International Journal of Electrical and Computer Engineering (IJECE)
Vol. 14, No. 3, June 2024, pp. 3372∼3381
ISSN: 2088-8708, DOI: 10.11591/ijece.v14i3.pp3372-3381

Probability distributions in Kerala's rainfall: implications for hydro energy planning

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Article Info

Article history:

Received Nov 28, 2023
Revised Feb 22, 2024
Accepted Feb 25, 2024

Keywords:

Dagum-distributions
Kaumarasamy-distribution
Probability distribution
Rainfall analysis
Rainfall data
Rainfall requirements
Statistics

ABSTRACT

Heavy rainfall has consistently acted as the primary catalyst for floods, resulting in numerous casualties and significant economic losses globally. Rainfall forecasting is accomplished by analysing existing rainfall data, which is then used to analyse the hydraulic system's features. Gaining an understanding of rainfall requirements is a crucial challenge for every location, particularly in the case of India, given its diverse geographical area, population, and other influencing factors that impact various demands. This study evaluated the rainfall data for a span of 1990-2021 in six districts of Kerala State, India. To match the rainfall data from all districts, we utilized both Kaumarasamy-distribution and Dagum-distributions. Various Probabilistic tests, were employed to comparing these distributions. The results revealed that, in Kasargod, the Kumarasamy distribution demonstrates superior goodness-of-fit with the lowest Kolmogorov-Smirnov statistic (0.0597) and Anderson-darling statistic (2.271). However, in Wayanad, Malappuram, Palakkad, Idukki, and Trivandrum, the Dagum distribution consistently exhibits the most accurate fit, evident from its lowest Kolmogorov-Smirnov statistics (0.07447, 0.05435, 0.0556, 0.03636, 0.04291) and favourable Chi-Squared statistics (19.471, 8.4907, 19.239, 5.7318, 7.5297). These results emphasize the regional variation in precipitation data and the suitability of specific distribution models for accurate representation across different locations.

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1. INTRODUCTION

Global climate models (GCM) precipitation behavior links to climate change, shifting distribution model mean. Annual maximum rainfall (AMR) categorizes into extreme rainfall regions, crafting future intensity-duration-frequency (IDF) curves. Envisioned: Framework cuts climate model bias, estimates reliable AMR rainfall by Sojan *et al.* [1]. The study aims to assess rainfall erosivity changes in Brazil's Tocantins-Araguaia basin amid future climate conditions. Employing daily rainfall data from regional climate models

(BESM, CanESM2, MIROC5, HadGEM2-ES) and RCP4.5/RCP8.5 scenarios, it examines 30-year intervals (2011–2040, 2041–2070, 2071–2099), contrasting with the 1961–1990 historical period by Santos *et al.* [2]. Northern Portugal has a low probability (0.01 to 0.05) of extreme rainfall in spring and harvest. While the chance of a 1993-like year is minimal, heavy rainfall in one or both seasons could cause significant harm, guiding decisions on adaptation measures by Sandersen *et al.* [3]. The study suggests an XGBoost-based stochastic framework for analyzing unsaturated slope stability during rainfall infiltration. Using a hypothetical slope with an initial groundwater table, the paper examines how rainfall intensity and pattern affect the probability of slope failure in spatially variable soils by Gu *et al.* [4]. The study assesses lasting trends in Estonia's annual peak rainfall intensities, focusing on short-term rainfall for urban stormwater system design. It analyzes climate change impacts on design storm intensities by Tamm *et al.* [5]. To improve urban planning and enhance the resilience of our communities against extreme rainfall events. They have been successfully applied in various scenarios to model precipitation extremes, such as the most precipitation in a single day during summer in Switzerland as well as the heaviest one day precipitation during autumn in France and drought in Rwanda, Africa by Saunders *et al.* [6]. The researchers develop a stochastic hydrological modeling system to improve daily streamflow prediction in uncertain conditions, scrutinizing error parameters and interactions by Shen *et al.* [7]. Anticipating heightened climate extremes, researchers evaluate diverse water quality models in Asia to address concerns about future drinking water quality and health risks by Fabian *et al.* [8]. The researchers explain that due to unpredictable rainfall peaks during rapid response precipitation (RRPs) and limited soil hydraulic conductivity, there exists a maximum threshold for the cumulative landslide area, and its dispersion increases with longer return periods, contributing to understanding the diverse and systematic progression of rainfall-induced landslides, Zhao *et al.* [9]. The insights gained from probable maximum precipitation (PMP) studies, crucial for designing structures like dams and reservoirs, also serve as a design parameter for hydraulic structures and water resources management by Panday *et al.* [10]. Researchers assess the strengths and limitations of radar-raingauge merged rainfall products versus traditional radar-only and raingauge-only products for both deterministic and stochastic discharge simulations in UK catchments using the project data management (PDM) model and generalized likelihood uncertainty estimation (GLUE) method, Nanding *et al.* [11]. This process continues iteratively until the desired resolution is obtained, as demonstrated by McIntyre et al. [12]. The researchers examined the spatiotemporal variability of rainfall across 33 sub-basins of the National College Health Assessment (NCHA) over a 105-year period (1911-2015), conducting trend and homogeneity tests on monthly, seasonal, and annual timescales by Animashaun *et al.* [13].

