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RESEARCH PAPER

# Wind speed and relative humidity influence spatial patterns of burn severity in boreal forests of northeastern China

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## Abstract

• ***Key message*** **We investigated relationships between the spatial patterns of burn severity in Chinese boreal forests and weather parameters. Patch size, shape and arrangement differed between high-severity and low/moderate-severity patches. Wind speed and relative humidity were dominant weather parameters of spatial variation in burn severity. Patch size negatively correlated with relative humidity; patch complexity and aggregation positively correlated with wind speed.**

• ***Context*** Spatial patterns of burn severity strongly control post-fire succession and numerous ecological processes in fire-prone boreal forests. Burn-severity patterns are strongly tied to weather conditions. Understanding how weather influences spatial patterns of burn severity is critical for predicting burn severity and fire management strategies.

• ***Aims*** We investigated relationships between spatial patterns of burn severity and weather variables in the Chinese boreal forests.

• ***Methods*** Using satellite imagery, we mapped burn severity for 22 fires that occurred between 2000 and 2005. For each fire, we calculated metrics of spatial pattern. Using Random Forest models, we quantified the relative importance of weather variables in determining spatial patterns of burn severity.

• ***Results*** High-severity fire patch, averaged 570.5 ha (SD = 1530.6), was the dominant outcome, occupying 67.8% of all area burned across the 22 fires. High-severity patches were larger, more aggregated, and simpler in shape than low- and moderate-severity patches. Patch size of high-severity fires increased in drier and less humid conditions, and patches were more complex and aggregated with higher wind speeds.

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**Contributions of the co-authors** Designing the experiment: Dr. Zhiwei Wu, Dr. Yu Liang, Prof. Hong S. He; Running the data analysis: Dr. Zhiwei Wu, Dr. Lei Fang; Writing the paper: Dr. Zhiwei Wu, Dr. Russell A. Parsons, Prof. Hong S. He, Dr. Yu Liang; Supervising the work: Prof. Hong S. He; Coordinating the research project: Dr. Zhiwei Wu, Dr. Yu Liang.

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• ***Conclusion*** With drier conditions predicted with climate change, spatial patterns of burn severity in Chinese boreal forests may become increasingly homogeneous, possibly affecting long term ecological functions.

**Keywords** Fire patch · Fire size · Landscape pattern metric · Fire severity · Boreal forest

## 1 Introduction

Fire is a frequent disturbance that annually impacts approximately 10–15 × $10^6$ ha of boreal forests (Lynch et al. 2004; Stocks et al. 2002; Turetsky et al. 2011). Recent research indicates that fire occurrence in boreal forests will substantially increase with prolonged growing seasons under warming climate scenarios. For example, in Canadian boreal forests, fire occurrence is predicted to increase by 75–140% by the end of this century (Wotton et al. 2010) and by 30–230% by the end of 2100 in Chinese boreal forests (Liu et al. 2012). Increases in fire occurrence would likely pose challenges to managers in maintaining forest structure and function.

Within the perimeter of a given fire, burn severity is often variable, ranging from crown fires in some areas to surface fires elsewhere, resulting in spatially heterogeneous mosaic patterns of fire patches across a forest landscape (Hayes and Robeson 2011). Such spatial heterogeneity is ecologically important, especially in boreal forests, affecting species composition, structure, succession trajectory, and numerous ecological processes (Johnstone and Chapin 2006; Pickett and White 1985). For example, spatial variation in burn severity can dominate over environmental constraints in determining early patterns of community assembly in Alaskan boreal forests (Hollingsworth et al. 2013). Understanding spatial patterns of burn severity in the fire-prone boreal forests is therefore critical to managing or enhancing the vegetation recovery of burned areas (Jin et al. 2012).

From a landscape ecology perspective, spatial patterns of burn severity are generally described in terms of composition, or proportion of area by different severity classes, and configuration, referring to the spatial arrangement of such classes (Haire and McGarigal 2009; Turner et al. 2001). Both composition and configuration of burn-severity patches can affect post-fire plant reestablishment patterns in a forest landscape. For example, the amount and configuration of edge between burned and unburned forest patches in a fire can affect distance to seed source and, subsequently, succession pathways of vegetation (Donato et al. 2009; Turner et al. 1994).

Spatial patterns of burn severity are driven by multiple factors, but weather and climate are often described as the dominant drivers in forest landscapes (Cansler and McKenzie 2014; Haire and McGarigal 2009; Harvey et al. 2016). Extreme weather conditions can override constraints of vegetation and topographic patterns to a significant extent and impose new spatial patterns of burn severity, typically large, high-severity patches in a forest landscape (Bessie and Johnson 1995; Harvey 2015; Kolden et al. 2015; Turner et al. 1994; Turner and Romme 1994). Examining links between weather and spatial patterns of burn severity is therefore critical for informing prediction strategies of burn severity in a forest landscape.

The boreal forests in the Great Xing'an Mountains of northeastern China are an important forest resource that delivers a range of societal, economic and environmental benefits to the country (Xu 1998; Zhou 1991). Fires in this region are usually large and account for the majority of the area burned in the country (Chang et al. 2015; Chen et al. 2017; Tian et al. 2013), mostly lightning caused, and closely associated with weather (Tian et al. 2011). As the climate has become warmer and drier in recent decades (Zhang and Hu 2008), understanding how and why fires burn larger and more severely has become a major concern for forest managers of this region.

The objective of this study was to explore relationships between spatial patterns of burn severity and fire danger and weather variables (temperature, relative humidity, precipitation, wind speed, and days since last rainfall) in Chinese boreal forests. Fire danger is the probability of a fire to start, the rate of spread and intensity of its burn. This study used the China Forest Fire Weather Index (FWI) to measure the degree of fire danger. We addressed three questions: (1) what are the spatial patterns of burn severity in the Chinese boreal forests? (2) how do spatial patterns of high-severity patches vary with weather conditions and (3) to what degree do different weather variables influence spatial patterns of high-severity patches?

