



## Analysis of summer monsoon rainfall: Sustainability of long-term modelling by machine learning methods

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**सार** – भारतीय मानसून भारतीय उपमहाद्वीप में अत्यंत महत्वपूर्ण सामाजिक-आर्थिक महत्व की एक विशिष्ट मौसम संबंधी घटना है। एक सदी से अधिक समय तक फैले उपलब्ध भारतीय और क्षेत्रीय डेटासेट के विश्लेषण से वर्षा की परिवर्तनशीलता के बारे में महत्वपूर्ण जानकारी मिलती है। भारतीय ग्रीष्मकालीन मानसून वर्षा (आईएसएमआर) और केरल ग्रीष्मकालीन मानसून वर्षा (केएसएमआर) के लिए दो प्रमुख विशेषताओं - दीर्घकालिक प्रवृत्ति और परिवर्तन बिंदु - का विश्लेषण किया गया है। केरल को इसलिए चुना गया है क्योंकि यह भारत में मानसून के आरंभ का प्रतीक है। आईएसएमआर और केएसएमआर दोनों के लिए 95% विश्वास स्तर पर कोई प्रवृत्ति नहीं होने की शून्य परिकल्पना के तहत, गैर-सामान्य डेटा में एकसमान प्रवृत्तियों का पता लगाने के लिए उपयुक्त गैर-पैरामीट्रिक मान-केंडल परीक्षण का उपयोग करके प्रवृत्ति विश्लेषण किया गया। वर्षा पैटर्न में बदलाव दर्शाने वाले परिवर्तन बिंदुओं की पहचान बायेसियन परिवर्तन बिंदु पहचान विधि का उपयोग करके की गई। मौसमी वर्षा का पूर्वानुमान योजना और शासन के लिए महत्वपूर्ण है, और मशीन लर्निंग मॉडल सटीक मौसम संबंधी पूर्वानुमान के लिए सिद्ध उपकरण हैं। हालांकि, क्या ऐसे पूर्वानुमान दीर्घकालिक सांख्यिकीय विशेषताओं को बनाए रख सकते हैं, यह अभी भी अनसुलझा है। इस अध्ययन में, हमने यह आकलन करने के लिए मशीन लर्निंग मॉडल विकसित किए कि क्या पूर्वानुमान परिवर्तन बिंदु अंतरालों में देखी गई प्रवृत्तियों और मापदंडों को संरक्षित करते हैं। सर्वश्रेष्ठ प्रदर्शन करने वाले LSTM मॉडल (लैग = 12) ने 147 (प्रशिक्षण) और 167 (परीक्षण) का RMSE प्राप्त किया, जिसमें सहसंबंध  $\geq 0.85$  था। इसने 5 में से 4 प्रेक्षित ब्रेक पॉइंट्स को पुनः प्रस्तुत किया और मैन-केंडल प्रवृत्ति परिणामों से मेल खाया। निष्कर्ष दर्शाते हैं कि ML-आधारित दीर्घकालिक मौसमी मानसून मॉडलिंग बहु-दशकीय अवधियों में प्रवृत्तियों, ब्रेक पॉइंट्स और सांख्यिकीय मापदंडों को बनाए रख सकती है।

**ABSTRACT.** The Indian monsoon is a distinct meteorological phenomenon of vital socio-economic importance in the Indian subcontinent. Analysis of available Indian and regional datasets spanning over a century provides critical insights into rainfall variability. Two major characteristics - long-term trend and break points - have been analysed for Indian summer monsoon rainfall (ISMR) and Kerala summer monsoon rainfall (KSMR). Kerala is selected as it marks the onset of monsoon in India. Trend analysis was performed using the non-parametric Mann-Kendall test, suited for detecting monotonic trends in non-normal data, under the null hypothesis of no trend at the 95% confidence level for both ISMR and KSMR. Break points, indicating shifts in rainfall regimes, were identified using a Bayesian change point detection method. Prediction of seasonal rain is vital for planning and governance, and machine learning models are proven tools for accurate meteorological prediction. However, whether such predictions can sustain long-term statistical characteristics remains underexplored. In this study, we developed ML models to assess if predictions preserve the observed trends and parameters across break point intervals. The best-performing LSTM model (lag = 12) achieved RMSE of 147 (train) and 167 (test) with correlations  $\geq 0.85$ , reproducing 4 of 5 observed break points and matching Mann-Kendall trend results. The findings demonstrate that ML-based long-term seasonal monsoon modelling can retain trends, break points, and statistical parameters over multi-decadal horizons.

**Key words** – Autocorrelations, Mann-Kendall test, Bayesian change point test, Break points.

### 1. Introduction

Rainfall is a crucial aspect of ecosystem. Humans, animals, birds, plants, in fact the complete biodiversity is dependent on rain for its survival. Growth

of many industries like agriculture sector, fertilizers, agrochemicals, automobiles, and powerhouse etc. directly or indirectly relies on rain. Thus, even a small variation in rainfall can cause a huge impact on Indian economy. Henceforth, it is necessary to understand and foresee

monsoon trend, onset of monsoon, how long it will last, and its intensity to have beforehand planning for managing water resources, finances, power, agriculture, and daily livelihood concerns faced by the common citizens. Consequently, this subject is utmost crucial and has been the focus of the whole research community for generations. Approaches to weather forecasting (Goyal et al., 2023) can broadly be classified into numerical methods (Palmer et al., 2004; Adcroft et al., 2004; Mellor et al., 1998; Pacanowski et al., 1993) and statistical methods (Tripathi et al., 2006; Shukla et al., 2011; Praveen et al., 2020; Dash et al., 2019; Rajan & Desamsetti, 2021; Liyew et al., 2021). Numerical methods involve mathematical equation representing the complex behaviour of atmosphere and ocean. Statistical methods, on the other hand, involve the study and analysis of huge dataset using machine learning techniques to infer the future outcome. Both approaches follow different methods to foresee climatic conditions such as long-range forecast (Munot et al., 2007; Mitsui et al., 2021) which involves predicting weather and climate conditions that are several weeks to months in advance. Medium-range forecasting (Prakash et al., 2016) covers a period of several days to many weeks to monitor and predict the behaviour of the monsoon and short-range forecast (Kumar et al., 2022; Ashok et al., 2022) spans the time from next few hours to 2-3 days.

Many hybrid and ensemble models have been explored on basis of above-mentioned methods in various researches for forecasting weather. But still more thorough historical and paleoclimate records are required to comprehend long-term trends and inherent variability in monsoon patterns of climatic data, which will aid in the analysis and comprehension of monsoon drift. An important aspect of weather is the Indian monsoon which has attracted the attention of meteorologists across the world (Gadgil et al., 2003; Saha et al., 2017; Saha et al., 2021; Kumar & Singh, 2021). When investigating the Indian rainfall researchers are interested in two broad aspects- the seasonal prediction of the monsoon rain (long range forecast) and short-range forecasts. The spatial resolution ranges from All India Rainfall (AIR) to regional rainfall (north-west, north-east, central, southern peninsula) and 36 meteorological subdivisions of India (Kelkar et al., 2020).

The objective of this paper is to study the monsoon patterns (i.e. seasonal rainfall recorded in the months of June-July-August-September abbreviated as JJAS) of all India and all 36 subdivisions of India in last 122 years with a special focus on Kerala. The seasonal rainfall recorded in JJAS period over the All India is termed as Indian Summer Monsoon Rainfall (ISMR). Hereafter the seasonal JJAS rainfall that occurs across Kerala is referred to as Kerala Summer Monsoon Rainfall (KSMR).

The study aims to find (i) any trend over time in last 122 years in ISMR and KSMR, (ii) the break points in the time series of ISMR and KSMR and (iii) if statistical models can reconstruct this deviation in trends and break points.

