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Observed trends in indices for daily rainfall extremes specific to the agriculture sector in Lower Vellar River sub-basin, India

Extreme rainfall trends over Lower Vellar sub-basin

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Globally, climate change has caused changes in frequency and intensity of climate extremes such as heat waves, droughts, floods and tropical cyclones. There is a need to understand the pattern of regional climate extremes to develop crucial adaptation strategies for the farming community. This paper focuses on developing the Expert Team on Climate Risk and Sector-specific Indices for rainfall, relevant for the agriculture and food security sector. The indices have been developed for Lower Vellar River sub-basin, a coastal basin in Tamil Nadu, India. Trend analysis has been done for the climatic and cropping seasons in the sub-basin. Overall, there has not been any trend in the annual rainfall index values. The monthly trend values for the different indices have mostly exhibited insignificant trends throughout the study period (1978–2015) except for a few indices. Overall, the southwest monsoon season has shown a significantly decreasing trend in the indices. The northeast monsoon season has shown insignificant trends with positive slopes for most indices. There were insignificant or no trends in the indices for the summer season. The findings from the study can be used as a guiding tool for developing adaptation strategies, for the farming community.

Keywords. Climate variability and change; monsoon; observations; extreme climate indices; agriculture and food security; trend analysis.

1. Introduction

Climate change is a global phenomenon with long-term changes in surface air temperature and precipitation for at least a period of 30 yr. Global warming is a main driver for change in global atmospheric temperatures and related meteorological parameters. Global warming is attributed to anthropogenic activities which mainly include emission of greenhouse gases into the atmosphere. Burning of fossil fuels is a major contributor for increased atmospheric aerosol concentration (Prasada Rao *et al.* 2010). Changes in frequency and intensity of climate extremes are due to such human influences on climate. Extreme weather events include unpredictable, severe or unseasonal events such as heat waves, droughts, floods and tropical cyclones. An extreme weather event becomes a disaster when the society or ecosystems are unable to cope with it effectively. It is difficult to determine the exact cause of an extreme event. The occurrence of extreme events such as heat waves has increased due to increased global warming, and the likelihood of other events such as frost or extremely cold nights, has decreased (Solomon *et al.* 2007). Changes in climate extremes can be studied both spatially and temporally. Rarer the extreme event, analysis becomes tedious since not many cases are available for consideration (Frei and Schär 2001; Klein Tank and Können 2003).

Since Indian economy is highly dependent on agriculture, much importance is given to any changes in rainfall. Agriculture is highly sensitive to climate and climate change. It may also be a driver for climate change. The impact of climate change on agriculture affects the food security of the growing population. The climate, cropping pattern, soil type, availability of resources and management practices vary from region to region. A comprehensive understanding of a region's climate is necessary for suggesting better adaptation strategies (Prasada Rao *et al.* 2010). Occurrence of climate extremes highly affects crop production leading to food insecurity, which in turn affects the country's economy. Food and non-food crop losses will increase with increase in weather-related disasters (Prasada Rao *et al.* 2010). As far as India is considered, there is an increased likelihood of wet summers, with greater flooding in the Asian monsoon region in a warmer climate (Palmer and Räisänen 2002). The increase in extreme events is very strong in many parts of India including the southern peninsular region (Sen Roy and Balling 2004). El Niño also has an effect on the monsoon in India resulting in heavy rainfall in the southern states of India, and it occurs once in 15–20 yr. This paper focuses on the assessment of climate extremes based on observational rainfall data. Trend analysis of extreme rainfall indices specific to the agricultural sector is carried out. Trends are calculated for the different climatic and local cropping seasons. Seasonal analysis has been conducted by averaging the monthly index values. The results of trend analysis have been verified with secondary data from previous studies.

The study is organised as follows. The description of the region of study is given in section 2. Data needed for the study, its processing and indices development, and trend analysis methodology are given in section 3. Section 4 highlights the results and discussion of the study followed by the conclusions in section 5.

2. Study area

Details concerning the area of study have been collected from the Water Resources Department–Public Works Department, Government of Tamil Nadu. Vellar River Basin is one of the 17 river basins in the state of Tamil Nadu in India. It is located between 11°10′56″–11°58′26″N and 78°14′09″–79°48′53″E. It is bounded by Pennaiyar and Paravanar River Basins in the north, Cauvery River Basin in the west and south, and the Bay of Bengal in the east near Porto Novo. The basin has a total geographical area of 7504.35 km^2, covering 22 taluks which include 40 blocks falling in parts of eight districts. The basin consists of seven sub-basins, namely Upper Vellar, Swethanadhi, Chinnar, Anaivari Odai, Gomukhinadhi, Manimukthanadhi and Lower Vellar. Physiographically, the Vellar Basin is divided into three divisions. They are (i) Western hilly terrain, (ii) Central hill valley complex terrain and (iii) Eastern deltaic plain and coastal region. Figure 1 shows the Vellar River Basin and its sub-basins.

Lower Vellar River sub-basin is located in the Eastern deltaic plain of Vellar Basin with the Bay of Bengal in the east. The sub-basin has a total geographical area of 1756.20 km^2 covering 20 blocks in five districts namely Cuddalore, Villupuram, Ariyalur, Perambalur and Salem which are shown in figure 2. About 77.61% of the total geographical area of the sub-basin is covered by Cuddalore district which is the highest in the sub-basin. It has been observed that agriculture is one of the major activities of the people in the sub-basin. Around 28% of the sub-basin area is under irrigation, which is the highest among the entire basin. Paddy and sugarcane are the major crops in the sub-basin which are grown throughout the year. Paddy and sugarcane are both water-dependent crops thus making the farmers highly dependent on the monsoon.

Lower Vellar River sub-basin lies within the tropical monsoon zone and has tropical wet and dry/savannah climate. Based on the hydro-meteorological features of the sub-basin, the year is divided into two periods: (i) monsoon period (June–December) and (ii) non-monsoon period (January–May). Rain during the monsoon season is due to the southwest (SW) trade winds which blow towards the Northern Hemisphere. The monsoon period is classified into SW monsoon period from June to September (4 months) and northeast (NE) monsoon period from October to December (3 months). During September the SW monsoon retreats followed by the onset of the NE monsoon. The NE monsoon is also known as the post-monsoon season or retreating SW monsoon

