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RAINFALL AND METEOROLOGICAL DROUGHT SIMULATION USING EXPONENTIAL SMOOTHING AND WINEXPO MODELS: A STUDY ON PURULIA DISTRICT, WEST BENGAL, INDIA

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ABSTRACT

Drought monitoring and prediction of a particular region is primarily meteorological. By far the main challenge to predict and analyze meteorological drought is a) Choice of appropriate method to interpret the drought events b) To identify the nature of meteorological drought c) to establish a perfect dimension to predict drought effectively. The primary objective of this study is to simulate rainfall and meteorological drought (SPI is taken as the indicator as it is one of the most accepted indicators of meteorological drought) up to 2035-36 by using the traditional exponential and Holt-Winter exponential smoothing after analyzing the trends of rainfall and SPI12 of Purulia District, West Bengal. Based on exponential smoothing and Winexpo model it becomes quite evitable that the drought severity will increase in the near future. Based on the performance evaluation Winexpo outperforms the other two models as it obtains minized RMSE, MSE, MAE and MPE. The study demonstrates a unique mwthodology which might be very useful in understanding the drought-proneness of the region.

Keywords: drought, SPI, winexpo indices, holt-winter model, exponential model.

1. INTRODUCTION

Drought is recurrent natural phenomena associated with the lack of water resources for a prolonged period of dryness (Rossi 2000, Mishra *et al* 2007, Mishra and Desai 2011, Wilhite and Glantz 1985). Drought forecasting is a critical element in drought risk management (Ozger *et al* 2012, Wilhite 2000, Anita *et al* 2016). Mishra (2015) rightly expressed his view in the editorial that accurate assessment of drought is essential for proper planning and management of water resources. Drought preparedness and mitigation depends upon the large scale drought monitoring and forecasting over a large geographical area (Ozger *et al* 2012, Wu *et al* 2011). Many drought forecasting models already developed in the field of civil engineering. ARIMA and multiplicative seasonal ARIMA models was developed by Mishra and Desai 2006 to forecast drought using SPI series. up to only 2 months lead time. Forecasting of drought using Artificial Neural Network (ANN) using Effective Drought Index (EDI) and SPI were done by Morid *et al* 2007. Barros and Bowden (2008) employed self-organizing maps (SOM) and multivariate linear regression analysis to forecast SPI of Murray Darling basin of Australia with 12 months forthcoming scenarios. Stagge *et al.* 2015, Tatli 2015 employed regression analysis to simulate drought whereas Mishra *et al* 2007, Durdu 2010 used time series method to simulate and predict drought though most of the statistics based predictions are in rather shorter time frames. This study allows simulation and prediction of drought upto 18 lead time which is essentially useful for planning purposes.

There is increasing evidence that Climate change will affect West Bengal and especially drought will affect Purulia District and this will be one of the challenging issues for future development particularly to the drier portions of the blocks (Khan *et al* 2011, Rogaly 2010, Rogaly *et al* 2001, De Haan and Rogaly 1994, Khatun and Roy, 2012). According to IPCC report 2007 Purulia is expected to receive less rain and likely to experience 0.5-1^{0}C rise in average temperature during 2025-2099 and 3.5-4^{0}C temperature increase in 2030-2099. Over the last few years the impact of climate change has felt severely in the counterpart (INCCA 2000). Late monsoon arrival has been observed with less intensity; duration of summer has been longer drought has become more frequent (WBSAPCC 2010, Mishra and Desai 2011, RPAPCC 2012). The problems are further been compounded with growing population, lack of water resource initiatives and adaptation of water intensive commercial crops. The Purulia including GWB is less experienced in coping the drought. Under such circumstances for the proper management and planning perspective long-term modelling and simulation of drought could be a good attempt.

2. STUDY AREA

Purulia District is the matter of concern for various authors since the last 5-8 years due to drought.This region is one of the westernmost districts of West Bengal and a tract of Rurh terrain. Its' latitudinal and longitudinal extensions are from 22^{0}42′35″N to 23^{0}42′N and 85^{0}49′25″E to 86^{0}54′37″E respectively. This region is affected by the shortage of rainfall and harsh terrain. Figure-1 depicts the location map of the study area. The figure demonstrates how the region has been selected from macro level to micro level (Purulia.nic.in).

