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Performance of Drought Indices in Trichy Region, Tamil Nadu

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Authors' contributions

This work was carried out in collaboration between both authors. Author LS designed the study, performed the statistical analysis, wrote the protocol and wrote the first draft of the manuscript. Author RL managed the analyses of the study and the literature searches. Both authors read and approved the final manuscript.

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ABSTRACT

Droughts are regional phenomena, which are considered as one of the major natural environmental hazards and severely affect the water resources. Climate variability may result in harmful drought periods in semiarid regions. Meteorological drought indices are considered as important tools for drought monitoring, they are embedded with different theoretical and experimental structures. This study compares the performance of three indices of Standardized Precipitation Index (SPI), Rainfall Anomaly Index (RAI) End Palmer Drought Severity Index (PNPI) to predict long-term drought events using the Thomas-Feiring Model and historical data. For studies of areal drought extent, the 61 years (1951-2011) historical rainfall data of Trichy District were utilized to generate 58 years (2012-2070) synthetic data series so that the characteristics of long-term drought might be determined and the performance of those three indices might be analyzed and compared. The results show that SPI and PNPI perform similarly with regard to drought identification and detailed analysis to determine the characteristics of long-term drought. Finally, the RAI indicated significant deviations from normalized natural processes.

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1. INTRODUCTION

Drought is one of the most complex, harmful and least understood type of climatic event, causing an annual average of 6–8 billion USD of damage globally [1]; and it is expected that the severity and frequency of droughts will change in the future due to climate change [2]. Droughts are classified into meteorological, agricultural, hydrological, and socioeconomic droughts [3]; Drought indices are commonly used for qualitative and quantitative evaluation of the drought phenomenon around the world [4]. Specifically, drought indices are extracted by assimilating drought indicators into a single numerical value. Drought indices generally tend to use rainfall individually or simultaneously in combination with other climatic elements, including evapotranspiration, temperature or soil moisture.

Single-parameter drought indices based on annual rainfall are among the most commonly used ones because it is easy to get access to annual rainfall data in different parts of the world [5]. Although the annual time scale seems a long-time one, it can be used effectively to summarize the characteristics and regional behaviours of droughts [6]. Meanwhile, the monthly-time scale seems more appropriate for identifying the effects of drought on agriculture and water supply issues [7]. Usually, the main objectives of drought studies can be classified as follows: a) Drought characteristics during data record length; b) Comparison of drought indices performance; c) Long-term or future drought events prediction.

In this study, annual rainfall data is required to investigate drought indices performance at annual levels. The annual rainfalls are generated using Thomas-Firing model approach [8]. Therefore, this study aimed to analyze and compare the performance of three common indices of SPI, RAI and PNPI as representatives of three different classes of meteorological drought indices to predict long-term drought events using the Thomas –Firing model and historical data of Trichy rainfall station.

2. METHODOLOGY

2.1 Study Rainfall Station and Data

The subject of this study concerns the region, In this study, the 61 years (1951-2011) annual rainfall time series of Tiruchirappalli Airport station geographically located in the latitude 10º 46’ N to longitude 78º43’ East and altitude of 088.1 m were used thereof. The general Statistical properties of the historical rainfall data for during the years 1951– 2011 and generated synthetic rainfall data series for 58 years periods (2012-2017) were presented in Table 1.

Table 1. The statistical properties of historical and generated annual rainfall data of Trichy station

Parameters	Historical (1951-2011)	Generated (2012-2070)
Ave (mm)	799.0	777.0
SD(mm)	219.2	223.5
Skew	0.84	-0.20
Lag- 1 serial Correlation	0.20	0.005

