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Forecasting Seasonal Drought Using Spatio-SPI and Machine Learning Algorithm: The Case of Borana Plateau of Southern Oromia, Ethiopia

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Abstract

Drought is a natural phenomenon that occurs in all parts of the world. Hence, drought monitoring and forecasting have been fundamental issue for developing and implementing a proactive drought mitigation plan. In the process of monitoring and forecasting drought occurrences; the major decisive factors are drought identification/quantification and selection of appropriate forecasting models. This study model seasonal drought forecasting using the Spatio-standardized Precipitation Index (SPI) data in the Borana plateau of Southern Oromia region of Ethiopia with the techniques of machine learning algorithm. Adjusted native resolution based historical rainfall data of 1981 to 2021 of the study area were used from NASA power project climate data repository website in the January 2022. Quantifications of SPI seasonal drought were done using SPEI package with in the RStudio software. The nonlinear outoregressive neural neuron network (NAR network) based Levenberg-Marquardt Back Propagation algorithm (LMBP) was used to model spatio-SPI seasonal drought forecasting of some sites in the study area using MATLAB software. The findings of this study showed SPI 3 months and SPI 6 months ANN based seasonal drought prediction model performance evaluation value of MSE ranged between 0.0022 and 5.5752 which were in the excellent acceptable range of validation. SPI 3 months and SPI 6 months model performance evaluation value of correlation coefficient (R) of all the study sites were above 0.9034 which was also in the excellent range of validation. The study results revealed that ANN modeling could works effectively for forecasting seasonal drought /SPI 3 months and SPI 6 months/ ahead of two months and five months lead times, respectively, in all the districts in the study area. This study identified that, actual/observed and ANN based Ganna and Hagayya seasons SPI 3 months and SPI 6-months prediction value of 1981–2021 discovered that Borana's zone rainfall seasons on which communities rely for their entire life supporting systems were/ are drought prone seasons.

Keywords: SPI seasonal; RStudio; ANN; Matlab; Drought forecast

Introduction

Drought is an environmental stress that originates from a deficiency in precipitation over an extended period of time. It is a natural recurrent 'climate phenomenon' which occurs in all parts of the world. However, drought is becoming too severe in all dimensions; and has causing a far reaching adverse impact across all sectors [1]. It has negative impacts on agriculture, domestic water use, hydrology, hydropower, economy, social systems, ecology and environment, trade, transport, healthy, education, transport and, etc. Drought has become one of the most severe climate events that need to be mitigated to reduce its negative impacts [2].

Hence, drought monitoring and forecasts are becoming fundamental for developing and implementing a proactive drought mitigation plan [3]. Furthermore, probabilistic and risk based drought monitoring and prediction information is not only useful for mitigation, but is also vital for successful drought relief management during an extreme event.

Drought prediction has been a challenging techniques owing to its complexity with diverse origins and occurrence at different temporal and spatial scales. In the process of drought monitoring and forecasting, the first and the most deceive factors are drought identification and quantification. Among the available drought indices; Standardized Precipitation Index (SPI) developed by Mckee, et al., are widely used, especially, for meteorological drought quantification across the world. Standardized Precipitation Index (SPI) expresses the actual rainfall as a standardized departure with respect to rainfall probability distribution function and permitted comparisons across space and time.

The computation of SPI requires long term data on precipitation to determine the probability distribution function which is then transformed to a normal distribution with mean zero and standard deviation of one. Thus, the values of SPI are expressed in standard deviations, positive SPI indicating greater than median precipitation and negative values indicating less than median precipitation [4]. However, at different locations; SPI could not correspond to the same deficits or surplus of precipitation. This means that SPI is site dependent and an absolute drought comparison among sites can be done through a deepened spatial analysis that takes the evolution of the characteristics of drought, namely: Duration, severity and intensity into account.

The most fundamental factor in drought forecasting is the selection of appropriate forecasting methods/model [5]. Generally, three methods

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have been used for drought prediction: Statistical, dynamical and composite/hybrid methods. The statistical prediction method uses empirical relationships of historical records which is difficult for solving practical application issues in non-leaner time series data for prediction. Hence, the complex character and non-linearity of the drought/rainfall data require methods that can simulate non-linear time series data. In this regard, with the increased computational capability and improved understanding of climate, drought prediction has been tackled more with state of the art General Circulation Models (GCMs), which provide drought prediction based on the physical processes of the atmosphere, ocean, and land surface [6]. The past decade has also witnessed the development of conceptual prediction methods that combine forecast from both statistical and dynamical methods.

Drought forecasting systems use models fed by climatic and atmospheric data to predict the probability of a drought occurrence in a region or area of interest. Machine learning algorithms/dynamical methods/for example, Artificial Neural Networks (ANNs) are used to predict drought using drought indicators such as the index (SPI) as input data. ANN is a mathematical model based on biological neural neuron networks. In most cases, an ANN is an adaptive system that changes its structure based on external or internal information which flows through the network during the learning phase. In more practical terms, neural networks are nonlinear statistical data modeling tools. Thus, they can be used to model complex relationships between inputs and outputs. ANN based drought prediction is one of the most well-known method [7]. Its parallel processing and its ability to learn the patterns are the main factors that make it popular in drought modeling. In this study, the SPI, the most widely used drought indicator which is recommended by the world meteorological organization was used as an input data for predicting SPI seasonal drought using machine learning algorithm NAR-neural network.