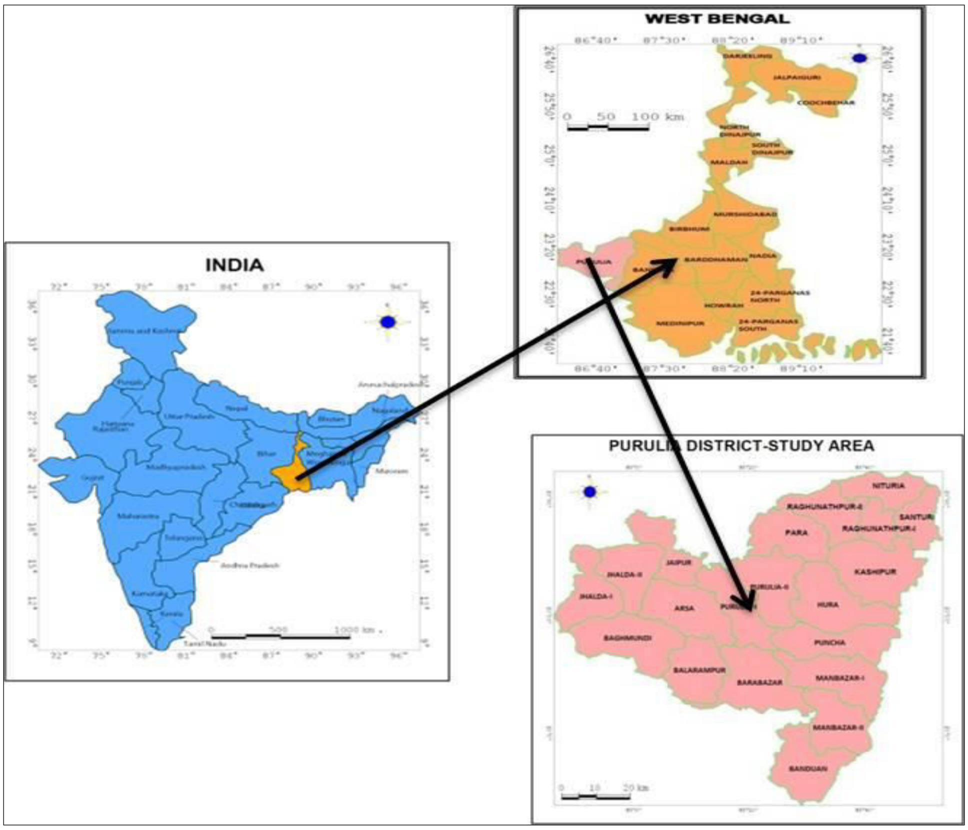

Figure-1. Location Map of the Study Area.

3. DATA SETS AND METHODOLOGY

Figure-2 determines the detailed methodological framework of the whole study. First from rainfall, SPI has been estimated. Holt-Winter and Exponential model have run for both the rainfall and SPI and Winexpo index has been derived for both of them. Adding Winexpo Models of rainfall and SPI a combined Winexpo model has been derived. Hazard prone zones are also identified based on PCA score generated using three models.

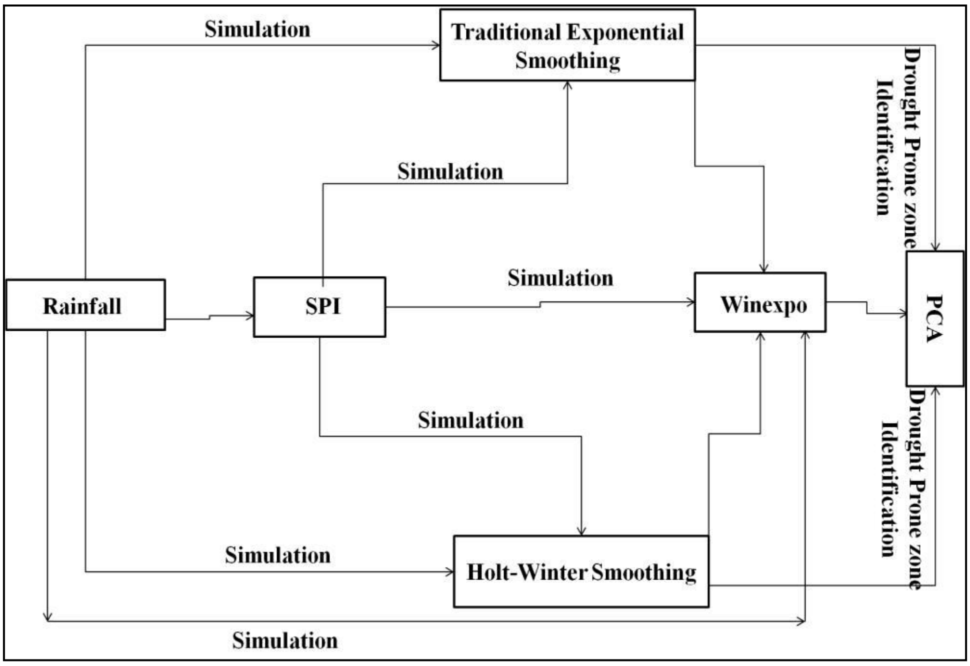

Figure-2. Methodological Framework.

