



# Precipitation concentration in Jiangsu province, southeast China and its indicating function on the fluctuation of rice yield

Jin Huang<sup>1,2</sup> · Limin Zhou<sup>1</sup> · Fangmin Zhang<sup>1,2</sup> · Zhenghua Hu<sup>1</sup>

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## Abstract

Based on the precipitation record and single-crop rice yield data at 52 meteorological stations in Jiangsu province, southeast China from 1961 to 2012, a total of 14 precipitation concentration indices (PCI) during rice-growing period (May–October) were calculated, and then, the relationship between PCI and rice yield was explored. Results showed that: (1) the higher precipitation concentration was observed in north Jiangsu, and total precipitation was mainly concentrated in the rainstorm events and July rainfalls. (2) Precipitation concentration was increasing in recent 50 years, which was embodied in the significant increasing trends of precipitation contribution of rainstorm events and August rainfalls occurred in south Jiangsu. (3) The correlation analysis between rice yield and 14 PCI indicated that the precipitation contribution of rainstorm events (CDP6) was more suitable for accessing the losses of rice yield caused by excessive rainfall. (4) During the study period, the losses of rice yield in south Jiangsu exceeded 2%, owing to the stronger increasing trend of CDP6.

## 1 Introduction

The excessive increase of aerosols, including greenhouse gas and sulfates, emitted by human activities will continue aggravating global warming. It is expected that an intensification of spatio-temporal change of precipitation will happen as global warming induces a large increase in atmospheric water vapor content, which will bring the varied impacts on human society and natural environment (Jiang et al. 2016). Changes in the intensity, amount, and pattern of precipitation would cause more frequent extreme events such as droughts and floods, and also have an directly or indirectly influence on agricultural development, energy

production, forest vegetation, water resource and environment, etc. (Yeşilirmak and Atatanır 2016; Caloiero 2014; Liu et al. 2016a; Wang et al. 2017). Precipitation structure provides a better insight into the spatial–temporal variability of precipitation as well as probabilistic nature of data or indirectly for investigating hydro-climatological nature of phenomena such as floods and drought, which have aroused increasing attention from meteorologist and hydrologist (Abolverdi et al. 2016).

Precipitation concentration is the most important connotation of precipitation structure, and it is represented not only by the daily rainfall heterogeneity but also by the irregularity of monthly precipitation distribution (Coscarelli and Caloiero 2012; De Luis et al. 2011). At present, daily precipitation concentration index (DPCI) defined by Martin-Vide (2004) and monthly precipitation concentration index (MPCI) proposed by Oliver (1980) were usually applied to depict precipitation concentration (Abolverdi et al. 2016). DPCI is used to access the contribution of the days with the highest rainfall to the total amount of rainfall, while MPCI represents the degree to which total precipitation is distributed over several months (Li et al. 2011). Apart from DPCI and MPCI, the contribution percentages of different rainy days, different months, and different seasons to the total precipitation were also used for evaluating precipitation concentration in several studies (Zubieta et al. 2016; De Luis et al. 2010). In the previous works, precipitation

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✉ Zhenghua Hu  
nuistecology@163.com

<sup>1</sup> Collaborative Innovation Center on Forecast and Evaluation of Meteorological Disasters, Jiangsu Key Laboratory of Agricultural Meteorology, Nanjing University of Information Science and Technology, Nanjing 210044, China

<sup>2</sup> Jiangsu Collaborative Innovation Center of Atmospheric Environment and Equipment Technology (CICAET), School of Applied Meteorology, Nanjing University of Information Science and Technology, Nanjing 210044, China

concentration indices (PCI) defined as above were widely used to explore the causes of inter-annual fluctuations of hydrological extremes and soil erosion around the world. However, the investigations for the relationship between crop yield and PCI were very few.

Rice (*Oryza sativa* L.) is one of the most important food source of more than half of the world's population, and China is the largest rice producing country in the world (Sawano et al. 2015). Located to the mid-lower Yangtze reaches, Jiangsu province is not only the one of five provinces with the highest rice production in China but also a province with frequent precipitation-related meteorological disasters in south China (Huang et al. 2016). In view of this, temporal changes in precipitation variables in Jiangsu have always been a concern (Zhu et al. 2012, 2013; Shuai et al. 2013; Huang et al. 2017a, b). The previous studies were mainly focused on the aspects on amount, and intensity of rainfalls events. However, the climatology of precipitation structure in Jiangsu has not been investigated. Thus, the objective of this paper is to explore the changing features of precipitation concentration in Jiangsu province and its possible impact on rice yield. The attempts in this paper are not only favorable to water resource management in Jiangsu, but will also provide a new approach to investigate the responds of crop yield to climate changes.

## 2 Study area and data

The study site (Jiangsu province) located in southeast China which is positioned between 113°E–119°E latitude and 24°N–31°N longitude, along the southern bank of the

mid-lower Yangtze River Basin. This province is situated in a transition belt from a subtropical to temperate zones and the province experiences a typical monsoon climate (Huang et al. 2017b). It has an average annual temperature of 17 °C and the average annual precipitation is between 1200 and 1900 mm (Huang et al. 2017a). In this province, the single-cropping is the main planting system of rice, and the rice-growing period is generally from May to October.

The daily precipitation data of 52 meteorological stations plotted in Fig. 1 during the period of 1961–2012 were offered by Meteorological Bureau of Jiangsu province, and the precipitation data in each station passed the quality control and homogeneity test using the RHtestsV4 software package. In addition, the total yield data of single-cropping rice for 52 years (1961–2012) in 52 producing areas corresponding to the stations listed in Fig. 1 were collected from the Statistical Bureau of Jiangsu province.

