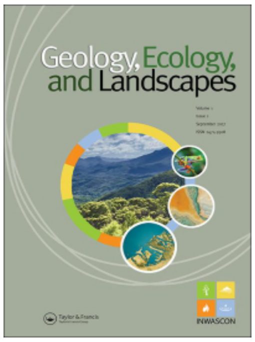

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RESEARCH ARTICLE

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Estimation of drought trends and comparison between SPI and SPEI with prediction using machine learning models in Rangpur, Bangladesh

Mst. Labony Akter[a], Md. Naimur Rahman[b], Syed Anowerul Azim[a], Md. Rakib Hasan Rony[a], Md. Salman Sohel[c] and Hazem Ghassan Abdo[d]

[a]Department of Geography and Environmental Science, Begum Rokeya University, Rangpur, Bangladesh; [b]Center for Archaeological Studies, University of Liberal Arts Bangladesh, Dhaka, Bangladesh; [c]Department of Development Studies, Daffodil International University, Dhaka, Bangladesh; [d]Geography Department, Faculty of Arts and Humanities, Tartous University, Tartous, Syria

ABSTRACT
This study investigates drought trends, SPI-SPEI comparisons, and predictions in Rangpur, Bangladesh, from 1979 to 2020. We employed Modified Mann-Kendall for trend analysis, SPI and SPEI for drought assessment, and Pearson Correlation Coefficient and Simple Linear Regression for evaluating SPI and SPEI relationships. Additionally, we utilized ANN, SVM, and RF for prediction. The study revealed notable negative trends in seasonal and annual drought, with the highest z statistics observed for SPI 06 (-2.75), SPI 09 (-4.50), SPI 12 (5.60), SPI 24 (-8.40), SPEI 06 (-5.13), SPEI 09 (-6.82), SPEI 12 (-8.04), and SPEI 24 (-11.20). Strong correlations were identified across all SPI and SPEI indices, with coefficients peaking at 97%, 98%, 98%, and 97% for 06, 09, 12, and 24-month periods, respectively. The comparative assessment favored SPEI over SPI, highlighting its superiority and accuracy. The ANN prediction model showed significant results for short-term and seasonal drought forecasts, projecting SPEI 03 and SPEI 06 increases of 0.02 and 0.24, respectively. However, long-term drought estimation exhibited insignificant performance across all predictive models. This emphasizes the need for developing essential predictive tools for future drought variability.

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Drought; SPI; SPEI; machine learning; rangpur

1. Introduction

The onset and duration of drought vary widely depending on the region, and is influenced by various climatic and atmospheric factors (Sheffield & Wood, 2008). In addition to a prolonged absence of rainfall, drought conditions are often associated with elevated temperatures, strong winds, and low moisture levels, which can profoundly impact both the natural and human systems (Mekonnen & Gokcekus, 2020). The effects of drought are felt globally, with an estimated 55 million people being impacted each year, and the most significant threat posed to crops, animals, and human populations in virtually every region (Shahfahad et al., 2022). The consequences of drought can be severe, including loss of livelihoods, increased risk of illness and death, and mass migration (Zinat et al., 2020). Thus, understanding the causes and impacts of drought is crucial for developing effective strategies to mitigate its effects and ensure the resilience of vulnerable communities.

The global water crisis poses a significant threat to the livelihoods and well-being of up to 700 million people, or 40% of the world's population (Islam et al., 2017). By 2030, millions may be forced to leave their homes due to severe drought conditions (Islam et al., 2017). Bangladesh is one of the most vulnerable countries in the world, facing a range of socioeconomic, geographic, and climatic challenges that leave it less resilient to the impacts of natural disasters (Kamruzzaman et al., 2022; Uddin et al., 2020). Despite its relatively high precipitation levels, the country experiences a dry period each year that can have severe consequences for local communities and the economy (Alam et al., 2021). The northern part of Bangladesh, with its diverse range of precipitation patterns and high concentrations of people, is particularly at risk of experiencing the effects of drought (Banglapedia, 2014).

Drought has been recognized as an ecological emergency and has been the subject of intense study across multiple scientific disciplines, including natural sciences, ecology, hydrology, meteorology, geology, and agriculture (Mainuddin et al., 2020; Mortuza et al., 2019; Rahman & Azim, 2021, 2022; Rahman et al., 2021). The effects of drought can be far-reaching and devastating, exacerbating job insecurity, reducing access to food, and causing abnormal price

CONTACT Md. Naimur Rahman naimurbrur@gmail.com Center for Archaeological Studies, University of Liberal Arts Bangladesh, Dhaka, Bangladesh
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spikes for rural residents. Extreme drought can result in crop losses, food shortages, and the loss of livestock and biodiversity, leading to migration in affected areas (Rahman & Azim, 2021). Therefore, it is crucial to better understand the present and future drought scenarios in Bangladesh and adopt effective management strategies to mitigate its impacts. Bangladesh is among the countries that are most vulnerable to weather-related disasters. Climate change is exacerbating the effects of droughts and monsoons in Southeast Asia, potentially leading to increased intensity of both flooding and dryness in the region. The National Drought Mitigation Center reported that the frequency of droughts in Bangladesh has increased over the past several decades. The northern part of the country is particularly susceptible to prolonged droughts due to its high variability in rainfall patterns (von Neumann, 1941). The prolonged drought in the northern region presents significant environmental, social, and economic challenges and highlights the need for effective strategies to mitigate the impacts of drought (Alexandersson, 1986).

Droughts have significantly impacted various aspects of life in Bangladesh, including agriculture, food production, land degradation, economics, and communities (Jerin et al., 2021). In particular, drought stress during crop growth can significantly affect crop production in Bangladesh and other LDCs in Asia (Uddin et al., 2020). Several studies have been conducted to assess and analyze the risks of drought in Bangladesh. The study by Rafiuddin (von Neumann, 1941) used the Standardized Precipitation Index (SPI) to detect dry spells and concluded that the use of SPI throughout an area provides better consistency of drought conditions compared to using single station data. The 1994 drought, which lasted from the end of 1994 to the start of the monsoons in 1995, was the worst in a century and had severe impacts on the country's northwestern region (Kendall, 1975). The effects of drought on the ecosystem, human health, society and economy, and agriculture have been explored in previous research (Hamed & Rao, 1998; McKee et al., 1993; Rahman & ARMT, 2019; Rahman & Azim, 2021; Wang et al., 2019; Zannat et al., 2019). For example, Alam (Pramudya & Onishi, 2018) evaluated the occurrence of dryness in northern Bangladesh and its relationship with water stress parameters and population health in a vulnerable region. Islam et al. studied northern and southern drought conditions using SPEI where no comparisons and predictions between SPI and SPEI is employed (Islam et al., 2017). Only two different studies are found for comparing SPI and SPEI where (Uddin et al., 2020) focused only three zones and ignored micro level study (Kamruzzaman et al., 2022); investigated different zones using traditional Mann-Kendall test for drought trend. Therefore, the explained literature investigates the effect of dry spells, as evaluated by such SPI, on daily death rates from natural causes, circulatory-related causes, and respiratory-related causes in northern Bangladesh between 2007 and 2017 (Alam et al., 2021). However, the northern region, particularly in Rangpur, has never been the focus of systematic drought research utilizing SPI and SPEI while revealing drought trends using the Modified Mann-Kendall test (MMK). In addition, no study contributed to the working efficiency of SPI and SPEI with their future variability. Hence, this study evaluated and predicted drought patterns in the northern regions of Rangpur in Bangladesh. The objectives of the study are:

(1) To identify temporal drought trends in the Rangpur district during 1979-2020;
(2) To determine the relationship and comparative assessment between the SPI and SPEI in drought variability;
(3) To predict temporal drought in the Rangpur district.

The sections of the study include firstly revealing drought trends using MMK, then finding the drought conditions and employing comparisons using SPI and SPEI, and finally predicting the drought variability.

2. Data and methods

2.1 Study area description

The northern region's Rangpur district was chosen as the study location due largely to the availability of specific climatic zone there (Figure 1). The area of the Rangpur district is 2,641.84 sq. km. Nilphamari and Gaibandha districts lie north, Kurigram and Dinajpur to the east, and Dinajpur to the west of this area. Weather-wise, Bangladesh has four different seasons: winter (December-February), pre-monsoon (March-May), monsoon (June-September), and post-monsoon (September-December) (October to November) (Banglapedia, 2014). Most of the country's territories have humid to subhumid climates with anomalous spatial and temporal patterns. The Rangpur district's digital elevation model (DEM) is also shown in Figure 1; the area is mostly plain, with some elevated regions areas, the province's northern and northeastern corners. The mean annual precipitation is 2428 mm, and more than 80% of precipitation falls during the monsoon season (Mainuddin et al., 2020). The Bangladesh Meteorological Department (BMD) stated that the yearly average temperature was 25.7°C. In addition, the highest temperatures registered during the summer vary from 30°C to 40°C, and the minimum temperatures during the winter vary from 5.2°C to 10°C, notably in January (Rahman & Azim, 2022). The weather patterns in

