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CORRELATING STREAM GAUGING STATIONS USING ARTIFICIAL NEURAL NETWORKS

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Abstract—**The present work aims at correlating stream gauging stations along river Krishna of the state of Maharashtra, India using Artificial Neural Networks. For this ANN models were developed with stream flow at the upstream stations(s) as inputs and stream flow at the downstream station as output. All the models show excellent results and prove the ability of ANNs to offer solutions with limited amount of data. The models will be useful to develop a decision support system for the downstream locations especially in case of flood events.**

Keywords—**Artificial Neural Networks, stream gauging, stream flow, models, decision support system.**

I. INTRODUCTION

Information about stream flow at a particular location is of vital importance for managing the water resources effectively. The stream flow modeling (estimation or forecasting of stream flow) can be done using mathematical models based on the physics of the process or system theoretic models which are data driven. The physics-based models are data intensive and computationally demanding, which call for alterative techniques to model the stream flow with relative ease and reasonable accuracy. The stream flow at 2 or more stations along a river if correlated can be useful to estimate the stream flow on the downstream locations using the same at the upstream location. The available numerical models require exogenous data as mentioned earlier and therefore there is always a scope for the model which works on the data which is available. The Artificial Neural Networks are data driven techniques which work like human brain and learn from the past experiences and are soft towards data. The biological neural networks when implemented artificially albeit doing the task of learning through weights and biases, transfer functions, system's causative variables in the form of input and output neurons and hidden layers for mapping the non-linearity and algorithms to reduce the error between the modelled and observed values (called training) are termed as ANNs. Details about working of ANN, types of ANN, learning algorithms can be found in [1-5].

Since last 3 decades or so ANN has been used to develop models for various hydrologic parameters like runoff, evaporation, infiltration, stage which are presented in over 400 publications in journals of repute. Readers can refer to [1-3] [6-9] to name a few.

The present work aims at developing ANN models to correlate the stream gauging stations along river Krishna in the state of Maharashtra, India.

II. STUDY AREA AND DATA: PLEASE GIVE KRISHNA INFORMATION IN VERY FEW LINES

As mentioned earlier, present study is done at the four stream gauging stations namely; Krishna, Khodashi, Irwin and Ankali in the Krishna River basin of Maharashtra. The Krishna River originates at Mahabaleshwar in the western Ghat of Maharashtra and is the fourth-largest river in terms of water inflows and river basin area in India. Krishan river passing from Khodashi gauging station and it's tributary Koyana river meet from front at the confluence point near Karad district and then further flows in the downstream passing from the Irwin and Ankali bridge station. To correlate the above mentioned 4 stations for estimating the stream flow, in the present study ANN models are developed to correlate 4 stream gauging stations at Krishna, Khodashi, Irwin Bridge (Sangli City), Ankali Bridge (Sangli City) along river Krishna in the state of Maharashtra, India. The daily stream flow data for the years 2016 to 2019 was measured (in cm3/s, cusecs) and made available by the irrigation Department of Pune division in the Maharashtra state, India. Figure 1 represents location map of the study area along with the Krishna River, Maharashtra state, India whereas figure 2 depicts the magnified view of the same study area.

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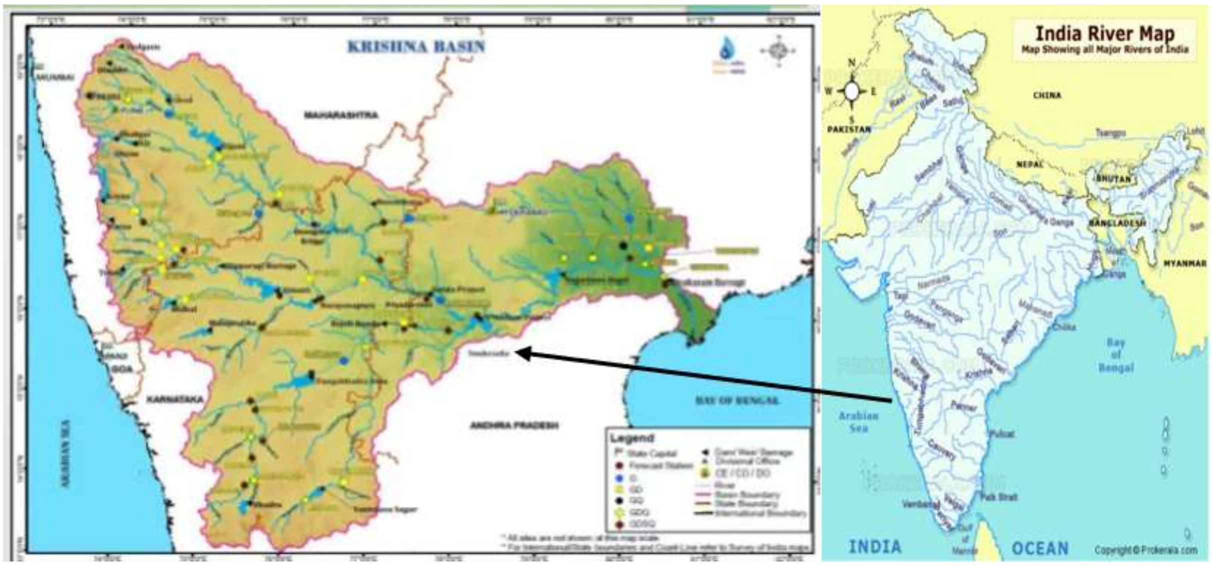