Drought is an environmental stress mostly originates from precipitation deficit over an extended period of time; while in certain cases it may result from the anomaly of other variables, such as temperature or evapotranspiration. Meteorological drought is measured in terms of days, weeks, months, seasons, years, or decades of precipitation deficit [8]. Mainly, it is the cause of the other three forms of drought and is derived by the pulling effects of the teleconnection with in land, atmosphere and sea surface. Hence, definition of meteorological drought is region specific; and is depend on the precipitation anomaly that is deviated from the historical average with in a given geographic area. This study was focused on the characterization and prediction of the SPI seasonal precipitation deficit/meteorological drought using SPI and machine learning algorithm, respectively.

Drought may occur with multiple processes driving its onset, persistence or recovery, happening at a wide range of time scales (sub-seasonal/weekly, seasonal, multiyear or decadal) and across different spatial scales of local, regional, continental, and global. Drought is commonly characterized at the seasonal time scale [9]. As mentioned in the above sections there are several research and operational models that provide drought monitoring and/or prediction information depending on the priority of the forms/types of the drought under concern with in a given area. In this regard, prediction of drought with machine learning algorithms through using SPI based drought characterization as input data were done in America, Iran, Algeria, Pakistan, Kenya, Awash basin of Ethiopia, upper blue Nile basin of Ethiopia, Botswana, etc.

According to IPCC, de Sherbinin and Kuwayama, et al., drought affected over an average of 53 million people each year [10]. Each year, the United States suffers losses of six to eight billion dollars as a result of droughts. Lin and Yu, et al., mentioned that drought is also a major natural disaster in China, with its frequency reaching 70% in certain places during the summer and with enormous socioeconomic losses. In Africa recurrence of each drought episode in 2-3 years in different scale, location and time is resulting in aggregate damage of up to 25% of each country‘s GDP. In Ethiopia in the past half a century new wave of drought is occurring before people/livelihood sources/systems are becoming recovered from the previous adverse impacts of drought without giving enough time for recovery. According to study by Salifu, Borana pastoralists lost more than 70% of their livestock during the severe drought of the 2011 and 2016 [11]. In addition, in Borana plateau of Southern Oromia region, Ethiopia; adverse impacts of drought are driven and are the driver of rangeland degradation, expansion of invasive species, water scarcity, and negative terms of trade and food insecurity. In this regard, mainly adverse impacts of drought in the study area has exacerbated by the lack of area specific appropriate drought forecasting information which allow early preparedness to minimize its negative impacts in advance. Hence, objective of this study was to model spatio-SPI seasonal drought forecasting through using machine learning algorithm in the Borana plateau of Southern Oromia region of Ethiopia.

Materials and Methods

This study used Standard Precipitation Index (SPI) and Artificial Neural Network (ANN) to characterize and predict SPI seasonal drought in the study area, respectively, by using historical rainfall data from 1981 up to 2021.

Study area

Description of the study area: This study was conducted in Borana zone of Oromia, Southern Ethiopia. Borana zone is between 3°31"31'" to 6°35"37'" latitude and 36°42‘’38'" to 39°45"15"E longitudes. It is located in the Southern part of Oromia regional state of Ethiopia. Yabello the capital town of Borana zone is 570 km South of the capital city, Addis Ababa. It borders Kenya in the South, Somali regional state and Gudji zone in the East and the Sidama region, Southern Nations, Nationalities and Peoples Region (SNNPR) in the North and West [12]. The landscape of the zone is mainly lowlands with slightly undulating peaks up to 2000 meters above sea level in some areas. The land area is 63,939 km^2. The projected population of Borana zone is 1,626,930 (male 821,733 and female 805,197) with the majority (97%) living in rural areas; Borana Oromo is the largest community in the area with interconnected Oromo groups of Garba and Burdji.

Agro ecologically, it is semi-arid lowlands and frequently prone to severe drought within year to year increasing trends in causing damage in the study area. There are four locally defined seasons in which annual rainfall distribution and the dry period patterns of the study area are bimodal in character. Mean annual rainfall of the area is between 400 mm to 700 mm. Normally the long/main rain season (Ganna rain) is between March and May; and the short rain season (Hagayya rain) is between September and November. The onset and cessation of both rainfall seasons are often irregular in duration and are scattered in spatial coverage. The warm dry seasons (Bona Hagayya) is between December and February with a high

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evapotranspiration rate and the cool dry season is between June and August [13].

Research methods

This study used Standard Precipitation Index (SPI) and Artificial Neural Network (ANN) to characterize and forecast seasonal drought in the study area, respectively, by using historical rainfall data from 1981 up to 2021.

In this regard, this study used native resolution based NASA power project climate data. In this study, NASA power project climate data were preferred due to the fact that the data/parameters in power release 901 are provided on a global grid with native resolutions equal to the input data/it provides original *in-situ* agro meteorological data which are not synthetic second hand data/. Power 901 release is also not only builds upon the data portal established with release 8, but it also adds more recent data releases from NASA's GEWEX SRB release 4, CERES SYN 10 and FLASHFlux Version 4A. The spatial resolution is 1.0° latitude by 1.0° longitude for the radiation data sets and ½°latitude by ⅝° longitude for the meteorological data sets [14]. The grid reference system is WGS84.

