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Incorporating non-uniformity and non-linearity of hydrologic and catchment characteristics in rainfall–runoff modeling using conceptual, data-driven, and hybrid techniques

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ABSTRACT

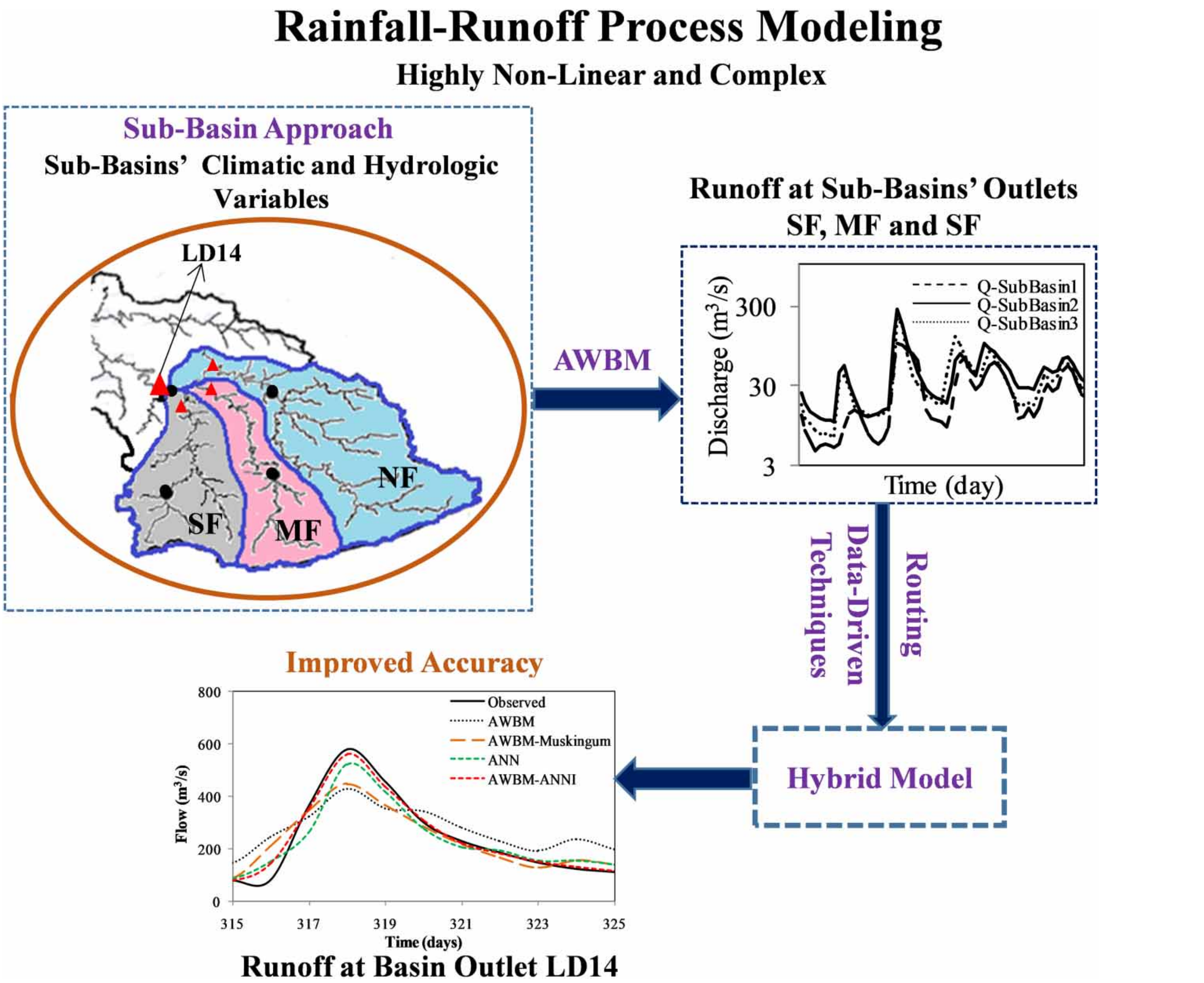
The rainfall–runoff (RR) process in a catchment is non-uniform, complex, dynamic, and non-linear in nature. Although a number of advanced conceptual and data-driven techniques have been proposed in the past, the accurate estimation of daily runoff still remains a challenging task. A majority of conceptual models proposed so far suffer from the assumptions of linearity during their modeling. In this paper, novel hybrid approaches are proposed that are capable of exploiting the strength of both conceptual and data-driven techniques in RR modeling. A conceptual technique is first used to generate sub-basins' runoff hydrographs in upstream reaches and then data-driven techniques are employed for routing them to the outlet of the catchment. The hybrid models' performances are compared with standalone conceptual and data-driven models by employing the daily rainfall, runoff, and temperature data derived from the Kentucky River basin, USA. The results show that the proposed hybrid models, which do not assume the RR process to be a linear process to simulate the flow, outperform their individual counterparts. It is concluded that in order to achieve improved accuracy in RR modeling, the real-life process needs to be represented as accurately as possible in the modeling effort rather than making simplified assumptions.

Key words: artificial neural network, conceptual modeling, hybrid modeling, hydrology, rainfall–runoff process, routing

HIGHLIGHTS

- Novel hybrid approaches are proposed to model the non-linear, complex, and dynamic rainfall–runoff process in a larger catchment.
- Spatial variations in hydrologic and catchment characteristics are modeled using a conceptual approach.
- Non-linearity and complexity in the rainfall–runoff process are modeled using data-driven techniques.
- Two conceptual and one data-driven models are developed for comparison purposes.

GRAPHICAL ABSTRACT



1. INTRODUCTION

The rainfall–runoff (RR) process is one of the most complex, dynamic, and highly non-linear hydrological phenomena which is affected by many temporal and spatial variations of the catchment, geo-morphological, and climatic characteristics (Beven 2000) and is often inter-related. The influence of these factors and many of their combinations in generating runoff is an extremely complex physical process and is not understood clearly (Zhang & Govindaraju 2000). The modeling of the RR process has been the subject of research among hydrologists and engineers for a very long time as it is an integral component in most water resource management projects (Reed *et al.* 2004; Moretti & Montanari 2007; Moradkhani & Sorooshian 2009; Dorum *et al.* 2010; Barati *et al.* 2012; Wolfs *et al.* 2015). Various modeling techniques have been used to model the RR process in the past that can be broadly classified into two categories: the theory-driven approach includes conceptual and physics-based techniques, and the data-driven approach includes empirical and black-box techniques (Solomatine & Dulal 2003). The conceptual approach is the best-explored technique in the early stage of modeling the RR process, which was first started by Mulvany (1850) called the rational method. Subsequently, a large number of daily conceptual streamflow simulation models were developed differing in complexity and sophistication. Some notable examples include Moisture Accounting and Routing (SMAR; O'Connell *et al.* 1970), SACRAMENTO model (Burnash *et al.* 1973), Système Hydrologique Europeén model (SHE; Abbott *et al.* 1986), the Institute of Hydrology Distributed Model (IHDM; Beven *et al.* 1987), Australian water balance model (AWBM; Boughton 1995), and SIMHYD model (Chiew *et al.* 2002). Due to the theoretical basis adopted in the development of conceptual models, it is expected that the conceptual models would be more realistic in terms of physical components and parameters in simulating the RR process. Although many of these models are simple and computationally efficient, there are many situations, where these models compromise their accuracy, and are affected by parameter uncertainties (Moradkhani & Sorooshian 2009; Zhang *et al.* 2016). Moreover, the conceptual RR models require a large amount of data and information on catchment for its calibration and validation (Grayson *et al.* 1992; Koycegiz & Buyukyildiz 2019). Due to these factors, researchers started to explore a new category of modeling technique called as data-driven models (DDMs). The DDMs in hydrological forecasting have received tremendous attention from researchers in the past decade (Jain & Kumar 2007; Solomatine *et al.* 2009; Bowden *et al.* 2012; Galelli *et al.* 2014; Nanda *et al.* 2016; Ahmadi *et al.* 2019; Sharghi *et al.* 2019; Vidyarthi & Chourasiya 2020; Vidyarthi *et al.* 2020; Hagen *et al.* 2021). These models develop relationships among input and output variables without considering the underlying physical process, which is why sometimes they are also labeled as black-box models (Vidyarthi & Jain 2020). DDMs learn the previously unknown relationships existing among the input and output data through a process of training, without a prior knowledge of the internal catchment characteristics, hence requiring less information on the catchment. As such, many researchers have employed DDMs in solving hydrologic problems (Solomatine *et al.* 2009; Maier *et al.* 2010). Many studies have demonstrated the superiority of DDMs in terms of accuracy over conventional methods for modeling the RR process (Solomatine & Ostfeld 2008; Talei *et al.* 2010; Rezaeianzadeh *et al.* 2013; Koycegiz & Buyukyildiz 2019; Lees *et al.* 2021). Despite having numerous advantages, the ANN approach is by no means a substitute for conceptual techniques (Hsu *et al.* 1995), and thereby, field practitioners show their reluctance to use artificial neural networks (ANNs) when it comes to an enhanced comprehensibility of the model (Sudheer & Jain 2009; Vidyarthi & Jain 2020).

The state of the art in the above two approaches suggests that the conceptual and data-driven techniques have their own benefits and it has been observed that the conceptual and DDMs outperform each other in certain conditions along with their limitations. Therefore, in order to overcome the drawbacks of both techniques, a hybrid modeling was first explored by Corzo *et al.* (2009). Later, few researchers have integrated the conceptual and data-driven techniques with the aim to improve the performance of the RR models by developing different kinds of hybrid models. Song *et al.* (2012) integrated the ANN technique with the Xinanjiang model and claimed that the results are promising for hourly event-based simulation. Mekonnen *et al.* (2015) combined the SWAT model with ANN to deal with the contributing and non-contributing areas of the catchment. Humphrey *et al.* (2016) integrated the Génie Rural à 4 paramètres Journalier (GR4 J) conceptual RR model with a Bayesian ANN to improve monthly streamflow prediction. Young *et al.* (2017) integrated the HEC-HMS model with a support vector machine to improve the hourly runoff discharges in the Chishan Creek catchment in southern Taiwan. More recently, Ghaith *et al.* (2020) integrated the conceptual hydrological model (HYMOD) with the ANN technique for daily streamflow simulation and reported that a better resemblance of streamflow patterns was achieved by the hybrid model. Farfán *et al.* (2020) combined physics-based WEAP and GR2M models with the ANN technique to improve flow forecasting in Andean watersheds.

