Local and Global Bayesian Network based Model for Flood Prediction

Yirui Wu†, Weigang Xu†, Jun Feng†*, Shivakumara Palaiahnakote§, and Tong Lu‡
†College of Computer and Information, Hohai University, Nanjing, China
‡National Key Lab for Novel Software Technology, Nanjing University, Nanjing, China
§Faculty of Computer Science and Information Technology, University of Malaya, Kuala Lumpur, Malaysia
{wuyirui@hhu.edu.cn;wei_gangxuu@163.com;fengjun@hhu.edu.cn;shiva@um.edu.my;lutong@nju.edu.cn}

***Abstract*—To minimize the negative impacts brought by floods, researchers from pattern recognition community pay special attention to the problem of flood prediction by involving technologies of machine learning. In this paper, we propose to construct hierarchical Bayesian network to predict floods for small rivers, which appropriately embed hydrology expert knowledge for high rationality and robustness. We present the construction of the hierarchical Bayesian network in two stages comprising local and global network construction. During the local network construction, we firstly divide the river watershed into small local regions. Following the idea of a famous hydrology model - the Xinanjiang model, we establish the entities and connections of the local Bayesian network to represent the variables and physical processes of the Xinanjiang model, respectively. During the global network construction, intermediate variables for local regions, computed by the local Bayesian network, are coupled to offer an estimation for time-varying values of flow rate by proper inferences of the global network. At last, we propose to improve the output of Bayesian network by utilizing former flow rate values. We demonstrate the accuracy and robustness of the proposed method by conducting experiments on a collected dataset with several comparative methods.**

I. Introduction

As one of the most common and largely distributed natural diasters, flood happens and brings damage. If we could accurately forecast flood by predicting its time-varying flow rate values in advance, hundreds of lives and quantity of property could be saved.

In the past decade, researchers from pattern recognition and hydrology community have proposed a variety of methods to construct accurate, robust and reasonable flood prediction models. We generally category them into two types, namely hydrology model [1], [2], [3] and data-driven model [4], [5], [6]. The methods in the first group solve highly non-linear systems, which describe the complex hydrology processes from clues to results by functions. However, such methods are extremely sensitive to parameters [7]. These parameters require to be different from one river to the another for good performance, while setting theses parameters requires special research effort on quantity of historical hydrology data when using hydrology model. The problem of sensitive parameters could be more obvious when predicting floods for small rivers, since small rivers are lack of special research as well as exhaustive hydrology data. The methods in the second group usually estimate the river flow rate based on historical time series observation, *i.e.* former rainfall and river runoff, by machine learning methods. Most of the data-driven models ignore the detailed hydrology processes. However, floods are complicated natural phenomena affected by multiple factors. It's hard to guarantee the rationality and robustness by utilizing such data-driven methods without considering hydrology processes.

In this paper, we pay special attention to the problem of flood prediction for small rivers, whose catchments are smaller than 3000 kilometers. Flood prediction of small rivers is more complicated than prediction of large rivers, due to the shortage of historical hydrology data and the varieties in geographical and spatial-temporal features. To solve such problem, we propose to predict floods for small rivers by constructing a hierarchical Bayesian network with hydrology processes embedded for high rationality and robustness. Our key idea stems from the thought that we should properly utilize the strength of hydrology model to improve the accuracy, robustness and rationality of data-driven model. The hydrology expert knowledge behind the hydrology model could relieve the requirement for large amount of data, which coincides with the purpose of predicting floods for small rivers. Essentially, the proposed method designs the structure of hierarchical Bayesian network, whose entities and connections correspond to the factors and processes extracted from a hydrology model, i.e. the XAJ model (short for the Xinanjiang model) [3], [8].

