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Impacts of changes in climate extremes on wildfire occurrences in China

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A R T I C L E I N F O

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A B S T R A C T

Climate change has caused more frequent instances of extreme climatic events around the world, being an influential factor on the occurrence of wildfires in China on large scale. However, the impact of changes in extreme climate on the occurrence of wildfires in different climate zones remains unclear. In the present study, 26 extreme climate indices were selected to analyze the thereof relationship with wildfire occurrences from 2005 to 2018 in different regions of China. Wildfires in China primarily occur in the south, with a measurable presence in the north. On an annual scale, the wildfire occurrences in southwestern China show stronger correlations with mean temperature than extreme temperature indices, but show stronger correlations with extreme precipitation indices than the total precipitation. On the contrary, the wildfire occurrences in southeastern China show stronger correlations with the total precipitation than extreme precipitation indices, but show stronger correlations with extreme temperature indices than the mean temperature. In Northeast China, wildfires show a more significant correlation with mean temperature than with any extreme climate indices, indicating a minimal impact from extreme climatic conditions. The fire-climate relationships in the main fire season (January-April) are similar to those in the annual scale. The wildfire occurrences in the southwestern, south-central, and southeastern China, which are located in the same latitudes, were affected by extreme climate indices of different types and on different time scales. Furthermore, we recommend that consecutive dry days (CDD) and diurnal temperature range (DTR) should be considered first when studying the relationship between wildfire occurrence and extreme climate in southwestern and southeastern China respectively.

1. Introduction

Wildfire is a significant factor in ecological succession, affecting the patterns and processes of global ecosystems, such as the distribution and structure of vegetation, carbon cycles, and climate (Cochrane, 2003; Loboda and Csiszar, 2007; Bowman et al., 2009). Due to being sudden, destructive, uncontrollable, and difficult to manage, wildfires generally cause large-scale devastation (Bowman et al., 2009; Kelly et al., 2013). Thus, in coexistence with wildfires, human beings need to determine the influencing factors thereof and understand the mechanisms of occurrence and development of wildfires (Moritz et al., 2014; McWethy et al., 2019). In previous studies, global warming has been predicted to facilitate wildfires in the short and long terms, as wildfires increase in frequency and severity (Randerson et al., 2006; Bond-Lamberty et al., 2007; Turetsky et al., 2011; Lu et al., 2016; Davis et al., 2019; Walker et al., 2019). Such findings suggest that the potential danger of wildfires will likely exacerbate across the globe, and the severity will also significantly increase (Liu et al., 2010). In addition to determining the flammability of fuels, climate will also influence the availability of fuels in the future (Marlon et al., 2008; Trouet et al., 2010). As such, as a principal large-scale driver of wildfire variability, climate profoundly impacts the occurrence and development of wildfires (Flannigan et al., 2009; Ganteaume et al., 2013). Therefore, knowledge concerning the connections between wildfires and climate change is of considerable

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significance for preventing and responding to wildfires (Doerr and Santín, 2016; Prichard et al., 2017).

Rapid climate warming is the general trend of current climate change (Masson-Delmotte et al., 2021), and climate extremes have occurred frequently (Zhang et al., 2006), inevitably exerting a significant impact on wildfires (Tian et al., 2013). For instance, extreme high temperatures and droughts undoubtedly promote the outbreak and spread of wildfires, making the study of extreme climate changes crucial for wildfire research. Existing research has been focused on the relationship between local climate and wildfire behavior in the context of climate change, the impact of individual extreme events on wildfires, and the application of social science to fire management. Despite such research, there is a scarcity of studies in which extreme climate indices and wildfires are correlated on large spatial scales and comprehensive analyses are conducted. Under the background of increasing extreme climate and weather events, although there are difficulties in capturing the regularity between extreme climate and wildfire through several independent extreme weather events, the use of the extreme climate index in wildfire research is novel and effective. The development of research on global extreme weather and climate events has been hindered by a lack of consistent definitions regarding extreme event indicators and thresholds in individual countries, as well as limitations imposed by the length of global climate data series. Importantly, the Expert Team on Climate Change Detection and Indices (ETCCDI), which was established by the World Meteorological Organization (WMO) and the World Climate Research Program (WCRP) in 1999, defined 27 representative climate indices for the study of global and regional extreme climate change. These indices were divided into different types such as the intensity index, absolute threshold index, relative threshold index, duration index (Zhou et al., 2016; Yin and Sun, 2018a, 2018b), which can promote the observation and research of global extreme climate change and accelerate the pace of extreme climate change simulation and attribution research (Alexander et al., 2006; Donat et al., 2013a, 2013b; Kim et al., 2016; Yin and Sun, 2018a). It also provides a basis for further studying the relationship between extreme climate and wildfire.

China covers a broad spectrum of latitudes and longitudes, resulting in a diverse range of climate and vegetation types. Particularly, the subtropical regions of China boast some of the world's most verdant and dense subtropical forests (Crowther et al., 2015). The predominance of wildfire occurrence in southern, subtropical China stands in contrast to the dominant fire patterns in both southern and northern China found in previous studies, which were primarily based on fire size (Wang and Shu, 2015; Ying et al., 2018). Therefore, conducting research on the relationship between extreme climate and wildfire occurrences in this region is of great significance. Thus, in this study, the core 26 of the 27 indices of extreme climate recommended by ETCCDI were considered for analyzing the relationships thereof with wildfires in different regions and seasons in China, and further, the relationships between extreme climate indices – wildfire and between mean temperature/precipitation - wildfire were compared, aiming to answer the following questions: (1) What has been the relationship between extreme climate and wildfires in China during the period from 2005 to 2018? (2) Are there differences in the responses of wildfires to various types of extreme climate indices in different regions of China? If so, what are these differences? (3) How does the relationship between wildfires and climate extremes compare to that with mean temperature/total precipitation in China? should extreme climate factors be more emphasized in future wildfire research in China?

2. Data sources and research methods

2.1. Wildfire dataset and extreme climate indices

The wildfire data in the present study include vegetation fire data from 2005 to 2018 provided by the Forest Fire Prevention and Monitoring Information Center (FFPMIC) polar-orbiting satellite wildfire monitoring system. Wildfire Atlas of China (WFAC) is a data product compiled by the FFPMIC that combines satellite images and field observations, including the locations, dates, and times of 135,246 wildfires in China from 2005 to 2018 (Fang et al., 2021). According to the FFPMIC data, the ground-truth-calibrated WFAC data set for fire occurrences is different from other satellite-based fire counting products.

The data concerning the extreme climate index were obtained from the HadEX3 gridded global surface extremes indices datasets released by the Met Office Hadley Centre (Dunn et al., 2014; Dunn et al., 2020). The dataset records land-based climate extremes produced through the coordination of the joint ETCCDI, which currently contains 27 temperature and precipitation indices on a 1.25° × 1.875° grid system from 1901 to 2018. Such indices represent seasonal, annual or both values derived from daily weather station data, and the data are provided in the form of a calculated ETCCDI index or a time series of standardized maximum temperature (T_{max}), minimum temperature (T_{min}), and daily precipitation values at each station. For each index, the Hadley Centre only selects sites with sufficient data and coverage and performs several quality controls to confirm that the indices of the interest are free of errors, while further screening is performed on data provided by duplicate sites. Such method can prevent mixing of metadata with the same content but in different formats, resulting in biased results. In the present study, 26 indices from the dataset (Table 1) were used, and the indices were calculated from the T_{max}, T_{min}, and daily precipitation records of 317 weather stations in China. Additional details can be obtained from https://www.metoffice.gov.uk/hadobs/hadex3/.