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3.1 Determination of drought:

SPI is calculated on the basis of year-wise gridded rainfall data (0.5^0*0.5^0) available in ERA Interim daily website. The time frame is taken here from1984 to 2016. The long-term rainfall is fitted to the probability distribution and then transformed into the Normal distribution to the mean SPI for the location and the desired period is zero (Mckee *et al* 1993, Stagge *et al* 2015),

$$SPI = (a - b)/c \quad (1)$$

Where, a=individual gamma cumulative distribution value, b=mean, c=standard deviation.

or, $SPI = (TotalRainfall - Longtermrainfallmean)/standarddeviation$ (2)

Kumar *et al* 2009 computed SPI for districts Andhra Pradesh using two parameters Gamma Function for a low rainfall and high rainfall. With following this methodology we use Microsoft Excel 2007 for the computation of Standard Precipitation Index (SPI). The required functions and procedures are as follows:

$$x = TotalRainfall$$
$$Mean(\bar{x}) = \frac{\sum x}{N} \quad (3)$$

Putting Value of Mean from Eq. (3) we get:

$$S = \frac{\sqrt{\sum\left(x - \frac{\sum x}{N}\right)^2}}{\sqrt{N}} \quad (4)$$

The precipitation is converted to lognormal values and the statistics U, shape and scale parameters of Gamma distribution are computed.

$$Log(mean) = In(\bar{x}) \quad (5)$$

$$U = In\overline{(x)} - \frac{\sum \log x}{N} \quad (6)$$

Putting Value of U from Equation (5)

$$\text{Shape-parameter } (\beta) = \frac{1 + \sqrt{1 + \frac{4U}{3}}}{4U} \quad (7)$$

$$\text{Scale-parameter } (\alpha) = \frac{\bar{x}}{\beta} \quad (8)$$

$$\frac{\int_0^x e^{-\frac{x}{\beta}} x^{a-1}}{\beta^{\alpha} \gamma(\alpha)} = G(X) \quad (9)$$

Based on user Guide WMO 2012 Table-1 describes drought severity classes based on SPI.

3.2 Exponential and Holt-Winter forecast:

Exponential smoothing is the technique to smoothing the time series in exponential window function. Exponential smoothing assigns decreasing weights over time. Holt in 1957 and winter in 1960 developed smoothing technique and later their method was combined and making Holt-Winter smoothing technique to forecast the recursive trend from the historically observed data series (https://otexts.org/fpp2/holt-winters.html,). Here we use the single exponential smoothing technique as Kaleker in 2004 used in his thesis:

$$S_{t+1} = \alpha * y_t + (1 - \alpha) * S_t \; 0 < \alpha < 1, t > 0 \quad (10)$$

Eq. (11) can be written as

$$S_{t+1} - S_t = \alpha * €_t \quad (11)$$

The Holt-Winter method time series can be represented using the following model:

$$y_t = (b_1 + b_2 t) * S_t + €_t \quad (12)$$

Where b_1 is the permanent component, b_2 is the linear trend component, S_t is the multiplicative seasonal factor, $€_t$ is the random error component, t is the time and t+1 is the lead time from t.
From the Eq. (13) we get

$$S_t = \frac{y_t}{b_1 + b_2 t} + €_t \quad (13)$$

Sum of all the seasons can be written as

$$\sum_{t=12} S_t = M \quad (14)$$

Where M is the length of the year.
So, the Eq. (13) can be written as,

$$\sum_{t=1}^{12} y_t = (b_1 + b_2 \sum_{t=1}^{12} t) * \sum_{t=1}^{12} S_t + €_t \quad (15)$$

Assuming, $\sum_{t=1}^{12} y_t = Y$, $\sum_{t=1}^{12} t = T$and $\sum_{t=1}^{12} S_t = M$ we get from Eq. (15)

$$Y_t = (b_1 + b_2 T) * M + €_t \quad (16)$$

And Eq. (14) can be written after the sum of all the seasons

$$M = \frac{Y_t - €_t}{b_1 + b_2 T} \quad (17)$$

Winexpo method has been developed by us to combine the traditional exponential and Holt-Winter method. Combining Eq. (12) and Eq. (18) we get,

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$$\frac{S_{t+1}-S_t}{M} = \frac{\alpha * €_t}{\frac{Y_t - €_t}{b_1+b_2T}} \tag{18}$$

Or, $\frac{S_{t+1}-S_t}{M} = \frac{\alpha*(b_1+b_2T)}{(Y_t-€_t)} + €_t$ (19)

Here we have considered the two variables rainfall (R) and SPI (S_p). The prediction up-to 2035-36 has been done using Exponential and Holt - winter trend method. After combining the two we have got here the following form of combined Win-expo indices:

$$\left(\frac{S_{t+1}-S_t}{M}\text{ofR}\right) + \left(\frac{S_{t+1}-S_t}{M}\text{of Sp}\right) = \text{CombinedWinexpo} \tag{20}$$

Based on winexpo indices we derive 6 broad and 17 subcategories (Table-1) under which 15 categories are found in Purulia District.