The RR process is a highly non-uniform, complex, dynamic, and non-linear process, and any technique attempting to model the RR process in a catchment must be capable of accounting for or handling the non-uniformity, complexity, non-linearity, and dynamics inherent in the physical process being modeled. Most of the conceptual models developed so far assume the RR process to be linear because the assumption of linearity facilitates and simplifies the modeling process. With the availability of non-linear data-driven techniques and their established superiority, it should be possible to model the inherent complexities and non-linearity in the RR process in mathematical models in a more efficient manner. The standalone ANN models developed so far for the RR process are capable of modeling the complexity and non-linearity in the RR process, which is probably the reason they have been found superior to the more conventional conceptual RR models in terms of forecast accuracies in the past. The previous research efforts have also demonstrated the superiority of the hybrid models over the standalone individual models. However, the integration of the conceptual and ANN models attempted so far has been arbitrary rather than based on domain knowledge of the RR process. It should be possible to incorporate non-uniformity, complexity, and non-linearity of the RR process in a catchment in DDMs in a gradual manner based on the domain knowledge. The transformation of the rainfall falling non-uniformly over a large catchment into runoff at the catchment outlet consists of several components, e.g. infiltration, surface flow, and sub-surface flow. Incorporation of the spatial variations in the hydrologic and catchment characteristics in a large catchment into a hybrid model requires a distributed or a semi-distributed approach capable of not only incorporating the non-uniformity in the input data, e.g. spatial variations in rainfall data and varying catchment characteristics, but also the complexity and non-linearity of the RR process. Routing of the runoff responses from the upstream reaches in a catchment to the runoff response at the outlet of the catchment is a non-linear process involving spatial variations in hydrologic and catchment characteristics. Therefore, the generation of the surface runoff in upstream reaches in a catchment and its subsequent routing to the outlet of the catchment must be performed using a mathematical technique capable of incorporating such complexities, non-linearity, and non-uniformity in the RR process. The hybrid models proposed in this study employ the conceptual methods capable of incorporating spatial variations in hydrologic and catchment characteristics in generating surface runoff in upstream reaches of a catchment and then exploit the strength of data-driven approaches in handling the non-linearity and complexity inherent in the RR process in order to carry out the routing of runoff hydrographs generated at the upstream reaches in a catchment to the outlet of the catchment. Such hybrid approaches attempting to incorporate non-uniformity and non-linearity based on domain knowledge may be able to offer improved modeling accuracies but it remains to be investigated. The conceptual method employed in this study is the AWBM to generate runoff hydrographs at individual sub-catchment levels in upstream reaches, while non-linear regression (NLR) and ANNs are employed as the data-driven techniques for carrying out surface flow routing. In addition, two individual standalone AWBMs (one lumped and another routed) and a standalone ANN model are also developed as the benchmark models for comparison purposes. The catchment was divided into three sub-catchments and the AWBMs were developed for generating runoff hydrographs from individual sub-catchments by using spatially varying hydrologic and catchment characteristics. The surface flow responses obtained from the three sub-catchments were then routed by using NLR and ANN techniques to obtain the runoff at the catchment outlet in the hybrid model and by using the hydrologically based routing method, popularly known as the Muskingum method in the semi-distributed AWBM. A wide variety of standard statistical performance evaluation measures have been employed to validate all the models investigated. To illustrate the applicability of proposed hybrid models, the rainfall, runoff, and temperature data derived from the Kentucky River basin have been employed.

The paper starts with a brief description of the material and methods which includes a brief description of the study area and data. A detailed description of the model development is then discussed. After a discussion of the obtained results, the paper ends with the concluding remarks.

2. MATERIAL AND METHODS

The complete modeling process and design are described in Figure 1. In the first approach, standalone AWBM and ANN models were developed which are lumped in nature, while conceptual (Muskingum method) and non-linear methods (NLR and ANN) were used for routing the sub-basins' flows in the second approach to obtain the basin's outlet. The modeling techniques employed in this study include the conceptual AWBM, NLR, and ANN techniques. The description of NLR can be obtained in any standard textbook of statistics (Rhinehart 2016). Three-layered (an input layer, one hidden layer and an output layer) feed-forward neural network trained with back-propagation (FFBP) using the Levenberg–Marquardt (LM)

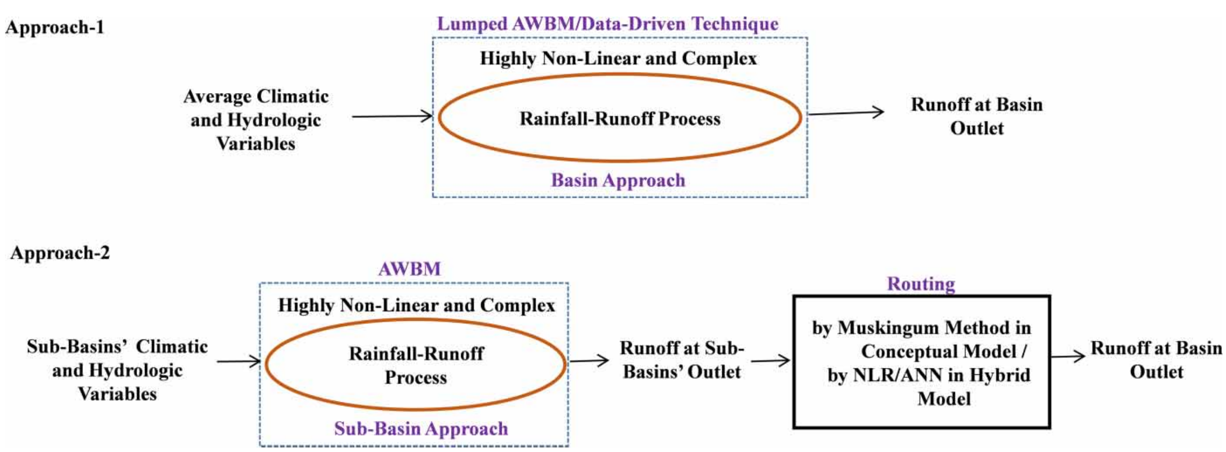


Figure 1 | Schematic diagram of the modeling process.

algorithm is used in this study and their detailed description can be obtained in Hagan & Menhaj (1994) and Hagan *et al.* (1996). A brief overview of the AWBM technique and the description of study area and data are presented in this section.

2.1. Australian water balance model

The AWBM was developed in the early 1990s (Boughton 1995), and after several modifications since its inception, it is now one of the most widely used RR models in Australia (Boughton 2004). The AWBM is a catchment water balance model that calculates runoff from rainfall at daily or hourly time increments; the schematic diagram is shown in Figure 2. The model uses three surface storage elements to simulate runoff using evapotranspiration (ET) data as an input in addition to rainfall data. The water balance of each surface storage element is calculated independently of the others. If the value of moisture in the store becomes negative, it is reset to zero, as the ET demand is superior to the available moisture. If the value of moisture in the store exceeds the capacity of the store, the moisture in excess of the capacity becomes runoff and the store is reset to the capacity. When runoff occurs from any storage element, part of the runoff becomes recharge of the base flow storage if there is base flow in the streamflow. The fraction of the runoff used to recharge the base flow storage is runoff multiplied by a factor called base flow index (BFI) which is the ratio of base flow to total flow in the stream. The remainder of the runoff, i.e., (1.0−FI)*runoff, is surface runoff.