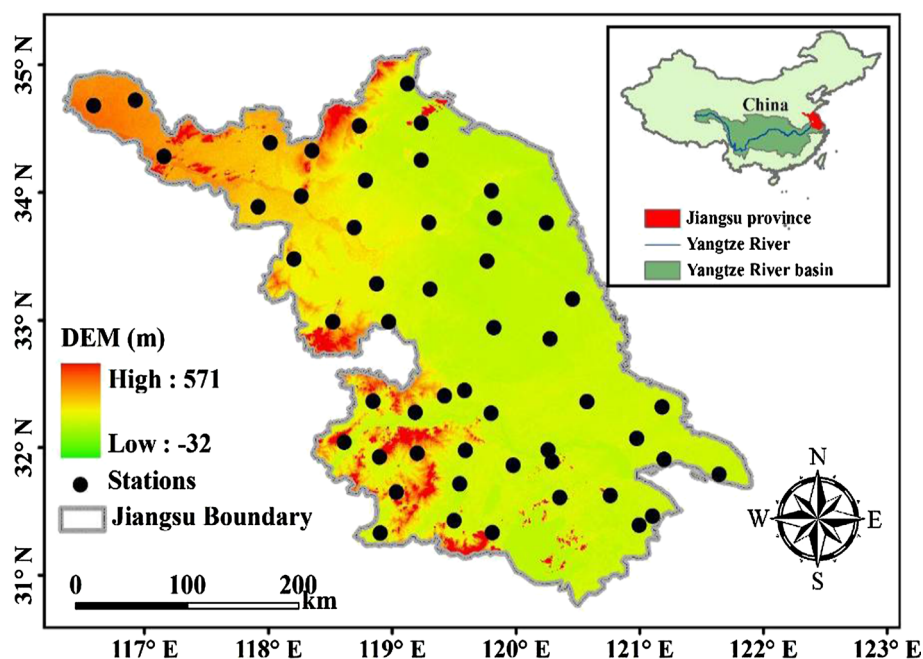
## 3 Methods

### 3.1 Precipitation concentration indices (PCI)

In this study, two major categories of PCI using daily and monthly data were calculated at the time scale of rice-growing period. Days with daily precipitation  $\geq 1$  mm are considered as rainy days in this study, which excludes the uncertainty and inaccuracy of observation for the very light rainfall events. The definitions of 14 PCI used in this study were introduced briefly as follows:

Based on the daily data, DPCI (Martin-Vide 2004) was used to evaluate the varying weight of daily precipitation,

**Fig. 1** Meteorological stations used in this study and location of Jiangsu province, China



i.e., the contribution of the days of the greatest rainfall to the total amount (Abolverdi et al. 2016). DPCI is developed on the fact that an exponential curve showing the accumulated percentage of precipitation ( $Y$ ) contributed by the accumulated percentages of days ( $X$ ) during the occurrence of  $Y$  (Yeşilirmak and Atatanır 2016), and the details of calculation of DPCI can be obtained from the studies of Zubieta et al. (2016). Meanwhile, the contribution percentages of daily rainfall events with different intensities to the total precipitation of rice-growing period (CDP) were applied to depict the daily rainfall heterogeneity in detail. The six CDP indices were CDP1 (daily precipitation < 10 mm), CDP2 ( $10 \leq$  daily precipitation < 20 mm), CDP3 ( $20 \leq$  daily precipitation < 30 mm), CDP4 ( $30 \leq$  daily precipitation < 40 mm), CDP5 ( $40 \leq$  daily precipitation < 50 mm), and CDP6 (daily precipitation  $\geq$  50 mm), respectively.

Based on the monthly data, the modified version of MPCCI (Oliver 1980) was used to analyze the homogeneity of the total precipitation among the months, and it can be calculated on the annual, supra-seasonal and seasonal scale (De Luis et al. 2011). To investigate the monthly precipitation concentration of rice-growing period, MPCCI was calculated on the supra-seasonal scale according to the following equation:

$$\text{MPCCI} = 50 \times \left( \frac{\sum_{i=1}^6 P_i^2}{\left( \sum_{i=1}^6 P_i \right)^2} \right), \quad (1)$$

where  $P_i$  is the monthly precipitation in month  $i$ . MPCCI values of less than 10 represent low precipitation concentration; MPCCI values from 11 to 15 denote a moderate precipitation concentration; and MPCCI values larger than 16 denote high precipitation concentration (De Luis et al. 2011). In addition to MPCCI, the contribution percentages of different months to the total precipitation of rice-growing period (CMP) were applied to depict the monthly rainfall heterogeneity in detail. The six CMP indices were CMP\_May, CMP\_Jun, CMP\_Jul, CMP\_Aug, CMP\_Sep, and CMP\_Oct, respectively.

### 3.2 Time series analysis for PCI

In this study, the non-parametric Mann–Kendall ( $M-K$ ) trend test was applied to test the significance of trends on the time series of PCI. When the absolute value of output of  $M-K$  test is larger than 1.96, a trend is regarded to be statistically significant at the 5% (Huang et al. 2017a). Meanwhile, the Hurst exponent ( $H$ ) test was used to estimate long-term persistence of PCI series. When  $H=0.5$ , it describes an independent and random time series; when  $0.5 < H \leq 1$ , it describes a dynamically persistent, or trend reinforcing series; when  $0 < H < 0.5$ , it describes an anti-persistent, or a mean reverting system.

Furthermore, the linear regression model was used to obtain the inter-annual changing amplitude of PCI, and the 5-year smoothing average method was applied to show the temporal evolution of PCI.