In this regard, monthly rainfall data of Yabello (4091’’60’’’N latitude and 380 12’’ 52’’’E longitude, at an elevation of 1549.25 meters), Dirre (4010’’01’’’N latitude and 33027’’62’’’E longitude at elevation of 1174.4 meters), Dilloo (4013’’84’’’N latitude and 37047’’15’’’E longitude at elevation of 772.1 meters), Guchi (4033’’97’’’N latitude and 39058’’77’’’E longitude at elevation of 1053.85) and Moyale (3053’’83’’’N latitude and 390 09’’20’’’E longitude at elevation of 903.) were retrieved from native resolution NASA power project climate data with adjusted missed data/the value for missing source data that cannot be computed or is outside of the sources availability range is -999. NASA/POWER CERES/MERRA2 native temporal resolution are available in hourly, daily, weekly, monthly, annual and climatology basis (month/day/year): 01/01/1981 up to now.

Standard Precipitation Index (SPI)

The SPI based drought classification was used in this study to characterize seasonal drought phenomena and to model ANN based SPI seasonal drought prediction in the study area [15]. SPI was computed at multiple timescales. It was developed by Mckee, et al. and Edwards and McKee to quantify precipitation anomaly with respect to long term normal conditions for multiple time scales. It uses monthly precipitation aggregates and has been widely applied in many studies. Mckee, et al., defined the Standardized Precipitation Index (SPI) often called the z score as the number of standard deviations that cumulative rainfall differs from the historical climatological average and has been used as a tool for monitoring and defining drought. SPI can be calculated at various time scales on which precipitation deficits/surpluses/can affect different aspects of the hydrologic cycles (drought and flooding). Positive and negative SPI values indicate wet and dry conditions, respectively. A drought event starts when SPI value reaches negative and ends when SPI becomes positive again. SPI reflect the natural lags in response to different water sources, such as river discharge, underground and reservoirs storage, snow pack and to precipitation anomalies [16].

As an illustration of the procedure, for a 3 months’ time scale, the precipitation accumulation from month j-2 to month j is summed and attributed to month j. At this time scale, the first two months of the data time series are missing. Next follows the normalization procedure, in which an appropriate probability density function is first fitted to the long term time series of aggregated precipitation. Then the fitted function is used to calculate the cumulative distribution of the data points, which are finally transformed into standardized normal varieties. This procedure is repeated for all needed time scales [17]. The most commonly used distribution for SPI calculation is the two parameter gamma distribution with a shape and scale parameter. Gamma distribution is used to fit to the frequency distribution of precipitation summed over individual month for various time scales, which is defined by its probability density function:

$$g(x) = \frac{1}{{}^{6}\Gamma(\partial)} \; 3^{6} e^{-1_{e}} \quad \frac{3}{} \; for \; \times > 0 \qquad (1)$$

Where the probability density function is given by g (x), ∂ is the shape parameter (β>0) β is a scale parameter and (σ>0) and

$$\Gamma(\partial) = \int_0^{\partial} y^{\partial-1_{e}-1_{dy}} - 1_{dy} \qquad (2)$$

Γ (∂) is the gamma function

The parameters σ and β are assessed as follows:

$$\partial = \frac{1}{1\,A} + \left(x = 1 + \frac{\sqrt{1+4A}}{3} \right) \qquad (3)$$

$$\beta = \frac{\times}{\partial}$$

$$A = \ln(\dot{x}) - \frac{\sum \ln(\ddot{X})}{n} \qquad (4)$$

Where n is the number of precipitation observations and x is the arithmetic mean over the analyzed time scale. A cumulative probability G(x) of an observed quantity of rainfall in each month and time scale (if α and β estimators were used to integrate the probability density function with respect to x) is computed as follows:

$$G(X) = \int_0^3 g(3)\,d3 = \frac{1}{\beta^{\acute{\sigma}}} \Gamma(0) \int_0^3 3^{\acute{\sigma}}_{e} \frac{x}{} dx \qquad (5)$$

The incomplete gamma function is obtained when substituting t for ẋ/Ƀ in the previous equation:

However, the gamma distribution function is undefined for x=0 and q=P(x=0)>0; where P (x=0) is the probability of zero precipitation. Therefore, the actual probability of non-exceedance H (x) should be computed as follows:

$$H(x) = q + (1 - q)G(x) \qquad (6)$$

Where q is the probability of x=0. If m is zero in a sample of size n, then q is calculated as

$$q=\frac{m}{n} \quad (7)$$

Finally, to compute the SPI, the cumulative probability distribution H(x) is standardized to a normal variable Z~N (0,1). Taking into account the SPI yielded results, the classification of wet or drought periods is shown in Table 1 as stated by Mckee, et al.

SPI value	Class
≥ 2.0	Extremely wet
1.5 to 1.99	Severely wet
1.0 to 1.49	Moderately wet
-0.99 to 0.99	Near normal
-1.49 to -0.99	Moderately dry
-1.99 to -1.49	Severely dry
≤ 2.0	Extremely dry

Table 1: Classification of standardized precipitation index values.

Since changes in precipitation have influence in many aspects of the hydrologic cycle, several time scales are used for SPI computation. The 3 months SPI value describes short and medium term moisture, the 6 months SPI value describes droughts that affect agriculture and the 12 months SPI describes droughts affecting water supply reservoir levels [18].

In this study, Ganna (March to May) and Hagayya (October to November) seasons SPI (SPI 3 months and SPI 6 months) were computed to characterize drought phenomena in the Borana plateau of Southern Oromia region of Ethiopia to prepare SPI based input data for machine learning algorithm based drought forecasting.