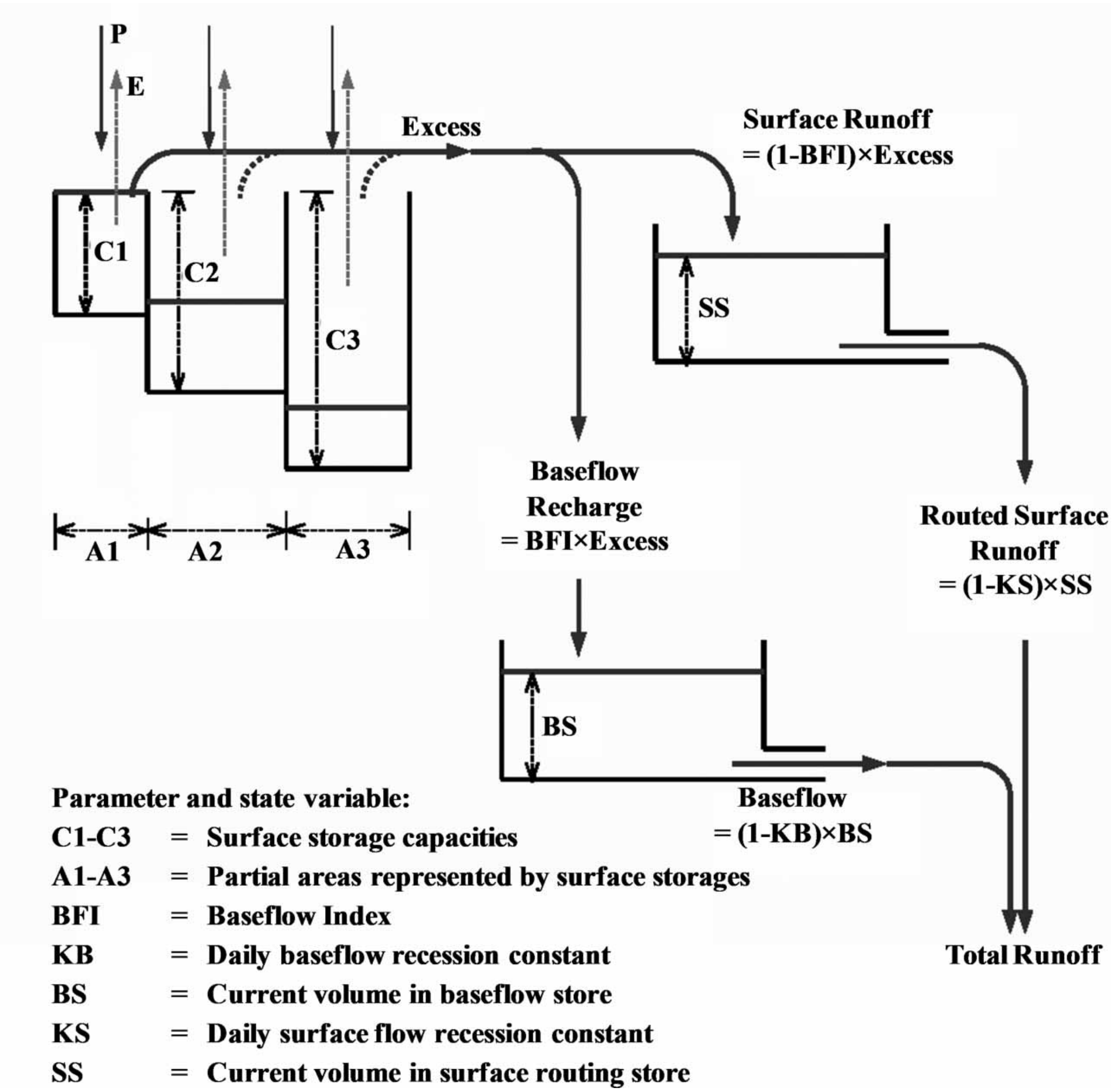


Figure 2 | Schematic diagram of the AWBM model.

The base flow storage is depleted at the rate of (1.0−KB)*BS, where BS is the current moisture in the base flow storage and KB is the base flow recession constant. The surface storage acts in the same way as the base flow storage and is depleted at the rate of (1.0−KS)*SS, where SS is the current moisture in the surface runoff storage and KS is the surface runoff recession constant of the time step being used. There are eight parameters in AWBM. All the AWBMs are calibrated by using the Rainfall–Runoff Library (RRL) of the Cooperation Research Centre for Catchment Hydrology, Australia. The RRL toolkit has eight choices of primary objective functions and three choices of secondary objective functions depending upon the need of the problem and selected model, as RRL contains many other models other than AWBM. Out of the available choices of objective functions and optimizers in RRL, the sum of square error (SSE) as an objective function and the genetic algorithm (GA) as an optimizer are used in the present study, as suggested by Kim *et al.* (2005).

2.2. Study area and data

The data derived from the Kentucky River basin, USA, as shown in Figure 3, are employed to develop the RR models in this study. The Kentucky River originates from Beattyville, Kentucky, and meets the Ohio River at the end. It fulfills the water needs of nearly one-sixth of the population of Kentucky State. The Lock and Dam 14 (LD14) is the first lock and dam along its flow direction. The drainage area of the Kentucky River at LD14 near Heidelberg, Kentucky, is approximately 6,881 km^2. The data used in this study include the average daily streamflow (m^3/s) from the Kentucky River at LD14 near Heidelberg, and the daily rainfalls (mm) from the four rain gauges (Manchester, Hyden, Jackson, and Heidelberg) scattered up to LD14. The daily rainfall values from these four rain gauge stations were averaged to get the mean daily rainfall values for the basin. The average of the temperature data (in °C) obtained at Manchester and Lexington Airport is used in this study. All the observation stations are shown in Figure 3(a). The rainfall, runoff, and temperature data for 26 years (between years 1960 and 1989) are used for model development in this study. For the development of the conceptual models, ET is calculated for the entire Kentucky basin using temperature data. To calculate ET, PET (potential evapotranspiration) is first calculated using the equation given by Thornthwaite (1948), and then using rainfall pattern, ET is calculated. At the time of using the Thornthwaite equation, the negative average monthly temperature is taken as zero (Xu & Singh 2001).

Using temperature data, PET (mm/month) is calculated for all months. A coefficient, $t_0 = (T_{\max})_j / \sum (T_{\max})$, is calculated for each day, where j is the individual day of the month. PET data for a day in any month are calculated by multiplying this coefficient by the PET (mm/month) of that month. The actual ET per day is calculated by comparing total daily rainfalls (PPT), i.e., if PPT≥2.5 mm/day, ET=PET/2, otherwise, ET=PET itself (Haan 1972). In the hybrid model development, the

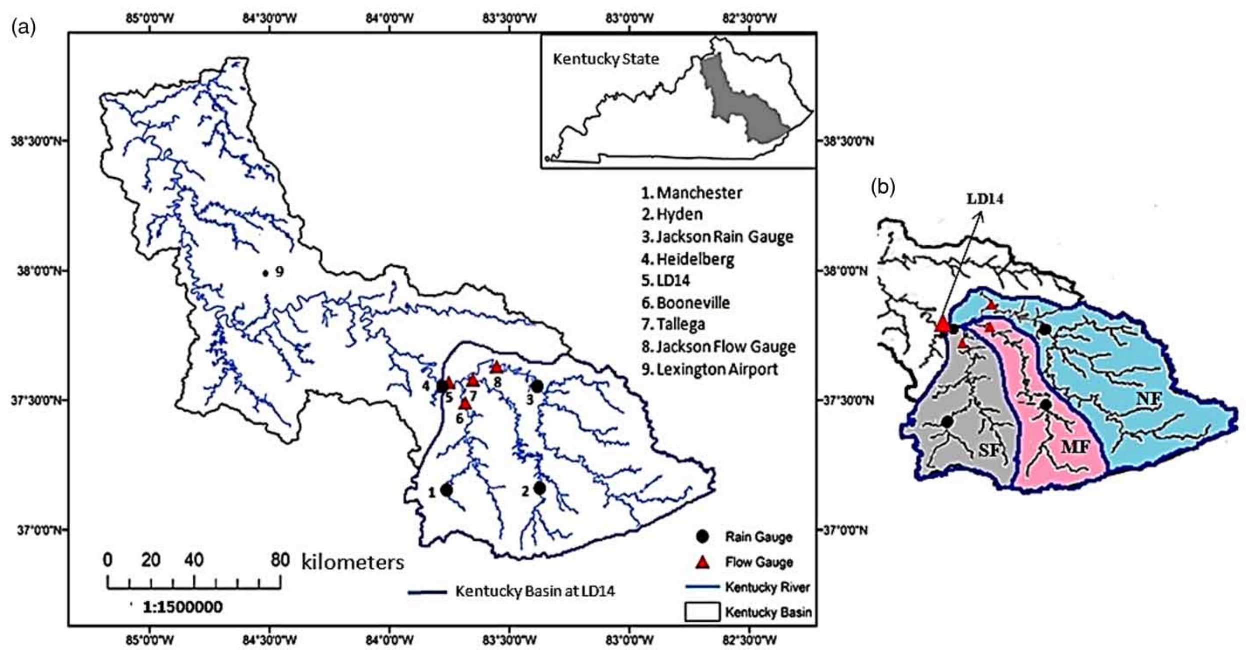


Figure 3 | River basins, USA: (a) Kentucky at LD14 and (b) Kentucky sub-basins at LD14.

entire Kentucky River basin is divided into three sub-basins called as North Fork (NF), Middle Fork (MF), and South Fork (SF), as shown in Figure 3(b). All these sub-basins are in the Eastern Kentucky Coal Field physiographic region which is characterized by mountainous terrain. The northern edge of the NF and SF sub-basins is in the plateau area of the coal field with more rolling terrain which causes somewhat less rapid surface runoff than the MF sub-basin. The MF sub-basin is underlain by coals, sandstones, and shales which are generally conducive to many wells in the region and cause of a moderate rate of groundwater drainage. The unconsolidated silts, sands, and gravels occur along the flood plain of the MF sub-basin. The drainage areas of the NF, MF, and SF sub-basins are 2,852, 1,391, and 1,870 km^2, respectively. Though these sub-basins contain other runoff sites, the proposed model is tested only by using the streamflow data near Jackson (Q_{NF}), Tallega (Q_{MF}), and Booneville (Q_{SF}) to access its performance for the basin which would have limited gages available in the area. Figure 4 presents a semi-log plot of observed daily flows for a randomly selected period to compare the flow patterns of three sub-basins. It can be seen form Figure 4 that the NF and SF sub-basins show somewhat similar behavior during higher flow events. On the other hand, the MF sub-basin exhibits quite distinguishable behavior having low flow as compared to NF and SF sub-basins with higher flow recession. The ET data calculated for the entire Kentucky River basin is used for the calibration of AWBM of the individual sub-basins in this study.

The data set is divided into two subsets: the first is used for calibration/training (covering the period 1 January 1960–31 December 1972) and another is used for validation/testing (covering the period 1 January 1977–31 December 1989) of the models. Table 1 presents the basic statistics of various data sets.

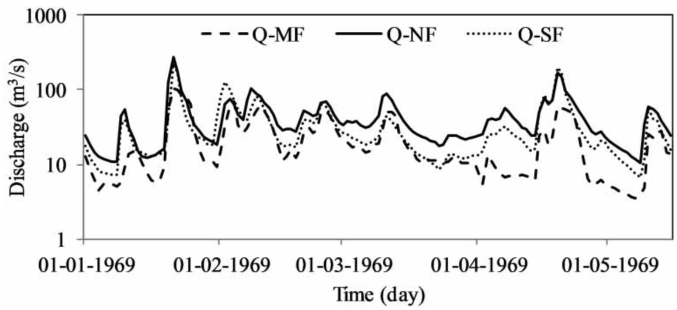


Figure 4 | Observed flows of the sub-basins.

