Energy Efficient IoT Based Cloud Framework for Early Flood Prediction

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Abstract Flood is a recurrent and crucial natural phenomenon affecting almost the entire planet. It is a critical problem that causes crop destruction, destruction to the population, loss of infrastructure, and demolition of several public utilities. An effective way to deal with this is to alert the community from incoming inundation and provide ample time to evacuate and protect property. In this article, we suggest an IoT-based energy efficient flood prediction and forecasting system. IoT sensor nodes are constrained in terms of battery and memory, so the fog layer uses an energy-saving approach based on data heterogeneity to preserve the system's power consumption. cloud storage is used for efficient storage. The environmental conditions such as temperature, humidity, rainfall, and water body parameters, i.e. water flow and water level, are being investigated for India's Kerala region to calibrate the flood phases. PCA (Principal Component Analysis) approach is used at the fog layer for attribute dimensionality reduction. To forecast the flood, the ANN (Artificial Neural Network) algorithm is used, and the simulation technique of Holt Winter is used to forecast the future flood. Data is obtained from the Indian government meteorological database and experimental assessment is carried out. The findings showed the feasibility of the proposed architecture.

Keywords Internet of Things · ANOVA · Tukey Post Hoc Test · Holt Winter · ANN

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1 Introduction

Natural disasters are universal incident and require significant assistance to tackle. Natural disasters such as earthquakes, hurricanes and floods are events that intensely impact wide zone, distressing population, affecting goods, and tremble the population on both economical as well as psychological viewpoint [1]. From these disasters, flood is one of the ordinary disastrous incidents that happen in various countries consistently around the world. Over the past two decades, floods have accounted for 44% of all disaster incidents and have affected 1.6 billion people worldwide [30]. China is the nation most impacted by floods from 2000 to 2019, with an average of 20 floods every year and a total of 900 million people affected [30]. 2017 floods in US caused 3019 fatalities and resulted in overall loss of US$ 95000 million [29].In India recently, in Gujrat, the floods impacted 6.44 lakh farmers in 17 districts. The crop damage is estimated to be worth Rs 867 crore. Assam deals with displacement of 61,923 people and approximately 160 deaths. In West Bengal, 1.67 lakh people had to be accommodated in relief camps, and atleast 4 people lost their lives [2] so as to consequence in part from the lack of development of warning systems and information at the community level of the imminent flood. There is needed to take special procedures to predict it and to manage the situation before it occurs. Flood prediction and detection is done using IoT sensors and cloud computing in a geographical area by providing proficient acquisition, processing and efficient storage of flood related information. IoT and cloud computing are in combination become a powerful platform for flood management by monitoring the water bodies from remote sites providing continuous information about flood to decision making agencies and rescue units. Flood forecast and warning intend to reduce threat of lives and economic influence. A framework for flood alert provides data accumulation, analysis of data, scrutinize and warning [3]. The presented model is based forecasting and detecting the flood in advance based on environmental factors like temperature, humidity, rainfall and hydrological parameters like water flow and water level. Non linear data is dimensionally reduced by using Principal Component Analysis (PCA) dimension reduction method. In this study, Principal Component Analysis is proposed as a novel pre-processing technique for the flood detection systems to reduce the dimensions of flood related attributes, and the resulting input representation is trained with Artificial Neural Networks (ANN) for classifying the data. Artificial Neural Network is a non linear computational structure comprising of a vast number of interconnected processing units [4]. ANN is used for because of its characteristics like high parallelism, fault tolerance, learning and generalization capabilities. In this study of flood prediction domain, IoT framework uses comprehensive historical dataset of continuous observations over a span of time to predict the flood and related activities. The paper contributes in this aspect by (i) Proposing IoT sensors with energy efficient gateway node. (ii) to provide a mechanism for the efficient energy utilization of hardware (iii) To predict and control the sleep interval of sensors (iv) Reduce the dimensionality of sensory data and geographical information. (v) Predict flood events using Artificial Neural Networks. (vi) Flood forecasting. In the proposed system, the general framework of IoT based flood prediction and forecasting system is described. A survey on various flood monitoring and management systems focused on IoT with different data mining methodologies has been addressed in section 2. Section 3 describes key terms relevant to our proposed flood data analysis model and computing framework with alert generation process. In section 4, complete experimental comparison of proposed approach with different techniques. Finally, section 5 concludes the paper with some important discussions.

2 Related work

This section analyzes various flood management systems and data mining techniques used for flood data. Firstly, different frameworks are discussed related to flood management system followed by data mining techniques.

2.1 Flood Management System

In 2017, Ray and Mukherjee [6] presents the model based on IoT to experience the significant issues with disasters for example remote monitoring and real- time analysis, cautioning, data analysis, information accumulation. A complete dialog is presented on state-of-the-art situations to deal with devastating incidents. Moreover, IoT-based guidelines and market-prepared deploy-able products are reviewed to tackle disaster problems. It is concluded that for disaster management and handle the disastrous situation the Internet of Things based technologies are suitable. This survey reveals key challenges and research patterns in IoT-enabled emergency response systems. In 2016, Afzaal and Zafar [10] propose a model in which sensors are installed to observe water level in different water bodies. Gateways are used as an interface with the cloud and to enable actors on the basis of information handled by the cloud. The Vienna Development Method-Specification Language (VDM-SL) is used for configuration and execution of system. VDM-SL is used to create potential test cases to reduce device failures and omissions. The result shows that there is no error in specification. In 2016, Ovando et al. [8] offers a sensor for calculating water level in rivers, reservoirs, lagoons and streams. A prototype is designed using a micro-model that is installed on a basic open circuit based on a water level measurement sensor. A programmable electronic board (Netduino Plus 2) is used to perform the micro-model. In 2015, Kumar et al. [7] presents an innovative approach to the recurrent issue of floods in India. The system is integrated flood prediction and alert generation system developed using Internet of Things techniques. The system uses an innovative approach to calculate and monitor several flood related parameters at different locations to reliably forecast river flooding in real-time. In 2015, Yusoff et al. [14] suggested that flood control and early warning monitoring can be tackled by cloud computing. The study is confirms that the GreenCloud supports crucial functions fro the growth of smart cities. In 2015, Lo et al. [13] presents an image processing techniques based model to determine the flood conditions. The experimental results indicates the reliability of visual sensing approach. In 2020, Hadid et al. [33] presents an approach for stream level prediction for a river using hybrid model and Dempster-Shafer algorithm for PWARX (Piecewise Auto-Regressive eXogeneous) model.

2.2 Meterological Data Analytics

In 2006, Owotoki et al. [12] proposes a model for integrated flood management (IFM) that is utilize the data mining techniques, in a three-tier web based framework dedicated to sustainable development for stakeholders as a micro-scale resilience technique of IFM. In 2011, Widmann et al. [15] presents a system for analysis of daily precipitation in switzerland using principal component analysis technique. A mathematical model is developed to observing precipitation patterns due to shifts in either the frequency or precipitation behavior of Alpine weather groups. In 2003, Marhaba et al. proposes a principal component analysis based system to monitor the spatial and temporal variations in water quality. In 2013, Aziz et al. [17] describe the implementation of artificial neural network for regional flood inundation mapping in the Australian case study. In 2010, Chau et al. [18] applied modular artificial neural networks technique to predict the rainfall time series. In 2018, Chu et al. [31] proposes a modified principal component analysis (MPCA) method for assessing environmental variables to track environmental changes in coastal recovery ares. Ghadim et al. [32] discuss the use of the Holt-Winters time series model's additive and multiplicative types of to forecast environmental variables for one year in advance.

3 Proposed Model

Fig.1 explains the proposed model for flood prediction and forecasting. It consists of data acquisition layer, fog layer and cloud layer. Data acquisition layer gathers environmental data from several sensors such as rainfall sensors, temperature sensors, waterflow sensors, humidity sensors, water level sensors at different locations and water bodies. The data collected is analysed at fog layer for data variation in order to adapt the sampling frequency of the sensor nodes. The data dimensionality is further reduced by using the Principal Component Analysis (PCA) on the fog layer and forwarding it to the cloud layer. Data is maintained in a cloud-based repository from which valuable information is extracted for efficient processing and effective decision making.

3.1 Data Acquisition Layer

The data acquisition layer gathers large amount of data. IoT sensor nodes are responsible for gathering data on flood events and related parameters in the local area. Successful flood prediction and forecasting is focused on information of the various meteorological and hydrological attributes that cause flooding. The overview of these attributes and accompanying sensors is shown in Table 1.

1. Meteorological attributes: Flood is greatly depends on meteorological conditions of particular location. Meteorological attributes comprises information about temperature, humidity, precipitation and also monsoon season significantly escalate the occurrence of maximum rainfall that causes flood conditions.

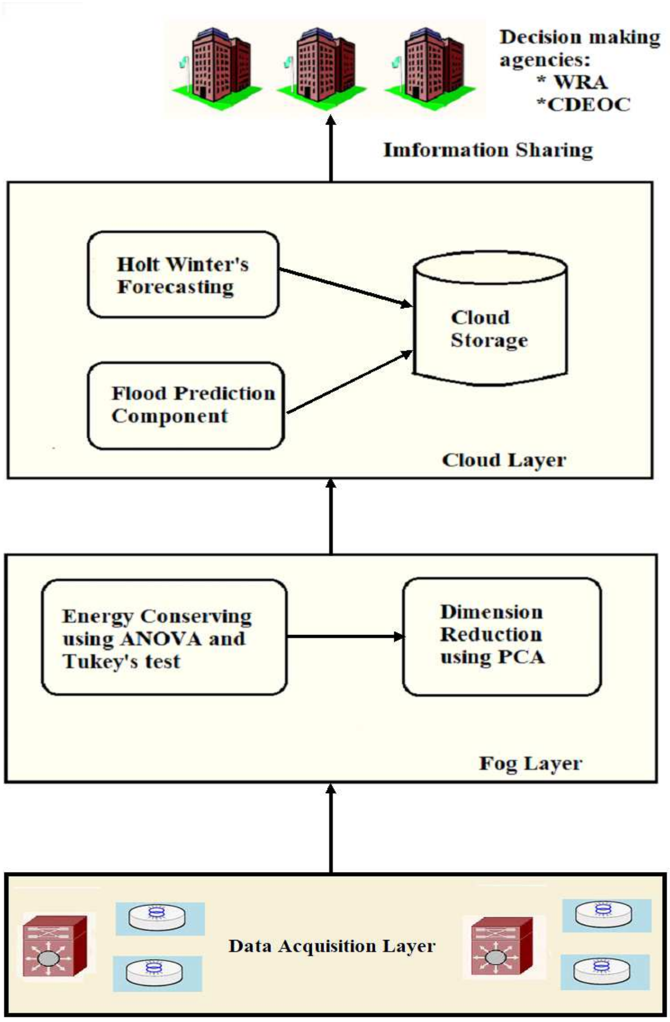

Fig. 1: Proposed framework

2. Hydrological attributes: Water level in water bodies of study area and flow of water with respect to time is considered as important factor for flood conditions.

