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Shifts in wetness pattern and periodicity across Tripura state in northeast India

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सार – पूर्वोत्तर भारत के त्रिपुरा राज्य (1971 **से** 2016) **में क्षेत्रीय नमी परिवर्तनशीलता का आकलन किया गया था। मल्टीपल चेंज पॉइंट डिटेक्शन परीक्षणों ने अध्ययन अवधि के दौरान नमी पैटर्न में पहचाने गए बदलावों के लिए स्थानिक कालिक परिवर्तनशीलता की उच्च डिग्री की पुष्टि की है। चयनित वर्षा मापी स्टेशनों के लिए परिवर्तनीय समय श्रृंखला पर गणना की गई एसपीआई समय स्केल के लिए भिन्न-भिन्न आर्द्रता समय-श्रृंखला की आवधि** 2-128 **महीनों के बीच भिन्न होती है। गणना की गई एसपीआई समय श्रृंखला के बढ़ते अस्थायी क्षेत्र में आवर्ती पैटर्न अधिक प्रमुख हो गया। पदानुक्रमित क्लस्टरिंग और प्रमुख घटक विश्लेषण (पीसीए) सभी एसपीआई समय श्रृंखला की यादृच्छिकता, प्रवृत्ति और आवर्तिता में परिवर्तनशीलता के लिए जिम्मेदार है। हमारे इस वर्तमान शोधपत्र में त्रिपुरा राज्य में वास्तविक समय में सूखे की निगरानी और निकट भविष्य में वर्षा के अनुपलब्ध डेटासेट के प्रतिवर्ती उपयोग के लिए उपयुक्त वर्षा-मापी स्टेशनों के सदृश समूहों की पहचान की गई है।**

ABSTRACT. Regional wetness variability was assessed across the Tripura state of North east India (1971 to 2016). Multiple Change point detection tests confirmed the high degree of spatiotemporal variability for the identified shifts in wetness pattern over the study period. The periodicity of different wetness time-series varied between 2-128 months for the calculated SPI time scales over variable time series for the selected rain gauge stations. The periodicity pattern became more prominent with an increasing temporal domain of calculated SPI time series. Hierarchical clustering and the Principal component analysis (PCA) accounted for the variability in randomness, trend, and periodicity of all the SPI time series. Our present study identified the homogeneous clusters of rain-gauge stations suitable for real-time drought monitoring and reversible use of missing datasets of rainfall in near future across the Tripura state.

Key words – Tripura, Rainfall variability, Change point analysis, Periodicity, Wetness zoning.

1. Introduction

Precipitation is one of the most crucial, highly variable and extensively studied climate elements in the hydrological cycle that determines the degree of eco-environmental feedback towards the climate change phenomenon. It also plays an important role in controlling the regional food production scenario as well as the water use patterns in Indian agriculture (Mall *et al*., 2006). The rain-dependent (mostly from southwest monsoon) agriculture sector is the backbone of the Indian economy that is presently facing the aggrandized challenge from localized climate variability (Jain and Kumar, 2012). The quantity, intensity, and frequency of seasonal and annual rainfall events have a direct influence on the cropping system, crop performance, cultural practices and productivity in farmers' fields. However, uneven spatiotemporal distribution and recent changes in rainfall or wetness trend influenced the regional water availability and overall growth of the country's agriculture sector

TABLE 1

Statistical summary of rainfall received at selected rain gauge stations in Tripura

Raingauge Stations	Location	Altitude (a.m.s.l.)	Data availability	Gap	Annual rainfall (mm)	SD (mm)	CoV (%)	V_n	C_s	C_k	Annual precipitation (mm)				Outliers(mm)	
											Minimum		Maximum			
											Rainfall	Year	Rainfall	Year	Rainfall	Year
Agartala	23° 49' N 91° 17' E	12	1971-2016	-	2153.3	420.7	19.5	2.54	0.19	-0.74	1349.1	1972	3074.40	1978	-	-
Kailashar	24° 19' N 92° 00' E	24	1971-2016	-	2447.6	406.3	16.6	2.35	-0.24	2.05	1457.0	1992	3525.80	1977	3525.80	1977
															3492.11	1991
															1457.00	1992
															1553.40	1994
A D Nagar	23° 48' N 91° 15' E	17	1971-2016	-	2285.1	699.8	30.6	2.06	0.46	-0.16	1257.9	1972	3989.10	1978	-	-
Amarpur	23° 33' N 91° 38' E	42	1971-2016	1999-2001	2250.9	668.6	29.7	2.13	0.17	1.02	1250.8	1972	3866.70	1973	3866.70 3790.03	1973 1974
Dharma nagar	24° 21' N 92° 11' E	21	1971-2016	-	2388.1	529.1	22.2	2.01	0.35	0.58	1403.3	1975	3921.76	1973	3921.76	1973
Belonia	23° 07' N 91° 23' E	256	1971-2016	-	2329.6	500.1	21.5	2.03	0.94	-0.12	1500.4	1992	3438.70	1983	-	-
Kamalpur	24° 11' N 91° 49' E	18	1971-2016	-	2342.7	745.1	31.8	2.04	0.11	1.25	1274.5	1979	3905.70	1993	-	-
Khowai	24° 01' N 91° 37' E	33	1971-2016	-	2394.3	634.9	26.5	2.31	0.69	1.45	1219.9	1972	4396.20	2002	4396.20	2002
Sabroom	23° 00' N 91° 43' E	45	1971-2016	-	2725.3	952.7	35.1	2.39	0.64	3.35	1503.2	1972	6034.70	1993	4747.70	1988
															4489.30	1990
															5246.80	1991
															6034.70	1993
															2494.31	2001
															3864.00	1988
Sonamura	23° 28' N 91° 16' E	17	1973-2016	-	2234.4	532.3	23.8	2.51	0.56	1.49	1403.1	1979	3864.00	1988	3589.90	1986
Udaipur	23° 32' N 91° 29' E	27	1971-2016	-	2200.2	610.0	27.7	2.30	0.28	1.73	1306.0	2006	4185.10	2007	3638.89	1976
															4185.10	2007

