

Article

Cluster Analysis and Atmospheric Circulation Features of Springtime Compound Dry-Hot Events in the Pearl River Basin

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Abstract: Compound dry-hot events refer to climate phenomena where drought and high temperatures occur simultaneously. Compared to single extreme events, compound dry-hot events may have greater adverse impacts. This study uses high-spatial-resolution observational data (i.e., temperature, precipitation, and climate water balance) to cluster and identify spring compound dry-hot events in the Pearl River Basin over the past nearly 50 years. It further investigates the associated large-scale atmospheric circulation conditions during compound dry-hot events. Using three clustering methods and twenty-six evaluation criteria, six events are identified. These events primarily exhibit negative anomalies in precipitation and climate water balance and positive anomalies in temperature. The spatial distribution results show that moisture deficits during compound events are mainly concentrated in the eastern Pearl River Basin, especially in the Pearl River Delta region. An atmospheric circulation analysis indicates that spring compound dry-hot events in the Pearl River Basin are commonly accompanied by persistent abnormal high-pressure systems, relatively weak westerly transport from subtropical regions such as the Indian Ocean and the Bay of Bengal (20–25 °N), and limited moisture input from the western Pacific region. The results of this study can help to better understand and analyze the risk changes of extreme events in the context of global warming.

Keywords: global warming; compound dry-hot events; cluster analysis; atmospheric circulation; Pearl River Basin



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1. Introduction

Compound dry-hot events are becoming increasingly frequent worldwide, especially in the context of climate change, and they have severe impacts on agriculture, water resources, and ecological environments [1–3]. More recently, the 2022 event in the Yangtze River Basin, China, affected over 4.08 million hectares of crops, 4.3 million people, and 350,000 livestock [4]. By the end of the 21st century, many regions around the world are expected to experience more severe and longer-lasting compound dry-hot events [5]. A large number of observational results indicate that, since the 1970s, spring precipitation in the Pearl River Basin (PRB) has shown a decreasing trend [6]. Additionally, the impact of compound events on water resource allocation and population in the Pearl River

Basin is significant [7,8]. Therefore, gaining an in-depth understanding of the evolution characteristics and occurrence mechanisms of compound dry and hot events is crucial for national disaster prevention, mitigation, and relief efforts.

In recent years, research on the occurrence and evolution of compound dry–hot events has achieved significant results [9,10]. One of the main objectives of these studies is to reveal the spatiotemporal variations in multiple characteristics of compound dry–hot events, such as frequency, intensity, and probability [11,12]. Strong observational evidence has shown an increase in the frequency of compound dry–hot events in continents or regions such as Europe, North America, and Asia [13,14]. Although different continents are located in different climate zones, various pieces of evidence confirm that the affected area of compound dry–hot events has become wider, their duration longer, and their damage more severe in the past decade [15,16]. For example, the 2010 summer compound dry–hot event in Russia resulted in an estimated 55,000 deaths, a 25% reduction in annual crop yields, and over one million hectares of burned area [17]. Additionally, observational evidence indicates that the frequency and intensity of compound dry–hot events in China have generally been on the rise in recent decades [18,19]. Some studies suggest differences in the occurrence and evolution of these events between different regions in China, but they consistently show that the frequent occurrence of compound dry–hot events has had significant adverse effects [20,21].

However, past methods for identifying compound dry–hot events are not unified, with different studies using various standards and methods [22]. A common approach is to identify compound dry–hot events by combining drought and heatwave indices [23,24]. The variables used in these calculations differ, as do the calculation methods, and the physical meanings of various indices are not completely the same [25,26]. This leads to poor comparability of the results. Additionally, the formation mechanisms and driving factors of compound dry–hot events, especially regarding the role of atmospheric circulation, require further research [27,28]. Strengthening the related research can help us to understand the response of compound events to global warming in more detail and provide scientifically effective recommendations for policymakers [29].

To address the increasing concern over compound climate extremes, this study aims to establish a robust identification framework for compound dry–hot events by applying optimal clustering techniques to key climate variables. Beyond identification, the study further investigates the associated large-scale atmospheric circulation patterns of typical compound events. Unlike previous approaches that often rely on fixed thresholds or single-variable analyses, this method integrates multivariate statistical learning to capture the inherent complexity of compound extremes. The proposed framework provides a transferable approach that can be extended to other types of compound events, thereby contributing to a better understanding of their physical mechanisms and enhancing their early warning capabilities.

2. Methodology

2.1. Study Area

The Pearl River Basin (PRB) (Figure 1) is situated in southeastern China, spanning the tropical and subtropical monsoon climate zones (102°14′–115°53′ E, 21°31′–26°49′ N). It covers an area of approximately 453,700 km², accounting for about 4.7% of China's total land area [30]. The basin encompasses major provinces such as Yunnan, Guizhou, Guangxi, Guangdong, Hunan, and Jiangxi, and includes several important cities, notably, Guangzhou, Shenzhen, Hong Kong, and Macao. The PRB is one of the most economically dynamic regions in China, with a high concentration of manufacturing, electronics, services,

and international trade [31]. Economic activities are concentrated in the southeast coastal areas, while the upstream regions are more mountainous and agriculturally oriented [32].

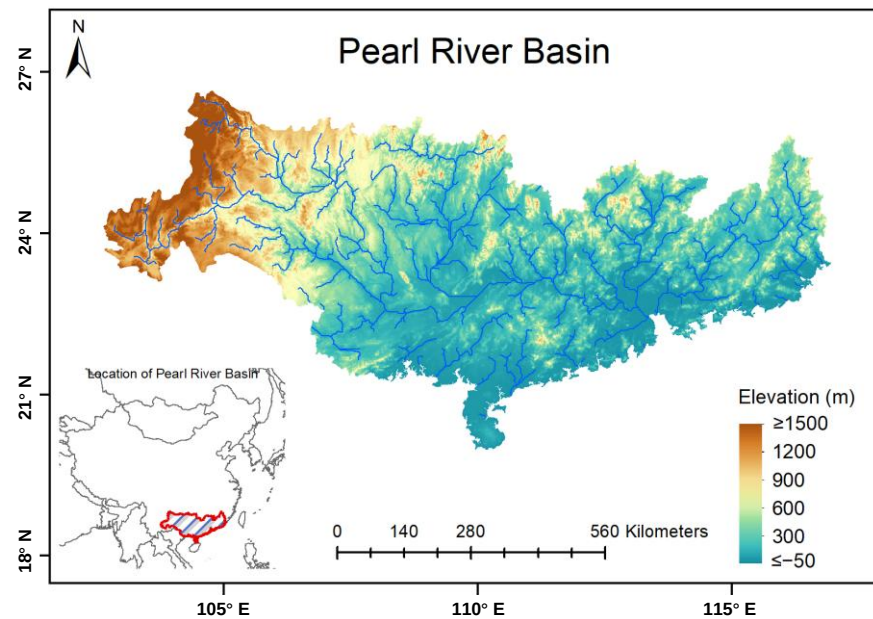


Figure 1. The location and elevation of the Pearl River Basin.

The topography of the basin slopes from the Yunnan–Guizhou Plateau in the northwest to the low-lying PRD in the southeast [33]. Major rivers such as the Xijiang, Beijiang, and Dongjiang converge to form the Pearl River, which flows into the South China Sea. The mean annual temperature across the basin ranges from 14 °C in the northwest to 22 °C in the southeast, while annual precipitation ranges from 1200 mm in the west to over 2200 mm in the east, showing a marked east–west gradient [34]. Approximately 80% of the precipitation occurs between April and September, driven primarily by the East Asian summer monsoon [35].

In recent years, the PRB has been increasingly affected by climate change, with notable rises in temperature and a growing frequency of compound extreme events [36,37]. These events pose serious threats to water resources, agriculture, energy security, and socio-economic stability. Therefore, a deeper understanding of their spatiotemporal characteristics and underlying causes is urgently needed.

2.2. Cluster Methods

This study uses three clustering methods: K-means clustering, hierarchical clustering (H-clust), and agglomerative nesting (Agnes). The main objective of the K-means method is to partition k sample points into k clusters, ensuring that similar samples are grouped together as much as possible [38,39]. Due to its practicality and ease of implementation, it has been widely used in many fields related to classification and regression [40]. Hierarchical clustering tends to build a hierarchy of clusters [41]. This method is divided into two types: bottom-up (agglomerative) and top-down (divisive). Additionally, this method requires the predefinition of a distance metric (e.g., Euclidean) and a linkage criterion (e.g., Ward’s method). More details about this clustering method are provided in previous studies [42]. The agglomerative nesting method works in a bottom-up manner [43]. Each object is initially considered as a leaf, representing a single element. At each step of the algorithm, the two most similar clusters are merged into a larger node. This process is repeated until all nodes belong to larger groups. This method is also widely used in many fields, and more detailed information can be found in previous research [44,45].

