

Change in the fire season pattern from bimodal to unimodal under climate change: The case of Daxing'anling in Northeast China

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ABSTRACT

The length of the wildfire season has become longer in many regions around the world under climate change. This study investigated changes in fire season pattern (i.e., the number of separate periods of a year when wildfires are most likely to ignite, spread, and affect resources) and the contributions of climate change in Daxing'anling, Northeast China. An expanded fire dataset in both spatial and temporal converge from ground reporting was used. A comparison with satellite detected burned areas showed good agreement in spring, summer, and entire fire season. The results showed that the number of fires used to appear in a bimodal pattern with spring and fall peaks in the last century, but transitioned to a unimodal pattern peaked in summer in this century. This conversion was mainly resulted from a remarkable increase in summer lightning fires, which was in turned associated with warming in Daxing'anling. Another factor for the conversion was decreased spring nonlightning fire occurrence in the northwest subregion, where the conversion was the most significant. This decrease of fire was mainly associated with increased precipitation. The analysis of a compositional fire series, built as the log of the ratio of lightning to nonlightning fires, suggests that climate change was a major factor for the conversion of fire season pattern. The finding from this study indicates a need to adjust the fire prevention implementation timeline by including summer fires and to develop strategies to reduce the related risks to firefighter safety and forest ecosystem health in Daxing'anling.

1. Introduction

A fire season consists of one or more discontinuous time periods throughout the year when wildland fires are likely to occur, spread, and affect resource values to a degree that warrants organized fire management activities (NWCG, 2006). The fire season pattern, defined as the number of the time periods, is an important feature of a fire season in addition to its length and onset and termination dates. An understanding of this feature is particularly helpful for fire agencies in their efforts to plan and implement specific fire prevention measures (USFA, 2005). Giglio et al. (2013) divided the global land surface into 14 regions based on the combination of continents and vegetation types and compared regional fire properties by using satellite-based fire data from 1995 to 2010. It was shown that fire seasons included a single period (unimodal pattern) in 12 regions and two discontinuous periods (bimodal pattern) in two regions. The bimodal pattern can be observed more often at the local scale. In the U.S., for example, bimodal fire seasonal patterns have been observed in the southern Appalachians

(spring and fall) (Lafon et al., 2017), Texas (winter/spring and late summer/early fall) (Cohen, 2013), and southern California (early summer and fall) (Jin et al., 2015). Studies in China have indicated a bimodal fire pattern in Northeast China, where Daxing'anling is located, as well as North China (Tian et al., 2015).

Climate is one of the major factors that influence the fire season pattern. Typically, fire periods align with times of the year when dry fuels are abundant, temperatures and winds are high, and humidity is low (Beals 1914; Gisborne, 1928). For example, the two fire periods in the southern Appalachians coincide with the times of the year with the lowest relative humidity and the highest wind speed (Lafon et al., 2017). Before deciduous trees grow new leaves in spring and after their leaves fall in fall, sun and wind can penetrate to the forest floor and dry the dead fuel (Byram and Jemison, 1943). The two fire periods in southern California are characterized by warming fuels under plenty of sunshine and hot and dry Santa Ana winds (Schroeder et al., 1964), respectively.

Fire seasons in many regions are changing with climate change

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acting as a major driver. The most noticeable change is a longer fire season due to an earlier start and/or a later end of the fire season (Flannigan et al., 2009; Westerling et al., 2006; Wotton and Flannigan, 1993). The length of global mean fire weather season increased by 18.7% from 1979 to 2013 (Jolly et al., 2015). The fire season in the western U.S. is 105 days longer than it was in the 1970s (Kenward et al., 2016). Fire season lengths have increased over large areas of North America, especially in eastern Canada and the southwestern U.S. (Jain et al., 2017). If climate change and other disturbances in a region with a bimodal fire pattern cause a longer fire season due to a later termination of the first period and/or an earlier onset of the second period, then the feature of low fire activity during the time between the two periods could become less apparent or even disappear; if the magnitude of increasing fires during the time of low fire activity is larger than the magnitude of the fires in one or both periods, then the bimodal pattern could be changed to a long unimodal one.

Such a change in the fire season pattern would affect forest management in many ways. In contrast to the current bimodal pattern with spring and fall peaks, there would no longer be a summer break for firefighters and fire suppression equipment maintenance. An increase in summer fires thus could increase firefighting safety risks. Notably, under hot weather conditions, heat stress can progress into heat strain, which in turn can lead to heat-related illnesses and even heat stroke (Becker and Stewart, 2011). Sixty percent of entrapment is related to high temperatures (Cardilano Molina-Terrén, 2015). Dense branches and leaves in summer reduce the mobility of firefighters and fire suppression equipment and the ability of firefighters to identify dangerous places such as valleys, which makes it especially difficult to suppress fires.

Daxing'anling (the Great Xing'an Mountains) in Northeast China has the largest intact virgin forest and the most frequent occurrences of lightning fires in China (Chen et al., 2015; Tian et al., 2013). The catastrophic Black Dragon Fire in May 1987, the largest wildfire in China in the past half a century, burned over 1 million ha (Cahoon et al., 1994). Thus, fire season predictions and management in this region are critical for forest health in China. Climate is an important driver in conjunction with other factors (land cover, topography, road accessibility, population density, etc.) for the spatial distributions and inter-annual variability of fires in Daxing'anling (Guo et al., 2017; Liu et al., 2012; Tian et al., 2011a; Wu et al., 2014; Yao et al., 2017). Earlier studies have shown that fires in Daxing'anling mainly have occurred in spring and fall (Tian et al., 2011b), and the intensity and duration have changed during both periods (Hu and Zhou, 2014). Lightning fires in Daxing'anling, which were absent in the summers during 1980–1998, were observed in a few summers during 1999–2005 (Fan et al., 2017).

This study investigated the conversion of the fire season pattern under climate change in Daxing'anling. A recently expanded fire dataset of more than half a century covering the entire area of Daxing'anling was analyzed to understand the long-term fire trends in various fire periods and the related changes in the fire season pattern. The trends of weather conditions and weather-fire correlations were also analyzed to understand the contributions of climate change to the fire trends. The results of this study are expected to be useful for the development of adaptation and mitigation strategies to address the impacts of climate change on fire prevention and safety in Daxing'anling as well as other regions around the world where fire season patterns are changing.

2. Methodology

2.1. Study area

Daxing'anling is located in the northwestern Heilongjiang (HL) Province and northeastern Inner Mongolia (IM) Autonomous Region of Northeast China (Fig. S1) (48°3'–53°3'N, 120°0'–127°0'E). It has an area of approximately 1.8×10^5 km². The terrain is relatively flat in the east

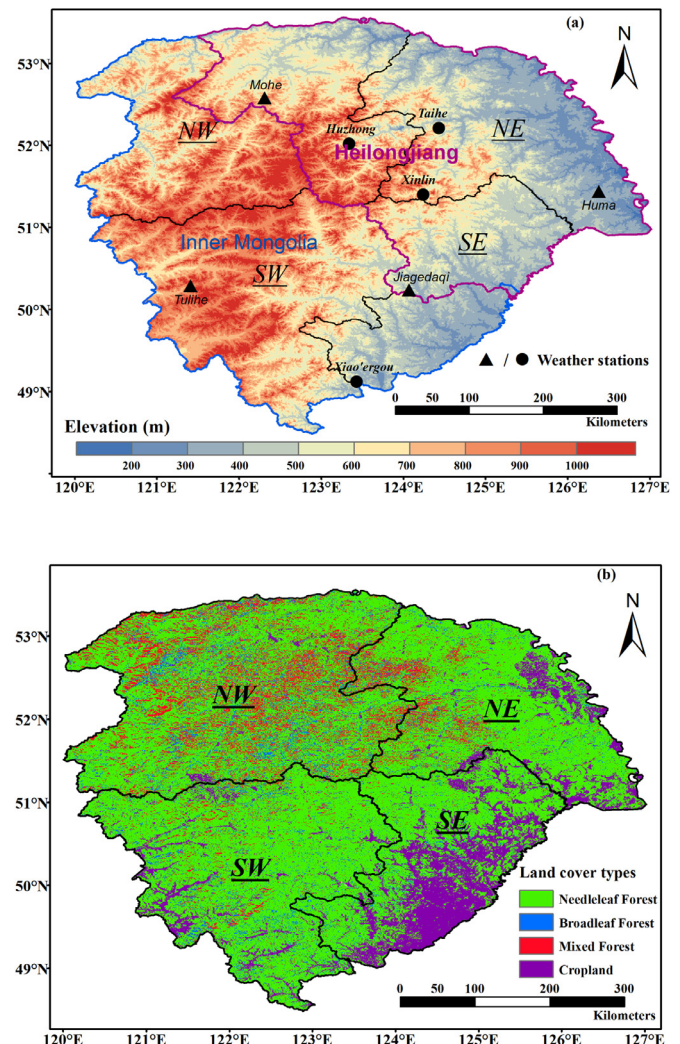


Fig. 1. Study area. (a) Topography (in meters). The internal pink line is the border of Daxing'anling in Heilongjiang Province and the Daxing'anling in Inner Mongolia Autonomous Region. The black lines are boundaries of the northwest (NW), southwest (SW), northeast (NE), and southeast (SE) subregions (northern SE and SW boundary is in pink). Triangles and circles are meteorological stations where the data were used for fire-weather and data representativeness analyses, respectively. (b) Land cover types. (The elevation and land cover data used to produce this figure were obtained from <https://globalmaps.github.io/>).

and mountainous in the west (Fig. 1a), with a peak of just over 2000 m and a forest coverage rate of 76.3% (Chen et al., 2015). The study area has a temperate continental monsoon climate with cool and humid summers with southeast airflows from the Pacific high-pressure system and cold and dry winters under the control of the Mongolia high pressure system (Tian et al., 2011a). The annual average temperature is -2.8°C , and the temperature is approximately -30°C in winter and 30°C in summer on average. The annual precipitation amount is 450–500 mm, two-thirds of which occurs from June to August.

The main forest types (Fig. 1b) are deciduous needle forests dominated by *Larix gemelini*, which cover 86.1% of the forest area (Tian et al., 2011b). Other common tree species are evergreen coniferous *Pinus sylvestris*, and deciduous *Betula platyphylla*, *Quercus mongolicus*, and *Populus davidiana*. The trees (especially deciduous species) in Daxing'anling do not experience much growth during the dormant season from October to April with a constant leaf area index (LAI) of about 0.5. Then, the LAI increases beginning in April and reaches a maximum value of about 4.5 in summer (Wang et al., 2017). There are farming lands in the study area, mainly in southeastern Daxing'anling.

To examine the spatial variability, the study area was divided into northwest (NW), southwest (SW), northeast (NE), and southeast (SE) subregions (Fig. 1). These areas were divided mainly by considering the topography. The NW and SW regions are in the western mountains and face north and south aspects, respectively. The NE and SE regions are in the relatively flat eastern part of Daxing'anling and face northeast and southeast aspects, respectively. The boundaries between the subregions were those of forestry divisions. In addition, the dominant vegetation types in these subregions are different, with mixed forest in the NW region, needle-leaf forest in the SW region, cropland in the SE region, and a combination of the three types in the NE region. The land cover changes since the early 1980s mainly have included forest-farming conversions in the SE region as well as very small areas of the NE and SW regions, and the instantaneous loss and gradual postfire tree regeneration in the NW region due to the catastrophic 1987 Black Dragon Fire (Liang et al., 2018).