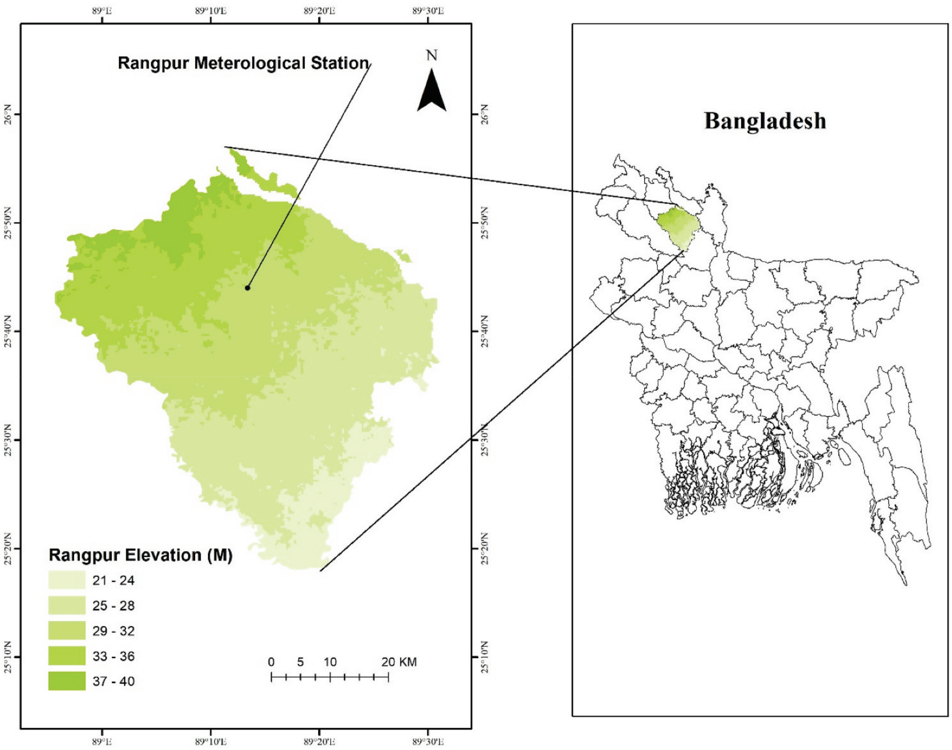

Figure 1. Study area of Rangpur district (Digital elevation model of Rangpur, Bangladesh). **Source**: Modified from humdata.org

Rangpur is thus classed as warm and temperate. In Rangpur, the summertime is significantly rainier than the winter. This climate has been classed as Cwa by Koppen and Geiger. The mean temperature in Rangpur is 24.3°C, and the annual precipitation is 2498 mm or 98.3 inches (Mainuddin et al., 2020).

2.2 Data sources and quality control

The monthly recorded rainfall observations were obtained from Bangladesh Agricultural Research Council (BARC) and Bangladesh Meteorological Department (BMD) for the years 1979 to 2020 (42 years). Additionally, from 1979 to 2018 data was acquired from the freely available source of BARC and from 2019 to 2020, data were collected from BMD. Moreover, only one station covers the northern part of the northern climatic zone and the entire Rangpur (Rahman & Azim, 2021). Buishand and von Neumann introduced the significance of testing homogeneity for observation data (Buishand, 1982; von Neumann, 1941). Additionally, datasets checked for homogeneity and homogenous (Alexandersson, 1986; Buishand, 1982; von Neumann, 1941). When utilizing historical information, missing data is a crucial concern. Two percent of the missing value is widely accepted because of its inefficiency in influencing outcomes where we found < 1% missing value (Mortuza et al., 2019; Rahman et al., 2021).

2.3 Methods

We performed linear regression as a part of the parametric test to detect the trend of monthly rainfall before applying non-parametric tests, including Modified Mann-Kendall for trend analysis, SPEI, and SPI for drought as well as dry and wet period variability (Hamed & Rao, 1998; Jerin et al., 2021; Kendall, 1975). Moreover, Pearson's Correlation Test was employed to illustrate a link between SPEI and SPI (Wang et al., 2019). TT.A.so predict the future variability of drought tendency patterns, we utilized the s The training and testing of these prediction methods were carried out using 70% and 30% of the data, respectively. The subsequent section of this article briefly presents the statistical phenomenon.

2.4 Modified Mann Kendall Trend test (MMK)

Hamed & Rao (1998) proposed the Modified Mann-Kendall (MMK) test, which considers autocorrelation in time series data when assessing trends. The variance of the MK statistic (Var(S)) is modified accordingly (Rahman & ARMT, 2019; Zannat et al., 2019). The autocorrelation of the data is calculated using the following equations:

$$Var(S) = Var(S) * \left(\frac{n}{n^*}\right)$$

$$\left(\frac{n}{n^*}\right) = 1 + \left(\frac{2}{n(n-1)(n-2)}\right) * \sum_{k=1}^{n-1}(n-k)(n-k-1)(n-k-2)^r.k$$

$$r_k = \frac{\left(\frac{1}{n-k}\right)\sum_{i=1}^{n-k}(x_i - x)(x_{i+k} - x)}{\left(\frac{1}{n}\right)\sum_{i=1}^{n}(x_i - x)^2}$$

Here, *Var(S)* is calculated via *Var(S)**, *nn** represents the adjusted equation of auto-correlated statistics, *rk* is the auto-correlation coefficients of the *kth* lag, and *x* defines the temporal-sequence records mean. Using the following equation, the relevance of the autocorrelation parameter of the *kth* lag at a 95% confidence interval is calculated:

$$\left(\frac{-1 - 1.96\sqrt{n = k - 1}}{n - k}\right) \leq r_k(95\%) \leq \left(\frac{-1 - 1.96\sqrt{n = k - 1}}{n - k}\right)$$

Whereas if acquired *rk* matches the aforementioned scenario, data with a 95% level of certainty may be retrieved. In order to discern the pattern in the response variable, it is imperative to eliminate the impact of auto-correlation across various temporal delays, provided that the variables are dependent. Moreover, the tendency in time series data can be inferred if Z falls below or exceeds the Z value of the normal distribution at a 95% level of significance.

2.5 Standardized Precipitation Index (SPI)

In drought assessment, the Standardized Precipitation Index (SPI) is a widely utilized method that estimates rainfall based on various timelines, including one, three, six, nine, twelve, and twenty-four months (McKee et al., 1993; Pramudya & Onishi, 2018; Shahid, 2008). This approach involves comparing time series rainfall records for a specific period to sums from a corresponding period, thus facilitating the analysis of tropical and temperate events. To calculate the SPI, time series rainfall records from the Rangpur weather station were fitted to a gamma probability distribution function:

$$\gamma(x) = \frac{1}{\beta^\alpha \Gamma(\alpha)} x^{\alpha-1} e^{-\frac{x}{\beta}} \; for \; x > 0$$

When the factor is more significant than zero, the curve is also greater than zero, indicating a positive level of rainfall. The gamma feature can be specified by alpha. However, the likelihood formulae used do not effectively calculate the gamma unit parameters alpha and alpha for each location and time period more significant$\alpha = \frac{1}{4A}\left(1a + \sqrt{1 + \frac{4A}{3}}\right)$

$$\beta = \frac{\bar{x}}{\alpha}$$

where $A = \ln(\bar{x}) - [\sum \ln(x)/n]$, n = quantity reflects measurements of rainfall. As a result, the amount of precipitation there at stations may be accurately characterized by a function of computational incremental probabilities, as shown below:

$$G(x) = \int_0^x g(x)dx = \frac{1}{\beta^\alpha \Gamma(\alpha)}\int_0^x x^{a-1} e^{-x/\beta} dx$$

Because the simulated data is confusing for x = 0 and a rainfall spectrum may contain zeros, the accumulated probability is: $H(x) = q + (1 - q)G(x)$. Where q is the probability of zero. This SPI is calculated by converting its continuous likelihood H(x) towards the probability of the ordinary distribution (McKee et al., 1993). It enables the calculation of an identifier property for SPI. McKee (Zou et al., 2003) classified wet and dry instances that matched SPI characteristics, as shown in Table 1.

Table 1. Drought index based on SPI values.

Category	SPI	Probability of Occurrence (%)
Extreme drought	−2.00 and less	2.3
Severe drought	−1.50 to−1.99	4.4
Moderate drought	−1.00 to−1.49	9.2
Near normal	.99 to−.99	34.1
Moderate wet	1.00 to 1.49	9.2
Severely wet	1.50 to 1.99	4.4
Extremely wet	2.0 and above	2.3

Table 2. Drought index based on SPEI values.

Category	SPEI Extremes
Extreme drought	−1.83 and less
Severe drought	−1.82 to −1.43
Moderate drought	−1.42 to −1.49
Near normal	−1.0 to 1.0
Moderate wet	1.42 to < 1.0
Severely wet	1.82 to <1.43
Extremely wet	1.83 and above

2.6 Standardized Precipitation Evapotranspiration Index (SPEI)

The Standardized Precipitation Evapotranspiration Index (SPEI) is a relatively new meteorological drought measure that combines the benefits of the Standardized Precipitation Index (SPI) with temperature variations. It has been suggested that SPEI is more suitable for drought monitoring and assessment in the context of climate change (Mohsenipour et al., 2018; Vicente-Serrano, 2015). Moreover, SPI lacks hydrological balance and has been used only to adjust statistical regions to specific objectives (WANG et al., 2018). To address these empirical shortcomings, SPEI is utilized as it incorporates the sensitivity of the Palmer Drought Severity Index (PDSI) to fluctuations in evaporative demand caused by temperature variations and trends with simpler SPI simulations (Vicente-Serrano, 2006). To estimate the SPEI, one could firstly determine the periodic potential evapotranspiration (PET), and after that identify the disparity in the periodic water level of a particular month (i.e., deficiency *Di*) by deducting PET out from rainfall measurement of that month (*Pi*).

$$D_i = P_i - \mathrm{PET}_i$$

Once a log-logistic likelihood functional model is applied to the normalized deficiency response variable, the SPEI level may be computed as the confidence interval of the accumulated likelihood of *Di*.

$$\mathrm{SPEI}i = wi - \frac{2.515517 + 0.802853Wi + 0.010328W2}{1 + 1.432788Wi + 0.189269Wi + 0.001308Wi}$$

$$wi = \sqrt{-21np} \text{ for } p < 0.05 \text{ and}$$

$$wi = \sqrt{-21n(1-p)} \text{ for p} < 0.05$$

When p is greater than 0.5, the symbol of such resulting SPEI flips.