Various methods have been extensively suggested to estimate rainfall using data from GEO satellites, despite the absence of a direct physical connection with precipitation. However, the key advantage of utilizing geostationary earth orbit (GEO) satellite data for rainfall estimation lies in its exceptional temporal resolution and spatial coverage by Lazri and Ameur [14]-[16]. CLIMACS generates ensembles of stochastically sampled rain events not aiming to match the true climate and precipitation pattern but to statistically represent rainfall for designing hydrological systems. The paper investigates ensemble variability and the required ensemble size in a given design process by Thorndahl and Andersen [17]. Historical research efforts have predominantly emphasized the fitting and evaluation of statistical distributions to analyze rainfall patterns. In the work by Juras [18], various studies analyzing diverse statistical distributions to achieve precise fitting of precipitation data are discussed. Legates globally assessed eight statistical distributions, including Kappa and Weibull, focusing on Rio de Janeiro's diverse topography; the analysis of rainfall data from 110 stations revealed Gumbel probability distribution function (PDF) ranking highest via the 2 test, while generalized extreme value (GEV) PDF was favored by the Anderson-Darling test by Lima *et al.* [19]. Sarfaraz [20] and Naheed *et al.* [21] research uncovers two main precipitation seasons in Pakistan in where summer and winter monsoons that affecting distinct regions. Trend analysis aids in understanding water resources and assessing rainfall impact, Yonus *et al.* [22]. A continuous probabilistic model simulated catchment-scale water transport, investigating the impact of spatial rainfall variability on streamflow distribution tail heaviness in five catchments of varying sizes and shapes. The study validated results using recorded data from 175 river catchments by Wang *et al.* [23]. The notable likelihood of extreme streamflow occurrences emphasizes an elevated flood risk concerning both the frequency and magnitude of the flow. Across different catchments worldwide, the presence of streamflow patterns with heavy tails has been observed by Wang *et al.* [24]. Rainfall has been largely overlooked in the majority of prior investigations, with only a small subset of recent studies concentrating on forecasting the yearly likelihood due to rainfall-induced slope failure on particular slopes [25], [26]. Nevertheless, the approach may face computational inefficiency, requiring multiple iterations for seepage and stability analyses on various random samples and rainfall patterns for slope assessment by Liu and Wang [27]. Within engineering practice, the proposal hurricane technique is extensively employed from a synthetic rainstorm of equivalent probability by Breinl *et al.* [28]. Deterministic quantitative precipitation forecast (QPFs) from numerical weather prediction (NWP) models offer a single-valued forecast but often contain errors due to disregarding inherent weather uncertainty. In contrast, probabilistic forecasts with multiple members depict various potential scenarios, capturing weather uncertainty by Samal *et al.* [29].

Numerous studies conducted by various authors have attempted to find the best appropriate probabilistic perceptions for analyzing observed wind and solar data. However, as far as the contributors are aware, there appears to be limited assessment regarding rainfall information. This research specifically focuses about choosing the best allocation of probabilities for monthly rainfall statistics in six districts of Kerala, India. To achieve this objective, multiple probability distributions are analyzed and utilized by certain trials, aiming to identify the optimal probability dataset. The study aims to identify the most suitable probability distribution for each district, shedding light on the statistical characteristics of rainfall in the region. This research is crucial for improving the precision of rainfall modeling and forecasting in the specified districts, contributing to better-informed water resource management and disaster preparedness strategies [30]-[34].

