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Flood Mitigation in Ethekwini Metropolitan Area – Empirical Evidence using Artificial Neural Network

Caroline C. Olanrewaju [1], Maliga Reddy[1] & Oludolapo A. Olanrewaju[2]
[1] Department of Public Management & Economics, Durban University of Technology. South Africa.
[2] Department of Industrial Engineering, Durban University of Technology. South Africa.

ABSTRACT
Knowledge of flood patterns is very crucial for developing mitigation strategies and flood risk management. Historical data for floods in the SADC region from 2000 to 2016 indicates 198 flood occurrences leading to total deaths of 3,974, injuries of 2,666, homelessness of 417,745, affected 16,142,359 and total damages of over USD 2.4 billion. The April 2022 flood disaster in the eThekwini Metropolitan Area was extremely devastating with high economic consequences. The loss to GDP since then is estimated to be about R737 million. Timely flood warnings can reduce or eliminate the devastating consequences of flood disasters by enabling effective evacuation and implementation of temporary flood mitigation measures. Accurate flood prediction can significantly lead to a precise mitigation of economic and physical damages and improve human safety. In this study, hydro-meteorological variables, which include rainfall (Intensity, duration, frequency, depth), temperature, wind speed, humidity, pressure and dewpoint, were used as input variables and flood was used as the output variable from 1985-2016 in the development of the Artificial Neural Network (ANN) model to forecast flood disasters in the eThekwini Metropolitan area. This was achieved by studying the relationship between the observed and predicted values. With the results obtained, it is possible to arrange the hydro-meteorological variables used in this study in order of importance, thus focusing on variables that are most significant when drawing up mitigation measures for floods in the study area. These measures, when implemented, can reduce floods and their consequences, reduce resources used to manage floods and improve flood management.

Keywords: Mitigation strategies, Flood management, hydro-meteorological, Artificial Neural Network, eThekwini Metropolitan Area

Correspondence
Caroline C. Olanrewaju
Email:
carolnwogu@gmail.com

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INTRODUCTION
Floods are known to be among the most destructive natural hazards, causing damage to health and property, such as pollution of drinking water leading to diseases, destruction of infrastructure, livestock and farmlands leading to food scarcity, landslides and human morbidity and mortality.[1] Flood is responsible for the death of approximately 157,000 people, and 2.3 billion others have been affected by flood damage over the past two decades.[2] Historical data for floods in the SADC region from 2000 to

[1] Amir Mosavi, Pinar Ozturk, and Kwok-wing Chau, "Flood Prediction Using Machine Learning Models: Literature Review," *Water* 10, no. 11 (October 27, 2018): 1536, https://doi.org/10.3390/w10111536; Khairah Jaafar et al., "A Review on Flood Modelling and Rainfall-Runoff Relationships," in *2015 IEEE 6th Control and System Graduate Research Colloquium (ICSGRC)* (IEEE, 2015), 158–62, https://doi.org/10.1109/ICSGRC.2015.7412484.
[2] UNISDR, "The Human Cost of Weather Related Disasters 1995-2015.," 2015.

2016 indicates 198 flood occurrences leading to total deaths of 3,974, injuries of 2,666, homelessness of 417,745, affected 16,142,359 and total damages of over USD 2.4 billion.[3] According to EM-Dat-IOM, 466,434 people were affected by floods in South Africa from 2000 to 2016.[4] From historical events, KwaZulu-Natal is subject to frequent flood events due to its coastal location and frequent and long-duration rainfall.[5] Flood disasters have continued to occur in KwaZulu-Natal on a yearly basis, with destruction to life and property. eThekwini, home to about 1150 businesses, is estimated to have lost approximately R751M as a result of the April 2022 flood disaster, which is said to be the most devastating flood disaster ever recorded.[6]

There are a lot of factors that contribute to flood events. These include topography, rainfall (intensity, duration, volume and spatial distribution), amount of water capacity and stream channel to convey the runoffs, vegetation cover, catchment, weather conditions prior to a rainfall event and tidal influences.[7] Research carried out in an area of annual rainfall of 300mm has shown that floods are caused by a combination of various characteristics of precipitation such as amount, duration, intensity and spatial distribution.[8] According to Jaafar et al., floods can be broadly classified into two categories, depending on their geography and topography: the seasonal floods and the flash floods.[9]

Urbanization in South Africa is increasing on a large scale. It is anticipated that by 2030, approximately 71% of the population of South Africa will have moved to urban areas, with about 70% of the urban population residing in informal settlements, making them more vulnerable to floods and other climate variables.[10] Development and urbanization result in more natural landscapes being converted to impervious surfaces such as houses, roads and other infrastructure, as well as the removal of vegetation for construction. This causes a reduction of water infiltration into the ground, thus leading to accelerated runoffs to streams, rivers and ditches. All these activities increase the volume of runoffs and shorten their time into rivers and streams, leading to increased peak discharge, volume and frequency of flood. These disruptions of surface runoff patterns affect hydrological processes by preventing proper infiltration, which is a precursor to urban floods.[11]

There are various flood mitigation measures as elucidated by Yevjevich.[12] These measures are classified according to prevention and reduction of flood damage, policy making on floods, adjustment to natural hazards and individual measures. These measures will translate into prediction, prevention, physical control, and insurance. Flood prediction allows for flood warning, strategic flood defence and evacuation prior to floods. Timely flood warnings can reduce or eliminate the devastating consequences of flood disasters. This will enable effective evacuation and implementation of temporary flood mitigation measures. Accurate flood prediction can significantly lead to a precise mitigation of economic and physical damages and improve human safety. This study utilizes the artificial intelligence method by using the Artificial Neural Network (ANN) interfaced with historical hydro-meteorological data, which include rainfall (depth, frequency, intensity), humidity, surface pressure, temperature, wind speed and dew point as the input variables and flood as the output variable from 1985-2016 to predict flood disasters in the eThekwini metropolitan area.

3 Elham Pourazar, "Spaces of Vulnerability and Areas Prone to Natural Disaster and Crisis in Six SADC Countries," *International Organization for Migration*, 2017, 1–132, https://doi.org/10.1016/j.compstruct.2016.09.063.

4 Pourazar, "Spaces of Vulnerability and Areas Prone to Natural Disaster and Crisis in Six SADC Countries."

5 Caroline C. Olanrewaju and Maliga Reddy, "Assessment and Prediction of Flood Hazards Using Standardized Precipitation Index—A Case Study of EThekwini Metropolitan Area," *Journal of Flood Risk Management* 15, no. 2 (2022): 1–12, https://doi.org/10.1111/jfr3.12788.