The statistical models developed for the above are machine learning models that employ state of the art learning algorithms for prediction and classification (Dangeti, 2017). These include Random Forest, Support Vector Machine, Recurrent Neural Network and Long Short-Term Memory. Model development to achieve accurate prediction is just a step, real objective is to ensure sustainability so that the models remain reliable and robust over extended time periods, demonstrating stable performance across multiple years and under varying climatic conditions. A seemingly good model with low RMSE may, in fact, fail to retain the quality of predictions when long term trends are considered. Such models may be “accurate” but not “sustainable”. This is explored in this study in context of ML models.

The remaining structure of the paper is organised as follows: section 2, summarizes the related work in monsoon prediction studies. Section 3 explains the dataset used for this work. Section 4, presents the methodology of the proposed work. Section 5 examines the results and finally paper Section 6 concludes the paper.

### 1.1 Literature Review

Extensive research has focused on developing models to simulate and predict the complex behaviour of the Indian summer monsoon under varying climatic influences. Conventional approaches such as regression analysis and empirical orthogonal functions have laid the groundwork for understanding monsoon behaviour, yet they often struggle to effectively represent the system’s non-linear characteristics and rare extreme events. In recent developments, machine learning and deep learning techniques have shown considerable promise in enhancing prediction accuracy by utilizing vast datasets and uncovering intricate patterns among climatic variables. A comprehensive review of recent literature, summarized in Table S1 (supplementary), outlines the methodologies, datasets used, performance indicators, and key findings across various studies. Despite these advancements, concerns persist regarding the reliability and sustainability of these predictive models-particularly in the context of evolving climate conditions. Ensuring long-term effectiveness requires models that are not only accurate but also stable, adaptable, and transparent, to support dependable decision-making in diverse and dynamic scenarios.

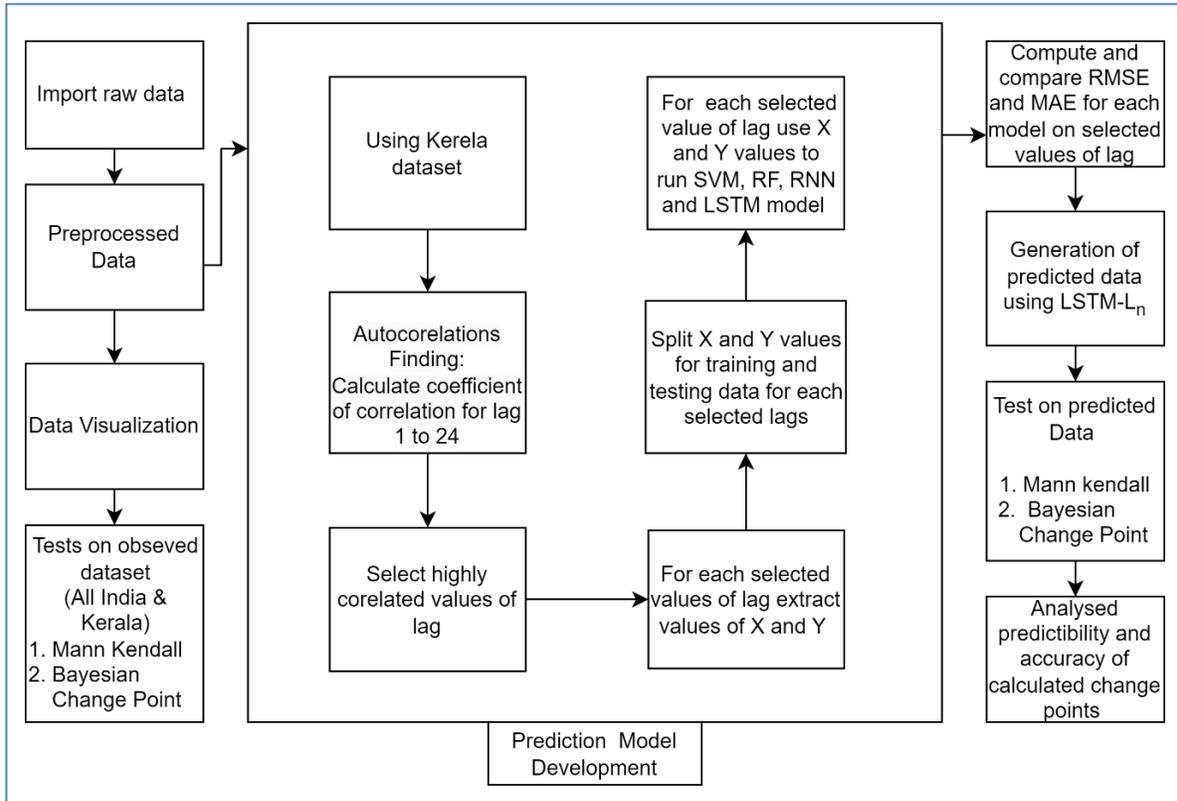


Fig.1 Proposed Methodology Framework.

## 2. Data and methodology

### 2.1 Data

The rainfall time series is taken from India Meteorology Department (IMD) (<https://impune.gov.in>). The website contains comprehensive data sets at various spatial and temporal resolutions. For the present study we have used the 122 years (1901-2022) monthly record of subdivisional rainfalls. The subdivisions have been defined in section 1. There are multiple observatories (rain gauge stations) that give daily, monthly, or seasonal rainfall measurements. The following methodology of calculating rainfall from rain stations is used in preparing the data (<https://www.imdpune.gov.in>, <https://data.gov.in>): Monthly rainfall: Sum of daily rainfalls observed at a station for all the days of the month.

District series: Simple arithmetic mean of the monthly rainfall data of all the available stations in the district for a particular month.

Subdivision and state series: Calculated by district area weighted average method.

All India series (AIR): Calculated by subdivision area weighted average method.

The weights in subdivisional and AIR are proportional to the geographical area.

$$R_{All\ India} = \sum_{s=1}^{36} \beta_s R_s \quad (1)$$

Where  $R_{All\ India}$ : All India rainfall,  $\beta_s$ : weight assigned to subdivision 's',  $R_s$ : Rainfall of subdivision 's'

This research work presents a holistic framework to identify drift in Indian monsoon using rainfall data of all 36 subdivisions of India. Monsoon patterns of the subdivisions have been investigated for significant trend, shifts or notable changes. An attempt has been made to construct machine learning models for long-range seasonal forecasting of Kerala subdivisions. The framework is presented in fig. 1.

In the sub sections below, we have discussed the methodology in the light of the framework depicted above.

