

Article

Spatiotemporal Evolution of Precipitation Concentration in the Yangtze River Basin (1960–2019): Associations with Extreme Heavy Precipitation and Validation Using GPM IMERG

Tao Jin ¹, Yuliang Zhou ^{1,*}, Ping Zhou ¹, Ziling Zheng ¹, Rongxing Zhou ², Yanqi Wei ¹ , Yuliang Zhang ¹ and Juliang Jin ¹

¹ College of Civil Engineering, Hefei University of Technology, Hefei 230009, China; 2024010092@mail.hfut.edu.cn (T.J.)

² School of Environment and Energy Engineering, Anhui Jianzhu University, Hefei 230601, China

* Correspondence: zhouyuliang@hfut.edu.cn; Tel.: +86-158-56954-795

Abstract

Precipitation concentration reflects the uneven temporal distribution of rainfall. It plays a critical role in water resource management and flood–drought risk under climate change. However, its long-term trends, associations with atmospheric teleconnections as potential drivers, and links to extreme heavy precipitation events remain poorly understood in complex basins like the Yangtze River Basin. This study analyzes these aspects using ground station data from 1960 to 2019 and conducts a comparison using the Global Precipitation Measurement Integrated Multi-satellite Retrievals for GPM (GPM IMERG) satellite product. We calculated three indices—Daily Precipitation Concentration Index (PCID), Monthly Precipitation Concentration Index (PCIM), and Seasonal Precipitation Concentration Index (SPCI)—to quantify rainfall unevenness, selected for their ability to capture multi-scale variability and associations with extremes. Key methods include Mann–Kendall trend tests for detecting changes, Hurst exponents for persistence, Pettitt detection for abrupt shifts, random forest modeling to assess atmospheric teleconnections, and hot spot analysis for spatial clustering. Results show a significant basin-wide decrease in PCID, driven by increased frequency of small-to-moderate rainfall events, with strong spatial synchrony to extreme heavy precipitation indices. PCIM is most strongly associated with El Niño–Southern Oscillation (ENSO) and Pacific Decadal Oscillation (PDO). GPM IMERG captures PCIM patterns well but underestimates PCID trends and magnitudes, highlighting limitations in daily-scale resolution. These findings provide a benchmark for satellite product improvement and support adaptive strategies for extreme precipitation risks in changing climates.

Keywords: precipitation concentration; atmospheric teleconnections; extreme heavy precipitation; spatiotemporal variations; Yangtze river basin



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1. Introduction

As a pivotal element in the interaction between natural climate systems and human society, precipitation serves not only as the primary driver of Earth’s hydrological equilibrium but also as an indispensable resource underpinning ecosystem services and socioeconomic development [1–6]. The spatiotemporal distribution patterns of precipitation fundamentally determine regional water availability, agricultural irrigation efficiency, and threshold risks of flood–drought disasters. Under the dual pressures of intensifying global warming

and escalating anthropogenic disturbances, hydrological processes have manifestly pronounced non-stationary characteristics, triggering systematic alterations in precipitation intensity, frequency, and spatial configuration [7–10]. The Intergovernmental Panel on Climate Change (IPCC) Sixth Assessment Report substantiates that each 1 °C increase in global temperature elevates atmospheric water-holding capacity by approximately 7% [11]. This thermodynamic amplification has resulted in marked intensification of extreme heavy precipitation events in both magnitude and frequency, subsequently exacerbating economic losses and ecological degradation as well as elevating mortality rates [12–15].

The Precipitation Concentration Index (PCI) serves as a quantitative indicator of the non-uniform temporal distribution of precipitation events and offers a valuable approach for elucidating the mechanisms behind extreme hydrological phenomena [16–18]. This methodology fundamentally characterizes the PCI across temporal scales by evaluating the equilibrium of intra-annual rainfall distribution [19–21]. Particularly at daily resolution, extreme heavy precipitation events, though typically lasting merely days, disproportionately contribute to monthly, seasonal, and annual precipitation totals [22]. The unique analytical strength of the PCI in capturing such hydroclimatic signatures has driven its broad application in investigating spatiotemporal precipitation patterns across diverse regions. For instance, Guo et al. [23] evaluated the spatiotemporal variations in the PCI over mainland China and its potential impact on drought, finding that rainfall is becoming increasingly concentrated in a few events, which in turn results in a higher frequency of extreme heavy precipitation. Similarly, Du et al. [24] employed the PCI to investigate changes in precipitation concentration across nine river basins in China and its relationship with precipitation patterns; their results indicated that a reduction in the proportion of summer rainfall, combined with increased contributions from spring and winter, has led to a declining PCI trend on the mainland. In another study, Roye and Martin-Vide [22] examined daily precipitation concentration in the United States and discovered a significant negative correlation between the concentration index (CI) and elevation, alongside a significant positive correlation with longitude. Their findings further demonstrate the effectiveness of the CI in identifying regions that are at elevated risk for precipitation-related, hydrological, and geomorphological hazards.

In addition, as extreme heavy precipitation events become more frequent and more intense, numerous scholars have conducted extensive detection and attribution studies using extreme heavy precipitation indices and atmospheric teleconnections, which are large-scale patterns linking distant climate anomalies. Nakigudde et al. [25] quantified the impacts of future warming and increased rainfall on the hydrological and climatic characteristics of the subarctic region through the application of precipitation indices. Similarly, Vinod and Mahesha [26] utilized daily precipitation data to evaluate 14 extreme heavy precipitation indices across seven climatic regions in India and established relationships between large-scale atmospheric teleconnections and these indices. Consequently, some studies have integrated the PCI with large-scale atmospheric teleconnections to investigate their interrelations. For example, Wang et al. [27] analyzed the spatiotemporal variations in the PCI in northeastern China and its association with large-scale atmospheric circulation, while Yang et al. [9] combined teleconnection indices to explore the causes behind abrupt changes in the PCI across major river basins in Central Asia. However, previous studies have not yet examined the relationship between the PCI derived from extreme heavy precipitation indices and extreme heavy precipitation events. This oversight neglects the potential link between the non-uniform temporal distribution of precipitation and anomalous intensity, thereby hindering a comprehensive understanding of the mechanisms underlying the spatiotemporal heterogeneity of extreme heavy precipitation.

In the context of intensifying global climate change and the increasing frequency of extreme droughts and floods, accurately identifying the spatiotemporal characteristics of precipitation and its co-evolution with extreme events is crucial for basin-scale flood and drought early warning and the formulation of water security strategies. The PCI and extreme heavy precipitation indices have been widely used in climate-hydrology research due to their ability to effectively capture the temporal clustering of rainfall and quantify abnormal intensity. However, studies that couple multi-temporal resolution PCIs with extreme heavy precipitation indices at the basin scale remain scarce. Compared with existing regional studies, an integrated approach that combines Pettitt breakpoint detection, random forest attribution modeling, and spatial cold-hot spot analysis can effectively reveal the nonlinear driving mechanisms of the atmospheric dynamic and thermodynamic factors underlying the evolution of the PCI. At the same time, satellite remote sensing products, represented by GPM, offer unprecedented opportunities for large-scale hydrological monitoring, especially in river basins where ground stations are sparse. However, the accuracy of these products in regions with complex terrain, particularly their ability to capture fine-grained hydroclimatic indicators like the PCI, still requires systematic evaluation. Therefore, another key objective of this study is to conduct a comprehensive validation of the GPM product's performance in reproducing the spatiotemporal characteristics and long-term trends of the PCI, using the long-term, dense ground observation network in the Yangtze River Basin. This aims to provide a critical scientific reference for the application and improvement of this remote sensing product in the region.

Accordingly, this study focuses on the Yangtze River Basin and constructs a multi-temporal PCI dataset based on ground observations from 1960 to 2019 to analyze the spatiotemporal distribution characteristics, trends, and abrupt change points of PCIs. A random forest model is then employed to quantitatively assess the influence of atmospheric teleconnections on the spatial heterogeneity of PCIs across different subbasins. Furthermore, the spatial patterns of PCI cold and hot spots at various temporal scales are identified, and the potential response relationship between PCIs and extreme heavy precipitation events is revealed by integrating four extreme heavy precipitation indices. Concurrently, through a comparative analysis between ground observations and the GPM satellite precipitation product, this study comprehensively evaluates the performance and limitations of GPM in monitoring PCIs in this complex basin, providing a critical benchmark for the evaluation and calibration of satellite precipitation products. The findings will support the scenario-based forecasting of extreme heavy precipitation risks and the development of adaptive flood management strategies under changing environmental conditions.

2. Materials and Methods

2.1. Study Area and Data

2.1.1. Study Area

The Yangtze River is the longest river in China, spanning the eastern, central, and western economic regions, with a total length of approximately 6300 km and a drainage area of 1.8 million km². The basin features a well-developed hydrological network and significant topographical variations, with terrain gradually descending from west to east. Except for the western plateau, which experiences an alpine climate, most of the basin falls within the East Asian or South Asian monsoon climate zones. Precipitation in the basin exhibits pronounced spatiotemporal variability, characterized by cold, dry winters with little rainfall and hot, humid summers with abundant precipitation. Spatially, precipitation decreases progressively from the southeast to the northwest.

To investigate the impacts of extreme heavy precipitation in the Yangtze River Basin under a changing environment, this study subdivided the basin into 12 subbasins based

on its tributaries: the upper Jinsha River upstream of Shigu (JSRU), the lower Jinsha River downstream of Shigu (JSRD), the Min-Tuo River Basin (MTR), the Jialing River Basin (JLR), the Wu River Basin (WR), the Han River Basin (HR), the Dongting Lake Basin (DTLR), the Poyang Lake Basin (PYLR), the Taihu Lake Basin (TLR), the upper mainstream (MSU), the middle mainstream (MSM), and the lower mainstream (MSD) (Figure 1).

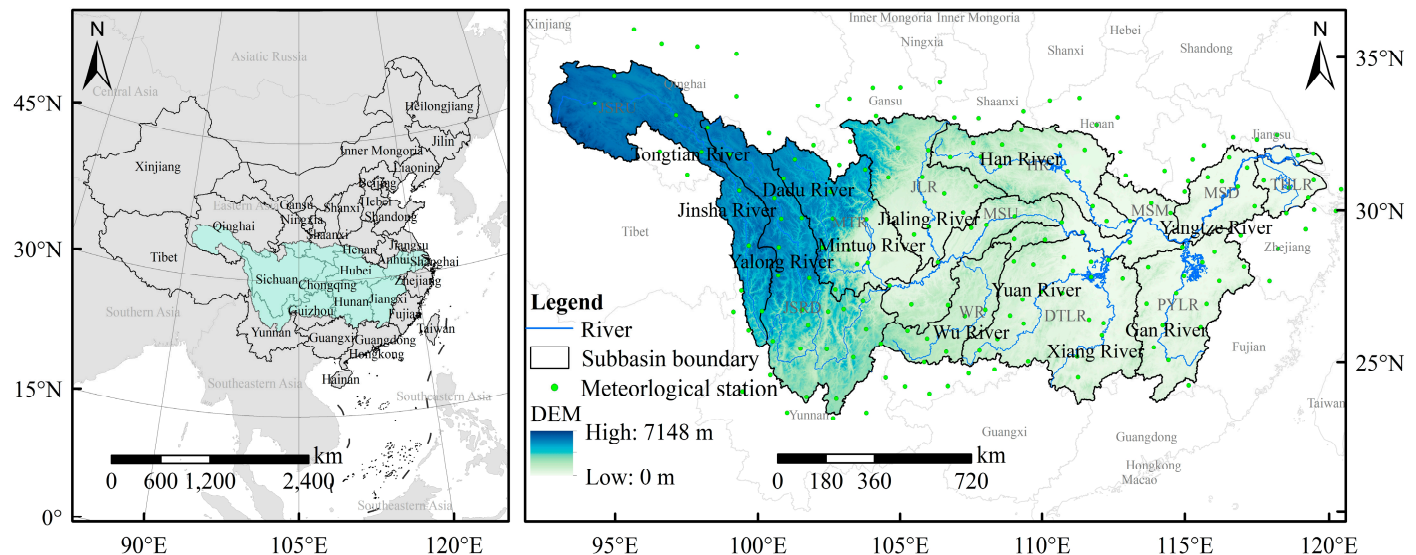


Figure 1. Geographical location and subbasin zoning diagram of the Yangtze River Basin.

2.1.2. Data Sources and Preprocessing

Daily precipitation data for 1960–2019 were obtained from the China Meteorological Data Service Centre (<https://data.cma.cn/>, accessed on 18 February 2022). To guarantee a high-quality dataset, 179 meteorological stations with excellent data integrity were chosen, each having a missing value percentage not exceeding 5%. The few sporadic missing entries were filled by imputation using the long-term average of the same calendar day from other years. Although this method might slightly underestimate precipitation variance and suppress the representation of short-duration extremes, its overall effect on the analysis is considered limited, given the small number of stations with missing data and the low proportion of such data. Satellite precipitation data were obtained from the GPM IMERG Final Run product (V07), provided by NASA (https://disc.gsfc.nasa.gov/datasets/GPM_3IMERGDF_07/summary?keywords=GPM, accessed on 23 July 2025). This dataset offers high spatial resolution gridded precipitation estimates at $0.1^\circ \times 0.1^\circ$, with daily temporal resolution, covering the period from 2000 to 2019.