6 L. Comins, " KZN Floods: Economic Impact Update | Freight News," Business Partners, 2022, https://www.freightnews.co.za/article/kzn-floods-economic-impact-update; David Nash, "The 2022 Durban Floods Were the Most Catastrophic yet Recorded in KwaZulu-Natal," Wits University, 2023.

7 Jaafar et al., "A Review on Flood Modelling and Rainfall-Runoff Relationships."

8 L. J Bracken, N. J Cox, and J Shannon, "The Relationship between Rainfall Inputs and Flood Generation in South-East Spain," *Hydrological Processes* 22 (2008): 683–96, https://doi.org/10.1002/hyp.

9 Jaafar et al., "A Review on Flood Modelling and Rainfall-Runoff Relationships."

10 Sithabile Hlahla and Trevor R. Hill, "Responses to Climate Variability in Urban Poor Communities in Pietermaritzburg, KwaZulu-Natal, South Africa," *Sage Open* 8, no. 3 (July 18, 2018), https://doi.org/10.1177/2158244018800914.

11 Jaafar et al., "A Review on Flood Modelling and Rainfall-Runoff Relationships."

12 Vujica Yevjevich, "Classification and Description of Flood Mitigation Measures," in *Coping with Floods* (Springer, 1994), 573–84.

LITERATURE REVIEW

Several techniques have been used for flood prediction.[13] Research on the advancement of models used in the prediction of floods contributed to the decrease in mortality and moridity, risk reduction, policy suggestions and reduction in damages caused by floods.[14] According to Mosavi et al., machine learning methods have been used since the 1990s to mimic the complex mathematical expressions of physical processes of floods and have been found to be highly effective predictive models providing cost-effective solutions and better predictive performance.[15] Flood prediction models are highly significant in the management of floods. Accurate prediction is very valuable for flood management strategies, analysis and suggestions of policies and evacuation.[16] Thus, it becomes necessary to employ advanced systems for short and long-term prediction of floods to minimize damage. However, the dynamic nature of climate conditions has made the prediction of floods complex.[17]

The traditional-based models were used to predict floods and other hydrological events with great capabilities for predicting a wide range of flooding scenarios. They required intensive computation of various types of hydro-geomorphological monitoring datasets, which disallow short-term predictions, and in many cases, the model development requires in-depth knowledge and expertise in hydrological parameters, which is highly challenging.[18] These models have been found to have weak capability in short-term prediction and have failed to predict properly.[19] Research on numerical prediction models was also found to be unreliable due to systematic error.[20] Data-driven models have been used for flood modelling and have recently gained more popularity than the physical and numerical models.[21] Data-driven models of flood prediction assimilate the hydro-meteorological parameters and climate indices to provide a good insight into flood predictions. Some examples include statistical models such as Multiple Linear Regression (MLR) and Autoregressive Moving Average (ARMA), which are the most common flood frequency analysis methods used to model flood predictions.[22] According to Mosavi et al., modified versions such as the Quantile Regression Technique (QRT) and the Bayesian Forecasting model were used to predict floods; however, they were found to also be deficient and unsuitable for short-term predictions due to lack of accuracy, robustness of the method, computation cost and being very complex to use.[23] Thompson also showed that for reliable long-term prediction, a large amount of data will be required for analysis for a trustworthy and meaningful forecast.[24]

These drawbacks of physical and statistical models have encouraged the use of advanced data-driven models such as machine learning models. These models are advantageous because they are solely based on historical data without requiring knowledge about underlying physical processes, they can numerically formulate the nonlinearity of floods and are quicker to develop with minimal inputs.[25] Machine learning is a field of Artificial Intelligence (AI) which induces regularities and patterns, is less complex and easier to implement with low computation cost. They are high performance models as

[13] Fazlina Ahmat Ruslan, Nur Khalidah Zakaria, and Ramli Adnan, "Flood Modelling Using Artificial Neural Network," in *2013 IEEE 4th Control and System Graduate Research Colloquium* (IEEE, 2013), 116–20, https://doi.org/10.1109/ICSGRC.2013.6653287.

[14] Mosavi, Ozturk, and Chau, "Flood Prediction Using Machine Learning Models: Literature Review."

[15] Mosavi, Ozturk, and Chau, "Flood Prediction Using Machine Learning Models: Literature Review."

[16] Jiaqiang Xie et al., "An Integrated Assessment of Urban Flooding Mitigation Strategies for Robust Decision Making," *Environmental Modelling & Software* 95 (2017): 143–55.

[17] Mosavi, Ozturk, and Chau, "Flood Prediction Using Machine Learning Models: Literature Review."

[18] P. C. Nayak et al., "Short-term Flood Forecasting with a Neurofuzzy Model," *Water Resources Research* 41, no. 4 (April 5, 2005), https://doi.org/10.1029/2004WR003562; Byunghyun Kim et al., "Urban Flood Modeling with Porous Shallow-Water Equations: A Case Study of Model Errors in the Presence of Anisotropic Porosity," *Journal of Hydrology* 523 (April 2015): 680–92, https://doi.org/10.1016/j.jhydrol.2015.01.059.

[19] Pierfranco Costabile and Francesco Macchione, "Enhancing River Model Set-up for 2-D Dynamic Flood Modelling," *Environmental Modelling & Software* 67 (May 2015): 89–107, https://doi.org/10.1016/j.envsoft.2015.01.009; Robin C. Van den Honert and John McAneney, "The 2011 Brisbane Floods: Causes, Impacts and Implications," *Water* 3, no. 4 (December 9, 2011): 1149–73, https://doi.org/10.3390/w3041149.

[20] D. L. Shrestha et al., "Evaluation of Numerical Weather Prediction Model Precipitation Forecasts for Short-Term Streamflow Forecasting Purpose," *Hydrology and Earth System Sciences* 17, no. 5 (May 21, 2013): 1913–31, https://doi.org/10.5194/hess-17-1913-2013.

[21] Mosavi, Ozturk, and Chau, "Flood Prediction Using Machine Learning Models: Literature Review."

[22] Mosavi, Ozturk, and Chau, "Flood Prediction Using Machine Learning Models: Literature Review."

[23] Mosavi, Ozturk, and Chau, "Flood Prediction Using Machine Learning Models: Literature Review."

[24] S. A. Thompson, *Hydrology for Water Management*, 1st ed. (London: CRC Press, 2017).

