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Application of ANNs for the modeling of streamflow, sediment transport, and erosion rate of a high-altitude river system in Western Himalaya, Uttarakhand

Aplicação de ANNs para a modelagem do fluxo, transporte de sedimentos e taxa de erosão de um sistema fluvial de alta altitude no Himalaia Ocidental, Uttarakhand

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ABSTRACT

The estimation of stream discharge is an essential component of planning and decision-making. It is highly correlated with many development activities involving water resources. The study of transportation of sediments in the rivers will help us to develop policies and plans for soil conservation, flood control, irrigation, navigation, and aquatic biodiversity problems. Using data-driven models such as Artificial Neural Networks (ANNs), modeling of streamflow and sediment transport is frequently adopted due to their applicability and problem-solving ability. This study has used three training algorithms such as Scaled Conjugate Gradient (SCG), Bayesian Regularization (BR), and Levenberg-Marquardt (LM) to simulate the streamflow and Suspended Sediments Concentration (SSC). After optimizing the best training algorithm based on the model efficiency parameters, L-M based-ANN model has been used to predict streamflow for two years and the modeling of suspended sediments was validated with the help of observed data. The result shows that the simulated results tracked the streamflow as well as SSC with the desired accuracy based on the model efficiency parameters such as coefficient of Determination (R^2), Nash Sutcliffe Efficiency (NSE), Root Mean Square Error (RMSE), and Root Mean Square Deviation (RMSD). The study's outcomes reveal that in the streamflow the concentration of suspended sediments is significantly affected by the base rock material, glaciers covered by debris, and moraine-laden ice. The transportation of the sediments is high in the Alaknanda basin as compared to the other basins and the previous studies. This might happen due to the severe anthropogenic activities in the surrounding basin.

Keywords: Artificial Neural Networks (ANNs); Data-driven; Decision-makers; Sediment transport; Streamflow modeling; Training algorithms.

RESUMO

A estimativa de fluxo descarga é um componente essencial do planejamento e da tomada de decisões. Está altamente correlacionado com muitas atividades de desenvolvimento envolvendo recursos hídricos. O estudo do transporte de sedimentos nos rios nos ajudará a desenvolver políticas e planos de conservação do solo, controle de enchentes, irrigação, navegação e problemas de biodiversidade aquática. Usando modelos baseados em dados, como Redes Neurais Artificiais (ANNs), a modelagem de vazão e do transporte de sedimentos é frequentemente adotada devido à sua aplicabilidade e capacidade de resolução de problemas. Este estudo utilizou três algoritmos de treinamento como Gradiente Conjugado Escalonado (SCG), Regularização Bayesiana (BR) e Levenberg-Marquardt (LM) para simular o fluxo de vazão e a concentração de sedimentos suspensos (SSC). Depois de otimizar o melhor algoritmo de treinamento baseado nos parâmetros de eficiência do modelo, o modelo LM-ANN foi utilizado para prever o fluxo vazão por dois anos e a modelagem de sedimentos suspensos foi validada com a ajuda de dados observados. O resultado mostrou que os resultados simulados acompanharam o fluxo de vazão, bem como o SSC com a precisão desejada com base nos parâmetros de eficiência do modelo, como coeficiente de determinação (R2), Nash Sutcliffe Efficiency (NSE), Root Mean Square Error (RMSE) e Root Mean Square Deviation (RMSD). Os resultados do estudo revelam que no fluxo de córregos a concentração de sedimentos suspensos é significativamente afetada pelo material de rocha base, geleiras cobertas por detritos e gelo carregado de detritos não consolidados. O transporte dos sedimentos é alto na bacia de Alaknanda em comparação com as outras bacias e os estudos anteriores. Isso pode acontecer devido às severas atividades antropogênicas na bacia circundante.

Palavras-chave: Redes Neurais Artificiais (ANNs); Modelos baseados em dados; Tomadores de decisão; Transporte de sedimentos; Modelagem de vazão; Algoritmos de treinamento.

INTRODUCTION

Flow and suspended sediments in the natural streams combine topographical and atmospheric processes (Woodward & Foster, 1997; Gunathilake et al., 2021; Rautela et al., 2022a). In developing a flow hydrograph, it is essential to use observed streamflow measurements (Sampath et al., 2015; Rautela et al., 2020, 2022a). Many methods, such as direct (Area-velocity, dilution methods) (Dobriyal et al., 2017) or indirect (hydraulic structures, hydrologic models, slope area methods) (Yang et al., 2014) are available to measure streamflow while the suspended sediments are measured by the vacuum filtration method (Bisht et al., 2021; Rautela et al., 2022a). However, in the high-altitude river system, rough topography and the worst climatic scenarios make monitoring the riverine flow and sediments more complicated (Lakshmi et al., 2018; Kuniyal et al., 2021; Rautela et al., 2022b). Also, the associated costs of these hydrological networks are quite high (Lakshmi et al., 2018). Furthermore, these regions often have no fine-resolution spatial datasets, including soil and land-use data (Chaplot 2014; Sofi et al., 2021). Therefore, computational models are given increased attention to estimate streamflow and sediment transport. It is still critical for many stakeholders and policymakers, including those involved with land and water resources management and hydropower development, to estimate streamflow accurately (Pradhan et al., 2020).

Among many other Computer-Based (CB) models used for the simulation of the hydrological process, such as the Hydrologic Engineering Centre-Hydrologic Modelling System (HEC-HMS) (Scharffenberg & Feldman 2000), Mike-NAM and SHE (Razad et al., 2018), Soil and Water Assessment Tool (SWAT) (Liang et al., 2018; Kumar & Bhattacharjya, 2020; Rautela et al., 2022c), Variable Infiltration Capacity (VIC) (Liang et al., 1994), etc. are frequency used by the researchers all over the world. Due to the inaccessibility of long-term data, including hydro-meteorological and concentration of suspended sediments, hydrological models may contain uncertainties in streamflow and SSC estimations (Alagha et al., 2012). The fact that there are not many climatic stations, especially in the higher elevations of the Himalayan region, has forced researchers to rely on Satellite-based Precipitation Products (SbPP's) (Krakauer et al., 2013; Gairola et al., 2015; Dahri et al., 2021; Rautela et al., 2022c). Using SbPP's for hydrological applications is particularly attractive since they are freely available and provide consistent data with fine spatial and temporal resolution (Gunathilake et al., 2021). As a result, SbPP's can address many shortcomings associated with using ground-based rain gauges to measure precipitation. However, it is important to test the accuracy of SbPP's before their use.

The advance in science and technology has enabled the creation of data-driven models viz; Artificial Neural Networks (ANNs) (Taşar et al., 2017; Dalkiliç & Hashimi 2020), Fuzzy Logic (Kambalimath & Deka, 2020), Adaptive Neuro-Fuzzy Inference Systems (ANFIS) (Sirabahenda et al., 2020; Dalkiliç & Hashimi, 2020), and Support Vector Systems (SVS) (Adnan et al., 2017), etc. (Olyaie et al., 2015). In addition to these data-driven models, it has been noted that ANNs are being used in various applications, including estimation of streamflows (Pradhan et al., 2020), sediment load, future hydropower generation (Khaniya et al., 2020), and predicting changes in climate and crop yield (Kisi et al., 2019; Amaratunga et al., 2020; Wickramasinghe et al., 2021). In a recent study, Cui et al. (2020) monitors river flow patterns on an hourly basis by using Emotional Neural Network (ENN), simulating the essential precautionary task of managing water resources, mitigating flooding risks, and reducing the impact of rivers. However, Choubin et al. (2019) estimate streamflow in an un-gauged river basin by fuzzy clustering and incorporating topography/morphology, land use types, soil properties, remote sensing (RS)-based parameters, and climate parameters. Malekian et al. (2019) developed a new framework (Salas model) for modeling the water balance component of the basin to find out the human interventions in the river basin. In a recent study, Kisi et al. (2019) examined the interactions between large-scale climate signals and streamflow patterns. The data-driven models have been used in forecasting streamflows and suspended sediment concentration in several countries worldwide, but this method has not been applied much to the Himalayan Rivers, where variations in the flow parameters are very high (Mehr et al., 2015; Dalkiliç & Hashimi, 2020).