2.2. Methods

The annual and the monthly numbers of wildfire events in the 2° × 2° grid of the WFAC wildfire data set for 14 years were calculated, as well as wildfire occurrences before (January to April), during (May to September), and after (October to December) the monsoon season of each year (Fig. S1). Given the increasing stringency of fire control policies in China over time, there has been a general decline in the number of wildfires (Fig. S2), reflecting the influence of these policies. To address the potential linear trends or systematic variations inherent in

Table 1
List of indices acronyms and descriptions.

Acronyms	Descriptions	Unit	Type
TXx	maximum T_{max}	°C	Monthly extreme temperature indices
TXn	minimum T_{max}	°C	
TNx	maximum T_{min}	°C	
TNn	minimum T_{min}	°C	
DTR	diurnal temperature range	°C	
TX90p	warm days	%	
TX10p	cool days	%	
TN90p	warm nights	%	
TN10p	cool nights	%	
SU	summer days	day	Annual extreme temperature indices
FD	frost days	day	
ID	ice days	day	
CSDI	cool spell duration	day	
WSDI	warm spell duration	day	
TR	tropical nights	day	
GSL	growing season length	day	
Rx1day	maximum 1 day total	mm	Monthly extreme precipitation indices
Rx5day	maximum 5 day total	mm	
R95p	number of very wet days	day	Annual extreme precipitation indices
R99p	number of extremely wet days	day	
R10mm	≥10 mm precipitation days	day	
R20mm	≥20 mm precipitation days	day	
CDD	consecutive dry days	day	
CWD	consecutive wet days	day	
PRCPTOT	total precipitation	mm	
SDII	specific daily intensity	mm	

the data, particularly those associated with fire control policies, the first-difference series method was employed. This technique computes the differences between consecutive observations, effectively mitigating the influence of any linear trends. By adopting the first-difference approach, the data was rendered more stationary, enhancing the precision of subsequent analyses. To further remove the trend effect of fire control policies, the raw wildfire event series grouped by monsoon season was simultaneously computed to obtain the first-difference series, and the same calculation process was performed for annual-scale wildfire events. A point-to-point correspondence between wildfire grid points and extreme climate index grid points was established, upon which the extra grids of extreme indices were deleted. Subsequently, the nearest interpolation was used to fill in the missing grids of the extreme indices.

The climate index data in the HadEX3 datasets were classified using annual and monthly scales, and data in the range of 75°E-135°E and 15°N-55°N were selected, which covered the study area. The original datasets had a resolution of $1.25^\circ \times 1.875^\circ$ grid points, the nearest interpolation method was used to convert that resolution to $2^\circ \times 2^\circ$ grid points. The monthly index data were divided into three groups: pre-monsoon season (January to April), monsoon season (May to September), and post-monsoon season (October to December), and the data for each group were averaged over the target time period. To obtain the first-order difference series of 26 indices, the first-order difference of the monthly exponential time series in each grid point was calculated, as well as the annual mean of each annual index. The temperature and precipitation data are from the China Climate Research Unit dataset (CRU TS4.03) (Harris et al., 2014). For the first-order difference series of mean temperature and precipitation at $0.5^\circ \times 0.5^\circ$resolution, we used piecewise linear interpolation to convert them into $2^\circ \times 2^\circ$grid points.

The Pearson correlation was applied for the correlation between the first-order difference series of the WFAC wildfires and the first-order difference series of 26 extreme climate indices at the same time scale and the same grid. Subsequently, the first-order difference series of the mean temperature/precipitation and wildfire occurrences in the corresponding grids were correlated to obtain the corresponding correlation coefficients. Then, these correlation coefficients were divided into three groups for discussion: pre-monsoon season, monsoon season, and post-monsoon season. The correlation coefficients for the three seasons were averaged, and so did for the annual correlation coefficients. To further assess the relationship between extreme climate indices and mean climate factors to wildfires, the absolute correlation coefficient values of the mean temperature (precipitation)-wildfire were subtracted from the absolute values of the extreme temperature (precipitation) index-wildfire correlation coefficient in the same grid. See Fig. S3 for a detailed flowchart of the methodology.

In the intricate endeavor of unraveling the spatial dynamics intertwined among extreme climate indices, the mean climate factors, and wildfires, we meticulously delineated contours for southeastern China (SEC) and southwestern China (SWC), anchored on the palpable spatial correlations observed. The southwestern realm's boundaries were profoundly influenced by the salient correlations between extreme temperature indices and wildfires from January through April. In contrast, the southeastern expanse was demarcated based on its intrinsic ties with extreme precipitation indices within the same temporal window. In pursuit of regions exhibiting heightened correlations between wildfires and extreme climate indices, the correlation coefficients at each grid point were subjected to absolute value transformations. Through judicious refinements of the regional parameters, it became evident that territorial adjustments imparted negligible deviations to the culminating results. Specifically, metrics within the SEC enclave exhibited modest oscillations between 0.55 and 0.65, while those within the SWC territory registered fluctuations confined to a 0.53 to 0.57 range, attesting to the robustness of the selected domains. The analytical lens was squarely focused on discerning overarching trajectories and paradigms, eschewing granular data points. As evinced in Figs. S4 and S5, the unwavering stability of both SEC and SWC was emphatically validated.

Furthermore, the mean absolute values of the correlation coefficients between extreme climate indices and wildfires in each region were calculated, and the distance to the mean absolute values of the correlation coefficients between mean temperature/precipitation and wildfires was derived, directly revealing the relationship strength between the two factors within the same region (Fig. S6).

3. Results

We conducted a statistical analysis of the total occurrences of wildfire in China from 2005 to 2018 (Fig. S1), and found that during this period, the wildfire occurrences in southern China ranged between 2,500 and 7,145. In contrast, wildfire occurrences in northern China were significantly lower, with most areas experiencing between 21 and 300, and only a few areas in the northeast reaching between 1,500 and 2,500. Additionally, from 2005 to 2018, there was an overall downward trend in the number of wildfire occurrences across various regions in China (Fig. S2a).

3.1. Relationship between wildfires and the annual extreme climate indices

The results of the correlation analysis of the annual extreme precipitation indices and wildfire occurrences indicate that in southeastern China (hereinafter referred to as SEC) the correlation coefficient between total precipitation and wildfires is generally higher than the selected extreme precipitation indices. However, in southwestern China (hereinafter referred to as SWC), the correlation between wildfires and extreme precipitation indices is notably stronger than with total precipitation (Fig. S6). Notably, consecutive dry days (CDD) and wildfires in SWC exhibited a significant positive correlation (Fig. 1a), is significantly higher than that betwween of total precipitation and wildfires (Fig. 1b). CDD represents the days of continuous drought; the longer the duration of continuous drought, the greater the probability of wildfire. Other indices, such as CWD, SDII, R10mm, R20mm, R95p and R99p, had a weak correlation with wildfires in SWC, while exhibiting a negative correlation with wildfires in southeast China (Figs. S7–S9), which is roughly equivalent to the correlation of total precipitation and wildfire. Different from SEC, the precipitation in SWC was found to be concentrated from June to August and due to the long drought time throughout the year, the occurrence of wildfires was more vulnerable to the impact of temperature (Chen et al., 2014). However, likely affected by the monsoon season, the precipitation in SEC had a stronger regulatory effect on wildfires.

