Interannual Variation and Statistical Prediction of Summer Dry and Hot Days in South China from 1970 to 2018

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Abstract: The frequent occurrence of dry and hot (DH) days in South China in summer has a negative impact on social development and human health. This study explored the variation characteristics of DH days and the possible reasons for this knotty problem. The findings revealed a notable increase in the number of DH days across most stations, indicating a significant upward trend. Additionally, DH events were observed to occur frequently. The number of DH days increased during 1970–1990, decreased from 1991 to 1997, and stayed stable after 1997. The key climate factors affecting the interannual variability of the number of DH days were the Indian Ocean Basin warming (IOBW) in spring and the East Asian Summer Monsoon (EASM). Compared with the negative phase of IOBW, in the positive phase of IOBW, 500 hPa and 850 hPa geopotential height enhanced, the West Pacific subtropical high strengthened and extended abnormally to the west, more solar radiation reached the surface, surface outgoing longwave radiation increased, and there was an abnormal anticyclone in eastern South China. The atmospheric circulation characteristics of the positive and negative phases of ESAM were opposite to those of IOBW, and the abnormal circulation of the positive (negative) phases of ESAM was unfavorable (favorable) for the increase in the number of DH days. A long-term prediction model for the number of summer DH days was established using multiple linear regression, incorporating the key climate factors. The correlation coefficient between the observed and predicted number of DH days was 0.65, and the root-mean-square error was 2.8. In addition, independent forecasts for 2019 showed a deviation of just 1 day. The results of the independent recovery test confirmed the stability of the model, providing evidence that climate factors did have an impact on DH days in South China.

Key words: dry and hot days; interannual variation; climate factors; statistical prediction

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1 INTRODUCTION

Under the background of global warming, extreme hot events are becoming more and more frequent. The continuous occurrence of extreme hot events will lead to higher morbidity and even higher mortality (Meehl and Tebaldi[1]). At the same time, drought is one of the costliest natural disasters worldwide. The effects of drought on human health are largely indirect. In the case of drought, dust and other particulate matter cannot settle and float in the air, which will increase the incidence of cardiopulmonary diseases, and drought will seriously affect human mental health and lead to a higher risk of death (Alpino et al.[2]; Berman et al.[3]; Stanke et al.[4]). Drought often occurs in conjunction with other climate phenomena (such as heat waves and wildfires), and the occurrence of drought can also affect human respiratory and circulatory systems, and in severe cases, it can cause death (Faustini et al.[5]; Bell et al.[6]). The severe negative impact of extreme heat and drying events on human health and the environment has attracted more attention.

Rapid changes in the global climate led to rapid changes in the hydrological cycle (Ma et al.[7]), including precipitation, evapotranspiration, runoff, and other related processes (Abdulahi et al.[8]; Supharatid et al.[9]). Moreover, extreme weather and climate events on a global and regional scale will increase in the future (Alexander et al.[10]; Coumou and Rahmstorf[11]). There have been many previous studies on extreme weather and climate, but they mainly focused on a single process or variable, for example, drought (e.g., Wu et al.[12]; Han et al.[13]; Feng et al.[14]), and extreme heat waves (e.g., Ding et al.[15]; Horton et al.[16]; Li and Amatus[17]; Luo et al.[18]). However, there is often a specific correlation between climate variables, and they may affect each other, so it may not be sufficient to fully describe the impact of extreme events by only exploring the effect of individual extreme variables. Compound extreme events that is, two or more extreme events occur simultaneously or consecutively; their influence is greater than the sum of the impacts of individual events, causing more serious consequences for the social and natural environment (Leonard et al.[19]). For...
instance, extreme hot and dry events like those experienced in Europe and Russia during the summers of 2003 and 2010 (Miralles et al. [20], Flach et al. [21]) had profound socioeconomic consequences. These events were associated with an estimated 40,000 deaths (García-Herrera et al. [22]), a 25% loss of annual crop yields (Barriopedro et al. [21]), and widespread forest fires (Fink et al. [24], Grumm [25]). Similarly, the extreme hot and dry event in the Yangtze River Delta in the summer of 2020 resulted in frequent mountain fires in Chongqing, causing significant losses in forest resources (Ma et al. [26]; Ma and Yuan [27]). Moreover, southern China experienced an intense drought and heat wave in July–August 2013, leading to the most substantial crop loss in the region since 1960 (Yuan et al. [28]).

