

Spatio-Temporal Variability and Trend Analysis of Rainfall Over Kerala, India, Using Persiann-Ccs Gridded Satellite Data (2003–2024)

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Abstract: Understanding the spatial and temporal distribution of rainfall is fundamental to water resource planning and disaster preparedness in monsoon-driven regions. This study investigated spatio-temporal variability and long-term trends of annual rainfall across the 14 administrative districts of Kerala, India, over 2003–2024, using satellite-derived estimates from PERSIANN-CCS (Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks — Cloud Classification System) at a native resolution of approximately 0.04° (~4 km). Rasters were reprojected to UTM Zone 43N and clipped to the Kerala boundary prior to analysis. The coefficient of variation (CV), annual anomaly, Mann-Kendall trend test, Sen's slope estimator and Moran's I spatial autocorrelation were applied. The state-wide long-term mean annual rainfall was 1,832.0 mm (CV = 23.7%). District-level CV ranged from 17.4% (Idukki) to 30.5% (Kasaragod), with 12 of 14 districts classified as moderately variable. Moran's I ($I = 0.1692$, $p = 0.112$) indicated no significant spatial clustering. The year 2018 recorded the highest positive anomaly (+79.5%), coinciding with the catastrophic Kerala floods, while 2016 was the driest year (−43.1%). Five southern and central districts — Alappuzha, Ernakulam, Thiruvananthapuram, Kottayam and Kollam — exhibited statistically significant increasing trends ($p < 0.05$), with Sen's slope values of +29.9 to +36.3 mm/yr; no district showed a decreasing trend. A pronounced decadal shift was observed, with the state mean rising from 1,677.1 mm (2003–2013) to 1,987.0 mm (2014–2024), an increase of 18.5%. The findings underscore rainfall intensification across Kerala's southern districts and the need for adaptive water resource strategies.

Key Words: Rainfall variability, PERSIANN-CCS, Mann-Kendall trend, Coefficient of Variation, Spatial autocorrelation.

1. Introduction

Rainfall is the primary driver of the hydrological cycle across South Asia, and its spatial distribution and temporal variability have direct consequences for agricultural productivity, freshwater availability and the frequency of hydrometeorological extremes. In India, where a large proportion of the population remains dependent on rain-fed agriculture and where the annual water budget is dominated by the south-west monsoon, understanding long-term changes in rainfall patterns has become a critical scientific and policy priority (Krishnakumar et al., 2009; Roxy et al., 2015). Climate variability mediated by large-scale ocean–atmosphere interactions — including the El Niño–Southern Oscillation (ENSO) and the Indian

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Ocean Dipole (IOD) — has been shown to modulate both the intensity and distribution of monsoon rainfall across the Indian subcontinent, with disproportionate impacts on smaller, topographically complex states such as Kerala (*Simon & Mohankumar, 2004; Roxy et al., 2017*).

Kerala, situated along the south-western coast of India between the Arabian Sea and the Western Ghats, receives approximately three times the national average annual rainfall and is widely regarded as the ‘Gateway of the Indian Summer Monsoon’ (*Krishnakumar et al., 2009*). The state’s complex physiography — encompassing a narrow coastal plain, undulating midland tracts and the steeply rising Western Ghats escarpment — produces marked spatial heterogeneity in rainfall distribution that cannot be resolved by sparse rain gauge networks alone (*Simon & Mohankumar, 2004; Nair et al., 2014*). Concurrently, the state has experienced dramatic inter-annual variability in recent decades, most strikingly illustrated by the catastrophic floods of August 2018, which were associated with rainfall approximately 80% above the long-term mean and were described as the most severe flooding event since 1924 (*Mishra & Shah, 2018; Mishra et al., 2018*). The co-occurrence of such extreme wet events with recent severe drought years — most notably 2016, which recorded rainfall more than 40% below the long-term mean — highlights the dual and escalating flood–drought risk that the state faces.

Despite the hydrological and socioeconomic significance of Kerala’s rainfall regime, a number of important knowledge gaps remain. First, most existing district-level analyses of Kerala’s rainfall (*e.g., Krishnakumar et al., 2009; Nair et al., 2014*) rely on rain gauge station data from the twentieth century and do not extend into the post-2000 period, which has seen a cluster of anomalous wet years and a potential decadal shift in the mean rainfall state. Second, satellite-based precipitation products, and specifically the PERSIANN-CCS algorithm (*Hong et al., 2004*), offer spatially continuous coverage at sub-district scales that station networks cannot provide, yet their application to district-level variability analysis over Kerala remains limited. Third, while the Mann-Kendall trend test and Sen’s slope estimator have been widely applied to Indian rainfall data (*Agarwal et al., 2021*), systematic analysis of trend spatial structure over Kerala’s 14 districts using the full 2003–2024 period has not been reported. Fourth, spatial autocorrelation analysis of rainfall variability using Moran’s I — which can reveal whether high-variability districts cluster spatially and thus inform basin-level management decisions — has not been applied to Kerala at the district scale.

This study addresses these gaps by conducting a comprehensive spatio-temporal analysis of annual rainfall over Kerala’s 14 districts for the 22-year period 2003–2024, using PERSIANN-CCS data. Specifically, the study aims to: (i) characterise the spatial distribution of long-term mean annual rainfall and its district-level variability using the coefficient of variation; (ii) examine inter-annual anomaly patterns and identify extreme wet and dry years; (iii) quantify long-term trends using the Mann-Kendall test and Sen’s slope estimator; (iv) assess whether rainfall variability exhibits spatial clustering using Moran’s I; and (v) analyse the decadal shift in mean annual rainfall between 2003–2013 and 2014–2024. Ordinary Kriging at 100 m resolution is applied to produce smooth district-level spatial surfaces for each variable, supporting cartographic representation and visual interpretation. The findings are intended to inform water resource planning, flood risk management and climate adaptation strategies for Kerala.