After analyzing the correlation between the annual extreme temperature indices and wildfires, we found that the correlation of wildfire occurrences with the mean temperature was generally higher than the extreme temperature indices in SWC. However, the results in SEC and SWC were opposite (Fig. S6). The WSDI, indicating continuous high-temperature weather, had a relatively significant positive correlation with wildfires nationwide (Fig. 1c), and in SEC, the correlation between the two was even stronger than the mean temperature-wildfire (Fig. 1d and Fig. S6). Growing season length (GSL) was also positively correlated with wildfires nationwide (Fig. S10). Continuous high-temperature weather accelerates evaporation, which makes plants grow faster, before converting into combustible substances, thereby increasing the occurrence of wildfires.

ID and FD were also found to have a significant negative correlation with wildfires in SWC (Fig. 2a and 2c), especially ID, which had a correlation with wildfires roughly equivalent to the correlation between mean temperature and wildfires. Both ID and FD indicate low-temperature days. Low temperature is not conducive to the growth of vegetation, and thus, more days of low temperature will reduce the availability of combustible materials, which could be a contributing factor to ID and FD being negatively correlated with wildfires in SWC. TR and SU had a significant positive correlation with wildfires in SWC,

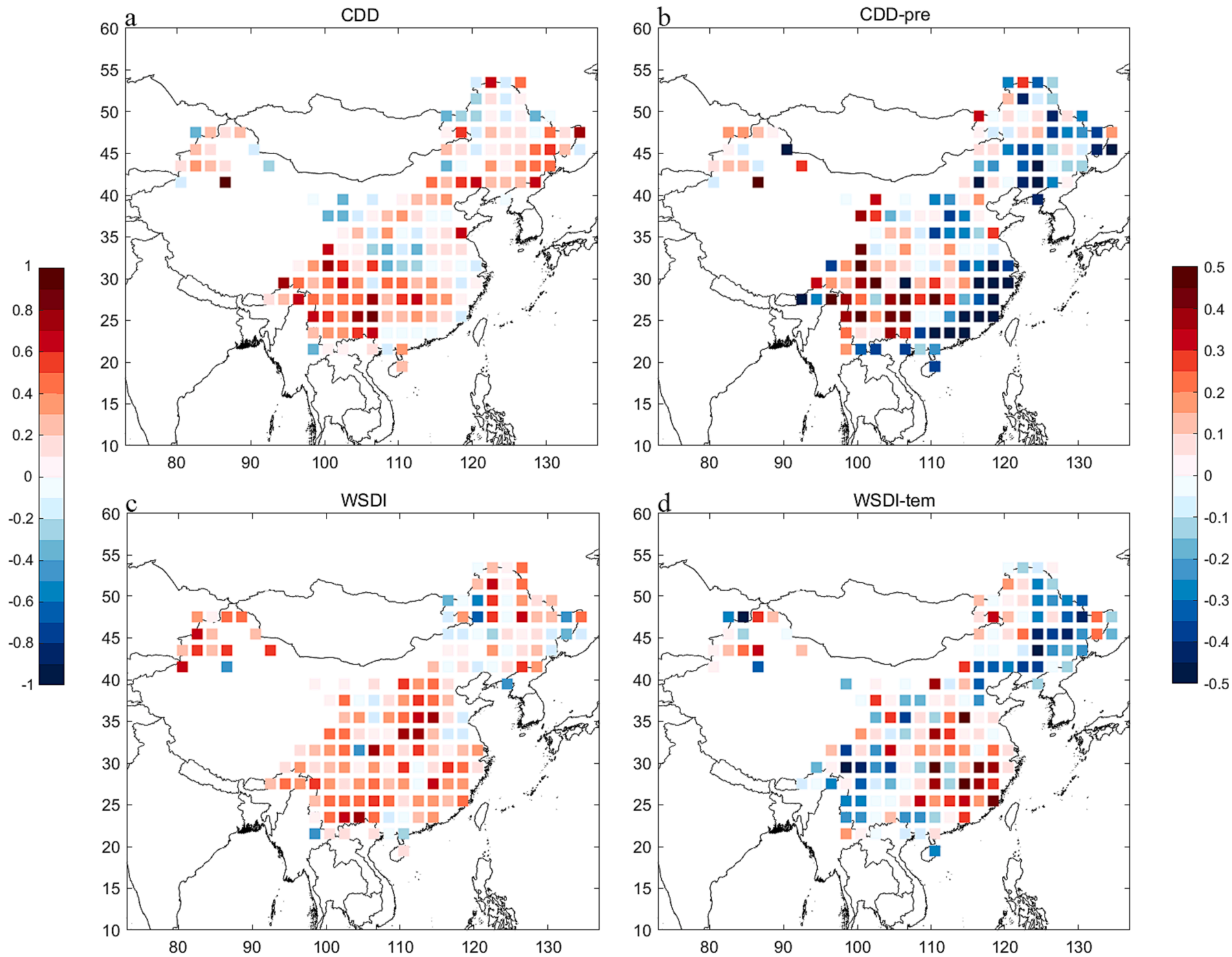

Fig. 1. Pointwise correlations between the first-order difference of WFAC wildfire occurrences (2005–2018) and the first-order difference of (a) consecutive dry days (CDD) and (c) warm spell duration (WSDI). (b) Comparison of the correlations between CDD and wildfire occurrences (I) and between the mean precipitation-wildfire occurrences (II) (I-II). (d) The same as (b), but for the correlations between WSDI and wildfire occurrences (I) and between the mean temperature and wildfire occurrences (II) (I-II). See the Discussion section for the comparison method. (In this figure, notations are used for clarity: '(I)' represents the first data analysis, '(II)' the second, and '(I-II)' a comparative analysis between them. These notations is uniformly applied in subsequent figure captions.).

and the correlation was roughly the same as that of mean temperature and wildfires, while the correlation with wildfires in SEC was not significant (Fig. S11). Both SU and TR indicate high-temperature days. Compared with low temperatures, a higher temperature is more conducive to biological activities and promotes plant growth. Additionally, high temperatures will lead to high evaporation and increase the load of combustible materials, which could contribute to the positive correlation with wildfire occurrences in SWC.

3.2. Relationship between wildfires and the monthly extreme climate index

A statistical analysis of wildfire occurrences in different months of China from 2005 to 2018 (Fig. S1) shows that before the monsoon season (January to April), wildfires occurred frequently. At such time, southern China had a high incidence of wildfires with occurrences also noted in north China and northeast China. However, wildfires occurrences in the monsoon season (May to September) dropped sharply all over China, and there were a few wildfires in the south and the northeast of China. After the monsoon season, the wildfire activities in the SEC significantly intensified, and there were also wildfire activities in the northeast.

During the pre-monsoon season, the indices of high temperature (TXx, TX90p, TXn, and TN90p) and low temperature (TNn, TNx, TN10p, and TX10p), and diurnal temperature range (DTR) exhibited significant correlations with wildfires in SWC (Figs. 3–5; Figs. S12–S17). Notably, the correlation of DTR with wildfires in the SWC was stronger than that of mean temperature-wildfire correlation during the same period (Fig. 3b). In SEC, two-thirds of the extreme temperature indices exhibit stronger correlations with wildfire occurrences as compared to the mean temperature. Among these indices, DTR and TX90p, TXn, TNx, which represent high temperatures, demonstrate more pronounced associations with wildfires. Conversely, the remaining temperature indices reveal relatively weaker correlations with wildfires in SEC, approximating the correlation strength observed between mean temperature and wildfire incidents (Fig. S6). From the aforementioned findings, the wildfires in SWC were probably affected by both low temperature and high temperature, while the wildfires in SEC were more vulnerable to high temperature.

