Terrain influence landscape patterns of burn severity in subtropical forests of southern China

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Abstract

Context

Understanding the landscape patterns of burn severity is vital for managing fire-prone ecosystems. Relatively limited research has been done about fire and burn severity patterns in subtropical forests.

Methods

Using Landsat 8 OLI remote sensing imagery, this paper spatially mapped the burn severity of 27 forest fires in the subtropical broadleaved evergreen forest in Southern China from 2017–2021. The landscape pattern of patches with different burn severity was quantified using landscape indices. In addition, factors influencing the patterns of burn severity across the landscape were determined using the Geodetector model.

Results

Burn severity of patches varied significantly. High burn severity was common in forest patches with low fragmentation, low patch density, and regular shape. In contrast, moderate and low burn severity was prevalent in patches with smaller patch size, high patch density, and complex shapes. Extensively burned forest patches were located at higher elevations, while more fragmented patches were located in gently sloping areas. Topographic factors were the most significant factors influencing variances in burn severity across the forest patches, followed by climatic conditions. A detailed understanding of burn severity patterns and driving factors in a landscape can help develop sustainable forest management and restoration strategies after severe forest fire disturbances.

Introduction

Forest fires are considered one of the most widespread disturbances in a forested landscape that drives changes in the structure and function of the forests (Keane et al. 1996; Liu et al. 2022; Gu et al. 2020). Burn severity is the extent to which forest fires affect or disturb various elements of forest ecosystems (Lentile et al. 2006; Chang et al. 2012; Key and Benson 2006). From a landscape ecology perspective, the pattern of burn severity refers to the spatial distribution of discrete patches of fires with different severity on the landscape (Wu et al. 2018; Haire and McGarigal 2009). Patterns of burn severity within forest landscapes affect patterns of post-fire ecological processes, including plant community structure and succession (Turner et al. 1999) and wildlife community dynamics (Carlson et al. 2017). Particularly, fire severity impacts seedling recruitment, germination of the soil seed bank, and tree seed rain. For example, the number and structure of edges between moderately burned patches and unburned patches can influence distance and the direction of seed dispersal and, subsequently, successional trajectories and rates of forest ecosystem recovery (Turner et al. 1994; Donato et al. 2009). Therefore, understanding the landscape patterns of burn severity is vital for managing fire-prone ecosystems.
Patterns of burn severity in a landscape are mostly controlled by three main factors: climate/weather, topography, and fire behavior and vegetation structure (Carlson et al. 2017; Cansler and McKenzie 2014a; Harvey et al. 2016). Climate conditions, such as high temperatures, affect the flammability of vegetation, and prevalent weather conditions, such as wind, temperature, and humidity, during a fire event determine the intensity, extent and spread of the fire. For example, vegetation provides the combustible material (i.e., fuel) needed for ignition (Falk et al. 2007; Rollins et al. 2002), while weather conditions provide impetus to spread the fire (Harvey et al. 2016). Therefore, the amount and type of fuel, together with weather conditions, can limit or facilitate fire spread, determine the fire size in a landscape, and most importantly, dictate the subsequent fire intensity that determines burn severity. Topography (e.g., slope, aspect, altitude, and complexity) also influences fire behavior. For instance, topographically, complex terrain conditions can limit fire spread, while relatively gentle terrain can facilitate it (Falk et al. 2007; Rollins et al. 2002). Therefore, topographic complexity can create variation and spatial heterogeneity in burn severity and spread. However, extreme weather conditions can override vegetation and topographic constraints on fire spread and contribute to the shifts in spatial patterns of burn severity, including the spread of large, high severity fire patches in a forest landscape (Wu et al. 2018; Crimmins 2011; Kolden et al. 2015). Therefore, examining the relative importance of weather, vegetation structure, and topographic factors on spatial patterns of burn severity is critical for predicting burn severity in a forest landscape.