The main contribution of the paper is to propose a hierarchal Bayesian network for flood prediction of small rivers, which embeds hydrology process extracted from the XAJ model to improve the accuracy, robustness and rationality. Involving prior and expert knowledge extracted from hydrology model, the prediction uncertainty of the proposed method could be largely reduced for high robustness and robustness. Meanwhile, the size for training dataset could be reduced to meet the requirement of predicting floods for small rivers. Moreover, the hierarchal structure is proposed to handle the geo-spatial characteristics of the inputting data in a proper way.

II. Related Work

Considering the relevance to the proposed method, we detailly describe the XAJ model and data-driven model in this section.

The XAJ Model. Floods could be represented as processes, in which the spatial and temporal distribution of the rainfall generally rules the flood waves formation [9]. The XAJ model not only considers the rains and runoffs, but also take other hydrology processes into account, such as evaporation from water bodies and surface, rain infiltrated and stored by the soil, and so on. Specifically, the runoff for a river is calculated by the following four modules in the XAJ model. Note that modules a, b, c are processes in local regions, while module d represents the routing process in a global sense.

(a) Evaporation module: The actual evaporation of the local region is computed based on the potential evaporation and the soil tension water capability in three layers, i.e., upper, lower and deep soil layers, where the tension water refers to soil water storage capability in relation with drought.

(b) Runoff generation module: The local runoff is generated according to the rainfall, evaporation and soil tension water capability. The XAJ model implies that runoff is not produced until the soil water content of the local region reaches its field capacity, and thereafter the excess rainfall becomes the runoff without further loss.

(c) Runoff separation module: The generated local runoff is subdivided into three components, including surface runoff, interflow runoff and groundwater runoff.

(d) Runoff routing module:The outflow from each sub-catchment is finally routed by the Muskingum successive-reaches model [3] to produce the outlet flow of the whole catchment.

Although some insensitive parameters of the XAJ model can be preset by experience, the sensitive parameters must be calibrated based on quantities of historical streamflow data using either a trial-and-error approach or an automatic optimization algorithm. This makes it difficult to apply the XAJ model on small rivers to achieve accuracy predicting results, due to the shortage of historical data.

Data-driven Model. From the viewpoint of a decision maker who should make a rational flood decision based on the information provided by a data-driven model, the prediction associated with the estimation of predicting uncertainty could provide more valuable information. The operational flood predicting system thus need provide convinced probability distribution instead of a single value of estimate. Researchers from the pattern recognition community have proposed a quantity of methods to involve uncertainty into predictions for enhancements of reliability and credibility, including Bayesian-based methods [4], [11], [12], Neural Network [9], deep learning methods [5], [6], [13] and so on.

Early, Krzysztofowicz *et al.* [11] introduce a Bayesian predicting system, which interprets the basic principles of Bayesian predictive inference and constructs numerical examples to show the quantification and integration of the uncertainties. With their introduction, utilizing the Bayesian theory for flood predicting has become possible and practical. Reggiani *et al.* [12] construct a modified Bayesian predicting system by involving numerical weather information to address the spatial-temporal variabilities of precipitation during prediction. Later, cheng *et al.* [14] perform accurate daily runoff forecasting by proposing an artificial neural network based on quantum-behaved particle swarm optimization, which trains the ANN parameters in an alternative way and achieves much better forecast accuracy than the basic ANN model.

(a)

Station Name	Catchment Area (km^2)
Changhua(CH)	20.8
Longmengsi(LMS)	120.4
Taohuacun(THC)	133.0
Shuangshi(SS)	96.8
Daoshiwu(DSW)	256.1
Lingxia(LX)	116.7
Yulingguan(YLG)	161.2
Total	905.0

(b)

Fig. 1. Information about the Changhua watershed, where (a) is the map for various kinds of stations and (b) represents catchment area corresponding to the listed rainfall stations. Note that Station CH is not only a rainfall station, but also a river gauging station whose river flow needs to be predicted. The station SS is a rainfall station and evaporation station.