Table 1 | Basic statistics of various data

Basic statistics	Jackson	Manchester	Heidelberg	Hyden	Avg.	Q_{NF}	Q_{MF}	Q_{SF}	LD14	Kentucky
	Training rainfall (mm)				**Training flow (m^3/s)**					**Training PET (mm)**
Minimum	0.0	0.0	0.0	0.0	0.0	0.1	0.4	0.0	2.0	0.0
Maximum	104.0	101.0	116.0	100.0	85.8	1,164.0	291.7	1,427.3	2,449.4	5.7
Average	3.0	3.4	3.2	3.3	3.2	38.7	21.2	30.0	102.8	2.0
Std. Dev.	7.8	8.4	8.3	7.8	6.7	77.0	29.7	67.8	171.0	1.7
Skewness	4.6	4.0	4.6	3.9	3.8	6.2	2.3	7.4	4.4	0.3
Kurtosis	30.2	22.8	31.2	21.9	21.6	55.2	6.4	86.6	30.8	−1.4
	Testing rainfall (mm)				**Testing flow (m^3/s)**					**Testing PET (mm)**
Minimum	0.0	0.0	0.0	0.0	0.0	0.7	0.3	0.0	1.3	0.0
Maximum	104.0	107.1	133.6	111.0	101.1	1,478.3	213.2	1,362.2	2,432.4	6.2
Average	3.2	3.3	3.1	3.4	3.2	37.4	19.6	28.5	100.9	2.1
Std. Dev.	7.9	8.5	8.4	8.1	6.7	73.9	27.1	64.1	168.3	1.8
Skewness	4.4	4.5	5.5	4.3	4.2	7.9	2.0	7.9	4.9	0.4
Kurtosis	26.8	30.3	46.9	27.2	28.7	94.3	4.0	98.4	38.3	−1.3

3. MODEL DEVELOPMENT

In this paper, two standalone conceptual AWBMs, one standalone ANN model, and two different hybrid models are developed. The first standalone conceptual AWBM is a lumped model, while the second conceptual AWBM is quasi-distributed in nature. The standalone ANN model and the lumped AWBM were developed using the average rainfall, runoff, and temperature data of the Kentucky River basin at LD14. The first hybrid model is developed by integrating the conceptual AWBM with NLR, and the second hybrid model is developed by integrating the AWBM with the ANN technique. For developing the quasi-distributed AWBM and the two hybrid models, the Kentucky River basin up to LD14 was divided into three sub-basins and the runoff generated from these sub-basins using conceptual AWBMs was taken as input for the development of the hybrid models. Later, two more improved hybrid models were developed by incorporating delayed surface runoff in the input vector of the ANN models based on domain knowledge and past practices. The detailed explanation of model developments is provided in the sub-section. Four different standard statistics were used to evaluate the performance of the models developed in this study. These are the average absolute relative error ($\text{AARE} = 1/N\left(\sum_{t=1}^{N} |Q_O(t) - Q_P(t)/Q_O(t)|\right) \times 100\%$), the root-mean-square error (RMSE), the Pearson coefficient of correlation (R), and the threshold statistics ($TS_x = n_x/N \times 100\,\%$) between observed discharge (Q_O (t)) and predicted discharge (Q_P (t)). The TS_x is the percentage of data points forecasted for which the absolute relative error is less than x%, where n_x is the number of the data points forecasted with the absolute relative error less than x% and N is the total number of observation points. Most of these error statistics have been extensively used for model selection by many researchers in the past (Chidthong *et al.* 2009; Vidyarthi *et al.* 2020).

3.1. Development of conceptual AWBMs

Two different standalone conceptual AWBMs are developed in this study. The first standalone conceptual AWBM is a lumped model (named as AWBM-lumped) which was developed using the average rainfall, runoff, and temperature of the Kentucky River basin at LD14. The second standalone conceptual AWBM is quasi-distributed in nature, which first generates individual runoff hydrographs at upstream reaches and then routes them to the outlet of the entire catchment using the linear hydrologic routing method popularly known as the Muskingum method; hence, the second standalone conceptual model is named as AWBM-Muskingum.

3.1.1. AWBM-lumped

In the development of the AWBM-lumped model, the average rainfall data obtained from Jackson, Hyden, Manchester, and Heidelberg and the runoff at the basin outlet LD14 were used. The ET data calculated for the entire Kentucky River basin was used for the calibration of the AWBM-lumped model. The AWBM-lumped parameters for the Kentucky River catchment were estimated using the RRL toolkit for the data of the calibration period by setting SSE as an objective function and GA as an optimizer. After implementing the calibration step, the conceptual models may sometimes give inappropriate parameter values which do not match with field situations, and to check this, the ranges of the parameters were fixed between meaningful values before performing the calibration step. The best parameter set was obtained by running the model multiple times using different initial values to get the suitable and meaningful calibrated parameters. The GA used in this study has four parameters: number of points (population), probability of mutation, trapezoidal probability density function (PDF), and maximum iterations. The best GA optimizer parameters were obtained using a trial and error method varying one parameter at a time. The trapezoidal PDF was varied from 1 to 2 and the number of iterations was varied from 20 to 100. The values of trapezoidal PDF=2, mutation probability=0.01, and iteration=80 were found to be the best for the calibration of the AWBM-lumped model. After the calibration step, the parameters of the AWBM for the Kentucky River basin were obtained as 0.134 and 0.433 for partial areas, A1 and A2, respectively; 0.722 for percolation constant, BFI; 48.6, 154.5, and 125.5 for surface storage capacities, C1, C2, and C3, respectively; 0.773 for base flow recession constant, KB; and 0.988 for surface flow recession constant, KS.

3.1.2. AWBM-Muskingum

For the development of the AWBM-Muskingum model, first, the conceptual AWBMs of individual sub-basins NF, MF, and SF were developed using the data of the corresponding sub-basins. The rainfall and runoff at Jackson were employed for developing the AWBM for the NF basin; the rainfall at Hyden and runoff at Tallega was employed for developing the AWBM for the MF basin; and the AWBM for the SF basin was developed using the averaged data of rainfall obtained from Manchester and Heidelberg and runoff at Booneville. The ET data calculated for the entire Kentucky River basin was used for the calibration of the AWBM of the individual sub-basins in this study. The individual AWBM parameters for the sub-basins were estimated using the RRL toolkit for the data of the calibration period by setting SSE as an objective function and GA as an optimizer following the similar procedure used for calibrating the AWBM-lumped parameters. The best GA optimizer parameters obtained from the AWBM-lumped model were found to be suitable for calibrating the AWBMs of the individual sub-basins also. Table 2 presents the calibrated model parameters for the AWBMs developed for NF, MF, and SF sub-basins along with the default range of the parameter values.

It can be observed from Table 2 that the calibrated parameters of the models are different in different sub-basins which show the variations in the physiography of the sub-basins. For example, the NF sub-basin recharges and depletes its base flow store at similar rate with the values of BFI=0.769 and KB=0.753. The base flow store of the MF sub-basin, on the other hand, recharges and depletes rapidly with the values of BFI=0.808 and KB=0.918, respectively. In contrast to NF and MF sub-basins, the base flow store of the SF sub-basin recharges rapidly with a value of BFI=0.910 and depletes with a little slower rate of recession with a value of KB=0.651. The value of surface flow recession parameter (KS) is nearly similar in all the sub-basins, while the parameters for surface storage capacity (C1, C2, and C3) are significantly different for different sub-basins presented in Table 2. After calibration, the runoff at Jackson for NF ($\hat{Q}_{NF}$), runoff at Tallega for MF ($\hat{Q}_{MF}$), and runoff at Booneville for SF ($\hat{Q}_{SF}$) sub-basins were estimated using the corresponding calibrated parameters of the sub-basins. In the last step of AWBM-Muskingum model development, the routing of sub-basins' calculated runoffs $\hat{Q}_{NF}$, $\hat{Q}_{MF}$, and $\hat{Q}_{SF}$ from AWBMs of NF, MF, and SF sub-basins, respectively, was performed using the hydrological routing method popularly known as the Muskingum method which assumes linear relation among the storage, input and output in a channel reach (see Srivastava & Jain (2017) for details of the Muskingum method). The Muskingum method of runoff-routing through river reaches consists of two important parameters: K and x that need to be calibrated. The parameters K (the slope of storage-weighted discharge curve, in days) and x (a dimensionless constant known as weighting factor) were estimated by the standard storage–weighted discharge method in this study and their values thus obtained are: K=1.5 days corresponding to the value of x=0.33.

3.2. Development of the ANN model

For the development of the ANN model, the significant input vectors were selected on the basis of the values of cross-correlation function (CCF), auto-correlation function (ACF) and partial auto-correlation function (PACF) of the daily data employed in this study. PACF is used in this study because, in the case of more than two independent variables, the use of PACF is very useful to know the association between two variables in presence of another influential variable. Based on the analysis, the flow values lagged up to 3 days, Q_{t-1}, Q_{t-2}, and Q_{t-3}, and the rainfalls, P_t, P_{t-1}, and P_{t-2}, were found as significant for predicting Q_t at LD14. The ANN model architecture, 6-N-1, was thus trained using the LM algorithm by varying the hidden neuron number (N) from 1 to 20. A number of trial values of the LM parameter, initial damping factor (μ), were tried, and a value of μ=0.001 was found to be the best and selected to train the ANN model. The objective function was taken as the mean squared error (MSE). As soon as the MSE reaches 0.0001 or a maximum iteration of 50,000 reaches, the training was terminated. The 6-4-1 architecture of the ANN model thus obtained was found to be the best among 20 different architectures as the error statistics of this architecture was found to be optimum.

