Research Article

A Comprehensive Flood Risk Inundation Mapping and Hybrid Model for Flood Forecasting in the Panam River Basin

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Abstract: The forecasting of flooding plays a pivotal role in the field of hydrology and serves as an essential measure for preventing any possible flood damage. This study presents an analysis of the utilization of an Adaptive Neuro-Fuzzy Inference System (ANFIS) to prevent floods in river basins. ANFIS represents a hybrid approach that combines elements of neural networks and fuzzy logic methodologies for the purpose of analyzing and comparing input and output data. Performance evaluation of ANFIS is based on the ratio of Discrepancy Ratio (D) along with the determination coefficient (R^2), Coefficient of correlation (R), and Root Mean Square Error (RMSE). Results: The best ANFIS model was the one that gave the best results during training. The RMSE was 622.43, with a correlation coefficient of 0.93 and an R^2 of 0.86. Nevertheless, its validation performance demonstrated slightly elevated RMSE figures and lower correlation and $R2$ values, with RMSE at 2847.99, R at 0.91, and R^2 at 0.83. An Artificial Neural Network (ANN) model with three transfer functions (SIGMOID, HYPERBOLIC TANGENT, and LINEAR) is developed and evaluated based on R = correlation and MSE = mean squared error. Furthermore, the study also entails the development of a flood model for the research area, consisting of 38 cross profiles for a detailed analysis of the river's profile and flood inundation. This analysis aims to provide precise recommendations for flood protection measures.

Keywords: flood prediction, precipitation, Panam watershed area, adaptive neuro-fuzzy inference system, precision forecasting, flood protection measures, inundation analysis, flood risk mitigation

Nomenclature

ANN	artificial neural network
ANFIS	adaptive neuro-fuzzy inference system
HEC-RAS	hydrologic engineering center-river analysis system

1. Introduction

Approximately 2.2 billion individuals, which accounts for about 29% of the global population, reside in areas projected to face varying degrees of flooding during a one-in-a-century flood event. Flood risk is a widespread danger that affects populations across all 189 countries studied. However, the concentration of vulnerable people is notably high in South and East Asia.

A critical component of flood management revolves around formulating a sound reservoir operation strategy to mitigate downstream flood impacts in a river. This challenge is particularly pronounced in growing nations, including India, where economic assets and infrastructure constraints create giant obstacles when it comes to augmenting the effectiveness of irrigation systems through physical enhancements.

Over the years, considerable endeavors have devoted themselves to improving the performance of irrigation systems, primarily at tertiary water level management. However, with the rapid advancement of computer technology and the ongoing progress in this field, there is an opportunity to rethink and redefine these approaches. In numerical methodologies, numerous one-dimensional hydrodynamic models have been created over time to enhance flood prediction and inundation mapping. In practical flood warning applications, the choice variables include discharge and river stage.

In recent research focusing on flood forecasting using soft computing methods, Sandeep Samantaray et al. [1] aimed to predict flood water levels accurately. Their study focused on forecasting the monsoon season in the Mahanadi River basin in India. They developed two hybrid models by combining ANFIS (Adaptive Neuro-Fuzzy Inference System) with optimization algorithms: the Whale Optimization Algorithm (WOA) and the Fruit-Fly Optimization Algorithm (FOA). The performance of these combined models was evaluated using various statistical metrics such as the coefficient of determination (R2), root mean square error (RMSE), mean absolute error (MAE), and Nash-Sutcliffe efficiency coefficient (ENS). To assess accuracy, the hybrid models were compared against a standalone ANFIS model. The outcomes indicated that in the schooling phase, the ANFIS-WOA hybrid model demonstrated promising performance. Outperforming both the ANFIS-FOA and the standalone ANFIS models. This study by Sandeep Samanta et al. [2] highlights the potential of combining optimization algorithms with ANFIS to beautify the accuracy of flood forecasting. The hybrid flood prediction version turned into assessed in opposition to the unbiased ANFIS version with the use of quantitative statistical measures which include the RMSE error, determination coefficient (R2), and Mean Absolute Error (MAE). Detchphol Chitwatkulsiri et al. [3] offer a complete evaluation of present-day techniques for leveraging radar records for rainfall prediction. They speak about the use of physics-primarily based totally hydraulic fashions for flood inundation forecasting and integrating records-pushed Machine intelligence fashions of instantaneous forecasting structures. The researchers additionally discover extraordinary modeling technologies, which include virtual floor fashions (DSMs), mainly that specialize in city drainage structures and finer terrain detail. The overall performance of the hybrid flood prediction version was evaluated in a study carried out via way of means of Zhou et al. [4] in northern China. The version as it should be anticipated flood ranges and timing throughout numerous rainfall situations and appreciably advanced computational speed, showing a fee growth of 19,585-fold as compared to a physically-primarily based totally hydrodynamic version. The suggested relative blunders of the version were also reported as only 9.5%. The flood maps also demonstrated high similarity in capturing spatial water depth patterns.

Ahmad et al. [5] employed a dataset spanning approximately four years from 2011 to 2014, consisting of discharge, rush, temperature, and evapotranspiration information for schooling and trying out the model's network. Their relative evaluation blanketed standards comparable to correlation factor (R), RMSE error, Mean Absolute Error (MAE), and a to estimate the model's performance. Wang et al. [6] advanced ANN system that combines traditional hydrological styles using inputs like the Antecedent Precipitation Index (API), downfall, upstream flux, and original inflow. This model predicts future flood flow and is optimized for physical relevance with a two-hidden-layer architecture.

