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RESEARCH ARTICLE

Spatial and temporal changes in rainfall in the southern zone of Tamil Nadu-An analysis

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Abstract

Rainfall plays a crucial role in planning and managing water resources. Climate fluctuations significantly impact water availability and rainfall patterns. This study analyses spatiotemporal changes and trends in extreme rainfall events from 1990 - 2022 in the Ramanathapuram district of Tamil Nadu. It also compares seasonal rainfall variability across four districts-Ramanathapuram, Virudhunagar, Sivaganga and Madurai-within the southern zone. The study employs Markov Chain modelling, the Mann-Kendall trend test and compound growth rate analysis, utilising secondary data from government sources. The findings indicate significant shifts in the pattern of rainfall in Ramanathapuram, exhibiting a downward trend. The transition matrix suggests a 75 % chance of heavy rain in November. The results provide significant insights into climate variability and its impacts on sustainable agriculture, suggesting that farmers plan for a better cropping system in advance to achieve a higher yield.

Keywords: compound growth rate (CGR); mann-kendall; markov chain analysis; rainfall temporal analysis

Introduction

Over the past century, significant changes in the Earth's climate have been observed, particularly in temperature and precipitation patterns. Among the most critical consequences of climate change are disruptions to rainfall distribution, which have far-reaching effects on water availability and the functioning of ecosystems. These alterations impact hydrological process, streamflow regimes and water demand, especially in agriculture (1). Researchers worldwide have examined the dynamics of climatic indicators to understand better rainfall variability at both regional and local levels (2,3). One major consequence of altered precipitation patterns is drought-a natural phenomenon characterised by below-average rainfall over a prolonged period, resulting in water scarcity and challenges for both human and environmental systems (4).

Several studies in India to identify regional and national rainfall trends using long-term meteorological data (5, 6). Trend analysis study has been regarded as a valuable tool since it offers important insights about the change in rainfall and frequency of rainfall intensity which shows the future changes (7, 8). By utilising the statistical method of trend analysis, the policymakers may create effective hydrological policies to combat drought and reduce the risk of floods with appropriate water resource management. To quantify changes in hydro-meteorological variables such as temperature and rainfall, both trend analysis (9, 10) and Markov Chain models have been effectively applied. A Markov Chain model has been fitted to monthly rainfall data to obtain sequences of dry and wet spells during the monsoon season. It is important for crop planning and acts as a benchmark for sustainable agricultural management. The. The climatology of the state has been characterized as Semi-Arid to Arid regions (11) As a result, the state is more susceptible to droughts of various severity and magnitude. The southern region is more vulnerable to drought conditions, particularly during the North East Monsoon Seasons (12, 13). In this context, the present study aims to evaluate the spatial and temporal variations in rainfall and assess the frequency and severity of drought in the Ramanathapuram district of Tamil Nadu. By analyzing long-term seasonal rainfall data from 1990 - 2022, the study seeks to identify emerging patterns and trends that can inform drought characterization and regional water resource planning. With the monthly rainfall trend analysis, the study also highlights the changes in cropping pattern which helps the farmers to pre plan their agricultural crop schedule.

Materials and methods

Study area

Tamil Nadu is classified into eight agroclimatic zones by the Indian Meteorological Department (IMD). Among these, the

North Eastern Zone and the Southern Zone account for approximately 24 % and 20 % of the total area, respectively. Next, behind are the Western Zone (12 %), North West Zone (14 %), Southern Zone (12 %) and Cauvery Delta Zone (15 %). The current study focuses on the Southern Zone, which includes the coastal district in the southern Indian state of Tamil Nadu, it lies adjacent to the Gulf of Mannar-an ecological sensitive marine region recognized by UNESCO. Despite its low global visibility, Ramanathapuram provides a unique setting to study the impacts of monsoonal variability, resource dependent livelihoods and ecosystem management under changing climatic conditions (Fig. 1). This region lies between latitudes 8° 9′ and 10° 50′ N and longitudes 77° 10′ and 79° 25′ E, stretching from the coastal plains in the east to the mountainous terrain in the west. The elevation generally average around 100 m above sea level.

