EPH – International Journal of Mathematics and Statistics
ISSN:2208-2212
https://eijms.com/index.php/ms/issue/archive

STATISTICAL MODELING OF RAINFALL VARIABILITY USING DISTRIBUTION FITTING AND TEMPORAL DEPENDENCE ANALYSIS

Saif Hosam Raheem

Department of Statistics, College of Administration and Economics, University of Al-Qadisiyah, Iraq. Email: saif.hosam@qu.edu.iq

Corresponding author: saif.hosam@qu.edu.iq

A R T I C L E I N F O

Received: 26/06/2026
Revised: 23/09/2026
Accepted: 11/10/2026
Published: 28/10/2026

DOI: https://doi.org/10.69980/t8ymgr83
Volume:12, Issue:04, October 2026

Abstract

In monsoon-dominated regions, rainfall variability is a crucial factor affecting hydrological processes, agricultural productivity and water-resource management. This study examined the characteristics of rainfall distribution and temporal dependence using 543,839 rainfall daily meteorological observations from 35 weather stations in Bangladesh. Precipitation variability and persistence were characterized using descriptive statistical analysis, fitting of probability distributions, goodness of fit and temporal autocorrelation techniques. Positive rainfall was fitted to the gamma, Weibull and Lognormal distribution, by applying maximum likelihood estimation. The results showed that the daily precipitation varied significantly across the region, with a mean daily precipitation of 6.73 mm and 67.64% of zero rainfall events. The mean rainfall for July was the highest (17.34 mm) while that of January was the lowest (0.24 mm). The Lognormal distribution had the smallest Akaike Information Criterion (AIC) of 1,390,345.7 and the smallest Kolmogorov–Smirnov statistic of 0.07313 with respect to the other distributions. The positive lag-one autocorrelation (0.3937) and significant persistence of wet days and dry days were found from the temporal analysis. The results highlight the importance of incorporating distributional and temporal analyses of rainfall data for characterizing rainfall for use in statistical applications relevant to hydrological assessment and sustainable water resource planning.

Keywords: Rainfall Variability; Probability Distribution Fitting; Temporal Autocorrelation; Precipitation Persistence; Statistical Hydrology.

1. Introduction

Variability in precipitation is one of the essential processes of the global water cycle, affecting water resources, crop yields, ecosystem health, and hydroclimatic hazards. Regional water balances can be significantly altered by changes in the intensity, frequency and temporal distribution of precipitation, especially in nations with a distinct seasonal precipitation pattern. These variations can only be understood by the use of statistical methods that describe not only the statistical properties of the rainfall itself but also the temporal relationships between consecutive precipitation events. The variability of precipitation is a complex phenomenon that involves the characteristics of its distribution, climatic conditions in regions, and variations in precipitation patterns, which highlights the need for a thorough statistical assessment of the phenomenon (Nazeri Tahroudi 2025). As a result, the definition of rainfall has increasingly moved away from the standard characterization of average precipitation and annual rainfall amounts to analytical frameworks that go beyond these aspects.

Probability distribution fitting is a well-established mathematical technique to represent rainfall characteristics, estimate rainfall probability and assess hydrological uncertainty. Rainfall data are often skewed, highly variable and sparse, and hence the choice of an appropriate probability model is of particular importance. Other models of positive rainfall intensity can be represented as continuous distributions such as the Gamma, Weibull and Lognormal models, but they are only suitable for certain types of precipitation. Comparative statistical investigations have shown that distributional assumptions, and the performance of the models, are crucial when characterizing and identifying possible changes in rainfall behavior, especially for characterizing rainfall extremes (Montes-Pajuelo et al., 2024). Moreover, an accurate assessment of hydrological extremes and an identification of the proper distribution structures for the observed climatic variability requires the use of proper statistical models (Panday & Kumar, 2022).

In addition to individual rainfall distributions, precipitation processes have temporal dependence due to atmospheric circulation, seasonal change and long spells of meteorological conditions. Thus, consecutive wet and dry days can be dependent and the intensity of rainfall can be correlated between successive observation periods. Temporal dependence analysis can be used to measure these relationships using autocorrelation coefficients, lagged associations, and rainfall occurrence transition probabilities. Since the hydroclimatic variables are related to each other, the dependence modeling has gained more and more significance in the study of the hydroclimatic phenomena, as the relations among these variables are essential to interpret the compound events in the hydroclimatic phenomena (Tootoonchi et al., 2022). Likewise, compound flooding studies have shown that the dependence properties, especially those of extreme observations, can significantly affect hydrological risk assessment (Phillips et al., 2022). These results highlight the need to consider dependence in addition to marginal precipitation distributions.

The temporal structure of rainfall also has implications with respect to the understanding of rainfall variability and the identification of persistent fluctuations from long-term directional changes. The interannual and seasonal variability of precipitation can also be large without necessarily having a consistent monotonic trend. Recent studies of precipitation variability in the Mediterranean have stressed the need to consider the temporal variability when addressing the precipitation behavior at the regional scale (Vicente-Serrano et al., 2025). At the same time, alterations in precipitation distributions and associated climatic conditions may lead to some difficulties in making the assumptions of stationarity, especially in the context of drought-related processes (Bazrafshan et al., 2022). Improved compound hydroclimatic event analysis also relies on shifts in the distribution of each individual hydroclimatic variable and on changes in the relationships between variables, which highlights the importance of integrating statistical analyses (François & Vrac, 2023).