Table 2 | Calibrated parameters for AWBM for sub-basins of Kentucky River

		Calibrated value			
AWBM parameters	**Physical meaning**	**Sub-1 NF**	**Sub-2 MF**	**Sub-3 SF**	**Default range**
A1	Area	0.134	0.134	0.134	0–1
A2		0.433	0.433	0.433	0–1
BFI	Percolation	0.769	0.808	0.910	0–1
C1	Surface storage capacity	12.4	13.3	30.0	0–50
C2		99.6	154.5	144.3	0–200
C3		451	123.5	154.9	0–500
KB	Base flow recession	0.753	0.918	0.651	0–1
KS	Surface flow recession	0.99	0.99	0.988	0–1

3.3. Hybrid model development

The procedure for the development of hybrid models is the same as adopted in AWBM-Muskingum model development except for the technique employed for routing of the upstream sub-basins' runoffs to the outlet of the entire catchment at LD14. In contrast to the AWBM-Muskingum model, the non-linear techniques, such as NLR and ANN, were used for developing the hybrid models. Therefore, the procedure for generating $\hat{Q}_{NF}$, $\hat{Q}_{MF}$, and $\hat{Q}_{SF}$ from AWBMs for NF, MF, and SF sub-basins, respectively, is similar to that explained for the development of the AWBM-Muskingum model. The general structure of the hybrid models is shown in Figure 5, which states that the flows obtained from AWBMs of individual sub-basins ($\hat{Q}_{NF}$, $\hat{Q}_{MF}$, and $\hat{Q}_{SF}$) are combined or routed using NLR and ANN techniques to obtain the LD14 runoff (Q_{LD14}). The structure of the hybrid models (AWBM-NLR and AWBM-ANN) can be represented as follows:

$$Q_{LD14}(t) = f[\hat{Q}_{NF}(t), \hat{Q}_{MF}(t), \hat{Q}_{SF}(t)] \tag{1}$$

The first hybrid model (named as AWBM-NLR) uses the NLR for routing the calculated runoffs $\hat{Q}_{NF}$, $\hat{Q}_{MF}$, and $\hat{Q}_{SF}$ from AWBMs of NF, MF, and SF sub-basins, respectively. The modeling structure of the AWBM-NLR model can be represented using the following equation:

$$Q_{LD14} = \beta_1 \times (\hat{Q}_{NF})^{\beta_5} + \beta_2 \times (\hat{Q}_{MF})^{\beta_6} + \beta_3 \times (\hat{Q}_{SF})^{\beta_7} + \beta_4 \tag{2}$$

where β_1, β_2, β_3, β_4, β_5, β_6, and β_7 are the parameters of the NLR model. For calculating the values of these parameters, the MATLAB function 'fminsearch' was used. Interested readers can refer to the user's guide of optimization toolbox of MATLAB 2012 for a detailed description of 'fminsearch' algorithm and its use in solving unconstrained optimization problems. The calibrated regression equation is given as follows:

$$Q_{LD14} = -0.57 \times (\hat{Q}_{NF})^{0.01} + 0.76 \times (\hat{Q}_{MF})^{1.13} + 0.53 \times (\hat{Q}_{SF})^{1.42} - 0.43 \tag{3}$$

The second hybrid model (named as AWBM-ANN) uses the ANN technique for routing the calculated runoffs $\hat{Q}_{NF}(t)$, $\hat{Q}_{MF}(t)$, and $\hat{Q}_{SF}(t)$ for predicting the runoff at LD14, i.e., $Q_{LD14}(t)$. The ANN model architecture, 3-N-1, was thus trained using the LM algorithm by varying the hidden neuron number (N) from 1 to 20 keeping the same objective function and conditions for stopping criteria used earlier. The values of LM parameters used earlier were found suitable for the development of hybrid models also. The 3-9-1 architecture of the AWBM-ANN model thus obtained was found to be the best among 20 different architectures.

3.4. Development of improved hybrid RR models

The ANN models are powerful tools for the modeling and forecasting of the hydrologic system. Many researchers have employed ANN models in the past in which the input vector has been selected based on the correlation analysis. Most of the ANN-RR models proposed in the past use past flows as inputs. In fact, the standalone model developed in this study also includes past flow as inputs. The past flows actually represent the moisture conditions of the catchment in the past few time steps. It is felt that the inclusion of *delayed surface runoff* from the three sub-basins in the upstream reaches of the Kentucky River may improve the performance of the hybrid models proposed in this study. The inclusion of the delayed

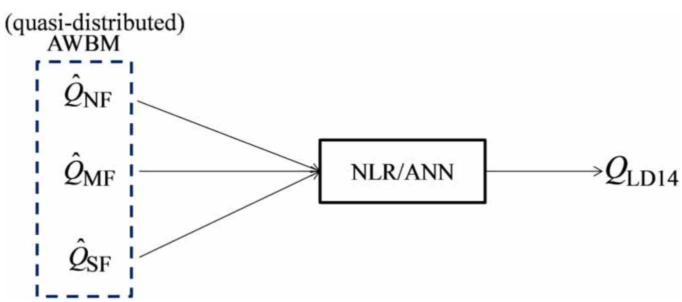


Figure 5 | Structure of hybrid models.

surface runoffs in the input vector of the ANN model may be able to capture the complexity, dynamics, and non-linearity in the flood-routing process in a catchment in a better manner; however, this remains to be explored. With this objective in mind, it was decided to include $\hat{Q}_{NF}(t-1)$, $\hat{Q}_{SF}(t-1)$, and $Q_{LD14}(t-1)$ in the AWBM-NLR and AWBM-ANN models for the routing of individual runoff hydrographs from upstream reaches of the Kentucky River to the outlet of the entire catchment. These new hybrid models are termed as AWBM-NLRI and AWBM-ANNI, where 'I' stands for improvement in the hybrid-modeling structure by way of including inputs in the hybrid models based on domain knowledge in the form of delayed surface runoff in the hope of attaining improved performance. Thus, the structure of the improved hybrid models (AWBM-NLRI and AWBM-ANNI) can be represented as follows:

$$Q_{LD14}(t) = f[\hat{Q}_{NF}(t),\ \hat{Q}_{MF}(t), \hat{Q}_{SF}(t), \hat{Q}_{NF}(t-1),\ \hat{Q}_{SF}(t-1), Q_{LD14}(t-1)] \tag{4}$$

The general structure of these hybrid models is shown in Figure 6.

The process of development of the AWBM-NLRI model is the same as the AWBM-NLR model except for the number of input variables. The proposed statistical equation for AWBM-NLRI is given as follows:

$$\begin{aligned} Q_{LD14}(t) &= b_1 \times (\hat{Q}_{NF}(t-1))^{b_8} + b_2 \times (\hat{Q}_{NF}(t))^{b_9} + b_3 \times (\hat{Q}_{MF}(t))^{b_{10}} + \\ b_4 &\times (\hat{Q}_{SF}(t-1))^{b_{11}} + b_5 \times (\hat{Q}_{SF}(t))^{b_{12}} + b_6 \times (\hat{Q}_{LD14}(t-1))^{b_{13}} + b_7 \end{aligned} \tag{5}$$

where b_1, b_2, b_3, b_4, b_5, b_6, b_7, b_8, b_9, b_{10}, b_{11}, b_{12}, and b_{13} are the parameters of the hybrid NLR model. These parameters were calculated using the similar procedure discussed in the previous sub-section. The calibrated regression equation for AWBM-NLRI thus obtained is given as follows:

$$\begin{aligned} Q_{LD14}(t) &= 2.28 \times (\hat{Q}_{NF}(t-1))^{9.33} + 0.92 \times (\hat{Q}_{NF}(t))^{0.28} - 0.19 \times (\hat{Q}_{MF}(t))^{1.21} \\ &+ 0.003 \times (\hat{Q}_{SF}(t-1))^{1.92} + 1.39 \times (\hat{Q}_{SF}(t))^{0.97} + 1.56 \times (\hat{Q}_{LD14}(t-1))^{0.82} \\ &+ 0.38 \end{aligned} \tag{6}$$

The procedure of development of the AWBM-ANNI model is similar in terms of combining the AWBM model with the ANN technique, but differs in the number of input variables, which is six in this case, and therefore, the ANN model architecture, 6-N-1, was explored using the LM algorithm by varying the hidden neuron number (N) from 1 to 20. The best architecture for the AWBM-ANNI model thus obtained was 6-9-1 as error statistics was optimum for this architecture.

4. RESULTS AND DISCUSSION

The results in terms of various performance statistics from all the RR models during calibration/training and validation/testing are presented in Table 3 starting from the simplest model to the model with increased complexities to draw inferences about the performance accordingly. The bar chart of AARE, TS50, and R for the visualization of the performances of various

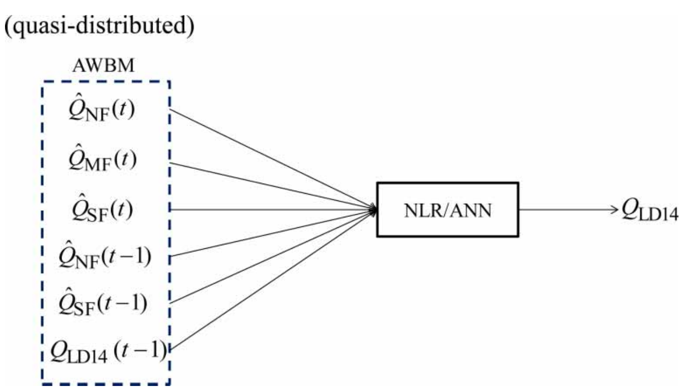


Figure 6 | Structure of the improved hybrid models.