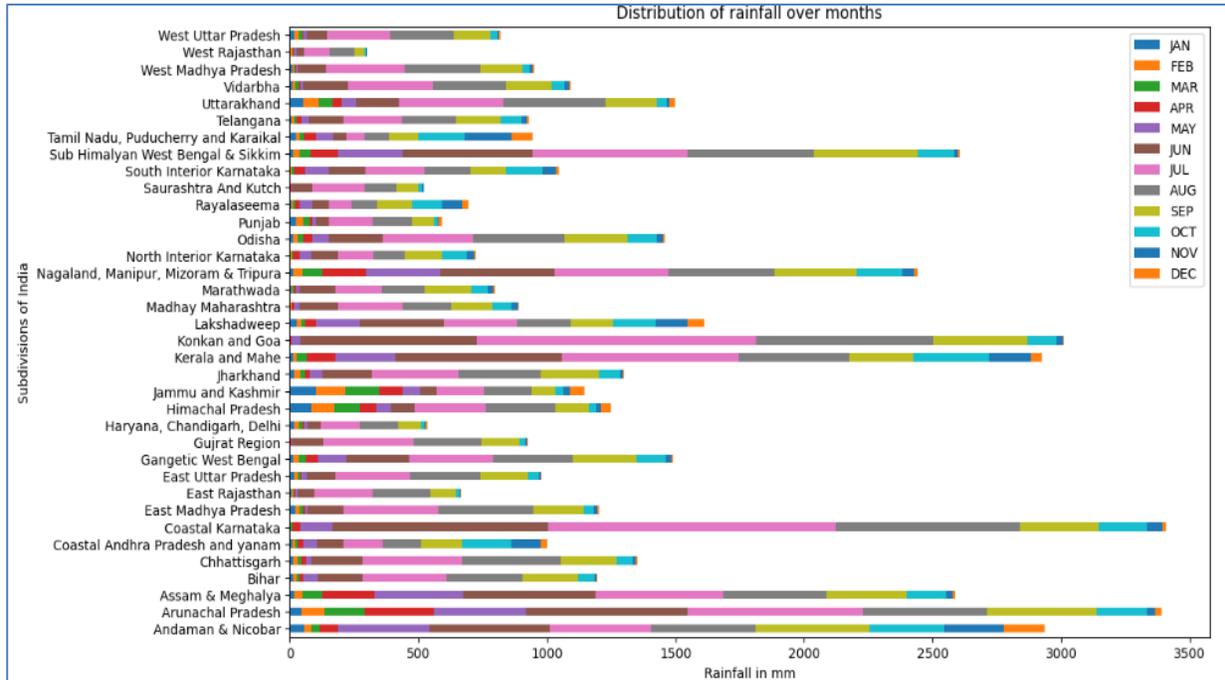


Fig. 2. Average monthly rainfall of 36 subdivisions of India

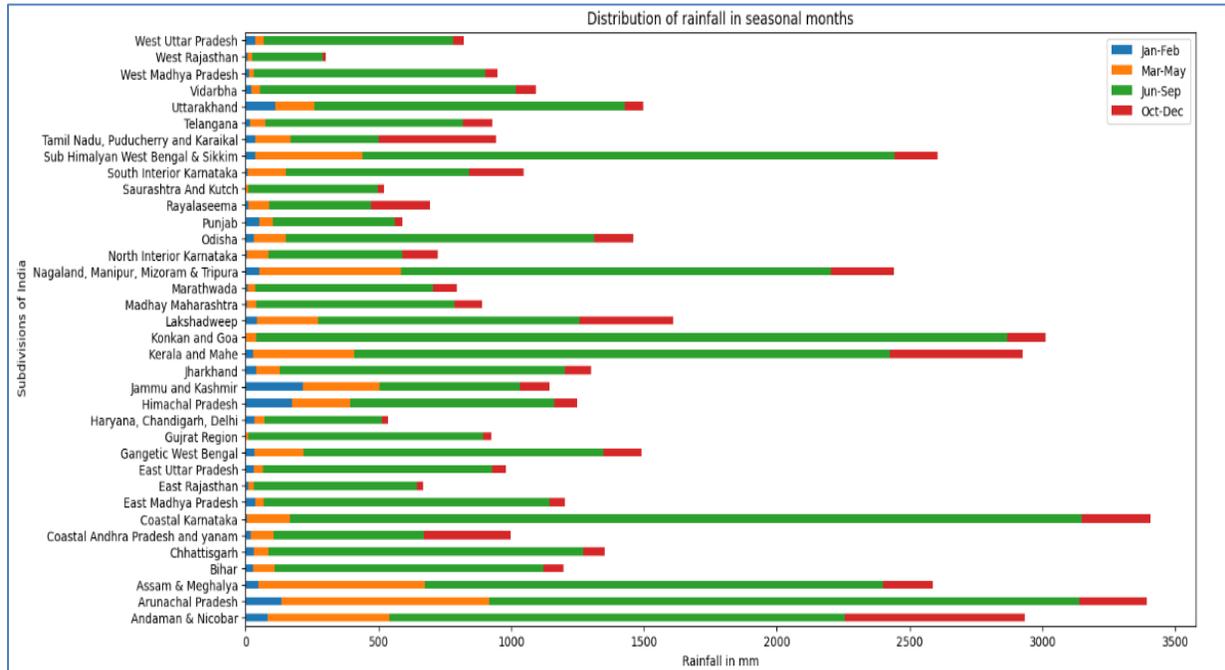


Fig. 3. Average seasonal rainfall of 36 subdivisions of India

2.1.1 Raw data

As listed in section 3, the raw data is taken from the IMD website (<https://imd pune.gov.in>) which is freely available.

2.1.2 Data Preprocessing

With daily, monthly, and annual rainfall levels recorded, the data is rich in diversity and detail. Kerala and Mahe’s data have been extracted from the dataset of 36 subdivisions.

### 2.1.3 Data Visualization

Data has been visualized from different perspectives to understand seasonality and trend. Fig. 2 depicts average monthly rainfall distribution of 36 subdivisions of India. It is evident that the observations are dominated by precipitation in June, July, August, and September. Seasonal rainfall is calculated by simply adding up the rainfall in each of the months that contribute to the season at the specific geographical area. Fig. 3 represents average seasonal rainfall of the subdivisions. The monsoon season (JJAS) depicts highest records.

### 2.1.4 Tests on observed dataset (identifying trends and change points)

#### 2.1.4.1 Trend in the series

To quantify the trend in the time series, Mann Kendal (MK) (Sudarsan & Lasitha, 2023) test was performed. This test is preferred in the current scenario over the regression line trend for few reasons- (i) MK test is non-parametric that does not assume any specific distribution or form, (ii) it uses rank correlation to assess the direction and significance, (iii) it is better suited for non-linear data (iv) outliers are better treated, (v) sensitive to order rather than magnitude and (vi) trend direction and strength are better quantified. At a later stage when we build model of prediction, the tests and prediction results are analysed. The following assumptions are used:

- (i) Observations are independent, meaning thereby that observation recorded at any point in time has no bearing on the observation recorded at subsequent times. It does not mean the time series is independent.
- (ii) The nature of trend is not assumed.

Further, we have used the JJAS seasonal rainfall and not the entire time series. The reason for this is there is a large variance among the rainfalls of individual months. The JJAS accounts for about 70% of total annual precipitation. Hence the data is largely biased towards JJAS. Keeping only the seasonal data maintains uniformity in the time series.

The argument in the MK test in the present case is all about existence of a positive trend, negative trend, or no trend. A brief description of is presented below:

$$S = \sum_{i=1}^n \sum_{j=i+1}^n \text{sgn}(x_j - x_i) \quad (2)$$

where the inner function is defined as:

$$\text{sgn}(x_j - x_i) = \begin{cases} 1, & x_j > x_i \\ -1, & x_j < x_i \\ 0, & x_j = x_i \end{cases} \quad (3)$$

The MK test has been applied on the Indian summer monsoon rainfall (ISMR) data as well as the Kerala summer monsoon rainfall (KSMR). The reason for choosing Kerala is that the summer monsoon strikes the Indian coast from Kerala and any major deviation in onset of KSMR can lead to significant deviations in other subdivisions.

#### 2.1.4.2 Break points in the series

Change points (Gallagher et al., 2013), also called break points or structural breaks, reflect the points in time where in vital statistics of the time series, such as the mean, variance, or trends, undergo significant changes. In the context of Indian monsoon change points may indicate a shift in climate pattern (like monsoon onset or retreat). Detection of change points is crucial for understanding shifts in monsoon drift and rain patterns. These points may reflect on the future behaviour of the parameter. Sudden changes in the future behaviour during the prediction process may render the prediction inaccurate, if there are change points in the near future. Knowledge of the future behaviour of the system based on change points coupled with the estimation of the future points by statistical or numerical models may give accurate picture of the future behaviour.

Consider a time series  $X = \{X_t: 1 \leq t \leq T\}$ . A change point is a temporal point ' $\tau$ ' such that some statistical property of  $X$  change after  $\tau$  i.e.

$$X_t = \begin{cases} f_1(\theta_1), & t = 1, 2, \dots, \tau \\ f_2(\theta_2), & t = \tau + 1, \tau + 2, \dots, T \end{cases} \quad (4)$$

where  $f_1$  and  $f_2$  are the governing distributions before and after the change point  $\tau$ .  $\theta_1$  and  $\theta_2$  are the sets of parameters of the distributions. Usually,  $f_1$  and  $f_2$  are same and only the parameters may change. Further, for practical purposes we may assume  $f_1$  and  $f_2$  to be normal distributions and  $\theta_1$  and  $\theta_2$  to be mean and standard deviations i.e.  $\theta_1 = (\mu_1, \sigma_1)$  and  $\theta_2 = (\mu_2, \sigma_2)$  where  $\mu_1$  and  $\mu_2$  are means and  $\sigma_1$  and  $\sigma_2$  are standard deviations. We have used Bayesian method to detect break points in the ISMR and KSMR time series.

