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EXTREME RAINFALL FORECASTING MODEL BASED ON DESCRIPTIVE INDICES

[1]Yasir Hilal Hadi, [2]Ku Ruhana Ku-Mahamud, & [3]Wan Hussain Wan Ishak
[1]University of Technology, Baghdad, Iraq
[2,3]School of Computing, Universiti Utara Malaysia, Malaysia

Corresponding author: yasirevo@yahoo.com

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ABSTRACT

Extreme rainfall is one of the disastrous events that occurred due to massive rainfall overcome time beyond the regular rainfall rate. The catastrophic effects of extreme rainfall on human, environment, and economy are enormous as most of the events are unpredictable. Modelling the extreme rainfall patterns is a challenge since the extreme rainfall patterns are infrequent. In this study, a model based on descriptive indices to forecast extreme rainfall is proposed. The indices that are calculated every month are used to develop a Back Propagation Neural Network model in forecasting extreme rainfall. Experiments were conducted using different combinations of indices and results were compared with actual data based on mean absolute error. The results showed that the combination of six indices achieved the best performance, and this proved that indices could be used for forecasting extreme rainfall values.

Keywords: Extreme event, back propagation neural network, forecasting model, extreme rainfall indices

INTRODUCTION

Floods are one of the most potent forces on Earth that have caused massive damages around the world. Statistics have shown that flood has a significant impact on the economy and human well-being (Rana, 2013). Economic damage, ecosystem damage, and loss of cultural and historical values constitute the direct outcomes of floods. Flood also leads to adverse health effects on humans and causes loss of life (Rana, 2013). Knowledge of extreme rainfall is useful in

planning, especially when designing new infrastructures to withstand the impact of flood disasters (Nigatu, 2011). This is because rainfall is one of the primary sources of water for the hydrological cycle that can cause a severe impact on the water source, rain-related activities, and the environment. In the case where rainfall of one location significantly deviates from the natural condition, this can be considered that the event will be less likely to occur. The values above a certain threshold are considered extreme values, which are the values (event) that are not likely to happen (Gu & Wan, 2010).

It is most common to appoint a percentile value as a threshold in identifying extreme rainfall events. Typically, intense rainfall occurrences in short temporal scales or persistent rainfall over a long period, often lead to massive floods (Syafrina et al., 2014). These floods represent one of the essential impacts of extreme climatic events, resulting in hazardous situations that cause adverse effects on humans and infrastructures. Due to its nature, extreme climate events is difficult to quantify (Ummenhofer & Meehl, 2017).

The extreme rainfall events in Malaysia showed an increasing trend in recent years. It is one of the major causes of severe floods in Malaysia in the past ten years. The impacts of these floods are enormous, and the recovery cost reaches millions of Malaysian Ringgit (Syafrina et al., 2014; Abdullah, 2013). Malaysia's climate has the following characteristic features: copious rainfall, high humidity and uniform temperature. Winds are generally light. Located in the central area, even with periods of severe drought, it is a high rarity to have a full day without clouds. On the other hand, it is also rare to have a completely no sunshine for a stretch of a few days except during the northeast monsoon seasons (Fakaruddin et al., 2017). Malaysia experiences rain almost one all year long, and for some regions, it is more substantial. Rainfall in peninsular Malaysia is mainly affected by the seasonal monsoons; northeast and southwest monsoons (Tan, 2018).

The extreme flood event that happened between December 2006 and January 2007 in southern peninsular Malaysia, for example, resulted in economic losses for more than 500 million U.S. dollars involving more than 200,000 people and 16 deaths (Juneng et al., 2010). Another memorable extreme rainfall event occurred in Malaysia in December 2014. The rainfall is causing massive flooding in several states in Malaysia where more than 200,000 peoples were affected ("Banjir di Kelantan…", 2014). For a developing country such as Malaysia which is prone to flood disaster having rainfall forecasting model is a very vital matter (El-Shafie et al., 2011). STAtistical and Regional dynamical Downscaling of EXtremes for European regions (STARDEX) is one of the successful projects developed in the European region to deal with extreme events (STARDEX, 2005). This study investigates and adapts STARDEX extreme rainfall indices into Malaysia's context where the upstream rainfall data of the Timah Tasoh reservoir were used as the case study.

This paper is organised as follows. Studies of extreme rainfall and its indices are presented in the second section, followed by the methodology section that describes the indices, datasets, and the temporal pattern segmentation process. The proposed model is described in Section 4, followed by the experimental results in Section 5. Concluding remark is presented in the final section.