Table 3 | Performance evaluation statistics from various RR models

Model	AARE	*R*	RMSE	TS50	TS75	TS100
During calibration/training[a]						
AWBM-lumped	116.3	0.874	0.047	46.2	57.9	65.8
AWBM-Muskingum	66.1	0.890	0.041	52.7	73.0	90.7
ANN	28.2	0.970	0.013	85.2	93.5	96.7
AWBM-NLR	75.0	0.883	0.036	41.6	57.7	79.0
AWBM-ANN	53.4	0.900	0.025	64.2	83.2	90.3
AWBM-NLRI	40.0	0.950	0.017	77.7	88.1	93.4
AWBM-ANNI	**18.9**	**0.974**	**0.013**	**92.5**	**97.1**	**98.6**
During validation/testing[a]						
AWBM-lumped	104.5	0.863	0.043	45.1	58.4	66.7
AWBM- Muskingum	61.2	0.880	0.033	52.2	73.5	90.2
ANN	30.3	0.960	0.015	84.3	92.0	95.4
AWBM-NLR	75.0	0.874	0.031	41.5	58.2	78.2
AWBM-ANN	58.5	0.880	0.024	63.0	79.9	86.7
AWBM-NLRI	39.5	0.920	0.022	74.6	86.4	92.0
AWBM-ANNI	**18.9**	**0.964**	**0.015**	**92.1**	**96.8**	**98.4**

[a]Calibration/validation is used for AWBM, AWBM-Muskingum, AWBM-NLR, and AWBM-NLRI, while for all other models, the term training/testing has been used.
Bold values represent the best error statistics.

models is shown in Figure 7. The graphical results in terms of observed and predicted flows from all the models for a testing/validation year are shown in Figure 8. It can be observed from Table 3 that the conceptual model which uses the linear Muskingum method for routing the upstream sub-basins' runoffs at basin's outlet performed better than the lumped AWBM model, as expected. The AWBM-routed model is better than the AWBM-lumped model because the AWBM-routed model is quasi-distributed in nature and uses the spatial variations of the data used in modeling the RR process and routes the upstream runoff hydrographs to the outlet of the catchment using the Muskingum method. Thus, the AWBM-Muskingum model is able to represent the field conditions in mathematical modeling in a better manner. The standalone ANN model is better than both the conceptual models developed in this study (AWBM-lumped and AWBM-Muskingum). This is also expected because of the powerful structure of the ANN technique in capturing the complexity, dynamics, and non-linearity of the physical process being modeled. In further analyzing the results from Table 3, it can be observed that the performance of the AWBM-NLR model is similar to the AWBM-Muskingum model, which shows that the NLR method is unable to capture the complexity and non-linearity in the process of transformation of surface runoff from upstream reaches to the outlet of

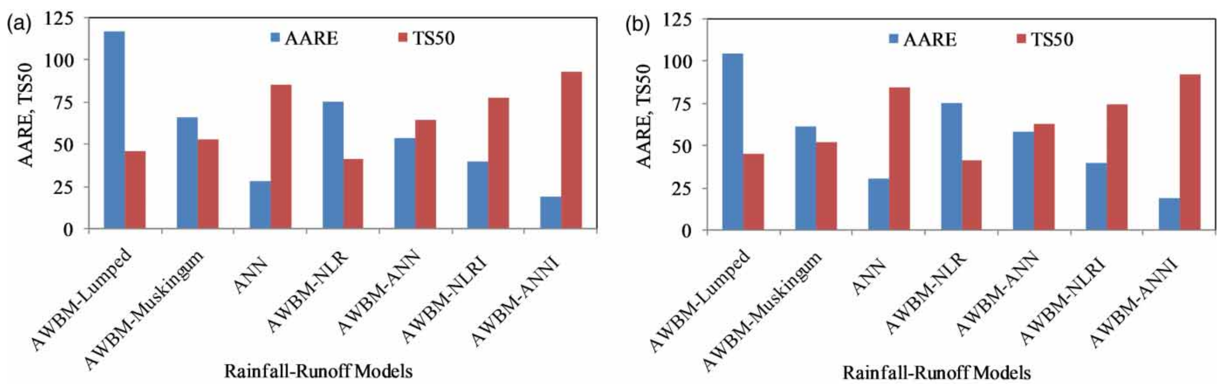


Figure 7 | Bar plots of error statistics for different RR models: (a) during training/calibration and (b) during testing/validation.

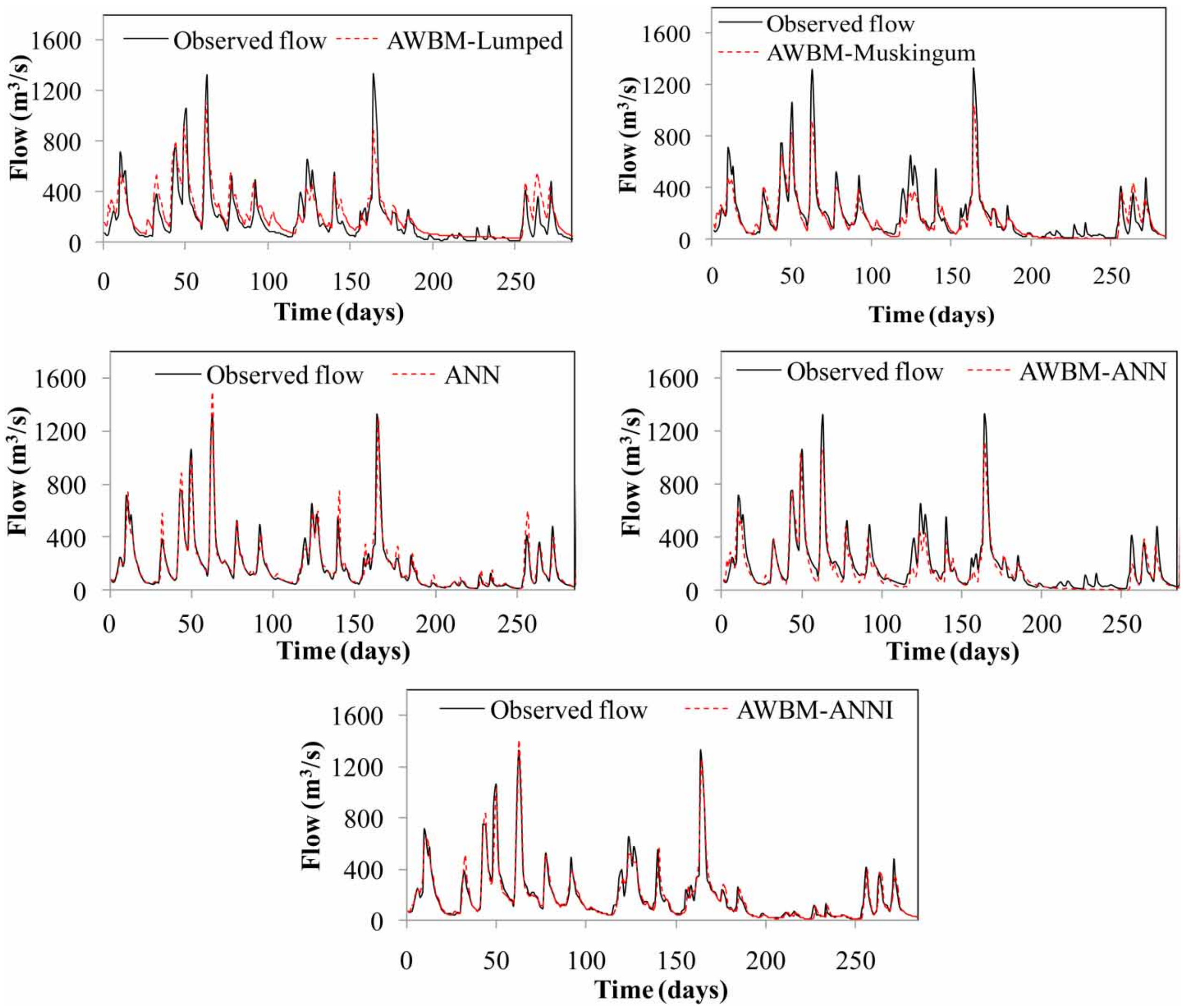


Figure 8 | Time-series plot for best models for testing year 1989.

the entire catchment. Analyzing the results from Table 3, it is clear that the hybrid model developed by integrating AWBM with ANN (AWBM-ANN model) performed better than the AWBM-NLR model during both training and testing data sets. This is true in the case of improved hybrid models also, where the AWBM-ANNI model performed better than the AWBM-NLRI model. The relative improvements in AARE, R, RMSE, TS50, TS75, and TS100 from the AWBM-NLR model to the AWBM-ANN model are approximately 29, 2, 31, 54, 44, and 14%, respectively, during training, and nearly similar relative improvements registered during testing also. The relative improvements in AARE, R, RMSE, TS50, TS75, and TS100 from the AWBM-NLRI model to the AWBM-ANNI model are approximately 53, 2, 24, 19, 10, and 6%, respectively, during training with a similar trend in relative improvements registered during testing also.