In recent decades, the number of days with little or no precipitation in South China shows a significant increase trend (Wang et al. [29]). Meanwhile, the frequency of extreme hot events in China has also increased markedly, leading to enormous social and economic losses (Ding et al. [15], Wei and Chen [30]). In addition, densely populated and highly urbanized southern China (Guangdong, Fujian, Hainan, Guangxi Zhuang Autonomous Region) is more vulnerable to extreme weather events. Moreover, compared with other regions in China, the frequency of extreme high-temperature events in South China is the highest (Sun et al. [31]). Therefore, it is necessary to gain insight into the physical processes and mechanisms that lead to their occurrence.

Previous studies have revealed that the extreme events in China are associated with the East Asia summer monsoon (EASM) (Wang [32], Yin et al. [13]), the South China Sea summer monsoon (SCSSM) (Chen et al. [34], Lin and Zhang [35]), the Southwest Australian monsoon circulation (SWAC) (Feng et al. [36]), the western north Pacific subtropical high (WNPSH) (Choi and Kim [37]), and the sea surface temperature (SST) anomaly of the tropical Indian Ocean (TIO). Specifically, the stronger EASM pushes the rainfall front to the northwest, pushing a large amount of water vapor over East Asia (Lau and Li [38]). The SCSSM can significantly impact the circulation and weather in the northern hemisphere and the monsoon system in Asia (Zhang et al. [39]). The SCSSMI is usually closely related to severe drought and flood disasters and rainy season precipitation in China. Changes in WNPSH latitudinal position can substantially affect the water vapor transport and the resulting rainfall in its northwest margin (Yang and Sun [40]; Zhou and Yu [41]). The north-south movement of the WPSh is also closely related to the transfer of the summer rain belt from central China to Japan (Zhou and Yu [41]). The extreme heat waves event in South China was attributed to the exceptional westward displacement of the WPSh (Cao et al. [42]). During the positive (negative) WNPSH phase, the precipitation intensifies (weakens) over the oceanic continent and the EASM region (Cheng et al. [43]). TIO can bring abundant water vapor to East Asia, which will affect the temperature and precipitation of East Asian countries (Xie et al. [44]), and the pattern of Indian Ocean basin warming mode (IOBW) of sea surface temperature (SST) during boreal summer may result in surface temperature and precipitation anomalies in a wide area of Asia (Sun et al. [45]).

The purposes of this study are as follows: (1) to explore the characteristics of the interannual variation of DH days in South China, and to find out the potential climatic factors affecting this variation; (2) to set up the statistical forecast model by the climate factor to predict the interannual trend of DH days.

2 DATA AND METHOD

2.1 Data

The China Meteorological Data Service Center provided data on total daily rainfall and maximum temperature (T_{mx}). In this study, a day is considered a no-precipitation (NP) day if the quantity of precipitation is 0 mm, and a hot day is one where the T_{mx} exceeds the 85th percentile (35 °C) of T_{mx} during the summer of 1970 to 2018 as suggested by Liu et al. [40], and a DH day is one when both conditions are true. Because of the difference in duration, DH days can be subdivided into three different groups: short-term events (1–2 days), moderately persistent events (3–5 days), and long-term events (more than five days).

NCEP/NCAR reanalysis data (Kalnay et al. [47]) from 1970 to 2018 were used to analyze atmospheric circulation anomalies for the difference in the number of DH days key climate factors’ positive and negative phases. The Physical Sciences Laboratory of the NOAA provided the monthly Southern Oscillation (SO) Index (SOI). The EASM Index (EASMI), the SCSSM Index (SCSSMI), and the SWAC Index (SWACI) are the monsoon indices employed in this study (Li and Zeng [48–50]). The intensity index of the WPSh and Indian Ocean Basin warming (IOBW) in spring was from the National Climate Center.

