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Projected Changes in the Temporal Organization of Heavy Precipitation under Future Climate Scenarios

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Abstract

This study evaluates future changes in the temporal organization of heavy precipitation using CMIP6 simulations (30 models, daily resolution, 1950–2100, ~3.8 million samples) under multiple emission scenarios. Temporal organization is quantified using a persistence index, event clustering coefficient, and a graph-based temporal connectivity metric. A gradient boosting regression model (GBDT, 800 trees) is used to relate climate drivers (temperature, humidity, circulation indices) to clustering behavior. Results show that clustered heavy precipitation events increase by 29–37% under SSP5-8.5, with the clustering coefficient rising from 0.34 to 0.48 by 2100. Mean inter-event intervals decrease from 6.3 days to 4.5 days, while event duration increases by 0.9–1.6 days. Variance decomposition indicates that thermodynamic factors explain 61% of clustering changes, while dynamic circulation contributes 39%. Model performance achieves R^2 = 0.79 and RMSE = 0.12 in reproducing clustering metrics. These findings indicate a structural shift toward more temporally concentrated and persistent precipitation extremes in a warming climate.

Keywords

Heavy precipitation; clustering; CMIP6; GBDT; climate extremes

INTRODUCTION

Heavy precipitation is expected to become more frequent and more intense under a warmer climate. A warmer atmosphere can hold more water vapor, which increases the likelihood of intense rainfall when uplift, moisture convergence, and favorable circulation conditions occur together [1]. In addition to changes in rainfall amount, the temporal clustering of heavy precipitation has also become an important issue in climate-impact studies. Previous evaluations have shown that global climate models can reproduce some aspects of heavy precipitation clustering, but their performance varies across regions and models, indicating that temporal organization remains a challenging feature in climate simulations [2]. Recent CMIP6 studies further suggest that future precipitation extremes are likely to increase in many regions, although

the magnitude and spatial pattern of change differ across models, seasons, and emission scenarios [3,4]. These differences reflect the combined effects of thermodynamic intensification, circulation uncertainty, model resolution, and regional moisture transport. Most studies on precipitation extremes have focused on rainfall intensity, annual maxima, return periods, or percentile-based indices such as Rx1day and Rx5day [5,6]. These indices are useful for identifying changes in short-duration extremes and for comparing projected risks across models and regions. However, they do not fully describe how heavy rainfall events are arranged in time. Flood risk is not controlled only by the intensity of a single rainfall event. It can also increase when heavy rainfall lasts longer, when events occur closer together, or when several heavy rainfall days form clustered sequences [7,8]. Closely spaced rainfall events may keep soil moisture at a high level, reduce infiltration capacity, increase runoff efficiency, and raise the probability of river flooding, urban waterlogging, and slope instability [9]. Therefore, a more complete assessment of future precipitation risk needs to consider not only rainfall intensity but also the persistence and temporal structure of heavy precipitation events. The temporal organization of heavy precipitation remains less studied than rainfall intensity. Common metrics such as frequency, duration, and consecutive wet days provide useful information, but they cannot fully capture event clustering, inter-event intervals, and temporal connectivity [10,11]. Two regions may have similar heavy rainfall frequency but very different hydrological risks if one region experiences isolated events while the other experiences repeated events within a short period. Similarly, the same total amount of heavy rainfall may lead to different impacts depending on whether the rainfall is concentrated in a connected sequence or distributed as separate events [12]. These features are particularly important for river basins, high-latitude regions, urban drainage systems, agricultural areas, and infrastructure networks that are sensitive to repeated wet conditions [13]. CMIP6 provides long-term simulations for evaluating historical and future changes in precipitation extremes under different emission scenarios. However, projections of heavy precipitation still contain considerable uncertainty because of model resolution, convective parameterization, circulation bias, land–atmosphere feedback, and regional differences in moisture transport [14,15]. These uncertainties may become more evident when the research focus shifts from rainfall amount to the timing and clustering of rainfall events. The formation of clustered heavy precipitation is influenced by both thermodynamic and dynamic factors. Higher atmospheric humidity can support stronger and more repeated rainfall events, while persistent circulation patterns can maintain uplift and moisture transport over the same region for several days [16,17]. Distinguishing these mechanisms is necessary for explaining why some regions may experience stronger increases in heavy rainfall clustering than others under future warming. This study investigates the temporal organization of heavy precipitation using daily CMIP6 outputs from 30 climate models during 1950–2100 under multiple emission scenarios. Instead of relying only on conventional intensity-based indices, this study measures heavy precipitation organization using a persistence index, an event clustering coefficient, and a graph-based temporal connectivity metric. These metrics are used to describe how long heavy rainfall conditions persist, how closely heavy rainfall events occur in time, and how separate events are connected into longer rainfall sequences. A gradient boosting decision tree model is then applied to link these temporal-organization metrics with temperature, humidity, and circulation-related predictors. This framework helps quantify the relative contributions of thermodynamic and dynamic factors to future changes in clustered heavy precipitation. By shifting the focus from single-event intensity to persistence, clustering, and temporal connectivity, this study provides a more detailed understanding of future precipitation risk. The results are expected to improve the interpretation of CMIP6 projections and provide useful evidence for flood-risk assessment, hydrological impact studies, and climate-adaptation planning under continued warming.