Several prior studies provide essential context for this work. *Krishnakumar et al. (2009)* examined long-term rainfall trends over Kerala for 1871–2005 using Mann-Kendall statistics, reporting a significant decrease in south-west monsoon rainfall alongside an increasing post-monsoon trend. *Simon and Mohankumar (2004)* delineated three spatially distinct rainfall regions within Kerala using factor analysis, demonstrating that stations north of 10°N receive a higher proportion of south-west monsoon rainfall, while southern stations are more influenced by the north-east monsoon. *Nair et al. (2014)* extended this work to produce a centennial (1901–2000) district-level trend analysis, finding large spatial and temporal variability in monthly and seasonal rainfall across the state. At the national scale, *Roxy et al. (2015)* demonstrated that rapid warming of the Indian Ocean has weakened the land–sea thermal gradient and contributed to a drying trend over central India, while *Roxy et al. (2017)* documented a threefold increase in widespread extreme rainfall events attributable to increasing variability in Arabian Sea low-level westerlies. These large-scale findings provide the mechanistic backdrop against which Kerala’s district-level trends observed in the present study must be interpreted. The extreme hydrometeorological event of 2018 has been examined by *Mishra and Shah (2018)* and *Mishra et al. (2018)*, who confirmed that the August 2018 extreme precipitation was unprecedented in the 66-year instrumental record and was driven primarily by anomalous atmospheric conditions combined with above-normal antecedent reservoir storage. The PERSIANN-CCS algorithm underpinning the present analysis was originally described by *Hong et al. (2004)*, and its application to regional hydrological and climatological analysis has since been validated in numerous tropical regions (*Ashouri et al., 2015*).

2. Study Area

Kerala, the study area, is a narrow coastal state situated along the south-western tip of the Indian peninsula, extending between 8.2°N to 12.8°N latitude and 74.9°E to 77.4°E longitude (*Fig. 1*). Bounded by the Arabian Sea to the west and the Western Ghats to the east, the state covers an area of approximately 38,852 km², representing only 1.18% of India’s total landmass (*Nair et al., 2014*). Physiographically, Kerala is divisible into three distinct zones: the eastern highlands of the Western Ghats (500–2,695 m), the central midland rolling hills (50–500 m), and the narrow western coastal lowlands (0–50 m). The Palakkad Gap, a natural break in the Western Ghats at approximately 10.5°N, significantly modifies the regional rainfall distribution by disrupting orographic enhancement and allowing eastward moisture penetration. The state receives rainfall from two monsoon systems: the south-west monsoon (June–September), which contributes 65–70% of the annual total, and the north-east monsoon (October–December), which is particularly significant for southern districts (*Simon & Mohankumar, 2004*). Mean annual rainfall is approximately 3,000 mm, roughly three times the national average (*Krishnakumar et al., 2009*). The

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study encompasses all 14 administrative districts: Kasaragod, Kannur, Wayanad, Kozhikode, Malappuram, Palakkad, Thrissur, Ernakulam, Idukki, Kottayam, Alappuzha, Pathanamthitta, Kollam and Thiruvananthapuram.

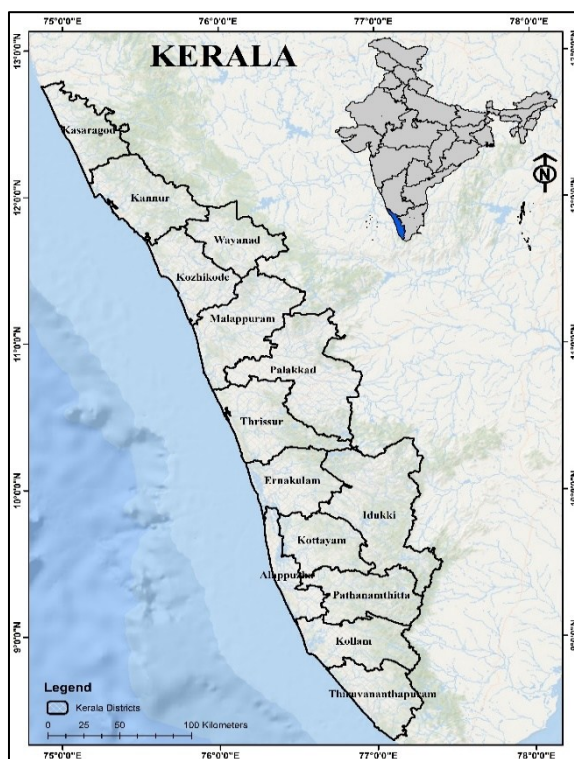


Fig. 1. Study Area

3. Data ad Methods

This study adopted a six-stage methodological workflow (**Fig. 2**): data acquisition, pre-processing, statistical and spatial analysis, zonal statistics extraction, derivation of analytical outputs, and spatial visualisation. The entire pipeline was implemented in Python using rasterio, geopandas, rasterstats, pymannkendall, libpysal and esda.