2. SELECTED BOUNDARY LOCATIONS

We collected average monthly rainfall data for six districts in Kerala spanning from 1990 to 2022. Figure 1 visually delineates the chosen districts for this study, including Kasargod, Wayanad, Malappuram, Palakkad, Idukki, and Thiruvananthapuram (Trivandrum). These districts were specifically selected to investigate rainfall patterns and trends over the specified time period.

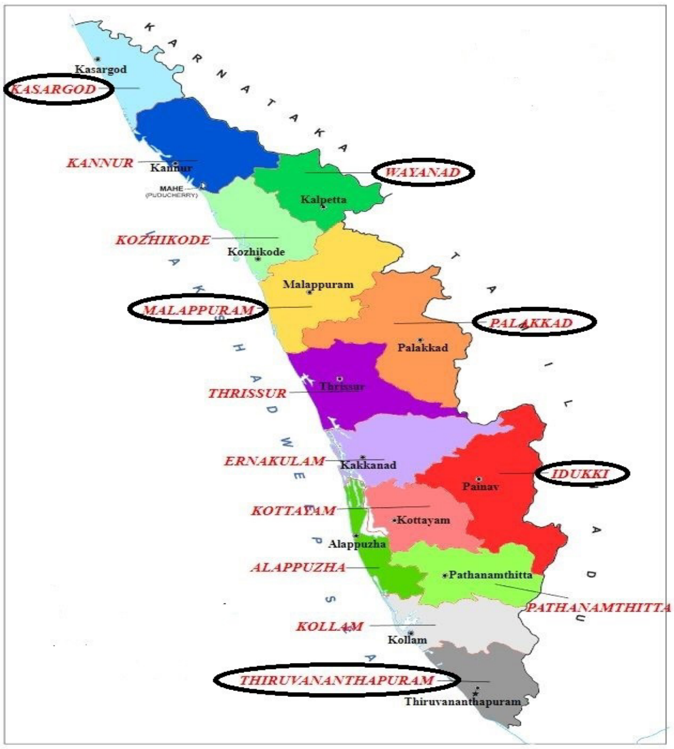


Figure 1. Location of study area

2.1. Kasargod

Kasaragod experiences a tropical monsoon climate influenced by its coastal location along the Arabian Sea. The district enjoys a relatively hot and humid climate throughout the year. Kasaragod is characterized by a varied topography. The district consists of coastal plains, undulating hills, and valleys. It is situated at the foothills of the Western Ghats. The district is well-connected through road and rail networks, facilitating transportation between major cities and towns in the region.

2.2. Wayanad

Wayanad experiences a tropical monsoon climate influenced by its location in the Western Ghats mountain range. The district enjoys a pleasant climate throughout the year, with moderate temperatures. It is characterized by lush green forests, rolling hills, valleys, and beautiful water bodies. The district is situated in the Western Ghats, a mountain range known for its rich biodiversity. The highest peak in Wayanad is Chembra Peak, standing at an elevation of 2,100 meters (6,890 feet).

2.3. Malappuram

Malappuram experiences a tropical monsoon climates influenced by its proximity to the Arabian Sea. Malappuram is characterized by diverse topography. The district consists of coastal plains, undulating hills, and fertile river valleys. It is located at the foothills of the Western Ghats. Malappuram is known for its greenery, extensive paddy fields, and rich biodiversity. It is located in the northern part of Kerala, sharing its borders with the districts of Kozhikode, Thrissur, and Palakkad.

2.4. Palakkad

Palakkad experiences a tropical wet and dry climates, influenced by its inland location and proximity to the Western Ghats. Palakkad is characterized by its flat to undulating terrain, interspersed with small hills and valleys. The district is situated in the Palakkad Gap, a low-lying area between the Western Ghats and the Nilgiri Hills. The Bharathapuzha River, one of the longest rivers in Kerala, flows through Palakkad.

