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Rainfall trend and variability analysis of the past 119 (1901-2019) years using statistical techniques : A case study of Kolkata, India

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सार — इस अध्ययन का मुख्य उद्देश्य 1901 और 2019 (लगभग 119 वर्ष) के बीच भारत के पश्चिम बंगाल के कोलकाता जिले में मासिक, मौसमी और वार्षिक वर्षा पैटर्न में स्थानिक विविधता की जांच करना है। प्रवृत्ति की विश्वसनीयता और तीव्रता का आकलन गैर-प्राचलिक रूप से मासिक वर्षा डेटा श्रृंखला और मान-केंडल (MK) और सेन के ढलान अनुमानकों को लागू करके किया गया। डेटा के अनुसार कोलकाता में मॉनसूनपूर्व, मॉनसून, मॉनसूनोत्तर और वार्षिक वर्षा में काफी वृद्धि हुई। जबकि शीतकालीन वर्षा में कमी हुई है। मॉनसून पूर्व, मॉनसून, मॉनसूनोत्तर और वार्षिक वर्षा की डेटा श्रृंखला में सकारात्मक प्रवृत्ति दिखी, हालांकि, शीतकालीन वर्षा ने नकारात्मक प्रवृत्ति को दर्शाया। वर्षा में सबसे अधिक वृद्धि मॉनसूनोत्तर ऋतु (0.365091 मिमी वर्ष$^{-1}$) के दौरान दिखी। सबसे कम वृद्धि (0.232591 मिमी वर्ष$^{-1}$) मॉनसूनपूर्व ऋतु के दौरान हुई। शीत ऋतु में, वर्षा में गिरावट (-0.01356 मिमी वर्ष$^{-1}$) आई। परिवर्तिता का गुणांक (सीवी), %, का उपयोग वर्षा परिवर्तिता के पैटर्न को निर्धारित करने के लिए किया गया। शीतकालीन वर्षा ने उच्चतम सीवी रेटिंग (72.89%) प्रदर्शित की, लेकिन वार्षिक वर्षा ने न्यूनतम सीवी मान (17.68%) दिखाया। सामान्यतः, सीवी में एक उच्च प्रसरण की खोज की गई, जो दर्शाता है कि पूरा क्षेत्र सूखे और बाढ़ के प्रति बेहद संवेदनशील है। भविष्य के पूर्वानुमानों के लिए, रैखिक समाश्रयण और अनुक्रमिक न्यूनतम अनुकूलन (SMoreg) के बीच मासिक वर्षा डेटा में काफी अंतर है, जबकि वार्षिक वर्षा रैखिक समाश्रयण, SMoreg और सेलुलर ऑटोमेटा- कृत्रिम तंत्रिका नेटवर्क (CA-ANN) विश्लेषण के बीच कम अंतर है।

ABSTRACT. The core purpose of this study is to investigate the spatial variation in monthly, seasonally and yearly rainfall patterns in the Kolkata district of West Bengal, India, between 1901 and 2019 (Around 119 years). The trend's reliability and intensity were assessed non-parametrically applying monthly rainfall data series and the Mann-Kendall (MK) and Sen's slope estimators.The data showed a considerable increase in pre-monsoon, monsoon, post-monsoonand also annual rainfall while decreasing in winter rainfall across the district of Kolkata. The positive trend is identified in the data series of pre-monsoon, monsoon, post-monsoon and annual rainfall, however, winter rainfall exhibited negative trends. The highest increase in rainfall was observed during the post-monsoon season (0.365091 mm year^{-1}), with the smallest increase (0.232591 mm year^{-1}) occurring during the pre-monsoon season.In the winter season, there was a notable rain that has declined (-0.01356 mm year^{-1}). The Coefficient of Variation (CV), %, was used to determine the pattern of rainfall variability. The winter rainfall exhibited the highest CV rating (72.89%), but annual rainfall showed a minimum CV value (17.68%). Generally speaking, a high variance in CV was discovered, indicating that the whole area is very sensitive to droughts and floods. For future forecasts, there is a considerable difference in monthly rainfall data between linear regression and Sequential Minimal Optimization (SMOreg), while the annual rainfall is little difference between linear regression, SMOreg and Cellular Automata-Artificial Neural Network (CA-ANN) analysis.

Key words – Trend of the Rainfall, Mann-Kendall test, Sen’s Slope Estimates, Linear Regression, SMOreg, CA-ANN, Kolkata.

1. Introduction

The most significant phenomenon is climate variability. It has an impact on rainfall patterns as well as global water supplies. Rainfall data has become more essential in planning and implementing regional initiatives such as sustainable agriculture and associated food production operations. It also influences hydrology,

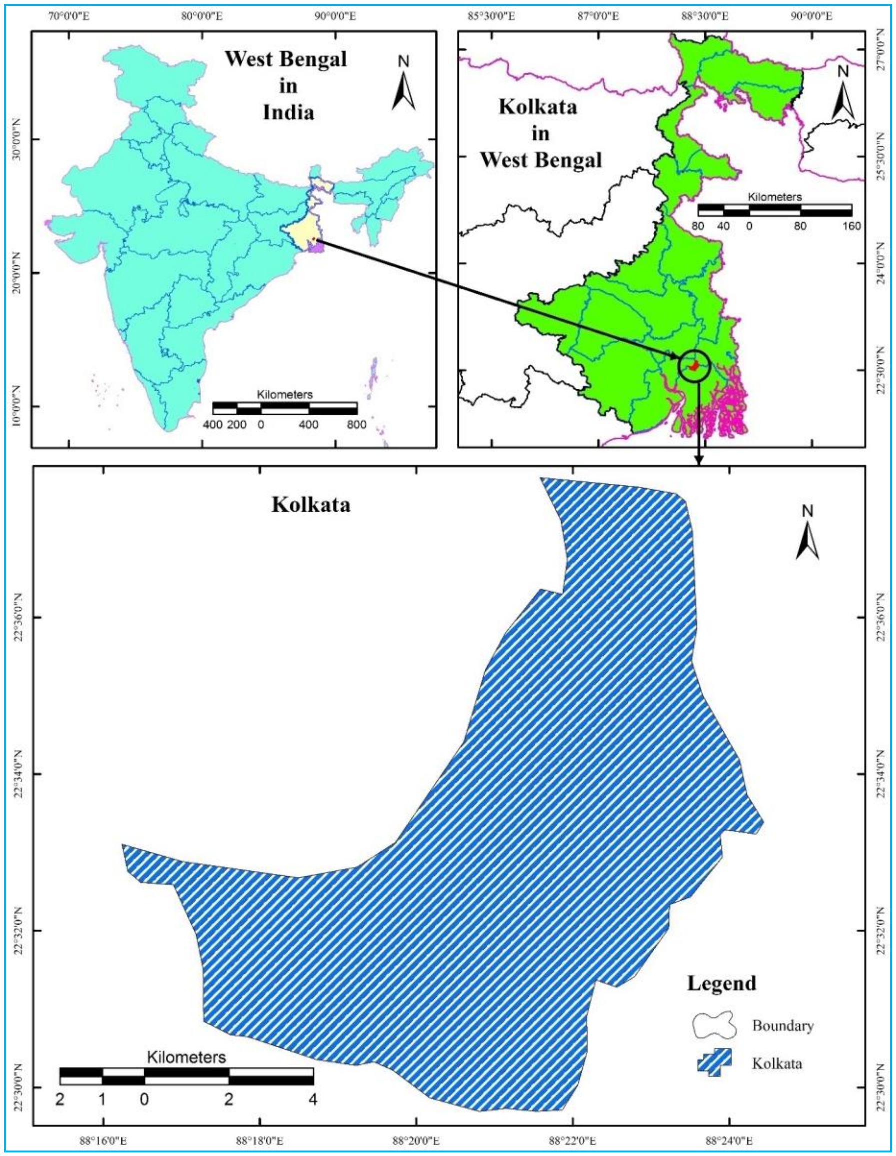


Fig. 1. Geographical Location of the study area

climate, water resource management, soil erosion forecasting, drought and flood forecasting as well as ecological modeling (Cavalcante *et al*., 2020). Currently, the historical distribution of rainfall is a significant aspect of climate change assessments (Vincent *et al*., 2005). As per the IPCC, worldwide surface temperatures increased at such an amount of 0.74 ± 0.18°C between 1906 and 2005; freshwater availability has been demonstrated to be reduced in the future as a result of climate change; By the middle of the twenty-first century, accessible water and estimated yearly surface runoff will have decreased by up to 10%-30% (IPCC, 2007). Indian regional climate is largely impacted by the South-West Monsoon and also has a major effect on agricultural production, water resource management and economic development of these areas (Jain and Kumar, 2012). Construction operations in developing societies are also among the most significant contributors to climate change, particularly when it comes to altering land usage as a result of cropping practices and irrigation operations (Kalnay and Cai, 2003). Indian climate is as fragile as noticed by the scientists, it is also established that the Indian summer monsoon's life cycle is too short in time (Ramesh and Goswami, 2007). Recently, India has become one of the world's most overpopulated nations, with its cities becoming overcrowded and the development of new cities occurring at such a quick pace that it influences the local climate. Kolkata's current climate research analyses that most areas of rainfall patterns have grown quite unreliable, erratic and unpredictable, creating issues for their livestock habitats.