The characterization of rainfall in a statistical way is especially important when dealing with precipitation extremes and the associated impacts on hydrological systems. Frequent extreme precipitation events are often embedded in summary statistics that have poor coverage of distributional tails. Rare environmental events and related uncertainties are analysed using advanced statistical methods that include peaks-over-threshold methods (de Fondeville & Davison, 2022). As shown by related methodological advances in flood frequency analysis, it is imperative to choose appropriate thresholds and probability models to describe extreme hydrological behaviour (Pan et al., 2022). The added complexity is due to spatial dependence, which can vary between meteorological stations and climatic regions and must be taken into account when analyzing extreme rainfall (Huser & Wadsworth, 2022). The historical precipitation variability also offers useful information for putting constraints on uncertainty in future projections of extreme precipitation (Zhang et al., 2022).

The Bangladesh country is relevant to the study of rainfall variability as it has a tropical monsoon climate with significant variations in precipitation in terms of both frequency and intensity over a range of seasons. The rain is more or less confined to a monsoon period while there is comparatively little rain during much of the winter. These variations impact on agricultural water demand, flood vulnerability, and regional water-resource management. Wider climatic studies have shown that the regional precipitation regime can be altered by the interaction of climatic processes, and that climatic variability can be complicated by the interaction of these processes (Franco et al., 2025). The study of rainfall forecasting in neighbouring India has also shown the relevance of the temporal rainfall pattern with the help of quantitative analytical approach (Mishra et al., 2024). However, these two types of forecasting applications are different in their statistical goals and before developing forecasting models, it is still necessary to understand what precipitation distributions are observed.

Current hydroclimatic studies developed and validated complex methods for dependence analysis, such as nonparametric copula estimation for compound hazards involving rainfall (Latif & Simonovic, 2022). There are also some examples of how the distribution characteristics vary over time, which can impact environmental extremes, using nonstationary frequency analysis (Razmi et al., 2022). But the specific methods are not sufficient to obviate the need to systematically consider the ordinary daily rainfall distributions and the short-term persistence. The present study fulfills

this analytical need by incorporating descriptive assessment of rainfall variability, probability distribution fitting, goodness-of-fit test and temporal dependence test based on daily rainfall data of 35 stations in Bangladesh. The study aims to offer an interpretable description of the variability and persistence of precipitation by incorporating rainfall intensity and occurrence in a single statistical framework. The specific objectives of this study are:

1.To quantify spatial and seasonal rainfall variability using descriptive statistics and daily precipitation occurrence patterns.

2.To evaluate Gamma, Weibull, and Lognormal distributions using parameter estimation and comparative goodness-of-fit criteria.

3.To investigate temporal rainfall dependence and wet–dry persistence through lagged autocorrelation and transition probability analysis.

2. Materials and Methods

2.1. Study Area and Meteorological Dataset Description

Historical weather observations from the South Asian country of Bangladesh, which has high monsoonal precipitation variability, were used in the study (Zubair et al., 2024). The weather data was taken from the public Mendeley High Volume Real-World Weather Data base. The total number of daily observations from this combined dataset was 543,839 observations at 35 meteorological stations from 1961 to 2023. The variables recorded were: rainfall, temperature, humidity, duration of sunshine, station identifier and calendar data. The major analytical variable was rainfall measured in mm and station identifier and date of observation were used for spatial comparison and temporal statistical modeling.

2.2. Data Preprocessing and Rainfall Variability Assessment

In this process, data preprocessing was carried out to check the completeness of variables, date of the data observed, duplicate station-date records, and to filter out data with negative rainfall. The daily rainfall observations were compiled chronologically in each meteorological station. Arithmetic means, standard deviations, coefficients of variation, and wet-day frequencies were used to describe the variability of rainfall. Rainfall statistics were then processed on a monthly basis to examine variations between the seasons in both the amount and intensity of rain. The coefficient of variation was taken as the standard deviation of the data divided by the mean value, and then multiplied by 100%. No-rainfall events were kept for descriptive and temporal analyses.

2.3. Probability Distribution Fitting and Parameter Estimation

A probability distribution fitting was done on the daily rainfall observations, which were supposed to be strictly positive, due to the high proportion of zero rainfall days. The intensity of rainfall events was considered and three continuous probability models, namely the Gamma, Weibull and Lognormal models were assessed. The distribution parameters were estimated by maximum likelihood estimation (MLE) using the SciPy statistical library. Location parameters were set to zero, so that all non-negative precipitation intensities were treated equally. The shape and scale parameters of each fitted model were estimated and characterized. Log-likelihood values were computed to compare the fit of the observed intensities of rainfall with the expected distributions.

2.4. Goodness-of-Fit Evaluation and Model Selection

The performance of the fitted rainfall distributions was compared by means of the Akaike Information Criterion, Bayesian Information Criterion and Kolmogorov–Smirnov statistic. Information criteria included maximized log likelihood and number of estimated model parameters, and smaller values signified better relative model support. The Kolmogorov-Smirnov statistic was the maximum deviation or difference between the empirical and fitted cumulative distribution functions. These were complementary indicators that were taken into consideration when selecting rainfall distribution models that were most consistent with observed rainfall intensities. Formal goodness-of-fit significance test was omitted due to the need for proper calibration of the null distribution for parameter estimation.