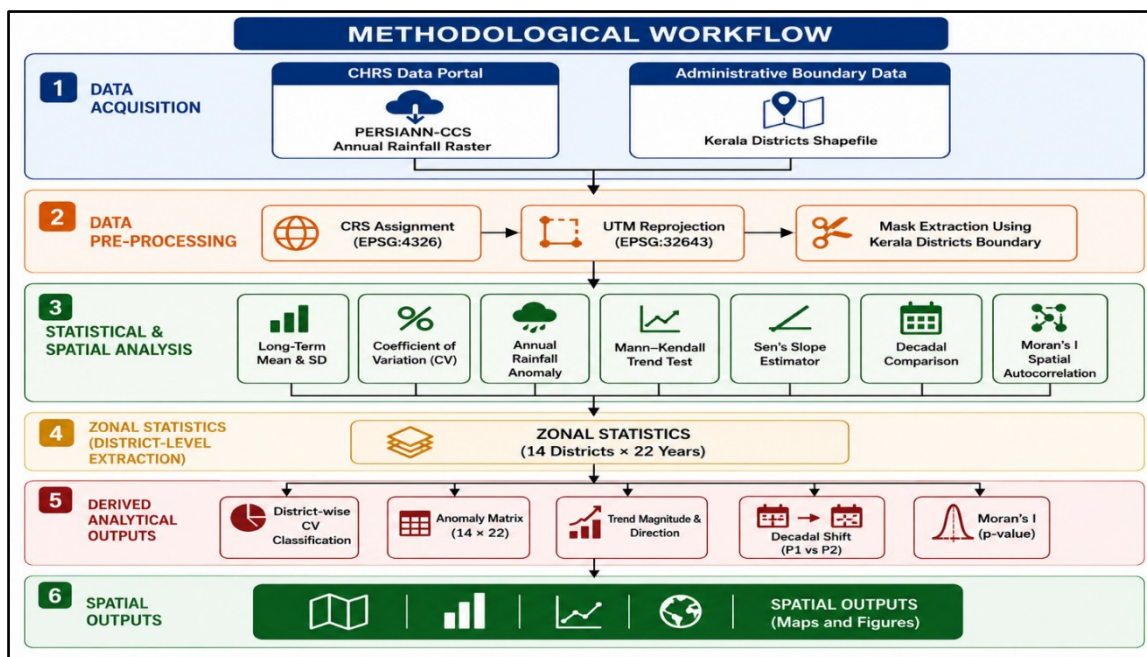


Fig. 2. Methodological workflow of the study

3.1 Data Source: PERSIANN-CCS

Annual total rainfall for 2003–2024 was obtained from the PERSIANN-CCS product (Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks — Cloud Classification System), developed by the Center for

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Hydrometeorology and Remote Sensing, University of California, Irvine (*Hong et al., 2004*). The algorithm extracts cloud features — height, coldness, areal extent and texture — from infrared geostationary imagery, classifies cloud patches into 400 groups via a Self-Organising Feature Map, and derives a brightness temperature–rainfall rate relationship for each group using gauge-corrected radar data (*Hong et al., 2004; Sadeghi et al., 2021*). Twenty-two annual GeoTIFF rasters at a native resolution of 0.04° (~4 km) were downloaded from the CHRS Data Portal (<https://chrsdata.eng.uci.edu>).

3.2 Data Preprocessing:

Raw rasters were delivered in WGS84 (EPSG:4326) and reprojected to UTM Zone 43N (EPSG:32643) via bilinear resampling using `rasterio.warp.reproject`, matching the coordinate system of the district shapefile. Each raster was then clipped to the dissolved Kerala state boundary using `rasterio.mask.mask` (`crop=True, all_touched=True`). The source NoData value (−99.0) was remapped to −99999 to maintain a consistent convention throughout the pipeline.

3.3 Statistical Analysis of Rainfall Variability

3.3.1 Long-Term Mean and Coefficient of Variation

The pixel-wise long-term mean (μ) and standard deviation (σ) of annual rainfall were computed across all 22 years using Welford's online algorithm (*Welford, 1962*), which processes one raster at a time and avoids loading the full time-stack into memory simultaneously — a requirement given the 22-raster dataset. The Coefficient of Variation (CV) was subsequently computed at each pixel as:

$$CV (\%) = (\sigma / \mu) \times 100$$

CV is a dimensionless measure of relative inter-annual variability that normalises variability by the mean, enabling meaningful spatial comparisons across districts with different mean rainfall totals (*Krishnakumar et al., 2009*). District-level CV values were derived by computing the mean CV within each district polygon using zonal statistics. Districts were classified into four variability classes following the widely adopted scheme: Low (CV < 20%), Moderate (20–30%), High (30–40%), and Very High (> 40%) (*Nair et al., 2014*).

3.3.2 Annual Rainfall Anomaly

Annual rainfall anomaly was computed for each year i and each pixel as:

$$\text{Anomaly}_i (\%) = [(P_i - \mu) / \mu] \times 100$$

where P_i is the annual rainfall for year i and μ is the long-term mean (2003–2024). Positive anomalies indicate above-normal rainfall and negative anomalies indicate below-normal conditions. Anomaly years were classified into five categories: Strongly Wet (> +20%), Moderately Wet (+10 to +20%), Near-Normal ($\pm 10\%$), Moderately Dry (−10 to −20%), and Strongly Dry (< −20%). District-level anomaly values were extracted using zonal statistics for each of the 22 years, producing a 14 × 22 anomaly matrix for temporal and spatial analysis.

3.4 Mann-Kendall Trend Test and Sen's Slope Estimator

Long-term monotonic trends in annual district rainfall were assessed using the non-parametric Mann-Kendall (MK) trend test (*Mann, 1945; Kendall, 1975*), which is widely applied to hydrometeorological time series because it makes no assumption about the underlying distribution of the data and is robust to the presence of outliers and missing values (*Agarwal et al., 2021*). The MK test statistic S is computed as:

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

where x_i and x_j are the annual rainfall values at years i and j , and $\text{sgn}(\cdot)$ is the sign function. Under the null hypothesis of no trend, S is approximately normally distributed for $n > 10$. A statistically significant trend was identified when the two-tailed p -value was less than 0.05 ($\alpha = 0.05$). The magnitude of the trend was quantified using Sen's non-parametric slope estimator (*Sen, 1968*), defined as the median of all pairwise slopes:

$$Q = \text{Median}[(x_j - x_i) / (j - i)] \text{ for all } i < j$$

A positive Q value indicates an increasing trend and a negative value indicates a decreasing trend, with units of mm per year. The MK test and Sen's slope were computed for each of the 14 districts using the `pymannkendall` Python package (*Hussain & Mahmud, 2019*). The analysis was conducted on the district-level zonal mean annual rainfall time series (22 data points per district).

3.5 Moran's I Spatial Autocorrelation

The global Moran's I statistic (*Moran, 1950*) was applied to the district-level CV values to assess whether spatially adjacent districts exhibited more similar variability than would be expected under spatial randomness. Moran's I is defined as:

$$I = [N / W] \times [\sum_i \sum_j w_{ij} (x_i - \bar{x})(x_j - \bar{x})] / [\sum_i (x_i - \bar{x})^2]$$

where N is the number of spatial units (14 districts), W is the sum of all spatial weights, x_i is the CV value for district i , $\bar{x}$ is the mean CV, and w_{ij} is the spatial weight between districts i and j . Queen contiguity weights (sharing at least one boundary point) were applied and row-standardised so that each row sums to unity (*Anselin, 1995*). Statistical significance was assessed using permutation testing with 999 random permutations. A positive I greater than the expected value $E[I] = -1/(N-1)$ indicates positive spatial autocorrelation (clustering of similar values), while a negative I indicates dispersion.