Climatic differences, along with forest vegetation structure and anthropogenic disturbances, influence important variations in the size and severity of fire across landscapes and climatic regions (Cansler and McKenzie 2014a; Wimberly and Reilly 2007; Kurbanov et al. 2017; Su et al. 2019; Cansler 2011; Birch et al. 2015). For instance, fires in subtropical forests are usually smaller in size and lower in severity than in cold temperate boreal forests (Guo et al. 2022). Notably, compared to cold temperate boreal forests, relatively limited research has been done about fire and burn severity patterns in subtropical forests (Delcourt et al. 2021; Chu et al. 2016). Therefore, exploring the influence of climate, vegetation, and topographic factors on the spatial pattern of burn severity in subtropical forests is important for the future management of forest fires in the subtropical region under changing climate and anthropogenic disturbances.

The Geodetector model is a useful tool for analyzing spatial stratification heterogeneity because it detects spatial heterogeneity of geographical phenomena and helps identify the driving forces behind it. The Geodetector model can quantitatively analyze the relative importance of each factor causing the heterogeneity of landscape pattern of burn severity, and also detect the interaction intensity between the two driving factors. Because of its effectiveness of spatial heterogeneity analysis, this study used a Geodetector model to assess the influence of different factors on the landscape patterns of burn severity.

The objectives of this study were to 1) evaluate the landscape scale patch composition and spatial structure of different burn severity and 2) determine how vegetation structure, topography, and climatic factors and their interactions influence the spatial pattern of fire intensity.

**Material and methods**
Study area

The study (Fig. 1) was carried out in the Gannan region, located in the south of Jiangxi Province (24°29′-27°09′N, 113°54′-116°38′E), covering a total area of 39,379.64 km$^2$. The terrain of the study area is predominantly mountainous and hilly, with an average altitude of 300–500 m above sea level (asl). There are 450 peaks over 1,000 m asl. The region experiences a subtropical monsoon climate, with an average annual temperature of 19.3°C and precipitation of 1,568.8 mm. The Gannan region has a well-developed infrastructure (e.g., road network) with a high human density.

The region has extensive and dense forest cover (forest coverage reached 76%), dominated by a mixture of broadleaved and evergreen coniferous forests (Wu et al. 2022). The most dominant tree species in the region include Masson pine (*Pinus massoniana*) and Chinese fir (*Cunninghamia lanceolata*). Masson's pine is a large area of artificial pure forest planted in subtropical area in south China, covering an area of about 928,000 hectares (accounting for 36% of the total forest area)(Guo et al. 2018). It has a single layer and simple structure. Moreover, the branches, trunks and needles of Masson's pine will secrete a lot of oil, and the fire resistance ability is weak. The crown fire conversion rate of 10 a and 20 a Masson's pine forest is high, which is easy to cause heavy losses after fire (Pan et al. 2017). Chinese fir is also the pioneer tree species and main afforestation tree species in subtropical area in south China. The oil content of Chinese fir fuel is high, low moisture content, the dead branches are difficult to wither, the decomposition rate is very slow, easy to occur crown fire, fire risk is very high (Deng et al. 2002).

The region experiences small-scale but more frequent forest fires fueled by manmade sources, such as the burning paper on graves, charcoal, and discarded cigarettes. Forest fires in the region are mostly concentrated in the first half of the year, especially from January to April. The critical annual forest fire prevention period runs from 1 October to 30 April each year.

Fire data and spatial mapping of burn severity

Using a field survey, we collected burn severity data from 27 forest fires that occurred in the Gannan region between 2017 and 2021.

Specifically, The CBI (Composite Burn Index) is used to assess burn severity in the field (Key and Benson, 2005). (Table A1). Field surveys of burned severity were conducted within 1 year after the occurrence of a fire event. To ensure that the pixels of the measured CBI and Landsat 8 OLI images were consistent in spatial location and size, 30 m × 30 m plots were used in field surveys. These plots were distributed in areas with different terrain conditions and burn severities. Each plot was divided into four layers according to vertical height: A, representing the surface combustible material and soil layer; B, representing herbs, short shrubs, and small trees (< 1 m height); C, representing tall shrubs and trees (> 1–5 m height); and D, representing forest canopy (> 5 m) (Key and Benson, 2005). Each layer had 4–5 variables that were visually estimated in the range 0 to 3: 0 (unburned), 1 (low burn severity), 2 (moderate
burn severity), and 3 (high burn severity). The estimated value of each layer synthesis was performed to obtain CBI of the entire plot.