3.2 Fog Layer

Fog layer is the transitional layer between the cloud layer and the data acquisition layer. The raw data obtained from data acquisition layer is pre-processed at the fog

Table 1: Flood causing attributes

Meteorological attributes	Description	Sensors
Temperature	Atmospheric air temperature	
Humidity	Water vapours in air	Temperature sensors, humidity sensors
Rainfall	amount of precipitation	rain guages, precipitation sensors
Season	Winter, Pre-Monsoon, Monsoon, Post-Monsoon	
Hydrological attributes	**Description**	**Sensors**
Water level	Level of water in water bodies	Water level sensors
Water flow	Volume of water flowing	Water flow sensors

layer. Fog layer performs a two-step preprocessing of data such as ANOVA and Tukey post hoc test aided energy conserving and PCA based data dimensional reduction.

3.2.1 ANOVA (Analysis of Variance) model and Tukey's Post Hoc Test

Fog layer receives datasets information from data acquisition layer. The sensors nodes are operated by batteries and power restricted sensors require an energy-efficient data collection strategy. A method for measuring the active and sleep duration based on the existence of sensor data has been presented in the proposed model. To avoid redundant information, sensor active and sleep durations of sensors are analyzed by using ANOVA (Analysis of Variance) method with Tukey Post Hoc Test. The one way ANOVA model is used to measure the total heterogeneity $(\mathbb{H}_t)$of data generated by sensor nodes in N time slots. Total heterogeneity $(\mathbb{H}_t)$ is calculated as the measure of the heterogeneity within duration $(\mathbb{H}_{within})$ and heterogeneity between duration $(\mathbb{H}_{btw})$, illustrated as:

$$(\mathbb{H}_t) = (\mathbb{H}_{within}) + (\mathbb{H}_{btw})$$

Each sensor node captures a new data value for every flood attribute:

$$F_a = (f_1, f_2, f_3, \ldots\ldots\ldots\ldots f_{T-1}, f_T)$$

$$\sum_{c=1}^{N}\sum_{a=1}^{n_c}(f_{ac} - Mean)^2 = \sum_{c=1}^{N}\sum_{a=1}^{n_c}(f_{ac} - Mean_c)^2 + \sum_{c=1}^{N} n_c \times (Mean_c - Mean)^2$$

Here f_{ac} is a^{th} reading taken by sensor node in c^{th} duration; n_c denotes number of readings in c^{th} duration; N denotes total number of durations; $Mean_c$ denotes mean of data values captured in c^{th} duration; $Mean$ denotes mean of data values captured in all N time duration. The findings of one-way ANOVA help to assess whether or not the means of seperate datasets obtained over successive time durations vary greatly. Further, Tukey Post Hoc Test is implemented to determine whether the variance between datavalues from different durations exceeds a certain threshold.

3.2.2 Dimension Reduction

Dimension reduction module can be used to acquire extracted features of the flood related geographical attributes and sensor data set which is substantially smaller in size, thus far intimately preserving the accuracy of the original data. Specifically, mining on smaller data set will be more effective and deliver the same (or nearly the same) outcomes. In this proposed system, principal component analysis (PCA) method is applied on sensed data and geographical attributes for dimension reduction according to Algorithm 1.

Algorithm 1: Dimension reduction of flood attributes by using PCA

Input: Data set: $s_1^{(1)}, s_2^{(2)}, \ldots\ldots\ldots\ldots, s_n^{(p)}$; n: number of flood attributes, p: number of observations.

1 Normalize the original data: Calculate the mean (μ_j), Variance (σ_j) and Covariance ($Cov(s_{jk})$).

2 Find the correlation coefficient ($c_{jk}^{(i)}$) and correlation matrix (C) of the normalized data.

$$c_{jk}^{(i)} = \frac{\mathrm{Cov}(s_{jk})}{\sigma_j . \sigma_k}$$

3 Determine the Eigen values ($\lambda_1, \lambda_2, \lambda_3, \ldots\ldots, \lambda_n$) from equation [C−?I] = 0 and Eigen vectors ($e_{i1}, e_{i2}, e_{i3}, \ldots\ldots e_{in}$) from equation $\left[C - \lambda_j I\right] e_{ij} = 0$ for the correlation coefficient matrix.

4 Sort the Eigen values and corresponding Eigen vectors so that $\lambda_1 \geq \lambda_2 \geq \lambda_3 \geq \ldots\ldots\cdots \geq \lambda_n$.

5 Select the first $c \leq n$ eigenvectors and generate the data set in the new representation.

c Eigenvectors generate the data set in new representation with reduced dimensions. The PCA restricts all new values to lower dimensionality and update the database. Now, that data is gathered and pre-processed, it must now be evaluated for determining the flood level severity on the basis of the data received.

3.3 Cloud Layer

The flood related environmental sensory IoT data from different locations is stored at Cloud. The data is pervasively sensed and periodically collected at different time intervals. Therefore, for further analysis data are stored in cloud servers. The flood related activities are adequately categorized based on reduced attributes by using artificial neural networks.

3.3.1 Flood Prediction sub-layer and Alert generation

The artificial neural network (ANN) method is adopted in this research for classified the dimensionally reduced data by Principal Component Analysis algorithm. ANN

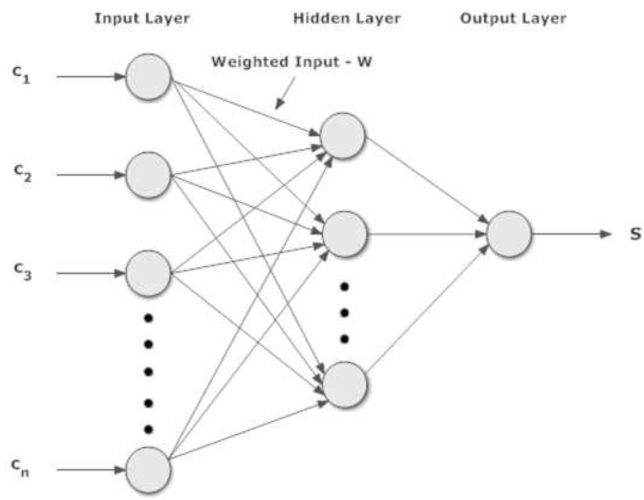

Fig. 2: Configuration of Artificial Neural Network (ANN)

model composed of 3 layers of node i.e. the input layer, the hidden layer and the output layer. Every node has a number of inputs (from dimensionally reduced flood related attributes) and a number of outputs (according to flood sensitivity factor). The structure of multi-layered feed-forward neural network is shown in Fig. 2. The nodes represented by circles and the relations represented by lines. Each input (c_1, c_2, c_3, ... ,c_n) is multiply by a relation parameter known as weight (W_i) and combined to generate a single value. This value is then regulated by a transfer function. The cumulative output value of a node can be expressed as below:

S_j = f (C $*$ $W_i - T_j$)

Alert generation components are reasonable for transmitting alert notifications to decision making agencies and citizens of particular flood detected area (Algorithm 2).

Algorithm 2: Classification and Alert Generation

Input: Dimensionally reduced flood attributes (C = c_1, c_2, c_3, ... ,c_n).
Output: Alert generation according to possibility of flood.

```
Calculate Flood sensitivity factor (S_j) according to various dimensionally reduced flood
  attributes. As S_j = f (C * W_i - T_j); Where, C = c_1, c_2, c_3, ......... ,c_n input to ANN model,
  W_i is weight associated with each node, T_j threshold value for each flood attribute.
if Flood sensitivity factor (S_j) > Predefined Threshold then
    Flood is detected and immediate alert is generated to decision making agencies
      (WRA,CDEOC) and citizens of that area.
    else
        Flood is not detected and no alert is generated
Exit.
```

3.3.2 Flood Forecasting sub-layer

This sub-layer forecasts the potential occurrences flood events by analyzing the current and historical values generated by flood prediction layer. For this task, Holt-Winters forecasting approach is used, which is one of the most frequently used exponential smoothing methods. Holt Winter's method considers three components to determine the future flood. The three components are:

1. Level $(L_t) = \alpha \frac{S_t}{Q_{t-x}}$ + (1-α) $(L_{t-1} + T_{t-1})$
2. Trend $(T_t) = \beta(L_t$- $L_{t-1})$ + (1- β)(T_t)
3. Seasonality $(Q_t) = \gamma \frac{S_t}{L_{t-1}}$ + (1- γ) Q_{t-x}

Where, L_t, T_t *and* Q_t are level, trend and seasonality components at time t. α, β and γ are model parameters. S_t is flood stage at time t and x is seasons' length. Flood stage for $t+p$ is determined as: $S_{t+p} = (L_t + pT_t)\ Q_{t-x+p}$. The initial values for Holt Winter's components are:

$$L_0 = \overline{S_1} - \frac{n}{2} T_0$$

$$T_0 = \frac{\overline{S_n} - \overline{S_1}}{(n-1)x}$$

$$Q_0 = \frac{\overline{S_z}}{\overline{S_y} - \left(\frac{x-1}{2} - z\right) T_0}$$

z = 1,2,3,. . . . . . x and y = 1,2,3,. . . . . . n.
Where, $\overline{S_y}$ is arithmetic mean of predicted flood stages for y^{th} year, n is the cumulative number of years considered.