Data collection

The study focuses on four meteorological seasons: Winter Season (WS: January-February), Hot Weather Season (HWS: March-May), South West Monsoon (SWM: June-September) and North East Monsoon (NEM: October-December). Seasonal rainfall and temperature data for the years 1990-2022 were collected for the four Southern Zone districts: Virudhunagar, Ramanathapuram, Sivagangai and Madurai. This temporal dataset enables the analysis of seasonal fluctuations and long-term trends. Particular emphasis is placed on the Ramanathapuram district to assess the localized impacts of drought and climate variability. Compared to the other districts, Ramanathapuram exhibits a more pronounced decline in seasonal rainfall over time.

The secondary dataset was obtained from by the Directorate of Economics and Statistics, Government of Tamil Nadu. The seasonal crop report, which provided a comprehensive data on rainfall distribution for Ramanathapuram district of Tamil Nadu for the four seasons. This comprehensive dataset serves as the foundation for the analysis of rainfall trends in the region. For analytical purposes, the Compound Growth Rate (CGR) was estimated using an exponential growth model. This model measures the average rate at which rainfall increased or decreased annually over the study period.

Compound Annual Growth Rate (CAGR)

The CAGR was assessed using the exponential function of the subsequent form

$$Y = ab^{t}e \qquad \text{(Eqn. 1)}$$

Where, Y is the variable for which growth rate is calculated and b1- regression coefficient of t on Y and t is the time variable,

$$CAGR = (\text{Antilog } b_1 - 1) \times 100 \qquad \text{(Eqn. 2)}$$

Mann-Kendall (MK) trend test

The non-parametric Mann-Kendall test was used to analyse the trend in rainfall. A time series' trend analysis includes both the trend's statistical significance and magnitude. This statistical technique is employed to investigate the temporal trends and spatial variation of hydroclimatic series (1).

$$\sum_{k=1}^{n-1} \sum_{j=k+1}^{n} sgn(xj - xk) \qquad \text{(Eqn. 3)}$$

$$Var\ s = \frac{n((n-1)(2n+5)) - \sum_{i=0}^{n} t(t-1)(2t+5)}{18} \qquad \text{(Eqn. 4)}$$

Where this MK test is applied to 2 time series, xk which is ranked from k=1, 2, …, n-1 and xj which is ranked from j=k+1, 2, …, n. Every data point xk is used as a reference and compared to other data points. sgn(θ)={1, θ >0, 0, θ =0, -1, θ}

Where the notation t indicates the extent of every specific tie and t represents the sum of all ties. Z statistics is computed