For each forest fire, we downloaded Landsat8 OLI (L1T processing level) images (30 m spatial resolution) from the Chinese Geospatial Data Cloud (http://www.gscloud.cn/sources) and the United States Geological Survey (USGS) website (https://glovis.usgs.gov/app). The downloaded data represent the near real-time post-fire burn severity conditions under no or low cloud cover. The remote sensing images were pre-processed, including radiation calibration and atmospheric correction, the burned boundary was visually interpreted by combining band 2 (Green), 5 (NIR) and 7 (SWIR2), was performed in the ENVI software. The total area covered by the 27 forest fires was 4610.54 ha, with the size of the forest fires ranging between 18.07-789.23 ha and an average size of 170.8 ha (Table A2).

We used the dNBR spectral index to map the burn severity. In a previous study (Guo et al. 2022), we modelled burn severity of 420 fires in the Gannan region using 13 spectral indices and compared accuracies of different models and indices to determine the best measure of burn severity. Our results showed that the dNBR spectral index based on the quadratic model was the best index for assessing burn severity ($R^2 = 0.7, p < 0.01$), supporting the method selected for this study. The threshold values selected for burn severity grading were unburned (dNBR < 0.214), low severity (0.214–0.455), moderate severity (0.455–0.665), and high severity (> 0.665). We used equations 1 and 2 to calculate dNBR, where $b_5$ is the near infrared band, and $b_7$ is the short infrared band. The spatial mapping of burn severity in the study area is shown in Fig. 2.

$$NBR = \frac{b_5 - b_7}{b_5 + b_7}$$

1

$$dNBR = NBR_{pre} - NBR_{post}$$

2

### Quantifying landscape patterns of burn severity

The spatial patterns of burn severity were quantified using. There are many landscape pattern indices, and there are often limitations in the pattern characteristics indicated by a single index, and often there is redundancy between multiple landscape pattern indices (Lustig et al. 2015; Rahimi et al. 2022). This study preliminary selected 14 different landscape indices to assess the spatial pattern of burn severity concerning patch size, patch distribution (fragmentation and aggregation), and patch shape (Table 1). The landscape pattern indices were calculated using the eight-neighbor in the “landscapemetrics” package of the statistical software R.
<table>
<thead>
<tr>
<th>Type</th>
<th>Landscape metrics</th>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Patch size</td>
<td>Percentage of landscape</td>
<td>Pland</td>
<td>Pland represents the ratio of the area of a particular patch type to the total area of the landscape. A value equal to 0 indicates that the patch type is rare in the landscape; a value equal to 100 indicates that the landscape consists of one type of patch.</td>
</tr>
<tr>
<td>Mean patch size</td>
<td>Area_mn</td>
<td></td>
<td>Area_mn is the ratio of the total area of patches to the number of patches, reflecting the average size of landscape patches.</td>
</tr>
<tr>
<td>Largest patch index</td>
<td>Lpi</td>
<td></td>
<td>The Lpi reflects the proportion of the largest patch in the patch type to the overall landscape area. The Lpi directly reflects the dominant type of landscape.</td>
</tr>
<tr>
<td>Total (class) area</td>
<td>Ca</td>
<td></td>
<td>Ca indicates the total area of patches within a given landscape type.</td>
</tr>
<tr>
<td>Patch aggregation</td>
<td>Edge density</td>
<td>Ed</td>
<td>Ed refers to the edge length between patches of heterogeneous landscape elements per unit area within the landscape. The larger the value, the more heterogeneous the landscape patches and the more fragmented the landscape.</td>
</tr>
<tr>
<td>Aggregation index</td>
<td>Ai</td>
<td></td>
<td>Ai indicates the connectivity between patches of each landscape type; the larger the value of Ai, the more aggregated the patches in the landscape; the smaller the value, the more dispersed the patches.</td>
</tr>
<tr>
<td>Interspersion and juxtaposition index</td>
<td>Iji</td>
<td></td>
<td>A small Iji value indicates that a patch type is adjacent to only a few other patch types. Iji = 100 indicates that the probability of proximity is equal across patches.</td>
</tr>
<tr>
<td>Landscape shape index</td>
<td>Lsi</td>
<td></td>
<td>The LSI reflects the variation in the shape of the landscape. The larger the value, the more complex the shape.</td>
</tr>
<tr>
<td>Patch density</td>
<td>Pd</td>
<td></td>
<td>Pd indicates the number of patches per 100ha of land area. The larger the Pd, the higher the landscape heterogeneity.</td>
</tr>
<tr>
<td>Number of patches</td>
<td>Np</td>
<td></td>
<td>Np is a metric representing patch dispersion. A larger NP indicates a more discrete patch type and a higher degree of landscape fragmentation.</td>
</tr>
<tr>
<td>Patch cohesion index</td>
<td>Cohesion</td>
<td></td>
<td>Cohesion represents the aggregation of landscape patches. Large Cohesion values indicate more aggregated patches, and small Cohesion values indicate high fragmentation of patches.</td>
</tr>
<tr>
<td>Type</td>
<td>Landscape metrics</td>
<td>Symbol</td>
<td>Description</td>
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<td>-----------------------------------------------------------------------------</td>
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<tr>
<td>Clumpiness index</td>
<td>Clumpy</td>
<td></td>
<td>Clumpy indicates the degree of aggregation of the plaques. The plaques are fully dispersed when Clumpy = -1, randomly dispersed when Clumpy = 0 and aggregated when Clumpy = 1.</td>
</tr>
<tr>
<td>Patch shape</td>
<td>Mean shape index</td>
<td>Shape_mn</td>
<td>Shape_mn = 1 for regular patch shape; as the index increases, the patch shape becomes more irregular.</td>
</tr>
<tr>
<td>Perimeter-area ratio</td>
<td>Para_mn</td>
<td></td>
<td>The Para_mn quantifies the degree of complexity of the boundary across a range of patch sizes. As the boundary complexity of the patch shape increases, the Para_mn generally increases.</td>
</tr>
</tbody>
</table>