Li [7] demonstrated the exceptional performance of the optimal PSO-ANN model, achieving an excessive degree of accuracy with an R2 cost of 0.846 throughout testing. The partial dependence plots (PDP) also highlighted the model's sensitivity to elements like liquid intake depth and the share of quartz sand, emphasizing their importance. In the area of modeling wetland water levels, Jayathilake et al. [8] located that the LM set of rules outperformed the SC set of regulations, handing over advanced consequences with average squared mistakes of 0.0002 and a correlation coefficient of

0.99. Furthermore, the LM algorithm demonstrated significantly better computational efficiency than the SC algorithm when predicting water levels. Chen et al. [9] synergize a numerically accurate model with a highly computationally efficient LSTM artificial neural network model to introduce a novel technique for rapidly predicting urban flooding risks. It leverages the numerical model's simulation outcomes for urban flooding as a foundation for developing LSTM neural network prediction models for individual waterlogging points. The outcomes indicate that this method achieves both exceptional prediction accuracy and swift computational speed, making it well-suited for daily flood control and emergency response requirements. Wanyama et al. [10] Hydraulic simulation models provide a practical an alternative approach to improving canal operation and management involves gaining a deep understanding of flow dynamics within canal networks under different design and operational conditions. Mehta and Mohammed [11, 12] conducted studies using the HEC-RAS software to predict discharge profiles and examine the relationships between head and discharge in river basins. Qasim's [13] observations pointed out that HEC-RAS tended to overestimate water levels and underestimate them during periods of low flow. Islam [14] introduced a Hydraulic simulation version tailor-made for simulating each constant and unsteady flow inside irrigation canal networks, whether or not they may be branched or looped, and prepared with diverse go with the drift manage and law structures. The study also presented model testing results to assess numerical precision and stability.

Karamouz [15] devised an approach to identify and ensure optimal results; it is imperative to implement the most cost-effective combination of permanent and emergency flood control measures while simultaneously optimizing crop patterns along a river. This optimization process relies on flood control options determined by the model. Flooding within a watershed result in substantial damage across various land uses, often exacerbated by improper use of floodplain areas. One notable advantage of employing the hydrologic routing method is its seamless integration with the optimization model. Additionally, using a river hydraulic simulation model serves the purpose of constructing. Mohaideen et al. [16] have demonstrated that the FLDCSaDE algorithm surpasses other evolutionary algorithms, exhibiting a 4% reduction in ripples for high-pass filters and a 1.5% reduction for band-stop filters compared to the SaDE algorithm. Alapati Ramadevi and the team conducted comprehensive testing of their data. The researchers in this study created FF-ANNC (Feedforward Artificial Neural Network Controller). The annex compares FF-ANNC with other methods commonly found in the existing literature, including PI-C, fuzzy common-sense control (FL-C), and synthetic neuro-fuzzy inference systems (ANFIS). Abdullah Saleh Alqahtani [17]. And associates assessed various information models to identify those capable of delivering precise forecasts for renewable energy generation, encompassing solar, wind, and pumped storage sources. In the realm of sustainable energy forecasting, several machine learning techniques are used. In the field of neural network designs, there exist different architectures like convolutional neural networks (CNN), recurrent neural networks (RNN), multilayer perceptron (MLP), and lengthy short-time period memory (LSTM) are frequently utilized. Pravin R Kshirsagar et al. [18] have designed a system for classifying skin diseases, employing the MobileNetV2 architecture in conjunction with LSTM. This system prioritizes accuracy in forecasting skin diseases while ensuring efficient storage of complete state information for precise predictions.

Selvaraj et al. [19] have demonstrated the effectiveness of Squeeze Net, achieving the model's impressive checking-out accuracy of 99.73% and an F1 rating of 0.9817 is worth mentioning. This achievement allows it to effectively detect environmental issues in solar panels, offering users a way to safeguard their panels. Selvaraj et al. [19] have fine-tuned convolutional neural networks, particularly SqueezeNet, to train thermal images of solar panels and detect environmental faults. The results demonstrated SqueezeNet's remarkable 99.74% testing accuracy and an F1 score of 0.9818, making it a successful tool for identifying and protecting solar panels from faults. Joshuva et al. [20] have proposed an algorithm that relies on thermal image processing to extract characteristics from functioning photovoltaic (PV) cells. Subsequently, these extracted attributes are contrasted with those of undamaged PV modules through a Support Vector Machine for assessment.

Flood forecasting is a critical practice. To forecast the arrival and intensity of floods in a particular area, data must be collected on factors such as rainfall, water levels, river flow, and different applicable variables that can contribute to flood incidents. This data is subjected to thorough analysis to generate forecasts regarding potential floods. These forecasts are pivotal for emergency management authorities, furnishing them with advanced notice of impending floods, thereby enabling proactive measures to safeguard lives and property. Additionally, flood forecasting aids in optimizing the allocation of resources, including items like sandbags, rescue boats, and emergency response personnel.

The ANFIS toolbox serves the specific purpose of creating a fuzzy inference system that is used to make decisions based on input/output data observations. This is done by adjusting adaptive operating boundaries dynamically with the usage of both a backpropagation set of rules or a least squares method. The ANFIS version includes numerous key elements, consisting of a layer of fuzzification, a mechanism of inference, a layer of defuzzification, and a very last output layer known as the "total" layer. Its principal goal is to apply a studying set of rules and enter records to decide the best parameters for the bushy inference system. During the schooling phase, modifications are made to the limits to reduce the distinction between the favoured goal and the real output. This process fine-tunes the model for optimal performance. To efficiently adjust these parameters, a hybrid algorithm is employed, which combines gradient descent and least square estimation techniques. Please confer with Figure 1 for a visible representation.
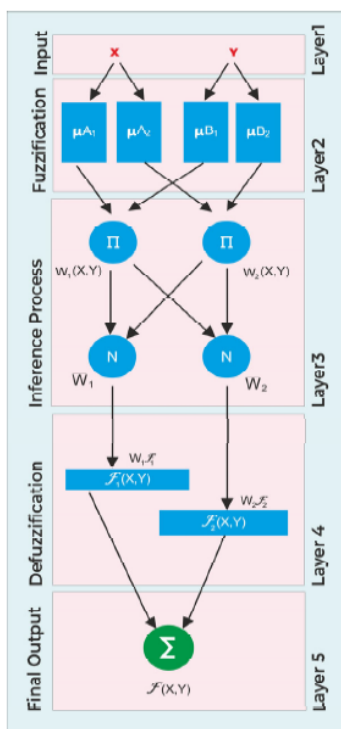

Figure 1. Standard Framework of The Adaptive Neuro-Fuzzy Inference System.