[25] Mosavi, Ozturk, and Chau, "Flood Prediction Using Machine Learning Models: Literature Review."

compared to the other models.[26] Machine learning models have been used for flood forecasting over the past two decades, with remarkable improvements in the accuracy of flood forecasts with different lead times.[27] Machine learning algorithms such as Artificial Neural Networks (ANN), for example, Multi-layered Perceptron (MLP), Neuro-fuzzy, Support Vector Machine (SVM) and Support Vector Regression (SVR) are effective for both long-term and short-term flood forecast and efficiently model floods, which are complex hydrological systems.[28]

ANN algorithms are the most popular in machine learning and the most efficient in modelling complex flood processes because of their versatility, accurate approximation and the ability to tolerate faults with great accuracy.[29] ANN is a reliable data-driven tool for constructing models of complex and non-linear relationships of rainfall and floods because it derives meaning from historical data, as well as being fast with the ability to generalize.[30] It does not require a detailed knowledge of the characteristics of the catchment, but simply forms a relationship between the inputs and the output variables due to the training the network had undergone to learn the patterns of the input and output variables.[31]

There are different classes of ANN. The ANN model used in this study is a feed-forward Multi-Layered Perceptron (MLP).[32] The MLP is a feed-forward neural network due to the flow of data information in one direction. The choice of the network is based on its ability to use historical data as compared to other ANNs.[33] The MLP is used on the basis of the back propagation algorithm and the Levenberg-Marquardt learning technique.[34] The Lavenberge-Marquardt technique is a quasi-Newton strategy observed to be the quickest and most effective.[35]

MLP neural networks have been widely used for the accurate predictions of floods due to their unique characteristics of simplicity, a high number of layers and nonlinear activation.[36] Prediction of rainfall alone has been found to be inadequate for accurate flood prediction.[37] Seo and Breidenbach established in their research that other flood resource variables are important in a catchment in addition to rainfall to obtain an accurate flood prediction.[38] The MLP neural network has been used to establish a relationship between rainfall and other meteorological parameters on a 32-year monthly data set of wind speed, mean temperature and relative humidity and found that the model was very effective in its prediction of rainfall-runoff.[39] Kaur and Singh, in their research, found that temperature has a great effect on forecasting rainfall. Their research also elucidated that other meteorological parameters, such as maximum and minimum humidity, when used with an MLP neural network, produced reasonable

[26] F. Mekanik et al., "Multiple Regression and Artificial Neural Network for Long-Term Rainfall Forecasting Using Large Scale Climate Modes," *Journal of Hydrology* 503 (October 2013): 11–21, https://doi.org/10.1016/j.jhydrol.2013.08.035.

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[36] S. Riad et al., "Rainfall-Runoff Model Using an Artificial Neural Network Approach," *Mathematical and Computer Modelling* 40, no. 7–8 (2004): 839–46, https://doi.org/10.1016/j.mcm.2004.10.012.

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[39] S. Kovithaa and D. Naidoo, "Rainfall–Runoff Modelling Using Artificial Neural Networks in South Africa," in *Proceedings of the 14th Water Net/WARFSA/GWP-SA Symposium, Maputo, Mozambique*, 2011.

accuracy of prediction of rainfall-runoff.[40] El-Shafie et al. established in their research that the MLP neural network was more effective than the classical regression model in learning and describing the relationship pattern between rainfall and runoff with more accuracy, thus producing more accurate predictions.[41] Toth et. al., in their comparison of rainfall prediction models for real-time flood forecasting, found that the MLP neural network provided significant improvement in flood predictions.[42] The ANN has been found to predict floods with good accuracy.[43] ANN model is used efficiently for real-time rainfall forecasting and flood management.[44] Several studies that have shown the superiority of the MLP back-propagation neural network as compared to other models have motivated the use of the model in this study. The aim of this paper is to study the pattern of flood disasters as well as identify the most influential hydro-meteorological variables of flood in the study area using the ANN model. The knowledge derived from the ANN model is used to predict flood disasters through understanding the patterns and trends of floods from 1985 to 2016 in the study area, thereby improving flood mitigation and management.

METHODOLOGY

The ANN is composed of artificial neurons that are interconnected and capable of mimicking the human brain in its capacity to act and make decisions. ANN is a data processing system composed of a high interconnection of processing elements known as neurons. The arrangement of neurons is such that the neurons of a layer are connected to the neurons of another layer. The two adjacent layers are connected by weights equivalent in strength to signals in a biological neural network.[45] Weights and activation functions are major parameters of an ANN. Weight transfers the input of a node onto the hidden layer of the network. The weight is multiplied by the input. The resultant value is observed and passed on to the next node. It is a learnable parameter whose value gets updated during the training period. The activation functions are differentiable functions added to the ANN to help the network learn complex patterns from the data. Typically, all hidden layers use the same activation function, and the output layer uses a different one, depending on the type of prediction required.[46]

The ANN functions by the principle of "learning by example".[47] In this process, a set of training, testing and validation datasets is fed into the neural network. The essence of the training, testing and validation dataset is to prevent overfitting and to allow good prediction. For computing the gradient and allowing an update of the weights and biases, training is important. The validation data, on the other hand, performs cross-validation to allow a generalized network based on the performance of the network. The test data set checks that the ANN is accurate after the optimum network parameters have been defined. The error back propagation algorithm is used to train the datasets to learn the structure of the data. Training is done by iteratively changing the interconnecting weights in the network in order to reduce the error between the observed values and modelled network output. The training of the network for this study used supervised learning. Supervised learning is made up of input and output data samples. The ANN can be optimized by comparing the simulated output with the expected output, followed by a subsequent modification of the ANN.[48] The ANN modification was achieved by the weight change. The ANN is adapted iteratively to minimize the difference between expectation and simulation output data.[49] Training of the network is done to ensure that an error minimum that is acceptable is reached.[50] The training

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[40] Amanpreet Kaur and Harpreet Singh, "Artificial Neural Networks in Forecasting Minimum Temperature," *International Journal of Electronics & Communication Technology* 2, no. 3 (2011): 101–5.
[41] A El-Shafie et al., "Performance of Artificial Neural Network and Regression Techniques for Rainfall-Runoff Prediction," *International Journal of Physical Sciences* 6, no. 8 (2011): 1997–2003.
[42] Toth, Brath, and Montanari, "Comparison of Short-Term Rainfall Prediction Models for Real-Time Flood Forecasting."
[43] Mosavi, Ozturk, and Chau, "Flood Prediction Using Machine Learning Models: Literature Review."
[44] N. Q. Hung et al., "An Artificial Neural Network Model for Rainfall Forecasting in Bangkok, Thailand," *Hydrology and Earth System Sciences* 13, no. 8 (August 7, 2009): 1413–25, https://doi.org/10.5194/hess-13-1413-2009.
[45] Rakesh Tanty and Tanweer S. Desmukh, "Application of Artificial Neural Network in Hydrology- A Review."
[46] Sreeparna Guha, Rabin K Jana, and Manas K Sanyal, "Artificial Neural Network Approaches for Disaster Management: A Literature Review," *International Journal of Disaster Risk Reduction* 81 (2022): 103276.
[47] Astrid Michielsen et al., "Predicting and Communicating Flood Risk of Transport Infrastructure Based on Watershed Characteristics," *Journal of Environmental Management* 182 (November 2016): 505–18, https://doi.org/10.1016/j.jenvman.2016.07.051.
[48] Simon Berkhahn, Lothar Fuchs, and Insa Neuweiler, "An Ensemble Neural Network Model for Real-Time Prediction of Urban Floods," *Journal of Hydrology* 575 (2019): 743–54.
[49] Berkhahn, Fuchs, and Neuweiler, "An Ensemble Neural Network Model for Real-Time Prediction of Urban Floods."
[50] Michielsen et al., "Predicting and Communicating Flood Risk of Transport Infrastructure Based on Watershed Characteristics."

algorithm for the adaptation of weight for this study is the backpropagation algorithm. The weights for each neuron are learned during training through backpropagation.