2.5. Temporal Dependence and Rainfall Persistence Analysis

The temporal dependence analysis was carried out by analyzing station specific daily rainfall sequences and lagged correlation. Pearson autocorrelation coefficients at 1, 2, 3, 7, 14 and 30 day time lags were computed. Additionally, rainfall occurrence was also converted to indicators of wet days and dry days to study persistence separately from the magnitude of the rainfall. First-order transition probabilities were used to measure the probability of wet and dry condition following wet or dry conditions. Avoiding cross-station temporal connections, as there were no geographical space-time relationships. Pairs of observations from each station were pooled and correlation estimates were computed.

3. Results

3.1. Descriptive Characteristics and Statistical Variability of Rainfall

The results of analysing the 543,839 daily observations showed that there was significant spatial variability in the rainfall features at 35 meteorological stations. The overall mean daily rainfall was 6.73 mm with a standard deviation of 19.37 mm and maximum rainfall of 590.00 mm, which shows that there is a high rainfall intermittency. Sylhet had the highest mean daily rainfall among the selected stations while Rajshahi had the lowest (3.88 mm). The Coefficients of variance were higher than 220% at all selected stations indicating that there is a great precipitation dispersion and great difference between occurrence of precipitation (Table 1) (Figure 1).

Table 1. Descriptive Statistical Characteristics of Daily Rainfall Across Selected Meteorological Stations

Station	Observations (n)	Mean (mm)	CV (%)	Wet days (%)
Barisal	20,819	5.65	276.4	32.5
Chittagong	23,010	7.90	299.7	32.7
Cox's Bazar	23,010	9.93	265.2	34.0
Dhaka	23,010	5.51	283.1	32.6
Khulna	14,610	4.92	294.3	31.0
Rajshahi	16,436	3.88	314.5	26.2
Rangpur	16,436	6.16	308.5	29.4
Sylhet	23,010	11.23	221.4	43.7

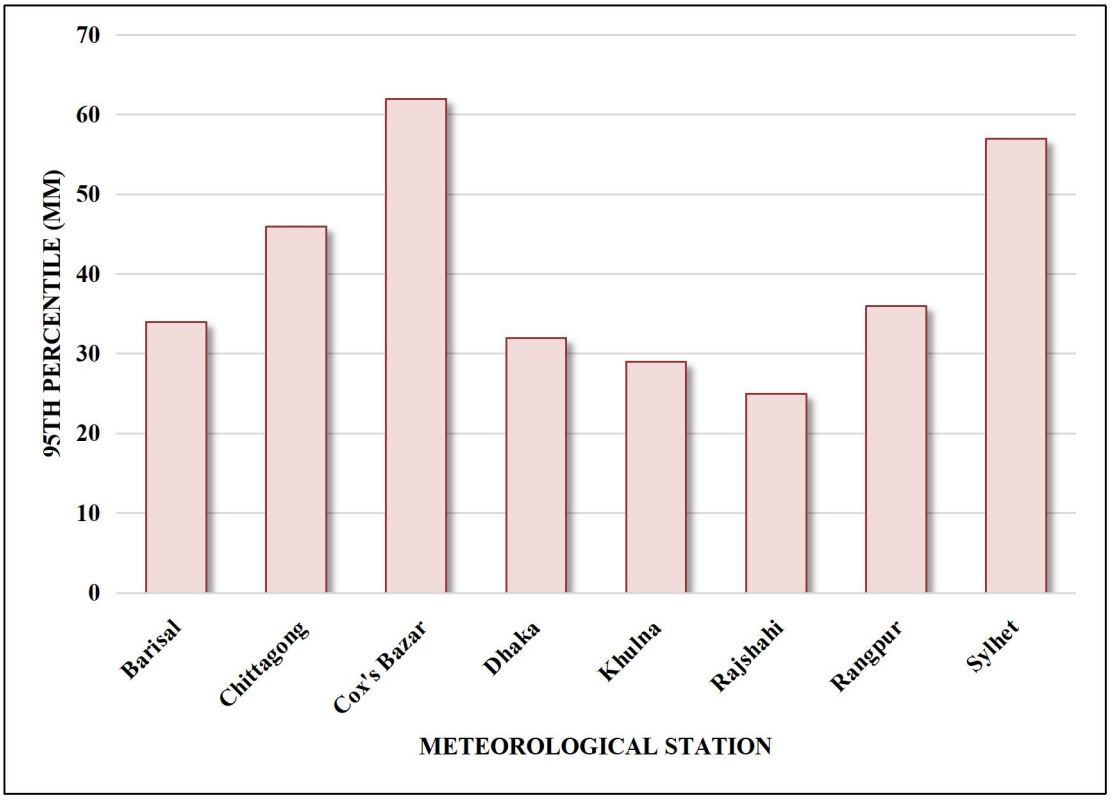


Figure 1. Spatial Variation in the 95th Percentile of Daily Rainfall Across Selected Stations

3.2. Monthly and Seasonal Patterns of Rainfall Variability

Rainfall analysis was carried out on a monthly basis showing significant seasonal variations in rainfall, mainly during the period from May to September. The highest mean daily rainfall was recorded during July (17.34 mm) followed by June (15.78 mm) and August (13.57 mm). The average rainfall of January (0.24 mm) was comparatively low during the winter season. There was a rise in the wet-day frequency from January (3.50%) to July (73.44%). However, the variability of rainfall was also quite high between the months, with July showing the highest standard deviation (30.04

mm), suggesting high variability during the main monsoon months (Table 2) (Figure 2).

