Proceedings of the 6th International Conference on Civil Engineering for Sustainable Development (ICCESD 2022), 10~12 February 2022, KUET, Khulna, Bangladesh (ISBN-978-984-35-1972-6)

WATER LEVEL PREDICTION OF BAHADURABAD TRANSIT OF BRAHMAPUTRA-JAMUNA USING DEEP LEARNING MODELS

Md. Imran Islam Rabbi[1*], Md. Mehedi Hassan Galib[2], Asif Hasan[3], Simoom Sadik[4] , Anika Baitullah[5], Akash Das[6] , Aneeca Farzana[7] , Murshida Munni[8]

[1*] *Undergraduate Student, Rajshahi University of Engineering & Technology, Bangladesh, e-mail: imran140105@gmail.com*

[2] *Undergraduate Student, Rajshahi University of Engineering & Technology, Bangladesh, e-mail: mehedihassangalib@gmail.com*

[3] *Postgraduate Student, University of Dhaka, Bangladesh, e-mail: asifhasanimon96@gmail.com*

[4] *Undergraduate Student, Rajshahi University of Engineering & Technology, Bangladesh, e-mail: simoomsadik@gmail.com*

[5] *Graduate Student, Rajshahi University of Engineering & Technology, Bangladesh, e-mail: anika.baitullah95@gmail.com*

[6] *Graduate Student, Rajshahi University of Engineering & Technology, Bangladesh, e-mail: akashruet69@gmail.com*

[3] *Undergraduate Student, Chittagong University of Engineering & Technology, Bangladesh, e-mail:aneeca.shammow@gmail.com*

[3] *Undergraduate Student, Rajshahi University of Engineering & Technology, Bangladesh, e-mail: murshidamunni12@gmail.com*

***Corresponding Author**

ABSTRACT

Brahmaputra and Jamuna are considered as two of the greatest reservoirs of water resources which play an important role in Bangladesh's ecology and hydrology. They also have a significant contribution in water transportation, agriculture and the livelihood of those people who live on the bank of these rivers. Therefore the prediction of the water level of these two rivers is very important for water resource management and allocation. Predicting water level can also provide the assumption that what will be the situation of river in the upcoming seasons and what kind of undesired incident may take place, whether the water level will increase too much and the flood will occur or not. If the situation including all these factors can be anticipated before, authorities can take necessary steps to reduce the risk and prevent any unusual incident. For predicting water level, several machine learning algorithms had been used. Nowadays deep learning is also used to predict the water level and becoming popular day by day for its higher accuracy. In this study, the average water level of Bahadurabad transit from 2005 to 2019 has been observed and three deep learning models- Recurrent Neural Network, Long Short Term Memory and Gated Recurrent Unit have been implemented using the historical data. Though all of these three models have performed quite similar, Recurrent Neural Network gives a better R-squared value and less mean absolute percentage error (MAPE) which are 0.9980 and 0.49% respectively. This accuracy level explicitly indicates that Recurrent Neural Network along with all other deep learning models can be used to predict the water level and using this prediction our flood management, water resource management and allocation can be improved in a more precise way.

Keywords: *Water Level Prediction; Deep Learning Models; Flood; MAPE; Bahadurabad Transit.*

1. INTRODUCTION

The availability of water has a significant impact on the population's well-being and livelihood. Increases in water levels and discharge rates, for example, might affect physical processes such as river circulation, causing changes in water mixing and sediment resuspension. As a result, predicting the discharge rate is becoming increasingly important (Ali et al., 2013). The Institute of Water and Flood Management (IWFM), for example, suggests that more efforts be made to improve water level control and prediction methods. Because of the several controlled variables, such as temperature and water sharing between the river and its watersheds, changes in the water level are considered dynamic hydrology (Mosavi et al., 2018). To predict actual changes in the water level and discharge rate, several models must be carefully chosen. Many conditions, such as influencing variables that affect water level, take a long period to calibrate and ensure the forecast is accurate (Sahoo et al., 1997). Recent investigations have evaluated water levels using deep learning models (DL) because process-driven approaches take too long (Corani et al., 2005). In this paper, many deep learning techniques were utilized to forecast water discharge rates (Benoudjit et al., 2019). Deep learning is becoming common in today's world for predicting water levels, discharge rates, and boosting accuracy. Using historical evidence, three deep learning models were employed in this report: Recurrent Neural Network, Long Short-Term Memory, and Gated Recurrent Unit. From 2005 to 2019, the average water level and discharge in Bahadurabad transits were monitored. Then, predicted results of the DL model is compared to the observed model. The influence of past variations in water level and meteorological variables is taken into account when creating DL models.