Table-1. Categorization of SPI.

SPI values	Drought Severity Class	D scale
2.0+	**Extremely Wet**	**W3**
1.5 to 1.99	Very Wet	W2
1.0 to 1.49	Moderately Wet	W1
-.99 to .99	Near Normal	N
-1.0 to -1.49	Moderately Dry	D1
-1.5 to -1.99	Severely Dry	D2
-2.0 or less	Extremely Dry	D3

Based on User Guide WMO 2012.

3.3 Accuracy assessment

Goodness of fit statistics judges the suitability of statistical model. The Kolmogorov-Smirnov test statistic and Shapiro Wilk test are two best methods to judge the normality and fit of the data set:

3.3.1 Kolmogorov-Smirnov test

Kolmogorov Smirnov test is a nonparametric test of the equality of continuous one dimensional probability distribution with compare of a sample with reference probability distribution (Kolmogorov 1933, Smirnov 1948, Justel *et al* 1997). Kolmogorov Smirnov test statistic can be expressed as

$$F_n(x) = 1/n \sum_{i=1}^{n} I_{[-\infty,x]}(X_i) \tag{22}$$

Where $I_{[-\infty,x]}(X_i)$ is the indicator function, equal 1 if $(X_i)\leq$ x and equal to 0 otherwise.

The Kolmogorov-Smirnov statistic of a given cumulative function F(x) is

$$D_n = \sup_x(F_n x - F_x) \tag{23}$$

Where sup is the supremum of the set of distance between the $F_n x$ and F_x. In our case this model has been run at 95% significance level.

3.3.2 Shapiro-Wilktest

Shapiro and Wilk in 1965 test the normality of the data set. The formula is:

$$W = \frac{(\sum_{i=1}^{n} a_i x_i)^2}{\sum_{i=1}^{n}(x_i-\bar{x})^2} \tag{24}$$

$a_i$is the (a_1………a_n), $\bar{x}$ is the mean.
The constants a_i can be written as $(a_1 \dots\dots\dots.. a_n) = \frac{m^T V^{-1}}{(m^T V^{-1} V^{-1} m)^{1/2}}$(Shapiro and Wilk 1965) here $m = (m_1 \dots\dots\dots.. m_n)^T$and $m_1 \dots\dots\dots.. m_n$ are the expected values of the order statistics of independent and identically distributed random variables sampled from the standard normal distribution, and V is the covariance matrix of those order statistics.

3.3.3 Error estimation

Error estimation judges statistical significance of the models. The RMSE, MAPE and MPE discussed below in detail.

3.3.3.1 Root of mean squared error (RMSE)

Root of mean squared error is the standard deviation of the residual values.

$$RMSE = \frac{\sqrt[2]{[\sum_{i=1}^{n}(z_f - z_o)^2\ ]}}{\sqrt{N}} \tag{25}$$

Where f is the forecasted value and o is the observed value of z and N is the total number of observations. Lower the RMSE better the model fit.

3.3.3.2 Mean absolute percentage error (MAPE)

Mean Absolute Percentage Error can be a measure of prediction accuracy:

$$M = 100/N \sum_{t=1}^{n}\left|\frac{z_f - z_0}{z_0}\right| \tag{26}$$

Where f is the forecasted value of z and o is the observed value of z and N is the total number of observations.

3.3.3.3 Mean percentage error (MPE)

Mean percentage error is the average of a percentage error which exists due to the difference between the observed value and expected value (Khan and Hildreth, 2003).

$$MPE = \sum_{t=1}^{n}\left|\frac{z_f - z_0}{z_0}\right| * 100 \tag{27}$$

Where f is the forecasted value of z and o is the observed value of z. Without the percentage term this can be termed as Mean Absolute Error (MAE). We use a constant

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multiplicative factor 0.001 to adjust the variability and validation of the data set z.

4. APPLICATION AND DISCUSSION

4.1 Trend of rainfall and SPI

From the 12 month time steps of SPI between 1984-2016, 10 major droughts can be identified. The tendency of drought is continuously increasing over the years (Figure-3). 1986, 1988, 1992, 1996, 2000, 2006, 2010, 2012, 2014 and 2016 are moderate to extreme drought affected years and rest are at the normal condition (Figure-3).

