Issue no: 01 | **Vol no:** 04 | **April** 2026: 1-15

Forecasting Flood Magnitudes and Annual Exceedance Probabilities (2015–2052) Using ANN and Gumbel Distribution

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Article History
Received: **2026.02.13**
Accepted: **2026.03.19**
Published: **2026.04.24**

Cite this article in APA
Onyango, E. A., Amisi, E. O., Wambua, R. M., & Otieno, H. (2026). Forecasting flood magnitudes and annual exceedance probabilities (2015–2052) using ANN and Gumbel distribution. *Editon consortium journal of geography and environmental sciences*, *4*(1), 1-15. https://doi.org/10.51317/ecjges.v4i1.691

Abstract
The purpose of this article is to forecast flood magnitudes and their respective P-per cent annual exceedance probabilities in the Gucha-Migori River Basin for the period 2015–2052 to support flood risk management and early warning planning. Historical river discharge and precipitation data were used to develop and validate forecasting models. An artificial neural network (ANN) with a 1-20-1 network topology, where the single input represents hydrological data, the twenty hidden neurons process patterns, and the single output represents predicted flood magnitude, was trained and validated to predict future flood events, while the Gumbel distribution model was applied to estimate annual exceedance probabilities. Model performance was evaluated using correlation coefficients and error metrics. The ANN effectively captured non-linear flood dynamics, with minimum R values of 9.20×10^{-1}, 9.27×10^{-1}, and 9.15×10^{-1} for training, validation, and testing, respectively. Forecasted maximum flood magnitudes for successive five-year periods from 2015 to 2052 ranged from 299 to 502 m^3/s. Corresponding annual non-exceedance probabilities derived from Gumbel's distribution varied between 64 per cent and 99.6 per cent. These results indicate a significant variability in future flood magnitudes, emphasising the need for proactive flood management strategies. The study provides critical information for decision-makers, enabling the development of flood response plans, early warning systems, and preparedness measures in the Gucha-Migori River Basin.

Key words: Artificial neural network, climate variability impact, flood event, forecasting, river discharge.

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INTRODUCTION

Floods are among the most devastating natural disasters, frequently affecting the Gucha-Migori River Basin nearly every year (JICA, 2014). Climate change and socio-economic development continue to alter hydrological regimes globally, threatening water, energy, and food security (Archer et al., 2010; IPCC, 2014; UNFCCC, 2005; Wambua et al., 2017). In Kenya, ecosystem deterioration, spatial and temporal uncertainties in water input, and changes in watershed storage exacerbate extreme hydrologic events such as floods (Juma et al., 2020; Opere, 2013). Flooding is primarily driven by intense and prolonged rainfall exceeding soil infiltration capacity or river channel flow capacity, generating surface runoff through Hortonian or saturation overland flow (Singo et al., 2012; Thavhana, 2018; Warburton et al., 2010). In the Gucha-Migori River Basin, heavy upstream rains cause significant surface runoff into the Gucha and Migori rivers, eroding soil and increasing sedimentation downstream (Adero, 2017). Flash floods in the floodplain also lead to crop losses and disruption of agricultural activities (Muiruri et al., 2014; Ogembo, 2018). Flood hazards in Kenya affect approximately (27%) of the population, with flood-related fatalities accounting for over (60%) of disaster victims (Akello, 2014; UNEP, 2010).

The increasing frequency and severity of floods necessitate non-structural interventions for comprehensive flood management, complementing structural measures such as dykes and dams (Gaya, 2020; WMO, 2011a, b). Non-structural approaches include land-use regulation, hydrologic modelling, disaster prevention, flood-proofing, continuous forecasting, and flood frequency analysis. These methods enhance preparedness, early warning, and real-time monitoring, providing flexible and adaptive solutions to flood risks.

However, despite these efforts, there is limited research integrating data-driven forecasting models with probabilistic analysis to predict both flood magnitudes and their associated exceedance probabilities in the Gucha-Migori River Basin, particularly under future climate variability scenarios.

This study focuses on forecasting flood magnitudes and P-per cent annual exceedance probabilities in the Gucha-Migori River Basin for 2015–2052. An artificial neural network (ANN) was employed alongside probability distribution models to predict future flood events and quantify their likelihood of occurrence. The ANN captures non-linear relationships between precipitation and river discharge, while probability distributions, such as the Gumbel distribution, provide estimates of annual exceedance probabilities (Dawson & Wilby, 2001; Maier & Dandy, 2000). This integrated approach aims to support basin rehabilitation, flood risk management, and the development of effective water resource management strategies, while addressing knowledge gaps regarding future flood scenarios in the basin.

LITERATURE REVIEW

Forecasting of Flood Events

The first activity in flood forecasting is the use of models or statistical tools to predict future flood magnitudes or peak discharges. Then, the relevant PD curve selected was used for the estimation of frequencies of the forecasted flood magnitudes. Although many techniques have been proposed and applied to predict hydrologic events, artificial neural networks have been preferred and most used (Das & Ghosh, 2018). ANN models may be a better option because of their power of adaptive learning, real-time operation, and fault tolerance, and they are used in modelling nonlinear and complex phenomena (Lee & Tuan, 2016; Ozoegwu, 2019; Somvanshi et al., 2006). Their capability comes from pattern capturing and statistical parallel processing of historical data (Ozoegwu, 2019).

