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Radar-Based Assessment of Consecutive Extreme Rainfall Events in Subtropical Monsoon Regions

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Abstract.

This study provides a high-resolution assessment of consecutive extreme rainfall events in subtropical monsoon regions using weather radar datasets (1 km spatial resolution, 5-minute temporal resolution, 2010–2022, approximately 3.1 billion grid–time observations). A spatiotemporal clustering framework based on density-based spatial clustering of applications with noise (DBSCAN) is employed to identify coherent rainfall event sequences, followed by a convolutional neural network (CNN) to classify intensity regimes. Extreme events are defined using a dynamic percentile threshold (top 5% of local rainfall intensity). Results indicate that 31% of extreme rainfall events occur in clusters lasting longer than 72 hours, with a mean cluster duration of 64.2 hours and a standard deviation of 18.7 hours. The CNN model achieves an overall classification accuracy of 90.1%, with a macro-averaged F1-score of 0.87 across intensity categories. Coastal regions exhibit 1.9 times higher clustering frequency than inland regions, primarily associated with sustained moisture flux convergence exceeding $120 \text{ kg} \cdot \text{m}^{-1} \cdot \text{s}^{-1}$. Temporal autocorrelation analysis reveals a persistence memory of 8–14 hours in rainfall intensity fields, indicating strong mesoscale organization. These findings highlight the critical role of spatiotemporal clustering and moisture transport in shaping extreme rainfall sequences in monsoon environments.

Keywords: *Radar precipitation; clustering; DBSCAN; CNN; monsoon rainfall*

INTRODUCTION

Extreme rainfall in subtropical monsoon regions is commonly associated with sustained moisture supply, strong convective instability, and repeated rainfall cells over the same or nearby areas. These events can last for many hours or several days, producing severe urban flooding

landslides, reservoir pressure, traffic disruption, and damage to drainage infrastructure [1,2]. Compared with isolated short-duration storms, consecutive rainfall events are often more hazardous because soil moisture, river discharge, and urban drainage systems may not return to normal before the next rainfall pulse occurs. Previous research has shown that the temporal clustering of heavy precipitation is an important feature of rainfall extremes and that climate models still have limitations in reproducing this clustering behavior accurately [3]. This issue is particularly important in coastal monsoon regions, where warm ocean surfaces and low-level moisture transport can repeatedly support convection and maintain rainfall systems over vulnerable urban and mountainous areas [4,5].

The physical processes behind consecutive extreme rainfall are complex. Moisture transport, boundary-layer convergence, local topography, and mesoscale convective organization may act together to increase rainfall persistence and spatial concentration [6]. In subtropical coastal areas, persistent onshore flow can provide a continuous moisture source, while local lifting and repeated convective triggering can cause rainfall cells to regenerate over the same region [7]. These processes increase the probability of multi-hour or multi-day rainfall accumulation and make disaster prevention more difficult. Although many studies have examined rainfall intensity, annual maxima, return periods, and short-term storm evolution, less attention has been given to the space–time clustering of consecutive extreme rainfall events, especially using long-term high-resolution radar observations [8,9]. Weather radar provides an important data source for studying these events because it records rainfall fields at high spatial and temporal resolution. Compared with rain gauges, radar data can describe the spatial structure and movement of rainfall systems more completely. Compared with satellite precipitation products, radar observations are usually better suited for identifying local rainfall intensity, storm morphology, and short-time rainfall evolution in urban and coastal regions [10,11]. These advantages make radar data useful for detecting rainfall clusters, tracking rainfall sequences, and distinguishing organized rainfall systems from scattered noisy signals. However, many radar-based studies still focus on individual storms, nowcasting, or short-term rainfall prediction. Long-term radar archives have not been fully used to examine how extreme rainfall events cluster, persist, and differ between coastal and inland environments [12,13]. Data-driven methods provide new opportunities for extracting useful information from long-term radar records. DBSCAN is suitable for rainfall cluster detection because it can identify irregularly shaped clusters without assuming a fixed cluster form. It can also separate organized rainfall systems from isolated noisy pixels, which is important when processing large radar datasets with strong spatial heterogeneity

[14,15]. CNN models are also effective for radar rainfall classification because they can learn spatial patterns, intensity gradients, and local texture features from gridded rainfall images [16,17]. However, clustering and classification are often applied separately. As a result, the relationship between rainfall sequence structure, intensity regime, and moisture flux convergence remains insufficiently tested. This limits the understanding of why some extreme rainfall events remain localized and short-lived, while others develop into persistent and high-impact rainfall sequences.