Study Area

The eThekwini Metropolitan area, also known as Durban, is located on the East coast of South Africa in KwaZulu-Natal province with a long shoreline on the Indian Ocean. It is made up of hilly topography with several ravines and gorges, with no true coastal plain. The eThekwini Metropolitan area spanning over an area of 2.55km is composed of large urban cities, making it the third largest city in South Africa with a population of 3.98 million, accounting for 34.7% [51]. Durban has a subtropical climate comprising humid wet summers, mildly dry winters and an annual precipitation of over 1000mm. The KwaZulu-Natal province is classified as the wettest part of South Africa, having more than 80% of rainfall between October and March, with an average probability of ten times per month, while the rest of the year has an average rainfall probability of three times a month.[52] Summer months have temperatures ranging from 23-33ºC and winter months 16- 25 °C. [53] According to the South African Weather Service, Durban experiences 320 days of sunshine a year, making summer months very humid and long and winter months warm and sunny.

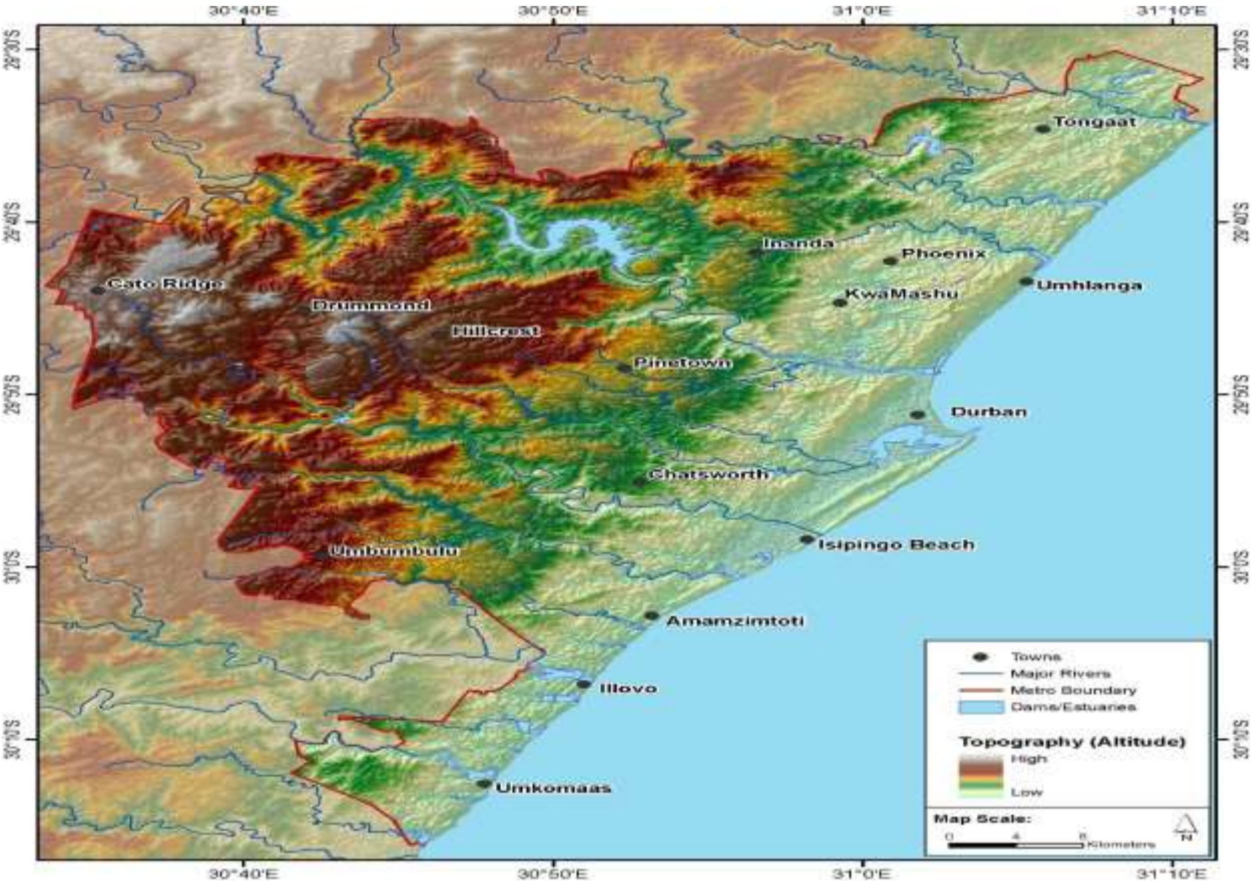

Figure 1: Topographical map of eThekwini Municipal Area [54]

[51] Metropolitan SDF, " Ethekwini Metropolitan KZN, COGTA," 2021, https://www.cogta.gov.za/ddm/wp-content/uploads/2020/07/Metro-Profile_Ethekwini.pdf.

[52] E. Vetrimurugan et al., "A View on South Africa's KwaZulu-Natal Coast: Stressors and Coastal Management," in *Coastal Management* (Elsevier, 2019), 121–39, https://doi.org/10.1016/B978-0-12-810473-6.00009-1; Climatemp, "Rainfall/Precipitation in Durban, South Africa," 2017, http://www.durban.climatemps.com/precipitation.php.

[53] Weather-Atlas, "Weather Atlas Monthly Weather Forecast and Climate Durban, South Africa," 2020, https://www.weather-atlas.com/en/south-africa/durban-climate.

[54] Jane Turpie et al., "Promoting Green Urban Development in Africa : Enhancing the Relationship between Urbanization ," The World Bank, 2017.

Rapid rainfall on saturated soil with poor absorption ability is a strong influencer of flash floods. Thus, an increase in rainfall intensity will lead to flash floods.[55] The geography, topography and urbanization of Durban are precursors of the regular flood events experienced in the region.

