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Computational approaches for annual maximum river flow series

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KEYWORDS

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Abstract Studies of annual peak discharge and its temporal variations are widely used in the planning and decision making process of water resources management. Very recently, soft computing techniques are gaining ground for time series analysis of hydrological events such as rainfall and runoff. In this study Artificial Neural Network (ANN) has been used in combination with wavelet to model the annual maximum flow discharge of rivers. The results of ANN-Wavelet (WANN) model indicate overall low coherence (R^2 = 0.39) better than ANN (R^2 = 0.31) in isolation. In the present analysis, the authors also conceded a probabilistic distributional analysis of river flow time series which has greater potential to better reflect peak flow dynamics. The results highlight that the overall performance of probability distribution models is superior to WANN model. Instead of that WANN is better than probabilistic models to find the global maxima of the series.

1. Introduction

River discharge measurements in general are carried out on discrete basis [1–3] and in particular on daily basis in India. Data and information on annual peak discharge supplements flood management, reservoir planning and irrigation scheduling [4,5]. Peak discharge is the consequence of summing up of the all contributing discharges from river tributaries. In hydrology, studies related to peak events (river discharge) are deemed necessary given its use in various statistical analyses [1–3].

Estimation of discharge is primarily carried out using two types of mathematical approaches: multivariate approach and univariate approach [6–8]. Physical hydrological modeling is a multivariate approach to estimate the peak discharge using hydro-meteorological data (rainfall, temperature, etc.) and geomorphological data (slope, soil type, etc.) [9,10]. Physical hydrological modeling requires enormous amounts of data and moreover it is a time-consuming process [11,12]. The recent trend is a marked shift from physical hydrological modeling to the use of soft computing techniques, which is gaining significance in a short spell of time [13,14]. Multivariate approach using soft computing techniques (ANN, SVM, etc.) is preferred over physical modeling owing to its limitations of time consumption and data volumes [15,16]. Some multivariate approaches may lead to underestimation of the events as well as the increased uncertainty associated with the given event [17–19]. In multivariate approach, underestimation may be attributed to cumulative effect of uncertainty

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Notations

Q	discharge, m^3/s	w	weights
p	time delay, Year	ε_t	fluctuations at time, t

existence in individual isolated factor. To minimize the cumulative uncertainty, univariate approach is useful given the point that all the external factors have previously influenced the production of the observed time series. It can also be said that the time series embodies all the information required to model the underlying generating process.

Soft computing has numerous applications in hydrological time series analyses, be it multivariate approach or univariate approach [20]. Stationary and non-stationary time series can be analyzed using soft computing techniques. The Artificial Neural Network (ANN) is a soft computing technique that comprises both linear and nonlinear concepts and can be operated with dynamic input–output system. Artificial Neural Network (ANN) is an influential processing tool which has been widely used in water resources research [21,22]. Processing time series components of water resources projects (WRP) with ANN requires a preprocessing stage for data reduction such as Wavelet Transform (WT) in order to gain advantages in training time and also to pass up the redundancy in input data. This helps to obtain a model with better generalization abilities. This is the prime reason for better performance of WANN in different aspects of water resources management [23,24].

Probability distribution is the process of statistical inference surveyed data. It is mainly of two types: parametric distribution and nonparametric distribution. Parametric distributions are probability distributions that can be described using an equation with a finite set of parameters. For a specified parametric distribution, the parameters are estimated by fitting to data. In the field of hydrology the concept of probabilistic distribution can be applied frequently [25,26].

There is a growing need to critically evaluate the annual maximum discharge (using univariate approach) in the river to assist the knowledge base for better planning and management of water resources projects. This promoted the use of ANN and Wavelet-ANN combination to study the annual maximum discharge. In the present study, analyses of extreme flood near the Kosi Mahasetu have been performed using annual maximum discharge time series over the 51 year period from 1964 to 2014. The goal of this study was to determine appropriate probability distributions for describing annual maximum stream flow series for the Kosi River. In this paper, three parameters based (shape, scale and location) study was carried out to characterize the maximum flow of Kosi River.

The major research findings of this study revolve around as follows:

(1) Trend analysis and autocorrelation analysis to detect time period of similar events.
(2) Performance evaluation of ANN and Wavelet-ANN time series analysis of annual maximum discharge series.
(3) Evaluation of probability distribution model for annual maximum discharge and comparison of the results with Wavelet-ANN model.

2. Description of techniques

2.1. Artificial neural network

Artificial Neural Networks (ANNs) may provide an alternative model to river discharge in areas which lack precise data and information about the internal hydrologic processes. ANN model has been developed with a correlation coefficient of 0.99 for the maximum daily river discharge [27].