(*Note* : SD = Standard deviation; CoV = Coefficient of Variation; Vn -Von Neumann ratio for homogeneity; Cs = Coefficient of skewness, Ck = Coefficient of kurtosis)

(Jha *et al*., 2013). Agriculture and hydroelectric power generation are the two sectors highly influenced by flood and drought events, resulting from excess or inadequate rainfall on a short to long-term basis (Mishra and Singh, 2010). Therefore, precise information generation on rainfall-dependent periodic moisture availability is essential to maximize resource productivity in Indian agriculture (Meshram *et al*., 2017).

Increased rainfall anomalies caused frequent weather extreme events across northeast India (Jain and Kumar, 2012). Chakraborty *et al*., (2017) identified significant spatio-temporal variability in identified change points in rainfall time series across several locations in northeast India, commonly attributed to the influence of fast-growing commercial activities across the region (Jaiswal *et al*., 2015). Conventional statistical or mathematical methods considered the periodicities of complex climate variability events in the frequency domain, *viz*., Fourier analysis, Singular-spectrum techniques which assume the progress of underlying processes as stationary over time. However, the wavelet transform emerged as a modern advanced analytical tool for identifying multi-scale non-stationary localized intermittent periodicities with expanding the time-frequency over space (Grossman and Morlet, 1984). Previous studies evaluated the frequency components of the irregularly spaced rainfall time series for shorter terms intermittent periodicities (quasi-periodicity) using Continuous Wavelet Transform functions (Murata, 1990; Ghosh *et al*., 2010; Subash *et al*., 2011).

The spatiotemporal variability in wetness periodicity and change point detection analysis is crucial for climate variability analysis across the high rainfall receiving regions of North East Indian states towards the identification of shifts due to increased anthropogenic activities in the recent past. Such events are rarely analyzed across the high rainfall receiving regions of different Northeast Indian states. Therefore, we fixed our present study objectives for identifying the spatiotemporal variability of change points (indicating shifts) and periodicity features of wetness time series across the Tripura state over variable time scales. We adopted the wavelet transformation for evaluating the similarity in spectral behavior of wetness time series among the neighboring rain gauge stations, for assessing their suitability to be grouped under the wetness zone clustering technique. The findings from our present study will act as the indicator for climate signaling towards the periodicity of drought occurrence; development of guidelines for location-specific recommendations on climate change adaptation strategies and reduction of in-farm sector disaster proneness towards the observed periodic wetness anomalies in Tripura.

2. Data and methodology

2.1. *Data source & SPI calculation*

We accessedthe recorded monthly rainfall dataset of twelve rain gauge stations across Tripura state from the 1970s to 2016 (Table 1). The data gap was replaced by the monthly average for Amarpur station. The present rainfall pattern analysis relied on four distinct seasons namely, winter (January-February), pre-monsoon (March-May), monsoon (June-September) and post-monsoon (October-December) months.Standardized precipitation index (SPI) was computed with the available rainfall time-series for various timescales, *viz.*, 1 month(1-SPI), 2 months (2-SPI), 3 months (3-SPI), 4 months(4-SPI), 6 months (6-SPI), 12 months (12-SPI) and 24 months (24-SPI).For any specific location, SPI was defined on each of the time scales as the difference between precipitation value (x_i) and the arithmetic mean (μ), divided by the standard deviation (δ) with their corresponding probability of occurrence (McKee *et al*., 1993) *i.e.*,

$$\text{SPI} = \frac{x_i - \mu}{\delta} \tag{1}$$

Positive values indicate increased wetness due to excess rainfall; whereas negative values indicate the moisture deficit condition due to less rainfall. SPI values less than -0.99 indicate the occurrence of the drought event. While SPI more than +0.99 confirm the advent of extreme wet event.

2.2. *Change-point detection analysis*

We adopted four distinguished abrupt change point (CP) detection test, *viz.*, Pettit’s test (P), Standard normal heterogeneity test (SNHT), Buishand test (B) and von Neumann’s test (V), for exact identification of the shift period in the calculated SPI-based wetness time series (Saha *et al*., 2018). After preliminary identification, we adopted two comparative evaluation tests, *i.e*., parametric *t*-test and non-parametric Mann-Whitney (M-W)test for further verification of significant identified change points (CPs). The detailed statistical expression are as follows:

2.2.1. *Pettit’s test*

The test is sensitive to identify the breaks in mid time series. The test statistics is defined as:

$$T_y = 2\sum_{i=1}^{y} r_i - y(n+1), \; y = 1,2,...,n \tag{2}$$

where, r_i = rank of the i^{th} data in time series and n= size of the series. The significant CP occurred at the point (in years) having a maximum value of $|T_y|$ as follows:

$$T^*_{CP} = max_{1\le k\le n}\left|T_y\right| \tag{3}$$

2.2.2. *Standard normal heterogeneity test (SNHT; Alexandersson and Moberg, 1997)*

For a specific time series with n data points (μ = 0; σ=1), the test statistics is defined as follows:

$$T_{SNH}^2 = \max_{1 \le a \le n-1} \{T_a^2\} = \max_{1 \le a \le n-1} \{a.\bar{z}_1^2 + (n-a).\bar{z}_2^2\} \quad (4)$$

where, $\bar{z}_1$ and $\bar{z}_2$ are the mean values of standardized data points from 1 to a and from a + 1 to n, respectively.