Data Collection

Data from 1985-2016 was obtained from using empirical data of rainfall volume, rainfall frequency, rainfall intensity, humidity, surface pressure, temperature, wind speed, and dew point archived and made available through satellite data from the NASA online database for the eThekwini Metropolitan area at coordinates of -29.8120ºS latitude and -30.8039ºE longitude. Satellites and high-resolution radars have been found to provide more reliable and accurate datasets as compared to the traditional methods of data collection.[56] Hydrometeorological elements are very important in the estimation of climate change and the prediction of floods.[57]

The ANN was built using the hydro-meteorological data. The input data includes the average of rainfall (frequency, humidity and intensity), surface pressure, temperature, wind speed and dew point from 1985-2016. The output variable is the average monthly flood for the same period (Table 1). The dataset was divided into 52% training, 26% testing and 22% validation. The training data is twice the amount of the testing data. This is in order for the neural network to have a better understanding of the relationship between the output and the input variables. The validation data is used to validate the achievement of the training and the testing data. The network disregards excess data that are of less importance and focuses more on important variables.[58]

Table 1: Input and output variables for the construction of the ANN model

	Peak Rainfall Mm/Day	Rainfall Frequency (Yr)	Rainfall Intensity Mm/Hr	Average Relative Humidity At 2m (%)	Average Surface Pressure (Kpa)	Average Tempt. At 2m C	Average Wind Speed At 10m M/S	Average Dew Point At 2m C	Flood (Spi-1)
Average	259.21	4.19	0.36	75.21	96.14	18.56	3.45	13.72	1.61
Standard Deviation	257.25	4.14	0.36	75.25	96.14	18.55	3.45	13.71	1.60

Flood data used as the output variable was obtained by calculating the Standardized Precipitation Index (SPI) for a monthly time scale (Figure 2).[59] The SPI computation involves fitting the gamma probability density function to a given frequency distribution of precipitation totals for the given eThekwini Metropolitan area coordinates.

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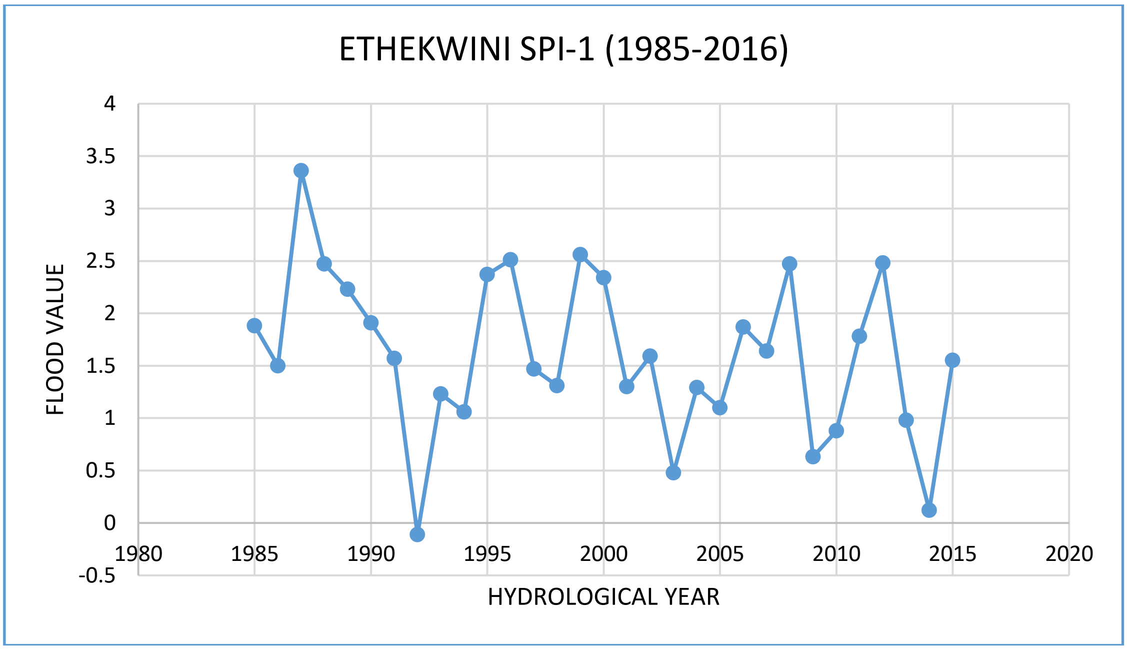

Figure 2: Monthly flood data for eThekwini Municipality

Connection Weight Approach

Using the connection weight approach, the ANN arranges the variables according to their importance. Olden and Jackson initiated the connection weight approach for contribution identification of each input variable, along with the directional relationship with the response variable.[60] The objective of the connection weight approach is to sum up the product of the weight of the connection from input neurons through to the output neurons for all input factors via the hidden neurons [30, 31]. The larger the sum of the connection weights, the greater the significance of the linked factor to the input neuron. Below is the connection weight approach equation:

$$Significance\ (i) = \sum nx = 1(cw_{ih}\ (x)*\ cw_{ho}\ (x)) \qquad (1)$$

Where:

Significance (i) is the comparative significance of various outputs (i); n represents the hidden nodes; x represents the hidden node's index number; (cw_{ih} *(x) represents the connectivity weight between input factor I and hidden node x;* cw_{ho} *(x) indicates the weight between hidden node x and the output node.*

The matrix laboratory 10.0 (MATLAB) was used to obtain the ANN computation.

PRESENTATION OF FINDINGS

The trained MLP neural network using the back-propagation algorithm architecture consists of three layers, which include the input, hidden and output layers. Each layer consists of neurons and connected bias neurons, which are linked to the output and input layers. The number of hidden neurons used is established by comparing the performance of various networks that were cross-validated.[61] Two to ten hidden neurons were used, and the number with the best network performance was selected. Thus, the network used eight inputs, five hidden and one output layer as shown in Figure 2.

[60] Julian D Olden and Donald A Jackson, "Illuminating the 'Black Box': A Randomization Approach for Understanding Variable Contributions in Artificial Neural Networks," *Ecological Modelling* 154, no. 1–2 (2002): 135–50.

[61] O A Olanrewaju, A A Jimoh, and P A Kholopane, "Evaluating GHG Components Using Artificial Intelligence: Connection Weight Approach," in *2012 IEEE International Conference on Industrial Engineering and Engineering Management* (IEEE, 2012), 1214–17.