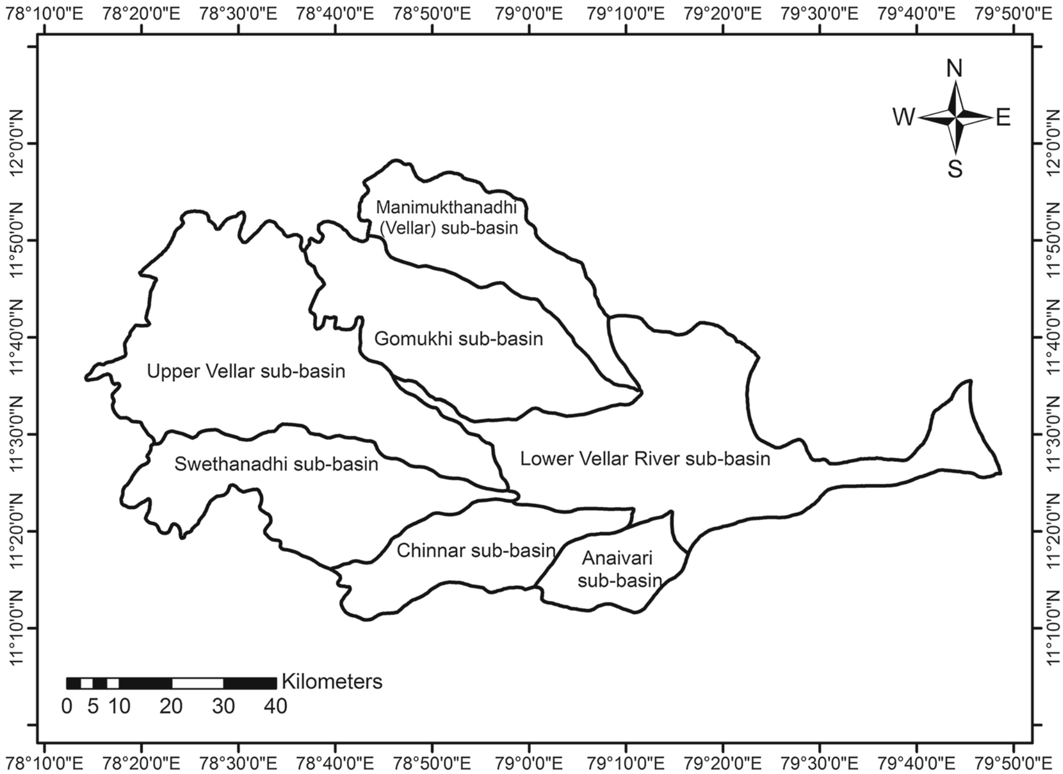

Figure 1. Location of Vellar River Basin and its sub-basins.

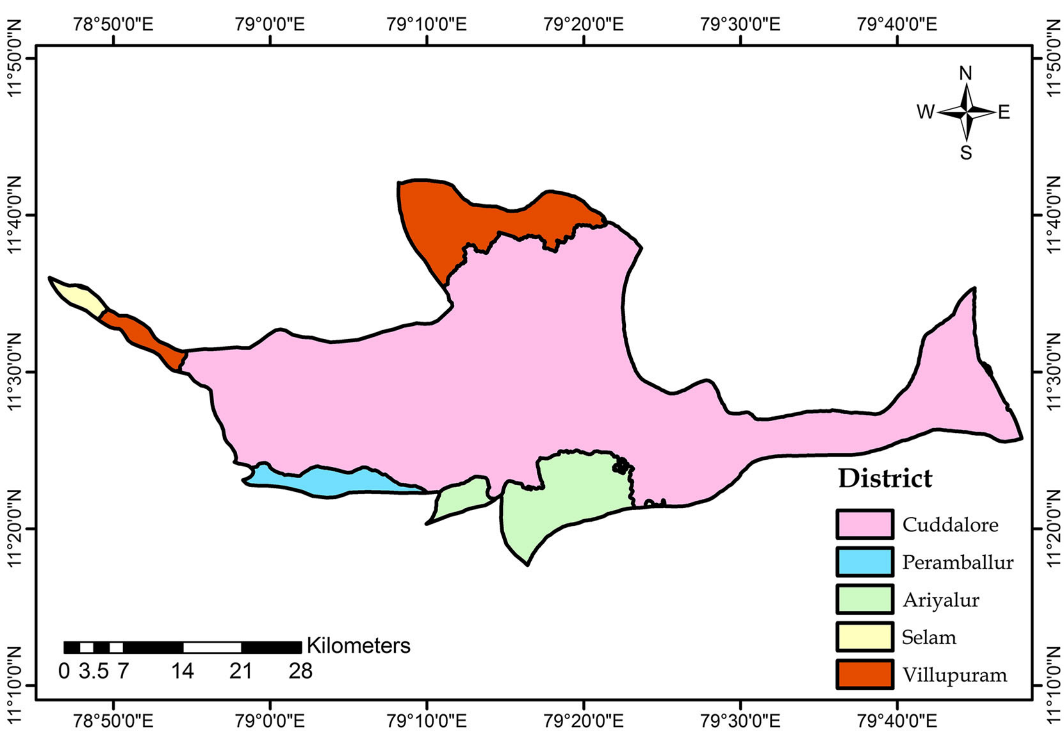

Figure 2. Districts falling within the Lower Vellar River sub-basin.

season. Retreat of SW monsoon is accompanied by rainfall from the tropical cyclones emerging in the neighbourhood of the Andaman Islands. During the month of December rainfall is from the dominant NE monsoon winds from the western disturbances emerging over the Mediterranean Sea. The NE monsoon supplies 60% of Tamil Nadu's annual water requirement and plays an important

Table 1. *Climatic and cropping seasons of Tamil Nadu.*

Month/season	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Climatic season	Winter season		Pre-monsoon season			SW monsoon				NE monsoon		
Agro-climatic season		Rabi season					Kharif season			Rabi season		
			Summer season									

role in the agriculture and water resources sector of the state. Also, El Niño has a positive correlation with the NE monsoon, resulting in heavy rainfall in Tamil Nadu during extreme El Niño years (Geethalakshmi *et al.* 2009).

The non-monsoon period is sub-divided into winter period from January to February and pre-monsoon period from March to May. Rainfall in the winter season is due to the NE trade winds. The average annual rainfall for the sub-basin is 1176.6 mm. The average rainfall during the NE monsoon season, SW monsoon season, winter season and pre-monsoon period are 654.6, 393.2, 32.6 and 96.2 mm, respectively.

The agricultural cropping seasons are Kharif, Rabi and summer season. Kharif season is between June and October which falls within the SW monsoon season. Rabi season is between November and April/May. The summer season is for a short duration between March and June. The sub-basin is entirely dependent on rain for recharging its water sources and monsoon failure lead to acute water scarcity and severe drought. Table 1 shows the different climatic and cropping seasons of Tamil Nadu.

The cropping seasons are based on the monsoon, with rain fed crops planted during the NE monsoon season as Tamil Nadu gets the maximum rainfall during that season. The SW monsoon does not bring much rainfall since the sub-basin falls in the rain shadow region of the Western Ghats. During the SW monsoon season irrigated crops are grown.