3.6 Decadal Comparison

To assess whether a systematic shift in the mean rainfall state occurred between the first and second halves of the study period, the 22 years were divided into two equal 11-year periods: Period 1 (P1: 2003–2013) and Period 2 (P2: 2014–2024). Pixel-wise mean annual rainfall rasters were computed independently for each period, and the decadal change was derived as

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the arithmetic difference ($P2 - P1$). District-level $P1$ mean, $P2$ mean, absolute change (mm) and proportional change (%) were extracted using zonal statistics. The division at 2013/2014 was selected to create equal period lengths while aligning with the observed transition from a predominantly dry anomaly regime ($P1$ included the dry years 2003, 2005, 2009, 2013) to a predominantly wet anomaly regime ($P2$ included the wet years 2018, 2019, 2020, 2021). After 6 weeks of follow up it was found that LDL-C went down by -32.81% on regular dose of Atorvastatin 40 mg, -37.28% on Rosuvastatin 20 mg daily and -37.53% on Rosuvastatin 20 mg alternate day.

4. Results and Discussion

4.1 Spatial Distribution of Mean Annual Rainfall

The long-term mean annual rainfall over Kerala during 2003–2024 stood at 1,832.0 mm ($\sigma = 434.0$ mm), revealing pronounced spatial heterogeneity across the 14 districts (**Fig. 4.1**). Kottayam (2,450 mm), Ernakulam (2,370 mm), Alappuzha (2,274 mm) and Pathanamthitta (2,165 mm) constituted the wettest cluster, while Wayanad (1,329 mm), Palakkad (1,468 mm) and Kasaragod (1,560 mm) recorded the lowest district means. This north–south and coast–interior gradient is governed primarily by the orographic interception of south-west monsoon airflow by the Western Ghats, which forces moisture ascent on the windward western slopes (*Krishnakumar et al., 2009*). The Palakkad Gap, a natural break in the range at approximately 10.5°N, suppresses orographic enhancement locally, explaining the comparatively lower rainfall in Palakkad and Malappuram (1,604 mm). Wayanad's low mean, despite its elevated terrain, reflects its leeward eastern exposure, consistent with the spatial gradients documented by *Nair et al. (2014)* across the nineteenth–twentieth century station record.

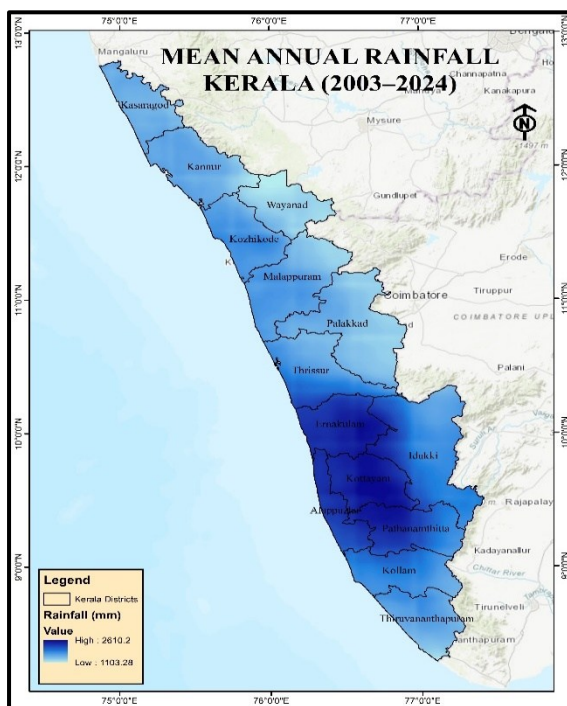


Fig. 4.1. Mean Annual Rainfall

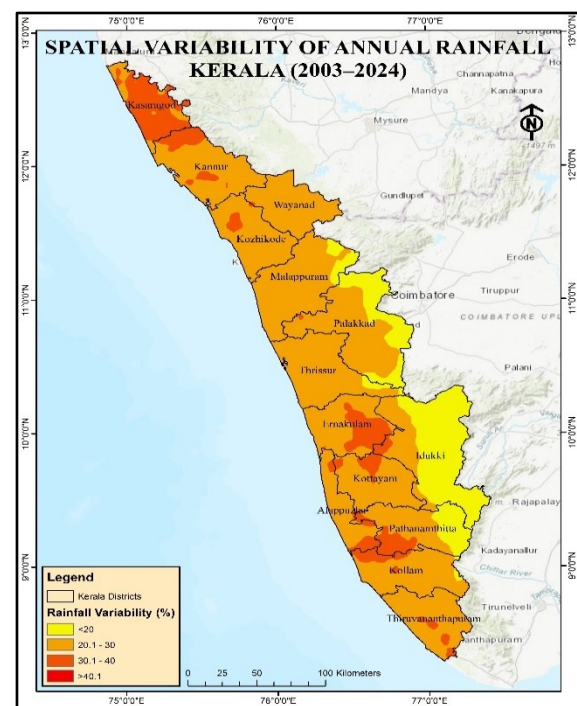


Fig. 4.2 Spatial Variability of rainfall

4.2 Inter-Annual Variability and Spatial Clustering

District-level CV ranged from 17.4% (Idukki) to 30.5% (Kasaragod), yielding a state mean of 23.7% (**Fig. 4.2**). Twelve of 14 districts fell within the moderate variability class (20–30%), with Kasaragod alone classified as high (30–40%) and Idukki as low (< 20%). Idukki's stability reflects the persistent orographic forcing of the Western Ghats interior, while Kasaragod's elevated CV arises from its sensitivity to both the south-west and north-east monsoon systems, each introducing independent sources of inter-annual uncertainty. The non-significant Moran's I result ($I = 0.1692$, $p = 0.112$, 999 permutations) indicates that high-CV districts do not cluster spatially (**Fig. 4.3**); the null hypothesis of spatial randomness could not be rejected. This absence of spatial structure implies that rainfall variability in Kerala is modulated by localised drivers — ENSO teleconnections, sea surface temperature anomalies and individual monsoon depression tracks — rather than a geographically coherent regional forcing.