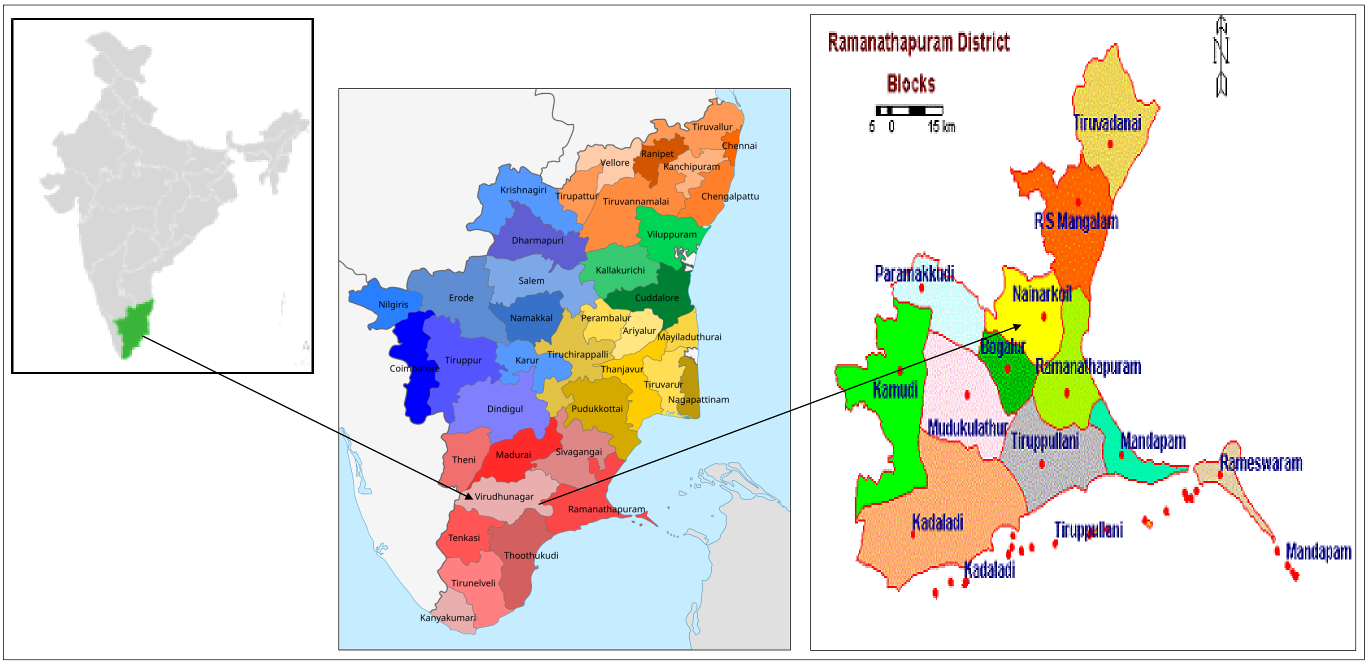

Fig.1. Map depicting the study area.

$$Z = \{ \frac{s+1}{\sqrt{var(s)}}\ if\ S > 0\}, 0\ if\ s = 0, \frac{s+1}{\sqrt{var(s)}}, if S < 0$$

(Eqn. 5)

using below equation, where the sample size n should be more than 10

The MK statistic (S) variance is calculated using below equation.

Where positive (+ ive) and negative (- ive) Z numbers denote the increasing and decreasing trends, respectively.

Markov chain analysis of the rainfall data

To forecast future rainfall probabilities in Ramanathapuram district, Markov Chain Analysis was employed using rainfall data from 1990 - 2022. This stochastic method models the likelihood of transitioning between various rainfall categories over time based on historical patterns. The analysis was conducted using R software version 4.4. By analysing the probability for each severity class, the timeframes it takes to get from any drought severity condition to the non-drought class and the residence times within each drought class, the Markov chain modelling approach helps us understand the features of droughts and rainfall (14). The Markov Chain technique offers a different approach to predict future rainfall variance, according to the examination of monthly rainfall data. These fluctuations can take the form of either too little water, which causes drought, or too much water, which causes flood. One approach that planners may employ to aid them evaluate the frequency, duration, severity and distribution of rainfall is Markov modelling.

The transition probabilities are independent of how the position was reached and depend solely on the present position. However, the theory is applied only when the probability distribution of the next step depends non-trivially on the current state. The Markov chain model is as follows: The probability of transitioning from state a to state b in n time steps is given as P(n) ab = Pr(Xn = b | X0 = a) (15) . In the above formula, 'n' represents number of steps, 'a' represents initial state, ‘b’ represents final state. In words, P(n) ab refers to probability of going from initial state (a) to final state (b) in ‘n’ number of steps and Pr (Xn=b|X0=a) refers to probability of attaining final state (a) in ‘n’ number of steps given that initial state (a) at 0. If n = 1, *i.e.,* one-step transition then the probability of going from a to b in a single step is as follows, Pab = Pr (X1=b|X0=a) For a time-homogeneous Markov chain: P(n) ab = Pr (Xk+n=b|Xk=a) and Pab = Pr (Xk+1=b|Xk=a)

The probabilities of no rain, low rain, moderate rain and heavy rain were determined for each month using their corresponding transition matrices. Transition matrices can be obtained by the conditional probability of the fact that the rainfall is in the any of the state as given in Table 1 at time t = n if it was in the any of the state as given in Table 1 at time t = 0. To determine the stable future probabilities, a steady-state matrix was calculated from the transition matrix by multiplying the probability vector by the transition probability matrix; hence, the same exact probability vector is obtained and it represents the steady state. In this study, Markov Chain analysis is used to study the rainy days in Ramanathapuram. The term Markov Chain is referred to which there are a certain number of states