## 2 Material and methods

### 2.1 Study area

Our study focuses on the Huzhong Forest Bureau (HFB), located on the north side of the Great Xing'an Mountains in northeastern China (52°25′00″N, 122°39′30″E to 51°14′40″N, 124°21′00″E). It covers 937,244 ha, ranging in elevation from 440 to 1500 m (Fig. 1). The Great Xing'an Mountains has a cool continental, subarctic climate with a mean annual temperature of −2.9 °C and mean annual precipitation of 495 mm between 1996 and 2015, of which more than 60% of rainfall occurs between June and August. The HFB is mostly forested, consisting primarily of larch (*Larix gmelinii* (Rupr.) Kuzen.), pine *(Pinus sylvestris* L. var. *mongolica*

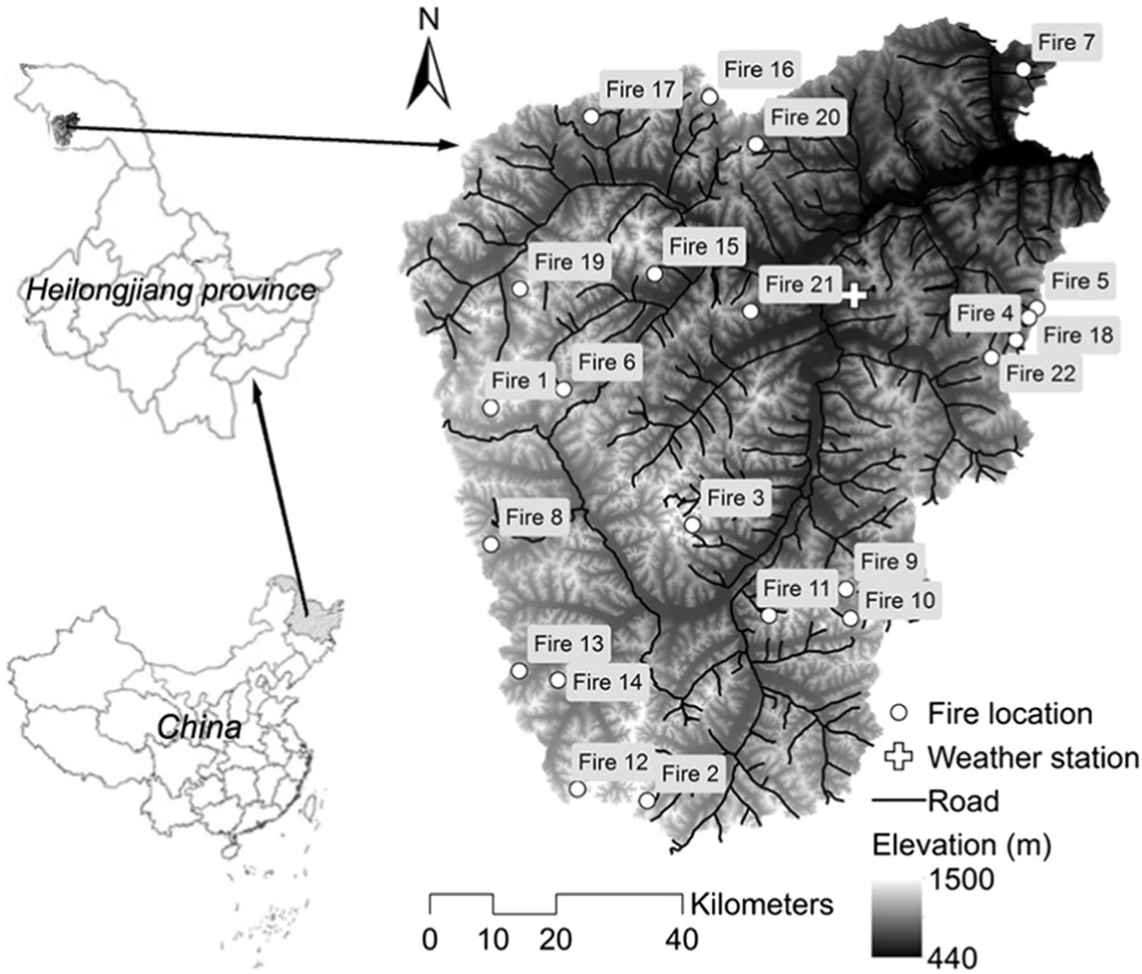


**Fig. 1** Topographic map of study area location in Huzhong Forest Bureau, in northeastern China, overlaid with locations of the local weather station and 22 fires that occurred between 2000 and 2005

Litv), spruce (*Picea koraiensis* Nakai), birch (*Betula platyphylla* Suk.), and two species of aspen (*Populus davidiana* Dode and *Populus suaveolens* Fisch). Larch is the dominant species, occupying 65% of the study site, often mixed with birch and pine (Xu 1998; Zhou 1991). In the HFB, birch is an early successional pioneer, aspen is confined to terraces along rivers, and higher elevations (> 800 m) support some Dwarf Siberian pine (*Pinus pumila*). Birch is mixed with larch in most areas owing to fire disturbance and forest harvesting (Zhou 1991). Spruce occurs sporadically, preferring colder and wetter sites in valleys and higher elevations (550-1000 m). Larch outcompetes spruce as the seral climax species because larch is drought tolerant (Xu 1998).

## 2.2 Fire data and spatial mapping

A fire database from local forest and fire managers identified 46 fires between 2000 and 2005 in our study area. Of these, 24 were compromised either by incorrect spatial coordinates, or were too small to analyze for spatial patterns of burn severity (Montealegre et al. 2014). For each fire, radiometrically and geometrically corrected, cloud-free Landsat TM/ETM images (path 121, row 024) from 2000 to 2005 were downloaded from the International Scientific Data Service Platform (http://datamirror.csdb.cn/index.jsp), and fire boundaries were visually identified in Bands 1, 4, and 7 composite images. The final fire dataset comprised 22 fires, totaling 16,270.9 ha and ranging from 21.6 to 8327.7 ha with an average size of 739.6 ha (Table 1).