To analyze the contribution of large-scale atmospheric teleconnections to the PCI, eight circulation indices were selected, including the Arctic Oscillation (AO), the Southern Oscillation Index (SOI), the El Niño–Southern Oscillation (ENSO, Niño 3.4), the Pacific Decadal Oscillation (PDO), the North Atlantic Oscillation (NAO), and the Atlantic Multidecadal Oscillation (AMO), which were obtained from the NOAA Physical Sciences Laboratory (https://psl.noaa.gov/gcos_wgsp/Timeseries/, accessed on 21 December 2024). The sunspot number (SS) was sourced from the Solar Influences Data Analysis Center (<https://www.sidc.be/SILSO/datafiles>, accessed on 22 December 2024), and the Antarctic Oscillation (AAO) was obtained from Professor Jianping Li’s homepage (<http://lijianping.cn/dct/page/1>, accessed on 22 December 2024).

The selection of these indices is based on their documented physical linkages to precipitation variability in the Yangtze River Basin. The ENSO (represented by Niño 3.4 and SOI), as the dominant ocean–atmosphere coupled mode in the tropics, significantly

modulates the East Asian monsoon and summer rainfall through its control over the western Pacific subtropical high. El Niño (La Niña) events typically lead to wetter (drier) conditions in the Yangtze region [28,29]. The PDO acts as a decadal background state that modifies the ENSO–monsoon teleconnection and contributes to long-term precipitation variability [30]. The AMO influences East Asian monsoon intensity by altering the thermal contrast between the North Atlantic and the Eurasian continent, thus affecting moisture transport into southern China [31]. The NAO and AO, although dominant in mid- and high-latitude regions, impact the East Asian summer monsoon through teleconnection pathways and modulation of the polar vortex and westerly jet stream [32,33]. The AAO may exert influence on East Asian summer circulation by modulating cross-equatorial flows and altering the strength of the western North Pacific subtropical high [34]. Lastly, solar activity, represented by sunspot numbers, serves as an external forcing mechanism that modulates the Earth’s radiation budget and atmospheric stability, potentially affecting precipitation periodicity in East Asia [35].

2.2. Precipitation Concentrate Index

The Daily Precipitation Concentration Index (PCID) is a critical metric for examining the spatiotemporal concentration characteristics of rainfall. Martin-Vide [17] first introduced the concept of the PCID to evaluate the relative or percentage contribution of rainfall events of varying intensities to the total precipitation, particularly highlighting the impact of extreme rainfall events. This index is derived from the exponential relationship between the cumulative percentage of rainfall and the cumulative frequency of rainy days. The specific calculation steps are as follows:

- Step 1: Categorize rainfall values at 1 mm intervals, ranging from 0 to the maximum value;
- Step 2: Count the number of rainy days within each rainfall classification range;
- Step 3: Calculate the number of rainy days and the corresponding rainfall amount for each category;
- Step 4: Perform cumulative summation of the results from Step 3 to obtain the cumulative percentages of rainy days and the corresponding cumulative rainfall percentages;
- Step 5: Establish the relationship between the cumulative percentage of rainy days and the cumulative percentage of rainfall for each year.

Let the cumulative frequency of rainy days be denoted as $\sum N_i$ and the cumulative frequency of rainfall be denoted as $\sum P_i$. The relationship between $\sum N_i$ and $\sum P_i$ exhibits a significant exponential distribution curve, expressed as follows:

$$Y = aX\exp(bX) \quad (1)$$

where a and b are constants determined using the least squares method. This curve is known as the Lorenz curve [36], and the area S enclosed between the Lorenz curve and the diagonal line ($Y = X$) represents the degree of concentration. A larger S indicates a higher degree of precipitation concentration and a more uneven spatiotemporal distribution of precipitation.

Based on the fitted parameters a and b , the definite integral A of the Lorenz curve over the range of 0 to 100 can be expressed as

$$A = \left[\frac{a}{b} e^{bx} \left(x - \frac{1}{b} \right) \right]_0^{100} \quad (2)$$

The area S can be expressed as

$$S = 5000 - A \quad (3)$$

Thus, the PCID is defined as

$$PCID = \frac{2S}{10000} = \frac{S}{5000} \quad (4)$$

A smaller PCID value indicates a lower degree of precipitation concentration, reflecting a more uniform distribution of precipitation.

The Monthly Precipitation Concentration Index (PCIM) is a vital metric for quantifying the uniformity of monthly rainfall distribution. Initially proposed by Oliver [37] and later refined by De Luis et al. [38], its formula is expressed as

$$PCIM = 100 \cdot \sum_{i=1}^{12} P_i^2 / \left(\sum_{i=1}^{12} P_i \right)^2 \quad (5)$$

where P_i denotes the rainfall in the i -th month. The PCIM value reflects the concentration of precipitation distribution within a year: when the annual precipitation is entirely concentrated in a single month, the PCIM reaches its maximum value of 100; when rainfall is evenly distributed across 12 months, the PCIM approaches its minimum value of approximately 0.08. Therefore, the PCIM provides an intuitive measure of the temporal distribution characteristics of rainfall. Specifically, when the PCIM value is below 10, it indicates a relatively uniform monthly distribution of precipitation, with no significant concentration. When the PCIM value ranges from 11 to 20, it suggests a seasonal pattern, meaning that precipitation is moderately concentrated within the year. If the PCIM value exceeds 20, it signifies an exceptionally high concentration of precipitation, with substantial monthly variations.

The Seasonal Precipitation Concentration Index (PCIS), based on monthly precipitation, is commonly used to describe the concentration of total precipitation within a season. Its formula is expressed as

$$PCIS = 25 \cdot \sum_{i=1}^3 P_i^2 / \left(\sum_{i=1}^3 P_i \right)^2 \quad (6)$$

2.3. Mann–Kendall Test and Hurst Index

The Mann–Kendall [39,40] (M–K) test is a non-parametric statistical method recommended by the World Meteorological Organization and has been widely applied. It does not require the sample data to follow a specific distribution, is robust against a small number of outliers, and is computationally efficient, making it well-suited for hydrological and meteorological data with non-normal distributions. In this study, the M–K test is employed to analyze the temporal trends in rainfall concentration across the Yangtze River Basin. The Kendall slope Z is used to determine monotonic trends: when $Z > 0$, it indicates an increasing trend, whereas when $Z < 0$, it signifies a decreasing trend. A two-tailed trend test is conducted to assess whether the trend is statistically significant at the 0.01, 0.05, or 0.1 significance levels.

The Hurst exponent, based on the rescaled range analysis method [41,42], is an effective metric for quantitatively characterizing the long-term dependence of time series data. Its fundamental principle is as follows:

Given a time series $\{\xi(t)\}$, $t = 1, 2, \dots, n$, for any positive integer $\tau = 1$, define the mean sequence as follows:

$$\overline{(\xi)}_t = \frac{1}{\tau} \sum_{\tau=1}^{\tau} \xi(t) \quad \tau = 1, 2, \dots, n \quad (7)$$

Cumulative deviation:

$$X(t, \tau) = \sum_{u=1}^t (\xi(t) - \overline{\xi})_t, 1 \leq t \leq \tau \quad (8)$$

Range:

$$R(\tau) = \max_{1 \leq t \leq \tau} X(t, \tau) - \min_{1 \leq t \leq \tau} X(t, \tau), \tau = 1, 2, \dots, n \quad (9)$$

Standard deviation:

$$S(\tau) = \left[\frac{1}{\tau} \sum_{t=1}^{\tau} (\xi(t) - \xi(\tau))^2 \right]^{\frac{1}{2}}, \tau = 1, 2, \dots, n \quad (10)$$

2.4. Pettitt Test

The Pettitt method is a widely adopted nonparametric approach for detecting abrupt changes in the central tendency of a time series [43]. Unlike many parametric methods that require assumptions about the distribution or variance, the Pettitt test relies solely on the relative ranks of observations, making it particularly robust in situations where parametric assumptions are difficult to justify. Formally, consider a time series $\{x_1, x_2, \dots, x_n\}$. Under the null hypothesis H_0 , all observations in the series are assumed to come from the same continuous distribution, indicating no change point. Under the alternative hypothesis H_1 , there exists an unknown time t ($1 \leq t \leq n$) at which the distribution shifts. The Pettitt test statistic $U(t)$ at time t is defined as

$$U(t) = \sum_{i=1}^t \sum_{j=t+1}^n \operatorname{sgn}(x_i - x_j) \quad (11)$$

where $\operatorname{sgn}(\cdot)$ is the sign function:

$$\operatorname{sgn}(x) = \begin{cases} +1, & x > 0 \\ 0, & x = 0 \\ -1, & x < 0 \end{cases} \quad (12)$$

To assess the presence of a change point, one identifies the most extreme value of $U(t)$:

$$K = \max_{1 \leq t \leq n} |U(t)| \quad (13)$$

A large $|U(t)|$ indicates a significant difference between the two segments $\{x_1, x_2, \dots, x_t\}$ and $\{x_{t+1}, x_{t+2}, \dots, x_n\}$. Under certain assumptions, the corresponding approximate p -value can be obtained from an asymptotic distribution, allowing researchers to determine whether the detected shift is statistically significant. Due to its flexibility and minimal assumptions, the Pettitt method has been employed across various disciplines such as hydrology, climatology, and environmental science to detect abrupt shifts in observational data.

2.5. Random Forest

Random Forest is fundamentally an ensemble approach that builds multiple decision trees on bootstrap samples of the training dataset [44]. Each tree recursively splits the feature space into regions of maximal homogeneity, and the overall prediction is obtained by averaging the outputs of all trees [45]. This ensemble design mitigates overfitting and reduces variance compared to a single decision tree.

A key principle of Random Forest is the random feature selection at each split node: instead of evaluating every predictor, the algorithm considers only a randomly

chosen subset, thereby reducing correlations among the trees and enhancing model stability. This mechanism enables Random Forest to capture complex, nonlinear relationships without presupposing any specific functional form. To further assess the relative importance of each predictor, we employed two evaluation metrics. The first is the Mean Decrease in Mean Squared Error, which quantifies each feature's contribution to reducing prediction error across all splits in the forest. The second is Permutation Importance, which measures the increase in prediction error—typically RMSE or MAE on out-of-bag (OOB) samples—after randomly permuting the values of a specific feature. A greater increase in error following permutation indicates a higher importance of the feature in the model's predictive performance [46,47].

2.6. Hot Spot Identification

To assess the spatial clustering of the PCI, we first used Moran's I statistic to test for significant spatial autocorrelation [48]. Subsequently, we applied the Getis-Ord G_i^* statistic to identify high-value (hot spots) and low-value (cold spots) clusters [49]. By comparing the attribute value of each spatial unit with its neighbors, Moran's I quantifies whether the observed spatial pattern is random, dispersed, or significantly clustered. The standardized formula for Moran's I is given by

$$I = \frac{N \sum_{i=1}^N \sum_{j=1}^N \omega_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\left(\sum_{i=1}^N (x_i - \bar{x})^2 \right) \sum_{i=1}^N \sum_{j=1}^N \omega_{ij}} \quad (14)$$

where N is the total number of spatial units, x_i is the value of the variable of interest in the i -th unit, $\bar{x}$ is the mean of all x_i , and ω_{ij} represents the spatial weight between units i and j . Typically, ω_{ij} is set to 1 if units i and j are neighbors and 0 otherwise, based on a defined contiguity or distance threshold. A significant positive value indicates the clustering of similar values, a significant negative value suggests a dispersed pattern, and values near zero imply no spatial dependence.

The Getis-Ord G_i^* statistic evaluates whether a given location, along with its surrounding neighbors, exhibits higher or lower values than would be expected under a random spatial process. The local G_i^* for the i -th spatial unit is computed as

$$G_i^* = \frac{\sum_{j=1}^N \omega_{ij} x_j - \bar{X} \sum_{j=1}^N \omega_{ij}}{S \sqrt{\frac{n \sum_{j=1}^N \omega_{ij}^2 - \left(\sum_{j=1}^N \omega_{ij} \right)^2}{n-1}}} \quad (15)$$

where x_j is the value of the variable at the j -th location, ω_{ij} is the spatial weight between locations i and j , n is the total number of spatial units, $\bar{X}$ is the mean of the variable over all n units, and S is the standard deviation of the variable. When G_i^* is significantly positive, the location i and its neighbors represent a hot spot, indicating a cluster of high rainfall concentration values. Conversely, a significantly negative G_i^* reflects a cold spot, indicating a cluster of low rainfall concentration values.

2.7. Extreme Heavy Precipitation Indices

To elucidate the potential linkages between rainfall concentration and extreme heavy precipitation, four extreme heavy precipitation indices were selected, following the guidelines of the World Meteorological Organization (WMO) and the Expert Team on Climate Change Detection and Indices (ETCCDI) [50,51]. These indices represent various durations and percentiles of extreme heavy precipitation, as outlined in Table 1. The Rx1day and Rx5day indices reflect short-duration extreme precipitation intensities, and R95p

and R99p highlight the contributions of very wet and extremely wet days to the total annual precipitation.

Table 1. Definitions and characteristics of extreme heavy precipitation indices.