Determining whether the number of clusters obtained is reasonable is crucial for subsequent result analysis. Since different clustering methods may yield different optimal numbers of clusters, practical evaluation criteria are essential for improving the accuracy of clustering results. This study predefines several possible optimal numbers of clusters (i.e., 3 to 10) and uses 26 clustering validity indices. The number of clusters that most indices indicate as optimal is considered the best. Detailed information about the cluster methods and validity indices can be found in the R package ‘cluster’ (i.e., <https://cran.r-project.org/web/packages/cluster/index.html>, accessed on 27 April 2025).

2.3. Dataset and Standardized Index

This study uses three monthly-scale climate variables, temperature, precipitation, and potential evapotranspiration, to identify spring compound dry–hot events in the Pearl River Basin from 1971 to 2018. The data come from the fifth-generation reanalysis dataset (ERA5) provided by the European Centre for Medium-Range Weather Forecasts (ECMWF), with a spatial resolution of $0.25^\circ \times 0.25^\circ$. The ERA5 dataset undergoes multi-level quality control and calibration to ensure data accuracy and reliability, and it is used in numerous studies [46,47]. The calculation of potential evapotranspiration (PET) is based on the Penman–Monteith equation provided by the Food and Agriculture Organization (FAO) [48]. All necessary data for the calculation, such as wind speed, also come from the ERA5 reanalysis dataset.

$$PET = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T + 273.16} U_2 (e_s - e_a)}{\Delta + \gamma(1 + 0.34U_2)} \quad (1)$$

where R_n is the net radiation on crop surface (unit: $\text{MJ m}^{-2} \text{ day}^{-1}$); G is the soil heat flux (unit: $\text{MJ m}^{-2} \text{ day}^{-1}$); T represents the air temperature at 2 m height (unit: $^\circ\text{C}$); U_2 is the wind speed at 2 m height (unit: m s^{-1}); e_s and e_a are the saturated vapor pressure (unit: kpa) and the actual vapor pressure (unit: kpa), respectively; Δ is the slope of water vapor pressure curve (unit: $\text{kPa } ^\circ\text{C}^{-1}$); and γ represents the psychrometric constant (unit: $\text{kPa } ^\circ\text{C}^{-1}$).

The spring dry and wet conditions in the Pearl River Basin over time are described using the standardized potential evapotranspiration and precipitation index.

$$PET\_std(\alpha) = \frac{PET(\alpha) - \eta(m)}{\sigma(m)} \quad (2)$$

where $PET(\alpha)$ is the PET at time step α (i.e., month m); and $\eta(m)$ and $\sigma(m)$ are the averages and standard deviation of the multi-year PET time series for month m . The calculation process of P_std is the same as above.

2.4. Atmospheric Circulations

Multiple sets of data from different pressure levels are used to explore the influence of large-scale atmospheric circulation on spring compound dry and hot events in the Pearl River Basin. These data, at a monthly scale, cover the period from 1971 to 2018 and include the 850 hPa wind field (i.e., U850 and V850), 500 hPa geopotential height (i.e., Z500), mean sea level pressure (i.e., SLP), and 700 hPa relative humidity (i.e., RH700). All data are extracted from the ERA5 dataset, with a spatial resolution of $0.25^\circ \times 0.25^\circ$. These datasets are widely used to describe atmospheric circulation anomalies during extreme events [49,50]. Additionally, this study uses monthly Nino3.4 index data to reveal the relationship between compound dry–hot events and El Niño/La Niña events [51,52]. These data are provided by the National Oceanic and Atmospheric Administration (NOAA).

3. Results

3.1. Temporal Variations of Climate Conditions

Figure 2 shows the temporal variation in temperature, precipitation, and potential evapotranspiration in the Pearl River Basin from 1971 to 2018. Figure 2A illustrates the annual total precipitation and average annual temperature. The results indicate an increasing trend in average temperature and a decreasing trend in annual total precipitation, but neither trend is statistically significant ($p > 0.05$, Mann–Kendall trend test). To further explore the multi-year variations in potential evapotranspiration and precipitation, Figure 2B presents the temporal changes in the standardized indices PET_std and P_std for the Pearl River Basin. The long-term series is divided into two 24-year periods for a comparative analysis: 1971–1994 and 1995–2018. In the first 24 years, the P_std (solid blue line) tends to remain positive, while the PET_std (solid red line) is mostly negative. However, in the latter 24 years, the patterns of the two standardized indices reverse. Specifically, the P_std results show that the mean value (dashed blue line) does not significantly change between the first 24 years (0.03) and the last 24 years (−0.03), indicating no significant difference in the precipitation-determined wet and dry conditions between the two 24-year periods. In contrast, the mean value of PET_std (dashed red line) is significantly higher in the last 24 years (0.16) compared to the first 24 years (−0.16) ($p < 0.05$, t -test). The above results clearly indicate that changes in precipitation alone are insufficient to reflect wet and dry conditions, and potential evapotranspiration plays a crucial role.

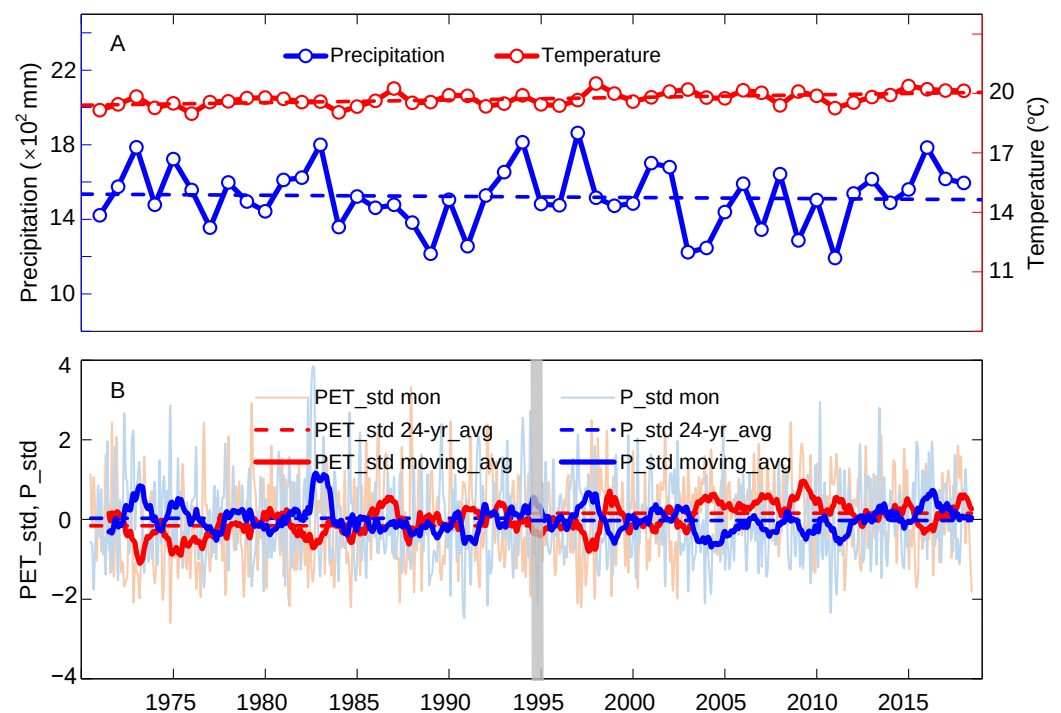


Figure 2. The temporal variation in temperature, precipitation, and potential evapotranspiration in the Pearl River Basin from 1971 to 2018. Panel (A) is the variation in annual total precipitation and average annual temperature over time; and the dashed lines represent the trends detected using the Mann–Kendall (MK) test. Panel (B) is the temporal changes of the two standardized indices.

3.2. Clustering of Compound Dry–Hot Events

The above content primarily analyzes the temporal variations in precipitation, temperature, and potential evapotranspiration in the Pearl River Basin. The results indicate that all three climate variables play significant roles in characterizing wet and dry conditions, especially potential evapotranspiration. Building on this, this section further

explores the spring anomalies of these three variables and clusters these anomalies using three different clustering methods (Figure 3). The climatology used to calculate anomalies is based on the average of the variables from 1971 to 2018, and only spring data are used. The variation pattern of the precipitation anomaly time series generally matches that of the climate water balance (i.e., P–PET) (Figure 3A). Using predefined thresholds (such as the two gray horizontal lines in the figure) allows for a clearer distinction of changes in different years. Figure 3B clearly shows the optimal clustering results of the combined anomalies of temperature, precipitation, and climate water balance using the three clustering methods. The optimal number of clusters, determined by 26 evaluation criteria (Tables S1–S3), is four, with the first cluster defined as compound dry–hot events. Since the focus of this study is on compound dry–hot events, the results of the other three clusters (Cluster 2: Relatively wet conditions; Cluster 3: Wet conditions; and Cluster 4: Relatively dry–hot conditions, though less extreme than Cluster 1) are not studied in depth.