Drivers of landscape patterns of burn severity

Fuel

Fuel data was represented by two different indices, the Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Moisture Index (NDMI). The NDVI is a good indicator of plant growth. It can be used to characterize vegetation cover (Jin et al. 2022) and combustible load, while the NDMI is a reliable indicator of the water content of combustible material. The NDVI and NDMI were calculated based on pre-fire Landsat 8 OLI. The NDVI and NDMI were calculated as follows:

\[
NDVI = \frac{b_5 - b_4}{b_5 + b_4}
\]

Topography

Topographic variation can lead to significant spatial variability in the forest fire environment. Here, topographic data (30 m spatial resolution) were obtained from the USGS National Elevation Dataset (https://glovis.usgs.gov/app). Topographic variables, aspect, slope, and elevation, were extracted using the ArcGIS spatial analysis module.

Climate
Climatic factors affect forest fire propagation by influencing soil and fuel (i.e., combustible plant material) moisture (Jones et al. 2022). Meteorological data were obtained from the National Meteorological Information Centre (http://data.cma.cn/). We acquired climatic variables, including average daily air temperature, average daily maximum air temperature, average daily minimum air temperature, average relative humidity, average minimum relative humidity, average precipitation, and average wind speed for 30 days, 15 days, 7 days, and 3 days before and throughout the fire periods.
Table 2
Environmental factor data

