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Artigo

Long Term Meteorological Drought Forecasting for North-western Region of Bangladesh Using Wavelet Artificial Neural Network

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Resumo

A seca meteorológica é um evento atmosférico temporário e recorrente, originado pela falta de precipitação por um período considerável em uma determinada área. A parte noroeste de Bangladesh enfrenta anomalias de precipitação que podem se transformar em seca meteorológica e, por isso, é necessário investigar a confirmação do surgimento de seca meteorológica nesta área em um futuro próximo. Neste estudo, usando Rede Neural Artificial (ANN), este fenômeno foi investigado para uma região da parte noroeste de Bangladesh que é o distrito de Bogra. Através do estudo de previsão do índice de seca meteorológica - o Índice de Precipitação Padronizada (SPI-12 e SPI-24), verificou-se que esta região enfrentará seca meteorológica extrema em 2030. Os dados foram pré-processados através da Transformação Wavelet Discreta (DWT) antes da previsão, o que melhorou a precisão. Os principais desafios para este estudo foram prever a seca por um período de tempo mais longo (quase 16 anos). Rede neural artificial autorregressiva não linear (NAR-NN) juntamente com DWT previu com sucesso isso com uma precisão razoável de valor R > 0,8 e um erro quadrático médio (MSE) ≤ 0,05. O resultado mostra que eventos extremamente secos e úmidos ocorrerão nessa área com muita frequência, afetando o fluxo do riacho, o armazenamento do reservatório e a recarga do lençol freático.

Palavras-chave: seca meteorológica, Índice de Precipitação Padronizada, Rede Neural Artificial Wavelet (WANN), região noroeste de Bangladesh.

Previsão de Seca Meteorológica de Longo Prazo para a Região Noroeste de Bangladesh Usando Rede Neural Artificial Wavelet

Abstract

Meteorological drought is a temporary and recurring atmospheric event, originating from a lack of precipitation over a considerable period in a particular area. The north-western part of Bangladesh is facing precipitation anomalies that may turn into meteorological drought, and for this reason, it is required to investigate the confirmation of the emergence of meteorological drought in this area near the future. In this study, using Artificial Neural Network (ANN), this phenomenon has been investigated for a region of the north-western part of Bangladesh that is the Bogra district. Through the prediction study of meteorological drought index- the Standardized Precipitation Index (SPI-12 and SPI-24), it has been found that this region will face extreme meteorological drought within 2030. The data has been pre-processed through Discrete Wavelet Transformation (DWT) before prediction, which has improved accuracy. The major challenges for this study were forecasting drought for a longer lead time (almost 16 years). Non-linear autoregressive artificial neural network (NAR-NN) coupled with DWT has successfully predicted that with a reasonable accuracy of R-value > 0.8 and a mean square error (MSE) ≤ 0.05. The result shows that extremely dry and wet events will occur in that area very frequently, affecting stream-flow, reservoir storage, and groundwater recharge.

Keywords: meteorological drought, Standardized Precipitation Index, Wavelet Artificial Neural Network (WANN), North-western region of Bangladesh.

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1. Introduction

Meteorological drought is an atmospheric event where a lack of precipitation occurs in a particular area over a period of time (Farokhnia *et al.*, 2011; Mazhar *et al.*, 2020). Globally 22% of the damage caused by natural disasters is accounted for drought, and 33% of the damage in terms of the number of persons affected may be attributed to drought(Wilhite and Pulwarty, 2005). Over the past 30 years, Europe has been laid low with a variety of major drought events, most notably in 1976 (Northern and Western Europe), in 1989 and 1991 (most of Europe), as well as, more recently, the prolonged event over large parts of Europe related to the summer wave in 2003. Since 1991, the yearly average economic impact of droughts in Europe was equation image 5.3 billion, with the economic damage of the 2003 drought in Europe amounting to a minimum of equation image 8.7 billion (Feyen and Dankers, 2009). In Asia, East Asia is greatly affected by drought. North and southwest China are the highest of them (Zhang and Zhou, 2015). In South Asia, the situation is worse. The extreme drought in South Asia that has been hit in 2000-2003, and 100 million people in that region, especially in India, Pakistan, Iran, and Afghanistan have been affected (Thenkabail *et al.*, 2004).

In Bangladesh, droughts occur as frequently as averaging about once in 2.5 years. The north-western region of the country experienced the major severe droughts and was the foremost vulnerable region of the country. Droughts were also prominent within the south-western part and the Chittagong hill tracts (Mondol *et al.*, 2016). Using Standardized Precipitation Index (SPI) and Geographic Information System (GIS) technology, it has been found that 45% area of Bangladesh is in high and very high drought hazards (Rahman and Lateh, 2016). Murad (2011) prepared a combined risk map of agricultural drought risk, showed that approximately 17% area has no risk, 23% has slight risk, 30% moderate risk, and 31% has severe to very severe risk in the north-western region of Bangladesh (Murad and Islam, 2011). Moreover, 42% area of Bangladesh is in groundwater scarcity (Shahid and Hazarika, 2010).

Several indices have been developed throughout the world to evaluate the water supply deficit concerning the time duration of the precipitation shortage. Agricultural drought has been estimated through the ground-based drought index Standardized Precipitation and Evapotranspiration Index (SPEI) (Feng *et al.*, 2019), Crop Moisture Index (CMI) (Bordi and Sutera, 2007), Reconnaissance Drought Index (RDI) (Tsakiris *et al.*, 2007). In hydrological drought monitoring, Drought Early Warning System (DEWS) coupled with Standardized Runoff Index (SRI) (Hatmoko *et al.*, 2015), Streamflow Drought Index (SDI) (Nalbantis and Tsakiris, 2009; Shamshirband *et al.*, 2020), Surface Water Supply Index (SWSI) (Shafer and Dezman, 1982) and many other indices have been developed and effectively applied. Several indices have been developed and used worldwide, including in Bangladesh, to estimate meteorological drought. Among them, the SPI (McKee *et al.*, 1993; Mondol *et al.*, 2016; Mortuza *et al.*, 2019; Murad and Islam, 2011; Rafiuddin *et al.*, 2011; Rahman and Lateh, 2016; Shahid and Behrawan, 2008; Shahid and Hazarika, 2010), Palmer Drought Severity Index (PDSI) (Dash *et al.*, 2012), and Effective Drought Index (EDI) (Park *et al.*, 2015)are noteworthy. However, SPI is most widely utilized for its drought characterization capability on different time scales, such as short-term drought (1 to 3 months), mid-term drought (6 to 9 months), and long term (12 to 24 months) (Hosseini-Moghari and Araghinejad, 2015). Besides, its simplicity and flexibility in the calculation and efficient characterization capability (Djerbouai and Souag-Gamane, 2016) make it more acceptable to the users. Only one input parameter that is precipitation data, is required to calculate this index.