2.1.1 Drought indices

The three drought indices under investigation included the Rainfall Anomaly Index (RAI), Percent of Normal Precipitation Index (PNPI) and Standardized Precipitation Index (SPI). The RAI was presented by [9]. The index is aimed to calculate the deviation of rainfall from the normal amount of rainfall and it evaluates monthly or annual rainfall on a linear scale resulting from a data series [10]. The PNPI (Percent of Normal Precipitation Index) has been one of the easiest ways to assess the drought severity and it is calculable for various time intervals. The PNPI can be obtained by dividing the actual amount of rainfall by the average rainfall multiplied by 100 [11]. The SPI was developed by McKee et al.in 1993 in order to determine and monitor drought. The U.S. Colorado Climate Center, the U.S. Western Regional Climate Center, and the U.S. National Drought Mitigation Center, among others, use SPI to assess the present drought situation in the United States. The SPI is able to determine a wet and dry state for a specific time scale for each location having rainfall data [12]. To determine this index, first, the appropriate probability distribution is fitted to the long-term rainfall data, and then the cumulative distribution function is turned into the normal distribution via equal probabilities. Finally, transformed data to normal distribution are used to calculate SPI values [13,14]. The following equations calculate RAI, PNPI and SPI indices:

$$RAI_i = \pm 3 \left(\frac{Pi-\bar{P}}{\bar{E}-\bar{P}}\right) \quad (1)$$

$$PNPI_i = \frac{P}{\bar{P}} \times 100 \quad (2)$$

$$SPI = \frac{Pi-\bar{P}}{\delta} \quad (3)$$

Where P_i is rainfall values in period I, $\bar{P}$ is long-term average rainfall, $\bar{E}$ is the mean of ten highest (for positive anomalies) and mean of ten lowest (for negative anomalies) values of P in the time series, δ is the standard deviation of rainfalls, SPI were computed at a 12-month time scale. The classifications of wet and dry states for RAI, PNPI and SPI indices are shown in Table 2. In order to simplify and to realize the evaluation and comparison of the performance of mentioned drought indices, a common quantitative classification (CQC), including seven categories of extremely wet (+3), severely wet (+2), moderately wet (+1), near normal (0), moderate drought (−1), severe drought (−2) and Extreme drought (−3), may be was specified to classify the criteria for drought as shown in Table.

2.2 Data Generation

The parameters of the data generation model were estimated from the available historical data. Annual rainfalls were generated according to the Lag-1 Auto-Regressive, AR(1), process as follows [15]:

$$P_{i+1} = \bar{P} + \rho(\mathrm{Pi} - \bar{P}) + \vartheta i\ \delta\sqrt{1-\rho 2} \quad (4)$$

Where, P_i+1 and P_i are the annual rainfalls for the years i+1 and i, respectively. $\bar{P}$ is the mean of annual rainfalls, δ is the standard deviation of annual rainfalls, ρ is Lag-1 serial correlation coefficient of annual rainfalls; and υ_i is the standardized normal random variate.

2.3 Data Analysis and Generation

Stationarity and randomness of historical data should be evaluated so that the rainfall data for drought may be analyzed [16]. The 'Run Theory' proposed by [17] to define hydrologic drought characteristics, was used to perform drought analysis (Fig. 2). In this concept, five main components of a hydrologic drought event have been identified as listed below [18,19,20] and shown in Fig. 2. Drought duration (Ldi): It is a time period between the beginning (Tdb) and end (Td_e) of a consecutive drought event. A mathematical expression of drought duration is presented as follow:

Drought duration (Ldi),; It is a time period between the beginning (Td_b) and end (Td_e) of a consecutive drought event.

$$Ldi = Th_e - Td_b \quad (5)$$

Drought severity (Sd_i), defined as the sum of the negative deviations, extended to the whole drought duration;

$$Sd_i = -\sum_{k=Tdb}^{\mathrm{Td}e} SPI \quad (6)$$

Where, SPI –drought index value in period K.

Drought intensity of (Id_i), defined as the ratio between drought severity and duration.

$$Id_i = \frac{\mathrm{Sdi}}{\mathrm{Ldi}} \quad (7)$$

Wet or non-drought duration (Lwi): It is a time period between the beginning (Tw_b) and end (Tw_o) of a consecutive wet event.

$$Lwi = Tw_e - Tw_b \quad (8)$$

Drought inter Qarrival time (Li): It is a time period between the beginnings of two consecutive droughts,

$$Li = Ld_i + Lw_i. \quad (9)$$

Table 2. Common quantitative classification of drought indices

CQC values	Drought class	SPI	PNPI	RAI
+3	Extremely Wet	≥ 2	≥160	>3
+2	Severely Wet	1.5-1.99	145 to 160	1.2-2.1
+1	Moderately Wet	1-1.49	130 to 145	0.3 to 1.2
0	Near Normal	-0.99 to 0.99	70 to 130	-0.3 to 0.3
-1	Moderate Drought	-1 to -1.49	55 – 70	-1.2 to -0.3
-2	Severe Drought	-1.5 to -1.99	40 to 55	-2.1 to -1.2
-3	Extreme Drought	≤ -2	< 40	<-3