During the monsoon season, DTR, TXx, TX90p, TNn, TNx, and TN10p were significantly correlated with the wildfires in the south-central China and adjacent regions (hereinafter referred to as SCC) (Fig. 3c, 4c and 5c), and the correlations were significantly stronger than that of the mean temperature (Fig. 3d, 4d and 5d; Figs. S14–S16), indicating that the wildfire activities in the region were more vulnerable to the impact of extreme temperatures in the season. During the post-monsoon season, DTR, TXx, and TX90p had significant positive correlations with wildfires in SWC and SEC (Fig. 3e, 4e and 5e), even

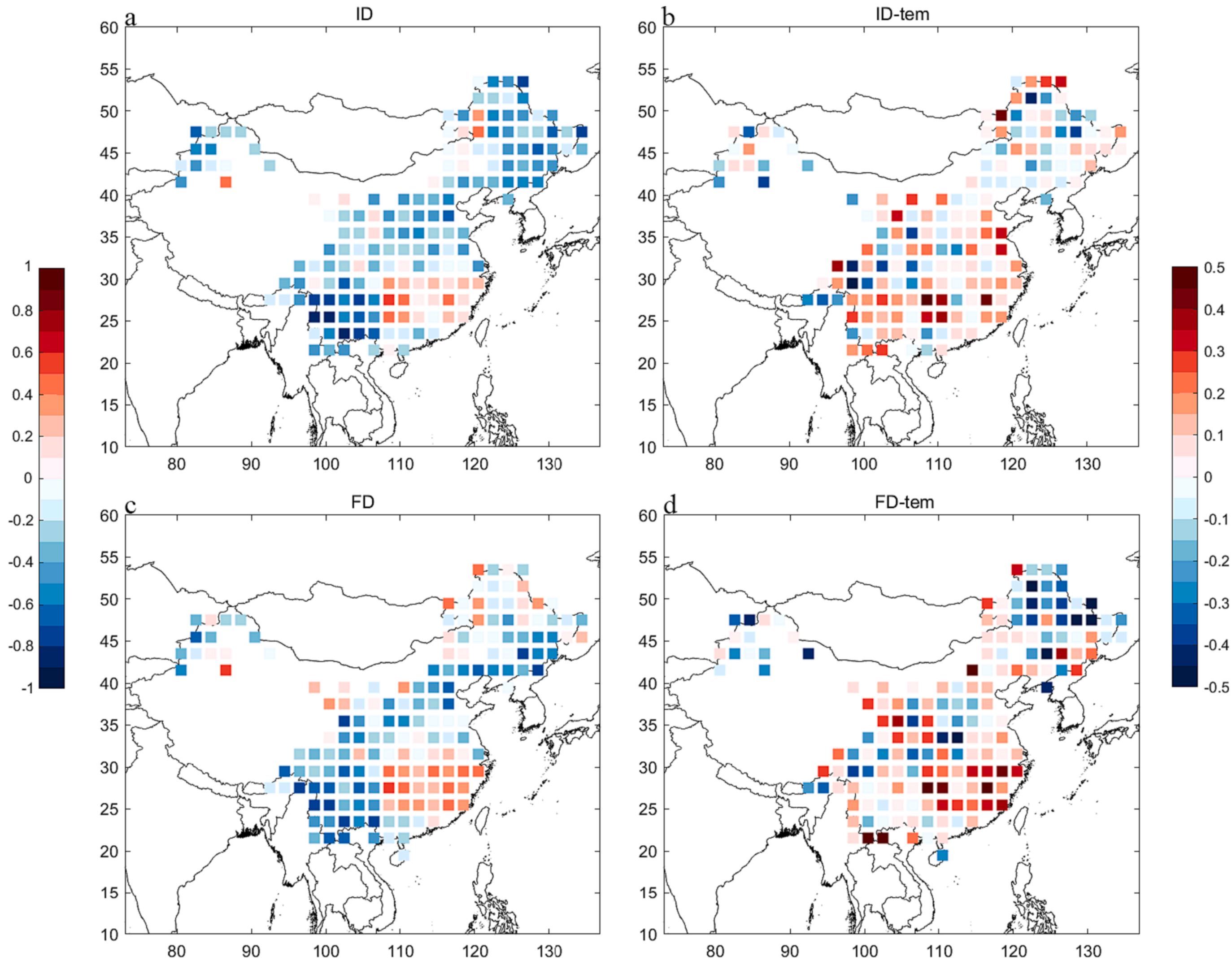

Fig. 2. Pointwise correlations between the first-order difference of WFAC wildfire occurrences (2005–2018) and the first-order difference of (a) ice days (ID) and (c) frost days (FD). (b) Comparison of the correlations between the ID and fire occurrences (I) and between the mean temperature and wildfire occurrences (II) (I-II). (d) the same as (b), but for the correlations between the FD and wildfire occurrences (I) and between the mean temperature and wildfire occurrences (II) (I-II). The comparison method is the same as above.

surpassing the correlation between average temperature and wildfires within the same regions (Fig. 3f, 4f and 5f). The other extreme temperature indices had no significant correlation with the wildfires in China.

The same method was adopted for analysis of the correlation between the extreme precipitation indices (Rx1day and Rx5day) and wildfires in China, and the correlation between the two indices and wildfire exhibited consistent changes (Fig. 6 and Fig. S18). During the pre-monsoon season, Rx1day and Rx5day were significantly negatively correlated with wildfires in SEC, and the correlation was slightly better than that of seasonal total precipitation and wildfire (Fig. S6), which likely indicates that the wildfire activities in SEC were also affected by extreme precipitation during such period, while being weakly negatively correlated or even uncorrelated in SWC. During the monsoon season, there was no significant correlation between the aforementioned indices and wildfires in the SEC and SWC. However, after the monsoon season, Rx1day and Rx5day had weak negative correlations with wildfires in SWC.

4. Discussion

In the context of escalating global warming, compounded climate extremes including heatwaves and droughts are intensifying, precipitating wildfire risks. The IPCC's Sixth Assessment Report (Chapter 11) illuminates the upsurge in such events since the 1950s, particularly prevalent in Southern Europe, Northern Eurasia, the US, and Australia (medium confidence). Anthropogenic influences are likely augmenting these incidents, with climate change expected to amplify their frequencies in multiple regions (high confidence). The intensifying severity of droughts and heatwaves foreseeably conduces to a higher frequency of conducive wildfire weather conditions, consequently escalating wildfire threats (high confidence) (Masson-Delmotte et al., 2021). Research on extreme climate and wildfires has become a trending topic in the field of climate and environment (Goss et al., 2020). However, there is a scarcity of research in which relationships between wildfires and extreme climate indices have been investigated in China. In the present study, 26 extreme climate indices were applied to comprehensively analyze wildfires in China. In this study, extreme temperature and precipitation indices were used as the main metrics, with results compared to the correlation between wildfire occurrences and mean temperature/precipitation, in an attempt to provide a research direction for the relationship between wildfires and climate extremes, even wildfire prediction.