LITERATURE REVIEW EXTREME RAINFALL AND INDICES

In recent years an increased interest was shown in regards to the apparent increase in the frequency and severity for predicting extreme events for many countries around the world. The development of an accurate and timely extreme event monitoring and predicting system stands as one of the most critical ways for avoiding the potential impacts that climate variations and extreme weather pose (Zeng et al., 2011). The traditional techniques for forecasting of statistical weather include ARMA models, Multivariate Adaptive Regression Splines and Box-Jenkins Models. Later, when the machine learning became widespread, many attempts have been made to develop rainfall forecasting models which used feed-forward neural networks, recurrent neural networks, that include input delays and backpropagation neural network (BPNN). Many attempts were made to involve extra weather parameters in the rainfall forecasting model for better predictions (Htike & Khalifa, 2010).

The extreme rainfall index is one of the outputs from the efforts ran by the European Union (EU) from 2001/02 to 2004/05 under the European Union Framework 5 Programme. This index is named as STAtistical and Regional dynamical Downscaling of EXtremes for European regions or in short STARDEX (STARDEX, 2005). The purpose of these indices is to observe the changes in weather and climate extremes using uniform measurement. Most of the indices are based on thresholds defined using percentile values rather than fixed values. The STARDEX consists of six core indices for rainfall is shown in Table 1. The indices encompass frequency (e.g., days of heavy rainfall) and persistence (e.g., the most prolonged dry period) of extremes. The rainfall indices provide a right mix of measures of intensity, frequency and proportion of the total. All thresholds are percentile-based and so can be used for a wide variety of climates (Haylock, 2005). Some of the indices consider the properties of just the rain day distribution while the others use the entire distribution. The maximum five-day accumulated precipitation (PX5D) is to identify extreme events that could affect human life and the natural environment. Previous studies have indicated the importance of evaluating extreme precipitation events based on successive days of precipitation amounts (Zeng et al., 2011; Foresti et al., 2010). This is significant because the risk of flood increases after several days of precipitation.

Table 1.

STARDEX Extreme Rainfall Indices

Index Name	Details	Description
PQ90	90th percentile of rain day amounts (mm/day)	Heavy rainfall threshold
PX5D	Most significant 5-day total rainfall (mm)	Most significant 5-day rainfall (amount)
PINT	Simple daily rainfall intensity (rain per rainy day)	Average wet-day rainfall (amount)
PFL90	% of total rainfall from events>long-term 90th percentile	Heavy rainfall proportion
PNL90	Number of events>long-term 90th percentile of rain days	Heavy rainfall days
PXCDD	Maximum number of consecutive dry days	Longest dry period

STARDEX has been applied in various studies. Gu & Wan (2010), for example, utilized STARDEX indices on Yangtze River's daily precipitation. Gu et al. develop an average extreme rainfall prediction model that is based on a BPNN. Stepwise regression analysis was applied to the six extreme precipitation indices (PX5D, PFL90, PNL90, PXCDD, PQ90, and PINT) to gain the main indicants. Results showed that the impact of PX5D, PFL90, PNL90, and PXCDD are significant in forecasting average extreme rainfall, while PINT and PQ90's impact is insignificant. Wan et al. (2012) utilised the six STARDEX indices as an input for their extreme rainfall forecasting model. The model employed BPNN as the intelligent classifier to learn the rainfall patterns in order to forecast the next year's average extreme rainfall event. Both Gu & Wan (2010) and Wan et al. (2012) have shown the importance of forecasting extreme rainfall using the six extreme rainfall indices as predictors.

Studies by Junaida & Hirose (2012), Sulaiman et al. (2013a), and Sulaiman et al. (2014) utilised the PX5D index as the forecasting target. These studies focused on the modelling and forecasting of extreme rainfall in the Malaysian context, but they are limited to specific locations. In Malaysia, different states may have different characteristics, and the rainfall patterns may vary among the states. Junaida & Hirose (2012) apply stepwise regression as the input variable selection (IVS) method, while the artificial neural networks (ANN) method was selected for model development. Based on the IVS results, it is revealed that average temperature, minimum temperature, and daily precipitation at previous one day and three days are the significant subset of input variables when predicting heavy precipitation. These inputs are then presented to the ANN models. The primary benefit that was found of IVS coupled with the ANN approach is that it identifies the minimum number of ANN input variables required in the prediction of heavy precipitation, without much loss of prediction accuracy.