Table 1. Classification of rainfall intensity

State	Rainfall (mm/day)
No Rain	<0
Low Rain	0 – 50
Moderate Rain	50 – 150
Heavy Rain	>150

(4 states) and with given probabilities and the structure changes from any state to another state. The four states are as follows:

If a Markov Chain consists of k states, then the transition matrix is of order k × k, whose entries indicate the likelihood of transitioning from one state to another. For this study, the transition matrix is of order 4 × 4 matrix. The rows of the transition matrix represent to the current state and the columns to the next state. For example, the data in row 1 and column 2 shows the chance of moving from state 1 to state 2. Remember, rows mean “from” and columns mean “to.

$$\lim p^n = \begin{pmatrix} P1 & P2 & \dots & Pk \\ \vdots & \ddots & & \vdots \\ P1 & P2 & \dots & Pk \end{pmatrix}$$

(Eqn. 6)

When time approaches infinity then the probability in that particular condition will become nearer to its limit and is represented by the rows of the limiting matrix. These probabilities are called steady-state probabilities.

$$P = \begin{pmatrix} P_{11} \dots P_{12} . P_{1k} \\ \vdots \quad \ddots \\ P_{k1} \quad P_{k2} \quad P_{kk} \end{pmatrix}$$

(Eqn. 7)

In other words, the probabilities won’t change much from one transition to the next. If the probability vector is multiplied by the probability transition matrix the same exact probability vector is obtained and it will be in a steady state. A State Vector pn is a vector that records the probabilities that the system is in any given state at a particular step of the process. The value of pn approaches a fixed square matrix as n increases.

Results and Discussions

Rainfall data for the Ramanathapuram district from 1990 - 2022 were statistically analyzed, as presented in Table 2 and Fig. 2. The district received an average annual rainfall of 844.85 mm during this period. October recorded the highest mean monthly rainfall (210.64 mm), while February experienced the lowest (18.93 mm). These patterns highlight the dominance of the North East Monsoon and the dry nature of the winter season.

The highest monthly rainfall occurs in October (398.7 mm) and November (398.6 mm), which coincide with the North East Monsoon season (Fig. 2). In contrast, rainfall was significatly lower during February, March and April, corresponding to the winter and hot weather seasons. Interannual variations were

Table 2. Statistical summary of monthly, rainfall of Ramanathapuram district (1990-2022)

Months	Minimum	Maximum	Mean	Std. Deviation	CV (%)	% contribution to rainfall
January	0.1	235.8	30.14	44.96	149.17	3.57
February	0.0	177.1	18.93	34.28	181.09	2.24
March	0.0	376.6	23.58	66.21	280.79	2.79
April	0.0	261.3	48.96	54.70	111.72	5.80
May	0.0	180.6	49.21	45.79	93.05	5.82
June	0.0	64.8	19.72	17.947	91.01	2.33
July	0.1	77.9	20.83	16.62	79.79	2.47
August	6.0	108	35.72	24.76	69.32	4.23
September	14.0	180.2	56.81	39.91	70.25	6.72
October	51.1	398.7	210.64	90.23	42.84	24.93
November	53.6	398.6	220.50	97.40	44.17	26.10
December	14.0	290	109.76	85.66	78.04	12.99
Total	428.3	1313.9	844.85	222.23	26.30	100