To address these gaps, this study uses 1 km, 5-minute radar rainfall data from 2010 to 2022, covering approximately 3.1 billion grid–time observations, to investigate consecutive extreme rainfall in subtropical monsoon regions. A dynamic local percentile threshold is applied to define extreme rainfall events while accounting for spatial differences in rainfall climatology. DBSCAN is then used to identify rainfall sequences and characterize their spatial extent, duration, and clustering behavior. A CNN model is further used to classify rainfall intensity regimes from radar rainfall fields. By combining radar-based clustering, deep-learning classification, and moisture flux convergence analysis, this study aims to quantify the space–time organization of consecutive extreme rainfall, compare coastal and inland differences, and clarify how moisture transport supports persistent extreme rainfall. The findings are expected to improve the understanding of rainfall clustering mechanisms in subtropical monsoon regions and provide useful evidence for urban flood warning, reservoir operation, and regional climate risk assessment.

2. Materials and Methods

2.1 Study Area and Sample Description

This study used weather radar data from subtropical monsoon regions from 2010 to 2022. The radar data had a spatial resolution of 1 km and a temporal resolution of 5 min. After data screening and event selection, about 3.1 billion grid–time observations were used. The study area included coastal and inland zones, which allowed comparison under different moisture conditions. Coastal zones were mainly affected by ocean moisture transport, while inland zones were more affected by local convection and terrain lifting. The study object was consecutive extreme rainfall events. Extreme rainfall was defined as rainfall intensity above the local top 5% threshold, so regional rainfall differences could be considered.

2.2 Experimental Design and Control Experiments

The experiment identified and classified consecutive extreme rainfall events from high-resolution radar data. The control experiment used only a percentile-based event definition

without spatiotemporal clustering. In this setting, each extreme rainfall grid cell was treated as an independent event. The experimental model used DBSCAN to group nearby extreme rainfall pixels into continuous rainfall sequences in space and time. This setting was used because monsoon rainfall often occurs as organized systems rather than isolated pixels. A CNN model was then used to classify rainfall intensity regimes in the clustered event sequences. The comparison between the control and clustered results was used to test whether clustering better described rainfall duration, event continuity, and coastal–inland differences.

2.3 Measurement Methods and Quality Control

Rainfall intensity was measured from radar precipitation products at 5 min intervals. Each radar grid cell provided rainfall intensity, event time, and spatial location. Moisture flux convergence was used to describe the moisture background of persistent rainfall events. Before analysis, radar fields were checked for missing scans, abnormal echoes, ground clutter, and beam blockage. Short missing periods were filled only when nearby scans showed stable rainfall structure. Isolated high-intensity pixels were removed when they were not connected to nearby rainfall echoes. Radar rainfall intensity was also compared with available rain-gauge records to reduce bias. Only events with clear spatial continuity and valid time coverage were kept for clustering and CNN classification.

2.4 Data Processing and Model Formulas

Radar rainfall fields were first converted into binary extreme-rainfall masks using the local top 5% rainfall intensity threshold. Extreme pixels were then arranged by longitude, latitude, and time for DBSCAN clustering. The local threshold was calculated as:

$$R_g^* = Q_{0.95}(R_{g,t})$$

Where R_g^* is the extreme rainfall threshold at grid cell g , $Q_{0.95}$ is the 95th percentile, and $R_{g,t}$ is rainfall intensity at grid cell g and time t . CNN classification performance was measured by the F1-score:

$$F1 = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

Where precision is the proportion of correctly classified samples among all samples predicted as a given class, and recall is the proportion of correctly classified samples among all observed samples in that class. These equations were used to define extreme rainfall events and assess intensity-regime classification.

2.5 Clustering, Classification, And Persistence Analysis

DBSCAN was used to identify rainfall clusters based on spatial distance and time continuity. This method grouped extreme rainfall pixels into event sequences and treated isolated pixels as noise. Cluster duration, cluster area, rainfall intensity, and coastal–inland location were then calculated for each event. The CNN model used radar rainfall patches as input and classified each event sequence into different intensity regimes. Model performance was measured by overall accuracy and macro-averaged F1-score. Temporal autocorrelation analysis was used to measure rainfall persistence memory. Persistence time was defined as the lag when rainfall autocorrelation dropped below a set significance level. Moisture flux convergence was compared between clustered and non-clustered events to test whether sustained moisture supply supported long-duration rainfall sequences.