3. Data and methodology

3.1 *Data source*

Daily rainfall data has been collected from Water Resources Department–Public Works Department, Government of Tamil Nadu. The list of influencing rain gauges within and nearby the sub-basin is given in table 2 along with the duration of data available. By visual analysis, missing data and its duration have been identified. Stations with missing data were not selected for the study. Based on the availability of data, the time period for the study has been fixed between 1978 and 2015, so that a longer duration of observed data could be included in the analysis for better results. Figure 3 shows the location of the rain gauge stations selected for the study.

3.2 *ET-SCI indices*

Over the past few years, analysis of climate change and its impacts on various sectors have been done based on changes in the averages of climate data, either annually or seasonally. Analysis of climate extremes is the need of the hour since it has some major impact on different sectors such as agriculture, water resources, health and environment. The impacts include environmental, economic, social and socio-economic. Comprehensive analysis of climate extremes at a global level has been done previously by many researchers and academicians (Kiktev *et al.* 2003; Alexander *et al.* 2006). Not many studies have been carried out to highlight climate extremes at local levels. There is a necessity to carry out such studies at the regional level for the Indian sub-continent, since there have been many extreme rainfall events in the past two decades which has led to significant human and crop loss.

The joint Commission for Climatology (CCl)/World Climate Research Programme (WCRP)/Joint Technical Commission for Oceanography and Marine Meteorology (JCOMM)/Expert Team on Climate Change Detection and Indices (ETCCDI) have developed a set of indices for detecting and identifying changes in climate extremes which include both temperature and precipitation. The indices have helped researchers to focus on measuring climatic variability and it has also been a guiding tool for recommending suitable measures to adapt to the changing climate. One main disadvantage of the ETCCDI indices was that the indices and their relevance for different sectors such as water resources, agriculture, health, etc., had not

Table 2. *List of rain gauge stations.*

Sl. no.	Stations	District	Latitude	Longitude	Data availability Start year	End year	Missing data (yr)	Influencing area (km^2)	Weight (%)
1	Annamalaiunvsit	Cuddalore	11.39	79.72	Oct-1976	Sep-2016		3.748	0.2
2	Chidambaram	Cuddalore	11.40	79.69	Oct-1976	Sep-2016	1981	29.481	1.7
3	Kattumailur	Villupuram	11.57	79.12	May-1977	Sep-2016		111.322	6.3
4	Katumanrkoil	Cuddalore	11.28	79.55	May-1977	Sep-2016	1981–1983	3.749	0.2
5	Kelacheruvai	Cuddalore	11.41	79.10	May-1977	Sep-2016		183.84	10.5
6	Kothuvacheri	Cuddalore	11.52	79.64	Oct-1976	Sep-2016		5.531	0.3
7	Kuppanatham	Cuddalore	11.53	79.36	May-1977	Sep-2016		88.308	5.0
8	Memathur	Cuddalore	11.56	79.22	May-1977	Sep-2016		212.652	12.1
9	Parangipetai	Cuddalore	11.49	79.77	Jan-1978	Sep-2016	1981, 1983	117.455	6.7
10	Pilandurai_SRG	Cuddalore	11.40	79.27	May-1977	Sep-2016		232.51	13.2
11	Sankagiri	Salem	11.47	78.87	Dec-1981	Sep-2016		64.531	3.7
12	Setiatopacut	Cuddalore	11.44	79.54	Oct-1976	Sep-2016		110.312	6.3
13	Srimushnam	Cuddalore	11.40	79.40	Oct-1976	Sep-2016	1981	205.159	11.7
14	Tholudur	Cuddalore	11.41	79.00	May-1977	Sep-2016		146.527	8.3
15	Ulundurpet	Villupuram	11.69	79.29	Jan-1986	Sep-2016		123.453	7.0
16	Virudalmrev	Cuddalore	11.52	79.33	Jan-1987	Sep-2016		117.608	6.7

been identified. This led to the development of the Expert Team on Climate Risk and Sector-specific Indices (ET-CRSCI) which were more application-relevant and could be developed to better support adaptation. As a part of the development of the ET-CRSCI indices, the ClimPact software version 1.2 has been developed for data quality control and indices calculation. For homogeneity assessment no provision has been provided in ClimPact and hence researchers still use RHTest software.

The extreme precipitation indices considered for the study include percentile-based indices, absolute indices, threshold indices, duration indices and other indices. Percentile-based indices include very wet days (R95p) and extremely wet days (R99p). The precipitation indices in this category represent the amount of rainfall falling above the 95th (R95p) and 99th (R99p) percentiles. The percentile-based indices include and are not restricted to, the most extreme precipitation events in a year. Absolute indices represent maximum or minimum values within a season or a year. They include maximum 1-day precipitation amount (RX1day) and maximum 5-day precipitation amount (RX5day). Threshold indices are defined as the number of days on which a precipitation value falls above or below a fixed threshold, including number of heavy precipitation days >10 mm (R10) and number of very heavy precipitation days >30 mm (R30). These indices are not necessarily expressive for all climates because the fixed thresholds used in the definitions may not be applicable to different regions. Duration indices define periods of excessive wetness or dryness. They include consecutive dry days (CDD) and consecutive wet days (CWD). The CDD index is the length of the longest dry spell in a year while the CWD index is defined as the longest wet spell in a year. Other indices include indices of annual precipitation total (PRCPTOT), simple daily intensity index (SDII) and annual contribution from very wet days (R95pT) (Alexander *et al.* 2006). The details of the different indices are given in table 3.

3.3 *Data quality control and homogeneity assessment*

Before the indices were calculated, the quality and homogeneity of the rainfall data was checked. Quality control of data includes identification of outliers and inhomogeneity. The presence of outliers in the data may be due to either genuine weather extremes or due to random recording errors.