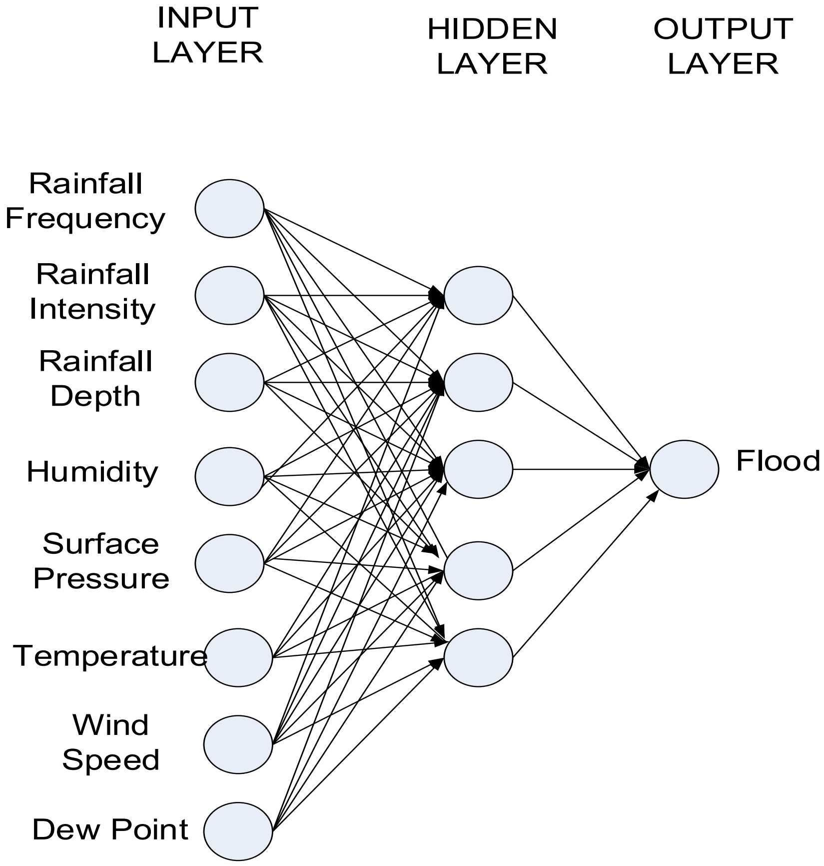

Figure 3: ANN architecture showing input, hidden and output layers

The Tansig activation function is used as the transfer function in this research. The Trainlm (Levenberg-Marquardt) learning technique is the training algorithm. The learning rate of the neural network is set at 0.07, and the momentum weight is 0.7. The running of the Neural Network was set at 1000 epochs and completed at 12 epochs, producing the best network validation performance of 0.26058 at epoch six (Figure 3).

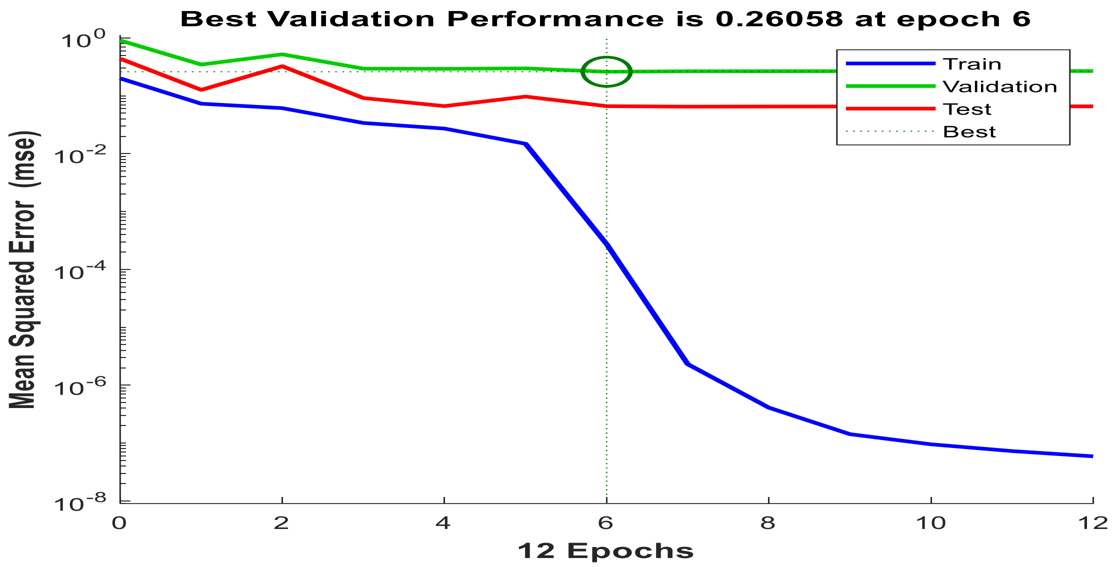

Figure 4: Validation of the Neural Network

A perfect prediction will give a correlation coefficient (r) of one (r=1)). r is the correlation between the actual flood and predicted flood values.[62] r takes values from zero to one. This means that values close to one imply more correlation, and zero implies no correlation. Thus, where the dependent variable (output) is highly dependent on all its independent variables (input), the value will be almost one. The closer the variables are to one, the better the correlation between the two variables. A coefficient correlation of 0.8 is described as very strong.[63] Using the scatter plots (Figure 4), the coefficient of regression (R) is 0.78844. This indicates a very strong relationship between the input and the output variables and a very reliable prediction.