#### 2.1.5 Autocorrelation and lag correlation analysis

Autocorrelation (Tabari et al., 2011) measures the

Table 1

Key hyperparameters used in the training of the ML models used

Model	Hyperparameter	Value	Function
<b>SVM</b>	Kernel	'rbf'	Captures non-linear patterns in data
<b>Random Forest</b>	n_estimators	100	Specifies number of decision trees in the ensemble.
	random_state	42	Ensures reproducibility of results
	units (SimpleRNN)	64	Number of units in the SimpleRNN layer to capture temporal dependencies
<b>RNN</b>	input_shape	(1, 1)	for one time step and one feature
	optimizer	'adam'	for adaptive learning
	loss	'mean_squared_error'	for regression
	epochs	1000	Number of training iterations
	batch_size	1	Training with one sample at a time.
	units (LSTM)	64	Number of units in the Simple RNN layer to capture temporal dependencies
<b>LSTM</b>	input_shape	(1, 1)	for one time step and one feature
	optimizer	'adam'	for adaptive learning
	loss	'mean_squared_error'	for regression
	epochs	1000	Number of training iterations
	batch_size	1	Training with one sample at a time.

strength of association between  $\{X_i: 1 \leq i \leq n\}$  and  $\{X_{i+l}: 1 \leq l \leq \tau; 1 \leq i \leq n+l\}$ , the length of the sequence being  $L = n + \tau$ . Utilizing autocorrelation can help predictive model to learn more about temporal dependencies required to decide predictors when modelling a time series. Autocorrelation is a widely accepted and interpretable method that allows us to detect repeated patterns or persistence over time, which is particularly relevant for data like rainfall that often exhibit seasonal or cyclical trends. Other methods over autocorrelation could have also be chosen but fig. 8 in section 5 shows significant correlation values like 0.78, 0.77, 0.88, 0.77, 0.76 and 0.87 at lag 1, 11, 12, 13, 23 and 24 respectively which makes it sufficient to determine lag predictors.

As pointed out earlier, considering the importance of Kerala and Mahe in the Indian monsoon, the model will be built using the Kerala and Mahe dataset. Therefore, the autocorrelations have been computed exclusively for the Kerala and Mahe subdivision.

#### 2.1.6 Prediction models

We have developed four machine learning models for long term modelling of the rainfall- Random Forest (RF) (Uddin et al., 2022), Support Vector Machine (SVM) (Hayaty et al., 2023), Recurrent Neural Network (RNN) (Kang et al., 2020) and Long Short-Term Memory (LSTM) (Poornima & Pushpalatha, 2019).

The key hyperparameters used in the training of above-mentioned models has been briefed in table 1. The

selected models reflect both conventional machine learning (RF, SVM) and deep learning (RNN, LSTM) methodologies. This makes sure that methods with various strengths like interpretability (RF), flexibility (SVM), and the capacity to describe sequential dependencies (RNN, LSTM) are thoroughly evaluated.

Previous studies pertaining to time-series forecasting and rainfall prediction have made substantial use of these models. They are deemed suitable for this domain because of their well-documented performance in the literature. As discussed in section 4.5 autocorrelation analysis has been done to select the predictors.

The data set is prepared as  $D = \{(x_t, x_{t+l}) | l = 1, 11, 12, 13, 23, 24\}$  where the first element is input and the second target. After training, models have been compared with respect to two performance metrics Root Mean Square Error and Mean Absolute Error.

### 3. Results and discussion

#### 3.1 MK test applied on Indian summer monsoon rainfall (ISMR)

Z-score is calculated by standard statistical methods (Meyer, 1965). The null hypothesis  $H_0$  is taken to mean “the time series doesn’t display any trend” which may be construed to mean “the data is randomly ordered”.

The critical Z-values are approximately 1.96 for 95% confidence and 2.58 for 99% confidence.

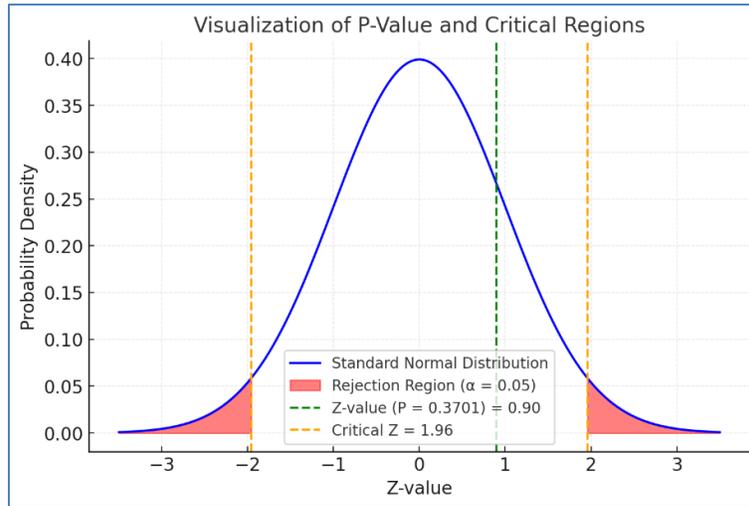


Fig. 4. Two tailed test result on ISMR data set. The p-value (0.3701) lies within the acceptance region

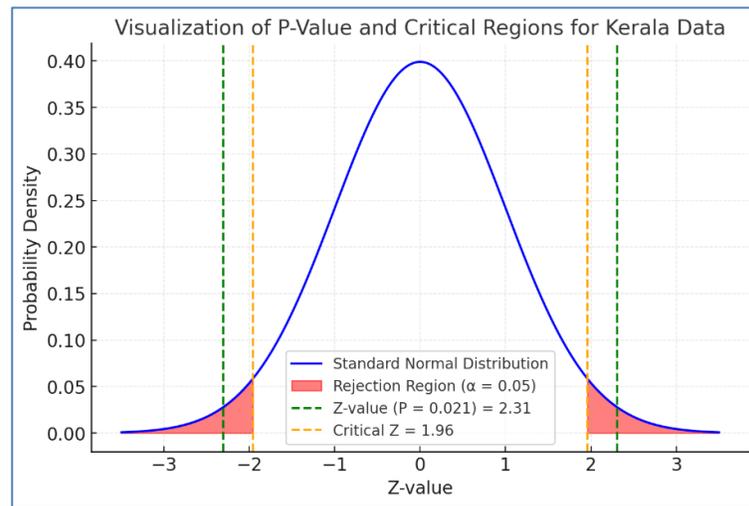
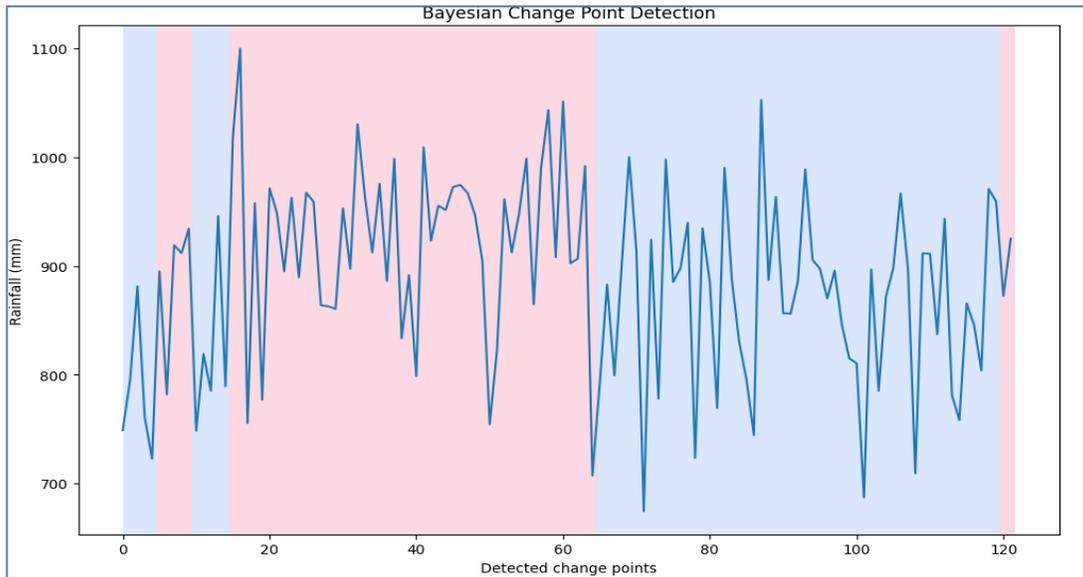