ANN model employs nonlinear functional mapping on the past observations to predict the future values. ANN uses logistic hidden layer transfer function and two model parameters as connection weights [28].

$$Q_t = f(Q_{t-1}, Q_{t-2}, Q_{t-3} \ldots, Q_{t-p}, w) + \varepsilon_t \quad (1)$$

2.2. Wavelet analysis

The hypothesis of wavelet analysis was developed based on Fourier analysis. A signal is broken up into smooth sinusoids of unlimited duration in Fourier analysis [13]. A wavelet is a mathematical function which can be used to localize a given function in both space and scaling [29,30]. Wavelets can be utilized to extract information from diverse kinds of data; such as seismic, finance, heartbeat and hydrological [27,31–36]. Wavelet analysis is often used to learn evolutionary behavior to characterize fluctuated daily discharge time series [37,38]. The major improvement of wavelet transforms is their capability to concurrently acquire information on the time, location and frequency of a signal, while the Fourier transform provides only the frequency information of a signal.

The continuous Wavelet Transform (CWT) of a discharge time series Q(t) is defined as follows:

$$W(\tau, s) = s^{-1/2} \int_{-\infty}^{+\infty} Q(t)\varphi^*\left(\frac{t-\tau}{s}\right)dt \quad (2)$$

W (τ, s) presents a two-dimensional representation of wavelet power under a different scale, where 's' is the wavelet scale, 't' is the time, 'τ' is the translation parameter and '*' denotes the conjugate complex function. The translation parameter 'τ' is the time step in which the window function is iterated.

2.3. WANN analysis

The Wavelet Artificial Neural Network (WANN) models are obtained combining two methods, Discrete Wavelet Transform (DWT) and ANN. The WANN model is an ANN model, which uses sub-time series components obtained using DWT on original data. The WANN model structure developed in the present study is shown in Fig. 1. For WANN model inputs, the original time series is decomposed into a certain number of sub-time series components (D_s). All component plays different role in the original time series and the behavior of each

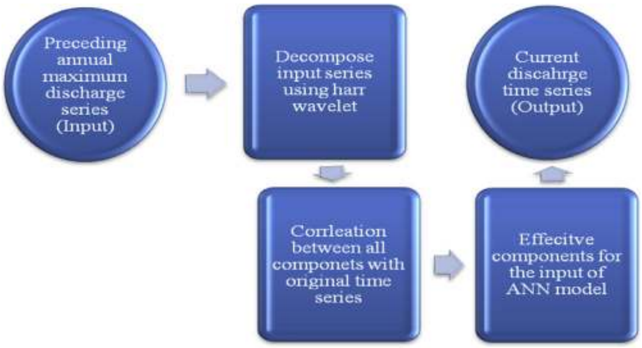

Figure 1 Model structure for WANN.

sub-time series is distinct [38]. In WANN model, the inputs to the model are the D_s of preceding annual maximum and the outputs are current maximum discharge.

2.3.1. Wavelet decomposition

Wavelet decomposition of preceding annual maximum time series (up to preceding three years) has been carried out using toolbox Wavelet 1-D in MATLAB R2013b. Three years of lagging was taken for this study and it was based on the point of first zero crossing of time series autocorrelation. Level of decomposition was kept constant (i.e. 3) for every time series (Fig. 2).

2.4. Distributional analysis

Distributional analysis of river discharge time series is considered very significant in areas related to hydrological engineering, including management of extreme events and optimal design of water storage and drainage networks [39–42]. In order to demonstrate the applicability of the probabilistic distribution model for annual maximum discharge, 51 years data from 1964 to 2014 have been also included in the present analysis.

3. Case study

3.1. Study area

Bihar, a state of India (Fig. 3), is located in the eastern part of the India. The total area of Bihar is about 94,163 km^2 and is third most populous state in India. Bihar comprises thirty-eight (38) districts and one hundred and one (101) sub-divisions. The study area of the present study is the Kosi River, which is termed as the sorrow of Bihar. The discharge gauge site is located at 86°39′3.11″E longitude and 26°17′2.66″N latitude in the vicinity of the Kosi Mahasetu bridge. Recurrent flood is a common phenomenon which affects large populations every year. The flood in the years 2004 and 2007 in the recent decades has been devastating. The 2008 flood leads to the breach of Kosi embankment which affected large populations and caused extensive damage. Hence, any study regarding peak discharge has a great social significance. Complexities in the study of peak discharge (major contributor of flood) are because of its large scale variations; in Kosi River it varies from 5704 to 22,319 m^3/s.