Table 2. Monthly Rainfall Intensity, Occurrence Frequency, and Variability

Month	Observations (n)	Mean (mm)	Wet days (%)	SD (mm)
January	46,159	0.24	3.50	2.17
February	42,046	0.70	6.91	4.40
March	46,159	1.44	10.58	7.37
April	44,670	3.83	22.56	12.28
May	46,159	8.77	42.18	19.56
June	44,670	15.78	62.28	29.89
July	46,159	17.34	73.44	30.04
August	46,159	13.57	68.81	24.84
September	44,670	10.89	57.63	22.88
October	46,159	6.32	29.10	19.97
November	44,670	1.19	6.60	8.55
December	46,159	0.36	3.05	3.54

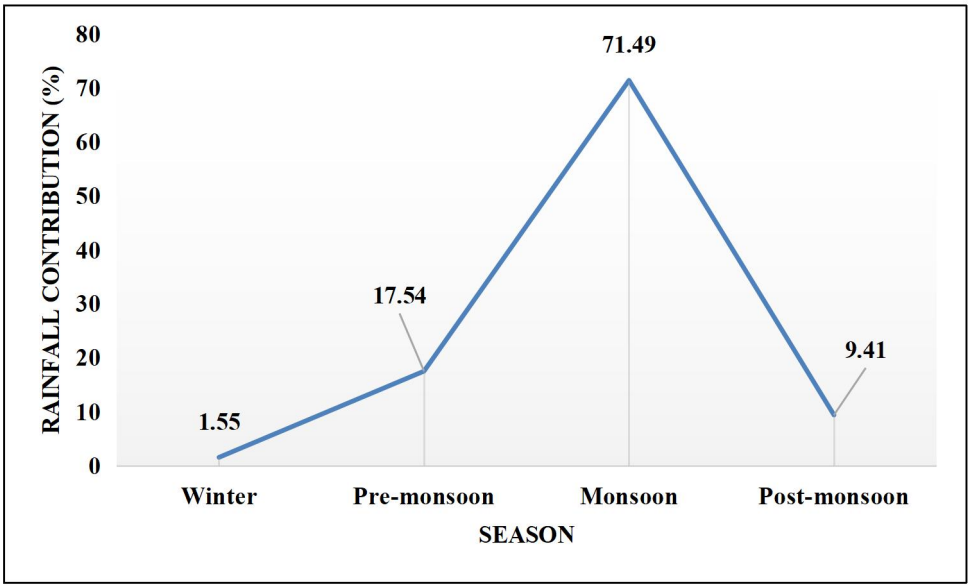


Figure 2. Seasonal Contribution to Total Recorded Rainfall

3.3. Probability Distribution Fitting and Estimated Rainfall Parameters

A total of 175,960 positive daily rainfall data (32.36% of total data) were used for the fitting of the probability

distributions. The shape parameter and scale parameter estimated using the Gamma distribution were 0.75380 and 27.60640, respectively. These Weibull estimates were 0.80755 and 18.22982, respectively. The Lognormal distribution had shape parameter = 1.33642 and scale parameter = 9.41026. The model with maximized log-likelihood value of the Lognormal distribution was the best of the models evaluated, indicating that the fitted model assumption has relatively stronger representation of the observed positive rainfall intensities (Table 3) (Figure 3).

Table 3. Maximum Likelihood Parameter Estimates for Candidate Rainfall Distributions

Distribution	Sample size (n)	Shape	Scale	Log-likelihood
Gamma	175,960	0.75380	27.60640	-704,903.8
Weibull	175,960	0.80755	18.22982	-702,001.5
Lognormal	175,960	1.33642	9.41026	-695,170.9