Artificial neural network models have been widely applied in hydrological studies, including flood predictions (Mitra et al., 2016; Mukerji et al., 2009; Rezaeianzadeh et al., 2014; Tiwari & Chatterjee, 2010). These studies have indicated that ANN models perform better than other statistical modelling techniques because of their robust performance in dealing with noisy input patterns and the ability to generalise from the input data, which makes them a reliable option for probability predictions.

Artificial Neural Network

An artificial neural network can be described as a mathematical structure capable of representing the arbitrary, complex, and non-linear process correlating the input and output of any system. The motivation for the development of neural network technology stemmed from the desire to develop an artificial system that could perform "intelligent" tasks similar to those performed by the human brain (Herreyre et al., 2023; Wambua, 2020).

ANN is a black box-type lumped model, which obtains knowledge through a pragmatic approach, which involves identifying a set of weights for the connections and boundary values referred to as biases, for the neurons (Sharghi et al., 2018; Wambua, 2019). Figure 1 shows typical artificial nodes with inputs (X_1, X_2, …, X_n) connected to neuron j with weights (W_{1j}, W_{2j}, …, W_{nj}) on each connection.

The neurons sum all the signals they receive, with each signal being multiplied by its associated weights on the connection. ANN output (Q) is then processed through an activation function f (.), which is usually non-linear to give the final output (Y).

As explained by Haykin (2010), the input and output signal relationship within the neural networks can be expressed as expressed in the following function:

$$Y = f(Q) = f\left(\sum_{i}^{n} W_i X_i + b_k\right)$$

(2.14)

where, X_i is the input signal i, W_i is the weight attached to the input signal i, n is the number of input signals, b_k is the bias at the cell of the body, f is the activation function, and Y is the output.

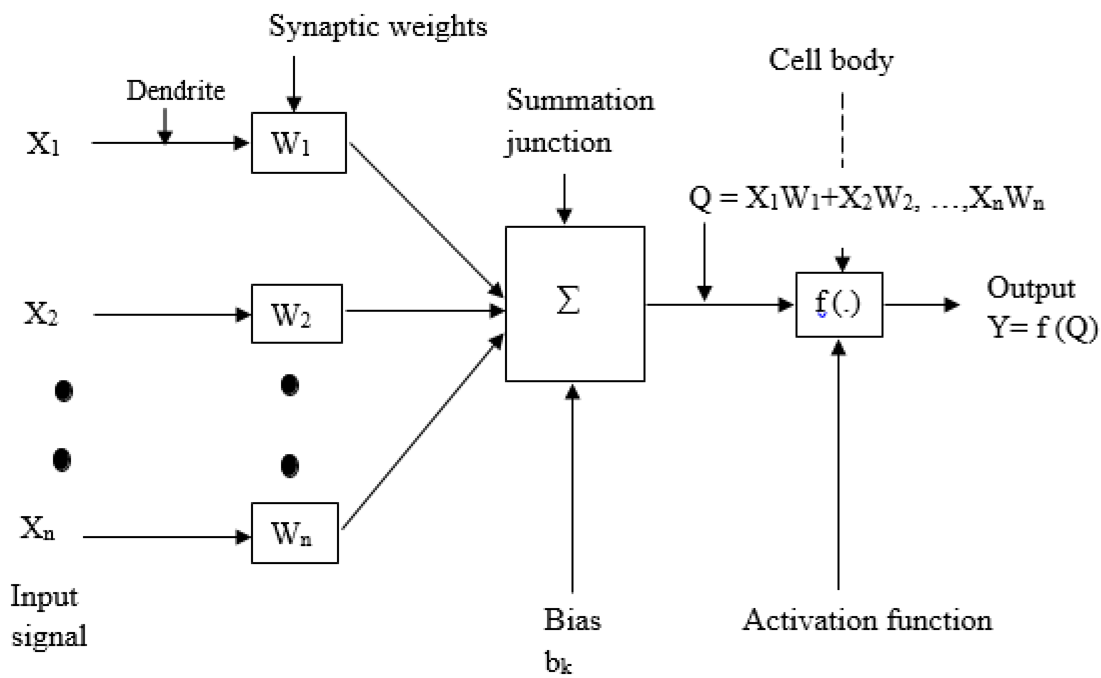

Figure 1: A typical Artificial Neurons Architecture
Source: Gurney, (2020).

The neurons are arranged in layers and are the components that map input to output. Weight (w) is part of what determines how a network behaves. Neural network knowledge is stored within interneuron connection strengths known as synaptic weights. The activation function used in ANN is dependent on the type, learning algorithm (Levenberg-Marquardt, Bayesian Regularisation, BFGS Quasi-Newton, Gradient Descent with Momentum, and Gradient Descent), and scaling approach used. The most important (and probably most used) transfer function is the sigmoid (logistic) function because of its easily differentiable properties, which is very convenient when the back-propagation algorithm is applied (Özbay & Tezel, 2010).

Figure 2 shows the most common transfer (activation) functions of artificial neural networks.