2.2. Fire data

A dataset developed based on reported individual fires in the entire Daxing'anling region during 1966–2017 was used. The dataset consisted of two parts, one from the HL Forestry and Grassland Bureau (<http://www.hljforest.gov.cn>) and the other from the IM Forestry and Grassland Bureau (<http://www.imfc.com.cn>). All individual fires, no matter they occurred in HL or IM, were reported by using the same protocol developed by the China National Forestry and Grassland Administration, although the specific reporting forms were different. Copies of the report forms for a month from HL (Table S1) and IM (Table S2) are provided in the supplementary materials. The HL portion of the dataset has been used in many fire-weather studies (e.g., Fan et al., 2017; Hu and Zhou, 2014), while the IM portion of the dataset has yet to be analyzed systematically. The fire dataset used in this study covered a longer period and larger spatial area than the fire datasets used in other studies. For example, the data period was only 1967–2006 in Hu & Zhou (2014) and 1980–2005 in Fan et al. (2017), and both studies only used the fire data in HL. The data of longer term were valuable for analyzing historical fire trends and fire pattern changes between different subperiods. Moreover, the larger spatial coverage of data was valuable for comparing the trends and pattern changes among the Daxing'anling subregions.

The quality of fire data was assured primarily by intense fire monitoring to prevent missing report of any fires. There were 326 fire monitoring towers as of 2017, approximately each tower every 30 km. In addition, it is required by the Management Regulations of Forest Fire Prevention in Daxing'anling (http://www.360doc.com/content/20/0320/20/11634934_900609342.shtml) to deploy a fire inspector every five (three) kilometers along a province (countryside) road according to. The forest divisions are required to report fire information in time. The fire data were recorded and coordinated by using a “bottom-up” approach by the government at various levels of individual forests, forest divisions, and province forestry bureaus. Errors and uncertainties in fire reports gradually increase during the process of “bottom-up” reporting systems (Guo et al., 2017). It is likely that some human caused fires were recorded as unknown by local forest managers to avoid punishment when lightning was ruled out as the possible cause (Hu and Zhou, 2014).

Satellite detected fires in Daxing'anling have been used without systematic comparisons with reported fire data (Guo et al., 2017; Tian et al., 2013). To assess the quality of the reported fire data, we compared them with the monthly burned area from the global fire emissions database (GFED) (Giglio et al., 2013), which was developed based on the Moderate Resolution Imaging Spectroradiometer (MODIS) products. The resolution of the GFED data was 0.25°, and the time period was 1997–2016 (Only emission data are available after 2016). The dataset included small fires (Randerson et al., 2012). The reported annual, spring, and summer burned areas generally had a similar inter-

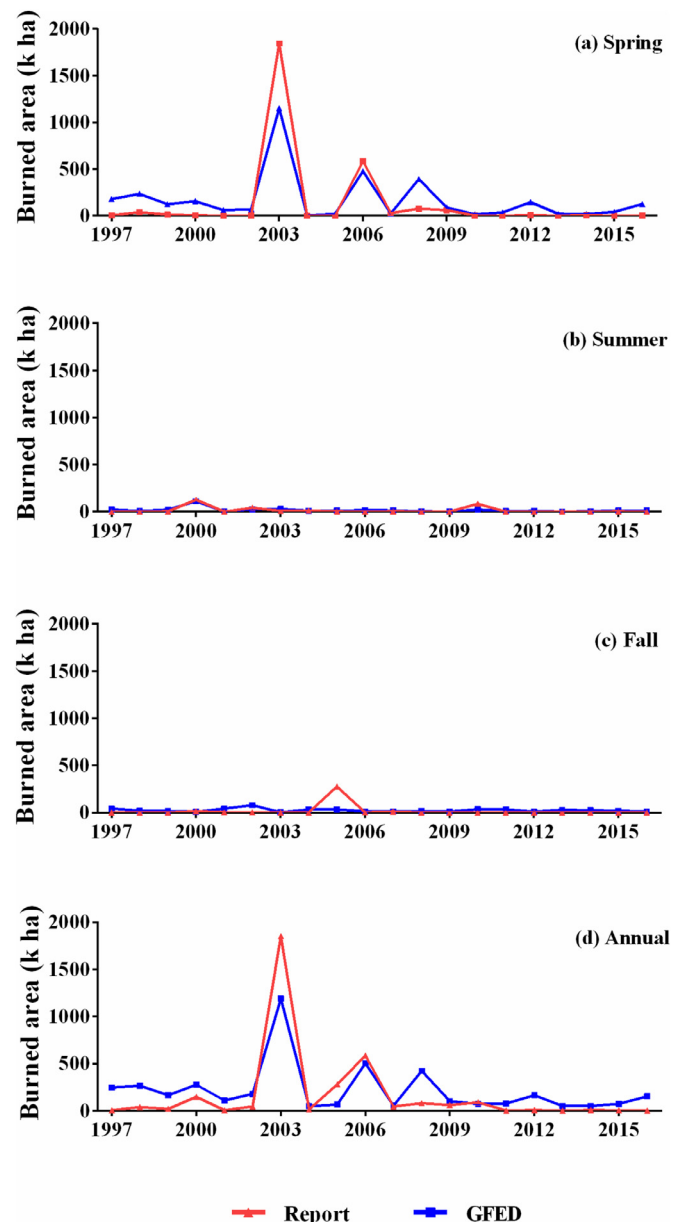


Fig. 2. A comparison of burned areas in Daxing'anling derived from the ground reported and GFED remotely sensed data.

annual variability as the GFED results (Fig. 2), and the correlation coefficients between the two datasets for these data products were 0.922, 0.945, and 0.842 ($p < 0.00001$), respectively. However, the correlation coefficient was only 0.116 (insignificant) for fall. A possible reason is that agricultural burns in Daxing'anling were conducted mostly in fall, and those burns that were not turned into wildfires were not included in the reported data. They, however, could be detected by satellite. The reported values were systematically smaller than the GFED values. The relative differences (i.e., the differences in burned area between the reported and GFED values divided by the GFED values) were -22.8% , -20.9% , -17.0% , and -36.0% for the annual, spring, summer, and fall, respectively. The magnitude of the annual difference was comparable to the value of 15% for the temperate and boreal North America over the period of 1997–2008 (Liu et al., 2014). In North America, the reported values were generally larger than the GFED values. One possible reason is that the GFED data did not include small fires at that time. The comparison results suggest that the reported burned areas of the Daxing'anling fires matched the GFED data

reasonably well in terms of the inter-annual variability and magnitude for the annual, spring, and summer periods. Note that a comparison was not conducted for fire number because the GFED data did include this property.

The major data parameters included the longitude, latitude, detected time, extinguished time, fire causes, and burned area. Fire causes included lightning, humans (such as through arson, cooking, smoking, and trains), other causes (such as agricultural burns turning into forest fires), and unknown causes. Similar to Hu and Zhou (2014), all causes were grouped into the following two types in this study: lightning fires (fires ignited by lightning) and nonlightning fires [fires ignited by other causes than lightning; this type was called human-caused fires in Hu and Zhou (2014)].

Besides lightning and nonlightning fires, we also analyzed their combinations in two forms, namely, the sum (denoted as total fire) and the log of the ratio of lightning to nonlightning fires (denoted as compositional fire). Such a ratio has been used as compositional multi-variate data in previous research (Barceló-Vidal et al., 2011; Kynčlová et al., 2015). Natural lightning fires are mainly related to climate, while nonlightning fires are mainly related to human factors. Thus, the compositional fire value could be used as a measure of the relative importance of climate change and human activity for fires. A value was assigned for any of the three situations in which a compositional fire value could not be obtained from its definition based on the following considerations: (1) for lightning fire = 0, the ratio of lightning fire / nonlightning fire = 0. The log function of zero is invalid. Thus, we assumed a zero compositional fire value. (2) for nonlightning = 0, the ratio is infinite. We assumed a compositional fire value of 1, although another positive value could be assigned too. (3) For lightning fire = 0 and nonlightning fire = 0, the ratio is invalid. A small value of 0.3 was assumed, though another value could be assigned too.

Two fire properties, namely, the number of fires and burned area, were analyzed. We denote the fire number and burned area as $F_n(i, t)$ and $F_a(i, t)$, respectively, where i is a fire type element [lightning (LTNG), nonlightning (nLTNG), the sum (TOTAL), or compositional (COMP)], and t is a time element that represents the spring fire period, summer fire period, fall fire period, or entire fire season (all three fire periods) for seasonal data, or an individual month of the year for monthly data. The fire periods will be defined below. The seasonal data were used for analyzing long-term trends and correlations between fire and meteorology. The monthly data were used to analyze changes in fire season patterns.

To confirm stationarities of the fire and meteorological series, the Dickey-Fuller test (Dickey and Fuller 1979) and its augmented version, the augmented Dickey-Fuller test (ADF), for a unit root with drift and deterministic time trend were conducted. The statistic values for all fire series of different properties (numbers and burned areas), types (lightning, nonlightning, total, and compositional), and periods (spring, summer, fall, and entire fire season) in Daxing'anling were significant at $p < 0.01$ (Table S3). The result indicates that the fire series were stationary.

2.3. Climate data

The climate data used for this study included several daily meteorological variables, namely, the temperature (T , °C) (used only in calculations of fuel moisture; see Eq. (3) below) and maximum temperature (T_{max} , °C), precipitation (P , mm/day), wind speed (U , m/s), and relative humidity (h , %) during 1966–2017. These data were obtained from the China Meteorological Data Sharing Network (<https://data.cma.cn/en>). Observations at the four meteorological stations in Huma, Mohe, Tulihe, and Jiagedaqi (Fig. 1) were used to represent the meteorological conditions in the NW, SW, NE, and SE regions, respectively. The observations for the first year at Jiagedaqi were not available; thus, the results for this area were supplemented with the observations at Xiaobergou, a station located near the boundary of the

southern SE and SW regions. There were three more meteorological stations in the study area. However, observations were not available for the first five years. These data were used only to calculate the correlation coefficients among all meteorological stations to analyze the representativeness of the four meteorological stations used for weather-fire relationships.

We also analyzed the following three fire indices: the fuel moisture content of 1000-hour (MC), which represents a forest fuel property but was regarded as a fire index for the convenience of descriptions, the Keetch–Byram Drought Index ($KBDI$) (Keetch and Byram 1968; Liu et al., 2010), and the modified Fosberg Fire Weather Index ($mFFWI$) (Goodrick, 2002). Long-term fuel moisture varied in good agreement with the drought index and fire weather index in Daxing'anling (Tian et al., 2013). $KBDI$ had a better fire relationship than the more widely used Palmer Severity Drought Index ($PSDI$) in Daxing'anling (Hu and Zhou, 2014; Jia et al., 2011). $mFFWI$, which was developed based on the Fosberg Fire Weather Index ($FFWI$) (Fosberg, 1978), is a function of T , h , P , and U and therefore includes the effects of all of these weather variables. We denote the meteorological variables or fire indices as $M(t)$.

Same as fire series, stationarities of the meteorological series were tested. The statistic values for weather variables and fire indices of different periods (spring, summer, fall, and entire fire season) in Daxing'anling were significant at $p < 0.01$ except for U and $mFFWI$ (Table S4). The results indicated that the weather series (except for U and $mFFWI$) were stationary.

The three fire indices were calculated by using the methods described below.

2.3.1. Fuel moisture

The method from the U.S. National Fire Danger Rating System (Cohen and Deeming, 1985; Deeming et al., 1977; Liu, 2017) was used to calculate the $MC1000$ based on the T , h , and P :

$$MC = MC_w + (\overline{BDY} - MC_w)(1 - 0.82e^{-0.168}) \quad (1)$$

where MC_w is the MC one week prior (the seventh previous day); $\overline{BDY}$ is the average of the daily precipitation property factor, P_f , over 7 days:

$$P_f = [(24 - P_{dur}MC_e + P_{dur}(2.7P_{dur} + 76)]/24 \quad (2)$$

where P_{dur} is a precipitation duration indicator that depends on the rainfall amount and climate class (moist for Daxing'anling). MC_e is a weighting average for the day and night equilibrium moisture content, which was approximated with daily values in this study:

$$MC_e = \begin{cases} a_1 + (a_2 - a_3 T)h & h \leq 10\% \\ a_4 + a_5 h - a_6 T & 10\% < h \leq 50\% \\ a_7 + (a_8 h - a_9 T - a_{10})h & h \geq 50\% \end{cases} \quad (3)$$

where a_i ($i = 1, 2, \dots, 10$) = 0.03229, 0.281073, 0.000578, 2.22749, 0.160107, 0.014784, 21.0606, 0.005565, 0.00035, and 0.483199.