2.Materials and Methods

2.1 Study Area and Sample Description

This study used daily precipitation data from 30 CMIP6 models for 1950–2100. The dataset included historical runs and future SSP scenarios, covering low-, medium-, and high-emission pathways. After spatial and temporal matching, about 3.8 million valid grid–time samples were kept. The analysis focused on land regions with clear seasonal rainfall changes and enough daily records for event detection. Heavy precipitation events were examined at the grid-cell scale to keep regional differences in rainfall amount, event duration, and event spacing. Climate variables, including near-surface temperature, humidity, vertical motion, and circulation indices, were also used to describe the background conditions of heavy rainfall clustering.

2.2 Experimental Design and Control Tests

The experiment tested whether future warming changes the timing pattern of heavy precipitation. Historical simulations were used as the reference group. Future simulations under different SSP scenarios were used as the experimental groups. SSP5-8.5 was used as the high-forcing case because it represents strong greenhouse gas forcing by the end of the century. Heavy precipitation was defined by local percentile thresholds to account for regional rainfall differences. Two control tests were used. The first used only rainfall intensity and frequency indices, without clustering metrics, to test whether future changes could be explained by stronger or more frequent rainfall alone. The second removed climate variables from the GBDT model to test their role in explaining rainfall clustering

2.3 Measurement Methods and Quality Control

Daily precipitation data from each CMIP6 model were converted to the same unit and regridded to a common spatial resolution. Calendar differences among models were corrected before event detection. Grid cells with many missing values, abnormal precipitation records, or poor data continuity were removed. Negative precipitation values and unrealistic peaks were also excluded. For each grid cell, heavy precipitation thresholds were calculated from the historical baseline period and then applied to both historical and future simulations. Event duration, inter-event interval, and clustering metrics were calculated from the cleaned daily series. All climate variables were matched to the same grid and daily time step as the precipitation data. Model outputs were checked across scenarios before multi-model analysis.

2.4 Data Processing and Model Formulation

Heavy precipitation events were identified from daily precipitation series using a local percentile threshold. For each grid cell, the binary event sequence was written as:

$$I_t=\begin{cases}1, & P_t \geq P_{95}\\ 0, & P_t < P_{95}\end{cases}$$

where P_t is daily precipitation on day t, and P_{95} is the local 95th percentile threshold during the baseline period. Consecutive days with $I_t=1$ were treated as one event. The event clustering coefficient was calculated as:

$$C=\frac{N_c}{N_e}$$

where C is the clustering coefficient, N_c is the number of heavy precipitation events occurring within a short interval after a previous event, and N_e is the total number of heavy precipitation events. A GBDT model with 800 trees was used to relate clustering metrics to temperature, humidity, and circulation variables.

2.5 Model Evaluation and Attribution Analysis

The GBDT model was evaluated using R^2 and RMSE. Historical samples were used for calibration, and future samples were used for scenario testing. The model was also tested under different SSP pathways to check whether clustering changes were consistent across forcing levels. Variable

contribution was measured using feature importance and variance decomposition. Thermodynamic factors included temperature and humidity. Dynamic factors included circulation indices, vertical motion, and wind-related variables. The contribution of each factor group was calculated to test whether future clustering changes were mainly driven by moisture increase or circulation change. Uncertainty was assessed using the spread among the 30 CMIP6 models. The analysis was also repeated under different heavy precipitation thresholds.

3.Results and Discussion

3.1 Future Changes in Heavy Precipitation Clustering

The CMIP6 results showed that heavy precipitation events become more clustered under future warming. Under SSP5-8.5, clustered heavy precipitation events increased by 29–37% by the end of the century. The clustering coefficient rose from 0.34 to 0.48, while the mean interval between events decreased from 6.3 days to 4.5 days. This result means that heavy precipitation events are likely to occur closer together in time [18,19]. Such a change can increase soil wetness, river flow, and flood risk, even when the intensity of a single event does not rise strongly. Previous CMIP6 studies also reported increases in future precipitation extremes under high-emission scenarios. However, most of them focused on rainfall intensity rather than event clustering. This study further shows that future heavy precipitation may become more concentrated in time, as shown in Fig. 1.