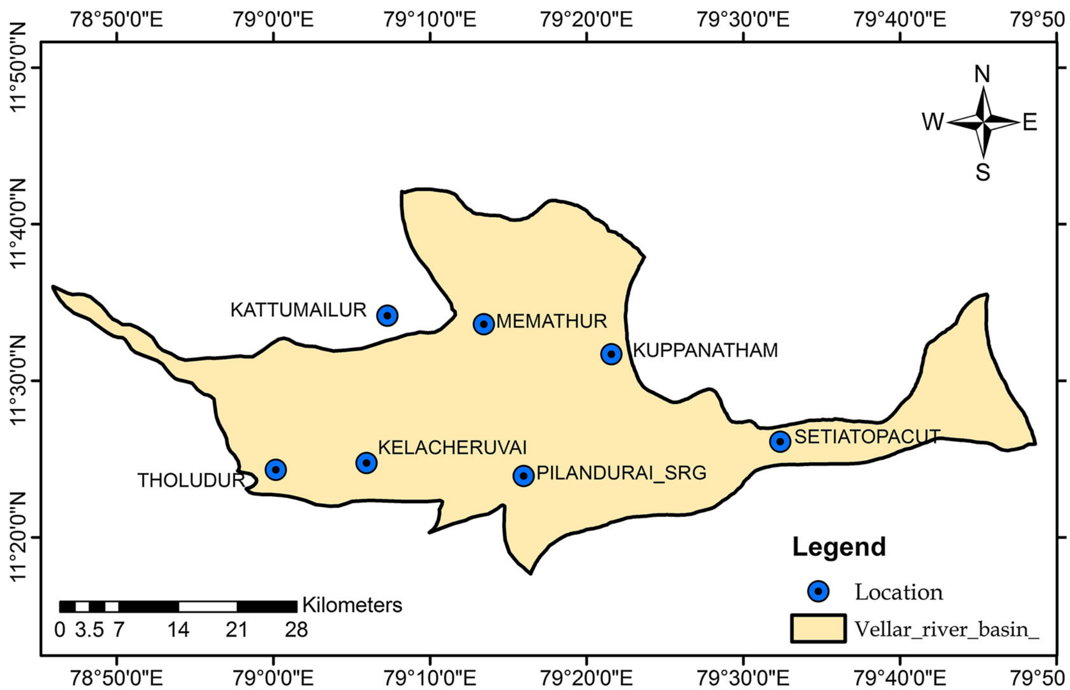

Figure 3. Spatial distribution of rain gauge stations selected for study in Lower Vellar River sub-basin.

Inhomogeneity or sudden step-change may be due to either genuine step-change in climate or due to changes in the way in which the data is recorded which include station location change or change in recording equipment. Generally, any such changes will be recorded and this 'metadata' will be maintained with the station records. With sufficient metadata available the discontinuity can potentially be corrected. If there is insufficient metadata, then it may be difficult to identify whether the step-change is a result of a real climatic shift or due to changed recording methods, and we may have to exclude the station from the analysis or consult with experts as to whether the data can be homogenised and used (McSweeney and Caesar 2013).

ClimPact software has been used for identification of outliers in the rainfall data. Since there is currently no provision for homogeneity assessment in ClimPact software, it has been done using RHtests_dlyPrcp software package which has been specifically designed for homogenisation of daily rainfall data time series (Wang *et al.* 2010; Wang and Feng 2013). Since metadata was unavailable for the rain gauge stations chosen for the analysis, the outliers were considered as missing data during homogeneity assessment. The software uses the penalised maximal F test (PMF) for identifying and adjusting for any number of changepoints. No reference series is needed for identifying the changepoints in the rainfall series using the PMF method. Changepoints were identified for the dataset and documented. Since metadata was unavailable for the stations selected, based on advice from experts, homogeneity assessment was carried out for specific data sets. Significant changepoints were only considered and quantile matching method of adjusting the rainfall series was used for homogenising the data (Wang 2008a, b). The outliers that were considered as missing data during homogeneity assessment were included in the adjusted rainfall series for further analysis, thus preserving the rainfall extremes within the data. The results of quality control and homogenisation of the data are given in table 4.

3.4 *Regional averaging of indices*

Since the indices were calculated at station level, a regionally averaged series was calculated for the indices data for all the rain gauge stations similar to the study of New *et al.* (2006). Standardisation was done for all the series such that it was not affected by stations having high or low indices values. The rainfall anomaly time series obtained from regional averaging has units in terms of standard deviation rather than the usual indices units. The anomaly series has been used for indices such as CDD, CWD, R10mm, R20mm, R30mm, R99pT, R95pT and SDII. For other indices data which have

Table 3. *Definition of precipitation indices used for the study.*

Indices	Definition	Units		Sector
CDD	Maximum number of consecutive days with $P < 1$mm	days	ET-CRSCI core sector-specific indices	AFS, WRH
CWD	Maximum number of consecutive days with P $\geq$ 1 mm	days	Non core-ET-CRSCI indices	
R10mm	Annual count of days when $P \geq 10$ mm	days	Non core-ET-CRSCI indices	
R20mm	Annual count of days when $P \geq 20$ mm	days	ET-CRSCI core sector-specific indices	AFS, WRH
R30mm	Annual count of days when $P \geq 30$ mm	days	Non core-ET-CRSCI indices	
RX1day	Monthly maximum consecutive 1-day precipitation	mm	ET-CRSCI core sector-specific indices	AFS, WRH
RX3day	Monthly maximum consecutive 3-day precipitation	mm	ET-CRSCI core sector-specific indices	AFS, WRH
RX5day	Monthly maximum consecutive 5-day precipitation	mm	ET-CRSCI core sector-specific indices	AFS, WRH
SDII	The ratio of annual total precipitation to the number of wet days (> 1 mm)	mm/day	Non core-ET-CRSCI indices	
PRCPTOT	PRCP from wet days ($P \geq 1$ mm)	mm	ET-CRSCI core sector-specific indices	AFS, WRH
R95p	Annual total precipitation from days > 95th percentile	mm	Non core-ET-CRSCI indices	
R95pT	Annual percentage of RR > 95th percentile/PRCPTOT	%	ET-CRSCI core sector-specific indices	AFS, WRH
R99p	Annual total precipitation from days > 99th percentile	mm	Non core-ET-CRSCI indices	
R99pT	Annual percentage of $P > 99$ th percentile/PRCPTOT	%	ET-CRSCI core sector-specific indices	AFS, WRH

AFS=Agriculture and Food Security, WRH=Water Resources and Hydrology.

units in millimetres, such as R95p, R99p, PRCPTOT, Rx1day, Rx3day and Rx5day, the anomaly series was de-normalised to convert it into a series having units in millimetre (Jones and Hulme 1996).

3.5 *Trend analysis*

In general climate data does not have Gaussian distribution and has outliers, and hence a simple linear least squares method of estimating the trend will not be suitable. A robust method for identifying trends and slope of trends is necessary. Trends for the regionally averaged series were calculated using the Mann–Kendall's trend test (Mann 1945; Kendall 1955). The mathematical equations for calculating Mann–Kendall statistic S, variance σ^2 and standardised test statistic Z are as follows:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \mathrm{sgn}(X_j - X_i), \tag{1}$$

$$\mathrm{sgn}(X_j - X_i) = \begin{cases} 1 & \text{if } (X_j - X_i) > 0, \\ 0 & \text{if } (X_j - X_i) = 0, \\ -1 & \text{if } (X_j - X_i) < 0, \end{cases} \tag{2}$$

$$\sigma^2 = \frac{1}{18}\left[n(n-1)(2n+5) - \sum_{p=1}^{q} t_p(t_p-1)(2t_p+5)\right], \tag{3}$$

$$Z = \begin{cases} \frac{S-1}{\sigma} & \text{if } S > 0, \\ 0 & \text{if } S = 0, \\ \frac{S+1}{\sigma} & \text{if } S < 0. \end{cases} \tag{4}$$

In the above equations X_i and X_j are the time series observations, n is the length of time series, t_p is the number of ties for pth value and q is the number of tied values. The test hypothesis for Mann–Kendall trend analysis is as follows:

Ho: There is no trend in the series.
Ha: There is a trend in the series.