This study set up an input file containing precipitation data tabulated with 3 column format: Year, Month, and Monthly precipitation value. In this regard, due to the difficulty of manually calculating SPI values, various computer programs have been developed for this purpose. This study used the 'SPEI' package for SPI computation. The 'SPEI' package is a library of R system 4.1.1. In this, regard, both system and packages are available at the comprehensive R archive network. Next to this, SPEI package in RStudio software was used to calculate the SPI 3-months and SPI 6-months to characterize drought situation in the study area.

Artificial Neural Networks (ANN)

In the majority of cases, time series applications are characterized by high variations and fleeting transient periods. This fact makes it difficult to model time series data using a linear model, especially, the complex interaction in the hydroclimatic system cannot be characterized by linear models. Hence, Artificial Neural Networks (ANN) was initially proposed by McCulloch and Pitts to analyze problems with variables of a non-linear or stochastic nature [19]. ANN is a computation paradigm of complex networking system that attempts to mimic the neural connections in the brain. Artificial neural networks helps to understand the brain, human cognition and perception and have been proven to be successful for solving different problems in pattern classification, decision making and predicting. In this regard, ANN Network has been frequently used for predicting and modeling nonlinear time series data, especially, in modeling climatological and/or hydrological, ecological, weather pollution, energy and water consumption, wind speed, marketing price data, stock data, health data and etc.

Through time, many algorithms have been proposed to find optimum structure of the network, but none of these methods guaranteed the optimal solution of the parameters for all types of forecasting problems. There are no hard and fast rules prevailing the correct structure of a neural network. Important factors such as the number of inputs, the number of hidden units, and the arrangement of these units into layers are often determined using trial and error methods or fixed in advance according to the subjective opinion of each individual designer. The procedure for MLPNN consists of four parts:

- Variable selection.
- Formulations of training, testing and validation.
- Architecture.
- Model verification and forecasting.

This employs that choosing variable for training, testing and validation is done by software itself.

Hence, this research used Non-Linear Autoregressive neural networks (NAR), which are to forecast samples framed in a one dimensional time series. A nonlinear autoregressive neural network applied to time series forecasting, describes a discrete, non-linear, autoregressive model that can be written as follows:

$$(y(t)=h(y(t\text{-}1),(y(t\text{-}2),\ldots,(t\text{-}p))t\epsilon(t) \quad (8)$$

This formula describes how a NAR network is used to predict the value of a data series y at time t, y(t), using the p past values of the series. The function h(·) is unknown in advance and the training of the neural network aims to approximate the function by means of the optimization of the network weights and neuron bias. Finally, the term ϵ (t) stands for the error of the approximation of the series y at time t. The topology of a NAR network is shown in Figures 1 and 2. The p features y(t−1), y(t−2), . . . , y(t−p), are called feedback delays [20]. The number of hidden layers and neurons per layer are completely flexible and are optimized through a trial and error procedure to obtain the network topology that can provide the best performance. Nevertheless, it is important to bear in mind that increasing the number of neurons makes the system more complex, while a low number of neurons may restrict the generalization capabilities and computing power of the network.

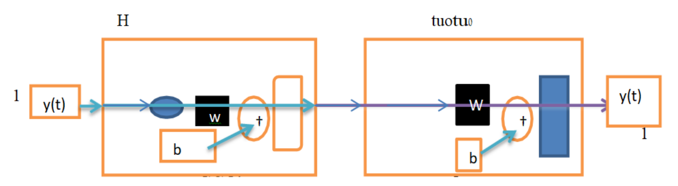

Figure 1: Schematic structures of NAR neural network. H stands for hidden layers.

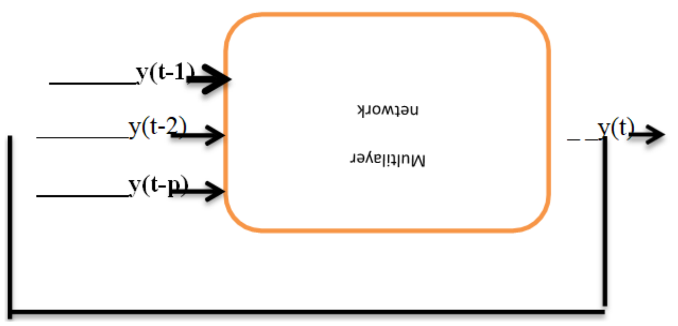

Figure 2: Schematic structures of NAR neural network.

In this study, NAR neural networks were used to model drought forecasting as follows: The network structures contains one input (SPI seasons/SPI 3 months and SPI 6 months) at time t-1, y(t-1) and one output (the next value of the time series, y(t), to be predicted). The n umber of delays is set experimentally after a data pre-processing and analysis stage. In this regard, this study used and compared three different combinations of ANN-NAR networking structures in which each represent 1 input layer, 8/6/12 hidden layers and 1 output layer that were constitutes (1,8,1); (1,6,1) and (1,12,1) to identify the model output/forecast that meet the best validation criteria in seasonal drought prediction using input data/SPI 3 months and SPI 6 months of the study area which was retrieved and computed from NASA climate raw data at native resolution. This study used the most common learning rule for the NAR network which is the Levenberg-Marquardt Back Propagation algorithm (LMBP). This training function is often the fastest back propagation type algorithm. The division of the historical time series data in this study was 70% for the training, 15% for the validation and 15% for the testing. Randomly, 490 data samples were divided into 342 data for the training, 74 data for the validation and 74 data for the testing.

Finally, this study used two criteria to evaluate the performance of the neural network prediction model. The mean square error calculated as:

$$MSE=\frac{\sum_{1}^{n}(y_i-\acute{y}_i)^2}{N} \qquad (9)$$

Where, N is the number of times, y_i and $\acute{y}_i$ are the observed and predicted SPI i^{th}, respectively. The best MSE value is 0 which is mostly unlikely.