Deep learning architectures have demonstrated the incredible power to solve different kinds of problems, such as object detection [15], text detection [16], action recognition [17] and so on. Due to high potentials of discovering effective features from data, many researchers thus utilize deep learning architectures for flood prediction. For example, Bai *et al.* [13] propose a multi-scale deep feature learning method with hybrid models to deal with the daily reservoir inflow forecasting. In their hybrid model, ensemble empirical mode decomposition and Fourier spectrum are first employed to extract multi-scale features and then represented by three deep belief networks (DBNs) respectively. Zhuang *et al.* [5] design a novel Spatio-Temporal Convolutional Neural Network (ST-CNN) to fully utilize the spatial and temporal information and automatically learn underlying patterns from data for extreme flood cluster prediction. Liu *et al.* [6] proposes a deep learning approach by integrating stacked auto-encoders (SAE) and back propagation neural networks (BPNN) for the prediction of stream flow, which simultaneously takes advantages of the powerful feature representation capability of SAE and superior predicting capacity of BPNN. However, the above deep learning methods need to be trained on large datasets and they simply use hydrology information as constraints and ignore the hydrology processes. Without the prior knowledge and reasonable inference extracted from hydrology processes, they can't predict floods successfully for small rivers.

III. The Proposed Method

Take a typical small river, i. e. Changhua river for example, we illuminate the steps to predict hourly flood runoffs using the proposed hierarchy Bayesian network. The general information about Changhua watershed is shown in Fig. 1, in which we can see 7 rainfall stations, 1 evaporation station and 1 river gauging station. In general, we aim to predict the

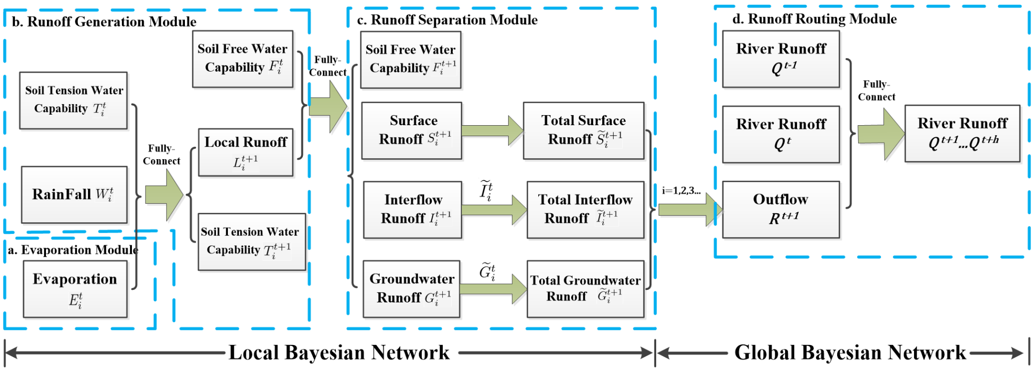

Fig. 2. The illumination of the proposed hierarchy Bayesian network. Note that step **a**, **b**, **c** and **d** refer to the specific module extracted from a hydrology model, i.e. the XAJ model.

runoff at the river gauging station CH for next few hours by utilizing various flood factors, including rainfalls observed at the rainfall stations, evaporation observed at the evaporation station SS and former river runoff observed at CH.

Considering the collected flood factors has sparse geo-spatial and spatial-temporal attributes, we design the proposed hierarchical Bayesian structure with Local and Global Bayesian network as shown in Fig. 2. Note that we embed the prior knowledge by designing such hierarchical structure, which corresponds to the hydrology process of the XAJ model described in the last section. During the **Local Bayesian Network** stage, we aim to predict the runoff contribution values in the local regions. We firstly divide the total river watershed into small local regions based on hydrology principles [18] and the locations of rainfall stations. The split results of local regions are represented in Fig. 1 (b). We then collect multiple kinds of inputs in each local region, *i. e.* soil moisture T_i^t, rainfall W_i^t and evaporation E_i^t by interpolation based on observed flood factors, where i refers to the index of local region. Recall that the calculation of soil moisture T_i^t is illuminated in the last section. Next, we follow the first three modules of the XAJ model as discussed in the last section, in order to embed the expert knowledge about hydrology processes into the construction of the local Bayesian network. Finally, the trained local Bayesian network could compute several hydrology intermediate variables, such as surface runoff $\widetilde{S}_i^{t+1}$, interflow runoff $\widetilde{I}_i^{t+1}$ and groundwater runoff $\widetilde{G}_i^{t+1}$. In the **Global Bayesian Network** stage, we utilize the last module of the XAJ model to construct the global Bayesian network, which predicts the river runoff for the next$h$ hours $\{Q^t, ..., Q^{t+h}\}$ based on the output of the local Bayesian network.