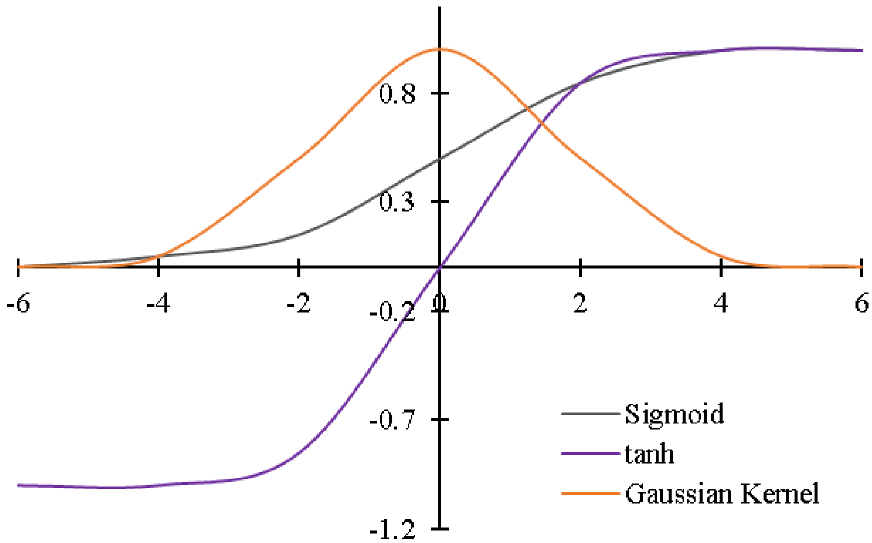

Figure 2: Types of Artificial Neural Network activation (Transfer) Functions

Artificial neural network models may be classified into feed-forward networks and recurrent neurons (Haykin, 2009). The recurrent network contains loops because of the feedback connections, and they include neural network time series applications for future scenario predictions. Unlike recurrent neuron networks, the feed-forward networks have neurons organised into layers having unidirectional connections, thus characterised by neither cycles nor loops in the network. They are used in pattern recognition, curve fitting, forecasting, classifications, and data clustering. Feed-forward neural networks have been applied widely in solving real and complex hydrologic problems with great accuracy, specifically the feed-forward backpropagation models (Maier & Dandy, 2000; Dawson & Wilby, 2001).

Coupling ANN with the Probability Distribution Models

Flood forecasting is normally done by the use of statistical probability distribution curves that encompass the prediction of recurrence interval corresponding to a specific magnitude (Rizwan et al., 2018). The best probability distribution curve is selected from the existing statistical distributions, such as Gumbel, Normal, Log-normal, Exponential, Weibull, Pearson, and Log-Pearson. These graphs are then used to estimate the design flow values corresponding to specific return periods, which can be used for hydrologic planning purposes. Therefore, relevant PD curves can then be applied to estimate the P-per cent annual exceedance probability of the flood magnitudes predicted by artificial neural networks. The option of coupling models in hydrology has been observed to improve prediction efficiency (Chen et al., 2011; Guo et al., 2021; Khashei et al., 2010).

However, despite the demonstrated advantages of coupling artificial neural networks with probability distribution models in hydrological forecasting, existing studies have largely focused on either flood magnitude prediction or frequency analysis independently, with limited integration of both approaches for comprehensive flood risk assessment. In addition, there is a scarcity of basin-specific studies that apply such integrated modelling frameworks to predict future flood scenarios and associated exceedance probabilities in the Gucha-Migori River Basin. This study addresses this gap by combining ANN-based flood forecasting with probability distribution analysis to simultaneously estimate flood magnitudes and their P-per cent annual exceedance probabilities, thereby providing a more comprehensive basis for flood risk management and planning.

METHODOLOGY

This study adopted a modelling and forecasting research design to predict flood magnitudes and their respective P-per cent annual exceedance probabilities in the Gucha-Migori River Basin for the period 2015–2052. Historical daily hydrological data, including river discharge records from 1969 to 2015, were obtained from the Water

Resources Authority and used as the primary dataset for model development.

Flood forecasting was conducted using a nonlinear autoregressive artificial neural network (NAR-ANN), where past flood magnitude values were used to predict future events. The NAR-ANN model was selected due to its ability to effectively capture temporal dependencies and non-linear patterns in hydrological time series data, which are often not adequately represented by traditional hydrological models or feedforward ANN variants. Unlike conventional models that require explicit physical parameterisation, the NAR-ANN can learn complex system dynamics directly from historical data, making it particularly suitable for flood forecasting in data-driven environments. The model utilised feedback delays based on previous observations, and the Levenberg–Marquardt backpropagation algorithm was applied for training due to its efficiency in optimising nonlinear systems (Alwakeel & Shaaban, 2010). Model performance was evaluated using the coefficient of determination (R^2) and mean square error (MSE), ensuring accuracy between predicted and observed values. All simulations, training, testing, and validation processes were performed in MATLAB version 2019.

To estimate annual exceedance probabilities, the selected probability distribution model was applied to the forecasted flood magnitudes. The modelling process involved analysing the relationship between flood magnitude and frequency, followed by the prediction of recurrence intervals and P-per cent annual exceedance probabilities for specified return periods. The integration of ANN and probability distribution modelling provided a robust framework for forecasting flood events. Data quality control procedures were undertaken to ensure consistency and reliability of the historical datasets used in the analysis.