The different time scales of SPI and SPEI have been employed, including 3-months, 6-months, 9-months, 12-months, and 24-months period (V-S et al., 2010). The 3-month period is a useful tool to assess short-term drought trends over a three-month period (Rahman et al., 2021; Vicente-Serrano & Beguería, 2016). However, it is crucial to examine the data over a longer time frame to avoid any misinterpretations about droughts, as a relatively normal 3-month period may occur within a more extensive drought (Rahman et al., 2021). Additionally, a 3-month period may be significantly useful for medium or seasonal drought pattern extraction which may help in cropping activities (Rahman et al., 2021). Furthermore, long-term droughts are identified by 9, 12 and 24 months period that can aid agricultural productions, and drought mitigation strategy development (Islam et al., 2017; Rahman et al., 2021; Shahfahad et al., 2022).

2.7 Pearson correlation coefficient

This study employs the Pearson correlation coefficient statistical technique to examine the correlation between SPI and SPEI (Tefera et al., 2019). Excel to calculate the correlation coefficient, considering the relevant parameters that constitute the Pearson mechanism. To perform a Pearson correlation test, the first array must contain distinct numerical quantities, while the second array should consist of variables to be analyzed. Only numeric or string values, array parameters, or pointers to integers used as responses are acceptable. Units with the quantity 0 can be retained, even if they contain text, resulting in either real or null strings, whereas units with other attributes are discarded. If both arrays are null or contain a variety of observations, the PEARSON function will generate the #N/A estimation error. The Pearson correlation coefficient, r, can be calculated as follows:

$$r = \frac{\sum (x - \bar{x})(y - \bar{y})}{\sqrt{\sum (x - \bar{x})^2 (y - \bar{y})^2}}$$

where x and y indicate first and second array, respectively.

2.8 Simple linear regression

In this research article, we utilized Simple Linear Regression to conduct a comparative analysis of SPEI and SPI (Zou et al., 2003). The Simple Linear Regression equation that was employed in this study is as follows:

$$\mathrm{y} = \mathrm{bx} + \mathrm{a} + \varepsilon$$

The formula explains dependent as y and independent value of x. The regression curve is defined by b and a intercept it where ε is the error.

2.9 Artificial Neural Network (ANN)

Artificial neural networks (ANNs), which learn from a training set, are used to predict drought. Multilayer perceptron (MLP) models with one input layer, a hidden layer, and an output layer are often employed. The backpropagation algorithm is used to train the MLP models, which adjusts the connectivity weights using error convergence approaches to provide the desired output for a given input. In this process, the mistake at the output layer in the backpropagation algorithm model propagates backward to the input layer via the network's hidden layer to produce the intended result (Chowdhury, 2017; Ferreira et al., 2019; Morid et al., 2007).

To mimic drought, numerous ANN models are tested with varied weather factors such as average temperatures and rainfall. The result for all models is the Standardized Precipitation-Evapotranspiration Index (SPEI) values. A correlation matrix between distinct input variables and SPEI is generated to examine the relative importance of different input variables on SPEI results. Seventy percent of the data is utilized to train the models, with the remaining 30% used for testing after enhancing the number of nodes in the hidden layer and the network topology. During training, the networks start with random weights and then perform a one-pass backpropagation method at each time step, which includes a forward pass that propagates the input vector through the network layer by layer and a backward pass that updates the gradient descent rule's weights.

Backpropagation has some drawbacks, such as becoming stuck in local minima and sluggish convergence, yet it is still the most used supervised learning paradigm for ANNs. ANNs can predict drought with reasonable accuracy when utilizing this methodology, making it a viable tool for drought prediction (Dastorani & Afkhami, 2011; Rumelhart et al., 1986).

2.10 Random Forest (RF)

(R.F.) introduced the RF modR.F., which uses a technique called "bagging" to ensemble a collection of decision trees with controlled variance. The RF modR.F. is frequently used in regression and forecasting applications and employs random binary trees trained using a subset of the training dataset via the bootstrapping technique. The RF modR.F. employs two views to train multiple decision trees: the sample dimension and the feature dimension. Combining the voting outcomes of multiple decision trees, the RF modR.F. mitigates the issue of decision trees being prone to over-fitting. Similar to the Bagging model, the core algorithm in the RF modR.F. is trained in parallel. The RF modR.F. is helpful in modeling hydrological features and provides high-precision forecasting without overfitting the data set. When using the RF model as a tree-based ensemble technique, it is essential to evaluate the significance of climatic factors (Wang et al., 2019). For more information on the RF ensemble algorithm, please refer to (Islam et al., 2017; Lotfirad et al., 2022; Park et al., 2018)

2.11 Support Vector machine (SVM)

The Support Vector Machine was initially developed for classification, but it has been extended to regression problems using support vector regression (SVR). This approach uses kernels to minimize the distance to training data and limit model complexity, resulting in better generalization capacity for data not in the training set. In SVR, the SVM regression-based model has two steps. First, the kernel function transforms independent variables such as remote sensing drought indices and weather or climate indices from the original space to a high-dimensional feature space. Second, a linear model is constructed in the new feature space to minimize errors. The most widely used kernel function in the literature is the Radial Basis Function (RBF), which has two hyperparameters: the penalty factor C and the kernel width gamma. Both are tuned using a grid search method. This SVM regression-based model for drought prediction offers high generalization capacity and reduces the risk of overfitting to training data. Further information about the SVM algorithm can be found in (Vapnik, 1995).

3. Results

3.1 Temporal drought trend of SPI and SPEI

MMK trend tests have been utilized in Rangpur Meteorological Station from 1979 to 2020 at the 95% confidence interval to visualize drought trends. The devastating potential trend of Z statistics is found for SPI 24 > −8.40. However, another periodical trend is also found in extreme measurement including SPI 12 > −5.60, SPI 09 > −4.50, SPI 06 > −2.75 and SPI 06 > −2.70, respectively (Figure 2). It must be acknowledged that the MMK trend outcome for SPI is in a heavy upward direction from short-term seasonal to annual variation.

On the other hand, the MMK test for all periodic observations of SPEI reveals a rise in negative trends (Figure 2). A severe drought trend is deemed to control of SPEI 24, which is Z > −11.20. In addition, other time-framed trend suggest the gradual lower Z statistics compared with SPEI 24. However, SPEI 12 is the second highest potential drought trend, with z statistics of >-8. Another periodical trend is also found in relatively decreased trend statistics, indicating the 09 months drought trend Z > −6.80, the 06 months drought trend Z > −5.10, 03-month period drought trend Z> −4.80 (Figure 2). Therefore, the primary comparison between SPEI and SPI trend consequences depicted Z statistics is more intense for SPEI where SPI fabricated relatively reduced trend statistics.

3.2 Relationship between SPI and SPEI

Monthly SPI and SPEI were estimated at five-time scales (3, 6, 9, 12 and 24 months) for the selected station from 1979 to 2020 (Figure 3). The average SPI and SPEI were then calculated and estimated for Pearson correlation coefficient at the 95% confidence interval to characterize drought episodes in the Rangpur district. All SPI and SPEI indices are shown to be significantly associated with an upward trend. It demonstrates a strong relationship ranging from 95% to 98%, where SPI and SPEI 03 score lowest of 95%. However, an increased heavy correlation is found for 9 months, and 12 months among all other indices, including $r = 0.98$. Future correlation estimation suggests that it will increase drought severity for both SPI and SPEI across all indices. Consequently, all future drought indicators exhibited a possible rising trend comparable to the present, with a range of r^2 0.95 and 0.97. Only the 3-month period scored a lower severity of $r^2 = 0.90$ compared to all other future