2.2.3. *Buishand test* (*Buishand 1982*)

The test statistic was based on weighted rescaled partial sums from mean value expressed as:

$$Z_k^* = \{(n-k)\}^{-1/2} S_k^*, \; k = 1,2,...,n \quad (5)$$

The probable breakpoint occurred at maxima as follows:

$$Z_{CP}^* = max_{1 \le k \le n} \left| Z_k^* \right| \quad (6)$$

2.2.4. *von Neumann's test* (*von Neumann, 1941*)

The von Neumann ratio test is related to the first-order serial correlation coefficient. The von Neumann ratio (V) is defined as the ratio of the mean square successive (year-to-year) difference to the variance. Its test statistics for change-point detection in the time series of x_1, x_2, x_3 …x_n is described as:

$$N = \frac{\sum_{i=1}^{n} (x_i - x_{i-1})^2}{\sum_{i=1}^{n} (x_i - \bar{x})^2} \quad (7)$$

For homogeneous series, the expected value E(N)=2 according to the null hypothesis with constant mean. Non-homogeneous series or sample with a break will get the value of N lower than 2, any other value implies that the time series has rapid variation in its mean. The stationarity of identified significant CPs in the respective series from the above mentioned adopted for CP detection tests was further confirmed through two comparative evaluation tests, *viz.*, parametric t-test and non-parametric Mann-Whitney test (Machiwal and Jha, 2012).

2.2.5. *Parametric t-test*

$$ts = \frac{|\bar{x}_1 - \bar{x}_2|}{S\sqrt{\frac{1}{n_1} + \frac{1}{n_2}}}$$

$$S = \sqrt{\frac{(n_1 - 1)s_1^2 + (n_2 - 1)s_2^2}{n-2}}$$

where, $\bar{x}_1$, $\bar{x}_2$, s_1 and s_2 are the estimated means and variances of the two sub-series, respective time series. The null hypothesis was rejected if ts > critical value at (n-2) d.f. (α = 0.05).

2.2.6. *Mann-Whitney (M-W) test*

$$u_c = \frac{\sum_{t=1}^{n_1} R(x_t) - n_1(n_1 + n_2 + 1)/2}{[n_1 n_2 (n_1 + n_2 + 1)/12]^{1/2}}$$

where $R(x_t)$ = rank of the ordered rainfall x_t series. The null hypothesis was rejected if u_c > critical value at α = 0.05

Periodicity assessment using wavelet analysis

We assessed the periodicity of short (1-SPI and 2 -SPI), mid (3-SPI and 6-SPI) to long-term (12-SPI) wetness time series for all the locations, based on their relative importance in meteorological phenomenon studies (1-SPI) and seasonal agricultural research and policy planning (2-SPI, 3-SPI, 4-SPI, 6-SPI and 12-SPI). The specified SPI time series were analysed for their respective robust wavelet components (with Morlet wavelet basis function) at 5% significance level using R software (version 3.5). Our analysis allowed the study of various decomposition patterns in different SPI time series calculated over different time scales independently. Errors may occur in the wavelet power spectrum for the beginning and termination region of any finite-length time series (Santos *et al*., 2001). Therefore, we rejected any variations observed within five years away from the initiation and termination point for each SPI time series (Machiwal and Jha, 2016).

Hierarchical clustering and Principal Component Analysis

The functional relationship assessment among the SPI time series calculated over variable time interval were initially performed using the hierarchical clustering algorithm, following Ward's method of minimum variance using Euclidean distance. Ward's method is one

TABLE 2

Characterization of past dry and wet spell events at 12-month time scale.

	Observed peak intensity			Longest duration				Most intense duration			
Raingauge stations	Peak SPI	Year	Month	Duration (months)	Years	Magnitude	Mean Intensity	Duration (months)	Years	Magnitude	Mean Intensity
(a) Dry Spell events											
Agartala	-2.83	1982	July	31	1981-1984	-50.69	-1.72	31	1981-1984	-50.69	-1.72
Kailashar	-3.35	1995	March	13	1998-1999	-33.2	-2.55	13	1998-1999	-33.2	-2.55
A D Nagar	-2.11	1995	April	17	2011-2012	-19.43	-1.14	13	1994-1996	-21.24	-1.63
Dharmanagar	-2.44	1976	February	22	1981-1983	-29.2	-1.33	14	1975-1976	-27.04	-1.93
Amarpur	-1.98	1999	August	13	1998-1999	-21.86	-1.68	13	1998-1999	-21.86	-1.68
Belonia	-3.4	2013	July	24	2012-2014	-48.83	-2.03	24	2012-2014	-48.83	-2.03
Kamalpur	-5.81	1973	April	15	1972-1973	-60.79	-3.80	15	1972-1973	-60.79	-3.80
Khowai	-2.5	1975	September	13	1994-1995	-17.68	-1.36	12	1972-1973	-24.01	-2.00
Sabroom	-1.71	1973	April	23	2011-2013	-28.56	-1.24	10	1972-1973	-14.82	-1.48
		2012	May								
Sonamura	-2.52	1994	July	22	1979-1981	-31.87	-1.45	14	1994-1995	-22.88	-1.76
Udaipur	-2.24	1995	April	17	2011-2013	-23.38	-1.38	11	1994-1995	-18.11	-1.65
								13	2006-2007	-21.57	
(b) Wet Spell events											
Agartala	2.74	1978	August	12	1978-1979	25.97	2.16	12	1978-1979	25.97	2.16
					1956-1957	19.43	1.62				
Kailashar	2.61	1991	July	12	1977-1978	27.62	2.30	12	1977-1978	27.62	2.30
					1992-1993	26.94	2.25				
A D Nagar	2.65	1988	June	31	1987-1989	49.91	1.61	12	1978-1979	25.62	2.14
Dharmanagar	2.64	1973	December	12	1973-1974	22.19	1.85	11	1993-1994	21.05	1.91
Amarpur	2.01	1973	December	18	1973-1975	30.86	1.68	18	1973-1975	30.86	1.68
Belonia	2.23	1974	October	15	1983-1984	25.91	1.73	12	1991-1992	22.14	1.85
Kamalpur	2.03	1973	July	12	1993-1994	18.41	1.42	12	1993-1994	18.41	1.42
Khowai	2.83	2003	June	15	1981-1982	15.19	1.17	12	1976-1977	26.64	2.05
Sabroom	3.12	1993	September	29	1990-1992	54.23	2.02	14	1993-1994	37.65	2.69
Sonamura	2.82	1988	December	35	1986-1989	71.86	2.05	35	1986-1989	71.86	2.05
Udaipur	2.93	1976	August	16	1976-1977	35.37	2.21	16	1976-1977	35.37	2.21