FINDINGS AND DISCUSSION

Forecasting of the Flood Magnitude and Per cent Annual Exceedance

Nonlinear Autoregressive Models Performance

Based on the results presented in Figure 3, the best prediction performance was achieved when the number of nodes in the hidden layer was 20. However, in all the trials, the efficiency was also relatively better when neurons in the hidden layer ranged from 20 to 50. From the analyses, it was revealed that the number of hidden layers and neurons per layer is completely flexible, and is optimised through an inbuilt algorithm of obtaining the network topology that provides the best performance (Ibnu Choldun et al., 2020). Nevertheless, increasing the number of neurons makes the system more complex, while a low number of neurons may restrict the generalisation capabilities and computing power of ANN (Karsoliya, 2012; Stathakis, 2009; Uzair & Jamil, 2020).

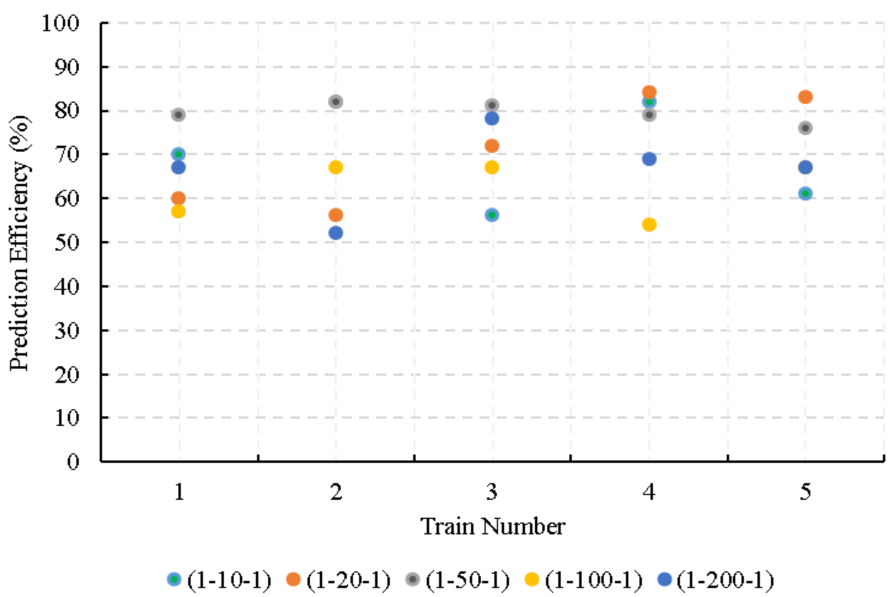

Figure 3: Performance Efficiency of Various NAR Models

1-10-1 is an architecture of the NAR model consisting of one input vector (historical datasets) and one hidden layer having 10 neurons to forecast a single output (future discharge).

The performance of various nonlinear autoregressive neural network models in the forecasting of discharge is presented in Table 1. Considering all the trials, the highest and the lowest values of the coefficient of correction (R= (9.15e-1 & 8.17e-1)) and mean squared error (MSE= (1613.54e-0 & 779.59e-0)) for testing, indicated a stronger correlation and that the models captured temporal discharge patterns at a very good level.

Using the comparative analysis, the network topology of 1-20-1 was adopted as the best NAR model for forecasting because of its minimum values of R for training (9.20e-1), validation (9.27e-1), and testing (9.15e-1). The minimum values of MSE were as follows: for training (875.67e-0), validation (815.06e-0), and testing (779.59e-0). The R-values of the aforementioned NAR model indicated that the ANN of network topology (1-20-1) at trial 4 was capable of accounting for at least (84%) of the variance of the input variable. It was the best model performance as per Moriasi et al.'s (2007) and Van Liew et al.'s (2003) recommendations. Practical recommendations for future research and water resource management have been provided. These include specific areas for further investigation and actionable advice for policymakers to improve flood management and mitigation strategies.

Table 1: Nonlinear Autoregressive Models Performance

Network Architecture	**Trial**		**Target Values**	**MSE**	**R**
1-10 -1	T2	Training	1652	840.66e-0	9.18e-1
		Validation	206	998.83e-0	9.11e-1
		Testing	206	971.39e-0	9.09e-1
1-20-1	T4	Training	1652	875.67e-0	9.20e-1
		Validation	206	815.06e-0	9.27e-1
		Testing	206	779.59e-0	9.15e-1
1-50-1	T3	Training	1652	859.50e-0	9.21e-1
		Validation	206	773.16e-0	9.17e-1
		Testing	206	809.14e-0	9.01e-1
1-100-1	T5	Training	1652	769.37e-0	9.28e-1
		Validation	206	1216.57e-0	8.96e-1
		Testing	206	2027.06e-0	8.17e-1
1-200-1	T4	Training	1652	838.52e-0	9.25e-1
		Validation	206	1292.36e-0	8.83e-1
		Testing	206	1613.54e-0	8.83e-1

Other NAR models like 1-10-1, 1-50-1, 1-100-1, and 1-200-1 could only account for 82, 81, 67, and 69 per cent of the variance of the input vectors, respectively. These results agree with findings from some studies, such as those of Maier & Dandy (2000).

