

3.2. Calibration of HEC-HMS Parameters

Table 2 shows the average of CN, K , and X for the basins before and after the calibration. Before the calibration, we estimated CN from the weighting average of the CN values of land usage in the basins. The parameter K was estimated using Equation (3), and X was estimated using suggested

values in previous studies [21]. The observed and calibrated flood hydrographs for the basins are presented in Figure 5. According to this figure, the peak flow and time to peak flow in the predicted and the observed flood hydrographs have a robust agreement. As the difference of the peak flow of the observed and predicted hydrographs were generally less than 1%, the calibration results of the HEC-HMS model indicate that this model can present acceptable results for predicting the peak flow and time of the peak flow for the typical floods. Since this model cannot reflect the effect of the sediment concentration on the flood hydrograph of the debris floods, we only employed typical floods for the calibration of this model.

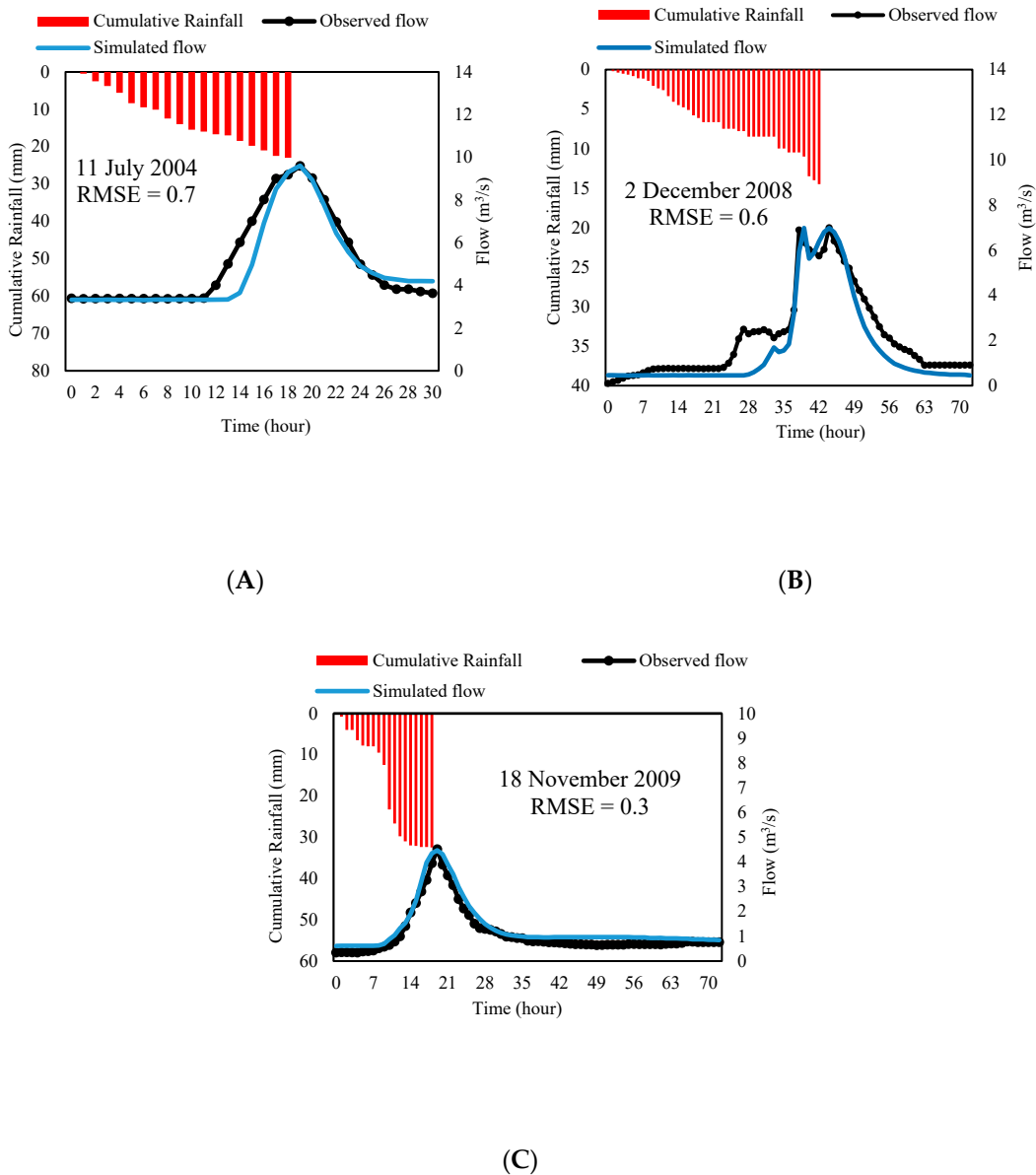


Figure 5. Observed and predicted typical flood hydrographs after the calibration of HEC-HMS in the basins (A) Navrood, (B) Kasilian, and (C) Amameh.

Table 2. The calibrated values of X, K, and CN.

Basin	Event	CN Average		X Average		K Average		MARE	RMSE