2.2 Analysis methods

2.2.1 TREND ANALYSIS

Mann-Kendall (MK) trend test (Mann [51], Kendall [52]) was used to calculate the long-term trend of DH days and test the significance of the trend, which is a non-parametric approach and one of the most frequently applied methods for detecting changes in hydrology and climatology.

2.2.2 HIGH-PASS FILTER

We opted for the Butterworth high-pass filter (BHPF) due to its flat frequency response within the passband and minimal fluctuations in the curve. It ensures a smooth transition and avoids sudden discontinuities at the cutoff frequency D_0. The system function of the BHPF, with the cutoff frequency positioned at a distance from the origin D_0, can be defined as follows:

$$H_{BHPF}(u,v) = \frac{1}{1 + (\frac{D_0}{D(u,v)})^{2n}}$$

where n represents the order of the Butterworth filter, D_0
represents the center of the frequency domain, and $D(u,v)$ represents the distance from the center of the frequency domain to the plane of the frequency domain, which is the cutoff frequency.

2.2.3 RECYCLING INDEPENDENT TEST

Considering the constraints posed by the available data timeframe, this study employs a recycling independent test using data from 1970 to 2008 as the training set. The objective is to assess the stability and robustness of the forecasting model. Specifically, the model is trained using observation data from 1970 to 2008 to predict the number of dry and hot days in the years 2009 to 2018. Subsequently, observation data from 1970 to 2009 is utilized to predict the number of dry and hot days from 2010 to 2018. Following this pattern, predictions are made for each year, with 10 predictions for 2018, 9 predictions for 2017, and a decreasing number of predictions from 2016 to 2009. This approach allows for a comprehensive evaluation of the model’s performance over multiple forecast periods.

2.2.4 OTHERS

To examine the correlation between climate factors and DH days, we employed Pearson correlation analysis along with the two-tailed Student’s $t$-test. Furthermore, we utilized multiple linear regression to explore the relationship between the interannual trend of climatic factors and DH days. Additionally, we conducted a relative importance test on the climate factors to determine their respective contributions in predicting DH days. Using a multiple linear regression model, we predicted the change characteristics of DH days based on these factors.

3. RESULTS AND DISCUSSIONS

3.1 Spatiotemporal variation characteristics of NP days, hot days, and DH days

The variation characteristics of the number of NP days, hot days, and DH days in South China from 1970 to 2018 are shown in Fig. 1. The spatial distribution of the trend of the number of hot days and DH days from 1970 to 2018 is almost identical, while the spatial distribution of NP days is different. The number of NP days shows a decreasing trend at most stations in eastern South China but an increasing trend in most stations in the western and southern regions (Fig. 1a). The number of hot days at most stations has a significant upward trend and a few coastal stations show a downward trend (Fig. 1b). The spatial variation characteristics of DH days are similar to hot days (Fig. 1c). In terms of relative changes (relative to the average of 1970 to 2018), the variations among different stations are more consistent (see Fig. S1 in Appendix).

Figure 2a shows the long-term trend of the number of NP days, hot days, and DH days in South China from 1970 to 2018. The three trends all show a significant upward trend from 1970 to 1990 and a downward trend from 1990 to 1997, and the trend is not important after 1997. After high-pass filtering (Fig. 2b), they all show significant interannual variation characteristics, with abnormally high values in 1996, 1998, and 2000 but abnormally low in 1997 and 1999. Except for Hainan Province, the long-term trend of NP days, hot days, and DH days in the other three provinces are basically consistent with the regional changing trends (see Figs. S2-S5 in Appendix).