3.2. Descriptive statistics

To comprehend the river's discharge regime, the descriptive statistics of maximum annual discharge at the study station has been computed (Table 1). The analysis indicates that the maximum of maximum annual discharge was 22,319 m^3/s

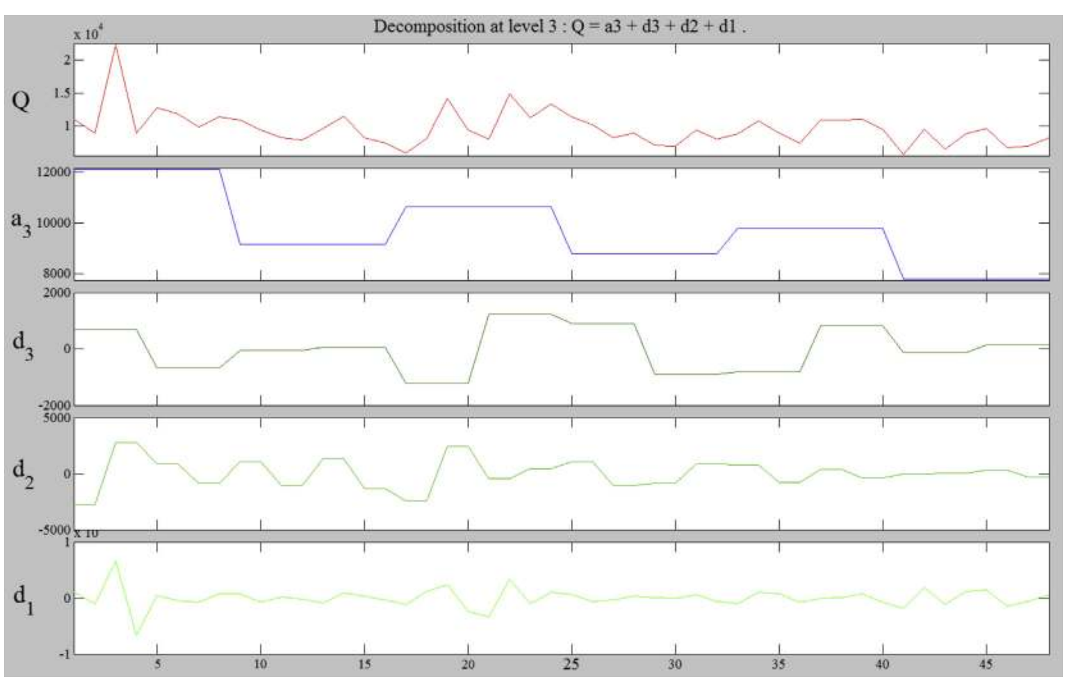

Figure 2 Wavelet decomposition.