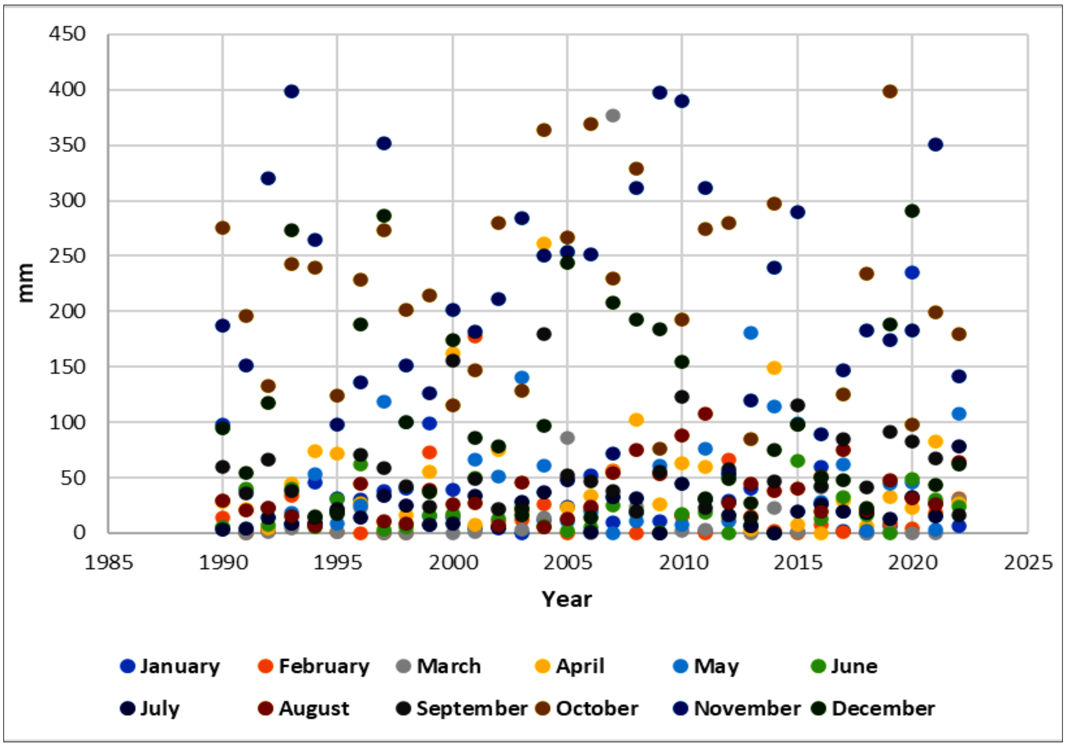

Fig. 2. Rainfall distribution over 33 (1990-2022) years across months.

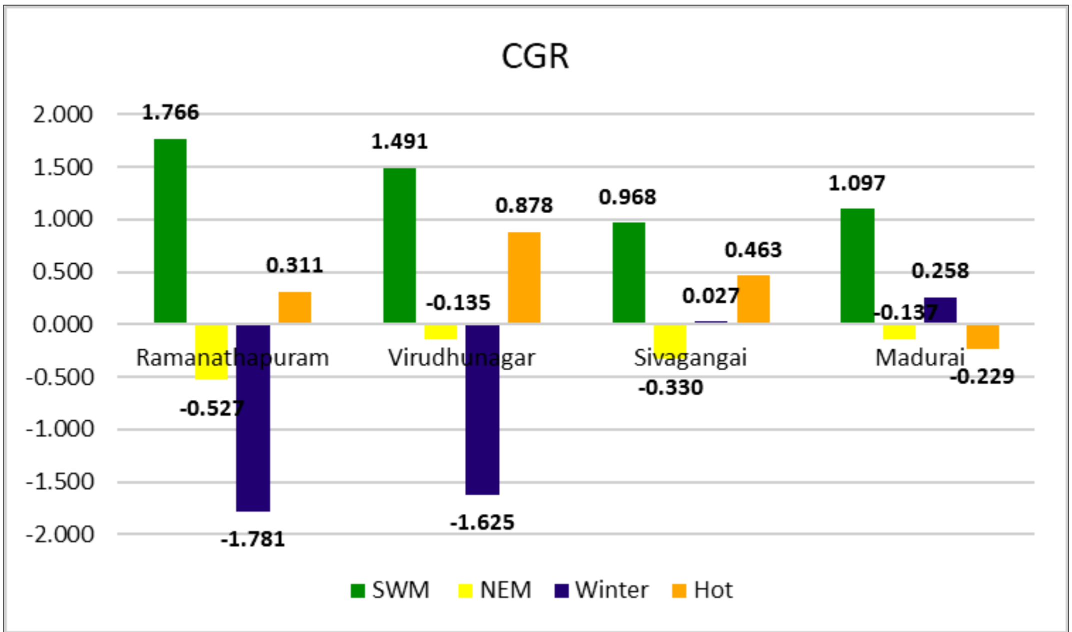

Fig 3. Compound growth rate (CGR) of rainfall depicted across seasons for 33 years (1990-2022).

also observed, with 2019 experiencing notably high rainfall, while 1997 and 1998 recorded some of the lowest annual rainfall totals.