2.3.2. KBDI

$KBDI$ was calculated as follows:

$$Q = Q_0 + dQ - dP \quad (4)$$

$$dQ = 10^{-3}(800 - Q)(0.968e^{0.0486T_{max}} - 8.3)d\tau/(1 + 10.88e^{-0.0441Pa}) \quad (5)$$

where Q is the $KBDI$, Q_0 is the previous day's Q , dQ is the $KBDI$ incremental rate, dP is the daily precipitation, T_{max} is the daily value, P_a is the mean annual rainfall used as a vegetation surrogate, and $d\tau$ is a time increment set equal to one day. Note that $dQ = 0$ when $T \leq 50^\circ\text{F}$ (10°C) and only the portion of daily precipitation above the net accumulated precipitation of 0.5 cm (0.20 inch) was used.

2.3.3. mFFWI

$mFFWI$ was calculated as follows:

Table 1

Criteria for contributions of meteorological variable $M(t)$ to trend and difference in fire $F(i,t)$. $\uparrow$ ($\downarrow$) represents increasing (decreasing). + (−) represents positive (negative) difference or correlation.

	$F(i,t)$	$M(t)$
Trend	(1) Significant $\uparrow$ trend	Significant trend in $M(t)$, and Significant correlation with $F(i,t)$, and + (−) correlation and $\uparrow$ ($\downarrow$) trend in $M(t)$ <u>if(1), or</u>
	(2) Significant $\downarrow$ trend	+ (−) correlation and $\downarrow$ ($\uparrow$) trend in $M(t)$ if (2).
Difference	(1) Significant + difference	Significant difference in $M(t)$, and Significant correlation with $F(i,t)$, and + (−) correlation and + (−) difference in $M(t)$ <u>if(1), or</u>
	(2) Significant − difference	+ (−) correlation and − (+) difference in $M(t)$ <u>if(2).</u>

$$FFWI = b_f \eta (1 + U^2)^{0.5} \quad (6)$$

$$\eta = 1 + c_1 M + c_2 M^2 + c_3 M^3 \quad (7)$$

$$M = d_{0,0} + d_{1,0}h + d_{0,1}T + d_{1,1}hT + d_{2,0}h^2 \quad (8)$$

where U , h , and T are in miles per hour, %, and F, respectively. η is the moisture damping coefficient. Other symbols are empirical constants with $b_f = 1/0.3002$; $c_1, c_2, c_3 = 1, 1.5$, and -0.5 , respectively; $d_{0,0}, d_{1,0}, d_{0,1}, d_{1,1}, d_{2,0} = 0.03229, 0.281073, 0, -0.000578$, and 0 for $h < 10\%$, $2.22749, 0.16010, -0.01478, 0$, and 0 for $10\% \leq h \leq 50\%$, or $21.0606, -0.483199, 0, 0.00035$, and 0.005565 for $h > 50\%$, respectively. The impact of precipitation was included by adding a weight factor, the fuel availability factor (FAF), which was determined by the KBDI:

$$mFFWI = FAF \times FFWI \quad (9)$$

$$FAF = e_{m0} + e_m Q^2 \quad (10)$$

where $e_{m0} = 0.72$, and $e_m = 0.000002$.

2.4. Analysis of fire patterns

Fires throughout a year were grouped into the following three periods based on the forest and grassland fire prevention regulations in Daxing'anling (HLFFPR, 2018; IMFFPR, 2016): the spring period from March 15th to June 15th [day of year (DOY) 74–166], the summer period from June 16th to September 14th (DOY 167–257), and the fall period from September 15th to November 15th (DOY 258–319).

In the same manner as Terando et al. (2012), a least-squares linear regression between the temporal fire data series (dependent variable) and year series (independent) was used to fit the linear trends to the fire data. A t-statistic, obtained based on the variance of the residuals of regression (that is, the difference between the fire data and the regression values), variance of the year series, and the regression slope, was used to test the significance (Brockwell and Davis, 1996; Harvey, 1993; Ito 2019). The slope was equal to the correlation coefficient between the normalized fire and year series.

Note that the popular Mann–Kendall trend test (Esterby, 1996) was not used for the trend analyses in this study. This test compares each of the two adjacent elements and requires non null elements in the analyzed time series. However, Daxing'anling had no lightning fires for 4, 15, and 40 years and no nonlightning fires for 0, 21, and 14 years in the spring, summer, and fall time series, respectively. Terando et al. (2012) used a technique to solve the issue of missing elements in the agriculture data series from weather stations spread across the continental U.S. and northern Mexico by excluding the stations with five or more consecutive years of missing data from the trend analysis. This technique was not used in the present study because the number of data series for the fire type and fire period (four of them, one for each subregion) was always small.

The change in the fire season pattern was identified by comparing monthly fires averaged over the years between the two stages of 1966–1999 and 2000–2017 with the separation year determined based

on the inter-annual variability of lightning fires to be shown later. To examine if the change was robust, comparisons were also made between the two stages with the same number of years, namely, 20 or 10. The stages for 20 years were 1978–1997 and 1998–2017. The following three cases were used for the 10-year comparisons: 1990–1999 and 2000–2009, 1989–1998 and 1999–2008, and 1991–2000 and 2001–2010. The statistical significance of the differences between the two stages was obtained by using the two-tailed Welch t -test (https://en.wikipedia.org/wiki/Welch%27s_t-test).

2.5. Criteria for climatic contributions

Similar to fire property, $F(i,t)$, the long-term trend and difference between two subperiods were calculated for a meteorological variable or fire index, $M(t)$. The criteria for $M(t)$ being a contributor to a significant fire trend or difference are listed in Table 1.

3. Results

First, some of the background information on fires and climate are presented in this section, and this is followed by a description of the major findings for changes in fire patterns.

3.1. Background information on fire and climate

3.1.1. Spatial distributions and temporal variations of fires

Lightning fires (Fig. 3a) occurred mainly in the NW, western NE, and northern SE regions in summer and fall, whereas nonlightning fires (Fig. 3b) occurred primarily in the SE, southern NE, and western SW regions in spring and summer. Overall, the total fire data (Fig. 3c) were primarily concentrated in the eastern flat areas in spring and summer and were spread relatively uniformly across Daxing'anling in summer.

A total number of approximately 4200 fires occurred during 1966–2017 (~81 fires per year) (Fig. 4). The fire numbers were larger in the SE and NW regions than in the NE and SW regions. Nonlightning (lightning) fires accounted for approximately 60% (40%) of the total fires in Daxing'anling, and these occurred mostly during the spring (summer) period. In all subregions except for the NW, the number of nonlightning fires was larger than the number of lightning fires. Most fires had sizes of 1–100 ha.

3.1.2. Inter-annual variability and long-term trends

The fire number, $F_n(i,t)$, and burned area, $F_a(i,t)$, varied differently over the years (Fig. 5). $F_n(LTNG,t)$ occurred mainly in summer and increased remarkably at the beginning of this century (Fig. 5a), the most noticeable in the NW region (Fig. S2a) but visible in the other subregions as well (Fig. S2b–d). The slopes of the least-squares linear regressions of $F_n(LTNG,t)$ (Fig. 6a–e), displayed by using the equivalent correlation coefficients of the normalized fire time series for easy comparisons among fire types and periods, were all positive ($p < 0.1$ or $p < 0.05$) in all periods in Daxing'anling (Fig. 6a) and the NW region (Fig. 6b), and in summer and entire fire season in other regions (Fig. 6c–

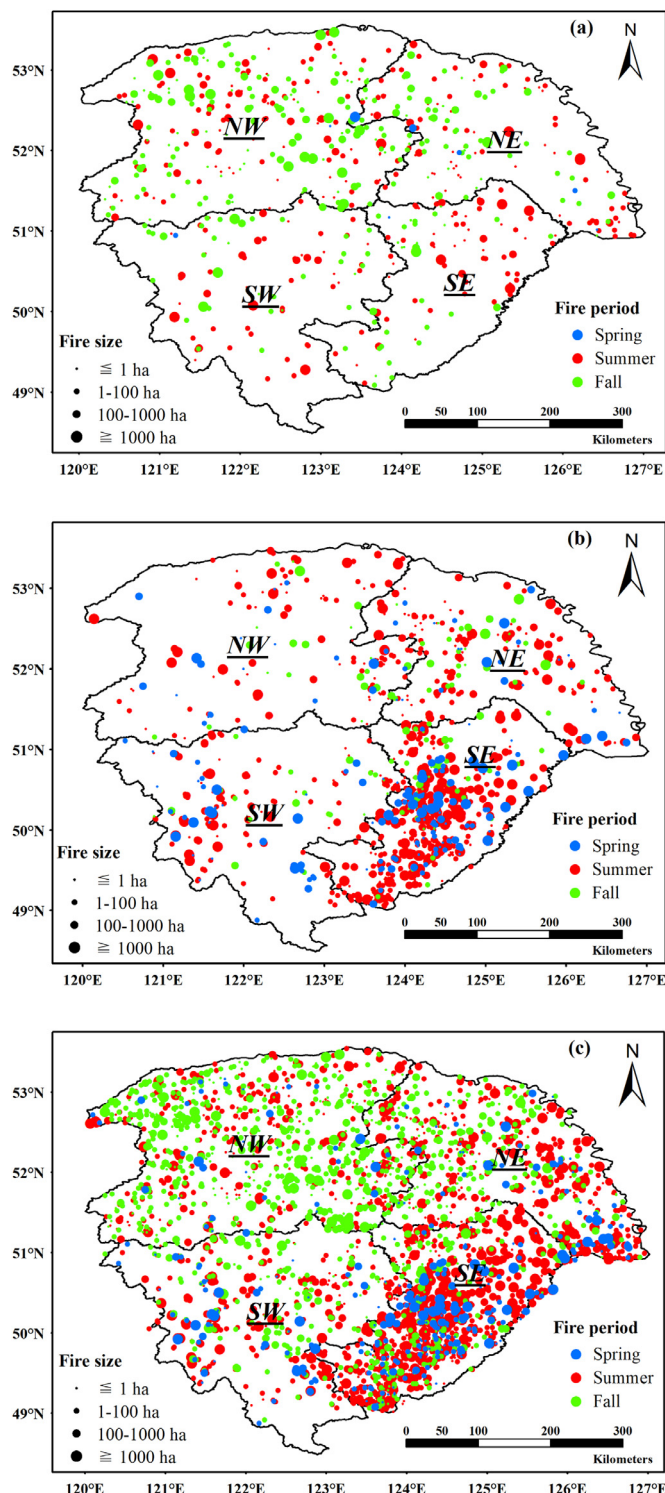


Fig. 3. Spatial distributions of individual fires in the spring, summer, and fall periods of a fire season. (a–c): Lightning, nonlightning, and all fires.

e), plus fall in the NE region. $F_n(nLTNG, t)$ occurred mainly in spring with very large values during 1981–1987 and 2002–2008 (Fig. 5b); the largest value was detected in the SE region (Fig. S2h). The slopes of $F_n(nLTNG, t)$ were all negative, but significant only in summer in Daxing'anling (Fig. 6a), in spring and the entire fire season in the NW (Fig. 6b) and NE (Fig. 6d) regions, and in fall in the SW region (Fig. 6c). $F_n(TOTAL, t)$ occurred mainly in spring and summer in accordance with the increasing trend in summer (Fig. 5c). The slopes of $F_n(TOTAL, t)$ were all positive and significant in summer in Daxing'anling (Fig. 6a)

and the NW (Fig. 6b) and NE (Fig. 6d) regions, and in the entire fire season in the NW region (Fig. 6b). $F_n(COMP, t)$ was mainly positive (negative) in summer (spring and fall) (Fig. 5d), indicating larger (smaller) $F_n(LTNG, t)$ than $F_n(nLTNG, t)$ in summer (spring and fall). The slopes of $F_n(COMP, t)$ were similar to those of $F_n(LTNG, t)$, but often with larger magnitudes (Fig. 6a–e).