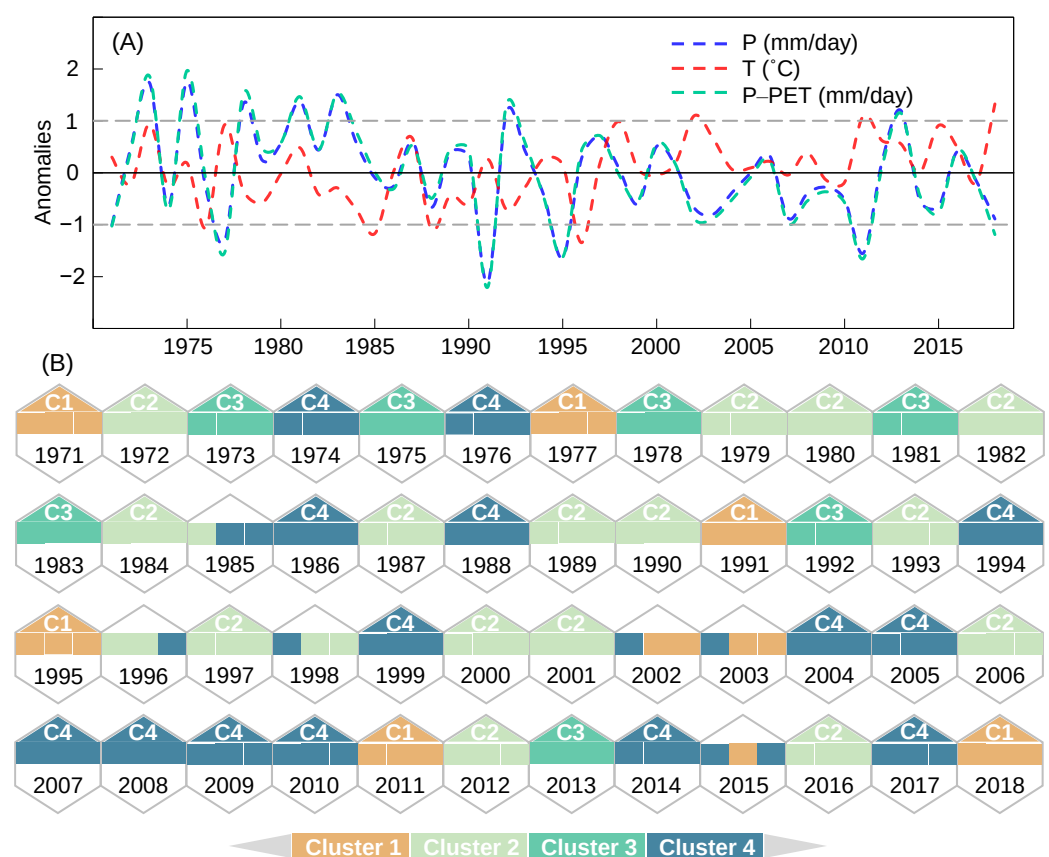


Figure 3. (A) Anomalies of three variables; and (B) clustering results based on three methods. The classification results for each year are represented by hexagons. Each hexagon includes a triangle at the top indicating the final class, and three small colored squares in the middle, from left to right, showing the classification result of that year by K-means, H-clust, and Agnes, respectively. Only when all three clustering methods yield consistent results is the year assigned to a specific class, as shown by a colored triangle (e.g., 1971 with all yellow squares and a yellow triangle indicating classification into Class 1). Years with inconsistent results across methods, such as 1985, are excluded from further analysis.

There are six years classified as compound dry–hot events: 1971, 1977, 1991, 1995, 2011, and 2018 (Table 1). A detailed analysis of the anomalies of the three variables in these six years shows that both precipitation and climate water balance anomalies are negative, indicating a significant water deficit that can lead to drought. Meanwhile, temperature anomalies are positive, which can lead to heat events.

Table 1. The compound dry–hot events obtained based on temperature, precipitation, and climate water balance anomalies through the three cluster methods.

Year	P Anomalies (mm/day)	P–PET Anomalies (mm/day)	T Anomalies (°C)
1971	−1.008	−1.027	0.301
1977	−1.320	−1.540	0.925
1991	−2.120	−2.206	0.263
1995	−1.638	−1.625	0.150
2011	−1.547	−1.653	1.099
2018	−0.889	−1.190	1.327

3.3. Characteristics of Compound Dry–Hot Events

The climate water balance includes both precipitation information and the effects of temperature. According to the clustering results, the climate water balance anomalies for the compound dry–hot events are all less than -1 (Table 1). Note that these anomalies are the mean values of grid points across the entire basin. Therefore, this study uses the variable to reflect the characteristic changes in compound dry–hot events. Figure 4 shows the spatial distribution of climate water balance anomalies for the six events. Overall, the water deficit indicated by the climate water balance anomalies is mostly concentrated in the eastern part of the Pearl River Basin, especially in the Pearl River Delta region. The spatial distribution exhibits a clear pattern of higher anomalies in the east and lower anomalies in the west. The eastern portion of the Pearl River Basin, especially the Pearl River Delta region, is characterized by a high population density and strong economic vitality, making it one of the most developed and urbanized areas in China. These characteristics highlight the region’s high exposure and sensitivity to climate extremes. Similar spatial patterns of water deficit anomalies have also been observed in other parts of China. For example, during the 2011 spring compound dry–hot event, a significant climate water imbalance was recorded across southern China, with the Yangtze River Basin among the most affected areas [53]. The consistency in spatial distributions across different studies further supports the reliability of our clustering-based identification framework.

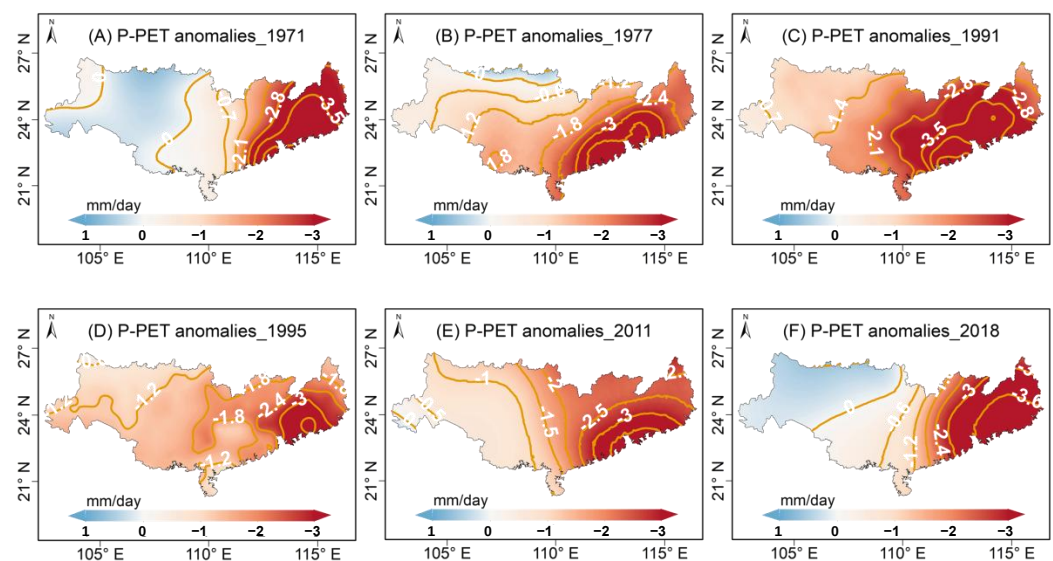


Figure 4. The spatial distribution of climate water balance (P–PET) anomalies (mm/day) during the compound dry–hot events.

The coverage area effectively reflects the spatiotemporal variation in compound dry-hot events. It is important to note that the area is represented as a percentage of grid points with a climate water balance less than -1 relative to the total number of grid points in the Pearl River Basin. Figure 5 shows the percentage change in the coverage area of compound dry-hot events in the Pearl River Basin from March to May and throughout the entire spring season. In 1971, the coverage area reaches its peak in March (55%) and then gradually decreases (i.e., monotonic decrease). Similarly, in 1977, the coverage area reaches its maximum in March (61%), experiences a decrease in April, and then increases again in May (i.e., decrease followed by increase). The coverage area in 1991 and 1995 exhibits similar patterns, steadily increasing from March and reaching a peak in May (i.e., monotonic increase). In contrast, the coverage area in 2011 and 2018 shows different patterns, increasing from March, peaking in April, and then decreasing in May (i.e., increase followed by decrease). The above analysis shows that the spatial coverage of compound dry-hot events varies in different ways. These differences reflect the spatiotemporal variability of the factors controlling the evolution of compound dry-hot events, such as atmospheric circulation. Therefore, the analysis in the next section can help us to better understand the spatiotemporal evolution of compound dry-hot events.