The inspiration for developing artificial neural networks (ANNs) came from the wish to create a decision-making process similar to that of the human brain (Gill, 2019). In ANN's, information is accepted, analyzed, and exchanged over a network of weighted connections between neurons. As a result, ANNs acquire knowledge through a pragmatic method involving the identification of weights for connections and boundary values, or biases, for neurons. Like a human brain, ANNs also store information for future use (ASCE Task Committee on Application of Artificial Neural Networks in Hydrology, 2000).

The present study was carried out in the Alaknanda River basin to acknowledge the need to simulate the long-term streamflow and visualize the concentration of suspended sediments to measure the erosion rate in the Himalayan River basin using artificial neural networks (ANNs). The present study's findings will provide reliable information for land and water resource management, including existing and proposed runoff river hydroelectric plants in the Alaknanda River basin. It is possible to replicate the methodology used in this study in other river basins without the availability of spatial and temporal data.

STUDY AREA

The Alaknanda River system (Figure 1) is a significant upstream tributary of the Ganges that originates at the confluence of the Satopath and Bhagirathi Kharak glaciers in the state of Uttarakhand. The Alaknanda river and its tributaries drain an area of 11064 km^2. The Alaknanda river travels a distance of 195 kilometres through the Chamoli, Rudraprayag, and Pauri districts of Uttrakhand, and after that, it confluences with the Bhagirathi river and forms the Ganges. Besides these cultural benefits, the river is located at the confluence of major tributaries and is called prayags (Vishnuprayag, Nandprayag, Karnaprayag, Rudraprayag, and Devprayad). The main tributaries of the Alaknanda river are Saraswati, western Dhauliganga, Nandakini, Pinder and Mandakini. Mountainous terrain creates microclimates in the basin, and temperatures vary seasonally and geographically (from river valleys to higher elevations) (Chopra et al., 2012). There are places with

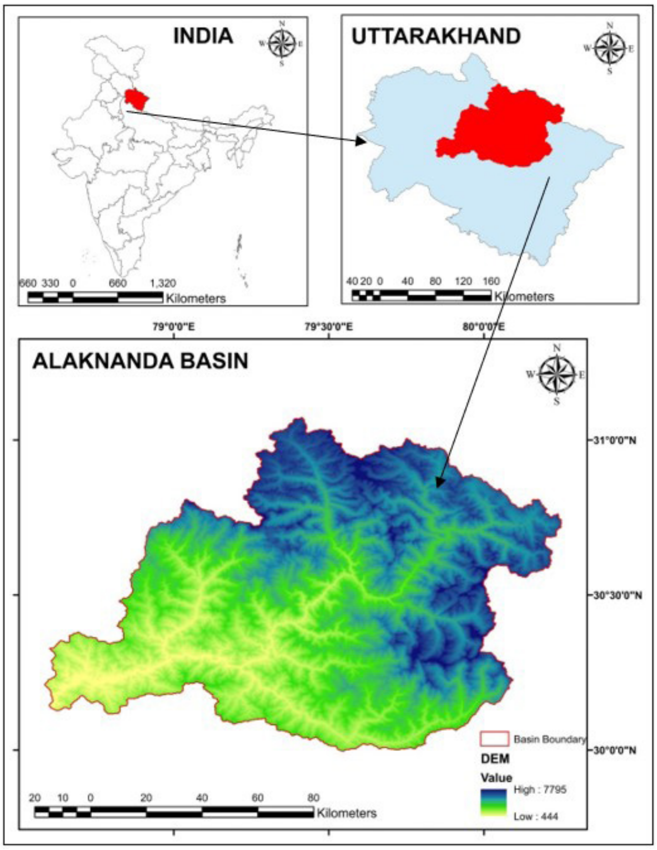

Figure 1. Location map of the study area.

the lowest average daily temperatures of 0.5 °C in January in the Alaknanda River basin and the highest average daily temperatures of 30 ^{0}C in June in the town of Srinagar (Panwar et al., 2017). Over 80 percent of India's annual precipitation occurs during the summer months of June to September due to the circulation of the Asian Summer Monsoon (ASM) (Kumar et al., 2010). Since the Alaknanda basin has narrow valleys and heavy rainfall, it is frequently damaged by cloud bursts, flash floods, riverine floods, and landslides. Tributaries such as western Dhauliganga, Nandakini, Pinder, and Mandakini all contribute significant flow and suspended sediments to the main river. In all of these tributaries, snowmelt, glacier melt, and seasonal rainfall are the primary sources of perennial flows.

METHODOLOGY

Data collection

The meteorological data set, including precipitation, solar radiation, relative humidity, average temperature, and soil moisture, was downloaded from NASA Agro Climatic Data from 1986-2021 with a temporal resolution of one day. In addition to that, the streamflow data from 1986-2015 will be acquired from Central Water Commission (CWC), and the rest of the streamflow from 2015-2021 will be acquired from Alaknanda Hydroelectric power project, Srinagar. Also, the concentration of the suspended sediments on a daily basis during the high flow period JJAS (June-September) for three years (2016-2018).

NASA POWER data access service is accessible as a single point, regional, and global coverage with daily, inter-annual, and temporal climatology averages (Rautela et al., 2022c). The single point endpoint generates a temporal data set from the registered coordinates. Additionally, the regional endpoint provides a time series based on a bounding box of geographical coordinates (Aboelkhair et al., 2019). The meteorological parameters in POWER Release 8 are based upon Goddard's Global Modeling and Assimilation Office (GMAO) Modern Era Retrospective-Analysis for Research and Applications (MERRA-2) assimilation model products and GMAO Forward Processing – Instrument Teams (FP-IT) GEOS 5.12.4 near-real-time products.

Modeling of streamflow and suspended sediment concentration using Artificial Neural Network

To develop the non-linear relationship between the input variables, ANNs are used widely to model basin hydrology. Accordingly, ANN was used to formulate the following relationship, where the streamflow and SSC are non-linear functions of the receiving hydro-meteorological parameters of various stations (Kisi, 2010). Rainfall information is insufficient to estimate the streamflow and SSC with the basin. Because the streamflow and SSC also depend on the catchment characteristics and the meteorological parameters (Forbes & Lamoureux, 2005). The proposed output variable for the study was streamflow at the outlet of the basin. ANN has no fixed method for determining the pairs of input and output data. To fill this void, the number of data pairs used for the training should equal to or greater than the number of parameters (weights) in the network (Gurney 2018). In the present study, 12054 input-output data sets have been used. Two approaches have simulated streamflow with the without flow and flow (Equations 1 and 2).

$$Q_t = \sum_{i=1}^{6} f(P_t, P_{t-1}, R_{H\,t}, R_{H\,t-1}, S_{r\,t}, S_{r\,t-1}, T_t, T_{t-1}, S_t, S_{t-1}) \tag{1}$$

$$Q_t = \sum_{i=1}^{6} f(P_t, P_{t-1}, R_{H\,t}, R_{H\,t-1}, S_{r\,t}, S_{r\,t-1}, T_t, T_{t-1}, S_t, S_{t-1}).f(Q_{t-1}) \tag{2}$$

For SSC following relation has been used:

$$SSC_t = \sum_{i=1}^{6} f(P_t, P_{t-1}, T_t, T_{t-1}).f(Q_t, Q_{t-1}, SSC_{t-1}) \tag{3}$$

Where; P, RH, S_r, T, S, and Q are the Precipitation, Relative Humidity, Solar radiation, Temperature, Soil moisture, and streamflow, respectively, t and t-1 denote the present and previous day data, and i=1 to 6 represents the number of the meteorological stations.