### 3.3 Response of rice yields to the changes of PCI

To investigate yield–PCI relationships and further quantify the effect of PCI trends over the past 50 years on rice yield, we used the first-difference operation suggested by Lobell (2007) to eliminate the confounding influence of long-term variations of non-climatic factors. In first-difference operation, we computed the first-difference time series (i.e., the difference in values from 1 year to the next) for rice yield ( $\Delta\text{Yield}$ ) and PCI ( $\Delta\text{PCI}$ ), and then, the correlation between  $\Delta\text{Yield}$  and  $\Delta\text{PCI}$  was evaluated using Pearson correlation analysis. When the  $P$  value of correlation analysis is smaller than 0.05, a correlation is regarded to be statistically significant at the 5% (Wang et al. 2016). According to the linear regression relationship formed as Eq. (2):

$$\Delta\text{Yield} = a \times \Delta\text{PCI} + b, \quad (2)$$

the sensitivity of yield change ( $\Delta\text{Yield}$ ) to PCI was represented by the coefficient  $a$  in Eq. (2) divided by the multi-annual mean values of rice yield and expressed as a percentage (Tao et al. 2012). The impact of PCI trend on rice yields during 1961–2012 was estimated by multiplying the sensitivity of yield change to PCI with the linear trend of PCI during the period (as a percentage) (Tao et al. 2008).

### 3.4 K-means cluster analysis

$K$ -means cluster is widely used to cluster the neighboring stations into homogeneous and distinct groups having members with similar climate features (Sönmez and Kömüscü 2011; Liu et al. 2018). The silhouette coefficient (SC) is often used to evaluate the cluster results, and it is calculated as

$$\text{SC}(i) = \frac{\min(b(i, k)) - a(i)}{\max\{a(i), \min(b(i, k))\}}, \quad (3)$$

where  $a(i)$  is the average distance of  $i$ th sample from the other members in the same cluster, and  $b(i, k)$  is the average distance of the  $i$ th sample from the members of the  $k$ th cluster. The SC ranges from  $-1$  to  $+1$ , and the optimal classification number is obtained when the average of SC reaches a maximum and the negative SC value reaches a minimum (Liu et al. 2016b).

## 4 Results

### 4.1 General features for PCI

The statistical results for multi-annual mean values of 14 PCI in each station are listed in Table 1. The average DPCI calculated for the study area was 0.57, with the lowest coefficient of variation (CV) of 1.61% and the lowest standard deviation (std) of 0.01. Some other information is obtained when CDP indices analyzed. Most notably, the contribution percentage of rainy days with daily precipitation exceeding 50 mm (CDP6) accounted for 30.91% of total precipitation amount of rice-growing period for entire Jiangsu, but each of other CDP indices did not exceed 20%. The average MPCl analyzed for all stations in this study area was 12.82, indicating the moderate precipitation concentration for monthly rainfall distribution in Jiangsu. In addition, it can be seen from CMP indices in Table 1 that monthly precipitation during rice-growing period presented an obvious single peaked distribution, and the most abundant rainfall occurred in July accounted for 28.38% of total precipitation amount for entire Jiangsu. Overall, as for daily and monthly precipitation concentration in this province, precipitation amount of rice-growing period was mainly concentrated in the rainstorm events and July rainfalls, respectively.

### 4.2 Spatial distribution of PCI

The spatial distributions of DPCI and CDP over the study area are shown in Fig. 2. It is clearly shown that the spatial variation of DPCI displayed an obvious gradient: increasing from the southern part to the northern part, and DPCI values ranged from a minimum of 0.55 to a maximum of 0.60 (Fig. 2a). Similar spatial distribution was also found

for CDP6 in Fig. 2g, and the values in some areas of north Jiangsu even exceeded 40%. By contrast, the spatial variation of CDP1 and CDP2 displayed obvious increasing gradients from north to south (Fig. 2b, c). When it comes to CDP3, CDP4, and CDP5, the spatial distribution characteristics were not obvious (Fig. 2d–f). Being similar to Fig. 2, the obvious south–north gradient was found for the most of monthly PCIs in Fig. 3. MPCl values ranged from a minimum of 11.5 to a maximum of 14.3 (Fig. 3a). It is clearly shown that MPCl, CMP\_Jul, and CMP\_Aug displayed in Fig. 3a, d, e had increasing gradients from south to north, while CMP\_May, CMP\_Jun, and CMP\_Oct displayed in Fig. 3b, c, g had diametrically opposite spatial variations. Especially in Fig. 3c–e, the regional difference between northern and southern areas was more prominent, and the higher values of CMP\_Jun, CMP\_Jul, and CMP\_Aug detected in north Jiangsu could exceed 20, 30, and 20%, respectively. In general, the spatial patterns of DPCI, CDP6, and MPCl given in Figs. 2 and 3 indicated that north Jiangsu had higher precipitation concentration during rice-growing period.

