DROUGHT ASSESSMENT IN THE TEL RIVER BASIN USING STANDARDIZED PRECIPITATION INDEX (SPI) AND STANDARDIZED PRECIPITATION - EVAPOTRANSPIRATION INDEX (SPEI)

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ABSTRACT

India is amongst the most vulnerable drought prone countries in the world. Where a drought has been reported at least once in three year in the last five decade. In this paper ,an attempt has been made to provide a comprehensive idea of drought interpetation and correlation of various drought causative parameter. In the Tel basin covering a area of 296 km and lies between18º to 21º latitude and 83ºto 86º longitude. Odisha, India was selected study area. Tel basin was analyzed by the standardized index (SPI) and standardized precipitation evapotranspiration index (SPEI).The analyzed show that dought assessment by basin approach and the combination of drought indices can offer better understanding and better monitoring of drought condition.

Key words : Drought, SPI ,SPEI

INTRODUCTION

1.1 Prolusion

Drought is one of the most serious natural hazards because of the complexity of the issue, arising from climatic variability which is a function of many factors such as latitude and altitude of a particular place, air mass influences, the location of global high- and low-pressure zones, heat exchange from ocean currents, distribution of mountain barriers, the pattern of prevailing winds and distribution of land and sea, etc. Therefore, the occurrence of drought must be understood, and appropriate drought indices should be investigated for different goals such as agriculture practices, engineering practices, water management and fire control.

Approximately 68% of India is at risk of drought to varying degrees. A total of 35% of the land is deemed drought-prone because it receives precipitation between 750 mm and 1,125 mm, while another 33% is considered dry because it receives less than 750 mm and frequently prone to drought. Arid, semi-arid, and subhumid region sake up three-fourths of India's 329 million hectares of drought-prone territory. Desert region (19.6%): Rajasthan, Gujarat, and parts of Haryana experience water shortages throughout the year because to the MAP of 100–400 mm. In this area, there are severe droughts. Semi-arid region (37.0%): MAP of 400–600 mm (water surplus in some months, shortage in others); includes sections of Haryana, Punjab, west Uttar Pradesh, west Madhya Pradesh, and the majority of the peninsular Western Ghats. In this area, droughts can range from moderate to severe.

A portion of the northern plains, the central highlands, the eastern plateau, a portion of the Eastern Ghats and plains, and a portion of the western Himalayas are all in India's dry sub-humid zone (21.0%), which has a MAP of 600-900 mm. In this region, the droughts are modest. Drought is uncommon in humid and per-humid areas like Assam and other northeastern States.

In Andhra Pradesh, droughts are a frequent occurrence; no district is completely free of them. One of India's regions most vulnerable to drought is Rajasthan. Eleven of the state's districts are in dry areas, with Jaisalmer being the driest. There is no perennial river in Jaisalmer. The district's groundwater table is between 125 and 250 feet deep and 400 feet deep in some locations. With only 164 mm, the district receives very little rainfall. On average, 355 days out of 365 in a year are dry. There are just over one million square kilometers of land that receives insufficient rainfall.

Less than 400 mm of rainfall per year falls in 12% of the country's entire geographic area, while less than 750 mm falls in 35% of the nation. Thus, 56 million ha of the country's total gross cultivable land are susceptible to insufficient and highly erratic rainfall. There are a lot of dry and semi-arid areas in the four states that use the Narmada waterfalls. 32% of Gujarat and nearly 57% of Rajasthan are both desert regions. Additionally, 46% of Gujarat and approximately 61% of Maharashtra are semi-arid regions. This demonstrates how crucial it is for these states to utilize the water they have in a wise manner.

1.2 Drought in Odisha

Drought seems to be a consistent phenomenon in the state Odisha and every year some or the other parts of the state are affected by it. Looking at the frequency and geographical spread of drought, all major river basin and sub basins are prone to drought. It is also necessary to know some vital features of droughts, such as duration, severity and spatiotemporal extension for the given period for drought vulnerability analysis.

1.3 Drought Definition

Drought can be defined in a variety of ways depending on the place and circumstance. Over time, scientists have attempted to characterize this phenomenon, but there is still no consensus on what it is. Any drought is primarily brought on by a lack of precipitation, specifically the timing, distribution, frequency, and intensity of this lack in relation to the current water storage, demand, and consumption. This shortfall may lead to a lack of water that is necessary for a natural (eco-) system to function as well as for some human activities.

1.4 Drought Assessment and Its Need

The quantification of drought severity is called as drought assessment. Drought assessment can be done with the use of a suitable drought index. The drought index selection depends upon the application of drought assessment. It could be meteorological, hydrological or Agricultural drought assessment. Remote sensing derived drought indices could aid a helping hand in this context.

There are several indices that measure to what extent precipitation for a given period has deviated from historically established norms. Although none of the major indices is inherently superior to the rest in all circumstances, some indices are better suited than others for certain uses. For example, the Palmer drought severity index (PDSI)(Palmer1965)hasbeenwidelyusedasameansofprovidingasinglemeasureof meteorological drought severity, for example for the previous 30 years. It is based on a monthly water balance accounting scheme involving precipitation, evapotranspiration, run-off and soil moisture. The PDSI has been used in making operational water management decisions and planning drought monitoring. Basic drought phenomena and drought preparedness studies are presented by Wilhite and Glantz (1985)and white(1996).

In order to understand whether a deficit of precipitation has diff erent impacts on the groundwater

,reservoir storage, soil moisture, snowpack, and streamflow, McKee *et al*. (1993) developed the standardized precipitation index (SPI). The SPI was designed to quantify the precipitation deficit for multiple time scales, which reflect the impact of drought on the availability of diff erent water resources. Soil moisture conditions respond to precipitation anomalies on a relatively short timescale, while groundwater, stream flow, and reservoir storage reflect the longer-term precipitation anomalies (Tonkaz2006). For these reasons, McKee *et al*. (1993) originally calculated the SPI for 3-, 6-, 12-, 24- and 48-month moving average timescales.

1.5 Objective of the study

This study is done to know the detail about the understand types, factors, indicators of droughts.

To study critical drought-prone area in special emphasis of on the state of Odisha. Using SPI and SPEI evaluation drought in the Tel river basin of Odisha.

LITERATURE REVIEW

When making decisions, a drought index value—typically one unit less than raw data such as rainfall, snowpack, stream flow, and other indicators of the availability of water—is far more helpful. The intensity, length, and geographic extent of drought are measured using a variety of indices by the Indian government, state governments, and the scientific community (Ministry of Agriculture, 2009). These scientific metrics can be used to track the drought condition on a national and state level. Sincere efforts have also been made to review the drought indices and the various climatic parameters, such as precipitation, soil moisture, vegetation moisture, land surface temperature, humidity, and land cover change, which play a direct or indirect role in the development of drought. There are more than 150 drought indices currently in existence, and many more have been added in recent decades.

(Zargar et al, 2011) Selection, however, is heavily influenced by factors including the availability of resources or data, the field of interest, certain boundary conditions, and the need for either geographical or temporal resolution. While certain drought indices can be set up to correlate to several impacts and, thus, different drought types, others only exclusively reflect one sort of impact or application. For longer time scales, SPI, a meteorological drought, can be used to depict impacts of agricultural and hydrological drought.

(Li et al, 2012). By unanimously agreeing that the Standardized Precipitation Index (SPI) should be used by all National Meteorological and Hydrological Services around the world to characterize meteorological droughts, 2009's Inter-Regional Workshop on Indices and Early Warning Systems for Drought, held at the University of Nebraska-Lincoln, USA, made a significant step forward. Traditional indicators (point-based) derived from meteorological observations are insufficient to track drought at the regional level. Since the 1970s, remote sensing data has played an increasingly significant role in drought monitoring since it can repeatedly give spatial information on drought events at a reduced cost.

Drought evaluation at the local level is required for establishing adaptation and mitigation strategies for that region. Based on the variable used to describe drought, it is divided into five categories: meteorological drought, hydrological drought, agricultural drought, socioeconomic drought, and groundwater drought. When a meteorological drought hits a region, it is preceded by an agricultural and hydrological drought. This study is focused on the meteorological drought, which is caused by a lack of net precipitation over the basin and is affected by climate variables. The Standardized Precipitation Index (SPI) and the Standardized Precipitation Evapotranspiration Index (SPEI) are suggested by the World Meteorological Organization (WMO) as basic indicators for evaluating drought intensity, duration, and spatial extent. In recent decades, the SPI index proposed by McKee et al., in 1993 and the SPEI developed by Vicente-Serrano et al., in 2010 has served as the foundation for drought monitoring. The SPI index is a useful tool for detecting and mapping droughts, and ArcGIS enhances the results visualization. SPI is probabilistic in nature, which gives it an edge over other drought indicators in terms of risk and decision analysis.

Standardized Precipitation Index (SPI) widely used index, which is developed mainly for defining and drought monitoring. Standardized Precipitation Index (SPI) is used to measure severity of drought situation. The monthly Standardized Precipitation Index (SPI) was first computed as per the equation developed by (McKee et al. 1993), which comprises fitting the gamma probability density function to the given distribution of mean monthly precipitation data.

Willeke et al. (1994) described the term Percent of Normal Index (PNI) as a percentage of normal precipitation. PNI is calculated in terms of month, season, and yearly. PNI is used to describe single station effective drought condition (Hayes, 2006). Hence PNI is specific to single station drought.

The Deciles Index is one of the important index in which ranking of the rainfall value of a specific time duration is assigned over whole historic period (Gibbs and Maher, 1967). Specifically, the historical monthly rainfall data are arranged in ascending order and finally divided into ten equal classes or decile. Therefore, rainfall for a month is placed into one of the different classes. It output values ranging from 0 to 10.

China-Z Index (CZI) was developed by National Climate Centre of China in 1995. This index is used as alternative of SPI (Ju et al., 1997). When mean rainfall of historic data follows Pearson type III distribution.

The modified china index is developed similarly like China-Z Index (CZI) but in this median precipitation is used in place of mean precipitation.it is also developed by National Climate Centre of China.

The term Z score is published by Edward I. Altman in 1968.The Z-Score Index (ZSI) is generally confused with Standard Precipitation Index. Though, ZSI is more similar to CZI, but there is no necessity of fitting rainfall data to either Pearson type III distribution or gamma distribution function.

The Rainfall Anomaly Index (RAI) is a drought monitoring index which is introduced by Rooy (1965). RAI is used to categorize the negative and positive anomalies. Firstly, The Rainfall data are sorted in descending order. A threshold is formed for positive anomaly having the mean of ten highest value and a threshold is formed for negative anomaly with the mean of ten lowest value.

