Characteristics of spring consecutive dry days with different durations across China based on the objective zoning approach

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Funding information National Natural Science Foundation of China, Grant/Award Numbers: 41825010, 41991281

Abstract
The duration of dry periods is closely related to drought conditions and is used to evaluate the degree of drought. In this article, using the rotated empirical orthogonal function (REOF) and K-medoids clustering methods and considering the spatial continuity, 500 stations in China are divided into 10 clusters to analyze the variation characteristics of consecutive dry days (CDDs) with different durations in spring. In Clusters 1–5 over the middle and lower reaches of the Yangtze River, South China, North China, and eastern and western Southwest China, the contribution percentage of short-duration CDDs to total dry days decreases, while that of medium- and/or long-duration CDDs increases, which leads to an increase in the total dry days and the duration of CDDs. In Clusters 6–8, the total dry days decrease, which are mainly contributed by the decreases in medium-duration CDDs (for Cluster 6 over southern Northeast China) or long-duration CDDs (for Clusters 7–8 over northern Northeast China and southern Xinjiang). The total dry days change little in Clusters 9–10 over eastern Northwest China and northern Xinjiang, which is attributed to the offset among the changes in the three-type duration CDDs. In Clusters 6–10, the duration of CDDs shortens overall. The decadal changes of spring dry days in China exhibit remarkable regional differences. The total day days and three-type duration CDDs in some clusters (1, 4, and 8) all have significant decadal changes, but they have not in Cluster 7. And the decadal change times also exhibit regional differences. The investigation of different-duration CDDs in this study provides more information on droughts at different time scales in China.

KEYWORDS
cluster, consecutive dry days, duration
1 | INTRODUCTION

The length of dry periods can directly reflect the degree of drought and is often used to assess drought conditions (Ye and Fetzer, 2019; Zhang et al., 2019a). A long dry period leads to insufficient precipitation and causes serious drought, which has adverse effects on agricultural production, vegetation growth, and human society (Huth et al., 2000; Tao et al., 2009; Zhang et al., 2015; Ye, 2018). Therefore, it is of great relevance to investigate the variation in the consecutive dry days (CDDs).

In China, previous studies on the spatial and temporal variations of dry periods have mainly focused on maximum CDDs (Wang and Yan, 2009; Ma and Zhou, 2015; Duan et al., 2017; Wang et al., 2021). Other studies investigated the variations in CDDs with different durations and their contribution to the total dry days. For example, Gong et al. (2004) found that the frequency of CDDs with durations of less than 10 days in summer decreases slightly in North China, while the CDDs with durations greater than or equal to 10 days substantially increase. Liu et al. (2015) indicated that over Northeast China, the frequency of CDDs with durations greater than or equal to 10 days increases during the summer half-year but decreases during the winter half-year, and the duration of dry periods during the summer half-year has extended since the 1990s.

In addition to the yearly mean or the winter/summer half-year mean, spring CDDs have also been emphasized because spring is the sowing season in China, and the precipitation conditions during this period are very important for plowing, sowing, and crop growth. It has been reported that in spring, the total dry days increase significantly in South China and Central China during 1958–2007 (Wu et al., 2011). Contrast to changes in the total dry days in these two regions, the spring precipitation frequency decreases significantly from the late 1950s to around 2010 (Zhang and Cong, 2014; Ma and Zhou, 2015). Furthermore, the maximum CDDs in spring increase in the middle reaches of the Yellow River and Southwest China but decrease in Northwest and Northeast China from the early 1960s to around 2010 (Wang and Yan, 2009; Huang et al., 2014). Comparable, few studies have focused on the variation in CDDs with different durations in China during spring. However, investigating CDDs with different durations is important. The total dry days and the maximum CDDs cannot accurately reflect the actual features of droughts at different timescales. Therefore, in this article, we try to analyze dry periods with different durations in spring across China, with the aim of improving our understanding of the variation in droughts at different timescales and providing more information to different stakeholders that are interested in droughts of different durations.