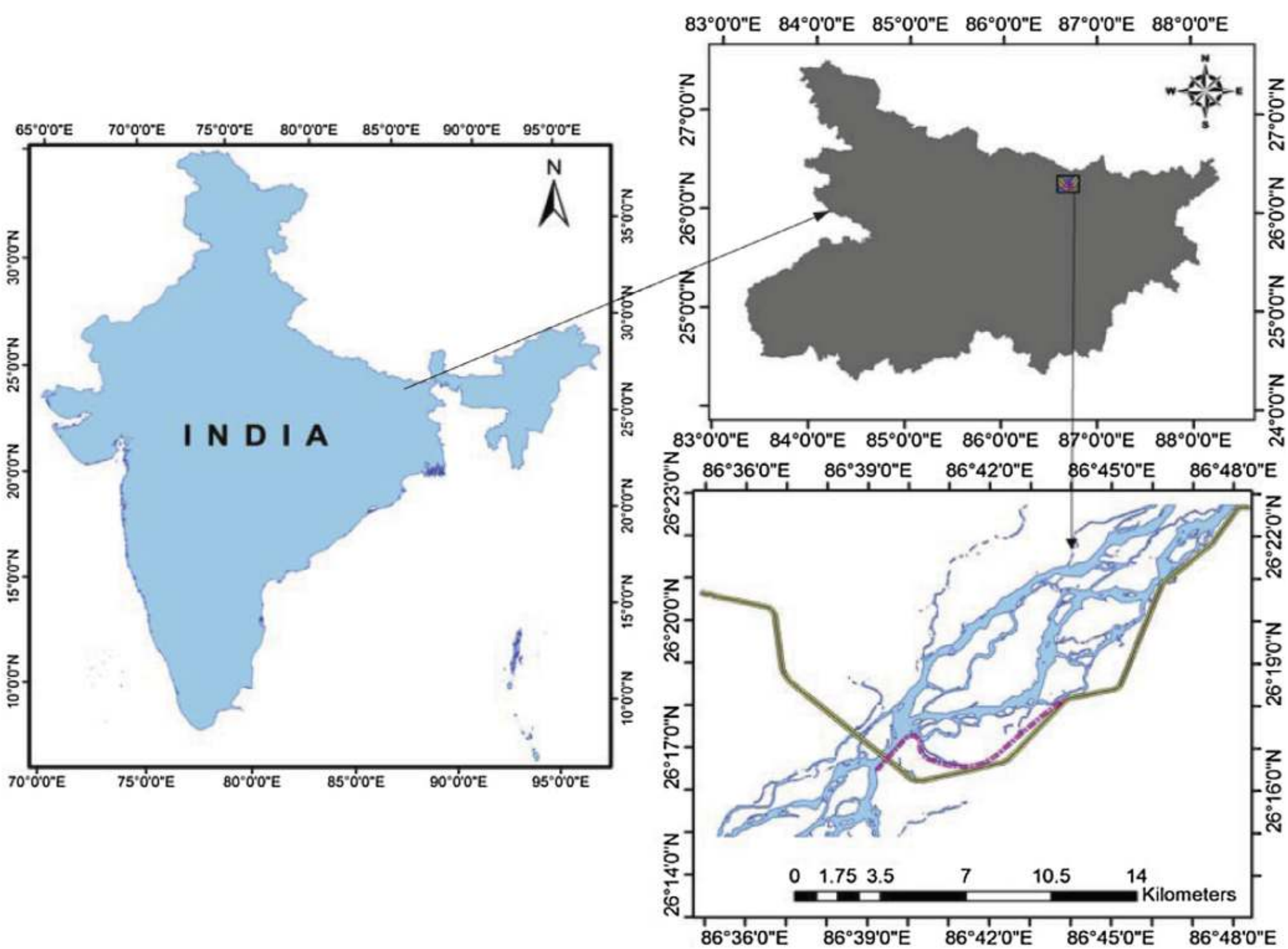

Figure 3 Index map of study area.

Table 1 Statistics of maximum annual discharge at study station.			
Statistics	Value	Statistics	Value (m^3/s)
Number of years	51	Min	5704
Mean (m^3/s)	9633.8	25%	8013
Std. Deviation (m^3/s)	2719.5	50%	9379
Coefficient of variation	0.28228	75%	10,982
Std. Error	380.8	90%	12,571
Skewness	2.1868	95%	14,458
Excess kurtosis	8.4899	Max	22,319

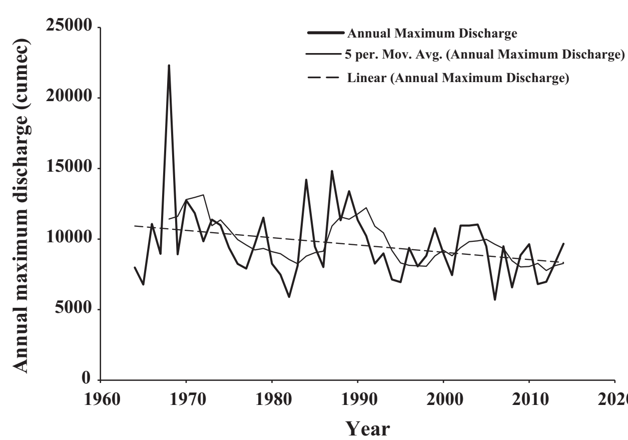

Figure 4 Trend of annual maximum time series.

while the minimum of maximum annual discharge was 5704 m^3/s, which is less than 25 percentile of the time series. Coefficient of variation of the time series is found to be 28.22%.

The decreasing trend line may be attributed to a combination of natural (climate) and anthropogenic (manmade) changes in the Kosi River catchment (Fig. 4). The five year moving average is unable to reveal all the information from the available time series data.

3.3. Autocorrelations

Autocorrelation is the cross-correlation of a time series with itself. It is a mathematical tool for finding repetitive patterns. It presents the resemblance between observations as a function of time separation. It is often used in the time series analysis of hydrological data [43–45]. Furthermore, changes observed are not in the same order (i.e., autocorrelation) for annual maximum discharge data (Fig. 5).

4. Model studies

4.1. ANN vs. WANN

ANN time series was used in isolation for annual maximum discharge time series. Coefficient of determination was found to be very low as 0.301 for the available time series. Peak of the time series (very important for flood management) was underestimated by ANN. Wavelet function can distinguish local events at different times so this feature can be integrated with ANN to match the peak.