Continuous occurrences of DH days will aggravate the adverse effects; therefore, we further investigate the changing characteristics of DH events (Fig. 3). Since 1970, there has been an increasing trend in the frequency of all DH events. The frequency of short-term and moderate-
duration events was relatively infrequent from 1971 to 1999 but increased substantially after 1999 (Figs. 3a and 3b). There is an obvious interannual variation for long-term events (Fig. 3c). It is evident from Fig. 3 that the change trends of short-term events and moderate-duration events align closely with the total number of hot and dry days. However, the long-term events exhibit distinct patterns. This suggests that short-term events and moderate-duration events have a more substantial influence on the annual variation of hot and dry days. Moreover, short-term events prove to be effective in capturing both the high and low values of the total number of hot and dry days.

3.2 Identification of key climate factors affecting DH days

Previous studies have highlighted the influence of various factors, such as EASM, WPSH, IOBW, SO, SCSSM, and SWAC, on DH days. In Table 1, we have summarized the correlation coefficients between these factors and the number of DH days. This suggests that their impact on the interannual variation of DH days is minimal. Consequently, we have narrowed our focus to EASM, SHI, IOBW, and SCSSM, as they exhibit stronger correlations. To observe their interannual variation trends over a 1–2 year period, we applied a high-pass filter to these four climate factors. Following the filtering process, the R between EASM, SHI, IOBW, SCSSM, and DH days are −0.56, 0.48, 0.58, and −0.53, respectively.

Figure 2. The observed time series (a) and the time series after high-pass filtering (b) of the annual average of the number of NP days, hot days, and DH days in summer from 1970 to 2018 (units: days).

Furthermore, we conducted a relative importance test on the climate factors to assess their respective contributions in predicting DH days. The results revealed that IOBW and EASM displayed relative importance exceeding 25%. This suggests that these two factors hold significant relevance and play a crucial role in predicting DH days.

These screened key climate factors were used to establish a multiple linear regression model to fit the time series of the number of DH days, and according to the coefficient of the multiple linear regression equation, the influence of the key climatic factors on the trend of DH days was quantified. As shown in Fig. 5, the fitted number of DH days and the observed number of DH days have consistent interannual variations and trends, with a correlation coefficient of 0.65. To eliminate the impact of the magnitude of each climate factor, a standardization was applied to these factors. The multiple linear regression model based on standardized climate factors is as follows:

The number of DH days = 0.56×IOBW–0.2×EASMI +3.5×10^{-16}.

According to the coefficients of the fitting equation, IOBW contributed more to the number of DH days.

3.3 Atmospheric circulation anomalies associated with DH days

We selected the maximum and the minimum ten years after the standardization of DH days and key climate factors as their positive and negative phases to further
analyze atmospheric circulation anomalies associated with DH days and to explore the process and mechanism of climate factors’ influence on the interannual variation and trend of DH days. The positive and negative phase years of DH days and climate factors are listed in Table 2.

An analysis of meteorological parameters was performed to examine the characteristics during the positive and negative phases of DH days. Notably, there is a substantial increase in the geopotential height at 500 hPa (H500) over South China, reaching a maximum amplitude of 20 gpm, suggesting the dominance of a high-pressure ridge controlling the region (Fig. 6a). Similar to the pattern at 500 hPa, the geopotential height anomaly at 850 hPa also exhibits a positive anomaly. The abnormally high pressure in South China correlates with the anomalous intensification and westward extension of the WNPSH, as indicated by the 5880-gpm contour (Fig. 6c).

In the negative phase of DH days, the western edge of South China experiences a decrease in geopotential height, with a maximum anomaly of -15 gpm at 500 hPa (Fig. 6b). This suggests a weakening and contraction of the high-pressure ridge, which is consistent with the decreased negative phase of the WNPSH (Fig. 6c). The positive and negative phase years of DH days and climate factors are listed in Table 2.

Figure 3. Time evolution trend of standardized frequency anomalies of DH days for (a) short-term, (b) moderate-duration, and (c) long-term events in summer from 1970 to 2018.