We will never be able to control the weather, but we can use simple measuring methods to analyze the historical data from this location. The analysis of trends can be carried out using both parametric and nonparametric tests; for example, the *t*-test is a parametric test, whereas the Mann-Kendall (MK) test (Mann, 1945; Kendall, 1975) provides a positive or negative correlation between seasonal and annual scale rainfall records for a given confidence level. The M-K test has been widely used by various researchers (Nikhil Raj and Azeez, 2012) to determine the trends in, temperature and rainfall on a month-wise, seasonal and annual scale, with the results showing some relevance in the case of temperature and rainfall in the past. In Zambia, the M-K test and the Cumulative Summation test were utilized to examine the long-term rainfall trend (Kampata *et al.*, 2008). The objective of this present study is to analyze the trend of rainfall, future forecasting and to determine the environmental impact over the selected study area by using the measuring methods of the M-K test, Sen's Slope Estimator, linear regression, SMOreg and CA-ANN analysis.

2. Study area

The Indian city of Kolkata is situated in the southern region of the state of West Bengal. In latitude and longitude, this region (Fig. 1) extends to 22°37′47.04″ N latitudes to 22°29′42.35″ N latitudes and 88°16′14.26″ E longitudes to 88°24′26.31″ E longitudes. The climate in Kolkata is tropical wet-dry. Kolkata receives significantly less rainfall in the winter than in the summer. The Köppen-Geiger climate classification for this location isAw. The average annual rainfall is 1656 mm and the average temperature is 26.0 °C. At an average elevation of 6.4 m above the MSL and it is located on the eastern bank of the Hooghly River in the lower Ganges Delta. The Kolkata district is bordered on the north and east by the North 24 Parganas district, on the south by the South 24 Parganas district and on the west by the Howrah district, which lies across the Hooghly River from Kolkata (District Census Handbook, 2011). Kolkata is the smallest district in terms of area among all the districts of West Bengal, yet it has the greatest population density of any of the districts in the state. The metropolitan area of Kolkata is 1851.41 square kilometers and it is India's sixth-largest metropolitan area.

3. Material and method

3.1. *Data sources*

The monthly precipitation data are collected from IMD, CHRS data portal and NASA data portal for the years 1901 to 2019. The forecast of rainfall was measurement, the rainfall was downloaded from the CHRS data portal and thereafter IDW tool was used in the GIS environment. The rainfall points over the study area were pointed as per the expert's recommendation.

3.2. *Methods*

For trend identification, the M-K test and Sen's Slope estimator are used and for future rainfall forecasting, linear regression, SMOreg and CA-ANN methods are used (Sarkar *et al.*, 2021). M-K test is a non-parametric method of determining tendencies that are commonly used in trending analysis (Mann, 1945; Kendall, 1975). The rainfall, temperature and stream flow, etc. are useful indicators, utilized for researching climatic features. These variables are very significant in determining the water resources and long-term planning plans for any place, regardless of climate. The patterns of change (both positive and negative) are analyzed for the months of the year and each of the four seasons.

3.2.1. *Auto-correlation test*

Before conducting a trend test on rainfall data, it is necessary to check for autocorrelation in the time series of data. The sample autocorrelation coefficient is an approximation of the population autocorrelation coefficient. It is possible to calculate the lag-1 autocorrelation coefficient or the serial coefficient (Salas *et al.*, 1980; Piyoosh and Ghosh, 2016; Yue *et al.*, 2002) although, the first serial correlation coefficient is the most often used measure of time series dependency. To determine whether or not there is serial independence (Basistha *et al.*, 2009; Mondal *et al.*, 2018a). A comparison is made between the null hypothesis and the alternative hypothesis. If the null hypothesis is rejected at a significance level, then the alternative hypothesis is accepted. A threshold of significance of 5% is deemed appropriate for this investigation.

3.2.2. *Rainfall trends analysis*

3.2.2.1. *Mann-Kendall (MK) test*

Mann Kendell, the non-parametric test is one of the most essential statistics techniques. There are a large number of researchers were used this statistical technique to carry out their research works. The MK test is used to determine if the variable of interest has a monotonic decreasing or rising trend over time. A monotonic rising (descending) trend indicates that the variable rises (declines) continuously through time, but the trend may or may not be linear. This non-parametric test is one of the most essential statistics techniques, which is used by the large number of researchers to carry out their research work (Krishnakumar *et al*., 2009; Asfaw *et al*., 2018; Sharma and Singh, 2017; Goyal, 2014; Lyra *et al*., 2017; Duhan and Pandey 2013; Shree and Kumar 2018; Jaiswal *et al*., 2015; Subash and Sikka, 2014; Meshram *et al*., 2017; Sarkar *et al*., 2021). In this present study, it was tried to determine the trend analysis (Onyutha, 2021) and future production of rainfall and the primary analysis reveals that there is no sign of Autocorrelation and Partial Autocorrelation lag1 in the rainfall data so that the modified Mann Kendell test is not to be needed instead the MK test is more preferable for trends analysis. The Mann-Kendall Statistic S for the trend (Eqn. 1 and Eqn. 2) is :

$$S = \sum_{i=1}^{n-1} \sum_{i=i+1}^{n} \operatorname{sgn}(xp - xq) \tag{1}$$

where the xi is the real-time data for a data series of i = 1, 2… n.

$$\operatorname{Sgn}(x_p - x_q) = \begin{cases} +1, & if\ (xp-xq) > 0 \\ 0, & if\ (xp-xq) = 0 \\ -1, & if\ (xp-xq) < 0 \end{cases} \tag{2}$$

when the data $n \geq 10$ the S statistics follow standard distribution in a sequence with the mean of E(S) = 0 and the dispersion (Eqn. 3).

$$\operatorname{Var}(S) = \frac{n(n-1)(2n+5) - \sum_{1=1}^{n} t_i(t_i-1)(2t_i+5)}{18} \tag{3}$$

Where t_i is the ties of the sample time series. The test statistics Zc is as follows (Eqn. 4):

$$Z_c = \begin{cases} \dfrac{s-1}{\sqrt{\operatorname{var}(s)}}, & if\ s > 0 \\ 0, & if\ s = 0 \\ \dfrac{s+1}{\sqrt{\operatorname{var}(s)}}, & if\ s < 0 \end{cases} \tag{4}$$

In situations where Z_c shows the normal distribution, a positive Z_c indicates an increasing trend for the period, while a negative Z_c indicates a decreasing trend for the time.When the significance value is, α, $Z_c \geq Z\alpha/2$, the data is regarded to be significant because of the tendency. The Mann Kendall measure compares the null hypothesis of zero tendencies in data against the alternate hypothesis of the presence of a trend in data, which is called the alternative hypothesis. When the number of observations n is less than ten, then the formula above is acceptable.

3.2.2.2. *Sen's Slope Estimation*

Some other, non-parametric technique for trend assessment is the Sen slope estimator (Sen, 1968). It is performed to determine the intensity of the trend (Eqn. 5).

$$T_i = \frac{(x_j - \varkappa_k)}{j-k} i = 1, 2 \ldots N \tag{5}$$

where $\varkappa_k$ are the data sets for j and k times in a period where $j>k$ and the slope is calculated for each observation of the timeframe. To compute Sen's Slope estimator, the slope N observations calculate the median.

$$Q_i = \begin{cases} \dfrac{T_{N+1}}{2}\ N \text{ is Odd} \\ \dfrac{1}{2}\left(T_{\frac{N}{2}} + T_{\frac{N+1}{2}}\right)\ N \text{ is Even} \end{cases} \tag{6}$$

when the data on the N slope indicate as Odd, the Sen's estimator is calculated as a $Q_{med}=(N+1)/2$ and the Slope estimate is calculated as a Q_{med} = {(N/2)+[(N+2)/2]}/2 for Even times of data. For the non-parametric analysis, the two-sided testing is conducted at a 100(1 – α) % confidence interval to determine the actual gradient for the sequence non-parametric test (Mondal *et al*., 2018b). It is possible to acquire a positive or negative slope Q_i by observing an uphill (growing) or downhill (decreasing) trend (Eqn. 6).

3.2.2.3. *Coefficient of variation (CV) statistic*

To calculate the standard deviation (σ) from a dataset or frequency distribution, the coefficient of variation (CV) statistic is used. Percentiles are used to express this. This statistical approach is being utilized in the current research to analyze the seasonal and yearly variability of the research area (Landsea and Gray, 1992; Muthoni *et al*. 2019; Onyutha, 2021). When the CV value is lower, it suggests that there is less variability within the given dataset and *vice versa*. In the following equation, the coefficient of variation (CV) is defined (Eqn. 7):

$$\mathrm{CV} = \frac{\mathrm{SD}(\sigma)}{\mathrm{Mean}(\mu)} \times 100 \tag{7}$$

3.2.2.4. *Identification of the Periodical trend point change*

3.2.2.4.1. *Pettitt test for single change point*

To identify change points (Onyutha, 2016) in time-series data, the nonparametric Mann-Whitney-Pettitt test

(Pettitt, 1979) (Piyoosh and Ghosh, 2016) is used. The change point occurs at time s if the time series data are expressed by (x_1, x_2, x_3,...x_T) for T time periods and x_t for t = 1, 2, 3,...s denotes common distribution function $F_1(x)$ and x_t for t = τ+1, τ+2, τ+3,...T denotes common distribution function $F_2(x)$ and both common distribution functions are unequal, [$F_1(x) = F_2(x)$]. If the time series (Pettitt, 1979) made no assumptions regarding $F_1(x)$ and $F_2(x)$ other than the fact that they are continuous functions. The statistic ($U_{t,T}$), which is equal to the Mann-Whitney statistic to evaluate the two samples (x_1; x_2; x_3...x_t) and (x_{t+1}; x_{t+2}; x_{t+3}...x_T) are taken from the same universe. Pettitt developed two-sided non-parametric test statistics for comparing the null hypothesis of no change point to the alternative hypothesis of change point to determine which is correct (K_T). For the most likely change point, $K_T$is high and has a modest value of significance likelihood, indicating that the change is likely.