Very few studies have been conducted to forecast the future meteorological drought hazard in that north-western region of Bangladesh. Most of the research has been conducted on the characterization of meteorological drought previously happened. And for this reason, it is required to investigate future meteorological drought hazards. Bogra is a major drought-prone district of that region that has a high population density. This study's primary aim is to predict the future long-term meteorological drought condition of Bogra district, the north-western part of Bangladesh, until 2031. Although there are 16 districts in the north-western region of Bangladesh, long historical, continuous data, which is the preliminary requirement for drought forecasting, has not been available for those districts except Bogra. Due to the widespread use and availability of input parameter data, SPI has been chosen as a drought index for this study. A larger dataset of SPI which has been generated from long historical precipitation data has been provided more excellent prediction capability with high accuracy. Different methods have been used throughout the world to forecast meteorological drought indices. They are logistic regression (Meng *et al.*, 2017; Stagge *et al.*, 2015) logistic regression along with statistical down-scaling (Tatli, 2015), time series analysis-Auto-Regressive Integrated Moving Average (ARIMA), Seasonal Auto-Regressive Integrated Moving Average (SARIMA), Recursive Multistep Neural Network (RMSNN), Direct Multistep Neural Network (DMSNN), Support Vector Regression (SVR), Wavelet Support Vector Regression (W-SVR) (Belayneh *et al.*, 2016), Artificial Neural Network (ANN), Wavelet Artificial Neural Network (W-ANN) (Oger *et al.*, 2012; Taormina and Chau, 2015) and many others. Time series stochastic models (ARIMA & SARIMA) can't forecast drought for a long term with reasonable accuracy (Mishra and Desai, 2005). Besides of being linear models, time series models have a lower capability to detect non-stationarities in data (Kim and Valdés, 2003). Machine learning-based modeling approaches were introduced to solve this problem. Recursive multistep neural network (RMSNN) and direct multistep neural network (DMSNN), which are machine learning approaches, cannot forecast drought for more than one month and four months, respectively (Mishra and Desai, 2006). But for long term drought forecasting, Belayneh *et al.*, (2014) have shown that W-ANN has better accuracy than SVR, W-SVR, ANN & ARIMA models through the lower root mean square error and the higher regression co-efficient value. As the primary objective of this study is to forecast the meteorological drought for a longer lead time and to identify the drought attribute, W-ANN has been adopted in this research for better prediction. As the drought event is a nonlinear problem and a single feature (SPI) has been used as the input parameter, the nonlinear autoregressive artificial neural network (NAR-NN) has been used in this study. NAR-NN is a multilayer perception (MLP) network, which is one of the basic neural network models, and MLP also carries greater capacity to forecast SPI than any other ANN method (Choubin *et al.*, 2016). Although there is another MLP network that is a nonlinear autoregressive artificial neural network with external input-output (NAREX-NN) that requires multiple features for the input parameter and for this reason only NAR-NN has been used here. Artificial neural network without pre-processing of data has lower prediction capability. Wavelet transformation is an effective pre-processing tool that significantly increases forecasting efficiency. Due to simplicity and short computation time Discrete Wavelet Transformation (DWT) is more convenient among all wavelet transformations (Djerbouai and Souag-Gamane, 2016). And for this reason, WANN that is ANN coupled with DWT has been applied in this study.

2. Materials and Methods

2.1. Study area

The study area is the Bogra district under the Rajshahi Division in the north-western region of Bangladesh (Fig. 1). The area covers the 2911 km^2 area, where the entire north-western part of Bangladesh covers 5498 km^2 (Rahman *et al.*, 2009). Purposively, this district has been selected for its widespread agricultural and economic activities and availability of an extensive set of chronological data. It has one rain gauge station in this area. That rain gauge station data has been used in this study.

2.2. Data

In this study, the Bogra rain gauge station's daily precipitation data has been used as raw data. The precipi-