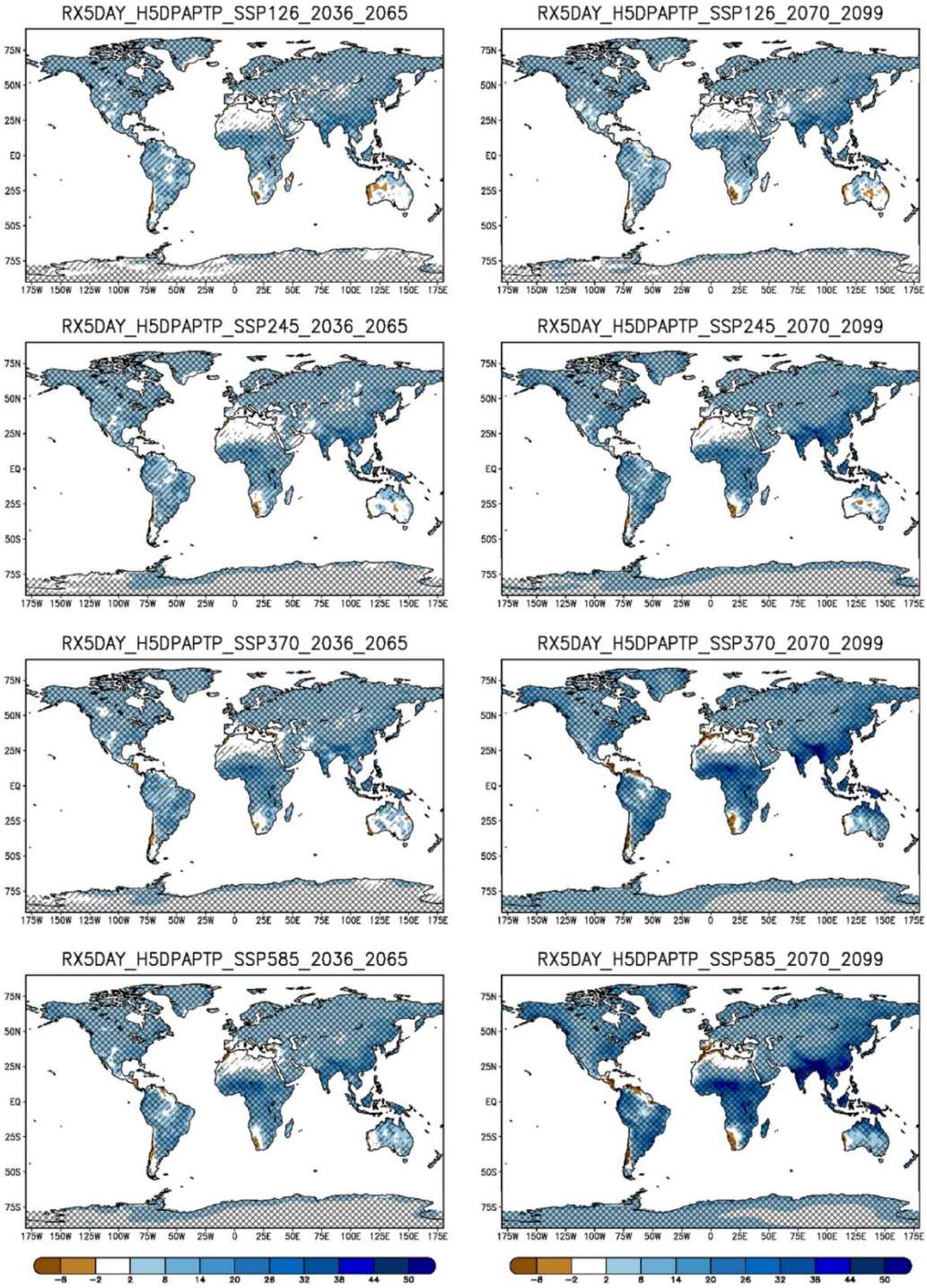


Fig. 1. Changes in heavy precipitation clustering under future climate scenarios.

3.2 Changes in Event Interval and Event Duration

Heavy precipitation events became more frequent, closer in time, and longer. Mean event duration increased by 0.9–1.6 days, while the interval between events became shorter. This pattern suggests a higher chance of repeated rainfall stress, where a new event occurs before the land surface or drainage system has recovered from the previous event [20,21]. Earlier studies on sub-seasonal clustering of extreme precipitation showed that CMIP6 models can reproduce broad clustering patterns and project stronger clustering in many regions under climate change. However, many of

these studies focused on large spatial scales. This study gives a clearer event-level view by using the persistence index, clustering coefficient, and temporal connectivity metric together. These results show that heavy precipitation risk should be assessed by event timing as well as rainfall amount.