3.2.2.4.2. *Multiple change points*

3.2.2.4.2.1. *CUSUM detect process shift*

In climate data series, the cumulative sum (CUSUM) chart (Page 1954, 1961; Piyoosh and Ghosh, 2016) is a statistical technique that may be used to identify trend shifts. For different samples of size $n \geq 1$, the CUSUM value C_i is shown for sample i and is defined (Eqn. 8) as follows (Montgomery, 2019).

$$C_i = \sum_{j-1}^{i} \left(\bar{x}_j - \mu_0\right) \tag{8}$$

where $\bar{x}_j$ represents the average of the j^{th} sample and C_i represents the cumulative total up to and including the i^{th} sample and μ_0 represents a constant indicating the goal value for the process means. It is possible to use the goal value as the mean of the distribution. CUSUM charts are useful when the number of participants is one. Cumulative deviations over and below the goal value are used in tubular CUSUM calculations and they are denoted by the letters C^+ and C^-, respectively. A one-sided upper and lower CUSUM are two statistical measures that are used to compare two different groups of data. The letters C^+ and C^- are defined as follows (Eqn. 9 and Eqn. 10).

$$C_i^+ = \max[0, x_i - (\mu_0 + k) + C^+_{i-1}]. \tag{9}$$

$$C_i^- = \max[0, (\mu_0 + k) - x_i + C^-_{i-1}]. \tag{10}$$

K is a number that is used to determine the upper and lower limits of CUSUM. It is also known as the reference, allowance, or slack value. This number is often chosen in such a manner that it is midway between the goal l0 and the out of control value of the mean l1, which must be identified using the CUSUM analysis method of selection. If any of the control variables C_i^+ or C_i^- exceeds the decision interval H for the CUSUM chart, the process is said to be out of control. To obtain a decent average run length, H and K may be defined as H = hδ and K = kδ, where r denotes the standard deviation of the sample variable used for building CUSUM, h and k denote the average run length. H and K are generally assumed to be equal to 4 or 5 and k to be equal to 0.5, respectively (Montgomery, 2019). In the current research, the allowance and decision interval are chosen as K = 0.5δ and H = ±2δ, respectively, to detect process change in the rainfall data series. Identical values have been employed in a variety of studies to detect process shifts in climatological data series, including this one (Singh *et al*., 2015).

3.2.2.4.2.2. *SegNeigh method for identifying multiple change points*

The CUSUM test statistic is used to detect multiple change points using the SegNeigh technique (Killick and Eckley, 2014) and then the Segment Neighbourhood method introduced (Auger and Lawrence, 1989), which investigated (Bai and Perron, 1998; Piyoosh and Ghosh, 2016). When it comes to change points, the null hypothesis is that there are none, whereas the alternative hypothesis is that there are a lot of change points. The likelihood approach involves the computation of maximum log-likelihood (ML) for both the null and alternative hypotheses to evaluate the hypothesis. ML is determined by identifying the greatest number of potential combinations. The procedure for detecting a large number of change points.

3.3.3. *Prediction of the future rainfall*

3.3.3.1. *Linear Regression Method*

It is a statistical approach for estimating future values derived from previous values.It is widely used as a quantitative technique to assess the basic trends as well as over levels.The linear regression graph utilizes the least-square technique to construct a straight line overvalues to minimize value distances and the resulting trend line.This linear regression measures the value of the trading range for each data point in the data set and it is used to calculate the value of the trend line (Eqn. 11).

$$\gamma_t = \beta_0 + \beta_0 \chi_t + \varepsilon_t \tag{11}$$

where, β_0 is forecast value of γ_t when X = 0; β_1 is the line's slope and tangent; ε_t this indicated an arbitrary error.

3.3.3.2. *Rainfall prediction using SMO-Regression Method*

The SMO method is used to address the simplest optimization issues. To solve classification issues, Platt introduced a Sequential Minimal Optimization method, which repeatedly selects the functional area and optimizes the goal value using analytic solutions to sub-problems. In the given below, this approach will be described in further detail later in this paper (Yang *et al*., 2007) (Eqn. 12; Eqn. 13; Eqn. 14; Eqn. 15).

$$L_P\left(\alpha^*,\alpha\right)=\varepsilon\sum_{i=1}^{n}\left(\alpha_i^*+\alpha_i\right)-\sum_{i}^{n}\gamma_i\left(\alpha_i^*-\alpha_i\right)+\frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}\left(\alpha_i^*-\alpha_i\right)\left(\alpha_j^*-\alpha_j\right)k\left(x_i x_j\right)$$

$$\sum_{i=1}^{n}\left(\alpha_i^*+\alpha_i\right)=0$$

$$0\le\alpha_i^*,\alpha\le C, i=1,2\ldots,n \tag{12}$$

In equation $**\alpha_i,\alpha_i^*$ are language multipliers.

$$f\left(\chi,\alpha\right)=\sum_{i=1}^{n}\left(\alpha_i^*-\alpha_i\right)k\left(x_i,x\right)+b \tag{13}$$

If λ_i = $\alpha_i^*-\alpha_i$, $\left|\lambda_i\right|=\alpha_i^*+\alpha_i$,the new values for $\lambda_i$will follow box restriction–c $<\lambda_i<$ c,i = 1,2…,n. substitution of λ_i and $\left|\lambda_i\right|$ into[8] and [9], thereafter the the equation is written as :

$$L_P\left(\lambda\right)=\varepsilon\sum_{i=1}^{n}\left|\lambda_i\right|-\sum_{i}^{n}\lambda_i\gamma_i+\frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}\lambda_i\lambda_j k_{ij} \tag{14}$$

$$\sum_{i=1}^{n}\lambda_i=0,$$

$–c <\lambda_i< c$

and

$$f\left(\chi,\lambda\right)=\sum_{i=1}^{n}\lambda_i k\left(x_i,x\right)+\lambda_0 \tag{15}$$

3.3.3.3. *Rainfall prediction using CA-ANN*

The ANN stands for Artificial Neural Network (ANN), it is a "connectionist" system model of artificial intelligence that was influenced by studies of human neuronal networks (Haykin, 1994; Hewitson and Crane, 1994; Levine *et al*., 1996). Under certain predefined geo-environmental conditions, the ANN model has been included to automatically detect the connection between multi-source data (including mixtures of qualitative and quantitative data) through an auto-learning method and to estimate the area that is most likely to obtain rainfall. Moreover, this model may construct links using linear or nonlinear modeling functions to appropriate accuracy (Licznar and Nearing, 2003). For their capacity to model complicated systems and identify patterns, the machine learning algorithms of the ANN are frequently employed in challenges in science and engineering (Bowden *et al*., 2002; Jain *et al*., 1996; Cracknell and Reading, 2014). Before the introduction of the ANN model, it was not possible to include any "hidden layers" into the algorithm's code. Although the current approach allows users to add several hidden layers of their choosing, the accuracy of the ANN algorithms is much improved as a result of the ability of the program to do so. In this research, the training algorithm technique is utilized to train the network consisting of three major phases: the reinforcement of input training pattern, the reinforcement of calculated errors and weight modification (Fausett 2005). Each neuron's activation functions at its output end are shown in Fig. 10. These include, among others, threshold function, piecewise linear function, sigmoid function and Gaussian function (Jain *et al*., 1996). For a μ network, the logistic function is specified as Eqn. 16.

$$f\left(\mu\right)=\left[\frac{1}{1+e^{\left(-\mu\right)}}\right] \tag{16}$$

When a given input is provided, the activation of j neuron (ϑj) of layer m is defined at the output unit by n iterations to generate the network response (*j*) for the input, which can be represented as like Eqn. 17.

$$\vartheta_j^{\{m\}}\{n\}=f\left(\mu_j^{\{M\}}\{n\}\right) \tag{17}$$

The following will be the signal generated by the network as an output (Eqn. 18).

$$\mu_j^{\{m\}}\{n\}=\sum_{i=0}^{k}\left[\vartheta_j^{\{M-1\}}\{n\}\times w_{ji}^{\{M\}}\{n\}\right]. \tag{18}$$

Specifically, the ANN model is analyzed with predictors of rainfall predictor as inputs to the network (continuous and categorical) in this research, the model is trained with varying numbers of undefined layers using the training datasets. In an ANN model, the number of hidden layers that should be included in the final model is determined depending on the maximum accuracy of the

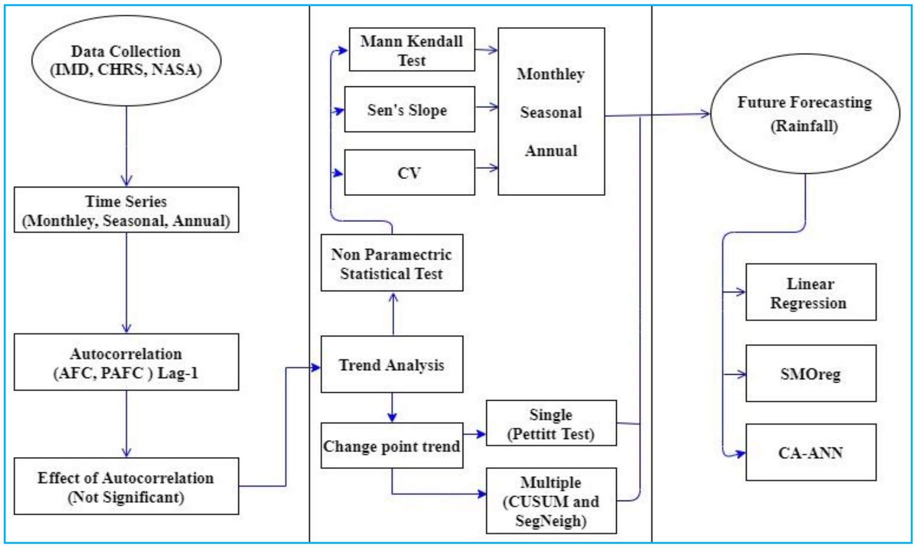


Fig. 2. Flow chart of the study (1901 to 2019)

TABLE 1

Lag-1 autocorrelation coefficients (q^) and Partial autocorrelation for seasonal and annual data series

Time Series	Auto- correlation	Partial auto-correlation	Standard error	Lower bound (95%)	Upper bound (95%)
Pre-Monsoon	0.135	0.135	0.0916	-0.1796	0.1796
Monsoon	-0.0812	-0.0812	0.0916	-0.1796	0.1796
Post-Monsoon	0.02621	0.0262	0.0916	-0.1796	0.1796
Winter	-0.0001	-0.0001	0.0916	-0.1796	0.1796
Annual	0.0152	0.0152	0.0916	-0.1796	0.1796

model output, since there is no universally accepted criterion for how many hidden layers should be included in the final model (Pijanowski *et al*., 2002).