$F_a(LTNG, t)$ was larger in spring and summer than in fall (Fig. 5e). Fall fires increased from the middle 1990s onward. The slopes of $F_a(i, t)$ had almost the same signs as the slopes of $F_n(i, t)$, but significant only for each fire type in one or more periods in Daxing'anling (Fig. 6f) and the SE region (Fig. 6j), as well as for $F_a(TOTAL, summer)$ in the NE region (Fig. 6i). $F_a(nLTNG, t)$ values were comparable among the three periods, and all displayed decreasing trends (Fig. 5f). $F_a(TOTAL, t)$ values were also comparable among all periods but the decreasing trends were visible only in spring and fall (Fig. 5g). Similar to $F_n(COMP, t)$, $F_a(COMP, t)$ was mainly positive in summer but negative in spring and fall (Fig. 5h). The slopes of $F_a(COMP, summer)$ were positive ($p < 0.05$) in Daxing'anling (Fig. 6f) and the NE region (Fig. 6i) although the slopes of $F_a(LTNG, summer)$ were insignificant. This was related to the significant negative slopes of $F_a(nCOMP, t)$.

The T_{max} averages in Daxing'anling were 12.6, 23.9, 6.9, and 14.4°C with the standard deviations of 1.3, 1.1, 1.5, and 0.9°C for spring, summer, fall, and the entire fire season, respectively. The corresponding P values were 1.0, 3.3, 0.7, and 1.7 mm/day for averages, and 0.3, 0.6, 0.4, and 0.3 mm/day for standard deviations. The inter-annual variations of T_{max} and P in Daxing'anling and the four subregions are showed in Fig. S3.

The slopes of the least-squares linear regressions of the meteorological variables and fire indices (Fig. 7), displayed using correlation coefficients of the normalized time series, can be placed into three groups. (1) T_{max} and U with positive and negative slopes, respectively ($p < 0.05$ or $p < 0.1$) (except for the insignificant summer U slope in the SW region), in favor of increasing fire trends. (2) P and $mFFWI$ with positive and negative slopes, respectively ($p < 0.05$ or $p < 0.1$) [except for P in all regions in summer, the NE region in fall, and the SW and NE regions in the entire fire season, and for $mFFWI$ in Daxing'anling and the SE region in summer (insignificant) and in the SW region in all periods except spring (either insignificant or significant but increasing)], in favor of decreasing fire trends in spring and fall. (3) h , MC , and $KBDI$ with small slopes in magnitude in most regions. The slopes were mostly negative and significant only in some fire periods in the SW region for h ; almost the same in sign as those of P , but significant only in spring in Daxing'anling and the NW and SE regions, and in fall and the entire fire season in the NW region for MC ; and almost the same signs as those of T_{max} , but significant only in one period in the SW and NE regions for $KBDI$.

3.2. Changes in fire season patterns

Mainly as a result of the trends of significant increasing $F_n(LTNG, summer)$, the fire season pattern in Daxing'anling for the total fire number changed (Fig. 8). According to Fig. 5a, we separated the entire fire series into the subperiods of 1966–1999 and 2000–2017. The monthly $F_n(LTNG, t)$ had a unimodal pattern in both subperiods (Fig. 8a), with large values in May–August that peaked in June. The differences between the two subperiods were significant in June–August ($p < 0.05$) and September ($p < 0.1$). In contrast, the monthly $F_n(nLTNG, t)$ had a bimodal pattern with a larger May peak and a smaller October peak in both subperiods (Fig. 8b). The peak values decreased from the first to second subperiod with significant differences in May ($p < 0.01$) and July ($p < 0.1$). The monthly $F_n(TOTAL, t)$ shifted from a bimodal pattern in the first subperiod to a unimodal pattern in the second subperiod with significant differences in July ($p < 0.1$) and August ($p < 0.05$) (Fig. 8c). $F_n(TOTAL, t)$ increased from the first to the second subperiod in all summer months in the NW region (Fig. 9a) and in two summer months in the NE region (Fig. 9c). However, no summer

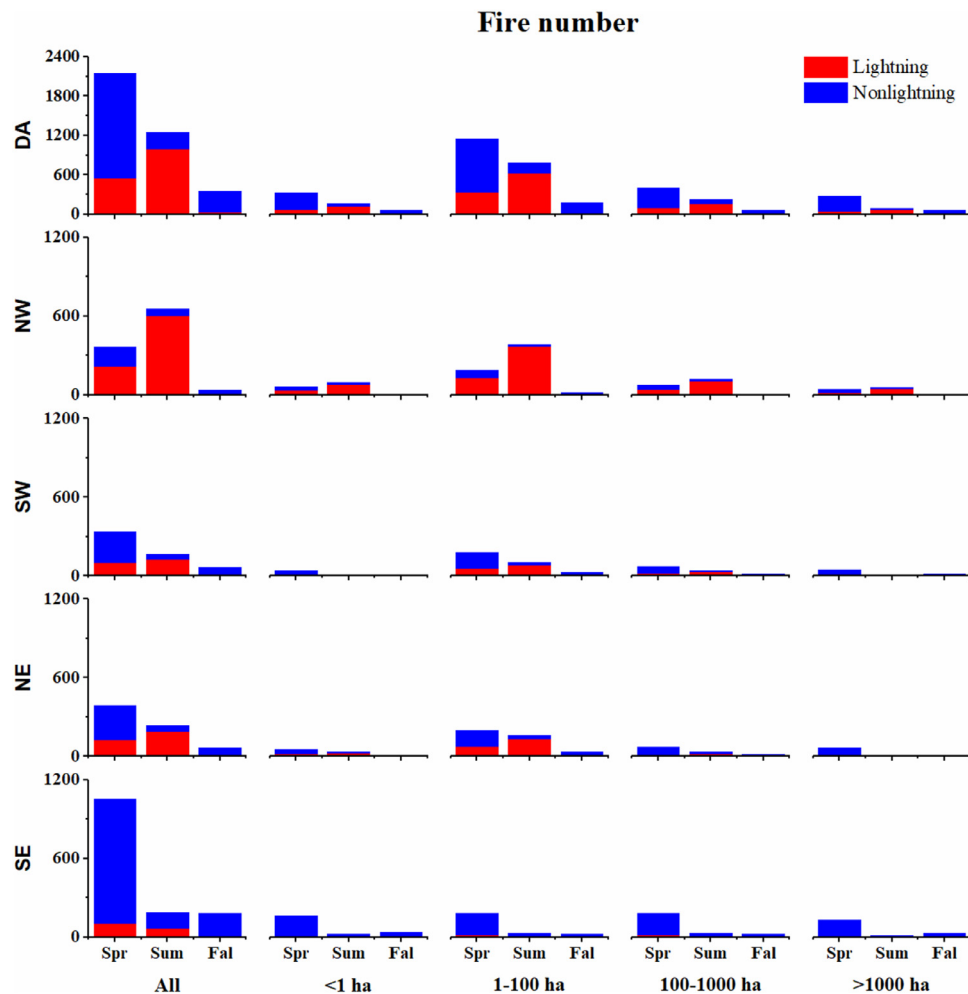


Fig. 4. Fire numbers during 1966–2017. From top to bottom are the data for Daxing'anling (DA) and the northwest (NW), southwest (SW), northeast (NE), and southeast (SE) regions. From left to right are fires of all sizes, <1, 1–100, 100–1000, and >1000 ha. Results for each region and fire size include data for the spring, summer, and fall periods. Results for each fire period consist of lightning and nonlightning fires.

months in the SW and SE regions showed significant differences (Fig. 9b and d).

The monthly $F_n(\text{COMP}, t)$ was smaller in spring and fall than summer because of smaller (larger) lightning than nonlightning fires in spring and fall (summer). $F_n(\text{COMP}, t)$ increased significantly in May through August ($p < 0.05$) and in September ($p < 0.1$) from the first to second subperiod (Fig. 8d). $F_n(\text{COMP}, t)$ was different from $F_n(\text{LTNG}, t)$ in two ways. First, it had more months with significant differences. Second, the significance levels for its differences were at $p < 0.01$, 0.02, and 0.05 for June, July, and August, respectively, thus suggesting a very small probability for type 1 error (https://en.wikipedia.org/wiki/Type_I_and_type_II_errors).

$F_a(i, t)$ also changed from the first to second subperiod, which however did not lead to a change in the fire season pattern because of the slight fire change in summer (except for $i = \text{COMP}$). $F_a(\text{LTNG}, t)$ was very small (Fig. 8e). $F_a(\text{nLTNG}, t)$ decreased from approximately 350 k ha to less than 50 k ha ($p < 0.1$) (Fig. 8f). $F_a(\text{TOTAL}, t)$ (Fig. 8g) results were similar to those of $F_a(\text{nLTNG}, t)$. $F_a(\text{COMP}, t)$ increased in June through September ($p < 0.1$ or $p < 0.05$) (Fig. 8h). Similar to $F_n(\text{COMP}, t)$, the number of months with significant differences was larger for $F_a(\text{COMP}, t)$ than $F_a(\text{LTNG}, t)$ (Fig. 8h and e). Regionally, only $F_a(\text{TOTAL}, \text{May})$ was significant (Fig. 9h).

The differences between the two subperiods were also calculated for seasonal fires (Table 2). The results will be used together with the differences in seasonal meteorological conditions (Table 3) below to analyze the contributions of climate to the differences in fires. The

differences in seasonal fires were significant for $F_n(\text{LTNG}, t)$ ($t = \text{all periods except spring}$), $F_n(\text{TOTAL}, t)$ ($t = \text{summer}$), and $F_n(\text{COMP}, t)$ ($t = \text{all periods except fall}$). The differences were significant for $F_a(\text{LTNG}, t)$ ($t = \text{summer and fall}$), $F_a(\text{nLTNG}, t)$ ($t = \text{spring and fire season}$), $F_a(\text{TOTAL}, t)$ ($t = \text{fire season}$), and $F_a(\text{COMP}, t)$ ($t = \text{all periods except fall}$). Although the differences in $F_n(\text{nLTNG}, t)$ in Daxing'anling were insignificant, those in $F_n(\text{nLTNG}, t)$ ($t = \text{spring, fire season}$) in the NW region were significant ($p < 0.05$ and $p < 0.1$, respectively) (not shown in Table 2).

The standard deviations (Figs. S4 and S5) were similar to the averages except large values for $F_n(\text{COMP}, t)$ (Fig. S4d) and $F_a(\text{COMP}, t)$ (Fig. S4h) for $t = \text{spring}$.

For the differences in $F_n(i, t)$ in Daxing'anling between the two subperiods of 20 years each (Table S5), $F_n(\text{LTNG}, t)$ increased significantly in July, September, and October, while $F_n(\text{nLTNG}, t)$ decreased significantly in May and October. As a result, $F_n(\text{COMP}, t)$ increased significantly in May through September with a larger magnitude in the summer months. $F_n(\text{TOTAL}, t)$ mainly increased in summer and decreased in spring and fall but the changes were insignificant. $F_n(\text{TOTAL}, t)$ increased in summer and decreased in spring and fall more noticeably in some subregions. The increases became significant in July in the NW region and in July and August in the NE region. The decreases became significant in October in the SW region and in April and May in the SE region.