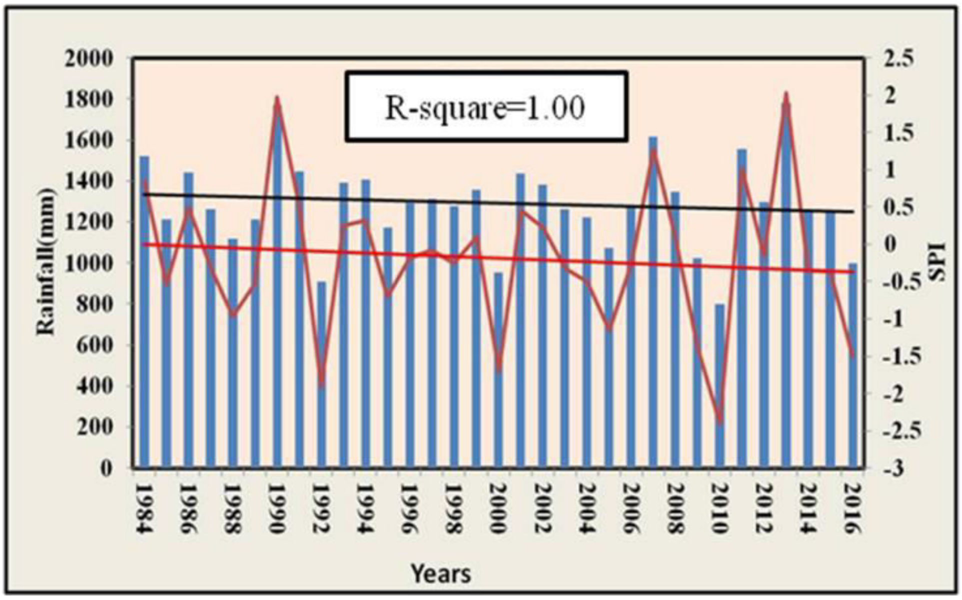

Figure-3. Rainfall and SPI variation in yearly scale.

4.2 Forecasting using the Holt-Winter and exponential model

Forecasting of the overall phenomena has been accomplished using exponential and Holt-Winter's trend test. Both models have run for rainfall and SPI. Later they are compiled as Winexpo model value.

4.2.1 Holt-Winter model of rainfall and SPI

Holt-winter rainfall model obtains a mean of 1220.892 and standard deviation of 227.050 According to the goodness of fit statistics of Holt-Winter rainfall and SPI model it never converges after 501 iterations. 9 independent values can be assigned to this model (Table-3). Validation has been done up to 20 points with 15.842 MAPE for Holt-Winter rainfall model and 52.318 MAPE for Holt-Winter SPI model in 95% confidence interval (Table-2). Upper boundary and lower boundary has been accurately assessed to determine fluctuation zones of rainfall and SPI. Alpha and Beta parameter of Holt-Winter filter model for rainfall and SPI experience 0.5204 and 0.01 respectively so the predicted value and initial values are equally strong. The Root of Mean Squared Error (RMSE) for Holt-Winter rainfall and SPI are 0.29 and 0.0013 respectively.

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Table-2. Goodness of fit statistics of Holt -Winter Rainfall and SPI.

Holt-Winter Rainfall			Holt-Winter SPI		
Statistic	**Data**	**Validation**	**Statistic**	**Data**	**Validation**
Observations	13	20	Observations	13	20
Degree of Freedom(DF)	9		Degree of Freedom (DF)	9	
Root of Mean Squared Error (RMSE)	0.29		Random Mean Squared Error (RMSE)	0.0013	
Mean Absolute Percentage Error(MAPE)	15.842	17.842	Mean AbsolutePercentage Error (MAPE)	52.318	9.1179
Mean Percentage Error(MPE)	4.171	11.638	Mean Percentage Error (MPE)	33.562	9.719
Mean Absolute Error (MAE)	0.1954	0.18526	Mean Absolute Error (MAE)	0.00086	0.000817
Iterations	501		Iterations	501	

4.2.2 Exponential model of rainfall and SPI

The traditional exponential model converges after the 424 iterations at 11 degrees of freedom both for rainfall and SPI (Table-3). The exponential rainfall amount obtains 1311.413mm at 2036 and the exponential SPI at -0.231 at 2036 (Table-6). Mean Absolute Percentage Error (MAPE) for the traditional exponential rainfall and SPI are 15.904 and 70.2112 respectively (Table-3).

Table-3. Goodness of fit statistics of traditional exponential model for rainfall and SPI.