Best NAR Performance Indicators

As presented in Figure 4, the statistical indicators, the best validation performance for the NAR (1-20-1) adopted for forecasting was 815.0594 at epoch 9.

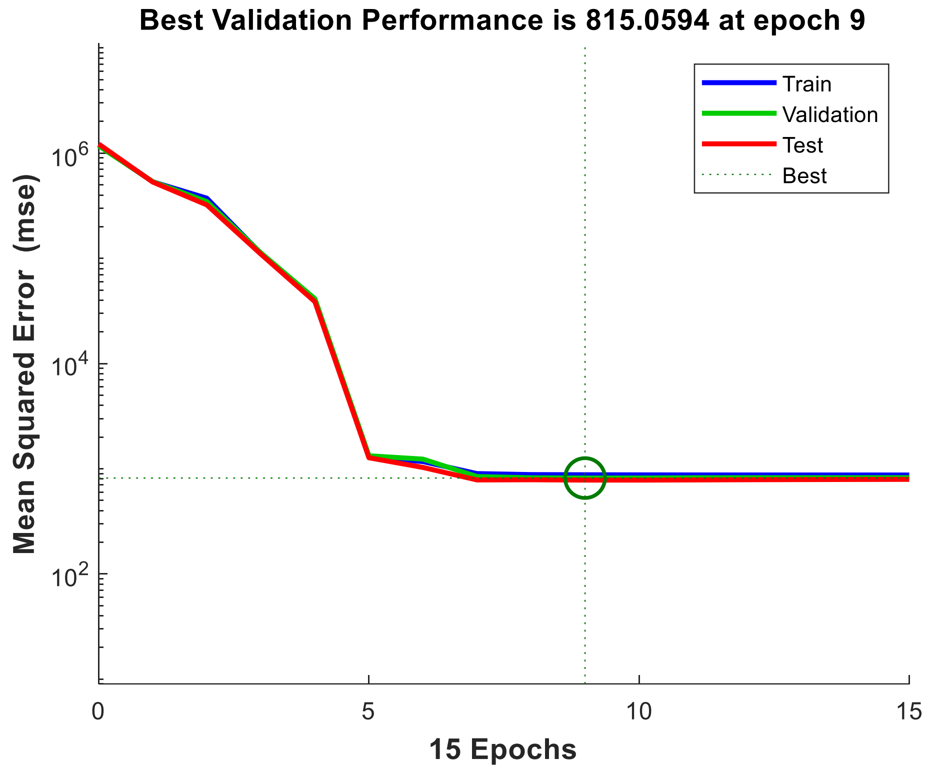

Figure 4: L-M algorithm MSE Output

Figure 5 shows the error between target values and predicted values after training the ANN model for the prediction of future discharge values for the G-M River Basin.

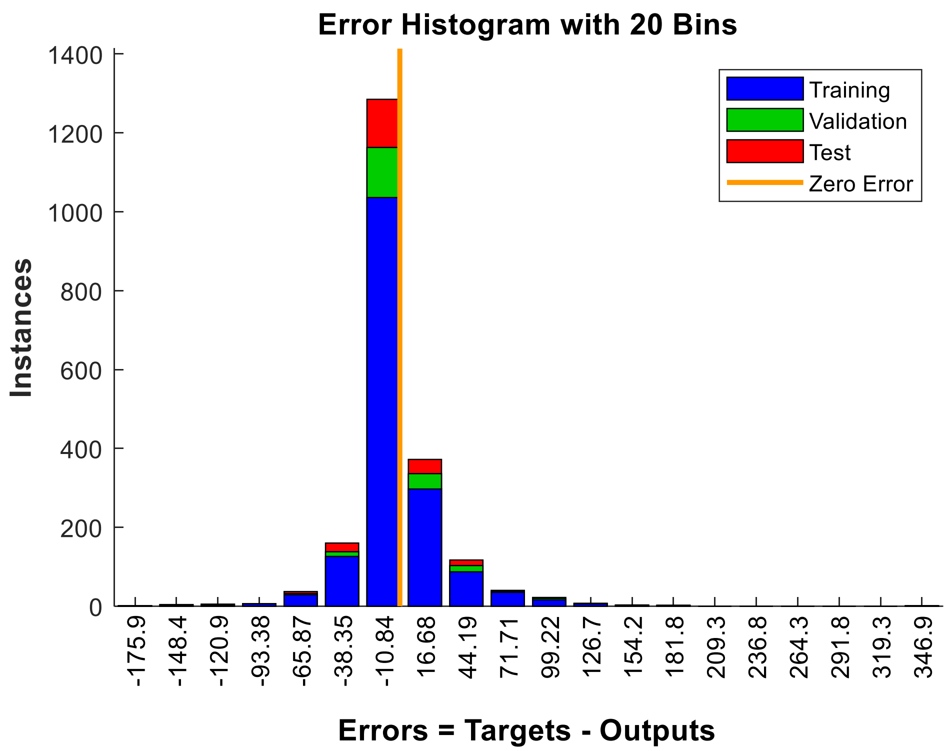

Figure 5: Error Histogram for the NAR Model

The number of vertical bars observed in this case was 20, hence, twenty smaller bins (Figure 5).In the middle of the plot, there is a bin corresponding to the error of -10.84, and the height of the bin for training datasets lies below, but near 1100, and validation and test datasets lie between 1100 and 1300, indicating that many samples had an error that lies in that following range. Nonetheless, these error values revealed a satisfactory performance.