The streamflow and SSC lag time were calculated using the float method at four prayags viz; Vishnuprayag, Nandaprayag, Karnapyrayag, and Devprayag by various field surveys during lean and high flow periods. The surface velocity of the river has been estimated as 2.70, 1.80, 1.75, and 1.45 m/s at Vishnuprayag, Nandaprayag, Karnapyrayag, and Devprayag, respectively, since the surface velocity decreases towards the banks and bed of the streams (Bisht et al., 2020; Rautela et al., 2022a). A correction factor of 0.8 has been applied to convert the surface velocity into average velocity (Rautela et al., 2022a), and it is estimated as 1.52 m/s. The total length of the river is 195 kilometres. So the lag time of the river is estimated as 1.4 days. So for the modeling of streamflow and SSC, the lag time is taken as one day as per the availability of the previous day's hydro-meteorological parameters.

The input and output pair of the datasets have been rearranged as per the hydrological year (i.e., June-1986 to May-2021). Further, the datasets have been divided into training/calibration (June-1986 to May-2019) and prediction/validation (June-2019 to May 2021). For modeling of Suspended Sediment Concentration (SSC), the datasets have been arranged from June-2016 to September-2017 for calibration and June-2018 to September-2018 for prediction. The ANN tool in the mathematical computing application (MATLAB 2017) was used to model the above relationship. Figure 2 illustrates the methodology adopted to estimate the streamflow using an artificial neural network with different algorithms. In addition to input and output layers, one hidden layer has been used to model the streamflow and SSC (Cybenko, 1989; Hornik et al., 1989). The present study uses a five-layered feed-forward neural network with a back-propagation algorithm to construct the model architecture. It consists of several neurons connected and distributed over each other. In ANN, data flow is unidirectional, i.e., feed-forward means the input data were propagated through the network, layer by layer in the forward direction. First, the network is trained on a set of paired data to manage the input-output meaning. Further, the weights of the connection between neurons are then fixed, and the network is used to determine the classification of a new set of data.

The present study used the most suitable algorithm based on the model evaluation criteria for forecasting the multilayer feed-forward method with back-propagation (Zhao et al., 2012). The artificial neurons were organized in the layers and sent their signals forward, and at the same time, the errors were propagated backward. The hidden and output neurons had sigmoid and pure linear transfer functions, respectively (Muluye, 2011). Also, the sigmoidal and hyperbolic tangent activation function was adopted, which is most suitable, continuously differentiable, monotonic, and non-linear (Yonaba et al., 2010). The range of recommended learning rates for the training of ANNs optimally varies from 0.001-0.006 will be suggested that the minimum learning rate parameter 'n' leads to smaller changes to the synaptic weights in the network from one iteration to another iteration, and optimization function will not converge (Brownlee, 2019; Wegayehu & Muluneh, 2022). So keep in mind with the above situation, a learning rate of 0.001 will be adopted in the present study (Wegayehu & Muluneh, 2022). Input data for the system were the daily hydro-meteorological data from the six stations. An artificial neural network was trained based on observed streamflows. The training process used 70% of the time-series data, while testing and validating processes used 15% of each (Sangiorgio et al., 2021; Gunathilake et al., 2021; Ouma et al., 2021; Singh & Panda, 2022). The training aims to determine the set of connections, weights, and biases that cause the neural network to estimate outputs close to the measured outputs. Also,

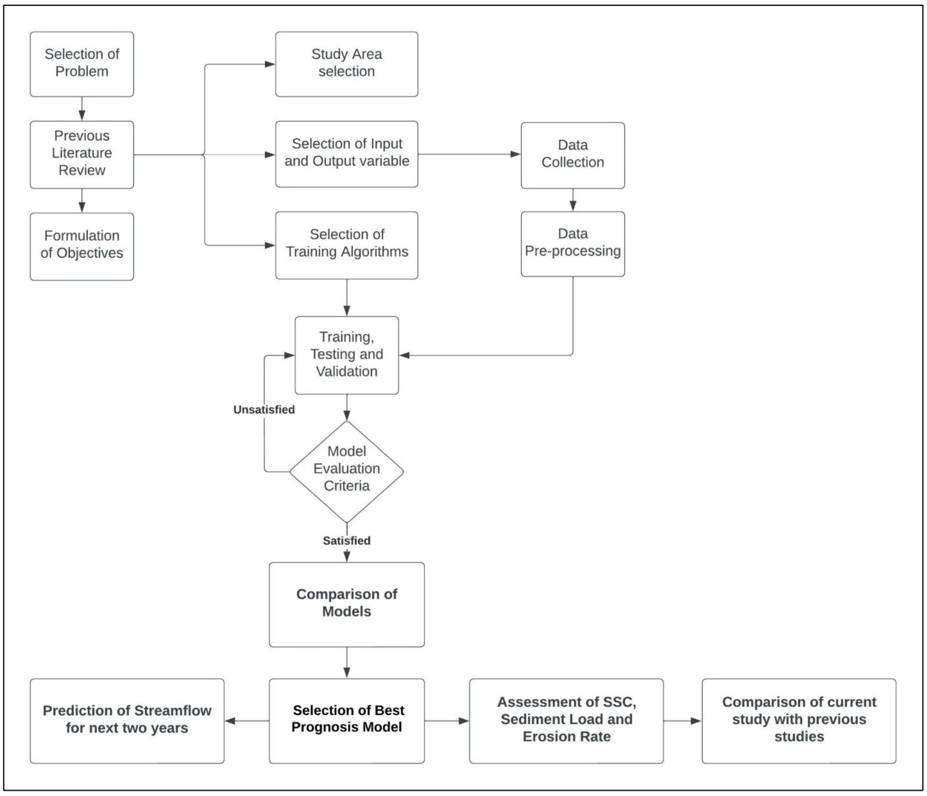

Figure 2. Methodology adopted for the simulation of streamflow and suspended sediments.

the training datasets were used to minimize the error. There are various training algorithms to train the input parameters to get an output with a reduced global error by adjusting weights and bias in the ANNs (Ehret et al., 2015; Haykin, 1999; Kröse et al., 1996; Christodoulou & Georgiopoulos, 2001). In the training process of the developed ANNs, Levenberg-Marquardt (LM) (Yadav et al., 2011), Bayesian Regularization (BR) (Burden & Winkler, 2008), and Scaled Conjugate Gradient (SCG) (Gunathilake et al., 2021) training algorithms were incorporated. Several studies used these algorithms to predict the groundwater depth (Maheshwara Babu et al., 2018) and water table depth (Coulibaly et al., 2001), streamflow simulation (Kisi, 2010; Bafitlhile et al., 2018; Gunathilake et al., 2021), and flood forecasting modeling (Tabbussum & Dar, 2020).