2.5. Idukki

Idukki experiences a tropical monsoon climate due to its geographical location and its proximity to the Western Ghats mountain range. Idukki is characterized by its rugged and mountainous terrain. The district boasts numerous peaks, valleys, and dense forests. Anamudi, the highest point in Idukki and South India, stands tall at an elevation of 2,695 meters (8,842 feet). It shares its borders with the neighboring states of Tamil Nadu and Karnataka. The district is traversed by the Periyar River, one of Kerala's longest rivers.

2.6. Thiruvananthapuram

Thiruvananthapuram experiences a tropical climate influenced by its coastal location along the Arabian Sea. Thiruvananthapuram is located on the southwestern coast of India and is characterized by a varied topography. The city features a mix of coastal plains, low-lying areas, and small hills. Thiruvananthapuram is bordered by the Arabian Sea to the west and is surrounded by other districts of Kerala, including Kollam and Pathanamthitta. Table 1 demonstrates that the region of Idukki is more than the other five districts. Similarly, population in Trivandrum is more than the other five districts. Table 2 shows a description of statistical rainfall data for six districts in Kerala from 1990 to 2022. Kasaragod district receives the maximum rainfall of 52.96 (mm/day) and Palakkad district receives the minimum rainfall of 0.1(mm/day).

Table 1. Study area details

Districts	units	Kasaragod	Wayanad	Malappuram	Palakkad	Idukki	Trivandrum
Geographical	degree	12°N	11°24' N	11°12'N	10°34' N	9°48' N	8°29' N
Location		74°E	75°46' E	76°27' E	76°12' E	76°55' E	76°52' E
Area	km^2	4358	2132	1992	3554	4482	2192
Mean rainfall	mm	69.51	501.2	923.15	609.74	464.82	331.09
Papulation	lakhs	10.9	8.47	13.9	44.9	29.5	36.64

Table 2. Summary of rainfall data

District	Minimum (mm/day)	Maximum (mm/day) (mm/day)	Mean (mm/day)	Standard deviation (mm/day)	Skewness	Kurtosis
KASARGOD	0.5	52.96	9.4371	11.626	1.3037	0.8369
WAYANAD	0.6	25.24	5.0768	5.3162	1.1885	0.9645
MALAPPURAM	0.4	24.61	5.3949	5.3562	1.0237	0.4060
PALAKKAD	0.1	12.99	3.1403	2.6671	0.6799	-0.2441
IDUKKI	0 .7	32.51	5.563	4.8578	0.98881	1.6497
TRIVANDRUM	0.9	29.68	4.9181	4.3561	1.145	2.3871

3. METHOD

In order to evaluate hypothesis and select the most suitable likelihood distribution for rainfall records, we employ various methods for model comparison. Our study utilizes non-parametric distribution tests optimal variables for each likelihood distributions, we employ least-squares testing and subsequently conduct each assessment. Let's now provide clear definitions for these assessment techniques.

3.1. K-S test

This assessment compares the data-based distribution functions of two samples. This test indicator, which is the supreme transformation between theoretical and data-based distributions, serves as a quantity of in what manner the hypothetical spreading fits this data .In essence, it quantifies the level of agreement between a data-based $F(x)$ and a theoretical based $F_0(x)$. The goodness-of-fit calculates the maximum difference between $F(x)$ and $F_0(x)$, denoted as L in (1). If the difference is significant, it indicates a disparity between the observed data with the mathematical simulations.

$$L = \max_x |F_X(x) - F_0(x)| \tag{1}$$

3.2. A-D test

It is a metric used to examine if a collection of statistical data fits into a certain distribution. the test assigns greater importance to the extremities of the distribution. It incorporates the particular distribution model to calculate critical values, which adds complexity to the assessment. One drawback is that the critical values must be determined independently for each distribution.

$$AD = -\frac{n-1}{n} \sum_{i-1}^{n} (2i-1)(\ln F(x_i) + \ln(1 - F(x_{n-i+1}))) \tag{2}$$

3.3. C-S test

The C-s test and goodness-of-fit test are commonly employed when dealing with binned data. It can assess various distributions, including Bernoulli and Poisson, but it is limited to testing only continuous distributions. Let's now define the expression for the C-s test statistic represents the observed frequencies of sample items and E_i represents the predicted frequency.