<table>
<thead>
<tr>
<th>Factors</th>
<th>Variables</th>
<th>Abbreviation</th>
<th>Units</th>
<th>Class</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Topographic</td>
<td>Elevation</td>
<td>Elev</td>
<td>m</td>
<td>Low hills: &lt;100</td>
<td><a href="http://seamless.usgs.gov">http://seamless.usgs.gov</a></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td>Middle hills: (100, 250)</td>
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<td>High hills: (250, 500)</td>
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<td>Low mountain: (500, 1000)</td>
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<tr>
<td>Slope</td>
<td>Slope</td>
<td>°</td>
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<td>flat slope: (0, 5)</td>
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<td>gentle slopes: (5, 15)</td>
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<td>slant slopes: (15, 25)</td>
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<td>steep slopes: (25, 35)</td>
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<td>Aspect</td>
<td>Aspect</td>
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<td>Shady: [0,45): [315 ~ 360)</td>
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<td>Semi-shady: [45 135)</td>
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<td>Semi-sunny: [225 315)</td>
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<td></td>
<td>Sunny: [135 ~ 225)</td>
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<tr>
<td>Climate</td>
<td>Average</td>
<td>T</td>
<td>°C</td>
<td>1: &lt;5</td>
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<tr>
<td></td>
<td>temperature</td>
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<td>2: (5, 10]</td>
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<td>Maximum</td>
<td>Max T</td>
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<td>3: (10, 15]</td>
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<tr>
<td></td>
<td>temperature</td>
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<td>4: (15, 20]</td>
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<td>5: (20, 25]</td>
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<td>6: &gt;25</td>
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<td>Factors</td>
<td>Variables</td>
<td>Abbreviation</td>
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<td>Minimum temperature</td>
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<td>Min T</td>
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<td>Average relative humidity</td>
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<td>%</td>
<td>1: &lt;50</td>
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<td>Minimum relative humidity</td>
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<td>MinH</td>
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<td>2: (50, 60]</td>
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<td>3: (60, 70]</td>
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<td>4: (70, 80]</td>
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<td>5: (80, 90]</td>
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<td>6: &gt;90</td>
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<tr>
<td>Precipitation</td>
<td></td>
<td>Prec</td>
<td>mm</td>
<td>1: (0, 1]</td>
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<td></td>
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<td>2: (1, 10]</td>
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<td>3: (10, 25]</td>
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<td>4: (25, 50]</td>
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<td>Average wind speed</td>
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<td>Win</td>
<td>m/s</td>
<td>1: &lt;1.5,</td>
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<td>2: (1.5, 3.5]</td>
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<td>3: (3.5, 5.6]</td>
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<td>4: (5.6, 8.1]</td>
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<td>5: (8.1, 10.9]</td>
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<td>6: (10.9, 14.0]</td>
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<td></td>
<td>7: (14.0, 17.2]</td>
<td></td>
</tr>
<tr>
<td>Fuel</td>
<td></td>
<td>NDVI</td>
<td>-</td>
<td>Low: (0, 0.3]</td>
<td>Landsat 8 OLI</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td>Moderate: (0.3, 0.6]</td>
<td></td>
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<td></td>
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<td></td>
<td>High: (0.6, 1]</td>
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<tr>
<td>Factors</td>
<td>Variables</td>
<td>Abbreviation</td>
<td>Units</td>
<td>Class</td>
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<td>--------</td>
</tr>
<tr>
<td>Normalized Difference moisture Index</td>
<td>NDMI</td>
<td>-</td>
<td>1: (-1, -0.8], 2: (-0.8, -0.6], 3: (-0.6, -0.4], 4: (-0.4, -0.2], 5: (-0.2, 0], 6: (0, 0.2], 7: (0.2, 0.4], 8: (0.4, 0.6], 9: (0.6, 0.8], 10: (0.8, 0.1]</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Statistical analysis**

**Variability analysis of landscape patterns of difference burn severity**

Distributions of landscape pattern indices within each burn severity class were graphically compared using frequency distribution histograms. In addition, the Duncan's multiple comparison procedure was used to test whether there was significant variability ($p = 0.05$) in the landscape patterns of low, moderate, and high burn severity.

**Analysis of the drivers of landscape patterns of burn severity**

Spatial discretization of various environmental factors

NDVI was classified into three classes (Chen et al. 2022) and NDMI into ten classes (Earth Observing System 2020). Following the technical regulations for the second-class forest resources survey in Jiangxi Province, altitude was classified into three classes, and slope and aspect were classified into four classes. Temperature and humidity were classified into six classes, precipitation into four classes, and wind speed into eight classes following the National Forest Fire Meteorological Class Classification Standard (GB/T 36743 – 2018) (Table 2).
Screening of landscape pattern indices and influencing factors

Initially, we selected 14 landscape pattern indices (Table 1) and 40 factors (Table 2) influencing burn severity. To avoid data redundancy, the pattern indices and influencing factors were screened through stepwise processes. First, the correlations between the landscape pattern indices and the influencing factors were calculated, the factors retained in the first step were subjected to collinearity analysis to address multi-collinearity among the factors. The factors with a Variance Inflation Factor (VIF) < -5 were retained. Second, a stepwise regression was performed using all the landscape pattern indices and the influencing factors retained in the second step, and we retained landscape pattern indices with $R^2 > 0.6$ for further consideration. In the end, six landscape pattern indices (Area_mn, Ed, Lsi, Pd, Cohesion, and Shape_mn) and seven burn severity impact factors (Prec3, Prec30, Minh30, Dem, Slope, NDVI, and NDMI) were retained and used to model landscape patterns of burn severity.