Scaled Conjugate Gradient (SCG) Algorithm

The scalable conjugate gradient is part of a class of conjugate gradient algorithms that display superlinear convergence for most problems (Møller, 1993). The scaled conjugate gradient algorithm, on the other hand, converges to the minimum error by initially proceeding in the direction of the steepest descent (Duncan, 2014). The scaled conjugate gradient avoids the need to carry out time-consuming line searches per learning iteration, making the algorithm faster than other second-order algorithms.

Bayesian Regularized (BR) Algorithm

The BR algorithm for the training of neural network attempt to incorporate Bay's theorem into the regularization scheme. The BR algorithm is also more robust than the standard back-propagation algorithm of neural networks; it can reduce or eliminate the lengthy cross-validation. It is a mathematical process that converts a non-linear regression into a well-posted ridge regression Burden & Winkler, 2008). Bayesian regularization sets optimum parameters for the objective function based on a set of mathematical rules. According to the method used in this study, all network weights and biases are taken to be random variables with specified distributions. A statistical technique is used to estimate the regularization parameters, which have to do with unknown variances. This algorithm is flexible in providing a measure of the number of network parameters (weights, biases) that are effectively utilized by the network so that over-fitting can be avoided regardless of the network size.

Levenberg-Marquardt (LM) Training Algorithm

The L-M training algorithm is an iterative strategy that finds the base of a multivariable function communicated as the sum of squares of non-linear genuine valued functions (Levenberg, 1944; Marquardt, 1963) for the most part, tackles the curve fitting arrangements and trains the ANNs several times quicker than the normal back-propagation algorithm (Bafitlhile et al., 2018) and nowadays a standard optimization that is comprehensively utilized in many disciplines. The algorithm varies the parameter updates between the gradient descent update and the Gauss-Newton update; it joins the benefits of the two strategies (Hariharan et al., 2015). To find the optimum solution to a minimization problem, the L-M algorithm modifies the classic Newton algorithm. A Newton-like weight update of the Hessian matrix is employed in the following:

$$X_{n+1} = X_n - \left\{J^T J + \mu I\right\}^{-1} J^T e \tag{4}$$

Where x is the weight of NNs, J represents the Jacobian matrix, e is the residual error vector, and μ represents the scaler that controls the learning process. L-M algorithm is very computationally and memory intensive, so it is best suited for small networks (Maier & Dandy, 1998).

A combination of Root Mean squared error (RMSE), coefficient of determination (R^2), and Nash Sutcliffe Efficiency (NSE) was used to determine which training algorithm was best for each simulation. After this, the streamflow and SSC prediction for the above said period were made using the same network.

Efficiency criteria of the model

Various statistical rules are accessible for numerical assessment of model accuracy every year, in a specific period, or a grouping of years or seasons. In an investigation of ANN-based models, Rajurkar et al. (2002) propose several efficiency standards that are especially valuable for ANN. In the present study, to achieve the desired optimum values as root mean square error (RMSE) (Equations 5 and 6), coefficient of determination (Equations 7 and 8), and Nash Sutcliffe Efficiency (NSE) (Equations 9 and 10) were used.

$$RMSE_Q = \sqrt{\frac{\sum_{i=1}^{n}\left(Q_i - \overline{Q_p}\right)^2}{N}} \tag{5}$$

$$RMSE_{SSC} = \sqrt{\frac{\sum_{i=1}^{n}\left(SSC_i - \overline{SSC_p}\right)^2}{N}} \tag{6}$$

$$R_Q^2 = 1 - \frac{\sum_{i=1}^{n}\left(Q_i - \overline{Q_p}\right)^2}{\sum_{i=1}^{n}(Q_i - \widehat{Q_i})} \tag{7}$$

$$R_{SSC}^2 = 1 - \frac{\sum_{i=1}^{n}\left(SSC_i - \overline{SSC_p}\right)^2}{\sum_{i=1}^{n}(SSC_i - \widehat{SSC_i})} \tag{8}$$

$$NSE_Q = 1 - \frac{\sum_{i=1}^{n}\left(Q_i - \overline{Q}_p\right)^2}{\sum_{i=1}^{n}(Q_i - \widehat{Q_i})^2} \tag{9}$$

$$NSE_{SSC} = 1 - \frac{\sum_{i=1}^{n}\left(SSC_i - \overline{SSC}_p\right)^2}{\sum_{i=1}^{n}(SSC_i - \widehat{SSC_i})^2} \tag{10}$$

Where; Q_i, $\overline{Q_p}$, $\widehat{Q_i}$ and SSC_i, $\overline{SSC_p}$, $\widehat{SSC_i}$ are observed, predicted, and mean streamflow and SSC values at the outlet of the Alaknanda basin, and n is the number of observed data sets.

3.4 Estimation of suspended sediment load (SSL), Suspended Sediment Yield (SSY), and Erosion rate

In the riverine flow dynamics, suspended sediment transportation is a natural phenomenon influenced by the surrounding geological actions and triggered by anthropogenic and natural activities. As per the previous studies conducted in the western and central regions of the Indian Himalayas (Bhutiyani 2000; Haritashya et al., 2006; Wulf et al., 2012; Singh et al., 2015a, 2015b, 2016; Kumar et al., 2018; Bisht et al., 2020; Rautela et al., 2022a) the SSL, SSY, and erosion rate have been estimated as (Equations 11, 12, 13):

$$SSL = Q * SSC \tag{11}$$

$$SSY = \frac{SSL}{A} \tag{12}$$

$$Erosion\,rate(mm) = \frac{SSY \times 1000\left(\frac{kg}{m^2}\right)}{Bed\,rock\,density\left(\frac{kg}{m^3}\right)} \tag{13}$$

Where; Q is measured daily average streamflow (m^3/s), A is the basin area in square kilometers, SSC, SSL, and SSY is the daily average Suspended Sediment Concentration (g/l), Suspended Sediment Load (t/day), and Suspended Sediment Yield (t/km^2) respectively. The bedrock density of the basin has been taken from previous works of literature as listed above.

RESULT AND DISCUSSION

Streamflow simulation using Artificial Neural Network

Snow and glacier-fed river's hydraulic characteristics are very important when determining the amount of water generated by the collection of rainfall and melting of snow and ice in the basin (Thakur et al., 2017). Wagner et al. (2017) explain that these hydraulic features depend on climatic and meteorological factors in a specific region. The database compiled represents 36 years of daily sets of hydro-meteorological values for the Alaknanda River basin. In this study, we used three algorithms viz; SCG, BR, and L-M algorithms for the training, testing, and validation of the streamflow with the flow and without flow conditions during 1986-2019 and the data for the two hydrological years (2019-2021) for the prediction. The calibration phase of the ANN model was terminated when the Root Mean Square Error (RMSE), Coefficient of determination (R^2), and Nash Sutcliffe Efficiency (NSE) met up with the model evaluation criteria. Figures 3 and 4 show that the estimated streamflow is plotted against observed streamflow using SCG, BR, and L-M algorithms. The LM algorithm-based ANN model has been selected for both approaches as the lowest RMSE compared to others (Table 1). Therefore, the LM-based training algorithm of the ANN model is selected as an acceptable training algorithm for simulating streamflow and suspended sediment concentration (SSC) of the Alaknanda River (Table 1). Also, the graph error versus epochs for the L-M-based training algorithm