Sulaiman et al. (2014) developed ANNs model to forecast extreme monthly precipitation using past PX5D data and global climate indices such as the Southern Oscillation Index (SOI), Madden Julian Oscillation (MJO), and Dipole Mode Index (DMI) in Kuantan and Kota Bharu, Malaysia. Two statistical methods, multiple linear regression and ARIMA models, were developed using the sample data used in the ANN model, the Performance metric means Mean Absolute Error (MAE) and Root-Mean-Square Error (RMSE) were calculated and compared for all the models in order to evaluate the ANN developed model. Inline with previous studies, the STARDEX indices are adopted in this study. These indices are used to represent the data for the rainfall forecasting model. As discussed above, STARDEX is well known method for data representation especially for extreme rainfall event.

METHODOLOGY

In this study, upstream rainfall data of Timah Tasoh reservoir were obtained from the Malaysian Department of Irrigation and Drainage (DID) as a case study. The rainfall data were collected through the gauging stations. The Timah Tasoh reservoir is located in the state of Perlis, Malaysia, and it is one of the largest multi-purpose reservoirs in Northern Peninsular Malaysia. The reservoir serves as flood mitigation and is the only reservoir which has a gate structure that is operated based on human decisions. Another reservoir in Malaysia operated based on both human decision and automatic water release or outflow. The upstream Timah Tasoh gauging stations (Figure 1) are Padang Besar (PB), Tasoh (TS), Lubuk Sireh (LS), Kaki Bukit (KB), and

Wang Kelian (WK). These gauging stations record the volume of rainfall that falls and disperses into the river flows into the Timah Tasoh reservoir. The daily rainfalls data recorded at those stations from April 1998 until October 2013 were obtained from DID.
These data were used to calculate the average of Timah Tasoh upstream daily rainfall. The sample of the data is shown in Table 2.

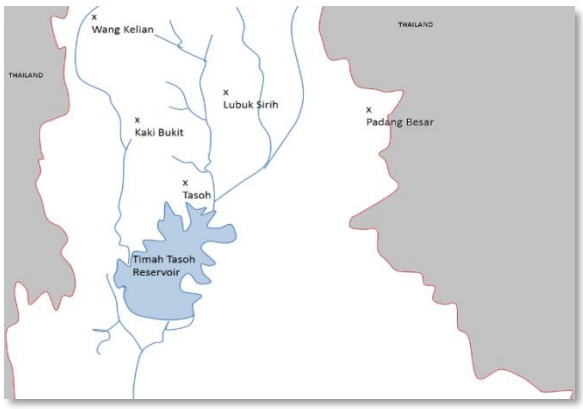

Figure 1. *Location of Timah Tasoh Reservoir and Gauging Stations*

Table 2

Sample of Data (In MM)

Date	PB	TS	LS	KB	WK	Average
16-Oct-06	35	55	50	0	49.5	37.9
17-Oct-06	0	0	0	10	39.5	9.9
18-Oct-06	0	0	0	0	29.5	5.9
19-Oct-06	0	50	91	20	47.5	41.7
20-Oct-06	0	0	2	11	2.5	3.1
21-Oct-06	5.5	0	25	100	7.5	27.6
22-Oct-06	25	43	9	20	4.5	20.3
23-Oct-06	14.5	0	6	10	5.5	7.2

The average daily rainfall was used to construct four datasets that are based on STARDEX indices, namely Dataset-A, Dataset-B1, Dataset-B2, and Dataset-B3. Dataset-A has the six core indices as predictors, and the target value is the PX5D value for the next month. Dataset-B1, Dataset-B2, and Dataset-B3 contain only the PX5D index value that is calculated based every month with different lag lengths. In this study, three different lag lengths experimented which are 3 for Dataset-B1, 6 for Dataset-B2 and 12 for Dataset-B3. The lag length was determined using the sliding window technique (Azahari et al., 2017; Mokhtar et al., 2016).