Algorithm 3: Flood Forecasting sub-layer procedure

Input: Flood prediction dataset
Initiate the level, trend and seasonal components using L_0, T_0, Q_0.
Determine level, trend and seasonal components' revised values using L_t, T_t, Q_t.
Evaluate the forecast value for t=t+p by using $S(t+p)$.
Exit.

4 Performance Evaluation

This portion of the paper discusses the findings of implementation and addresses the reliability assessment of the proposed approach. The phases are addressed ahead:

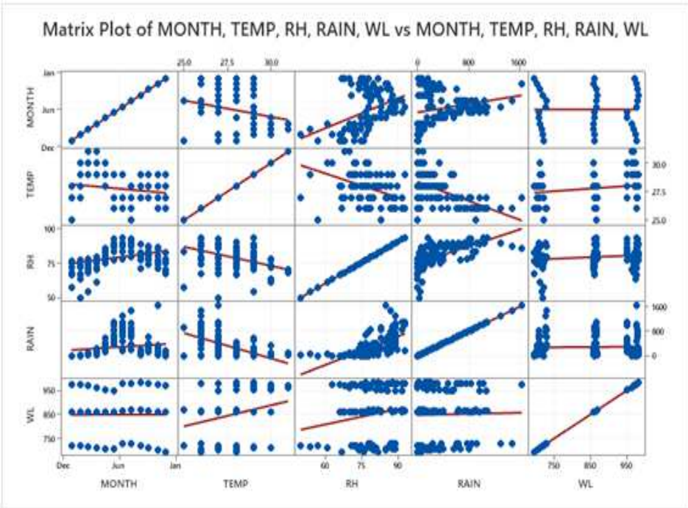

Fig. 3: Correlation structure of flood attributes

4.1 Data accumulation and integration

Data cannot be derived directly from the environment for applying the proposed model but can be gathered from multiple official sources of data. We have generated flood attributes systematically by collecting data from India's different government sites [26][23] and dataset repository [27] for the Kerala region. The environmental dataset is created in such a way that all possible flood-related attributes are considered. The dataset contains 180 cases (about 14 districts of Kerala in 2018) with information on 5 attributes, i.e. season, temperature, relative humidity, rainfall, water level. The relationships between the flood attributes are presented by using the correlation matrix. Figure 3 depicts the correlation matrix of 5 independent variables.

4.2 Energy conservation using ANOVA and Tukey's post hoc test

Water level sensor data and temperature data is retrieved from sensor dataset [28] for several lakes in Alaska, to determine the performance of proposed energy conserving mechanism. The dataset contains hourly data for the attributes water level and temperature. 24 hours water level sensor data is considered for implementation of ANOVA and Tukey's test. Considered data is divided into 6 intervals with 4 hours in each interval. The result of ANOVA and Tukey Post Hoc Test is shown in Figure 4. The result shows maximum overlap of mean intervals.

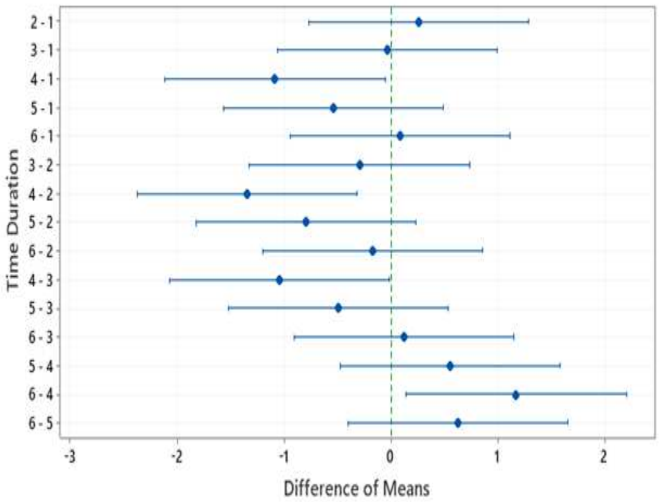

Fig. 4: Tukey's simultaneous 95% of CIs

Table 2: Principal components and corresponding Eigen value & cumulative variance

	PC1	PC2	PC3	PC4	PC5
Eigen Value	2.2988	1.1234	0.8827	0.4430	0.2521
Cumulative Variance	46%	78.4%	86.1%	95%	100%

4.3 Dimension Reduction

The dimensionality of the final dataset is minimized by the principal component analysis (PCA) approach. All modern statistical analysis packages use programs to measure the vector pair (eigenvalue-eigenvector) of the sample correlation matrix. The PCA algorithm is available in Minitab and is applied directly on generated dataset. Figure 5 shows the Scree plot of flood attributes corresponding to eigenvalues and principal components. First two principal components are selected out of 5 principal components, since its corresponding eigen values are greater than unity. Selected principal components clarified 78.4% of the overall variable heterogeneity in PCA (Table 2). The plot of first principal component against second principal component (Figure 6) shows that samples were clearly divided. These two principal components are directed to the cloud layer for forecasting and prediction of floods.

4.4 Flood prediction analysis

Two PCs, which explains 78.4% of the total variance, were extracted to utilize the ANN technique for flood prediction. The generated dataset is divided into two subsets. The first subset (70% of data) is used for training purposes and remainder 30% data

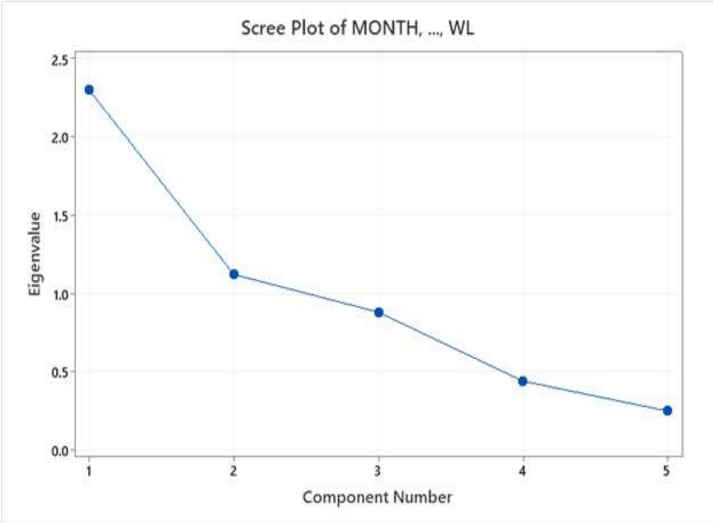

Fig. 5: Scree plot for Flood related variables

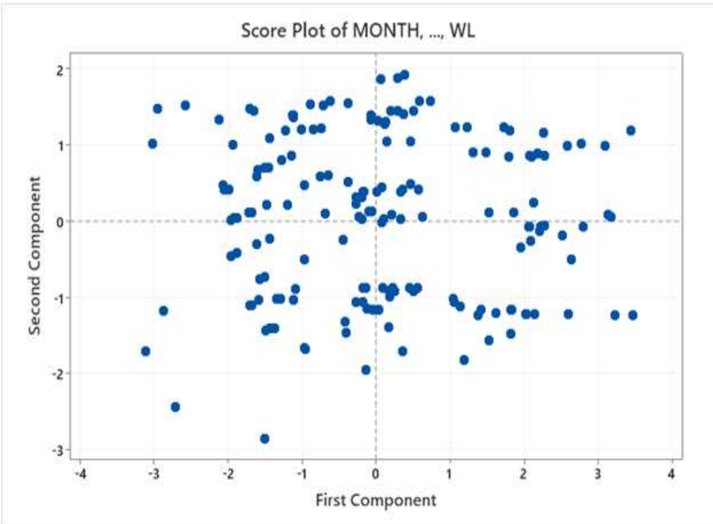

Fig. 6: Scree plot of two principal components

is used for testing purposes. The accuracy of predictive model is assessed in terms of confusion Matrix ROC curve analysis. The results of ANN show the overall 94.2% accuracy. Table 3 displays the predicted and observed accuracy of analysed data. The ROC curve of the predictive model (ANN) is shown in Fig. 7. The area under curve is 0.9807.

Efficiency in data classification concerns the classification of data instances into vari-

Table 3: Predicted and observed accuracy

Observed	Predicted		% correct
	Event	No Event	
Event	73	2	97.3
No event	8	97	92.4
All	81	99	94.4

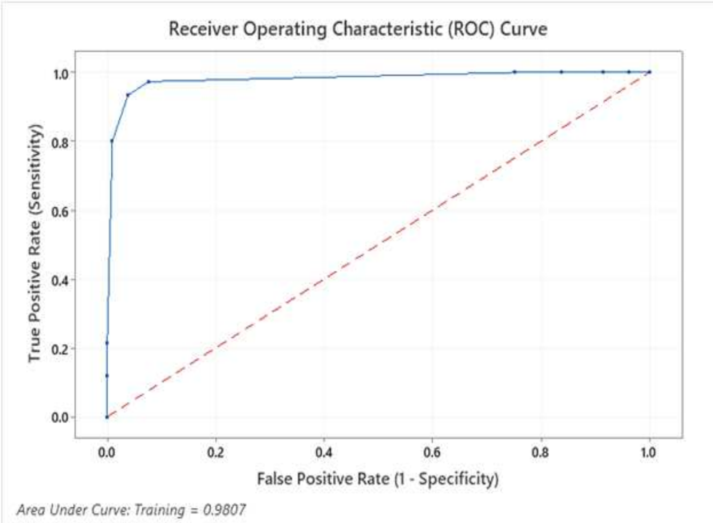

Fig. 7: ROC curve for ANN

ous groups using the Artificial Neural Network technique. Different statistical methods are used to test and evaluate the classification efficiency of the proposed model. These include accuracy, sensitivity, specificity and F-measure. Various baseline classifiers are used for comparative study. We have used three separate classifier models as a baseline classifier model for comparison, namely KNN, Decision Tree, BBN. Results have been obtained for various classifier models and are shown in Fig 8.