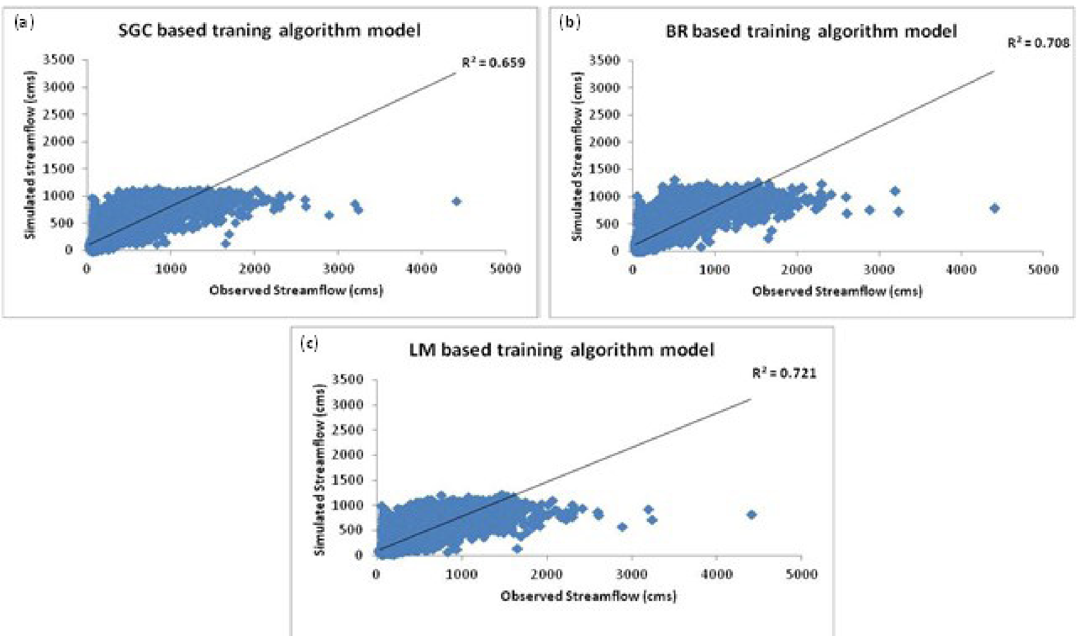

Figure 3. Without flow approach: ANN-based models with simulated and observed streamflow: (a) for SCG algorithm, (b) for BR algorithm, and (c) for LM algorithm.

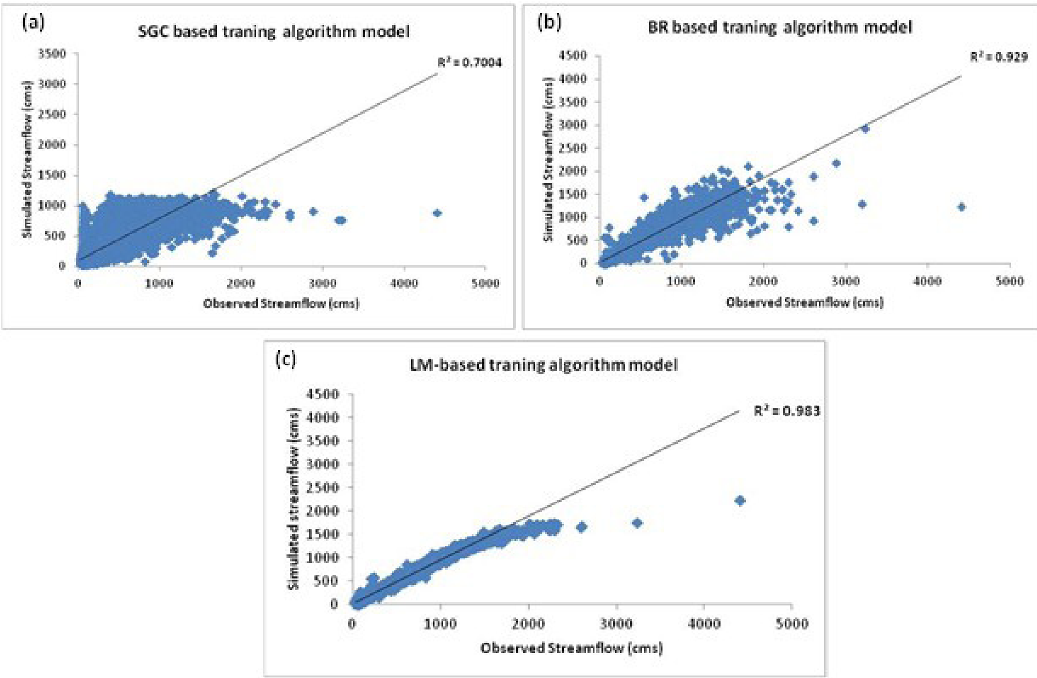

Figure 4. With flow approach: ANN-based models with simulated and observed streamflow: (a) for SCG algorithm, (b) for BR algorithm, and (c) for LM algorithm.

Table 1. Model efficiency parameters for the training period with (a) without flow and (b) with flow.

Parameters	RMSE	RMSD	NSE	R^2
Training Algorithm			(a) Without streamflow	
Scaled Conjugate Gradient (SCG)	194.05	354.25	0.62	0.66
Bayesian Regularization (BR)	191.74	354.14	0.71	0.71
Levenberg-Marquardt (LM)	189.89	354.38	0.72	0.72
Training Algorithm			(b) With flow	
Scaled Conjugate Gradient (SCG)	173.29	356.10	0.70	0.70
Bayesian Regularization (BR)	94.08	354.10	0.92	0.93
Levenberg-Marquardt (LM)	93.08	354.13	0.93	0.98

shows the overlapping of all the lines, and it shows the lesser variation in the observed and simulated streamflow (Figure 5). In training/calibration, some hydrograph peaks are not appropriately captured in both approaches. This might be because the data-driven model does not hold the possible information about soil texture, land use, and other catchment characteristics that influences the streamflow. During a rainfall event, some soils hold a considerable amount of moisture and release it further when the soil reaches its limit. On the other hand, the basin's land use and other basin characteristics play an essential role in the runoff generation. The basin is well elongated in shape, covered with dense forests in the mid-elevation range, and covered with snow in the higher elevations. During monsoons, the combined effect of rainfall and snowmelt generates a considerable amount of streamflow which is sometimes not captured by the data-driven models. To prevent this accurate dataset with the distributed hydrological models that use each characteristic of the basin.

There is no doubt that the streamflow patterns follow a similar pattern and are consistent with observed streamflow in both approaches (Figure 6a & b), but when the previous day's streamflow is used as an input for simulating the current day's streamflow, it will give better results. The correlation of both approaches is shown in Figures 3 and 4. As a result of the prediction of streamflow with the desired accuracy, L-M training-based ANN model is used for the next two hydrological years. By giving the previous day's streamflow as an input to predict the current day's streamflow, this predicted streamflow is the input for predicting the next day's streamflow. The predicted results are validated with the observed results are shown in Figures 7a & b. The results show the predicted streamflow by the model follows the pattern of observed streamflow (Figure 7a). The model efficiency parameters such as RMSE, RMSD, NSE, and R^2 for the prediction/validation period are 33.39, 103.07, 0.88, and 0.89, respectively (Table 2) and show very good performance as per the criteria of these parameters. Further, this network will be used to predict future flows and streamflow of an un-gauged river watershed with similar characteristics.