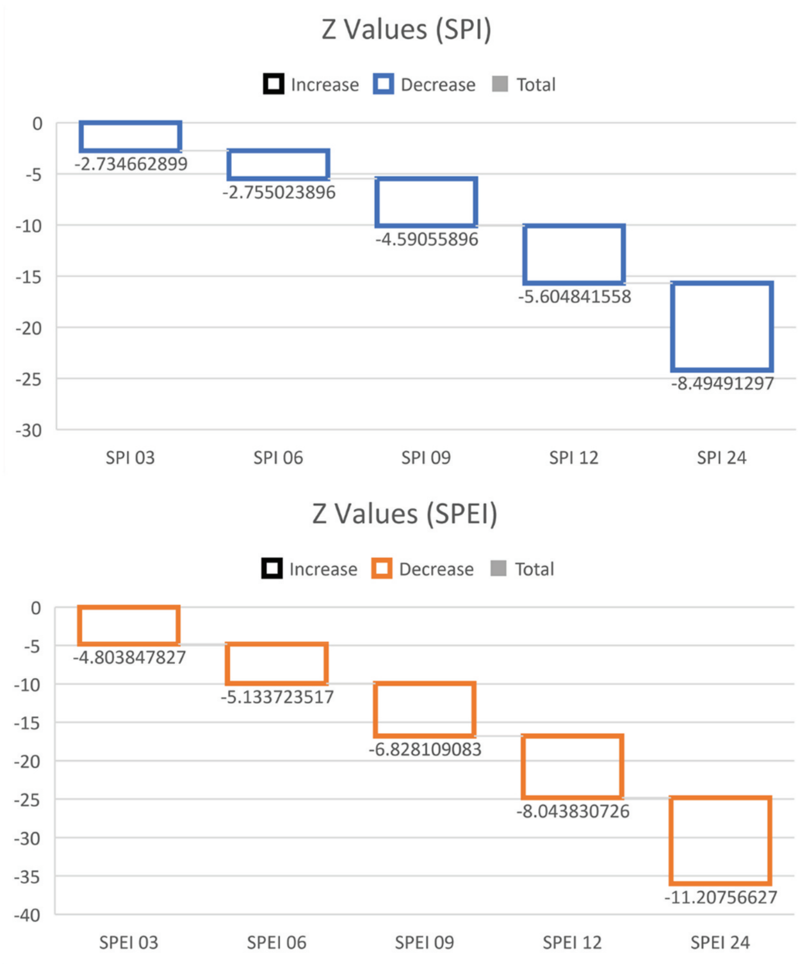

Figure 2. Trend values of Z statistics for SPI and SPEI. Source: Author's own calculation

relationship indices. Thus, the overall scenario indicates a strong association between SPI and SPEI for both present and future variability. Moreover, the 3-month drought-relationship is vulnerable compared to all other indicators, namely 6,9,12, and 24-month periods.

3.3 Comparative assessment between SPI and SPEI

A comparative evaluation was conducted using simple linear regression. The output of the study includes (Figure 4). SPI was unable to identify severe droughts in the Rangpur region based on the brief droughts that occurred in 1983, 1987, 1993, 2002, and 2012; yet, it was able to identify extended periodic drought episodes (in 1984, 1993, 1995, 2007, 2011, and 2013). At this location, this is obvious as SPEI is much more equipped than SPI to recognize instances of drought. It is crucial to understand that SPI exaggerated in many years, including 1994, 1995, 2002, 2007, and 2012. In the years 1989, 1993, 1994, 1995, 1996, 1998, 2004, 2009, 2011, 2014, 2015, and 2016, the SPI could not distinguish between harsh long-term droughts and mild droughts. There were extreme droughts in 1989, 1993, 1994, 1995, 1996, 1998, 2004, 2009, 2011, 2014, 2015, and 2016. These years were identified as severe drought years by SPEI but not by SPI.

3.4 Drought prediction

In this study, three different models were utilized for prediction purposes, namely Random Forest (RF), Support Vector Machine (SVM), and Artificial Neural Networks (ANN). Model accuracy evaluation is a crucial phase in machine learning model development as it enables one to assess the model's performance in terms of prediction. Model performance is evaluated using various metrics such as Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Coefficient of Determination (R-Squared). The training model was developed using 70% of the data, and the testing model was built using the remaining 30%. As we have measured in our previous section, SPEI provides the most accurate drought results, so we have utilized SPEI values for drought prediction. Thus, testing outcomes are also evaluated to demonstrate the prediction results.

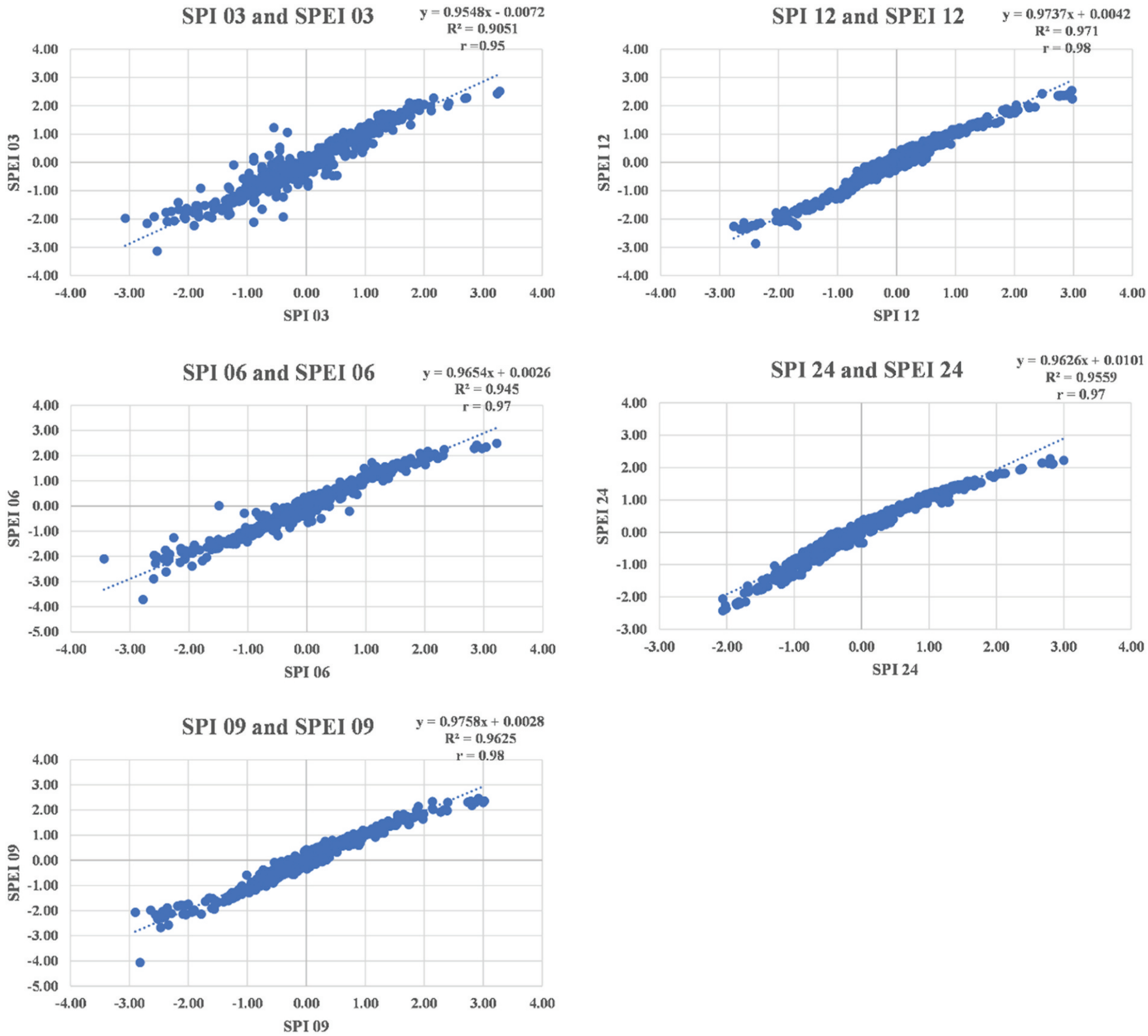

Figure 3. Correlation between SPI and SPEI for the 3-, 6-, 9-, 12- and 24-months. Source: Author's calculation.

In some cases, the R-Squared value may be harmful, indicating that the model is not well-fitted with the datasets. However, for this study evaluation, a negative R-Squared value is considered as 0 statistics. Therefore, we have found 0 statistics for all the model of long-term drought prediction, namely SPEI 09, SPEI 12, and SPEI 24.

Additionally, to visualize 0 statistics clearly, we coloured it bold in blue. However, for short-term drought prediction of SPEI 03 only ANN provides a significant value of 0.06 r^2 where considerable RMSE, MSE and MAE is found. Thus, for the seasonal drought prediction ANN found superior over RF where RMSE, MSE and MAE is found lower in ANN model. This ANN result also indicates the increase of seasonal drought of 24%. All models, however, demonstrated low prediction accuracy (negative R2 values). Overall, the models' performance varied according to the SPEI value, and more study is required to increase the precision of drought prediction models.

4. Discussion

The primary objective was to evaluate drought trends, determine the relationship between SPI and SPEI, and develop predictions. Drought was either steady, diminished, or exacerbated in various ways, according to the outcomes. Therefore, SPI and SPEI exhibited a strong positive correlation, and both indices rose (Figure 3). Similar to this study (Adnan et al., 2018), determined that SPEI has adequate capacity to assess drought conditions in Pakistan. These results are congruent with those of (Homdee et al., 2016). In contrast to this study (Mahmoudi et al., 2019), recognized SPI and effective drought index (EDI) as Iran's primary and second choice dryness detection indicators (Kamruzzaman et al., 2019). Kamruzzan discovered that EDI significantly improved than SPI for detecting longer and shorter periodic shortages in Bangladesh. This anomaly may be attributed to our project region's plain, low-lying geography, which promotes seafloor airflow inconsistencies. Concerning intensity and amplitude, the association across SPI and SPEI were highest for 3-, 6-, 9-, 12-, and 24-month timelines (0.95, 0.97, 0.98, 0.98, and 0.97, correspondingly) (Figure 3). Following the period of transition, severe droughts became increasingly prevalent. This could lend support to (Cook et al., 2014) assertions that the greenhouse effect has exacerbated drought in various parts of the world in the twenty-first century.