$$x^2 = \sum \left(\frac{(O_i - E_i)^2}{E_i} \right) \tag{3}$$

3.4. Probability distributions

The best-fit probability distribution was determined using the subsequent approach. Within the probability distributions offered for adjusting precipitation outcomes are the x and y distributions. The mathematical formulae for the probability density function for the aforementioned distributions is provided in (4)-(5).

$$f(x \mid a, b) = (abx)^{a-1}(1 - x^a)^{b-1} \tag{4}$$

$$f(x \mid p, a, b) = \frac{ap}{b}(1 + \frac{(x-b)^2}{a^2})^{-p-1} \tag{5}$$

where in a and b are positive form variables. In the study area's rain fall data, the aforementioned goodness-of-fit tests were employed. The calculated test statistic yielded a value of computed and assessed at significance level. Consequently, the minimum test statistic rank was utilized to compare the probability distributions. Detailed descriptions of distribution factors and goodness-in-fit, can be found in Tables 3 and 4.

Table 3. Distribution factors

TYPES	KASARGOD	WAYANAD	MALAPPURAM	PALAKKAD	IDUKKI	TRIVANDRUM
Kumarasamy	$\alpha_1 = 0.35067$	$\alpha_1 = 0.24966$	$\alpha_1 = 0.24479$	$\alpha_1 = 0.45956$	$\alpha_1 = 0.55486$	$\alpha_1 = 0.39296$
	$\alpha_2 = 1.3225$	$\alpha_2 = 1.091$	$\alpha_2 = 0.79919$	$\alpha_2 = 1.6648$	$\alpha_2 = 1.9339$	$\alpha_2 = 1.5234$
	a=-1.723E-15	a=1.1371E-14	a=7.0729E-15	a=1.1348E-15	a=1.7368E-1	a=4.891E-15
	b=53.128	b=28.887	b=27.471	b=13.467	b=32.797	b=31.298
Dagum	$K = 0.04238$	$K = 0.08626$	$K = 0.0706$	$K = 0.06942$	$K = 0.07552$	$K = 0.1106$
	$\alpha = 8.461$	$\alpha = 5.8686$	$\alpha = 7.2667$	$\alpha = 8.7515$	$\alpha = 7.9056$	$\alpha = 5.8902$
	$\beta = 37.316$	$\beta = 15.151$	$\beta = 16.006$	$\beta = 8.1194$	$\beta = 14.226$	$\beta = 11.822$

Table 4. Extraction of goodness in six various districts

Place	Type	Kolmogorov Smirnov	rank	Anderson Darling	rank	Chi-Squared	rank
KASARGOD	Kumarasamy	0.0597	1	2.271	1	33.067	7
	Dagum	0.07411	4	9.4802	3	24.641	3
WAYANAD	Kumarasamy	0.1605	29	96.053	38	N/A	N/A
	Dagum	0.07447	1	36.938	11	19.471	3
MALAPPURAM	Kumarasamy	0.14905	29	69.720	39	N/A	N/A
	Dagum	0.05435	1	26.408	11	8.4907	2
PALAKKAD	Kumarasamy	0.18851	38	61.56	40	N/A	N/A
	Dagum	0.0556	1	19.732	11	19.239	2
IDUKKI	Kumarasamy	0.10399	16	26.016	29	N/A	N/A
	Dagum	0.03636	1	10.323	6	5.7318	1
TRIVANDRUM	Kumarasamy	0.15309	29	58.371	36	N/A	N/A
	Dagum	0.04291	1	19.086	12	7.5297	1

4. RESULTS AND DISCUSSION

4.1. Probability distributions analysis

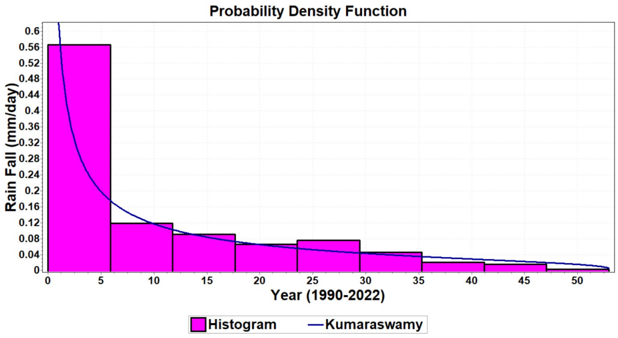
In the study area's rain fall data, the aforementioned goodness-of-fit tests were employed. The calculated test statistic yielded a value of computed and assessed at significance level. Consequently, the minimum test statistic rank was utilized to compare the probability distributions. Detailed descriptions of distribution factors and goodness-in-fit, can be found in Tables 3 and 4.