4.5 Flood forecasting analysis

Holt-Winters forecasting model is used to estimate the future trends in flood stages. Minitab software is used for implementing Holt-Winter's model using. The results of ANN are used as feedback for the model. The result of flood forecasting for time span of one month is shown in Fig 9 and for seasonal forecasting is depicted in Fig 10. The results show variation in observed and forecasted values. The accuracy assessment parameters, i.e., mean square deviation, mean absolute deviation, and mean absolute percentage error, are shown in Table 4.

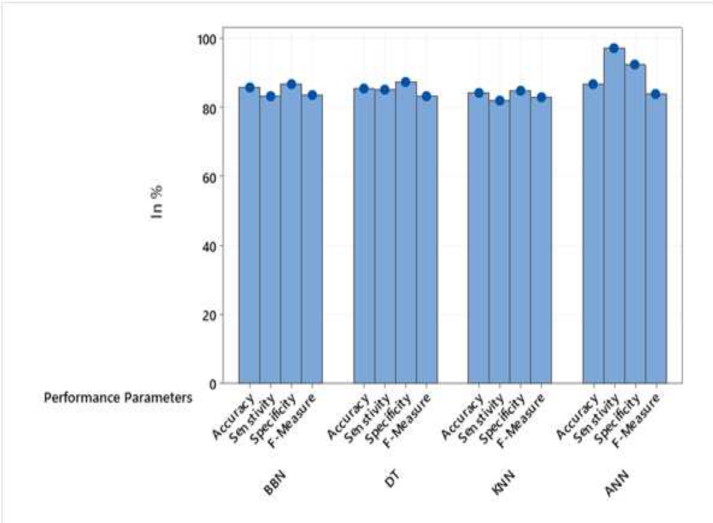

Fig. 8: ANN performance analysis

Table 4: Accuracy assessment parameters

Statistical Parameters	Values		
	One month	Seasonal	Average
Mean Absolute Deviation	0.13889	0.13889	0.13889
Mean Square Deviation	0.27778	0.55556	0.41669
Mean Absolute Percentage Error	1.208871%	3.267913%	2.238392%

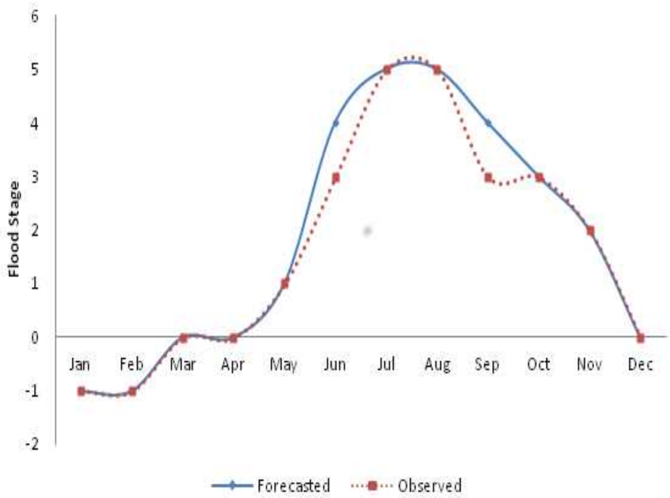

Fig. 9: Flood forecasting for one month

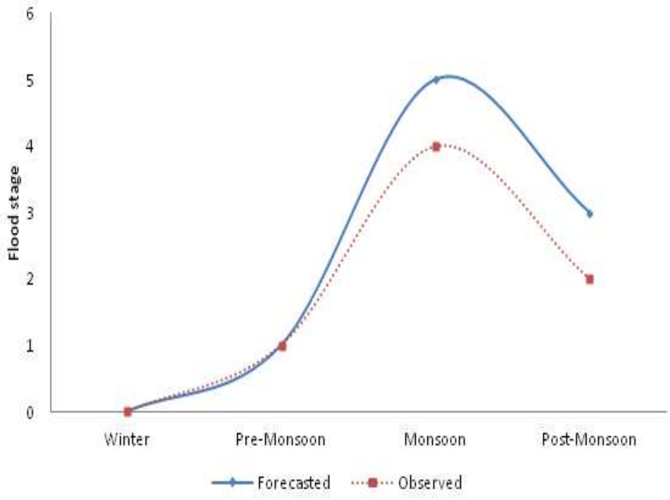

Fig. 10: Seasonal flood forecasting

5 Conclusion

This paper proposes an energy-efficient cloud system for flood prediction and forecasting based on IoT. The proposed model is effectively determines the prediction and forecasting measures for the particular study area (Kerala, India). This framework is contributed for optimistically data generation with efficiently enhance the sensor lifetime. Dimension reduction algorithm is applied at fog layer to maintain the optimization of network bandwidth. Moreover, ANN predictive algorithm is produced efficient results with 97.3% sensitivity, 92.4% specificity and future flood stages are forecasted using Holt Winter's model at cloud layer. Experimentation results are stored at cloud storage for water management agencies and disaster management groups so that effective measures can be taken on time and reduce the post and during disaster destruction.

Conflict of interest

The authors declare that they have no conflict of interest.

References

1. Avvenuti M., Cresci S., Vigna FD, Tesconi M. (2017). On the need of opening up crowdsourced emergency management systems. Article in AI & Society
2. www.newsclick.in
3. Syed Nazmus Sakib, Tanjea Ane, Nafisa Matin, M. Shamim Kaiser (2016), An intelligent flood monitoring system for Bangladesh using wireless sensor networks. 5th International Conference on Informatics, Electronics and Vision (ICIEV)

4. Can Elmar Balas, M.Levent Koc, Rifat Tur (2010) Artificial neural networks based on principal component analysis, fuzzy systems and fuzzy neural networks for preliminary design of rubble mound breakwaters. Applied Ocean Research
5. Elizabeth A. Basha, Sai Ravela, Daniela Rus, “ Model based monitoring for early warning flood detection”, SenSys’08, November 5–7, 2008, Raleigh, North Carolina, USA.
6. Partha Pratim Ray and Mithun Mukherjee, “Internet of things for disaster management: State-of-the-art and Prospects”. 2169-3536 (c) 2017 IEEE.
7. V. A. Kumar, B. Girish, and K. Rajesh, “Integrated weather & flood alerting system,” International Advanced Research Journal in Science, Engineering and Technology, vol. 2, no. 6, pp. 21–24, June 2015.
8. J. A. Hernandez-Nolasco, M. A. W. Ovando, F. D. Acosta, and P. Pancardo, “Water level meter for alerting population about floods,” in Proc. 30th IEEE Int. Conf. on Advanced Information Networking and Applications (AINA), Mar. 2016, pp. 879–884.
9. Prabodh Sakhardande, Sumeet Hanagal and Savita Kulkarni, “Design of disaster management system using IOT based interconnected network with smart city monitoring”. International conference on Internet of Things and Applications (IOTA), India 2016.
10. Hamra Afzaal and Nazir Ahmad Zafar, “Cloud computing based flood detection and management system using WSANs”. 978-1-5090-3552-6/16/2016 IEEE.
11. Joaquim Leitao, Alberto Cardoso, Jose Alfeu Marques and Nuno Simoes, “Flood Management in Urban Drainage”. International Conference 2017, University of Algarve, Faro, Portugal. 978-1-5386-0810-4/17/2017 IEEE.
12. Peter Owotoki, Nataša Manojlovic, Friedrich Mayer-Lindenberg and Erik Pasche, “A data mining approach for capacity building of stakeholders in integrated flood management”. Proceedings of the Sixth International Conference on Data Mining (ICDM’06). 0-7695-2701-9/06-2006 IEEE.
13. Shi-Wei Lo, Jyh-Horng Wu, Fang-Pang Lin and Ching-Han Hsu, “Visual sensing for urban flood monitoring”. www.mdpi.com/journal/sensors 2015, 15, 20006-20029.
14. Aziyati Yusoff, Intan Shafinaz Mustafa, Salman Yussof and Norashidah Md. Din, “Green cloud platform for flood early detection warning system in smart city”. 978-1-4799-7626-3/15/2015 IEEE.
15. Martin Widmann, Christoph Schar, “ Principal Component and long-term trend analysis of daily precipitation in Switzerland”, International Journal of Climatology, Vol. 17, 1333-1356 (1997).
16. Roohollah Noori, Amir Khakpour, Babak Omidvar, Ashkan Farokhnia, “ Comparison of ANN and principal component analysis-multivariate linear regression models for predicting the river flow based on developed discrepancy ratio statistic”, Expert Systems with Applications 37 (2010) 5856-5862. doi:10.1016/j.eswa.2010.02.020.
17. K. Aziz, A. Rahman, G. Fang, S. Shrestha, “ Application of artificial neural networks in regional flood frequency analysis: a case study for Australia”, DOI 10.1007/s00477-013-0771-5. Springer-Verlag Berlin Heidelberg 2013.
18. C. L. Wu, K. W. Chau, C. Fan, “ Prediction of rainfall time series using modular artificial neural networks coupled with data preprocessing techniques” , Journal of Hydrology, Vol. 389, No. 1-2, 2010, pp. 146-167.
19. Floods - National Disaster Management Authority.” [Online]. Available: http: //www.ndma.gov.in/en/mediapublic- awareness/disaster/naturaldisaster/ floods.html.
20. D. S. Shih, C. H. Chen, and G. T. Yeh, “Improving our understanding of flood forecasting using earlier hydrometeorological intelligence,” J. Hydrol., vol. 512, pp. 470–481, May 2014.
21. . K. T. Nguyen, L. H. C. Chua, and L. H. Son, “Flood forecasting in large rivers with data-driven models,” Nat. Hazards, vol. 71, no. 1, pp. 767–784, Nov. 2014.
22. . Gourbesville, J. Batica, J. Y. Tigli, S. Lavirotte, G. Rey, and D. K. Raju, “Flood warning systems and ubiquitous computing,” La Houille Blanche, no. 6. pp. 11–16, 01-Dec-2013.
23. India Water Portal, http://www.indiawaterportal.org/articles/district-wise-monthly-rainfall-datalist-rain-stations-india-metrologicaldepartment.
24. FMIS.” [Online]. Available: http://fmis.bih.nic.in/Riverbasin.html.
25. “UttarakhandStat Provides Comprehensive Information on All The Major Sectors of The State Level Consolidated Research Statistical Data.” [Online]. Available: http:// www. uttarakhand-stat.com/default.aspx
26. Indian Meteorological Department, http:/www.imd.gov.in.
27. https://www.kaggle.com/biphili/india-rainfall-kerala-flood.
28. Lyons, E.A., Y. Sheng, L.C. Smith, J. Li, H.M. Hinkel, J.D. Lenters, J. Wang, 2011. Quantifying sources of error in multitemporal, Landsat-based lake mapping, International Journal of Remote Sensing, in review.