Table 1. Correlation coefficients between DH days and climatic factors.

<table>
<thead>
<tr>
<th></th>
<th>EASM</th>
<th>SHI</th>
<th>IOBW</th>
<th>SO</th>
<th>SCSSM</th>
<th>SWAC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Observed</td>
<td>-0.39*</td>
<td>0.57**</td>
<td>0.63**</td>
<td>0.15*</td>
<td>-0.46**</td>
<td>-0.0001</td>
</tr>
<tr>
<td>High-pass filtered</td>
<td>-0.56**</td>
<td>0.48**</td>
<td>0.58**</td>
<td>-0.53**</td>
<td></td>
<td></td>
</tr>
</tbody>
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Note: *Significant at the 95% level based on a two-tailed Student’s t test. **Significant at the 99% level.
WNPSH is situated around 125°E. However, during the positive phase of DH days, WNPSH extends further eastward, reaching approximately 145°E. Comparatively, during the positive phase of DH days, abnormal anticyclones appear at both 500 hPa (UV500) and 850 hPa (UV850) along the eastern coast of South China, providing further evidence of the abnormally strong and westward extension of WNPSH.

Furthermore, during the positive phase of DH days, the westerly jet stream in South China experiences a weakening trend (Fig. 7a). This weakening of the jet stream can potentially contribute to high temperatures and dry conditions in the region. Concurrently, there is a decrease in total cloud cover (TCC) over South China (Fig. 7b). Reduced cloud cover facilitates the penetration of shortwave solar radiation (DSSR), which, in turn, leads to an increase in surface temperatures (Fig. 7c). The warming of the surface intensifies the outward long-wave radiation (USLR) emitted from the surface (Fig. 7d), subsequently warming the atmosphere (SAT) in South China (Fig. 7e). Consequently, the frequency of hot and dry days in South China rises.

3.4 Impacts of key climate factors on DH days

Anticyclonic anomalies are responsible for extreme hot events in various regions (Maheras et al. [53]). In eastern China, the anticyclonic abnormalities leading to extreme high temperatures are associated with the enhancement and westward or northwestward extension of the WPSH (Ding et al. [17]; Chen et al. [54]; Ren et al. [55]). The strong circulation anomaly at 500 hPa is associated with extreme heat events, and the strength of circulation patterns strength influences high-temperature days (Meehl et al. [56]).

Figure 8 shows the difference in the number of DH days in key climate factors’ positive and negative phases. From the difference in IOBW (Fig. 8a), compared with the negative phase of IOBW, the number of DH days in the positive phase of IOBW increased dramatically. The difference between the positive and negative phases of EASM shows obvious differences in most stations in the northeast of South China and Hainan Province but not in other regions (Fig. 8b). In the positive phase of EASM, the number of DH days is less.

To investigate the impact of IOBW on DH days in South China during the summer period from 1970 to 2018,
we conducted a detailed analysis of meteorological parameters during the positive and negative phases of IOBW (Fig. 9). Our findings reveal a significant rise in geopotential height at 500 hPa (H500) and 850 hPa (H850) over South China, reaching a maximum amplitude of 25 gpm and 20 gpm, respectively, indicating the dominance of a high-pressure ridge in the region (Fig. 9a–9b). The presence of abnormally high pressure intensifies subsidence, reduces humidity, and diminishes rainfall, resulting in an increase in solar radiation reaching the surface (Fig. 9c) and enhanced vertical adiabatic heating (Black et al. [57]). During the positive phase of IOBW, the western boundary of WNPSH extends to approximately 125°E (Fig. 9e). In contrast, it is situated on the US west coast near the Pacific Ocean during the negative phase (Fig. S6). A noteworthy observation is the occurrence of abnormal anticyclones at both 500 hPa (UV500) and 850 hPa (UV850) along the eastern coast of South China in the positive phase of IOBW (Fig. 9e–9f), accompanied by an increase in surface outgoing longwave radiation (Fig. 9d).