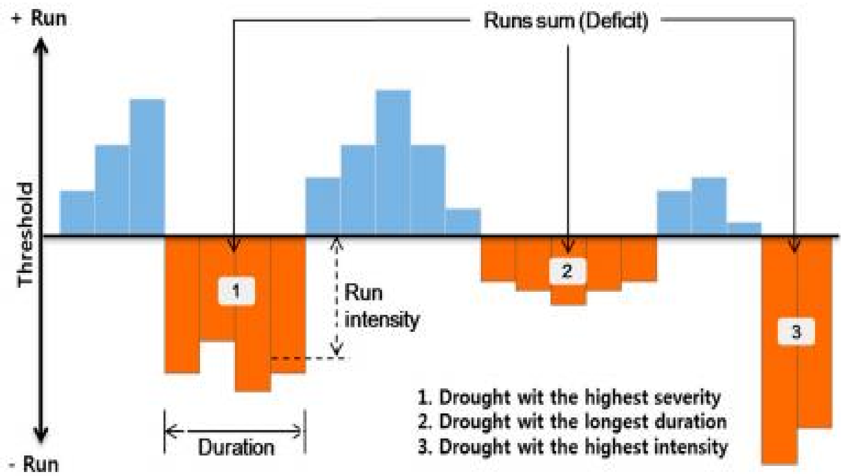

Fig. 1. Drought characteristics using the run theory for a given threshold level

3. RESULTS AND DISCUSSION

3.1 The Probability Density Function (PDF) of Wet and Dry Periods

The historical and generated probability density function of wet and dry periods were considered for three drought indices on the basis of the CQC drought events classification (Table 2).

To establish the generated PDF of wet and dry periods, average probability values of each category based on the stochastic population of drought index values (i.e. 58 sequences) were employed. Fig. 3 shows the PDF of three drought indices values based on stochastic population and historical values at Trichy Station. Comparison of the PDF based on historical and stochastic population values (i.e. based on generated data) did not show the same behaviours and, thus, realistic and accurate monitoring of long-term drought events using only historical data would be problematic.

According to Fig. 2, the PDF of wet and dry periods for the SPI and PNPI were similar to the PDF of the standard normal distribution. Thus, the probability of a normal state (0) was approximately 0.80 and the sum of different wet and dry states was equivalent to each other. The PDF of wet and dry periods for the SPI and PNPI was symmetrical.

The PDF of wet and dry periods for the RAI was not symmetric and it also had a significant range of variation. Moreover, it did not follow the PDF of the standard normal distribution and the probability of normal state (0) for this index was equivalent to 0.04 and the sum of wet and dry periods was not equivalent.

According to the results, the SPI had relatively higher priority for drought monitoring than the RAI and PNPI indices because of wet and dry events, as the expected events of a normalized natural phenomenon, would better fit to a normal distribution.

3.2 Relationship between the Drought Indices

Fig. 3a, b shows the generated and historical linear correlation between the values of SPI and two other indices for the Trichy station on the basis of historical and generated annual rainfall data. Fig. 3 a, b clarifies that there is no linear relationship between RAI drought index values with SPI and PNPI values and that each relationship demonstrated a different behaviour. Also, both relationships for the historical and generated data demonstrated similar behaviour.

3.3 The Main Characteristics of Drought

Having used the historical and generated rainfall data, it was attempted to examine three main drought characteristics of (i) duration, (ii) intensity and (iii) the inter arrival times between droughts. Given the SPI, RAI and PNPI indices, the relationship between drought duration and probability of exceedance and their historical and generated values for Trichy station were presented in the Fig. 4. The threshold SPI=0 is more suitable for drought identification.