ANNs are essential details for synthetic intelligence, with the goal of copying the features of the human brain. ANNs are composed of processing gadgets with the cap potential to get hold of and bring information. Their layout attracts notions from computational factors that use predetermined activation features to method inputs and generate appropriate outputs. By emulating the neural community shape of the human brain, ANNs permit machines to research records and make knowledgeable decisions that resemble human cognitive processes.

Diverging from conventional machines that operate through linear programming, ANNs establish connections akin to the synapses between neurons in the human brain. This allows them to construct a computational model featuring numerous processing elements; each assigned the task of receiving inputs and delivering outputs in accordance with their designated activation functions. Figure 2 comprehensively depicts the Artificial Neural Network version and tricky processing components.
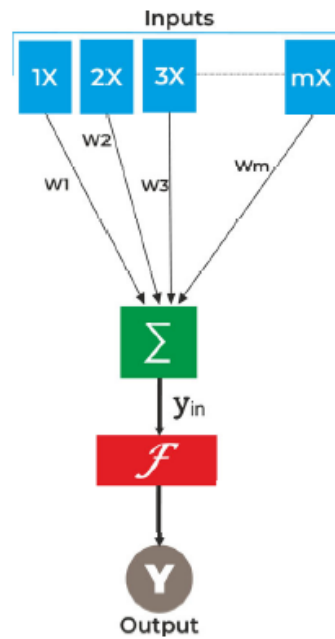
Figure 2. Structural Framework of Artificial Neural Network.

HEC-RAS 6.4.1 is a freely available software tool accessible through the US Army Corps website. This software can perform gradually varied flow analysis on river and channel geometries, we have employed the constant gradual flow simulation model to carry out one-dimensional hydraulic computations encompassing the entire network of the natural riverbed. Figure 3 outlines the methodology used in modeling performance. For the analysis of steady flow, it is imperative to ascertain the left bank and proper bank elevations, along with considering roughness coefficients.

We have applied HEC-RAS to perform one-dimensional hydraulic calculations encompassing natural and constructed channel networks. To conduct flow simulation through HEC-RAS 6.4.1, one needs geometry, boundary conditions, and basin resistance. For the current study, The Digital Elevation Model (DEM) is used.
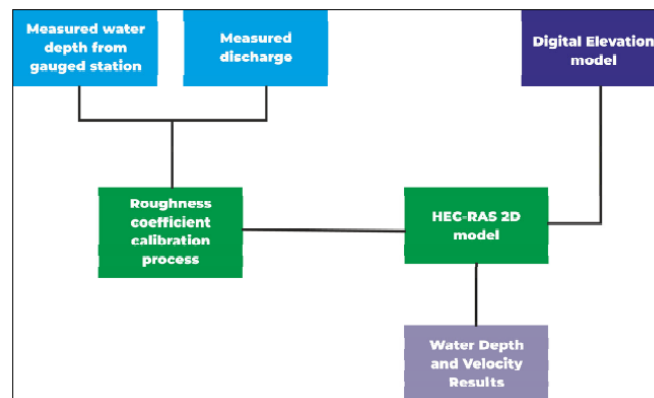

Figure 3. HEC-RAS Simulation Process.

In this approach, discharge-elevation and elevation-harm curves are evolved for every precise section. These curves are eventually included in the optimization version to estimate flood damage. The calculations don't forget numerous

factors, which include flood volume, floodplain zoning, land use inside the floodplain, and the financial charges related to broken regions in keeping with rectangular meters. The damages are calculated for different flood return periods, providing a comprehensive assessment of flood-related economic impacts.

The organization of the paper is as follows: Section 2 mentions details about the research study area selected for the current research work. Section 3 describes the methodology used for flood forecasting and flood inundation mapping. Section 4 contains flood modeling results and analysis. Section 5 provides a conclusion regarding the comparative study.

2. Study area

This study examines the Panam River Basin as the chosen area for research study purposes. The basin area of the Panam River is a vital portion of the larger river basin of Mahi, with the Panam River truly being taken into consideration as one of every one of its contributing tributaries. The Panam River's adventure starts inside the Devgadh Baria Taluka of the Dahod district. Notably, the Mahi River is significant in the western direction of the region, originating from the Vindhya mountains and eventually flowing into the Gulf of Khambhat. The Mahi Basin covers an extensive area of 34,842 square kilometers across Madhya Pradesh, Rajasthan, and Gujarat.

The strategically located Panam Dam is approximately 25 kilometers upstream from where the river Panam meets the river Mahi. The Panam River flows about 21.77 km from the Panam Dam up to its confluence with Mahi River. For a visual representation of the selected research study area, please refer to Figure 4, which depicts an aerial map [21, 22].

Figure 4. Study area of Panam river basin.

3. Methodology

3.1 *ANFIS model for rainfall-based peak inflow discharge forecasting inside the Panam river basin*

The improvement of the ANFIS version worried about splitting the entire dataset into parts. Seventy percent of the statistics become set apart for schooling the version, whilst the final 30% are used for validation. The ANFIS model was designed with a single input, rainfall, and a single output, peak inflow discharge.