The remainder of this article is organized as follows: the data and analysis methods are introduced in Section 2. The division of the dry days in spring is shown in Section 3. In Section 4, the contribution of CDDs with different durations to the total dry days and the corresponding intra-annual and interdecadal variations are investigated. Finally, a summary and discussion are given in Section 5.

2 | DATA AND METHODS

2.1 | Data

Daily station precipitation data for the period of 1961–2016 are provided by the National Meteorological Information Center of China Meteorological Administration (http://data.cma.cn). The data were subjected to strict quality control before release. In this study, the stations with missing data for more than 10% of the days in a given year or 1% of the days over the 56-year period are removed, and the remaining missing daily records are filled by their climatological values, which is consistent with a previous study (Sun and Ao, 2013). Then, according to the previous study of Han and Zhai (2015), the stations with an altitude greater than 3 km, which are mainly over the Tibetan Plateau, are removed because these sparsely distributed stations over the complex terrain region could show limited representativeness for the regional precipitation variability (Li and Li, 2017). Finally, precipitation data at 500 stations are used in this study.

2.2 | Methods

A threshold value of 0.1 mm is used, and days with precipitation less than this threshold are considered dry days (Gong et al., 2004; Rajah et al., 2014). The duration of CDDs indicates the number of consecutive days with daily precipitation less than this threshold. The Cressman method is used to interpolate the total dry days at stations to a 0.5° × 0.5° grid for climate analysis.

The Theil–Sen trend estimation method is used to analyze the trend of CDDs (Sen, 1968), and the nonparametric Mann–Kendall test is used to test the significance (Kendall, 1975). For a detailed description of these methods, please refer to Mondal et al. (2012). The 11-year moving t-test is used to analyze the decadal variation of CDDs with different durations.

In terms of regional identification, we use a combination of the rotated empirical orthogonal function (REOF) and cluster analysis and consider the spatial continuity of the clustering results. Clustering with the reduced dimensions from the REOF is very effective in data classification (Saha et al., 2019) and has been applied to
geographical zoning in many studies (Han and Zhai, 2015; Yao, 2020). In this article, the K-medoids clustering method is selected. In the K-medoids clustering, each cluster is identified by its most representative observation. Compared to the k-means clustering that is based on means, K-medoids clustering is insensitive to outliers. For a detailed description of this method, please refer to Kabacoff (2015).

The specific scheme is as follows. First, the REOF method is used to extract the main modes of the total dry days. Then, the K-medoids method is used to cluster the load factors to obtain the initial station division. On this basis, this article uses a distance coefficient \(D\) to improve the results. We take the stations with the largest load factor in each cluster as center points and calculate \(D\) between all stations and central stations. If \(D\) is the smallest between a certain station and the center point, then the station and the center point are grouped into one cluster. The selection of the coefficient mainly follows Du et al. (2016), but some changes have been made.

\[
R(i,j) = \begin{cases} 
0 & \text{if } pr(i,j) \leq 0.01 \\
1 - r(i,j) & \text{if } pr(i,j) > 0.01, 
\end{cases} 
\]

\[
A(i,j) = 1 - ASR(i,j), 
\]

\[
G(i,j) = \begin{cases} 
0 & \text{if } GCD(i,j) \leq \text{res} \\
GCD(i,j)/\text{Ceof} & \text{if } GCD(i,j) > \text{res}, 
\end{cases} 
\]

\[
D(i,j) = R(i,j) + A(i,j) + G(i,j). 
\]

The calculation of the coefficient is shown in formulas (1)–(4), where \(R(i,j), A(i,j),\) and \(G(i,j),\) respectively, reflect the correlation of the total dry days, the consistency of the anomalies of the total dry days, and the geographical difference between stations; \(r\) is the correlation coefficient of the total dry days between stations, and \(pr\) is the significant level; \(ASR\) is the same sign rate of the total dry days anomalies; \(GCD\) is the great circle distance, and \(\text{res}\) is the threshold of the great circle distance. Due to the large spatial area and relatively sparse stations in western China, for the central station in eastern/western China (east/west of 97.5°E), the res is 300/500 km. Ceof is the great circle distance coefficient, which is mainly used to make the magnitude uniform. Similarly, the Ceof is 500/1000 km for central stations in eastern/western China.