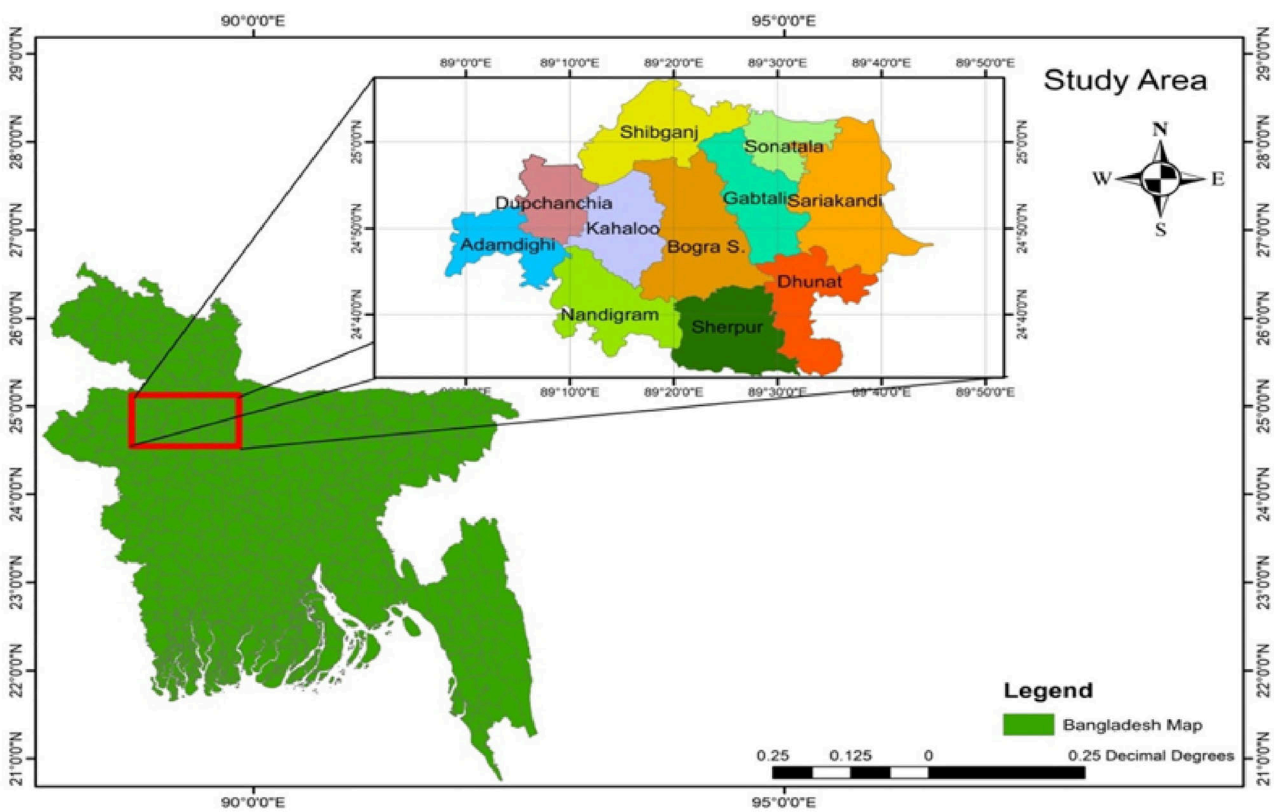

Fig. 1 - Study area map.

tation data has been collected from a secondary source, Bangladesh Meteorological Department (BMD) website ("Bangladesh Climate Data Portal," 2020.). Continuous precipitation data, which is mandatory for SPI analysis, has been available from 1948 to 2014 for that region. Missing data reduces the confidence of the result (Svobodia *et al.*, 2012). There are almost 67 years of daily precipitation data, which contains a set of 24,796 data. For the lack of continuous data, some recent years of data have not been included in the dataset, but due to using a large dataset, the probability of creating significant changes for this deduction in prediction study has been very less. From this precipitation data, the drought index standardized precipitation index (SPI) for a monthly basis has been calculated through transmitting that precipitation data into gamma distribution function.

2.3. Process flow

The daily precipitation data collected from the BMD database have converted into monthly drought index SPI (SPI-12 and SPI-24). Those SPI-12 and SPI-24have been decomposed through the wavelet (2D) decomposition method and have got three series for each SPI series (one approximation-a2, two details-d1, d2). Those three series have been run into the artificial neural network through simulating in different network architecture for prediction. After simulation, the most accurate prediction model and three predicted series (predicted-a2, predicted-d1, predicted-d2) for each SPI series have been found. Finally, those three predicted for each SPI series have been combined further to get predicted SPI. The entire process has shown in Fig 2.

2.4. Standardized Precipitation Index (SPI)

The SPI permits determinative the rarity of a drought or associate degree anomalously wet event at a selected duration. For any location, that features a precipitation record which can be calculated through gamma distribution function (Hosseini-Moghari and Araghinejad, 2015). That gamma probability density function is defined in Eq. (1):

$$f(x) = \frac{1}{\beta^x \Gamma(x)} x^{\alpha - 1} e^{\frac{-x}{\beta}}, x > 0 \tag{1}$$

where α is a shape factor, β is the scale factor of distribution, and Γ(*x*) is a gamma function, which is defined at Eq. (2):

$$\Gamma(x) = \int_0^\infty y^{\alpha - 1} e^{-y} dy \tag{2}$$

Here optimized coefficients of α and β are calculated by the following 3rd, 4th and 5th equation:

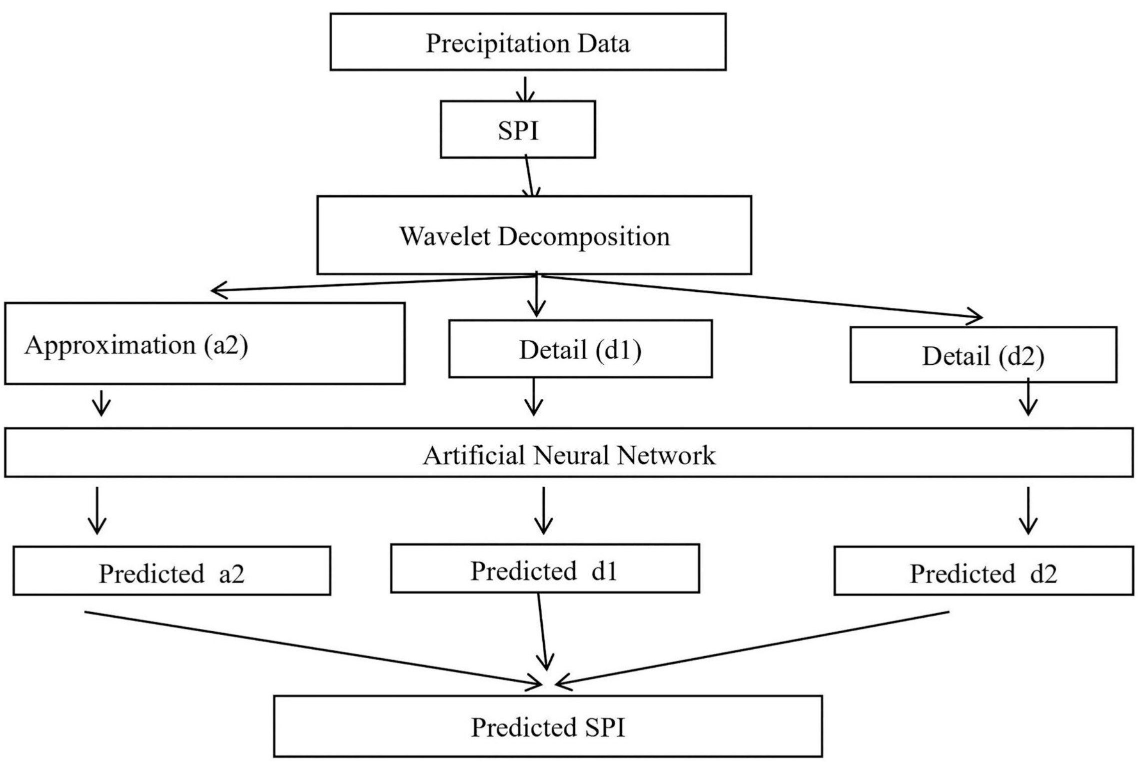

Fig. 2 - Process flow diagram.

$$\hat{\alpha} = \frac{1}{4A}\left[1 + \sqrt{1 + \frac{4A}{3}}\right] \tag{3}$$

$$A = \ln(\overline{x}) - \frac{\sum \ln(\overline{x})}{n} \tag{4}$$

$$\hat{\beta} = \frac{\hat{x}}{\hat{\alpha}} \tag{5}$$

In the calculation of A, n is the number of precipitation events that occurred. In this calculation, the gamma cumulative distribution function is used through Eq. (6).