The performance of the forecasts from the data driven models was evaluated. The Pearson correlation coefficient is one of the most commonly used performance in selecting proper inputs for the ANN. Correlation coefficient is described as the degree of correlation between the empirical and modeled values (equation 10):

$$R=\frac{\sum_{1}^{N}(y_i-\acute{y}_i)^2(y_{mi}-\acute{y}_m)^2}{\sqrt{\sum_{1}^{N}(y_i-\acute{y}_i)^2\ \sum^{N}(y_{mi}-\acute{y}_m)^2}} \qquad (10)$$

Where y_i and y_{mi} enounce the network output and measured value from the i^{th} element; $\bar{y}$ and $\bar{y}_m$ conceive their average respectively and N describes the number of times. The best R value is 1. In this study, all the ANN drought forecasting model was done with in the MATLAB ANN toolbox.

Results and Discussion

Historical rainfall data (1981-2021) was subjected to SPI 3 months and SPI 6 months departure analysis for identification of drought and the extent of moisture deficit. In this study, ANN/machine learning algorithm based seasonal drought prediction was done using actual SPI 3 months and SP 6 months forecasting value of 1981–2021 discovered that Borana zone was/is drought prone area. These revealed that there were extreme meteorological and agricultural drought in the aforementioned years during Ganna and Hagayya rainfall seasons in the study area. Actual/observed and predicted seasonal SPI 3 months and SPI 6 months values of 1981–2021 were displayed in Figures 2-4 and Table 2. Table 2 might used as a reference for making future drought prediction in the study area.

In all study districts with different combinations of ANN architectures/structures which constitutes (1,8,1); (1,6,1) and (1,12,1) in seasonal prediction (SPI 3 months and SPI 6 months) there were no significant differences in values of MSE and R. In this regard, SPI 3 months and SPI 6 months ANN based seasonal drought prediction model performance evaluation value of MSE was between 0.0022 and 5.5752 which were in the best acceptable range of validation. Hence, this current study results show that ANN modeling was works best for forecasting seasonal drought /SPI 3 months and SPI 6 months ahead of two months and five months lead times, respectively, in all the districts.

Characterization of drought in the study area

Seasonal SPI 3 months and SPI 6 months value of drought characterization finding of this study revealed that there were moderate, severe and extreme drought in the Ganna and Hagayya rainfall period in the years between 1981-2021 in the study area. Ganna and Hagayya seasons SPI 3 months and SPI 6 months drought classifications values of Dilloo, Dirree, Guchi, Moyale and Yabello districts of Borana zone are displayed in Figures 2 and 3.

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Accordingly, in all the districts in the period between 1981 to 2021 only 1 to 2 out of 41 Ganna and Hagayya rainfall seasons had received 1.5 up to 2.12 (wet and extreme wet) SPI 3 months and SPI 6 months value. In addition in this period (1981 to 2021); in all the districts 13 up to 23 out of 41 Ganna and Hagayya seasons had received -1.49 up to -0.99 (moderate drought class) SPI 3 months value in the last 41 years. According to Ganna and Hagayya seasons SPI 3 months and SPI 6 months of this study; drought, severe drought and extreme drought were occurred in Ganna and Hagayya rainfall seasons of 2000, 2004, 2005, 2007, 2008, 2009, 2010, 2011, 2013, 2016, 2017, 2019 and 2021 with in SPI 3 months and SPI 6 months value of -3.19 to -1.5. Model output showed that major extreme drought was recorded during Ganna and Hagayya seasons in Dirre in 2000 (SPI 3 months value of -3.19), Dillo in 2000 (SPI 3 months value of -2.97), Yabello in 2000 (SPI 3 months value -2.74), Guchi 1999 (SPI 3 months value -2.54) and Moyale in 2000 (SPI 3 months value -2.51).

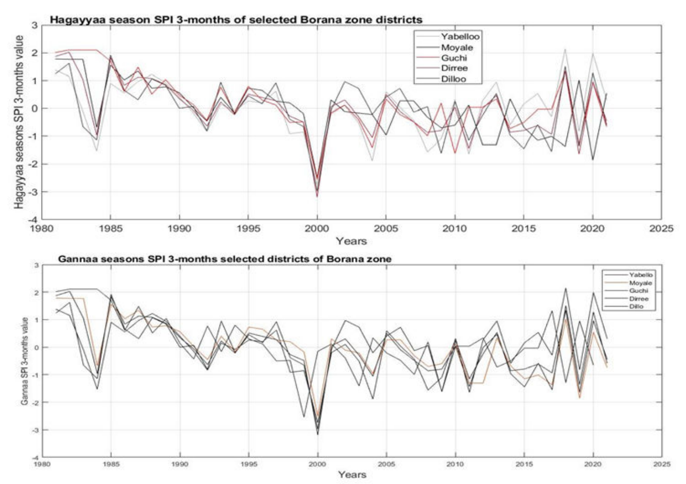

Figure 3: Gannaa and Hagayyaa Seasons SPI 3 months.