These atmospheric patterns contribute to elevated temperatures and reduced precipitation, consequently leading to an upsurge in the number of DH days. The difference in geopotential height and wind field between the positive and negative phases of EASM is shown in Fig. 10. When the EASM is in a positive phase, H500 in South China appears as a negative anomaly (Fig. 10a), and the East Asian trough deepens, resulting in static and stable weather. The negative anomaly of H850 is still obvious (Fig. 10b). Meanwhile, the western edge of WNPSH is located at about 127°E when the EASM is negative but retreats to about 145°E when the EASM is positive (Fig. 10c). Compared with the negative phase of EASM, abnormal cyclones appeared in South China at both 500 hPa and 850 hPa during the positive phase of EASM (Fig. 10c–10d), which would make the high-temperature atmospheric circulation easily meet with the warm and humid airflow to produce rainfall. Moreover, during the positive phase of EASM, the westerly jet (U200) intensifies (Fig. 11a), accompanied by

Table 2. Positive and negative phase years of DH days and climatic factors.

<table>
<thead>
<tr>
<th>DH days and climatic factors</th>
<th>Positive phase years</th>
<th>Negative phase years</th>
</tr>
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Figure 6. Geopotential height anomalies at (a) 500 hPa and (b) 850 hPa, and wind anomalies at (c) 500 hPa and (d) 850 hPa between DH Days positive and negative phases. The Orange dashed line in (c) denotes the WNPSH position for DH Days positive phase, and the black dashed line denotes the negative phase. The dotted area indicates a 95% significance test.
a 2–4% increase in total cloud cover (TCC) (Fig. 11b). Additionally, there is an 8–12 W m\(^{-2}\) reduction in downward surface solar radiation flux (DSSR) (Fig. 11c) and approximately 4 W m\(^{-2}\) decrease in upward surface longwave radiation flux (USLR) (Fig. 11d). This combination of factors leads to a decrease in surface air temperature (SA T) by around 0–2 °C (Fig. 11e).

Collectively, these conditions are unfavorable for the occurrence of DH days. Consequently, the positive phase of EASM is associated with a lower frequency of DH days.

3.5 Prediction of the number of DH days by a statistical model

Climate factors can be used to predict precipitation and extreme heat in South China (Lü et al. [58]). For example, spring rainfall in eastern Australia and summer rainfall in northeastern Australia can be forecast months in advance using the ENSO indicator (Chiew et al. [59]). The SO can influence the estimation of global surface temperature anomalies (Halpert and Ropelewski [60]). However, there are few studies on predicting the number of DH days by using climatic factors in South China, and the key climate factors affecting DH days are different in different regions. Therefore, it is essential to identify accurate key climate factors and use them to predict DH days in South China.

In this study, we use the key climate factors, EASM and IOBW, finally identified in the previous section, as the predictor’s input to the multiple linear regression model to predict the interannual trend of DH days. By using the adjusted optimal subset model (AOSM, Zhao et al. [61]), the prediction model of the number of DH days in summer in South China is established as follows:

\[
\text{Fitted number of DH days} = 6.5 \times \text{IOBW} - 2.5 \times \text{EASM} + 14.6
\]

Figure 12a shows that the variation of the number of DH days fitted by multiple linear regression matches the observed variation of the number of DH days well. The correlation coefficient between the fitted and the observed number of DH days can be up to 0.7. In addition, the \(R^2\), MAE, and RMSE of the prediction model established by IOBW and EASM are 0.45, 2.8 days, and 2.2 days, respectively, indicating that the interannual variation of the number of DH days can be well reproduced by using this model. We input the 2019 predictors into a multiple linear regression model based on key climate factors to predict the number of DH days in 2019 (Fig. 12a). The predicted
The value of the number of DH days in 2019 is 13.1 days, and the observed value is 14.1 days (bias=1 day). The deviation between the observed and predicted values is slight, indicating that the model's predictive ability is acceptable. Besides the deviation, the stability of the prediction model is also an important aspect of testing the model's performance. Therefore, a recycling independent test to assess the stability of the prediction was performed.
**Figure 10.** The same as Fig. 6, but for EASM.