Positive Z values indicate an upward trend in the hydrologic time series and negative Z values indicate a negative trend. The statistic Z has a normal distribution. To test for either an upward or a downward monotone trend (a two-tailed test) at α level of significance, Ho was rejected if $|Z| > Z_{(1-\alpha/2)}$, where $Z_{(1-\alpha/2)}$ was obtained from the standard normal cumulative distribution tables. The Z values were tested at 10% level of significance.

Table 4. *Stations selected for the study with the results of quality control and homogenisation of rainfall data of the individual rain gauge stations.*

Sl. no.	Stations	Outliers (mm/dd/yyyy)	Homogeneity	Changepoint	Significance of changepoint	Remarks
1	Kattumailur	14/12/1996, 11/12/2015	Homogenous	22/10/1981	Significant	By increasing the (*p*-value) level of confidence from 0.95 to 0.99, the changepoint became insignificant
2	Kelacheruvai	27/12/1984, 14/12/1996, 15/12/1996	Non-homogenous	17/05/1982, 12/12/1982	Significant	Homogenised by quantile matching algorithm
3	Kuppanatham	14/12/1996, 20/12/2007	Homogenous	No changepoint	–	
4	Memathur	22/12/1993	Non-homogenous	10/11/1992	Significant	Homogenised by quantile matching algorithm
5	Pilandurai_SRG	Nil	Homogenous	No changepoint	–	
6	Setiatopacut	11/12/1996, 14/12/1996	Homogenous	22/10/2003	Not significant	
7	Tholudur	19/12/2007	Homogenous	No changepoint	–	

The trend slope was estimated following an approach by Sen (1968). Sen's slope estimator is insensitive to outliers and is the most popular non-parametric technique for estimating a linear trend. The significance of the trend has been assessed using the Kendall's test since it does not assume a distribution for the residuals and is robust to the effect of outliers in the series (Alexander *et al.* 2006). The Sen's slope estimate is the median of the slopes calculated from all joining pairs of points in the series and the confidence interval is obtained from the tabulated values of Kendall (1955). Autocorrelation in the indices data is the presence of observations which are similar to each other, as a function of the time lag between them. A positive autocorrelation (which is usually present in time series of climate data) tends to increase the probability of detecting trends when actually none exist, and vice versa, thus making this test unreliable (Zwiers and Von Storch 1995). Hence the Durbin–Watson statistic, a test used to detect the presence of autocorrelation in the residuals obtained from regression analysis was used in the study. The Durbin–Watson test statistic D has the following mathematical equation:

$$D = \frac{\sum_{t=2}^{n}(\epsilon_t - \epsilon_{t-1})^2}{\sum_{t=1}^{n}\epsilon_t^2}, \quad (5)$$

where ϵ_t are the residuals from ordinary least squares regression. The hypothesis for the Durbin–Watson test is as follows:

H_0: no first-order autocorrelation.
H_1: first-order correlation exists.

If autocorrelation existed in the data, the Hamed and Rao (1998) method at 10% significant level was taken into account while estimating the trend and trend slope. Hamed and Rao (1998) proposed correcting the variance of the Mann–Kendall test statistic S by using an effective sample size that reflects the effect of serial correlation.

XLSTAT 2016.06.37917 software, an add-in for MS-Excel was used for statistical analysis. The trial version of the software is freely downloadable online. During the trend analysis if ties were detected in the data especially in frequency-related indices, appropriate corrections were applied by the software itself. In this study, a trend was considered to be statistically significant if it was significant at the 10% level. From the annual and month-wise trendanalysis, *p*-value and Sen's slope were calculated for each of the regionally averaged series for all the indices.

4. Results

4.1 *Annual trend analysis*

The significance of annual precipitation extreme indices was found to be very low in Central and South Asia from 1961 to 2000. Also regional precipitation extreme indices have not shown any significant trends in Asia (Klein Tank *et al.* 2006). Previous studies on the trends of rainfall and extreme rainfall events in India have highlighted the following: (i) increased intensity of extreme rainfall especially 1 day rainfall, over the East coast, (ii) increased significance of flood risk over the East coast and (iii) alternating sequence of droughts and flood years in India once in every 30 yr. 1961–1990 were dry periods followed by the beginning of the next sequence of 30 yr, (i.e., 1991–2000) experiencing a wet period (Guhathakurta and Rajeevan 2008; Guhathakurta *et al.* 2011). Based on the understanding of historical trends of rainfall in India from previous studies, the results of trend analysis for Lower Vellar River sub-basin have been interpreted. The results of annual trend analysis for the study area are given in table 5.

PRCPTOT has shown a decreasing trend with a slope value of −17.40 mm per decade. This

Table 5. *Regionally averaged annual trends for rainfall indices at 10% significance level. p-values and Sen's slope values for the different series are given.*

		Mann–Kendall trend analysis	
Indices	Units	*p*-value (two-tailed)	Sen's slope
CDD	days	0.960	0.000
CWD	days	0.618	0.007
R10mm	days	0.727	−0.002
R20mm	days	0.508	−0.006
R30mm	days	0.653	−0.004
RX1day	mm	0.282	0.533
RX3day	mm	0.861	0.155
RX5day	mm	0.940	0.104
SDII	mm/day	0.960	−0.001
PRCPTOT	mm	0.690	−1.740
R95p	mm	0.960	0.308
R95pT	%	0.500	0.007
R99p	mm	0.320	1.092
R99pT	%	0.252	0.013

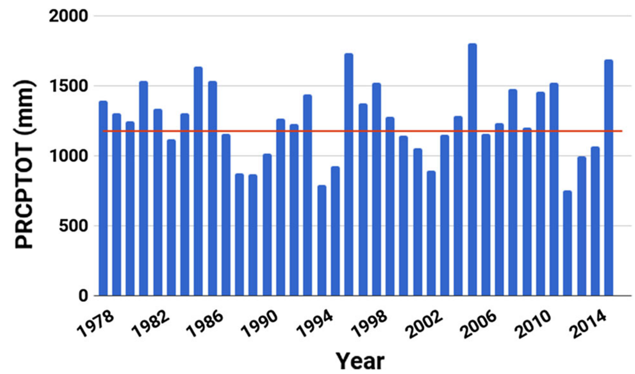

Figure 4. Departures of annual rainfall from the normal in Lower Vellar River sub-basin are represented by the bars. Straight line represents the average annual rainfall of the sub-basin of 1176.6 mm. Twenty-three years had surplus rainfall (above normal) and 15 yr had deficit rainfall (below normal).