Exponential Rainfall			Exponential SPI		
Statistic	**Data**	**Validation**	**Statistic**	**Data**	**Validation**
Observations	13	20	Observations	13	20
Degree of Freedom (DF)	11		Degree of Freedom (DF)	11	
Random Mean Squared Error (RMSE)	0.2595		Random Mean Squared Error (RMSE)	0.0015	
Mean Absolute Percentage Error (MAPE)	15.904	21.240	Mean Absolute Percentage Error (MAPE)	70.2112	39.7082
Mean Percentage Error (MPE)	0.9877	1.717	Mean Percentage Error (MPE)	41.3120	18.9473
Mean Absolute Error (MAE)	0.1902	0.2177	Mean Absolute Error (MAE)	0.837	0.959
Iterations	24		Iterations	24	

The forecasting of rainfall and SPI are associated with residual plots within 95% confidence interval (Figure 4(b), 4(d) and Figure-5(b), 5(d)). The forecasting functions by Holt-Winter SPI and traditional exponential model with their validation within 95% confidence interval are programmed (Figure-4(a), Figure-4(c), Figure-4(b) and Figure-4(d)).

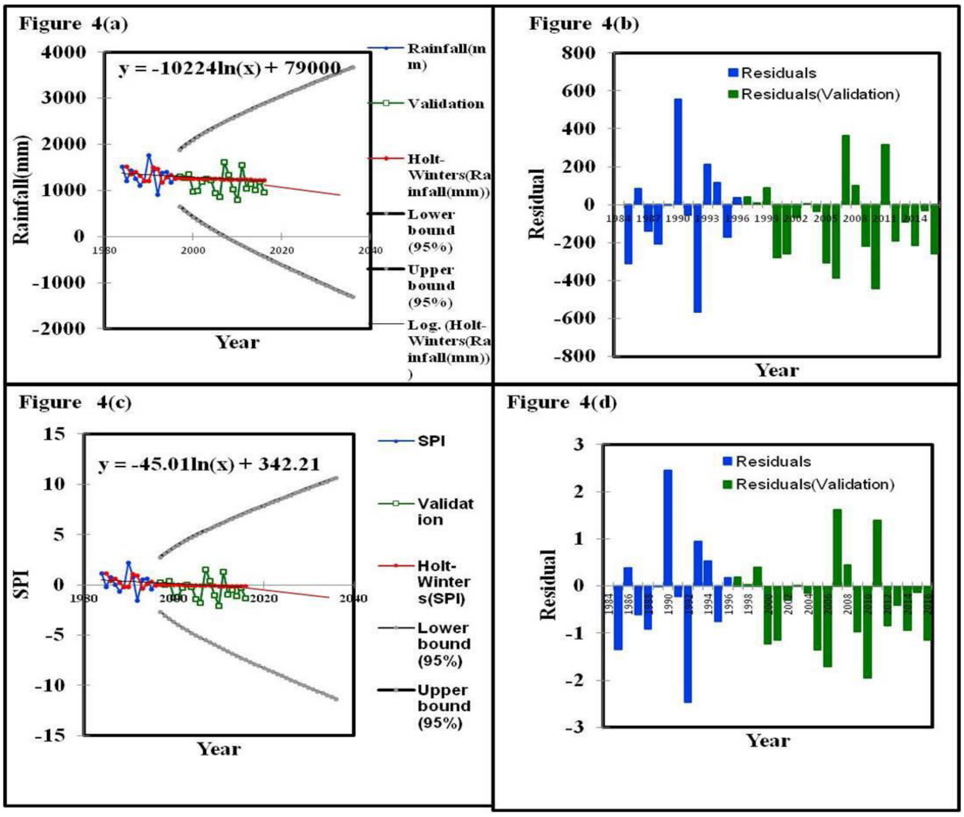

Figure-4. (a) Holt-Winter's rainfall Forecast, Figure-4(b) Holt-Winter's Residual Rainfalls, Figure-4(c) Holt-winter's SPI Forecast, Figure 4(d) Holt-Winter's Residual Rainfalls.