Index	Intensity	Definition	Unit
Rx1day	Max 1-day precipitation	Annual maximum 1-day precipitation	mm
Rx5day	Max 5-day precipitation	Annual maximum 5-day precipitation	mm
R95p	Annual contribution from very wet days	Annual sum of daily precipitation > 95th percentile (baseline period 1990–2019)	mm
R99p	Annual contribution from extremely wet days	Annual sum of daily precipitation > 99th percentile (baseline period 1990–2019)	mm

3. Results

3.1. Verification of Lorenz Curve

To evaluate whether the Lorenz curve effectively represents the precipitation distribution in the Yangtze River Basin, this study selected one meteorological station from each of the 12 subbasins. The Lorenz curve was used to fit the daily precipitation distribution for the year 1960, and the correlation coefficient (R^2) was calculated, as shown in Figure 2. The results indicate that the Lorenz curve accurately captures the relationship between the cumulative number of rainy days and the corresponding cumulative precipitation percentage at all stations, with R^2 values exceeding 0.97. This confirms its applicability for studying the PCI in the Yangtze River Basin.

Moreover, the varying curvature of the Lorenz curve reflects differences in the contribution of different precipitation intensities to the total annual rainfall. For example, in the MSU subbasin (Figure 2e), 80% of rainy days contributed 38.7% of the total precipitation, whereas in the WR subbasin (Figure 2f), the same proportion of rainy days accounted for only 23.9% of the total precipitation. This significant difference suggests that in 1960, precipitation in the MSU subbasin was more evenly distributed throughout the year, while in WR, rainfall was more concentrated, with a higher proportion of extreme heavy precipitation events.

3.2. Spatial Distribution Characteristics of Precipitation Concentration Index

To explore the spatial distribution characteristics of PCIs across different temporal scales in the Yangtze River Basin, this study employed the Inverse Distance Weighting method to interpolate the PCI values at various stations (Figure 3, left panels). The results reveal distinct spatial patterns among the PCID, PCIM, and SPCI. High PCID values, exceeding 0.67, are primarily concentrated around the Sichuan Basin in the central-western Yangtze River Basin, indicating a strong clustering of precipitation in this region and a heightened susceptibility to extreme heavy precipitation events. In contrast, the JSR basin in the northwestern part of the Sichuan Basin exhibits relatively low PCID values but relatively high PCIM values, suggesting that while daily precipitation distribution is more uniform, its intra-annual distribution remains uneven. The PCIM generally exhibits a southeast-to-northwest increasing trend, with all values exceeding 11, indicating pronounced seasonal variations in precipitation across the Yangtze River Basin. This pattern aligns with the region's mid-latitude subtropical monsoon climate, which is significantly influenced by monsoonal activity.

Despite abundant precipitation, its distribution across the Yangtze River Basin varies greatly in both space and time. Figure 3e,g,i,k illustrates the spatial patterns of seasonal SPCIs across spring, summer, autumn, and winter based on station data. The spring SPCI distribution closely mirrors that of the PCIM, with values below 10 in the lower reaches of

the basin, indicating a relatively even distribution of precipitation throughout the spring season. Conversely, the Jinsha River Basin in the western Yangtze River Basin consistently exhibits high SPCI values during spring, autumn, and winter, reflecting highly uneven seasonal precipitation distribution. Additionally, while the summer SPCI maintains a pronounced east–west spatial difference, its overall variation remains relatively small, with all values below 12. This suggests that during the rainy summer season, precipitation is more evenly distributed across the three months.

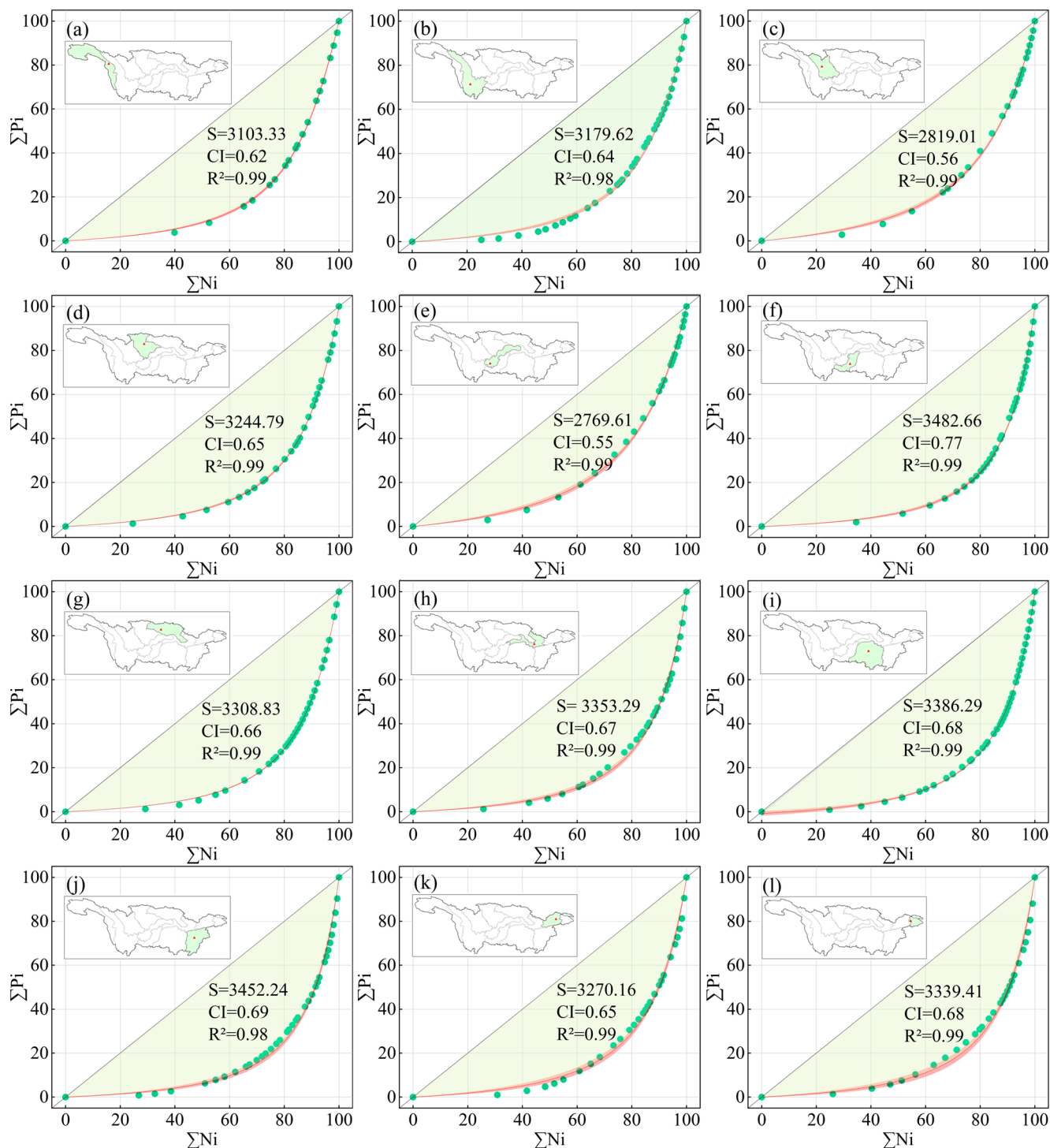


Figure 2. Verification of Lorenz curve in 12 subbasins: (a) JSRU; (b) JSRD; (c) MTR; (d) JLR; (e) MSU; (f) WR; (g) HR; (h) MSM; (i) DTLR; (j) PYLR; (k) MSD; (l) THLR.

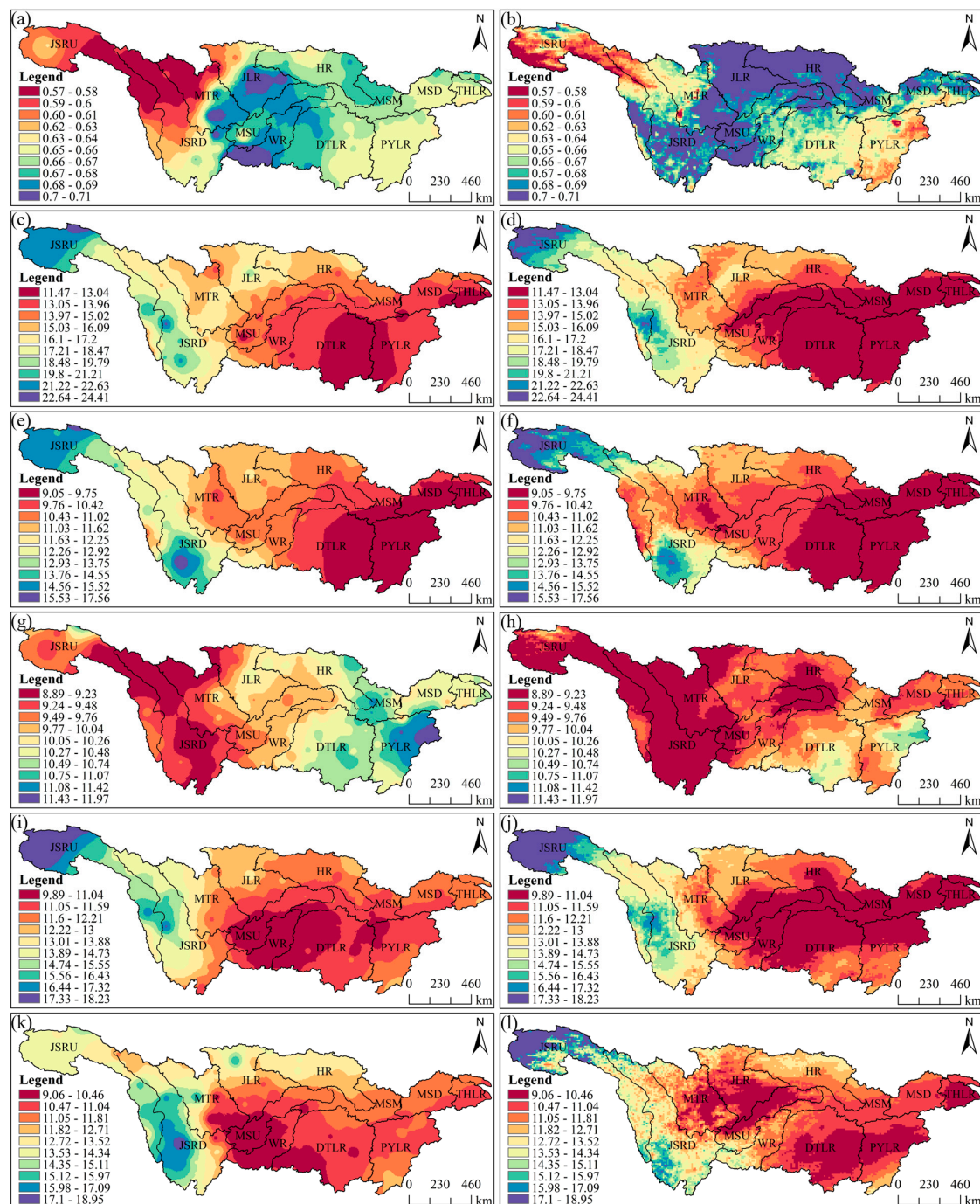


Figure 3. Spatial patterns of the PCI from station observations (left) and GPM (right): (a,b) PCID; (c,d) PCIM; (e,f) spring SPCI; (g,h) summer SPCI; (i,j) autumn SPCI; (k,l) winter SPCI.

To evaluate the performance of the GPM IMERG product in capturing PCI spatial patterns, a parallel analysis was conducted (Figure 3, right panels). For the PCIM, GPM demonstrates strong capability in reproducing the spatial patterns observed from station data. Specifically, GPM successfully captures the prominent southeast-to-northwest increasing gradient (Figure 3c vs. Figure 3d), indicating its reliability for analyzing the overall intra-annual precipitation distribution.

However, significant biases are observed at the daily and seasonal scales. The GPM product systematically overestimates the PCID across most of the basin (Figure 3a vs. Figure 3b), suggesting that the satellite product may perceive precipitation as being concentrated into fewer, more intense days than what is recorded on the ground. This overes-

timation could stem from satellite algorithms' potential difficulties in detecting light and frequent rainfall events, which would artificially increase the PCI. For the SPCI, GPM also exhibits some regional biases. In summer, GPM tends to underestimate the SPCI in the middle and lower reaches, while in winter, it significantly overestimates the SPCI in the upstream mountainous regions. The pronounced overestimation in winter in the upper basin is particularly noteworthy, as it may be linked to challenges in accurately retrieving snowfall or mixed-phase precipitation by microwave sensors. These findings highlight the limitations of GPM in accurately representing the fine-scale temporal structure of precipitation, particularly in complex terrain and during specific seasons. Therefore, ground-based observations remain indispensable as a benchmark for validating and calibrating satellite precipitation products.