4. Result and discussion

In this current work, a trend analysis of the rainfall in the district of Kolkata is carried out using Mann-Kendall to collect monthly, seasonal, average monthly and annual data from Sen's Slope Estimator over 119 years (1901-2019). Fig. 4 illustrates the monthly variations in rainfall over the whole study period. It is currently unknown whether the fluctuation in annual mean rainfall will persist over the period 1901-2019; further research is needed to determine whether it will.

4.1. *Basic characteristics of monthly, seasonal and annual rainfall data*

For the period 1901-2019, statistical rainfall characteristics of the Kolkata district were evaluated and given in Table 2, Fig. 4, Fig. 5 and Fig. 6 shows the monthly, seasonal and annual rainfall fluctuations during the study period. The average annual precipitation of Kolkata was 1627.58 mm with seasonal precipitations of 66.94098 mm for pre-moon, 311.5089 mm for monsoon, 148.8459 mm for post-moon and 15.23074 mm for winter, the highest mean precipitation in August 350.2868 and the lowest average precipitation in December 6.673429 mm. The outcome of calculated statistical datasets suggests that the high rainfall season has less variability than the substantially lower rainfall season.The rainfall data record analysis found that the greatest rainfall of 2326.694 mm was reported in 1978 and the lowest rainfall of 1635.988 mm in the district of Kolkata in 1935.

During the Southwest monsoon season, “the frequency of cyclonic storms and the intensity of the jet stream over the Indian Ocean, which serve as the driving force for monsoon depression, may vary and this could explain why the year 1978 had the most rainfall and the year 1935 had the least rainfall”(Sharma and Singh

TABLE 2

Statistical summary of monthly, seasonal and annual rainfall of Kolkata district (1901-2019)

Variable	Observations	Minimum	Maximum	Mean	Std. Deviation	CV, %	% Contribution to Rainfall
Jan	119	0	63.286	12.8866	15.8393	122.913	0.79177
Feb	119	0	120.228	26.1322	24.4288	93.4816	1.60558
Mar	119	0.398	177.227	38.3422	41.4438	108.089	2.35578
Apr	119	0.599	209.486	57.7101	46.2814	80.1963	3.54576
May	119	9.2	406.066	104.771	66.2186	63.2034	6.4372
Jun	119	41.618	796.939	266.202	129.992	48.8322	16.3557
Jul	119	109.519	748.021	318.038	115.068	36.1806	19.5405
Aug	119	167.227	635.45	350.287	105.576	30.1399	21.5219
Sep	119	70.65	892.145	285.238	133.316	46.7383	17.5253
Oct	119	1.329	518.703	144.213	95.5891	66.2833	8.86057
Nov	119	0	99.322	17.0867	22.875	133.876	1.04982
Dec	119	0	77.421	6.67343	14.4015	215.804	0.41002
Pre-Monsoon	119	9.05433	170.459	66.941	32.1234	47.9876	12.3387
Monsoon	119	188.834	531.288	311.509	70.7223	22.7031	57.4182
Post-Monsoon	119	51.0653	360.5	148.846	59.6187	40.054	27.4357
Winter	119	0	54.9537	15.2307	11.1016	72.8897	2.80737
Monthly Average	119	84.7733	193.891	135.632	23.9826	17.6822	
Annual	119	1017.28	2326.69	1627.58	287.791	17.6822	100

TABLE 3

Month-wise rainfall variance

Month	Variance	Month	Variance	Month	Variance
Jan	250.884	Jul	13240.7	Pre Monsoon	1031.91
Feb	596.765	Aug	11146.3	Monsoon	5001.64
Mar	1717.59	Sep	17773.1	Post Monsoon	3554.39
Apr	2141.96	Oct	9137.27	Winter	123.246
May	4384.91	Nov	523.263	Monthly Average	575.166
Jun	16898	Dec	207.403	Annual	82823.9

2017). Monsoon season delivers the most 57.42 percent of total annual rainfall in Kolkata districts; while winter accounts for the lowest 2.81 percent and, monthly, provides the maximum 21.52 percent in August while the lowest 0.41 percent in December.

4.2. *Auto-correlation*

Before performing trend analysis to the rainfall data, the data was verified against autocorrelation and partial autocorrelation. It's calculatedover the period 1901-2019,

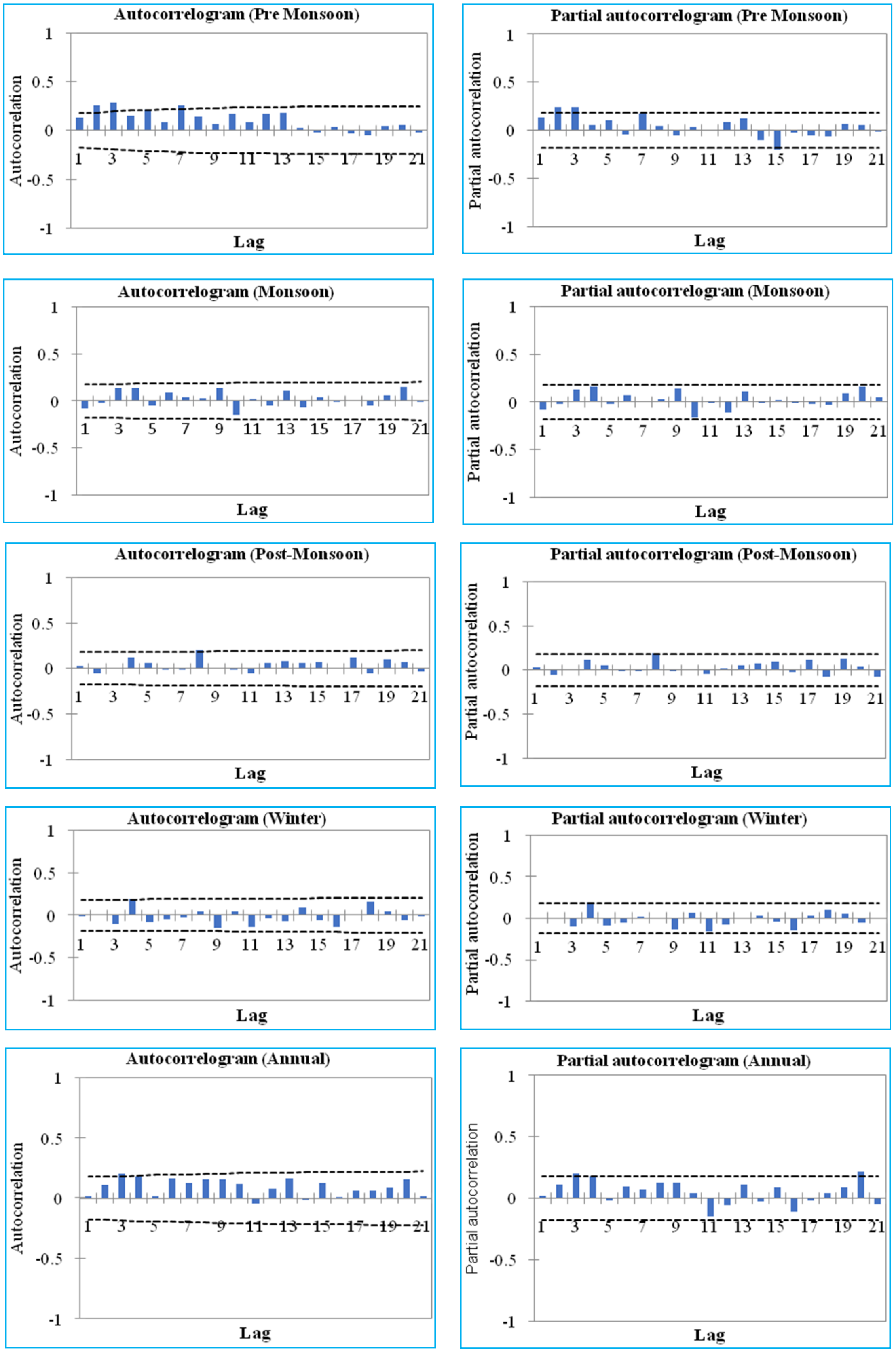
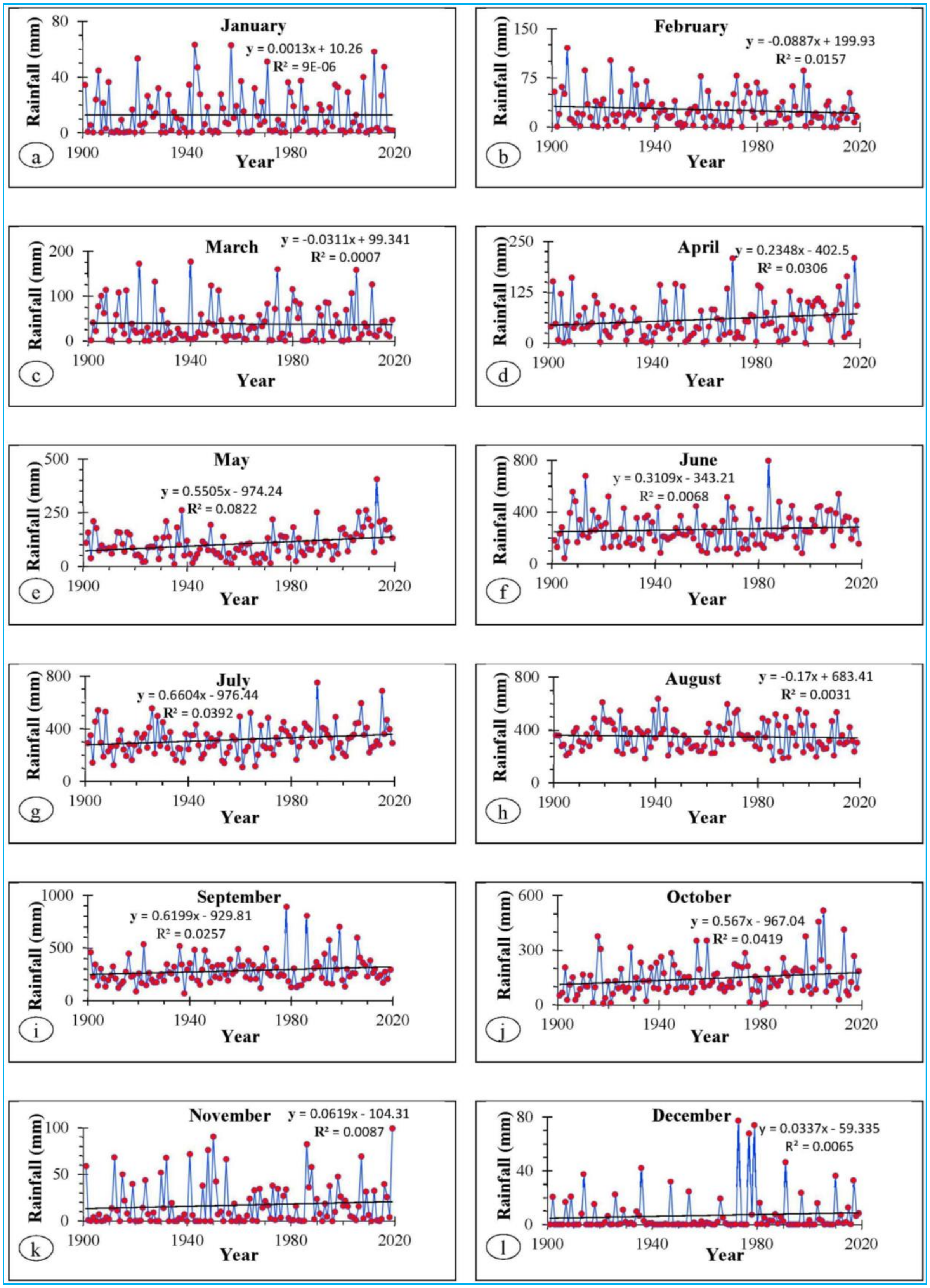