Figure 6 represents the regression plots of the NAR model. The label of these graphs denotes an equation between the predicted value and the target value, with output as the dependent variable and target as the independent variable.

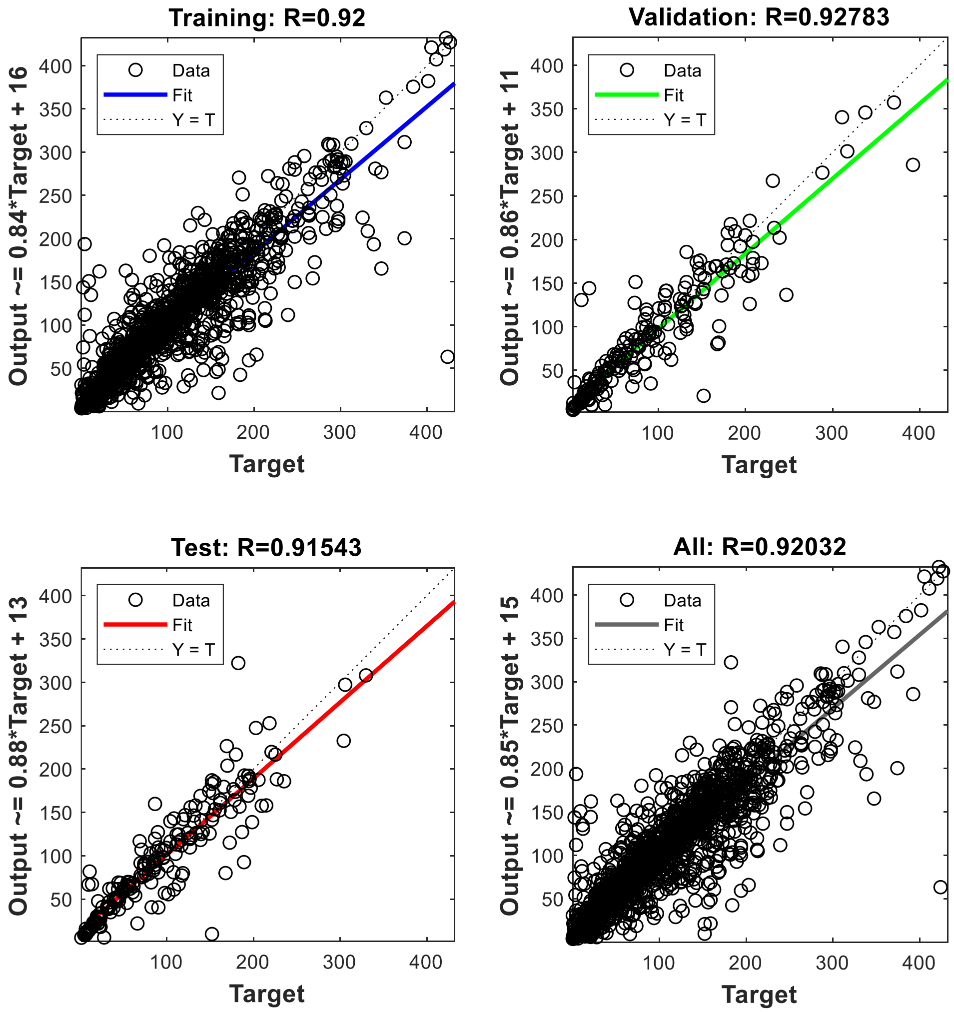

Figure 6: Regression of the Best Nonlinear Autoregressive Neural Network

These equations clearly show that the nonlinear autoregressive model performance was highly acceptable and very good for forecasting discharge datasets. For example, it can be inferred that the correlation coefficient values for training, validation, and testing (R = 0.92, 0.93, and 0.92) implied that the NAR model was capable of explaining at least (84 %) of the variance of observed discharge datasets. The coefficient of the target shows the proportionality between the output and the targets (Karul et al., 2000; Sargent, 2001). Thus, for this scenario, the NAR was selected based on good performance criteria, which was evident in that the correlation coefficient was as close to a unit as possible, with a negligible disparity between the training and the testing accuracy.

Figure 7 shows the frequency-domain analysis for training, validation, and testing of a 1-20-1 ANN to understand the stability and performance properties of the model adopted for forecasting.