In addition, in this period (1981 to 2021); in all the districts 8 up to 16 out of 41 Ganna and Hagayya rainfall seasons had received 0.113 to 0.972 (near normal) SPI 3 months value in the last 41 years. The SPI 3 months and SPI 6 months value revealed that 23 Ganna seasons SPI 3 months and SPI 6 months (out of 41) in the study area were categorized under moderate, severe and extreme drought. In addition, as it is seen from figures 3, in all the districts between 1981 to 2021; SPI 6 months drought magnitude was very high when compared with SPI 3 months. There was drought, severe drought and extreme drought in Ganna and Hagayya rainfall seasons of 2000, 2004, 2005, 2007, 2008, 2009, 2010, 2011, 2013, 2016, 2017, 2019 and 2021 with in SPI 6 months value of -4 to -1.5. In general, according to seasonal SPI 3 months and SPI 6 months drought characterization finding of this study both Ganna and Hagayya rainfall seasons were drought prone seasons in the years between 1981-2021. These revealed that there was extreme meteorological and agricultural drought in the aforementioned years during Ganna and Hagayya rainfall seasons in the study area. Hence, designing of multidimensional, interconnected/ integrated, and implementation of area specific drought risk management activities are mandatory to minimize the adverse effects of drought on the socio economy and over all development of the study area.

This is consistent with the study of the Palmer, WMO, Karavitis et al., that stated 3 months SPI index provides an indication of short and medium term moisture conditions, precipitation estimates over a season which is appropriate in agricultural areas to highlight the nature of soil moisture. The 6 months SPI provides an indication of precipitation trends over a season, study found that 3 months SPI specifies short term as well as medium term moisture conditions and offers an estimate of seasonal precipitation. A 3 months SPI is more helpful in emphasizing existing moisture conditions of major agricultural regions than many other hydrological indices. Similarly, Ahmad, et al., used SPI 3 months for the period 1985-2015 to characterize seasonal precipitation in Shalimar, India. Figure 3, depicted the SPI 6 months of the Borana plateau of Southern Oromia region of Ethiopia.

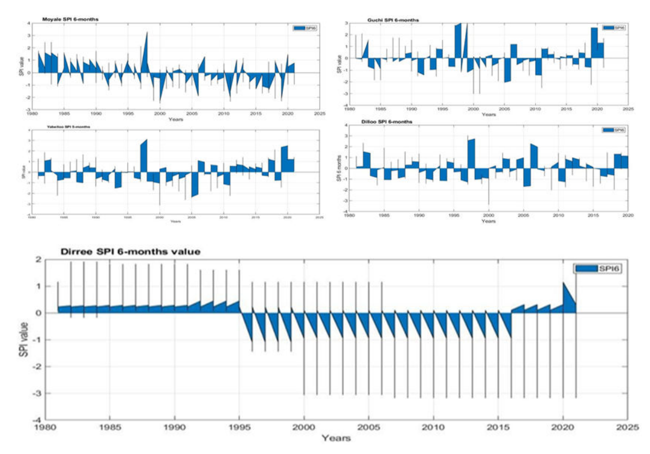

Figure 3: SPI 6 months of the study area.

ANN based seasonal drought forecasting

Model results of the seasonal/ANN based SPI 3 months and SPI 6 months drought prediction of two months and five months lead times, respectively of the selected Borana zone districts between 1981 and 2021 were displayed in Table 2 and Figure 4. Table 2, show that the seasonal/the SPI 3 months forecasts output value of medium years SPI 3-months and SPI 6 months input data (10–15 years SPI 3 months ANN input data value) were more close to seasonal observed SPI 3 months and SPI 6 months value than the results of long years SPI 3 months and SPI 6 months data (more than 30 years SPI 3 months ANN input data value). Predicted seasonal SPI 3 months and SPI 6 months (ANN based prediction) value showed that the study area was in drought class of extreme, severe, moderate drought, near normal drought and wet in Ganna and Hagayya rainfall seasons during 1981-2021.

Apparently, ANN model output of the SPI 3 months and SPI 6 months seasonal drought prediction were properly signaled observed value of SPI 3 months and SPI 6 months in Dirre, Guchi and Moyale districts than Yabello and Dillo. Dillo. Yabello and Dillo results demonstrated the differences between the seasonal forecasted value of (SPI 3 months and SPI 6 months) ANN output and seasonal observed value of (SPI 3 months and SPI 6 months) that were derived from historical rainfall data. The differences were resulted from two reasons:

As the years from where the ANN input/ SPI months ANN input data were derived is longer; it causes the increase in accumulation of error between seasonal observed SPI 3 months value and seasonal forecasted value which is inevitable.

Continuous variation in historical seasonal precipitation data hinder the ANN model to simulate it in the predicted SPI 3 months and SPI 6 months value. This is consistent with the study of which found that ANN represent a non-linear system to the nearest possible approximation. In addition, similar studies in USA. Brust et al., argued that ANN has the capacity to capture different drought types occurring across diverse climate regimes. Furthermore, it is also consistent with similar study in Algeria. Achour et al., which stated that the best model ANN design results was found to vary from one plain to another and from one-time scale to another. In general, finding of this study discovered that the ANN model based seasonal drought forecast of (SPI 3 months and SPI 6 months) could signals/ identify occurrence of drought in two months and five months lead time in the study area.