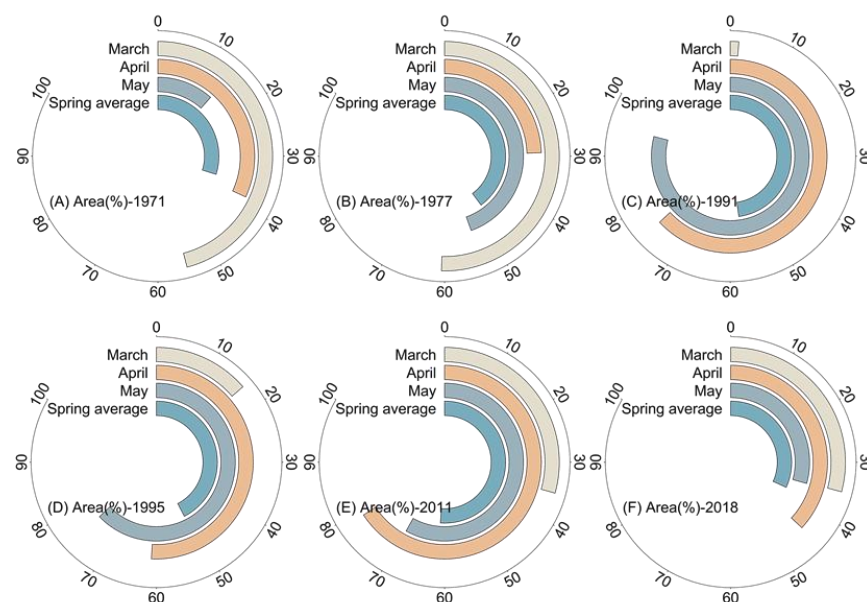


Figure 5. The percentage of the area affected by compound dry-hot events. The percentage is calculated as the ratio of grid points with a climate water balance less than -1 to the total number of grid points in the Pearl River Basin.

3.4. Variations of Atmospheric Circulation

In weather systems, a mid-level relative humidity (such as at 700 hPa) can reflect the degree of atmospheric moisture and dryness and help understand the distribution and transport of atmospheric water vapor. Figure 6 shows the anomalies in the 700 hPa relative humidity during compound dry-hot events. Here, the anomalies are the differences between the annual relative humidity and the multi-year average (i.e., 1971–2018). In the first four events (i.e., 1971, 1977, 1991, and 1995), most of the Pearl River Basin shows positive relative humidity anomalies. Particularly in 1991, the positive anomalies across the entire basin are close to 10%. Coincidentally, significant negative anomalies are observed in major moisture source areas such as the South China Sea and the Western Pacific, especially in the South China Sea. Conversely, during the 2011 and 2018 compound events, most of the Pearl River Basin exhibits negative relative humidity anomalies (around -10%). However, the main moisture source areas show positive anomalies. Figure S1 shows the anomalies in relative humidity for

individual months, clearly indicating the changes in relative humidity during the compound events. Generally, a higher relative humidity means more abundant moisture and a higher likelihood of precipitation. However, according to the relative humidity analysis results, in several years (such as 1991), even though the relative humidity shows positive anomalies, the overall coverage area of compound dry-hot events remains large (Figure 5). Therefore, further in-depth investigation from more atmospheric circulation perspectives is needed.

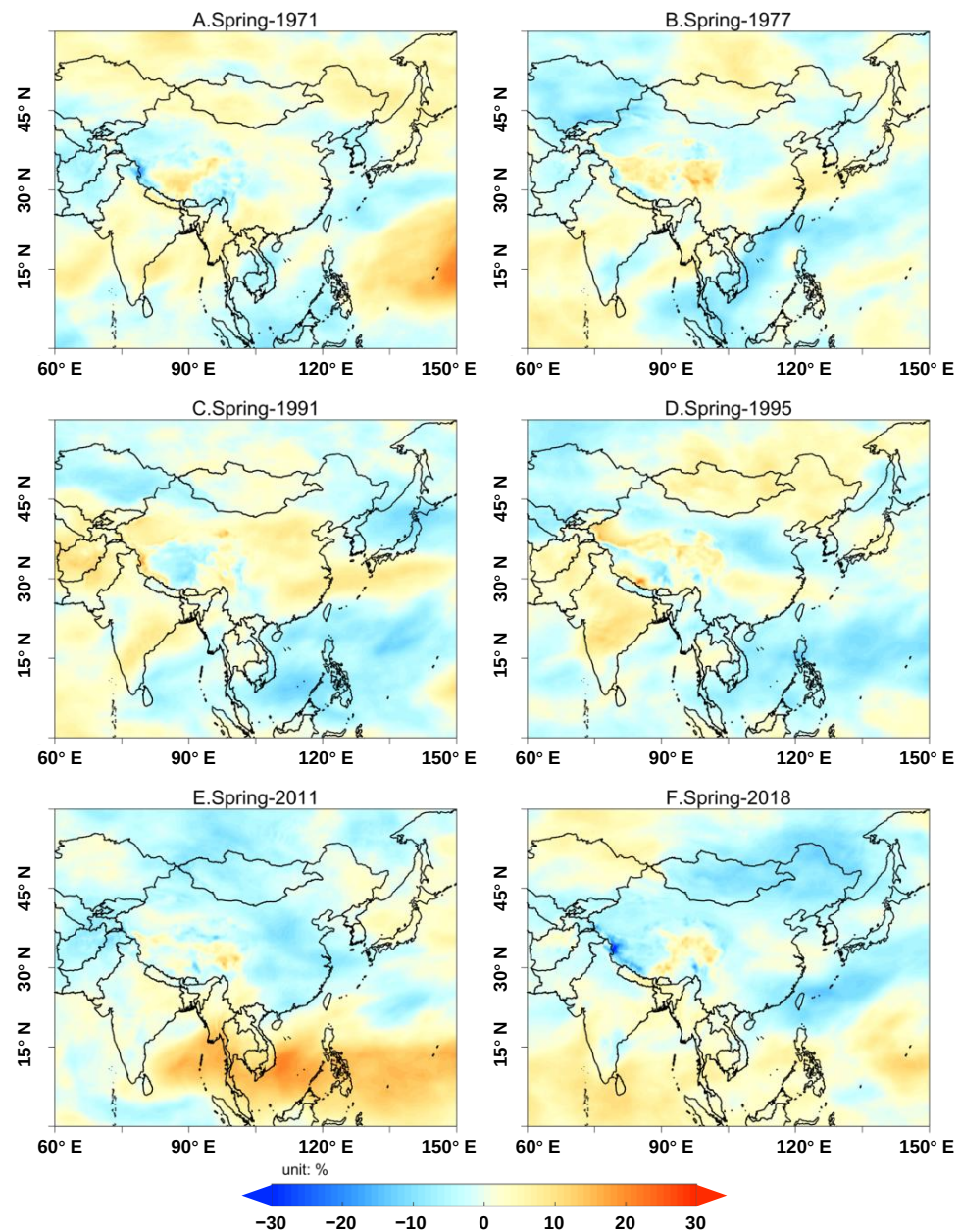


Figure 6. The difference in 700 hPa relative humidity (unit: %) for (A) 1971, (B) 1977, (C) 1991, (D) 1995, (E) 2011, and (F) 2018 compared to the multi-year average (i.e., 1971–2018). Note that these data are only for the spring season.

Figure 7 shows the anomalies in sea level pressure and 850 hPa wind fields. Similar to the relative humidity analysis, the sea level pressure and wind field anomalies are the differences between the annual values and the historical multi-year averages. Overall, during the six compound events, positive sea level pressure anomalies are observed across the entire basin. Persistent high-pressure systems stabilize the atmosphere, leading to prolonged dry weather and increasing the risk of dry-hot related extreme events.