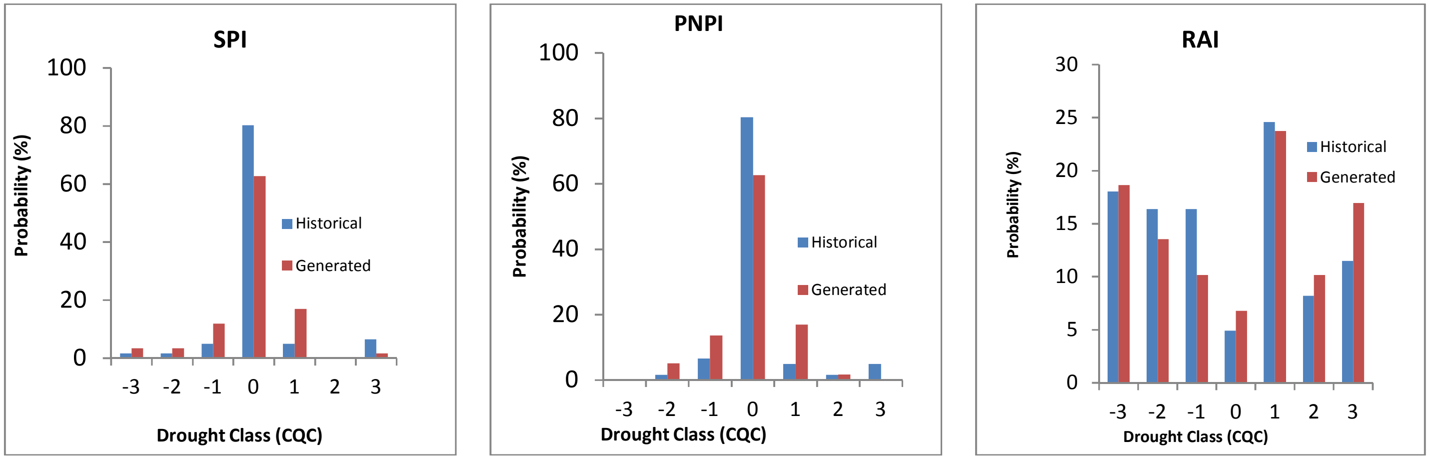

Fig. 2. Comparison of the PDF of wet and dry periods based on generated and historical rainfall data for three drought indices at Trichy station with normal probability density function