Different rain-based metrological drought are very essential to analyse drought situation in Tel river basin (Odisha).

To warn drought condition effective strategies are being developed and proposed. It is very important to forecast SPI for drought management. Powerful mitigation and moderation methodology is required for the cautious thoughts of models which give quantitative information to the future drought conditions (Şen 2015, Wilhite and Hayes 1998, Wilhite et al. 2000a).

Observation of drought event is concluded by concentrating the difference in drought records in future with present and chronicled hydrological information (Deo and Şahin 2016, Stahl and van Lanen 2014, Wolters et al. 2015). However, predictive models are assessed to comprehend future drought. Predictive models are assessed to check reliable condition to admonish drought occurrence (Mishra and Singh 2011). For the development of warning system, the framework requires an activity situated models that are applied in hazard risk management program (Mishra and Singh 2011, Sheffield and Wood 2008, Wilhite et al. 2000b).

Morideet.al.(2017) used artificial neural networks and time series of drought indices for forecasting drought in Tehran province Iran. The objective of this study is to predict SPI and EDI with six rain gauge station. Two precipitation based drought indices EDI and SPI – was used as predictor, while different drought indices combinations, rainfall and large climate signals like SOI and NAO were used as predictors.

Moreira et.al. (2015) worked on SPI prediction using log-linear model in Alentejo and Algarve regions (South of Portugal). the objective of this study is a short-term prediction of drought severity classes.

Rahmat et al. (2016) for worked on SPI modelling using Markov chain model. Markove chain model is fully illustrated and forecasting of SPI is done, which is very important socioeconomic regions.

Agana et.al. (2017) worked on long-term drought Prediction in United States using deep learning approach. Deep Belief Network is based on two regulated Boltzmann Machines for drought prediction. Standardized Streamflow Index (SSI) are lagged and used as a input variable. The efficiency of developed model is compared to that of traditional models like Multilayer Perceptron (MLP) and Support Vector Regression (SVR) for forecasting the drought conditions.

Sen et. al. (2015) used Effective strategies were developed to warn of drought condition. For drought management forecasting of SPI is very important. Powerful alleviation and moderation methodology were required for the cautious thought of models which give quantitative information to the future drought condition (Şen 2015, Wilhite and Hayes 1998, Wilhite et al. 2000a).

Cheng and Cao (2014) used MARS to solve regression type problem. MARS tends to analyze the contribution of each input variable and build the model for forecasting based on input variables(Cheng and Cao 2014).

Mishra and Singh (2011) studied and concluded that the predictive models are assessed to comprehend future drought. Predictive models are assessed to check reliability condition to admonish drought occurrence.

Forecasting of Drought is dependent on SPI where drought indicator is a data-driven model, developed for anticipating in various geographic areas. An SPI-based philosophy for calculating drought transition possibility is done in Sicily, Italy **(Cancelliere et al. 2007).** Adaptive-network-based fuzzy inference system (ANFIS), Artificial neural network (ANN), Wavelet-ANFIS and Wavelet-ANN were used for Predicting SPI for Azerbaijan, Iran (Shirmohammadi et al. 2013). The different multivariate model was developed and compared with Multilayer Perceptron(MLP), Artificial neural network (ANN), Support Vector Machine (SVM), Adaptive-network-based fuzzy inference system (ANFIS), and Autoregressive integrated moving average (ARIMAX) multivariate models to predict SPI for Yazd , Iran (Jalalkamali et al. 2015). The SPI-based estimates were developed using ANN for San Francisco (Santos et al. 2009). The models ANN, Support vector regression (SVR) and wavelet neural system models are developed and compared for SPI estimating in Awash River, Ethiopia (Belayneh and Adamowski 2012).

ANFIS, M5 display tree (M5Tree) and an MLP were developed and used for calculation of SPI (Choubin et al. 2016). The MARS, LSSVM, and M-5 TREE model were developed and compared to forecast drought in new south walesAustralia(Deo et al. 2017).

Four model of NN, SVR, LSSVR, and ANFIS were compared for forecasting drought from time series based metrological and remotely sensed (RS) drought indices in eastern Isfahan(Iran) during 2000–2014(Khosravi et al. 2017). The choice of Decomposition Level for Wavelet-Based hydro metrological data Modeling in Heihe River basin, China (Yang et al. 2016).

In this paper we used a wavelet coupled MARS (WMARS) and wavelet coupled SVM (WSVM) models for SPI forecasting in the Tel river basin of Odisha region using historical precipitation data for three districts. Finally, a comparative study is done between the traditional MARS, SVM and wavelet coupled model i.e., WMARS and WSVM with the help of different model performance matrices.

Monitoring of Drought in India

Rainfall maps are prepared by the Indian Meteorological Department (IMD) based on sub-division throughout the year. The rainfall map shows rainfall received over a week and analogous deviation from normal. These maps indicate the drought development during monsoon season. Additionally, IMD also gives daily rainfall information for district level of entire country. The information of rainfall is used to identify the districts, which are having rainfall deficit for prevailing meteorological drought condition. IMD to address agricultural drought also uses water balance methods. In India agricultural drought is measured with aridity index. It is calculated as follows;

Aridity Index=(potential evapotranspiration-Actual evapotranspiration)/(potential evapotranspiration)

IMD provides weekly aridity anomaly charts since 1979 onwards, which is based point observatories in the period south- west monsoon. The aridity anomaly charts are showing the actual departure from normal aridity, which show the severity condition of water deficit weekly. The IMD also provides the rainfall, relative humidity, temperature, and cloud cover detailed map.

Latest approaches & techniques to study drought are subject of interest. Due to global warming and climate, change condition there is increase in drought situation in recent years across the world. Different models are used to understand the drought properties and management of drought condition. Drought mitigation or management should be done by calculating different drought indices across the globe, which is very helpful to identify the drought severity. The planning and proper management should be done to overcome from drought situation. Thus, understanding of different drought indices is very crucial for drought mitigation and management operations.

STUDY AREA AND DATA COLLECTION

3.1 STUDY AREA

The Tel River flows in Nabarangpur, Kalahandi, Balangir, Boudh, Sonepur District of Odisha, India. Tel is an important tributary of Mahanadi. It flows just eight kilometers away from the town of Titilagarh. About 32 kilometres to the west of Jorigam, in the Plain of Koraput district of Odisha, is where the Tel River begins (Figure 1). It is the second-largest river in Orissa and a crucial Mahanadi River tributary. A total of 296 km are covered by the river before it joins the Mahanadi River on the right bank, 1.6 km below Sonepur. The total drainage area is 22,818 km^2 of the Tel River, of which 11960 km^2 are up to Kesinga and 19600 km^2 are up to Kantamal. The Tel sub-basin is restricted to the latitudes of 18° to 21° and 83° to 86° longitude. This significant tributary of the Mahanadi River meets the main river at Sonepur. The convergence of the two rivers offers a remarkable view against a colorful landscape. Baidyanath temple, which is famous for the Kosaleshwar Shiva temple, is located on the left bank of the Tel River.

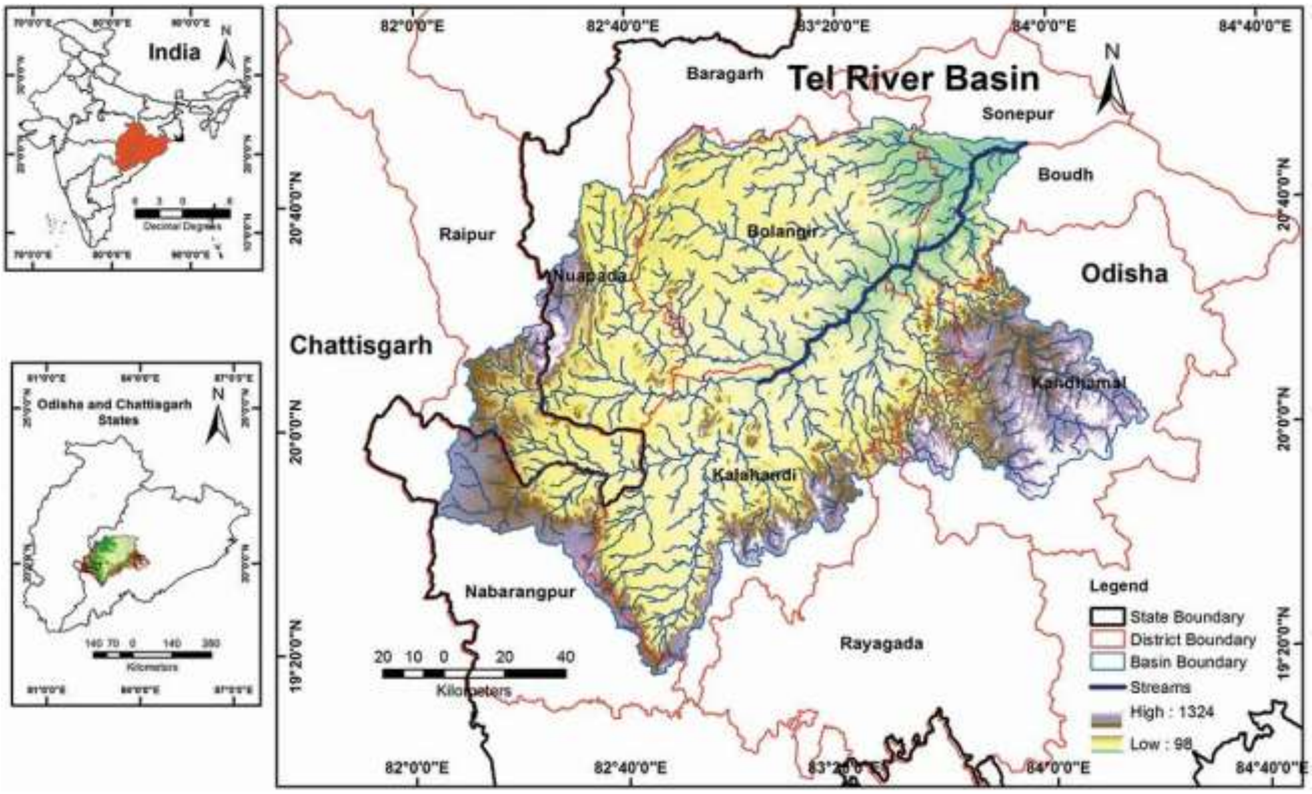


Figure 1 Study area map

3.2 Data Collection

The monthly precipitation (observed) from 1990 to 2010 has been collected from Indian Metrological Department (IMD) Pune for rain-gauge stations Bolangir, Nuapada, Kalahandi, and Kandhamal. Daily maximum Temperature (Tmax) and minimum temperature (Tmin) gridded data was also obtained for the duration 1991 to 2015 from the IMD website (https://www.imdpune.gov.in/Clim_Pred_LRF_New/Grided_Data_Download.html).The monthly average and the annual average temperature have been calculated. When a continuous observed data collection is not available, gridded data can be used for hydrometeorological and climatic studies.