**Figure 11.** The same as Fig. 7, but for EASM.
As shown in Fig. 12b, the histograms of the number of DH days for each annual cycle prediction value are highly consistent, indicating that the model has good stability. The ten models’ average $R^2$, MAE, and RMSE were 0.43, 2.2 days, and 2.9 days, respectively, showing that the established model can predict DH days in South China stably and efficiently.

4. SUMMARY AND CONCLUSIONS

During the summer of 1970–2018, the number of DH days in most stations in South China showed a significant increasing trend, while only a few stations in the west showed a decreasing trend. The overall increasing trend in the number of DH days was 1.5 days decade$^{-1}$. Specifically, there was a significant upward trend from 1970 to 1990, a downward trend from 1991 to 1997, and no significant trend after 1997. The overall changes in the mean state of meteorological parameters may explain the varying trends to some extent (Mei et al. [62]) since the hot days and subsequent DH days in this study were identified by a relative threshold value. Before 1999, the frequency of short-term and medium-sustained DH events was less and then increased significantly, while long-term events fluctuated wildly from year to year.

IOBW and EASM were identified as the key climate factors that affect the DH days in South China. Furthermore, a multiple linear regression model was established to fit the number of DH days by using these two key climate factors. According to the coefficient of each factor in the model, IOBW had a more significant effect on DH weather. The influence mechanism of these key climate factors was investigated by composite analysis of geopotential height and wind fields. Compared with the negative phase of IOBW, in the positive phase of IOBW, 500 hPa and 850 hPa geopotential height enhanced, the West Pacific subtropical high strengthened and extended abnormally to the west, more solar radiation reaching the surface, surface outgoing longwave radiation increases and there was an anomalous anticyclone in eastern South China, which is conducive to increasing the number of DH days in South China in summer. The positive and negative phases of ESAM have the opposite atmospheric circulation characteristics of IOBW.

The key climate factors selected by the AOSM method were used to establish a multiple linear regression model to predict the number of summer DH days in South China. Since climate factors tend to interact with each other, their synergy should also be taken into account when establishing the model. Finally, IOBW and EASM were chosen as the predictors. The simulated number of DH days matches the observed number of DH days well ($R = 0.65$), showing that using this model can reasonably fit the long-term change of DH days. In addition, we also conducted an independent prediction experiment for 2019.
and the results showed that the forecast deviation was only 1 day. Furthermore, from the results of recycling independent tests, the predictive performance of the model is stable from 2009–2018. In summary, the good predictive ability and stable predictive performance of the model strongly prove that it is feasible to use the predictor variables selected by AOSM to predict the interannual trend of DH days in South China.

It is essential to acknowledge that the key climate factors and the prediction model developed in this study are specifically applicable to the number of summer DH days in South China. The characteristics of other regions may differ, and in some cases, they may even exhibit contrasting patterns (Mei et al. [62]). Therefore, it is crucial to identify the climate factors relevant to specific regions and conduct further in-depth research.

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REFERENCES


Appendix

Figure S1. Relative change trends in the number of NP days (a), hot days (b), and DH days (c) in the summer of 1970 to 2018 (stations marked with a cross (“×”) inside the circle are at the 95% confidence level).

Figure S2. The observed time series (a) and the time series after high-pass filtering (b) of the annual average of the number of NP days, hot days, and DH days in summer from 1970 to 2018 in Guangdong Province (units: days).
Figure S3. The same as Fig. S2, but for Fujian Province.

Figure S4. The same as Fig. S2, but for Guangxi Province.
No.4  XUE Xin (薛鑫), WU Yan-xing (吴燕星), et al. 447

Figure S5. The same as Fig. S2, but for Hainan Province.

Figure S6. Position of IOBW positive and negative phase WNPSH. The Orange dashed line denotes the WNPSH position during the IOBW positive phase.