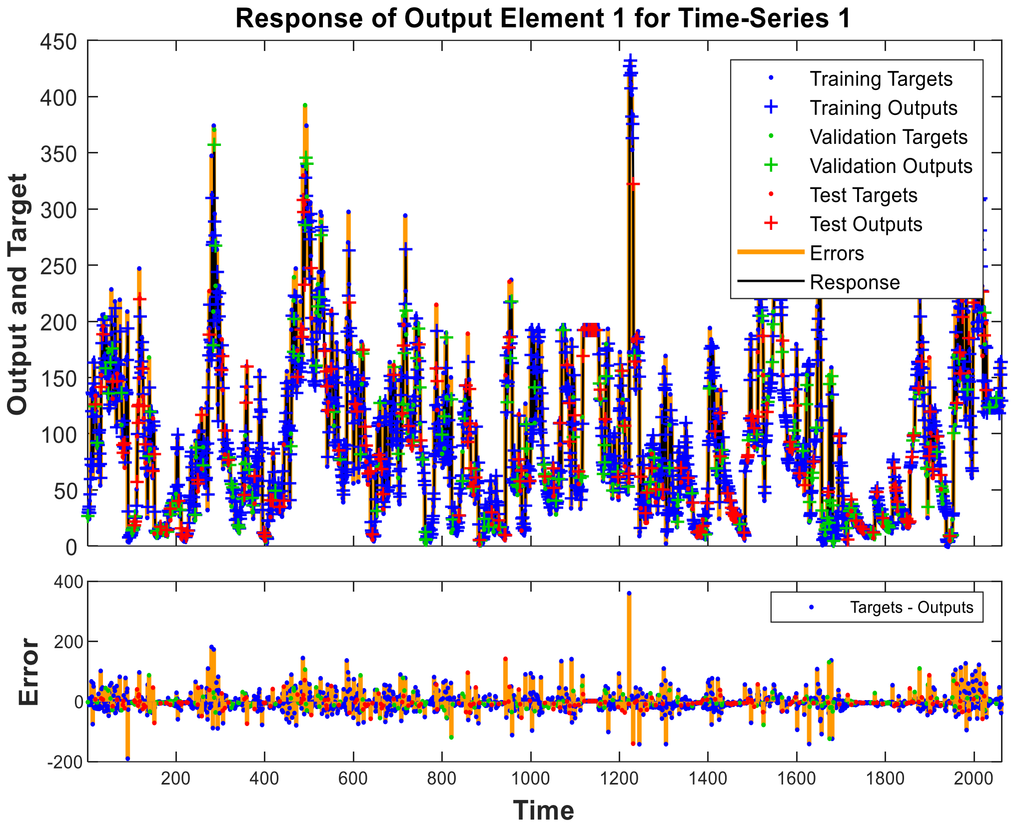

Figure 7: Time-Series Response of Nonlinear Autoregressive Neural Network

Validation and testing outputs of the nonlinear autoregressive neural networks showed a satisfactory response to peaks (flood magnitudes) related to extreme occurrences. The statistical indicators of the time series analysis (Figure 7) imply an NAR model with a high prediction accuracy and a relatively perfect linear covariation between observed and forecasted datasets. Other studies with similar modelling characteristics based on trained Artificial Neural Network models include Khan and Gupta (2020), Li and Chan (2017), and Wang et al. (2017).

Error autocorrelation is plotted in Figure 8. The results from the graph revealed the maximum correlations at zero lag.

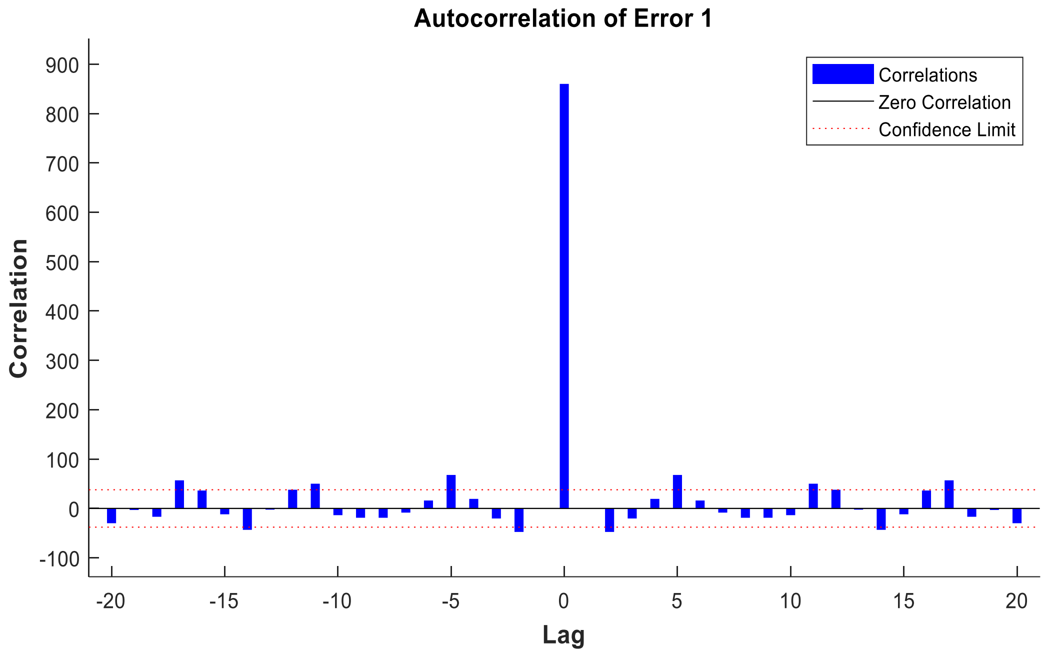

Figure 8: Error Autocorrelation of Trained Nonlinear Autoregressive Neural Network

Time Series of Observed and Predicted Future Flood Events

Figure 9 shows a time series of observed and forecasted flood magnitudes with their respective annual non-exceedance probabilities.