of the most frequently used techniques for climatological classification. The average linkage analysis focused on segregating the agglomerative group variables for the formation of leaves; leaves to branches; branches to limbs and finally limbs to the trunk that finally ends to a single-rooted cluster that includes all the observations. The re-affirmation of the generated homogeneous sub-clusters relied on other supportive statistical testing (Principal Component Analysis and correlation studies) with prior subjective knowledge of the identified region. Principal Component Analysis extracted the respective principal components (PCs) using varimax rotation with Kaiser Normalization method, variance explained criteria, mean eigen value and associated scree plot for preliminary regionalization, for the entire SPI dataset. The relative scoring identified the key stations from each preliminary

TABLE 3

Abrupt change point detection in long period SPI based wetness time series at selected raingauge stations across Tripura

Period	Stations	Pettit Test	Standard Normal Homogeneity Test	Buishand Test	Von Neuman Test	Change Point Detection Test	*T*-Test	Mann–Whitney test
A D Nagar	Pre-monsoon	265* (1991)	9.28* (1991)	1.66* (1991)	2.06 ^{NS}	Pettit and SNH Test	2.93**	358**
						Buishand Test	3.34**	374**
	Annual	265* (1991)	1.54* (1991)	1.81** (1991)	1.22**	Pettit and SNH Test	3.15**	361**
						Buishand Test	3.53**	375**
	Bi-annual	267* (1991)	12.16** (1991)	2.08** (1991)	0.48**	Pettit and SNH Test	3.64**	363**
						Buishand Test	3.96**	384**
Dharmanagar	Bi-annual	240* (1987)	8.81* (1987)	2.36** (1987)	0.42**	Pettit and SNH Test	-0.84 ^{NS}	185 ^{NS}
						Buishand Test	-0.95 ^{NS}	187 ^{NS}
Amarpur	Annual	221 ^{NS}	6.87 ^{NS}	1.65* (1994)	1.79 ^{NS}	Buishand Test	2.88**	350**
	Bi-annual	260* (1994)	9.41* (1994)	1.95** (1994)	0.65**	Pettit and SNH Test	3.31**	365**
						Buishand Test	3.59**	370.1**
Belonia	Bi-annual	264* (1992)	10.06* (2008)	1.63* (1992)	0.97**	Pettit Test	3.34**	367**
						SNH Test	3.11**	218**
						Buishand Test	3.53**	374**
Kamalpur	Winter	145 ^{NS}	5.72 ^{NS}	1.94** (2002)	1.51*	Buishand Test	3.25**	270 ^{NS}
	Monsoon	185 ^{NS}	6.76 ^{NS}	1.82** (2004)	1.26**	Buishand Test	2.97**	274*
	Post monsoon	176 ^{NS}	5.33 ^{NS}	1.66* (1985)	1.89 ^{NS}	Buishand Test	-2.49*	122*
	Annual	217 ^{NS}	9.49* (2003)	2.16** (2003)	1.32**	SNH Test	3.43**	299**
						Buishand Test	3.65**	290**
	Bi-annual	267** (2003)	13.05** (2003)	2.58** (2003)	0.485**	Pettit and SNH Test	3.89**	314**
						Buishand Test	5.15**	316**
Khowai	Bi-annual	130 ^{NS}	6.32 ^{NS}	1.63* (1984)	0.51**	Buishand Test	1.66 ^{NS}	280 ^{NS}
Sabroom	Monsoon	172 ^{NS}	6.08 ^{NS}	1.80** (2004)	1.50*	Buishand Test	2.97**	251*
	Annual	166 ^{NS}	5.16 ^{NS}	1.97** (1988)	1.41*	Buishand Test	-2.68*	138*
	Bi-annual	240* (1987)	8.81* (1987)	2.36** (1987)	0.41*	SNH Test	-3.37**	112**
						Buishand Test	3.74**	101**
Sonamura	Annual	184 ^{NS}	5.51 ^{NS}	1.65* (1994)	1.48*	Buishand Test	2.53*	302*
	Bi-annual	232 ^{NS}	8.11 ^{NS}	1.85** (1995)	0.46**	Buishand Test	3.32**	325**
Udaipur	Bi-annual	158 ^{NS}	8.91* (2008)	1.45 ^{NS}	1.02**	SNH Test	4.73**	112 ^{NS}

[*Note*: ** and * denote significant trend at P < 0.01 and P <0.05 level, respectively. Values indicate Pettit's test, SNHT Test, Buishand Test and Von Neumann's test statistics; year of the change in the parentheses if the change was significant.]

group. Final agglomeration accounted for the calculated correlation matrix values among the key station's SPI series with the respective groups.