Fig. 3. ACF and PACF of seasonal and annual rainfall series (1901-2019)



Figs. 4(a-l). Monthly rainfall (mm) trends of Kolkata (1901-2019)

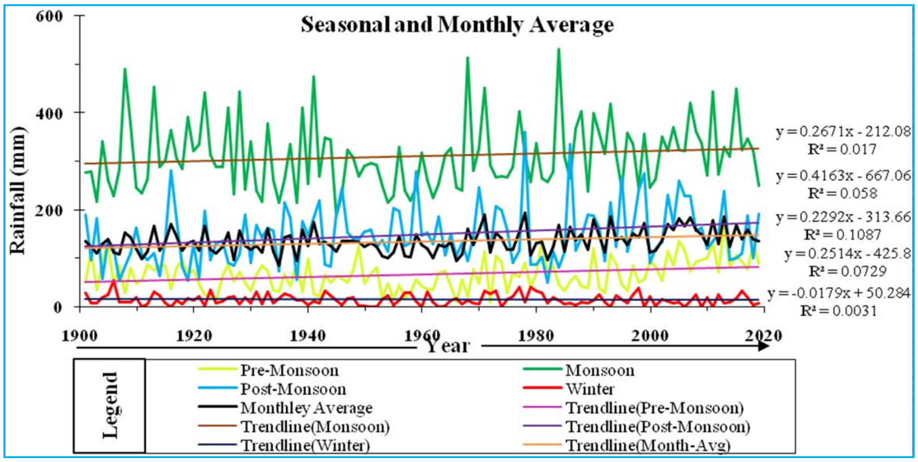


Fig. 5. Comparison within Seasonal and Monthly Average rainfall (mm) of Kolkata (1901-2019)

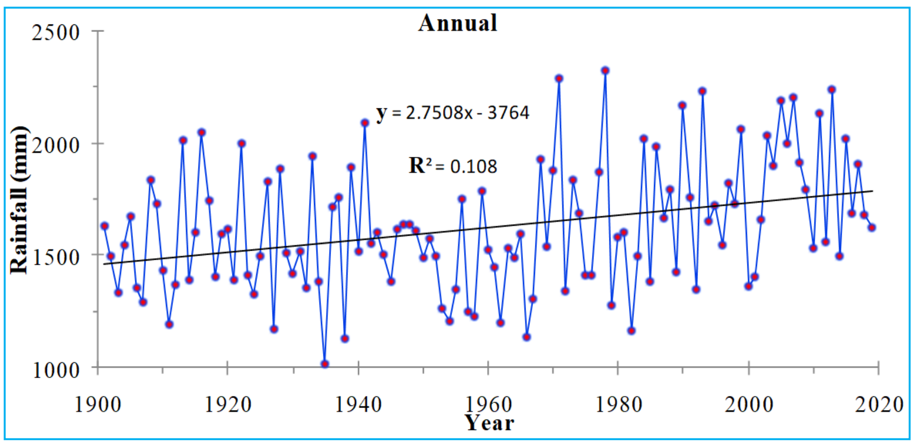


Fig. 6. Annual rainfall (mm) trend of Kolkata (1901-2019)

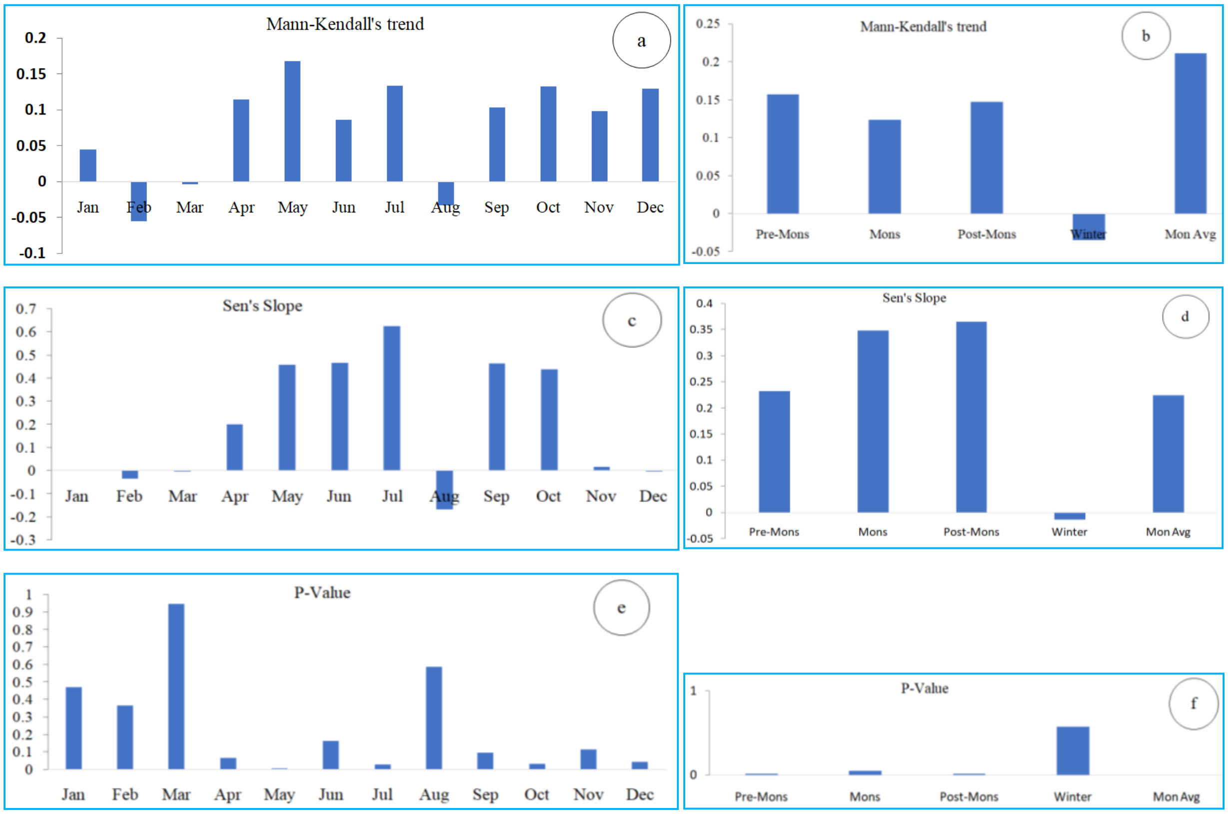
were the lag-1 ACF and PACF for all the series. The results are shown in Table 1 of this document.The significance levels of lag-1 ACF and PACF were determined by comparing the respective values of 95 percent confidence level. The series lag-1 ACF and PACF at the 5 percent level is not to be auto-correlated, not significantand may not be used in further analysis. In this research, the seasonally and annualACF and PACF structuresare being used for trend analysis within the period showing in Fig. 3.