3 | REGIONAL DIVISION OF TOTAL DRY DAYS IN SPRING

The regional identification scheme used in this article is based on the total dry days, so it is necessary to first discuss the climatology and temporal variation in the total dry days in spring. As shown in Figure 1, climatologically, the total dry days gradually increase from the southeast coast to the northwest inland. The low-value areas are mainly in southern China, with values below 40 days. The high-value areas are located in southern Xinjiang, with values greater than 85 days. Additionally, there are large regional differences in the total dry days in Northeast China and Xinjiang, with an approximately 10-day difference between eastern and western Northeast China and a more than 15-day difference between southern and northern Xinjiang.

In terms of trends, the total dry days increase significantly in the middle and lower reaches of the Yangtze River and the Huanghuai region, with values greater than 2.5 days per decade. The significant increase in the total dry days in Southwest China mainly occurs in the Sichuan Basin, and the total dry days in North China and the coastal areas of South China increase slightly. In contrast, there is a significant decreasing trend in the total dry days in Northeast China, with a maximum decrease of more than 1.5 days per decade. The total dry days in Northwest China show nearly zero trends.

It should be noted that in Figure 1, the trends of two stations are different from adjacent stations in North China and Sichuan Province. We further check the rainfall data at these two stations. We find that the time series of precipitation and dry days shows inhomogeneity at the station in North China (Wutai mountain station), which could be related to the changes in the station location in 1998 (Gao et al., 2008). The time series of precipitation and dry days at the station in Sichuan Province seem to be reasonable, and we do not find the relocation
record of this station; however, considering the trend in the total dry days at this station is much stronger than its adjacent stations, the changes in this station could mainly reflect the local information. Therefore, to more reasonably reflect the regional features of the dry days over the two regions, in the following analysis, these two stations are removed.

Then, the REOF is performed on the total dry days in spring. As shown in Figure 2, the accumulated variance contribution of the first eight modes is more than 60%. The eight modes are located in North China, South China, the middle and lower reaches of the Yangtze River, southern Northeast China, southern Northwest China, northern Xinjiang, northern Northeast China, and Southwest China, covering the main regions of China; therefore, these modes are selected as the basis for clustering.

After obtaining the first eight modes, K-medoids clustering is performed based on the load factor of each mode. It should be noted that the optimal number of clusters is nine. Southwest China is divided into two clusters: western and eastern Southwest China. In addition, the K-medoids clustering classifies southern Northwest China into one cluster (the figure is omitted). However, due to the large east–west geographic span and the variation in precipitation in the eastern and western parts of this area being affected by different circulation systems (Zhang et al., 2019b), we further divide this region into two clusters (southern Xinjiang and eastern Northwest China) with the boundary at 97.5°E (Shi and Xu, 2007). Therefore, all stations are divided into 10 clusters. Considering the spatial continuity further, the distance coefficient is introduced to improve the clustering results, as introduced in Section 2. Finally, we obtain the regional division of the total dry days over China in spring, as shown in Figure 2i and Table 1.

## 4 Spatial and Temporal Variations in CDDs

Based on the abovementioned divisions, this section investigates the variation in CDDs with different
The variations in contribution percentages of CDDs in Clusters 6 and 9 are somewhat reversed. The CDDs increase/decrease for durations of 1–4 days in Cluster 6/9. Although the trends of CDDs with durations of 5–18/5–14 days show a wave variation, the accumulated
trends generally exhibit a decreasing/increasing trend. When the duration is greater than 18/14 days, the trend and accumulated trend increase/decrease weakly and then are nearly zero. Hence, CDDs in Cluster 6/9 can be generally divided into three categories with durations of 1–4 days (short duration), 5–18/5–14 days (medium duration), and greater than 18/14 days (long duration). The short-duration CDDs climatologically contribute 24 and 24.7% of the total dry days in Clusters 6 and 9, respectively. The medium-duration CDDs contribute 58.4 and 41.6%, and the long-duration CDDs contribute 17.6 and 33.7%, in Clusters 6 and 9, respectively. For the trend, only the contribution percentages of medium-duration CDDs in Cluster 6 exhibits a significantly decreasing trend with a value of 1.2% per decade.