		Initial	Calibrated	Initial	Calibrated	Initial	Calibrated		
Navrood	11 July 2004	78.61	86.61	0.3	0.36	0.26	0.26	0.00	0.7
Kasilian	2 December 2008	79.5	92.53	0.3	0.35	0.48	0.38	0.00	0.6
Amameh	18 November 2009	82.69	60.00	0.4	0.3	0.39	0.5	0.00	0.3

3.3. Validation of HEC-HMS Model

After calibrating the model and obtaining the calibrated values for the model’s parameters, the validity of the model should be checked. Figure 6 shows the validated flood hydrographs for the typical floods and debris floods in the studied basins. The left side and the right side in this figure respectively demonstrate the typical flood hydrographs and the debris flood hydrographs. According to the left side of the figure, predicted typical flood hydrographs are in strong agreement with the observed flood hydrographs, indicating the validity of HEC-HMS for the prediction of typical floods. Furthermore, as shown in the figure, the peak flow of typical floods was estimated with high precision. Since the HEC-HMS model disregards the effect of sediment concentration in the predicted debris flood hydrographs, there is a difference between observed peak flows and predicted peak flow for debris floods. In other words, since the HEC-HMS model cannot reflect debris floods’ sediment concentration on the predicted floods, it predicts debris flood peak flows with relatively lower accuracy.