This research employed a hybrid optimization method with a specified 100-epoch value. Several trials were conducted, and different configurations were tested. These configurations involved varying the number of membership functions, such as 2, 4, 6, 8, and 10, and utilizing various membership function types, including Trim, entice me, belief, Gauss, Gauss2mf,

and others inside the ANFIS version development. Subsequently, all of the generated fashions underwent a complete assessment of the usage of numerous evaluation parameters. These parameters blanketed the Discrepancy Ratio along with the determination coefficient (R^2), Coefficient of correlation (R), and Root Mean Square Error (RMSE). The aim has become to be privy to the most appropriate ANFIS model tailored to the basin area of the Panam River. The way of developing the Adaptive Neuro-Fuzzy Inference systems involved the steps outlined in Figure 5.
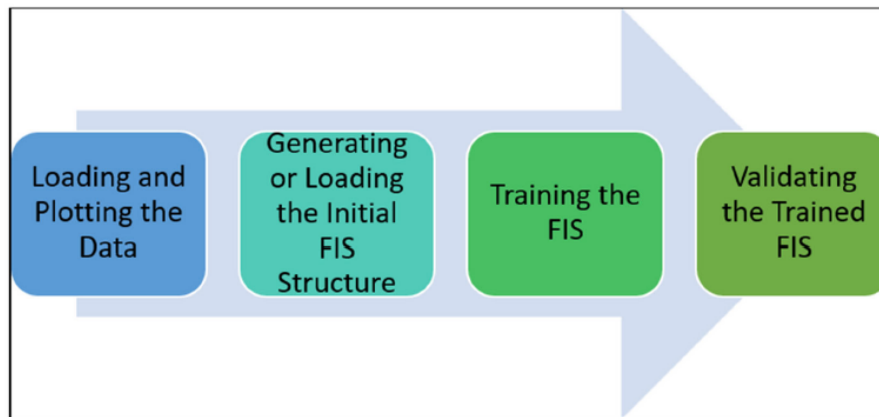

Figure 5. User Interface Workflow of ANFIS.

3.2 *Artificial neural network (ANN) models*

For the current research study, we developed ANN models with the use of three one-of-a-type schooling algorithms: Scaled Conjugate Gradient, Bayesian Regularization & Levenberg-Marquardt. Each ANN version consisted of hidden layers, with 5 neurons in every layer. The conduct of each neuron was simulated by performing simple computations. These computations involved gathering input signals from connections, computing activation levels or outputs based on these inputs, and transmitting the values other neurons through output the data connections.

Within the used of neural network framework, three unique transfer functions were employed for each layer: SIGMOID, HYPERBOLIC TANGENT, and LINEAR. Consequently, all possible combinations of these functions were tested for both hidden layers. This rigorous exploration resulted in the creation of a total of 270 distinct network models. These models' creation involved applying all three training algorithms, utilizing nine distinct combinations of transfer function types for each of the two hidden layers. Two network types were also implemented: the Forward Propagation, Error Backpropagation, Sequential Forward Error Backpropagation.

To assess of performance and efficiency of these models, two significant metrics were utilized: The two important statistical measures that are commonly used in data analysis are the correlation factor (C) and the Average Squared Deviation (ASD). System diagrams for both the Feed-Forward Backpropagation and Cascade-Forward Backpropagation architectures are visually depicted in Figure 6.
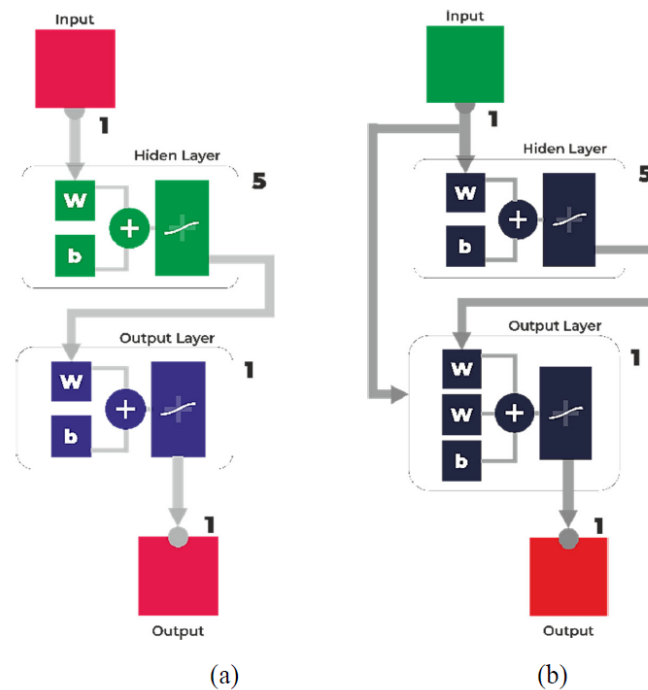
Figure 6. Bidirectional feedforward backpropagation (**a**) and cascade feedforward back propagation (**b**) networks with two layers.

3.3 *HEC-RAS*

To replicate actual historical flood events, unsteady flow data was integrated into the HEC-RAS, developed with assistance of Hydrologic Engineering, as a vital boundary condition. In this research, a comprehensive dataset of recorded stream flow data from the years 1987 to 2017 was thoughtfully chosen to represent the occurrences of flood events accurately. These data were certain because the upstream boundary situations for the river model, at the same time as ordinary intensity changed into installed because the downstream boundary condition. It was crucial to meticulously synchronize the simulation time within HEC-RAS with the provided flow data to ensure precision and reliability in the results.