3. Results and Discussion

3.1 Spatial Distribution of Consecutive Extreme Rainfall Events

The radar results showed that consecutive extreme rainfall events were unevenly distributed across the study region. Coastal areas had a higher clustering frequency than inland areas, with a coastal-to-inland ratio of about 1.9. This pattern suggests that ocean moisture transport helped maintain repeated rainfall cells. About 31% of extreme rainfall events occurred in clusters lasting longer than 72 h. This result indicates that much of the rainfall risk came from multi-stage rainfall sequences rather than isolated storms [18]. As shown in Fig. 1, clustered events were mainly located along coastal belts and moisture convergence zones. This finding is consistent with previous radar and monsoon rainfall studies, which reported that coastal convergence and steady water vapor supply can support long-lasting convective rainfall [19].

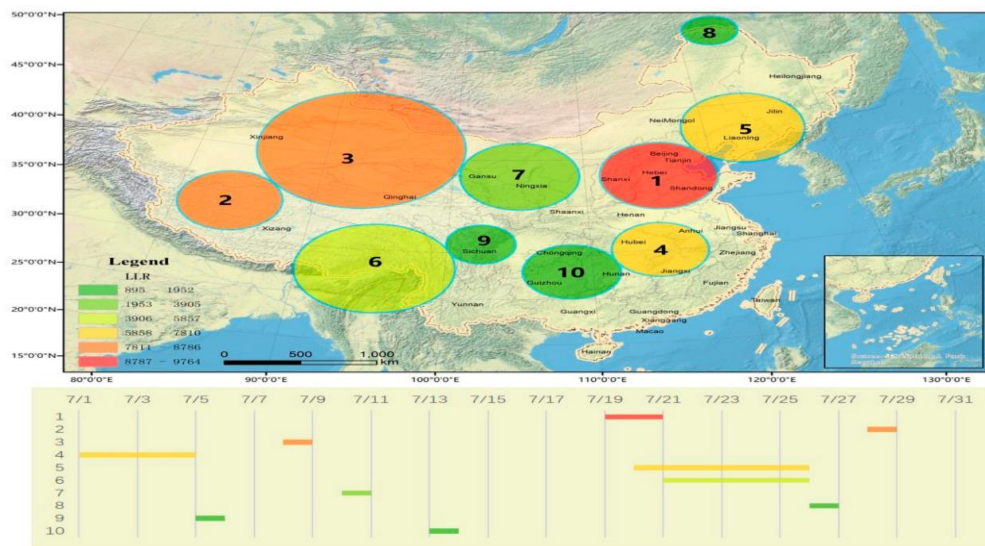


Figure 1 Spatial pattern of consecutive extreme rainfall clusters in coastal and inland monsoon regions.

3.2 Duration and Persistence of Rainfall Clusters

The mean duration of rainfall clusters was 64.2 h, with a standard deviation of 18.7 h. This result shows that many extreme rainfall sequences lasted for several days. Temporal autocorrelation analysis showed a rainfall memory of 8–14 h in the radar intensity fields. This means that rainfall intensity did not change independently between adjacent time steps. Instead, it kept a clear mesoscale pattern for several hours. This result is important because short recovery time between rainfall pulses can increase flood risk, especially in urban and low-lying coastal areas [20,21]. Compared with daily rain-gauge data, the 5-min radar data used in this study provided a clearer view of rainfall persistence and short-term event continuity.

3.3 Cnn-Based Classification of Rainfall Intensity Regimes

The CNN model classified radar rainfall intensity regimes with an overall accuracy of 90.1% and a macro-averaged F1-score of 0.87. This result shows that radar rainfall patches contained clear spatial information for separating intensity regimes. The model performed well because CNNs can learn rainfall texture, echo shape, and intensity gradients from radar images. As shown in Fig. 2, high-intensity regimes were usually related to compact and organized radar echoes, while weaker regimes showed more scattered structures. This finding agrees with recent deep-learning rainfall studies showing that radar images are useful for short-term rainfall prediction and intensity classification [22]. However, model accuracy may still be affected by radar noise, beam blockage, and weak echo contamination.