Analysis of the drivers of landscape patterns of burn severity across the forest patches

We used a Geodetector model to analyze mechanisms driving the spatial differences in burn severity across forest patches. The Geodetector models consisted of four components, where the core part is a factor detector that quantifies the relative importance of different geographic variables, and the other three components include a risk detector, an interaction detector, and an ecological detector (Wu et al. 2016; Song et al. 2020; Wang and Xu 2017). We ran the Geodetector model using the GD package in statistical software R.

The factor detector was used to detect the extent to which different explanatory variables explain the spatial variation in burn severity. It provides the relative importance of the explanatory variables explaining spatial variation in burn severity through the q-statistic. The q-statistic was calculated using the gd () function within the GD package in R, and the formula used in the calculation is listed in Eq. 5.

$$Q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N \sigma^2}$$

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Where $h = 1, 2, \ldots, L$, denotes the broad category of the explanatory variable, and $N_h$ and $N$ represent the total number of subcategories and subcategories of an explanatory variable, respectively. $\sigma_h^2$ and $\sigma^2$ denote the variance of the subcategory $h$ and the total number of subcategories of an explanatory variable, respectively. The $Q$ value ranged from 0 to 1 and was tested for significance using a non-central F distribution.

The risk detector was used to determine whether there was a significant difference in the mean value of the attributes of each burn severity patch between the different sub-regions. A t-test was performed to detect the significant difference using a formula in Eq. 6.
Where: $\bar{Y}_{h1}$ and $\bar{Y}_{h1}$ represent the mean values of the landscape pattern indices within the sub-regions $h1$ and $h2$, respectively. $n_{h1}$ and $n_{h2}$ represent the sample size within the sub-regions $h1$ and $h2$, respectively.

Interaction detection was used to examine the explanatory power of independent variables interactively and independently in explaining dependent variables. Interaction detection was performed using the gdinteract () function within the GD package in R.

<table>
<thead>
<tr>
<th>Basis of judgement</th>
<th>Interaction</th>
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<tbody>
<tr>
<td>$q(X_1 \cap X_2) &lt; \min [q(X_1), q(X_2)]$</td>
<td>Nonlinear-weaken</td>
</tr>
<tr>
<td>$\min [q(X_1), q(X_2) &lt; q(X_1 \cap X_2) &lt; \max [q(X_1), q(X_2)]$</td>
<td>Uni-variable weaken</td>
</tr>
<tr>
<td>$q(X_1 \cap X_2) &gt; \max [q(X_1), q(X_2)]$</td>
<td>Bi-variable enhance</td>
</tr>
<tr>
<td>$q(X_1 \cap X_2) = q(X_1) + q(X_2)$</td>
<td>Independent</td>
</tr>
<tr>
<td>$q(X_1 \cap X_2) &gt; q(X_1) + q(X_2)$</td>
<td>Nonlinear-enhance</td>
</tr>
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</table>

Ecological detectors were used to compare the significant difference between the effect of one influencing factor and another on the spatial distribution of burn severity patches. The $F$ statistic (Eq. 7) was used to test whether group means are equal statistically.

$$F = \frac{N_a (N_b - 1) SSW_a}{N_b (N_a - 1) SSW_b}$$

Where $N_a$ and $N_b$ are the sample size of explanatory variables a and b, respectively, $SSW_a$ and $SSW_b$ represent the sum of the within-stratum variance of the stratum forming explanatory variables a and b.
respectively.