Back Propagation neural network (BPNN) is a multilayer feedforward neural network that consists of three or more layers of neurons. It includes an input layer, hidden layer (middle layer) and output layer. BPNN is one of the well known neural network models and has been deployed

in the various problem domain. In this study, BPNN is run using the Levenberg-Marquardt algorithm. In time series forecasting, particularly in the climate domain, LM is seen as a common choice as a BPNN learning algorithm (Sulaiman et al., 2014; Mokhtar et al., 2016). Choosing the number of nodes (represented as circles) for each layer will depend on the problem NN is trying to solve, the types of data network it is dealing with, and the quality of data. The number of input and output nodes depends on the training set in hand. The number of hidden nodes is determined by an empirical approach, in which NN is retrained with varying numbers of hidden neurons, and the output error is observed as a function of the number of hidden units (Mokhtar et al., 2016). The algorithm used for the initialisation of BPNN weights is the Nguyen-Widrow weight initialisation algorithm. The Nguyen-Widrow method generates initial weights and bias values for a layer so that the active regions of the layers of neurons will be distributed approximately evenly over the input space (El-Shafie et al., 2012).

Proposed Backprogation Neural Network Model

Four experiments, namely Experiment-A, Experiment-B1, Experiment-B2, and Experiment-B3, have been conducted using the developed BPNN Model. Each experiment uses different combinations of inputs: Experiment-A applies the six extreme rainfall indices as predictors; in Experiment-B1, the values of PX5D for the previous three months are applied as predictors; for Experiment-B2, the previous six months of PX5D index values are applied as predictors; whereas in Experiment-B3, the values of PX5D for the last twelve months are used as predictors. The experiments' target is the monthly maximum five consecutive days of rainfall amount (PX5D) index for one month ahead. Figure 2 shows the underlying architecture of the developed BPNN model. BPNN consists of three layers: input, hidden and output layer. Time is represented as *t*, which mean current month, while *t+1* means next month.

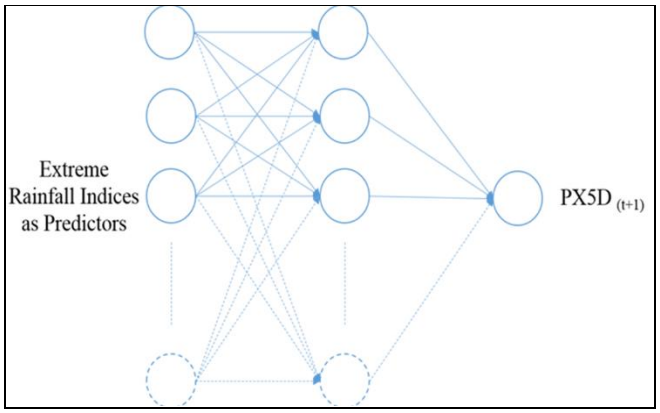

Figure 2. *Basic BPNN Architecture Diagram*

Experiment-A is developed using the six extreme rainfall core indices (outlined by STARDEX) of the current month (*t*) as inputs, while the output is the PX5D index value of the next month (*t+1*). The dataset used to train and test BPNN in this experiment is Dataset-A (Table 3). Dataset-A has been created to have the values of the six core indices in the predictor part.

Meanwhile, the target part has only one variable, which is the PX5D value of the next month (Figure 3).

Table 3.

Sample of Dataset A

Predictors						Target
$PQ90_{(t)}$	$PX5D_{(t)}$	$PINT_{(t)}$	$PFL90_{(t)}$	$PNL90_{(t)}$	$PXCDD_{(t)}$	$PX5D_{(t+1)}$
28.00	77.00	15.73	6	0.21	1	45.50
29.50	81.00	20.07	8	0.25	1	56.50
24.60	68.00	11.94	4	0.30	2	34.00
30.40	76.00	13.06	4	0.36	2	39.50
30.70	75.00	12.55	4	0.41	2	85.25

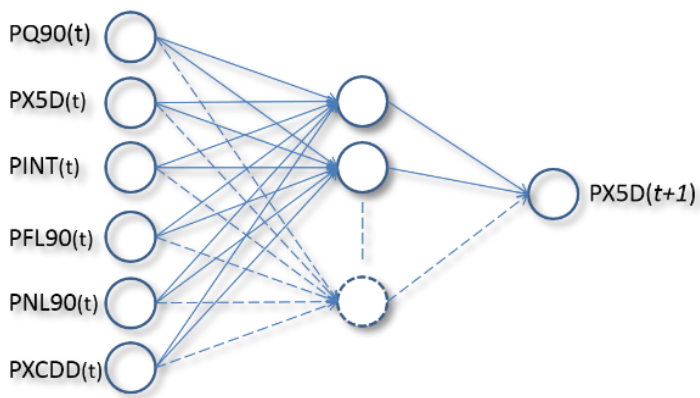

Figure 3. *Initial BPNN Architecture for Experiment-A*

Experiment-B1 has been developed to forecast the maximum five consecutive days for a month ahead using the values of the PX5D of three months before. Dataset-B1 was used to train and test the BPNN of this experiment (Table 4). Dataset-B1 was created using a sliding window size of 3. The predictors of this model are the three-month delay of the PX5D values (*t*, *t-1*, *t-2*). The output is the PX5D index value of the next month (Figure 4).