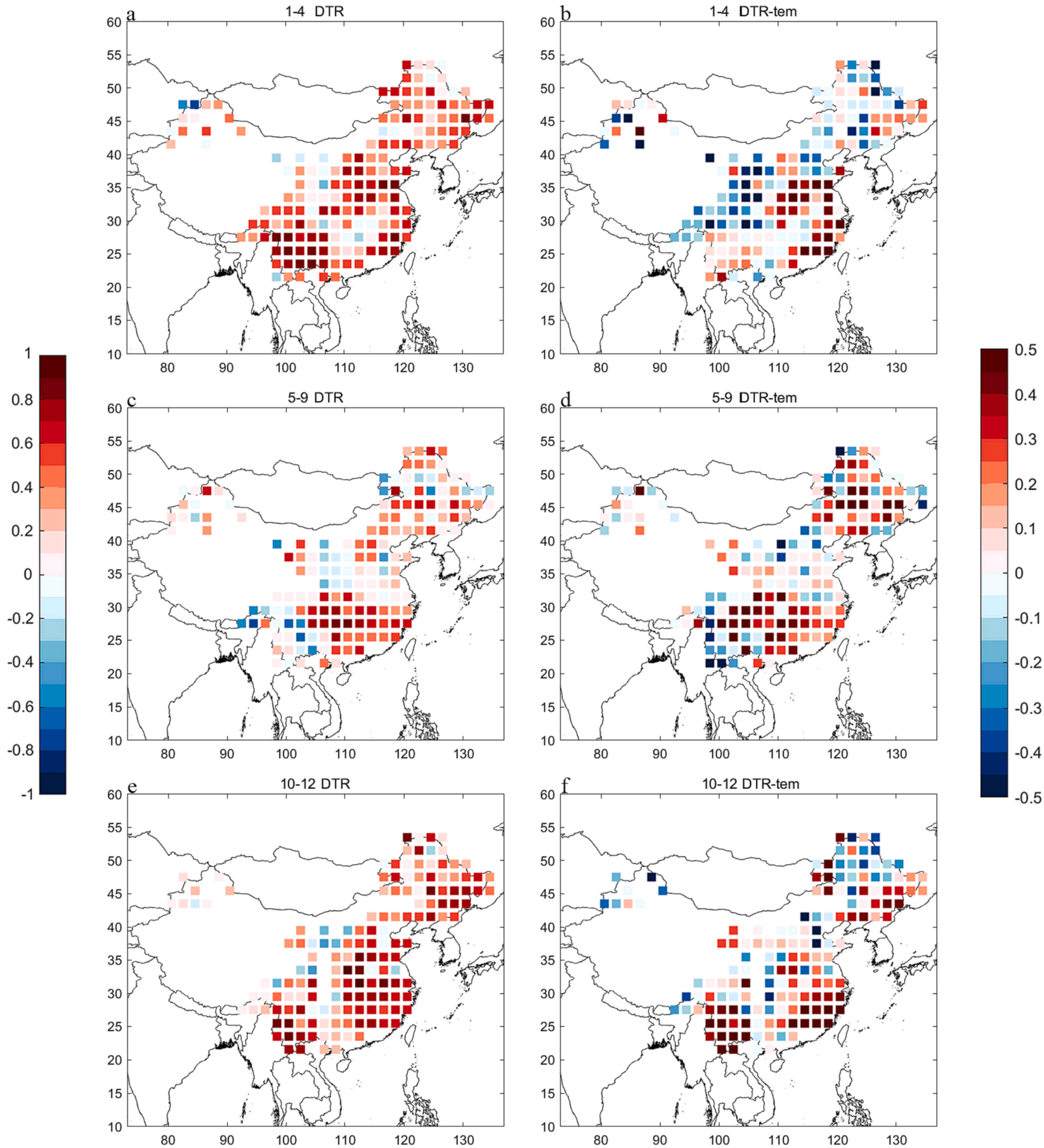

Fig. 3. Pointwise correlations between the first-order difference of WFAC wildfire occurrences (2005–2018) and the first-order difference of diurnal temperature range (DTR) in (a) pre-monsoon season (January to April), (c) monsoon season (May to September), and (e) post-monsoon season (October to December). Comparison of the wildfire occurrence-DTR correlation and the wildfire occurrence-mean precipitation relationship in (b) pre-monsoon season, (d) monsoon season, and (f) post-monsoon season.

4.1. Relationship between wildfires and climate extremes in SWC

Overall, from 2005 to 2018, the region with the highest occurrence of wildfires was predominantly concentrated in southern, subtropical China. Compared with precipitation, wildfires in SWC are mainly driven by temperature, because both extreme temperature index and mean temperature are significantly correlated with wildfires in SWC. Through comparison, we found that the correlation between mean temperature and wildfire was more significant because compared with climate extremes, the continuous change of temperature can have a more significant impact on wildfires. The climate is dry with minimal rain and high temperatures in spring in SWC. At the same time, blocked by the