Fig. 5. Two tailed test result on KSMR data set. The p-value (0.021) lies within the rejection region

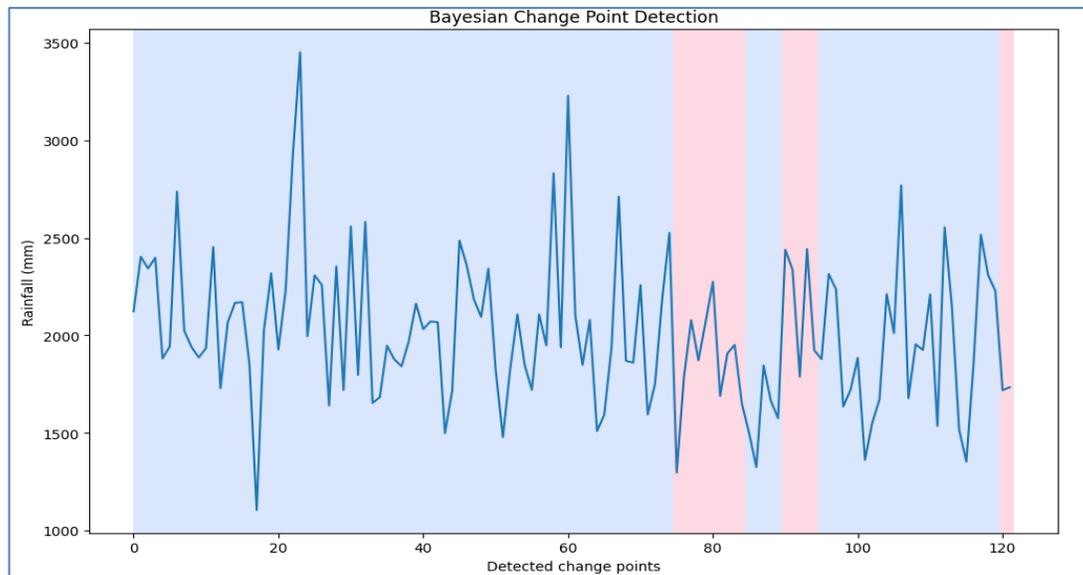
In the present case we have worked with probability values (or p-values). Since the null hypothesis is about the existence of trend and not about the magnitude, we performed two-tail test. A p-value of 0.3701 is obtained. Interpretation of this p-value along with standard regions for 95% confidence (or significance  $\alpha = 0.05$ ) is shown in fig. 4. The critical z-value at 95% confidence is 1.96 as shown in the fig. 4. The z-value corresponding to the obtained p-value (0.3701) is 0.90. As the p-value is clearly inside the acceptable range, with z-value significantly less than the critical value, the hypothesis is accepted, and we deduce that the data does not show any trends. The value of Kendall's  $\tau$  is -0.0549 indicating a very weak negative trend. Since the p-value test is in the acceptance region this slight negative trend

may be due to random and local variations rather than system dynamics. These two observations lead to the conclusion that null hypothesis cannot be rejected or that there is no significant trend. This is a vital conclusion as the calculations were performed on 122 years long seasonal time series. Similar analysis on the KSMR gives the p-value 0.021 and  $\tau = -0.14$ . The result is presented in fig. 5.

As seen from fig. 5, the hypothesis of “no trend” must be rejected. The value  $\tau = -0.14$  indicates weak negative trend. This negative trend, though weak, is statistically significant. The reason for this trend cannot be statistically ascribed to local processes or random events. The dynamics of the system must be investigated for



**Fig. 6:** Detection of Multiple change points in ISMR Bayesian change point analysis



**Fig. 7:** Detection of Multiple change points in KSMR Bayesian change point analysis

meteorological reasons (Goyal et al., 2024). That the KSMR has a weak decreasing but statistically significant trend whereas the ISMR has statistically non-significant trend can be explained by the fact that Kerala is located on the windward side of the Western Ghats and is directly influenced by the Arabian Sea branch (Ramesh et. Al., 2009), leading to early, intense rainfall. Oceanic drivers such as the Indian Ocean Dipole, ENSO, and regional Indian Ocean warming episodes also exert a disproportionate influence on the early monsoon rainfall over Kerala. By contrast, ISMR represents an area-weighted average over 36 meteorological subdivisions,

where variability in individual regions tends to offset each other, resulting in no significant long-term trend.

### 3.2 Bayesian break points analysis

Bayesian test (Harlé et al., 2016) has been applied on ISMR and KSMR. Fig. 6 represents seasonal time series of ISMR for the entire span of 122 years. The change points are observed at time steps  $T$ :

$$T = \{5, 10, 15, 65, 120\} \tag{5}$$

**Table 2****Parameters of normal distribution in the intervals obtained (ISMR)**

Range	Years	Mean ( $\mu$ )	Standard Deviation ( $\sigma$ )
0-5	1901-1906	800.55	71.84
6-10	1907-1911	859.08	86.94
11-15	1912-1916	871.48	104.88
16-65	1917-1966	921.41	104.88
66-120	1967-2021	870.09	82.68

**Table 3****Parameters of normal distribution in the intervals obtained (KSMR)**

Range	Years	Mean ( $\mu$ )	Standard Deviation ( $\sigma$ )
0-75	1901-1976	2068.62	401.28
76-85	1977-1986	1877.68	231.09
86-90	1987-1991	1769.82	418.54
91-95	1992-1996	2073.76	294.53
96-120	1997-2021	1954.90	384.63

The parameters (mean and standard deviation) of the time series obtained in these intervals are depicted in table 2.

The numbers indicate swift change in parameters from 1901 to 1915. Although the mean does not vary much, the standard deviation shows a significant change in during 1912-1916. This represents relatively stable monsoon conditions. The high standard deviation of about 105 in the mid-20<sup>th</sup> century indicate abrupt monsoon rain. These may be attributed to ENSO variability (Krishnamurthy et al., 2000; Kumar et al., 2006), Pacific Decadal Oscillations (Krishnan, R., & Sugi, M., 2003; Krishnamurthy, & Krishnamurthy, 2014), Post-War aerosol emissions (Ashok et al., 2001) and Indian Ocean warming (Ashok et al., 2001; Joseph, & Zeng, 2011). An outcome of these were the 1965 floods. A long span of 54 years (1967-2021) did not witness much variability although there may be intermittent years that saw fluctuations. These are small variations and did not affect the climatology on large scale.

Fig. 7 represents seasonal time series of KSMR for the entire span of 122 years. The change points are observed at time steps:

$$T = \{75, 85, 90, 95, 120\} \quad (6)$$

The parameters (mean and standard deviation) of the time series obtained in these intervals are depicted in table 3.

Results suggest shifts in the rainfall regime, potentially linked to changes in regional climate patterns or local factors. The rain patterns demonstrate high variability in the initial long spells 1901-1976 and a small period of 1987-1991. The increase in the mean rainfall after the third breakpoint (from 1769.82 to 2073.76 in the fourth interval) suggests a return to higher rainfall levels and further followed by a small decline in the last interval 1996-2020.

The recent observations indicate return to usual variability. It may be noted that while the ISMR is most variable during 1912-1966 (104.88) the KSMR is more variable during 1901-1976 (401.28). This can be understood as the KSMR drives the ISMR on most occasions. However, there is a stark difference. More break points in the ISMR are observed during the initial periods of observations (1901-1916) while for the KSMR maximum breakpoints are observed during the last periods (1987-2021). This may be attributed to local factors like western disturbances influencing the KSMR. These tend to die down while progressing northwards or eastwards.