2. STUDY REGION

The Brahmaputra-Jamuna is one of Bangladesh's major rivers and the country's primary water source in the northwest. Significant monsoon rainfall will bring increased flood inundation in the future, according to the IPCC and Bangladesh Climate Change Cell Research. It is critical to make accurate projections of water level and discharge for this reason. The Bahadurabad discharge gauge station on the river Jamuna was chosen for this study (Rabbi et al., 2021). The Bangladesh Water Development Board provided daily water level, discharge, and maximum velocity data for this station from January 2005 to March 2019. (BWDB).

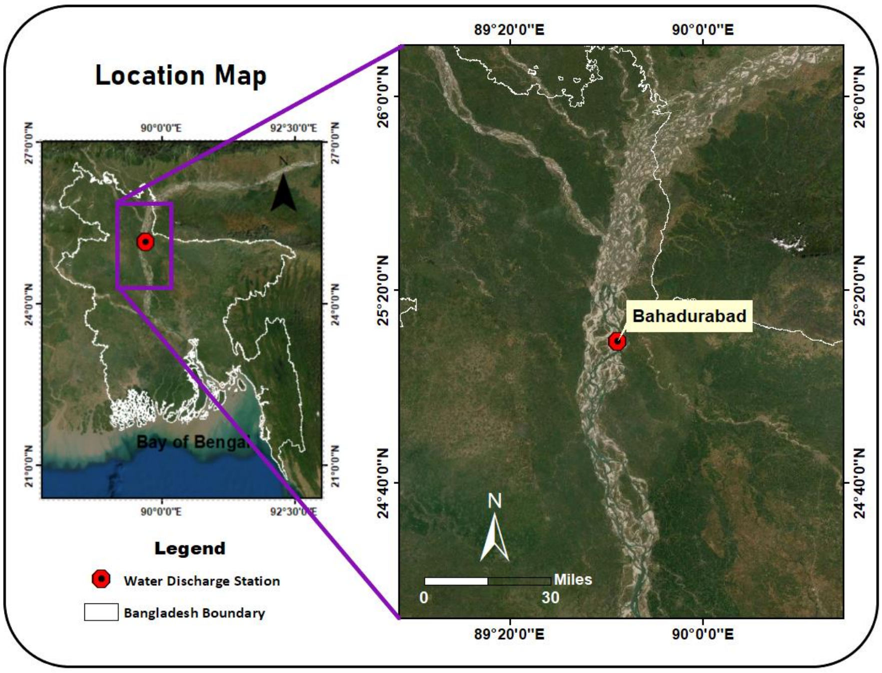

Figure 1: Location of the study area.

3. METHODOLOGY

The complete dataset was divided into two categories once the outliers were removed. To train the models, data from January 2005 to September 2013 was used as a train set. The rest of the data was utilized as a test set to ensure the models' accuracy and performance. Both sets were then separated into explanatory and response variables. The discharge was used as the response variable, while the water level and maximum velocity were used as explanatory variables.