3. Results and discussion

The statistical summary of the location-specific rainfall pattern showed that the mean annual rainfall varied from 2153.3 mm (Agartala) to 2725.3 mm (Sabroom) (Table 1) with the supportive variations in the location-specific best-fitted probability distribution function for each location (Appendix1). All series were homogeneous, having Von Neumann ratio (V_n) > 2.0 (Owen, 1962). The coefficient of variation ranged between 16.6% (Kailashar) to 35.1% (Sabroom) in Tripura with higher values of peakedness; which may be due to the presence of infrequent extreme deviations. The only leptokurtic rainfall distribution at Sabroom signified the highest number of outliers in the primary rainfall time series. The negatively skewed distribution at Kailashar indicated the presence of more below-normal values than average in the annual rainfall time series. The positively skewed distribution in the annual rainfall series for rest of the stations indicated non-normal behaviour; thus indicating the need for SPI index based drought event analysis for the available rainfall time series across Tripura (Saha *et al*., 2018).

SPI based historical excess dry and excess wet events

The SPI series derived from the respective annual wetness series (12-SPI based) had sufficient longer time-period that showed a reliable huge location-specific variation in their occurrence probability, extent, magnitude, and severity. The likelihood of extreme drought and wetness event occurrence based on 12 SPI time series showed the maximum probability for 'Near normal' event occurrence (40.4-48.7%) for all the selected stations. The relative probability for exceptional drought or extreme wet event occurrence was least at Amarpur station and maximum at Belonia. The past extreme dry and wetness events were also characterized (Table 2). Kamalpur experienced the driest session (12-SPI value = -5.81 on April 1973) over the entire study period, which prevailed over 15 consecutive months with an average intensity of -3.80, during 1972-73. The second most intense dry event occurred during 2013 at Belonia (peak SPI= -3.4) followed by Kailashar during 1998-1999, with an observed peak 12 SPI value at -3.35 during March 1995. The longest dry spell extended over 31 months at Agartala during 1981-84, followed by 24 months at Belonia during 2012-14. The observed peak wet event occurred during September 1993 (12 SPI = 3.12) at Sabroom with a most intense duration of 14 months.

The longest extreme wet spell prevailed for consecutive 35 months during 1986-89, at Sonamura station, followed by 31 months in AD Nagar during 1987-89.The significant declining trend in standard deviation further supported the low variability of extreme wet and dry spell occurrence at Amarpur (Supplementary S3). In contrary to the reported lower frequency of extreme dryness/ wetness events over NE India (Nageswararao *et al*., 2017), we observed the significant reduction in annual and pre-monsoon rainfall at Belonia overturned the higher occurrence probability of extreme dry spell events and no-significant change in standard deviation of annual rainfall values over the study period. Periodic variations in land use and land cover change and regional geomorphology dynamics may be responsible for the reported erratic pattern of rainfall driven localized excess dry and wet events in Tripura (Deo *et al*., 2009, Kasei *et al*., 2010). Such information will be useful for building a location-specific state-level network on drought monitoring, early warning, and mitigation strategies (Zhang and Jia, 2013; Wang *et al*., 2015).

Abrupt change point detection in SPI time-series

The expected years for abrupt change points (CPs) in the seasonal, annual, and bi-annual SPI time series showed considerable spatio-temporal variability across the Tripura state (Table 3). To avoid incorrect interpretation from insufficient verified data availability, we rejected the significant CPs if present within five years from starting and termination point of the respective SPI-based wetness time series. Commonly identified CPs from four different statistical tests with statistically significant comparative evaluation test results were carried out. For the monthly wetness time series, the SNH test identified CPs were identical to Pettit and Buishand test during July (1993 at Amarpur). The identified CPs from three different statistical tests were not always identical for any specific location in the monthly, seasonal, annual and biannual SPI-based wetness time series. Buishand test was more regular for identifying CPs in the majority of the time series followed by the Pettitt test. In contrast, three CP detection tests initially indicated the presence of CPs in September during 2003 at Kamalpur, but the von Newman test and two comparative evaluation techniques finally nullified the presence of the identified CP. Abrupt change point in seasonal to bi-annual wetness was prominent from four statistical tests at AD Nagar during 1991. Abrupt change points were also evident in the bi-annual wetness series at Amarpur (1994), Kamalpur (2003) and Sabroom (1987). However, it differs for Belonia (2008 for SNHT test; 1992 for Pettit and Buishand test). At Dharmanagar, two comparative evaluation tests rejected the identified breakpoint in bi-annual wetness time series during 1987. Therefore, the results justified the need for adapting multiple statistical tests for change point detection in wetness time series (Goyal, 2014). Moreover, we observed no affinity of the SNH test for identifying CPs towards the beginning or end of the time series (Machiwal *et al*., 2017).The identified abrupt CPs in seasonal, and biannual wetness time series may be attributed to the periodic changes in land use patterns (Jaiswal *et al*., 2015).Similar localized variability in the wetness phenomenon is evident over the entire North East India (Pai *et al*., 2011; Saha *et al*., 2015) and adjacent northeast Bangladesh region (Abul Basher *et al*., 2017).