A. Local Bayesian Network

In this subsection, we firstly introduce the theory foundation and novelty by modeling hydrology processes with Bayesian Network for flood predicting problem. After that, we will describe the construction of local Baysian network in detail.

Given data D, Bayesian theory can be used to determine the posterior distribution of θ as follows:

$$P(\theta|D) = \frac{L(D|\theta)P(\theta)}{P(D)} \tag{1}$$

where $L(D|\theta)$ is the likelihood function and $P(\theta)$ is the prior distribution of random variable θ. Note that the denominator of Eq. 1 is a constant related only to the data set. During the calculation of the posterior distribution $P(\theta|D)$, the most important part is the choice of the prior distribution $P(\theta)$. Selecting the prior distribution $P(\theta)$ requires considering both the measured data and available prior knowledge. A prior distribution obtained from the existing data and research results is called data-based prior distribution, while non-data-based prior distribution refers to a prior distribution resulted from subjective judgments or theory.

Following the conception of Bayesian theory, we propose to conclude the river runoff by construction proper prior distribution and analyzing the likelihood between test data and train data. Specifically, we achieve the prior distribution by first extracting hydrology processes from the XAJ model as non-data-based prior distribution and then extracting the data-based prior distribution from the historic observation data. By considering prior expert hydrology knowledge from the predefined hydrology model - the XAJ model and the historic observation data, we believe the proposed method could couple the strength of hydrology model and data-driven methods to improve the accuracy, robustness and rationality. Moreover, the introduce of non-data-based prior knowledge could relieve the requirement for large amount of data.

Bayesian Network offers an appropriate structure to joint learn the posterior distribution with the prior knowledge. Essentially, it expresses the conditional dependence structure between variables by Directed Acyclic Graph (DAG). It's noted that each attribute represented by a node of the DAG graph is independent with his non-children attributes under the definition of the Bayesian Network. Specifically, the proposed method considers the given observation data D is formed by a set of hydrology attributes $\{X_i|i = 1...n\}$ and the predicted run-off value is a node of the Bayesian network, which could be further represented as an attribute X_0. Therefore, we could write down the joint distribution of $\{X_i|i = 0...n\}$ as

$$P(X_0, X_1, X_2, ..., X_n) = \prod_{i=0}^{n} P(X_i|\zeta(Parents(X_i))) \quad (2)$$

where function $Parents()$ and $\zeta()$ represents the sets of his directly precursor attributes and the corresponding joint distribution, respectively. Based on Eq. 2, we can easily get the conditional probabilities, i.e. posterior distribution, by the use of magrinalization [19]. Furthermore, we could simplify this problem to network-based dependency relations, which form a Conditional Probability Table (CPT) to describe probabilities between dependency attributes.

After explaining the theory and novelty of applying Bayesian network, we describe the construction of local Baysian network in detail. Considering the rainfall, soil moisture, evaporation and other input factors are spatial-sensitive distributions, hydrology models often divide river watershed into smaller catchments based on the locations of rainfall stations. We follow this idea and utilize a hydrology-related division algorithm [18] to construct small local regions. Taking the ith local region as an example, we present the structure of the corresponding local Bayesian network in Fig. 2. We can notice the local model adopt the potential evaporation, the rainfall W_i^t, the soil tension water capability T_i^t, the evaporation E_i^t and the soil free water capacity F_i^t as inputs. Among them, the potential evaporation and W_i^t are collected by rainfall stations, while T_i^t and F_i^t are pre-set values between a reasonable range and will iteratively be close to their real values during the training.