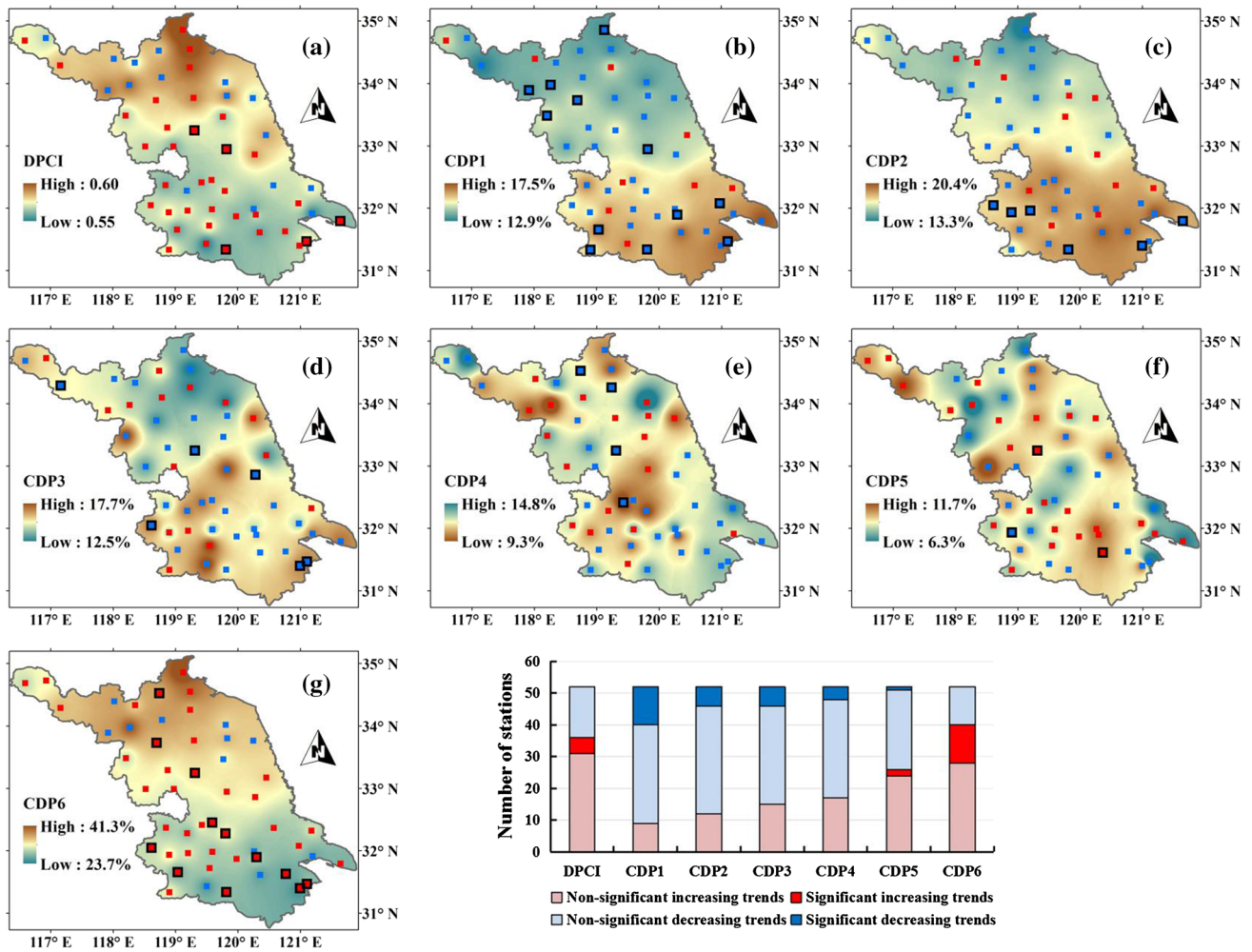
### 4.3 Changing trends of PCI

Spatial distributions of trends of daily precipitation concentration in Jiangsu are also shown in Fig. 2. For both of DPCI and CDP6, more than 70% of stations were characterized by increasing trends (Fig. 2a, g). Being opposite from the trends of DPCI and CDP6, most of stations exhibited the decreasing trends for CDP1, CDP2, CDP3, and CDP4 (Fig. 2b–e). When it comes to CDP5, there was almost no obvious difference between the number of stations with increasing and decreasing trends. In the light of the number of stations with significant trends, the changes in CDP6 should be more obvious, and the ten stations with significant positive trends

**Table 1** Statistical characteristics for multi-annual mean values of 14 PCI in all the stations

	Maximum	Minimum	Mean	Median	Std	CV (%)	Skewness	Kurtosis
DPCI	0.60	0.55	0.57	0.57	0.01	1.61	0.70	3.18
CDP1 (%)	17.52	12.92	15.09	15.15	1.24	8.22	0.16	1.96
CDP2 (%)	20.41	13.33	17.64	17.71	1.51	8.54	−0.34	2.77
CDP3 (%)	17.68	12.48	15.07	14.97	1.34	8.92	0.10	2.35
CDP4 (%)	14.84	9.31	11.82	12.00	1.14	9.63	−0.15	3.15
CDP5 (%)	11.75	6.34	9.47	9.65	1.15	12.14	−0.51	2.93
CDP6 (%)	41.33	23.71	30.91	30.98	3.64	11.78	0.47	3.14
MPCl	14.27	11.50	12.82	12.68	0.70	5.50	0.39	2.12
CMP_May (%)	16.18	8.33	11.61	11.25	2.09	18.02	0.28	1.76
CMP_Jun (%)	24.92	13.87	19.27	19.63	3.63	18.87	−0.03	1.42
CMP_Jul (%)	36.49	19.10	28.38	27.71	4.66	16.42	−0.14	1.88
CMP_Aug (%)	26.82	16.46	20.92	20.26	2.68	12.79	0.46	2.26
CMP_Sep (%)	15.51	11.16	12.96	12.97	1.02	7.89	0.25	2.79
CMP_Oct (%)	9.45	5.19	6.87	7.02	1.00	14.57	0.14	2.24





**Fig. 2** Spatial distribution of multi-annual mean values and *M-K* trends in DPCI and CMP across Jiangsu (the color within Jiangsu denotes the mean values of considered index; the red squares mean increasing trends; the blue squares mean decreasing trends; squares

with black border show significant trends at the 95% confidence level; the histogram represents number of stations with different trends for considered index)

for CDP6 were mainly located in south Jiangsu. All these above may indicate that daily precipitation changes during rice-growing period in Jiangsu tend to have higher percentages of total precipitation in few rainy days.