29. MunichRENatCatSERVICE.
Availableonline:https://natcatservice.munichre.com/
30. Human cost of disasters: An overview of the last 20 years 2000-2019. Centre for Research on the Epidemiology of Disasters (CRED), UNDRR.
31. K. Chu, W. Liu, Y. She, Z. Hua, M. Tan, X. Liu, L. Gu, Y. Jia, (2018). "Modified Principal Component Analysis for Identifying Key Environmental Indicators and Application to a Large-Scale Tidal Flat Reclamation". Water. 10. 69. 10.3390/w10010069.
32. H.B. Ghadim, M. Heydari, M. Rashidi, M. Noori. (2018). "Application of Holt-Winters Time Series Models for Predicting Climatic Parameters (Case Study: Robat Garah-Bil Station, Iran)". Polish Journal of Environmental Studies. 29. 10.15244/pjoes/100496.
33. B. Hadid, E. Duviella, S. Lecoeuche. (2020). "Data-driven modeling for river flood forecasting based on a Piecewise Linear ARX system identification". Journal of Process Control. 86. 44-86. 10.1016/j.jprocont.2019.12.007.

Figures

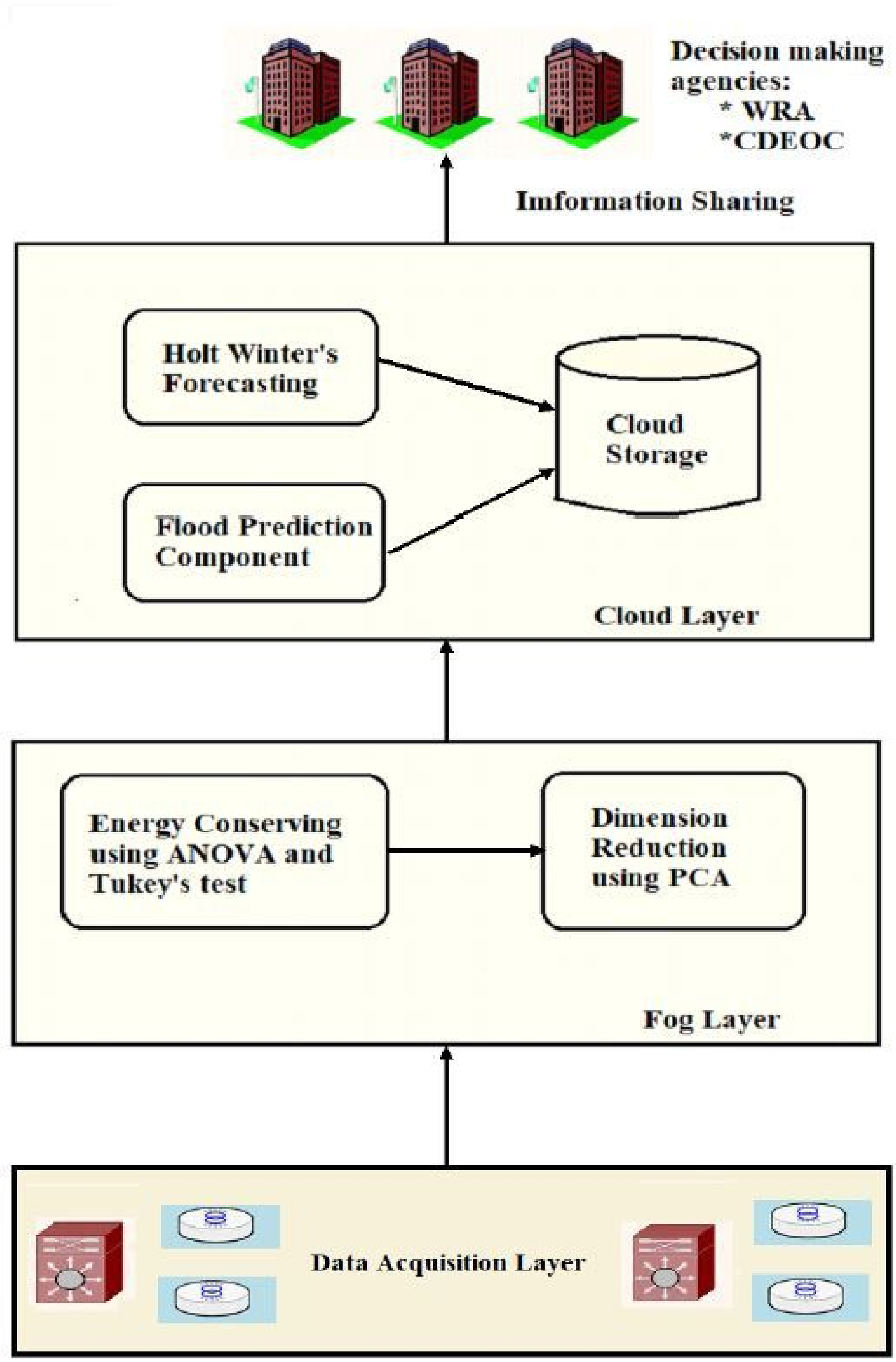

Figure 1

Proposed framework

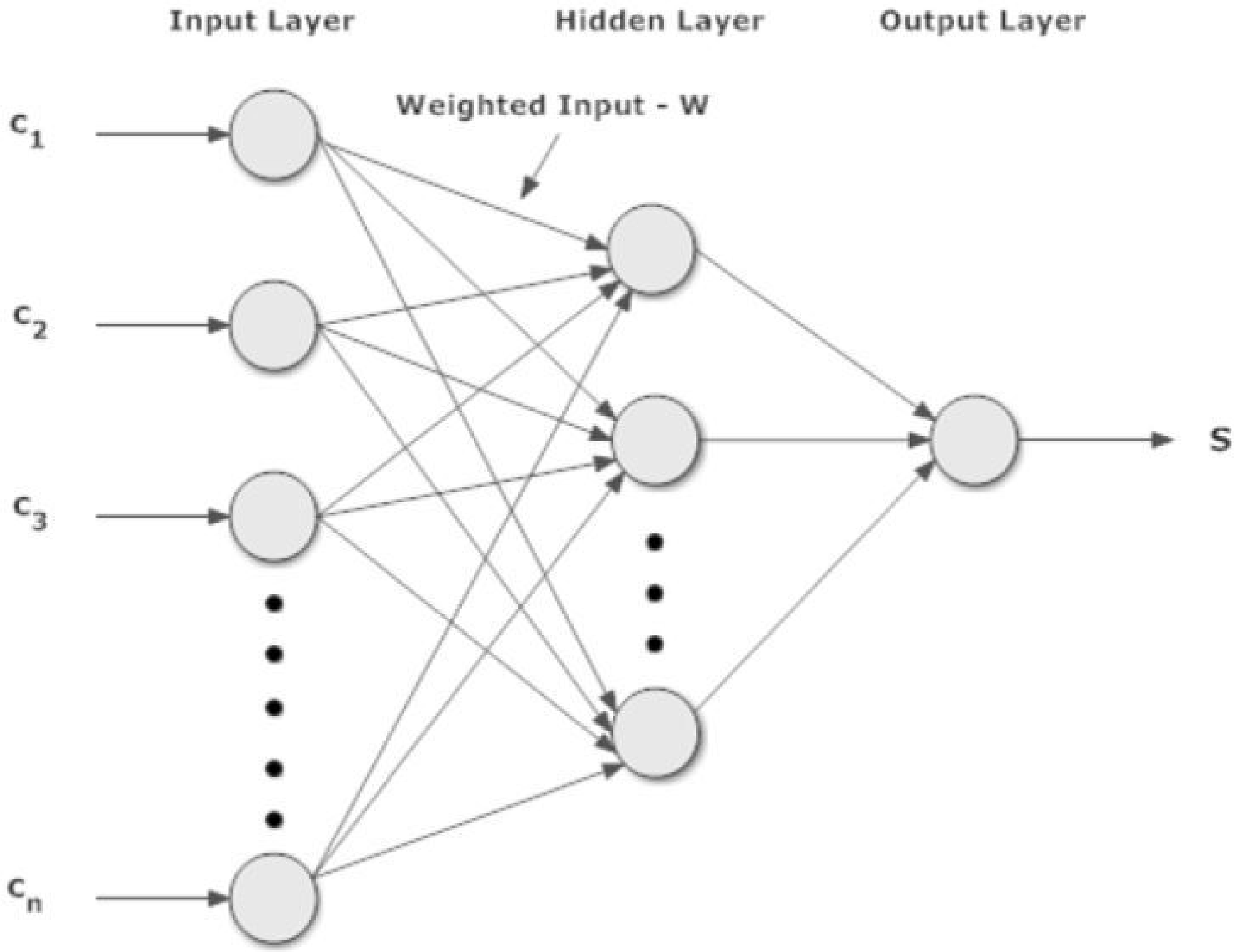

Figure 2

Configuration of Artificial Neural Network (ANN)