$$F(x) = \int_0^x f(x)dx = \frac{1}{\hat{\beta}^{\hat{\alpha}}\Gamma(\hat{\alpha})}\int_0^x x^{\hat{\alpha}-1}e^{-x/\hat{\beta}}dx \tag{6}$$

Gamma distribution function is not defined for zero value ($x = 0$). But there might be precipitation zero value. And for that reason, the cumulative gamma density distribution function used that is mentioned in Eq. (7).

$$H(x) = q + (1 - q)F(x) \tag{7}$$

Here q is the probability of precipitation is equals to zero. After calculating $H(x)$, it has been passed into the standardized cumulative normal distribution because the SPI is a variable of the standardized normal distribution function. Here its cumulative probability and the cumulative probability of the target variable at gamma distribution are the same in amount (Hosseini-Moghari and Araghinejad, 2015). SPI can be calculated on different time scales, which is called accumulation time. Among them, SPI calculated on 12 (SPI-12) and 24 (SPI-24) months accumulation time has been chosen for this study because of their representativeness of long-term drought (Belayneh *et al.*, 2016). The drought categories through SPI value are given in Table 1.

Table 1 - SPI drought category (McKee *et al.*, 1993).

SPI Value	Category
2.00 and above	Extremely wet
1.5 to 1.99	Very Wet
1.00 to 1.49	Moderately Wet
-0.99 to 0.99	Near normal
-1.0 to -1.49	Moderately Dry
-1.5 to -1.99	Severely Dry
-2.00 and less	Extremely Dry

2.5. Wavelet transformation

Wavelet transformation is a mathematical tool to deal with local discontinuities of time series data that is an effective pre-processing tool to compress or de-noise signal and provide time-series representation of a transformed signal (Belayneh *et al.*, 2014). Although there are several data pre-processing methods such as linear transformation, statistical standardization, sigmoidal transformation, etc. (Kuzniar and Zajac, 2015), wavelet transformation has the greater capability to deal with breakdown points, discontinuities, local minima, and maxima that other pre-processing methods do not have (Adamowski and Sun, 2010). For this reason, wavelet transformation has been chosen for this study. There are two types of wavelet transformation or wavelet decomposition. They are Continuous Wavelet Transformation (CWT) & Discrete Wavelet Transformation (DWT). CWT is rarely used in prediction due to its complexity and long computation times. But DWT is simple to implement and requires less computational time (Nason and Sachs, 1999). That's why in this study DWT has been used for pre-processing of data that is defined in Eq. (8).

$$\psi_{jk}(t) = \frac{1}{\sqrt{|s_0^j|}}\psi\left(\frac{t - k\tau_0 s_0^j}{s_0^j}\right) \tag{8}$$

Here ψ is the mother wavelet, j and k are integers and S is a scale parameter. They control both scale and translation, while $S_0 > 1$ is a fixed dilation step translation factor and t is the time step (Cannas *et al.*, 2005). In this study, a "Haar" wavelet has been used to prevent any future information from being used during decomposition. Morlet and Daubechies wavelet might be feasible alternatives to Haar wavelet, but, being a low-pass filter concentrated with the narrowest support band, Haar wavelet has a better localization property than others which is appropriate for detecting changes within time series (Maheswaran and Khosa, 2012).

At the wavelet analysis, the decomposition level has been calculated through the following equation L = int[log (N)], where the L is the level of decomposition, N is the length of the signal. In the dataset, there are the signals of monthly SPI value of 798 months that detect the level L = 2 (Belayneh and Adamowski, 2013).

The wavelet transformation process has been decomposed the original SPI signal to approximation subsignal(a) at level L and detail sub-signal (d) from level 1to L(Deo *et al.*, 2016). The details(d) information has been produced through passing the data at high pass filter and approximation(a) information has been generated through low-pass filter (Djerbouai and Souag-Gamane, 2016). If the SPI signal is S, then S = a2(approximation sub-signal) + d1(detail sub-signal 1) + d2(detail sub-signal 2).

2.6. Artificial neural network

From several artificial neural network algorithms, the Non-linear Auto-regressive Neural network (NARNN) has been used in this study. Periodically sampled data that is equally spaced can be analyzed through this method easily

(Walker, 1931). In this study, predictive analysis has been used through NAR neural network to predict future drought conditions of Bogra. The non-linear auto-regressive model is defined for an order $p \in \mathrm{N}$ is defined in Eq. (9):

$$f(t) = F(f(t-1), f(t-2), ..f(t-p)) + \varepsilon(t) \quad (9)$$

Here $f(t)$ is the prevalent value and, similarly $f(t - i)$, i =1, 2, …, p is the i^{th} previous value of the given time series, F is a nonlinear function defining the dependence of the prevalent value on the previous p values of the time series, ε is a white noise. It indicates that all the current value depends on the p values. The major aim of all statistical analysis is the approximation with minimal error of F. In the simplest case, F is a linear function that is provided in Eq. (10):

$$f(t) = F_0 + \sum_{i=1}^{p} F_i f(t-1) + \varepsilon(t) \quad (10)$$

Here F_0 and F_i, (i = 1,2, …, p) are constants(Raturi and Sargsyan, 2018). The feed-forward method is used at a nonlinear autoregressive model which is given in Eqs. (11) and (12).

$$\hat{f}(t) = \hat{F}(f(t-1), f(t-2), \ldots\ldots f(t-p)) \quad (11)$$

$$\hat{f}(t) = \alpha_0 + \sum_{i=1}^{N} \alpha_i A\left(\beta_k + \sum_{k=1}^{p} w_{ik} f(t)\right) \quad (12)$$

β_k are the biases, α_i, i = 1,2 …, N are constants, w_{ik} are the weights, A is the activation function, (Tealab *et al.*, 2017).

In the Eq. (9), $f(t-1), f(t-2), \ldots\ldots f(t-p)$ are the feedback delay. The neural network architecture depends on that feedback delay along with the hidden neuron. Any change of these two parameters can change the network architecture. To get the best performance, the number of hidden layers or neurons per layer has been optimized through a trial-and-error procedure. A higher number of neurons make the system complex and a lower number of neurons can reduce the generalization capability (Ruiz *et al.*, 2016).