Correlation between decomposed (Fig. 2) sub-series (Q, d_1, d_2 and d_3) and actual time series was computed (Table 2). Among the four decomposed sub-series the least correlated series was left out in the final approximated wavelet series. Effective time series was formed by excluding the least correlated component.

Correlation between Lag 1, Lag 2 and Lag 3 wavelet decomposed component are 0.552, 0.471, and 0.199 respectively. ANN was again employed on the effective discharge time series obtained above and results were marginally improved from isolated ANN time series (correlation coefficient improved from 0.301 to 0.390 (Fig. 6)). In addition to the improvement of correlation coefficient (0.301–0.390), the integrated approach led to the matching of peak discharge.

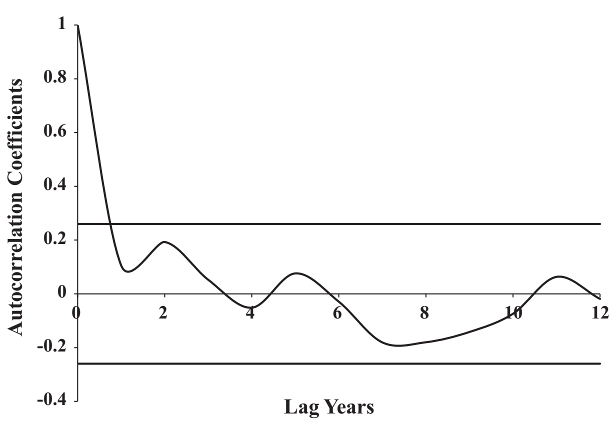

Figure 5 Autocorrelation coefficients for annual maximum time series.

Table 2 Correlation of wavelet component with real time observed data with lagged data.

	$Q^{*}_{(t-1)}$	$Q^{**}_{(t-2)}$	$Q^{***}_{(t-3)}$
a_3	0.52	0.447	0.382
d_1	−0.21	0.2	0.008
d_2	−0.15	−0.287	−0.234
d_3	0.198	0.187	0.022

$Q^{*}_{(t-1)}$ = Observed time series with one year lag,
$Q^{**}_{(t-2)}$ = Observed time series with two year lag, and
$Q^{***}_{(t-3)}$ = Observed time series with three year lag.

4.2. Probabilistic distribution model

Six probabilistic distribution models were applied to the 51 years available maximum discharge data based on three parameters (shape, scale and location). The results of the K–S test for annual maximum discharge indicate that the Pearson 5 (3P) distribution with P-values of 0.957 performed the best.

Scale parameter generally indicates the proportionality with the variance of the series. The scale parameter is found to be the highest for Pearson 5 (3P) distribution. Weibull (3P) had the lowest P value for both K–S and Chi-square test. Different parameters of probabilistic distribution time series have been summarized in Table 3.

The location parameter for the Generalized Logistic Probability distribution was found to be closest to the mean of the series and even the scale parameter (1259.1) was found to be low. The scale parameter of Generalized Logistic Probability distribution is greater than that of log normal probability distribution. Probability differences show the lower positive probability difference for Generalized Logistic Probability distribution as indicated in Figs. 7 and 9 shows its suitability and applicability for the annual maximum discharge series. Correlation of the model established using Generalized Logistic Probability distribution is of the order of 0.983, which can be considered as good in comparison with Wavelet-ANN model used for annual maximum discharge time series. Various probabilistic distributions as given in Fig. 9 consolidate the view for future use of probabilistic models to successfully analyze and predict peak discharge.

The empirical Cumulative Distribution Function (CDF) plot (Fig. 8) reveals the following:

- The Generalized Logistic Probability distribution provides the best fit for the annual maximum discharge.
- The mean annual maximum discharge is 9155.8 m^3/s.
- Approximately 90% of the data falls below 15,000 m^3/s.

5. Discussions and conclusions

From the analysis, it is observed that the combination of Wavelet-ANN has improved the performance of time series analysis but the ability to replicate information of the observed

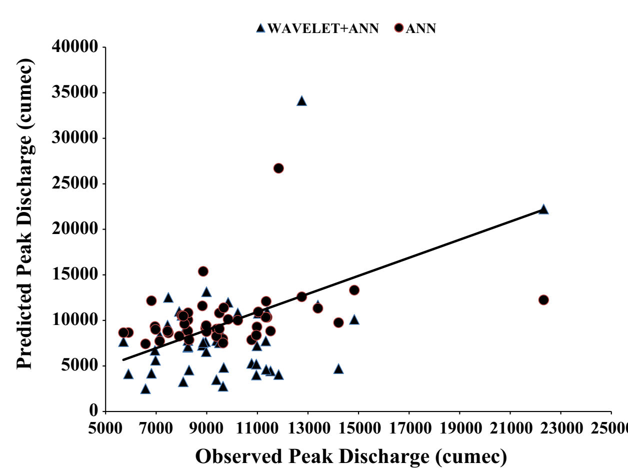

Figure 6 Predicted discharge using ANN and WANN.