indicates that the study area is moving towards a drier climate which conforms to the results reported by Guhathakurta and Rajeevan (2008), which show decreasing trends in annual mean rainfall over Tamil Nadu. Figure 4 shows the annual rainfall of the sub-basin plotted with respect to the average annual rainfall of the sub-basin. A total of 23 yr in the duration selected for study had surplus rainfall and 15 yr had deficit rainfall. The years 1981–1982, 1985–1986, 1996–1998, 2005, 2008, 2010, 2011 and 2015 have had the maximum annual rainfall. The above normal rainfall in the aforementioned years can be attributed to cyclonic events in the sub-basin. 2005, 2008, 2010 and 2011 witnessed the impact of cyclones formed as a part of the North Indian Ocean Cyclone Season. 1997, 1982 and 2015 were active El Niño years. The above findings can be validated with the results estimated by Guhathakurta *et al.* (2011) for India which highlighted the increased flood risk during the years 1971–2000.

SDII showed a decreasing trend with a slope value of −0.01 mm/day per decade, which is negligible having no significant effect on the rainfall in the study area. This is similar to the trends of threshold indices R10mm, R20mm and R30mm which also showed a decreasing trend indicating the reduced rainfall intensity. The annual trends have not shown any significance at 10% level. The duration indices CDD and CWD have shown no trends or insignificant trends with negligible slope values (<1 day). The trends of RX1day, RX3day, RX5day, R95p, R95pT, R99p and R99pT have shown an insignificant positive slope. This is consistent with similar insignificant increasing trends for South Asia (Klein Tank *et al.* 2006),

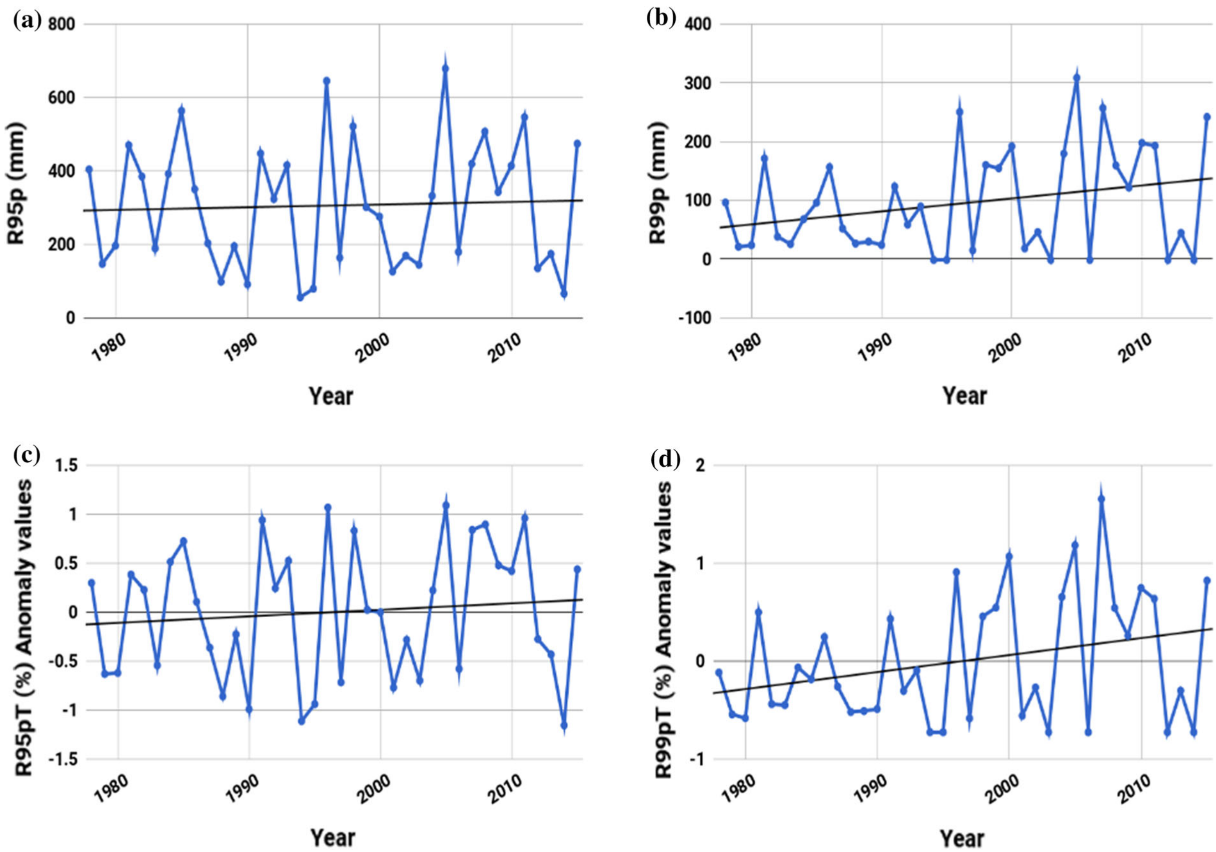

Figure 5. Regionally averaged annual index values of (**a**) R95p; (**b**) R99p; (**c**) R95pT; and (**d**) R99pT; plotted against time. The straight line represents the linear trend of the indices data.

specifically India (Guhathakurta and Rajeevan 2008; Guhathakurta *et al.* 2011). Figure 5 shows the positive trends of R95p, R95pT, R99p and R99pT indices. The trend values imply that there is a slight increase in the amount of rainfall and wet days. The slope per decade for R99p was 10.92 mm which shows that there is an increase in extremely wet days in a year. This is coherent with the significant increasing trend in R95p values and insignificant increasing trends of R95pT and R99pT values for the South Asian region between 1961 and 2000 (Klein Tank *et al.* 2006). This can be further brought down to the months with increased rainfall extremes, from the seasonal trend analysis.

4.2 *Seasonal trend analysis*

The monthly trend values obtained from the analysis were mostly insignificant and the trend slopes have very small slope values. Kumar *et al.* (2010) have carried out an analysis of long-term trends of rainfall over India, which had also shown very little trend in monsoon rainfall and annual rainfall over Tamil Nadu between 1875–2005 when compared to the other regions of India. The monthly trend analysis results of regionally averaged indices are given in table 6, and are used for further seasonal analysis.

4.2.1 *Kharif season*

Kharif season is between June and mid-October. CWD has shown a decreasing trend in the Kharif season with June having a significant decreasing trend. This agrees with PRCPTOT which also shows a decreasing trend though it is insignificant. For the other indices other than CWD and PRCPTOT there has been a consistent increase or decrease in trend corresponding to a particular month. June and July have shown a decreasing trend for nearly all the indices indicating a drier climate. This also implies that not much rain has been received from the SW monsoon. During the month of August comparatively there has been a negligible increase in trends for all indices. September has shown significant negative trends for RX1day, R10mm and PRCPTOT which is given in figure 6.