To some extent, the trends of the contribution percentages of CDDs in Clusters 7 and 8 show similar features. The CDDs with durations of 1–3/1–13 days increase and the CDDs with durations of 4–15/14–50 days decrease and increase alternately in Cluster 7/8. When the duration is greater than 15/50 days, the trends of CDDs are first decreasing and
then nearly zero. Therefore, CDDs can be generally divided into three categories with durations of 1–3/1–13 days (short duration), 4–15/14–50 days (medium duration), and greater than 15/50 days (long duration) in Cluster 7/8. The short-duration CDDs climatologically contribute 17.6 and 18.9%, the medium-duration CDDs contribute 62 and 47.5%, and the long-duration CDDs contribute 20.4 and 33.6% of the total dry days in Clusters 7 and 8, respectively. In Cluster 7, only the contribution percentages of long-duration CDDs show a significant decreasing trend with a value of 1.3% per decade. In Cluster 8, the contribution percentages of short-duration CDDs have a significant increasing trend with a value of 0.9% per decade.

The aforementioned results indicate that the CDDs with different durations show different trends. If we only investigate the total dry days, the average of the different-duration CDDs may miss important features. For example, the short- and medium-duration CDDs increase, but the long-duration CDDs decrease in Cluster 8; the weak

**FIGURE 4** The time series of the total dry days and accumulated days of the short-, medium-, and long-duration CDDs (thick solid line, unit: day) in 10 clusters, and the corresponding linear regression lines (thin dashed line). The thick horizontal lines indicate that averaged dry days over the two 11 years before and after the significant decadal change. The values to the right of the colon indicate the linear trends (unit: day/10a) and the confidence level (the values in the brackets), and the different colors of the values are related to different time series
trends of the total dry days could mask this situation. Therefore, it is necessary to investigate the variation in the CDDs with different durations; in particular, we should focus on medium- and long-duration CDDs because these CDDs can result in dry conditions.

Next, we investigate the time series of total dry days and accumulated days of short-, medium-, and long-duration CDDs in 10 clusters. As shown in Figure 4, the total dry days in Clusters 1, 3, and 4 show a significant increasing trend during the past half-century, and the increase is mainly attributed to the changes in the medium-duration CDDs. There is a significant trend in the medium-duration CDDs for Clusters 2, 6, and 10 and the long-duration CDDs for Cluster 7, but this change is offset by the other two types of CDDs, so the total dry days change insignificantly in these four clusters. For Cluster 5, the increase in the total dry days is mainly caused by the long-duration CDDs. In Clusters 8 and 9, the CDDs with different durations change insignificantly, so the total dry days in these two clusters have little change.

The CDDs also exhibit a significant decadal change in the past half-century. Figure 4 shows that the total dry days in Clusters 1, 2, and 4 have a generally common decadal increase around the early 2000s, which is mainly attributed to the changes in the medium-duration CDDs (Clusters 1 and 4) or short-duration CDDs (Cluster 2). In addition, the medium-duration CDDs in Clusters 1, 2, and 4 show a decadal increase around the mid-1980s.