Table 3 Parameters and *P* values of probabilistic distribution time series.

Distribution	Parameters			*P* Values	
	Shape	Scale	Location	K–S test	Chi-square test
Pearson 5 (3P)	10.753	73,645	2070.8	0.95667	0.67918
Weibull (3P)	1.5842	4516.9	5580.2	0.66	0.69309
Generalized Extreme Value	0.07376	1828.6	8435.1	0.934	0.82
Log-Logistic (3P)	4.315	5357.5	3802.5	0.943	0.77
Lognormal (3P)	0.4121	8.5965	3730.4	0.943	0.825
Generalized Logistic	0.21821	1259.1	9155.8	0.946	0.782

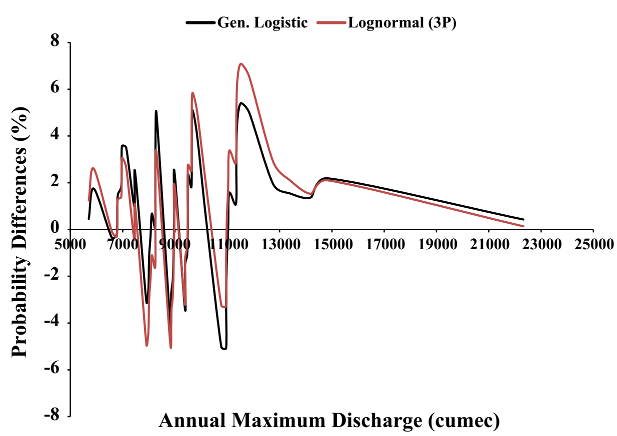

Figure 7 Probability differences for two (Gen. logistic and Lognormal) distributions.

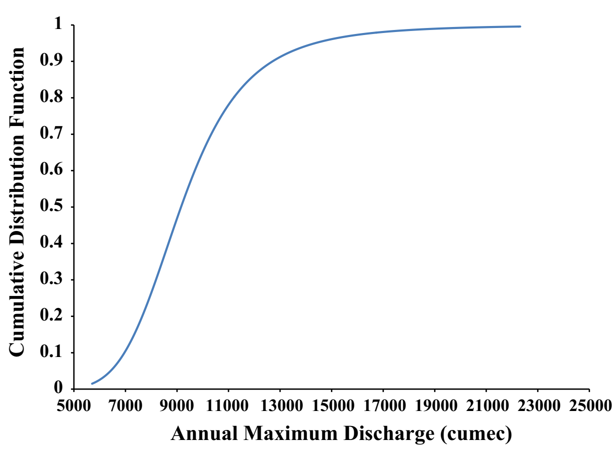

Figure 8 CDF of Generalized Logistic distributions.

time series based on probability distributions time series is higher than that of Wavelet-ANN. Probability distribution time series (Fig. 9) can serve as an improvement over the Wavelet-ANN time series. Peak of peak was best estimated by WANN (Fig. 6) due to local reflection characteristics of wavelet.

Five hundred year return period flood was estimated using Weibull distribution and it was found 14,875 m^3/s in comparison with the 21,000 m^3/s for Generalized Logistic Probabilistic distribution. The peak of peak was found to be on the lower side (underestimated) using Weibull distribution. Following conclusions have been drawn over the study:

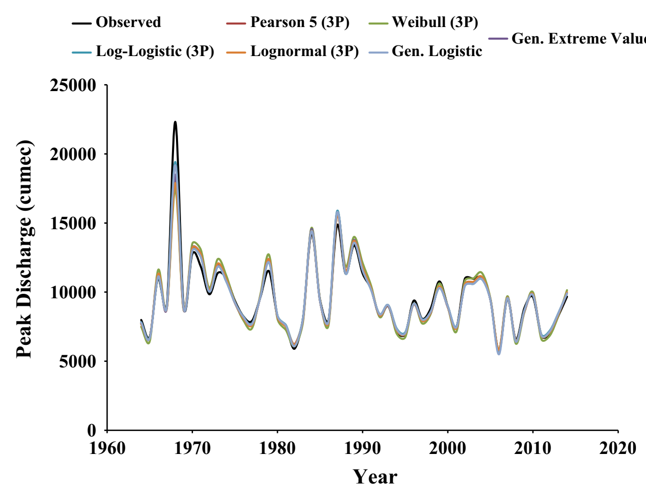

Figure 9 Observed and Probabilistic model.