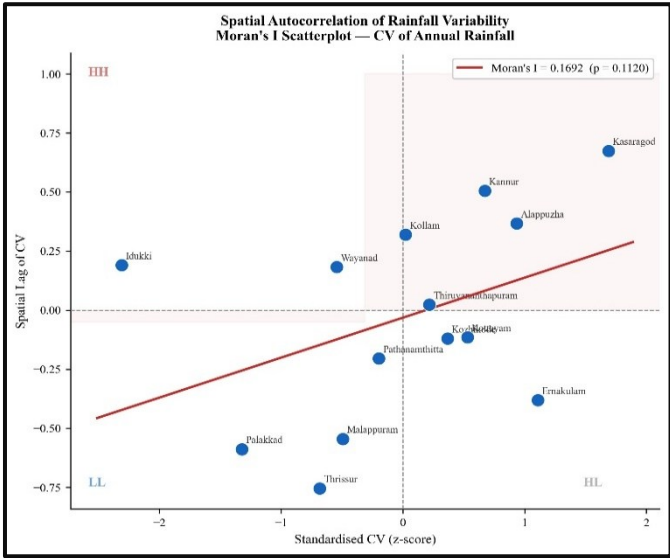


Fig. 4.3 Moran's I Moran's I Scatterplot

4.3 Annual Rainfall Anomaly

Six years were classified as wet (anomaly > +10%): 2010 (+13.8%), 2014 (+10.6%), 2018 (+79.5%), 2019 (+11.8%), 2020 (+14.4%) and 2021 (+23.0%); six were dry (< -10%): 2003, 2005, 2009, 2013, 2016 and 2023; ten remained near-normal (Fig. 4.4). The 2016 drought produced the most severe negative anomaly at -43.1% (state mean: 1,048 mm), with district deficits ranging from -27.2% (Idukki) to -52.2% (Kozhikode), coinciding with one of the strongest El Niño episodes of the satellite era. The 2018 positive anomaly of +79.5% — the largest in the 22-year record — resulted from the convergence of an above-normal south-west monsoon, successive low-pressure systems and concurrent reservoir releases across the Periyar basin (Mishra et al., 2018). Kasaragod (+104.5%), Ernakulam (+105.2%) and Alappuzha (+101.0%) each exceeded +100%, confirming near-state-wide extreme conditions.

The spatial anomaly maps (Fig. 4.5) for 2018, 2016, 2021 and the near-normal benchmark year 2008 (+1.4%) illustrate the full range of inter-annual spatial variability. A systematic shift toward positive anomaly years post-2013 is discernible, with wet or near-normal conditions dominating Period 2 (2014–2024).