4.3. *Trend analysis*

4.3.1. *Monthly rainfall trend analysis*

Monthly variations in rainfall data (trend) are calculated separately for each month using the statistical method of Mann-Kendall, as well as the slope estimator is computed using Sen's pitch estimator as shown in Fig.4. The statistical changes in monthly precipitation data have been found, which indicates that there has been a rising (upward) trend in certain months and a decline in monthly precipitation data has been shown in other months.

In Fig.7(a), Fig. 7(b) and Table 2, the estimated Man-Kendell and Sen's Slope reveal that nine months (January through December) exhibit growing trends whereas the other three months (February through August) show declining trends. The estimated Man-Kendell and Sen's Slope are displayed in Fig. 7(a); Fig. 7(b) and Table 2. Based on the results of the Man-Kendell and Sen's Slope statistics, the analysis presented in Figs. 7(a and b) revealed that April, May, June, July, September, October and December show a statistically significant increasing trend, whereas January showed a non-significant increasing trend. Due to the negative



Figs. 7(a-f). Mann-Kendall's trend, Sen's Slope and P-Value

values of both the Man-Kendell and Sen's Slope statistics, the month of March exhibits a non-significant falling trend.

4.3.2. *Seasonally rainfall trend analysis*

An investigation of the seasonal rainfall pattern was conducted pre-monsoon (March to May), monsoon (June to August), post-monsoon (September to November) and winter (December to February) are the four seasons utilized, depending on the quantity of rainfall received (December to February. The pre-monsoon, monsoon and posterior monsoon seasons exhibited a considerable upwards tendency with positive values of Man-Kendell and Sen's Slope statistics, whereas the winter seasons exhibited a downward tendency because of the negative values from Man-Kendell and Sen's Slope as shown in Fig. 7(d).

4.3.3. *Annual rainfall trend analysis*

Fig. 6 demonstrates the trend in total yearly rainfall over 119 years.The fact that both Man-Kendell and Sen's Slope statistics were positive indicated that there is an increasing trend with an upward slope of rainfall yearly, as shown in Table 2.

TABLE 4

Statistical Analysis of Rainfall data along with Mann-Kendall Trend, Sen's Slope estimator and P-Value

Series\Test	Kendall's tau	p-value	Sen's slope
January	0.04485	0.47304	0.00428
February	-0.0559	0.3679	-0.0335
March	-0.004	0.94872	-0.0013
April	0.11395	0.06615	0.20269
May	0.16793	0.00677	0.45921
June	0.08617	0.16467	0.46663
July	0.13346	0.03139	0.6271
August	-0.0335	0.58938	-0.167
September	0.10326	0.09588	0.46497
October	0.13203	0.03325	0.44013
November	0.09758	0.11753	0.01778
December	0.12954	0.04509	3.66E-05
Pre-Monsoon	0.15739	0.01115	0.23259
Monsoon	0.12349	0.04645	0.34894
Post-Monsoon	0.14742	0.01745	0.36509
Winter	-0.0349	0.57363	-0.0136
Monthly Average	0.21094	0.00067	0.22488
Annual	0.21094	0.00067	2.69853

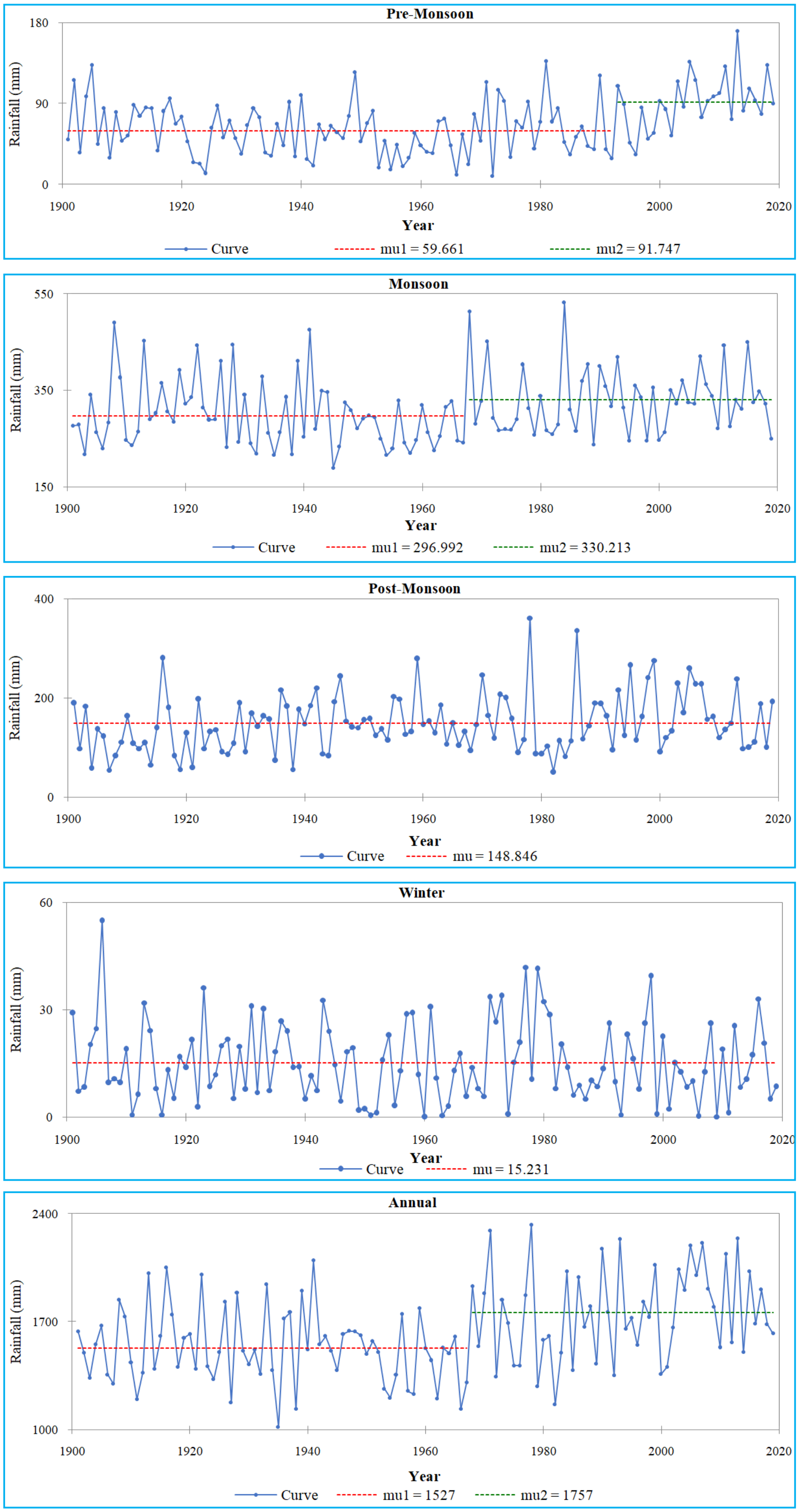


Fig. 8. The Change point of seasonal and annual rainfall data series

TABLE 5

Pettitt test for single change point

Time Series	K_T	Year	p-value (Two-tailed)	alpha
Pre-Monsoon	1430	1992	0.0012	0.05
Monsoon	1088	1967	0.0452	0.05
Post-Monsoon	1020	1930	0.075	0.05
Winter	398	1984	0.2082	0.05
Annual	1552	1967	0.0002	0.05

4.4. *Mann-Kendall Trend and Sen's Slope*

The central tendency parameters (mean and median) were used in the statistical analysis of rainfall data and the dispersion of data from the mean was measured using the standard deviation and coefficient of variance, as shown in Table 1. It's demonstrated 119 observations of minimum, maximum, mean, standard deviation, CV and percent contribution to rainfall data on a monthly, seasonal and yearly basis, as well as their respective standard deviations.

Table 4 shows the Mann-Kendall trend, its statistical significance, as well as the amount of Sen's slope, for rainfall data spanning the years 1901 to 2019.The months of Jan, Feb, Mar, Apr, Jun, Aug, Sep and Nov exhibited no trends with a significance level of 0.05, meaning there is a 95 % possibility of not making a mistake while adopting the trendless Ho (null hypothesis).On the other hand, the months of May, Jul, Oct and Dec showed the trends with a significance level of 0.05, which means there is a 95 % probability of not making a mistake when rejecting the Ho (null hypothesis) and accepting the trend's Ha (alternative hypothesis), similarly in the winter season accepting the Ho (null hypothesis) of no trend and pre-monsoon, monsoon, post-monsoon and annual rainfall rejects the Ho (null hypothesis) and accepts the Ha (alternative hypothesis) of a trend.