With all the essential inputs now in place, HEC-RAS was poised to initiate the hydrodynamic modeling process. The final phase entailed executing the unsteady flow model within the 'Run' window of the software. During this computational phase, the 1D HEC-RAS model effectively captured the unsteady flow dynamics as it propagated downstream in a one-dimensional manner. The cross-sections provided a comprehensive representation of the river environment, further enhancing the precision of the simulation. To achieve this, a total of 38 cross-sections were meticulously established along the river's length, as visually depicted in Figure 7.
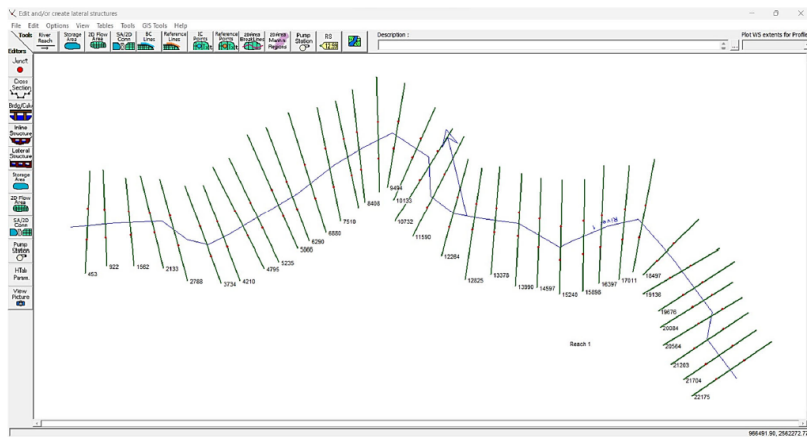
Figure 7. 38 Panama river cross-section analysis.

4. Result and discussion

4.1 *ANFIS outcomes*

The findings and discourse segment of the ANFIS model typically encompasses a thorough analysis of its performance. This involves an evaluation of its accuracy, its capacity for generalization, the extraction of rules, and a comparison with other models. Performance assessment aims to gauge the ANFIS model's accuracy through metrics like RMSE, R, R2, and more. A complete evaluation of the ANFIS model's overall performance in the education dataset is presented, highlighting its capacity to effectively seize and constitute the information. Furthermore, the model's cap potential to generalize is classed via way of means of analyzing its overall performance on a separate validation dataset. Table 1 gives a precis of overall performance assessment metrics for diverse ANFIS models, encompassing the Discrepancy Ratio along with the determination coefficient (R^2), Coefficient of correlation (R), and Root Mean Square Error (RMSE) for each education and validation dataset and validation datasets.

Table 1. The training and validating the ANFIS model, it is important to consider the parameters used for performance evaluation.

Type of Mfs	No. of Mfs		ANFIS Error	RMSE (cumec)	R	R²
Gbellmf	**3**	Training	685.62	685.62	0.91	0.77
		Validation	3592.81	3592.81	0.88	0.77
	5	Training	579.69	579.69	0.95	0.85
		Validation	1203.98	1203.98	0.91	0.82
	7	Training	331.72	331.72	0.89	0.94
		Validation	237368.28	237368.28	0.86	0.96
Gaussmf	**3**	Training	697.08	697.08	0.89	0.77
		Validation	2182.91	2182.91	0.95	0.96
	8	Training	622.43	622.43	0.93	0.81
		Validation	2847.99	2847.99	0.91	0.98
	10	Training	340.07	340.07	1.01	0.96
		Validation	280239.2	280239.2	1.02	0.98

Type of Mfs	No. of Mfs		ANFIS Error	RMSE (cumec)	R	R^2
Gauss2mf	3	Training	729.59	729.59	0.9	0.76
		Validation	5872.66	5872.66	0.7	0.45
	4	Training	384.89	384.89	0.85	0.94
		Validation	19204	19204	1.02	0.98
	6	Training	334.91	334.91	1.01	0.96
		Validation	2063.74	2063.74	0.98	0.90
Pimf	8	Training	734.3	734.29	0.9	0.76
		Validation	6026	6025.76	0.74	0.50
	10	Training	932.59	932.59	0.79	0.58
		Validation	6152.11	6152.11	0.24	0.04

The analysis of the table reveals that ANFIS models. Among the different ANFIS models, those equipped with 7 Gauss2 type membership functions have demonstrated superior performance. These models exhibit the bottom Root Mean Square Error (RMSE) and the top-quality Correlation Coefficient (R), drawing close to a cost of 1, representing the execution of all developed models. For showing the efficacy of all models, visible comparisons are provided through graphs that depict determined and expected discharge for each of the education and validation datasets are available in Figures 8 and 9. Please refer to the respective figures for more in-depth insights into these graphical representations.
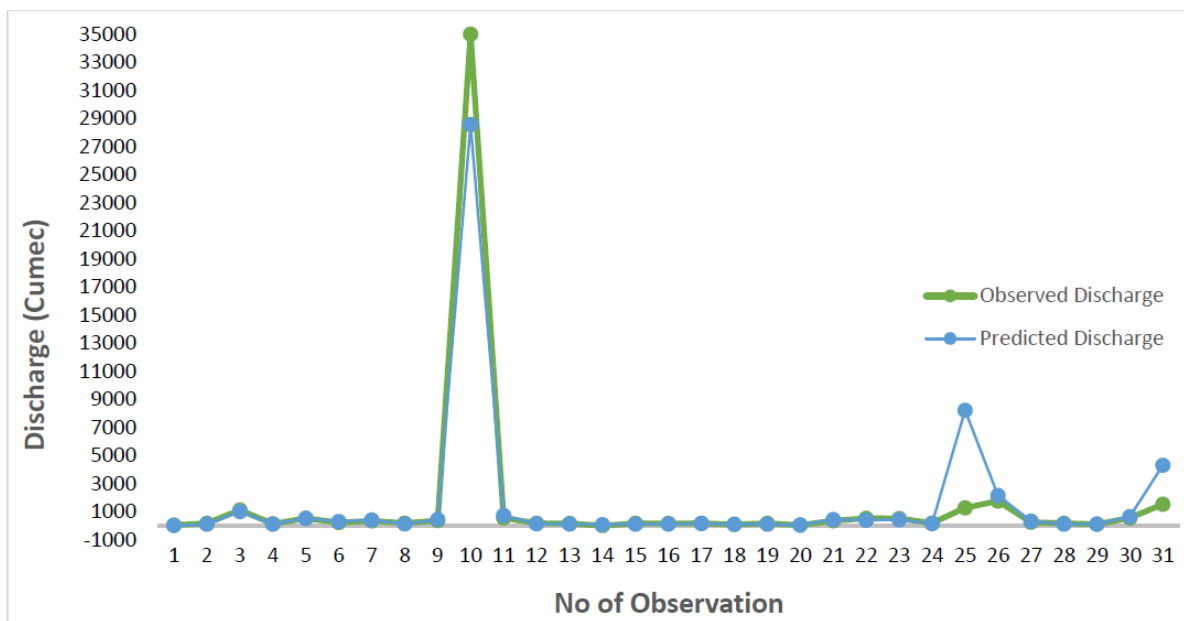