2.7. Model performance analysis

The coefficient of determination (R) and mean square error (MSE) has been used to determine the performance of the model.

$$R = \frac{\sum_{i=1}^{n} (O_i - \overline{O})(P_i - \overline{P})}{\sqrt{\sum_{i=1}^{n} (O_i - \overline{O})^2}\sqrt{\sum_{i=1}^{n} (P_i - \overline{P})^2}}$$

$$MSE = \frac{\sum_{i=1}^{n} (O_i - P_i)^2}{n}$$

where n = number of samples, O_i and P_i are observed and predicted values and $\overline{O}$ and $\overline{P}$ are the means of observed and predicted values (Binieli, 2018).

3. Result

The SPI-12 (Fig. 3) and SPI-24 (Fig. 4) data, calculated from precipitation data of 1948 to 2014, have been

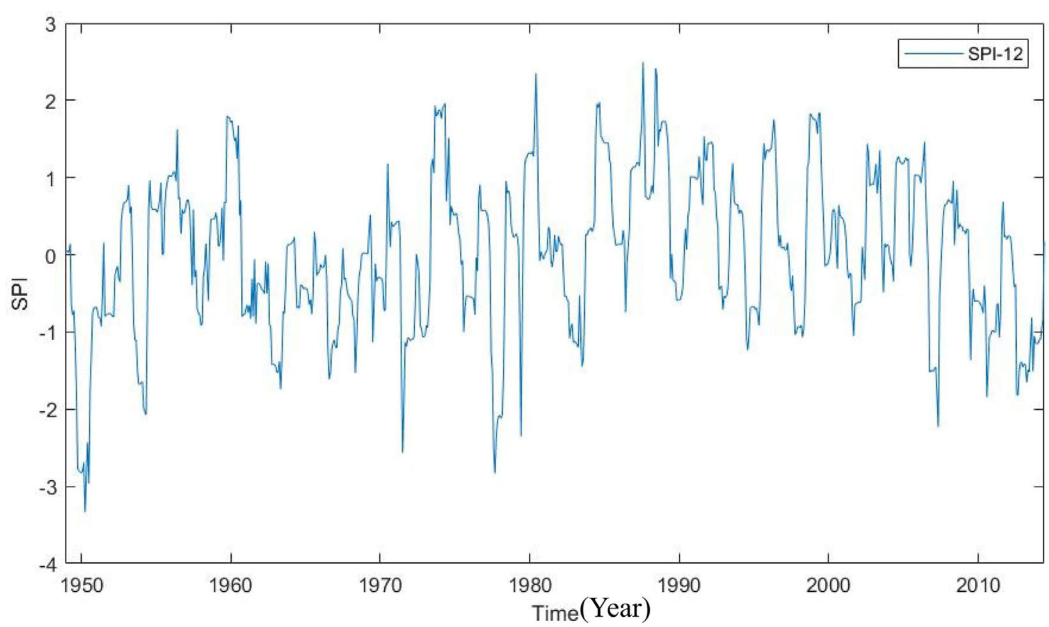

Fig. 3 - SPI-12 from Dec-1948 to Jun-2014.

pre-processed through wavelet analysis, which have divided every SPI series into 3 distinct series, that are 1 approximation (a2) and 2 details (d1, d2) (Fig. 5, Fig. 6). These approximation and details series have been simulated as training, validation, and test data to build the prediction model and have found predicted approximation

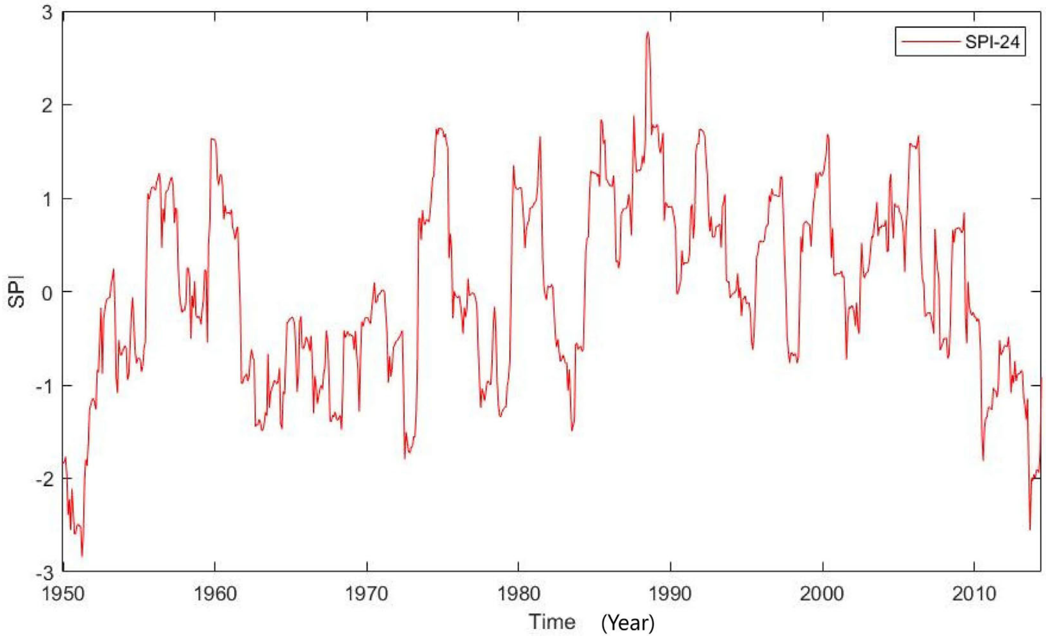

Fig. 4 - SPI-24 from Dec-1949 to Jun-2014.