To ascertain the optimal likelihood fit for annual rainfall data, we conducted a probability analysis using recorded data from six districts spanning the years 1990 to 2022. For this analysis, we considered probability distributions such as the Kumarasamy-distribution and Dagum-distribution. Table 3 provides a summary of the distributions along with their corresponding parameters for the rainfall data. Additionally, Table 4 presents the results of 3 tests. We ranked each PDF in descending order based on the rank value obtained through the three comparison procedures, considering each district separately. By evaluating the rank and select the distribution with lowest overall rank, we determine the suitable distribution for each district. Table 4 displays the district-specific distribution selection based on this ranking method. The findings of our analysis reveal that the Kumarasamy-distribution yields a perfect match for the rainfall data in Kasaragod, as indicated by the 2 tests.

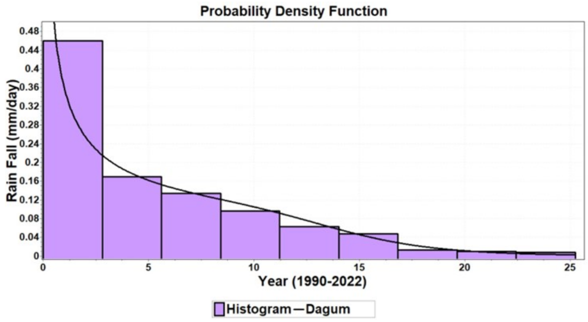
Figure 2(a) and 2(b) display the rainfall data represented as probability density functions (PDFs) for Kasargod and Wayanad districts. It is detected that the rainfall data for Wayanad district exhibits the closest resemblance to the Dagum-distribution. The Figure 3(a) provide a visual representation of the PDFs of the various distributions analyzed in this study. The count of approved extreme level of standards identified using the probability density function outlines is directly related to magnitude of Dagum-distribution component. Similarly, in both the K-S test and C-s test, Dagum-distribution demonstrates a remarkable alignment with the rainfall data observed in Malappuram. Figure 3(b) illustrates the PDFs of the various distributions investigated in this study. The overall count of approved extreme level of standards is directly associated with the Dagum-distribution module. The graph clearly depicts the precise suitable of the Dagum-distribution to the rainfall statistics in the Malappuram district. Likewise, the Dagum-distribution provides a satisfactory correlation with the rainfall data observed in Palakkad.

Figure 4(a) visually presents the PDFs of various distributions. Magnitude of Dagum-distributions component directly corresponds to the overall count of accepted extreme level of standards. The figure unequivocally demonstrates the accurate fit of the Dagum-distribution to the data from Palakkad district. From the above we observed a satisfactory alignment of the Dagum-distribution with the rainfall data recorded in Idukki. Figure 4(b) visually displays the PDFs of various distributions analyzed in this study of rainfall data. The magnitude of the Dagum-distribution component directly correlates with the overall count of accepted extreme level of standards. From this figure, it may be concluded that the Dagum-distribution accurately fits to Idukki district.

Similarly, the K-S test and C-s test demonstrate that the Dagum-distribution adequately fits the Trivandrum district data. Figure 4(b) visually represents the PDFs of the different distributions determined in this learning. The magnitude of the Dagum-distribution component is closely associated with the overall number of accepted extreme criteria. The figure clearly demonstrates the accurate fit of the Dagum-distribution to the data from Trivandrum.

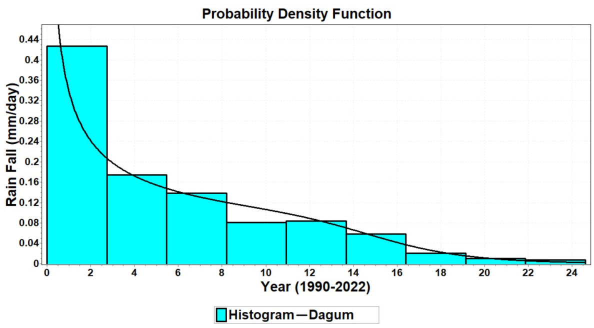


(a)