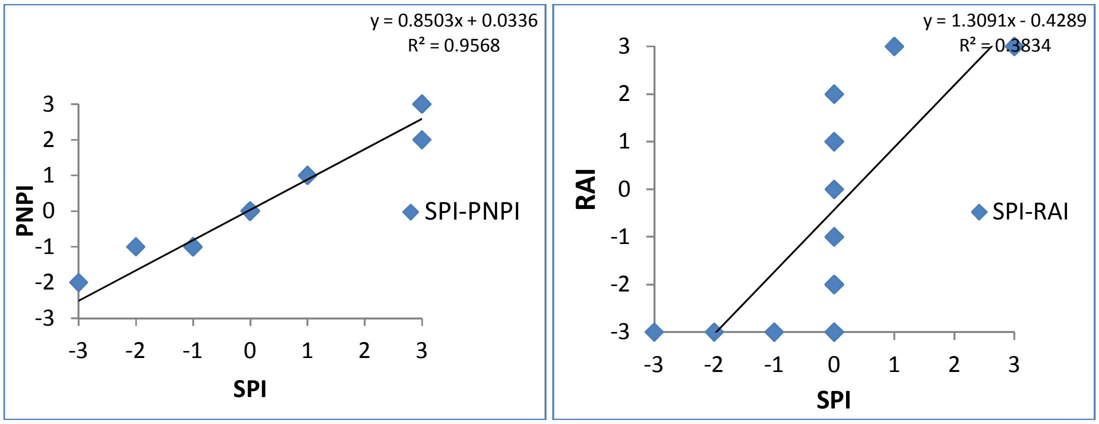

Fig. 3a. Relationship between the drought indices –Historical Data

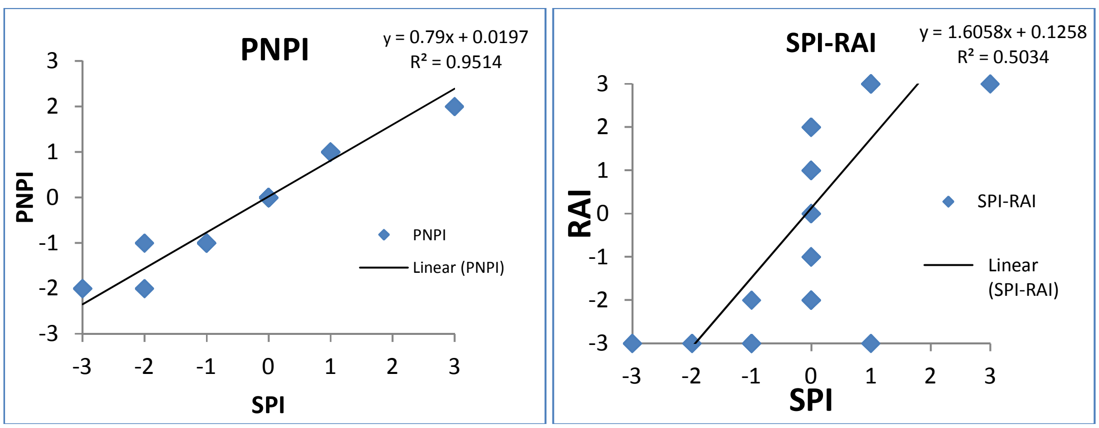

Fig. 3b. Relationship between the drought indices –generated data

Table 3. Three-state transition probability matrix: Drought (D), Normal (N) and Wet (W) of Trichy station in terms of three drought indices

Historical Lag- 1 serial Correlation (0.2)				Generated Lag- 1 serial Correlation (0.005)			
SPI	**D**	**N**	**W**	**SPI**	**D**	**N**	**W**
D	0.0	0.8	0.2	D	0.18	0.73	0.09
N	0.1	0.8	0.1	N	0.24	0.51	0.24
W	0.0	0.8	0.2	W	0.00	0.90	0.10
PNPI	D	N	W	PNPI	D	N	W
D	0.00	0.80	0.20	D	0.18	0.73	0.09
N	0.10	0.81	0.08	N	0.24	0.51	0.24
W	0.00	0.71	0.29	W	0.10	0.80	0.10
RAI	D	N	W	RAI	D	N	W
D	0.68	0.06	0.26	D	0.4	0.0	0.6
N	0.33	0.00	0.67	N	1.0	0.0	0.0
W	0.31	0.04	0.65	W	0.5	0.1	0.5

The probability of drought duration in the SPI was less than the probability of drought duration in the RAI. Accordingly, the probability of a one-year, two-year and three-year drought duration in the RAI (14.75%, 5% and 3.43%) was estimated to be about two, four and eight times larger than SPI (11.66%, 2.7% and 0.5%) (Fig. 4). In addition, the range of variation in drought duration in SPI was very low values for Trichy station and this variation considerably increased in the RAI.