3.3 Thermodynamic and Dynamic Drivers of Clustering

Variance decomposition showed that thermodynamic factors explained 61% of the projected clustering change, while circulation factors explained 39%. This result indicates that higher humidity and temperature are the main drivers of tighter heavy precipitation clustering. A warmer atmosphere can hold more water vapor, which supports repeated heavy rainfall when uplift is present. Circulation changes also played a clear role. Vertical motion, wind fields, and large-scale circulation indices affected the timing and duration of rainfall events. This result is consistent with studies showing that future precipitation extremes are controlled by both moisture increase and circulation change [22]. The driver contribution and model response are shown in Fig. 2.

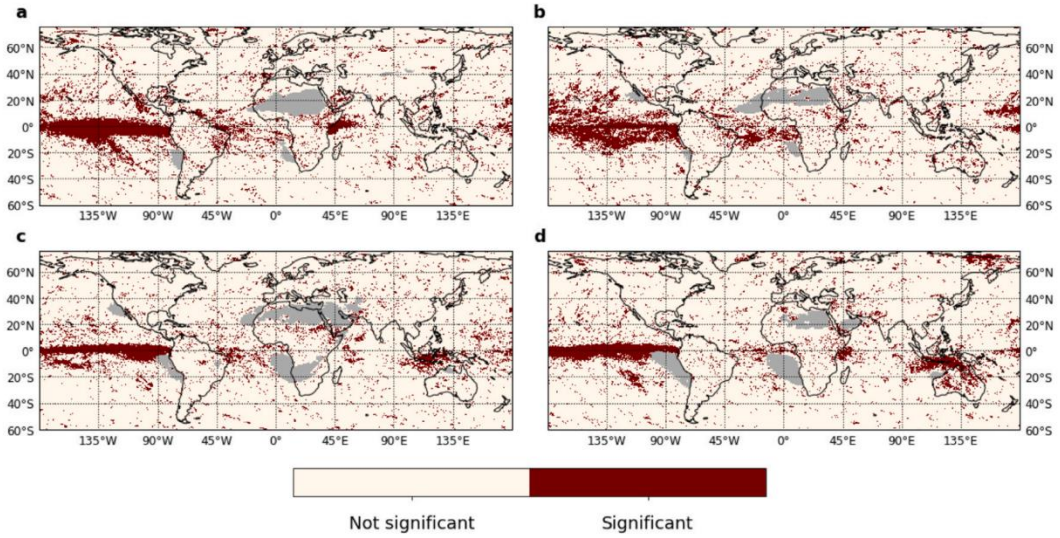


Fig. 2. Temperature, humidity, and circulation effects on future heavy precipitation clustering.

3.4 Model Performance and Scientific Meaning

The GBDT model reproduced clustering metrics with $R^2 = 0.79$ and RMSE = 0.12. This result shows that temperature, humidity, and circulation variables can explain much of the timing structure of heavy precipitation. Compared with simple regression or single-index methods, the GBDT model better described nonlinear links between climate drivers and rainfall clustering. The main value of this study is that it treats heavy precipitation as a sequence of related events rather than separate daily extremes. This method gives a clearer view of future flood risk under warming. However, uncertainty remains because CMIP6 models differ in their treatment of convection, storm tracks, and regional rainfall processes. Future work should use higher-resolution regional simulations and longer observation records to improve the assessment of clustered heavy precipitation [23].

4.Conclusion

This study examined future changes in the timing pattern of heavy precipitation using daily CMIP6 data from 30 models under several emission scenarios. The results showed that heavy precipitation events become more clustered, last longer, and occur closer together under future warming, especially under SSP5-8.5. Clustered events increased by 29–37%, the clustering coefficient rose from 0.34 to 0.48, and the mean interval between events decreased from 6.3 days to 4.5 days by the end of the century. Variance decomposition showed that temperature and humidity explained

61% of the clustering change, while circulation factors explained 39%. The GBDT model reproduced clustering metrics with good accuracy, suggesting that climate drivers can explain much of the timing change in heavy precipitation. The main value of this study is that it treats heavy precipitation as connected event sequences rather than separate daily extremes. This method gives a clearer view of future flood risk, because repeated rainfall can cause damage even when single-event intensity does not increase strongly. The results may support flood-risk assessment, drainage planning, reservoir operation, and climate adaptation. However, uncertainty remains because CMIP6 models differ in their description of convection, storm tracks, and regional rainfall processes. Future work should use higher-resolution regional simulations and longer observation records to better assess clustered heavy precipitation under climate change.

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