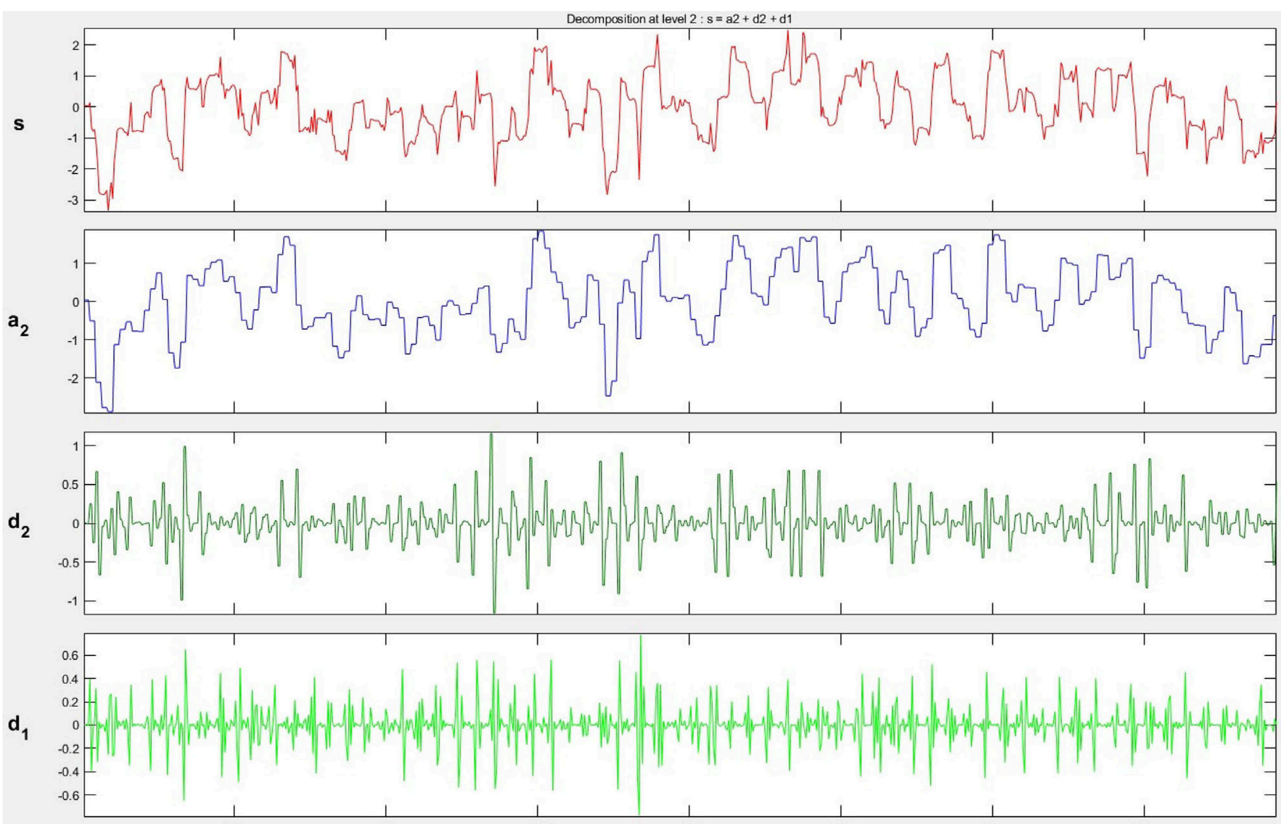

Fig. 5 - Wavelet transformation of SPI-12.

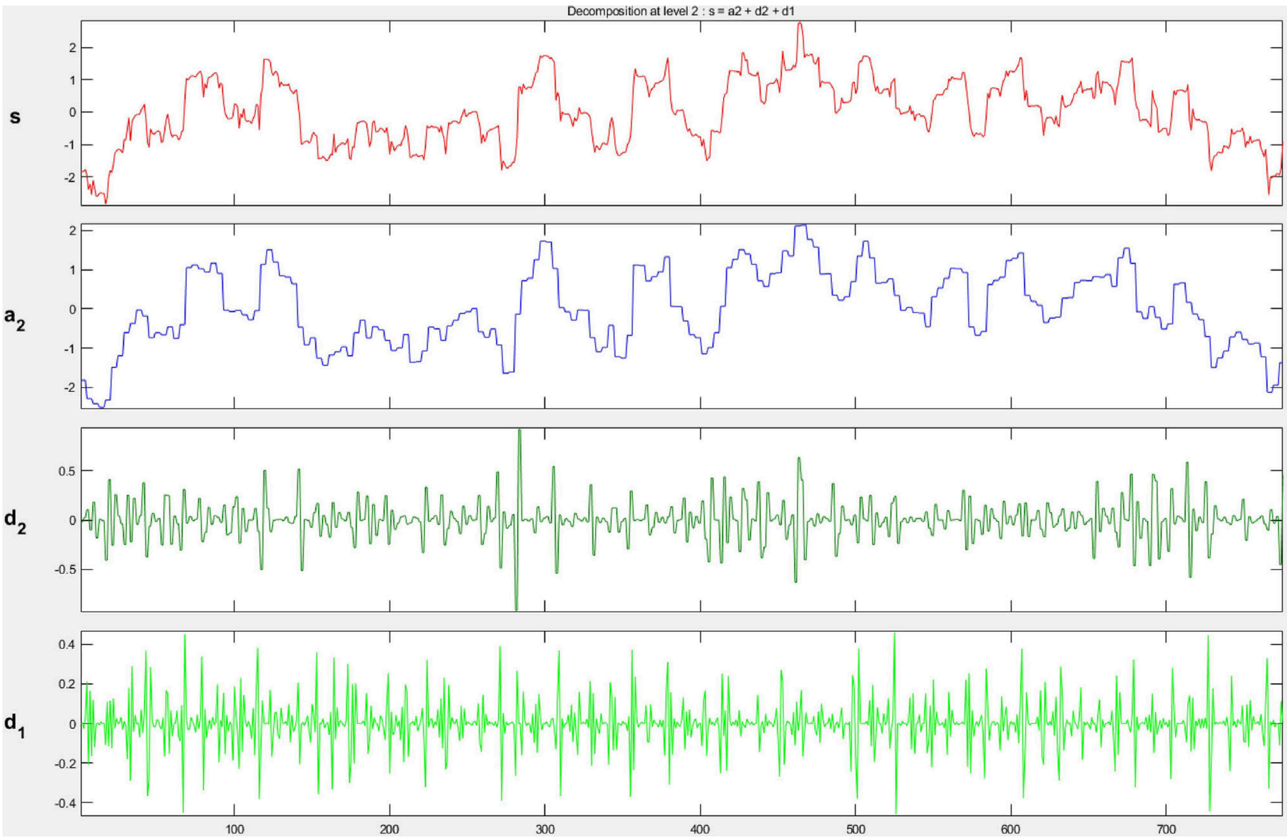

Fig. 6 - Wavelet transformation of SPI-24.

and details series. After combining predicted approximation and details series for each SPI series, predicted SPI-12 (Fig. 7) and SPI-24 (Fig. 8) have been found, where the prediction is until February 2031.

Before 2014 the extreme dry and wet conditions happened very less time, and the intensity range was 2.5 to -3.3 for SPI-12 (Fig. 3), and 2.8 to -2.8 for SPI-24 (Fig. 4). But after 2000 (Fig. 3, Fig. 4), it has observed a sharp inclination and declination. For the predicted result (Fig. 7, Fig. 8), the range of SPI value might become 11.08 to -9.3 for SPI-12 and 12.1 to -12.8 for SPI-24 within 2031.