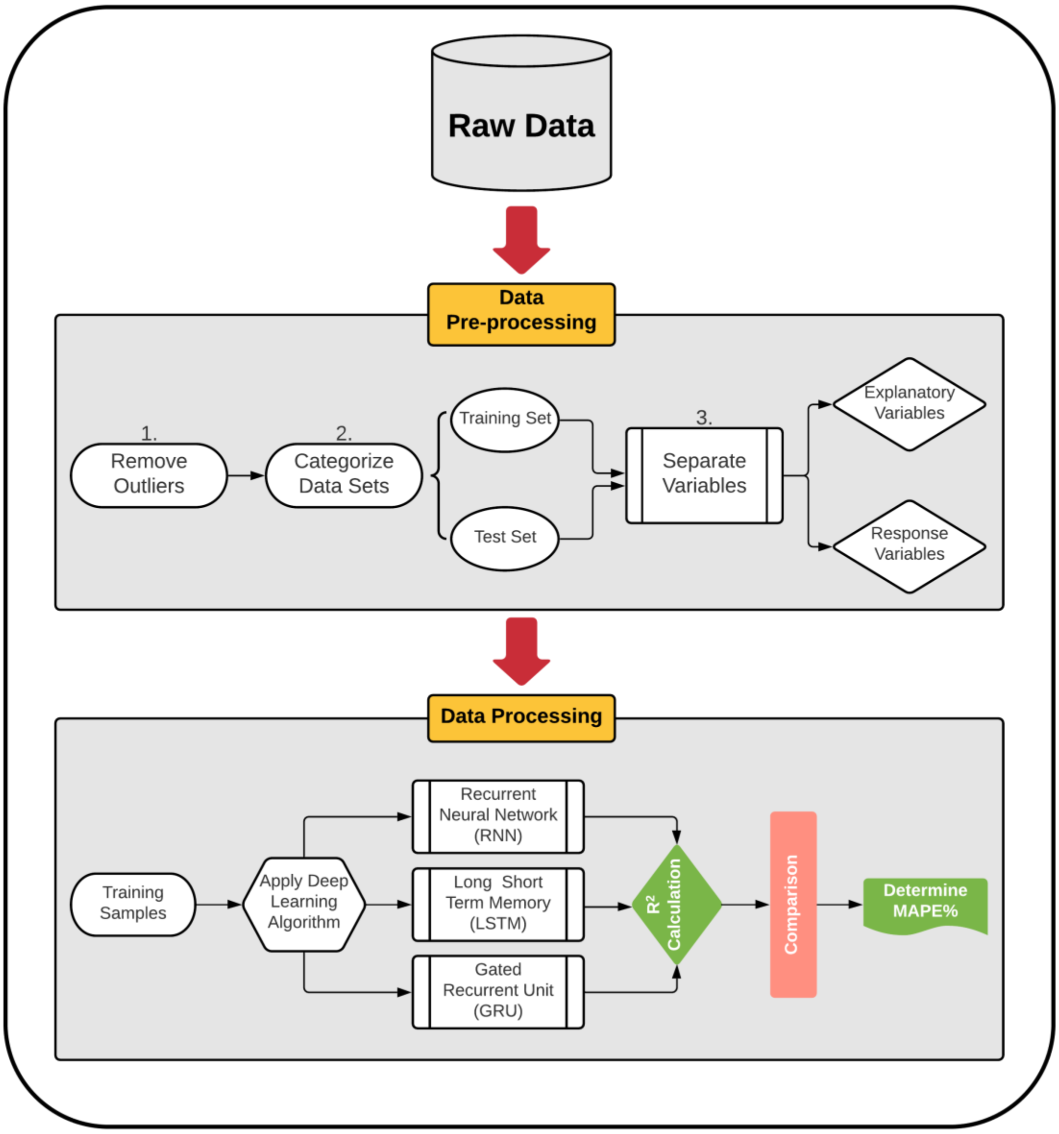

Figure 2: Flow chart of the process.

In this study, the water level of the Brahmaputra-Jamuna at Bahadurabad transit from 01 January, 2005 to 31 March, 2019 was analysed and used for building different deep learning models. Daily water level data of first 9 years were used for training the model, next 3 years data were used as validation set and the last 2 years data were used as test set by which the accuracy of the model was ascertained. Before setting up different architectures of deep learning layers with the data, the data was prepared by dividing the whole sequence into an input-output pattern as well as exploratory and response variables. If the sequence is x1, x2, x3, x4, x5, x6, x7, …. and the time step is 4, the input-output pattern will be like mentioned in Table 1 below.

Table 1: Comparison of three different models

Input (Exploratory variable)	Output (Response variable)
x1, x2, x3, x4	x5
x2, x3, x4, x5	x6
x3, x4, x5, x6	x7
….	…..