Results

Landscape patterns of burn severity across forest patches

Analysis of landscape pattern indices of the fire patches showed that the high severity patches were sparse, continuous, and regular in shape (Fig. 3). There were significant differences between high severity patches and low and moderate severity patches for four landscape pattern indices ($p < 0.05$). However, we found no significant differences in Area_mn (Fig. 3a) and Cohesion (Fig. 3d) indices among burn severity classes ($p > 0.05$).

The frequency distribution histograms of the landscape pattern indices (Fig. 4) showed that fires were concentrated in smaller patches (i.e., $\text{Area}_m = 0–5$), regardless of burn severity. However, a few larger patches experienced low and high severity fires ($\text{Area}_m = 15$ in low and 20 in high severity). The patch density index indicates that the high severity patches were less heterogeneous and less fragmented with high patch connectivity. Specifically, there were a few high severity patches (i.e., low density) compared to the low and moderate severity patches. Results also showed that low- and moderate severity patches had a patch density value of 60 compared to less than 30 for high severity patches.

Regarding the Edge density index, the frequency distribution histogram suggested that the highly fragmented landscape experienced low and moderate burn severity. In contrast, less fragmented landscape patches experienced high burn severity. Results for the Cohesion index showed that the index did not vary much across burn severity classes. However, moderate and high burn severity patches were more concentrated compared to low burn severity (i.e., cohesion index range 85–100 and 80–100, respectively, for moderate and high severity patches and 70–100 for low severity patches). The frequency distribution graph of the shape index showed that the high severity patches were most regular in shape compared to other burn severity classes. Results also showed that the low severity patches were the most irregularly shaped.

Drivers of landscape patterns of burn severity across the forest patches

Using factor detector analysis, we detected variations in the explanatory power among the factors influencing the landscape pattern indices (Fig. 5). Elevation was the main influencing factor for Area_mn and Patch density, while slope influenced Edge density, Cohesion, and Shape_mn. The pre-fire NDVI, slope, and pre-fire 30-day precipitation influenced the landscape shape index. The risk detector analysis showed that the areas from the high elevation influenced the Area_mn index the most. Results also showed that gently sloping areas influenced the Edge density index, and the areas with moderate vegetation cover influenced the landscape shape index.
Interaction detection showed that various combinations of explanatory variables enhanced or weakened their influences on the landscape pattern indices. For instance, the Area_mn index was strongly influenced by elevation, but the interaction between elevation and other explanatory variables weakened the effect (q max of 0.51). Results showed that the interaction between slope and 30-day pre-fire average minimum relative humidity enhanced the influencing power on the Edge density index (q value of 0.36). The interaction between NDVI and NDMI increased the effect on the Landscape shape index (q value of 0.4). In contrast, slope and all other explanatory variables showed the weakest effect except the 30 days pre-fire average precipitation on the Cohesion index. Finally, the interaction between elevation and pre-fire 30-days average minimum relative humidity enhanced the explanatory power (q value of 0.34), far beyond the individual explanatory power of these factors, on the Shape_mn index.

Ecological detector analysis showed that pre-fire three days average precipitation significantly differed from other factors in explaining the landscape pattern indices in the high burn severity patches. The influence of NDVI on the Edge density index and the Shape_mn index was significantly different from other variables. The influence of elevation on the Area_mn index and Patch density index was significantly different from other explanatory variables.

**Discussion**

**Landscape patterns of burn severity across forest patches**

This study analyzed the landscape patterns of burn severity and influencing factors in a subtropical forest in China. The results showed that high burn severity forest patches were more regular in shape than the low and moderate severity fire patches. Long-term fire prevention and exclusion creating subsequent accumulation of fuel load within pine dominated forests resulted in a higher fire risk. Alternatively, from the perspective of landscape ecology, the margin area ratio decreased with the increase of patch area (Jones 2002; Potter 2017). Consistent with this argument, Turner et al. (1994) found a smaller edge-to-area ratio in high severity patches compared to low and moderate severity patches in Yellowstone National Park, USA.

Our study also showed that the low and moderate burn severity patches were denser and more fragmented than high severity patches. This is because the study area was dominated by moderate and low intensity fires (large number of patches). However, low fragmentation in high severity patches does not necessarily translate into a higher degree of patch aggregation (Hayes and Robeson 2011). Indeed, this study reported no significant differences in Cohesion index across the burn severity classes. Wu et al. (2018) also reported an increase in fire size with the increase in the size of high burn severity patches but did not report the higher spatial aggregation.