Before 2010, the months were moderate dry to very wet conditions, sometimes it became extremely dry to

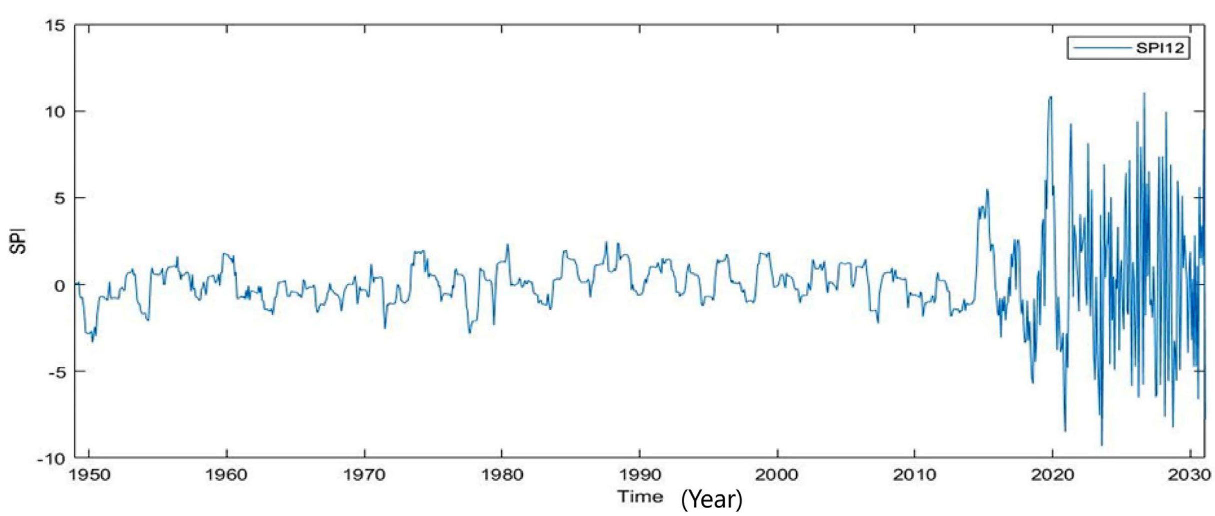

Fig. 7 - SPI-12 from Dec-1948 to Feb-2031.

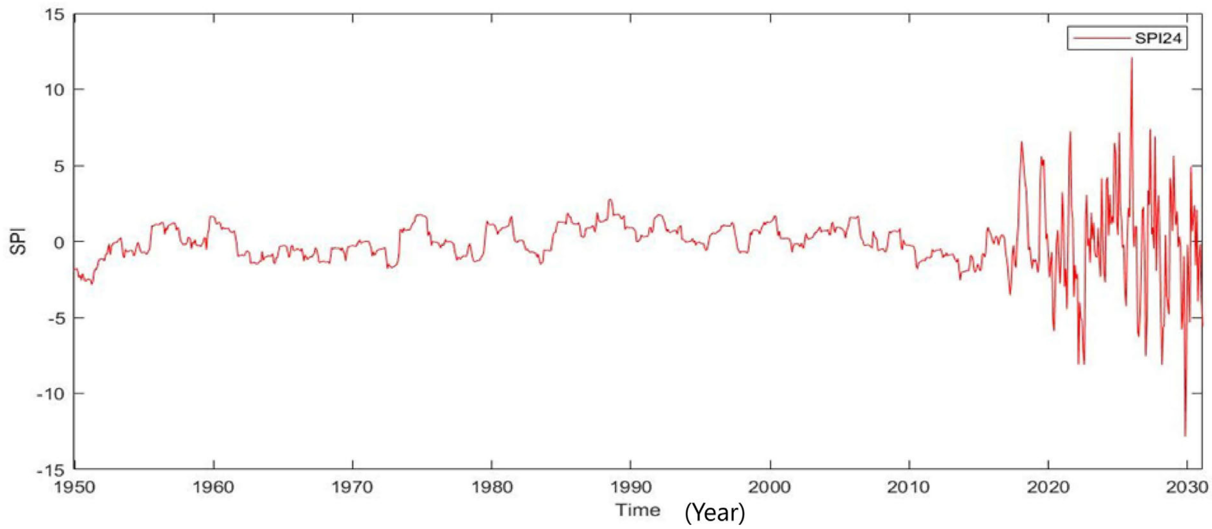

Fig. 8 - SPI-24 from Dec-1949 to Feb-2031.

extreme wet conditions, but these conditions were not frequent. But through the predicted result (Fig. 7, Fig. 8), it has been identified that both SPI-12 and SPI-24 within 2031 might be extremely dry to extremely wet conditions for a persistent time. The transition from extremely dry to extremely wet months might also be very frequent.

From the regression analysis, it has been found that (Table 2), all the coefficient of determinations or *R*-values are very close to 1, which represents the higher accuracy of the model. The performance or mean square error (MSE) is very close to 0 (Table 2), representing the model's higher prediction capability. The accuracy level of the model and higher forecasting capability indicates that a significant probability of predicted result occurs in a specified timeline.

4. Discussion

4.1. Prediction of SPI-12

Meteorological drought with 12 months accumulation time affects stream-flow and reservoir storage, and similarly, 24 months accumulation time impacts groundwater storage (Svobodia *et al.*, 2012). The result predicted through the artificial neural network shows that the future long term meteorological drought conditionSPI-12 (Fig. 7) and SPI-24 (Fig. 8) shall be more uneven within 2031. Extreme dry and extreme wet months rather than the previous12 and 24 months accumulation time shall be faced by Bogra very frequently, and the dryness and wetness shall be too high within 2031. This high-intensity dryness and wetness shall directly affect the stream-flow, reservoir storage, and groundwater recharge of that region. Sharp changes in SPI shall be visible within 2031, which indicates the probability of flash drought. Flash drought is a drought that has a rapid escalation of drought situations without sufficient early warning. It raises the risk of food and water security, environmental sustainability, or perhaps human mortality because of low predictability and their potential for triggering extreme compound events with heatwaves. It also significantly reduces the soil moisture through high evapotranspiration (Yuan *et al.*, 2019). Due to flash drought, Bogra and its adjacent regions may also face such kinds of environmental issues.

A significant positive correlation exists between SPI and Stream-flow Drought Index (SDI) (Moglen, 2015).