For our dataset, it has been found that the time step value 180 has performed comparatively better than the other values. This means model will analyze 180 historical values of water level and predict the water level for the next day. The data was scaled with normalization to reduce the difference in the range of values. After normalization the minimum and maximum water level of the dataset became 0.00 and 0.99 from 11.91 and 20.83 respectively.

$$Normalization: \quad x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{1}$$

As the model expects the exploratory variables in three-dimensional shape, the train and validation set were reshaped with the format- number of observations, time step and number of features.

Here,
Number of observations = size of the dataset
Time step = 180
Number of features = 1 (As this is a univariate time series analysis)

For Recurrent Neural Network, a very simple model architecture was built with 100 'Simple RNN' units with the activation function Rectified Linear Unit. The hyper parameter 'return sequences' was set to true for getting corresponding output of each input. Then another 'Simple RNN' layer with 50 units along with a dense layer was used. Adaptive moment estimation was used as optimizer along with mean squared error (mse) as loss function. For avoiding the repetition of same accuracy, 'Early Stopping' was used with the hyper parameter 'patience' set to 10. If there isn't any improvement on the accuracy of the model for 10 epochs, Early Stopping will stop the model from fitting. And for finding the minimum loss function with efficient learning rate, 'Reduce LR On Plateau' was used with hyper parameters 'factor', 'patience' and 'min lr' set to the value 0.1, 3 and 0.00001 respectively. For fitting the model, it has been found that epochs 100 and batch size 64 has performed comparatively better. The Long-Short Term Memory, a modified and developed type of Recurrent Neural Network was also implemented in the same manner. But this time, the model architecture was built with 180 Long-Short Term Memory units in the first layer and 50 units in the second layer. In the last portion, all the outputs were combined with the help of dense layer. Here it has been found that epochs 90 and batch size 64 has performed quite well. Other hyper parameters were remained unchanged. In Gated Recurrent Unit, 100 GRU unit was used in the first layer and 50 GRU unit in the second layer. Epochs and batch size were set to 100 and 64 respectively. Optimizer, activation function and loss function were Adaptive moment estimation, Rectified Linear Unit and Mean squared error respectively like the other two models. After the completion of fitting the models, water level from the test set was predicted and the accuracy of the models were ascertained with R2 value and mean absolute percentage error (mape).

4. RESULTS

In all three models, there is a reasonable agreement between predicted and observed water levels, with correlation coefficient values (R2) near about value 1.00. With mean absolute percentage errors (MAPE) ranging from 0.49 to 0.78% (Table 2), the Recurrent Neural Network appears to give the greatest R2 values (>0.9), indicating a more accurate prediction. In addition, in compared to the other two models, figure 3(a) shows that there is less disagreement between observed and anticipated curves. The other two models, on the other hand, gave nearly identical correlation coefficient values. Their large MAPE (%), however, makes them unsuitable for forecasting.