## 2.3 Calculating and classifying burn severity

Using the TM/ETM images, we calculated burn severity for each fire using the post-fire Normalized Burn Ratio index (NBR) (Fig. 2). The NBR is calculated by using the reflectances obtained from TM/ETM bands 4 and 7 (Key and Benson 2006; Wang et al. 2013), which have been widely used to evaluate vegetation affected by fire (García and Caselles 1991). NBR values are typically classified using thresholds to high, moderate and low severity classes. Here, we used thresholds developed from an earlier study which examined 16 fires in our study area (Wang et al. 2013), as

**Table 1** Fire occurrence date and Landsat TM/ETM information for the 22 fires that occurred between 2000 and 2005

| Fire ID | Burn period | Area (ha) | Landsat TM/ETM information | |
|---|---|---|---|---|
| | | | Type | Date |
| 1 | 6/17/2000–6/23/2000 | 8327.7 | TM | 8/30/2000 |
| 2 | 6/17/2000–6/24/2000 | 2788.2 | TM | 8/30/2000 |
| 3 | 6/18/2000–6/24/2000 | 1411.7 | TM | 8/30/2000 |
| 4 | 6/17/2000–6/20/2000 | 1346.2 | TM | 8/30/2000 |
| 5 | 5/13/2001–5/14/2001 | 437.0 | ETM | 6/22/2001 |
| 6 | 8/1/2002–8/1/2002 | 73.6 | ETM | 9/13/2002 |
| 7 | 8/11/2002–8/11/2002 | 62.3 | ETM | 9/13/2002 |
| 8 | 8/14/2002–8/14/2002 | 142.6 | ETM | 9/13/2002 |
| 9 | 5/22/2003–5/23/2003 | 238.1 | TM | 6/20/2003 |
| 10 | 5/22/2003–5/22/2003 | 64.7 | TM | 6/20/2003 |
| 11 | 5/22/2003–5/22/2003 | 36.1 | TM | 6/20/2003 |
| 12 | 6/24/2004–6/25/2004 | 145.0 | TM | 8/9/2004 |
| 13 | 7/10/2004–7/13/2004 | 504.6 | TM | 8/9/2004 |
| 14 | 7/11/2004–7/13/2004 | 213.4 | TM | 8/9/2004 |
| 15 | 7/12/2004–7/13/2004 | 21.6 | TM | 8/9/2004 |
| 16 | 7/14/2004–7/15/2004 | 46.7 | TM | 8/9/2004 |
| 17 | 7/14/2004–7/15/2004 | 105.6 | TM | 8/9/2004 |
| 18 | 8/5/2005–8/6/2005 | 141.1 | TM | 9/21/2005 |
| 19 | 8/5/2005–8/5/2005 | 29.2 | TM | 9/21/2005 |
| 20 | 8/10/2005–8/10/2005 | 59.3 | TM | 9/21/2005 |
| 21 | 8/13/2005–8/13/2005 | 40.6 | TM | 9/21/2005 |
| 22 | 8/26/2005–8/26/2005 | 35.6 | TM | 9/21/2005 |

follows: unburned, >585, low, 252–585, Moderate, 53–252, and High, <= 53. Further details regarding our use of this widely applied method were presented in the Supplementary Materials (Method S1).

## 2.4 Quantifying spatial patterns of burn severity

For each fire, we characterized the spatial pattern of burn severity patches using the FRAGSTATS program (Haire and McGarigal 2009), focusing on metrics previously used to measure differences in spatial patterns of burn severity (Cansler and McKenzie 2014). Metrics were calculated at the class level (McGarigal et al. 2012), using the eight-neighbor rule. We examined composition and patch size with the percentage of landscape (PLAND) and area-weighted mean patch size (Area_AM) metrics (Cansler and McKenzie 2014; Harvey et al. 2016). To characterize patch shapes, we used the area-weighted mean fractal dimension index (FRAC_AM) and perimeter–area ratio (PARA_AM) (McGarigal et al. 2012). Finally, we used patch density (PD) and aggregation index (AI) to assess the spatial arrangement of burn-severity patches within a fire (Haire and McGarigal 2009). More details regarding these metrics were provided in the Supplementary Materials (Method S2).

## 2.5 Weather data and fire weather rating index calculation

Weather data for each fire, including daily temperature (°C), relative humidity (%), wind speed (m/s), precipitation (mm), and days since last rainfall, were acquired from the Huzhong weather station (longitude: 123.67E, latitude 52.05 N; elevation 521.6 m) (Fig. 1; Table 2). We used this data to calculate a fire danger metric, forest fire weather rating index (FWI) according to the China National Forest Fire Weather Rating Standard (LY/T 1172–95) (Wang et al. 1995), for each fire. We used the average daily weather parameters data over each fire's duration to calculate FWI for each fire. The FWI values are typically classified into five classes using thresholds: extreme low (≤25), low (26–50), moderate (51–72), high (73–90), and extreme high (≥91). More details regarding the fire weather rating index calculation were provided in the Supplementary Materials (Method S3).

## 2.6 Statistical analysis

We carried out a series of statistical analyses to assess spatial patterns of burn severity and relationships between those patterns and weather variables (Fig. 3). Fire size, although not a focal explanatory variable in this study, was included in our statistical analysis as it has strong effect on spatial patterns of burn severity (Cansler and McKenzie 2014; Harvey et al. 2016). First, as the spatial pattern metrics of the three burn-severity classes were non-normally distributed, we used the non-parametric Friedman's test to detect significant differences of spatial pattern metrics among low-, moderate-, and high-severity classes in the R programming environment (R-Core-Team 2014). The Friedman's test is a statistical approach for testing the difference between several related samples. We used the Wilcoxon-Nemenyi-McDonald-Thompson post-hoc tests to decide which burn-severity classes are significantly different from each other. We employed the Generalized Additive Models (GAM) to explore how much the variation of spatial pattern metrics of high-severity patches could be explained by fire weather index (FWI), which is expressed as the deviance explained (%). We used the residuals after modeling spatial pattern metrics and fire size relationships to assess the effects of FWI on spatial patterns of high-severity patches. The GAM allows non-parametric fits on the relationship between response and predictor (Hastie and Tibshirani 1990). We used the "mgcv" package in R to the implement the GAM analysis. Finally, we used the Random Forest (RF) model's importance values to rank fire size and weather variables based on the strength of their relation to spatial patterns of high-severity patches (Breiman 2001). We calculated the