Table 4.

Sample of Dataset B1

Predictors			Target
$PX5D_{(t-2)}$	$PX5D_{(t-1)}$	$PX5D_{(t)}$	$PX5D_{(t+1)}$
56.00	90.00	140.00	64.00
90.00	140.00	64.00	110.00
140.00	64.00	110.00	76.00
64.00	110.00	76.00	18.00
110.00	76.00	18.00	123.00

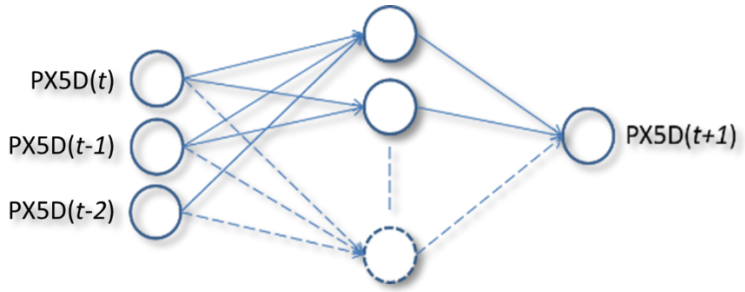

Figure 4. *Initial BPNN Architecture for Experiment-B1*

Dataset-B2 (Table 5) is developed to fit the BPNN architecture of Experiment-B2 (Figure 5). This dataset has been created to have the values of the previous six months in the predictor part. Dataset-B2 was created using the sliding window technique with a window size of 6. The values of the PX5D index of a six-month delay is set to be introduced to the BPNN of this model as inputs, and the target is the PX5D value of the next month.

Table 5.
Sample of Dataset B2

Predictors						Target
$PX5D_{(t-5)}$	$PX5D_{(t-4)}$	$PX5D_{(t-3)}$	$PX5D_{(t-2)}$	$PX5D_{(t-1)}$	$PX5D_{(t)}$	$PX5D_{(t+1}$
76.00	39.50	87.00	56.00	90.00	140.00	64.00
39.50	87.00	56.00	90.00	140.00	64.00	110.00
87.00	56.00	90.00	140.00	64.00	110.00	76.00
56.00	90.00	140.00	64.00	110.00	76.00	18.00
90.00	140.00	64.00	110.00	76.00	18.00	123.00

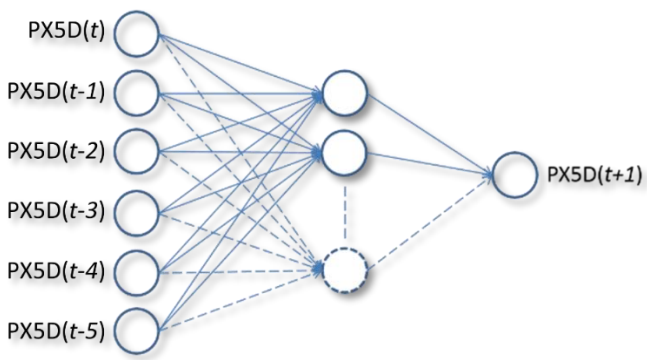

Figure 5. *Initial BPNN Architecture for Experiment-B2*

Experiment-B3 has been developed using the values of the PX5D index of the past year (12 months) to forecast the PX5D value of the next month (*t+1*). Dataset-B3 was created to train and test the BPNN of Experiment-B3 (Table 6). Dataset-B3 was created using the sliding window technique with a window size of 12. In order to obtain the values of the PX5D index for the last twelve months in the predictor part of the dataset.
Whereas the target part of this dataset is the same as other datasets, which is the PX5D index value for the next month (Figure 6).

