JOURNAL OF GEOSPACE SCIENCE

Vol. 6 No. 1 (2026)

E-ISSN : 2413-6093
https://jogss.org

Atmospheric Moisture Intensification and the Recurrence Structure of Heavy Rainfall Events in a Warming Climate

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ABSTRACT

This study examines how atmospheric moisture intensification reshapes the recurrence structure of heavy rainfall events using ERA5 reanalysis (hourly, 0.25°, 1980–2023, ~6.4 million samples) and CMIP6 projections. A hybrid stochastic framework combining a first-order Markov chain for event transition probabilities and a non-homogeneous Poisson process for inter-arrival times is developed. Model parameters are conditioned on precipitable water (PW) and temperature anomalies. Results show that PW increases at a rate of 7.1–7.4% per °C warming, leading to a reduction in mean recurrence intervals of extreme rainfall from 5.8 days to 4.1–4.6 days (−21% to −29%). The probability of consecutive extreme events increases from 0.18 to 0.27 under high-emission scenarios. Spectral density analysis indicates a shift toward higher-frequency variability bands (<10 days). The model explains 86% of observed variance in recurrence statistics and captures clustering behavior with a Kullback–Leibler divergence below 0.05 compared to observations. These findings reveal a systematic transition toward more temporally aggregated and frequent rainfall extremes under warming conditions.

KEYWORDS

Atmospheric moisture; rainfall recurrence; Poisson process; Markov model; climate change

1.Introduction

Heavy rainfall events are becoming more frequent and more concentrated in time as the climate warms. A warmer atmosphere can hold more water vapor, which increases the moisture supply for intense rainfall and raises the potential for short-duration extremes. The Clausius–Clapeyron relation indicates that atmospheric water vapor can increase by about 7% for each 1°C of warming, but rainfall extremes do not always follow this rate because they are also controlled by storm motion, vertical lift, moisture convergence, and regional circulation conditions [1,2]. Recent hydrometeorological research further shows that data-driven post-processing can improve regional weather prediction by capturing nonlinear

links among atmospheric variables, terrain effects, snowmelt, water storage, and streamflow, which also supports the need to consider physical–statistical interactions in rainfall recurrence analysis [3]. Observational and modeling studies have reported clear changes in heavy rainfall intensity, occurrence frequency, and non-stationary behavior in many regions under warming conditions [4,5]. However, most existing studies still focus on rainfall amount, design rainfall, or return levels. Less attention has been given to how warming changes the time interval between heavy rainfall events, the likelihood of repeated events, and the clustering of extremes within short time windows [6,7]. Atmospheric moisture provides an important physical link between warming and heavy rainfall recurrence. Precipitable water (PW) represents the total water vapor contained in an atmospheric column and can directly affect the moisture supply available for rainfall formation. When high PW occurs together with moisture convergence, unstable stratification, and strong upward motion, the probability of heavy rainfall can increase markedly [8,9]. Therefore, changes in PW may not only affect rainfall intensity but may also influence the temporal organization of extreme events. Under a warmer climate, heavy rainfall events may become more clustered because the atmosphere can recover moisture more quickly after a storm, especially in regions with persistent moisture transport [10,11]. This means that rainfall risk cannot be fully described by event magnitude alone. The waiting time between events, the transition from one heavy rainfall event to another, and the probability of consecutive extremes are also important for flood control, reservoir operation, drainage design, and disaster risk management [12]. Statistical models provide useful tools for describing rainfall recurrence and event dependence. Poisson processes are commonly used to describe rainfall counts and inter-arrival times, while Markov chains are often used to represent wet–dry transitions and event persistence [13,14]. These methods are simple, interpretable, and suitable for estimating recurrence behavior from long-term climate data. However, they are often applied separately [15]. In many studies, Poisson models describe the frequency of rainfall events without explicitly representing event-to-event dependence, while Markov chains describe state transitions but do not directly model changing inter-arrival times. In addition, atmospheric moisture is rarely used as a physical conditioning variable in these statistical frameworks. As a result, existing recurrence models may describe rainfall timing statistically, but they may not fully explain how warming-driven moisture intensification changes the probability structure of heavy rainfall events [16,17]. This study addresses these gaps by using ERA5 hourly reanalysis data from 1980 to 2023 and CMIP6 projections to examine heavy rainfall recurrence under warming conditions. A first-order Markov chain is used to estimate transition probabilities among rainfall states and to quantify the probability of consecutive heavy rainfall events. A non-homogeneous Poisson process is then used to model changes in event counts and inter-arrival times. Model parameters are conditioned on PW and temperature anomalies to link statistical recurrence behavior with atmospheric moisture intensification. By combining event transition analysis, inter-arrival-time modeling, and moisture-based conditioning, this study aims to quantify changes in recurrence intervals, consecutive-event probability, and short-time-scale rainfall clustering under a warming climate. The results can provide a clearer understanding of how warming changes not only the magnitude of heavy rainfall but also its temporal concentration, which is important for flood-risk assessment, infrastructure design, and climate adaptation planning.