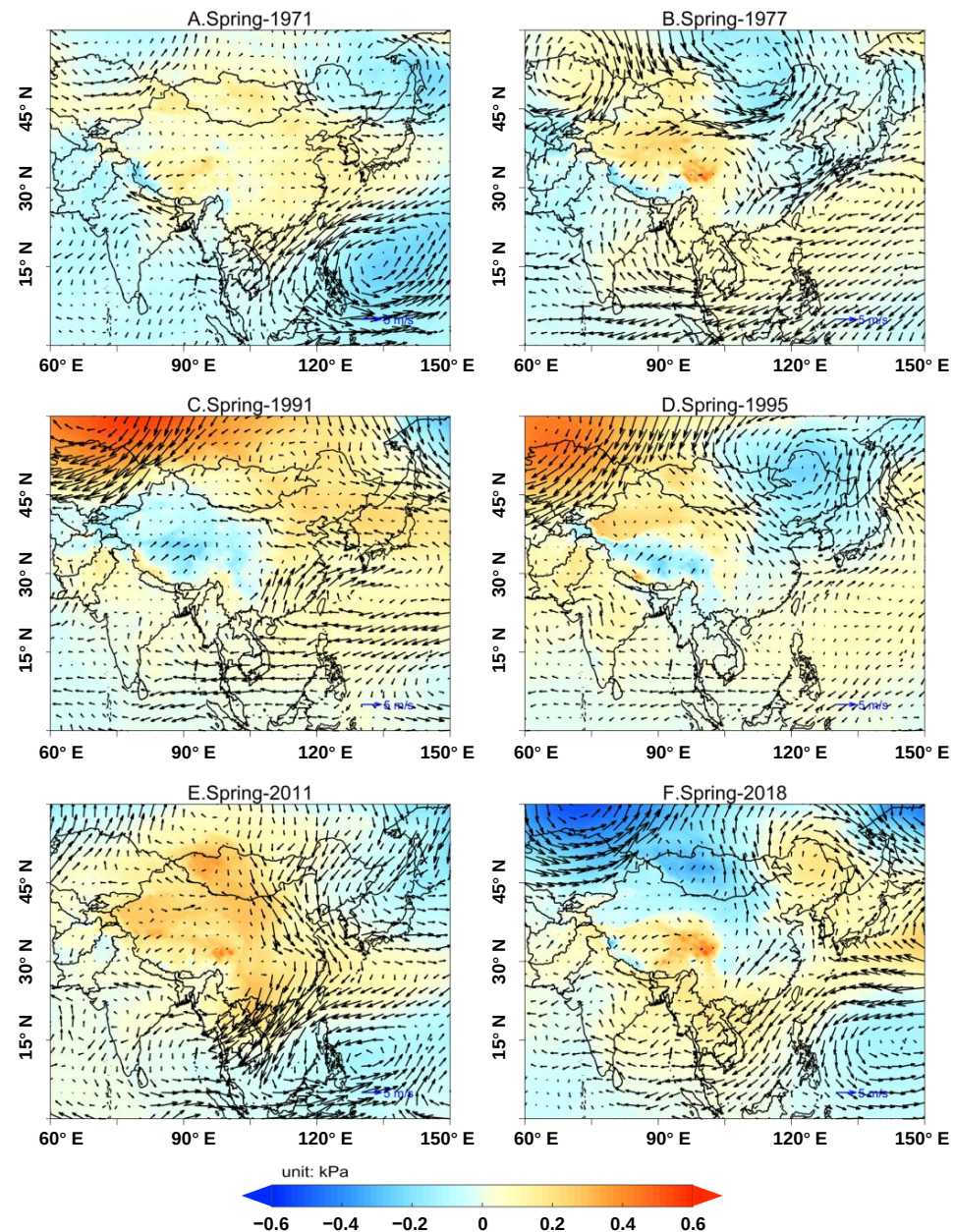


Figure 7. The difference in mean sea level pressure (shading; kPa) and 850 hPa wind field (vector; m/s) for (A) 1971, (B) 1977, (C) 1991, (D) 1995, (E) 2011, and (F) 2018 compared to the multi-year average (i.e., 1971–2018). Note that these data are only for the spring season.

The 850 hPa wind fields reflect the pathways and intensity of water vapor transport in the lower atmosphere [54]. The westerly transport from subtropical regions such as the Indian Ocean and the Bay of Bengal (20–25° N) is relatively weak. Additionally, water vapor from the western Pacific is also limited. For the compound event in 1971, strong easterly winds transport water vapor from the cyclonic region of the western Pacific (15° N, 135° E) southwestward, but the transport path has little impact on the Pearl River Basin. Similar patterns are observed in the compound events of 2011 and 2018. Notably, in the 2011 compound event, a strong low-level jet from Mongolia and Siberia is present, which also hinders water vapor retention. In the 1977 compound event, there is a northward airflow over the Pearl River Basin, but the weak easterly trade winds from the western Pacific convergence zone have little impact on the basin. Similar patterns are observed in the compound events of 1991 and 1995. Overall, the results from the 850 hPa wind fields indicate an insufficient water vapor input into the Pearl River Basin from multiple sources, increasing

the risk of prolonged dry conditions. Figure S2 shows the anomalies in sea level pressure and 850 hPa wind fields for individual months. No further analysis is provided here.

The Western Pacific Subtropical High (WPSH) is an important circulation system affecting weather and climate in East Asia, including China [55]. However, its influence on southern China is relatively limited in the spring. Figure 8 shows the anomalies in 500 hPa geopotential height. Within the illustrated geographic range (0° – 60° N; 60° – 150° E), the presence of the WPSH is only observed during the compound events of 1991 and 1995 (i.e., here, it only refers to the spring average). In the spring of 1991, the WPSH covers the South China Sea, possibly delaying the onset of the East Asian summer monsoon. Consequently, it hinders the northward movement of warm and moist air, leading to reduced precipitation in southern and eastern China. This circulation pattern also exacerbates the drying effect in southern regions, including the Pearl River Basin.

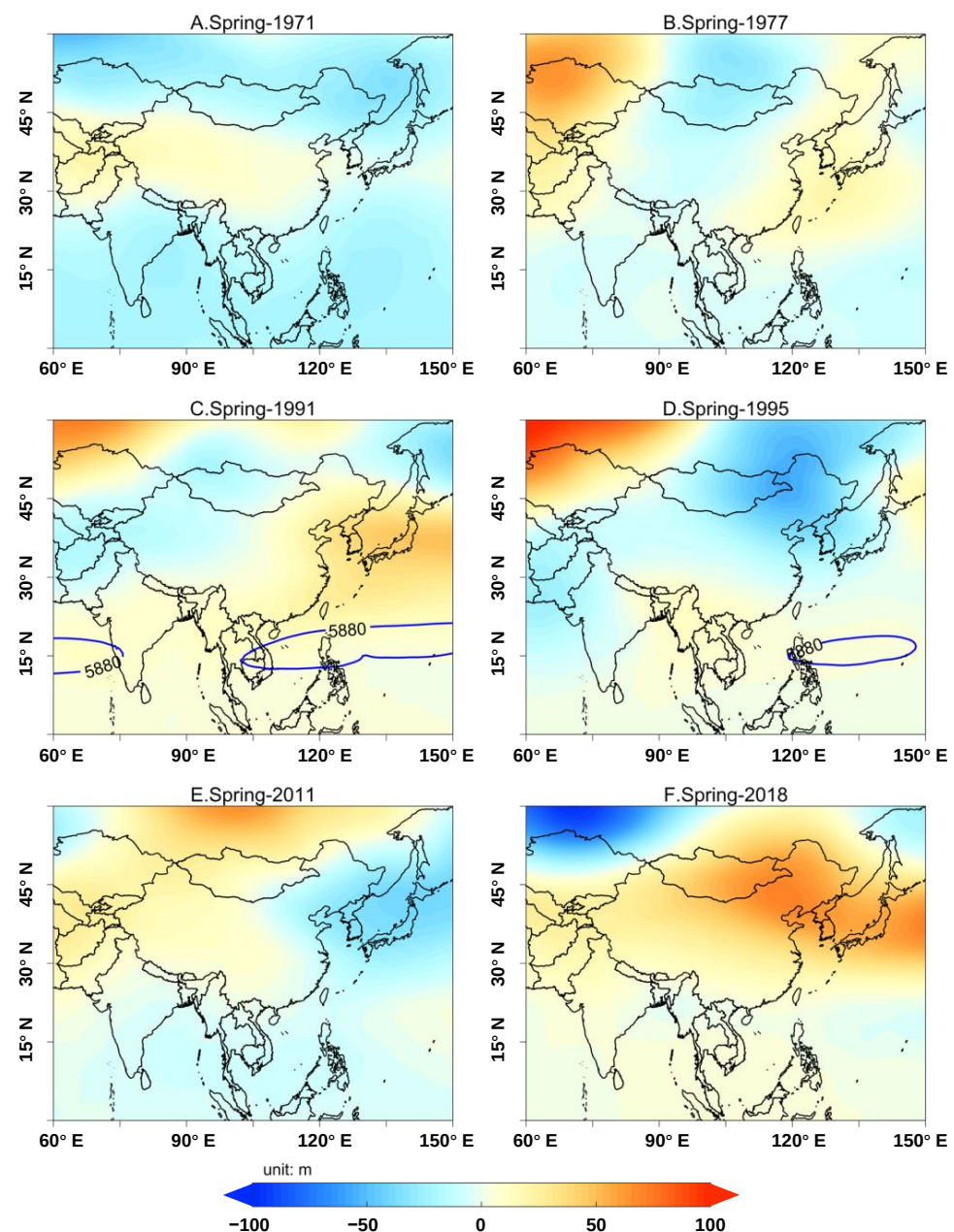


Figure 8. The difference in 500 hPa geopotential height (unit: m) for (A) 1971, (B) 1977, (C) 1991, (D) 1995, (E) 2011, and (F) 2018 compared to the multi-year average (i.e., 1971–2018). Note that these data are only for the spring season.