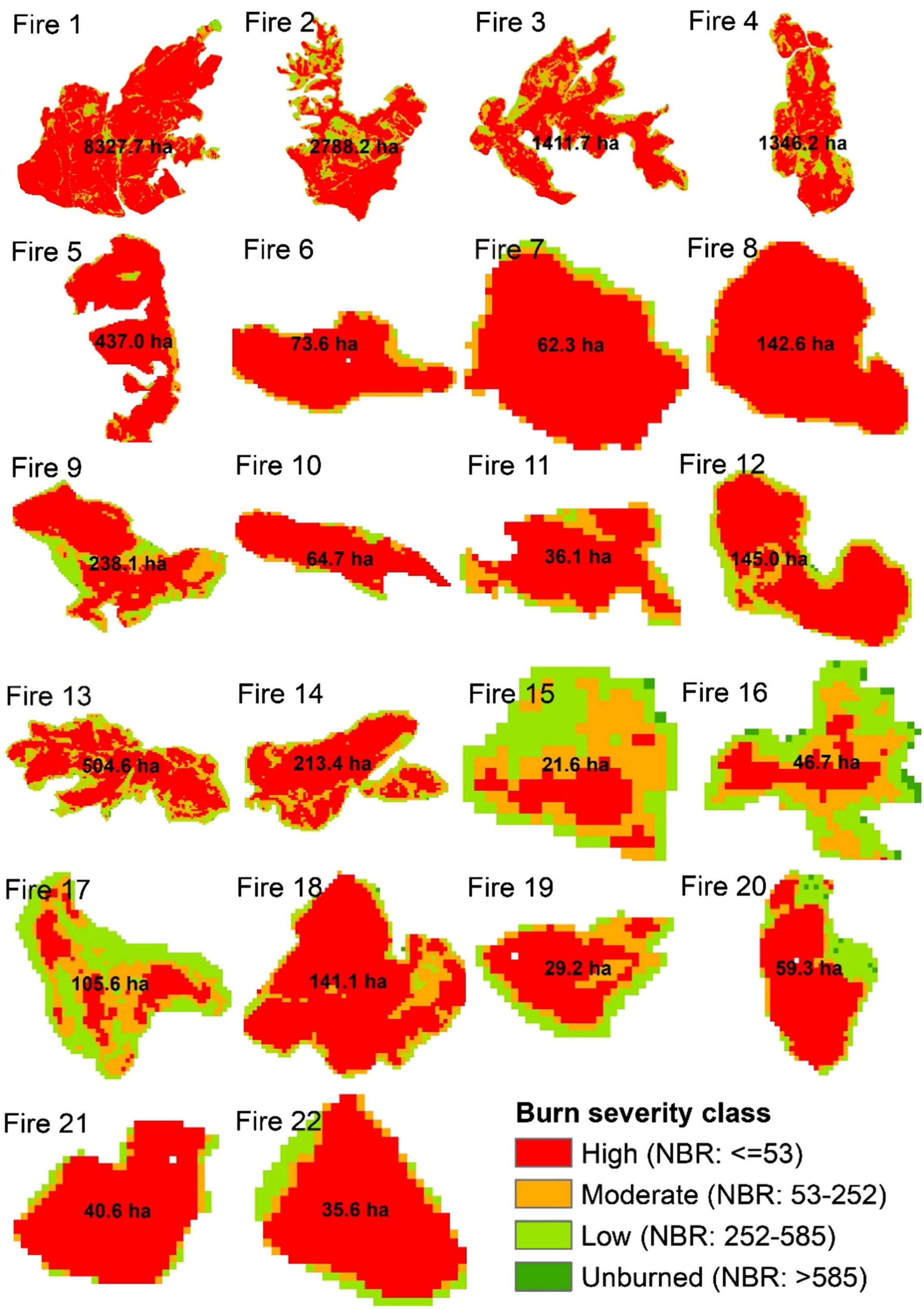


**Fig. 2** Maps of burn-severity classes (NBR values) of the 22 fires

partial dependence to show the responses of spatial pattern metrics to the changes of the first two most influential variables in the RF model. We used the "randomForest" package in R to the implement the RF analysis.

**Table 2** Descriptive statistics for weather variables of the 22 fires between 2000 and 2005

| Variables | Min | Max | Mean | Std. Dev. |
|---|---|---|---|---|
| Mean temperature (°C) | 8.7 | 26.1 | 18.3 | 4.3 |
| Maximum temperature (°C) | 18.6 | 36.2 | 29.1 | 4.6 |
| Mean relative humidity (%) | 57.0 | 79.0 | 68.0 | 6.9 |
| Minimum relative humidity (%) | 21.8 | 44.3 | 33.8 | 6.4 |
| Mean wind speed (m/s) | 0.9 | 3.1 | 1.6 | 0.6 |
| Maximum wind speed (m/s) | 3.0 | 8.5 | 5.5 | 1.2 |
| Precipitation (mm) | 0.0 | 7.7 | 2.7 | 3.0 |
| Days since last rainfall (day) | 0.0 | 11.0 | 4.5 | 3.9 |
| Fire weather rating index (0–100) | 32.0 | 97.0 | 56.4 | 19.2 |

**Data availability** The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

# 3 Results

## 3.1 Spatial patterns of burn severity

High-severity fire patch, averaged 570.5 ha (SD = 1530.6), was the dominant outcome, comprising 67.8% of all area burned across the 22 fires. High-severity patches differed significantly ($p < 0.05$) from low- and moderate- severity patches for five of six spatial pattern metrics, with lower patch density and area-weighted mean perimeter-area ratio, and higher values for all other metrics, except fractal dimension index, for which differences were not statistically significant ($p =$ 0.320) (Fig. 4). Collectively, these results indicate that high-severity patches are typically larger, simpler in shape, and more aggregated than low- and moderate-severity patches. More details regarding the comparison results of the spatial pattern metrics were provided in the Supplementary Materials (Result S1).

## 3.2 High-severity patterns and weather relationships

GAM analysis results indicate that spatial pattern metrics vary with fire weather indexes in different ways, and to different degrees, explaining between 3.2 and 13.6% of the deviance (Fig. 5). Generally, the percentage of landscape and patch size were largest under the moderate fire weather danger (fire weather index). The fire patches under low fire weather index had the highest perimeter-area ratio but lowest fractal dimension index. These results indicate that fire patches burned under low fire weather index are less complex in shape. The patch density was higher and aggregation index was lower under the low fire weather index (Fig. 5).