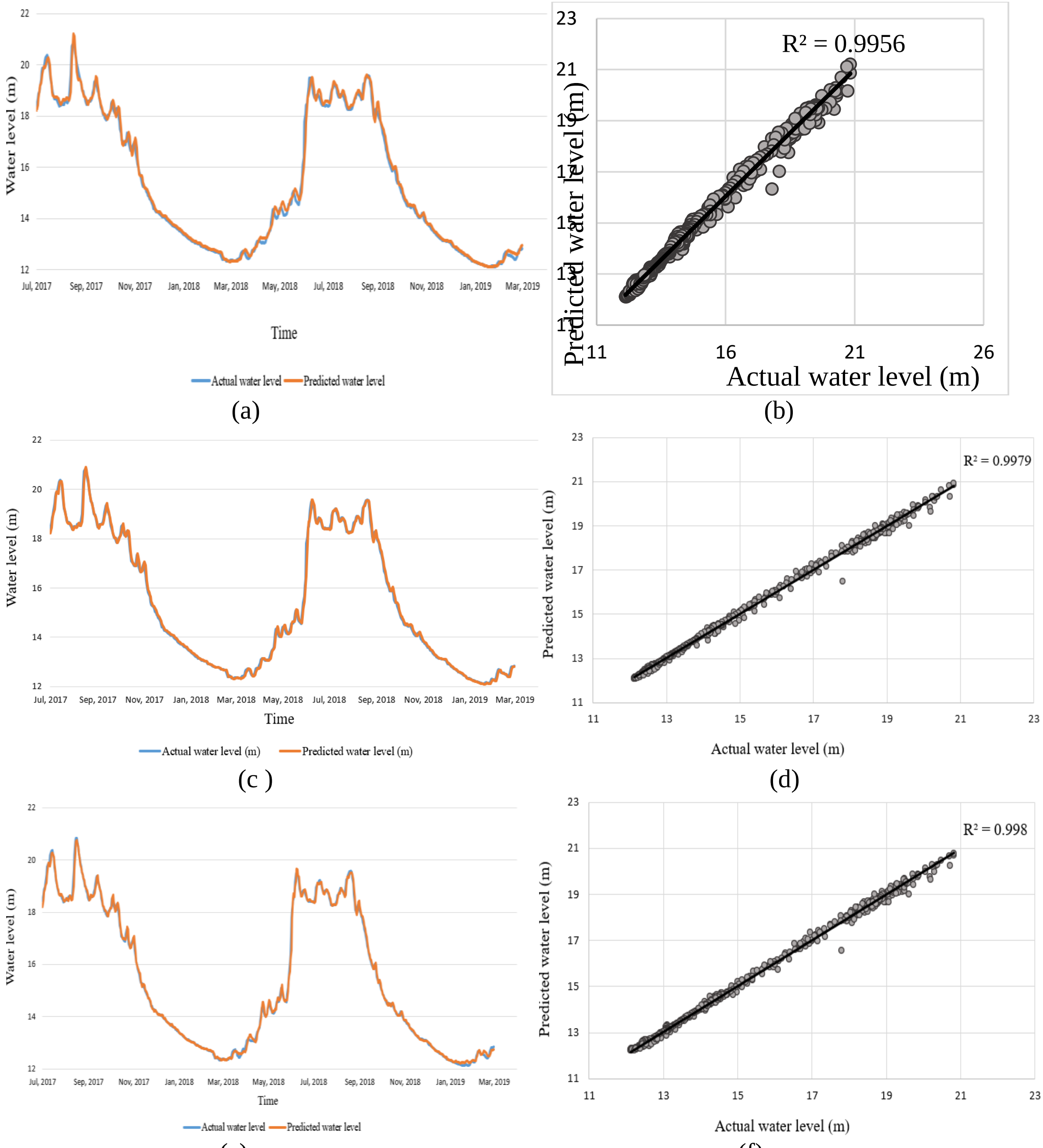

Figure 3: Water discharge prediction using- LSTM model – (a) water level varying with time, (b) predicted water level variation with respect to observed water level; Grated Recurrent Unit model - (c) water level varying with time, (d) predicted water level variation with respect to observed water level; RNN Model - (e) water level varying with time, (f) predicted water level variation with respect to observed water level.

The predicted water levels are compared to existing observations, and the setup is then confirmed using seasonal average discharge data from the previous 15 years. The findings reveal that river discharge affects water level seasonally (Figure 3). Seasonally, the mean water level ranges between 14 m (dry season) and 16 m (wet season) (wet season). Higher water levels occur from the substantial monsoonal river discharge at the end of the summer season. At peak discharge, it can reach a height of up to 18 meters (Figure 4).