Compound growth rate of rainfall in four districts

The Compound Growth Rate (CGR) analysis, presented in Fig. 3, reveals that rainfall during the South West Monsoon has shown a positive growth trend in Ramanathapuram district, at 1.7 %. In contrast, a declining trend was observed in winter rainfall, with CGRs of -1.7 % and -1.6 % in Ramanathapuram and Virudhunagar districts, respectively. These changes indicate increasing rainfall seasonality and may have implications for water availability during non-monsoon months.

Table 3. Statistical analysis of rainfall data along with Mann-Kendall trend and p-value

Series	Kendall's tau	p-value
January	-0.116	0.345
February	0.073	0.555
March	0.056	0.652
April	-0.038	0.757
May	0.068	0.577
June	-0.006	0.963
July	0.163	0.183
August	0.286	0.019
September	0.083	0.495
October	-0.068	0.577
November	-0.049	0.687
December	-0.076	0.535

The Mann-Kendall trend test results (Table 3) indicate a statistically significant decreasing trend in rainfall during January, June, October and December over the 33 years. Among these, the trend in August was found to be significant at the 0.05 level, indicating a 95 % confidence level in rejecting the null hypothesis of no trend. These trends suggest a reduction in rainfall during both early and late monsoon periods, which could affect sowing and harvesting cycles.

Markov chain analysis

Monthly rainfall data from 1990 - 2022 were analyzed using a Markov Chain model to assess the likelihood of transitioning between different rainfall states: No Rain (a), Low Rain (b), Moderate Rain (c) and Heavy Rain (d). Transition probability matrices were generated for each month, predicting the likelihood of each rainfall category occurring the following day based on current conditions. Table 4 presents these month-wise transition probabilities, capturing seasonal variability and rainfall persistence. A preliminary analysis of the rainfall data collected over the 33-year period (1990-2022) across the four seasons reveals that the rainfall pattern is not evenly distributed.

For January, Table 4 clearly shows that if today is no rain, then there is a 0.00 % chance of it being no rain again, 0 % chance of it being low rain, 0 % chance of it being moderate rain and 0 % chance of it being heavy rain on the next day. And if today is low rain, then there is a 0 % chance of it being no rain, 85 % chance of it being low rain again, 11 % chance of it being moderate rain and 3 % chance of it being heavy rain on next day and so on. For February, Table 4 clearly shows that if today is no rain, then there is a 20 % chance of it being no rain again, 60 % chance of it being low rain, 20 % chance of it being moderate rain and 0 % chance of it being heavy rain on the next day. And if today is low rain, then there is a 13.00 % chance of it being no rain, 73 % chance of it being low rain again, 8 % chance of it being moderate rain and 4 % chance of it being heavy rain on the next day and so on.

In Table 4, ‘n’ represents the number of years, January attains a steady state after 9 years with a chance of 19 % heavy rain, 56 % low rain, 23 % moderate rain. February attains a steady state after 9 years with a chance of 23 % no rain, 29 % low rain, 23 % moderate rain and 23.00 % heavy rain and so on. The probability of receiving moderate rainfall remains low during the dry months of January - March, while heavy rainfall is particularly scarce in January and August. The study reported that the availability of water for crop production is higher from September to November. Finally, one can plan a suitable cropping system in advance, which is also useful for farmers to achieve a better yield and income. For a normal year the farmers can plan for Rice (Sep.-Jan.), cotton (Jan.-Feb.). For moderate drought year they can go for Rice / ragi / chillies / maize (Sep.-Jan.), Sweet sorghum (Jun-Sept) - rice (Oct-Jan) - pulses (Feb-May) and for severe drought year they can grow Ragi / kuthiraivali /gingelly (Sep.-Jan.). Other techniques, such as the utilisation of micro-irrigation systems like drip and sprinkler irrigation to improve water use efficiency, implementing rainwater harvesting techniques and using climate forecasting tools to make informed decisions about planting times, irrigation needs and pest control measures, can be followed to overcome the effects of climate change. Farmers can adopt climate-resilient crop cultivation by combining precision farming with artificial intelligence (AI). AI breakthroughs offer a complex response to the rapidly changing climate, rising global food consumption and environmental sustainability challenges.