SPI failed to detect severe drought occurrences in this region in 1987, 1989, 2002, 2004, and 2009 (Figure 4). SPI and SPEI have done an excellent performance in detecting short-term droughts in the middle section of the country. According to Malik (Deye et al., 2016), a severe and widespread drought afflicted most of Southeast Asia between 1999 and 2002, coinciding with this study's findings. In contrast, SPI failed to recognize protracted severe dryness in 1993, 1995, 2014, and 2016, misclassifying these years as moderate water shortages (Figure 4). There were significant water shortages in 1989, 1993, 1994, 1995, 1996, 1998, 2004, 2009, 2011, 2014, 2015, and 2016 (Figure 4). SPEI proved that it can identify these periods as severe drought, although SPI did not. This research highlighted droughts during the 1980s, 1990s, 2000s, and 2010s. These findings can be linked to those of (Miah et al., 2017) and (Rahman & Lateh, 2016a). An exaggeration or underestimating could be due to rainfall being the primary entry parameter in the SPI computation. In contrast, SPEI fared exceptionally well in detecting previous droughts in Rangpur. According to (Stagge et al., 2015; Tan et al., 2015), SPEI exhibited actual drought conditions since higher air temperatures or little precipitation led in significant evaporation. Thusion, SPEI can reveal the effects of rains and evaporate on dryness (Vicente-Serrano et al., 2014); PET showed excellent agreement with the meteorological drought indicator (Joetzjer et al., 2013). This discovery validates significant findings from (Miah et al., 2017). According to the researchers, PET is a major component of the hydrology in the western part of Bangladesh and also in Rangpur, and thus its variation is mostly driven by precipitation (Alamgir et al., 2015; Islam et al., 2017)

Table 3 and supplementary figures (s1, and s2) depict visual examination and appraisal of prediction systems in the context of conventional output indicators as regression analysis. In addition, only the ANN prediction model performed well for short-term and seasonal drought prediction of SPEI 03 and SPEI 06, which is an upward trend. Such results are consistent with those of (Ali et al., 2017; Poornima & Pushpalatha, 2019). In the Asian region, ANN provides better result for drought prediction than SVM and ANN (Mokhtar et al., 2021; Park et al., 2018). The Table 2 indicates drought index based on SPEI values.

In contrast, several studies suggested that future changes in precipitation could reduce the severity of drought in the respected research region (Bari et al., 2016; Habiba et al., 2013b). But the predictive power of each model was subpar. While some models performed slightly better in some scenarios than others, overall, all models performed below expectations. More research is required to increase the accuracy of drought prediction models, especially for longer term droughts like SPEI 12 and SPEI 24. However, despite being a minor outlier, most environmental warming forecasts imply that temperatures will climb significantly in Bangladesh, and the dry periods' dryness (November to May) intensify in the foreseeable future (Hasda et al., 2020; Rahman & Lateh, 2016b; Yaseen et al., 2021). Bangladesh makes drought forecasting challenging due to its nonlinear climate pattern. When considering the relevance of regression analysis, the drought prediction model varies according to the periodic and yearly phases. The drought prediction accuracy of the created systems was examined in the existing kinds of the literature and quantitative parameters in the region (Bari et al., 2016; Mahsin et al., 2012) and concluded to be superior (Alamgir et al., 2020; Hasda et al., 2020; Kamruzzaman et al., 2019; Rahman et al., 2021). Drought has a considerable negative effect on different species and subsistence agriculture; for instance, a severe drought in 1978 decreased rice productivity by 2 million tons (Habiba et al., 2013a). During 1982, dryness impacts were much and more significant than twice flooding effects (Umma & Rajib, 2014).

Additionally, more than 2 million hectares of farmland were lost to the droughts of 1997 (Habiba et al., 2013b). This area's drought caused crop loss or decreased output, leading to the acquisition of many farm products (PR, 1995). Since rice is grown in Bangladesh throughout the summertime, the country may face water scarcity, mostly in times of inclusive growth, because of the waste of precious groundwater (Mainuddin et al., 2020). However, in recent years, an exceptional drought event has developed in Rangpur district, primarily affecting the northern zone's northern section. Drought incidence has been particularly severe during SPI 24 and SPEI 24, SPI 12 and SPEI 12, SPI 06 and SPEI 06. Rangpur district is in conventional measures of extreme drought for 6 months, 12 months, and 24 months, but 3 months and 9 months droughts are also becoming more severe.

Furthermore, according to the trend study, and prediction the Rangpur district is at critical drought risk. Similar findings have been acknowledged by (Abdullah, 2014; Rahman et al., 2021). The reason for these changes is that precipitation varies spatially, temporally and seasonally (Rahman & Lateh, 2016a). Therefore, monsoon season wind and precipitation, as well as Himalayas features, play a role in the dry spell

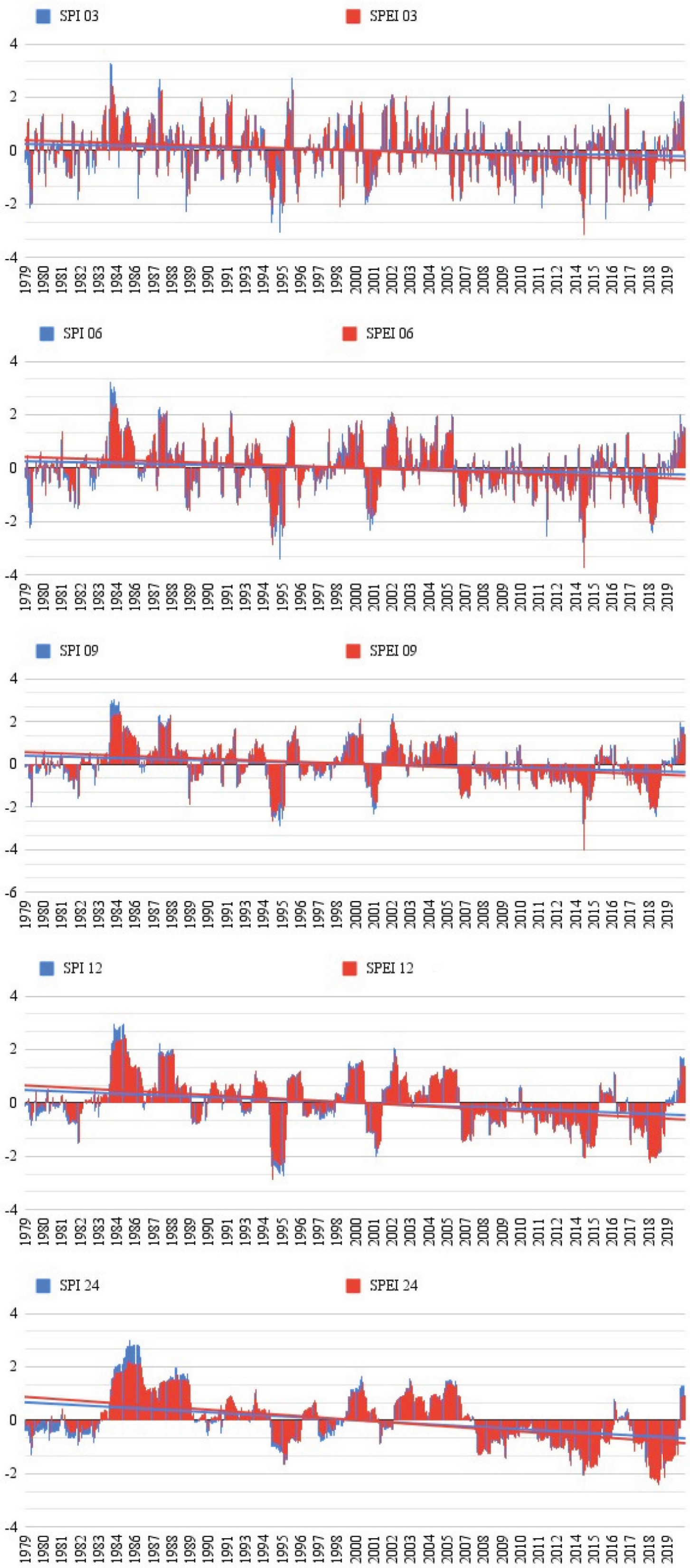

Figure 4. Comparative assessment between SPI and SPEI. Source: Author's calculation

and precipitation patterns of Bangladesh and Rangpur (Das, 2021). El Nino also significantly affected Bangladesh's climate, resulting in decreased precipitation and drought in different seasons (Islam et al., 2021). Another very probable proof is that greenhouse gas emissions are responsible for Rangpur's persistent dryness (Mora et al., 2018). However, it should be noted that extreme dryness persists because of a shortage of precipitation and the prevalence of water stress regions in Rangpur (Rahman & Azim,

Table 3. The prediction outcome of drought.