3.3. Temporal Trends of Precipitation Concentration Index

Based on the Mann–Kendall trend test and the Hurst persistence index, we analyzed the spatiotemporal trends and future persistence of the PCI in the Yangtze River Basin from 1960 to 2019 (Figure 4). The results indicate that annual precipitation (AP) in the central basin exhibits a non-significant declining trend characterized by continuous attenuation, whereas AP at the western and eastern stations shows a significant increase at a rate exceeding the 99% confidence level. This suggests that precipitation in the monsoon fringe areas may increase under future climate scenarios. Notably, the PCID demonstrates an overall significant decreasing trend across the basin, with only a few stations showing a non-significant increase. This is primarily because the increase in total rainfall is most pronounced in small-to-moderate intensity events, which alters the structure of the precipitation Lorenz curve. For instance, in the THLR subbasin, 60% of rainy days, which historically contributed only 8.49% of the total rainfall, now contribute 13.6%; similarly, the contribution from 80% of rainy days increased from 26.3% to 33.9%. The relative increase in light-to-moderate rain events flattens the extremes of daily precipitation, reducing the proportional contribution of a few high-intensity events to the total, thus leading to an overall decrease in the PCID. In contrast was the evolution of the PCIM, with only stations in the northwest displaying a persistent declining trend. This finding suggests that in that region, despite an overall increase in precipitation, the distribution of both daily and monthly rainfall is trending toward greater uniformity—a trend that may persist into the future. This phenomenon might be attributed to global warming, which enhances the atmosphere's moisture-holding capacity and leads to increased precipitation, while concomitant adjustments in atmospheric circulation shift moisture release from short-term convective events to a more sustained lifting process.

Compared to ground observations, GPM provides invaluable large-scale and continuous precipitation information for hydrometeorological monitoring, which is particularly crucial in regions with sparse station networks. Our results show that GPM correctly identifies the overall decreasing direction of the PCID trend across large parts of the basin. This consistency in the trend demonstrates its potential for qualitative assessments of hydroclimatic change over broad areas. However, the magnitude of the decrease and the statistical significance detected by GPM are notably weaker than those from station data (Figure 4c vs. Figure 4d). This suggests that while GPM may be sensitive to the direction of change, it lacks the fidelity to capture its full intensity. This discrepancy likely stems from GPM's inability to fully resolve the long-term increase in the frequency of small-to-moderate rainfall events. Furthermore, GPM also struggles to reproduce the spatial patterns of AP trends, failing to capture the significant increasing trend in the middle and lower reaches of the basin that is clearly visible in the station data (Figure 4a vs. Figure 4b). This deficiency in accurately representing the trend in the daily distribution structure of pre-

cipitation highlights a key challenge for satellite-based climate studies. It emphasizes that although satellite products are valuable for their spatial coverage, they may underestimate the magnitude of regional climate change signals.

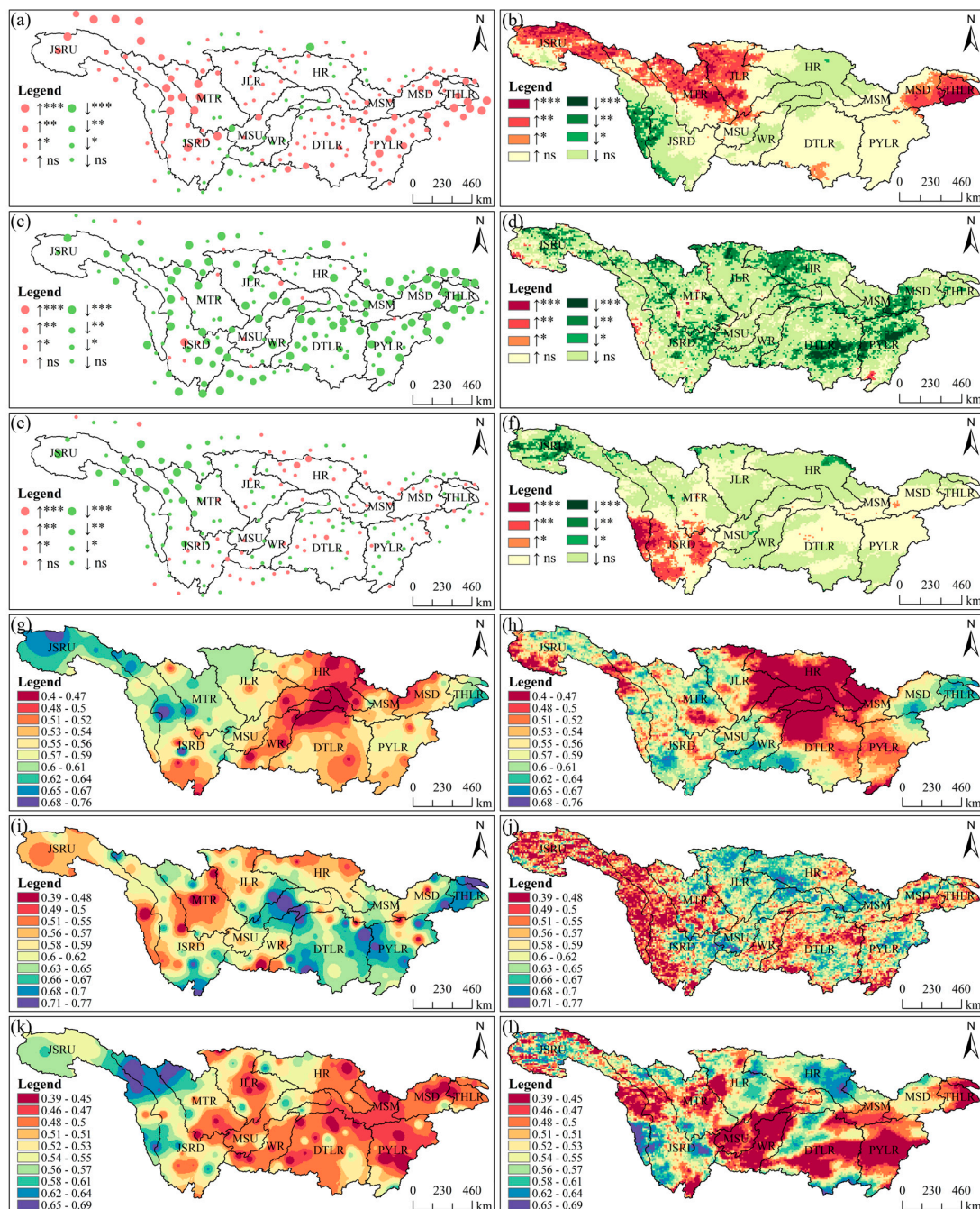


Figure 4. Trends and persistence of the AP, PCID, and PCIM from station observations (left) and GPM (right). Panels (a–f) display Mann–Kendall (MK) trends for the (a,b) AP, (c,d) PCID, and (e,f) PCIM. Panels (g–l) display the corresponding Hurst exponents for the (g,h) AP, (i,j) PCID, and (k,l) PCIM (increasing trend: ↑; decreasing trend: ↓; $p < 0.01$: ***; $p < 0.05$: **; $p < 0.1$: *; no significant trend: ns).

Figure 5 illustrates the temporal trends of the AP, PCID, and PCIM across different subbasins. The AP shows an increasing trend in 83.3% of the subbasins, with THLR emerging as a hot spot for climate change response due to its most pronounced increase ($Z = 3.86$) within the entire basin. Notably, the downstream subbasins (PYLR, MSD, THLR) not only exhibit high AP values but also display an interannual variability that is significantly

greater than that of the mid-upper reaches. This pattern may be attributed to amplified precipitation variability, resulting from enhanced meridional activity of the East Asian summer monsoon. The PCID demonstrates a systematic decline throughout the basin, with all subbasins recording Z -values below -2.58 . Furthermore, the rate of decline in urbanized downstream areas is significantly faster than that in predominantly natural regions, suggesting that the urban heat island effect may induce a phase shift in the daily precipitation cycle by altering the thermodynamic structure of the boundary layer. In contrast, the evolution of the PCIM exhibits clear regional differences: only the MTR subbasin in the midstream of the Yangtze displays a persistent declining trend, while changes in the other subbasins do not reach statistical significance. This observation indicates that, although the decrease in the PCID promotes a more uniform daily precipitation distribution, the monthly-scale precipitation concentration remains in dynamic balance. The underlying reason lies in the differing dominant mechanisms governing precipitation variability across temporal scales: daily precipitation is primarily influenced by local thermodynamic perturbations, whereas the monthly response is also modulated by large-scale, low-frequency signals such as the Pacific Decadal Oscillation.

The temporal trends of multi-year average seasonal precipitation in the Yangtze River Basin are illustrated in Figure 6. The results indicate that spring precipitation in the western Tibetan Plateau exhibits a significant increasing trend, with strong persistence ($Hurst > 0.58$), suggesting that this trend may intensify with the enhancement of plateau sensible heat flux. Although the downstream region currently shows a weak decreasing trend, the critical reversal of the persistence index implies a potential shift toward an increasing trend in the future. During summer, precipitation across the Yangtze River Basin displays significant spatial clustering, with the middle and lower reaches experiencing the highest increase within the entire basin. The persistence characteristic ($Hurst > 0.61$) is strongly correlated with sea surface temperature anomalies in the Northwest Pacific. Climate warming has prolonged the Meiyu front activity, resulting in a more concentrated distribution of precipitation in summer. In autumn, the overall precipitation trend is not significant, with only some western regions showing a noticeable increase. In winter, precipitation across the Yangtze River Basin exhibits an increasing trend, particularly in the eastern coastal and northwestern inland areas. The strong persistence of these trends ($Hurst > 0.6$) may be significantly linked to the intensified negative phase of the Arctic Oscillation [52].

Figure 7 further illustrates the temporal variations of seasonal precipitation across the 12 subbasins of the Yangtze River Basin. Most subbasins show a significant increasing trend in summer precipitation, especially in the middle and lower reaches, indicating a continuous rise in summer rainfall over the past 60 years. This trend aligns with the frequent flood disasters in these regions in recent years and may be associated with the intensification of the East Asian summer monsoon and enhanced moisture transport capacity. Additionally, the Hurst indices for the PYLR and TLR subbasins in summer are relatively high, at 0.67 and 0.66, respectively, indicating strong persistence in precipitation trends. Spring precipitation in the upstream JSR and JLR subbasins also shows an increasing trend, although the magnitude and significance are lower than in summer. Hurst index analysis further confirms that precipitation changes in JSR and JLR exhibit strong persistence, implying that the current upward trend in summer precipitation is likely to continue, further increasing flood risks in upstream mountainous areas. Autumn precipitation trends display substantial spatial differences, with some subbasins experiencing a decreasing trend while others show slight increases. For example, the MTR subbasin ($Z = -1.26$) exhibits a decreasing trend in autumn precipitation, whereas the DTL subbasin shows a slight increase. These divergent trends may be influenced by different regional climate systems and topographic factors.

The Hurst indices for autumn precipitation in MTR ($H = 0.68$) and MSU ($H = 0.66$) are relatively high, suggesting that the currently insignificant decreasing trend may become more pronounced in the future. Winter precipitation remains lower than in other seasons and exhibits a generally insignificant increasing trend. However, in the downstream MSD ($Z = 2.98$) and THLR ($Z = 3.1$) subbasins, the increasing trend is statistically significant, indicating a continuous rise in winter precipitation over the past decades. This trend may help alleviate water shortages during the dry season, providing positive effects on agricultural production and ecological sustainability in downstream regions. The Hurst index for winter precipitation generally suggests the continuation of current trends, though its lower values indicate a degree of randomness or anti-persistence in the winter precipitation time series.

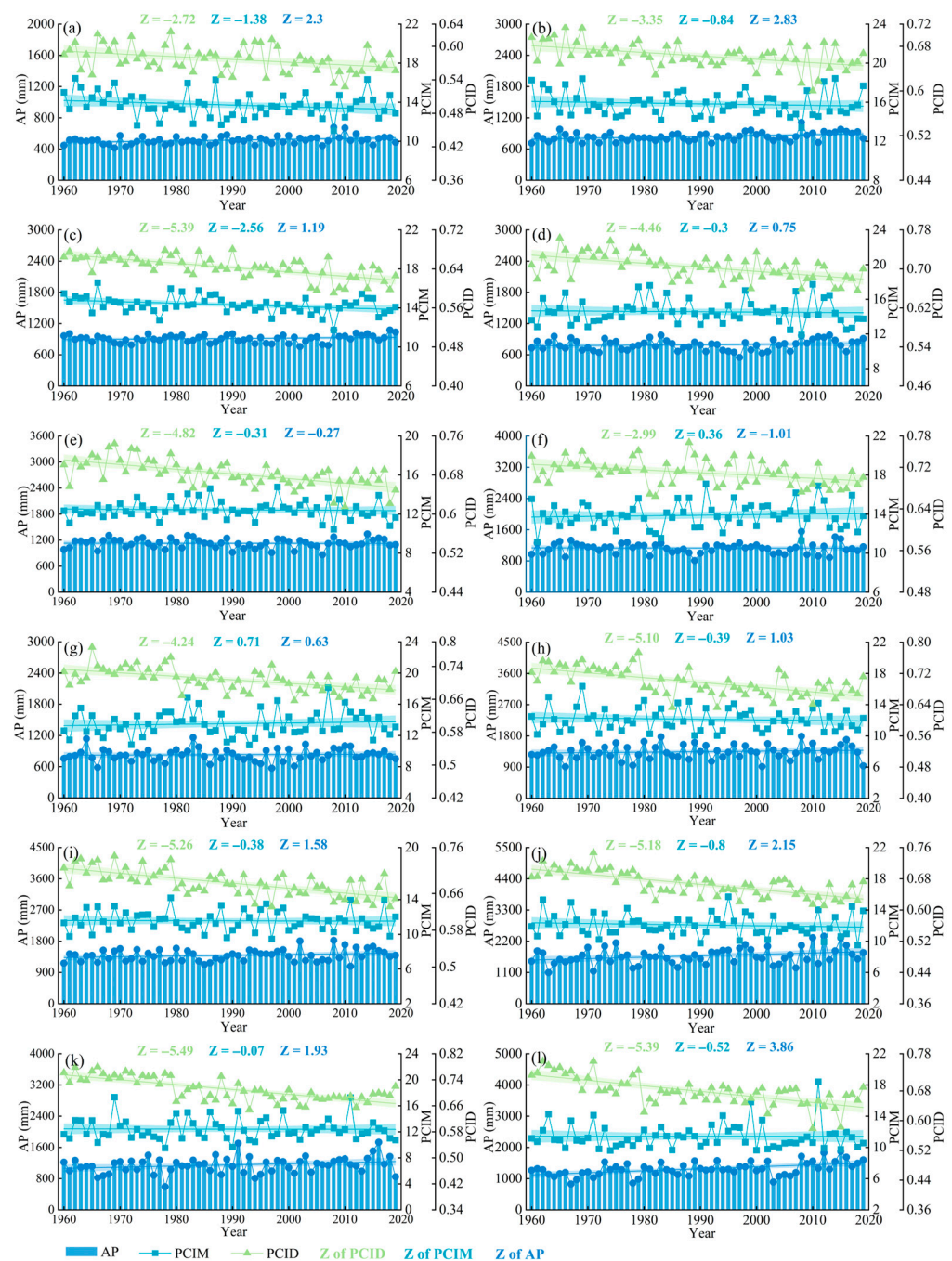


Figure 5. Mann–Kendall trend analysis of the AP, PCID, and PCIM for the twelve subbasins: (a) JSRU; (b) JSRD; (c) MTR; (d) JLR; (e) MSU; (f) WR; (g) HR; (h) MSM; (i) DTLR; (j) PYLR; (k) MSD; (l) THLR.