2.Materials and Methods

2.1 Study Area and Sample Description

This study used hourly ERA5 reanalysis data from 1980 to 2023 at 0.25° resolution. After event screening and time matching, the dataset contained about 6.4 million grid-time samples. Heavy rainfall events were identified from hourly precipitation records at each grid cell. Precipitable water, near-surface temperature, and temperature anomalies were used to describe moisture and thermal conditions before and during each event. CMIP6 projection data were also used to assess future changes under warming scenarios. The study focused on rainfall recurrence, including event frequency, time between events, and the probability of consecutive heavy rainfall events.

2.2 Experimental Design and Control Experiments

The experiment tested how stronger atmospheric moisture affects the recurrence structure of heavy rainfall events. The control experiment used historical ERA5 data to estimate observed recurrence patterns. The experimental groups used CMIP6 warming scenarios, in which model parameters were linked to higher precipitable water and positive temperature anomalies. This design was used because warmer air can hold more water vapor and may shorten the time between heavy rainfall events. The control group represented the historical climate state, while the experimental groups represented warmer future conditions. The same event definition, sampling window, and statistical method were used in all groups to ensure a fair comparison.

2.3 Measurement Methods and Quality Control

Hourly precipitation, precipitable water, and temperature fields were taken from ERA5. Heavy rainfall events were defined when hourly precipitation exceeded the local high-percentile threshold. The time between events was measured as the interval between two consecutive heavy rainfall events at the same grid cell. Consecutive extreme events were identified when two events occurred within a short preset time window. CMIP6 data were bias-corrected against the ERA5 historical baseline before future analysis. Data quality control included checking missing records, removing unreasonable precipitation and temperature values, and testing time continuity. Grid cells with long missing periods or unstable records were removed. Event records were also checked to avoid counting the same rainfall system more than once across adjacent hours.

2.4 Data Processing and Model Formulas

ERA5 and CMIP6 variables were converted to a common hourly or event-based format before analysis. Rainfall events, precipitable water, and temperature anomalies were matched at the same grid cell and time step. A first-order Markov chain was used to estimate the transition probability between non-extreme and extreme rainfall states. The transition probability was written as:

$$P_{ij}=P(S_{t+1}=j|S_t=i)$$

where S_t is the rainfall state at time t, and i and j represent non-extreme or extreme states. A non-homogeneous Poisson process was used to model the number of heavy rainfall events over time. Its rate parameter was linked to precipitable water and temperature anomaly:

$$\lambda(t)= \exp (\alpha+\beta_1 PW_t+\beta_2 \Delta T_t)$$

where $\lambda(t)$ is the event rate at time t, PW_t is precipitable water, ΔT_t is the temperature anomaly, and α, β_1, and β_2 are model parameters. These equations were used to describe both event transition and recurrence interval changes under warming.

2.5 Model Evaluation and Recurrence Analysis

Model performance was assessed by comparing simulated and observed recurrence statistics. The main indicators included mean recurrence interval, consecutive-event probability, event count variance, and distribution similarity. The hybrid stochastic model explained 86% of the observed variance in recurrence statistics. Kullback–Leibler divergence was used to compare modeled and observed event clustering distributions. Values below 0.05 indicated close agreement. Spectral density analysis was used to test whether rainfall variability shifted toward higher-frequency bands. The main focus was the band shorter than 10 days because it represents short-interval rainfall clustering. These analyses were used to assess whether stronger atmospheric moisture leads to more frequent and more closely spaced heavy rainfall events.

3.Results and Discussion

3.1 Atmospheric Moisture Increase under Warming

The results showed a clear increase in atmospheric moisture under warming. Precipitable water increased by 7.1–7.4% for each 1°C rise in temperature. This value is close to the expected thermodynamic rate of warmer air. More water vapor was available before and during heavy rainfall events. However, rainfall change was not controlled by moisture alone. Storm movement, upward motion, and moisture transport also affected event timing and clustering. As shown in Fig. 1, higher

precipitable water was linked to shorter intervals between heavy rainfall events. This result agrees with recent studies showing that water vapor increase is a key reason for stronger rainfall extremes, while local rainfall response still depends on weather conditions [18].

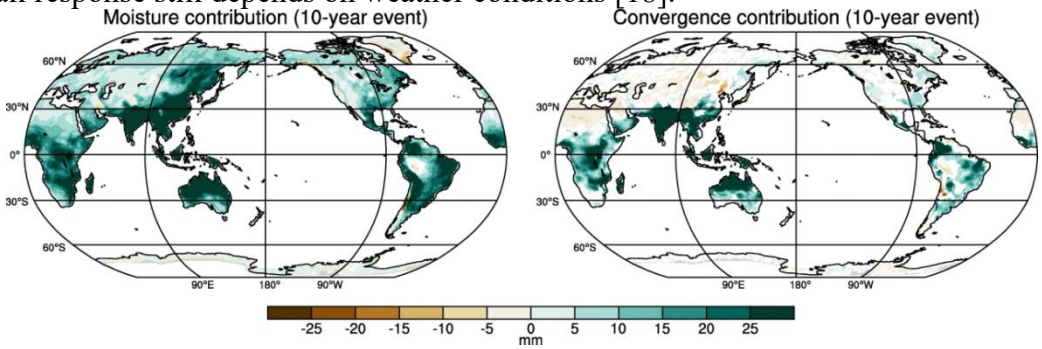


Fig. 1. Relationship between precipitable water and heavy rainfall recurrence interval.