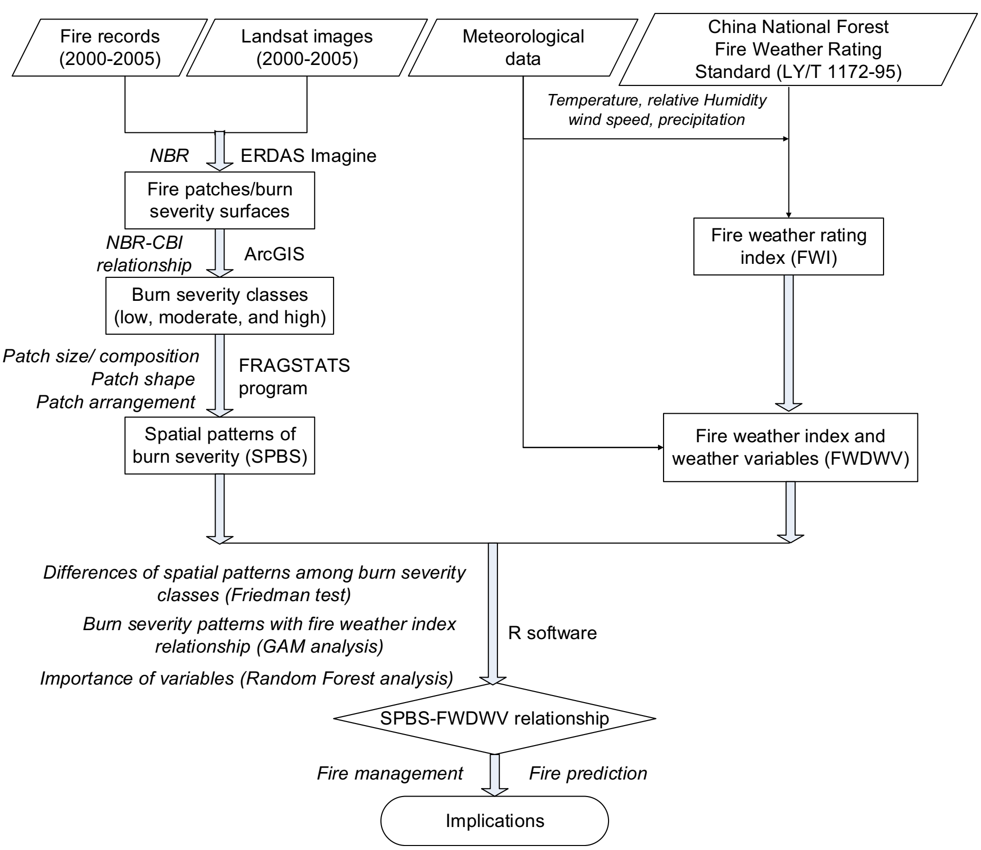


**Fig. 3** The steps used to quantify the relationships between spatial patterns of burn-severity and fire danger and weather variables

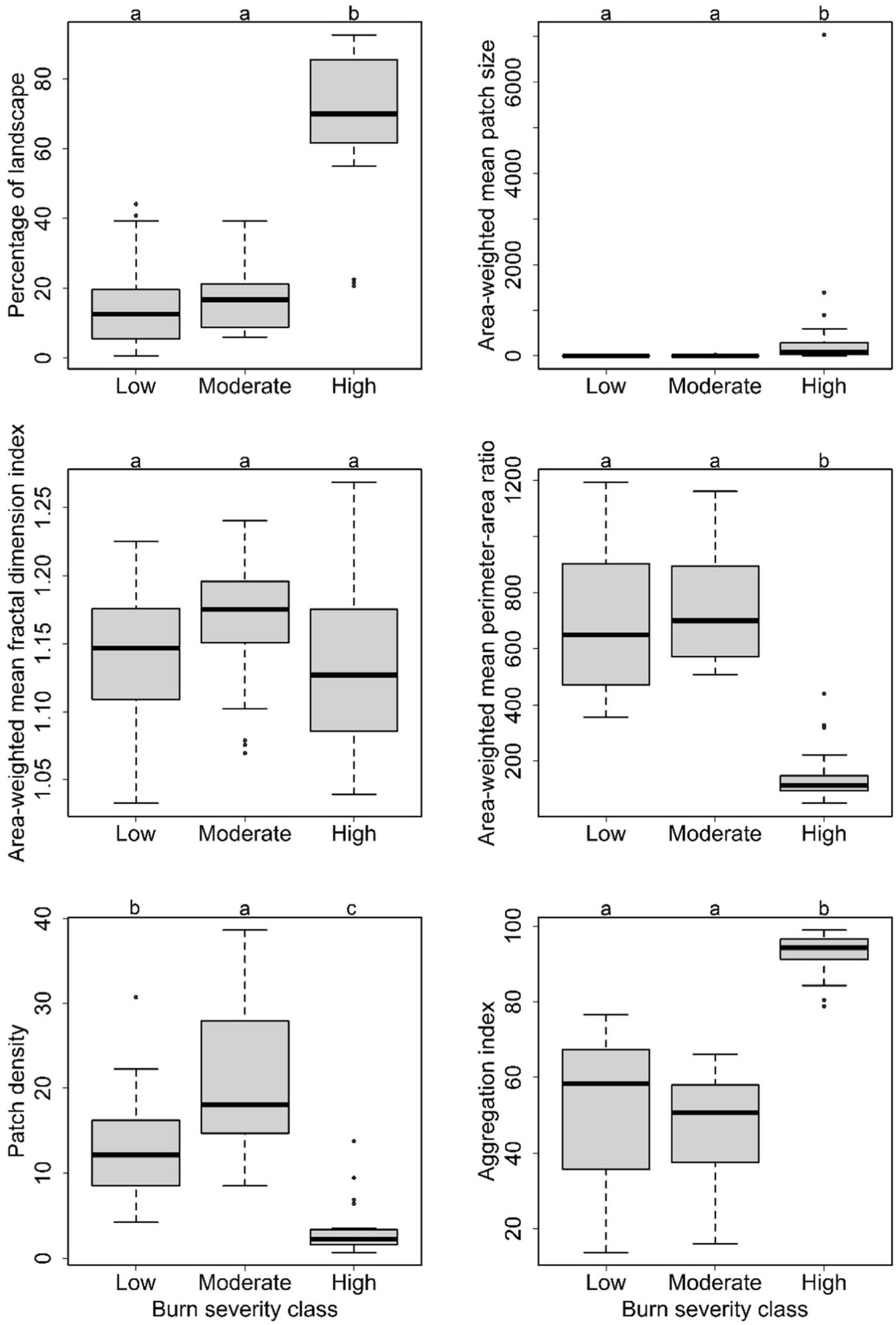


**Fig. 4** Boxplots showing distributions of spatial pattern metrics by burn-severity classes. Different letters at the top of the boxplots indicate statistically significance differences ($\alpha = 0.05$) among the burn-severity classes