Periodicity pattern analysis

The wavelet power spectrum showed some common predominant short to long-term periodicity features in all the selected rain gauge stations (Fig. 1). 1-SPI time series

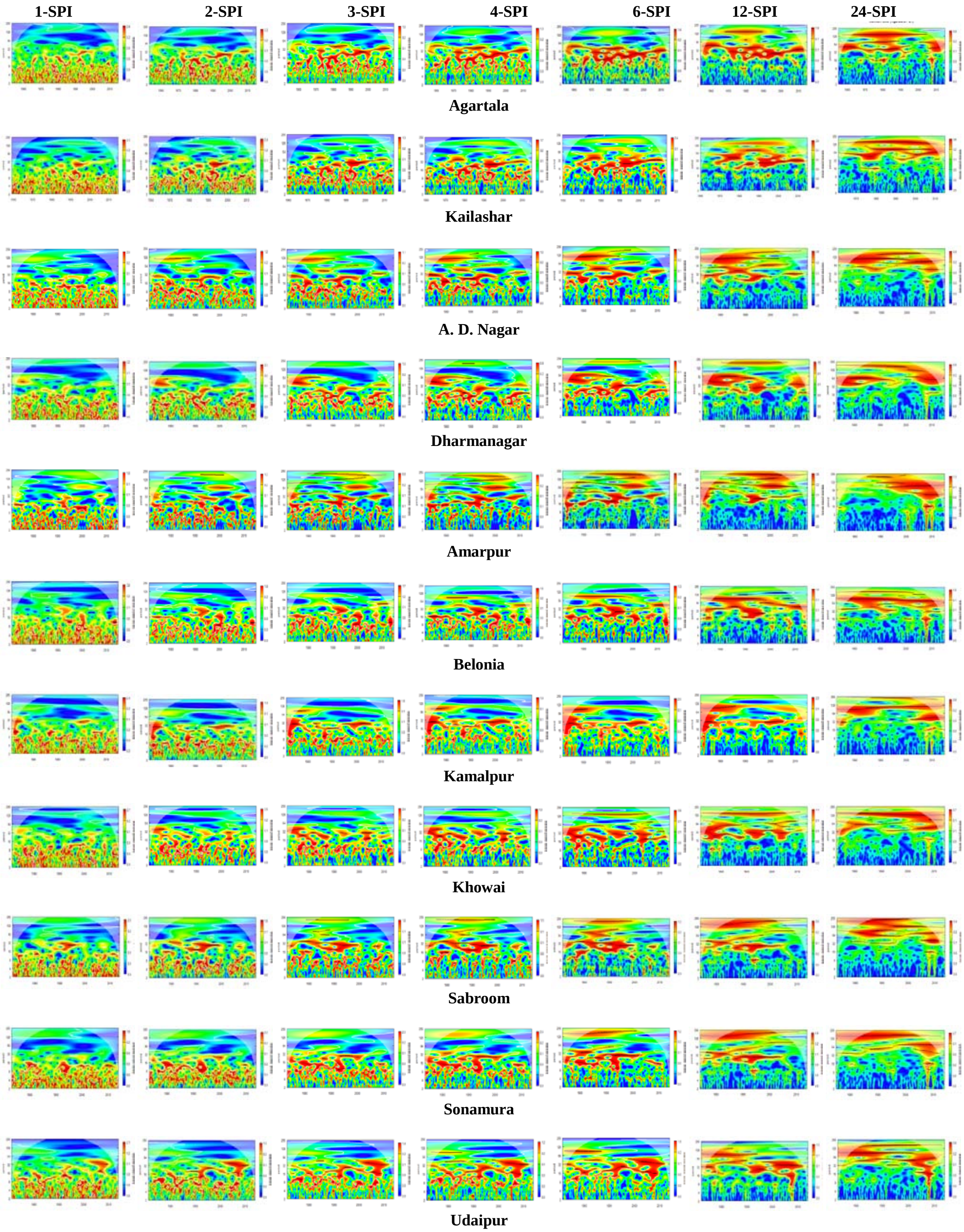


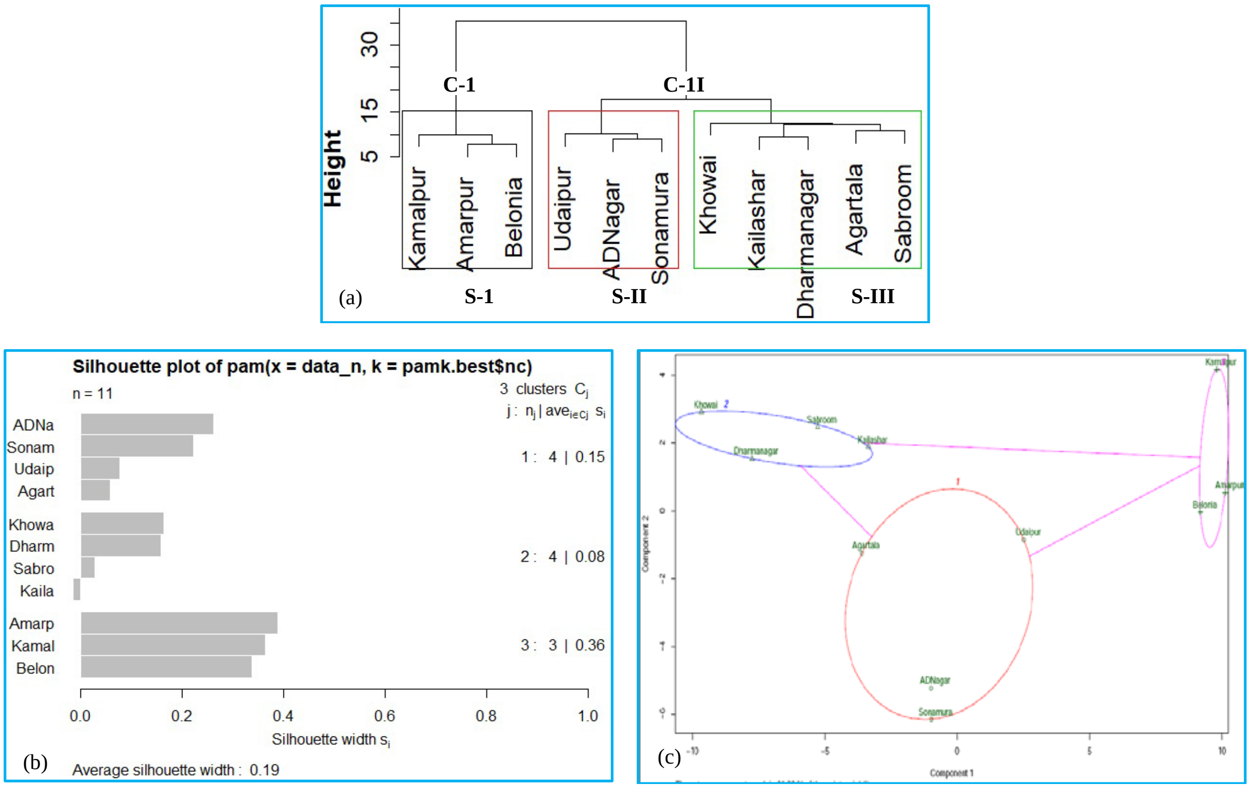
Fig. 1. Wavelet power spectrum for the periodicity assessment in different SPI time series