1. To better reflect and reproduce the complex peak flow dynamics, it is attempted to use soft computing techniques namely artificial neural network and wavelet for continuous annual maximum river discharge measurements as well as separately carried out probabilistic distributional analysis on the data obtained. Based on the analysis carried out, it was found that the peak discharge data fit more realistically and also with higher accuracy by probabilistic distribution rather than ANN-Wavelet modeling.
2. Graphical methods have been utilized in the selection of probabilistic distribution model, while Kolmogorov–Smirnov (K–S) and chi-square tests were employed to assess goodness of fit for the selected probabilistic models. The final selection of the appropriate model was based on the considerations of all the three parameters (shape, scale and location) as well as the *P*-values.
3. It has been suggested to make use of the Generalized Logistic distribution in flood frequency analysis of the Kosi region.

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References

[1] Koutsoyiannis D, Efstratiadis A, Georgakakos KP. Uncertainty assessment of future hydroclimatic predictions: a comparison of probabilistic and scenario-based approaches. J Hydrometeorol 2007;8:261–81.
[2] Shamir E, Georgakakos KP, Murphy MJ. Frequency analysis of the 7–8 December 2010 extreme precipitation in the Panama Canal Watershed. J Hydrol 2013;480:136–48.
[3] Stedinger JR, Cohn TA. Flood frequency analysis with historical and paleoflood information. Water Resour Res 1986;22:785–93.
[4] Ali MH, Shui LT, Walker W. Optimal water management for reservoir based irrigation projects using geographic information system. J Irrig Drain Eng 2003;129:1–10.
[5] Malano HM, van Hofwegen P. Management of irrigation and drainage systems, vol. 3. CRC Press; 1999.
[6] Michele C, Salvadori G, Vezzoli R, Pecora S. Multivariate assessment of droughts: frequency analysis and dynamic return period. Water Resour Res 2013;49:6985–94.
[7] Vismara R, Azzellino A, Bosi R, Crosa G, Gentili G. Habitat suitability curves for brown trout (Salmo trutta fario L.) in the River Adda, Northern Italy: comparing univariate and multivariate approaches. Regul Rivers: Res Manage 2001;17: 37–50.
[8] Porporato A, Ridolfi L. Multivariate nonlinear prediction of river flows. J Hydrol 2001;248:109–22.
[9] Clark MP, Nijssen B, Lundquist JD, Kavetski D, Rupp DE, Woods RA, et al. A unified approach for process-based hydrologic modeling: 1. Modeling concept. Water Resour Res 2015;51:2498–514.
[10] Diodato N, Guerriero L, Fiorillo F, Esposito L, Revellino P, Grelle G, et al. Predicting monthly spring discharges using a simple statistical model. Water Resour Manage 2014;28:969–78.
[11] Gupta H, Perrin C, Bloschl G, Montanari A, Kumar R, Clark M, et al. Large-sample hydrology: a need to balance depth with breadth. Hydrol Earth Syst Sci 2014;18:463–77.
[12] Dingman SL. Physical hydrology. Waveland Press; 2015.
[13] Kisi O, Cimen M. Precipitation forecasting by using wavelet-support vector machine conjunction model. Eng Appl Artif Intell 2012;25:783–92.
[14] Partal T, Kişi Ö. Wavelet and neuro-fuzzy conjunction model for precipitation forecasting. J Hydrol 2007;342:199–212.
[15] Rajaee T. Wavelet and ANN combination model for prediction of daily suspended sediment load in rivers. Sci Total Environ 2011;409:2917–28.
[16] Rajaee T, Mirbagheri SA, Zounemat-Kermani M, Nourani V. Daily suspended sediment concentration simulation using ANN and neuro-fuzzy models. Sci Total Environ 2009;407: 4916–27.
[17] Nayak PC, Sudheer KP, Jain SK. River flow forecasting through nonlinear local approximation in a fuzzy model. Neural Comput Appl 2014;25:1951–65.
[18] Sudheer K, Nayak P, Ramasastri K. Improving peak flow estimates in artificial neural network river flow models. Hydrol Process 2003;17:677–86.
[19] Sudheer KP, Gosain AK, Ramasastri KS. A data-driven algorithm for constructing artificial neural network rainfall-runoff models. Hydrol Process 2002;16:1325–30.