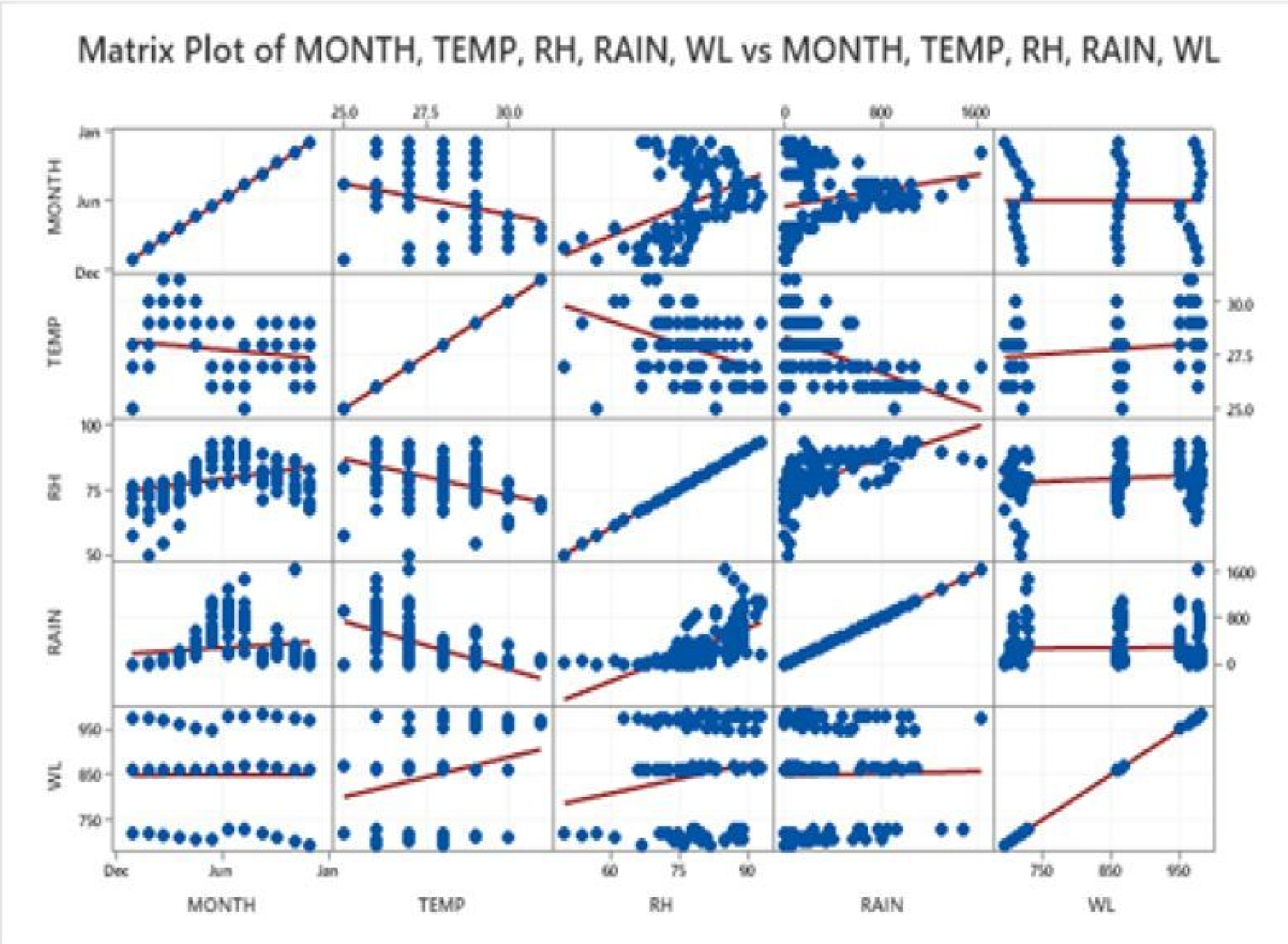

Figure 3

Correlation structure of flood attributes

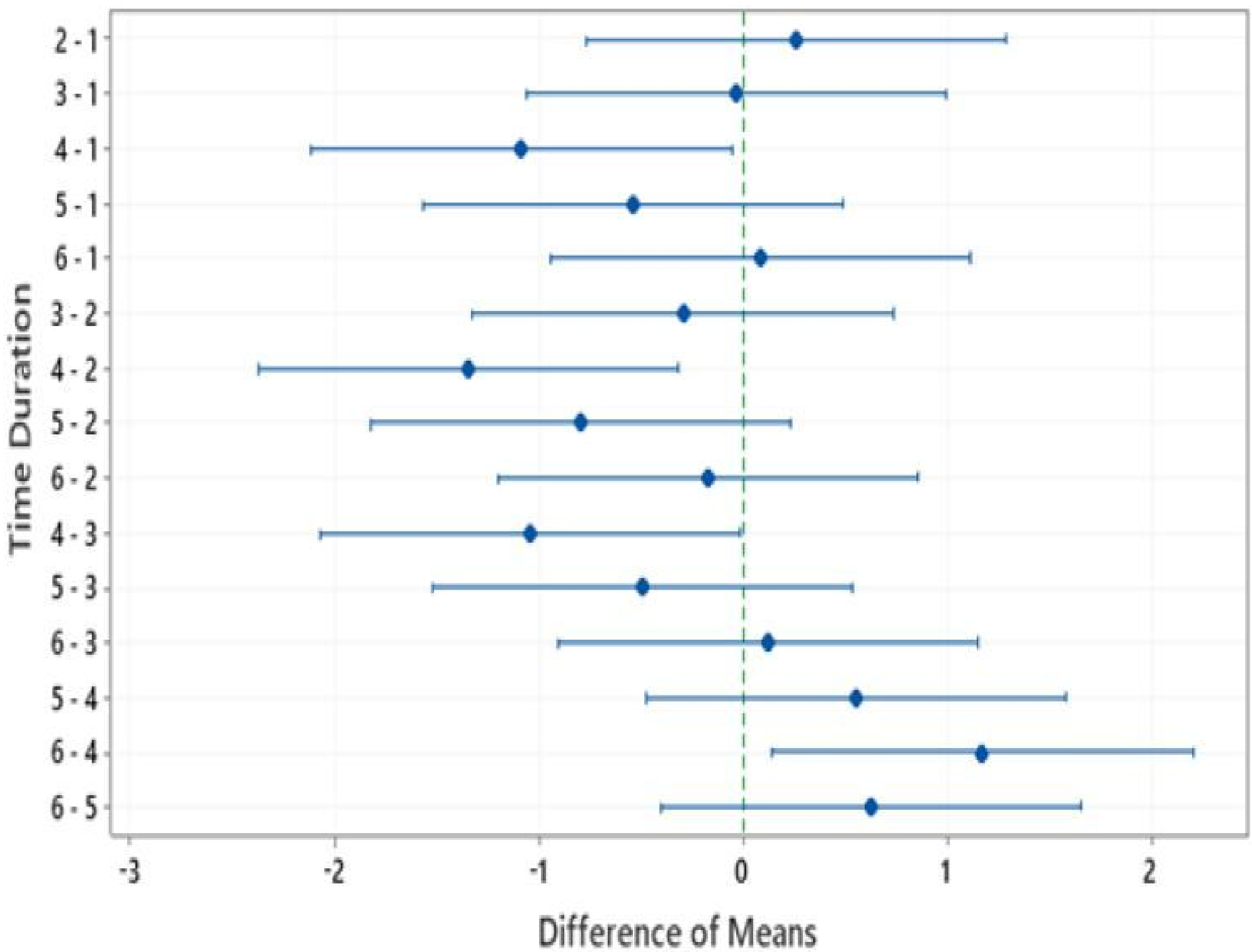

Figure 4

Tukey’s simultaneous 95% of CIs

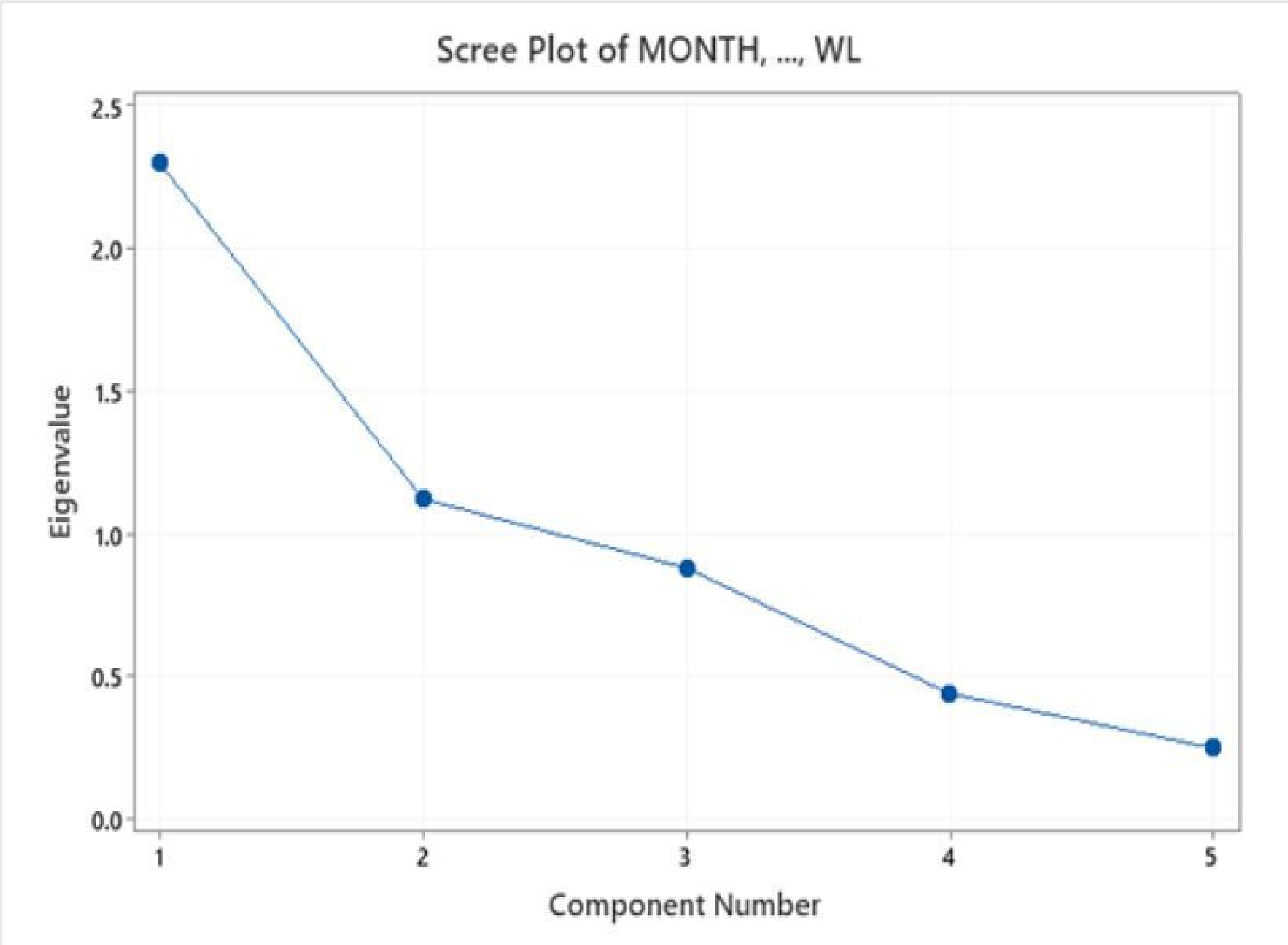