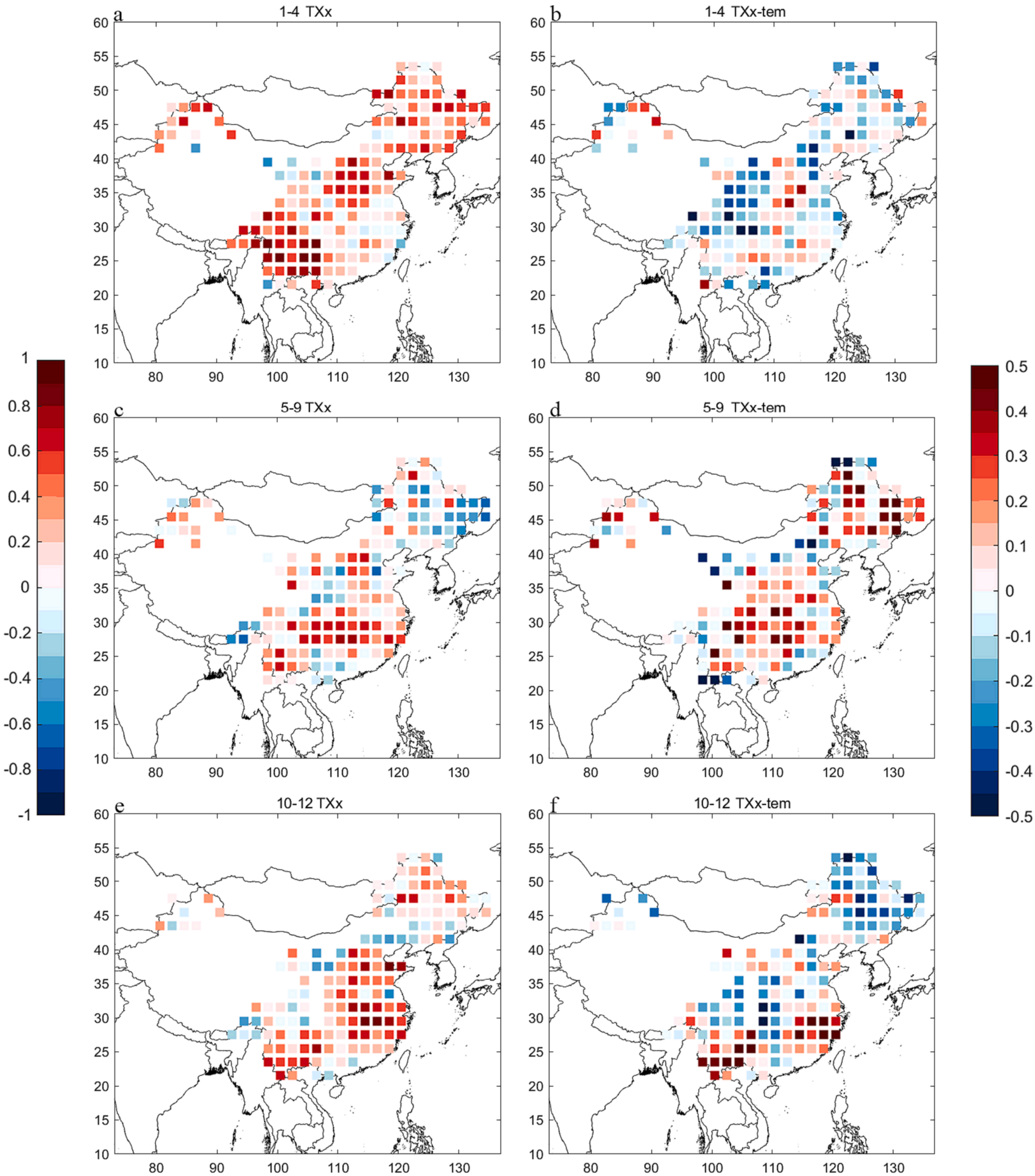

Fig. 4. Pointwise correlations between the first-order difference of WFAC wildfire occurrences (2005–2018) and the first-order difference maximum T_{max} (TXx) in (a) pre-monsoon season (January to April), (c) monsoon season (May to September), and (e) post-monsoon season (October to December). Comparison of wildfire occurrence-TXx correlation and wildfire occurrence-mean temperature association in (b) pre-monsoon season, (d) monsoon season, and (f) post-monsoon season.

Qinghai-Tibet Plateau and the surrounding high mountains thereof, the cold and dry airflow from the north is weakened, making the temperature higher than that in SEC with the same latitudes (Lian et al., 2015), thereby forming an ideal environment for the occurrence of wildfires during the pre-monsoon season. In such case, the impact of extremely high temperature on wildfires is weakened, and the relationship therebetween is not as good as the mean temperature-wildfire. However, in environments with high temperature, the correlation between extreme index indicating low temperature (for example, ID and FD has a significant negative correlation with wildfire in SWC) and wildfires is roughly equivalent to the mean temperature-wildfire correlation (Fig. 2b and 2d). Once the temperature is lower than 0 ℃, the water on

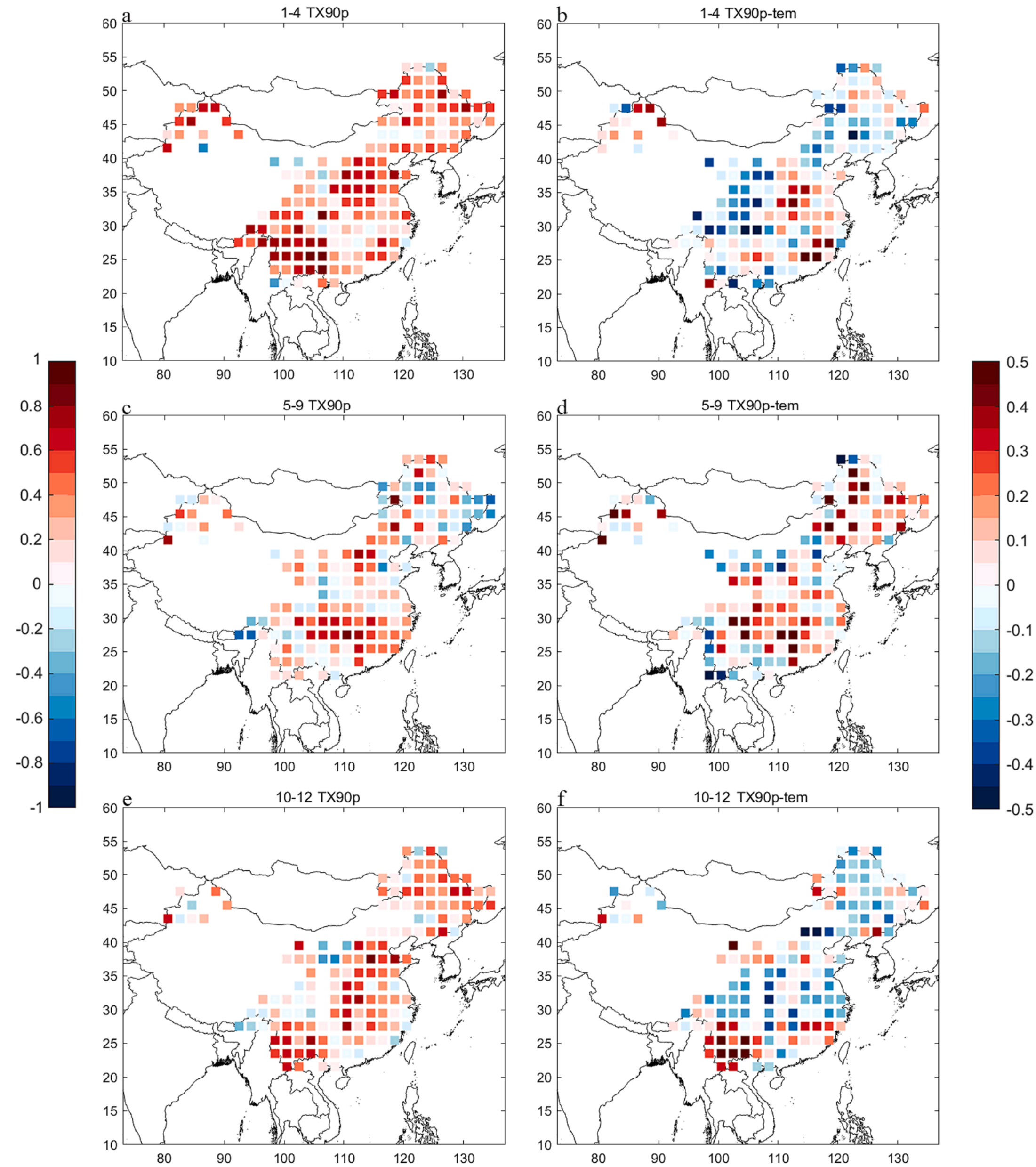

Fig. 5. Pointwise correlations between the first-order difference of WFAC wildfire occurrences (2005–2018) and the first-order difference of Warm Days (TX90p) in (a) pre-monsoon season (January to April), (c) monsoon season (May to September), and (e) post-monsoon season (October to December). Comparison of wildfire occurrence-TX90p correlation and wildfire occurrence-mean temperature correlation in (b) pre-monsoon season, (d) monsoon season, and (f) post-monsoon season.

the ground is not easy to evaporate and can even be retained in solid form, significantly reducing the probability of wildfires. Despite such findings, there is a high annual mean temperature in SEC due to the low latitude, thus, the extreme case of ID can be ignored in wildfire research when the mean temperature is used.