The results from the differences between the two subperiods of 10 years (three cases) were similar (Tables S6–S8). However, $F_n(\text{TOTAL}, t)$ increased significantly in June in Daxing'anling and the SW and SE

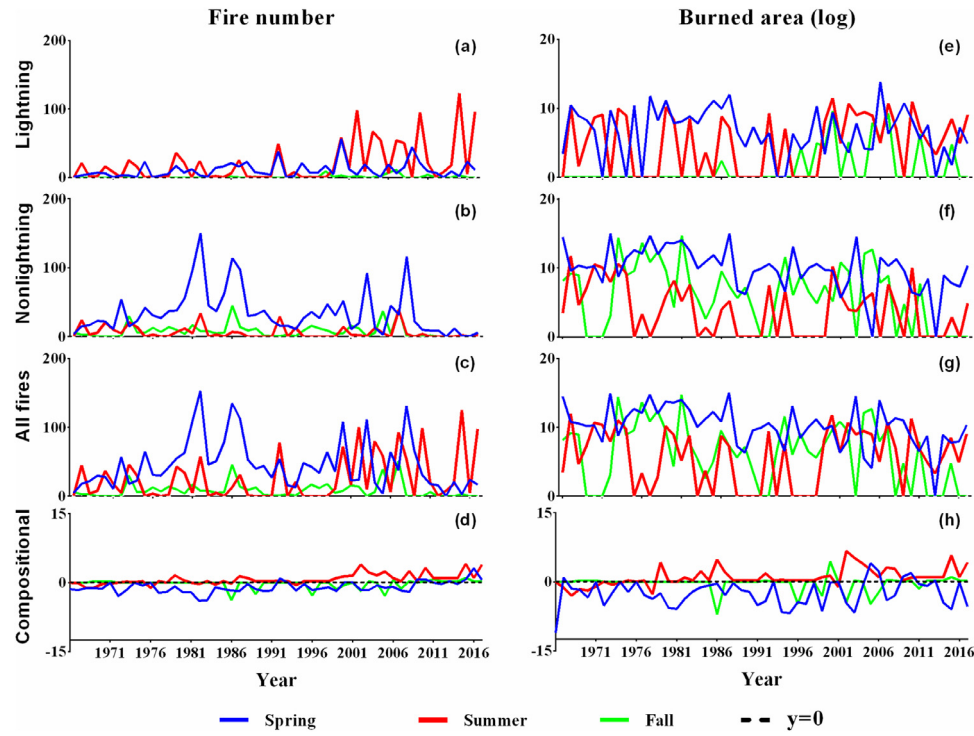


Fig. 5. Interannual variations of wildfires in Daxing'anling during various periods of a fire season. (a–d) Number of lightning, nonlightning, total, and compositional fires. (e–h) The corresponding burned area.

regions in the last case. The results from the differences of the 20-year and 10-year data suggest that the conversion of the fire season pattern displayed in Figs. 8 and 9 was likely to be robust.

Monthly meteorological conditions of each subperiod (Fig. 10) had

one peak in summer for T_{max} and P (Fig. 10a–b), and two extremely high or low values in spring and fall for U , h , and the three fire indices (Fig. 10c–g), corresponding to the spring and fall peaks of the bimodal fire pattern. The differences in M ($t = summer$) between the two

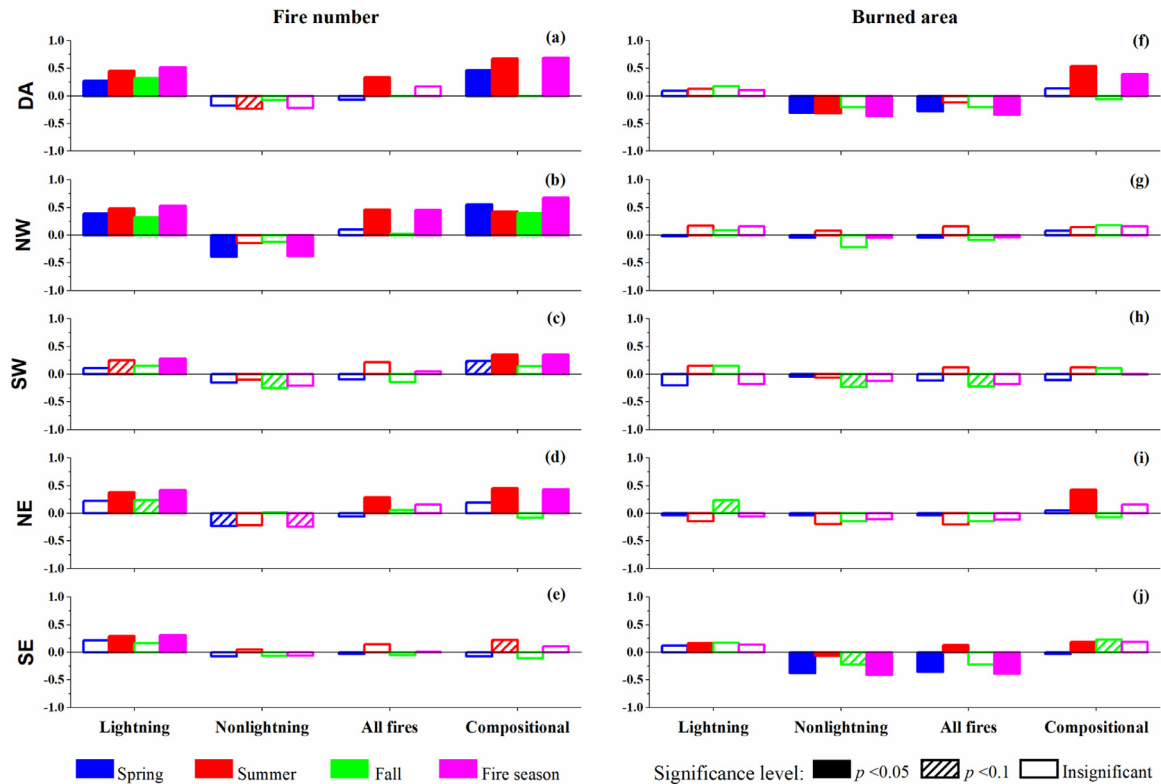


Fig. 6. Correlation coefficients between the normalized fire series and time series, which were equal to the slopes of fire least-squares linear regressions. (a–e) Fire number in Daxing'anling and the four subregions. (f–j) The corresponding burned area.

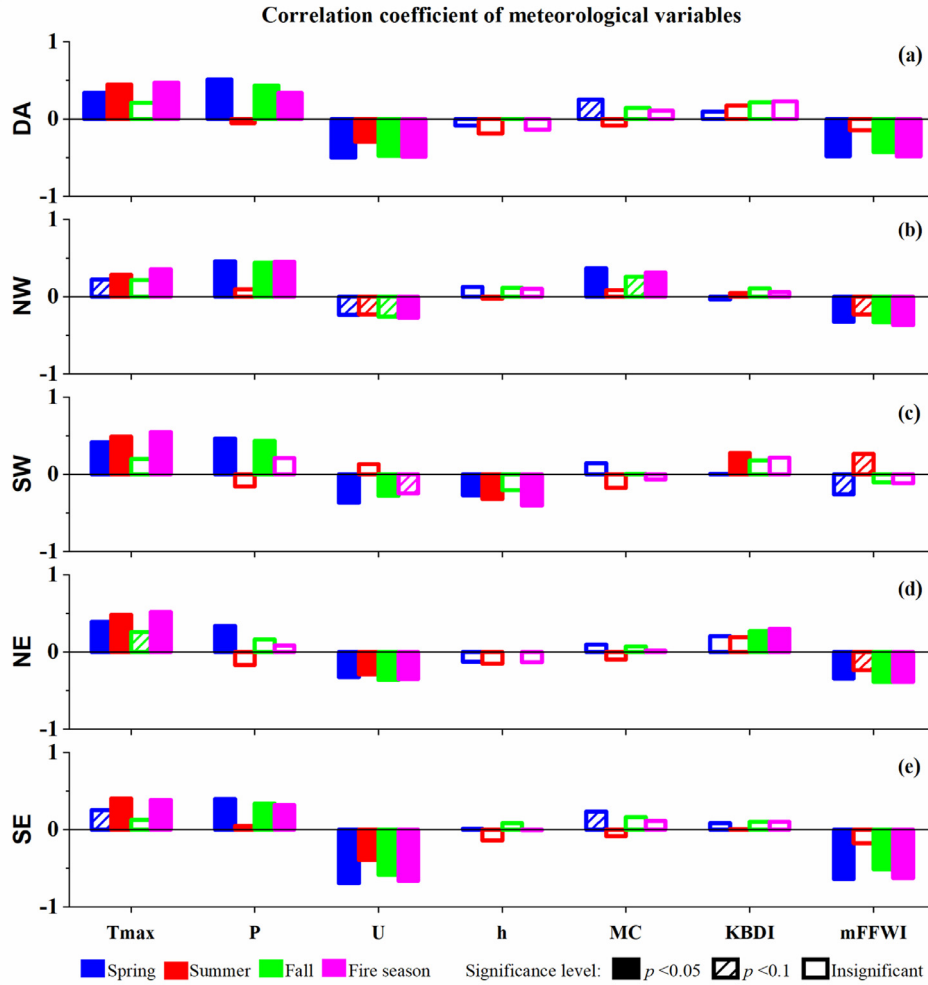


Fig. 7. Correlation coefficients between the normalized weather variables and fire index series and time series, which were equal to the slopes of the least-squares linear regressions of weather variables and fire index data. (a–e): DA (Daxing'anling), NW, SW, NE, and SE. From left to right are the maximum temperature (T_{max}), precipitation (P), wind speed (U), relative humidity (h), fuel moisture (MC), $KBDI$, and modified Fosberg Fire Weather Index ($mFFWI$).

subperiods were positive for T_{max} (significant all summer months) (Fig. 10a) and $KBDI$ (significant in August) (Fig. 10f), but negative and significant for P (August), U (June), h (July and August), and MC (August) (Fig. 10b–e), all in favor of increasing fires. The differences in M ($t = \text{spring or fall}$) were also positive for T_{max} (September) and $KBDI$ (September to November) and negative in some months for h (March) and MC (March and September), in favor of increasing fires. However, the differences were positive for P (March, May, October, November) and negative for U (April, May, September–November). In particular in May, the differences showed large increases in P , h , and MC , and large decreases in U and $mFFWI$, all in favor of decreasing fires.

The differences of seasonal meteorological conditions (Table 3) were significant for T_{max} , U , $KBDI$, and $mFFWI$ of all periods (except summer U and $mFFWI$ and spring $KBDI$), P of spring and summer, h of summer and entire fire season, and MC of summer. The difference in P of the NW region was also significant ($p < 0.1$) in spring (not shown in Table 3).

The seasonal cycles of some weather variables and fire indices were much different between the averages and standard deviations (Fig. S6). For example, the standard deviations of T_{max} (Fig. S6a) still had one cycle but with an opposite phase (small in summer and large in winter). The differences fluctuated with sign changes throughout the year. The differences in standard deviations for h were mostly positive (Fig. S6d) rather than negative for its differences in averages.

3.3. Contributions of climate change to fire trends and differences

The meteorological–fire correlation coefficients were mostly positive for $M = T_{max}$, $KBDI$, and $mFFWI$ (Fig. 11). The correlations for T_{max} in summer were significant and much larger than the correlations in spring and fall except for $F_a(nLGTN, t)$. The correlations were negative for P , h , and MC , significant for $F_n(i, t)$ ($i = \text{all types}$, $t = \text{summer}$; $i = nLGTN$ and $TOTAL$, $t = \text{spring and fall}$), and for $F_a(i, t)$ ($i = LGTN$, $t = \text{summer}$, all variables; $i = COMP$, $t = \text{summer}$, h and MC ; $i = \text{all types}$ except $LGTN$, $t = \text{spring and / or fall}$). The sign of correlations for U varied with fire type and property, and the magnitude was larger in spring than summer. The results indicate that both thermal conditions (T_{max} and $KBDI$) and humid conditions (P , h , and MC) were closely correlated to summer fires except $F_a(nLGTN, t)$, while the humid conditions were also closely correlated to nonlightning and total fires in spring and fall fires except $F_a(TOTAL, \text{spring})$.