Figure 5

Scree plot for Flood related variables

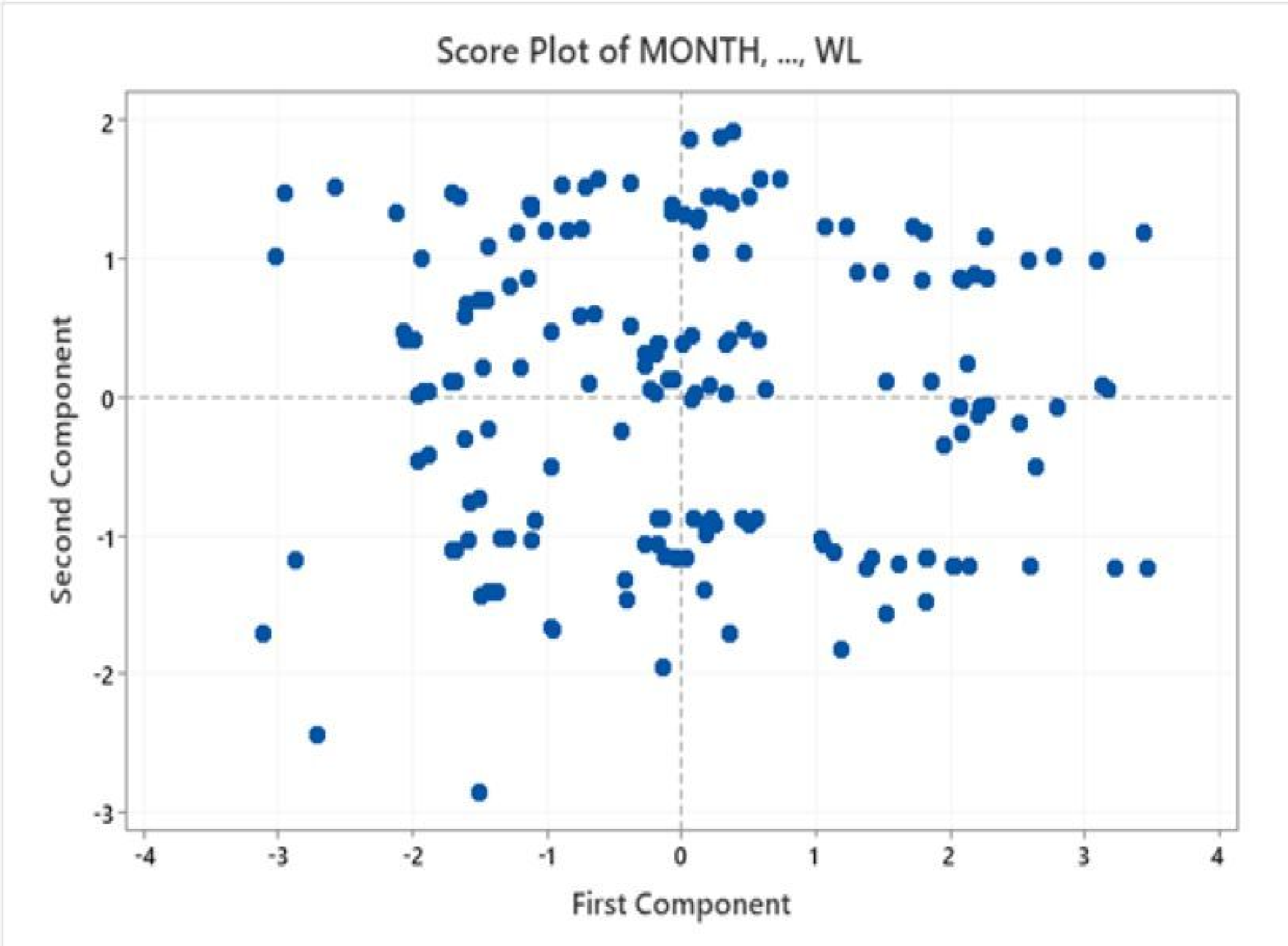

Figure 6

Scree plot of two principal components

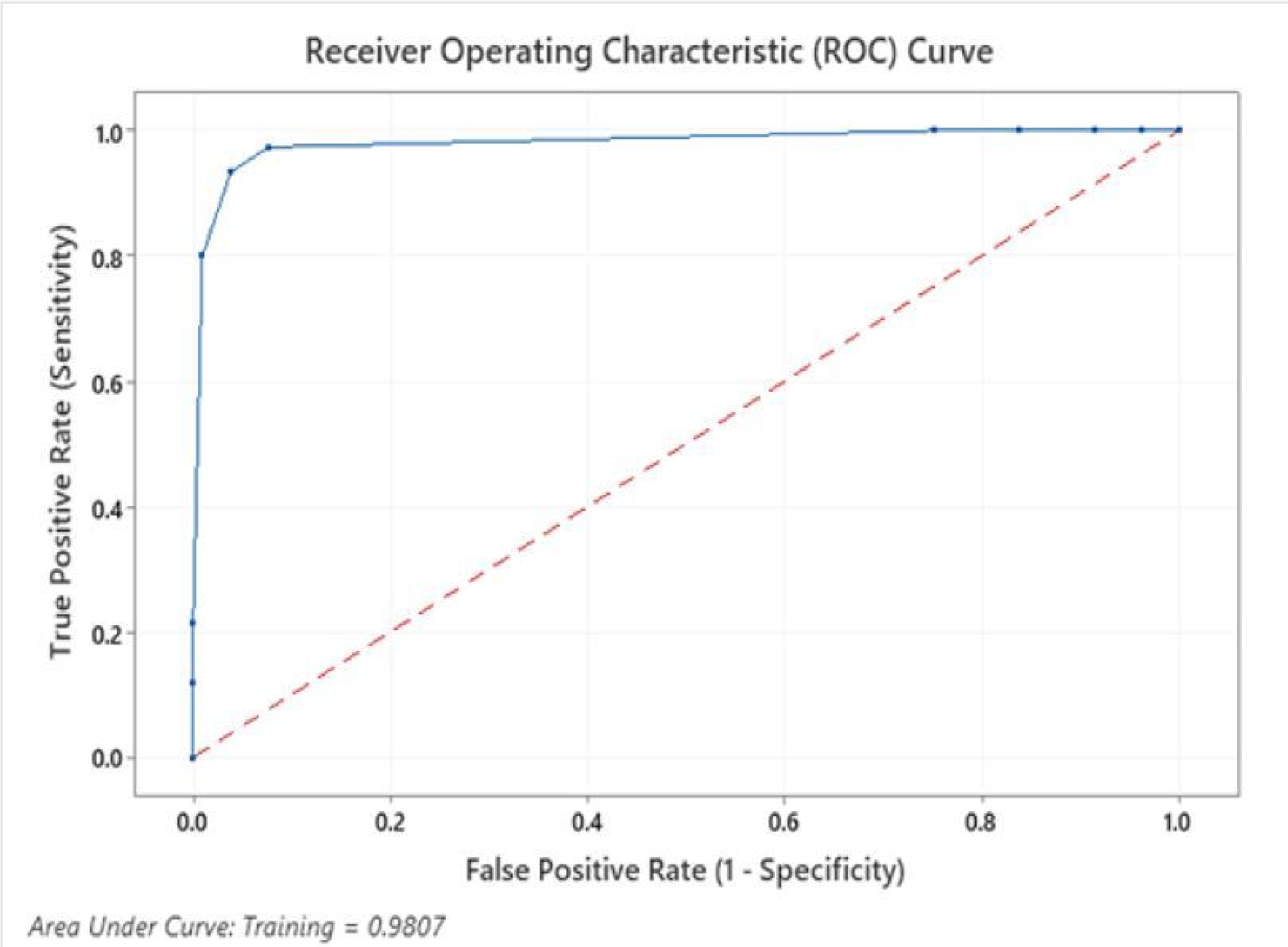

Figure 7

ROC curve for ANN