The Markov plot for 33 years is depicted in Fig. 4. It can be noticed that the probability of low rainfall (0.4) is higher compared to moderate (0.3) and heavy rainfall.

Conclusion

This study analysed the seasonal rainfall variability in Ramanathapuram district, Tamil Nadu, over a 33-year period (1990-2022), using spatiotemporal trend analysis. The results revealed a decline in rainfall days during the winter season, with increased rainfall concentrated in October and November, consistent with the North East Monsoon period. Despite some positive trends, the overall monsoon rainfall showed a declining pattern in both intensity and distribution. These findings underscore the impact of climate change and variability on local rainfall patterns. By integrating quantitative trend analysis with seasonal and spatial perspectives, the study provides valuable insights into how rainfall regimes are shifting in the region. This information is essential for developing climate-resilient agricultural practices, optimizing water resource management and informing drought preparedness strategies. The results can guide policymakers and farmers in planning appropriate cropping systems and water usage, enhancing productivity and sustainability .in agriculture under changing climatic conditions. Based on the data, farmers may grow short-duration crops like pulses, sorghum, maize and millets during summer that can endure drought conditions and produce an adequate amount of with less water in the face of considerable climate fluctuation.

Table 4. Markov chain analysis of rainfall data for Ramanathapuram district

Month	Transition matrix (p)				n	Steady-state matrix			
	a	b	c	d		a	b	c	d
January									
a	0.00	0.00	0.00	0.00	9	0.00	0.56	0.23	0.19
b	0.00	0.85	0.11	0.71					
c	0.00	1.00	0.00	0.00					
d	0.00	1.00	0.00	0.00					
February									
a	0.20	0.60	0.20	0.00	9	0.23	0.29	0.23	0.23
b	0.13	0.73	0.08	0.08					
c	0.33	0.66	0.00	0.00					
d	0.00	1.00	0.00	0.00					
March									
a	0.16	0.83	0.00	0.00	9	0.23	0.29	0.23	0.23
b	0.17	0.69	0.08	0.04					
c	0.50	0.50	0.00	0.00					
d	0.00	1.00	0.00	0.00					
April									
a	0.00	1.00	0.00	0.00	9	0.13	0.34	0.29	0.22
b	0.05	0.52	0.36	0.52					
c	0.00	0.60	0.30	0.10					
d	0.00	1.00	0.00	0.00					
May									
a	0.00	1.00	0.00	0.00	9	0.13	0.34	0.29	0.22
b	0.05	0.50	0.38	0.05					
c	0.00	0.58	0.41	0.00					
d	0.00	0.00	1.00	0.00					
June									
a	0.00	0.60	0.33	0.00	9	0.22	0.30	0.26	0.26
b	0.11	0.85	0.37	0.00					
c	0.00	0.00	0.00	0.00					
d	0.00	0.00	0.00	0.00					
July									
a	0.00	0.00	0.00	0.00	8	0.00	0.48	0.30	0.21
b	0.00	0.96	0.03	0.00					
c	0.00	0.50	0.50	0.00					
d	0.00	0.00	0.00	0.00					
August									
a	0.00	0.00	0.00	0.00	7	0.00	0.53	0.27	0.19
b	0.00	0.88	0.11	0.00					
c	0.00	0.33	0.66	0.00					
d	0.00	0.00	0.00	0.00					
September									
a	0.00	0.00	0.00	0.00	11	0.00	0.32	0.40	0.26
b	0.00	0.47	0.41	0.11					
c	0.00	0.69	0.30	0.00					
d	0.00	0.50	0.50	0.00					
October									
a	0.00	0.00	0.00	0.00	7	0.00	0.55	0.00	0.44
b	0.00	0.85	0.00	0.14					
c	0.00	0.00	0.00	0.00					
d	0.00	0.80	0.00	0.20					
November									
a	0.00	0.00	0.00	0.00	10	0.00	0.62	0.00	0.37
b	0.00	0.00	0.00	0.00					
c	0.00	0.00	0.37	0.62					
d	0.00	0.00	0.25	0.75					
December									
a	0.00	0.00	0.00	0.00	10	0.00	0.40	0.31	0.27
b	0.00	0.36	0.27	0.36					
c	0.00	0.30	0.50	0.20					
d	0.00	0.36	0.18	0.45					