SPEI		SVM (Training)	SVM (Testing)	RF (Training)	RF (Testing)	ANN (Training)	ANN (Testing)
SPEI 03	RMSE	0.87968	0.94284	1.0385	1.0481	0.85976	0.87125
	R2	0.23	−0.10	−0.08	−0.36	0.26	0.06
	MSE	0.77383	0.88895	1.0786	1.0985	0.73918	0.75907
	MAE	0.70715	0.73716	0.83896	0.85388	0.6836	0.68255
SPEI 06	RMSE	0.93909	0.96639	0.9927	1.1563	0.91918	0.97256
	R2	0.12	−0.23	−0.76	0.02	0.16	0.24
	MSE	0.88189	0.93392	0.98545	1.337	0.8449	0.94587
	MAE	0.73435	0.74689	0.80116	0.90589	0.72274	0.76796
SPEI 09	RMSE	0.94458	1.0672	1.0727	1.1617	0.96318	1.0683
	R2	0.09	−0.75	−0.17	−1.07	0.06	−0.75
	MSE	0.89223	1.1388	1.1506	1.3495	0.92771	1.1412
	MAE	0.73814	0.86251	0.83782	0.92703	0.75958	0.86711
SPEI 12	RMSE	0.95255	1.1277	1.0567	1.2821	0.9687	1.1015
	R2	0.04	−1.27	−0.19	−1.94	0.00	−1.17
	MSE	0.90734	1.2717	1.1166	1.6438	0.93837	1.2134
	MAE	0.732	0.95535	0.81839	1.049	0.75617	0.94519
SPEI 24	RMSE	0.8114	1.3762	0.99313	1.632	0.87045	1.4436
	R2	−0.01	−3.06	−0.51	−4.71	−0.16	−3.47
	MSE	0.65837	1.894	0.98631	2.6633	0.75768	2.0841
	MAE	0.65787	1.2343	0.81963	1.4055	0.70871	1.2998

Source: Authors own calculation.

2022; Rahman et al., 2021). The correlation between the amount of heat in the water and the amount of rainfall is a possible reason for the prolonged extreme drought (BS, 2007). Bangladesh's northwestern region, including the Rangpur district, endures drought during dry periods because of the Farakka Barrage, which hinders the Padma river's movement. This causes 57% severe water scarcity (WBB, 1998). Consequently, temperature and rainfall would probably rise in the coming years, possibly resulting in a water stress deficiency in the Rangpur area district (Chowdhury et al., 2020; Rahman & Azim, 2022). Conversely, rising temperatures, on the other hand, might reduce annual precipitation in the coming decades, which could lead to extended dry spells in Bangladesh (Rahman & Lateh, 2016a).

Nevertheless, drought monitoring and prediction is essential for crop management, water scarcity management, water demand and supply evaluation, city and regional planning. The limitation of the study includes only one station-based drought characterization and prediction. However, the study area contains only one station it can be further studied based on remote sensing approaches. Therefore, more specifically further study may analyse more aspects and properties of drought in Bangladesh to find the most effective drought mitigation strategy on the reported trends with public perception.

5. Conclusion

This investigation examined the temporal tendencies of drought based on the relationship and comparative evaluation between SPEI and SPI. Also, predictions of temporal drought occurrence in Rangpur district during 1979–2020 have been performed. Therefore, several techniques have been used to identify drought trend exploration, relationship and comparative assessment evaluation as well as prediction. The statistical measurement of linear regression was used as a part of parametric test to detect the trend of monthly rainfall and temperature before applying non-parametric test including Modified Mann-Kendall for trend analysis for acquiring SPEI and SPI or drought as well as dry and wet period variability. As a part of correlation, Pearson correlation coefficient have been utilized. Additionally, ANN, RF and SVM machine learning method was employed to predict future variability of drought trend for SPEI. Significant downward negative trend is found for SPI 03, 06, 09, 12 and 24 which corresponds to Z >-2.70, Z > −2.75, Z>-4.50, Z > 5.60, Z >-8.40, respectively. Additionally, SPEI has an extensive adverse growth of negative trend compared with SPI Z statistics that includes SPEI 03>-4.80, SPEI 06>-5.13, SPEI 09>-6.82, SPEI 12>-8.04 and SPEI 24>-11.20. A significant correlation is observed for all the indices of SPEI and SPI indicates $r = 0.95$, $r = 0.97$, $r = 0.98$, $r = 0.98$ and $r = 0.97$ for 03, 06, 09, 12 and 24-months period, respectively. Comparative assessment distinguished SPEI is extensively suitable for drought variability measurement with the comparison of SPI. Moreover, no predictive model performed well for annual drought estimation. Hence, seasonal drought will increase of 24% for SPEI 06. The results stress the significance of improving control of hydro resources and reallocating crop production policy frameworks in Bangladesh as a means of dealing with disasters. This long-range prediction is designed to aid policy in arranging for more effective drought monitoring, rainwater collection, and cultivation practices.

Disclosure statement

No potential conflict of interest was reported by the author(s).

References

Abdullah, H. M. Water harvest for drought resilient agriculture: Prospect and possibilities in Bangladesh. In: Proceedings of the IARU Sustainability Science Congress. University of Copenhagen, Denmark;. 2014.

Adnan, S., Ullah, K., Shuanglin, L., Gao, S., Khan, A. H., & Mahmood, R. (2018). Comparison of various drought indices to monitor drought status in Pakistan. *Climate Dynamics*, *51*(5), 1885–1899. https://doi.org/10.1007/s00382-017-3987-0

Ahmed, Rafique . 2014 (Banglapedia)https://en.banglapedia.org/index.php/Climate . Climate.

Alamgir, M., Khan, N., Shahid, S., Yaseen, Z. M., Dewan, A., Hassan, Q. (2020). Evaluating severity–area–frequency (SAF) of seasonal droughts in Bangladesh under climate change scenarios. *Stochastic Environmental Research and Risk Assessment: Research Journal*, *34*(2), 447–464. https://doi.org/10.1007/s00477-020-01768-2

Alamgir, M., Shahid, S., Hazarika, M. K., Nashrrullah, S., Bin, H. S., & Shamsudin, S. (2015). Analysis of Meteorological drought pattern during different climatic and cropping seasons in Bangladesh. *JAWRA Journal of the American Water Resources Association*, *51*(3), 794–806. https://doi.org/10.1111/jawr.12276

Alam, I., Otani, S., Majbauddin, A., Qing, Q., Ishizu, S. F., Masumoto, T., Amano, H., & Kurozawa, Y. (2021). The effects of drought severity and its aftereffects on mortality in Bangladesh. *Yonago Acta Medica*, *64*(3), 292–302. https://doi.org/10.33160/yam.2021.08.007

Alexandersson, H. (1986). A homogeneity test applied to precipitation data. *Journal of Climatology*, *6*(6), 661–675. https://doi.org/10.1002/joc.3370060607

Ali, Z., Hussain, I., Faisal, M., Nazir, H. M., Hussain, T., Shad, M. Y., Mohamd Shoukry, A., & Hussain Gani, S. (2017). Forecasting drought using multilayer perceptron artificial neural network model. *Advances in Meteorology*, *2017*, 1–9. https://doi.org/10.1155/2017/5681308

Bari, S. H., Rahman, M. T. U., Hoque, M. A., & Hussain, M. M. (2016). Analysis of seasonal and annual rainfall trends in the northern region of Bangladesh. *Atmospheric Research*, *176–177*, 148–158. https://doi.org/10.1016/j.atmosres.2016.02.008

BS, R. S. (2007). *Climate variability and change: Adaptation to drought in Bangladesh-A resource book and training guidetle*. FAO.

Buishand, T. A. (1982). Some methods for testing the homogeneity of rainfall records. *Journal of Hydrology*, *58*(1), 11–27. https://www.sciencedirect.com/science/article/pii/002216948290066X

Chowdhury, A. (2017). Estimation of reference evapotranspiration using artificial neural network for mohanpur, nadia district, West Bengal: A case study. *International Journal of Research in Engineering and Technology*, *06*(7), 125–130. https://doi.org/10.15623/ijret.2017.0607021

Chowdhury, F. R., Ibrahim, Q. S. U., Shafiqul Bari, M., Jahangir Alam, M. M., Dunachie, S. J., Rodriguez-Morales, A. J., & Patwary, M. I. (2020). Correction: The association between temperature, rainfall and humidity with common climate-sensitive infectious diseases in Bangladesh (PLoS ONE(2020)13: 6(e0199579)Doi: 10.1371/journal.Pone.0199579. *PloS One*, *15*(4), 3–5. https://doi.org/10.1371/journal.pone.0232285

Cook, B. I., Smerdon, J. E., Seager, R., & Coats, S. (2014). Global warming and 21st century drying. *Climate Dynamics*, *43*(9), 2607–2627. https://doi.org/10.1007/s00382-014-2075-y

Das, S. (2021). Extreme rainfall estimation at ungauged locations: Information that needs to be included in low-lying monsoon climate regions like Bangladesh. *Journal of Hydrology*, *601*, 126616. https://doi.org/10.1016/j.jhydrol.2021.126616

Dastorani, M. T. T., & Afkhami, H. (2011). Application of artificial neural networks on drought prediction in Yazd (Central Iran). *Desert*, *16*(1), 39–48. https://doi.org/10.22059/JDESERT.2011.23021

Deye, N., Vincent, F., Michel, P., Ehrmann, S., Da Silva, D., Piagnerelli, M. . . . Laterre, P.-F. (2016). Changes in cardiac arrest patientsâ€TM temperature management after the 2013 â€œTTMâ€ trial: Results from an international survey. *Annals of Intensive*, *6*(1), https://doi.org/10.1186/s13613-015-0104-6 Al-Hussaini, M., & Mustafa, S. (2016). Adolescentsâ€TM knowledge and awareness of diabetes mellitus in Kuwait. Alexandria Journal of Medicine, 52(1) 61–66. http://doi.org/10.1016/j.ajme.2015.04.001, Pollach, G., Brunkhorst, F., Mipando, M., Namboya, F., Mndolo, S., & Luiz, T. (2016). The â€œfirst digit lawâ€ â€"A hypothesis on its possible impact on medicine and development aid. Medical Hypotheses, 97 102–106. http://doi.org/10.1016/j.mehy.2016.10.021, Asiedu, K., Kyei, S., Ayobi, B., Agyemang, F. O., & Ablordeppey, R. K. (2016). Survey of eye practitionersâ€TM preference of diagnostic tests and treatment modalities for dry eye in Ghana. Contact Lens Anterior Eye, 39(6) 411–415. http://doi.org/10.1016/j.clae.2016.08.001, Barakat, K. H., Gajewski, M. M., & Tuszynski, J. A. (2012). DNA polymerase beta (pol β) inhibitors: A comprehensive overview. Drug Discovery Today, 17 (15–16) 913–920. http://doi.org/10.1016/j.drudis.2012.04.008, Mocan, O., & Dumitraşcu, D. L. (2016). The broad spectrum of celiac disease and gluten sensitive enteropathy. Clujul Medical, 89(3) 335–342. http://doi.org/10.15386/cjmed-698, et al. Development of limited sampling strategy for mycophenolic acid: Influence of post-transplant period and second peak. Ther Drug Monit. 2013;.