The significant fire and meteorological trends and the significant correlations between fires and meteorological conditions are listed in Table 4. According to the trend criteria (Table 1), T_{max} was found to be a contributor to the trends of $F_n(i, t)$. The increasing T_{max} trends contributed to the increasing trends in $F_n(i, t)$ ($i = LGTN$ and $t = \text{all periods}$ except fall; $i = TOTAL$ and $t = \text{summer}$; $i = COMP$ and $t = \text{summer}$ and fire season). In addition, the decreasing $mFFWI$ trends contributed to the increasing trends in $F_n(i, t)$ ($i = LGTN$ and $COMP$, $t = \text{spring}$). Meanwhile, the increasing T_{max} trend contributed to the increasing trend in $F_a(i, t)$

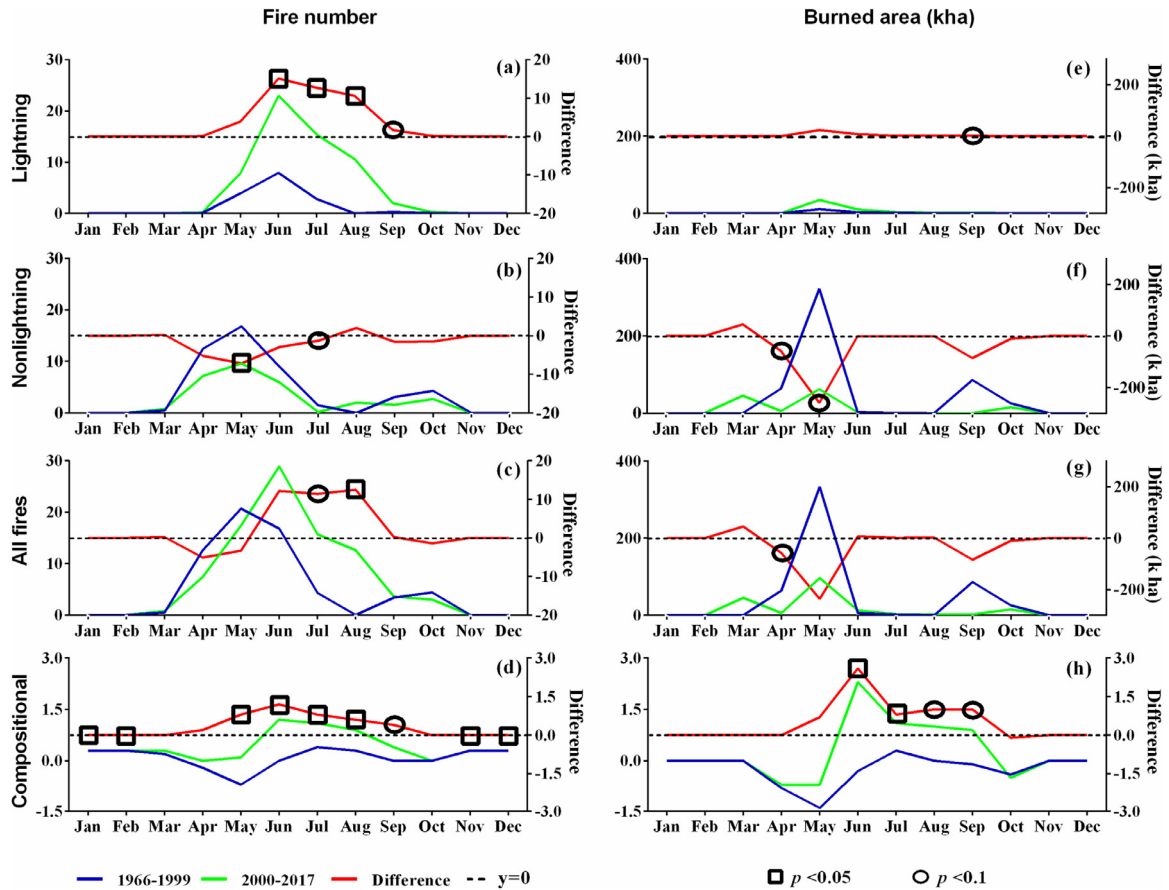


Fig. 8. Monthly fires averaged over the substages of 1966–1999 and 2000–2017 (left axis) and their differences (right axis). (a–d) The numbers of lightning, nonlightning, total, and compositional fires. (e–h) The corresponding burned area.

($i = \text{COMP}$, $t = \text{summer}$ and fire season). The increasing P and MC and decreasing $mFFWI$ trends contributed to the decreasing trend in $F_a(i, t)$ ($i = \text{nLGTN}$, $t = \text{spring}$). The increasing T_{max} and MC trends and decreasing $mFFWI$ trends contributed to the decreasing trend in $F_a(i, t)$ ($i = \text{TOTAL}$, $t = \text{spring}$). In addition, P was found to be a contributor to F_n (nLGTN , spring) of the NW region according to Fig. 6b, Fig. 7b, and Fig. 11b (not shown in Table 4). Note that h and $KBDI$ are not included in the table because their trends were insignificant and that the contributions of U (all seasons except fall) and $mFFWI$ (summer and fire season) are not taken into account because their time series were not stationary.

The significant fire and meteorological differences between the two subperiods and the significant correlations between fires and meteorological conditions are listed in Table 5. According to the difference criteria (Table 1), the increases in T_{max} were a contributor to all significant differences in fires except $F_n(i, t)$ ($i = \text{COMP}$, $t = \text{spring}$) and $F_a(i, t)$ ($i = \text{nLGTN}$ and COMP , $t = \text{spring}$). In comparison with T_{max} , the increases in $KBDI$ had additional contributions to $F_a(i, t)$ ($i = \text{LGTN}$, $t = \text{fall}$) but did not contribute to $F_n(i, t)$ ($i = \text{COMP}$, $i = \text{summer}$) and $F_a(i, t)$ ($i = \text{nLGTN}$, TOTAL , and COMP , $t = \text{fire season}$). The decrease (increase) in summer (spring) in P contributed to the increases in $F_n(i, t)$ ($i = \text{LGTN}$, TOTAL , and COMP , $t = \text{summer}$) and $F_a(i, t)$ ($i = \text{LGTN}$, $t = \text{summer}$) and the decrease in $F_a(i, t)$ ($i = \text{nLGTN}$, $t = \text{spring}$). The contributions from the differences in h and MC were similar to those for P . The decreases in $mFFWI$ contributed to the increases in $F_n(i, t)$ and $F_a(i, t)$ ($i = \text{COMP}$, $t = \text{spring}$) and the decrease in $F_a(i, t)$ ($i = \text{nLGTN}$, $t = \text{spring}$). In addition, P was found to be a contributor to the negative difference in $F_n(\text{nLGTN}$, $\text{spring})$ in the NW region according to Fig. 11b and the difference in spring P of this region.

4. Discussion

4.1. Fire trends and meteorological and fire correlations

The trend analyses from this study obtained the same results as Hu & Zhou (2014) whereby the data indicated that the annual lightning fire numbers (Fig. 6a) and nonlightning fire burned areas (Fig. 6f) in Daxing'anling significantly increased and decreased, respectively. Both studies obtained decreasing nonlightning fire numbers, but the trend was significant only in their study. This difference was likely due to the fact that our fire data showed a large number of spring nonlightning fires throughout the entire Daxing'anling area in 2008 (Fig. 5b), while their data only covered the HL portion until 2006. Our results of total fires during different periods of spring, summer, and fall indicated decreasing trends in burned areas, significant in spring but insignificant in summer and fall. This is different from Fan et al. (2017) who showed that total fire burned areas increased in summer and fall but remained stable in spring over 1980–2005. The difference was likely due to the fact that our data contained large burned areas in several years before 1980 (Fig. 5e), but their data did not start until that year.

Our study found the same significant positive correlations of lightning fires with $KBDI$ during entire fire season as Hu & Zhou (2014). However, the positive correlation of lightning fires with T_{max} was significant in our study but insignificant in their study.

4.2. Change in fire season pattern and contributions of climate change

A major finding of this study is a change of the fire season pattern from a bimodal with a larger peak of the number of total fires in spring and a smaller peak in fall to a unimodal with a peak in summer in

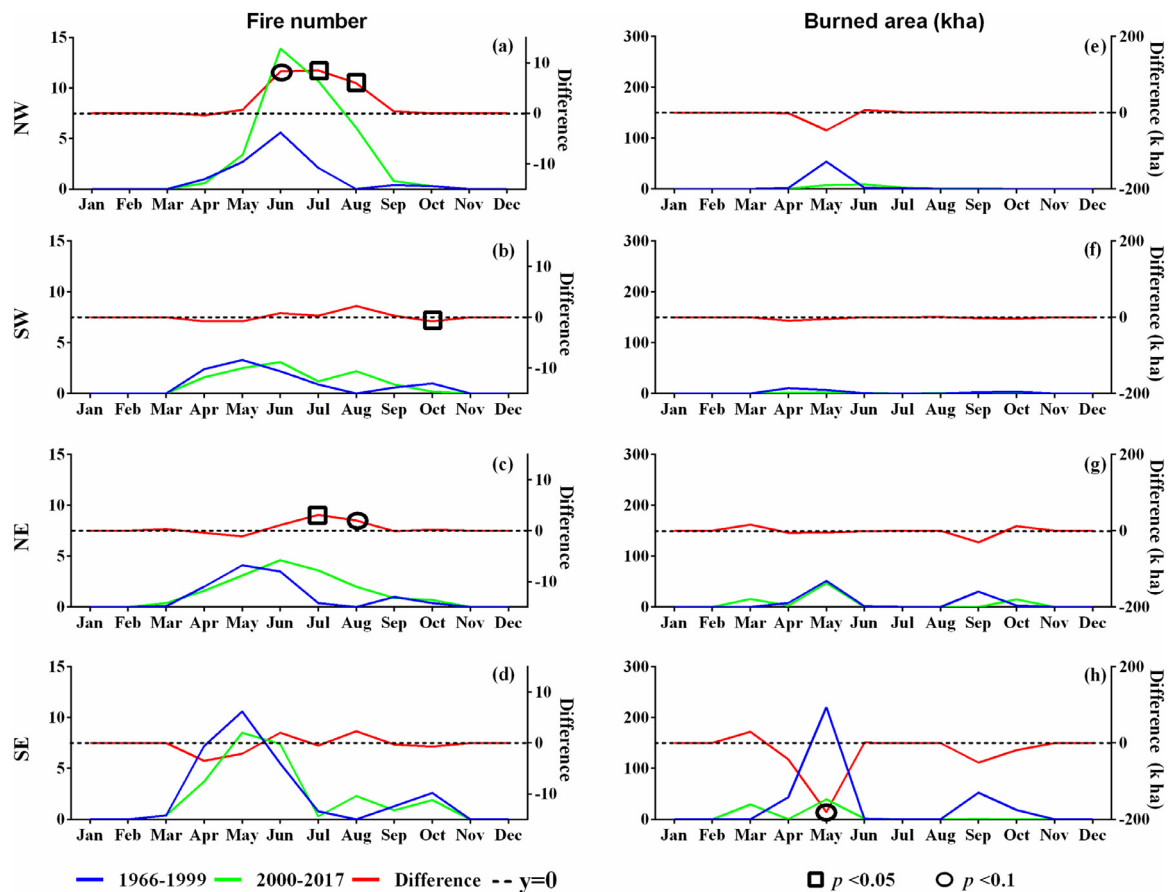


Fig. 9. Monthly total fires averaged over the subperiods of 1966–1999 and 2000–2017 (left axis) and their differences (right axis). (a–d) Fire numbers in the NW, SW, NE, and SE. (e–h) The corresponding burned area.

Table 2

Differences of seasonal fires between the subperiods of 1966–1999 and 2000–2017. LGTN, nLGTN, TOTAL, and COMP are lightning fire, nonlightning fire, total fire, and compositional fire, respectively. Bold values indicate that the differences are significant at $p < 0.05$ ($p < 0.1$ if with *).

Fire property	Fire type	Fire period			
		Spring	Summer	Fall	Season
Number	LTGN	5.78	35.08	1.40*	42.25
	nLTGN	–14.54	–1.67	–1.55	–17.77
	TOTAL	–8.76	33.40	–0.15	24.48
	COMP	1.27	1.50	0.15	2.37
Area (k ha for first three types)	LTGN	42.3	12.1*	1.6*	56.0
	nLTGN	–328.4*	–4.3	–134.3	–466.9
	TOTAL	–286.1	7.8	–132.7	–410.9*
	COMP	2.24	1.85	0.62	3.46

Daxing'anling (Fig. 8c). It was resulted mainly from the significant increase in summer lightning fires (Fig. 6a and Fig. 8a) in Daxing'anling as well as significant negative difference in spring nonlightning fires of the NW region.