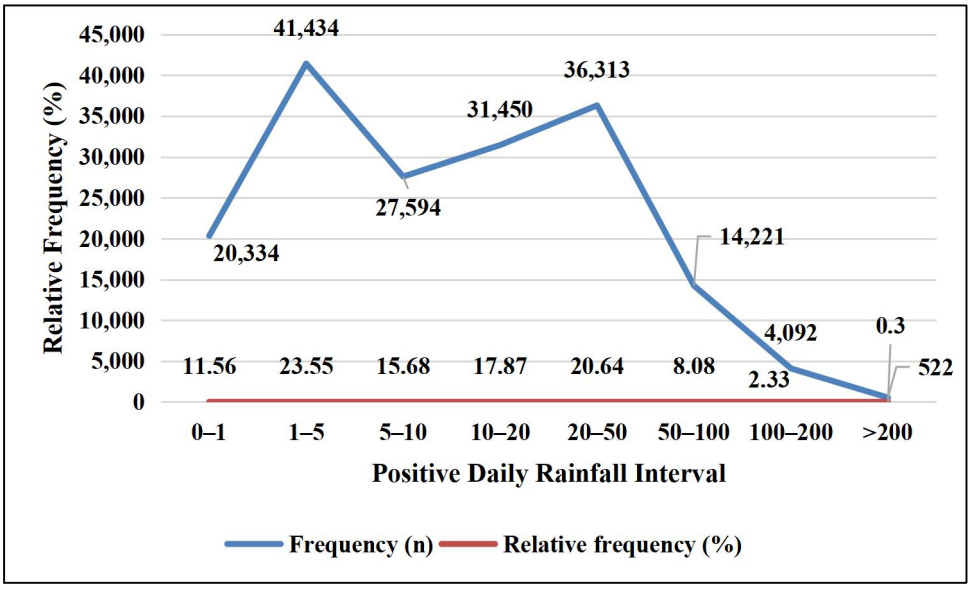


Figure 3. Frequency Distribution of Positive Daily Rainfall Intensity

3.4. Goodness-of-Fit Performance and Optimal Distribution Selection

The Lognormal distribution was found to be the best fit when looking at the goodness-of-fit of the models selected and found by a comparative analysis using daily rainfall intensity data. It had the lowest Akaike Information Criterion (AIC) value (1,390,345.7) and the lowest Bayesian Information Criterion (BIC) value (1,390,365.9) compared with the Gamma and Weibull alternatives. The Kolmogorov–Smirnov statistic value for the Lognormal model was also the smallest (0.07313), suggesting that the model's fit with the empirical rainfall data is relatively close. Weibull distribution was better than the Gamma distribution in information criteria, but its Kolmogorov–Smirnov statistic was slightly higher. These results were used to confirm the selection of Lognormal distribution from the candidate distributions, but did not prove the absolute goodness of fit for the Lognormal (Table 4) (Figure 4).

Table 4. Comparative Goodness-of-Fit Statistics for Rainfall Probability Models

Distribution	AIC	BIC	KS statistic	AIC rank
Gamma	1,409,811.5	1,409,831.7	0.08687	3
Weibull	1,404,006.9	1,404,027.1	0.09057	2
Lognormal	1,390,345.7	1,390,365.9	0.07313	1

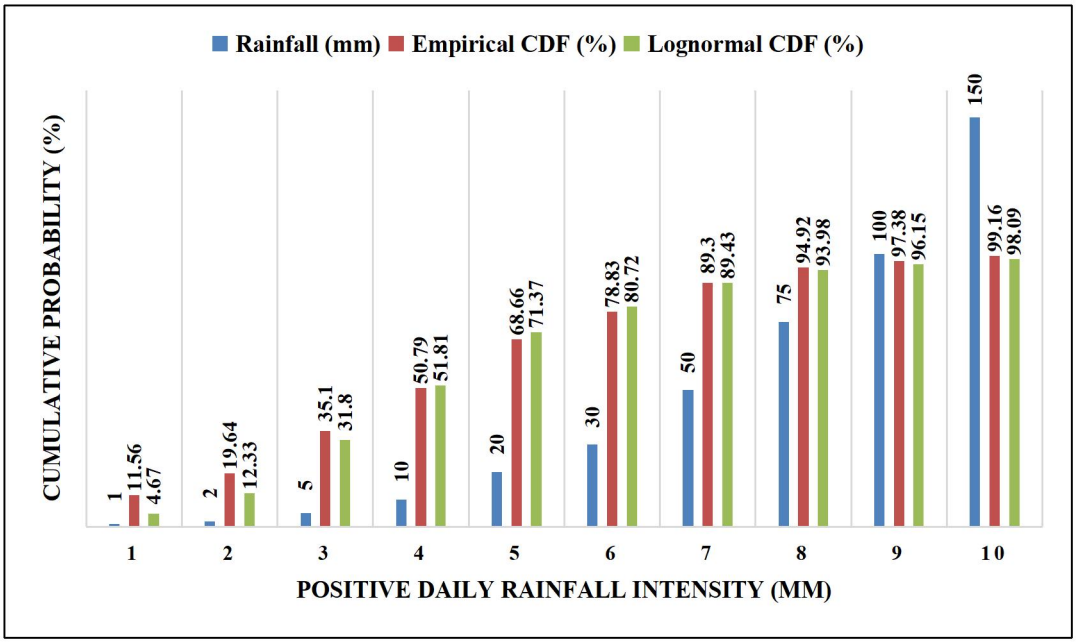


Figure 4. Empirical and Lognormal Cumulative Rainfall Distributions

3.5. Temporal Autocorrelation and Rainfall Persistence Characteristics

The temporal dependence analysis indicated that all the rainfall lags examined had positive rainfall autocorrelation. The highest correlation was at lag one (r = 0.3937) to 0.2463 at lag two, then 0.1796 at lag three. The correlation between the occurrence of rainfall and its magnitude was consistently greater than rainfall occurrence correlations. Results from order of transition analysis (first order) indicated that the probability of wet following wet was 67.74% and that of dry following dry was 84.57%, respectively. Moderate to positive correlations were still present at longer lags, however, seasonal effects may also be a factor in the associations. In general, the daily pattern of precipitation was more persistent than the daily pattern in precipitation intensity (Table 5) (Figure 5).