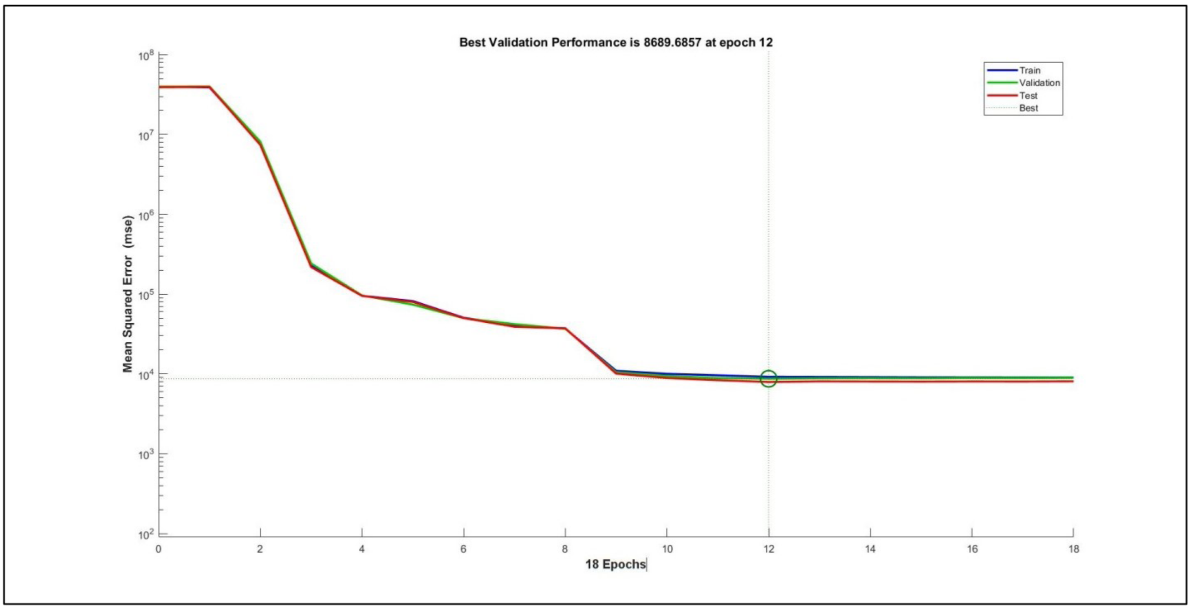

Figure 5. Best validation performance of the L-M based training algorithm.

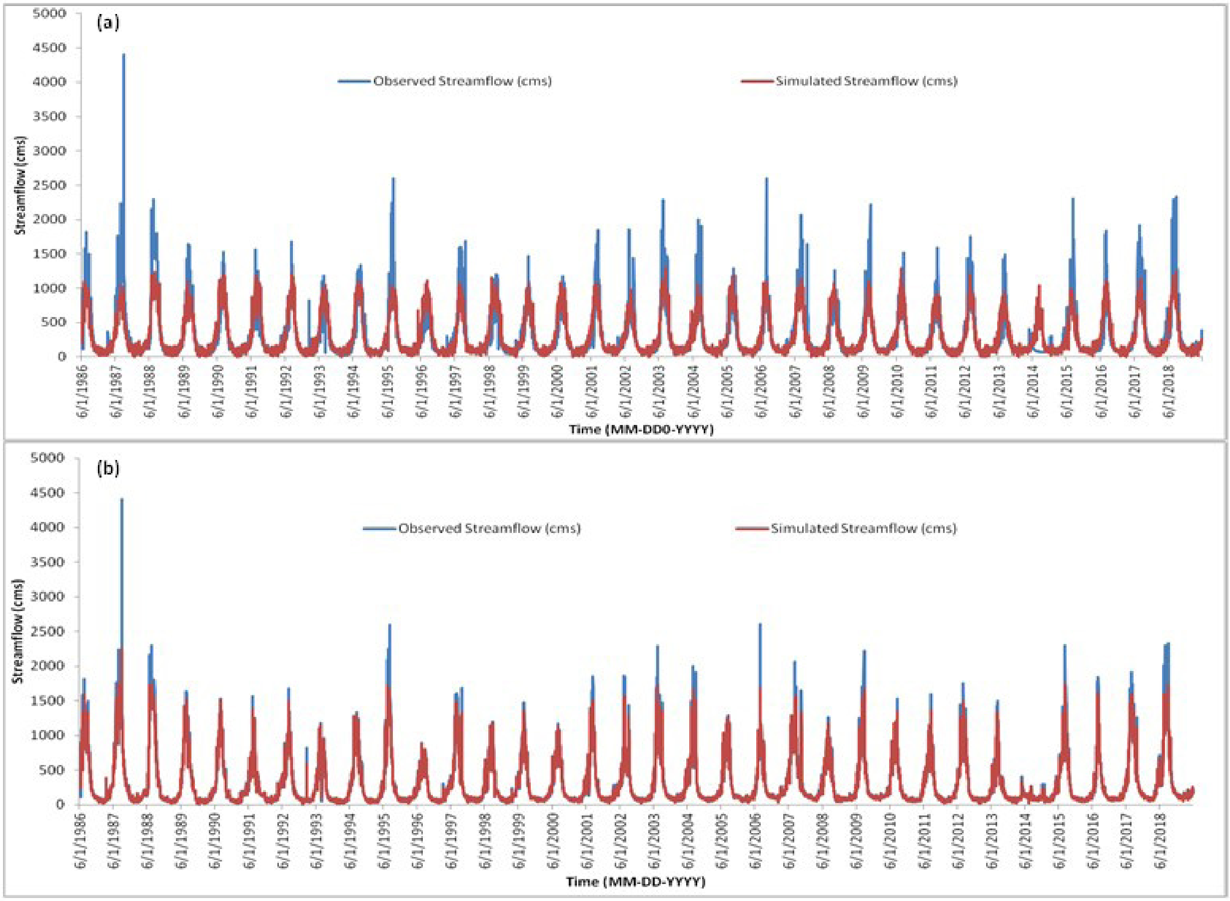

Figure 6. Comparison of simulated streamflow versus observed streamflow based on LM training algorithm based ANN model (a) without flow (b) with flow.

Table 2. Model efficiency parameters for the validation period.