[20] Nayak P, Sudheer K, Rangan D, Ramasastri K. A neuro-fuzzy computing technique for modeling hydrological time series. J Hydrol 2004;291:52–66.
[21] Tiwari H, Rai SP. Review of Information and soft computing techniques (ISCT) approaches in Water Resources Projects. In: Managing information technology. Delhi: DESIDOC; 2015. p. 89–94.
[22] Kisi O, Shiri J, Tombul M. Modeling rainfall-runoff process using soft computing techniques. Comput Geosci 2013;51:108–17.
[23] Nourani V, Hosseini Baghanam A, Adamowski J, Kisi O. Applications of hybrid wavelet–artificial Intelligence models in hydrology: a review. J Hydrol 2014;514:358–77.
[24] Nourani V, Komasi M, Mano A. A multivariate ANN-Wavelet approach for rainfall-runoff modeling. Water Resour Manage 2009;23:2877–94.
[25] Vogel RM, Wilson I. Probability distribution of annual maximum, mean, and minimum stream flows in the united states. J Hydrol Eng 1996;1:69–76.
[26] Yevjevich V, Engineer Y, Yevjevich V, Yevjevich V, Ingénieur Y. Probability and statistics in hydrology. Fort Collins, Colorado, USA: Water Resources Publications; 1972.
[27] Ahmad S, Simonovic SP. An artificial neural network model for generating hydrograph from hydro-meteorological parameters. J Hydrol 2005;315:236–51.
[28] Peter ZG. Time series forecasting using a hybrid ARIMA and neural network model. Neurocomputing 2003;50:159–75.
[29] Labat D. Recent advances in wavelet analyses: Part 1. A review of concepts. J Hydrol 2005;314:275–88.
[30] Labat D, Ronchail J, Guyot JL. Recent advances in wavelet analyses: Part 2—Amazon, Parana, Orinoco and Congo discharges time scale variability. J Hydrol 2005;314:289–311.
[31] Ivanov PC, Amaral LAN, Goldberger AL, Havlin S, Rosenblum MG, Struzik ZR, et al. Multifractality in human heartbeat dynamics. Nature 1999;399:461–5.
[32] Ivanov PC, Rosenblum MG, Peng C, Mietus J, Havlin S, Stanley H, et al. Scaling behaviour of heartbeat intervals obtained by wavelet-based time-series analysis. Nature 1996;383:323–7.
[33] Chakraborty A, Okaya D. Frequency-time decomposition of seismic data using wavelet-based methods. Geophysics 1995;60:1906–16.
[34] Sinha S, Routh PS, Anno PD, Castagna JP. Spectral decomposition of seismic data with continuous-wavelet transform. Geophysics 2005;70:P19–25.
[35] Michael PHF, Clementsa P, Swansonc Norman R. Forecasting economic and financial time-series with non-linear models. Int J Forecast 2004;20:169–83.
[36] Agarwal A, Singh R, Mishra S, Bhunya P. ANN-based sediment yield models for Vamsadhara river basin (India). Water SA 2005;31:85–100.
[37] Smith LC, Turcotte DL, Isacks BL. Stream flow characterization and feature detection using a discrete wavelet transform. Hydrol Process 1998;12:233–49.
[38] Wang W, Ding J. Wavelet network model and its application to the prediction of hydrology. Nat Sci 2003;1:67–71.
[39] Guo Y, Adams BJ. Hydrologic analysis of urban catchments with event-based probabilistic models: 2. Peak discharge rate. Water Resour Res 1998;34:3433–43.
[40] Madsen H, Rasmussen PF, Rosbjerg D. Comparison of annual maximum series and partial duration series methods for modeling extreme hydrologic events: 1. At-site modeling. Water Resour Res 1997;33:747–57.
[41] Bowers MC, Tung WW, Gao JB. On the distributions of seasonal river flows: lognormal or power law. Water Resour Res 2012;48, n/a–n/a.
[42] Te Linde AH, Aerts JCJH, Bakker AMR, Kwadijk JCJ. Simulating low-probability peak discharges for the Rhine basin using resampled climate modeling data. Water Resour Res 2010;46, n/a–n/a.
[43] Milly PC, Dunne KA, Vecchia AV. Global pattern of trends in stream flow and water availability in a changing climate. Nature 2005;438:347–50.
[44] Lisi F, Villi V. Chaotic forecasting of discharge time series: a case study. Wiley Online Library; 2001.
[45] Zanchettin D, Traverso P, Tomasino M. Po River discharges: a preliminary analysis of a 200-year time series. Climatic Change 2008;89:411–33.

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