The relative importance of fire size and weather variables varied between spatial pattern metrics (Figs. 6 and 7). Mean wind speed and minimum relative humidity were most influential for the metrics of percentage of landscape (areal percentage) and aggregation index of high-severity patches. Metrics of percentage of landscape and aggregation index generally increased with decreasing relative humidity and increasing wind speed. High-severity patch size was determined by fire size and days since no rainfall. Increasing fire size and days since last rainfall increased the size of high-severity patch. Fractal dimension index of high-severity patches was affected by fire size and mean wind speed, and increased as increasing fire size and wind speed. Fire size and relative humidity were the most important variables influencing metrics of perimeter-area ration and patch density. The perimeter-area ratio and patch

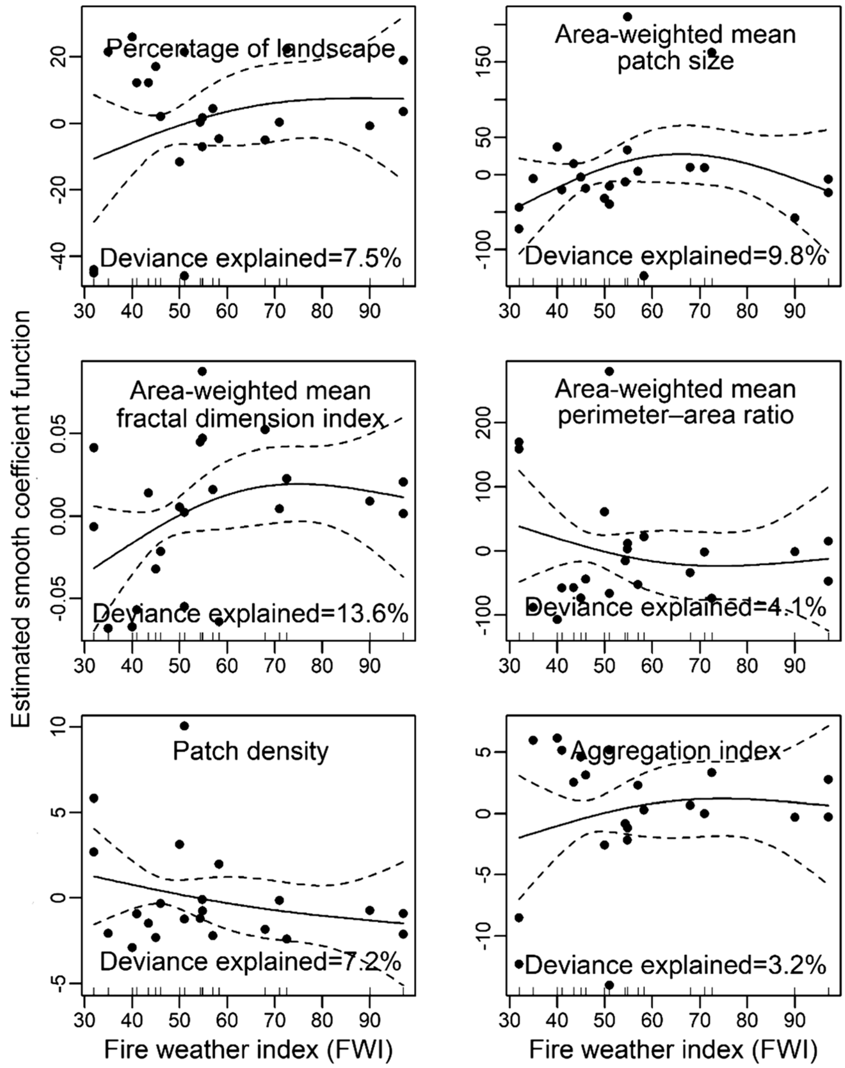


**Fig. 5** Plots of the GAM estimated smooth coefficient function for landscape pattern metrics of high-severity patches in relation to the fire weather index (FWI). The solid line is the estimated smoother, and the dotted lines are 95% confidence intervals. The FWI values (0–100) are classified as: extreme low (≤25), low (26–50), moderate (51–72), high (73–90), and extreme high (≥91)

density increased as increasing relative humidity and decreasing fire size.

## 4 Discussion

### 4.1 Spatial composition and pattern of burn severity

Our results highlight the prevalence of high-severity patches (67.8%) within fires in the Chinese boreal forest landscapes. Our findings are similar to those reported in previous studies, especially in the North American boreal forest landscapes (Beck et al. 2011; Kelly et al. 2013; Lentile et al. 2007). For example, Lentile et al. (2007) found that 58% of the landscape was mapped as high-burn severity in Alaska boreal forests, USA. High-severity fires often create a more homogeneous landscape pattern by increasing patch sizes while reducing the proportion of the landscape in low- and moderate-severity patches (Cansler and McKenzie 2014).

The perimeter-area ratio of high-severity patches was significantly lower than that of low- and moderate-severity patches. From a landscape ecology perspective, perimeter-area ratio of patches decreased as patches became larger (Turner et al. 2001). Large fires tended to have larger high-severity patches (Cansler and McKenzie 2014), which were more regular in shape and had less edge than smaller fires. Our findings on perimeter-area ratio of fire patches are similar to other researchers. For example, Turner et al. (1994) found that the edge-to-area ratio (calculated for all severity classes) decreased from early fires to later fires (higher in severity) in the Yellowstone National Park, USA. The fractal dimension index of high-severity patches was nearly identical across low- and high-severity patches (Fig. 4), similar to previous studies. For example, Keane et al. (2008) investigated 36 fires in the forests of northern Rocky Mountains, USA, and found that fractal dimension index (calculated for all severity classes) was not significantly different between burn severity of small and larger fires ($p = 0.36$). They proposed that