revealed a very less definitive pattern for all the stations. However, the periodicity pattern became clearer with the increasing temporal domain of the SPI time series and the temporal variation of each periodicity showed non-stationary changes for the selected locations in Tripura (Murata, 1990). The reconstructed series from the estimated wavelet power spectrum were in harmony with the original annual and seasonal SPI-based wetness series (data not presented). Therefore, we considered the most of frequency components present in the SPI series in our present analysis so that the co-movement of the actual and reconstructed series was ensured in this study. We explored the magnitude of changes in wetness periodicity with changes in the temporal scale of SPI calculation using wavelet spectrum analysis. The image plot of the wavelet power spectrum for most of the stations was almost identical (with few exceptions) for the respective SPI time series in twelve selected stations of Tripura. The specific periodicity among those time-specific calculated SPI time series was also not uniform preferably due to discontinuities or abrupt changes in the time series (De Jongh *et al*., 2006).

The periodicity of the 1-SPI series varied between 2-16 months, albeit for some intermittent duration of series. The periodicities do not continue for a longer time in all the stations. The periodicity of the 2-SPI wetness series mostly varied from 2-8 months for most of the stations, extending over several short duration of the series. However, the periodicity of 16-32 months was evident to extend for a longer duration of time in 2 SPI series from early 1993 till the end of 2005 at Agartala and from early 1980 till early 2000 at Sabroom. The higher periodicity of 32-64 months was evident from 1999 till 2001 at Amarpur; the initial 4 years of the series (1975-1979) at Dharmanager; late 2000 to early 2010 at Udaipur. A similar periodicity pattern of 16-32 months was evident for respective 3-SPI time series at Agartala. Amarpur showed 64 months 3-SPI periodicity from 1998 to 2002. At Sonamura, the 8-16 months periodicity extends for a longer period until early 1995 while from late 2001 onwards it showed around 4-8 months periodicity. The periodicity of the 4-SPI time series dominantly ranged between 16-32 months, with some scattered periodicity of 32-64 months from late 1970 to early 1998 at Agartala station. Intermittent lower periodicity of 8-32 months was evident at Sabroom (during 2009), Kailashar (1978-1995), Dharmanagar (1975-1997). An intermittent higher value of 4-SPI periodicity of 64-128 months was observed at Amarpur (1995- 2005) and AD Nagar (1980 to early 1990).

The 6-SPI periodicity was confined to 32-64 months and 8-32 months episodes during pre-1970s and post 1970sat Agartala, respectively. Kailashar showed the gradual increasing periodicity up to 64 months from 1978 to the end of the series. For the rest of the stations, the periodicity of 6-SPI time series varied from16-32 months that dominated over the significant parts of the respective time series. An intermittent periodicity of 16-32 months was evident from 1990 to 1999 and 2008 to 2010 at Amarpur; 1990 to till 1995 at Belonia. Higher periodicity of 64-128 months was observed from 1995 to 2008 at Belonia and early 1990s at Sonamura. The 12-SPI periodicity varied considerably among majority of the stations. A 12-SPI periodicity of 16-64 months with scattered higher periodicity of 128 months (between 1970 and 1990) was prominent at Agartala. However, some moderate deviations in 12-SPI periodicity pattern from Agartala station were prominent for other stations. Kailashar had a varying degree of periodicity of 16-128 months. 64-128 months periodicity dominated at Amarpur during 1996-2010. At Belonia, 64-128 months periodicity dominated over the major length of the time series with 16-32 months periodicity during 1981-1996. Khowai bears 128 month’s periodicity with 16-64 months periodicity in some parts of the time series. Sonamura had the periodicity of 16-32 months for significant length of the series (1985-2010) with a higher periodicity of 128 months in some scattered part of the time series. The 24-SPI data shower periodicity starting from 32 months for all the stations. A D Nagar beard a periodicity of 128 months throughout the entire series. Agartala, towards the beginning and end of the series showed a periodicity of 32-64 months, while a periodicity of 128 months was evident towards the middle of the series. Amarpur barely showed any periodicity at the beginning of the series. However, from 1990 onwards, periodicity of 64-128 months can be observed and 32-128 months periodicity was visible towards the end of the series. Belonia had a periodicity of 64-128 months for the entire series. Sabroom and Sonamura showed exceptionally high periodicity of 128-256 months and beyond for a reasonable length of the series. The present wavelet-based approach for periodicity identification in the SPI series calculated over variable time scale was useful to understand the location-specific natural rhythm of seasonal wetness cycle that was differed from the reported intra-seasonal variation of summer monsoon rainfall over India (Pai *et al*., 2011).