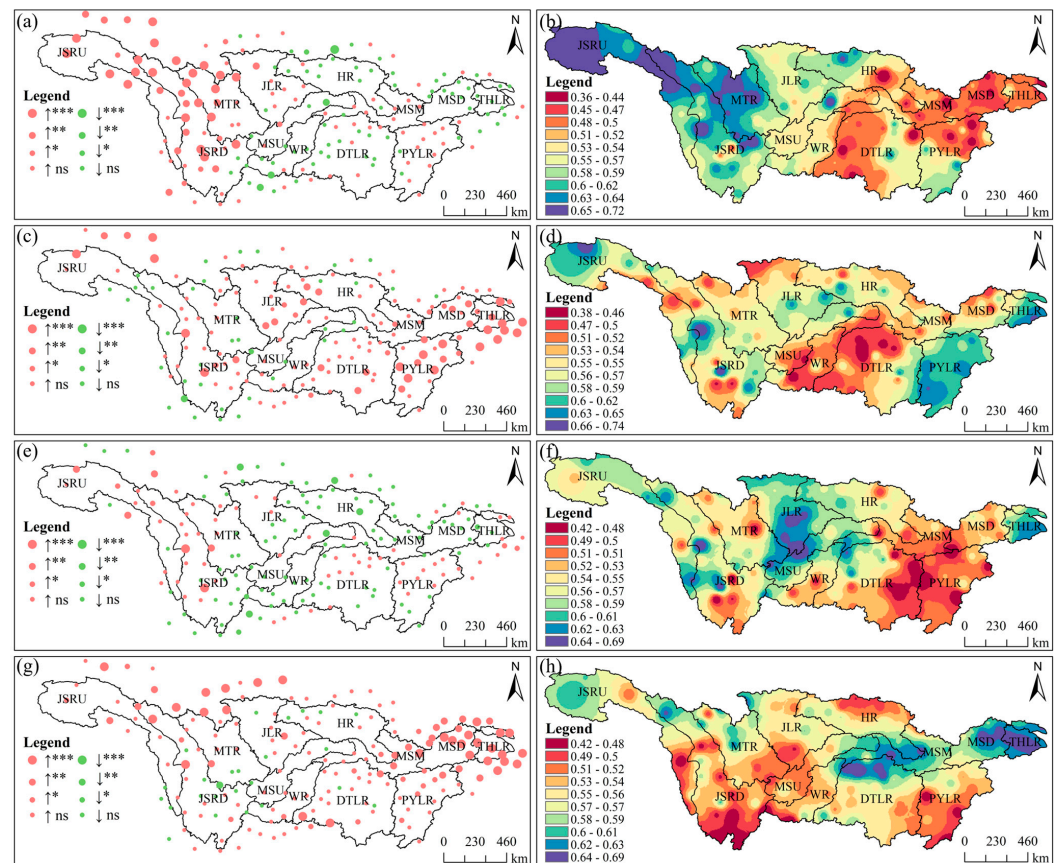


Figure 6. Trends in AP across different seasons: (a,b) spring; (c,d) summer; (e,f) autumn; (g,h) winter (increasing trend: ↑; decreasing trend: ↓; $p < 0.01$: ***; $p < 0.05$: **; $p < 0.1$: *; no significant trend: ns).

The temporal trends of the SPCI in the Yangtze River Basin are shown in Figure 8. In spring (Figure 8a,b), the western basin exhibits a widespread decreasing trend, while the northeastern part shows a non-significant increasing trend. This pattern is opposite to the summer SPCI trends, where the western basin shows an overall increasing trend while the eastern basin experiences a decreasing trend. This suggests that precipitation in the western region is becoming more evenly distributed in spring, whereas summer precipitation is increasingly concentrated within fewer months. The Hurst values in both spring and summer show significantly low values in the Hengduan Mountains region of the JSRD subbasin, indicating high precipitation randomness or an anti-persistent trend. In autumn (Figure 8e,f), only the northwestern stations in the basin show a significant decreasing trend in the SPCI, coupled with strong persistence, suggesting that monthly precipitation distribution in these regions has become more uniform and precipitation concentration has weakened. In winter (Figure 8g,h), the overall change is not significant, but the downstream eastern region shows a decreasing trend in the SPCI, indicating that winter precipitation is becoming more evenly distributed. However, the Hurst index in this region is as low as 0.35, implying a stronger anti-persistence in precipitation changes.

The temporal variations of SPCIs across the 12 subbasins of the Yangtze River Basin are illustrated in Figure 9. In spring, most subbasins exhibit a decreasing trend in precipitation concentration, particularly in the JLRD ($Z = -1.64$) and WR ($Z = -2.11$) subbasins in the upper and middle reaches, where the SPCI has significantly declined. This suggests that spring precipitation has become more evenly distributed over time, potentially reducing the frequency of extreme heavy precipitation events. The Hurst index analysis shows low persistence in most subbasins, indicating strong variability in spring precipitation patterns and making future trends difficult to predict. Summer is the season with the highest

precipitation in the Yangtze River Basin, and SPCI values are relatively low compared to other seasons, with fewer occurrences of extreme high values. This indicates a relatively even distribution of precipitation across the three summer months. Specifically, the HR ($Z = -1.19$) and MSM ($Z = -1.35$) subbasins show a declining trend in the SPCI, and their Hurst indices suggest high persistence. This persistent change may help mitigate future flood risks. The autumn SPCI trends exhibit significant spatial heterogeneity, with substantial variations in direction and magnitude among different subbasins. The MTR and JLR subbasins in the upper reaches have higher SPCI values in autumn, with strong interannual variability. Their low Z and H values indicate unstable regional precipitation patterns. The complex topography of these subbasins may contribute to the spatial and temporal variability of local precipitation. Orographic lifting often causes precipitation to be concentrated in certain periods, leading to higher autumn precipitation concentration. Additionally, mountainous regions are more susceptible to localized weather systems, such as orographic rainfall and short-duration heavy rainfall events, which further amplify the interannual variability in PCIs. Winter is the dry season in the Yangtze River Basin, with weak moisture transport from atmospheric circulation and overall low precipitation levels. The temporal trends of the winter SPCI in the 12 subbasins are not significant, and the Hurst index indicates near-random behavior in the time series. Due to the low precipitation baseline, even if the PCI exhibits some fluctuations, the magnitude of change may not be sufficient to form a significant trend.

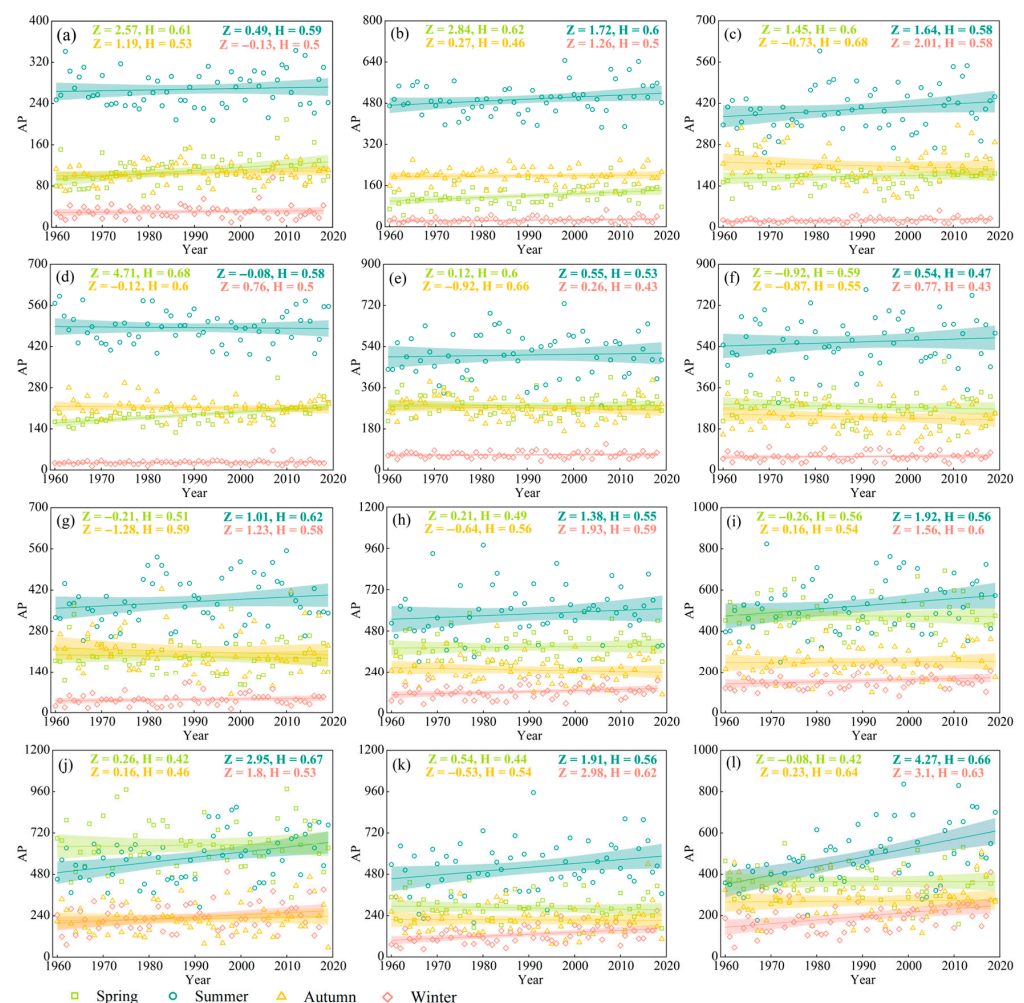


Figure 7. Trends in precipitation across 12 subregions in spring, summer, autumn, and winter. (a) JSRU; (b) JSRD; (c) MTR; (d) JLR; (e) MSU; (f) WR; (g) HR; (h) MSM; (i) DTLR; (j) PYLR; (k) MSD; (l) THLR.

3.4. Variability Diagnosis of Precipitation Concentration Index

This study employs the Pettitt test to detect change points in the PCIM and PCID at various stations within the Yangtze River Basin (Figure 10), with the aim of elucidating the spatiotemporal characteristics of the PCI. The results indicate that the PCI in the basin underwent abrupt changes, with the timing of these changes differing significantly across regions. Temporally, the change points for the PCIM are predominantly concentrated between the late 1980s and early 1990s. This period of abrupt change may be associated with significant shifts in the global climate system, particularly the accelerated warming after the 1980s and the phase transition of the Pacific Decadal Oscillation (PDO). Additionally, the weakening of the East Asian summer monsoon and positional shifts in the Western Pacific subtropical high may have also played critical roles in inducing these changes. In contrast, the change points for the PCID are mostly observed from the late 1970s to the mid-1980s. This earlier phase of change could be driven by multiple factors, including the initial impacts of global warming in the 1970s, natural variability in regional climate systems (such as frequent ENSO events), and early local climatic disturbances due to human activities like land-use changes and urbanization.