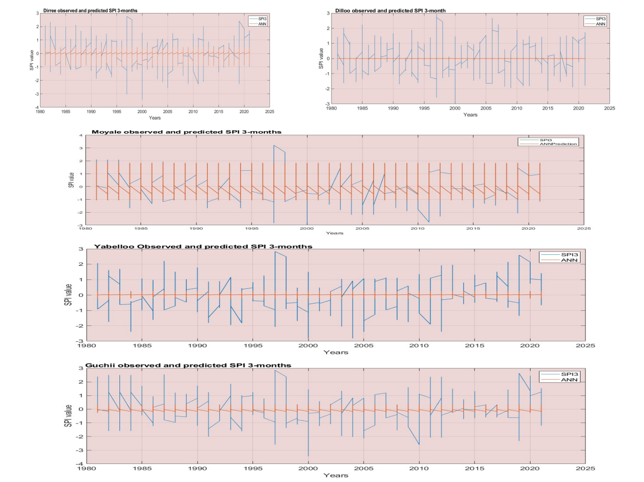

Figure 4: Observed and predicted SPI 3 months of 1980 to 2021.

		Period	Jan	Feb	Mar	Apr	May	Jun	July	Aug	Sep	Oct	Nov	Dec
SP13	Dilloo	1981-2021	-0.013	0.013	0.027	-0.037	-0.021	0.059	-0.057	0.04	-0.017	0.01	-0.002	0.0035
		2008-2021	-1.998	-0.161	-0.971	-1.236	-0.151	0.512	0.525	0.581	-0.342	2.473	-3.902	-0.1246
SP16		1981-2021	0.011	-0.011	-0.015	-0.036	0.035	0.059	-0.108	0.131	-0.101	0.055	-0.025	-0.0011
		2008-2021	-1.902	-0.552	0.897	1.611	0.948	0.737	1.324	0.129	0.412	2.015	-8.887	1.65712
SP13	Dirree	1981-2021	0.096	-0.185	0.101	0.112	-0.263	-0.032	0.472	0.301	-0.903	0.449	-0.167	-0.0589
		2008-2021	-0.216	0.23	-0.183	0.066	-0.002	-0.168	0.386	0.035	-0.867	0.545	-0.186	-0.0819
SP16		1981-2021	0.004	-0.024	0.057	-0.06	-0.015	0.088	-0.077	0.024	-0.007	0.009	7.00E-04	-0.001
		2008-2021	0.017	-0.05	0.057	0.054	-0.015	-0.126	-0.035	0.193	-0.22	0.176	-0.065	-0.0111
SP13	Guchi	1981-2021	-0.013	0.037	-0.079	0.089	-0.052	0.099	-0.177	0.146	-0.048	0.027	-0.006	-0.0023

		2008-2021	0.162	0.479	-0.265	-0.78	-0.337	0.11	-0.01	0.636	2.702	3.98	-7.03	-0.5447
SP16		1981-2021	-0.012	0.025	-0.017	0.009	0.016	-0.052	-0.014	0.108	-0.09	0.025	0.007	3.84E-04
		2008-2021	0.095	-0.541	-0.264	0.082	-0.151	0.033	0.24	-0.969	-0.236	3.87	-1.93	0.68919
SP13	Moyale	1981-2021	-0.573	0.195	0.378	0.336	-0.613	-0.472	0.895	-0.751	-1.074	1.829	-0.599	0.07129
		2008-2021	-0.041	0.041	0.1	0.033	-0.06	-0.223	0.139	0.294	-0.382	0.181	-0.077	0.0026
SP16		1981-2021	-0.133	0.181	0.008	-0.113	0.088	-0.013	-0.039	0.104	-0.142	0.081	-0.022	0.0094
		2008-2021	0.73	-0.348	0.061	0.061	0.061	0.061	0.061	0.061	0.061	0.061	0.061	0.06114
SP13	Yabelloo	1981-2021	0.028	0.021	0.038	0.038	-0.051	-0.227	0.023	0.253	-0.173	0.157	-0.044	0.00866
		2008-2021	-0.044	0.089	-0.062	-0.095	0.14	-0.055	-0.012	0.092	-0.141	0.138	-0.063	0.01846
SP16		1981-2021	-0.039	-0.227	-0.066	0.202	0.08	-0.198	0.297	0.199	-0.63	0.138	0.015	-0.0452
		2008-2021	0.301	-0.299	-0.186	0.305	0.14	-0.852	-0.105	0.616	-0.675	0.442	-0.184	0.00632

Table 2: ANN model output of seasonal drought prediction value, 1981-2021.

Model performance evaluation

Inall the studied districts with different combinations of ANN architectures/structures which constitutes of (1,8,1); (1,6,1) and (1,12,1) seasonal prediction (SPI 3 months and SPI 6-months) had no significant differences in values of MSE and R (Table 3). The SPI 3 months and SPI 6 months ANN based seasonal drought prediction model performance evaluation value of MSE were between 0.0022 and 5.5752 with in the very acceptable range of validation. Dirre site had 5.0456 and 5.5752 values of MSE for long years and middle years SPI 3 months ANN input data, respectively which was in great acceptable range of validation. In line with this, SPI 3 months and SPI 6 months model performance evaluation value of correlation coefficient (R) of all the districts were above 0.9034. This showed that the model output value mean square error (variation between observed SPI value and ANN based SPI 3-months and 6 months predicted value) was very law and the relation between (R) seasonal input/observed SPI value and seasonal output/predicted SPI value of the model was equally strong for both SPI 3 months and SPI 6 months in all the districts. This implies that variation in precipitation and elevation has no impacts on the forecast performance of the ANN model in the study area. The current study results showed that ANN modeling was works well for forecasting seasonal drought/SPI 3 months and SPI 6 months ahead of two months and five months lead times, respectively, in all the districts. In this study there was no significant difference in forecast effectiveness vis-a-vis of SPI 3 months and SPI 6 months. This study was not consistent with the study of Belayneh and Adamowski in Awash valley of Ethiopia which found that forecast effectiveness was increased as the SPI months lead times are increasing. It is also not consistent with the study in Sri Lanka which stated that when the lead time was increased, model predictions were degraded at each time step into the future. Similar studies in Algeria confirmed that the effectiveness of ANN models for predicting monthly SPI and an accurate drought warning system with 2 months lead time based on meteorological drought information.