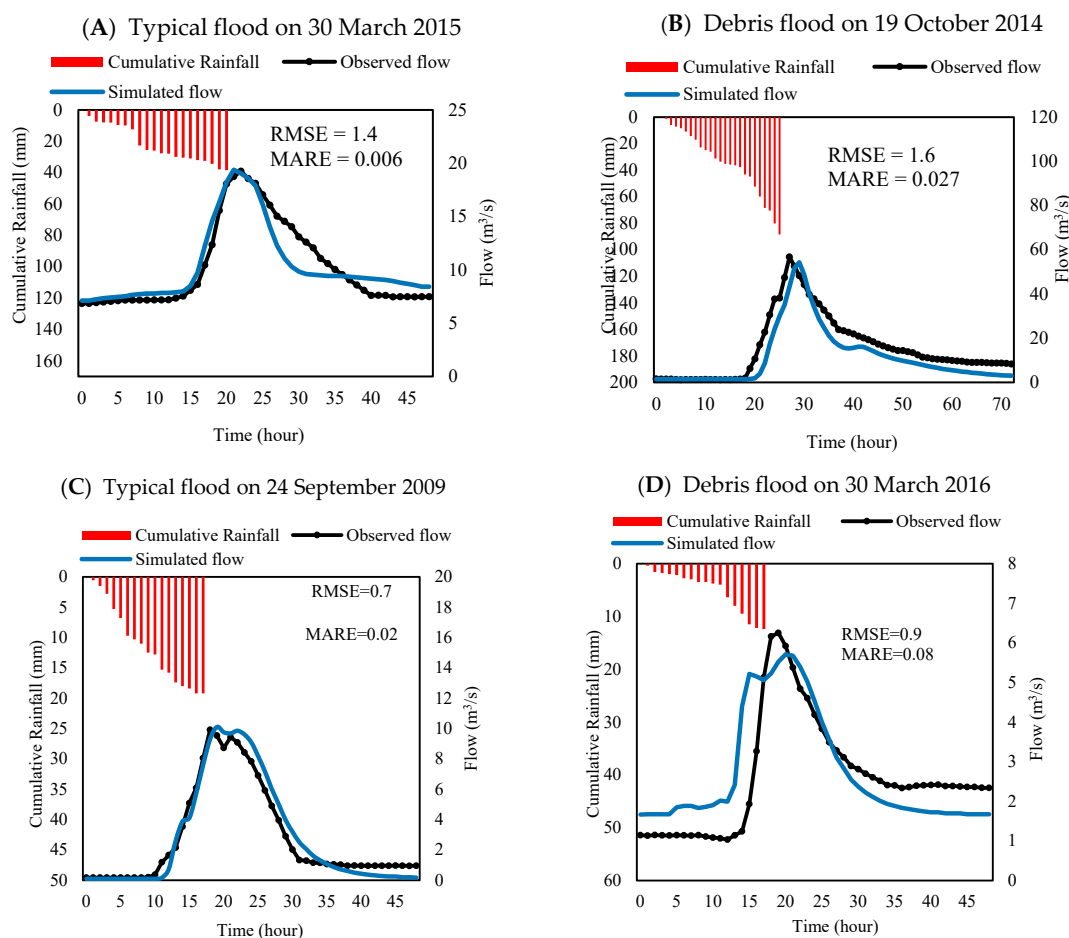


Figure 6. Cont.

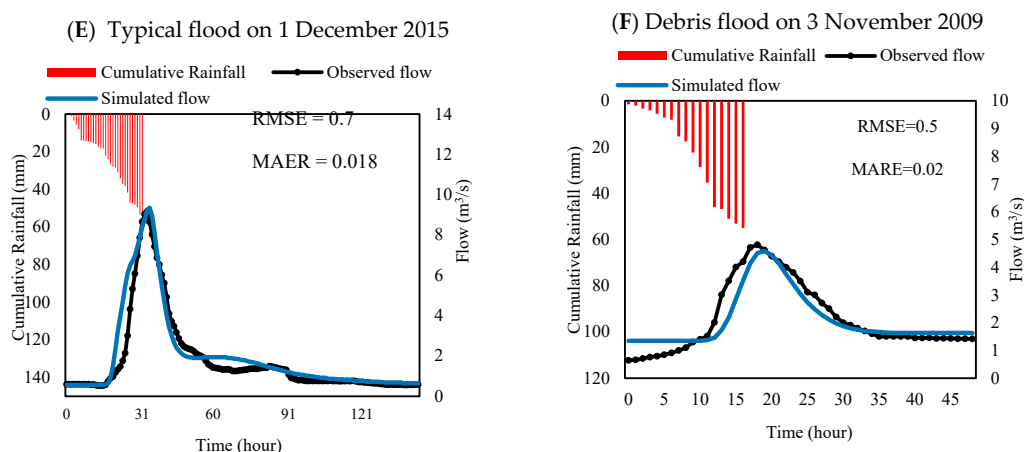


Figure 6. Observed and predicted hydrographs for the test stage: (A,B) for Navrood, (C,D) for Kasilian, and (E,F) for Amameh (data obtained from the HEC-HMS model).

In Figure 6, for the Kasilian basin (Figure 6C,D), it can be seen that rainfall of 15 mm produced debris flood in March, while rainfall of about 20 mm led to a typical flood in September. The rainfall duration was about 18 h in both cases. It is worthwhile to note that in addition to rainfall, sufficient sediment and previous moisture are essential for the occurrence of debris floods. The influence of antecedent rainfall is important for previous moisture and triggering debris floods. Sometimes in Iran, rainfall occurs for several consecutive days in the spring and supplies antecedent soil moisture. Thus, the occurrence of light rain produces debris flood the next day, which happened in the March flood. However, due to insufficient previous soil moisture, the bigger rainfall did not produce a debris flood in September.