Parameters	**RMSE**	**RMSD**	**NSE**	**R^2**
Values	33.93	103.07	0.88	0.89

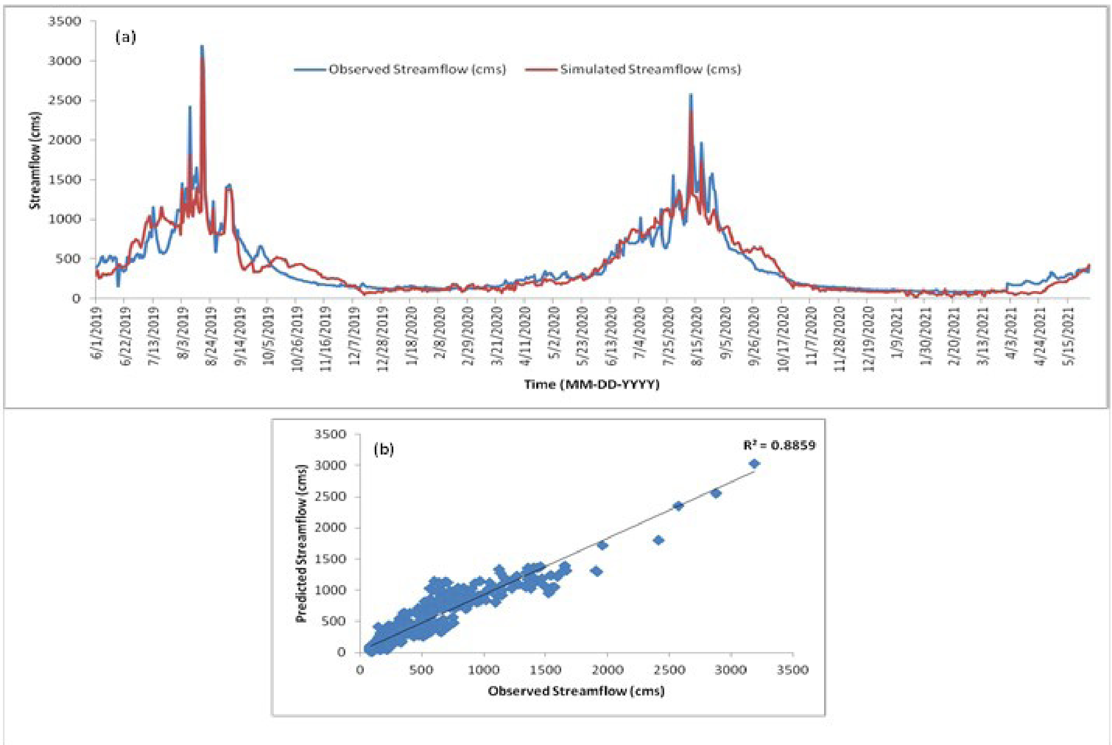

Figure 7. (a) Comparison and (b) correlation of predicted streamflow versus observed streamflow

Modeling of Suspended Sediment Concentration using Artificial Neural Network

Sedimentation in glacier-fed rivers is primarily caused by moraine-filled glaciers (Rautela et al., 2020; Bisht et al., 2020; Rautela et al., 2022a). As a result, the sediment concentration in the flowing water increases from its starting locations until the ablation period shows an increase (Bisht et al., 2020). Additionally, the river basin is affected by intense rainfall, affecting sediment concentration in the riverine flow (Rustomji et al., 2008). The concentration of sediments in the river is measured during the monsoon and ranges from 75-17000 ppm during JJAS for three years (2016-2018). After the monsoon, the ablation of glaciers and rainfall is negligible. The concentration of sediments in the river is also very low. The sampling of SSC has been done only in the high flow seasons. In the training/calibration of the model, the estimated SSC tracked the pattern of observed SSC (Figure 8a); only at a few points did the model overestimates the SSC. The model efficiency parameters such as RMSE, RMSD, NSE, and R^2 during the calibration/training period are 87.46, 255.99, 0.87, and 0.88, respectively. The trained network is further used to predict SSC for the year 2018 (June-September) and validated through the observed SSC (Figure 8b). A similar pattern has been shown for the prediction of the SSC as RMSE, RMSD, NSE, and R^2 are 81.28, 264.83, 0.88, and 0.88, respectively. In the present study, a higher correlation is found between the observed and simulated SSC for both calibration (Figure 9a) and validation (Figure 9b) period. The findings of the current study suggest the temporal variation between the streamflow and SSC is significantly influenced by the factors like basin area, geology, land use, relief, and climatic variables (Bisht et al., 2018; Rautela et al., 2022a). Overall, the concentration of suspended sediments in the streamflow is very high during JJAS, which will affects the water quality as well as river ecosystem. Afterward, it can affect the HEPs in the downstream regions by increasing dead loads in the reservoirs. Later, it can also cause wear and tear in the mechanical components, viz; blades, shaft, gearbox, etc., of the turbines.

Modeling of Suspended Sediment Load (SSL), Suspended Sediment Yield (SSY), and erosion rate of the basin

The sediment transport in the streamflow is an essential component of the flow dynamics of a high-altitude river system and is affected by various geological processes in the drainage basin. The availability of sediments controls sediment transport in rivers. The higher variability in SSC may be caused by local factors, such as the falling of moraine-filled ice blocks and sediment transport away from crushed rock (Bisht et al., 2018). Natural processes incorporate further erosion of the riverbed and banks due to scouring and producing extra sediment in streams. Mishra et al. (2019) report that glaciers are the primary source of sediment transportation through river runoff in glacier-fed basins. But, due to the monsoonal activities in the Basin of Himalayan Rivers, the sediment load may increase due to the intense rainfall and higher melting rate of the snow and glaciers due to climate change. During high flows, the average observed suspended sediment load (SSL) in the Alaknanda River basin will vary from 0.21×10^4 t/day to 218.7×10^4 t/day, while the average observed

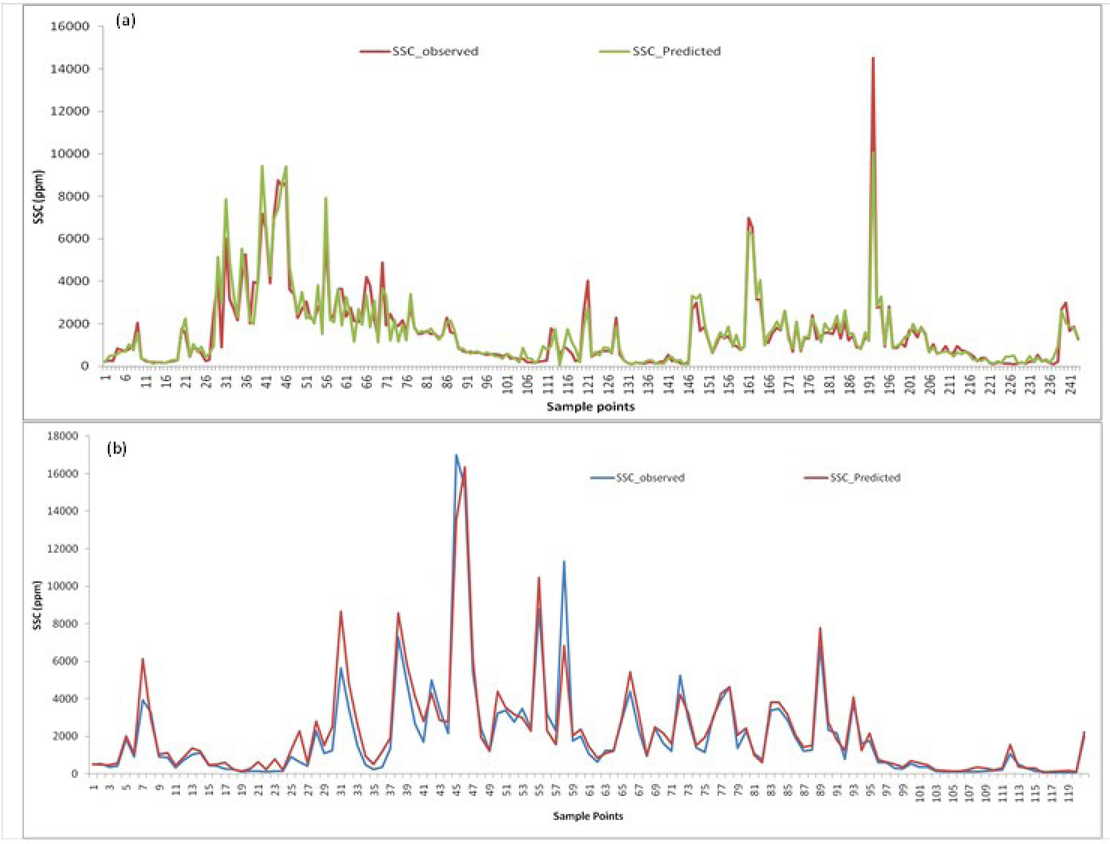

Figure 8. Temporal variations in the suspended sediment concentration (a) Calibration/Training period (b) Validation period.