Table 6

Sample of Dataset B3

Predictors												Target
$PX5D_{(t-11)}$	$PX5D_{(t-10)}$	$PX5D_{(t-9)}$	$PX5D_{(t-8)}$	$PX5D_{(t-7)}$	$PX5D_{(t-6)}$	$PX5D_{(t-5)}$	$PX5D_{(t-4)}$	$PX5D_{(t-3)}$	$PX5D_{(t-2)}$	$PX5D_{(t-1)}$	$PX5D_{(t)}$	$PX5D_{(t+1)}$
38.5	52	73	78	223	82.5	91	172	62	32	131	77	45.5
52	73	78	223	82.5	91	172	62	32	131	77	45	44
73	78	223	82.5	91	172	62	32	131	77	45.5	44	61
78	223	82.5	91	172	62	32	131	77	45.5	44	61	38.2
223	82.5	91	172	62	32	131	77	45.5	44	61	38.2	71

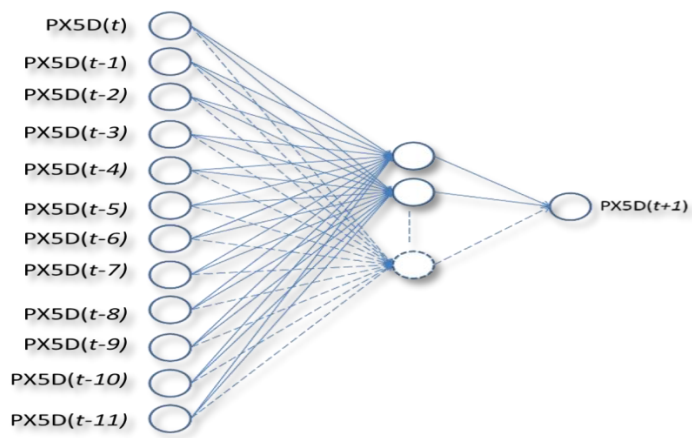

Figure 6. *Initial BPNN Architecture for Experiment-B3*

RESULT

Results of the four BPNN experiments are compared to find which experiment has the lowest error rate. The mean absolute error formula (Equation 1) is applied to calculate the error between the network output and the target of each experiment.

$$MAE = \frac{1}{n}\sum_{k=1}^{n}|t_k - y_k| \quad (1)$$

Where n is the number of the output, t_o represents the target value, while y_k represent the BPNN output. Experiment-A has been developed using Dataset-A. The number of input units is six. The

number of hidden units has been determined using the heuristic approach by training BPNN with different numbers of hidden units. The selection criterion was the model output's MAE. It was found that when the number of hidden units is three, and the error is the lowest. The MAE value for this experiment is 31.62. The final BPNN architecture for Experiment-A with three hidden nodes is shown in Figure 7.

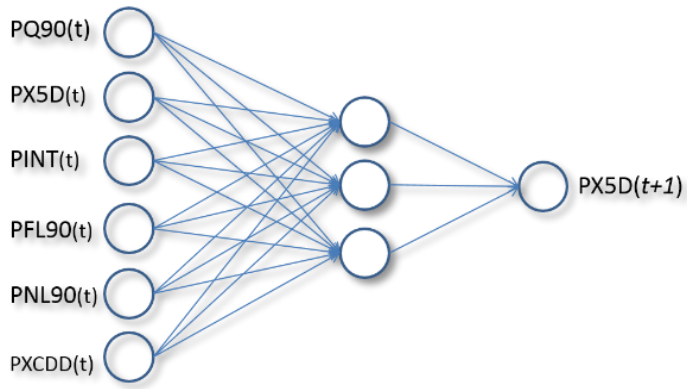

Figure 7. *Final BPNN Architecture for Experiment-A (6-3-1)*

Experiment-B1 was developed using Dataset-B1. This means Experiment-B1's BPNN has three units in the input layer. The number of hidden units has been determined by training BPNN with different numbers of hidden units and then selecting the network with the lowest MAE. It was found that when the network was trained with eleven units in the hidden layer, the network output error was the lowest, equal to 33.44. The final BPNN architecture for Experiment-B1 with eleven hidden nodes is shown in Figure 8.