METHODOLOGY

4.1 Standardized Precipitation Index (SPI)

McKee et al. created the Standardized Precipitation Index (SPI) (1993). The SPI only considers precipitation. The SPI gives the precipitation a single numerical number that may be compared across time scales and regions with distinctly varied climates. There are several indices to quantify drought using meteorological data, according to Jain et al. (2010), but the SPI is the most popular index. SPI can quantify water deficits of varying duration because it can be calculated at several time scales (Table 2). SPI was created to demonstrate that moist conditions can exist on one or more-time scales while dry conditions exist on another time scale. Only the precipitation record is required for the index's calculation. It is calculated by dividing the precipitation anomaly by its standard deviation when compared to the mean value for a specific time scale. The distribution of precipitation is not typical, at least not for timescales less than a year. As a result, the variable is changed to make the SPI have a Gaussian distribution with a unit variance and zero mean. A so-adjusted index enables comparison of values associated with various regions. Additionally, wet and dry climates may be tracked in the same way because the SPI is normalized. The following formulae form the basis for the index calculation:

$$SPI = \frac{X_i - X}{\sigma}$$

Table 1: SPI values and its indication on drought.

SPI values	Class
>2	extremely wet
1.5 to 1.99	very wet
1.0 to 1.49	moderately wet
-.99 to .99	near normal
-1.0 to -1.49	moderately dry
-1.5 to -1.99	severely dry
<-2	extremely dry

4.2 Standardized Precipitation and Evapotranspiration Index (SPEI)

The Standardized Precipitation and Evapotranspiration Index (SPEI) was suggested by Vicente Serrano et al. in2010 on the basis of the SPI. It quantifies both precipitation and potential evapotranspiration for the analysis of the drought process. Thornthwaite method was followed for calculation of PET which is described as

$$PET = 16K\left(\frac{10T}{I}\right)^{m}$$

where, T represents monthly-mean temperature (°C), and heat index (I) is computed as the summation of 12 monthly heat index values, obtained from mean monthly temperature using:

$$i = \left(\frac{T}{5}\right)^{1.514}$$

where m is a deduced coefficient which depends on I (m = 6.75×10-7 I3-7.71×10-5 I2+1.79×10-2 I+0.492); and K is a coefficient of correction which is dependent on the latitude and month,

$$K = \left(\frac{N}{12}\right)\left(\frac{NDM}{30}\right)$$

where NDM is the total number of days in the given month. The maximum number of sun hours (N), computed as:

$$N = \left(\frac{24}{\pi}\right)\omega_s$$

where (ω_s) the hourly angle of the sun rising, given as:

$$\omega_s = \arccos(-\tan\varphi\tan\delta)$$

where, φ represents the latitude in radians, and δ represents the solar declination in radians computed from:

$$\delta = 0.4093\sin\left(\frac{2\pi J}{365} - 1.405\right)$$

where J is the particular month's average Julian day.

The climate–water balance was calculated as follows:

$$D_i = P_i - PET_i$$

where D_i is the i_{th} month moisture deficit (mm), P_i is the i_{th} month precipitation (mm), and PET_i is the i_{th} month potential evapotranspiration (mm)

The value of D_i were aggregated on different time scales:

$$D_n^k = \sum_{i=0}^{k-1}(P_{n-i} - PET_{n-i}),\ n \geq k,$$

where k is the monthly timescale and n is the number of calculations.

In the context of SPEI, a three-parameter probability distribution is utilized and the D series is standardized using a log-logistic distribution f(x):

$$f(x) = \frac{\beta}{\alpha}\left(\frac{x-\gamma}{\alpha}\right)^{\beta-1}\left[1 + \left(\frac{x-\gamma}{\alpha}\right)^{\beta}\right]^{-2}$$

where, α, β and γ represent the scale, shape, and origin parameters, respectively.

Therefore, for a given time scale, the cumulative distribution function was determined as:

$$F(x) = \left[1 + \left(\frac{\alpha}{x-\gamma}\right)^{\beta}\right]^{-1}$$

SPEI has been calculated as follows:

$$SPEI = W - \frac{C_0+C_1W+C_2W^2}{1+d_1W+d_2W^2+d_3W^3}$$

Where, $W = \sqrt{-2\ln(P)}$ for P≤ 0.5 and $W = \sqrt{-2\ln(1-P)}$ for P > 0.5, $C_0 = 2.5155$, $C_1 = 0.8028$, $C_2 = 0.0203$, $d_1 = 1.4327$, $d_2 = 0.1892$, $d_3 = 0.0013$.

The sum of all negative SPEI values shows the severity of the drought, while the minimum SPEI value denotes the peak intensity of the drought, and the sum of consecutive months with negative SPEIs represents the drought's duration. Table 1 shows the classification of drought severity based on SPI values. A negative SPI number indicates a dry situation, while a positive value indicates a moist condition. The drought severity classification for SPEI is similar to SPI shown in Table 1.

The SPI and SPEI are multi-scale drought indices that have been widely used. In this study, 1-, 3-, 6-, 9-, and 12month timescales SPI and SPEI were computed using the “SPEI” package in R-statistical software. The flowchart of the methodology is presented in figure 2.

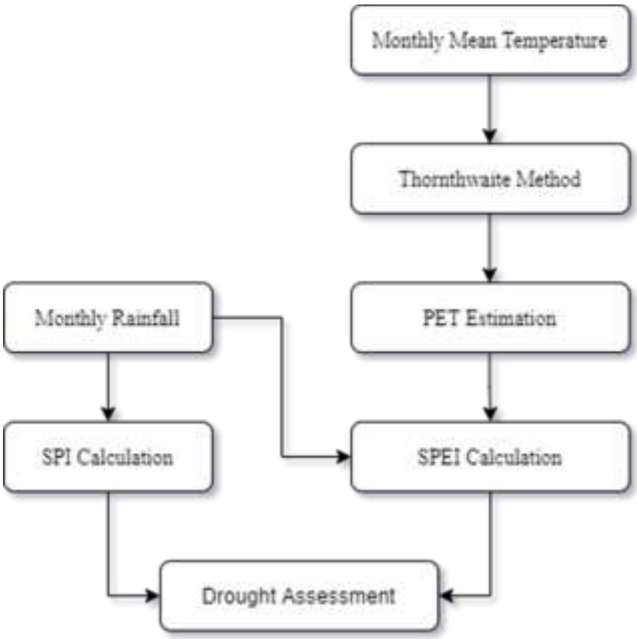


Figure 2. The flowchart of the methodology

RESULTS AND DISCUSSION

5.1 Annual Rainfall

Monthly rainfall data averaged over the Tel river basin has been calculated from daily rainfall data obtained from the Indian Meteorological Department (IMD) website over ten grid points of grid size 0.25°×0.25°. Figure 3 shows the correlation between monthly observed rainfall and monthly gridded rainfall data of the Tel river basin. Since the correlation between observed and gridded data is 0.92, hence gridded data is used in the present study.

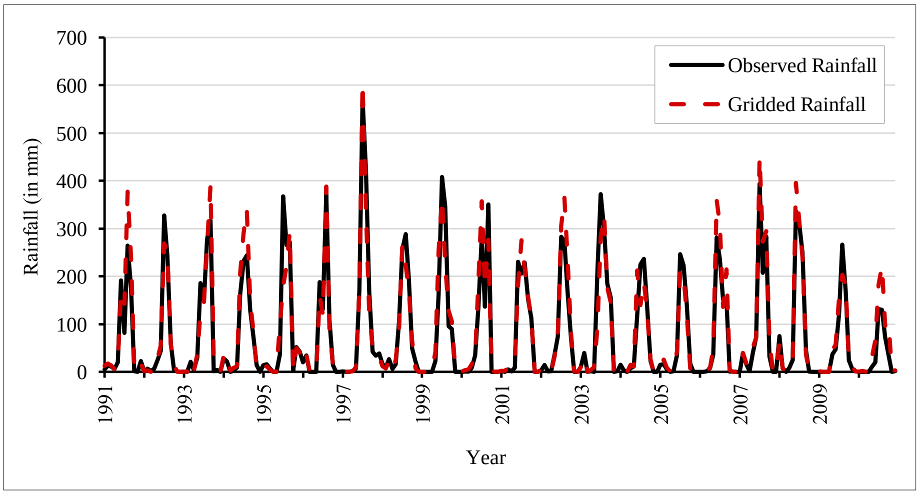


Figure 3. Assessment between observed and gridded rainfall data

5.2 Annual Temperature

Figure 4 shows the annual mean temperature variation averaged over the Tel river basin. It is observed that the annual mean temperature over the Tel river basin is increasing during the period from 1991 to 2015. Also, the maximum value of annual mean temperature observed in 2010 was 26.43°C.

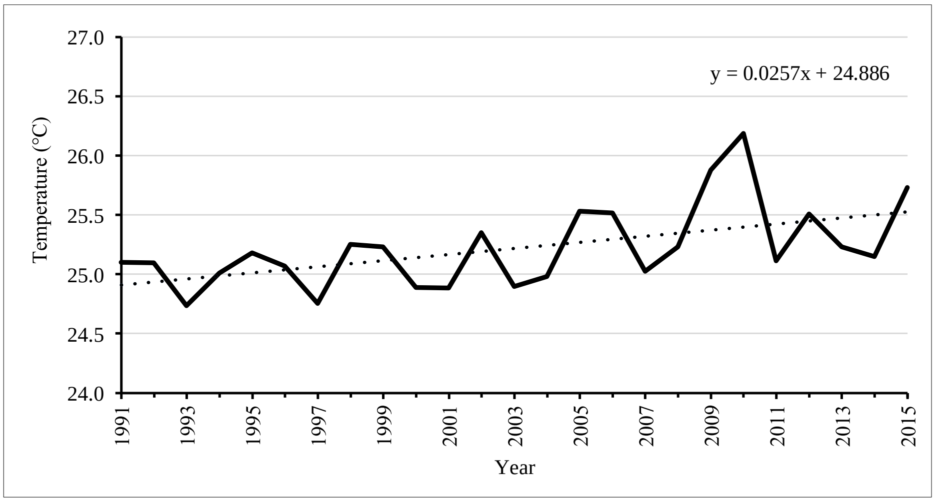


Figure 4. Variation of annual average temperature over the basin (1991-2015)

5.3. Annual Water Deficit

The annual water deficit was computed using climate water balance and is shown in Figure 5. Potential evapotranspiration (PET) was calculated using the Thornthwaite method. The value of annual PET was observed to be greater than annual rainfall from the year 1992 to 2015. Therefore, there was a deficit of water throughout the observed duration. Also, in Figure 5, the variation of annual rainfall and annual PET for the duration 1991 to 2015 is shown.