While evaluating the landscape pattern indices, results showed no difference in the mean patch size (Area_mn) across burn severity classes. This finding is likely explained by the sizes of 27 forest fire sites, where 15 fire sites had an area of less than 100 ha and the mean patch size (Area_mn) was the average
value of 27 fires. Previous studies have also shown that as the burned area increases, so does the burn severity and the aggregation of high severity patches (Cansler and McKenzie 2014b; Cansler and McKenzie 2011). The current study area is located in a subtropical broadleaved evergreen forest. The influence of climate, vegetation type, and anthropogenic activities has resulted in a much smaller fire area than in the more northern cold temperate coniferous forest, making it difficult for the landscape scale spread of high burn severity patches.

**Relationship between landscape patterns of burn severity and environmental factors**

Elevation is the most important environmental factor controlling the size of high severity burn patches, with severity burned patches located at higher elevations. The higher elevation of the study area is dominated by the Masson pine, which may contribute to high burn severity. In addition, higher solar radiation at a higher altitude likely increases the surface temperatures and reduces humidity and moisture content, making high elevation particularly suitable for high severity forest fires (Carlson et al. 2017; Wimberly and Reilly 2007). Slope affects the degree of fragmentation and aggregation of fire patches and influences the occurrence of forest fires by affecting airflow and local microclimate (Birch et al. 2015). Fires spread quickly in steep slopes and are more likely to develop into high severity fires with large and continuous patches. In contrast, gentle slopes tend to burn less severely with smaller and irregularly shaped patches. The high variability of slopes in the study area leads to a mosaic of patches with different burn severity. Pre-fire vegetation cover affects the complexity and shapes of fire patches. Higher vegetation cover (usually with higher combustible fuel loads), generally found in more regularly shaped patches, tends to produce high burn severity (Lee et al. 2009; Birch et al. 2015). Most of the study area has high vegetation cover with regularly shaped patches, resulting in high severity burn patches.

Climatic factors also significantly influenced the landscape patterns of high burn severity. Pre-fire 30-day average precipitation primarily influenced patch shape and connectivity, and pre-fire 30-day average minimum relative humidity influenced the fragmentation of the patches. These results implied that smaller average precipitation and humidity values might lead to greater fire severity covering a larger spatial area (Cansler and McKenzie 2014a). The relative humidity is also an important determinant of the spatial arrangement of high severity patches, as it determines the moisture content of the combustible material that subsequently influences the fire conditions.

**Conclusion**

The landscape patterns of patches with different burn severity varied significantly. High severity patches were less dense and fragmented and had regular shapes. The Patch density index, Edge density index, and Landscape shape index of the high severity patches were significantly different from those of the low and moderate severity patches. For the Shape_mn index, there were significant differences across the burn severity classes, while the Area_mn and Cohesion index did not differ significantly.
Topographic factors (e.g., altitude and slope) significantly influenced the landscape pattern of high burn severity across forest patches, followed by climatic factors. High elevation forest patches were the most extensive and experienced high burn severity. The patch fragmentation was more pronounced in gently sloping areas. Climatic factors influenced the patch edge density, connectivity, shape, and degree of fragmentation of high severity patches.

**Declarations**

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**Author contributions** LG: Methodology, data curation, writing-original draft. ZW: Supervision, Writing—review and editing, Funding acquisition. RAP: Review and editing. SL: Editing and supervision. GX: Writing—review and editing. All authors read and approved the final manuscript.

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**Conflict of interest** The authors declare that there are no conflicts of interest.

**References**


**Figures**
Figure 1

Location map of the study area showing fire distribution sites
Figure 2
Maps showing burn severity classes (dNBR values) for 27 forest fires
Figure 3

Variability in landscape pattern indices across different burn severity
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Histograms showing the frequency distribution of landscape pattern indices across burn severities
Figure 5

The explanatory power of factors influencing landscape pattern indices based on the Geodetector model, from left to right, each column represents factor detection, risk detection, interaction detection, and ecological detection, respectively.

Supplementary Files
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- SupplementaryMaterial.docx