Table 5. Temporal Autocorrelation of Daily Rainfall Magnitude and Occurrence

Lag (days)	Valid pairs (n)	Rainfall correlation	Occurrence correlation
1	543,804	0.3937	0.5231
2	543,769	0.2463	0.4291
3	543,734	0.1796	0.3807
7	543,594	0.1211	0.3379
14	543,349	0.1218	0.3269
30	542,789	0.1201	0.2901

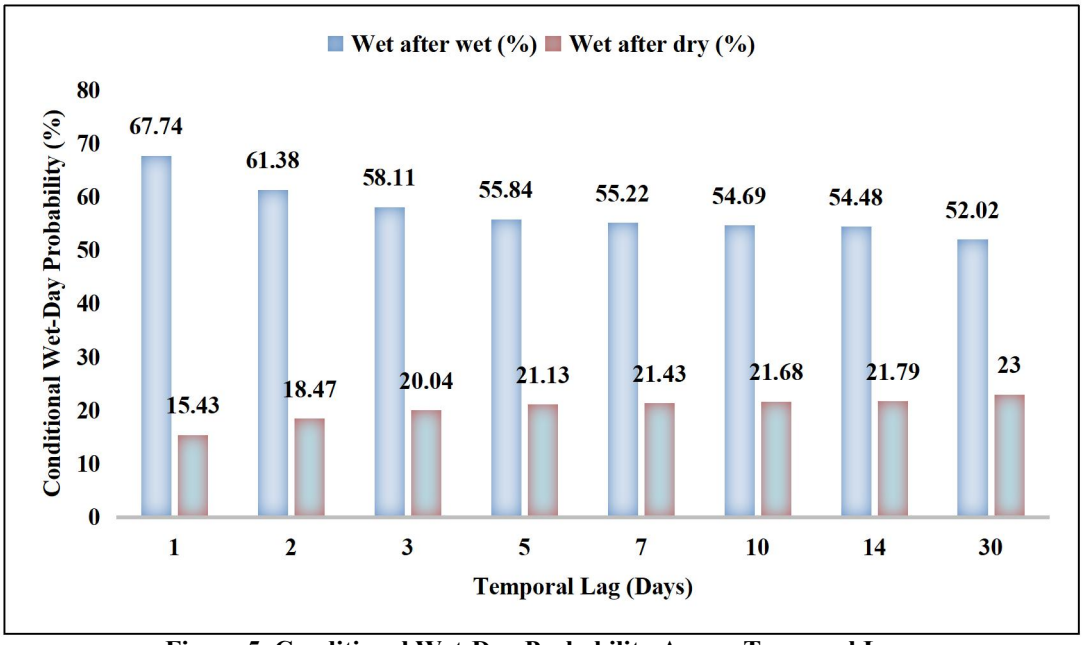


Figure 5. Conditional Wet-Day Probability Across Temporal Lags

4. Discussion

An extensive statistical characterization of rainfall variability, probability distribution characteristics and temporal dependence at 35 meteorological stations in Bangladesh. Precipitation intensity, frequency, and duration of precipitation events were found to be highly variable from one event to another based on the analysis of 543,839 precipitation events measured on a daily basis. The overall mean daily rainfall was 6.73 mm with a standard deviation of 19.37 mm which is considerable from the central value. The intermittent nature of precipitation is highlighted by the fact that about 67.64% of observations were of zero rainfall days. The above attributes highlight the need for separating the duration of rainfall from the positive rainfall intensity in designing statistical models. The geographical differences observed further confirm the appropriateness of spatially heterogeneous statistical approaches that can capture variations in environmental processes between spatial positions or locations of observations (Wang et al., 2024).

The results of the spatial comparisons indicated significant differences in rainfall characteristics between meteorological stations. Sylhet had the highest mean daily precipitation (11.23 mm) and Rajshahi had the lowest mean daily precipitation (3.88 mm). These differences show that the distribution of rainfall cannot be adequately described with a single rain average on a regional scale. The variations in the precipitation amount and fluctuations could be due to geographic, monsoonal circulation and local environmental variations. The same methodological issues are present in spatial statistical investigations, where the model must be flexible enough to capture the variation that occurs in space, and the geological features are heterogeneous (Cressie et al., 2022). The present analysis did not use any spatial covariance modelling, but nonetheless the results provide a basis for further research that includes geographical dependence and spatially varying precipitation parameters.

Rainfall was found to be well concentrated in the rainy season as shown in the seasonal analysis, with July having the highest mean daily rainfall of 17.34mm, and June at 15.78mm, while January had only 0.24mm of rainfall. This shows that there are significant differences in rainfall from one season to the next. The frequency of wet-days rose from 3.50% in January to 73.44% in July, reflecting that seasonal variability not only includes variations in the occurrence of wet days, but also variations in the intensity of the wet days. The results are in line with the overall relevance of meteorological seasonality in rainfall modelling, especially for developing representative datasets of weather to support environmental applications (Bourcet et al., 2023). Moreover, the studies conducted on rainfall forecasting in geographically varied Himalayan regions have highlighted the importance of temporal variations and regional climatic differences in forecasting the behavior of rainfall (Wani et al., 2024). The current results enrich this view by describing the phenomenon, not predicting it.

The results of the probability distribution fitting showed that the Lognormal model was the best in comparison to the other three distributions tested with respect to the relative representativeness of positive daily rainfall observations. The Akaike Information Criterion values of Weibull and Gamma were 1,404,006.9 and 1,409,811.5 respectively, which were greater than the Akaike Information Criterion value of its 1,390,345.7. The Lognormal distribution also had the smallest Kolmogorov–Smirnov statistic (0.07313) suggesting it was in close agreement with the actual rainfall distribution. These results, however, only indicate relative model preference and not distributional sufficiency. The selection of probability models that capture the statistical nature of hydrometeorological processes is also highlighted in research using stochastic simulation of extremes in the environment (Rashid et al., 2024). The present analysis did not involve the extreme-value analysis frameworks, which were more specialized.