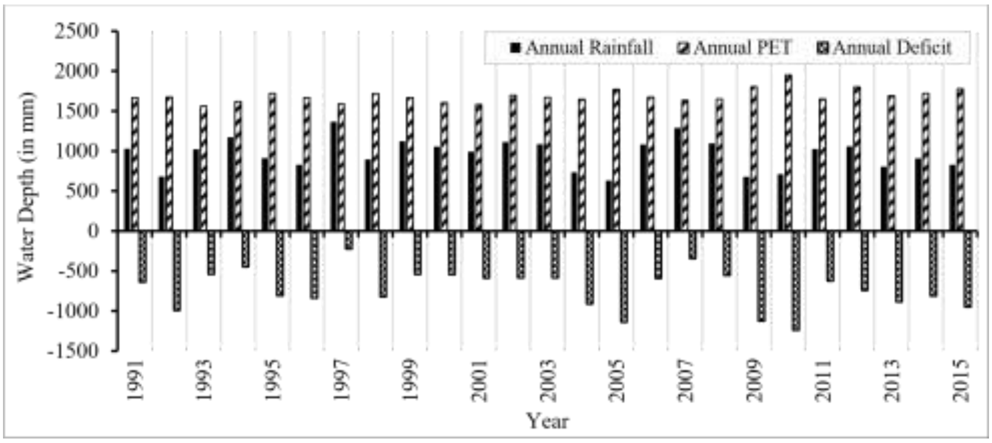
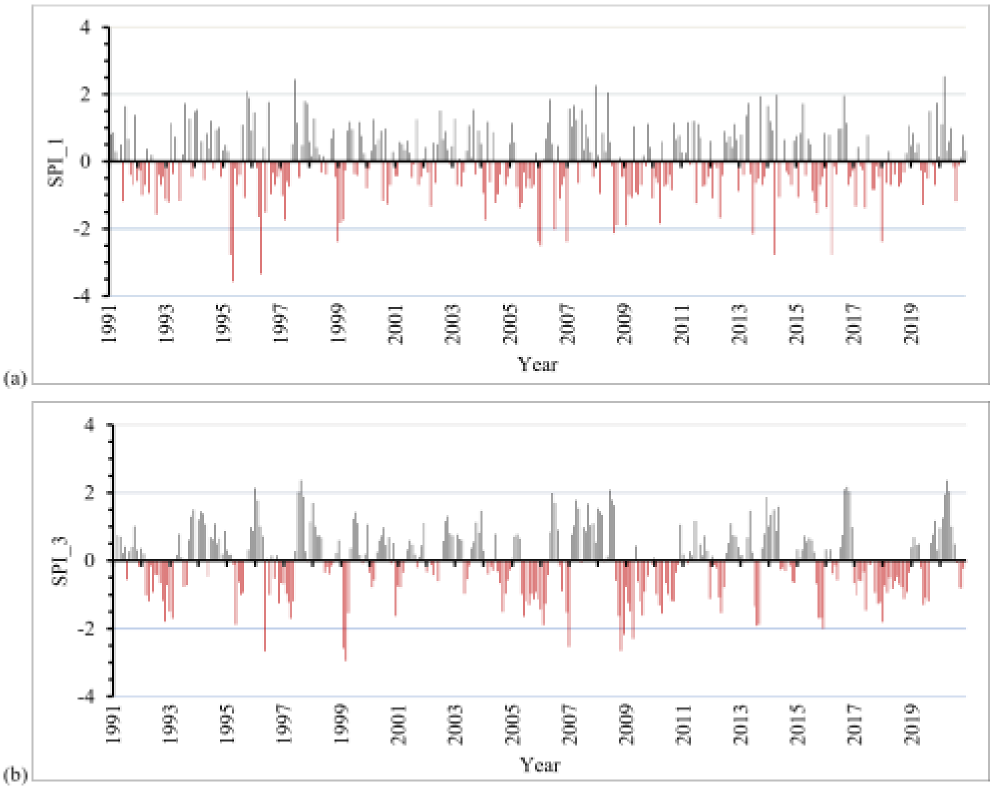


Figure 5. Annual variation of rainfall, PET, and annual water deficit (1991-2015)

5.4 Monthly Variation of SPI

Figure 6 presents the temporal variation of monthly SPI for timescale (1-, 3-, 6-, 9- and 12-month), which have been computed using 30 years (1991 to 2020) rainfall data. The monthly variation of the SPI was visible at various timescales, indicating a distinct change in the dry and wet degrees of each month in the study area, particularly after 2004, when the dry degree of some months expanded considerably. Extreme drought has been observed during the years 1995, 1999, 2006, 2007, 2008, 2013, 2014, 2016, and 2018 having 1-month SPI less than -2.0. Extreme drought occurs in 2008 and 2010 according to 3-, 6- and 9-month SPI with intensity less than -2.0. The maximum duration of drought events occurs from 2017 to 2020 with an intensity of -1.5 in 2018 on a 9-month timescale. For the 12-month timescale, SPI, the maximum duration of drought event occurs during 2017 to 2020 with an intensity of -1.54 in 2020 which shows extreme drought during this duration.



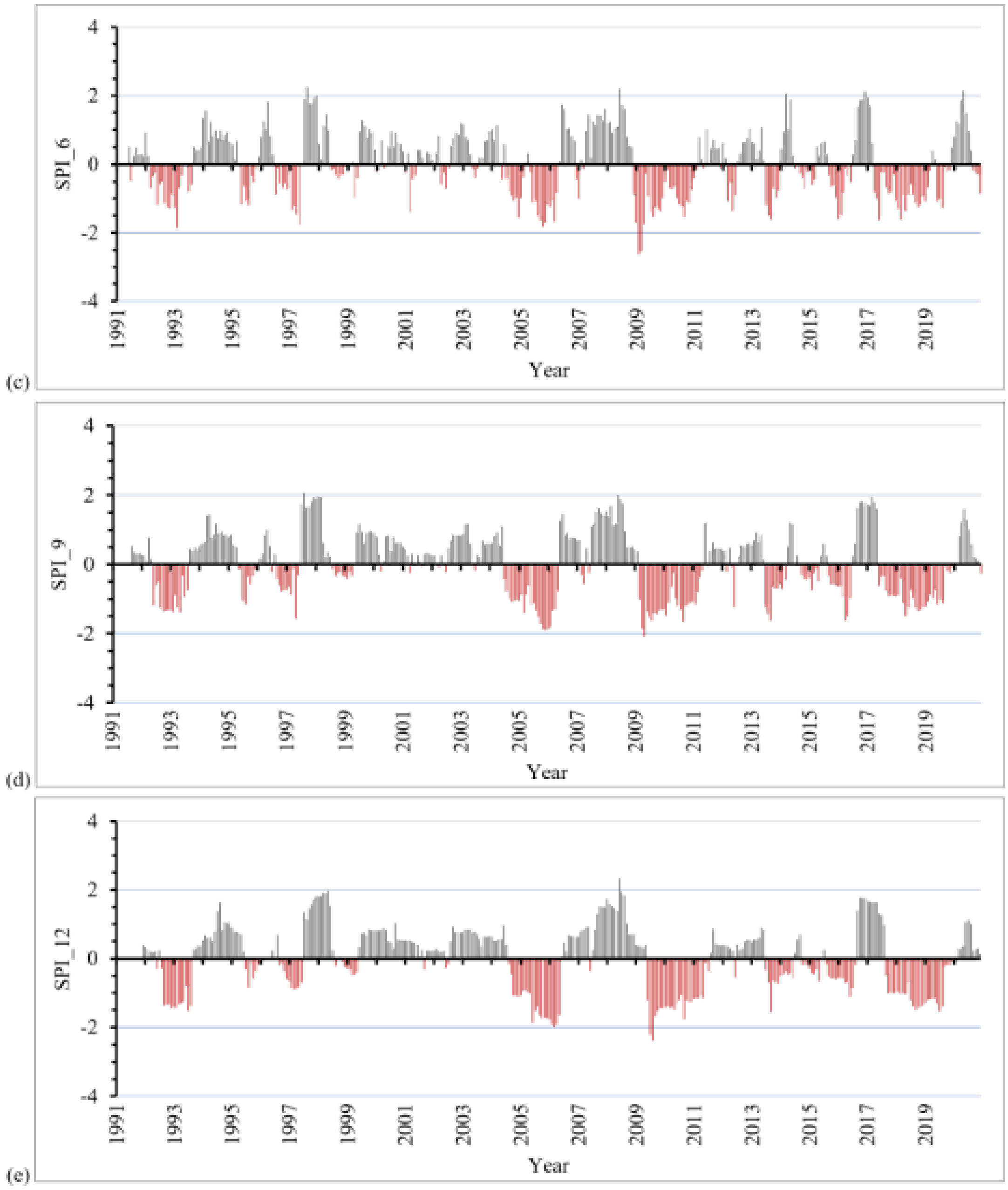


Figure 6. Temporal variation of SPI in the Tel River basin for (a) 1-month, (b) 3-month, (c) 6-month, (d) 9-month, and (e) 12-month timescale

5.5 Monthly Variation of SPEI

(1991 to 2015) rainfall and temperature data and is presented in Figure 7. Almost in all timescale, 2009-2010 has SPEI less than -2.0 which suggests that this duration is an extreme drought period. The 1-month SPEI data shows that 2006, 2009, and 2010 has extreme drought with intensity -2.08, -2.35, and -2.62 respectively. Extreme drought occurs in 2009 and 2010 according to 3-and 6-month SPEI with intensity less than -2.0. The 9-month SPEI also shows the extreme drought in the year 2009. There is no extreme drought event observed for the 12-month SPEI but the negative value of the index shows moderate and severe drought. The 2009 to 2010 years are observed as drought periods for almost all-time series calculated. Years 2004 to 2006 has also been observed as drought duration but it is not as severe as 2009 to 2010 duration drought. The intensity and duration of drought have increased after The temporal variation of monthly SPEI for different timescale (1-, 3-, 6-, 9- and 12-month) have been computed using 25 years 2004.