The WPSH remains relatively stable and persists over the Western Pacific throughout the year. Its activity can be influenced by various factors and on multiple time scales, showing significant seasonal and interannual variations. For its interannual variations, existing research indicates that the El Niño–Southern Oscillation (ENSO) may play a crucial role [56,57]. Based on this, this study identifies El Niño and La Niña events using the indicators shown in Figure S4 and further evaluates their impact on the WPSH. The results show that all six compound dry–hot events occur during El Niño (1977, 1991, and 1995) or La Niña (1971, 2011, and 2018) periods. According to the previous research, El Niño tends to cause the WPSH to be abnormally strong and shift westward, while La Niña results in the opposite characteristics [58]. Figure S3, which shows monthly changes in the geopotential height, also confirms this. For example, in 1991, an El Niño event starts in March, and the WPSH persists over the South China Sea. Notably, after the La Niña event in March 2018, an anomalous WPSH is observed. In particular, in May, the WPSH abnormally persists over the South China Sea, hindering warm moist airflow from entering the Pearl River Basin region. This result also aligns with the previous study [59]. For detailed reasons on the anomalous WPSH following La Niña events, one can refer to previous studies, as this study does not delve into this aspect [58]. Overall, El Niño/La Niña events impact the intensity and position of the WPSH. The anomalous WPSH then affects temperature and precipitation, thereby exacerbating the occurrence of compound dry–hot extreme events.

4. Discussion

4.1. Importance of Studying Spring Compound Dry–Hot Events

Understanding compound dry–hot events during the spring season in the Pearl River Basin (PRB) holds significant scientific and practical importance. Spring is a critical transitional period in southern China, marked by the high sensitivity in agriculture and ecosystems to climatic anomalies [60]. In particular, compound dry–hot events in this season may amplify the adverse impacts on early crop growth, water resource allocation, and ecological stability [61]. The combination of high temperatures and rainfall deficits during this period can disrupt the soil moisture balance and increase evapotranspiration, ultimately exacerbating drought stress and reducing agricultural productivity [62]. Given the PRB's role as an economic and agricultural hub, the effective identification and early warning of spring compound dry–hot events are crucial for disaster prevention and mitigation. Comparatively, research in other regions of China and globally has also revealed the occurrence of springtime compound dry–hot events, though their spatiotemporal characteristics differ due to regional climate dynamics. For example, in North China, spring droughts accompanied by warming trends have been observed in recent decades; yet, the co-occurrence of extreme dryness and heat is less frequent than in southern regions [60]. Studies in parts of mid- to high-latitude regions have also documented the occurrence of spring compound dry–hot events [63]. These studies suggest that warm and dry springs may trigger or exacerbate subsequent summer droughts, thereby reducing summer productivity.

This study conducts a clustering analysis of compound dry–hot events in the Pearl River Basin during spring, based on key variables such as temperature, precipitation, and climatic water balance. This approach somewhat mitigates the issues present in multi-indicator combination methods. However, it must be acknowledged that there is still considerable room for improvement in identifying compound dry–hot events. This improvement primarily focuses on data usage and clustering methods. Undeniably, temperature and precipitation are critical variables for identifying and defining compound dry–hot events. Yet, given the complexity of compound events, relying solely on a

limited set of climate variables may not fully capture the characteristic changes in the events. Related variables such as wind speed, radiation, and soil moisture, among other multi-source data, also need to be considered. Additionally, there are various clustering methods, each with its own advantages and disadvantages. Therefore, the choice of clustering method affects the accuracy of compound event identification. While the clustering results of this study are credible, it is necessary that we introduce more clustering methods and clear physical criteria. This will make the identification and assessment of compound events more robust.

4.2. Atmospheric Circulation Characteristics During Compound Events

The occurrence of compound dry-hot events is influenced by complex atmospheric conditions, often associated with the interaction of multiple large-scale circulation systems. Previous research has extensively studied this issue, focusing mainly on the following aspects: Firstly, climate change is a key driving factor. Global warming leads to rising temperatures and an increase in the frequency of extreme heat events. It also alters precipitation patterns, making some regions more prone to drought [13,14]. Secondly, changes in atmospheric circulation patterns significantly impact the occurrence of compound dry-hot events [59]. Additionally, changes in land use and vegetation play crucial roles in compound dry-hot events. Increased deforestation and agricultural activities alter surface evaporation and transpiration processes, thereby affecting the local water vapor balance and temperature [22]. Finally, ocean-atmosphere interactions, such as El Niño and La Niña phenomena, significantly affect the occurrence of compound dry-hot events [64].

Previous studies indicate that high-pressure systems can induce drought and heatwaves, often leading to their simultaneous occurrence [65]. Typically, high-pressure systems reduce moisture input, promoting drought, while also increasing clear sky conditions and shortwave radiation, resulting in extreme heatwaves. The findings of this study align with previous results. All six compound events analyzed show abnormal high-pressure systems over the Pearl River Basin, accompanied by anomalous wind fields that hinder moisture input. It should be acknowledged that the current analysis of compound dry-hot events remains preliminary. This study primarily focuses on characterizing large-scale atmospheric circulation patterns—such as the sea level pressure, wind fields, relative humidity, and geopotential height—during these events, aiming to identify circulation anomalies associated with their occurrence. However, other physical processes, including thermodynamic factors and land-atmosphere interactions, have not been fully examined. Future work incorporating multiple perspectives is essential in order to more comprehensively understand the environmental conditions under which compound events develop, particularly in the context of global warming.

5. Conclusions

This study establishes a novel analytical framework for identifying compound dry-hot events in the Pearl River Basin using multiple clustering methods. Unlike traditional approaches, the proposed framework captures the inherent complexity of compound events by integrating key climatic variables and ensuring classification consistency across different methods. This methodological advancement not only enhances the objectivity and robustness of event identification but also provides a solid foundation for the further exploration of their underlying physical mechanisms. Moreover, it contributes to improving the predictive capacity for potential future compound dry-hot events under a changing climate.

Based on three climatic variables (temperature, precipitation, and climate water balance anomalies), six spring compound dry–hot events are identified using three clustering methods and twenty-six evaluation criteria. Common characteristics show that precipitation and climate water balance exhibit negative anomalies, indicating severe water deficits that may lead to drought, while temperature shows positive anomalies, potentially increasing heat events. It is noteworthy that, during the six compound events, water deficits mainly concentrate in the eastern Pearl River Basin, especially in the Pearl River Delta region. Considering the high population density and significant contribution to China's GDP in the eastern Pearl River Basin, this spatial distribution pattern may adversely impact livelihoods and economic development. An atmospheric circulation analysis results show that a persistent abnormal high-pressure system exists, with relatively weak westerly transport from subtropical regions such as the Indian Ocean and the Bay of Bengal (20–25 °N), and limited moisture input from the western Pacific region. These circulation anomalies are often associated with the occurrence of spring compound dry–hot events in the Pearl River Basin.

While the analysis reveals meaningful patterns in the occurrence of springtime compound dry–hot events and offers insights into their potential large-scale circulation drivers, more sustained and multidimensional research is needed. Future work should focus on expanding the spatial–temporal scales, incorporating more meteorological and socioeconomic variables, and deepening the physical interpretation of such events under the influence of climate change.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/atmos16050516/s1>, Table S1. The criteria used to select the optimal number of clusters through the K-means method; Table S2. The criteria used to select the optimal number of clusters through the H-clust method; Table S3. The criteria used to select the optimal number of clusters through the Agnes method; Figure S1. Same to Figure 6, but for individual month; Figure S2. Same to Figure 7, but for individual month; Figure S3. Same to Figure 8, but for individual month; Figure S4. Monthly NINO 3.4 index.