Figure.1 Location Map

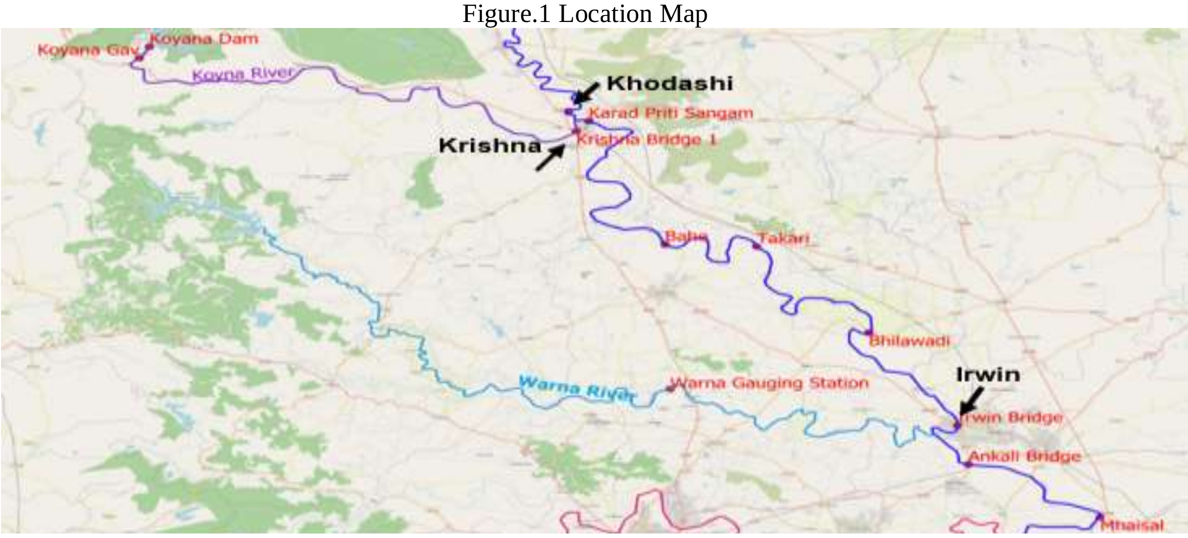

Figure. 2: Study Area

III. METHODOLOGY AND MODEL DEVELOPMENT

The discharge (or stream flow) at Ankali station was estimated using discharges of Krishna, Khodashi and Irwin bridge which are on the upstream side of Ankali. For this measured value of daily discharges at all these four stations from 2016 to 2019 (total values 1670) were used for development of ANN models. To decide the inputs, the cross correlation analysis between the discharge at Ankali and other 3 stations Krishna, Khodashi, Irwin separately was done (table 1). The first Model (Model I) was developed to estimate discharge at Ankali using the discharges at Krishna, Khodashi and Irwin station together. As correlation of Khodashi with Ankali was less (0.6) compared to the other two stations with Ankali (0.73 and 0.89), in the second and third model, it was not used as input. Model II contains Krishna and Irwin as input and Ankali as output whereas Model III was developed using only discharge values at Irwin bridge as input to estimate the discharge at Ankali station. This exercise was done to judge the capability of the developed ANN models to estimate the discharge at the output station when discharges at the 3 upstream stations are not available simultaneously. Table 2 shows the details of the models with ANN architecture and data division as well. For all the three models LM algorithm is used along with the two transfer functions of “logsig” and “pureline”. 70% data was used to train the model and remaining 30% (15% validation and 15% testing) data was used to test the developed models. Performance of developed models were judged by the traditional error measures of correlation coefficient (“r”), Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE) along with the scatterplots and hydrographs.