Followed by hydrology process extracted from the XAJ model, we firstly compute the evaporation E_i^t following the process of the evaporation module illuminated in the last section. Next, we calculate local runoff L_i^{t+1} by establishing the joint distribution among E_i^t, W_i^t and T_i^t. During this step, we not only utilizes the spirit of runoff generation module of the XAJ model, but also iteratively modifies T_i^t during learning, which results in a more convinced T_i^t. After that, we utilize the soil free water capacity F_i^t to divide the local runoff L_i^{t+1} into three components, i.e. surface runoff S_i^{t+1}, interflow runoff I_i^{t+1} and groundwater runoff G_i^{t+1}. This step follows the spirit of runoff separation module of the XAJ model. Finally, we involves these inputting variables to train learned distributions, which could compute the results of the divided components, i.e. the total surface runoff $\tilde{S}_i^{t+1}$, interflow runoff $\tilde{I}_i^{t+1}$ and groundwater runoff $\tilde{G}_i^{t+1}$. To sum up, we properly embed the hydrology process and variables into the local Bayesian Network and replace equations in the XAJ model with the learning structures.

B. Global Bayesian Network

In this subsection, we first describe the construction of the global Bayesian network and then offer several details for implementing the hierarchical Bayesian network.

The structure of the global Bayesian network is presented as the right part of Fig. 2, which adopts river runoff Q^{t-1}, Q^t in former times and the output of the local Bayesian network as input. We construct the global Bayesian network to achieve rough predicting results of river runoff in the next few hours $\{Q^t, ..., Q^{t+h}\}$. Note that the river runoff, like Q^{t-1} and Q^t, could only be measured by the river gauging station. We firstly convert inputting variables of different local regions, i.e. the total surface runoff $\tilde{S}_i^{t+1}$, interflow runoff $\tilde{I}_i^{t+1}$ and groundwater runoff $\tilde{G}_i^{t+1}$, into outflow R^{t+1} with the Muskingum successive-reaches method [3]. After that, we fully-connect the inputtings and outputs of predicting variables to learn the joint distribution.

During training, we use loopy belief propagation to estimate the parameters of conditional probability table. Due to the loopy structure of the network, it is difficult to check for the convergence and we adopt the following trick: training is terminated when 10 iterations of gradient decent go not yield averagely improved likelihood over the previous 10. Moreover, we discretizate the inputting variables of Bayesian network for better generality. Recall the fact for the hydrology model that the accuracy of the predicting is highly related with its parameters, such as soil tension water T_i^t and soil Free water F_i^t. However, the parameters of conditional probability table corresponding to the proposed Bayesian network could be modified iteratively to tend for their real values during learning.

C. Bayesian Network for Flood Prediction

In this section, we develop a novel method by utilizing the error of former predictions and observations to help hourly flood prediction. Specifically, when intending to predict the runoff for k hours later, we should utilize the former predicting runoff values and observed runoff values of former ρ hours to help forecast.

To utilize such information, we firstly define predicting confidence $\alpha(a, b)$ as the confidence weight for the predicting runoff at time b based on the predicting and observed data starting from time a, which could be expressed as:

$$\alpha(a, b) = \frac{1}{b - a - 1} \sum_{k=a+1}^{b-1} \frac{P(a, k) - R(k)}{R(k)}, where\ a < b \quad (3)$$

where $P(a, k)$ represent the predicted run-off values for time k when predicting at time a, and $R(k)$ represent the observed run-off values at time k. It's noted $\alpha(a, b)$ adopts the relative errors between the observed and predicting data as weight. Then, a time-related weight $\gamma(a, b)$ is defined to express weight for predicting at different time during former ρ hours:

$$\gamma(a, b) = 1 - \xi(b - a + 1) \quad (4)$$

where ξ is a preset time-related forgetting factor. Finally, we could improve the predicted runoff value a achieved in last section as

$$\delta(a, b) = \frac{\tau P(a, b) + \sum_{k=a-\rho+1}^{b-1} \alpha(k, b)\gamma(k, b)P(k, b)}{\tau P(a, b) + \sum_{k=a-\rho+1}^{b-1} \alpha(k, b)\gamma(k, b)} \quad (5)$$

where τ is a preset constant value.

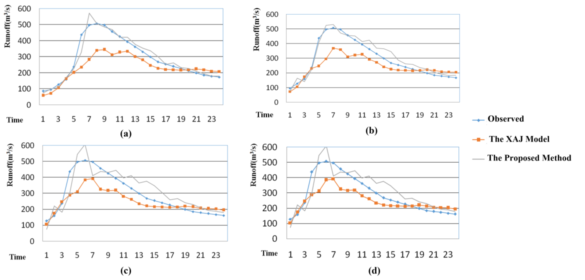

Fig. 3. Comparison with the ground truth runoff and predicted runoff computed by the XAJ model, where the predicting time of (a), (b), (c) and (d) are predicting in one hour, two hours, three hours and four hours, respectively.

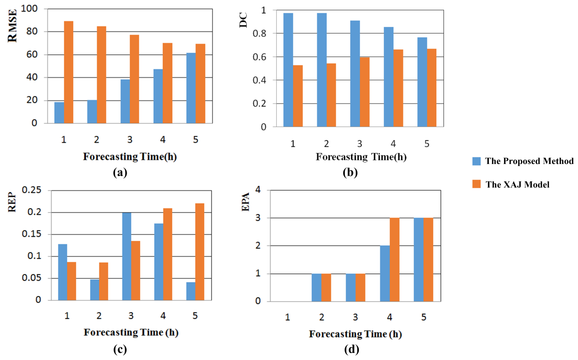

Fig. 4. Comparison with the predicted runoff of the XAJ model on Changhua dataset evaluated by different measurements, where (a), (b), (c) and (d) represent values of RMSE, DC, REP and EPA, respectively.

IV. Experiments

A. Dataset and Evaluation

We collect hourly data of 40 floods happened from 1998 to 2010 in Changhua river and utilize 8-folder cross validation to evaluate our proposed method. We use standard quality measures such as Root Mean Square Error (RMSE), Deterministic Coefficient (DC), Relative Error of the Flood Peak (REP) and Error of the Flood Peak Appearance (EPA) for measuring the quality of flood predicting given by the proposed method. Note that the latter two measurements are specially designed for flood predicting by emphasizing the appearance time and values of flood peak, which often brings most serious damage to persons and property. These four measurements could be represented as $RMSE = \sqrt{\frac{1}{n}\sum_{j=1}^{n}(y_j - q_j)^2}$,$DC = 1 - \frac{\sum_{j=1}^{n}(y_j - q_j)^2}{\sum_{j=1}^{n}(y_j - \bar{q})^2}$, $REP = \frac{1}{n}\sum_{j=1}^{n}\frac{|p_j - r_j|}{r_j} \times 100\%$ and $EPA = \frac{1}{n}\sum_{j=1}^{n}|d_j - s_j|$ where n refers to the size of dataset, y_j and q_j represent the predicted and observed runoff value respectively, $\bar{q}$ refers to the mean value of the observed runoff during one flood, p_j and r_j represent the predicted and observed flood peak value respectively, d_j and s_j represent the predicted and observed flood peak appearance time respectively. Note that larger DC value implies more convinced the predict is, while smaller values of RMSE, REP and EPA imply better performance the predicting achieves.