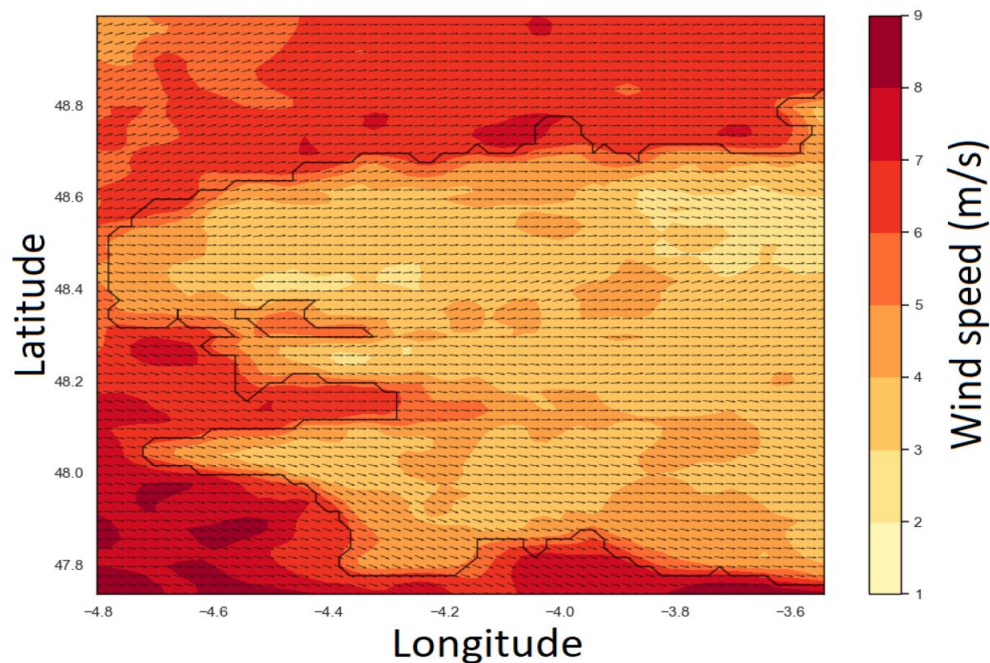


Figure 2 CNN classification of radar rainfall intensity classes from clustered event sequences.

3.4 Comparison with Previous Studies and Hydrological Implications

Compared with previous studies, this work focuses more on consecutive extreme rainfall sequences than on single rainfall events. Many earlier radar studies mainly examined rainfall estimation or short-term nowcasting. Other extreme rainfall studies used station or satellite data, which may miss local storm structure and short-lived convective cells. This study used 1 km and 5-min radar data to identify rainfall clusters in both space and time. DBSCAN retained the structure of rainfall sequences, while the CNN model classified rainfall intensity regimes. The results showed that moisture flux convergence greater than $120 \text{ kg} \cdot \text{m}^{-1} \cdot \text{s}^{-1}$ was closely related to persistent rainfall clustering. This finding is useful for flood warning, drainage operation, and monsoon rainfall risk assessment. Future studies should include radar–gauge merging, storm tracking, soil wetness, and hydrological response to better estimate flood impacts after consecutive rainfall events.

4. Conclusion

This study examined consecutive extreme rainfall events in subtropical monsoon regions using 1 km and 5-min radar data from 2010 to 2022. The results showed that 31% of extreme rainfall events occurred in clusters lasting more than 72 h, with a mean duration of 64.2 h. Coastal regions had 1.9 times more clustered events than inland regions, mainly due to stronger moisture flux convergence. Temporal autocorrelation showed an 8–14 h memory in rainfall intensity fields, which indicates clear mesoscale persistence. The CNN model classified rainfall intensity classes with 90.1% accuracy and a macro-averaged F1-score of 0.87. The main value of this study is the combined use of radar-based clustering and CNN classification to describe rainfall organization and intensity structure. The findings can support flood warning, drainage management, and monsoon rainfall risk assessment. However, this study mainly used radar rainfall and moisture flux data. Future studies should include radar–gauge merged rainfall, storm tracking, soil wetness, and runoff response to better assess flood impacts after consecutive extreme rainfall events.

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