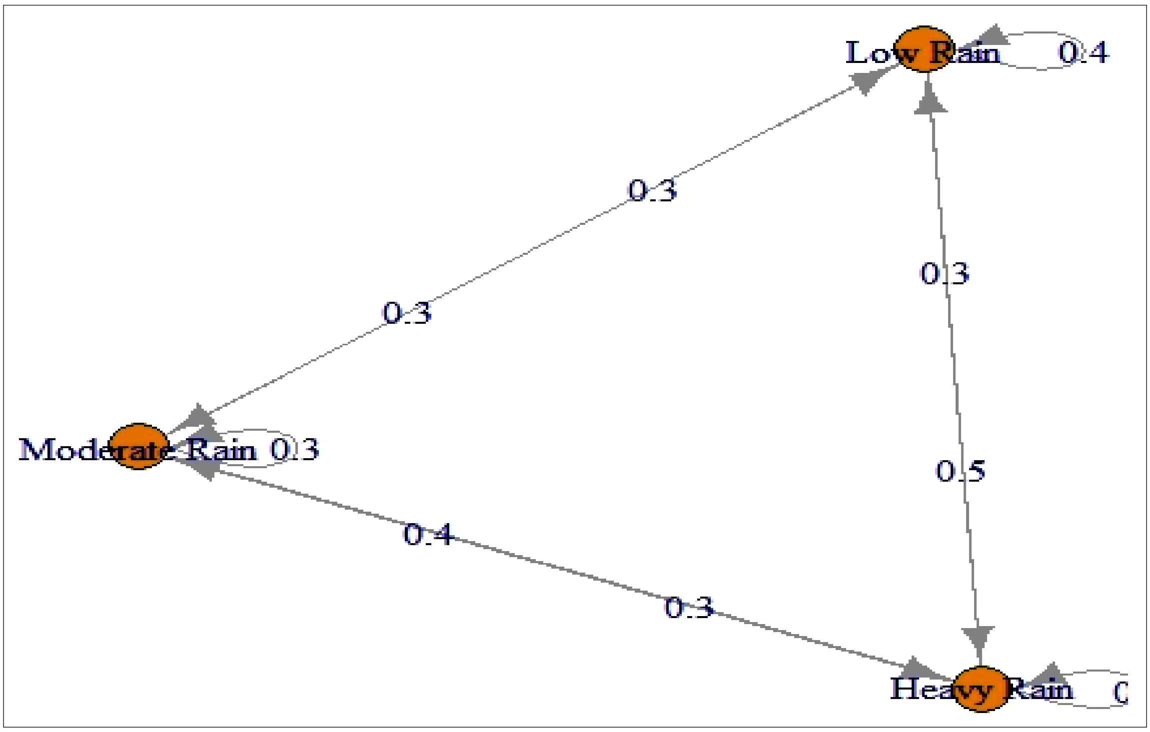

Fig. 4. Probabilistic transitions between rainfall categories.

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Authors' contributions

PR designed the study, was involved in its execution and contributed to manuscript preparation. SN collected secondary data and provided inputs, was involved in execution and contributed to manuscript preparation. SR is involved in the analysis of data & interpretation. KS helped with the execution and provided input. KP contributed to the documentation and understanding of the data. PI assisted in execution and offered feedback. RS fine-tuned and gave critical comments to improve the manuscript.

Compliance with ethical standards

Conflict of interest: Authors do not have any conflict of interest to declare.

Ethical issues: None

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