### 3.3 Development of machine learning models for long term modelling of the time series

As discussed in section 4.5, autocorrelation analysis was done to select the predictors of the time series ahead. The result of autocorrelation analysis of the ISMR time series is presented in fig. 8.

A significant correlation of 0.78, 0.77, 0.88, 0.77, 0.76 and 0.87 are observed at lag values of 1, 11, 12, 13, 23 and 24 respectively. Lag zero is not considered because of the obvious trivial case. Machine learning models SVM, RF, RNN and LSTM were developed using these lag values for predictions: 1, 11, 12, 13, 23, and 24 time steps ahead. The results are presented in tables 4 (a-f).

It can be observed that best RMSE on training (147) and test (167) cases are obtained by the LSTM model at lag = 12. These RMSE values are significantly less than the standard deviation of the corresponding observed data. The model using lag 12 as the correlated index, LSTM<sub>12</sub>, has been trained as 64-unit LSTM layer to capture sequential patterns and a dense layer for continuous rainfall prediction. To enable LSTM, learn complex patterns, the activation function that is employed is 'tanh'.

A custom callback monitors RMSE and MAE, saving the optimal weights during training. With a batch size of 1, the model is trained across 1250 epochs, and performance is tracked using validation data. Lastly, the

**Table 4**  
**Performance of machine learning models for time series modelling of the KSMR at various lag values**  
**(a): Performance at L<sub>1</sub> (lag=1)**

**Training data at lag 1: coefficient of correlation= .777 and standard deviation=257.2**

	SVM <sub>1</sub>	RF <sub>1</sub>	RNN <sub>1</sub>	LSTM <sub>1</sub>
MAE	151.124	170.063	164.958	156.857
RMSE	231.584	239.995	224.141	218.799

**Testing data at lag 11: coefficient of correlation= .777 and standard deviation=231.963**

	SVM <sub>1</sub>	RF <sub>1</sub>	RNN <sub>1</sub>	LSTM <sub>1</sub>
MAE	142.836	161.145	146.173	144.147
RMSE	200.526	225.218	193.660	189.542

**(b): Performance at L<sub>11</sub> (lag=11)**

**Training data at lag 11: coefficient of correlation= .772 and standard deviation=257.2**

	SVM <sub>11</sub>	RF <sub>11</sub>	RNN <sub>11</sub>	LSTM <sub>11</sub>
MAE	167.275	176.774	165.513	159.258
RMSE	243.562	246.791	228.455	218.724

**Testing data at lag 11: coefficient of correlation= .772 and standard deviation=231.963**

	SVM <sub>11</sub>	RF <sub>11</sub>	RNN <sub>11</sub>	LSTM <sub>11</sub>
MAE	154.890	177.802	155.721	149.653
RMSE	220.431	242.831	210.738	201.947

**(c): Performance at L<sub>12</sub> (lag=12)**

**Training data at lag 12: coefficient of correlation= .88 and standard deviation=257.2**

	SVM <sub>12</sub>	RF <sub>12</sub>	RNN <sub>12</sub>	LSTM <sub>12</sub>
MAE	132.359	122.236	138.033	95.5628,
RMSE	214.667	184.938	209.513	147.9189

**Testing data at lag 12: coefficient of correlation= .88 and standard deviation=231.963**

	SVM <sub>12</sub>	RF <sub>12</sub>	RNN <sub>12</sub>	LSTM <sub>12</sub>
MAE	129.624	125.167	126.916	105.4112
RMSE	186.914	183.446	177.387	167.9367

**(d): Performance at L<sub>13</sub> (lag=13)**

**Training data at lag 13: coefficient of correlation= .772 and standard deviation=257.2**

	SVM <sub>13</sub>	RF <sub>13</sub>	RNN <sub>13</sub>	LSTM <sub>13</sub>
MAE	162.481	168.462	167.307	158.370
RMSE	241.050	139.307	226.224	220.787

**Testing data at lag 13: coefficient of correlation= .772 and standard deviation=231.963**

	SVM <sub>13</sub>	RF <sub>13</sub>	RNN <sub>13</sub>	LSTM <sub>13</sub>
MAE	155.943	177.786	155.503	150.342
RMSE	214.887	241.635	203.016	197.466

(e): Performance at  $L_{23}$  (lag=23)

Training data at lag 23: coefficient of correlation= .756 and standard deviation=257.2

	SVM <sub>23</sub>	RF <sub>23</sub>	RNN <sub>23</sub>	LSTM <sub>23</sub>
MAE	175.900	174.102	174.864	167.594
RMSE	266.530	246.955	248.955	223.750

Testing data at lag 23: coefficient of correlation= .756 and standard deviation=231.963

	SVM <sub>23</sub>	RF <sub>23</sub>	RNN <sub>23</sub>	LSTM <sub>23</sub>
MAE	162.927	148.985	155.393	143.645
RMSE	236.266	213.849	214.673	201.675

(f): Performance at  $L_{24}$  (lag=24)

Training data at lag 24: coefficient of correlation= .88 and standard deviation=257.2

	SVM <sub>24</sub>	RF <sub>24</sub>	RNN <sub>24</sub>	LSTM <sub>24</sub>
MAE	136.118	123.757	148.896	127.601
RMSE	210.411	183.799	198.142	189.524

Testing data at lag 24: coefficient of correlation= .88 and standard deviation=231.963

	SVM <sub>24</sub>	RF <sub>24</sub>	RNN <sub>24</sub>	LSTM <sub>24</sub>
MAE	131.566	124.892	134.976	114.323
RMSE	200.794	204.284	178.721	173.497

model with the optimal weights is saved after RMSE and MAE trends are stabilised which happens at epoch 1016. The results are shown in table 4(c).

In order to analyse the models for sustainability, we proceed to do the MK and Bayesian tests on the results obtained by the best model (LSTM at lag = 12). The result of break point analysis is presented in fig. 9.

As seen from the fig., the change points are observed at

$$T1 = \{20, 75, 90, 100, 105\} \quad (7)$$

Comparison with (6) is presented in table 5.

The second, third, fourth and fifth break points are observed almost at same values in both the time series. We have compared the values of the parameters in the predicted time series in the intervals of the observed time series. The results are presented in table 6.

It is evident that there is a persistent bias, of around 300-400 in the mean. This is systemic bias of the model and can be removed using methods like z-score normalization, or statistical bias correction. However, the

range of mean in the predicted series is less variable. This means that the variance in the mean is not captured. The

**Table 5**  
Comparison between observed and predicted break points for Kerala and Mahe

Break point no.	Observed data	Predicted data
1	75	20
2	85	75
3	90	90
4	95	100
5	120	105

**Table 6**  
Observed and predicted parameters in the break intervals

Range	Mean ( $\mu$ ) observed	Mean ( $\mu$ ) predicted	Standard Deviation ( $\sigma$ ) observed	Standard Deviation ( $\sigma$ ) Predicted
1-75	2068.62	1602.3420	401.28	166.4324
76-85	1877.68	1538.2822	231.09	156.1677
86-90	1769.82	1440.8948	418.54	122.1056
91-95	2073.76	1615.0712	294.53	118.2733
96-120	1954.90	1628.5736	384.63	195.3989