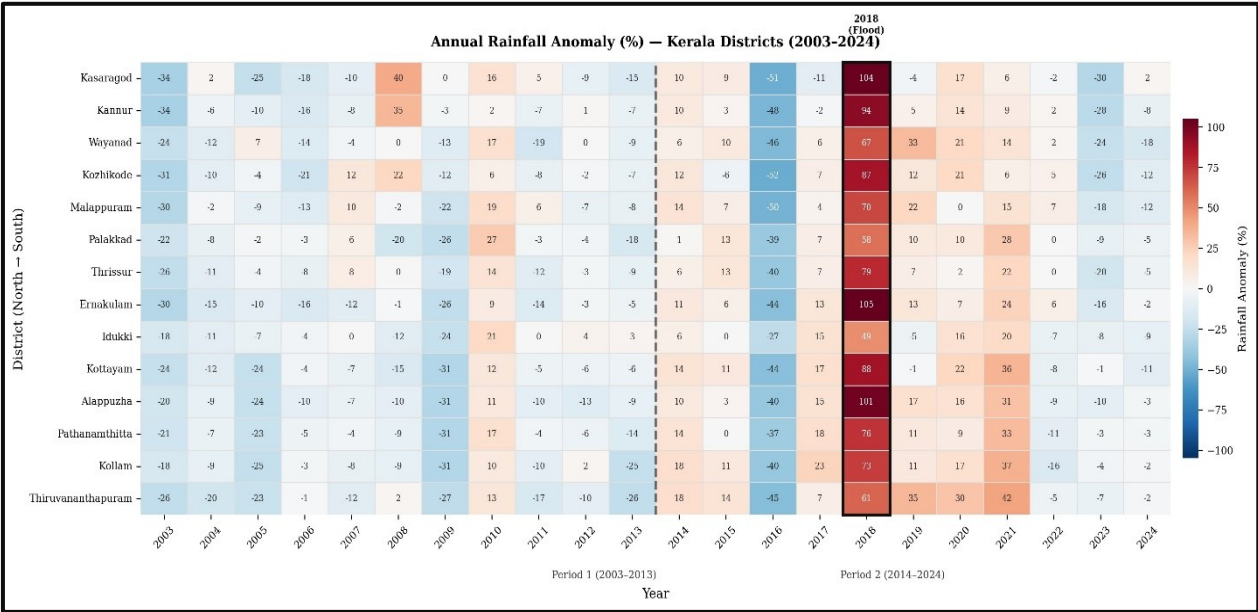


Fig. 4.4 Annual Rainfall Anomaly Heatmap

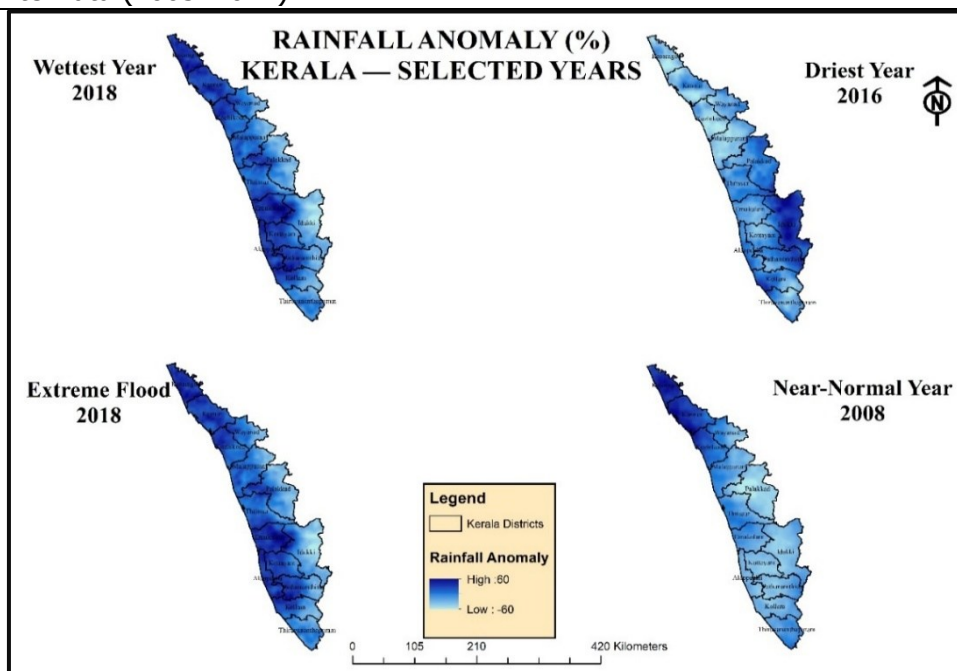


Fig. 4.5 Annual Rainfall Anomaly of selected years

4.4 Long-Term Trend Analysis

The Mann-Kendall test identified statistically significant increasing trends ($p < 0.05$) in five southern and central districts: Alappuzha (+34.6 mm/yr), Ernakulam (+36.3 mm/yr), Thiruvananthapuram (+29.9 mm/yr), Kottayam (+35.3 mm/yr) and Kollam (+32.2 mm/yr), with no district recording a significant decreasing trend (**Figs. 4.6 and 4.7**). The remaining nine districts including Kasaragod, Wayanad and Palakkad — returned positive but non-significant Sen's slope values (range: +10.4 to +25.1 mm/yr), reflecting a broad but spatially uneven upward signal across the state.

The concentration of significant trends in the southern coastal belt is consistent with documented intensification of the south-west monsoon over the eastern Arabian Sea (*Roxy et al., 2017*). Rapid warming of Arabian Sea sea surface temperatures has been associated with enhanced low-level moisture flux toward the Indian subcontinent (*Roxy et al., 2015*), preferentially benefiting the windward western districts that record the steepest Sen's slope values.

The lower statistical detectability in northern districts likely reflects a higher noise-to-signal ratio rather than an absence of underlying change.