FIGURE 5  Schematic diagram of the variations in the total dry days and accumulated days of short-, medium-, and long-duration CDDs in 10 clusters of China. The different (black) marks in China indicate the stations (central station) of each cluster. The (solid) arrows of ↑ and ↓ denote the (significant) increasing and decreasing trends, respectively, and the arrow of = denotes nearly zero trends. The values in the brackets denote the years when the significant decadal change occurs, and the marks of +/− indicate the increase/decrease decadal change.
consistent decadal changes in medium-duration and long-duration CDDs in Cluster 4 contribute to the decadal increase in the total dry days around the mid-1980s. The total dry days in Clusters 3, 6, and 9 (5) have an increasing decadal change around the mid-1990s (mid-2000s); however, the three-type duration CDDs in these clusters do not show a corresponding significant decadal change. The total dry days in Clusters 8 and 9 show a decadal decrease around the early 1980s, which is mainly from the changes in the long-duration CDDs. In Cluster 10, the only significant decadal change occurs for the medium-duration CDDs around the late 1990s. Different from the aforementioned nine clusters, the CDDs in Cluster 7 have no significant decadal change during the past half-century. These results further indicate the importance of investigations of different durations. The total dry days or the maximum CDDs cannot accurately reflect the variability of the CDDs in China during spring.

5 SUMMARY AND DISCUSSION

In this article, based on the REOF, K-medoids clustering method, and the distance coefficient accounting for the spatial continuity, the spatiotemporal characteristics of the CDDs in spring across China are investigated. Climatologically, the total dry days in spring across China increase from the southeast coast to the northwest inland, with southeast–northwest and south–north gradients, and China can be divided into 10 clusters.

Figure 5 summarizes the variation in the total dry days and the different-duration CDDs for each cluster. Generally, the total dry days increase and the short-duration CDDs decrease in southern China and North China, while the medium-duration and/or long-duration CDDs increase, indicating a longer drought over these regions. The total dry days decrease over northern Northeast China and southern Xinjiang (southern Northeast China), which is mainly attributed to the changes in the long-duration (medium-duration) CDDs. Over eastern Northwest China and northern Xinjiang, the medium-duration CDDs increase; however, this change is offset by the other two durations of CDDs, resulting in a little change in the total dry days. In brief, for the 10 clusters in China, the medium-duration CDDs increase in the most of clusters (increase in 9 clusters vs decrease in 1 cluster), the short-duration CDDs decrease in the most of clusters (decrease in 6 clusters vs increase in 3 clusters), and the long-duration CDDs decrease in half of the clusters. Such changes in the different duration CDDs contribute to the increase in total dry days in all clusters in southern China but the decrease in most clusters in northern China.

On the decadal scale, the three significant decadal changes in the total dry days are around the early 2000s in most clusters in southern China, the mid-1990s in North China, southern Northeast China, and eastern Northwest China as well as the early 1980s in southern Northwest China. For the short-duration CDDs, the significant decadal change is around the early 1980s in the middle and lower reaches of the Yangtze River, South China, eastern Southwest China, and southern Xinjiang, and another is around the late 1990s in South China. The three main significant decadal changes in the medium-duration CDDs are around the late 1990s to early 2000s in half of all clusters, around the mid-1980s in southern Northeast China and most clusters in southern China, and around the early 1970s in western Southwest China and southern Northeast China. For the long-duration CDDs, the decadal changes are mainly occurring around the mid-1980s in eastern Southwest China and southern Northwest China; another two decadal changes are around the early 1970s in southern Northeast China and eastern Southwest China and the late 1970s in the middle and lower reaches of the Yangtze River.

This analysis indicates that the CDDs in China during spring exhibit complicated variations. Investigating the different-duration CDDs can provide more information to reflect the different timescale droughts, which could be valuable for local agricultural activity. To better understand the variation in the CDDs, the reasons for the variation in different-duration CDDs need to be known. Therefore, in future research, the impact factor and predictor for spring CDDs should be systematically studied.

ACKNOWLEDGEMENTS
This study was supported by the National Natural Science Foundation of China (Grant No. 41825010 and 41991281).

CONFLICT OF INTEREST
The authors declare no conflicts of interest.

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How to cite this article: Zeng Z, Sun J. Characteristics of spring consecutive dry days with different durations across China based on the objective zoning approach. *Atmos Sci Lett*. 2021;22:e1035. https://doi.org/10.1002/asl.1035