The dominancy of short-term periodicities (up to 48 months) in short to medium period wetness series(*i.e.*,2-SPI, 3-SPI, 4-SPI and 6-SPI) were probably linked with long term periodicities in annual (12-SPI) wetness series were connected with ENSO phenomenon (Kumar *et al*., 2013). The reported periodicity information will increase our future capability to advance preparedness while facing the short and long-term seasonal extreme wet and dry spell events, preferably useful for assessment of



Figs.2(a-c). (a) Hierarchical clustering with heat map, (b) Silhouette plot for determining optimum number of clusters and (c) Principal Component plot in rotated space for accounting the variability in Principal Components in the combined SPI based wetness series at Tripura

hydropower generation potential of the state; irrigation planning and exploring cropping pattern alteration options in the agriculture sector of Tripura.

Spatial wetness zoning

Hierarchical cluster analysis (Ward method) classified the relatively similar pattern in excess dry and excess wet events for all the combined SPI wetness series into two representative relatively broad homogeneous groups (C I and C II), based on the respective Euclidean distances [Fig. 2(a)] that was further divided into three distinct sub-clusters. The station-wise observations may be reciprocated for wetness pattern zoning. The segregated tree-like dendogram depicted the strong consistent gap for C-I, *i.e.*, Kamalpur, Amarpur, and Belonia station. The progressive distinctness got amplified further with the higher spatial coherence between S-II (Udaipur, A D Nagar and Sonamura) and S-III (Khowai, Kailashar, Sabroom, Dharmanagar, and Agartala). Since there was no universal norm for determining the optimum number of clusters (Gong and Richman, 1995), we adopted Silhouette plot to determine the optimum number of clusters to be considered based on the stopping distances between the merged clusters as the representative of their increasing complexity among each agglomerative group based on our subjective choices [Fig. 2(b)]. The average silhouette width was 0.19. In contrast to the hierarchical clustering output, we observed the proximity of Agartala station was more towards S-II as further supported by the principal component plot [Fig. 2(c)]. Eigenvalues of two principal components (PC 1 = 6.476; PC 2 = 1.248) accounted 71.46% of the total variability. The three-dimensional principal component plot reduced the information bias from redundant inter-correlations among the original variables (> 0.60) in the SPI series (De Gaetano, 1996). The first PC loaded strongly on three stations under final root-cluster I (S-I). However, the second and third PC was separately loaded strongly on the four stations, each designated under final root-cluster II and III (S-II and S-III). Thus, it finally supported the Silhouette plot output and verified the co-existence of three significantly distinct types of wetness time series (based on trend, periodicity, and randomness of SPI series) across the Tripura state. Forecasters and agricultural policy managers and planners may ask for the establishment of detailed micro-level real-time weather monitoring system for periodic assessment of agro-ecosystem productivity and associated other watershed level surface hydrological characteristics over these three proposed distinct wetness zones in Tripura (Jha *et al*., 2013, Saha *et al*., 2018).

4. Conclusion

The essentiality of adopting multiple statistical tests for abrupt change point detection was justified. Buishand test was more efficient for identifying CPs in the seasonal, annual, and bi-annual wetness time series followed by Pettitt test. The periodicity pattern varied for the SPI time series over various time scales likely, 2-8 months for 2-SPI to 128 months for 12 SPI-based wetness time series. The historical weather data analysis is not in tune with the future GCM based wetness projection. Grouping of the rain gauge locations based on their relative similarity in micro-level wetness variability will be useful for the policymakers and agricultural scientists for designing the suitable strategies for the development and management of water resources in agriculture and handling the public health sector under the probable climatic eventualities over the region. The present study will improve our existing scientific understanding of local climatic variability (periodicity and abrupt change points) and its' potential impact on the crop production sector with their supportive role in explaining regional climate change phenomenon over the Tripura state, NE India.Our present methodology is suitable for further replication to identify the non-stationary changes in wetness time series from similar other humid tropical high rainfall receiving regions of India.

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Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

Disclaimer : The contents and views expressed in this study are the views of the authors and do not necessarily reflect the views of the organizations they belong to.

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APPENDIX 1

Results of best fitted probability distribution function based on Chi square test and Kolmogorov Smirnov test

Stations	Chi square test		Kolmogorov Smirnov test	
	Distribution	Parameters	Distribution	Parameters
Agartala	Beta	a1=1.2329 a2=1.4916 a=1349.1 b=3074.4	Johnson SB	g=0.26554 d=0.91634 l=2064.7 x=1213.3
Kailashar	Beta	a1=2.3051 a2=2.5284 a=1457 b=3525.8	Logistic	s=240.56 m=2437.1
AD Nagar	Gamma (3P)	a=2.3595 b=484.38 g=1135.9	Johnson SB	g=0.97705 d=1.0247 l=3876.3 x=1075.7
Amarpur	Johnson SB	g=0.95801 d=0.95914 l=2626.7 x=1538.8	Log-Logistic (3P)	a=4.299 b=1278.5 g=869.8
Dharmanagar	Johnson SB	g=1.1185 d=1.5109 l=3426.5 x=1223.0	Johnson SB	g=1.1185 d=1.5109 l=3426.5 x=1223.0
Belonia	Lognormal	s=0.2029 m=7.7377	Log-Logistic (3P)	a=4.1426 b=1099.4 g=1147.7
Kamalpur	Gamma	a=14.507 b=166.94	Inv. Gaussian	l=35134.0 m=2421.8
Khowai	Erlang (3P)	m=7 b=234.54 g=727.79	Erlang	m=14 b=170.31
Sabroom	Lognormal (3P)	s=0.5137 m=7.2952 g=1049.5	Log-Logistic (3P)	a=3.2981 b=1389.1 g=1127.9
Sonamura	Log-Pearson 3	a=23.078 b=0.04805 g=6.5808	Log-Pearson 3	a=23.078 b=0.04805 g=6.5808
Udaipur	Log-Pearson 3	a=48.87 b=0.03644 g=5.8887	Lognormal	s=0.25179 m=7.6697