Ferreira, L. B., da Cunha FF, de Oliveira RA, Fernandes Filho, E. I. (2019). Estimation of reference evapotranspiration in Brazil with limited meteorological data using ANN and SVM–A new approach. *Journal of Hydrology*, *572*, 556–570. https://doi.org/10.1016/j.jhydrol.2019.03.028

Habiba, U., Shaw, R., & Hassan, A. W. R. (2013a). *Drought risk and Reduction approaches in Bangladesh BT - Disaster risk Reduction approaches in Bangladesh*. Shaw R, Mallick F, Islam A, editors. Springer Japan. https://doi.org/10.1007/978-4-431-54252-0_7

Habiba, U., Shaw, R., & Hassan, A. W. R. (2013b). Drought risk and Reduction approaches in Bangladesh, 131–164. https://doi.org/10.1007/978-4-431-54252-0_7

Hamed, K. H., & Rao, A. R. (1998). A modified Mann-Kendall trend test for autocorrelated data. *Journal of Hydrology*, *204*(1–4), 182–196. https://doi.org/10.1016/S0022-1694(97)00125-X

Hasda, R., Rahaman, M. F., Jahan, C. S., Molla, K. I., & Mazumder, Q. H. (2020). Climatic data analysis for groundwater level simulation in drought prone Barind Tract, Bangladesh: Modelling approach using artificial neural network. *Groundwater for Sustainable Development*, *10*, 100361. https://doi.org/10.1016/j.gsd.2020.100361

Homdee, T., Pongput, K., & Kanae, S. (2016). A comparative performance analysis of three standardized climatic drought indices in the Chi river basin, Thailand. *Agriculture and Natural Resources*, *50*(3), 211–219. https://doi.org/10.1016/j.anres.2016.02.002

Islam, A. R. M. T., Islam, H. M. T., Shahid, S., Khatun, M. K., Ali, M. M., Rahman, M. S., Ibrahim, S. M., & Almoajel, A. M. (2021). Spatiotemporal nexus between vegetation change and extreme climatic indices and their possible causes of change. *Journal of Environmental Management*, *289*, 112505. https://www.sciencedirect.com/science/article/pii/S0301479721005673

Islam, A. R. T., Shen, S., Hu, Z., & Rahman, M. A. (2017). Drought hazard evaluation in Boro Paddy Cultivated areas of western Bangladesh at Current and future climate change conditions. *Advances in Meteorology*, *2017*, 1–12. https://doi.org/10.1155/2017/3514381

Jerin, J. N., Islam, H. M. T., Islam, A. R. M. T., Shahid, S., Hu, Z., Badhan, M. A., Chu, R., & Elbeltagi, A. (2021). Spatiotemporal trends in reference evapotranspiration and its driving factors in Bangladesh. *Theoretical and Applied Climatology*, *144*(1), 793–808. https://doi.org/10.1007/s00704-021-03566-4

Joetzjer, E., Douville, H., Delire, C., Ciais, P., Decharme, B., & Tyteca, S. (2013). Hydrologic benchmarking of meteorological drought indices at interannual to climate change timescales: A case study over the Amazon and Mississippi river basins. *Hydrology and Earth System Sciences*, *17*(12), 4885–4895. https://doi.org/10.5194/hess-17-4885-2013

Kamruzzaman, M., Almazroui, M., Salam, M. A., Mondol, A. H., Rahman, M., Deb, L., et al. Spatiotemporal drought analysis in Bangladesh using the standardized precipitation index (SPI) and standardized precipitation evapotranspiration index (SPEI). Research Square [Internet], 2022;1–17. https://www.researchsquare.com/article/rs-1323693/v1?utm_source=researcher_app&utm_medium=referral&utm_campaign=RESR_MRKT_Researcher_inbound

Kamruzzaman, M., Hwang, S., Cho, J., Jang, M. W., & Jeong, H. (2019). Evaluating the spatiotemporal characteristics of agricultural drought in bangladesh using effective drought index. *Water*, *11*(12), 2437. https://doi.org/10.3390/w11122437

Kamruzzaman, M., Jang, M. W., Cho, J., & Hwang, S. (2019). Future changes in precipitation and drought characteristics over Bangladesh under CMIP5 climatological projections. *Water*, *11*(11), 2219. https://doi.org/10.3390/w11112219

Kendall, M. G. (1975). *Rank correlation methods* (4th edn. ed.). Charles Griffin.

Lotfirad, M., Esmaeili-Gisavandani, H., & Adib, A. (2022). Drought monitoring and prediction using SPI, SPEI, and random forest model in various climates of Iran. *Journal of Water and Climate Change*, *13*(2), 383–406. https://doi.org/10.2166/wcc.2021.287

Mahmoudi, P., Rigi, A., & Miri Kamak, M. (2019). A comparative study of precipitation-based drought indices with the aim of selecting the best index for drought monitoring in Iran. *Theoretical and Applied Climatology*, *137*(3), 3123–3138. https://doi.org/10.1007/s00704-019-02778-z

Mahsin, M., Akhter, Y., & Begum, M. (2012). Modeling rainfall in Dhaka division of Bangladesh using time series analysis. *Journal of Mathematical Analysis and Applications*, *1*(5), 67–73.

Mainuddin, M., Maniruzzaman, M., Alam, M. M., Mojid, M. A., Schmidt, E. J., Islam, M. T., & Scobie, M. (2020). Water usage and productivity of Boro rice at the field level and their impacts on the sustainable groundwater irrigation in the North-West Bangladesh. *Agricultural Water Management*, *240*, 106294. https://www.sciencedirect.com/science/article/pii/S0378377420301153

McKee, T. B., Nolan, J., & Kleist, J. (1993). The relationship of drought frequency and duration to time scales. *Preprint Eighth Conference Applied Climatology American Meteorology, Society*, *192*, 110245. https://doi.org/10.1016/j.envres.2020.110245

Mekonnen, Y. A., & Gokcekus, P. H. (2020). Genomic investigations of acute munitions exposures on the health and skin microbiome composition of leopard frog (Rana pipiens) tadpoles. *Environmental Research*, *192* (December). https://doi.org/10.1016/j.envres.2020.110245

Miah, M. G., Abdullah, H. M., & Jeong, C. (2017). Exploring standardized precipitation evapotranspiration index for drought assessment in Bangladesh. *Environmental Monitoring and Assessment*, *189*(11), 547. https://doi.org/10.1007/s10661-017-6235-5

Mohsenipour, M., Shahid, S., Sung, C. E., & Wang, X. (2018, June). Changing pattern of droughts during cropping seasons of Bangladesh. *Water Resources Management*, *32*(5), 1555–1568. https://doi.org/10.1007/s11269-017-1890-4

Mokhtar, A., Jalali, M., He, H., Al-Ansari, N., Elbeltagi, A., Alsafadi, K., Abdo, H. G., Sammen, S. S., Gyasi-Agyei, Y., & Rodrigo-Comino, J. (2021). Estimation of SPEI Meteorological drought using machine learning Algorithms. *Institute of Electrical and Electronics Engineers Access*, *9*, 65503–65523. https://doi.org/10.1109/ACCESS.2021.3074305

Mora, C., Spirandelli, D., Franklin, E. C., Lynham, J., Kantar, M. B., Miles, W., Smith, C. Z., Freel, K., Moy, J., Louis, L. V., Barba, E. W., Bettinger, K., Frazier, A. G., Colburn IX, J. F., Hanasaki, N., Hawkins, E., Hirabayashi, Y., Knorr, W. . . . Patz, J. A. (2018). Broad threat to humanity from cumulative climate hazards intensified by greenhouse gas emissions. *Nature Climate Change*, *8*(12), 1062–1071. https://doi.org/10.1038/s41558-018-0315-6

Morid, S., Smakhtin, V., & Bagherzadeh, K. (2007). Drought forecasting using artificial neural networks and time series of drought indices. *International Journal of Climatology*, *27* (15), 2103–2111. https://doi.org/10.1002/joc.1498

Mortuza, M. R., Moges, E., Demissie, Y., & Li, H. Y. (2019). Historical and future drought in Bangladesh using copula-based bivariate regional frequency analysis. *Theoretical and Applied Climatology*, *135*(3–4), 855–871. https://doi.org/10.1007/s00704-018-2407-7

Park, S., Seo, E., Kang, D., Im, J., & Lee, M. I. (2018). Prediction of drought on pentad scale using remote sensing data and MJO index through random forest over East Asia. *Remote Sensing*, *10*(11), 1811. https://doi.org/10.3390/rs10111811

Poornima, S., & Pushpalatha, M. (2019). Drought prediction based on SPI and SPEI with varying timescales using LSTM recurrent neural network. *Soft Computing*, *23* (18), 8399–8412. https://doi.org/10.1007/s00500-019-04120-1

PR, B. (1995). Food: Stock, import and price. *Dhaka Court*, *11*(34), 9.