4.5. *Rainfall variability patterns*

Predicting and recognizing monthly, seasonal and annual variation patterns in rainfall is important for agricultural, fishing and industrial sectors because it facilitates them to estimate their precise water requirements. Recognizing monthly, seasonal and annual variations is essential for estimating precise water requirements. The outcome of the precipitation variability pattern derived using CVs for the study period indicates considerable inter-annual variations for the district of Kolkata. During winter rainfall data showing the highest value of CV (72.89%), whereas annual rainfall data analysis, the lowest value of CV (17.68%) during pre-monsoon, post-monsoon and monsoon the rainfall value of CV were 47.99%, 40.05% and 22.70%, respectively, whereas the December month showing the highest value of CV (215.80%), the month of August showed the minimum value of CV (30.14) and it's presented in Table 4. It's showing the more inter-annual vulnerability of winter rainfall than other seasonal rainfall. The results of the variability study are consistent with the findings of (Chandniha *et al*., 2017; Warwade *et al*., 2018). Higher rainfall variability was detected during winter rainfall, pre-monsoon rainfall and post-monsoon rainfall, whereas monsoon rainfall and annual rainfall exhibited lower rainfall variability. The entire season, except for the monsoon season, exhibits significant rainfall diversity. In general, there was a lot of fluctuation between years, which indicated that the whole area was very sensitive to droughts and floods in general (Türkeş, 1996; Pandey and Ramasastri, 2001).

From the estimation of rainfall variance (Table 3), it is found that a lower value of the variance of rainfall is responsible for a steeper slope of the trend line and vice-versa. The month of January indicates a variance value of 250.884 (lowest) indicate a lower rainfall trend whereas in June to September (16897.95-17773.06) the variance values about 5001.639 (average) which is indicating the higher trend of rainfall.

4.6. *Single change point (Pettitt test)*

The original Pettitt's test was used to identify change points in the seasonal and annual series at the outset of the study. Table 5 and Fig. 8 display the seasonal and annual values of the test statistic K_T, year, the *p*-value and alpha in which the change point was discovered.At the 5 percent level of significance, the pre-monsoon season has a change point in the year 1992 (p-value 0.0012), while the monsoon and annual data series have a shift or change point in the year 1967 (both with p-values are 0.0452 and 0.0002 respectively), while the alpha is 0.05. On the other hand, in the post-monsoon and winter season, there has

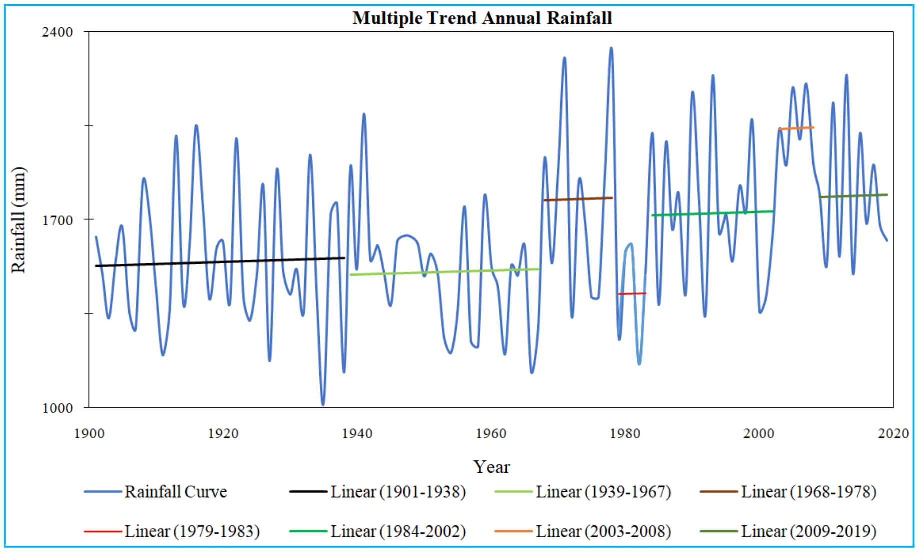


Fig. 9. Multiple trends change points in annual rainfall series

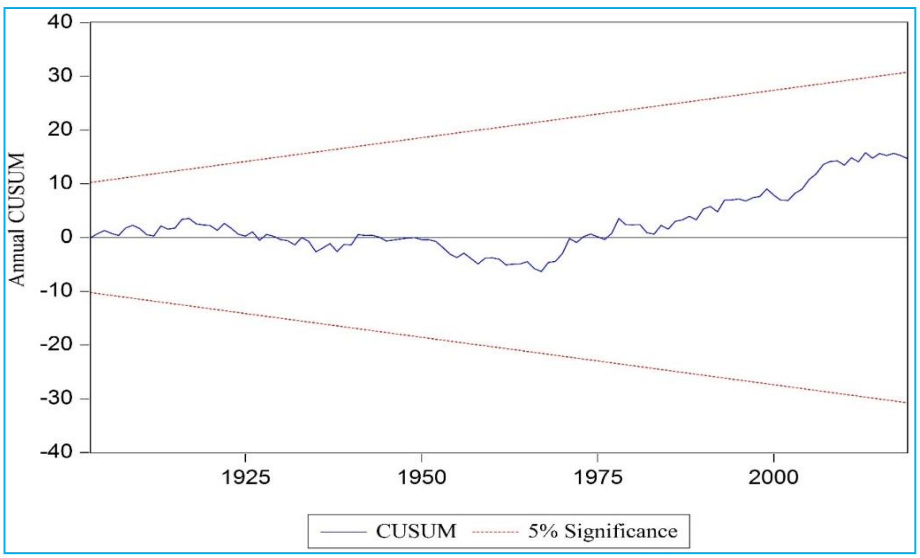


Fig. 10. CUSUM for annual rainfall data series

been no apparent shift and have not been changed points detected (p-value 0.0750 and 2082 respectively).

4.7. *Multiple change points (CUSUM and SegNeigh)*

The CUSUM (Fig. 10), SegNeigh, likelihood andvisualization techniques were used to identify the multiple change points of the trend over the period 1901-2019, which are shown in Fig. 9 as change points. The years 1938, 1967, 1978, 1983, 2002 and 2008 are the years that have been recognized as having several transition points. The *p*-values for the difference in the mean of consecutive segments are defined by multiple change points. Between 1938 and 1983, there is a significant variation in rainfall. By visualizing at Fig. 9, it is also possible to identify these change points.

4.8. *Future Forecasting of the rainfall*

4.8.1. *Linear Regression and SMOreg*

The future forecasting data set for the study region of Kolkata was generated utilizing data from the preceding 119 years, Linear Regression and SMOreg techniques and it was shown in Table 6.There is a statistically

TABLE 6

Future rainfall (mm) Forecasting of Kolkata (2020-2025)

Linear reg	Pre-Monsoon	Monsoon	Post Monsoon	Winter	Monthly Average	Annual
2020*	87.6803	327.428	172.654	16.7362	146.084	1753
2021*	93.4074	369.116	163.119	14.5849	155.752	1869.02
2022*	70.1113	326.369	174.191	13.3553	151.433	1817.2
2023*	85.8146	304.787	184.969	13.0664	147.018	1764.22
2024*	83.1756	342.33	178.493	13.7965	152.264	1827.17
2025*	87.1033	339.654	171.114	14.086	152.105	1825.26
SMOreg	Pre-Monsoon	Monsoon	Post Monsoon	Winter	Monthly Average	Annual
2020*	113.577	377.212	111.327	13.9984	156.794	1880.66
2021*	100.941	351.913	123.33	18.7809	152.261	1825.64
2022*	70.7671	337.385	144.562	14.5493	152.648	1832.69
2023*	98.686	351.742	141.854	12.9097	162.684	1951.09
2024*	70.7346	346.312	149.792	14.8118	149.753	1796.6
2025*	94.9409	347.957	139.998	17.0372	151.938	1822.64

TABLE 7

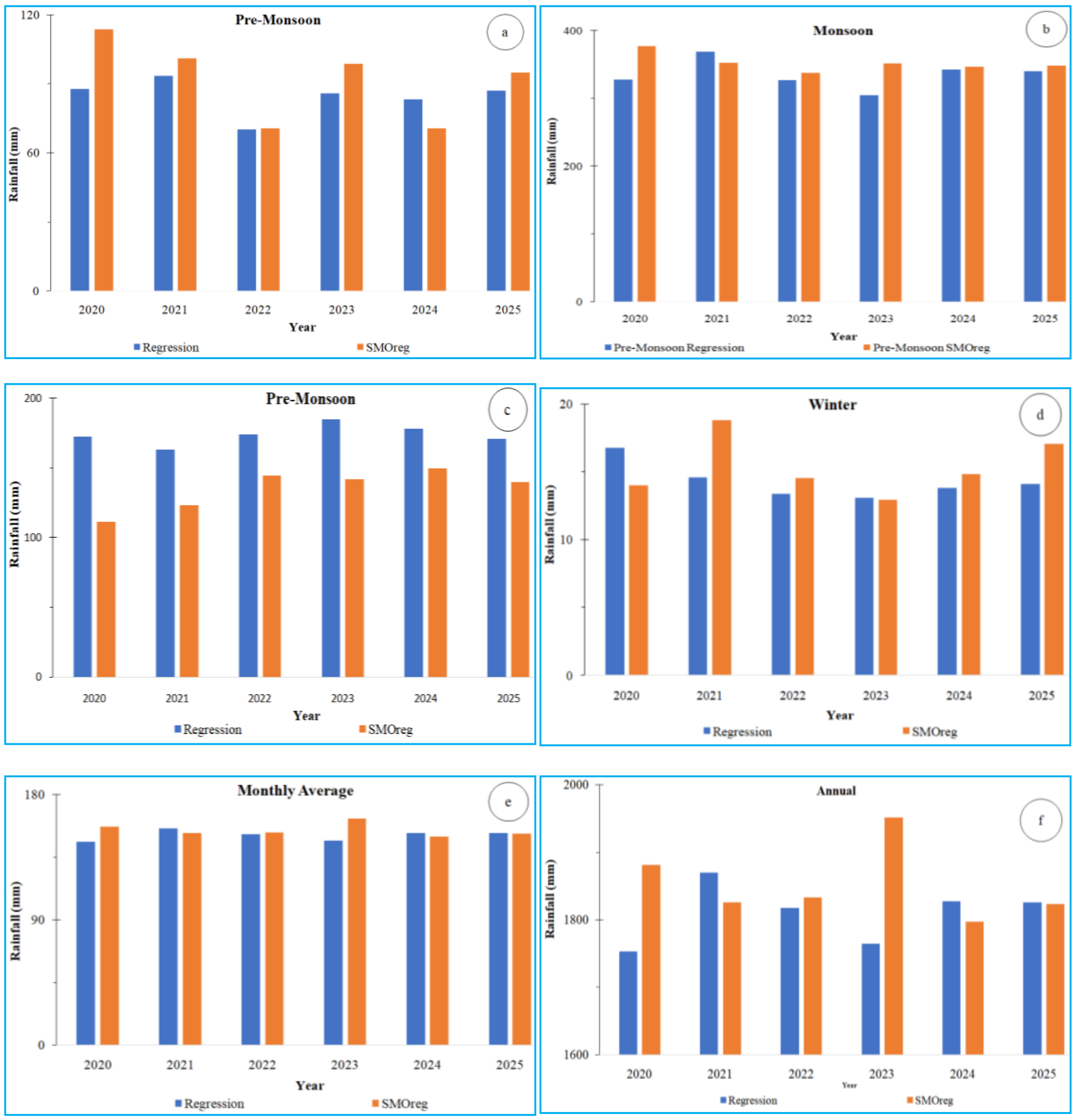
Comparison of Future rainfall (mm) forecasting of Kolkata (2019-2027)