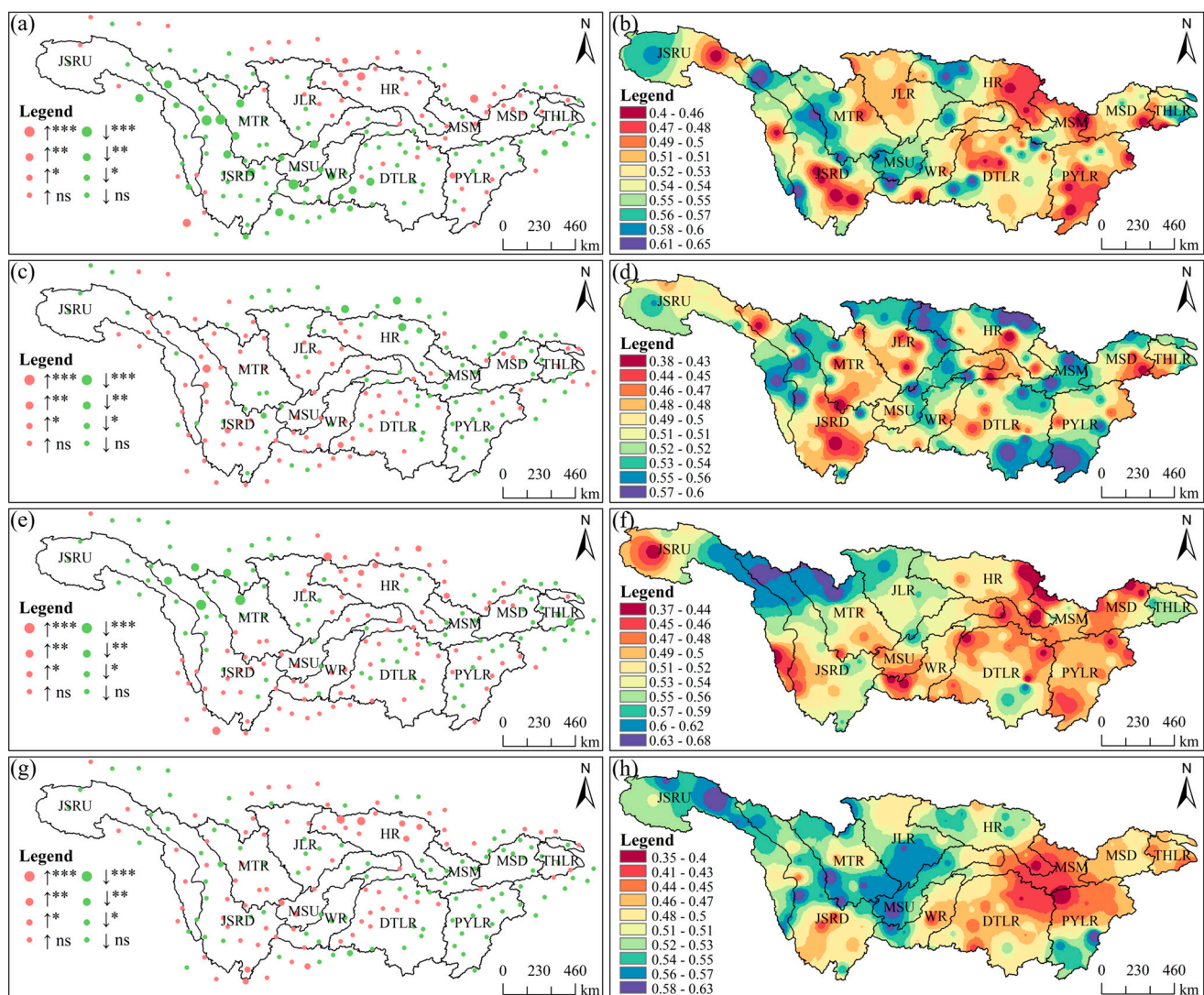


Figure 8. Trends in the SPCI across different seasons: (a,b) spring; (c,d) summer; (e,f) autumn; (g,h) winter (increasing trend: ↑; decreasing trend: ↓; $p < 0.01$: ***; $p < 0.05$: **; $p < 0.1$: *; no significant trend: ns).

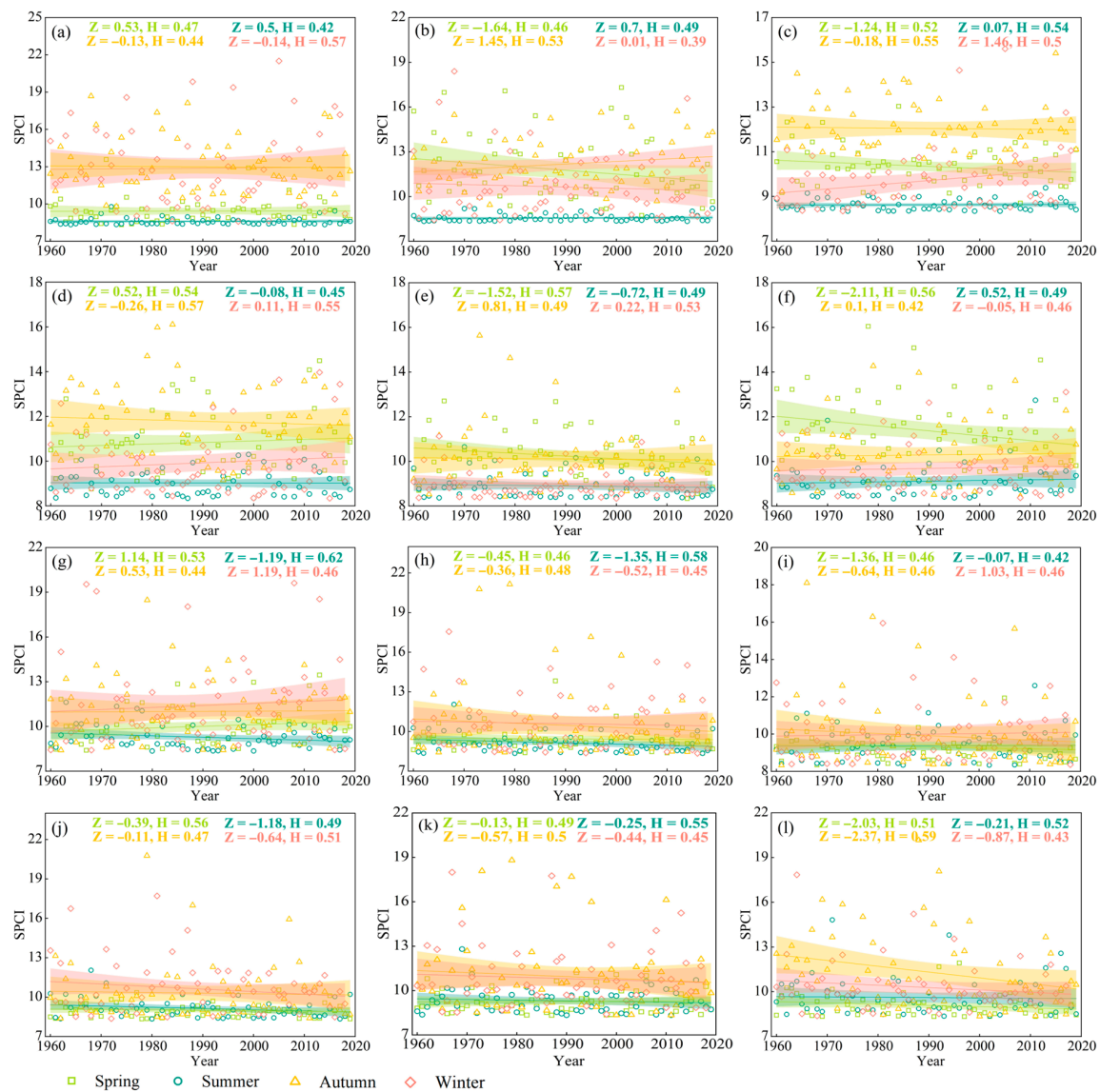


Figure 9. Trends in the SPCI across 12 subregions in spring, summer, autumn, and winter. (a) JSRU; (b) JSRD; (c) MTR; (d) JLR; (e) MSU; (f) WR; (g) HR; (h) MSM; (i) DTLR; (j) PYLR; (k) MSD; (l) THLR.

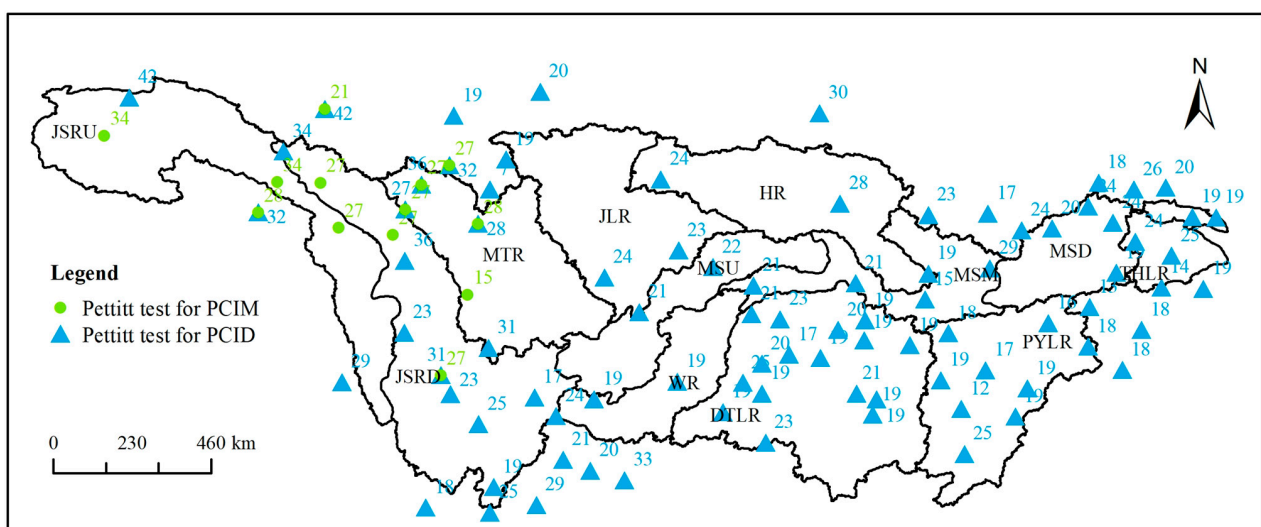


Figure 10. Spatial distribution of change points in the PCIM and PCID in the Yangtze River Basin based on the Pettitt test (numbers 1–60 represent years from 1960 to 2019).

Spatially, the change points for both the PCIM and PCID show distinct regional differences. Upstream regions tend to exhibit later change points, possibly linked to interdecadal variations in the thermal effects of the Tibetan Plateau and its modulation of the East Asian monsoon circulation. Conversely, the middle and lower reaches experience earlier change points, which may be closely related to regional urbanization and other human-induced climatic disturbances. Moreover, the spatial distribution of these change points reflects the non-uniform evolution of the PCI within the Yangtze River Basin—a variability that carries significant implications for hydrological processes, flood and drought management, and ecosystem stability.

3.5. Identification of Hotspots and Coldspots

Regions with highly concentrated precipitation can be regarded as hot spots for extreme rainfall and serve as critical nodes in the spatial distribution of basin-scale precipitation. This study employs cold-hot spot analysis to systematically map the spatial clustering of the PCI in the Yangtze River Basin and its 12 subbasins across different time scales (Figure 11). The results indicate that the PCI forms distinct clusters that vary in space and time. For the PCID, hot spot areas are primarily located in the upper and middle reaches—specifically, the Sichuan Basin and the regions surrounding the Wu River basin—while cold spots are mainly found in the northwestern part of the basin. The Sichuan Basin, identified as a PCID hot spot region, is primarily controlled by the coupling of topography and the monsoon. In particular, the Hengduan Mountains along the basin’s western margin force the southwest monsoon to undergo rapid orographic uplift, and together with summer convective heating, this creates a distinctive “funnel-shaped” topographic effect. Conversely, cold spots in the northwest are influenced by the dynamic barrier of the Tibetan Plateau, which impedes moisture transport from the westerlies, leading to scarce precipitation.

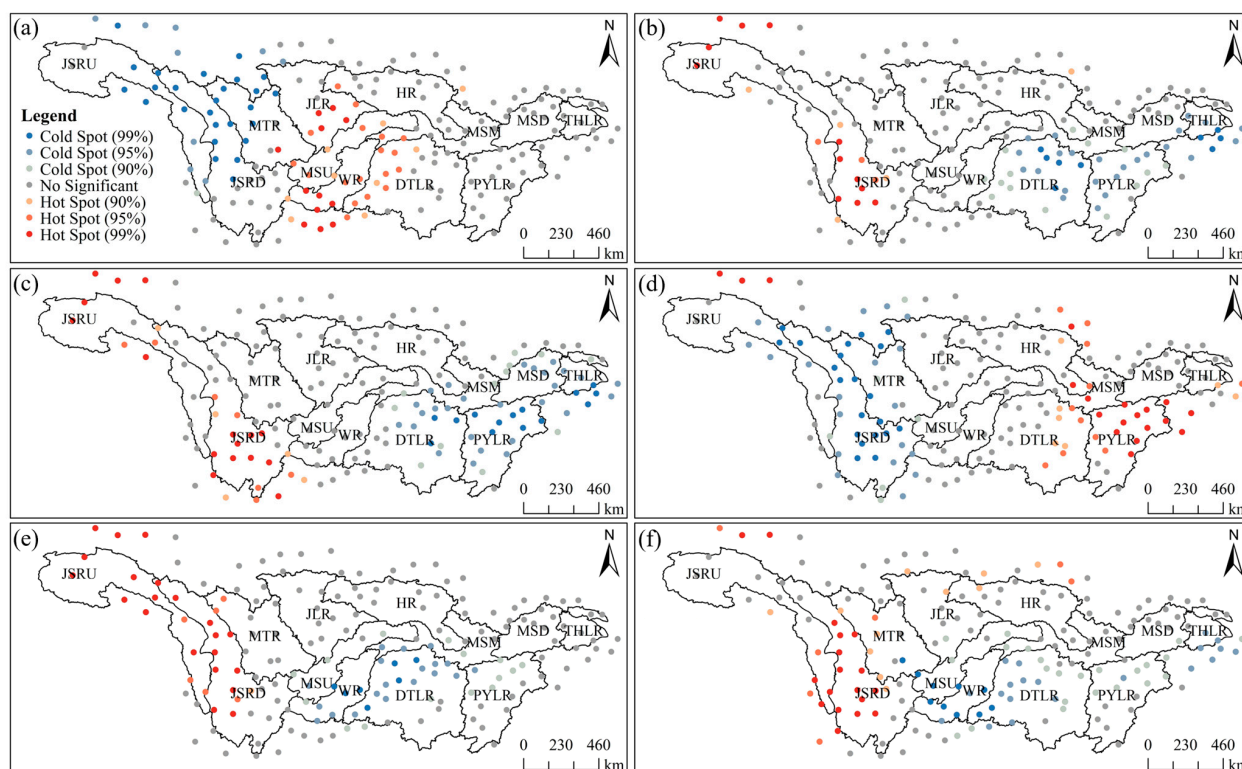


Figure 11. Spatial distribution of hot and cold spots of precipitation concentration at different time scales. (a) PCID, (b) PCIM, (c) spring, (d) summer, (e) autumn, (f) winter.