Table 6. *Month-wise averaged regional trends for the indices at 10% significance level. p-value and Sen's slope for the time series are given.*

Indices	Regional series	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
p-value													
CWD	Anomaly	0.108	0.145	0.427	0.623	0.678	**0.007**	0.635	0.842	0.784	0.132	0.549	0.484
R10mm	Anomaly	**0.048**	0.187	0.175	0.420	0.469	0.199	0.618	1.000	**0.053**	0.635	0.690	0.555
R20mm	Anomaly	0.166	0.474	0.189	0.559	0.305	0.521	0.454	0.842	0.146	0.881	0.980	0.372
R30mm	Anomaly	0.520	0.180	0.298	0.470	0.167	0.371	0.497	0.727	0.132	0.549	0.784	0.263
RX1day	RA	0.116	0.104	**0.097**	0.669	0.132	0.439	0.260	0.784	**0.053**	0.600	0.708	0.424
RX3day	RA	0.208	0.169	**0.055**	1.000	0.153	0.282	0.516	0.980	0.600	0.532	0.901	0.293
RX5day	RA	0.247	0.301	**0.038**	0.990	0.120	0.500	0.271	0.980	0.566	0.395	1.000	0.305
PRCPTOT	RA	**0.033**	**0.079**	0.220	0.365	0.176	0.125	0.395	0.861	**0.044**	0.671	0.765	0.317
Sen's slope													
CWD	Anomaly	−0.01	−0.002	0	−0.004	0.003	**−0.018**	−0.006	−0.002	−0.004	0.016	−0.006	−0.005
R10mm	Anomaly	**−0.003**	0	0	−0.007	0.006	−0.01	−0.004	0.000	**−0.02**	0.006	0.006	−0.006
R20mm	Anomaly	0	0	0	0	0.007	0.006	−0.008	0.003	−0.015	0.001	0.000	−0.012
R30mm	Anomaly	0	0	0	0	0.009	−0.005	−0.007	0.004	−0.013	0.005	0.004	−0.013
RX1day	RA	−0.087	−0.016	0	−0.05	0.282	−0.152	−0.22	0.091	**−0.372**	0.198	0.399	−0.379
RX3day	RA	−0.084	−0.032	**−0.004**	0	0.326	−0.208	−0.215	0.02	−0.216	0.289	0.121	−1.084
RX5day	RA	−0.169	−0.026	**−0.01**	0	0.419	−0.2	−0.394	0.037	−0.246	0.707	−0.016	−1.53
PRCPTOT	RA	**−0.267**	**−0.041**	0	−0.261	0.176	−0.528	−0.545	−0.217	**−1.487**	0.541	0.758	−1.697

The bold values represent statistically significant trends and '–' sign represents negative trend.

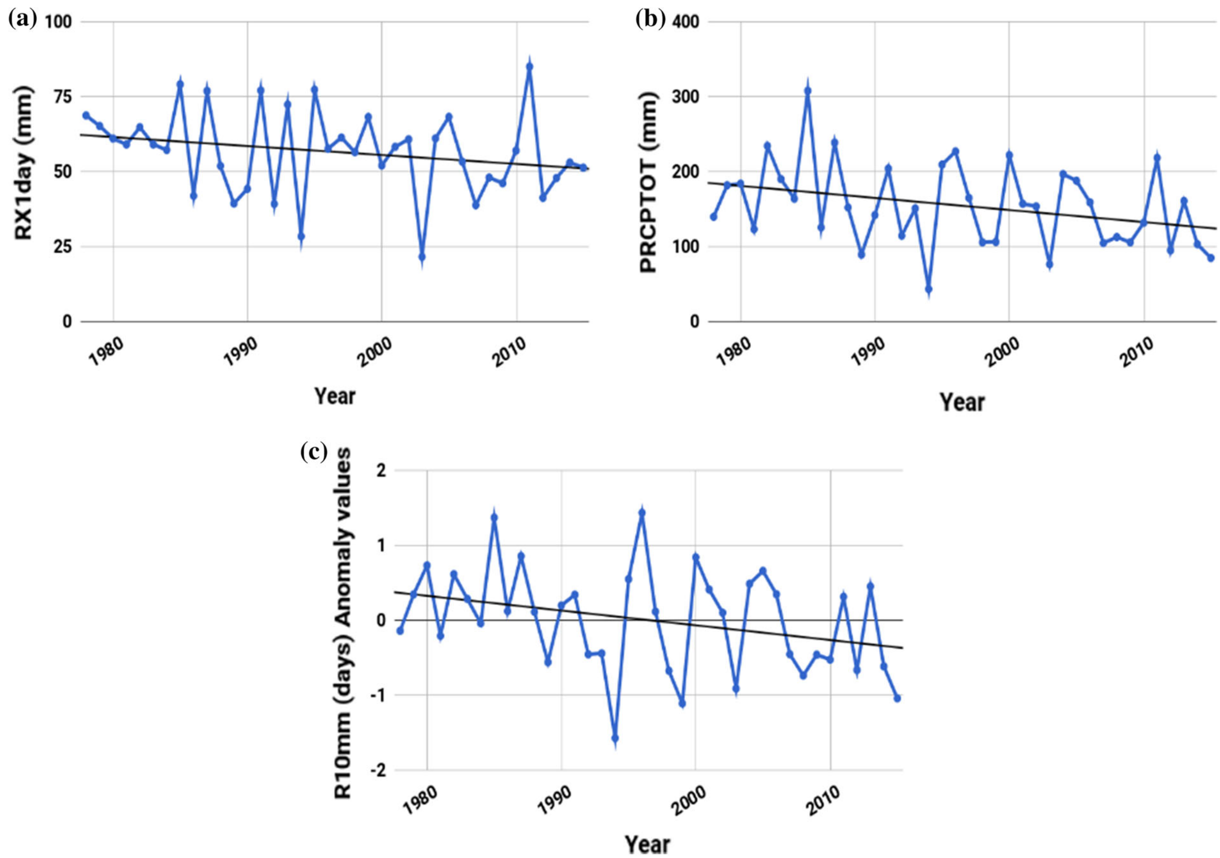

Figure 6. The monthly regional averages for the indices (**a**) RX1day; (**b**) PRCPTOT; and (**c**) R10mm for the month of September which has shown significant trends. The straight line represents linear trend of the indices data.

The values of trend slope per decade were −3.172 and −14.87 mm for RX1day and PRCPTOT, respectively. Thus the analysis shows that there is reduced rainfall occurrence during the retreat of monsoon in September. One day maximum rainfall events, one day rainfall intensity and total rainfall from tropical cyclones have considerably reduced since 1978. Overall the trends show that the Kharif season is moving towards a drier condition.