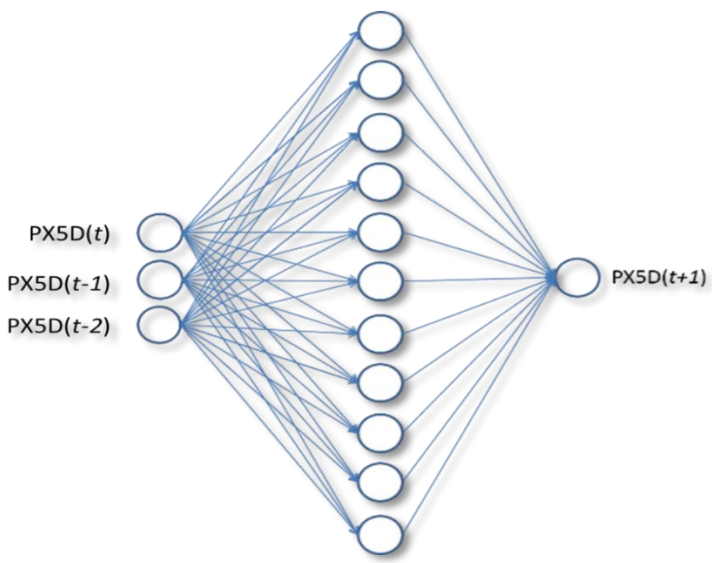

Figure 8. *Final BPNN Architecture for Experiment-B1(3-11-1)*

Experiment-B2's BPNN has been developed to forecast the maximum five consecutive days of rainfall amount of one month by using Dataset-B2. The best MAE of this model output was 32.95 when the network was trained with seven units in the hidden layer. The final BPNN architecture for Experiment-B2 with seven hidden nodes is shown in Figure 9.

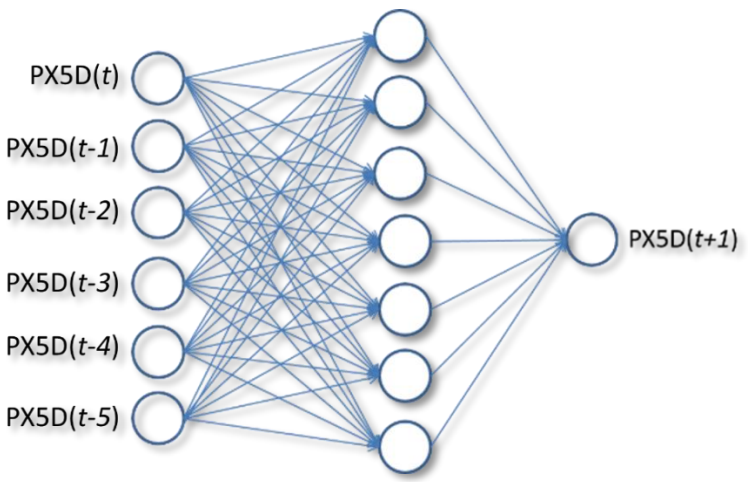

Figure 9. *Final BPNN Architecture for Experiment-B2 (6-7-1)*

Experiment-B3 has been developed using the values of the PX5D index of the past year (Dataset-B3) to forecast the PX5D value of the next month. This model has twelve units in the input layer, nine units in the hidden layer, and one unit in the output layer. The number of units in the hidden layer has been determined by training BPNN with different numbers of hidden units. The best MAE obtained from the Model-B3 output was 33.82. The final BPNN architecture for Experiment-B3 with nine hidden nodes is shown in Figure 10.