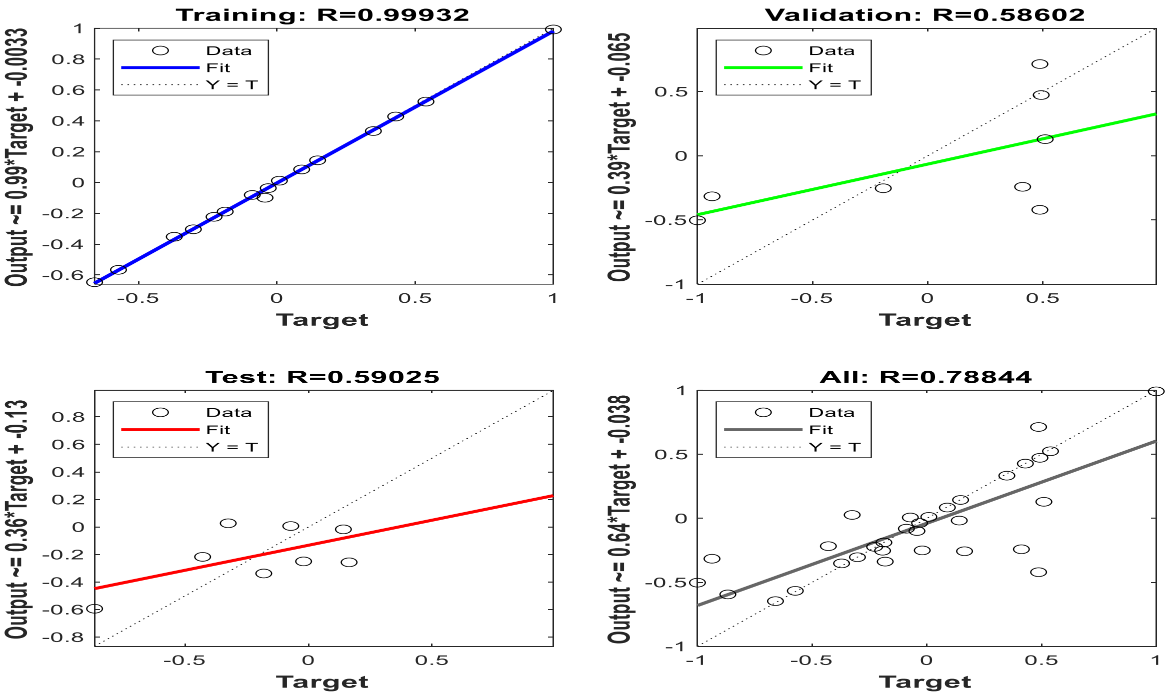

Figure 5: Regression plot using five hidden neurons

Visual inspection (Figure 5) shows the comparison between the actual flood (blue broken lines) and the predicted flood (red lines) values generated by the ANN network. It depicts the similarity of the actual to the predicted flood values.

[62] Bruce Ratner, "The Correlation Coefficient: Its Values Range between +1/−1, or Do They?," *Journal of Targeting, Measurement and Analysis for Marketing* 17, no. 2 (June 18, 2009): 139–42, https://doi.org/10.1057/jt.2009.5.

[63] Salim Daya, "Correlation Coefficient," *Evidence-Based Obstetrics and Gynecology* 6, no. 2 (2004): 48–50, https://doi.org/10.1016/j.ebobgyn.2004.04.015.

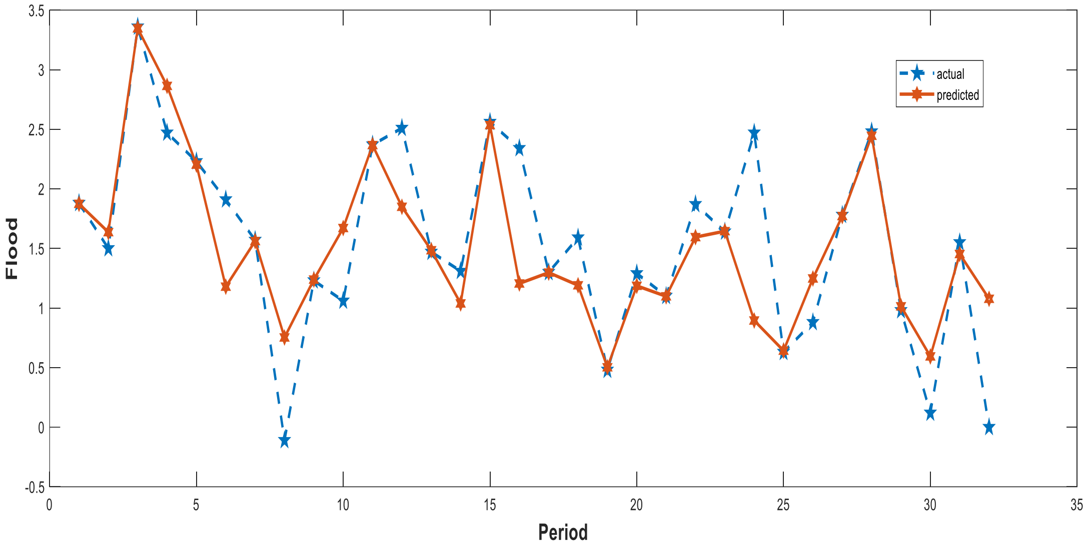

Figure 6: Visual inspection between the actual and predicted flood

Using the connection weight approach, the input variables are ranked according to the level of importance as shown in Table 2. Using the ranking generated by the ANN model, rainfall frequency is seen to be the least important in predicting the occurrence of a flood disaster in the study area, while temperature and wind speed are very important for an accurate prediction.

Table 2: Connection weight approach to rank the level of importance of the inputs

INPUTS	CONNECTION WEIGHTS					COMPUTATION FOR EACH CONTRIBUTION	PERCENTAGE CONTRIBUTION	PRIORITY ORDER
	1	2	3	4	5			
Rainfall Depth	-0,316	-1,7393	0,7539	0,8068	0,3567	1,63	-72,44	7th
Rainfall Intensity	-0,4759	0,5412	0,3797	0,7899	-0,6246	-1,16	51,65	3rd
Rainfall Frequency	-1,2883	0,3339	-0,3225	-1,3216	0,1347	2,07	-91,69	8th
Relative Humidity	0,626	0,3013	0,2231	0,0712	0,1357	-0,66	29,30	5th
Surface Pressure	1,4668	0,1344	0,8642	0,8151	1,2278	-0,61	27,28	6th
Temperature	-0,3489	0,5861	1,1729	-0,3886	-1,9755	-1,35	59,66	1st
Wind speed	0,599	-0,3024	-0,0304	1,7689	0,6042	-1,24	55,23	2nd
Dew point	0,3575	0,0138	-0,4776	-1,0539	-1,3277	-0,92	41,01	4th
			x					
Flood	-0,9195	-0,8116	0,3739	-0,8683	0,9978	-2,26286203		

DISCUSSION

In this study, the ANN model was employed to predict floods by studying the relationship between the different hydro-meteorological variables that are responsible for floods. Afterwards, the connection weight approach was used to successfully assess the components in their order of significance. The results of the connection weight imply that temperature, wind speed, rainfall intensity and dew point will have a better connection with one another in predicting flood disasters in the study area.