By contrast, the increasing trends of MPCCI in Jiangsu were more significant. There are 39 stations characterized by increasing MPCCI, and 14 stations with significant decreasing trends are mainly observed in the south Jiangsu. These results may indicate that the distribution of the monthly precipitation during the rice-growing period became more nonuniform in this province, which is well confirmed by the results obtained by applying the *MK* test to CMP indices. Most of stations presented increasing trends for CMP\_Jun, CMP\_Jul and CMP\_Aug (Fig. 3c–e), while most of stations presented decreasing trends for CMP\_Jun, CMP\_Jul and CMP\_Aug (Fig. 3b, f, g). Especially, for CMP\_Jul and CMP\_Sep, the number of stations with significant trends

was larger than 20, and these stations were mainly located in south Jiangsu. In general, the obvious wet tendency in summer and dry tendency in autumn caused the increase of MPCCI.

#### 4.4 Correlation between rice yield and PCI

Firstly, the provincial series of rice yield and PCI were calculated as the arithmetic mean at all stations, and then the correlation analysis between rice yield and 14 PCI using first-difference method were showed in Fig. 4a. For daily precipitation concentration, DPCI and CDP6 were negatively correlated with rice yield, while the other indices demonstrated negative correlations with rice yield. As for monthly precipitation concentration, a negative correlation was observed between rice yield with most of indices except for CMP\_May and CMP\_Jun. It was worthwhile

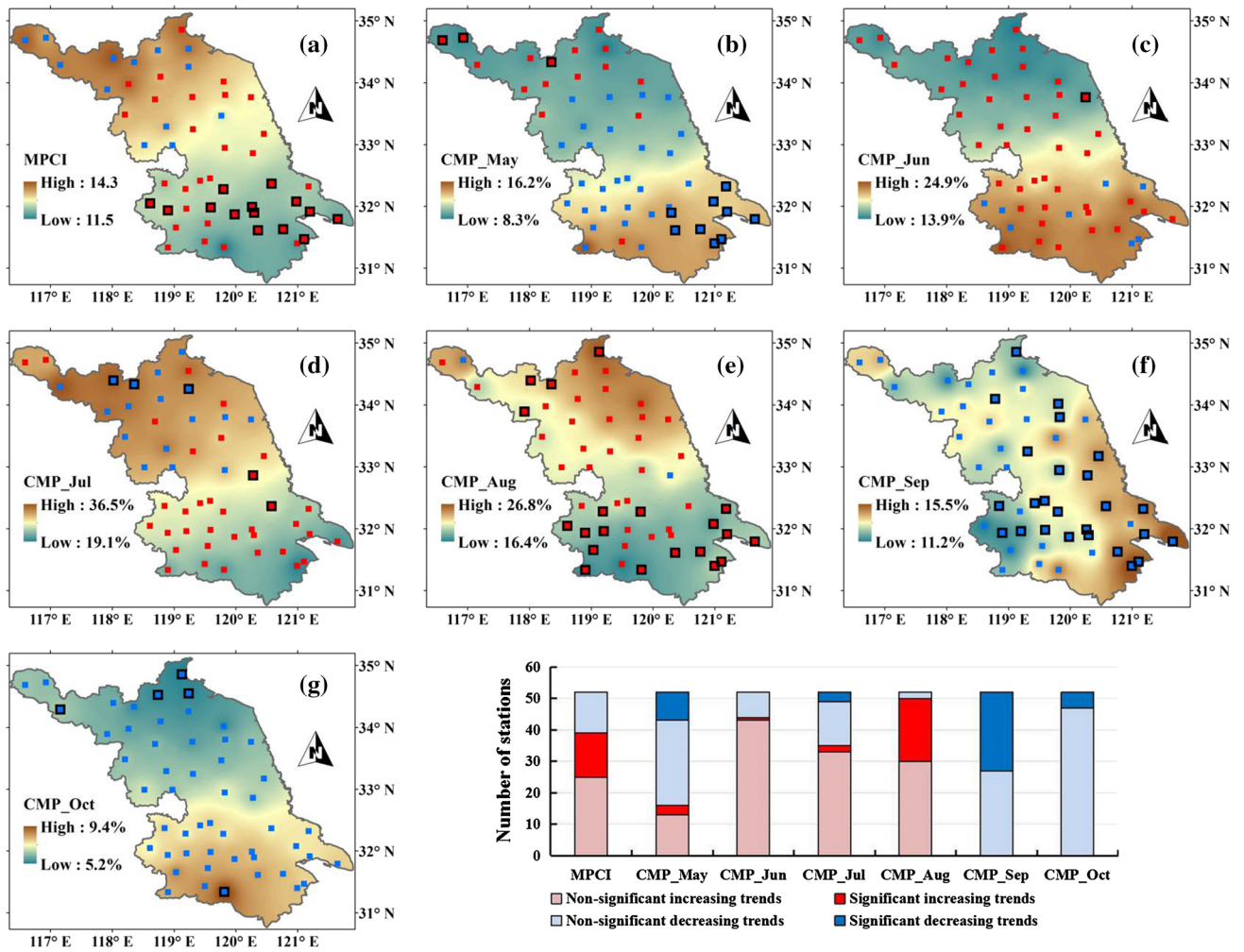


Fig. 3 Spatial distribution of multi-annual mean values and *M-K* trends in MPCl and CMP across Jiangsu (the signification of legends in Fig. 3 is same to those of Fig. 2)