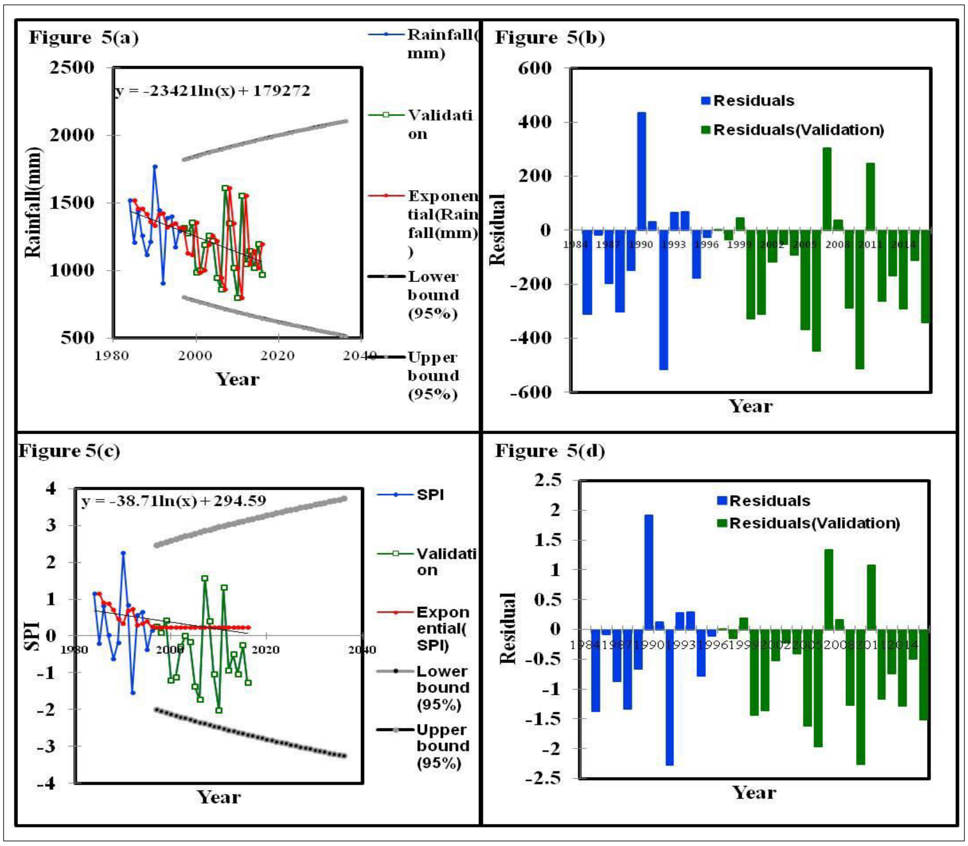

Figure-5. (a) Exponential rainfall Forecast, Figure-5(b) Exponential residual rainfalls, Figure-5(c) Exponential SPI Forecast, Figure-5(d) Residual values of SPI.

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4.3 Forecasting of SPI using combined Winexpomodel, yearly fluctuation

The overall 12 month trend (1984-2036) of SPI using Winexpo seems to be slightly deteriorating (Figure-6(a)). From observation of Winexpo simulation over the years from 1984 to 2035 can be classified into 3 broad categories a) Slight deficit phase (1984-1995) b) short surplus phase (1996-2001), c) Oscillatory or near normal phase (2003-2013) d) Longest and peak deficit phase (2014-2035). From relative percentage weightage of broad categories of drought 37 relative percentage weightage for extremely dry (D3), 25 weightage for moderately dry (D1), 4 for severely dry (D2) and moderately wet (W1), 29 and 2 for both of the near normal (N) and extremely wet categories of drought (Figure 6(b), Table-7). Goodness of fit statistics of Winexpo model obtains 0.003 for RMSE, 11.234 for MAPE, 0.4321 for MPE, 0.0902 for MAE (Table-4). So, obviously this model fits better in comparison with Holt-Winter exponential smoothing and traditional exponential smoothing procedure.

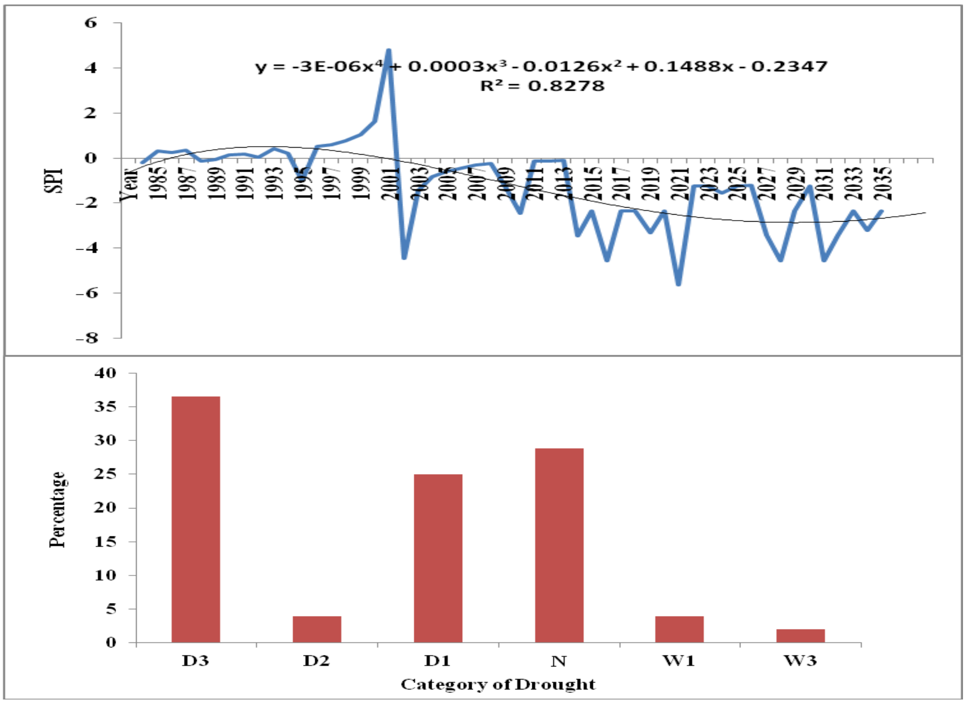

Figure-6. (a) Fluctuation of Winexpo Indices over the years, Figure 6(b) Percentage of year under each drought category.