Table 3 illustrates the average of MARE and RMSE for all flood events (33 flood events in the Navrood, Kasilian, and Amameh basins) in the test stage. According to this table, the average MARE for all predicted peak flows of the typical floods by HEC-HMS was estimated in Navrood, Kasilian, and Amameh basins as 0.024, 0.038, and 0.024, respectively, while the average MARE errors of the debris flood events, respectively, were 0.038, 0.074, and 0.040. Comparing the error indicators in two flood states, we found that the error indicators for the predicted debris floods were higher than the typical floods in the basins if HEC-HMS was used for the prediction of the debris floods. Similar outcomes can be derived through comparing the other indicators (RMSE), as shown in Table 3. Generally, it can be comprehended that the HEC-HMS model performs adequately in terms of predicting the typical floods, but it simulates the debris floods with some errors. Applying the effect of sediment concentration in the prediction of the debris floods it is not quite suitable for this model capability. Therefore, neglecting the effect of the sediment concentration on the flood flow leads to an error in the estimation of the peak flow of the debris floods, and the peak flow was estimated less than its actual value. Since the prediction of the sediment concentration of the debris flood is essential to determine the peak flow of these floods [13], in the next step, we applied the artificial intelligence models to predict the sediment concentration of the debris floods.

Table 3. HEC-HMS model error indicator for all typical and the debris floods in the studied basins in the test stage.

Basin	Flood Type	Number of Events	Average MARE	Average RMSE (m ³ /s)
Navrood	ordinary	7	0.024	1.74
	debris	5	0.038	2.04
Kasilian	ordinary	7	0.038	0.714
	debris	4	0.073	0.8
Amameh	ordinary	6	0.024	0.466
	debris	4	0.040	0.575

3.4. BN and SVR-PSO Models

The R^2 , RMSE, and MARE evaluation indicators for the BN and SVR-PSO models are given in Table 4. The MARE for BN and SVR-PSO models in the training stage were 0.072% and 0.126%, respectively. The BN model MARE was about 5.44% lower than the SVR-PSO model MARE. The determination coefficient and the RMSE for both models were almost similar. The test stage results were similar to the training stage, and the MARE in the test stage for the BN model was about 5.83% less than the ones for the SVR-PSO model. Thus, The BN model performed slightly superior to the SVR-PSO model in both the training and the test stages in terms of predicting the sediment concentration of floods.

Table 4. Comparison of artificial intelligence model results for forecasting sediment concentration in training and test stages.

Model	Test			Train		
	R^2	RMSE	MARE	R^2	RMSE	MARE
BN	0.973	0.001	0.085	0.984	0.001	0.072
SVR-PSO	0.964	0.003	0.143	0.98	0.002	0.126

3.5. Prediction of Debris Flood Peak Flows by Proposed Hybrid Model

The HEC-HMS model predicts the peak flow of the typical floods with considerable precision, while it predicts debris floods slightly inaccurately. Debris floods contain a large amount of sediments, and the sediment concentration increases the peak flow of the debris floods considerably [45]. The HEC-HMS model's performance diminishes for estimating the peak flow of debris floods due to its inability to reflect the sediment concentration on the predicted debris floods. Thus, in this research, we predicted the debris flood peak flows using the proposed hybrid model, which combines the results of predicted flood hydrographs using the HEC-HMS model and the sediment concentration by the proposed artificial intelligence models. To examine the results of the hybrid model, we employed MARE to compare the predicted peak flow of the debris floods and the observed peak flows.