Pramudya, Y., & Onishi, T. (2018). Assessment of the Standardized precipitation index (SPI) in Tegal city, Central Java, Indonesia. *IOP Conference Series: Earth and Environmental Science*, *129*, 12019. https://doi.org/10.1088/1755-1315/129/1/012019

Rahman, M. S., & ARMT, I. (2019). Are precipitation concentration and intensity changing in Bangladesh overtimes? Analysis of the possible causes of changes in precipitation systems. *The Science of the Total Environment*, *690*, 370–387. https://doi.org/10.1016/j.scitotenv.2019.06.529

Rahman, M. N., & Azim, S. A. (2021). Meteorological drought in Bangladesh using Standardized precipitation index: A Spatiotemporal approach. *The Dhaka University Journal of Earth and Environmental Sciences*, *10*(3), 1–16. https://www.banglajol.info/index.php/DUJEES/article/view/59067

Rahman, M. N., & Azim, S. A. (2022). Spatiotemporal evaluation of rainfall trend during 1979-2019 in Seven climatic zones of Bangladesh. *Geology, Ecology & Landscapes*, 1–16. https://doi.org/10.1080/24749508.2021.2022425

Rahman, M. R., & Lateh, H. (2016a). Meteorological drought in Bangladesh: Assessing, analysing and hazard mapping using SPI, GIS and monthly rainfall data. *Environmental Earth Sciences*, *75*(12), 1–20. https://doi.org/10.1007/s12665-016-5829-5

Rahman, M. R., & Lateh, H. (2016b). Meteorological drought in Bangladesh: Assessing, analysing and hazard mapping using SPI, GIS and monthly rainfall data. *Environmental Earth Sciences*, *75*(12). https://doi.org/10.1007/s12665-016-5829-5

Rahman, M. N., Rony, M. R. H., & Jannat, F. A. (2021). Spatiotemporal evaluation of drought trend during 1979–2019 in seven climatic zones of Bangladesh. *Heliyon*, *7*(11), e08249. https://doi.org/10.1016/j.heliyon.2021.e08249

Rumelhart, D. E., Hinton, G. E., & Williams, R. J. (1986). Learning representations by back-propagating errors. *Nature*, *323*(6088), 533–536. https://doi.org/10.1038/323533a0

Shahfahad, T. S., Ali, R., Nguyen, K.-A., Naikoo, M. W., Liou, Y.-A., Liou, Y.-A., Islam, A. R. M. T., Mallick, J., & Rahman, A. (2022). Monitoring drought pattern for pre- and post-monsoon seasons in a semi-arid region of western part of India. *Environmental Monitoring and Assessment*, *194*(6), 396. https://doi.org/10.1007/s10661-022-10028-5

Shahid, S. (2008). Spatial and temporal characteristics of droughts in the western part of Bangladesh. *Hydrological Processes*, *22*(13), 2235–2247. https://doi.org/10.1002/hyp.6820

Sheffield, J., & Wood, E. F. (2008). Projected changes in drought occurrence under future global warming from multi-model, multi-scenario, IPCC AR4 simulations. *Climate Dynamics Drought*, *31*(1), 79–105.

Stagge, J. H., Tallaksen, L. M., Gudmundsson, L., Van Loon, A. F., & Stahl, K. (2015, November). Candidate distributions for climatological drought indices (SPI and SPEI). *International Journal of Climatology*, *35*(13), 4027–4040. https://doi.org/10.1002/joc.4267

Tan, C., Yang, J., & Li, M. (2015). *Temporal-spatial variation of drought Indicated by SPI and SPEI in Ningxia Hui Autonomous region* (Vol. 6). Atmosphere.

Tefera, A. S., Ayoade, J. O., & Bello, N. J. (2019). Comparative analyses of SPI and SPEI as drought assessment tools in Tigray region, northern Ethiopia. *SN Applied Sciences*, *1*(10), 1265. https://doi.org/10.1007/s42452-019-1326-2

Uddin, M. J., Hu, J., ARMT, I., Eibek, K. U., & Nasrin, Z. M. (2020). A comprehensive statistical assessment of drought indices to monitor drought status in Bangladesh. *Arabian Journal of Geosciences*, *13*(9), 323. https://doi.org/10.1007/s12517-020-05302-0

Umma, H., & Rajib, S. (2014). Farmers' response to drought in northwestern Bangladesh. *Risks and Conflicts: Local Responses to Natural Disasters [Internet]*, Vol 14, Emerald Group Publishing Limitedpp. 131–161. Community, Environment and Disaster Risk Management https://doi.org/10.1108/S2040-7262(2013)0000014012

Vapnik, V. N. (1995). *The Nature of statistical learning Theory*. Springer. https://doi.org/10.1007/978-1-4757-3264-1

Vicente-Serrano, S. M., & Beguería, S. (2016). Comment on 'Candidate distributions for climatological drought indices (SPI and SPEI)'by James H. Stagge et al. *International Journal of Climatology*, *36*(4), 2120–2131. https://doi.org/10.1002/joc.4474

Vicente-Serrano, M. S. (2015). *The climate data Guide: Standardized precipitation evapotranspiration index (SPEI)*. National Center for Atmospheric Research.

Vicente-Serrano, S. M. (2006). Differences in spatial patterns of drought on different time scales: An analysis of the Iberian Peninsula. *Water Resources Management*, *20*(1), 37–60. https://doi.org/10.1007/s11269-006-2974-8

Vicente-Serrano, S. M., Lopez-Moreno, J.-I., Beguería, S., Lorenzo-Lacruz, J., Sanchez-Lorenzo, A., García-Ruiz, J. M., Azorin-Molina, C., Morán-Tejeda, E., Revuelto, J., Trigo, R., Coelho, F., & Espejo, F. (2014). Evidence of increasing drought severity caused by temperature rise in southern Europe. *Environmental Research Letters*, *9*(4), 44001. https://doi.org/10.1088/1748-9326/9/4/044001

von Neumann, J. (1941 Jul 29). Distribution of the Ratio of the Mean Square Successive Difference to the variance. *Annals of Mathematical Statistics*, *12*(4),367–395. https://doi.org/10.1214/aoms/1177731677

V-S, S. M., L-M, J. I., & B, S. (2010). A multi-scalardrought index sensitive to global warming: The StandardizedPrecipitation evapotranspiration index. *Journal of Climate*, *23*(7), 1696–1718. https://doi.org/10.1175/2009JCLI2909.1

Wang, H., Chen, Y., Pan, Y., Chen, Z., & Ren, Z. (2019, September). Assessment of candidate distributions for SPI/SPEI and sensitivity of drought to climatic variables in China. *International Journal of Climatology*, *39*(11), 4392–4412. https://doi.org/10.1002/joc.6081

Wang, S., Lian, J., Peng, Y., Hu, B., & Chen, H. (2019). Generalized reference evapotranspiration models with limited climatic data based on random forest and gene expression programming in Guangxi, China. *Agricultural Water Management*, *221*, 220–230. https://doi.org/10.1016/j.agwat.2019.03.027

WANG, F., WANG, Z., YANG, H., & ZHAO, Y. (2018). Study of the temporal and spatial patterns of drought in the YellowRiver basin based on SPEI. *Science China Earth Sciences*, *61*(8), 1098–1111. https://doi.org/10.1007/s11430-017-9198-2

WBB. (1998). *Water resource management in Bangladesh: Steps towards a new national water plan*. Ministry of Water Resources.

Yaseen, Z. M., Ali, M., Sharafati, A., Al-Ansari, N., & Shahid, S. (2021). Forecasting standardized precipitation index using data intelligence models: Regional investigation of Bangladesh. *Scientific Reports*, *11*(1), 1–25. https://doi.org/10.1038/s41598-021-82977-9

Zannat, F., ARMT, I., & Rahman, M. A. (2019). Spatiotemporal variability of rainfall linked to ground water level under changing climate in northwestern region, Bangladesh. *European Journal of Geosciences*, *56* (April), 35–56. https://doi.org/10.34154/2019-EJGS-0101-35-56/euraass

Zinat, M. R. M., Salam, R., Badhan, M. A., & Islam, A. R. M. T. (2020). Appraising drought hazard during Boro rice growing period in western Bangladesh. *International Journal of Biometeorology*, *64*(10), 1687–1697. https://doi.org/10.1007/s00484-020-01949-2

Zou, K. H., Tuncali, K., & Silverman, S. G. (2003, June). Correlation and Simple linear regression. *Radiology*, *227* (3), 617–628. https://doi.org/10.1148/radiol.2273011499