The temporal dependent analysis showed that there was a meaningful short term persistence in daily precipitation. The lag-one autocorrelation for rainfall magnitude was 0.3937 that dropped to 0.2463 and 0.1796 for lag two and three, respectively. There was a desirable temporal association for rainfall occurrence, with a lag-one correlation of 0.5231. The probabilities of transition from wet to wet and dry to dry were 67.74% and 84.57%, respectively, which provided

evidence of significant persistence in consecutive precipitation states. The results indicate that occurrence of rainfall carries additional temporal information which is not adequately represented by marginal probability distributions. Time-series principles also highlight the significance of serial correlation when observing a time series, especially in light of its impact on statistical uncertainty and the assumptions of the models (Diggle & Giorgi, 2025). However, the persistence estimates may be partially due to seasonal cycles of rainfall, and not necessarily to meteorological dependence on a short term basis.

Distribution fitting and temporal dependence analysis are of practical importance for hydrological assessment. Rainfall intensity distributions represent the size of the precipitation event and transition probabilities the probability of continuation in wet or dry state. The statistical properties can be combined to develop more realistic precipitation generators and to facilitate further hydrological modeling. Studies on the dynamics between precipitation, groundwater recharge and streamflow have shown the significance of including the variability of rainfall in the study of interconnected hydrological processes (Gao et al., 2025). Likewise, joint rainfall and storm surge modeling shows the importance of accounting for precipitation uncertainty in creating hydrological design scenarios (Kim et al., 2023). The present investigation did not specifically assess the effects on runoff, groundwater recharge or compound flooding, however.

A number of methodological disadvantages need to be taken into account. Pooled statistical estimates may be affected by differences in station record lengths, and the results may not be directly interpreted as the national rainfall characteristics because of the differences in the geographical coverage of the stations. Longer-lag autocorrelation estimates can also be biased upwards due to the lack of explicit seasonal adjustment. Also, the fitted distributions were tested with pooled positive rains, which may mask station-to-station differences in rain behavior. The above-mentioned review of compound flood modelling also highlights the dependency assumptions, data properties, and uncertainty representation as additional factors in the statistical applications to the environment (Xu et al., 2023). Future studies should, subsequently, include station-level distribution fitting, seasonal adjustment, uncertainty quantification, and independent model validation. The overall results show that the combination of probability distribution fitting and temporal dependence analysis gives a unified approach for the characterization of the rainfall variability and persistence in the monsoon dominated environment.

5. Conclusion

The effectiveness of an integrated solution of probability distribution fitting and temporal dependence analysis for characterizing rainfall variability over 35 meteorological stations in Bangladesh. A total of 543,839 daily observations were used in the analysis which showed significant variations in precipitation intensity, frequency, and duration from place to place and from season to season. The overall mean daily rainfall was 6.73 mm with 67.64% (210 days) of observations showing zero rainfall, indicating the intermittent and highly variable nature of rainfall. The results of seasonal analysis revealed that the wettest month was July and the least rainiest month was January, suggesting high monsoonal influence in the region's rainfall. The distribution fitting performed in a comparative manner resulted in the Lognormal distribution being the most appropriate one among those that were evaluated, since it presented the lowest information criteria and Kolmogorov–Smirnov statistic. Temporal dependence analysis showed positive short term auto-correlation with stronger persistence in rainfall occurrence as compared to rainfall intensity. The significance of the sequential rainfall relationships was further illustrated by high transition probabilities from wet-to-wet and dry-to-dry. The results create a meaningful statistical model for rainfall characterization which can be used in hydrological evaluation, agricultural planning, and water-resource management. However, it is not possible to make broad generalizations due to unequal station coverage, pooled distributional estimates and unadjusted seasonal effects. Modeling at the station level, adjusting for seasonality and independent validation could be added in future studies to improve the statistical robustness and enable more reliable precipitation risk assessments.

References

1. Bazrafshan, J., Cheraghalizadeh, M., & Shahgholian, K. (2022). Development of a non-stationary standardized precipitation evapotranspiration index (NSPEI) for drought monitoring in a changing climate. Water Resources Management, 36(10), 3523-3543.
2. Bourcet, J., Kubilay, A., Derome, D., & Carmeliet, J. (2023). Representative meteorological data for long-term wind-driven rain obtained from Latin Hypercube Sampling–Application to impact analysis of climate change. Building and Environment, 228, 109875.
3. Cressie, N., Sainsbury-Dale, M., & Zammit-Mangion, A. (2022). Basis-function models in spatial statistics. Annual Review of Statistics and Its Application, 9, 373-400.
4. de Fondeville, R., & Davison, A. C. (2022). Functional peaks-over-threshold analysis. Journal of the Royal Statistical Society Series B: Statistical Methodology, 84(4), 1392-1422.
5. Diggle, P., & Giorgi, E. (2025). Time Series: A Biostatistical Introduction: A Biostatistical Introduction. Oxford University Press.
6. Franco, M. A., Rizzo, L. V., Teixeira, M. J., Artaxo, P., Azevedo, T., Lelieveld, J., ... & Machado, L. A. (2025). How climate change and deforestation interact in the transformation of the Amazon rainforest. Nature Communications, 16(1), 7944.
7. François, B., & Vrac, M. (2023). Time of emergence of compound events: contribution of univariate and dependence properties. Natural Hazards and Earth System Sciences, 23(1), 21-44.
8. Gao, H., Ju, Q., Zhang, D., Wang, Z., Hao, Z., & Kirchner, J. W. (2025). Quantifying dynamic linkages between