The comparison of the results presented in Table 5 shows that BN and the SVR-PSO models have a respectable performance for predicting the sediment concentration and thus the estimation of the debris flood peak flows by both the HMS-BN hybrid model (HEC-HMS-BN) and the HMS-SVR-PSO hybrid model (HEC-HMS-SVRPSO), performing more accurately than the HEC-HMS. According to Table 5, the average MARE for all predicted debris-flood events was found to be 0.013 for the HMS-BN hybrid model and 0.014 for the HMS-SVR-PSO hybrid model. This showed a slightly better performance of the HMS-BN hybrid model than the HMS-SVR-PSO hybrid model for predicting the debris floods. The average MARE by the HEC-HMS model was estimated at 0.041 for all flood events. Therefore, using the hybrid models of this study, the error decreased by about one-third. Consequently, considering these results, we introduced the HMS-BN hybrid model as the superior hybrid model for predicting the debris floods. Therefore, the proposed HMS-BN hybrid model can be employed and examined for predicting and warning against debris floods in other similar basins as it improves the limitations of the traditional hydrological model (HEC-HMS) for predicting debris floods.

Table 5. Prediction of debris flood peak flows with the proposed hybrid model.

Basin	Event Date	Observed Peak Flow (m ³ /s)	Observed Time of Peak Flow (hr)	HEC-HMS			HMS-BN Hybrid Model		HMS-SVR-PSO Hybrid Model		
				Predicted Time of Peak Flow (hr)	MARE	Predicted Peak Flow (m ³ /s)	MARE	Predicted Peak Flow (m ³ /s)	MARE	Predicted Peak Flow (m ³ /s)	MARE
Amameh	14 April 2012	4.6	8	8	0.00	4.5	0.021	4.64	0.011	4.66	0.013
Navrood	26 August 2015	5.1	2	3	0.5	4.9	0.039	5.05	0.006	5.11	0.003
Navrood	17 September 2015	11.1	14	14	0.00	10.8	0.027	11.16	0.006	11.21	0.009
Kasilian	30 March 2016	6.2	19	20	0.052	5.7	0.08	6	0.032	6	0.032
Average					0.138		0.042		0.013		0.014

4. Conclusions

In this study, we developed and examined hybrid models that use proposed BN and SVR-PSO models to overcome the flaws of the HEC-HMS hydrological model in terms of simulation of debris floods. Briefly, the key outcomes of the present study are as follows:

A calibrated HEC-HMS model has a high capability for predicting typical flood peak flows. This result was previously certified by researchers [12,46,47]. However, the HEC-HMS model is not capable of predicting debris floods since it does not reflect the effect of the sediment concentration on the predicted debris floods. Thus, we improved it by hybridization with artificial intelligence models.

Developing the hybrid models using proposed BN and SVR-PSO models considerably promotes the model efficiency for predicting debris floods by decreasing the error index to one-third. Since the sediment concentration in the tested debris floods was not very high, and they should thus be referred to as light debris floods, the impact of sediment concentration of increasing peak flows was 3–5%. In this study, the results indicated that the debris flood peak flows were predicted with relatively low accuracy by using the HEC-HMS model, and the prediction accuracy was improved by the proposed framework (see Figure 6). However, it is recommended that more events with higher sediment concentrations should be examined in future research by the proposed model of this study. For this purpose, researchers should monitor future floods to obtain data from rare heavy debris floods around the world. Sediment concentration was not high for the debris floods of this study. Thus, they can be referred to light debris floods. It is suggested that a classification be performed for debris floods on the basis of sediment concentration.

The proposed HMS-BN model performs slightly better than HMS-SVR-PSO, and thus this hybrid model is proposed for further examination in the similar basins to predict the debris floods.

Generally, the results of this study imply that the proposed hybrid model can be employed to predict debris flood peak flows in the flood warning system for similar basins where both typical and debris floods prevail. We used physiographic, hydrologic, geometric, and land use data for the proposed hybrid model. If forecasted meteorological rainfall is used, the proposed hybrid model can be exerted for flood warning.

Supplementary Materials: The following are available online at <http://www.mdpi.com/2073-4441/12/8/2246/s1>, Table S1: The information of case study basins, Table S2: The information of Subbasin, Table S3: The information of floods occurrence.

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