SPI	Years	ANN structures	Dillo		Dirre		Guchi		Moyale		Yabello	
			MSE	R	MSE	R	MSE	R	MSE	R	MSE	R
SPI 3	1981-2021	1,8,1	0.2159	0.2147	1.38	1.000	0.0066	0.9997	0.0010	0.9999	2.9463	0.9034
		1,6,1	0.4691	0.7513	0.714	0.9971	0.0501	0.9978	0.0365	0.9984	0.0413	0.9994
		1,12,1	0.0760	0.9969	5.5752	1.0000	0.0023	0.9999	0.0098	0.9996	0.5214	0,99998
	2008-2021	1,8,1	0.0165	0.9997	2.63	1.000	0.0145	0.9995	0.0100	0.9996	0.0016	0.9999

		1,6,1,	1.9992	0.9000	5.0456	0,8094	0.0034	0.9999	2.0703	0.9209	0.2182	0.9899
		1,12,1	0.0022	0.9999	0.0251	0.9990	3.3959	1.0000	0.1986	0.9878	4.3271	1.0000
SPI 6	1981-2021	1,8,1	0.0043	0.9998	0.0030	0.9999	5.0851	0.9983	1.7085	0.9588	0.0452	0.9980
		1,6,1	0.125	0.9994	0.0424	0.9900	0.0151	0.9993	0.545	0.9980	0.0606	0.9981
		1,12,1	3.0115	1.0000	1.7977	1.0000	4.7756	1.0000	2.0878	1.0000	0.0554	0.9975
	2008-2021	1,8,1	0.0083	0.9996	0.0110	0.9996	0.0127	0,9995	0.0441	0.9977	0.0098	0.9998
		1,6,1	0.0080	0.9997	0.0080	0.9996	2.3633	0.9334	4.0124	0.9002	0.0093	0.9996
		1,12,1	0.1842	0.9919	0.4592	0.9760	0.0019	0.9999	8.5612	1.0000	0.0013	0.9999

Table 3: NAR-ANN model forecast performance validation result for long and medium years input data of SPI 3 months and SPI 6 months value at two and five months lead times, respectively.

Conclusion

Actual/observed and ANN model based predicted seasonal SPI 3 months and SPI 6 months drought characterization finding of this study showed that both Ganna and Hagayya rainfall seasons were drought prone seasons in the years between 1981-2021 in the study area. Especially, there was extreme drought in Ganna and Hagayya seasons (SPI 3 months and SPI 6 months) of 2000, 2004, 2005, 2007, 2008, 2009, 2010, 2011, 2013, 2016, 2017, 2019 and 2021 with in SPI 3 months and SPI 6 months value of 4 to -1.5. These revealed that there was extreme meteorological and agricultural drought in the aforementioned years during Ganna and Hagayya rainfall seasons in the study area.

In addition, finding of this study discovered that the ANN model based seasonal drought forecast (SPI 3 months and SPI 6 months) could signals/identify occurrence of drought in two months and five months lead time, respectively, in the study area. In this regard, SPI 3 months and SPI 6 months ANN based seasonal drought prediction model performance evaluation value of MSE was between 0.0022 and 5.5752 which were in the very acceptable range of validation. In line with this, SPI 3 months and SPI 6 months model performance evaluation value of correlation coefficient (R) of all the districts were above 0.9034. Hence, this current study results show that ANN modeling was works well for forecasting seasonal drought/SPI 3 months and SPI 6 months/ahead of two months and five months lead times, respectively, in all the districts in the study area.

Recommendations

Actual/observed and predicted seasonal SPI 3 months and SPI 6 months drought characterization finding of this study showed that both Ganna and Hagayya rainfall seasons were drought prone seasons in the years between 1981-2021. In the study area, there was extreme meteorological drought which is mainly the driver of agricultural, hydrological and economic drought. Hence, in order to minimize adverse effects of drought on the lives and livelihoods of the community in the study area in sustainable basis the following recommendations are mandatory:

- Providing up to date drought early warning information through making continuous drought monitoring and prediction by using/ linking indigenous and scientific drought forecasting methods will minimize adverse effects of drought on the livelihood sources of the community in the study area. In this regard, since this current study is only focused on the seasonal drought prediction mainly of meteorological droughts and its data were derived from point data; continuous and detail specific studies will be also required on the long SPI months to have full information on the agricultural, hydrological including reservoir/water storage, snow pack, stream flow, underground water balance and socio economic droughts in the study area.
- Integrated drought risk management/knowledge based holistic development approach will sustainably minimize adverse effects of drought in the study area. This includes improving decision making capacity of the local community through provision of information, technology, data, training and extension service concerning natural resources management (soil and water conservation, water harvesting, forest management and development, rangeland management and development); livestock husbandry and crop farming; expansion of water, irrigation and other infrastructures, social and economic service delivery, finance and market, etc.
- In general, linking local community to production enhancing technologies and digital economies will help to spread the adverse effects of drought in sustainable manner. Hence, designing of multidimensional, interconnected/integrated and implementation of area specific drought risk management activities are mandatory to minimize the adverse effects of drought on the socio economy and over all development of the study area.

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