Mitigation of floods requires good knowledge of the degree of significance of the flood variables in order to draw up accurate and cost-effective strategies. From the outcome of the connection weight technique, rainfall frequency was seen to be the least significant variable that causes floods in the study area. This implies that frequent rainfall is not a significant parameter in the prediction of floods. This can be authenticated by the fact that KwaZulu-Natal experiences an average probability of at least three times of rainfall per month throughout the year and is known to be the wettest province in South Africa, with more than 80% of rainfall between October and March. Rainfall depth was found to have less significance in flood prediction. This explains that Durban experiencing an annual precipitation of over 1000mm can be attributed to the frequency of rainfall and not a criterion for predicting floods. Surface pressure was also found to have less significance in flood prediction in the study area. Temperature, wind speed and rainfall intensity play a major role in flood prediction in the study area. This implies that the higher the temperature, the more water vapour is held in the atmosphere, leading to frequent and intense rainfall events, which may result in flash floods. Wind is very fundamental in studying weather patterns and significantly influences climate conditions.[64] Wind speed directly affects weather outcomes by influencing how storms develop and the daily changes in temperature. According to Bhatia, high wind speeds indicate a developing storm. Wind speed also escalates storm intensity, leading to severe weather events.[65] The findings in this research align with findings by Bhatia that climate behaviour is influenced by wind speed and shapes daily weather predictions faster, making it a very important variable for flood prediction.[66] Rainfall intensity plays a very crucial role in influencing flooding.[67] This research shows that it is a key factor in predicting floods. Rainfall of high intensity can lead to rapid surface runoff into streams and rivers. Rainfall of high intensity over a short period of time also leads to flash floods, which are rapid and severe.[68] Urbanization in the presence of intense rainfall also leads to surface runoffs as water is unable to filter into the ground as a result of impermeable surfaces.

The interplay of these three variables (temperature, wind speed and rainfall intensity) is very significant because Durban is highly populated, has a wet, humid and hot climate with 320 days of sunshine and has numerous water bodies. This will explain why temperature, wind speed and rainfall intensity, in order of significance, are the most significant flood-causing variables. A good knowledge of these variables will help in creating effective flood management strategies by improving flood predictions, developing early warnings and mitigating the impact of flood disasters in communities and the economy.

CONCLUSION

This study shows the prediction of floods by using the relationship between several hydro-meteorological variables to learn the pattern of flood disasters. It is clear that different variables have different levels of importance in their ability to influence flood activities. Several studies have shown the different causes of floods, with rainfall being the most implicated. However, without going into details of the intensity, depth and frequency of rainfall, important facts may be omitted during decision-making on how to manage rainfall as a cause of floods. The study has shown that though temperature,

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[64] Ishan Bhatia, "Understanding Wind Speed and Its Weather Impact," 2025.

[65] I. Bhatia, "Understanding Wind Speed and Its Weather Impact," 2025, https://luminwaves.com/articles/understanding-wind-speed-weather-impact/.

[66] Bhatia, "Understanding Wind Speed and Its Weather Impact," 2025.

[67] Winona Fritzie Putri Qatrinnada et al., "A Literature Review: Rainfall Thresholds as Flash Flood Monitoring for an Early Warning System," *Water Practice & Technology* 19, no. 11 (November 1, 2024): 4486–98, https://doi.org/10.2166/wpt.2024.271.

[68] Qatrinnada et al., "A Literature Review: Rainfall Thresholds as Flash Flood Monitoring for an Early Warning System."

wind speed and rainfall intensity are extremely important flood-causing variables, rainfall frequency and rainfall depth are not as important as dew point and relative humidity in causing floods in the study area. There is also the myth that when there is a very high temperature, there is a tendency for rainfall, but the study has shown that rainfall frequency does not necessarily have to lead to flood events, considering the fact that Durban experiences sunshine days almost the whole year.

Understanding the pattern of flood disasters in the study area can be extremely useful in predicting future flood events and thereby preventing flood disasters and their associated consequences. This study will help decision makers and practitioners have a strong focus on the major variables that cause floods as compared to all the variables, thus reducing cost and promoting efficiency of flood risk management. From this study, the ANN model used with the connection weight approach is able to produce useful information as a flood prediction model towards improved flood risk management planning and practice to be adopted by practitioners, experts, decision makers and researchers across a diverse and multi-sectoral field.

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ABOUT AUTHORS

Caroline Olanrewaju, PhD, is a disaster and risk management scholar whose work focuses on strengthening community resilience, improving institutional preparedness, and advancing evidence-based approaches to hazard mitigation. Her research integrates public management, resilience theory, and systems thinking to address the complex and evolving risks faced by vulnerable populations. She has developed analytical frameworks that support decision-makers in planning for floods, climate-related hazards, and other high-impact events, with particular emphasis on equitable policy design and community-centered interventions.

Dr Maliga Reddy is a Senior Academic and Associate Director in the Department of Public Management and Economics at the Durban University of Technology. With extensive experience in her field, Dr. Reddy plays a pivotal role in representing DUT on the various National, Provincial and Local structures both in a professional and academic capacity. She was part of the National Disaster Management Project Team that was instrumental in the development of the National Disaster Management Education and Training Framework for South Africa. Mal served on the USAID/North-West University Steering Committee responsible for the project on the Disaster Risk Reduction Knowledge Shop, creating, sharing and exchanging information and practices in Disaster Risk Reduction. She serves on the Professional Board for Disaster Management: Disaster Management Institute of Southern Africa (DMISA). Her professional achievement was her election as the President of the Disaster Management Institute of Southern Africa (2012-2014). She continues her involvement by serving on the Executive Committee/Council and Board of the Institute. Her areas of interest and research include Public Management, Leadership, Local Government Management, and Disaster Risk Management. She serves on the Editorial Board of JAMBA- Journal of Disaster Risk Studies and Reviews for various Journals, including: the Journal of Human Ecology (JHE) and *Alter*nation: Interdisciplinary Journal for the Study of the Arts and Humanities in Southern Africa.

Oludolapo Akanni Olanrewaju is currently a Full Professor, Head of the Department of Industrial Engineering, and the Director of System Science at the Durban University of Technology, South Africa. He earned his BSc in Electrical Electronics Engineering and MSc in Industrial Engineering from the University of Ibadan, Nigeria and his Doctorate in Industrial Engineering from the Tshwane University of Technology, South Africa. His research interests are not limited to energy/greenhouse gas analysis/management, life cycle assessment, or the application of intelligence techniques. His contribution is on the various optimization strategies that aim to achieve sustainable development in the energy sector. He has developed integrated models to achieve this, which require steps to ensure that society is able to transition towards sustainability and the prevention of global warming. Such contributions assist to realize the United Nations Sustainable Development Goals (SDGs) on affordable and clean energy (SDG7) and climate action (SDG13), which are fundamental to facilitating such steps. Each of the models that make up the integrated model has the advantage of offsetting the bias of the others, making them compatible with one another. He has papers published in peer-reviewed journals, conferences and book chapters and is currently editing a book. He is a Guest Editor for Special Issues in Atmosphere and Sustainability and an Editorial Board Member of Renewable Energies (SAGE). He collaborates with some universities under BRICS, African Institutions and some North American Universities. His future interests include (1) engaging in solution development and testing: advancing development of emissions detection, (2) engaging in measurement informed inventory: applying stochastic modelling on a mechanistic air emissions simulator, and (3) engaging in pipeline emissions and safety: accelerating pipeline leak detection quantification solutions through transparent and rigorous scientific validation. He is a C2 NRF Rated Researcher.