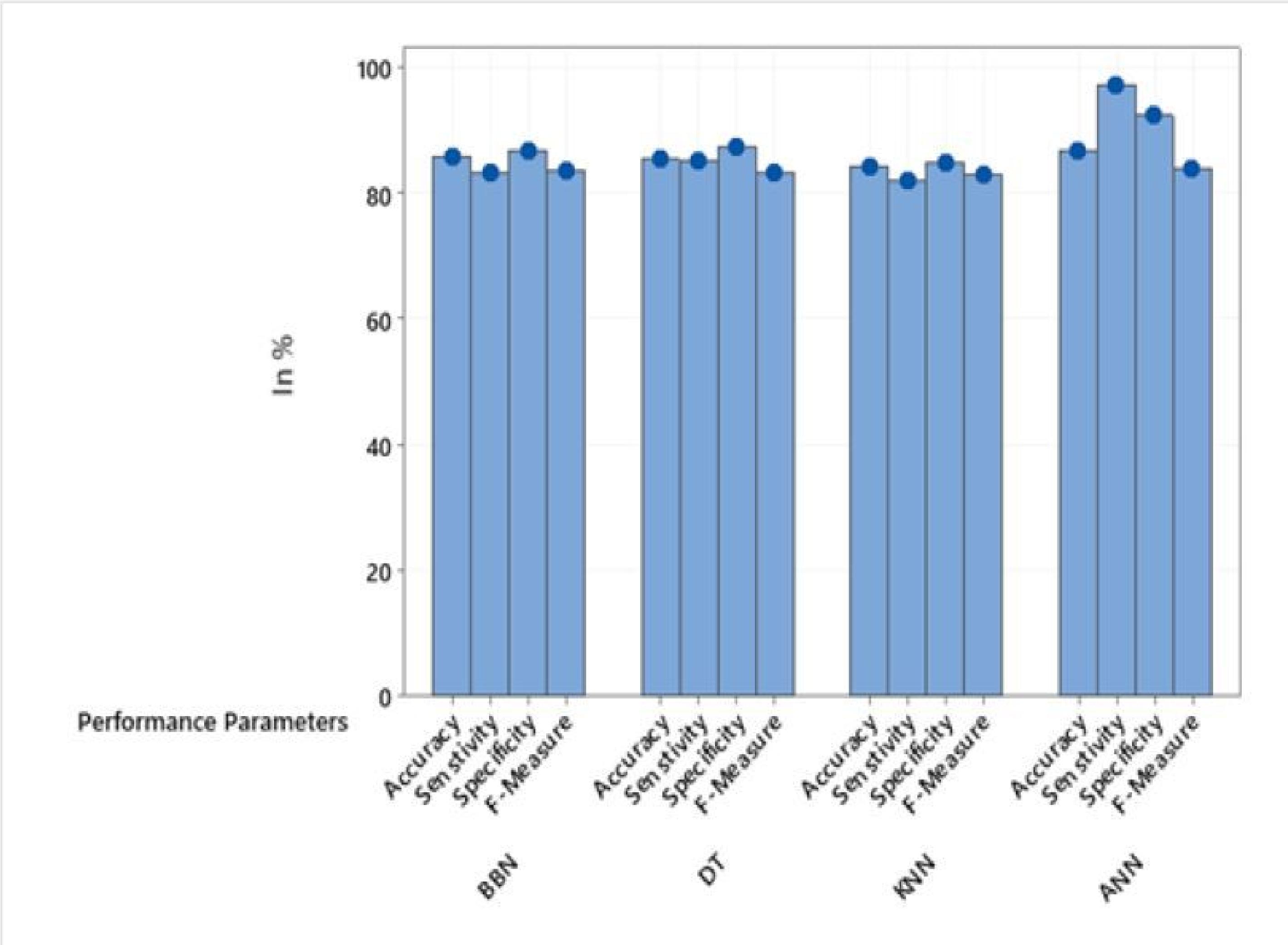

Figure 8

ANN performance analysis

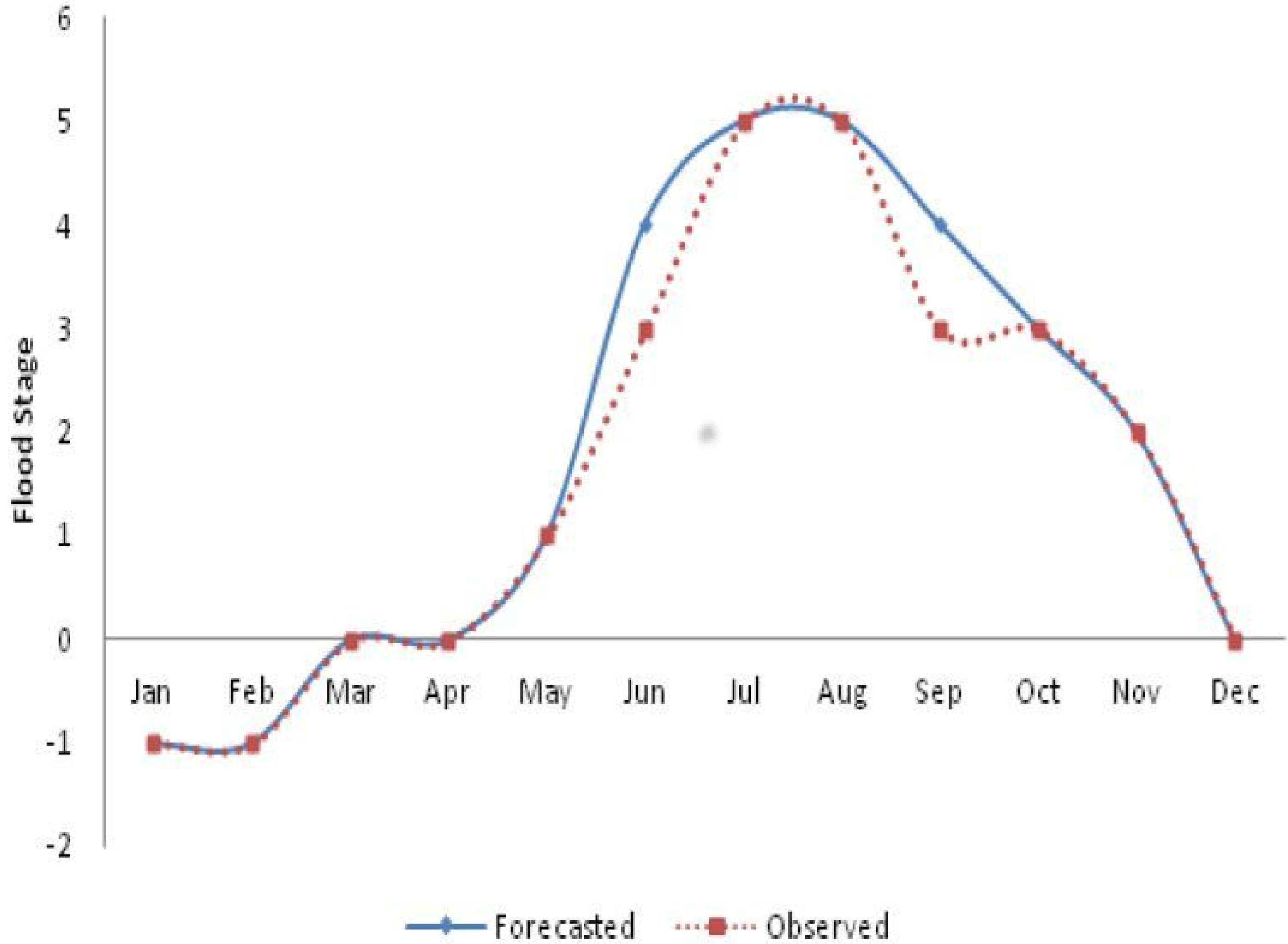

Figure 9

Flood forecasting for one month

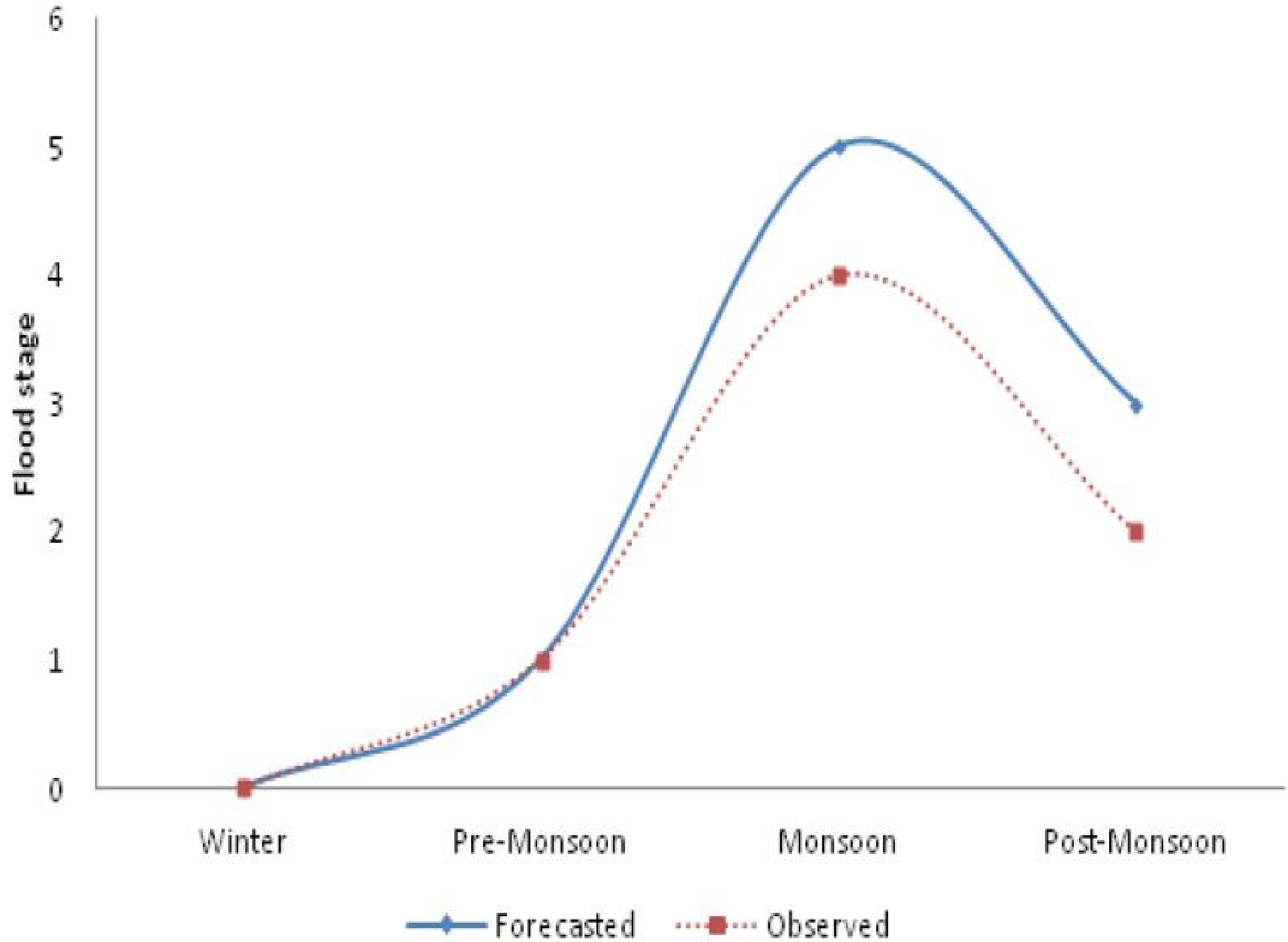

Figure 10

Seasonal flood forecasting