Figure 8. A comparative analysis was conducted between the observed and predicted peak discharge during training.
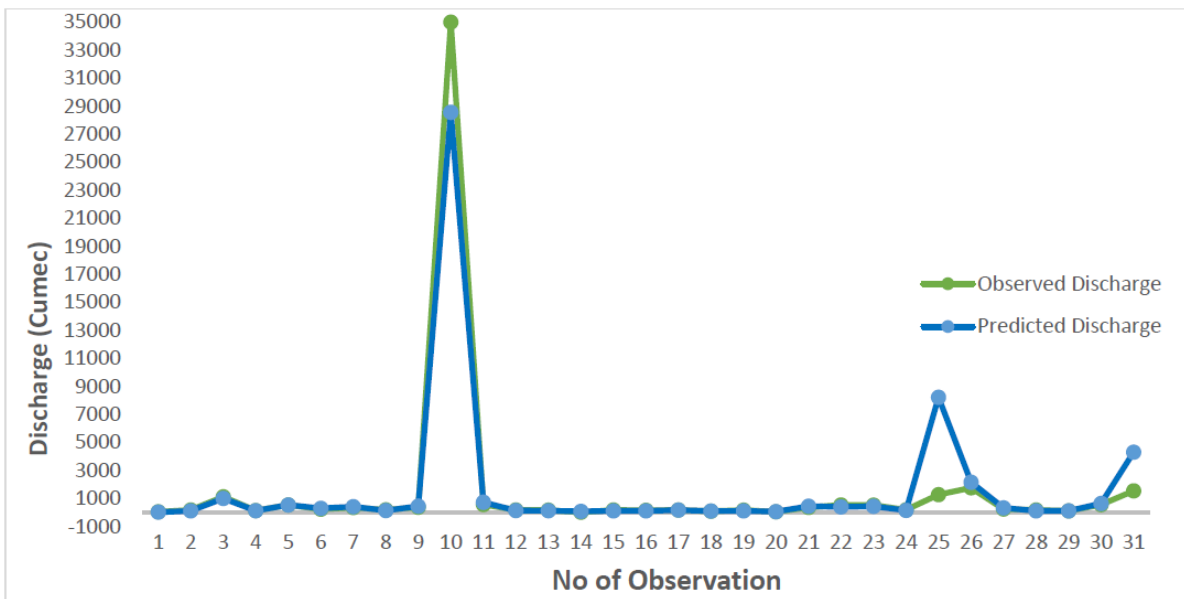
Figure 9. Comparing Observed and Predicted Peak Discharge in Validation.

Comparing ANFIS with other models showcase their capability in managing uncertainty, acquiring knowledge Comprehending intricate relationships from data.

Figures 10 and 11 show regression plots for the training and validation phases. When examining the effectiveness of ANFIS alongside alternative models or algorithms applied within the same problem area, ANFIS demonstrates distinct advantages. These include its capacity to manage uncertainty, acquire insights from data, and model intricate relationships effectively. This comparative analysis underscores the unique strengths of ANFIS in addressing complex challenges within its domain.
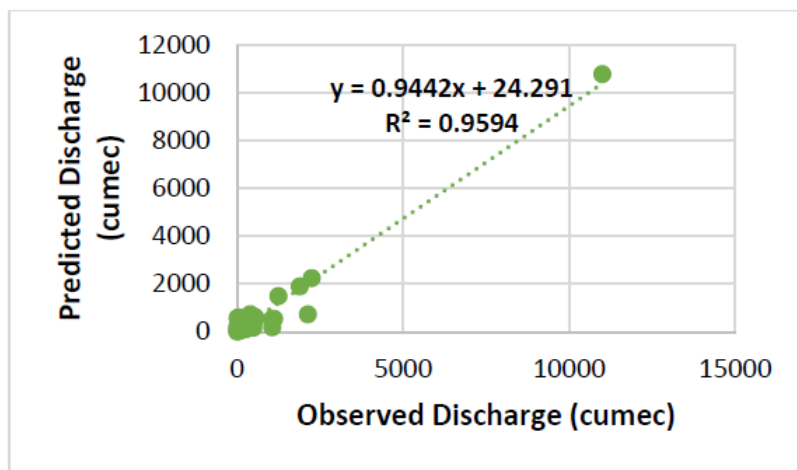

Figure 10. Regression Analysis: Predicted vs. Observed Discharge (ANFIS Model).
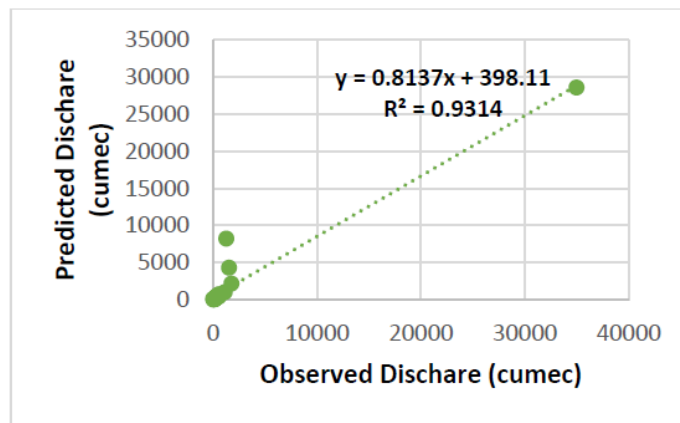
Figure 11. Validation Phase Regression Analysis: Predicted vs. Observed Discharge (ANFIS Model).