2015	Dev. %	2019	Dev. %	2023	Dev. %	2027
1991.5	-11.4514	1455	-3.77387	1437.39	0	1437.39
2014.5	-11.3767	1481.5	22.06459	1584.46	26.6446	1620.75
2037.5	-11.2914	1508.5	-21.1431	1409.84	-10.0367	1396.17
2060.5	-11.1953	1536	9.283587	1579.32	-10.2056	1565.42
2083.5	-11.1099	1563	-12.5603	1504.39	-15.6828	1483.03
2106.5	-11.0352	1589.5	18.3593	1675.17	24.97063	1709.18
2129	-10.9392	1616.5	-4.46821	1595.65	-8.31865	1584.32
2151.5	-10.8431	1643.5	-6.16334	1614.74	-0.11747	1614.58
2174.5	-10.7577	1670.5	-2.18374	1660.31	-4.02349	1654.83
	100		100		100	

significant difference between the Linear and SMOreg of the pre-monsoon, post-monsoon and yearly rainfall, however, the results for the monsoon and winter are quite different, as shown in Fig. 11. The maximum annual rainfall by Linear regression will be 1869,024mm in the year 2021, but by the SMOreg it will be 1951,088mm in the year 2023, while the minimum annual rainfall by regression will be 1753,003mm in the year 2020, but by the SMOreg it will be 1796,596mm in the year 2024.There is a significant difference in monthly rainfall data between the regression and SMOreg but the amount of the annual rainfall is slightly different between the regression and SMOreg.

4.8.2. *CA-ANN*

The study area, utilizing data from previous years 2015 and 2019, CA-ANN approaches created future prediction data for the 2023 and 2027 years using IDW in ArcGIS 10.5 and demonstrated Table 7 and Fig. 12. Between the years 2015 and 2019, we observed a decreasing deviation (Avg. -11.11) in annual rainfall, with the highest deviation being 22.06 and the lowest deviation being -21.14 between the years 2019 and 2023 and the highest deviation being 26.64 and the lowest deviation being -15.68 between the years 2019 and 2023. Fig. 12 shows the projected rainfall distributions for the years



Figs. 11(a-f). Future rainfall (mm) Forecasting of Kolkata (2020-2025)

2023 and 2027 used to define the base years 2015 and 2019. The southern portion of the study area receives the most rainfall, with 1675.17mm predicted for 2023 and 1709.18mm predicted for 2027.The declining rainfall trend is northward, with 1409.84mm predicted for 2023 and 1396.17mm predicted for 2027.

5. Conclusion

The findings of the research show that there is great variability in the rainfall pattern on a monthly, annual and seasonal basis for analyzing rainfall trends throughout the districts of Kolkata, West Bengal State, India, using the non-parametric statistic Mann-Kendall (MK) and Sen's slope test. The rainfall statistics results of testing suggested that there is a growing tendency in certain months, while the tendency of rainfall decreases in certain other months. Separately nine months (Jan, Apr, May, Jun, Jul, Sep, Oct, Nov and Dec) represent an increasing trend while the other three months (Feb, Mar and Aug) represent declining trends pre-monsoon, monsoon and post-monsoon periods demonstrate increasing trends while winter showed decreasing trends. That the months of Apr, May, Jun, Jul, Sep, Oct and Dec exhibit a substantial upward trend owing to the positive value of both Man-Kendell and Sen's Slope statistics whereas the months of Jan exhibited a non-significant upward trend. Due to the negative values of both the Man-Kendell and Sen's Slope statistics, the month of March exhibits a non-significant falling trend. The trend of the whole data set on an annual basis revealed a positive growing tendency throughout the period. During the mentioned period, the

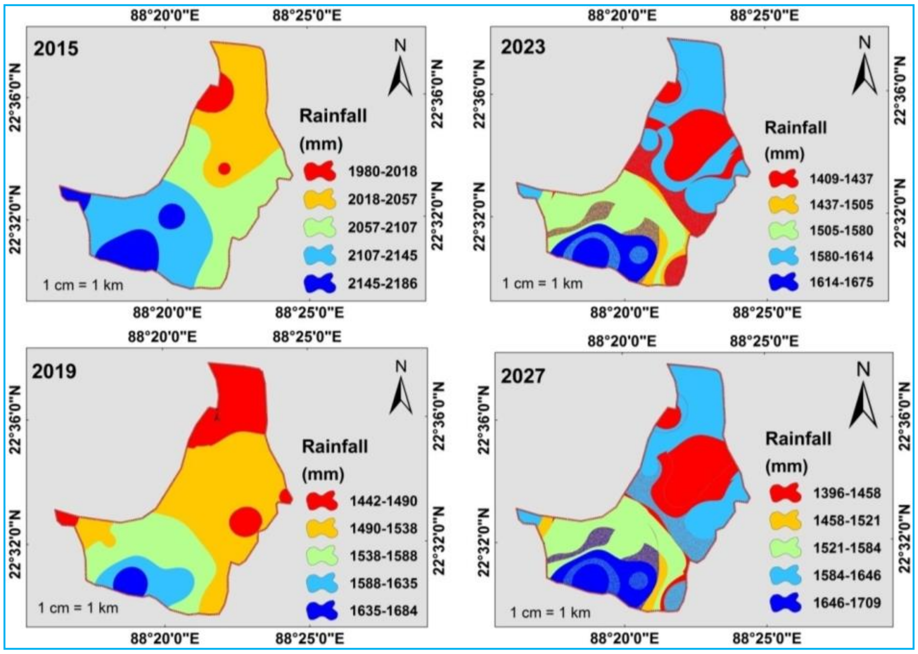


Fig. 12. Comparison of Future rainfall (mm) Forecasting of Kolkata (2015-2027)

annual mean rainfall was 1627.58 mm, with the highest annual rainfall of 2326.694 mm recorded in the year 1978 and the lowest annual rainfall of 1635.988 mm recorded in the year 1935. The Monsoon season delivers a maximum of 57.42 % oftotal annual rainfall in Kolkata districts; whilst winter accounts for the lowest 2.81 %. The greatest increase in rainfall was seen during the post-monsoon season (0.365091 mm year^{-1}), with the smallest increase (0.232591 mm year^{-1}) occurring during the pre-monsoon season. A tendency of water shortages occurred in winter (-0.01356 mm year^{-1}). The rainfall variability pattern was determined using coefficient CV, %. Winter rainfall exhibited the highest CV value (72.89%), but yearly rainfall showed a low CV value (17.68%). In general, there was a significant CV variation which indicated the whole area is highly susceptible to drought and flood.After analyzing NCEP/NCAR data it is found thatover the Bay of Bengal here decrease the tropical easterly jet stream, for the causes monsoon depression during the south-west monsoon season and plays an important role in bearing rain during the southwest monsoon found declining cyclonic storm frequency across the Indian Ocean (1981-1997). Reducing the jet stream strength and reducing the cyclonic storm over the Indian Ocean may explain the loss in rainfall over the study region. For future forecasts, there is a considerable difference in monthly rainfall data between linear regression and SMOreg, while the annual rainfall is little difference between linear regression, SMOreg and CA-ANN analysis. The conclusions and findings of the rainfall data analysis might play a vital role in better district management of farming practices, hydropower production, water resource management and weather forecasting.

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Author statement

All authors officially confirm that they take part well enough in the present research work to take public responsibility for the subject matter, including involvement in the concept, design, assessment, writing, or revised version of the manuscript. Furthermore, each person who wrote this article confirms that this material or similar material has not been and will not be submitted to or published in any other media outlet before its appearance in the MAUSAM journal.

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Abbreviations

CA-ANN	:	Cellular Automata-Artificial Neural Network
CHRS	:	Centre for Hydrometeorology and Remote Sensing
CUSUM	:	Cumulative Sum
CV	:	Coefficient of Variation
IDW	:	Inverse Distance Weighting
IMD	:	Indian Meteorological Department
IPCC	:	Intergovernmental Panel on Climate Change
MK	:	Mann-Kendall
NASA	:	National Aeronautics and Space Administration
SMOreg	:	Sequential Minimal Optimization