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References

1. Bevacqua, E.; Zappa, G.; Lehner, F.; Zscheischler, J. Precipitation trends determine future occurrences of compound hot–dry events. *Nat. Clim. Change* **2022**, *12*, 350–355. [[CrossRef](#)]

2. Tian, R.; Li, J.; Zheng, J.; Liu, L.; Han, W.; Liu, Y. The impact of compound drought and heatwave events from 1982 to 2022 on the phenology of Central Asian grasslands. *J. Environ. Manag.* **2024**, *365*, 121624. [[CrossRef](#)] [[PubMed](#)]
3. Zhang, G.; Wang, H.; Liu, W.; Wang, H. Projections and uncertainty analysis of socioeconomic exposure to compound dry and hot events under 1.5 °C and 2.0 °C warming levels across China. *Theor. Appl. Climatol.* **2024**, *155*, 7539–7556. [[CrossRef](#)]
4. Chen, D.; Qiao, S.; Yang, J.; Tang, S.; Zuo, D.; Feng, G. Contribution of anthropogenic influence to the 2022-like Yangtze River valley compound heatwave and drought event. *npj Clim. Atmos. Sci.* **2024**, *7*, 172. [[CrossRef](#)]
5. Tabari, H.; Willems, P. Global risk assessment of compound hot-dry events in the context of future climate change and socioeconomic factors. *NPJ Clim. Atmos. Sci.* **2023**, *6*, 74. [[CrossRef](#)]
6. Zhang, Q.; Xu, C.Y.; Zhang, Z.; Chen, Y.D. Changes of atmospheric water vapor budget in the Pearl River basin and possible implications for hydrological cycle. *Theor. Appl. Climatol.* **2010**, *102*, 185–195. [[CrossRef](#)]
7. Qiang, Y.; Zhang, L.; He, J.; Xiao, T.; Huang, H.; Wang, H. Urban flood analysis for Pearl River Delta cities using an equivalent drainage method upon combined rainfall-high tide-storm surge events. *J. Hydrol.* **2021**, *597*, 126293. [[CrossRef](#)]
8. Yu, R.; Zhai, P. Changes in compound drought and hot extreme events in summer over populated eastern China. *Weather Clim. Extrem.* **2020**, *30*, 100295. [[CrossRef](#)]
9. Ridder, N.N.; Pitman, A.J.; Westra, S.; Ukkola, A.; Do, H.X.; Bador, M.; Hirsch, A.L.; Evans, J.P.; Di Luca, A.; Zscheischler, J. Global hotspots for the occurrence of compound events. *Nat. Commun.* **2020**, *11*, 5956. [[CrossRef](#)]
10. Ionita, M.; Caldarescu, D.E.; Nagavciuc, V. Compound hot and dry events in Europe: Variability and large-scale drivers. *Front. Clim.* **2021**, *3*, 688991. [[CrossRef](#)]
11. Manning, C.; Widmann, M.; Bevacqua, E.; Van Loon, A.F.; Maraun, D.; Vrac, M. Increased probability of compound long-duration dry and hot events in Europe during summer (1950–2013). *Environ. Res. Lett.* **2019**, *14*, 094006. [[CrossRef](#)]
12. Sutanto, S.J.; Vitolo, C.; Di Napoli, C.; D’Andrea, M.; Van Lanen, H.A. Heatwaves, droughts, and fires: Exploring compound and cascading dry hazards at the pan-European scale. *Environ. Int.* **2020**, *134*, 105276. [[CrossRef](#)] [[PubMed](#)]
13. Alizadeh, M.R.; Adamowski, J.; Nikoo, M.R.; AghaKouchak, A.; Dennison, P.; Sadegh, M. A century of observations reveals increasing likelihood of continental-scale compound dry-hot extremes. *Sci. Adv.* **2020**, *6*, eaaz4571. [[CrossRef](#)]
14. Abella, D.J.; Ahn, K.H. Investigating the spatial and temporal characteristics of compound dry hazard occurrences across the pan-Asian region. *Weather Clim. Extrem.* **2024**, *44*, 100669. [[CrossRef](#)]
15. Wu, X.; Hao, Z.; Tang, Q.; Singh, V.P.; Zhang, X.; Hao, F. Projected increase in compound dry and hot events over global land areas. *Int. J. Climatol.* **2021**, *41*, 393–403. [[CrossRef](#)]
16. Tripathy, K.P.; Mukherjee, S.; Mishra, A.K.; Mann, M.E.; Williams, A.P. Climate change will accelerate the high-end risk of compound drought and heatwave events. *Proc. Natl. Acad. Sci. USA* **2023**, *120*, e2219825120. [[CrossRef](#)]
17. Barriopedro, D.; Fischer, E.M.; Luterbacher, J.; Trigo, R.M.; García-Herrera, R. The hot summer of 2010: Redrawing the temperature record map of Europe. *Science* **2011**, *332*, 220–224. [[CrossRef](#)]
18. Lu, Y.; Hu, H.; Li, C.; Tian, F. Increasing compound events of extreme hot and dry days during growing seasons of wheat and maize in China. *Sci. Rep.* **2018**, *8*, 16700. [[CrossRef](#)]
19. Hu, Y.; Wang, W.; Wang, P.; Teuling, A.J.; Zhu, Y. Spatial-temporal variations and drivers of the compound dry-hot event in China. *Atmos. Res.* **2024**, *299*, 107160. [[CrossRef](#)]
20. He, Y.; Hu, X.; Xu, W.; Fang, J.; Shi, P. Increased probability and severity of compound dry and hot growing seasons over world’s major croplands. *Sci. Total Environ.* **2022**, *824*, 153885. [[CrossRef](#)]
21. Li, J.; Bevacqua, E.; Chen, C.; Wang, Z.; Chen, X.; Myneni, R.B.; Wu, X.; Xu, C.-Y.; Zhang, Z.; Zscheischler, J. Regional asymmetry in the response of global vegetation growth to springtime compound climate events. *Commun. Earth Environ.* **2022**, *3*, 123. [[CrossRef](#)]
22. Hao, Z.; Hao, F.; Xia, Y.; Feng, S.; Sun, C.; Zhang, X.; Fu, Y.; Hao, Y.; Zhang, Y.; Meng, Y. Compound droughts and hot extremes: Characteristics, drivers, changes, and impacts. *Earth-Sci. Rev.* **2022**, *235*, 104241. [[CrossRef](#)]
23. Mo, K.C.; Lettenmaier, D.P. Prediction of flash droughts over the United States. *J. Hydrometeorol.* **2020**, *21*, 1793–1810. [[CrossRef](#)]
24. Mukherjee, S.; Mishra, A.K. Increase in compound drought and heatwaves in a warming world. *Geophys. Res. Lett.* **2021**, *48*, e2020GL090617. [[CrossRef](#)]
25. McKinnon, K.A.; Poppick, A.; Simpson, I.R. Hot extremes have become drier in the United States Southwest. *Nat. Clim. Change* **2021**, *11*, 598–604. [[CrossRef](#)]
26. Vogel, J.; Paton, E.; Aich, V.; Bronstert, A. Increasing compound warm spells and droughts in the Mediterranean Basin. *Weather Clim. Extrem.* **2021**, *32*, 100312. [[CrossRef](#)]
27. Mukherjee, S.; Ashfaq, M.; Mishra, A.K. Compound drought and heatwaves at a global scale: The role of natural climate variability-associated synoptic patterns and land-surface energy budget anomalies. *J. Geophys. Res. Atmos.* **2020**, *125*, e2019JD031943. [[CrossRef](#)]
28. Zscheischler, J.; Fischer, E.M. The record-breaking compound hot and dry 2018 growing season in Germany. *Weather Clim. Extrem.* **2020**, *29*, 100270. [[CrossRef](#)]