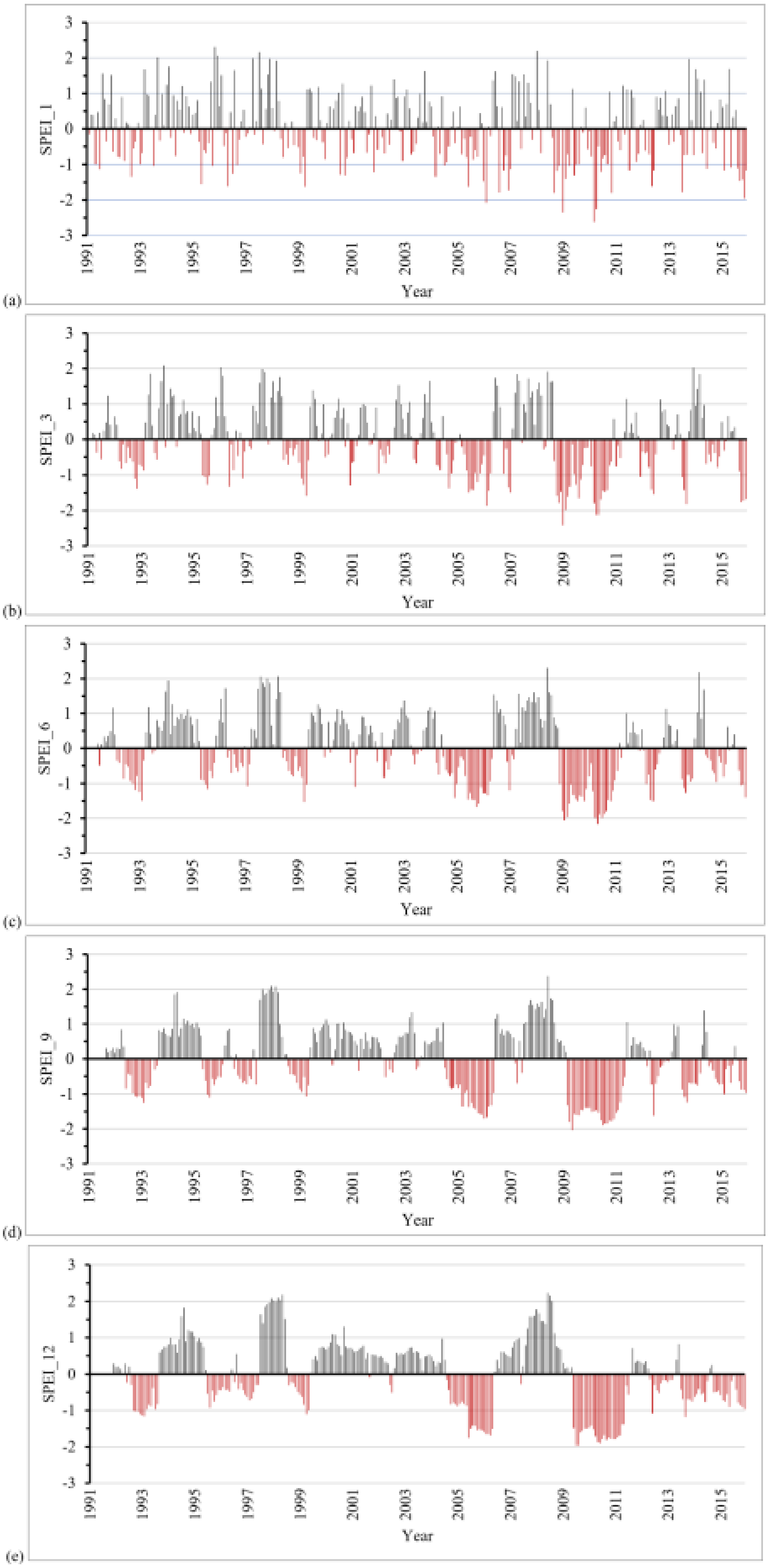


Figure 7. Temporal variation of SPEI in the Tel River basin for (a) 1-month, (b) 3-month, (c) 6-month, (d) 9-month, and(e) 12-month timescale.

5.6 Correlation Analysis of SPI and SPEI

Correlation analysis is a method used to determine the direction and strength of the relationship between the two variables. Since drought indices are based on standardization, Pearson correlation analysis was used for correlation analysis in this study. Table 2 presents the Pearson correlation matrix of drought indices. Correlation coefficient values greater than or equal to 0.8 are chosen as critical values indicating a strong positive relationship.

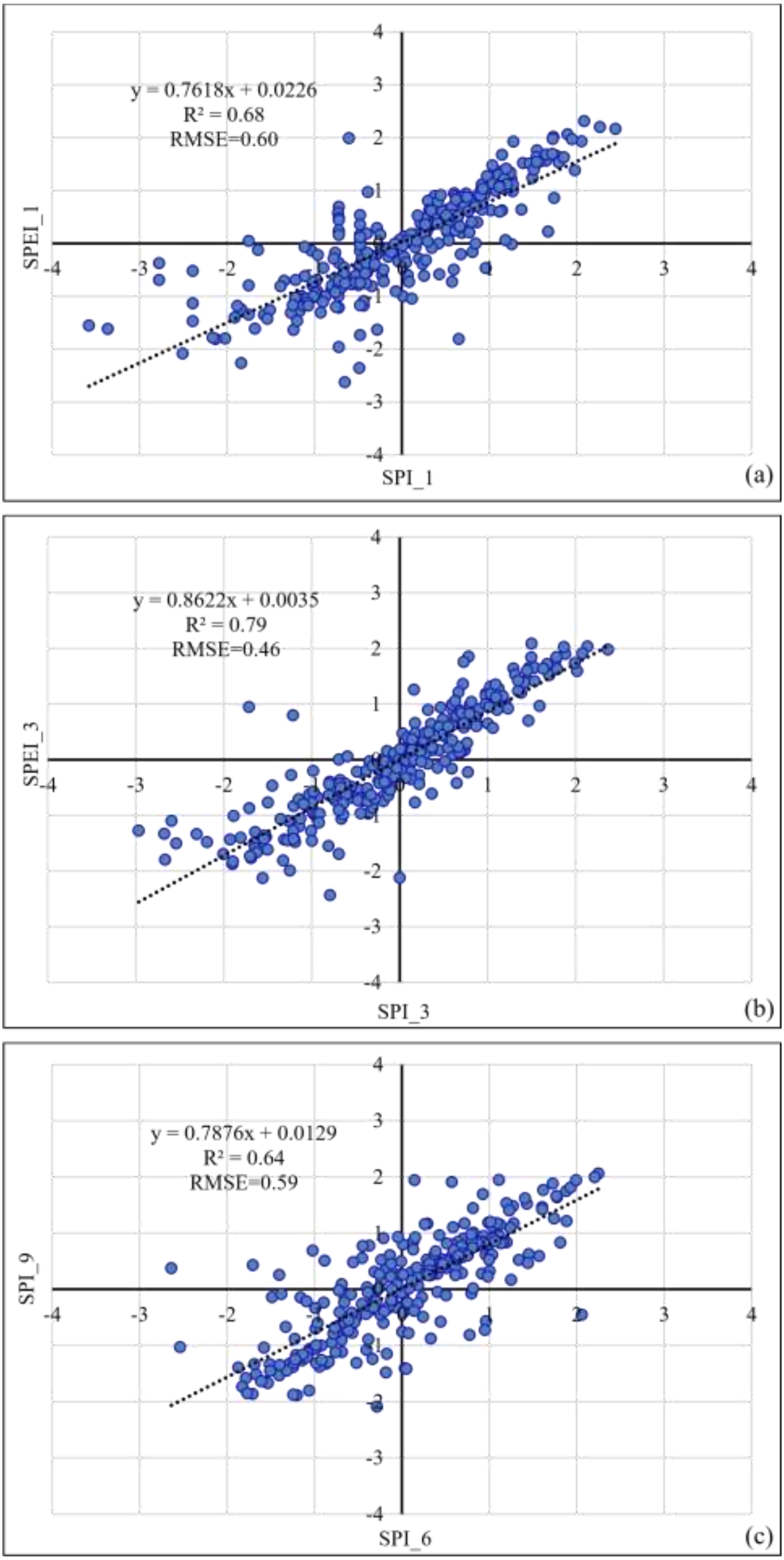
Table 2. Pearson correlation coefficient matrix of SPI and SPEI of different timescale

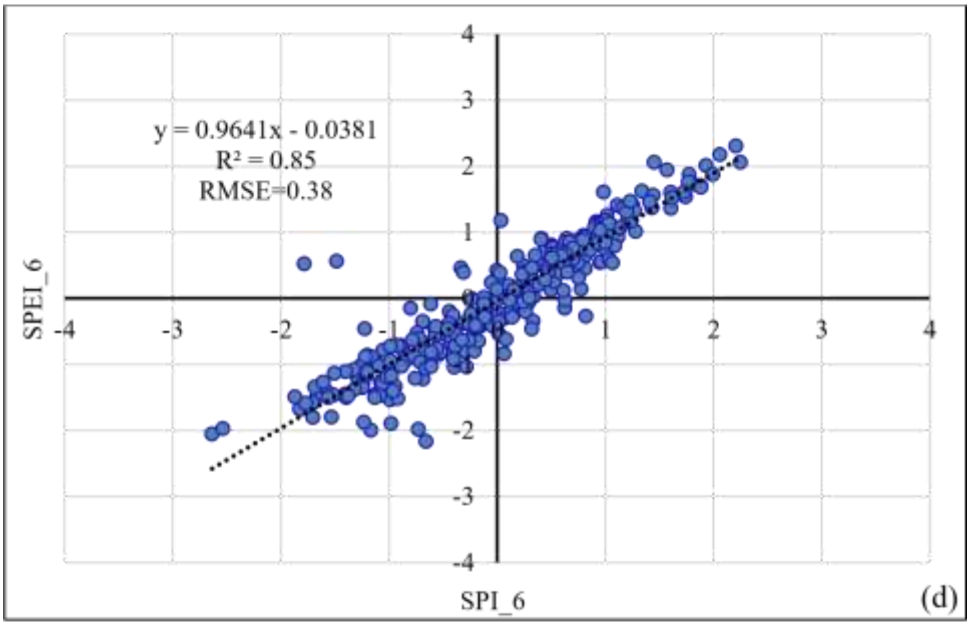
INDEX	SPI_1	SPI_3	SPI_6	SPI_9	SPI_12	SPEI_1	SPEI_3	SPEI_6	SPEI_9	SPEI_12
SPI_1	1	0.66	0.43	0.27	0.29	**0.83**	0.54	0.40	0.26	0.28
SPI_3		1	0.71	0.53	0.47	0.59	**0.88**	0.66	0.54	0.44
SPI_6			1	**0.81**	0.69	0.45	0.70	**0.93**	0.76	0.66
SPI_9				1	**0.85**	0.32	0.53	0.76	**0.95**	**0.84**
SPI_12					1	0.32	0.50	0.65	**0.86**	**0.92**
SPEI_1						1	0.63	0.50	0.33	0.32
SPEI_3							1	0.78	0.56	0.53
SPEI_6								1	**0.82**	0.72
SPEI_9									1	**0.89**
SPEI_12										1