4.2.2 *Rabi season*

The Rabi season extends from mid-October to May. The onset of the NE monsoon is during October and the analysis has consistently shown an increasing trend for all the indices in October and November, indicating that the months are moving to wetter conditions. From the trend values for monthly maximum 1, 3 and 5 days rainfall (RX1day, RX3day, RX5day) trend in October and December, it can be inferred that there has been increased rainfall intensity. The slope values per decade for RX1day during October and November are 1.98 and 3.99 mm, respectively, which indicate that 1 day rainfall intensity has increased over the time period under consideration. This increased rainfall intensity during a specified duration (in this study it is 1, 3 or 5 days) can attribute to flash flood events in the sub-basin. December has shown decreased trend values for all indices indicating that the NE monsoon which gives maximum rainfall during October–December is moving up in the seasonal calendar providing maximum rainfall from late October/November to early December. This is evident from the RX5day rainfall for the month of October which has a slope value of 7.07 mm per decade which is higher than the RX5day value for the month of November and December which have slope values of −0.16 mm per decade and −15.3 mm per decade, respectively. The RX3day slope value for December has also shown decreasing trend of −10.84 mm per decade. This is evident from Cyclone Thane of 2008 and Cyclone Nisha of 2011 which affected Cuddalore district during November and early December, respectively. The two systems were tropical cyclones over the North

Indian Ocean which brought heavy rains to the sub-basin during November.

CWD has shown a decreasing or no trend between January and April with an average slope value of −0.04 days per decade. This is in agreement with PRCPTOT which also shows a decreasing trend during the same time period with significant negative trends in January (−2.67 mm per decade) and February (−0.41 mm per decade). The absolute and threshold indices have also shown an overall decreasing or no trend between January and April. This shows that the non-monsoon period is fairly dry with not much rainfall events during the period of study.

During March the absolute indices have shown a significant decreasing trend. The RX3day and RX5day indices have slope values of −0.04 mm per decade and −0.1 mm per decade. The decreasing trend can be related to the decrease in Mango showers which are characteristic to South India. Mango showers are light showers to heavy and persistent thunderstorms formed in the Bay of Bengal. These rains normally occur from March, although their arrival is often difficult to predict. They help in the early ripening of mangoes, a tropical fruit. If this decreasing trend continues it might affect the mango growing belts in the sub-basin.

The month of May is when the summer is at its peak in the study area. The month of May has shown a positive trend for all the indices though they are insignificant. This indicates that there is a slight increase in the occurrence of summer rains also known as pre-monsoon rains or Kodai Mazhai. This rain is advantageous for agriculture as it is the time when farmers prepare their fields for the sowing of Kharif crops. It helps in boosting Kharif sowing in the state. Though there is insignificant increasing trend, it is apparent that the summer rains have remained patchy over Tamil Nadu during the time period 1978–2015.

4.2.3 *Links with El Niño*

Since the NE monsoon rainfall is important for agricultural production in Tamil Nadu (Geethalakshmi *et al.* 2003), the links between El Niño and the local precipitation need to be studied for guiding the farmers to plan different agricultural activities. Geethalakshmi *et al.* (2005) investigated the relationship of Southern Oscillation Index (SOI) and Nino-3 sea surface temperature on the NE monsoon rainfall of Tamil Nadu and concluded that the SOI is negatively correlated with the NE monsoon rainfall of Tamil Nadu. This indicates that NE monsoon rainfall of Tamil Nadu is affected by the global climatological signals (Geethalakshmi *et al.* 2003). Zubair and Ropelewski (2006) have emphasised that the relationship between El Niño–Southern Oscillation (ENSO) and the NE monsoon rainfall of Tamil Nadu is strengthening.

The effects of El Niño have caused depressions, low-pressure systems and severe cyclones making the NE monsoon very intense in coastal Tamil Nadu. The main consequences of the El Niño years were that the intensity of rainfall was very high and concentrated only for a few days. The rains in Tamil Nadu were excessive in 1997 and 1982, which saw strong El Niño years followed by 2015 which is the strongest El Niño year on record. The 2015 South Indian Floods severely affected Cuddalore district between mid-November and early December. Eleven blocks had been affected by floods and seven blocks had been put under the most affected list. Out of the seven blocks, five blocks – Kurinjipadi, Bhuvanagiri, Keerapalayam, Kattumannarkoil and Kumaratchi fall within the sub-basin under study. On 23 November 2015 the 1 day rainfall in the Cuddalore rain gauge station was 144 mm. The resumption of heavy rainfall from 1 December 2015 again inundated Cuddalore district, causing major crop loss. The highest 1 day rainfall for the month of December was recorded on 2 December 2015 and 3 December 2015 which were 134.8 and 132.8 mm, respectively.

5. Conclusions

Though there are not many significant trends in the rainfall indices, the trend slopes obtained from the analysis seem to be factual that there has been an increased occurrence of extreme events such as cyclones in the past 30–40 yr during the month of November and early December. The NE monsoon season has shown a predominantly increasing trend between October and November, and the SW monsoon season has shown a significantly decreasing trend. Regional trend analysis for all indices has shown that there is decreasing or no trend during the non-monsoon season. Values of station-wise PRCPTOT conform to the existing rainfall pattern within the study area. The trends are mostly significant and negative between January and March.

The increasing trends of different rainfall extreme indices during the NE monsoon season which is the main crop growing season in Tamil

Nadu and the early onset of the NE monsoon over the last few decades are some of the key findings from the study which can be considered as a guiding tool for researchers to develop suitable adaptation strategies for farmers in the Lower Vellar River sub-basin. Adaptation measures can also be developed taking into consideration the occurrence of floods and tropical cyclones in the study area. Since rainfall extremes cause much crop loss both directly and indirectly, the results obtained from the study can help the farmers be wary of such disasters in the future. Water resources planning and development can also be done based on the findings of the study. Water tapped from extreme rainfall events can be used in an efficient manner during the non-monsoon seasons.

Most of the previous studies on rainfall trend analysis have been done for India on an annual/ monthly timescale or for climatic seasons. For the first time, we have developed extreme rainfall indices from the daily rainfall time series for a small region, to calculate the local trends annually and month-wise. The month-wise trends have been analysed for the agricultural cropping seasons of Tamil Nadu to make the data more suitable to help develop adaptation measures.

A systematic analysis of rainfall, rainy days, heavy rainfall spells, etc., on a weekly scale along with radiation, growing degree days, onset and withdrawal dates of monsoon, length of season using onset and withdrawal date, moisture availability and sowing rains, etc., can be done to suggest feasible adaptation strategies. Also, there is scope for developing the extreme climate indices for future modelled data obtained from regional climate models so that it can benefit farmers who are the main stakeholders in agriculture.

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