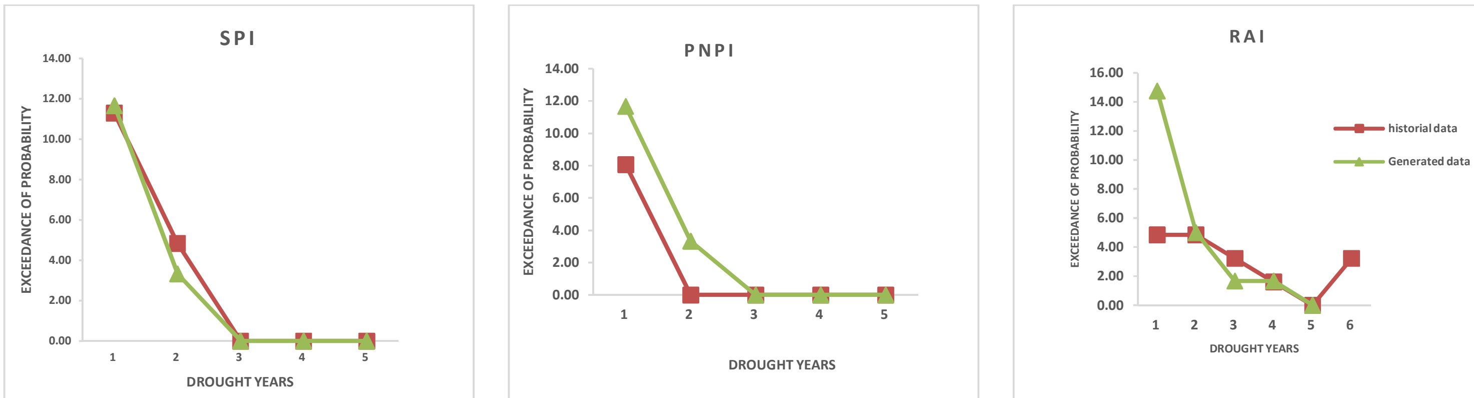

Fig. 4. Relationship between drought duration and probability of exceedance

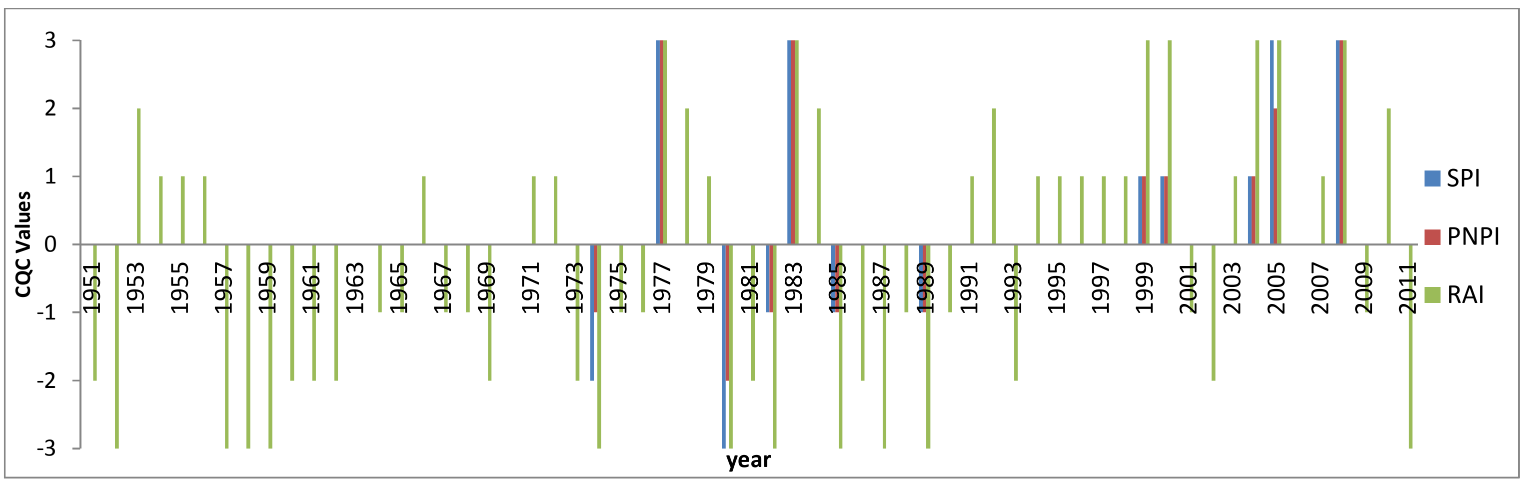

Fig. 5a. Drought events identified by SPI, PNPI, RAI –Historical data

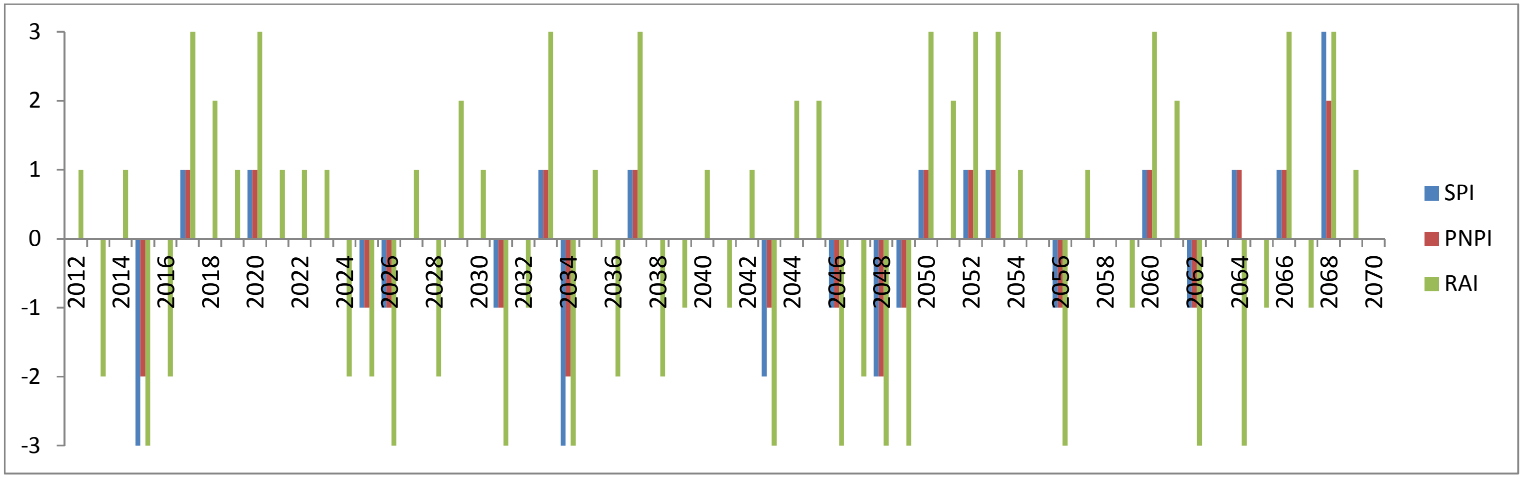

Fig. 5b. Drought events identified by SPI, PNPI, RAI –Generated data

3.4 Transition Probability Matrix

The transition probability matrix was applied on the basis of seven classified drought states to evaluate the conditional probability of different states of drought (see Table 3). As mentioned in section 3.1, the behaviour of historical results was quite different from the typical behaviour of stochastic population outcomes (see Table 1) and this was due to this fact that the historical rainfall data record is a sample of rainfall population over the past and future 59 years. Therefore, a single historical rainfall data was insufficient and unrealistic for a long-term drought characteristics investigation and it was necessary to utilize the Thomas- firing model for such studies. Furthermore, we found that the annual conditional probability of various dry and wet states strongly correlated with lag-1 serial correlation of annual rainfall data. The three dry and wet states of moderate, severe and extreme were combined in two general classes of dry and wet states (D: Dry, W: Wet) to focus more clearly on the relationship. Table 3 presents the generated and historical transition matrix of various dry and wet states across stations in terms of three drought indices. Consequently, it was observed that both historical and generated results yielded that the conditional probability of the DD (a dry year occurs after a dry year), DW (a wet year occurs after a dry year), WD, and WW states was a function of Lag-1 serial correlation of annual rainfall data. Thus, the probability of dry after a dry year (DD) and wet after a wet year (WW) increased parallel with the increase in lag-1 serial correlation and the conditional probability of DW and WD decreased parallel with the increase in lag-1 serial correlation.

4. CONCLUSION

This study aimed to analyze and compare the performance of three common indices of SPI, RAI and PNPI as representatives of three different classes of meteorological drought indices to predict long-term drought events using the Thomas –Firing model and historical data of Trichy rainfall station. It was found that a long-term drought event characterizing on the basis of historical rainfall time series were insufficient and erroneous. However, the results extracted on the basis of a historical rainfall data were quite accurate for the data record length. Hence, a Thomas Fiering Model approach as a powerful tool could be adapted to generate stochastic rainfall time series and result in a 'population' for a long-term drought characteristics investigation.

The results of the conditional probabilities of different states of wet and dry periods showed the conditional probability of DD, WW, DW and WD for all indices and it could be described as functions of Lag-1 serial correlation of rainfall data. So, Lag-1 serial correlation played an important role in the conditional probability for monitoring droughts events.

Finally, the results of this study indicated that the application of the SPI and PNPI would result in relatively high advantage for a comprehensive and accurate analysis. Accordingly, the application of RAI in drought events had a significant deviation from the expected events of normalized natural processes and its results could not be trusted to predict the events of drought.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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