An important issue is the relative importance of climate and human factors for the conversion. This issue could be examined in two steps. First is to analyze the possible roles of the two factors in fire changes. The results obtained using both trend and difference criteria indicated that warming contributed to the increasing fire numbers in summer. The changes in precipitation contributed too, though the contribution was dependent on the type and region of fire changes. The negative difference in precipitation contributed to the positive difference in summer lightning fire number in Daxing'anling. In addition, the increasing trend (positive difference) in spring precipitation contributed

Table 3

Differences of seasonal meteorological variables and drought indices between subperiods of 1966–1999 and 2000–2017. The variables and indices include maximum temperature (T_{max}), precipitation (P), wind speed (U), relative humidity (h), fuel moisture (MC), $KBDI$, and $mFFWI$. Bold values indicate that the differences are significant at $p < 0.05$ ($p < 0.1$ if with *).

Variable / index	Fire period			
	Spring	Summer	Fall	Season
T_{max} (°C)	0.83	1.19	0.76*	0.92
P (mm/day)	0.24	–0.32*	0.16	0.03
U (m/s)	–0.21	–0.04	–0.19	–0.15
h (%)	–0.62	–2.23	–0.14	–1.0*
MC (%)	0.23	–0.8*	–0.16	–0.24
$KBDI$	5.8	12.9	13.8*	10.8
$mFFWI$	–0.52	0.11	–0.42	–0.28

to the decreasing trend (negative difference) in spring nonlightning fire number in the NW region.

Fire policies and management practices might have been a contributor to the decreasing nonlightning fire number and burned area trends in summer. Since the 1987 Black Dragon Fire in Daxing'anling, China has implemented a strict forest fire suppression policy with a substantial investment both in terms of funding and labor forces, including support from the army, forestry policemen, and local residents for fire prevention and control (Zhao et al., 2009). Once a fire is observed, the local government is notified immediately, and it determines the amount of human resources to deploy to fight the fire (Chang et al., 2008). The above scenario could be attributed to the role of the fire management policy in reducing human-induced fires. Terando et al. (2017) investigated the contributions of land cover

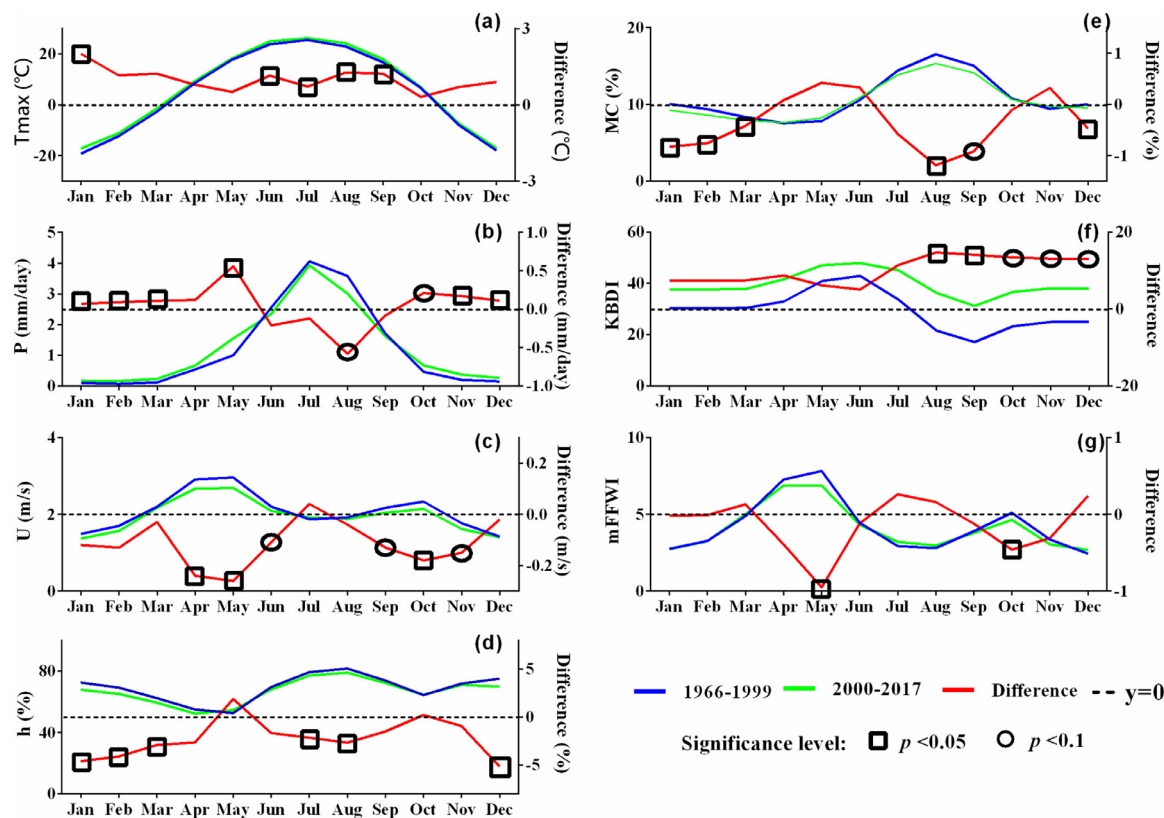


Fig. 10. Monthly weather variables and fire indices averaged over the subperiods of 1966–1999 and 2000–2017 (left axis) and their differences (right axis). (a–g) Maximum temperature (T_{max}), precipitation (P), wind speed (U), relative humidity (h), fuel moisture (MC), $KBDI$, and $mFFWI$.

change to the trends in burned area of the coastal plain of Georgia, USA. The forest-to-framing land conversion in Daxing'anling, mainly in the SE region, might have contributed to the decreasing nonlightning fire trends. However, the increasing lightning trends and seasonal fire pattern shift occurred mainly in the NW region where land cover change has been minimal over the past four decades, thus suggesting that the land cover change in Daxing'anling likely contributed little to the increasing lightning fire number trends.

The second step is to evaluate the relative importance of climate change and human activity to the conversion of fire season pattern using the results of the compositional fire value obtained from this study. Both the trends over the analysis period (Fig. 6a) and the differences between two stages (Fig. 8d) of the compositional value for fire number showed significant increases in spring and summer, with larger magnitude in summer, indicating the increasing importance of the climate contribution to fire occurrence. The increasing importance was especially remarkable in summer, when the value turned from negative in the first subperiod to positive in the second one (Fig. 8d) and therefore climate became a more important factor than human. The analysis of the compositional fire value therefore suggests that climate change was a major factor for the conversion of fire season patterns from bimodal to unimodal in Daxing'anling.

Another useful technique to obtain a more complete and quantitative understanding of the issue of relative importance between climate and human factors is the Earth modeling systems. Such systems include atmospheric models to predict temperature, precipitation (including lightning) and other meteorological conditions and processes, and dynamical global vegetation models to simulate wildfires and the impacts of meteorological and human disturbances (Liu, 2018; Zou et al., 2019).

4.3. Ecological and management implications of fire pattern changes

A major finding from the present study is that the seasonal pattern

of fire occurrence changed from bimodal to unimodal at the beginning of this century due to the increasing total fire number trends in summer. With little growth during the dormant season, fires result in minimal damage to trees. However, an increase in summer fires will create disturbances in forests with negative ecological impacts. For example, fires that involve the burning of above ground wet fuels (growing season) in summer often spread slowly and easily cause underground fires that burn the base and roots of trees and cause tree death. Also, the death rate of *Pinus ponderosa* due to crown scorch by growing season fires is approximately 2.5 times that caused by dormant season fires (Harrington, 1993).

Current fire prevention in Daxing'anling is implemented during the two periods of March 15th to June 15th and September 15th to November 15th according to the Fire Prevention Regulations (HLFFPR, 2018; IMFFPR, 2016). The change from a bimodal to a unimodal fire season pattern necessitates a new fire prevention implementation timeline for a single period from March 15th to November 15th without a summer break. Furthermore, decreasing fires in spring and increasing fires in summer require a seasonal reallocation of fire suppression resources. In addition, increasing summer fires increases the exposure of firefighters to heat stress, toxic fire emissions, equipment mobility problems, and high tree mortality rates. Thus, there is a need for more forest management efforts to mitigate the impacts on firefighting safety and forest ecosystems. Summer fires in Daxing'anling are ignited mainly by lightning. Improved capabilities to obtain lightning data and their relationships with fires would help with fire predictions and the acquisition of other information needed for safely preparing and implementing fire suppression activities. Applications of drones could help with the monitoring of fire spread and road conditions, which are critical data that allow firefighters to identify safe spots and access them. More usage of fire shelters (a safety device of last resort used by wildland firefighters when trapped by wildfires. https://en.wikipedia.org/wiki/Fire_shelter) would be an efficient means to

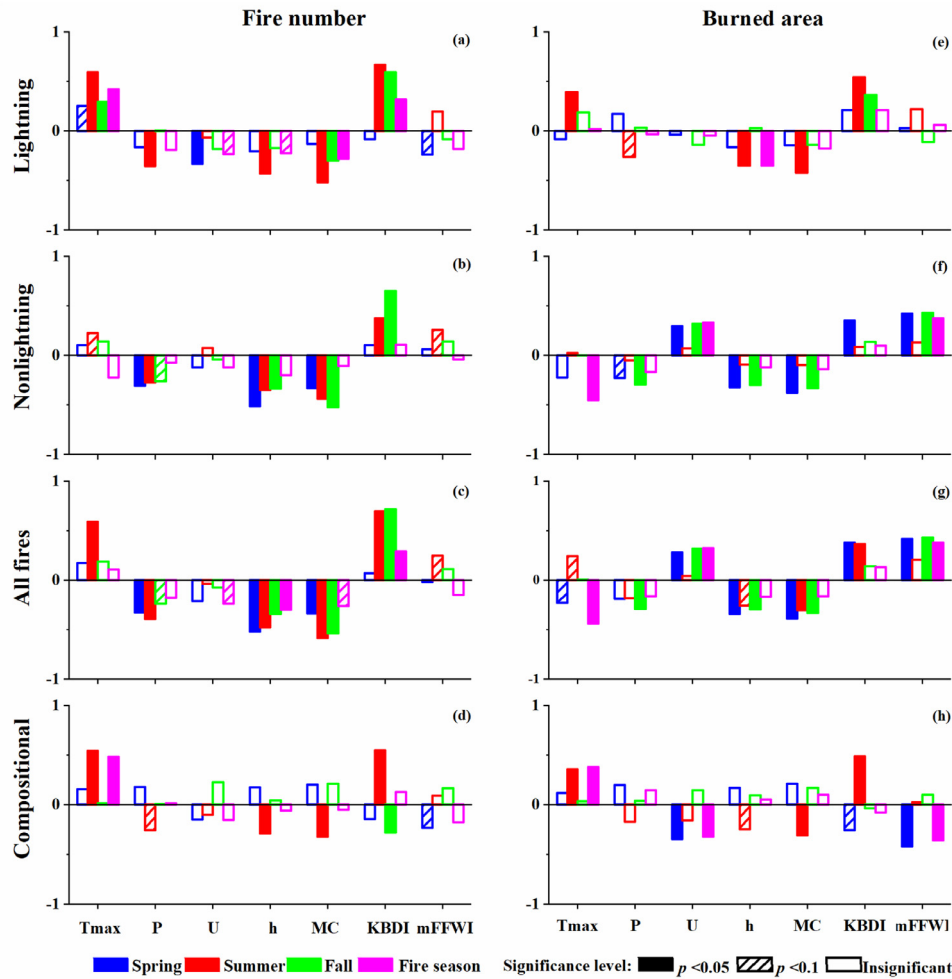


Fig. 11. Correlation coefficients between fires and weather variables / fire indices. (a–d) Number of lightning, nonlightning, and total fires, and compositional fire value. (e–h) The corresponding burned area. From left to right are the maximum temperature (T_{max}), precipitation (P), wind speed (U), relative humidity (h), fuel moisture (MC), Keetch–Byram Drought Index ($KBDI$), and modified Fosberg Fire Weather Index ($mFFWI$).

protect firefighters. Implementation of prescribed fires to reduce duff accumulation with controllable damage to roots would reduce tree mortality due to massive ground wildfires during summer drought conditions.