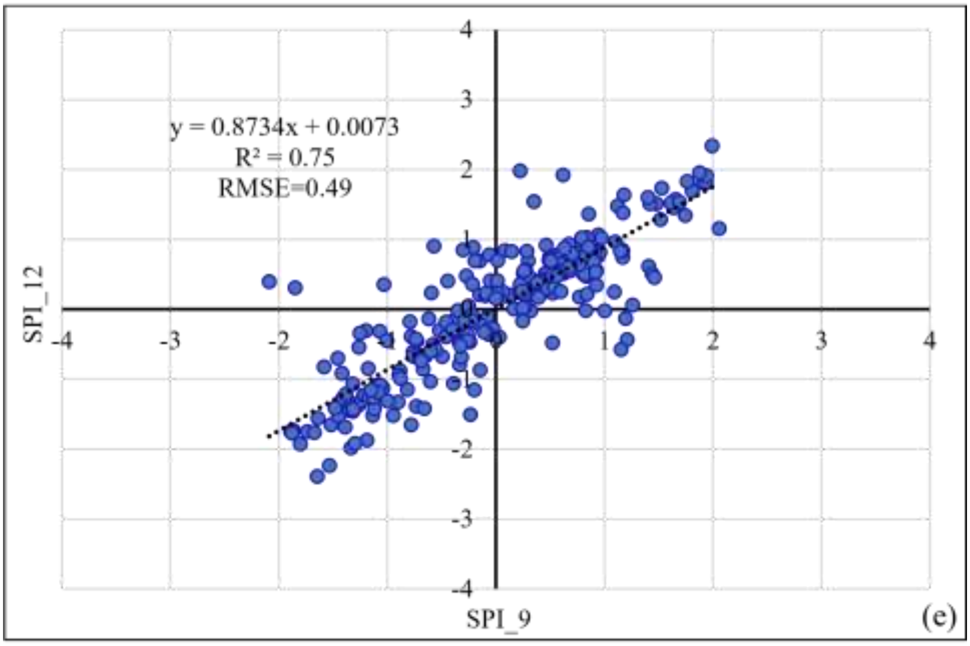
When the correlation matrix is examined, the strongest relationship was observed among the indices in the same timescale. The strongest correlation coefficient (0.92) was observed between SPI_12 and SPEI_12 and the lowest correlation coefficient (0.26) was between SPI_1 and SPEI_9.

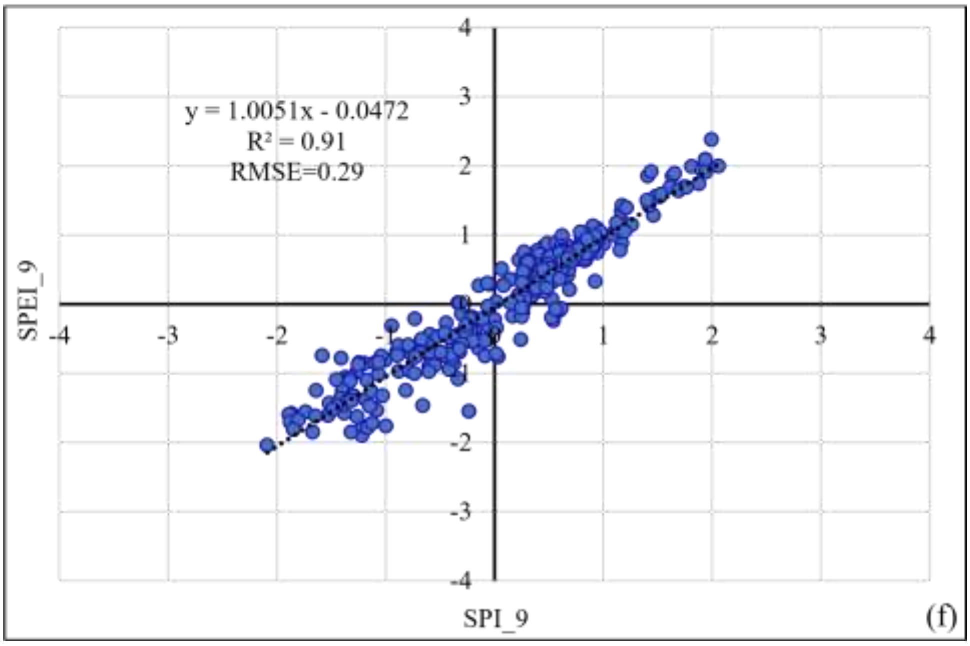
5.7 Linear Regression Analysis

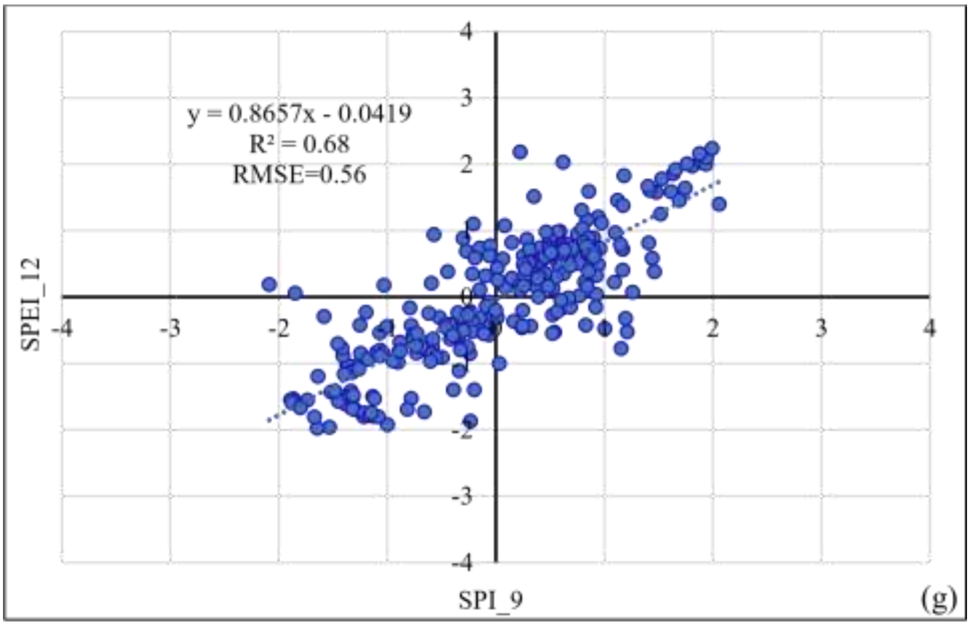
Regression analysis has been used in this study to compare drought indices of different timescale having correlation coefficient value greater than or equal to 0.8. For the comparison of drought indices, scatter diagram (Figure. 8) has been drawn and statistically evaluated by using the coefficient of determination (R^2) and RMSE .

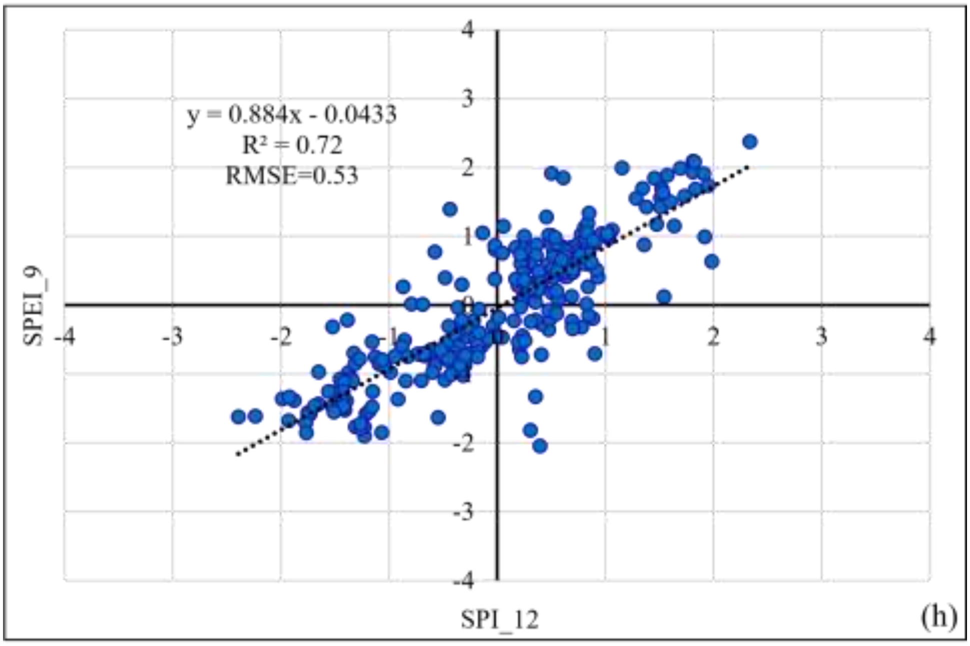

y = 0.7618x + 0.0226
R² = 0.68
RMSE=0.60
SPEI_1
SPI_1
(a)
y = 0.8622x + 0.0035
R² = 0.79
RMSE=0.46
SPEI_3
SPI_3
(b)
y = 0.7876x + 0.0129
R² = 0.64
RMSE=0.59
SPI_9
SPI_6
(c)

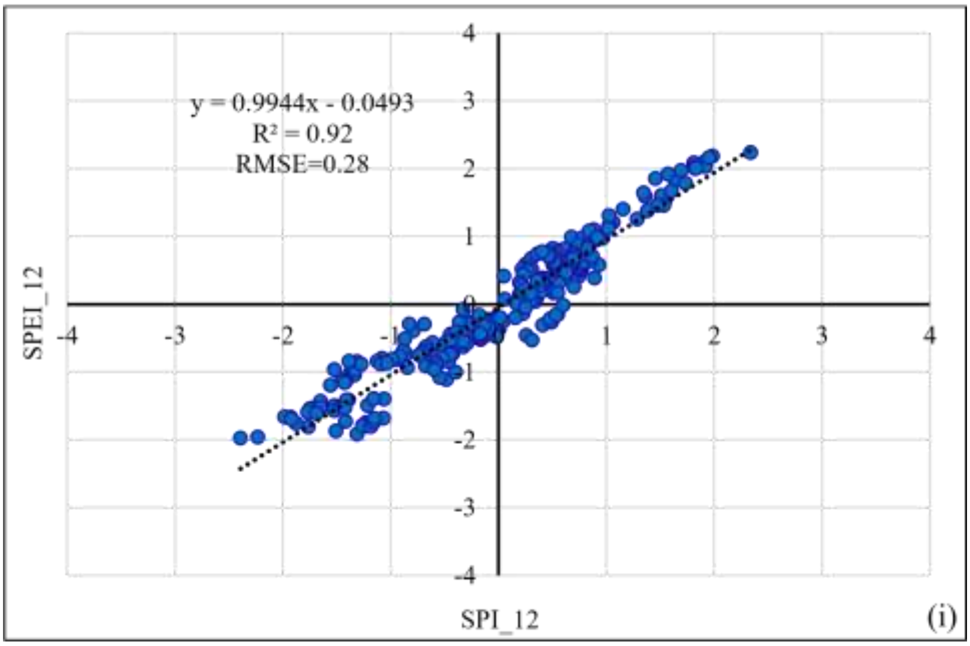

y = 0.9641x - 0.0381
R² = 0.85
RMSE=0.38
SPEI_6
SPI_6
(d)