For the PCIM, the patterns of hot and cold spots are not as pronounced across the entire basin. Hot spots are largely concentrated in the Jinsha River basin, while cold spots are mainly located in the southeastern region—a pattern primarily attributable to the combined effects of monsoonal rainfall and typhoon activity. Notably, the spatial differentiation on a seasonal scale is even more complex. The distribution patterns of cold and hot spots in spring, autumn, and winter generally mirror those observed for the PCIM, albeit with significantly enhanced spatial heterogeneity. In contrast, the spatial pattern in summer is reversed: hot spots are concentrated in the downstream areas of the Yangtze River Basin, whereas cold spots are particularly pronounced in the upstream regions of the western basin. In many subbasins, areas that act as hot spots in other seasons shift to cold spots during summer, a phenomenon that may be related to the intensification of the East Asian summer monsoon and the frequent landfall of typhoons, which deliver additional rainfall to downstream regions. Furthermore, in winter, the overall number of cold spots increases, indicating that precipitation during this season becomes more dispersed and that extreme rainfall events are markedly reduced.

4. Discussion

4.1. Drivers of Precipitation Concentration Index

This study, based on a random forest model, systematically evaluates the influence of atmospheric teleconnections on the PCIM and PCID in the Yangtze River Basin, revealing pronounced spatiotemporal heterogeneity and multi-scale interaction mechanisms. At the monthly scale (Figure 12), the tropical ocean–atmosphere coupled system (indicated by ENSO-related indices) and interdecadal sea surface temperature oscillations (PDO and AMO) are identified as the most important predictors for precipitation concentration. Specifically, ENSO modulates moisture transport by influencing the Western Pacific subtropical high, while the PDO is strongly associated with the spatial distribution of precipitation by altering the East Asia–Pacific sea surface temperature gradient. Mid-to-high latitude circulation factors (AO and NAO) also exert significant effects in the Wu and Han River basins, reflecting the dynamical forcing of the westerly jet and Eurasian planetary wave patterns. Spatially, the upstream region is highly sensitive to AO and ENSO, the midstream region is jointly modulated by NAO and AO, and the downstream region is primarily linked to PDO and ENSO, highlighting the notable effects of topography–circulation coupling.

At the daily scale (Figure 13), the impact of mid-to-high latitude circulation factors (NAO and AO) and local thermal forcing (SS) is markedly enhanced. Notably, NAO emerges as the strongest predictor in the JSRD (0.29), while SS shows a significant association in the WR basin (0.23), underscoring the high sensitivity of daily precipitation processes to short-term oscillations in the westerlies and local thermal circulations. Compared with the monthly scale, the influence of ENSO-related factors exhibits spatial differentiation on a daily basis: SOI maintains a strong effect in the upstream and DTLR basins, whereas ENSO3.4 is more prominent in the downstream regions, suggesting a regionally differentiated modulation of the subtropical high on daily timescales. Furthermore, the significant effect of the Antarctic Oscillation (AAO) in the MSD basin (0.22) reveals the potential contribution of cross-hemispheric interactions to daily precipitation processes. Overall, the PCIM is found to be predominantly associated with large-scale circulation and interdecadal sea surface temperature anomalies, while the PCID is more closely related to sub-seasonal circulation oscillations and local thermal forcing. This scale dependence reflects the differentiated association mechanisms of circulation factors on precipitation processes across various temporal scales, providing essential scientific support for the multi-scale prediction of extreme heavy precipitation events in the Yangtze River Basin.

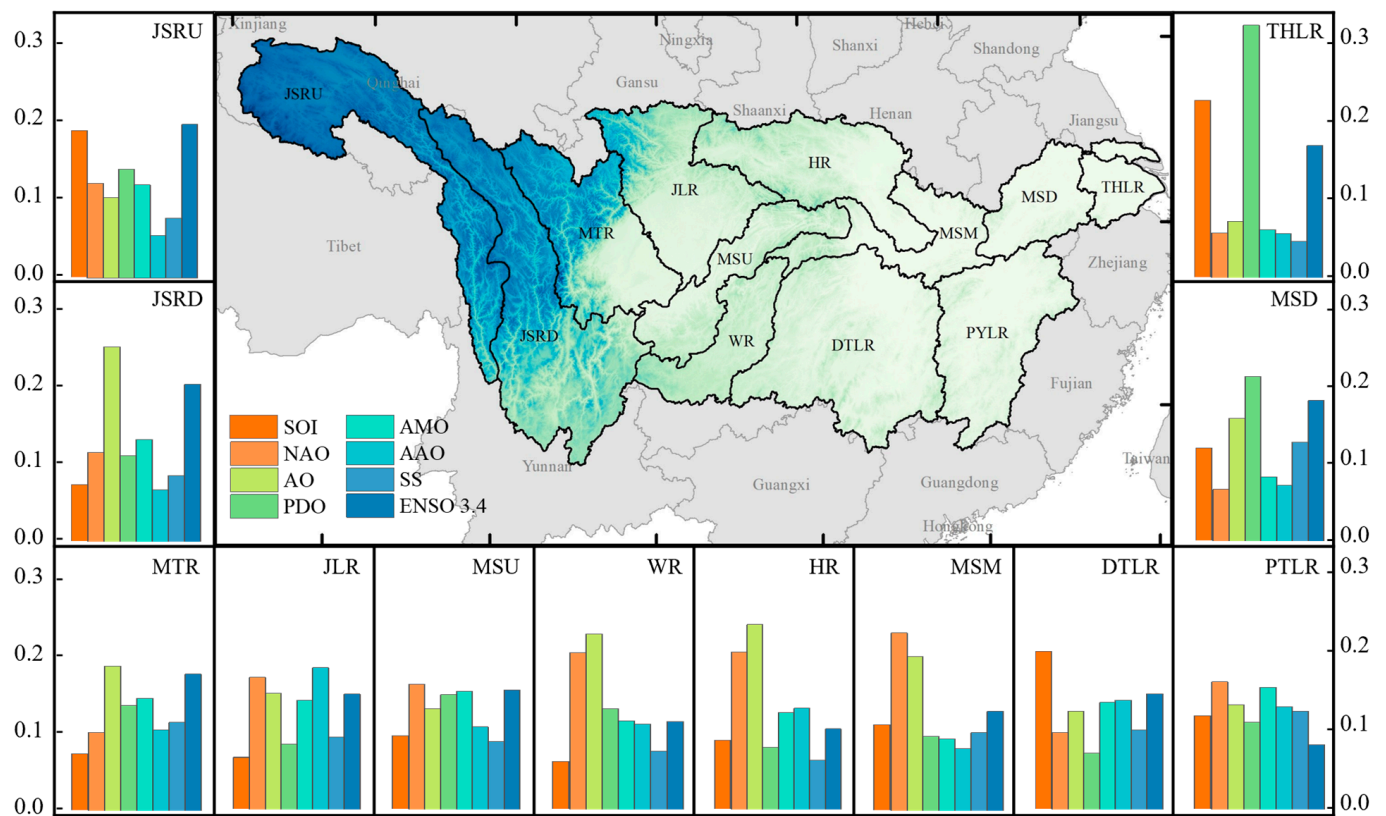


Figure 12. Influence of atmospheric-oceanic circulation factors on the PCIM in 12 subregions.

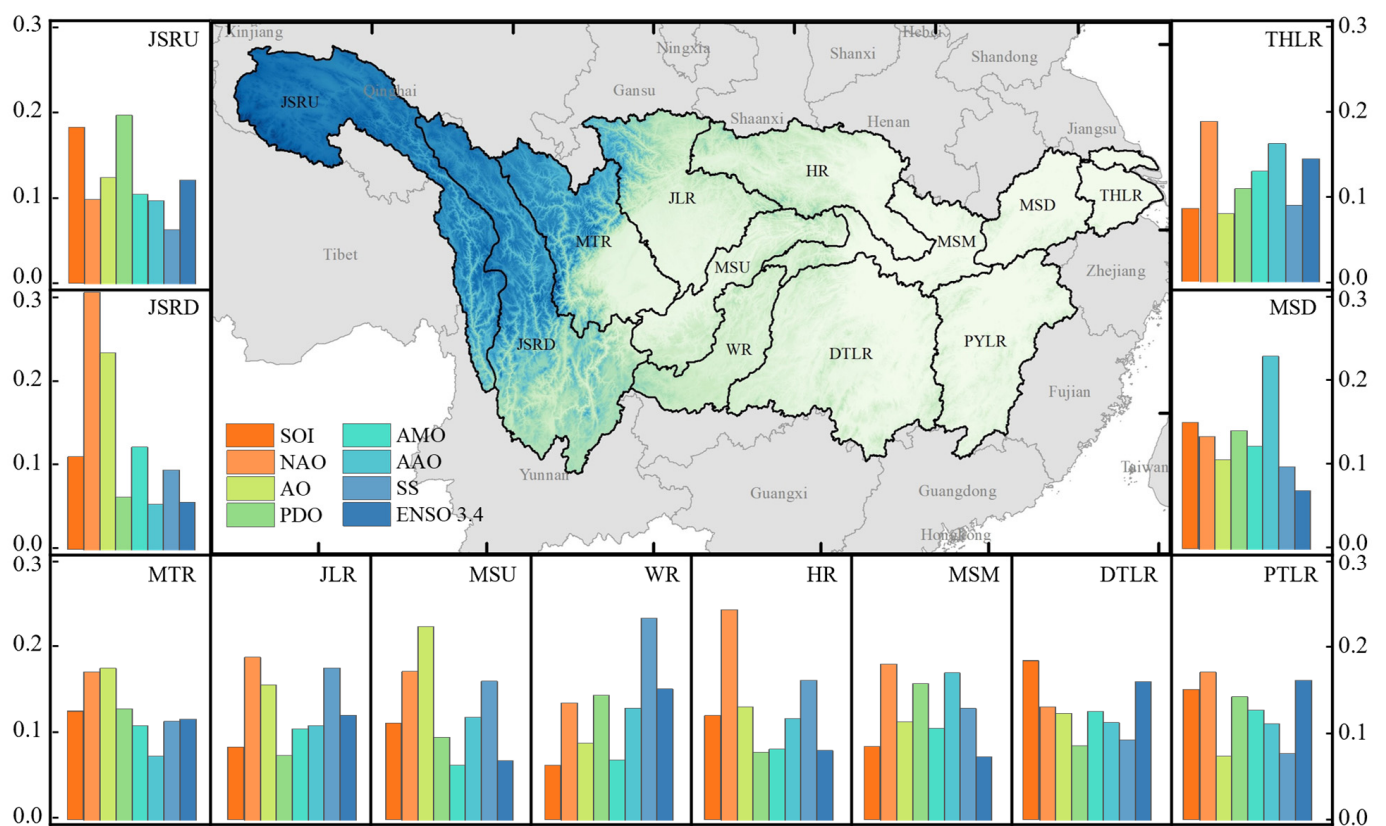


Figure 13. Influence of atmospheric-oceanic circulation factors on the PCID in 12 subregions.

4.2. Relationship Between Precipitation Concentration Index and Extreme Heavy Precipitation

To reveal the complex spatiotemporal relationship between the PCID and extreme heavy precipitation events in the Yangtze River Basin, this study plots extreme heavy precipitation indices (Rx1day, Rx5day, R95p, and R99p) alongside PCID values on a common time axis to investigate their coupled mechanisms (Figure 14). On an interannual scale, the PCID and the extreme heavy precipitation indices fluctuate in close synchrony. For instance, the PCID peak in 1983 coincides with anomalously high values of R95p and Rx5day, whereas in low-value years such as 2018, all indices generally recede. This phenomenon may be associated with the synergistic effects of large-scale circulation anomalies. For example, the northward shift and intensification of the Western Pacific subtropical high can simultaneously enhance moisture convergence and the frequency of short-duration heavy rainfall, thus coupling extreme heavy precipitation intensity with its concentration over time. However, this synchrony varies notably across different regions. In the JSR basin, the steep terrain's uplift effect on local convective activity renders PCID fluctuations particularly sensitive to Rx1day and Rx5day. Conversely, in the MTR basin, located in a climatic transition zone, the persistent Meiyu front system causes the marginal effects of R99p and R95p on PCID changes to be most pronounced. Notably, although the downstream THLR Basin exhibits significant upward trends in Rx5day and R95p, its PCID does not increase correspondingly; this may be due to increased total precipitation or anthropogenic activities altering the temporal distribution of rainfall or surface runoff, thereby diminishing the representation of extreme heavy precipitation events in terms of concentration.