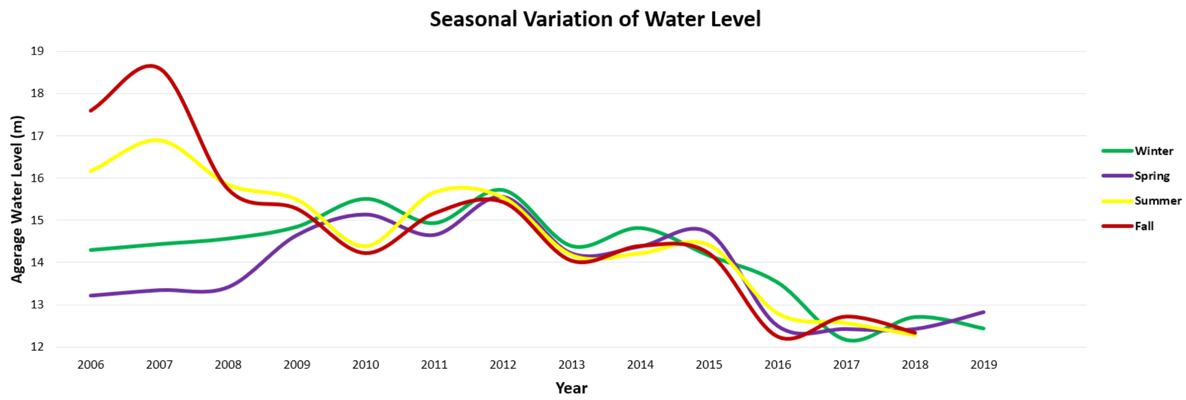

Figure 4: Seasonal variation of water level.

Table 2: Comparison of three different models

Model	R^2 value	MAPE (%)
Recurrent Neural Network	0.9980	0.49
Long Short Term Memory	0.9956	0.78
Gated Recurrent Unit	0.9979	0.49

5. CONCLUSIONS

The current status of DL modelling for water level prediction is relatively new and yet in its infancy. The findings of this work are critical for better understanding, modelling, and managing complex river systems like the Ganges-Brahmaputra-Meghna. In addition, the model configurations that have been built can now be used to examine flood risk assessment.

REFERENCES

Sahoo, A., Samantaray, S. & Ghose, D.K. Prediction of Flood in Barak River using Hybrid Machine Learning Approaches: A Case Study. J Geol Soc India 97, 186–198 (2021). https://doi.org/10.1007/s12594-021-1650-1.

Mosavi A, Ozturk P, Chau K-w. Flood Prediction Using Machine Learning Models: Literature Review. Water. 2018; 10(11):1536. https://doi.org/10.3390/w10111536.

G. Corani and G. Guariso, “Coupling fuzzy modeling and neural networks for river flood prediction,” IEEE Trans. on Systems Man and Cybernetics, vol.35, no.3, pp.382-390, Aug.2005.

D.P. Lettenmaier and E.F. Wood, 1993, Hydrological Forecasting, Chapter 26 in Handbook of Hydrology. (D. Maidment, ed.), McGraw-Hill. D.P.

Benoudjit, A., & Guida, R. (2019). A Novel Fully Automated Mapping of the Flood Extent on SAR Images Using a Supervised Classifier. Remote Sensing, 11(7), 779.

Zhao, G., Pang, B., Xu, Z., Peng, D., & Xu, L. (2019). Assessment of urban flood susceptibility using semi-supervised machine learning model. Science of The Total Environment, 659, 940-949.

M. I. I. Rabbi, M.A. Hasan, M. M. H. Galib, P. M. Toma, M. Ahamed. (2021). Discharge Prediction at Bahadurabad Transit of Brahmaputra-Jamuna Using Machine Learning and Assessment Of Flooding, Journal of Water Resources & Pollution Studies, Vol. 6, Issue-3 (Sep.-Dec., 2021).

H. M. Noor, D. Ndzi, G. Yang and N. Z. M. Safar, "Rainfall-based River flow prediction using NARX in Malaysia," 2017 IEEE 13th International Colloquium on Signal Processing & its Applications (CSPA), Batu Ferringhi, 2017, pp. 67-72.

Q. A. Lukman, F. A. Ruslan and R. Adnan, "5 Hours ahead of time flood water level prediction modelling using NNARX technique: Case study terengganu," 2016 7th IEEE Control and System Graduate Research Colloquium (ICSGRC), Shah Alam, 2016, pp. 104-108.

Ali, M., Qamar, A. M., & Ali, B. (2013). Data analysis, discharge classifications, and predictions of hydrological parameters for the management of Rawal Dam in Pakistan. In 2013 12th International Conference on Machine Learning and Applications.1, pp. 382-385. IEEE.