Although wildfires in SWC were found to be mainly controlled by temperature rather than precipitation, the correlation between the most climate extreme index related to precipitation and wildfire was higher than that of the total precipitation. Such findings could be attributed to the fact that when a meteorological factor is not the dominant factor for the occurrence of wildfire in the region, only when such factor is extreme can wildfires be impacted. CDD represents the continuous drought days, and was found to be significantly positively correlated with wildfires in SWC (Fig. 1a), and the correlation between CDD and wildfire in such area is obviously better than that of the total annual precipitation-wildfire (Fig. 1b and Fig. S6). The total annual precipitation represents the accumulation of precipitation in a year, which cannot reflect the drought/humidity condition in a certain period, such as in a few days. Meanwhile, the CDD represents the extreme drought for a period of time in the year, with a longer lasting drought indicating a higher probability of wildfire occurrences. As such, through analysis of the correlation between CDD and wildfires, the relationship between drought/humidity and wildfires can be more accurately captured in a certain period. In addition, compared to the SEC, SWC has distinct dry and wet seasons. With the occurrence of concentrated rainfall, the combustible material load would increase, resulting in an increase in wildfire occurrence. Therefore, certain extreme precipitation indices, such as R95p, R99p, SDII, and others, were positively correlated with wildfires in SWC, and the correlations were stronger than that of the total annual precipitation and wildfires in the region (Fig. S6). This phenomenon further indicates that, in SWC, extreme precipitation may have a greater impact on the occurrence of wildfires. It was also proved by Ying et al. (2022) that wildfires in the SWC are regulated by precipitation.

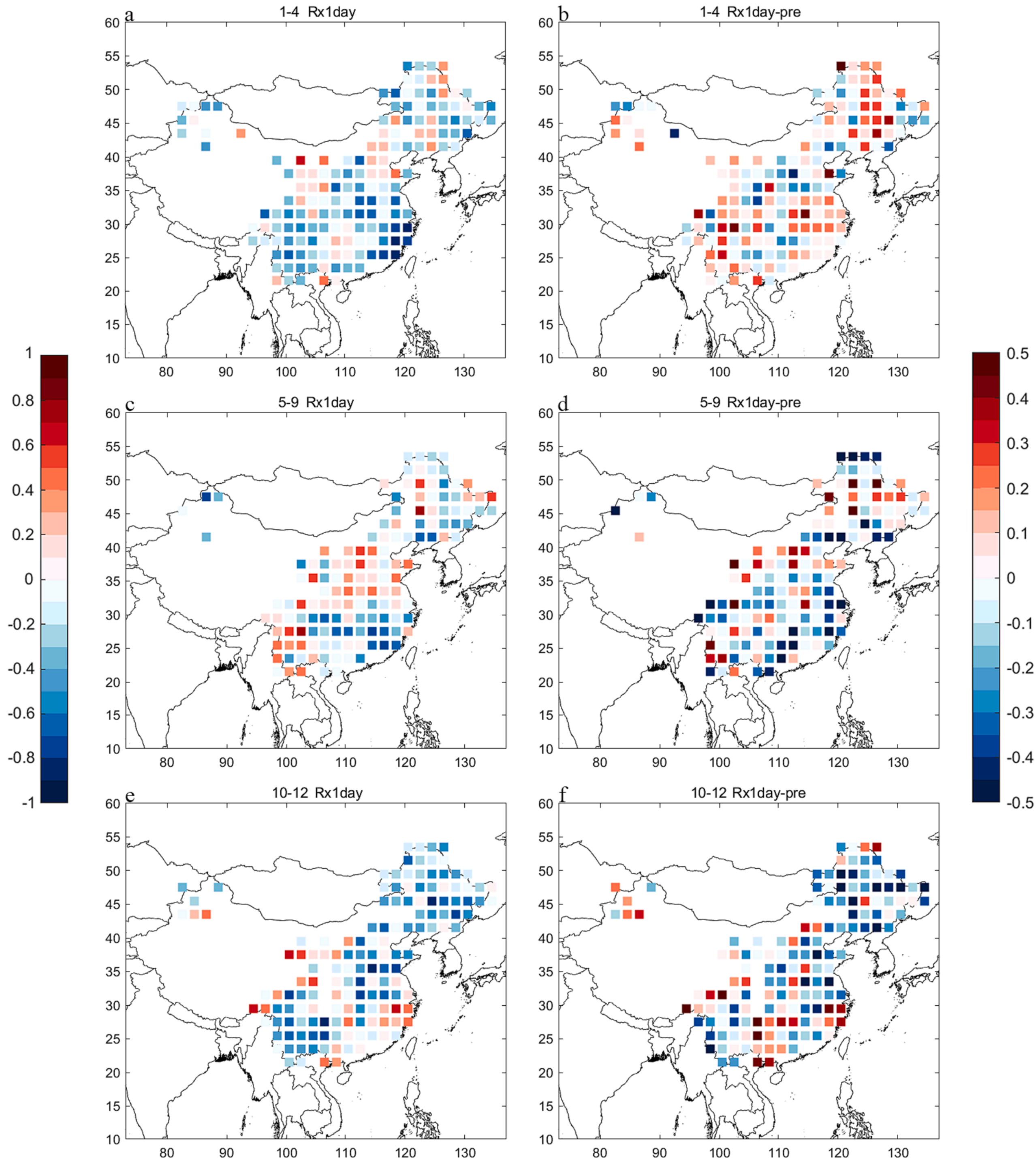

Fig. 6. Pointwise correlations between the first-order difference of WFAC wildfire occurrences (2005–2018) and the first-order difference of maximum 1 day total (RX1day) in (a) pre-monsoon season (January to April), (c) monsoon season (May to September), and (e) post-monsoon season (October to December). Comparison of the wildfire occurrence-RX1day association and the wildfire occurrence-mean precipitation correlation in (b) pre-monsoon season, (d) monsoon season, and (f) post-monsoon season.

4.2. *Relationship between wildfire and climate extremes in SEC*

Contrary to the findings in SWC, the occurrence of wildfires in SEC was found to be primarily modulated by precipitation, and the correlation thereof with the total precipitation was higher than the extreme precipitation indices. In SEC, R10mm, R20mm, R95p, and R99p, all of which indicate extreme precipitation, had strong negative correlations with wildfires in SEC (Figs. S8 and S9). R10mm and R20mm indicate the total number of days with the annual daily precipitation ≥10 mm and ≥20 mm, respectively. R95p and R99p indicate the sum of precipitation exceeding the 95 % and 99 % quantiles, respectively. All of the aforementioned indices represent extreme precipitation, but the impact on wildfire activities is generally less than the total precipitation. In the southeast coastal area of China, due to its proximity to the Pacific Ocean, the airflow from the ocean can carry a large amount of water vapour and bring abundant precipitation to the region. Thus, SEC is an area with more precipitation, and the time of precipitation in SEC is also considerably longer than that in other regions of China (Li et al., 2013). Under such conditions, the occurrence of wildfire is suppressed for a long period, leading to a weaker influence of extreme precipitation on wildfires.

Although wildfires in SEC are largely controlled by precipitation, the correlation between all extreme temperature indices and wildfires in the region is higher than that of mean temperature-wildfire. Because of the low latitude of SEC and the proximity to the sea, the temperature in the region is relatively stable. At the same time, temperature does not have a major impact on wildfires, meaning that there will only be a relatively significant impact on wildfires under extreme conditions. ID and FD are indices indicating the number of days of extremely low-temperature. Located in the subtropical region with low latitude, the extremely low-temperature days of SEC are concentrated in winter. Unlike other regions, in SEC, such indices were positively correlated with wildfires, since the higher number of cold days that last longer result in humans needing to ignite for heating. WSDI indicates continuous high-temperature weather, and was found to have a positive correlation with wildfire nationwide. Further, the correlation thereof with wildfires in SEC was also stronger than the correlation of the mean temperature-wildfire. In the case of sufficient precipitation, if continuous high-temperature weather occurred, the evaporation of water vapor in the area would accelerate, make the plants grow quicker, and have sufficient time to convert into combustibles, thereby increasing the wildfire occurrence.