4.2 *ANN results*

When delving into the realm of Artificial Neural Networks, it's customary "In explore different aspects" of the model. This typically includes examining the model's accuracy, overall performance, the intricacies of its training process, architectural elements, its ability to generalize, comparisons with alternative models, and prospective applications. Key metrics such as the Correlation coefficient (R) and Average Squared Deviation are calculated using Matlab's analytical tools to assess the effectiveness of the constructed ANN models. Table 2 presents various combinations of transfer function for showcasing the performance of these models. Table 3 gives performance results for for Bayesian Regularization Algorithm. Table 4 provides the performance of Scaled Conjugate Gradient Algorithm for flood forecasting.

Table 2. Layerwise ANN model combinations.

Feed Forward Back Proporgation					
Transfer Function					
Layer 1	Layer 2	Layer 1	Layer 2	Layer 1	Layer 2
SIGMOID	SIGMOID	SIGMOID	HYPERBOLIC TANGENT	SIGMOID	LINEAR
LINEAR	HYPERBOLIC TANGENT	LINEAR	LINEAR	LINEAR	SIGMOID
HYPERBOLIC TANGENT	LINEAR	HYPERBOLIC TANGENT	SIGMOID	HYPERBOLIC TANGENT	HYPERBOLIC TANGENT
Cascade Forward Back Proporgation					
SIGMOID	SIGMOID	SIGMOID	HYPERBOLIC TANGENT	SIGMOID	LINEAR
LINEAR	HYPERBOLIC TANGENT	LINEAR	LINEAR	LINEAR	SIGMOID
HYPERBOLIC TANGENT	LINEAR	HYPERBOLIC TANGENT	SIGMOID	HYPERBOLIC TANGENT	HYPERBOLIC TANGENT

Table 3. Performance of ANN models using bayesian regularization.

Feed Forward Back Proporgation						
Transfer Function		Values of Corelation Coefficient R				
Activation in Layer 1	Activation in Layer 2	Training Correlation	Validation Correlation	Testing Correlation	Overall Correlation	Mean Squared Error
SIGMOID	SIGMOID	0.36	0.87	-0.09	0.24	780325.25
LINEAR	LINEAR	0.57	0.77	0.51	0.67	141794.56
HYPERBOLIC TANGENT	HYPERBOLIC TANGENT	0.77	0.63	0.7	0.48	18793.43
CASCADE FORWARD BACK PROPORGATION						
SIGMOID	HYPERBOLIC TANGENT	0.99	0.86	0.45	0.99	16140

Table 4. Comparative analysis of ANN models using scaled conjugate gradient algorithm.

Feed Forward Back Proporgation						
Transfer Function		Values of Correlation Coefficient R				
Layer 1	Layer 2	Training	Validation	Testing	Overall	MSE
SIGMOID	LINEAR	0.89	0.86	0.88	0.67	782630
HYPERBOLIC TANGENT	LINEAR	0.81	0.76	0.85	0.88	16140
Cascade Forward Back Proporgation						
SIGMOID	LINEAR	0.56	0.76	0.52	0.67	750432.7
LINEAR	LINEAR	0.76	0.64	0.7	0.48	112346.45