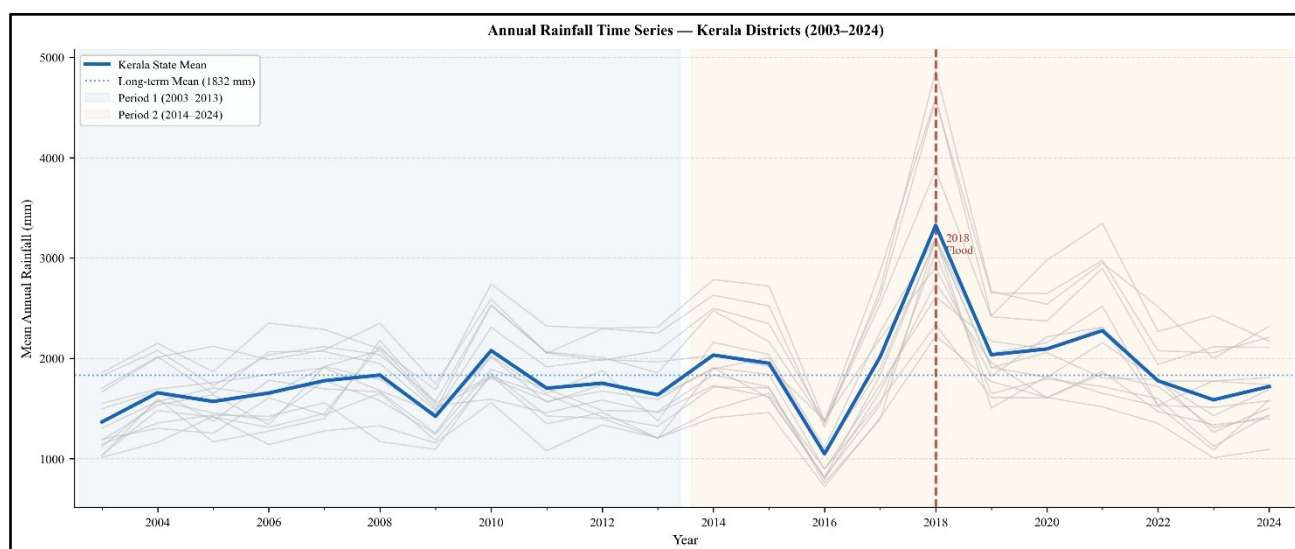


Fig. 4.6 Rainfall Time Series

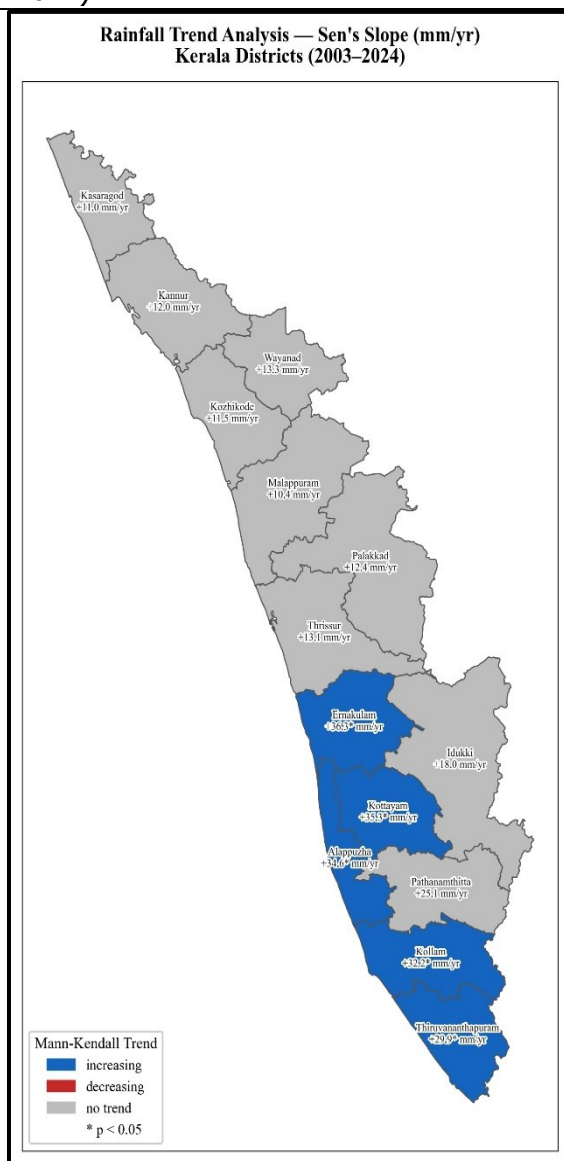


Fig. 4.7 Mann-Kendall Trend Map

4.5 Decadal Shift in Rainfall

The state mean annual rainfall increased from 1,677.1 mm in Period 1 (2003–2013) to 1,987.0 mm in Period 2 (2014–2024), a gain of +309.9 mm (+18.5%), with all 14 districts recording positive shifts (**Fig. 4.8**). The largest absolute gains occurred in Alappuzha (+544.6 mm, +27.2%), Kottayam (+543.9 mm, +25.0%) and Ernakulam (+532.8 mm, +25.3%); the smallest in Kasaragod (+140.1 mm, +9.4%), Kannur (+148.2 mm, +9.9%) and Kozhikode (+168.2 mm, +10.4%), mirroring the spatial pattern of Mann-Kendall significance. The decadal shift is attributable to a combination of Arabian Sea warming, a phase transition in the Indian Ocean Dipole favouring positive IOD conditions post-2013, and possible urban heat island intensification in the Ernakulam–Thiruvananthapuram corridor. The co-occurrence of severe droughts (2003, 2009, 2016) within this overall wetting trend underlines the dual flood–drought exposure that water resource planners in Kerala must simultaneously manage. These findings reinforce the case for adaptive reservoir operating rules and integrated flood-drought contingency frameworks, particularly in the southern districts where both trend magnitude and population density are highest. PERSIANN-CCS's native 4 km resolution constrains sub-district interpretation and may underestimate peak rainfall over steep Western Ghats terrain (*Prakash et al., 2015*); validation against IMD gauge networks is recommended for future work.

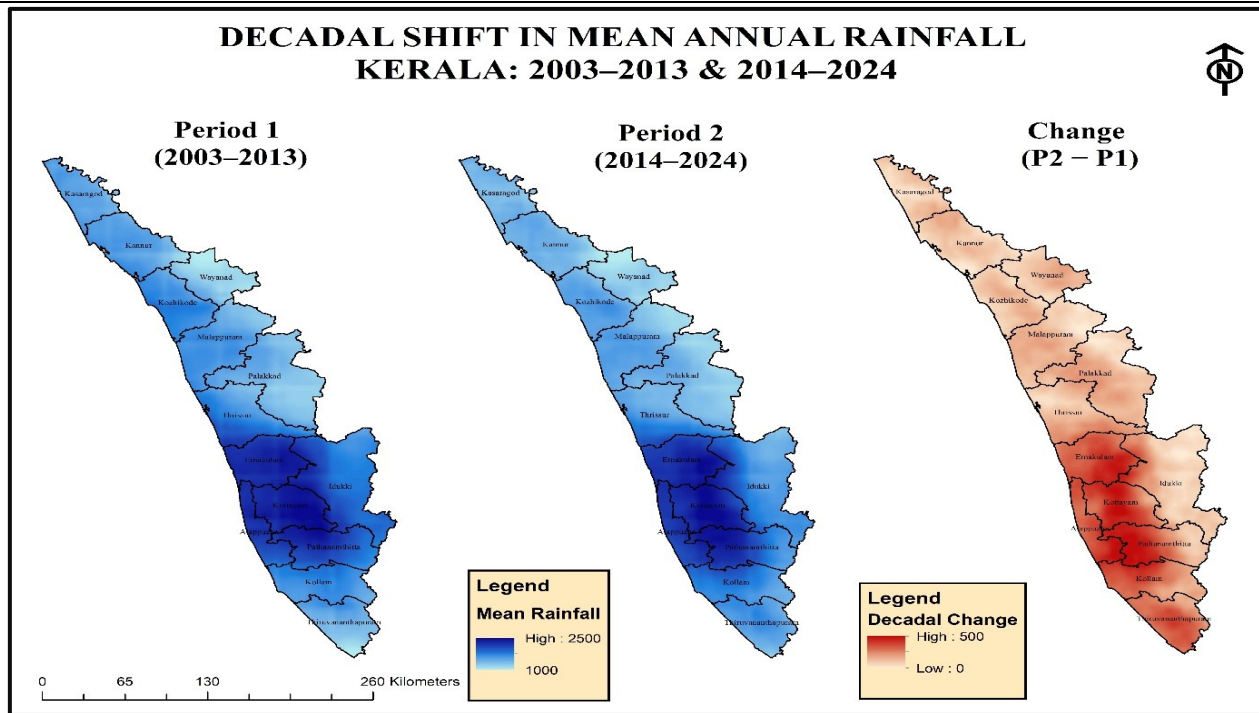


Fig. 4.8 Decadal Shift Comparison Map

5. Conclusion

Rosuvastatin 20 mg on every other regimen had equal effect when compared to daily dose regimen of atorvastatin 40 mg & rosuvastatin 20mg. Annual rainfall variability and long-term trends across Kerala's 14 districts were examined over 2003–2024 using PERSIANN-CCS data, yielding five key findings. Mean annual rainfall of 1,832.0 mm varied from 1,329 mm (Wayanad) to 2,450 mm (Kottayam), governed by Western Ghats orography and the Palakkad Gap rain-shadow (*Krishnakumar et al., 2009*). Inter-annual variability was moderate across 12 districts (CV 20–30%), with Kasaragod the most erratic (30.5%) and Idukki the most stable (17.4%); Moran's I ($I = 0.1692$, $p = 0.112$) confirmed spatial randomness in this variability pattern. Anomalies ranged from –43.1% in 2016 (El Niño-driven drought) to +79.5% in 2018 (Mishra & Shah, 2018), marking the extremes of a record that included six wet and six dry years within the 22-year window. Mann-Kendall analysis returned statistically significant increasing trends in five southern and central districts — Alappuzha, Ernakulam, Thiruvananthapuram, Kottayam and Kollam — with Sen's slope values of +29.9 to +36.3 mm/yr and no significant decreasing trend anywhere in the state. A state-wide decadal shift from 1,677.1 mm (2003–2013) to 1,987.0 mm (2014–2024), an 18.5% rise, confirmed a broad intensification concentrated in the south. The concurrent occurrence of extreme wet and dry episodes within an overall wetting trajectory signals a dual flood–drought risk that demands adaptive reservoir management and integrated water resource planning across the state. Future work should validate PERSIANN-CCS against IMD gauge networks and investigate Arabian Sea warming, ENSO and Indian Ocean Dipole forcing as drivers of the observed decadal shift (Roxy et al., 2015).