precipitation, groundwater recharge, and streamflow using ensemble rainfall-runoff analysis. Water Resources Research, 61(1), e2024WR037821.
9. Huser, R., & Wadsworth, J. L. (2022). Advances in statistical modeling of spatial extremes. Wiley Interdisciplinary Reviews: Computational Statistics, 14(1), e1537.
10. Kim, H., Villarini, G., Jane, R., Wahl, T., Misra, S., & Michalek, A. (2023). On the generation of high-resolution probabilistic design events capturing the joint occurrence of rainfall and storm surge in coastal basins. International Journal of Climatology, 43(2).
11. Latif, S., & Simonovic, S. P. (2022). Nonparametric approach to copula estimation in compounding the joint impact of storm surge and rainfall events in coastal flood analysis. Water Resources Management, 36(14), 5599-5632.
12. Mishra, P., Al Khatib, A. M. G., Yadav, S., Ray, S., Lama, A., Kumari, B., ... & Yadav, R. (2024). Modeling and forecasting rainfall patterns in India: a time series analysis with XGBoost algorithm. Environmental Earth Sciences, 83(6), 163.
13. Montes-Pajuelo, R., Rodríguez-Pérez, Á. M., López, R., & Rodríguez, C. A. (2024). Analysis of probability distributions for modelling extreme rainfall events and detecting climate change: Insights from mathematical and statistical methods. Mathematics, 12(7), 1093.
14. Nazeri Tahroudi, M. (2025). Comprehensive global assessment of precipitation trend and pattern variability considering their distribution dynamics. Scientific Reports, 15(1), 22458.
15. Pan, X., Rahman, A., Haddad, K., & Ouarda, T. B. (2022). Peaks-over-threshold model in flood frequency analysis: a scoping review. Stochastic Environmental Research and Risk Assessment, 36(9), 2419-2435.
16. Panday, D. P., & Kumar, M. (2022). Climate indices and hydrological extremes: deciphering the best fit model. Environmental Research, 215, 114301.
17. Phillips, R. C., Samadi, S., Hitchcock, D. B., Meadows, M. E., & Wilson, C. A. M. E. (2022). The devil is in the tail dependence: An assessment of multivariate copula-based frameworks and dependence concepts for coastal compound flood dynamics. Earth's Future, 10(9), e2022EF002705.
18. Rashid, M. M., Moftakhari, H., & Moradkhani, H. (2024). Stochastic simulation of storm surge extremes along the contiguous United States coastlines using the max-stable process. Communications Earth & Environment, 5(1), 39.
19. Razmi, A., Mardani-Fard, H. A., Golian, S., & Zahmatkesh, Z. (2022). Time-Varying Univariate and Bivariate Frequency Analysis of Nonstationary Extreme Sea Level for New York City: Time-Varying Univariate and Bivariate Frequency Analysis of Nonstationary Extreme Sea Level for New York City. Environmental Processes, 9(1), 8.
20. Tootoonchi, F., Sadegh, M., Haerter, J. O., Räty, O., Grabs, T., & Teutschbein, C. (2022). Copulas for hydroclimatic analysis: A practice-oriented overview. Wiley Interdisciplinary Reviews: Water, 9(2), e1579.
21. Vicente-Serrano, S. M., Tramblay, Y., Reig, F., González-Hidalgo, J. C., Beguería, S., Brunetti, M., ... & Potopová, V. (2025). High temporal variability not trend dominates Mediterranean precipitation. Nature, 639(8055), 658-666.
22. Wang, J., Haining, R., Zhang, T., Xu, C., Hu, M., Yin, Q., ... & Chen, H. (2024). Statistical modeling of spatially stratified heterogeneous data. Annals of the American Association of Geographers, 114(3), 499-519.
23. Wani, O. A., Mahdi, S. S., Yeasin, M., Kumar, S. S., Gagnon, A. S., Danish, F., ... & Mattar, M. A. (2024). Predicting rainfall using machine learning, deep learning, and time series models across an altitudinal gradient in the North-Western Himalayas. Scientific Reports, 14(1), 27876.
24. Xu, K., Wang, C., & Bin, L. (2023). Compound flood models in coastal areas: a review of methods and uncertainty analysis. Natural Hazards, 116(1), 469-496.
25. Zhang, W., Furtado, K., Zhou, T., Wu, P., & Chen, X. (2022). Constraining extreme precipitation projections using past precipitation variability. Nature Communications, 13(1), 6319.
26. Zubair, M., Mahee, M. N. I., Reza, K. M., Salim, M. S., & Ahmed, N. (2024). High volume real-world weather data (Version 1) [Data set]. Mendeley Data. https://doi.org/10.17632/tbrhznpwg9.1

EPH – International Journal of Mathematics and Statistics
https://eijms.com/index.php/ms/index



This work is licensed under a Creative Commons Attribution 4.0 International License. The authors retain ownership of the copyright for their article,You are free to: Share — copy and redistribute the material in any medium or format for any purpose, even commercially. To see the complete license contents,

please visit **http://creativecommons.org/licenses/by/4.0/.**