Table-4. Goodness of fit statistics of Winexpo Model.

Statistic	Data	Validation
Observations	**13**	**20**
Degree of Freedom (DF)	11	
RMSE	0.003	
MAPE	11.234	14.321
MPE	0.4321	1.654
MAE	0.0902	0.1145
Iterations	24	

4.4 Statistical significance test and normality test

Statistical significance test and normality test by Kolmogorov-Smirnov and Shapiro-Wilk has been done at 95% significance level. Holt-Winter rainfall attains .247 statistic and attains significance .004 for Kolmogorov-Smirnov test whereas Shapiro-Wilk test estimate Holt-Winter rainfall statistic as .747 and attains significance as .003. Holt-Winter SPI similarly attains .191 statistic and .014 significance value. Shapiro-Wilk test estimates Holt-Winter rainfall statistic as .961 and .004 as significance level. Similarly estimation of exponential rainfall, exponential SPI, and Winexpo rainfall and Winexpo SPI attain significance level of <.005 that means those all are statistically significant. But Winexpo attains perfectly .000 for both the test so they are proved to be on perfection again (Table-5). From the Q-Q plot of rainfall and SPI (Figure-9a to 9n) it is quite evitable that the whole data set of rainfall and SPI are not normal. So, it is assured that null hypothesis i.e. there are differences between the observed and predicted values of rainfall and SPI. From the overall assessment of three models run over rainfall and SPI it is quite evitable that drought severity will increase in the near future.

Table-5. Statistical significance test of the models.

Parameters	Kolmogorov-Smirnov**			Shapiro-Wilk Test		
	Statistic	df	Sig.	Statistic	df	Sig.
Holt-Winter Rainfall	.247	53	.004	.747	53	.003
Holt-Winter SPI	.191	53	.014	.961	53	.004
Exponential Rainfall	.136	53	.005	.882	53	.000
Exponential SPI	.262	53	.004	.610	53	.003
Winexpo Rainfall	.234	53	.000	.556	53	.002
Winexpo SPI	.456	53	.000	.554	53	.000

** Lilliefors significance correlation

Table-6. Year-wise categorization based on combined Winexpo Model.

Category	No. of years under each drought category	Relative Percentage (%)
Extremely Wet (W3)	1	2
Very Wet (W2)	0	0
Moderately Wet (W1)	2	4
Near normal (N)	15	29
Moderately dry (D1)	13	25
Severely dry (D2)	2	4
Extremely dry (D3)	19	37

5. CONCLUSIONS

The present study provides results of assessment of meteorological drought condition for the Purulia District over the fifty two years in the context of climate change. By widely accepting scientific methodology the present assessment let judgement of the circumstances that supposed to improve our understanding of drought in Purulia. The Purulia is widely known for its' drought proneness (WBPCB 2009) but the most importantly the study predicts the tendency of drought of the future condition using exponential smoothing and also assess the spatial variation of drought as a whole.

The observations are also harmonizing with few available studies on related grounds for the present study area. Study of Ghosh (2018) and Ghosh (2016) confirmed that rainfall trend in this study area is decreasing. Halder and Saha (2015) demonstrated the water scarcity of Purulia District due to drought. Palchoudhuri and Biswas in 2013 identified meteorological drought of Purulia District through SPI and identified hazard severity zones according to it. Mishra and Desai (2005) forecasted and analyzed drought in Kangsabati River Basin using artificial recursive neural network. Markov chain model was applied to estimate drought of Purulia District by Banik, Mondal and Rahman (2002). Gupta, *et al* (2011) identified drought in Bundelkhand and Chhotanagpur Plateau region. Drought prediction was also highlighted by Karamaouz*et al* 2009, Aghakouchak 2015, Oguntoyinbo 1986, Yan *et al* 2017. Lohar and Pal (1995, 1999) showed that mean monthly pre-monsoonal rainfall has decreased and temperature has increased significantly in the last decades of twentieth century. The extremities of rainfall and temperature drive a potential threat to agriculture, food security and socio-economic vulnerability. Thus a more detailed structural study is required to explore the synergetic effects of trends and patterns of other climatic variables. However the conclusion reached in this study can be an elementary step to improve the risk management strategy, review of agricultural practices and water use in this counterpart.

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