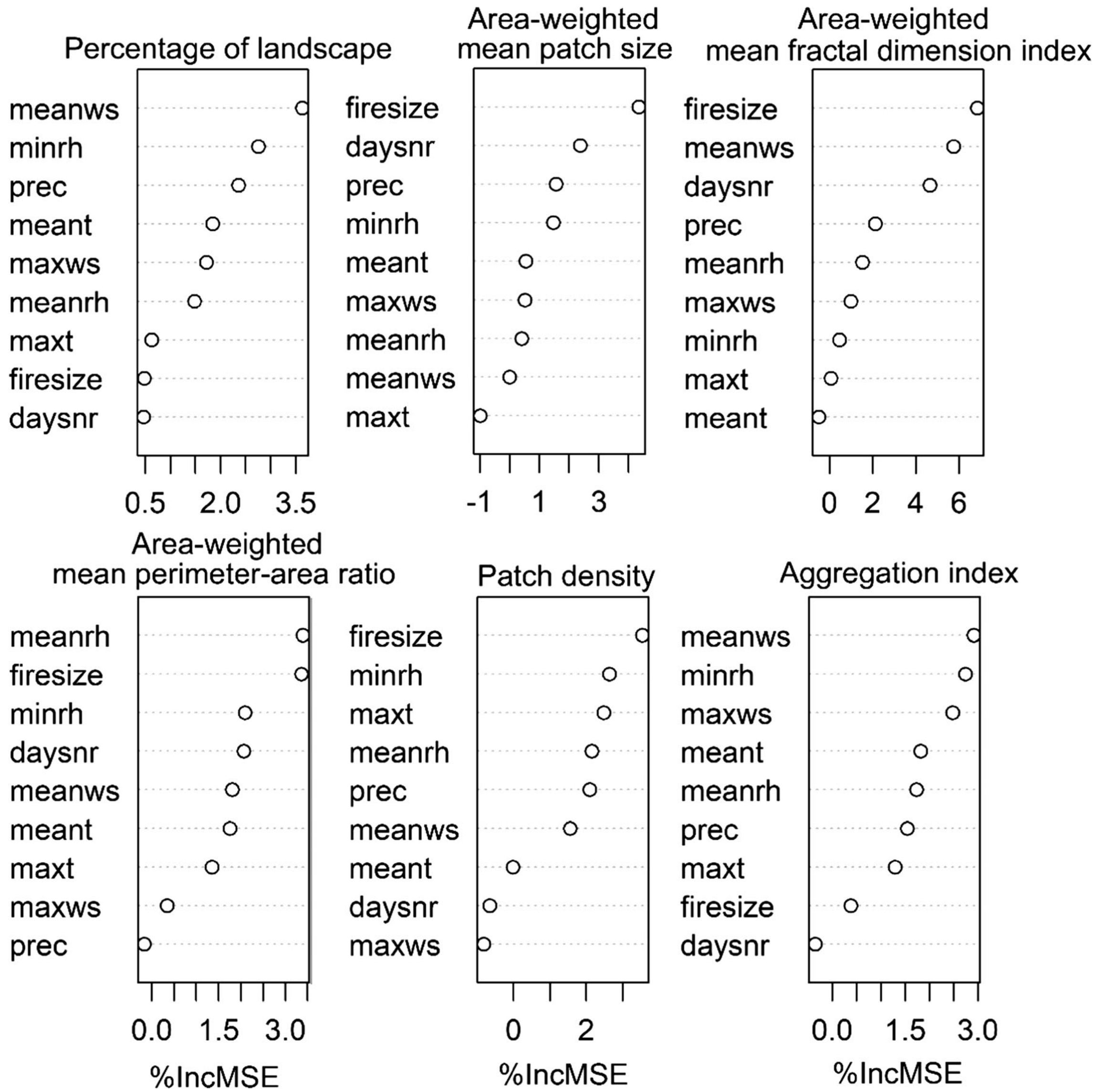


**Fig. 6** Relative contributions of weather variables to spatial patterns of high-severity patches. The percent increase in prediction mean squared errors (%incMSE) was used to rank the relative contribution of the variables. Maxt: maximum temperature; meant: mean temperature; minrh: minimum relative humidity; meanrh: mean relative humidity; meanws: mean wind speed; maxws: maximum wind speed; prec: precipitation; daysnr: days since last rainfall

although the patches were burned more severely in large fires, the patches tended to be adjacent to the lower-severity classes, creating diverse landscape mosaics (Keane et al. 2008).

We observed lower patch density in high-severity patches than in low- and moderate-severity patches. The higher patch density for lower severity patches is due to the large number of small patches making up this class within a fire. But, high patch density does not necessarily mean that the burn-severity class is heavily aggregated (Hayes and Robeson 2011). This is indicated by the aggregation index calculated in our study, which showed that high-severity patches were more spatially aggregated than low- and moderate-severity patches. Fires which burn rapidly and cause high burn-severity often result in larger patches. We found that fire size positively correlated with patch size (spearman's correlation test: $r = 0.99$, $p < 0.01$), but not significantly correlated with aggregation index ($r = 0.13$, $p = 0.57$) of high-severity patches. Therefore, our study confirms that increased fire size is commensurate with increased patch size of high-severity (Cansler and McKenzie 2014), but not necessarily indicates higher spatial aggregation for this burn-severity class.

### 4.2 Burn severity patterns and weather relationships

The spatial patterns of burn severity are products of several interacting controls, which are generally categorized as "top-down" (external to ecosystems) and "bottom-up" (internal to ecosystems) controls (Kent et al. 2017). The