4.4. Uncertainties

The comparison of burned areas (Fig. 2) shows big disagreement in fall between the GFED and ground-based data. Further validation using other sources, including those with fire number information, is needed to understand the causes and potential problems with the ground-based fall fire data quality. However, it is likely that such potential problems if any would have minimal effects on the major finding of the change of fire season pattern from bimodal to unimodal in Daxing'anling because this change was caused mainly by the increased number in summer lightning fires in Daxing'anling as well as deceased fire number in spring nonlightning fires in the NW region. The fire number itself and / or its change in fall were much smaller than spring in Daxing'anling (Fig. 8c) and the NW region (Fig. 9a).

The dates of the three fire periods specified based on the fire prevention implementation schedule in Daxing'anling were different from those of the calendar seasons, that is, spring (March 1st to May 31st), summer (June 1st to August 31st), and fall (September 1st to November 30th). To examine the sensitivity of the fire and weather trends and fire-weather correlations to the fire period dates, we compared the results

obtained by using two different sets of fire period dates (Table S9). Among the 24 pairs of results, both were significant at $p < 0.05$ for 12 pairs, both were significant but one at $p < 0.05$ and the others at $p < 0.1$ for three pairs, both were insignificant for five pairs, and one was significant at $p < 0.05$ or $p < 0.1$ but the others were insignificant for four pairs. All four pairs of the last case occurred for nonlightning fires. These results indicate that the features of fire and weather trends and their relationships obtained from this study are not very sensitive to the dates of the fire periods for lightning fires, but data would be slightly different for nonlightning fires.

The observations from only four meteorological stations were used for the fire-weather relationships analysis, with each station located in one of the four subregions for full coverage of the study area. Four other stations, one in the NW region, two in the NE region, and one in the SE region were not used, three of which had missing observations for the first five years, and one was located near the SE and SW border. We examined the representativeness of the first four stations by analyzing the correlations of the fire-season variables from 1971 to 2017 among all of the eight stations (Table S10). The results indicated that T_{max} had the best correlations, which were significant at $p < 0.001$ for all 28 station pairs. P also had good correlations, which were significant at $p < 0.001$ for 23 pairs, at $p < 0.01$ for three pairs, and at $p < 0.05$ for two pairs. h had acceptable correlations, which were significant at $p < 0.001$ for 18 pairs, at $p < 0.01$ for two pairs, and at $p < 0.05$ for five pairs, and were insignificant for only three pairs (none was located in the same

Table 4

Meteorological contributors (C) to fire trends. T represents a fire / meteorological trend. ↑ (↓) indicates a significant increasing (decreasing) fire / meteorological trend, or positive (negative) contribution to fire. Bold is used for fire trend and for meteorological contribution that has the same arrow direction as fire. + (−) indicates a significant positive (negative) correlation, *r*, between fire and meteorological condition. F is the figure showing the result. x indicates a correlation from a non-stationary series. *T_{max}*, *P*, *U*, *MC*, and *mFFWI* represent maximum temperature, precipitation, wind, fuel moisture, and modified Fosberg Fire Weather Index. *LGTN*, *nLGTN*, *TOTAL*, and *COMP* represent lightning, nonlightning, and total fire and compositional fire property.

Fire Type		Period	T	T _{max}	r	C	P	r	C	U	r	C	MC	r	C	mFFWI	r	C
			F6	F7	F11		F7	F11		F7	F11		F7	F11		F7	F11	
Fire number	LGTN	Spring	↑	↑	+	↑	↑						↑			↓	−	↑
		Summer	↑	↑	+	↑		−		↓	−x			−				
		Fall	↑		+		↑			↓				−		↓		
	nLGTN	Season	↑	↑	+	↑	↑				−x			−		↓		
		Spring		↑			↑	−	↓	↓			↑	−	↓	↓		
		Summer	↓	↑	+	↑		−		↓				−			+x	
	TOTAL	Fall				↑		−	↓	↓				−		↓		
		Season		↑			↑			↓				−		↓		
		Spring		↑			↑	−	↓	↓			↑	−	↓	↓		
	COMP	Summer	↑	↑	+	↑		−		↓				−			+x	
		Fall					↑		−	↓				−		↓		
		Season		↑			↑			↓	−x			−		↓		
Burned area	LGTN	Spring	↑	↑		↑	↑						↑			↓		
		Summer		↑	+	↑		−		↓				−		↓		
		Fall					↑			↓						↓		
	nLGTN	Season		↑		↑	↑			↓						↓		
		Spring	↓	↑			↑	−	↓	↓	+x		↑	−	↓	↓	+	↓
		Summer	↓	↑						↓								
	TOTAL	Fall					↑	−	↓	↓	+	↓		−		↓	+	↓
		Season	↓	↑	−	↓	↑			↓	+x			−		↓	+x	
		Spring	↓	↑	−	↓	↑			↓	+x		↑	−	↓	↓	+	↓
	COMP	Summer		↑	+	↑				↓				−				
		Fall					↑	−	↓	↓	+	↓		−		↓	+	↓
		Season	↓	↑	−	↓	↑			↓	+x					↓	+x	

subregion). *U* had relatively low correlations, which were significant at $p < 0.001$ for 12 pairs, at $p < 0.01$ for three pairs, and at $p < 0.05$ for four pairs, and were insignificant for nine pairs (negative values regarded as insignificant; three pairs were located in the same subregion). The results suggest that *T_{max}* and *P* for the fire season had consistent inter-annual variability across Daxing'anling; *h* had consistent inter-annual variability within subregions, but *U* showed different variability within a subregion. However, large spatial heterogeneity in atmospheric conditions is expected in the western mountains. The surface temperature decreases from the foothills to summit, and from the south to north ascent. This will affect the thermal structure in terms of vertical and relative humidity, which will further affect clouds and precipitation. The mountain–valley air flows affect the formation of clouds and precipitation too. It is likely that the magnitudes of the observed temperature and precipitation changes over the analyzed period of this study could be different across the mountainous areas. High-resolution meteorological modeling of such changes is needed to provide the data for analyzing the dependence of the results obtained from this study on topography.

4.5. Issues for further research

Tian et al. (2017) projected future changes in fire weather indices and fire seasons in Daxing'anling under various climate change scenarios. These scenarios showed increases in both the annual temperature and precipitation in the following three decades, which are results similar to the historical trends obtained in this study. Thus, we expect that the trends of lightning fires obtained in this study will continue by

the middle of the 21st century, assuming the same fire management policies and land cover change. However, that study only examined annual meteorological conditions and therefore was unable to examine future changes in the fire season pattern. There is a need to expand that study by using monthly meteorological conditions.

A recent study showed that increasing North American boreal lightning fires were linked to increases in temperature and precipitation (Veraverbeke et al., 2017). It will be interesting to see if more thunderstorms with lightning have occurred recently in Daxing'anling, which would have resulted in more lightning strikes. This is a complex issue because fire ignition is actually dependent on dry thunderstorms. This is a valuable issue for future research.

The change in the fire season pattern identified in this study may also be occurring in other regions around the world such as in Texas of the U.S. (Cohen, 2013). Obtaining more information on the impacts of climate change on fire season patterns worldwide will be valuable.

Declaration of Competing Interest

The authors do not have a conflict of interest.

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Table 5

Meteorological contributors (C) to fire differences. D represents a fire / meteorological difference between two subperiods. r represents meteorological-fire correlation. + (-) indicates a significant positive (negative) difference, correlation, or contribution. Bold + or - sign indicates difference in fire or in a contribution that has the same sign as fire difference. F / T is the figure / table showing the result. x indicates a correlation from a non-stationary series. T_{max} , P , U , h , MC , $KBDI$, and $mFFWI$ represent maximum temperature, precipitation, wind, relative humidity, fuel moisture, Keetch-Bryan Drought Index, and modified Fosberg Fire Weather Index. $LGTN$, $nLGTN$, $TOTAL$, and $COMP$ represent lightning, nonlightning, and total fire and compositional fire property.

Fire Type	Period	T_{max}			P			U			h			MC			$KBDI$			$mFFWI$		
		D	r	C	D	r	C	D	r	C	D	r	C	D	r	C	D	r	C	D	r	C
		T1	T2	F11	T2	F11		T2	F11		T2	F11		T2	F11		T2	F11		T2	F11	
Fire number	LGTN	Spring	+	+	+	+		-	-x											-	-	+
		Summer	+	+	+	+	-	-	+		-	-	+	-	-	+	+	+	+	+	+	
		Fall	+	+	+	+		-									+	+	+	+	+	
	nLGTN	Spring	+	+	+	+		-	-x		-	-	+	-	-	+	+	+	+	+	+	
		Summer	+	+	+	+	-	-	+		-	-	+	-	-	+	+	+	+	+	+	+x
		Fall	+	+	+	+		-			-	-		-	-		+	+	+	+	+	
	TOTAL	Spring	+	+	+	+		-			-	-		-	-		+	+	+	+	+	
		Summer	+	+	+	+	-	-	+		-	-	+	-	-	+	+	+	+	+	+	+x
		Fall	+	+	+	+		-			-	-		-	-		+	+	+	+	+	
	COMP	Spring	+	+	+	+		-	-x		-	-	+	-	-	+	+	+	+	+	+	
		Summer	+	+	+	+	-	-	+		-	-	+	-	-	+	+	+	+	+	+	
		Fall	+	+	+	+		-			-	-		-	-		+	+	+	+	+	
Burned area	LGTN	Spring	+	+	+	+		-			-	-		-	-		+	+	+	+	+	
		Summer	+	+	+	+	-	-	+		-	-	+	-	-	+	+	+	+	+	+	
		Fall	+	+	+	+		-			-	-		-	-		+	+	+	+	+	
	nLGTN	Spring	+	+	+	+		-			-	-		-	-		+	+	+	+	+	
		Summer	+	+	+	+	-	-	+		-	-	+	-	-	+	+	+	+	+	+	
		Fall	+	+	+	+		-			-	-		-	-		+	+	+	+	+	
	TOTAL	Spring	+	+	+	+		-			-	-		-	-		+	+	+	+	+	
		Summer	+	+	+	+	-	-	+		-	-	+	-	-	+	+	+	+	+	+	
		Fall	+	+	+	+		-			-	-		-	-		+	+	+	+	+	
	COMP	Spring	+	+	+	+		-	-x		-	-	+	-	-	+	+	+	+	+	+	
		Summer	+	+	+	+	-	-	+		-	-	+	-	-	+	+	+	+	+	+	
		Fall	+	+	+	+		-			-	-		-	-		+	+	+	+	+	
	TOTAL	Spring	+	+	+	+		-			-	-		-	-		+	+	+	+	+	
		Summer	+	+	+	+	-	-	+		-	-	+	-	-	+	+	+	+	+	+	
		Fall	+	+	+	+		-			-	-		-	-		+	+	+	+	+	
	COMP	Spring	+	+	+	+		-	-x		-	-	+	-	-	+	+	+	+	+	+	
		Summer	+	+	+	+	-	-	+		-	-	+	-	-	+	+	+	+	+	+	
		Fall	+	+	+	+		-			-	-		-	-		+	+	+	+	+	
	TOTAL	Spring	+	+	+	+		-			-	-		-	-		+	+	+	+	+	
		Summer	+	+	+	+	-	-	+		-	-	+	-	-	+	+	+	+	+	+	
		Fall	+	+	+	+		-			-	-		-	-		+	+	+	+	+	

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at [doi:10.1016/j.agrformet.2020.108075](https://doi.org/10.1016/j.agrformet.2020.108075).

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