In general, all the hybrid and improved hybrid models that use the ANN technique for routing consistently outperformed their regression counterparts. Analyzing the error statistics further (from Table 3), it is clear that the performances of improved hybrid models, AWBM-NLRI and AWBM-ANNI, are significantly better than their corresponding hybrid models, AWBM-NLR and AWBM-ANN, respectively, during both training and testing. Looking at the performances of conceptual AWBM and ANN models from Table 3, it is observed that the standalone conceptual AWBM is showing a reasonable accuracy only, while the standalone ANN model performance is very good and even better than all hybrid and improved hybrid models except for the AWBM-ANNI model. This may be because of two reasons: (a) the ANN technique is much more robust and powerful in capturing the complexity, dynamics, and the non-linearity inherent in the physical process

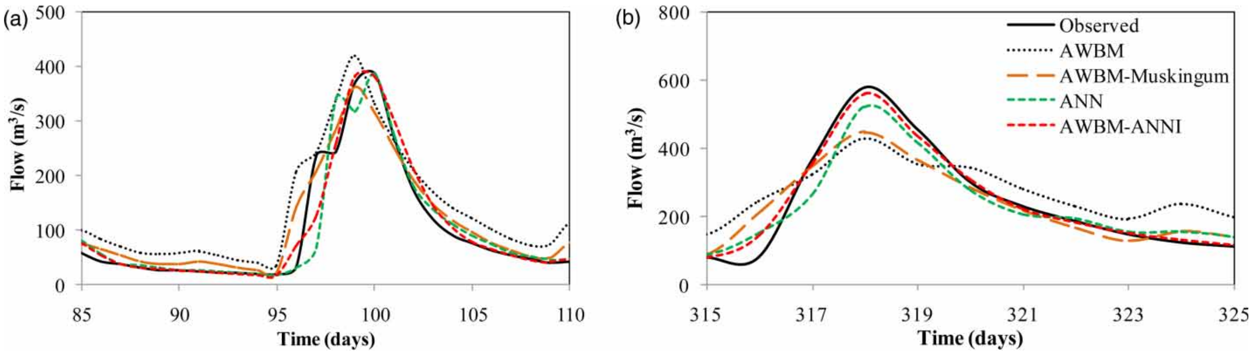


Figure 9 | Runoff mapping by the best RR models during the testing period: (a) peak flow at less than 400 m^3/s and (b) peak flow at more than 400 m^3/s.

being modeled and (b) both the models employed delayed flows/surface flows, which helps represent the field conditions in the form of catchment's antecedent moisture conditions in a much better manner in the modeling process. Both ANN and AWBM-ANNI RR models are showing the same robustness in terms of R (0.970 and 0.974), but the accuracy of the AWBM-ANNI model in terms of AARE (18.9), TS50 (92.5), TS75 (97.1), and TS100 (98.6) is significantly better than that of the ANN model during training with relative improvements of 49, 8, and 4% in AARE, TS50, and TS75, respectively. During testing also, the performance of the AWBM-ANNI model shows a similar trend of relative improvements to the ANN model.

The improved hybrid model AWBM-ANNI is the best model among all the developed RR models including their conceptual counterparts, where the relative improvements from AWBM to AWBM-ANNI in AARE, R, RMSE, TS50, TS75, and TS100 are 515, 10, 262, 50, 40, and 33%, respectively, during training.

During testing also, the performance of the AWBM-ANNI model shows a similar trend of relative improvements to the AWBM model. The graphical results in terms of observed and predicted flows from the best models in each category, i.e., conceptual, ANN, hybrid and improved hybrid (i.e., AWBM-lumped, AWBM-Muskingum, ANN, AWBM-ANN, and AWBM-ANNI), and the AWBM-lumped for a testing year are shown in Figure 9. It can be observed from Figure 8 that, though the ANN model exhibits very close competitor to the AWBM-ANNI model in capturing the RR relationship, the improved hybrid model, AWBM-ANNI, captured the flows most smoothly as compared to any other model developed in this study which can also be seen in Figure 9, where the AWBM-ANNI model captured two of the randomly selected hydrographs (from the testing period) with different peak flows most accurately than other RR models.

Through the proposed hybrid models, the calibrated parameters of AWBM for three sub-basins provided the sub-basin characteristics, and by combining them with two data-driven techniques, the accuracy of runoff simulation has been improved significantly. For example, the best hybrid model AWBM-ANNI provides excellent modeling accuracy with the physiographic information that the NF sub-basin recharges and depletes its base flow store at a similar rate. The base flow store of the MF sub-basin, on the other hand, recharges and depletes rapidly. In contrast to NF and MF sub-basins, the base flow store of the SF sub-basin recharges rapidly and depletes with a slower rate of recession. The surface flow recession is nearly similar in all the sub-basins. The surface storage capacities are significantly different for different sub-basins. Also, among all the sub-basins, the MF sub-basin has the highest groundwater drainage in terms of baseflow recession which is obvious as the MF sub-basin physiography is conducive to a moderate rate of groundwater drainage. Thus, while the conceptual models capture the spatially varying hydrologic and catchment characteristics, the ANN models are able to capture the complexity and non-linearity in the RR process giving improved accuracies in modeling.

5. SUMMARY AND CONCLUSIONS

This paper proposes hybrid-modeling approaches to simulate the RR process in a catchment which integrates the conceptual model (AWBM) with NLR and ANN techniques and compares its performance with their individual counterparts. In the hybrid approach, the basin was divided into sub-basins and individual runoff hydrographs were generated separately by calibrating the AWBM parameters using the data of individual sub-basins. These sub-basin runoffs were then routed by integrating the conceptual model components with the NLR and ANN techniques to obtain the runoff at the basin outlet.

Delayed surface runoffs were later employed in the hybrid models in an attempt to improve the model performance based on domain knowledge. A wide variety of standard statistical performance evaluation measures were employed to evaluate the performances of various models developed in this study.

Quasi-distributed conceptual models may be employed in hydrologic applications instead of the lumped models. While quasi-distributed conceptual models are capable of capturing the spatial variations in the hydrologic and catchment characteristics, they do require more data from individual sub-basins. Among the standalone models investigated in this study, the ANN model performed the best because of its powerful, complex, and non-linear structure that is capable of capturing the complexity and non-linearity in the physical process being modeled. The data-driven techniques such as NLR and ANNs have the potential to improve the runoff simulation in a basin and can be used for routing of the surface flow. The proposed hybrid models are comprehensible and provided improved runoff simulation performance. The results obtained in this study indicate that the NLR technique is not suitable for the purpose of surface flow routing when compared to the ANN technique. The improved hybrid model that integrated conceptual and ANN techniques and employed delayed surface runoffs as inputs in the model development provided the best performance in RR modeling among all the models developed in this study including their conceptual and ANN counterparts. The structure of the best performing hybrid model was able to capture the spatial variations in the hydrologic and catchment characteristics, complexity, and non-linearity of the mechanisms involved in flood-routing in a catchment, and was able to represent the actual overall field conditions in the best possible manner. Thus, it can be said that special efforts are required to be spent in developing the mathematical model structures to capture the non-uniformity, complexity, dynamics, and non-linearity inherent in the RR process in a catchment rather than making simplified assumptions.

No study is complete and there is always scope for improvement. The findings obtained here are based on an application of proposed methodologies to the data derived from a single catchment. Also, one conceptual model (AWBM) and two data-driven techniques (regression and ANN) were used. There are several other conceptual and data-driven techniques available. It is hoped that the future research efforts will focus on implementing the methodologies proposed here in other catchments of varying hydrologic and climatic conditions and based on several other combinations of the conceptual and data-driven techniques. Such special, co-ordinated, and focused efforts are required in developing RR models capable of producing improved runoff forecasts that can be employed in better planning, design, operation, and management of various water resources activities.

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DATA AVAILABILITY STATEMENT

All relevant data are available from an online repository or repositories (https://waterdata.usgs.gov/nwis/uv/?referred_module=sw).

REFERENCES

Abbott, M. B., Bathrust, J. C., Cunge, J. A., O'Connell, P. E. & Rasmussen, J. 1986 An introduction to European Hydrological System – Système Hydrologique Europeén, 'SHE', 1: history and philosophy of a physically-based, distributed modeling system. *Journal of Hydrology* **87**, 45–59.

Ahmadi, A., Nasseri, M. & Solomatine, D. P. 2019 Parametric uncertainty assessment of hydrological models: coupling UNEEC-P and a fuzzy general regression neural network. *Hydrological Sciences Journal* **64**, 1080–1094. https://doi.org/10.1080/02626667.2019.1610565.

Barati, R., Rahimi, S., Akbari, G. & Yu, Y. 2012 Analysis of dynamic wave model for flood routing in natural rivers. *Water Science and Engineering* **5** (3), 243–258. https://doi.org/10.3882/j.issn.1674-2370.2012.03.001.

Beven, K. J. 2000 *Rainfall-Runoff Modelling: The Primer*. John Wiley, Hoboken, NJ.

Beven, K. J., Calver, A. & Morris, E. M. 1987 *The Institute of Hydrology Distributed Model (HDM)*. Report 98. Institute of Hydrology, Wallingford, UK.

Boughton, W. C. 1995 An Australian water balance model for semiarid watersheds. *Journal of Soil Water Conservation* **50** (5), 454–457.

Boughton, W. C. 2004 The Australian water balance model. *Environmental Modelling and Software* **19** (10), 943–956.

Bowden, G. J., Maier, H. R. & Dandy, G. C. 2012 Real-time deployment of artificial neural network forecasting models: understanding the range of applicability. *Water Resources Research* **48**, W10549. https://doi.org/10.1029/2012WR011984.

Burnash, R. J. C., Ferral, R. L. & McGuire, R. A. 1973 *A Generalized Streamflow Simulation System – Conceptual Modelling for Digital Computers. Jointly Developed by Federal-State River Forecast Center and National Weather Service*. Department of Water Resources, California, USA.

Chidthong, Y., Tanaka, H. & Supharatid, S. 2009 Developing a hybrid multi-model for peak flood forecasting. *Hydrological Processes* **23**, 1725–1738.

Chiew, F. H. S., Peel, M. C. & Western, A. W. 2002 Application and testing of the simple rainfall-runoff model SIMHYD. In: *Mathematical Models of Small Watershed Hydrology and Applications* (Singh, V. P. & Frevert, D. K., eds). Water Resources Publication, Colorado, pp. 335–367.

Corzo, G. A., Solomatine, D. P., Hidayat, de Wit, M., Werner, M., Uhlenbrook, S. & Price, R. K. 2009 Combining semi-distributed process-based and data-driven models in flow simulation: a case study of the Meuse river basin. *Hydrology and Earth System Sciences* **13**, 1619–1634. https://doi.org/10.5194/hess-13-1619-2009.

Dorum, A., Yarar, A., Sevimli, M. F. & Onüçyıldız, M. 2010 Modelling the rainfall-runoff data of Susurluk Basin. *Expert Systems with Applications* **37** (9), 6587–6593. https://doi.org/10.1016/j.eswa.2010.02.127.

Farfán, J. F., Palacios, K., Ulloa, J. & Avilés, A. 2020 A hybrid neural network-based technique to improve the flow forecasting of physical and data-driven models: methodology and case studies in Andean watersheds. *Journal of Hydrology: Regional Studies* **27**, 100652. https://doi.org/10.1016/j.ejrh.2019.100652.