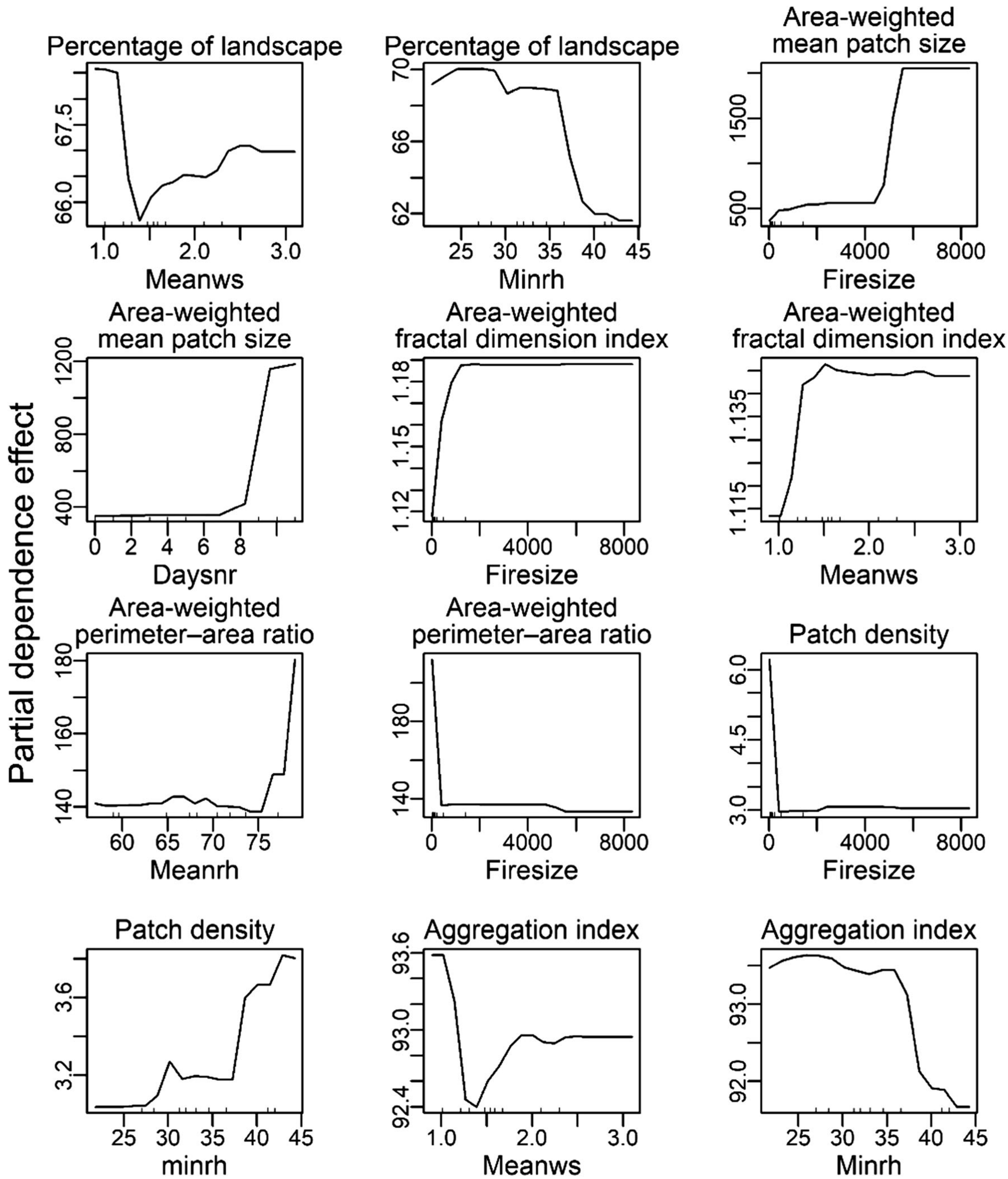


**Fig. 7** The partial dependence of spatial pattern metrics of high-severity patches on fire size and weather variables. Minrh: minimum relative humidity; meanrh: mean relative humidity; meanws: mean wind speed; daysnr: days since last rainfall

"top-down" controls (e.g., climate and weather) are operating at higher levels such as at regional scales, whereas the "bottom-up" controls (e.g., vegetation and topography) are operating at lower levels such as at local scales. Variation in "top-down" controls could override "bottom-up" controls in shaping spatial patterns of burn severity (Gill and Taylor 2009). Our results showed that spatial patterns of high-severity patches differed with weather conditions. For example, fire patch size increased in drier and less humid conditions, and patches were more complex and aggregated with higher wind speeds. These results are agree with the theory on "top-down" and "bottom-up" controls on fire burning patterns. Higher fire weather danger usually produces fires burning with large in size and high in severity. Large fires are less responsive to variation in fuels and even topography and therefore would be more severe (Cansler and McKenzie 2014; Harvey et al. 2016). For example, Turner et al. (1994) found that the proportion of high-severity burns during the 1988 Yellowstone fires increased relative to low- and moderate-severity burns as the gross daily area burned increased. In contrast, under lower fire weather danger (burning conditions are not extreme), spatial patterns of fuels and topographic features may have strong effects on fire burning patterns (Turner and Romme 1994).

We identified mean wind speed, minimum relative humidity and days since last rainfall as variables having highest effects on spatial pattern metrics of percentage of landscape and patch size. This is an expected finding because lower values of humidity and more days without rainfall, as well as high wind speed, may lead to increased size and severity of fires (Kelly et al. 2013; Westerling et al. 2011). With regard to the weather variables most influential to perimeter-area ratio and patch density, we found that relative humidity was the most important, indicating that fire-created patches become more homogenous as relative humidity decreases. Variables of relative humidity and wind speed effects were observed to be important determinants of spatial arrangement of high-severity patches because they determine fuel moisture conditions that subsequently influence fire regimes (e.g., burn severity) (Viedma et al. 2015; Wastl et al. 2013).

### 4.3 Implications

Post-fire successional changes over time can be impacted by patch structure and configuration of burn severity (Harvey 2015; Liu and Yang 2014; Pickett and White 1985; Turner et al. 1994). For example, Johnstone and Chapin (2006) found that variations in burn severity can influence multiple aspects of forest stand structure by affecting the density and composition of tree seedlings that establish after fire in North American boreal forests. Our study found that fires burned with different spatial patterns of severity, which can affect the post-fire forest recovery and structure in Chinese boreal forests (Cai et al. 2013). For example, fires that burned under lower fire danger had smaller patch sizes and greater perimeter-area ratio of high-severity patches that would be closer to seed source from lower severity patches and unburned forests as compared to fires that burned under higher fire danger.

With climate change expected to result hotter and drier weather, future conditions will likely face increasing fire danger (Carvalho et al. 2011; Liu et al. 2012). Increased fire danger would significantly affect burn severity of a fire and its spatial pattern in boreal forests (van Bellen et al. 2010); therefore, it is important to examine fire-weather relationships to identify climate contexts in which fires can produce a desired range of spatial patterns and subsequently ecological effects (Haire and McGarigal 2009). For example, our study showed that wind speed and relative humidity greatly influenced spatial patterns of burn severity. Therefore, fire pattern prediction should include more intensive attention to these weather variables in the Chinese boreal forests.

## 5 Conclusion

High-severity patches are predominant in the Chinese boreal forests, and the spatial pattern of high-severity patches generally differed from those of low- and moderate-severity patches. Larger patches occurred under the moderate fire weather index. Wind speed and relative humidity were the two most important weather variables in shaping spatial patterns of burn severity in Chinese boreal forests.

Our study explored effects of weather on spatial patterns of burn severity. However, a limitation to our study may have been that spatial variation in vegetation, topography, and fuels were not considered, which produced the relatively low amount of variation in spatial patterns of burn severity explained by the GAM analysis. Vegetation and topography variables may have shaped patterns of burn severity across forest landscapes. For example, forest structure (e.g., tree height and understory cover) can determine vertical continuity of fuels that affect the probability of a surface fire to transition to a crown fire. This is especially true for landscapes that experienced significant changes in environments and fire regimes.

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## Compliance with ethical standards

**Declaration on conflicts of interest** The authors declare that they have no conflict of interest.

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