B. Experiments on Flood Prediction

We learn the parameters of the hierarchal Bayesian network with Maximum Likelihood Method and do experiments on a PC with Core i7 CPU (3.6GHz) and 16GB RAM. Due to the complicated structure of the proposed Bayesian network, the training process on Changhua dataset costs 10128s in total. Once the parameters of conditional probability table are determined, the average testing time for a sequence of flow rate values is only 0.00693s. We firstly compare the prediction results of the proposed method with the results computed by a hydrology model - the XAJ model. Fig. 3 represents the comparison of the predicted runoff in different predicting time, while Fig. 4 represents the comparison over the Changhua dataset with different measurements. From Fig. 3, the hydrology model fails to predict flood peak values from 5th to 15th hour due to its sensitive parameters and lack of data. Since decision makers mainly concern the predicted runoff values during flood peak under the consideration of its terrible damage, the hydrology model is not suitable and operable to predict floods of small rivers. On the contrary, the proposed method achieves nearly the same predicted runoff as the ground truth runoff for 1 and 2 hours prediction, and slightly different predicted runoff with the ground truth values for 3 and 4 hours prediction during flood peak period. This proves the efficiency and robustness of the proposed method when predicting flood peak values for small rivers. In Fig. 4, the proposed method achieves much better results in RMSE, DC, REP and slightly better result than the hydrology model in EPA, which proves the proposed method is more suitable than the hydrology model to predict floods of small rivers. The proposed method achieves a slightly decreasing performance in RMSE and DC with large predicting time, which proves the robustness of the proposed method by embedding hydrology model. The discontinuous REP performance of the proposed method is mainly caused by the small dataset.

Table. 1 gives the detailed statistics of the proposed method and other data-driven based methods for the Changhua dataset. It's noted the predicting time is settled to 4 hours for all methods. Among these comparative methods, the cores of Han et. al [20], Dawson et. al [21], Chang et. al [22] and Lima et. al [23] are SVM, Neural Network, Radical Basis Function Network and Extreme Learning Machine, respectively. All these machine learning structures are popular to predict floods in pattern recognition community. We implement these algorithms according to the instructions given in their papers. From Table. 1, we could see the proposed method achieves the best performance in RMSE, REP and EPA, and the second best performance in DC. The small values of REP and EPA achieved by the proposed method imply our method is more proper to predict the appearance time and runoff values of flood peaks. This is because the embedded hydrology processes and variables increase prior knowledge to predict flood peaks, while other machine learning structures are short of such prior knowledge. The proposed method achieves the

TABLE I
PERFORMANCE COMPARISON WITH COMPARATIVE DATA-DRIVEN METHODS ON CHANGHUA DATASET.

Methods	DC	RMSE	REP	EPA
Han et. al [20]	0.777	166.38	3.92	0.313
Dawson et. al [21]	0.745	164.99	4.10	0.19
Chang et. al [22]	**0.806**	152.57	4.23	0.263
Lima et. al [23]	0.701	155.35	4.19	0.19
The Proposed	0.785	**149.55**	**2.96**	**0.176**

smallest RMSE value, which proves the proposed method is more appropriate to predict floods in small rivers than other structures. The second best DC value obtained by the proposed method implies our method could quantify uncertainty to a certain extent, while Chang et. al [22] is better at quantifying uncertainty by introducing uncertainty as a main factor in their method. To sum up, coupling the strength of the data-driven and hydrology methods helps predict floods of small rivers.

V. CONCLUSIONS

In this paper, we propose a novel and effective method to predict floods of small rivers, which constructs a hierarchical Bayesian network with hydrology processes embedded for higher rationality and robustness. We establish a hierarchal Bayesian network, whose entities and connections describes factors and processes extracted from the XAJ model. Experiment results on the Changhua dataset show the proposed method outperforms the XAJ model and several data-driven flood prediction methods. Our future work includes the exploration on other hydrology purposes with the proposed method, such as mid-term flood predicting.

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