Galelli, S., Humphrey, G. B., Maier, H. R., Castelletti, A., Dandy, G. C. & Gibbs, M. S. 2014 An evaluation framework for input variable selection algorithms for environmental data-driven models. *Environmental Modelling & Software* **62**, 33–51. https://doi.org/10.1016/j.envsoft2014.08.015.

Ghaith, M., Siam, A., Li, Z. & El-Dakhakhni, W. 2020 Hybrid hydrological data-driven approach for daily streamflow forecasting. *Journal of Hydrologic Engineering* **25** (2), 04019063. doi:10.1061/(ASCE)HE.1943-5584.0001866.

Grayson, R., Moore, I. & McMahon, T. 1992 Physically based hydrologic modelling. 2. Is the concept realistic? *Water Resources Research* **28** (10), 2659–2666.

Haan, C. T. 1972 A water yield model for small watersheds. *Water Resources Research* **8** (1), 58–69.

Hagan, M. T. & Menhaj, M. B. 1994 Training feedforward networks with the Marquardt algorithm. *IEEE Transactions on Neural Networks* **5**, 998–993.

Hagan, M. T., Demuth, H. B. & Beale, M. H. 1996 *Neural Network Design*. PWS Publishing, Boston, MA, USA.

Hagen, J. S., Leblois, E., Lawrence, D., Solomatine, D. & Sorteberg, A. 2021 Identifying major drivers of daily streamflow from large-scale atmospheric circulation with machine learning. *Journal of Hydrology* **596**, 126086. https://doi.org/10.1016/j.jhydrol.2021.126086.

Hsu, K., Gupta, H. V. & Sorooshian, S. 1995 Artificial neural network modeling of the rainfall-runoff process. *Water Resources Research* **31** (10), 2517–2530.

Humphrey, G. B., Gibbs, M. S., Dandy, G. C. & Maier, H. R. 2016 A hybrid approach to monthly streamflow forecasting: integrating hydrological model outputs into a Bayesian artificial neural network. *Journal of Hydrology* **540**, 623–640. https://doi.org/10.1016/j.jhydrol.2016.06.026.

Jain, A. & Kumar, A. M. 2007 Hybrid neural network models for hydrologic time series forecasting. *Applied Soft Computing* **7** (2), 585–592.

Kim, S., Vertessy, R. A., Perraud, J. M. & Sung, Y. 2005 Integration and application of the rainfall runoff library. *Water Science and Technology* **52** (9), 275–282.

Koycegiz, C. & Buyukyildiz, M. 2019 Calibration of SWAT and two data-driven models for a data-scarce mountainous headwater in semi-arid Konya closed basin. *Water* **11**, 147. doi:10.3390/w11010147.

Lees, T., Buechel, M., Anderson, B., Slater, L., Reece, S., Coxon, G. & Dadson, S. J. 2021 Benchmarking data-driven rainfall-runoff models in Great Britain: a comparison of LSTM-based models with four lumped conceptual models. *Hydrology and Earth System Sciences*. https://doi.org/10.5194/hess-2021-127.

Maier, H. R., Jain, A., Dandy, G. C. & Sudheer, K. P. 2010 Methods used for the development of neural networks for the prediction of water resources variables in river systems: current status and future directions. *Environmental Modelling & Software* **25**, 891–909.

Mekonnen, B. A., Nazemi, A., Mazurek, K. A., Elshorbagy, A. & Putz, G. 2015 Hybrid modelling approach to prairie hydrology: fusing data-driven and process-based hydrological models. *Hydrological Sciences Journal* **60** (9), 1473–1489. doi:10.1080/02626667.2014.935778.

Moradkhani, H. & Sorooshian, S. 2009 General review of rainfall-runoff modeling: model calibration, data assimilation, and uncertainty analysis. In: *Hydrological Modelling and the Water Cycle: Water Science and Technology Library*, Vol. 63 (Sorooshian, S., Hsu, K. L., Coppola, E., Tomassetti, B., Verdecchia, M. & Visconti, G., eds). Springer, Berlin, Heidelberg.

Moretti, G. & Montanari, A. 2007 AFFDEF: A spatially distributed grid based rainfall-runoff model for continuous time simulations of river discharge. *Environmental Modelling & Software* **22**, 823–836.

Mulvany, T. J. 1850 On the use of self-registering rain and flood gauges. *Proceedings of Institution of Civil Engineers* **4** (2), 1–8.

Nanda, T., Sahoo, B., Beria, H. & Chatterjee, C. 2016 A wavelet-based non-linear autoregressive with exogenous inputs (WNARX) dynamic neural network model for real-time flood forecasting using satellite based rainfall products. *Journal of Hydrology* **539**, 57–73. https://doi.org/10.1016/j.jhydrol.2016.05.014.

O'Connell, P. E., Nash, J. E. & Farrel, J. P. 1970 Riverflow forecasting through conceptual models, part 2, the Brosna Catchment at Ferbane. *Journal of Hydrology* **10**, 317–329.

Reed, S., Koren, V., Smith, M., Zhang, Z., Moreda, F. & Seo, D.-J. & DMIP Participants 2004 Overall distributed model intercomparison project results. *Journal of Hydrology* **298** (1–4), 27–60.

Rezaeianzadeh, M., Stein, A., Tabari, H., Abghari, H., Jalalkamali, N., Hosseinipour, E. Z. & Singh, V. P. 2013 Assessment of a conceptual hydrological model and artificial neural networks for daily outflows forecasting. *International Journal of Environmental Science and Technology* **10** (6), 1181–1192.

Rhinehart, R. R. 2016 *Nonlinear Regression Modeling for Engineering Applications: Modeling, Model Validation, and Enabling Design of Experiments*. John Wiley & Sons Ltd, West Sussex, UK.

Sharghi, E., Nourani, V., Molajou, A. & Najafi, H. 2019 Conjunction of emotional ANN (EANN) and wavelet transform for rainfall-runoff modeling. *Journal of Hydroinformatics* **21** (1), 136–152. https://doi.org/10.2166/hydro.2018.054.

Solomatine, D. P. & Dulal, K. N. 2003 Assessment of a conceptual hydrological model and artificial neural networks for daily outflows forecasting. *Hydrological Sciences Journal* **48** (3), 399–411.

Solomatine, D. & Ostfeld, A. 2008 Data-driven modelling: some past experiences and new approaches. *Journal of Hydroinformatics* **10**, 3–22.

Solomatine, D., See, L. & Abrahart, R. 2009 Data-driven modelling: concepts, approaches and experiences. In: *Practical Hydroinformatics: Water Science and Technology Library*, Vol. 68 (Abrahart, R. J., See, L. M. & Solomatine, D. P., eds). Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-540-79881-1_2.

Song, X., Kong, F., Zhan, C. & Han, J. 2012 Hybrid optimization rainfall-runoff simulation based on Xinanjiang model and artificial neural network. *Journal of Hydrological Engineering* **17** (9), 1033–1041. https://doi.org/10.1061/(ASCE)HE.1943-5584.0000548.

Srivastava, R. & Jain, A. 2017 *Engineering Hydrology.* McGraw Hill Education, India.

Sudheer, K. P. & Jain, A. 2009 Recent advances in knowledge extraction from neural network based hydrologic models. *ISH Journal of Hydraulic Engineering* **15** (sup1), 75–83. doi:10.1080/09715010.2009.10514969.

Talei, A., Chua, L. H. C. & Quek, C. 2010 A novel application of a neuro-fuzzy computational technique in event-based rainfall–runoff modeling. *Expert Systems with Applications* **37**, 7456–7468.

Thornthwaite, C. W. 1948 An approach toward a rational classification of climate. *Geographical Review* **38**, 55–94.

Vidyarthi, V. K. & Chourasiya, S. 2020 Particle swarm optimization for training artificial neural network-based rainfall–runoff model, case study: Jardine River Basin. In: *Micro-Electronics and Telecommunication Engineering: Lecture Notes in Networks and Systems*, Vol. 106 (Sharma, D. K., Balas, V. E., Son, L. H., Sharma, R. & Cengiz, K., eds). Springer, Singapore. https://doi.org/10.1007/978-981-15-2329-8_65.

Vidyarthi, V. K. & Jain, A. 2020 Knowledge extraction from trained ANN drought classification model. *Journal of Hydrology* 124804. https://doi.org/10.1016/j.jhydrol.2020.124804.

Vidyarthi, V. K., Jain, A. & Chourasiya, S. 2020 Modeling rainfall-runoff process using artificial neural network with emphasis on parameter sensitivity. *Modeling Earth Systems and Environment*. https://doi.org/10.1007/s40808-020-00833-7.

Wolfs, V., Meert, P. & Willems, P. 2015 Modular conceptual modeling approach and software for river hydraulic simulations. *Environmental Modelling and Software* **71**, 60–77. https://doi.org/10.1016/j.envsoft.

Xu, C. Y. & Singh, V. P. 2001 Evaluation and generalization of radiation-based methods for calculating evaporation. *Hydrologic Processes* **15**, 305–319.

Young, C. C., Liu, W. C. & Wu, M. C. 2017 A physically based and machine learning hybrid approach for accurate rainfall-runoff modelling during extreme typhoon events. *Applied Soft Computing* **53**, 205–216. https://doi.org/10.1016/j.asoc.2016.12.052.

Zhang, B. & Govindaraju, R. S. 2000 Prediction of watershed runoff using Bayesian concepts and modular neural networks. *Water Resources Research* **36** (3), 753–762.

Zhang, J., Li, Y., Huang, G., Chen, X. & Bao, A. 2016 Assessment of parameter uncertainty in hydrological model using a Markov-Chain-Monte-Carlo-based multilevel-factorial-analysis method. *Journal of Hydrology* **538**, 471–486. https://doi.org/10.1016/j.jhydrol.2016.04.044.

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