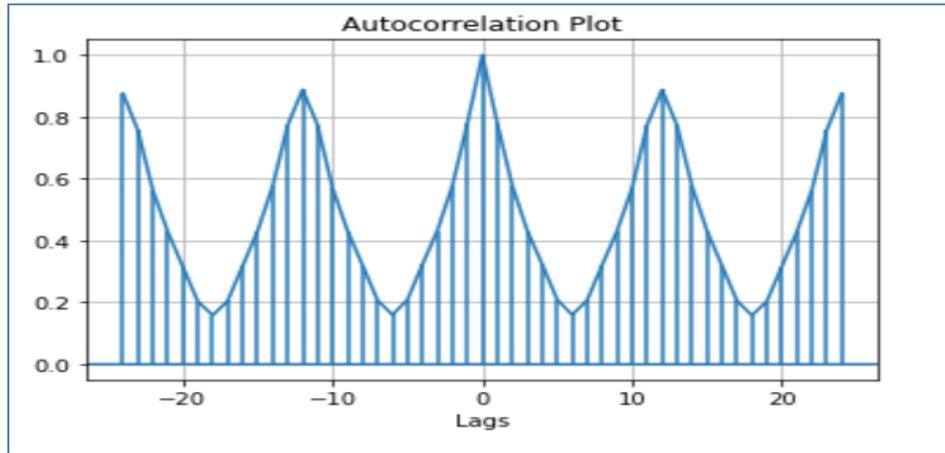


Fig. 8: Autocorrelation plot at different interval of time in training dataset of Kerala

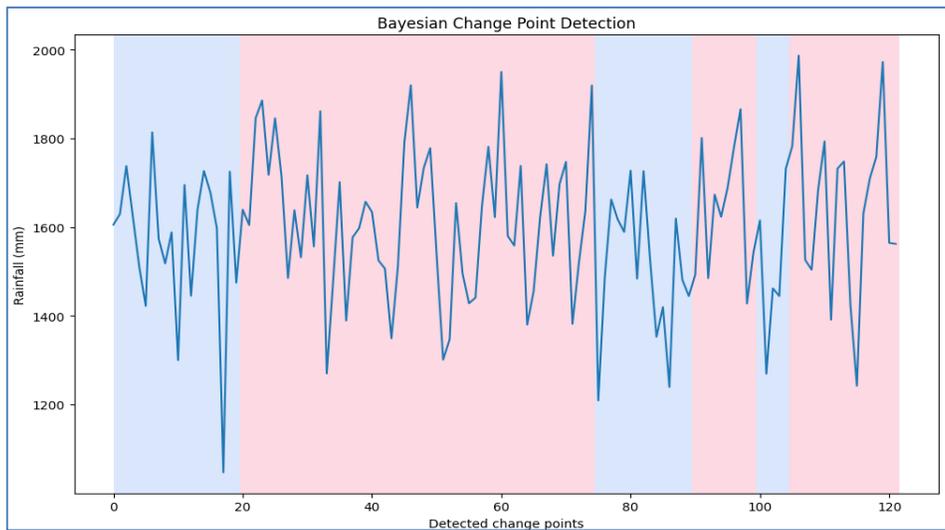


Fig. 9. Detection of Multiple change points in total JJAS rainfall of Kerala and Mahe in predicted data

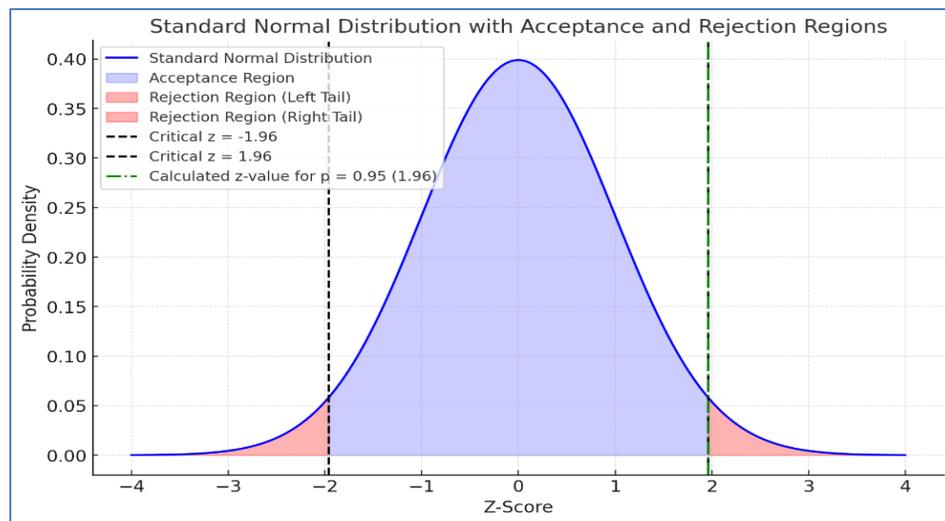


Fig. 10. Two tailed test result on KSMR prediction data set. The p-value (0.95) lies exactly on the critical line.

same is the case with standard deviations. The standard deviations are less varied in the predicted time series, although the standard deviations do not vary abruptly and is in the scope of the observed series, the predicted series is less variable. The persistent bias of around 300–400 mm in the predicted means likely reflects the absence of explicit bias-correction in the modelling pipeline. While the present study prioritised the sustainability of long-term statistical characteristics such as trends and break points, standard post-processing methods (e.g., normalization, mean adjustment, or variance scaling) could help to reduce this offset without altering the statistical structure of the predictions. This aspect will be taken up in future work to refine absolute rainfall estimates.

This result is remarkable seeing the time series of KSMR was modelled and we are predicting with lag 12. This means we are predicting 12 “seasons” ahead or 12 years ahead. Hence the LSTM model has significantly captured the long statistics of the time series.

The result of MK analysis on the KSMR predicted series gives p-value 0.95 and  $\tau = -0.003$ . The result is presented in fig. 10. The small negative value of  $\tau$  indicates a very weak negative trend. This is in line with the trend in the observed data. It may be noted that this result is borderline, lying exactly on the critical threshold ( $z = \pm 1.96$  at 95% confidence). While this does not strongly confirm or reject the null hypothesis, the outcome remains consistent with the weak negative trend found in the observed KSMR data. Hence, the borderline result does not alter our conclusion but rather highlights that the model is able to replicate even marginal statistical signals in the observed series. As can be seen, it is a peculiar case here as the obtained z-value aligns with the corresponding critical line (1.96 at confidence level of 95%). Thus, the hypothesis of “no trend” may be rejected. This is in line with calculations on the observe data set where the trend was weak but statistically significant. However, in the prediction case the significance is a border-line significance.

### 3.4 Limitations

The present study has certain limitations that should be noted. First, the Mann–Kendall test applied to the predicted KSMR series yielded a borderline result, lying exactly on the 95% confidence threshold; while this does not change our overall conclusion, it indicates marginal statistical significance. Second, the prediction models exhibit a persistent bias of around 300–400 mm in the mean, which was acknowledged but not post-processed in this work. Third, break point analysis was conducted using a Bayesian method, and results may vary

if alternative change-point detection techniques are applied. Finally, the modelling framework relied solely on rainfall time series, without incorporating external predictors such as SST anomalies or atmospheric circulation indices that may further improve robustness. These limitations do not detract from the main findings but highlight areas for refinement in future studies.

## 4. Conclusions

The trend analysis indicates no significant trend in the ISMR while a statistically significant one in the KSMR. There is also a difference in the positions of maximum break points observed in the ISMR and the KSMR. While the ISMR witnessed more breakpoints in the initial phases the KSMR witnessed more in the recent years. It may thus be concluded that while the onset of monsoon in India is from the Kerala, the trend and pattern of Kerala does not decide the trends of the remaining parts. While the local factors affect Kerala, the all-India pattern is dominated by global factors. Four different machine learning models were developed to model these break points and trends using the autocorrelations in the KSMR time series. It was seen that the model was able to correlate with the mean and standard deviations in the intervals of break points. Further, the prediction results were in line with the observed values in the MK test. It can thus be concluded that the machine learning based very long term modelled series is statistically sustainable. Further research is needed to corroborate the findings based on dynamical nature of the time series and analysis with external forcings. Further research is needed to extend the present approach by incorporating large-scale dynamical forcings such as the El Niño–Southern Oscillation (ENSO), Indian Ocean Dipole (IOD), and regional Indian Ocean warming events, which are known to strongly modulate monsoon rainfall variability. Including such predictors in the modelling framework could enhance the robustness and physical interpretability of long-term rainfall forecasts.