Table 2 - Prediction model accuracy.

Neural Network architecture (feedback Delay, hidden neuron)	SPI	Decompositions (haar-level2)	Performance (Mean square Error)	Regression-R (all)
1:40,50	SPI-12	a2	0.05	0.96843
		d1	0.0117	0.82
		d2	0.0139	0.92034
	SPI-24	a2	0.0055	0.81788
		d1	0.0131	0.86943
		d2	0.0242	0.98583

And for this reason, it can be assumed that a significant reduction of SPI will reduce stream-flow significantly and may dry the surrounding catchment area for a certain period. The major streams of the Bogra region are the Meghna river, its tributaries, and its distributaries. The SPI-12 data used as input (Fig. 3) shows that the number of extreme drought events in that region is very less in amount. For that reason, the surface water level or stream-flow of that region has not been changed significantly, although the surrounding region of Bogra has been faced stream-flow shortage (Khan and Islam, 2018). But within 2031, that region shall face extreme dry conditions very frequently. Indeed, the stream-flow shall be reduced in response to the predicted SPI-12 or, more specifically, SPI-SDI relationship.

In Bogra district, 43460.3 ha area is water-body, which includes streams and reservoir storages (Rahman *et al.*, 2009). Extreme dryness reduces the water holding capacity of reservoirs (Melo *et al.*, 2015). That situation may appear for the reservoirs in that region. Excessive wetness may create an overflow of reservoirs.

4.2. Prediction of SPI-24

Drought, characterized by 24 months accumulation time, affects groundwater recharge. Due to moderately dry and wet conditions in the north-western region characterized through SPI-24 value, groundwater deficit conditions arose in this area in previous days (Shahid and Hazarika, 2010). Extreme dryness and wetness predicted through SPI 24 (Fig. 8) within 2031 shall reduce groundwater recharge, which will decrease the groundwater level significantly. The research conducted by Abdullah(2014) also supports this claim, and they also have predicted that the Bogra region shall face the depletion of the artesian aquifer from 0 to 2.92 cm/year for mean depth and 1.2 cm/year to 14.45 cm/year for maximum depth within 2030.

Frequent change of dryness and wetness condition in the months in a rapidly intensifying manner is a characteristic of flash drought. Such types of drought generally create moisture shortage in soil and increase the evapotranspiration rate, which results in soil quality loss (Yuan *et al.*, 2019). In the extremely wet months near future, when the precipitation will be higher, degraded soil due to flash drought will increase the runoff and decrease the groundwater recharge because the infiltration capacity of water of that soil shall continuously be reduced.

Moreover, the reduction of groundwater at the adjoining aquifer shall reduce the base-flow supported by SPI 12 prediction (Fig. 7) (Mukherjee *et al.*, 2018). Using weighted criteria through the analytical hierarchy process (AHP), Hoque *et al.*, (2020), also validated that this region is in the extreme to severe drought vulnerability.

Reduction of stream-flow, reservoir storage level, and groundwater recharge will be expected from extreme meteorological drought conditions characterized through SPI-12 and SPI-24, creating potable and agricultural water crises in that area.

WANN method has shown a higher accuracy level in predicting SPI 12 and SPI 24 in the north-western part of Bangladesh, with R-values of more than 0.8 and MSE-values less than 0.05. This method was already used to predict the long-term drought scenario (SPI 12 and SPI 24) worldwide with different accuracy levels. Belayneh *et al.*, (2016) used this method in Awash Basin and found R-values of more than 0.93 and MSE values of less than 0.02. Deo and Sahin (2015) used ANN to predict another drought index, Effective Drought Index (EDI) in eastern Australia, and found an R-value of 0.7 and an MSE-value of 0.029. They also used ANN to predict SPI and found R-values of 0.0466 to 0.1117 and MSE-values of 0.001 to 0.01(Deo and Sahin, 2015b). In the Algerios basin of Northern Algeria, Djerbouai and Souag-Gamane, (2016) used the WANN method and found MSE-values of 0.1 to 0.6 for different lead times of SPI 12 series prediction. Overall, the WANN method showed its greater efficiency and higher accuracy in forecasting long-term meteorological drought throughout the world.

5. Conclusion

The study has tried to forecast future long term meteorological drought scenario of a north-western part of Bangladesh that is Bogra. Wavelet Artificial Neural Network has been used to predicting drought index Standardized Precipitation Index (SPI). Here, long-term drought has been indicated through the drought index with 12 months accumulation time (SPI 12) and drought index 24 months (SPI 24). The fundamental difference between SPI 12 and SPI 24 is, SPI 12 can detect the effects of drought on stream-flow and reservoir storage where SPI 24 can detect the impact of drought on groundwater recharge.

The major outcome of this study is that the region might face an extremely dry and wet situation in the long term, very frequently within 2031. It indicates that the stream-flow, reservoir storage, and groundwater condition might face extremely dry and wet conditions very frequently along with frequent flash drought compared to the previous 12 and 24 months accumulation period before 2014. Such conditions will reduce the soil quality, water-holding capability of the soil, increase surface runoff and soil erosion, change vegetation cover, and overall weather conditions. This condition shall also gear up the desertification process of that region.

The drought forecasting information is a mandatory tool for water resource planning for that region. A curious research question that has been arisen from this study that requires a detailed study is, what is the intensity of the effect of long-term meteorological drought on stream-flow, reservoir storage, and groundwater recharge at Bogra within 2031. Due to the erratic behavior of precipitation in the future, it will be much more challenging for policy-makers to plan in different sectors such as agriculture, water resources, land uses, etc.

The only limitation of this study is lacking of a large set of continuous precipitation data for all the rain- gauge stations of the entire north-western part of Bangladesh. For this reason, the Bogra rain gauge station has been purposively sampled due to its availability of a large set of continuous data. The wavelet artificial neural network (WANN) method has also provided enough confidence to overcome that limitation.

There are further research opportunities to evaluate the risk of drought and the intensity of drought vulnerabilities through other machine learning and deep learning methods. The impacts prediction of future droughts in different areas such as agriculture, fisheries, forestry, social and economic sectors is yet to be analyzed, which can be done through various machine learning methods.

Therefore, it can be recommended that the Bangladesh government should incorporate this drought scenario forecasting information in various sectoral planning, including water resource planning for Bogra along with the north-western part of Bangladesh also. Besides, researchers, especially agriculture scientists, can develop strategies to cope with the situation. Moreover, the same research could be practiced for other stressed areas using WANN.

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