Further analysis indicates that the spatial differentiation of extreme heavy precipitation events is closely linked to the underlying surface characteristics of the basin. Boxplot results (Figure 15) reveal that the extreme heavy precipitation intensities in the mainstem and lake regions (PYLR and THLR Basins) are significantly higher than those in upstream areas. For example, the 75th percentile of R95p in the PYLR Basin exceeds 390 mm, with the greatest interannual variability observed in this region, possibly due to enhanced local convection triggered by land–lake thermal contrasts. In the THLR Basin, although Rx1day and Rx5day frequently exhibit extreme values, the PCID response is delayed. This likely reflects that the area has approached a nonlinear threshold in the extreme heavy precipitation–concentration relationship: once the intensity of extreme events surpasses a critical value, the dilution effect of increased total precipitation or the dispersion of precipitation days may dominate changes in concentration. In contrast, upstream regions such as the JSR basin, regulated by the homogenizing effect of the Hengduan Mountains on moisture transport, display a much narrower range of extreme heavy precipitation indices. This spatial gradient suggests that the interplay between natural climate variability and human activities may be reshaping the spatiotemporal patterns of extreme heavy precipitation.

The observed lag in PCID response to extreme heavy precipitation in the Taihu Basin highlights the “dilution effect”—where the PCID does not rise with increasing extremes—revealing a key shift in rainfall patterns that traditional risk assessments may overlook. This phenomenon is likely influenced by both natural and anthropogenic factors. The increased frequency of small-to-moderate rainfall events may be exacerbated by urbanization and water conservancy projects. These insights can guide flood management through targeted strategies, such as optimized reservoir operations in high-risk subbasins. Future research could quantify this dilution effect by integrating high-resolution remote sensing data to analyze its spatiotemporal dynamics.

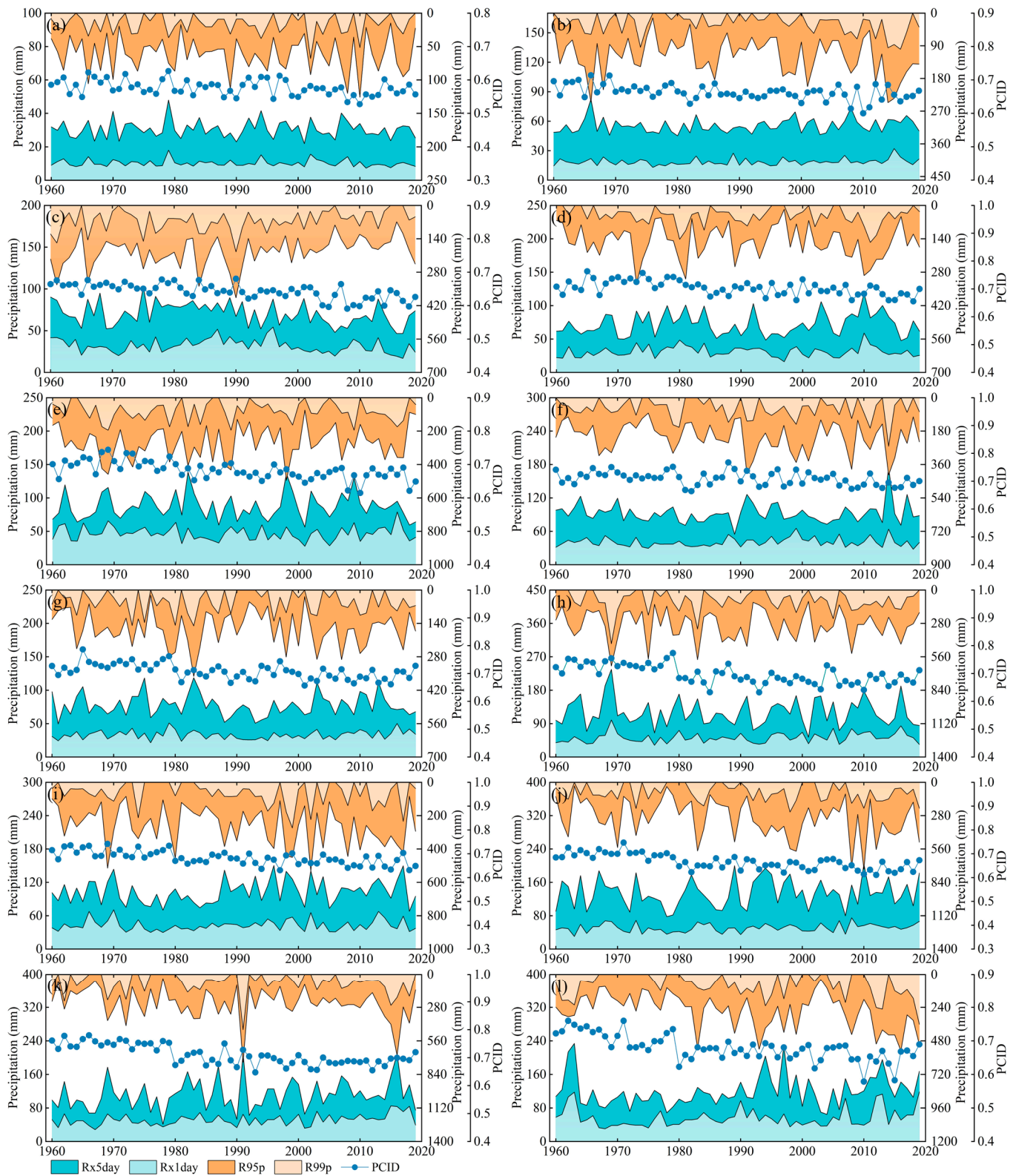


Figure 14. Spatiotemporal coupling between the PCID and extreme heavy precipitation indices. (a) JSRU; (b) JSRD; (c) MTR; (d) JLR; (e) MSU; (f) WR; (g) HR; (h) MSM; (i) DTLR; (j) PYLR; (k) MSD; (l) THLR.

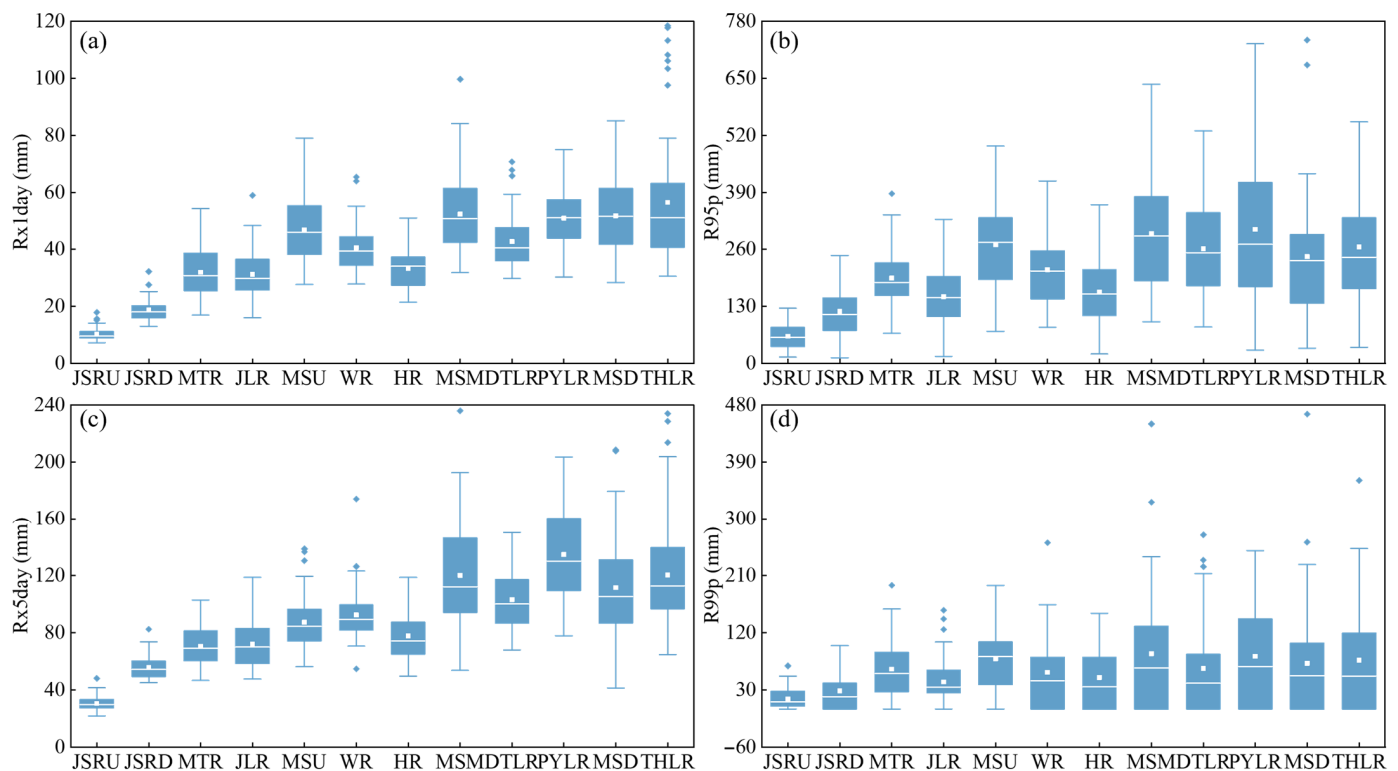


Figure 15. Box plots of extreme heavy precipitation indices in the 12 subregions: (a) Rx1day; (b) R95p; (c) Rx5day; (d) R99p.

5. Conclusions

This study systematically examined the spatiotemporal evolution of precipitation concentration in the Yangtze River Basin using multi-timescale Precipitation Concentration Indices (PCIs) and identified years of abrupt change. Based on a random forest model, we assessed the influence of eight atmospheric teleconnections on the spatial heterogeneity of PCIs across different subbasins and further explored the potential link between PCIs and extreme heavy precipitation indices. The main conclusions are as follows:

- (1) The PCI in the Yangtze River Basin shows distinct spatial patterns. In regions surrounding the Sichuan Basin, the PCID values exceed 0.67, indicating a high risk of extreme heavy precipitation events. Precipitation within the basin shows significant seasonal variations, with PCIM values greater than 11 and an overall increasing trend from southeast to northwest. In the Jinsha River Basin, SPCI values are elevated during spring, autumn, and winter, whereas during summer the SPCI values across the entire basin are generally below 12.
- (2) Annual precipitation shows a significant increasing trend on the eastern and western sides of the basin, while seasonal variations exhibit clear regional differences. In spring, precipitation increases notably over the Tibetan Plateau; in summer, it peaks in the middle and lower reaches, linked to enhanced East Asian monsoon activity and a prolonged Meiyu front; in winter, increases in the lower reaches help alleviate dry-season water shortages. Overall, the PCID declines systematically across the basin (Z -values below -2.58), faster in urbanized downstream areas than in natural regions. SPCI patterns, influenced by orographic uplift and local disturbances, decrease in the western basin during spring, increase there in summer, decline in the northwest during autumn, and show slight downstream decreases with anti-persistence in winter.
- (3) The PCIM is primarily associated with large-scale atmospheric teleconnections such as ENSO and PDO. Change points for the PCIM are concentrated between the late 1980s

and early 1990s. In contrast, the PCID is closely linked to sub-seasonal circulation oscillations and local thermal forcing, exhibiting upstream sensitivity to AO and ENSO, while downstream regions are predominantly associated with PDO and ENSO. Its change points occur earlier, from the late 1970s to the mid-1980s. Spatially, changes in the upstream region lag behind those in the middle and lower reaches, where human activities have prompted earlier shifts.

- (4) Extreme heavy precipitation events in the Yangtze River Basin are closely coupled with the PCID, showing strong temporal synchrony but with clear regional differences. On an interannual scale, the fluctuation trends of the PCID are highly consistent with those of R95p and Rx5day. Spatially, due to orographic uplift effects, the PCID in the Jinsha River Basin is tightly coupled with short-duration heavy rainfall, whereas in the Min-Tuo River Basin, the persistent influence of the Meiyu front renders the marginal effect of R99p on the PCID more pronounced. In the downstream Taihu Basin, the anomalously high values of Rx1day and the corresponding PCID response exhibits a lag, suggesting that when the intensity of extreme heavy precipitation exceeds a critical threshold, the dilution effect of increased total rainfall or the impact of human activities may weaken the capacity of the concentration index to capture extreme events.
- (5) The comparison with GPM IMERG reveals its mixed performance in monitoring precipitation concentration. Although GPM provides valuable large-scale coverage and correctly captures PCIM patterns as well as the overall decreasing direction of PCID trends, it tends to overestimate the PCID. Furthermore, it fails to capture the observed intensity and statistical significance of the decreasing trend and exhibits complex seasonal biases, such as overestimating concentration in the high-altitude upstream regions during winter.

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