### Authors' Contributions

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**Supplementary Material**  
**Table S1**  
**Summary of related work**

Ref	Objective	Model/Technique Used	Dataset	Performance Metrics	Findings
Valipour et al., 2024	To acquire short-term precipitation projections for each day	WPSOANFIS: Wavelet Particle Swarm Optimization Adaptive Neuro-Fuzzy Inference System. WGMDH: Wavelet Group Method of Data Handling. WLSTM: wavelet long short-term memory	1995 -2019	MAE (Mean Absolute Error) RMSE (Root Mean Square Error)	WGMDH and WLSTM produce better forecasts than WPSOANFIS.
Lenka et al., 2024	To estimate onset and withdrawal date of the monsoon based on daily rainfall data	The principal component neural network model created by combining two existing models	1901-1997, IMD	RMSE	Proposed model outperformed than other two models and currently employed by IMD for LRF of Indian summer monsoon.
Calvo-Olivera et al., 2024	To assess weather prediction's unreliability produced by forecasting model.	Model Evaluator (MoEv), a Scikit-Learn library wrapper	Self-created dataset using inputs from WRF model	RMSE, Uncertainty index 'u'	Ensemble techniques based on decision trees achieve the lowest generalization error. Accuracy-90%
Wangwongchai et al., 2023	To impute missing daily rainfall data in northern Thailand using statistical and AI techniques.	Statistical Techniques (STs) and Artificial Intelligence-based Techniques (AITs)	30 years of daily rainfall data from 20 northern Thailand rainfall stations.	MAE, RMSE, R (Corelation Coefficient) R <sup>2</sup> (Coefficient of Determination)	Multiple linear regression model outperformed.
Kumar et al., 2023	Comprehension of the semi-arid region of Karnataka's rainfall pattern.	Innovative trend analysis (ITA) and the modified Mann-Kendall test (MMK), ARIMA model.	1952-2019, IMD	The SNHT, Pettitt, and Buishand tests for homogeneity test.	Compared to the ITA, the MMK approach demonstrated a greater occurrence of a significant growing trend.
Zenker et al., 2023	To forecast the weather for the upcoming 24 and 72 hours based on the last 120 hours.	Two different models of Bi-LSTM recurrent neural networks	2015- 2021, Met Office, London	RMSE	First model shows temperature prediction with $\pm 2$ °C accuracy and RMSE of 1.45 °C Second model predicted air temperature and relative humidity over a 72-hour period with RMSE of 2.26 °C and 14% .
Bhatla et al., 2023	To assess how the Indian subcontinent's geographic variability in ISMR	Studied ISM time scale trends on the tricadal and decadal scales.	1901-2013 from IMD.	Standard deviation and Coefficient of variation	improvement in ISMR over Western India but a significant decrease over Northeast Indian regions, indicating a shift in ISMR toward the west due to climate change.

Rajput et al., 2023	To track the National Capital Region's rainfall and temperature trends over a period of 31 years.	Mann-Kendall (MK) test, Theil Sen slope estimator test, and Pettitte Test	1990-2020, IARI meteorological station, Pusa, New Delhi.	Mean, median, mode, standard deviation, variance, skewness, kurtosis, maximum, minimum, 25 <sup>th</sup> , 50 <sup>th</sup> , and 75 <sup>th</sup> percentile	Found a tendency of upward increase in the relative humidity data series.
Rao et al., 2023	To examine and measure the distribution of rainfall in the Andhra Pradesh, India district of Chintapalli, Visakhapatnam.	Linear Regression, Sen's slope estimates, the Mann-Kendall test, and Rainfall Anomaly Index (RAI)	1990-2020, Regional Agricultural Research Station (RARS), Chintapalle.	Standard Precipitation Index (SPI), Mean, median, standard deviation, coefficient of variation, percentage of annual rainfall and ZC test	Positive increasing trend in rainfall, the extremely dry year was 2002. Three drought events have occurred in the last ten years; however, they have not been very large.
Saminathan et al. 2021	To improve daily predictions of precipitation over the Indian subcontinent.	Global Ensemble Forecast System (GEFS) using Analog (AN) and Logistic Regression (LR) techniques.	IMD	Brier Skill Score (BSS) and Root Mean Square Error (RMSE)	The post-processing technique combining LR and AN significantly enhanced short- to medium-range (1–7 day) precipitation forecasts over India.
Ali et al., 2020	To overcome the non-stationarity issues that are encountered by rainfall forecasting models	CEEMD-RF-KRR: Complete Ensemble Empirical Mode Decomposition in conjunction with Random Forest and Kernel Ridge Regression algorithm	1962 to 2013 Pakistan Meteorological Department (PMD)	Correlation coefficient, Willmott's index, Nash-Sutcliffe coefficient, Legates-McCabe's index	The suggested model outperforms the compared models in terms of performance.
Ni et al., 2020	Investigating LSTM's potential for rainfall and streamflow forecasting	Wavelet-LSTM (WLSTM), Convolutional LSTM (CLSTM)	National Meteorological Information Centre, China	RMSE, MARE, (NSE) Nash-Sutcliffe model efficiency coefficient	While LSTM could be used to predict time series, WLSTM and CLSTM performed better.
Perera et al., 2020	To evaluate and contrast three trend analysis methods for Colombo, Sri Lanka	Sen's slope estimator, Spearman's rho test, Mann-Kendall test, and novel graphical technique.	30 years of rainfall data collected for 10 gauging stations	Three resolution levels: yearly, seasonal, and monthly rainfall.	Spearman's rho and the Mann-Kendall test produced similar trends. While, the graphical approach yielded contradictory results occasionally.
Ferreira et al., 2020	To estimate daily ETo in several steps ahead using direct, iterated, and multi-input multi output forecasting techniques.	CNN-LSTM, CNN-1D, and LSTM and traditional machine learning models including ANN and RF	53 stations, Minas Gerais, Brazil	Mean RMSE	Compared to machine learning models, deep learning models outperformed them by a little margin.
Suman & Maity, 2020	To analyze ISM rainfall records	Coupled Model Intercomparison Project Phase 5 (CMIP5)	CORDEX data	Daily mean precipitation, yearly mean precipitation, Mann-Kendall test, and precipitation thresholds-P95 and P-99	Extraordinary precipitation in south India from 1971 to 2017 in contrast to north and central India. Indicates shift in precipitation towards the south over South Asia.

Acharya et al., 2019	Long range forecasting of ISMR	ANN model with nonlinear perceptron rule with two set of predictors: Set I and Set II	IMD, 1980-2017	Willmott's index	North Central Pacific zonal wind and North Atlantic Sea surface pressure anomaly in the input matrix makes the second-stage forecast superior than the first-stage forecast.
Wang et al., 2019	To create a data-driven approach that uses an efficient information from NWP	New Loss Function based on negative log-likelihood error (NLE).	Public dataset, Beijing, China	MSE, MAE	Concurrently applies uncertain quantification and single-value forecasting, improving accuracy by 47.76%
Che et al., 2018	Utilizing the missing patterns for efficient imputation to enhance prediction accuracy	GRU-D model based on Gated Recurrent Unit (GRU)	clinical real-world datasets (PhysioNet, MIMIC-III) and artificial datasets	AUC score (Area Under ROC curve)	Improved prediction results by capturing the long-term temporal interdependence of time series observations and missing patterns.
Scher & Messori, 2018	To estimate future forecast uncertainty from previous forecasts using machine learning	CNN	GEFS reforecast v2 dataset, updated on daily basis.	RMSE	It determines if the predictability by assigning a scalar value of confidence to medium-range forecasts initiated from the stated atmospheric state
Zaz et al., 2018	Examined six stations for specific long- and short-term characteristics, localized fluctuations in temperature and precipitation.	WRF model, Linear Regression, Mann-Kendall, Spearman Rho, Cumulative Standard Deviation, and Student's T-test	1980-2016, IMD for stations of Jammu and Kashmir.	Different confidence levels of S; S=99%, S=95% and S=90%.	Increased temperature of higher altitude is correlated with minor drop in yearly precipitation. Winter NAO index and long-term variations in temperature and precipitation are well correlated.