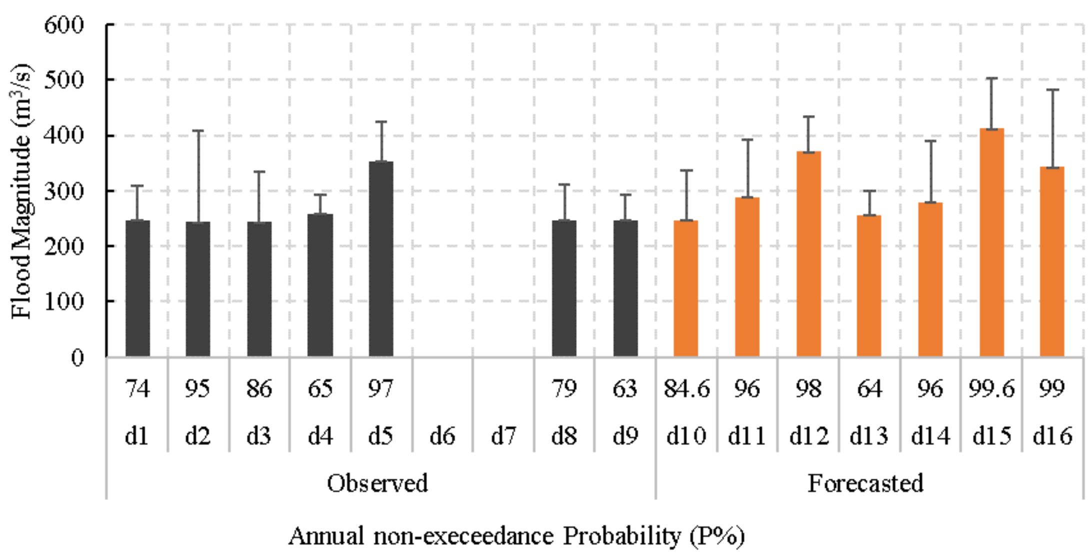

Figure 9: Forecasted Flood Magnitudes and their Frequencies

From the analysis, d1, d2, d3, d4, d5, d6, d7, d8, d9, d10, d11, d12, d13, d14, d15, and d16 represent (1969-1973), (1974-1969), (1979-1983), (1984-1988), (1989-1993), (1994-1998), (1999-2003), (2004-2008), (2009-2013), (2014-2018), (2019-2023), (2024-2028), (2029-2033), (2034-2038), (2039-2043, and (2048-2052) respectively. The findings show that the daily river discharges and flood magnitudes will progressively increase in the periods 2022 and 2052. The positive trend was significant at $p < 0.01$, and the events may be described relatively perfectly by time as the independent variable (Figure 9). Daily river discharges show positive trends in the Gucha-Migori River Basin, which will likely continue climatic scenarios following a polynomial curve of the third order.

Forecasted minimum flood magnitudes were 247, 289, 371, 256, 279, 412, and 343 m3/s for the periods (2014-2018), (2019-2023), (2024-2028), (2029-2033), (2034-2038), (2039-2043, and (2048-2052), respectively. In addition, the maximum forecasted flood magnitudes were 336, 391, 433, 299, 389, 502, and 483 m^3/s for the periods 2014–2018, 2019–2023, 2024–2028, 2029–2033, 2034–2038, 2039–2043, and 2048–2052, respectively. Their respective annual non-exceedance probabilities from Gumbel's curve were 84.6, 96, 98, 64, 96, 99.6, and 99 per cent, respectively. Forecasted flood magnitudes results agreed with flood studies within the catchments neighbouring the Gucha-Migori River Basin, such as Amisi (2021) in Njoro, Githui et al. (2009) in Nzoia, Rwigi (2014) in Sondu, Mwangi et al. (2016) in the upper Mara River, and Mbote (2016). The aforementioned studies' projections of an increase in water yield in future climatic scenarios are attributed to an increase in precipitation and surface air temperature.

CONCLUSION AND RECOMMENDATIONS

Conclusion: The use of Artificial Neural Networks (ANN) combined with the Gumbel Probability Distribution achieved the best performance in forecasting flood magnitudes and their respective annual exceedance probabilities for the period between 2022 and 2052. The optimal configuration was found with 20 nodes in the hidden layer. This approach demonstrates the potential of integrating machine learning techniques with traditional hydrological models to enhance flood forecasting accuracy and reliability.

Recommendations: Future research should explore hydrological forecasting by integrating various types of Artificial Neural Networks (ANNs) and Probability Distribution Models to predict hydrologic variables under different future scenarios, including climate change projections and extreme weather conditions. This technique should also be tested in other catchments to validate its effectiveness. Furthermore, the use of artificial intelligence (AI) and machine learning (ML) techniques should be expanded to enhance predictive accuracy and reliability, particularly through the development of real-time flood early warning systems, automated flood monitoring platforms, and decision-support tools for water resource management and disaster preparedness.

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