29. Zhao, R.; Zhou, X.; Liu, J.; Li, Y.P.; Huang, G.H.; Li, C.H. Projections of compound wet-warm and dry-warm extreme events in summer over China. *J. Hydrol.* **2024**, *639*, 131635. [\[CrossRef\]](#)
30. Duan, R.; Huang, G.; Li, Y.; Zhou, X.; Ren, J.; Tian, C. Stepwise clustering future meteorological drought projection and multi-level factorial analysis under climate change: A case study of the Pearl River Basin, China. *Environ. Res.* **2021**, *196*, 110368. [\[CrossRef\]](#)
31. Baccour, S.; Goelema, G.; Kahil, T.; Albiac, J.; van Vliet, M.T.; Zhu, X.; Strokal, M. Water quality management could halve future water scarcity cost-effectively in the Pearl River Basin. *Nat. Commun.* **2024**, *15*, 5669. [\[CrossRef\]](#) [\[PubMed\]](#)
32. Yang, Y.; Zhang, Y.; Zhang, J.; Yu, C.; Xu, Z. Impacts of watershed nutrient loads on eutrophication risks under multiple socio-economic development scenarios in the Pearl River Estuary, China. *J. Clean. Prod.* **2025**, *496*, 145133. [\[CrossRef\]](#)
33. Duan, R.; Huang, G.; Zhou, X.; Li, Y.; Tian, C. Ensemble drought exposure projection for multifactorial interactive effects of climate change and population dynamics: Application to the Pearl River Basin. *Earth's Future* **2021**, *9*, e2021EF002215. [\[CrossRef\]](#)
34. Yang, T.; Shao, Q.; Hao, Z.C.; Chen, X.; Zhang, Z.; Xu, C.Y.; Sun, L. Regional frequency analysis and spatio-temporal pattern characterization of rainfall extremes in the Pearl River Basin, China. *J. Hydrol.* **2010**, *380*, 386–405. [\[CrossRef\]](#)
35. Zhang, Q.; Xiao, M.; Singh, V.P.; Li, J. Regionalization and spatial changing properties of droughts across the Pearl River basin, China. *J. Hydrol.* **2012**, *472*, 355–366. [\[CrossRef\]](#)
36. Chen, Y.D.; Zhang, Q.; Xiao, M.; Singh, V.P. Transition probability behaviors of drought events in the Pearl River basin, China. *Stoch. Environ. Res. Risk Assess.* **2017**, *31*, 159–170. [\[CrossRef\]](#)
37. Xu, F.; Zhou, Y.; Zhao, L. Spatial and temporal variability in extreme precipitation in the Pearl River Basin, China from 1960 to 2018. *Int. J. Climatol.* **2022**, *42*, 797–816. [\[CrossRef\]](#)
38. Ahmed, M.; Seraj, R.; Islam, S.M.S. The k-means algorithm: A comprehensive survey and performance evaluation. *Electronics* **2020**, *9*, 1295. [\[CrossRef\]](#)
39. Pike, M.; Lintner, B.R. Application of clustering algorithms to TRMM precipitation over the tropical and South Pacific Ocean. *J. Clim.* **2020**, *33*, 5767–5785. [\[CrossRef\]](#)
40. Ikotun, A.M.; Ezugwu, A.E.; Abualigah, L.; Abuhaija, B.; Heming, J. K-means clustering algorithms: A comprehensive review, variants analysis, and advances in the era of big data. *Inf. Sci.* **2023**, *622*, 178–210. [\[CrossRef\]](#)
41. Murtagh, F.; Contreras, P. Algorithms for hierarchical clustering: An overview. *Wiley Interdiscip. Rev. Data Min. Knowl. Discov.* **2012**, *2*, 86–97. [\[CrossRef\]](#)
42. Murtagh, F.; Legendre, P. Ward's hierarchical agglomerative clustering method: Which algorithms implement Ward's criterion? *J. Classif.* **2014**, *31*, 274–295. [\[CrossRef\]](#)
43. Wang, F.; Huang, G.H.; Cheng, G.H.; Li, Y.P. Impacts of climate variations on non-stationarity of streamflow over Canada. *Environ. Res.* **2021**, *197*, 111118. [\[CrossRef\]](#)
44. Yan, J.; Chen, J.; Zhan, J.; Song, S.; Zhang, Y.; Zhao, M.; Liu, Y.; Xu, W. Automatic identification of rock discontinuity sets using modified agglomerative nesting algorithm. *Bull. Eng. Geol. Environ.* **2022**, *81*, 229. [\[CrossRef\]](#)
45. Wijuniamurti, S.; Nugroho, S.; Rachmawati, R. Agglomerative Nesting (AGNES) Method and Divisive Analysis (DIANA) Method For Hierarchical Clustering On Some Distance Measurement Concepts. *J. Stat. Data Sci.* **2022**, *1*, 7–11. [\[CrossRef\]](#)
46. Jiang, Q.; Li, W.; Fan, Z.; He, X.; Sun, W.; Chen, S.; Wen, J.; Gao, J.; Wang, J. Evaluation of the ERA5 reanalysis precipitation dataset over Chinese Mainland. *J. Hydrol.* **2021**, *595*, 125660. [\[CrossRef\]](#)
47. Lavers, D.A.; Simmons, A.; Vamborg, F.; Rodwell, M.J. An evaluation of ERA5 precipitation for climate monitoring. *Q. J. R. Meteorol. Soc.* **2022**, *148*, 3152–3165. [\[CrossRef\]](#)
48. Paredes, P.; Pereira, L.S.; Almorox, J.; Darouich, H. Reference grass evapotranspiration with reduced data sets: Parameterization of the FAO Penman-Monteith temperature approach and the Hargeaves-Samani equation using local climatic variables. *Agric. Water Manag.* **2020**, *240*, 106210. [\[CrossRef\]](#)
49. Wang, T.; Zhang, Q.; Hannachi, A.; Hirooka, T.; Hegglin, M.I. Tropical water vapour in the lower stratosphere and its relationship to tropical/extratropical dynamical processes in ERA5. *Q. J. R. Meteorol. Soc.* **2020**, *146*, 2432–2449. [\[CrossRef\]](#)
50. Simmons, A.J. Trends in the tropospheric general circulation from 1979 to 2022. *Weather Clim. Dyn.* **2022**, *3*, 777–809. [\[CrossRef\]](#)
51. Revadekar, J.V.; Kothawale, D.R.; Rupa Kumar, K. Role of El Niño/La Niña in temperature extremes over India. *Int. J. Climatol.* **2009**, *29*, 2121. [\[CrossRef\]](#)
52. Tangang, F.; Farzanmanesh, R.; Mirzaei, A.; Supari, Salimun, E.; Jamaluddin, A.F.; Juneng, L. Characteristics of precipitation extremes in Malaysia associated with El Niño and La Niña events. *Int. J. Climatol.* **2017**, *37*, 696–716. [\[CrossRef\]](#)
53. Lu, E.; Cai, W.; Jiang, Z.; Zhang, Q.; Zhang, C.; Higgins, R.W.; Halpert, M.S. The day-to-day monitoring of the 2011 severe drought in China. *Clim. Dyn.* **2014**, *43*, 1–9. [\[CrossRef\]](#)
54. Zhou, T.J.; Yu, R.C. Atmospheric water vapor transport associated with typical anomalous summer rainfall patterns in China. *J. Geophys. Res. Atmos.* **2005**, *110*. [\[CrossRef\]](#)
55. Matsumura, S.; Horinouchi, T. Pacific Ocean decadal forcing of long-term changes in the western Pacific subtropical high. *Sci. Rep.* **2016**, *6*, 37765. [\[CrossRef\]](#)

56. He, C.; Zhou, T.; Wu, B. The key oceanic regions responsible for the interannual variability of the western North Pacific subtropical high and associated mechanisms. *J. Meteorol. Res.* **2015**, *29*, 562–575. [[CrossRef](#)]
57. Yun, K.S.; Ha, K.J.; Yeh, S.W.; Wang, B.; Xiang, B. Critical role of boreal summer North Pacific subtropical highs in ENSO transition. *Clim. Dyn.* **2015**, *44*, 1979–1992. [[CrossRef](#)]
58. Ke, M.; Wang, Z.; Pan, W.; Luo, H.; Yang, S.; Guo, R. Extremely strong western Pacific subtropical high in May 2021 following a La Niña event: Role of the persistent convective forcing over the Indian Ocean. *Asia-Pac. J. Atmos. Sci.* **2023**, *59*, 47–58. [[CrossRef](#)]
59. Zhang, L.; Zhou, T.; Chen, X.; Wu, P.; Christidis, N.; Lott, F.C. The Late Spring Drought of 2018 in South China. *Bull. Am. Meteorol. Soc.* **2020**, *101*, S59–S64. [[CrossRef](#)]
60. Li, J.; Wang, Z.; Wu, X.; Zscheischler, J.; Guo, S.; Chen, X. A standardized index for assessing sub-monthly compound dry and hot conditions with application in China. *Hydrol. Earth Syst. Sci.* **2021**, *25*, 1587–1601. [[CrossRef](#)]
61. Wu, X.; Hao, Z.; Hao, F.; Zhang, X. Variations of compound precipitation and temperature extremes in China during 1961–2014. *Sci. Total Environ.* **2019**, *663*, 731–737. [[CrossRef](#)] [[PubMed](#)]
62. Otkin, J.A.; Anderson, M.C.; Hain, C.; Mladenova, I.E.; Basara, J.B.; Svoboda, M. Examining rapid onset drought development using the thermal infrared-based evaporative stress index. *J. Hydrometeorol.* **2013**, *14*, 1057–1074. [[CrossRef](#)]
63. Li, E.; Zhao, J.; Pullens, J.W.; Yang, X. The compound effects of drought and high temperature stresses will be the main constraints on maize yield in Northeast China. *Sci. Total Environ.* **2022**, *812*, 152461. [[CrossRef](#)] [[PubMed](#)]
64. Zhang, Y.; Hao, Z.; Feng, S.; Zhang, X.; Hao, F. Changed relationship between compound dry-hot events and ENSO at the global scale. *J. Hydrol.* **2023**, *621*, 129559. [[CrossRef](#)]
65. Quesada, B.; Vautard, R.; Yiou, P.; Hirschi, M.; Seneviratne, S.I. Asymmetric European summer heat predictability from wet and dry southern winters and springs. *Nat. Clim. Change* **2012**, *2*, 736–741. [[CrossRef](#)]

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