The regression analysis plot generated by Artificial Neural Network is shown in Figures 12 and 13 for training and validation of ANN model. Flood forecasting results have diverse practical applications, including early warnings, emergency planning, infrastructure management, land use guidance, insurance risk assessment, water resource optimization, climate adaptation, and scientific research. These applications help reduce flood impacts on people, infrastructure, and the environment.
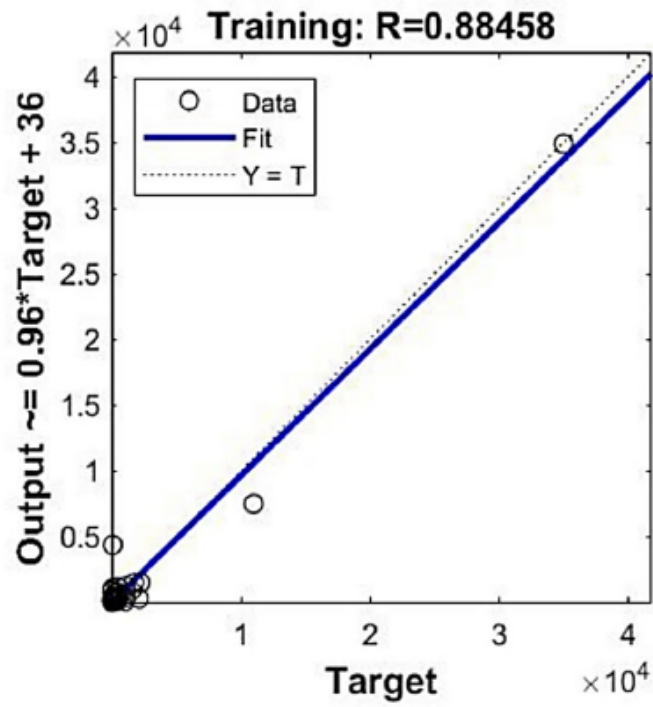
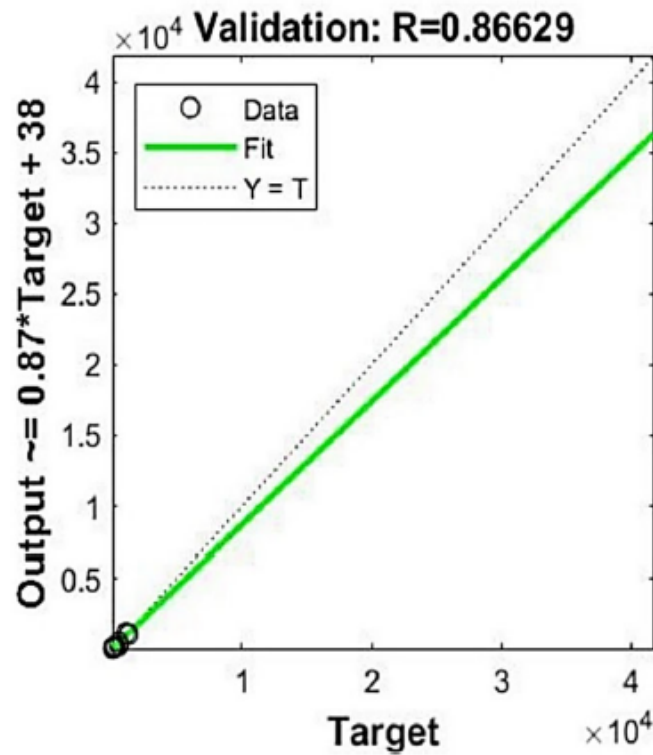**Figure 12.** Regression analysis plot in training the data into ANN.

Figure 13. Regression analysis plot in validation the data into ANN.

4.3 *Comparision*

	Type of membership function	No. of membership function	Phases	Root Mean Square Error	Coefficient of correlation (*R*)	Coefficientof determination (*R²*)
ANFIS	Gauss2	10	Training	622.43	0.93	0.86
			Validation	2847.99	0.91	0.83
	Transfer Function	**Neurons**	**Phases**	**Root Mean Square Error**	**Coefficient of correlation (*R*)**	**Coefficientof determination (*R²*)**
ANN	SIGMOID	5	Training	16140	0.88	0.79
	LINEAR	5	Validation		0.86	0.74

4.4 *HEC-RAS results*

Using the RAS mapper and 1-D unsteady flow analysis, the extent and depth of flood inundation for different scenarios, mainly focusing on critical flood events, are analyzed. The HEC RAS 1-D unsteady flow analysis also generates the Water Surface Profile. Figure 14 shows the water surface for stating cross section and ending cross section.
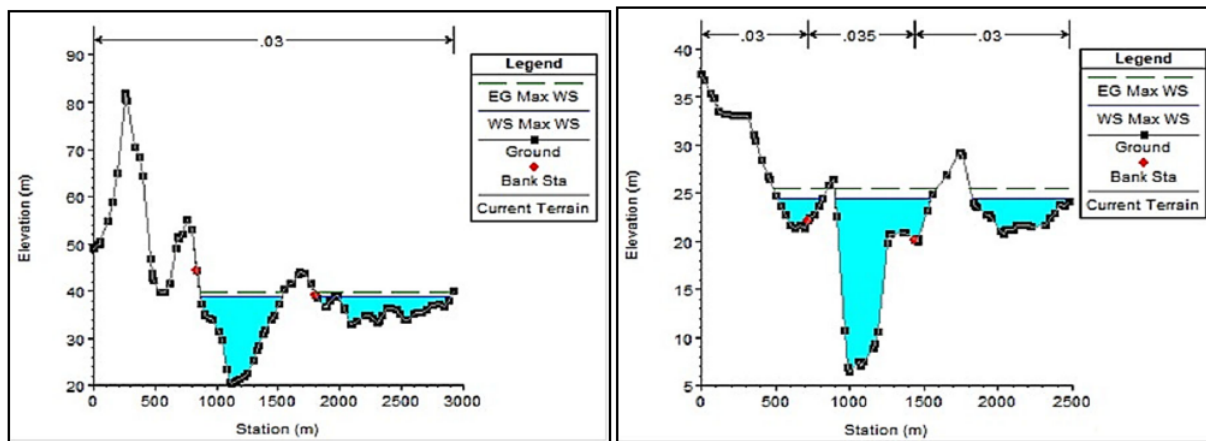

Figure 14. River cross section at chainage 22175 m and 953 m.

Figure 14 depicts river cross sections at the Panam River Basin's inception and termination points. These cross-sections provide details about the elevation and width of the river channel and its associated floodplain, utilizing a color gradient from blue to green. Blue signifies lower elevation, while green represents higher elevation. Additionally, the cross sections display the water surface elevation for various flood discharge scenarios, indicated by a color spectrum from blue to red. Here, blue denotes lower water elevation, while red indicates higher elevation. These cross-sections serve as valuable tools for visualizing the river's geometrical and hydraulic attributes at different locations and during varying flood conditions.

5. Conclusions

The ANFIS model, using ten Gauss2-type membership functions, exhibits superior predictive performance for flood forecasting in the Panam River basin. Training results include an RMSE of 622.43, R of 0.93, and R2 of 0.86, while

validation shows RMSE of 2847.99, R of 0.91, and R2 of 0.83. The ANN model, although commendable, does not match the ANFIS model's predictive capabilities.

In conclusion, the ANFIS model has diverse applications, such as flood risk management, hazard reduction, evacuation planning, insurance assessments, and environmental system management.

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Conflict of interest

There is no conflict of interest for this study.

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