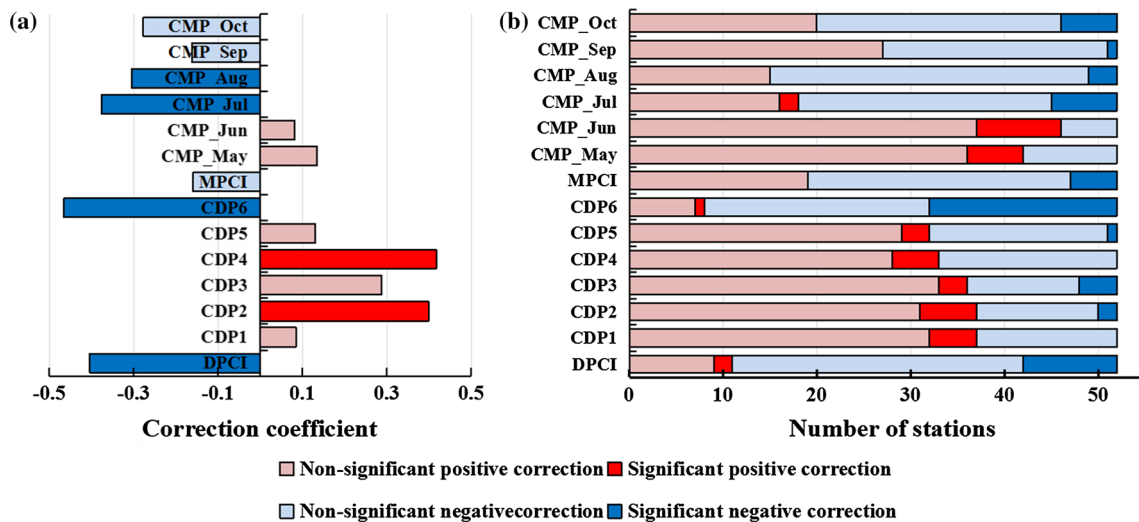


Fig. 4 Correlation between rice yield and 14 PCI at the scales of Jiangsu (a) and individual stations (b)

mentioning that the correlation between rice yield and DPCI, CDP6, CMP\_Jul, and CMP\_Aug had all passed the significance test. Being consistent with provincial results, rice yield was negatively correlated with five PCI including DPCI, CDP6, MPCl, CMP\_Jul, and CMP\_Aug in more than 60% of stations. Especially, there were 18 stations characterized by significant negative correlation between rice yield and CDP6, while the number of stations with significant negative correlation between rice yield and DPCI, MPCl, CMP\_Jul, and CMP\_Aug did not exceed 10. All the above results mean that the higher daily and monthly precipitation concentration was unfavorable to rice production. The correlation between rice yield and CDP6 was most significant at both of provincial and station level, which indicating that CDP6 should be selected as an optimal indicator for depicting the adverse effect of higher precipitation concentration on rice yield.

#### 4.5 Regional linear relationship between CDP6 and rice yield

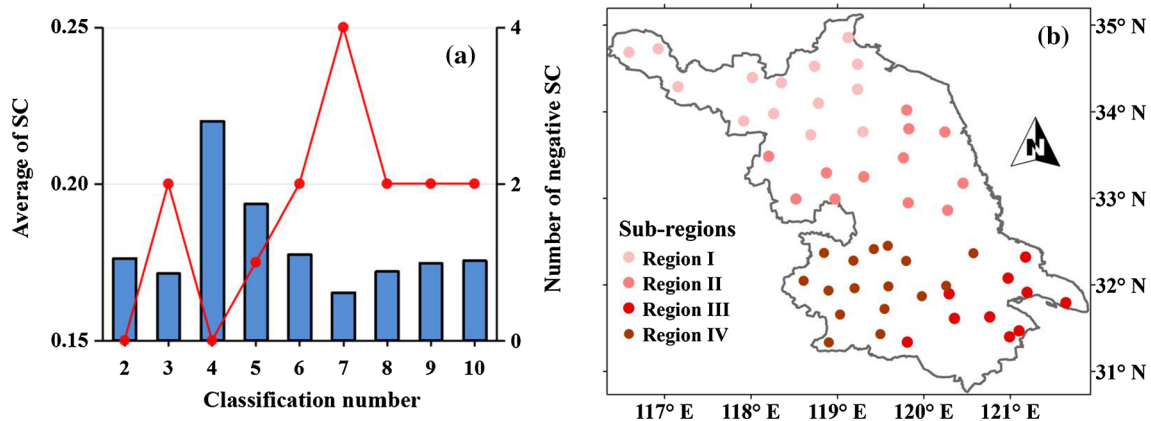
Understanding regional difference in the responds of rice yield to CDP6 changes should be beneficial for rice production safety. Thus, the *K*-means clustering method was applied to the matrix composed by the time series of CDP6 in all stations. As the results in Fig. 5a, four sub-regions with different temporal variations in CDP6 were identified as follows: Region I (northwest Jiangsu), Region II (north-central Jiangsu), Region III (southeast Jiangsu), and Region IV (southwest Jiangsu). Then, the sub-regional series of CDP6 and rice yield were constructed as the arithmetic mean at stations of each cluster identified in Fig. 5b. Among the four sub-regions, southeast Jiangsu was the only sub-region with a significant increasing trend of CDP6 during 1961–2012, and the non-significant increase of CDP6 was observed in other three sub-regions (Fig. 6). Meanwhile, the Hurst

exponent for each sub-region was larger than 0.5 (Fig. 6), which indicated the long-term memory with the higher predictability for CDP6. Using 5-year smoothing average method, CDP6 in each sub-regions had a V-shape changing pattern (decreasing–increasing), especially an obvious increase was found after the 1980s (Fig. 6).

Based on the first-difference time series for yield ( $\Delta$ Yield) and CDP6 ( $\Delta$ CDP6) in four sub-regions, the yield–CDP6 linear relationships were constructed to quantify the effect of CDP6 trends over the past 50 years on rice yield. As showed in the regression equations in Fig. 7, the yield–CDP6 relationships presented a distinct regional difference. According to the higher  $R^2$ , the yield–CDP6 relationships in southeast and southwest Jiangsu were obviously more significant. If CDP6 of rice-growing period increased by 10%, rice yield was likely to decrease by up to 2.48% and 1.98% in southeast and southwest Jiangsu, respectively. When it moves to northwest and north-central Jiangsu, rice yield was likely to decrease by up to 1.53% and 0.93%, respectively, due to the increase of CDP6 by 10%. Thus, the rice-growing in southeast and southwest Jiangsu should be more sensitive to the negative effects of higher precipitation concentration. Furthermore, the rice yield in northwest, north-central, southeast, and southwest Jiangsu declined by 1.59, 0.85, 4.96, and 2.59%, respectively, owing to the upward trend of CDP6 during 1961–2012 (Fig. 7).