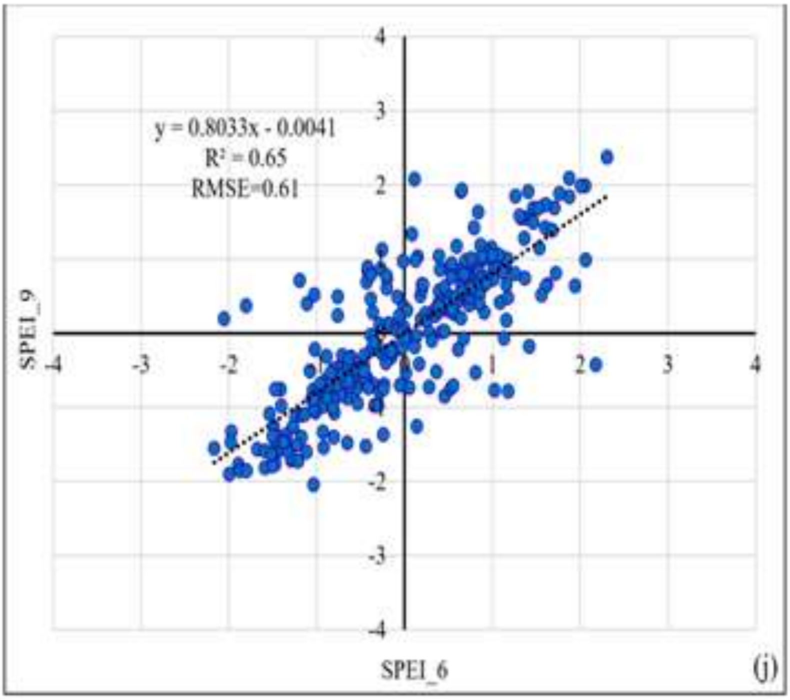

y = 0.8734x + 0.0073
R² = 0.75
RMSE=0.49
SPI_12
SPI_9
(e)


y = 1.0051x - 0.0472
R² = 0.91
RMSE=0.29
SPEI_9
SPI_9
(f)


y = 0.8657x - 0.0419
R² = 0.68
RMSE=0.56
SPEI_12
SPI_9
(g)


y = 0.884x - 0.0433
R² = 0.72
RMSE=0.53
SPEI_9
SPI_12
(h)


y = 0.9944x - 0.0493
R² = 0.92
RMSE=0.28
SPEI_12
SPI_12
(i)



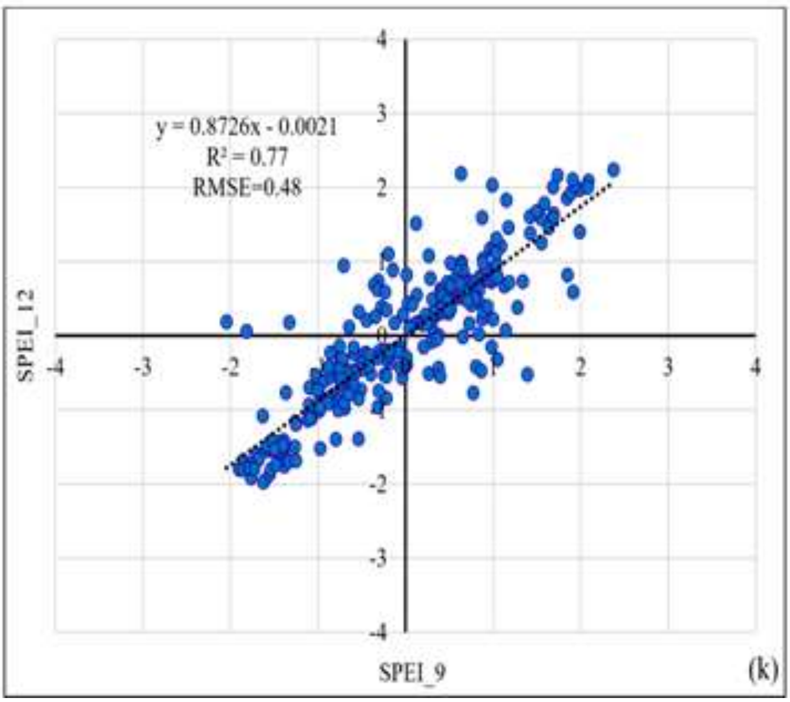


Figure 8. Scatter diagrams of drought indices: (a) SPI_1 AND SPEI_1, (b) SPI_3 and SPEI_3, (c) SPI_6 and SPI_9, (d) SPI_6 and SPEI_6, (e) SPI_9 and SPI_12, (f) SPI_9 and SPEI_9, (g) SPI_9 and SPEI_12, (h) SPI_12 and SPEI_9, (i) SPI_12 and SPEI_12, (j) SPEI_6 and SPEI_9, (k) SPEI_9 and SPEI_12**.**

When the diagrams are examined, strongest fit has been shown by values of SPI_12 and SPEI_12 (Figure 8. i).

Also, the results of statistical indicators shows that the value of SPI gives close result with SPEI in the same timescale. Greatest value of R^2 is 0.92 and lowest value RMSE is 0.28 for SPI_12 and SPEI_12 scatter diagram, which indicated that the indices give close results.

5.8. Comparison of SPI_12 and SPEI_12

It has been seen that there is good relationship between SPI and SPEI. Table 2 suggest, there is strong correlation between SPI_12 and SPEI_12. Both the indices have correlation coefficient of 0.96 and shows similar pattern of drought occurrence. These index values have been compared for the duration 1991 to 2015 and presented in Figure 9. Both the drought indices suggest drought event occur during 2004-2005 and 2009 and 2010.

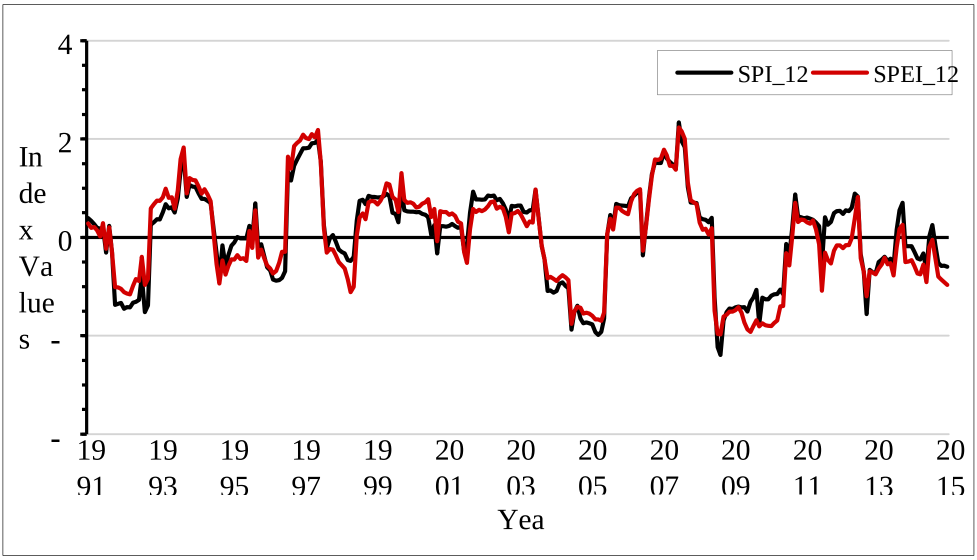


Figure 9. Comparison plot between SPI and SPEI

5.9. Variation of SPEI_12 with Temperature

Figure 10 displays the variation of SPEI_12 with temperature. It is observed that when the temperature is rising, index value decreases. Negative index value shows significant drought. It is also observed that in 2010, when the annual mean temperature is maximum the value of SPEI is minimum in the observed duration. This shows that temperature is one of the critical variables along with rainfall in the analysis of drought.

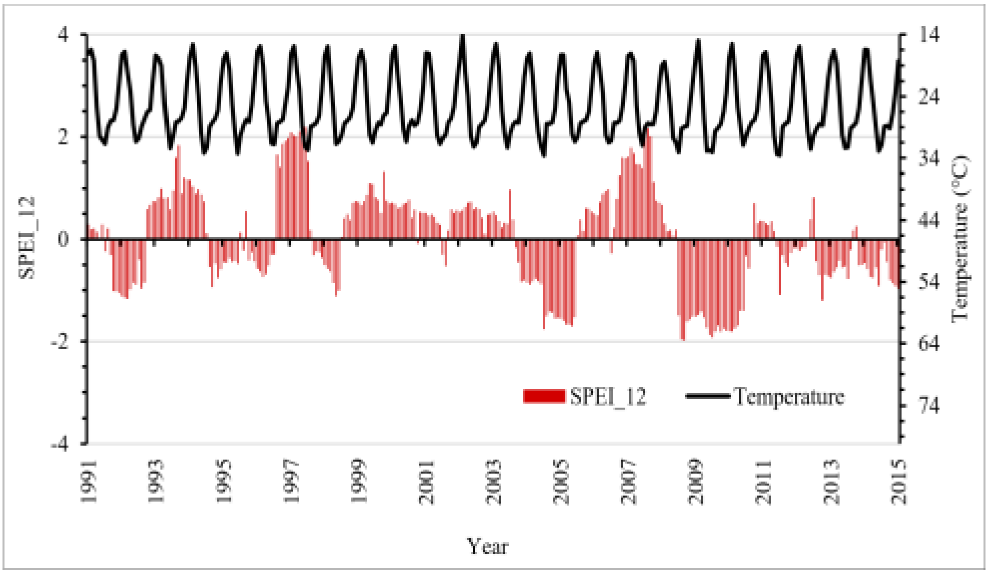


Figure 10. Variation of SPEI_12 with Temperature (1991 -2015)

5.10. Analysis of Seasonal Drought

In this study, winter (December to February), pre-monsoon (March to May), monsoon (June to September), and post-monsoon (October to November) are considered as the four seasons. Figures 11 and 12 show the seasonal variation of SPI_12 and SPEI_12 in the Tel River basin. Values of both the indices shows negative trend in all the seasons for 12-months timescale. This implies that the probability of drought occurrence is increasing. Both SPI and SPEI show only moderate and severe drought during monsoon and post-monsoon season and the occasional session of the extreme drought event.