References

- [1]. Agarwal, S., Suchithra, A. S., & Singh, S. P. (2021). Analysis and interpretation of rainfall trend using Mann-Kendall's and Sen's slope method. *Indian Journal of Ecology*, 48(2), 453–457.
- [2]. Anselin, L. (1995). Local indicators of spatial association — LISA. *Geographical Analysis*, 27(2), 93–115. <https://doi.org/10.1111/j.1538-4632.1995.tb00338.x>
- [3]. Ashouri, H., Hsu, K.-L., Sorooshian, S., Braithwaite, D. K., Knapp, K. R., Cecil, L. D., Nelson, B. R., & Prat, O. P. (2015). PERSIANN-CDR: Daily precipitation climate data record from multisatellite observations for hydrological and climate studies. *Bulletin of the American Meteorological Society*, 96(1), 69–83. <https://doi.org/10.1175/BAMS-D-13-00068.1>
- [4]. Hong, Y., Hsu, K.-L., Sorooshian, S., & Gao, X. (2004). Precipitation estimation from remotely sensed imagery using an artificial neural network cloud classification system. *Journal of Applied Meteorology*, 43(12), 1834–1852. <https://doi.org/10.1175/JAM2173.1>
- [5]. Hsu, K., Gao, X., Sorooshian, S., & Gupta, H. V. (1997). Precipitation estimation from remotely sensed information using artificial neural networks. *Journal of Applied Meteorology and Climatology*, 36(9), 1176–1190. [https://doi.org/10.1175/1520-0450\(1997\)036<1176:PEFRSI>2.0.CO;2](https://doi.org/10.1175/1520-0450(1997)036<1176:PEFRSI>2.0.CO;2)
- [6]. Hussain, M., & Mahmud, I. (2019). pyMannKendall: A python package for non parametric Mann Kendall family of trend tests. *Journal of Open Source Software*, 4(39), 1556. <https://doi.org/10.21105/joss.01556>
- [7]. Kendall, M. G. (1975). *Rank Correlation Methods* (4th ed.). Charles Griffin.
- [8]. Krishnakumar, K. N., Prasada Rao, G. S. L. H. V., & Gopakumar, C. S. (2009). Rainfall trends in twentieth century over Kerala, India. *Atmospheric Environment*, 43(11), 1940–1944. <https://doi.org/10.1016/j.atmosenv.2008.12.053>
- [9]. Mann, H. B. (1945). Nonparametric tests against trend. *Econometrica*, 13(3), 245–259. <https://doi.org/10.2307/1907187>
- [10]. Mishra, V., & Shah, H. L. (2018). Hydro climatological perspective of the Kerala flood of 2018. *Journal of the Geological Society of India*, 92(5), 645–650. <https://doi.org/10.1007/s12594-018-1079-3>

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- [11]. Mishra, V., Aadhar, S., Shah, H., Kumar, R., Pattanaik, D. R., & Tiwari, A. D. (2018). The Kerala flood of 2018: Combined impact of extreme rainfall and reservoir storage. *Hydrology and Earth System Sciences Discussions*. <https://doi.org/10.5194/hess-2018-480>
- [12]. Moran, P. A. P. (1950). Notes on continuous stochastic phenomena. *Biometrika*, 37(1–2), 17–23. <https://doi.org/10.1093/biomet/37.1-2.17>
- [13]. Nair, A., Ajayamohan, R. S., Joshi, M., & Bhattacharyya, S. (2014). Spatio-temporal analysis of rainfall trends over a maritime state (Kerala) of India during the last 100 years. *Atmospheric Environment*, 88, 123–132. <https://doi.org/10.1016/j.atmosenv.2014.01.055>
- [14]. Roxy, M. K., Ghosh, S., Pathak, A., Athulya, R., Mujumdar, M., Murtugudde, R., Terray, P., & Rajeevan, M. (2017). A threefold rise in widespread extreme rain events over central India. *Nature Communications*, 8, 708. <https://doi.org/10.1038/s41467-017-00744-9>
- [15]. Sadeghi, M., Nguyen, P., Nacini, M. R., Hsu, K., Braithwaite, D., & Sorooshian, S. (2021). PERSIANN-CCS-CDR: A 3-hourly 0.04° global precipitation climate data record for heavy precipitation studies. *Scientific Data*, 8, 157. <https://doi.org/10.1038/s41597-021-00940-9>
- [16]. Sen, P. K. (1968). Estimates of the regression coefficient based on Kendall's tau. *Journal of the American Statistical Association*, 63(324), 1379–1389. <https://doi.org/10.1080/01621459.1968.10480934>
- [17]. Simon, A., & Mohankumar, K. (2004). Spatial variability and rainfall characteristics of Kerala. *Journal of Earth System Science*, 113(2), 211–221. <https://doi.org/10.1007/BF02709788>
- [18]. Soman, M. K., Kumar, K. K., & Singh, N. (1988). Decreasing trend in the rainfall of Kerala. *Current Science*, 57(7), 7–12.
- [19]. Webster, R., & Oliver, M. A. (2007). *Geostatistics for Environmental Scientists* (2nd ed.). Wiley. <https://doi.org/10.1002/9780470517277>
- [20]. Welford, B. P. (1962). Note on a method for calculating corrected sums of squares and products. *Technometrics*, 4(3), 419–420. <https://doi.org/10.1080/00401706.1962.10490022>