## 5 Discussion

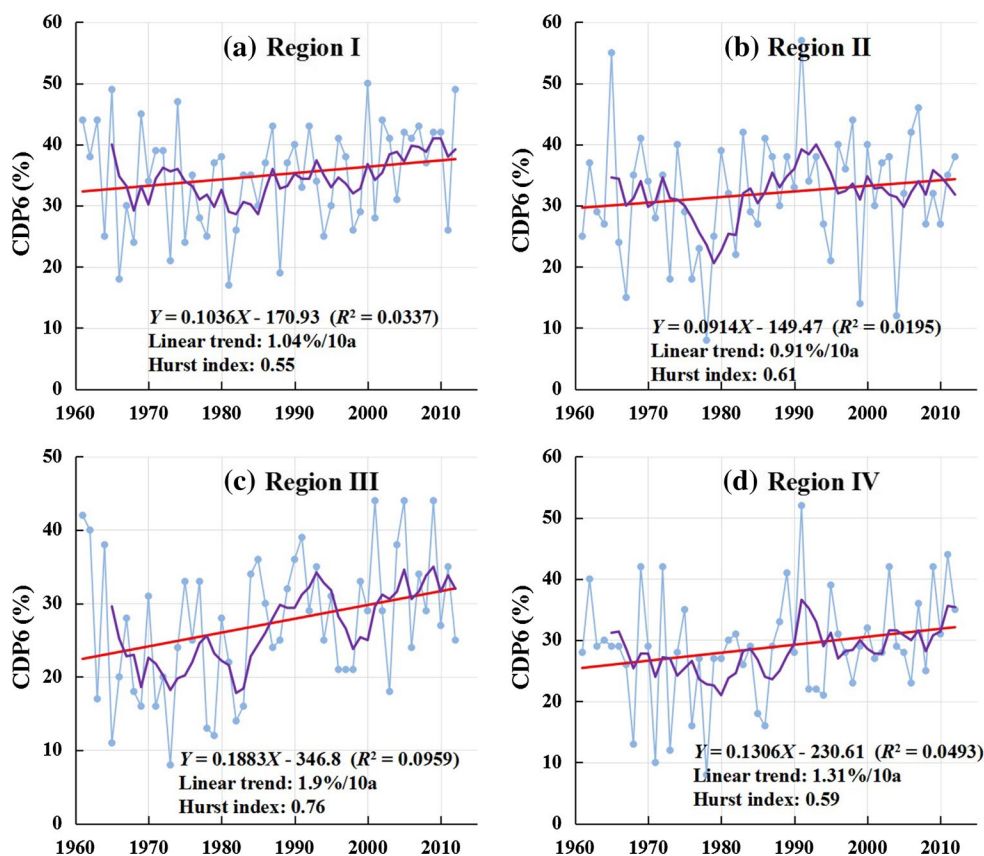
Compared to south Jiangsu, north Jiangsu had higher daily and monthly precipitation concentration during rice-growing period. These may be attributed to the higher occurrence of rainstorm events and shorter rainy season in northern area. Due to the south–north extension of Jiangsu, the northward uplift of west-pacific subtropical high (WPSH) combined



**Fig. 5** Climatic regionalization based on the inter-annual fluctuation of CDP6 in Jiangsu. **a** Results of *K*-means cluster analysis for annual series of CDP6 in all stations; **b** four sub-regions with different temporal variations of CDP6 in Jiangsu)



**Fig. 6** Temporal evolution of CDP6 in four sub-regions (the weather blue line chart is the annual series of CDP6; the red line is the linear trend; the purple line is the 5-year smoothing average curve)