It is noteworthy that indices such as WSDI, CSDI, CDD, and CWD, emphasizing the continuity of climate extremes, all show their highest values in SWC (Fig. S19). In this region, only the indices for continuous high temperatures and droughts show a significant positive correlation with wildfires. Undoubtedly, persistent hot and dry conditions increase the load of combustibles and facilitate combustion. However, the situation in the SEC differs significantly. With abundant rainfall and longer rainy seasons in SEC, the impact of extreme rainfall on wildfire occurrence in this area is relatively minor, though there are frequent extreme rainfall and a significant correlation between extreme precipitation and wildfires in SEC. In SEC, both CDD and CWD are fewer than in SWC, indicating that rainfall in SEC is more dispersed throughout the year. Therefore, in SWC, where the number of CDD is longer, extreme precipitation can promote vegetation growth and increase the load of combustibles. However, in SEC, where the total amount of rainfall is high but not concentrated in time, the impact of extreme rainfall on wildfires is diminished.

4.3. Seasonal dynamics of wildfire occurrences in China: influences of monsoon and climate extremes

It is evident that the relationship between wildfire occurrences in China and extreme climate indices exhibits significant seasonal variations. In general, during the main fire seasons in China (from January to April), the correlation between the wildfire and the monthly extreme temperature index in the SWC and SEC is roughly consistent with the annual extreme temperature index. This consistency may arise from the fact that wildfires in January to April hold a higher weight in illustrating the relationship between wildfires and climate. During the period, the correlation between the monthly extreme temperature index and the wildfire in SWC is higher than that in other regions, but lower than the correlation between the seasonal mean temperature and wildfire in this region. January to April is the late winter to spring in the northern hemisphere, and then the temperature in the northern hemisphere gradually warms up. The wildfire activities in SWC and northeast China have also exhibited an increasing trend month by month in the season (Fang et al., 2021). The East Asian summer monsoon has not yet prevailed in China from January to April, and most parts of the country have sunny and dry weather controlled by the high pressure, which is conducive to the activities of wildfires. Such conditions could be contributing factors to DTR being highly correlated with wildfires in most parts of China. In this season, the wildfires in southwest, north and northeast China were also significantly positively correlated with the TXx and TX90p, both of which represent extremely high temperature. In this season, the climate in most parts of China tends to be cold and dry, and once extremely high temperature occurs, the probability of wildfires will greatly increase. Additionally, before the monsoon season, wildfires in the southeast coastal area had negative correlations with Rx1day and Rx5day, which is consistent with the spatial distribution of the correlation between the annual extreme precipitation index and the wildfire. The southeast coastal area is close to the western Pacific, and the water vapor from the western Pacific can bring abundant precipitation to the area, reducing the potentiality of the ignition and the spread of wildfires, which will cause a reduction in wildfire activities. However, during this period, the SEC experiences a high wildfire occurrences. Combined with the annual analysis, it is evident that precipitation in SEC exerts a strong regulatory effect on wildfires. Consequently, prior to the onset of the monsoon season, the reduced precipitation contributes to a heightened period of wildfire occurrences (Fig. S20).

In the summer of the northern hemisphere, the frequency of climate extremes in China (especially in south China) was higher than in other seasons (Xu et al., 2011). But affected by the East Asian summer monsoon, wildfire occurrences significantly decreased, and the relationship between wildfire and climate generally weakened. However, there is a high correlation between wildfire and the extremely high-temperature indices (TXx, TX90p) and extremely low-temperature indices (TNn, TN10p) in SCC (25°∼33°N, 105°∼120°E), and the correlation was significantly stronger than that between the mean temperature and the wildfire. Influenced by the subtropical high-pressure ridges, precipitation decreased and sunny weather occurred more frequently in SCC during the monsoon season, which is conducive to fire activities. After the monsoon season, DTR, TXx, and TX90p were significantly positively associated with wildfires in SWC and eastern regions, indicating that wildfire activity becomes more frequent with the occurrence of high temperatures, particularly against the backdrop of generally lower temperatures across China. During this period, however, wildfires were mainly concentrated in SEC (Fig. S1), primarily due to lower rainfall in the winter (Figs. S21 and S22), which significantly reduces the inhibitory effect on wildfires, and secondly, the region's low winter temperatures combined with high population density lead to a significant increase in human-induced fire ignitions (such as for heating).

Consequently, wildfire activity in Southern China is significantly influenced by the monsoon season, resulting in distinct wildfire occurrence mechanisms and peak seasons compared to Northern China and other regions at similar latitudes. Southern China, especially its subtropical areas, hosts some of the most lush subtropical forests globally, characterized by high fuel utilization, abundance, and flammability. Particularly during the non-monsoon season (approximately from October to April), seasonal droughts dry out the available fuel, increasing wildfire susceptibility. The seasonal characteristics of fire seasons here also differ from those in other parts of the world. In Southern China, 71 % of wildfires occurred in winter and early spring, in stark contrast to the weaker wildfire activity during the summer due to moist conditions brought by the monsoon. This forms a sharp contrast with the boreal forests, where wildfire peaks occur in summer, driven by high temperature (Randerson et al., 2006; Bond-Lamberty et al., 2007; Guo et al., 2017; Kim et al., 2020). In China's northernmost parts, lying on the edge of the summer monsoon, wildfire peaks are seen in summer and autumn. Regions along the Mediterranean coast and in California, USA, which are at the same latitude as Southern China, also witness peak wildfire activities in summer and autumn. Influenced by the Mediterranean climate, the hot and dry conditions prevalent in summer are highly conducive to wildfire occurrences (Trouet et al., 2006; Westerling et al., 2006; Wahl et al., 2019). This presents a stark contrast to the subtropical areas of China, where the weakest wildfire activity occurs in summer (June to August) (Fig. S2b), a period dominated by the summer monsoon that brings humid conditions. The number of wildfires associated with the summer monsoon is notably lower.

5. Conclusion

Utilizing wildfire data from the Wildfire Atlas of China (WFAC), extreme climate index data from the Hadley Center, and temperature and precipitation data from the China Climate Research Unit datasets (CRUTS4.03), we studied the main meteorological factors affecting wildfires in different regions in China through analyzing the correlations between wildfire occurrences, extreme climate indices, and mean temperature/precipitation in China from 2005 to 2018. The results indicate that on an annual scale, wildfire occurrences in southwest China were primarily driven by temperature, with a stronger correlation to mean temperature than to extreme temperature indices being observed. Conversely, a closer relationship was found between the extreme precipitation index and wildfires in southwest China than between mean precipitation and wildfires. In southeast China, wildfire occurrences were primarily regulated by precipitation, but more by the mean precipitation than extreme precipitation indices, while the extreme temperature index was more responsive to wildfires than the mean temperature. In Northeast China, wildfires show a more significant correlation with mean temperature than with any extreme climate indices, indicating a minimal impact from extreme climatic conditions. On the seasonal scale, the spatial relationship between the monthly extreme temperature index and wildfires in the pre-monsoon season (main fire season) was essentially consistent with the annual scale results. Additionally, wildfires in the southeast China were more closely related to extreme precipitation indices. During the monsoon season, there was a high correlation of wildfire occurrence with extreme temperature indices in and around central and southern China, and the correlation was stronger than that with mean temperature. We also found that the relationship between CDD/seasonal mean DTR and wildfires in the southwest/southeast China was stronger than those of the annual total precipitation or seasonal mean temperature. These findings on the regional differences in the main factors controlling fire occurrence would be useful for regional ecosystem and fire management.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

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