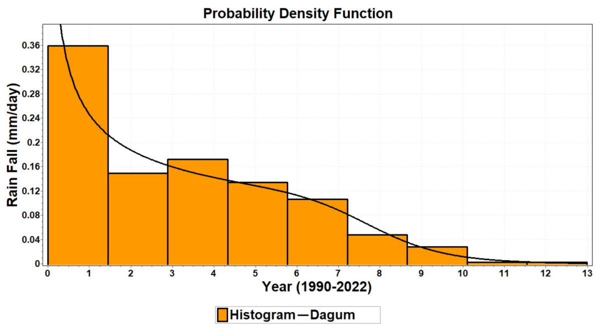


(b)

Figure 2. Rainfall data PDF for (a) Kasargod and (b) Wayanad

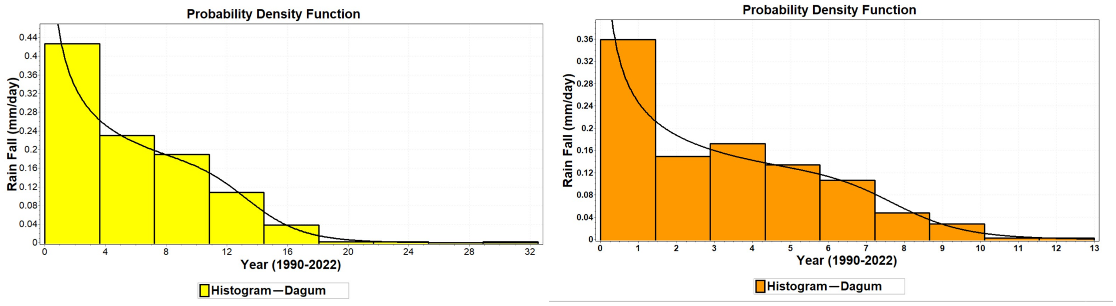


(a)



(b)

Figure 3. Rainfall data PDF for (a) Malappuram and (b) Palakkad



(a) (b)

Figure 4. Rainfall data PDF for (a) Idukki and (b) Trivandrum

5. CONCLUSION

We conducted comprehensive analysis to determine the suitable distribution for average rainfall data records in six districts of Kerala. This study began with the consideration of two unique probability distributions, and the properties of each distribution were analysed. Various tests were then apply to identify the perfect statistical distribution. To match the rainfall data from all districts, we utilized both Kaumarasamy-distribution and Dagum-distributions. Various tests were employed to comparing these distributions.The results revealed that the Kumarasamy distribution has the lowest Kolmogorov-Smirnov statistics: 0.0597 (rank 1) and Anderson-Darling statistics: 2.271 (rank 1), it indicating a better fit compared to the Dagum distribution in Kasaragod. However, the Dagum distributions has the lowest Kolmogorov-Smirnov statistic: 0.07447 (rank 1) and Chi-Squared statistic: 19.471 (rank 3) in Wayanad, Kolmogorov-Smirnov statistic: 0.05435 (rank 1) and Chi-Squared statistic: 8.4907 (rank 2) in Malappuram, Kolmogorov-Smirnov statistic: 0.0556 (rank 1) and Chi-Squared statistic: 19.239 (rank 2) in Palakkad, Kolmogorov-Smirnov statistic: 0.03636 (rank 1) and Chi-Squared statistic: 5.7318 (rank 1) in Idukki and Kolmogorov-Smirnov statistic: 0.04291 (rank 1) and Chi-Squared statistic: 7.5297 (rank 1) in Trivandrum. The solution includes statistical analyses and assessments to determine the distribution(s) that best characterize the average rainfall data in the specified districts, contributing to an improved understanding of the precipitation dynamics in the regions. Localised hydro energy planning aspects the appropriate probability distributions that have been established can be used to increase the accuracy of hydro energy planning in each district. Local hydroelectric power plants can better manage their energy production and distribution by understanding the statistical nature of rainfall patterns, resulting in more effective utilisation of resources and lower environmental impact. Water resource management aspects using the selected distributions, local governments and water resource management organisations can better plan for water supply, irrigation, and flood control. Accurate forecasting can aid in improving water usage, reducing drought and excess water challenges, and assuring long-term water management procedures.

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