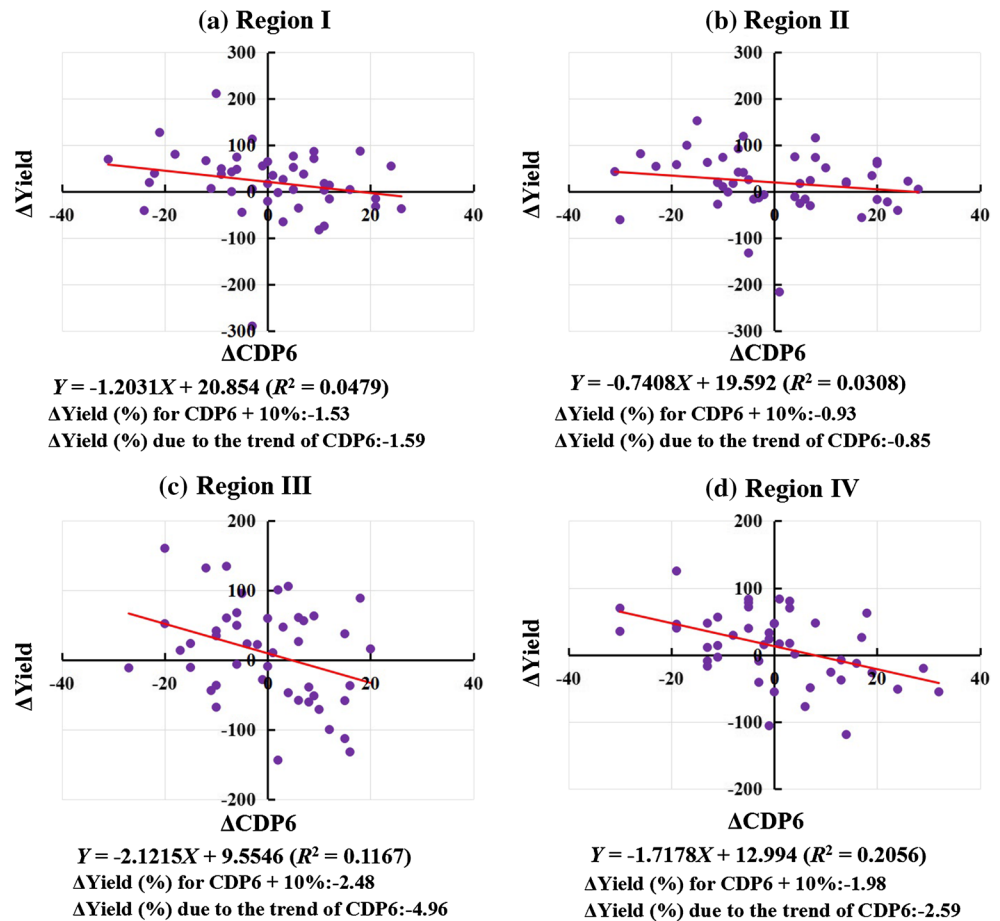
with Meiyu front would usually cause the higher frequency of rainstorm events in north Jiangsu (Xiao et al. 2006). As located in the bottom side of westerly trough, north Jiangsu were affected by the southward motion of the cold air obviously, and the interaction impact between cold air and the warm-wet flows in the edge of WPSH would also bring more rainstorm events (Fei et al. 2014). In addition, Huai River was taken as the approximate demarcation between north and south in this province, and south Jiangsu has a subtropical monsoon climate, while north Jiangsu has a warm moist monsoon climate (Huang et al. 2017b). Accompanying with the northward movement of monsoon rain band from South China, south Jiangsu has the longer rainy season from May to August, while north Jiangsu had the shorter rainy season from July to August.

The correlation coefficient between rice yield and precipitation contribution percentage of rainstorm events (CDP6) at all-Jiangsu scale in this study was up to be  $-0.47$ , which was more significant than the negative correlation between rice yield and calculated by Huang et al. (2017a, b). In addition, the study results constructed by Zhu et al. (2012, 2013) and Shuai et al. (2013) indicated that the adverse effect of total precipitation changes on rice yield across Jiangsu did not exceed 1%. In contrast, the losses of rice yield due to the increasing trend of CDP6 in most of Jiangsu ranged from 1.59 to 4.56%. All these above may prove that CDP6 was

more suitable for accessing the losses of rice yield caused by excessive rainfall, and the rainstorm events should be key precipitation variable for the fluctuation in rice yield. From a spacial perspective, rice-growing in southeast and southwest Jiangsu seemed to be more sensitive to the CDP6 changes. This mainly should be attributed to the complex hilly landforms, poorer soil permeability, and larger drainage density in southern areas of Jiangsu, which caused the higher sensibility for crop waterlogging stress (Wu et al. 2015). In this case, using CP6 to construct the meteorological disasters risk regionalization for rice production is a worthwhile attempt in the future.

In view of the importance of CDP6, the regional temporal variability of CDP6 was explored using  $K$ -means clustering method. This province could be divided into four sub-regions characterized by different changing patterns of CDP6, and the increasing trends of CDP6 in southeast and southwest Jiangsu were more significant than those of northeast and north-central Jiangsu. The obvious north-south difference may be related to the inter-annual variability of East Asian summer monsoon (EASM) and the rainy inland effect of city. EASM has experienced significant weakening in the recent two decades, which causing a longer stay of Meiyu front in the mid-lower reaches of Yangtze river, and then leading to more deficient moisture supply for the rainstorm events in the south of Huaihe river (Ding et al. 2008). Due to

**Fig. 7** Quantification for responses of rice yield to the changes of CDP6 in four sub-regions



the rapid development of urbanization of south Jiangsu in recent years, the more complex atmospheric components and stronger heat island effect are liable to form condensation nodules and induce convective weather, and the more prominent blocking effect of underlying surface should cause the longer retention and higher strength of extreme precipitation events, which would further intensify the increase of CDP6 in south Jiangsu (Xia et al. 2015).

## 6 Conclusions

1. On the basis of the multi-annual average values of 14 PCIs of 52 stations across Jiangsu province, a fairly high level of daily and monthly precipitation concentration were observed in Jiangsu. This was clearly illustrated by that precipitation of rice-growing period was mainly concentrated in the rainstorm events and the July rainfalls. From a spatial perspective, north Jiangsu had higher precipitation concentration.
2. The results of changing trends in 14 PCI, using the *MK* test, indicated that both of daily and monthly precipitation concentration in Jiangsu presented increasing trends. From a spatial perspective, a lot of stations located in south Jiangsu had significant increasing trends for the contribution of rainstorm events and rainfalls in August.
3. At both all-Jiangsu and individual stations, the correlation analysis between rice yield and PCI indicated that the higher concentration of both daily and monthly precipitation distribution had obvious adverse influence on rice yield, and the contribution percentage of rainstorm events to total precipitation of rice-growing period (CDP6) should be regarded as the key precipitation indicator for indicating the fluctuation of rice yield in Jiangsu.
4. Using *K*-means clustering method, this province was divided into four sub-regions with different temporal variability for CDP6 (northwest, north-central, southeast, and southwest Jiangsu). The linear relationship between rice yield and CDP6 constructed in four sub-regions indicated that southeast and southwest Jiangsu should be identified as the sensitive areas, and losses of rice yield in the two sub-regions due to the increasing trend of CDP6 exceeded 2%.



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