SSL was 11.5 $\times 10^4$ t/day. The simulated SSL by the model during training/calibration will range from 0.13 $\times 10^4$ t/day to 136.62 $\times 10^4$ t/days, while the average simulated SSL was 11.28 $\times 10^4$ t/days. The average simulated values of the SSL are nearer to the observed values, while there is a slight variation in the minimum and maximum values. Similarly, the average observed SSL used for the validation/prediction ranges from 2.4 $\times 10^4$ t/day to 264.5 $\times 10^4$ t/day, while the average observed SSL was 227.3 $\times 10^4$ t/day. The simulated SSL by the model during validation/prediction ranges from 3.04 $\times 10^4$ t/day to 4.97 $\times 10^4$ t/day, while the average simulated SSL was 69.2 $\times 10^4$ t/day. The amount of SSL in the riverine flow is high, and it will affect the riverine ecosystem, water quality, and the basin's biodiversity.

Steep slopes create water currents and waves with high flow velocities, leading to vortices forming and influencing the scouring of a Himalayan River basin (Rautela et al., 2020). There will be a difference in the scouring of the stream channel by the waves and the scouring by the water currents. When the water currents in the rivers increase by 50% compared to waves, the maximum scouring depth will increase by approximately 2.36 times (Yamini et al., 2018). Streamflow is related to sediment yield, but the quantity and frequency of sediment yield are highly variable daily, monthly, and yearly. The observed SSY of the basin for the calibration/training period ranges from 68.40 t/km^2 to 72158.80 t/km^2, and the average observed SSY was 3789.30 t/km^2. However, the simulated SSY in the streamflow ranges from 43.26 t/km^2 to 44959.06 t/km^2, and the simulated average SSY was 3724.16 t/

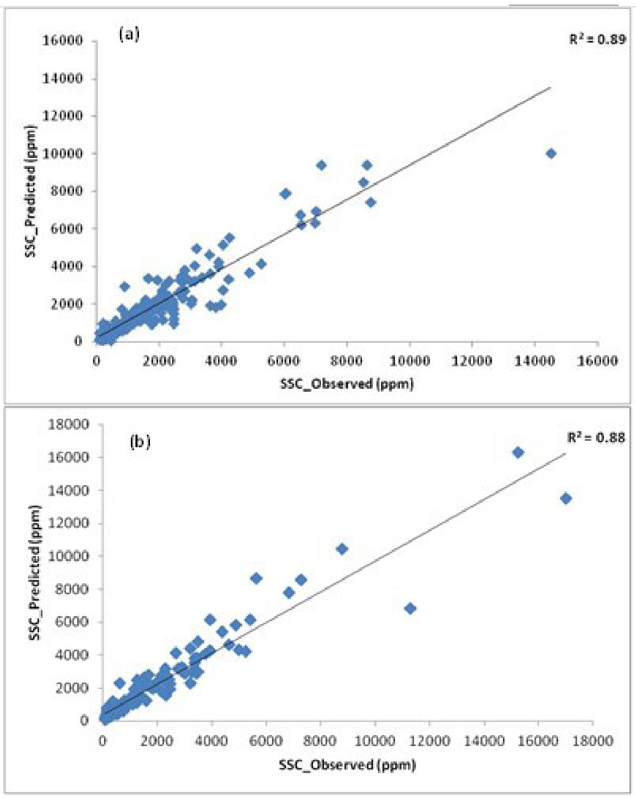

Figure 9. Correlation of Observed SSC with (a) Estimated by the model in the training/calibration period (b) Validation period.

Table 3. Comparison of SSL, SSY, and Erosion rate with the other Himalayan river Catchments.

River Basin	Gauging Site	Latitude	Longitude	Elevation (m)	Area (km^2)	SSL (t/day)	SSY (t/km^2)	Erosion (mm/y)	Reference
Chenab	Dhamkund	33.24	75.14	600	18750	35.6	1900	0.72	Rao et al. (1997)
Sutlej	Kasol	31.38	76.88	520	53768	43.2	816	0.31	Jain et al. (2003)
Indus	Besham	34.92	72.88	580	162393	194.4	1197	0.45	Ali & De Boer (2007)
Alaknanda (previous)	Srinagar	30.23	78.77	524	11064	10.2	995	0.38	Chakrapani & Saini (2009)
Alaknanda (Observed)	Srinagar (2021)	30.23	78.77	524	11064	315	3789	1.40	Current Study
Alaknanda (Estimated)	Srinagar (2021)	30.23	78.77	524	11064	309	3724	1.38	Current Study

km^2. Similarly, the observed SSY for the validation/prediction ranges from 793.30 t/km^2 to 872578.87 t/km^2, and the average observed SSY was 74976.04 t/km^2. The simulated SSY by the model ranges from 1002.93 t/km^2 to 163860.06 t/km^2, and the simulated average SSY was 22829.73 t/km^2. The higher sediment yield produced by the basin is caused by higher rainfall received by this region caused by the circulation of the Asian summer monsoon and various anthropogenic activities conducted within the study area.

In the present study, the observed erosion rate of the Alaknanda basin was found as 1.40 mm/year, while the model simulates the erosion rate as 1.38 mm/year while considering a standard base rock density of 2.7 g/cm^3. Similarly, for the validation, the observed erosion rate was found as 1.76 mm/year, and the model predicts the erosion rate of the Alaknanda basin as 2.45 mm/year. The observed and simulated values of the present study are compared with the other Himalayan River basins to understand sediment transportation (Table 3). Overall, the model simulates the SSL, SSY, and erosion rate values are nearer to the observed values, which are estimated using the standard formulae. The concentration of SSC in the riverine flow is high, which may be triggered by bank erosion, and several anthropogenic activities with a combination of natural disasters such as cloudbursts, landslides, etc., in the region. To control the SSC in the riverine flow protection of the banks of the river and control the anthropogenic activities in the upper reaches of the river.

CONCLUSION

The study modeled the streamflow and SSC and assessed the magnitude and temporal variation of SSL, SSY, and erosion rate of a Himalayan River basin. The streamflow simulation was done with three algorithms such as SCG, BR, and L-M, and two approaches, such as when the previous day streamflow is not taken as input and when the previous day streamflow is taken as input for the period of June 1986- May 2019. The L-M based training algorithm gives better results with higher accuracy in both approaches. Further, L-M based ANN model will be used to predict streamflow for the next two hydrological years and validated with the observed streamflow. Similarly, the same network is further used for the calibration/training and prediction of the SSC for the high flow period of 3 years (June-September, 2016-2018). The results show it predicted streamflow, and SSC tracked the observed streamflow and SSC with excellent performance; as a result, the estimated values of the streamflow and SSC are relatively nearer to the observed values for training/calibration and validation. The observed and simulated SSL, SSY, and erosion rates of the basin are quite high when we compare this data with the previous studies and other river basins. This might be due to the glaciers covered by debris and moraine, base rock material. The modeling of streamflow and SSC and assessment of SSY, SSL, and erosion rate of a high-altitude river system provide needful information to the land and water resource managers, policymakers, and stakeholders regarding streamflow availability and sediment transport. Also, this study provides a piece of information about the existing and developed HEP's by using primitive measures towards mechanical disasters such as siltation in the reservoirs and damage to the mechanical components of the turbines.

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