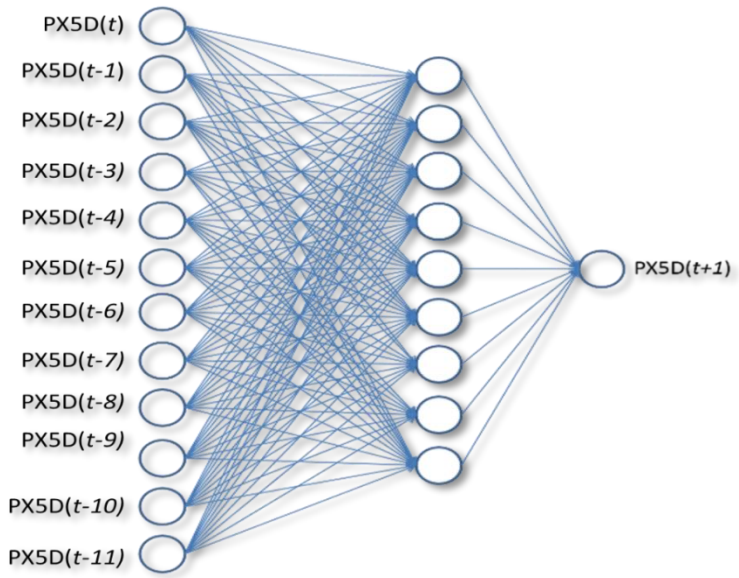

Figure 10. *Final BPNN Architecture for Experiment-B3 (12-9-1)*

The main aim of developing four experiments is to find which input combination would give a better forecasting accuracy. MAE evaluation metric was calculated for the test period of each experiment separately. Table 7 shows the obtained MAE values and the BPNN model from each experiment. The results are illustrated as a graph as in Figure 7. As can be seen in Figure 7, using the descriptive indices of extreme rainfall contributes to making the forecasting error lower than when using only the lagged value of the PX5D index. Experiment-A has outperformed Experiment-B1, Experiment-B2, and Experiment-B3 in extreme rainfall forecasting.

Table 7

Summary of the Results

Experiment	MAE	Number of Units in BPNN		
		Input	Hidden Nodes	Output
A	31.62	6	3	1
B1	33.44	3	11	1
B2	32.95	6	7	1
B3	33.82	12	9	1

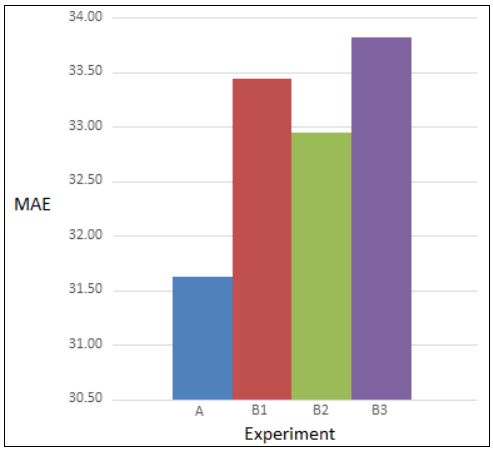

Figure 7. *MAE values of the four BPNN model experiments*

Experiment-A, which was developed using BPNN and the six extreme rainfall indices as predictors, has outperformed the other developed models. Using the six extreme rainfall indices as predictors have contributed in obtaining a lower forecasting error rate than using the value of only one index. Utilising BPNN in forecasting extreme rainfall based on the six extreme rainfall indices as predictors led to having a lower error rate. This proves that adding more descriptive indices helps in obtaining lower error measurements. An equivalent statistical model to the BPNN model in Experiment-A is also developed as a comparison. The statistical model is a multiple regression model. The same data series used to train and test Experiment-A BPNN has been used to calculate the multiple regression model. Figure 9 shows the comparison of MAE for the BPNN model (from Experiment-A) and the multiple regression model. As shown in the

figure, the MAE for the multiple regression model is 34.15 higher compared to the BPNN model.
This means the BPNN model has better performance compared to the multiple regression model.

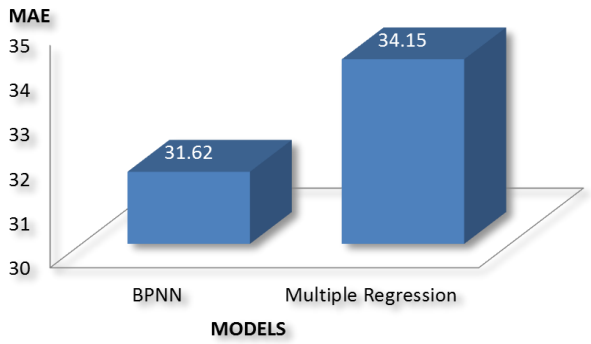

Figure 9. *Comparison of the BPNN with Multiple Regression*

CONCLUSIONS

This study presented four different methods for extreme rainfall forecasting. Different forecasting models have been employed using different types of variables. All the models share the same goal: forecasting the maximum five consecutive days of rainfall amount of a month ahead. Using BPNN to forecast extreme rainfall events with six extreme rainfall descriptive indices as predictors produce a lower error measurement as compared to using the multiple regression model or applying one extreme rainfall index as a predictor. When a comparison was conducted between the BPNN model (Experiment-A), which uses the six core extreme rainfall indices, and the other BPNN experiments that used lagged values of the maximum five consecutive days of rainfall amount, it was found that Experiment-A produced the lowest error measurement. The extreme rainfall forecasting error can be reduced in order to develop a forecasting model with higher accuracy. Thus more variables can be combined with extreme rainfall indices to decrease the forecasting models' output error. Different lag lengths can be experimented to find the most significant period of previous months.

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