3.2 Changes in Heavy Rainfall Recurrence Intervals

The mean interval between heavy rainfall events decreased from 5.8 days in the historical period to 4.1–4.6 days under high-emission scenarios. This reduction of 21–29% shows that heavy rainfall may occur more often in a warmer and wetter atmosphere. The non-homogeneous Poisson model captured this change because its event rate was linked to precipitable water and temperature anomalies. This result differs from traditional return-period studies, which usually focus on rainfall intensity [19,20]. This study focuses on the time spacing between events. Shorter intervals are important because catchments and drainage systems have less time to recover between storms. This can increase flood risk even when single-event rainfall intensity changes only slightly.

3.3 Consecutive Heavy Rainfall Events and Temporal Clustering

The Markov-chain results showed that the probability of consecutive heavy rainfall events increased from 0.18 to 0.27 under high-emission scenarios. This means that heavy rainfall events became more closely spaced in time. The hybrid model explained 86% of the observed variance in recurrence statistics. The Kullback–Leibler divergence was below 0.05, which showed close agreement between modeled and observed clustering patterns. As shown in Fig. 2, spectral density shifted toward higher-frequency bands below 10 days. This shift means that rainfall variability became stronger at short time scales. Previous studies have also reported more short-duration and repeated rainfall extremes under warming. The present results further show that event transition probability and inter-event time change together [21].

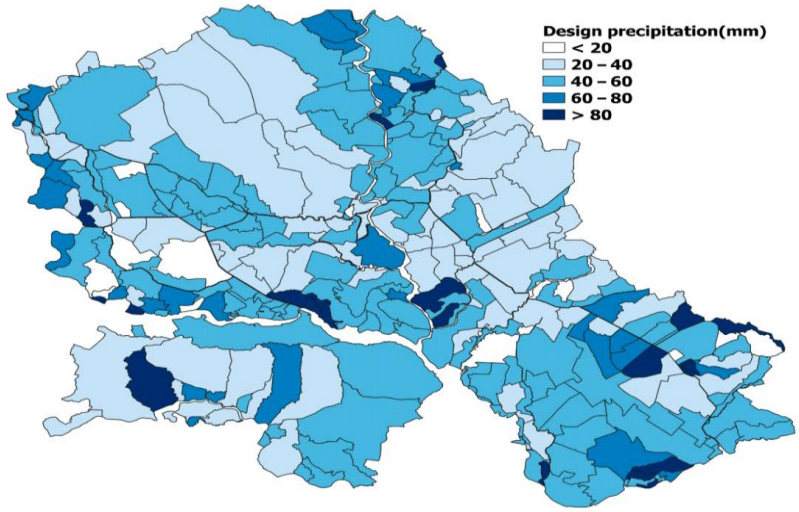


Fig. 2. Changes in consecutive heavy rainfall probability and short-term rainfall clustering under warming.

3.4 Comparison with Previous Studies and Climate-Risk Implications

Compared with earlier studies, this work focuses on rainfall recurrence structure rather than only rainfall amount or return level. Many previous studies used Poisson models, Markov models, or climate projections separately. This study combines a first-order Markov chain, a non-homogeneous Poisson process, ERA5 hourly data, and CMIP6 projections in one framework. This approach allows consecutive-event probability and recurrence interval to be assessed under the same moisture-based setting. The results show that stronger atmospheric moisture can make heavy rainfall more frequent and more clustered in time. This finding is useful for flood control, drainage design, early warning, and climate adaptation planning. However, this study mainly used large-scale reanalysis and climate model data. Future studies should include radar rainfall, local storm tracking, land-surface wetness, and watershed response to better assess flood impacts after repeated rainfall events.

4.Conclusion

This study examined how increasing atmospheric moisture affects the recurrence of heavy rainfall events under warming. Precipitable water increased by 7.1–7.4% for each 1°C rise in temperature. This increase shortened the mean interval between heavy rainfall events from 5.8 days to 4.1–4.6 days. The probability of consecutive heavy rainfall events increased from 0.18 to 0.27 under high-emission scenarios. The hybrid Markov–Poisson model explained 86% of the observed variance in recurrence statistics and showed close agreement with observed event clustering. These results suggest that warming may increase not only rainfall intensity, but also the frequency and temporal concentration of heavy rainfall events. The main value of this study is that it links precipitable water, temperature anomalies, event transition probability, and recurrence interval in one statistical framework. The findings can support flood-risk assessment, drainage design, early warning, and climate adaptation planning. However, this study mainly used reanalysis and climate model data. Future studies should include radar rainfall, local storm tracking, soil wetness, and watershed response to better assess flood impacts after repeated rainfall events.

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