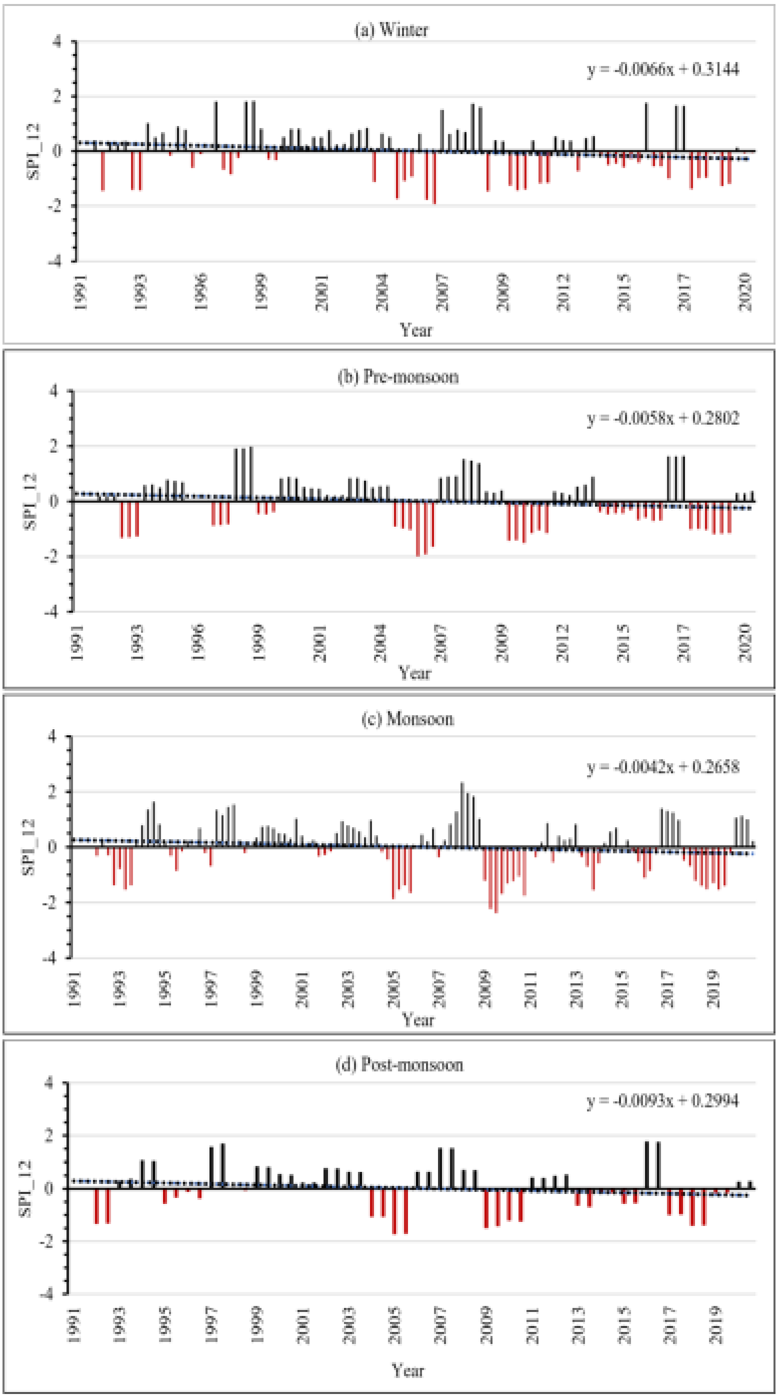


Figure 11. Seasonal Variation of SPI_12 in Tel River basin (a) Winter, (b) Pre- monsoon, (c) Monsoon, and (d) Post-monsoon

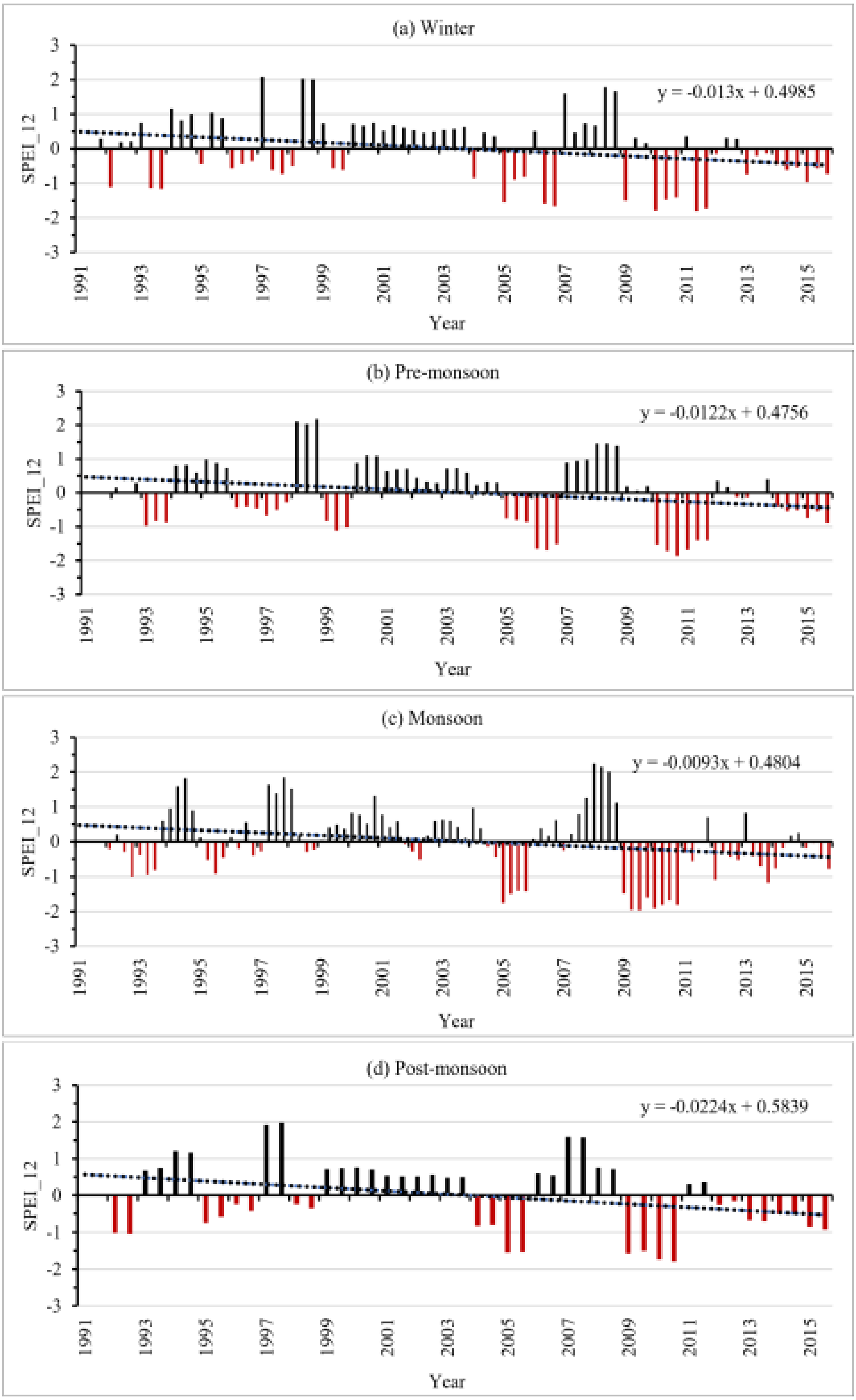


Figure 12. Seasonal variation of SPEI_12 in Tel river basin (a) Winter, (b) Pre- monsoon, (c) Monsoon, and (d) post-monsoon

5.11. Performance of Drought Indices with Respect to Historic Drought

All the districts of the study area were facing shortage of water and declared drought affected area by the state government. Drought led recession in agricultural economy has been reported by 66th round of consumption survey by National Sample Survey Office (NSSO). It is also evident from the Figure 12, that drought has occurred during 2004-2005 and 2009-2010. Both the drought indices, (i.e., SPI and SPEI) is indicating occurrence of drought on all timescale in the present study.

Meteorological drought becomes critical if it persists for longer duration. In this study 1-, 3-, 6-, 9-, and 12-month scale indices has been used for drought analysis. Shorter timescale indices talk about the meteorological condition whereas higher timescale can be used for the water availability for the crops having crop period more than 3-4 months. If drought situation continues for longer period, it will affect the agricultural economy and consequently socio-economic drought will occur. Gridded data has been used for the analysis in this paper, since available observed data was not uniformly available in the study area. Policies maker may use the results of this study to counter water scarcity related issues in future and better measures can be adopted for reducing the effects of drought.

CONCLUSIONS

In any river basin, drought assessment using a suitable drought index is vital for effective water resources management. In this study, the drought situation has been evaluated using two globally accepted drought indices namely SPI and SPEI at different timescales. The performance of both indices at different timescale has been examined with an aim of identifying a suitable drought index for the Tel river basin. Based on the results of this study, it can be concluded that the Water deficit is constantly increasing over the study duration, as a result of decreasing rainfall and increasing PET trend in the basin. Both the drought indices indicated drought conditions from 2008 to 2010 for all timescale used in the study. The correlation matrix of 1-, 3-, 6-, 9-, and 12-month scale indices of SPI and SPEI indicates that both the indices show a strong relationship for the same timescale. Also, there was the highest correlation coefficient R^2 is 0.92 and the lowest value of RMSE is 0.28. The observation of SPI and SPEI indicated drought period during 2009 to 2010 for almost all timescale. The period 2004 to 2006 has also been observed as drought period but it is not as severe as 2009 to 2010 duration drought. The intensity and duration of drought have also increased after 2004. A negative trend of both the indices have been observed in all seasons on all timescale. The 12-month scale indices perform better in detecting historic drought. The dependency of SPEI on temperature is also clearly observed in this study. Hence, SPEI at a 12-month scale is recommended for drought monitoring in the study area. This analysis may be used for effective planning and water management practices.

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