Table 1: Correlation of discharges

Discharge at	Discharge at	correlation
Krishna	Ankali	0.73
Khodashi	Ankali	0.60
Irwin	Ankali	0.89

Table 2: Models to estimate discharge at Ankali

Model	Input Discharge (cusec)	Output Discharge (cusec)	Architecture	Training-testing data
Model I	Krishna, Khodashi, Irwin	Ankali	3:12:1	Train set :538 Test set: 230
Model II	Krishna, Irwin	Ankali	2:29:1	Train set :538 Test set: 230
Model III	Irwin	Ankali	1:9:1	Train set :538 Test set: 230

IV. RESULTS AND DISCUSSION

All the models were trained till a very low error was achieved. The trained models when tested for unseen inputs yielded excellent results as evident by the high value of correlation coefficient (> 0.9) between the model outputs and targets accompanied by low value of root mean squared error (RMSE) and mean absolute error (MAE) as shown in table 3.

From the results (table 3), it can be seen that the correlation coefficient of all the three models is above 0.90 which proves the capability of ANN models to correlate these stations using the measured data of discharges and avoiding any exogenous data requirement. It may be noted that the results are better than cross correlation results shown in table 2 which shows the necessity of model development using rather than merely using the cross correlation between various stations. The developed models can thus yield the stream flow at Ankali bridge with high level of accuracy by using the same at one or more locations. Thus, it can be said that ANN models are capable of working with limited amount of data as well. The developed models will be useful as early warning systems in flood situations which can be useful as flood mitigation measure.

Figures 3 shows the hydrograph for observed and estimated stream flow values by model 1.

Table 3: Results

Model	"r" (correlation coefficient)	RMSE (cusec)	MAE (cusec)
Model I	0.986	22377	256.8
Model II	0.902	30587	312.0
Model III	0.934	25634	259.2

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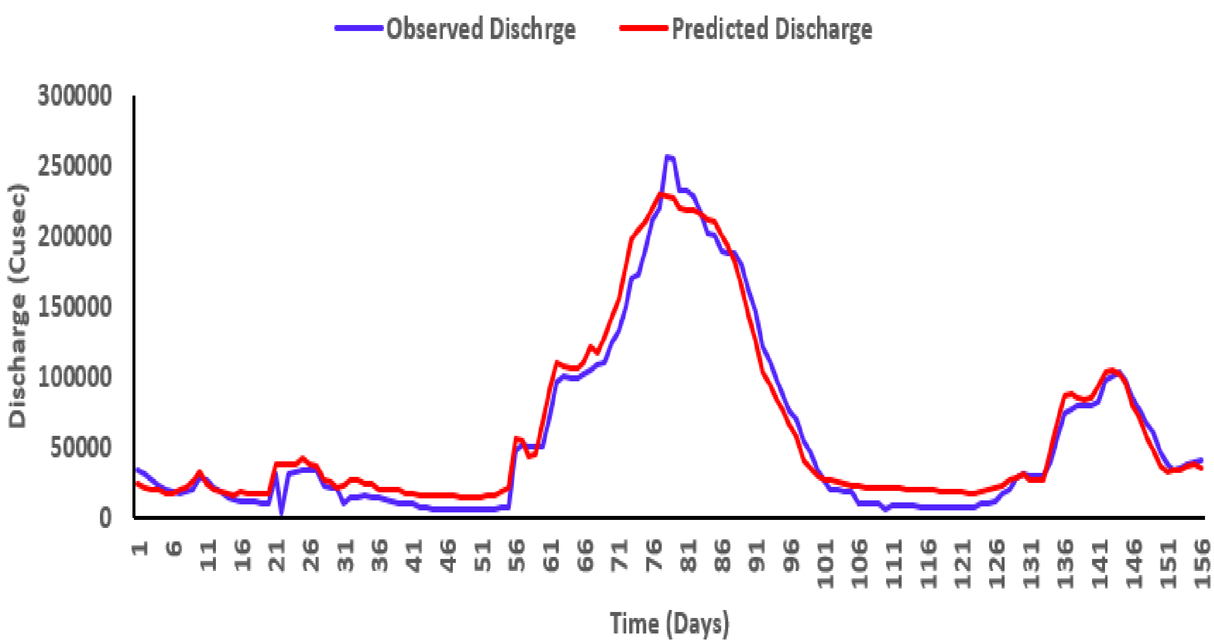

Figure 3: Model I

V. CONCLUSION

The foregoing sections presented development of ANN models for correlating 4 stream gauging stations along river Krishna in the state of Maharashtra India. The models were developed to estimate stream flow at the downstream location (Ankali) using the stream flow at 3 upstream stations namely Krishna, Khodashi, Irwin stations jointly or separately. All the models performed well with high level of accuracy. The developed models can provide an early warning at Ankali which will be useful in the extreme situations like floods.

Data Availability Statement:
Some or all data, models, or code that support the findings of this study are originally developed by authors and are available at the corresponding author's end.
All data, models, and code generated or used during the study appear in the submitted article.

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