EFFECTS OF METEOROLOGICAL CONDITIONS ON GRASSLAND FIRES IN NORTHEAST CHINA


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Abstract. Using meteorological and grassland fire data for Hulun Buir, China, from 1990 to 2019, we explored variation in meteorological factors, assessed the frequencies and areas of grassland fires, and used an autoregressive distributed lag (ARDL) model to investigate correlations between burned areas and meteorological factors. Fires in Hulun Buir grassland mainly occurred between 1990 and 1999; from 1990 to 2009, most fires occurred in Prairie Chenbarhu Banner, Xin Barag Right Banner and Xin Barag Left Banner. Grassland fires in Hulun Buir decreased significantly from 2010 to 2019. From 1990 to 2019, grassland fires mostly occurred in spring and autumn. Among the seven meteorological factors, wind speed, relative humidity and sunshine hours were most strongly correlated with burned areas. Regarding long-term and short-term effects, relative humidity had the biggest influence on burned area. The results demonstrated that ARDL models can reveal the long-term and short-term sensitivity of meteorological factors related to fire, and the ARDL econometrics method can be used effectively to study trends in grassland fire burning area.

Keywords: Hulun Buir Grassland, grassland fire, area burned, meteorological factors, ARDL model

Introduction

Grassland fire is an important ecological factor that has sudden and destructive effects on grassland resources and ecosystems, and rescues are extremely dangerous (Zhang et al., 2010; Finch et al., 2011; Liu et al., 2017). It is a threat to people’s lives and property in pastoral areas, and it has a great influence on economic development and social stability (Liu et al., 2010; Moinuddin et al., 2018; Phillipse et al., 2020). Natural grassland areas cover 41.7% of China (Su and Liu, 2004; Zhou et al., 2020), 1/3 of which are fire-prone, and 1/6 of which experience frequent fires (Tong et al., 2008). Hulun Buir Grassland is a major area in northern China that provides ecosystem services, and grassland fire here impacts economic development, social stability and livestock husbandry (Zhou et al., 2022).

Climate is an important factor determining the occurrence of grassland fire, and the temporal and spatial dynamics of grassland fire are the result of the synergistic effects of different meteorological and climate factors (Duffy et al., 2005; Nunes, 2012). Due to the
influence of the earth’s rotation, solar radiation received by the same area differs across seasons, and weather conditions in each month also differ, resulting in dynamic temporal and spatial changes in grassland fires (Seol et al., 2012; McKenzie et al., 2010; Syphard et al., 2017). In the North American Prairie, grassland fires are mostly concentrated in winter and early spring (Engle et al., 2001), but grassland fires in the southwest of this area are mainly concentrated in late spring and early summer (Gosz et al., 1996). Savanna grassland fires in Africa are mainly concentrated in the dry June to August period (Sheuyange et al., 2005). Grassland fires in China mostly occur in the northeast area and are concentrated in the spring and autumn (Fu et al., 2001). The Inner Mongolia Autonomous Region endures extremely frequent grassland fires, and Xilingol League and Hulun Buir City are key fire danger areas (Zhijun et al., 2009; Shabbir et al., 2019; Liu et al., 2019; Wang et al., 2023). Furthermore, the northeastern part of China is located at middle and high latitudes in the northern hemisphere and is sensitive to climate warming (He et al., 2022). During 1956–2017, the temperature in this area increased significantly, and the average temperature tendency rate was 0.327°C/10a (Wu et al., 2021), making it one of the most significant warming areas in China (He et al., 2013). The frequency of forest and grassland fires is increasing due to the direct effects of global warming (Kasischke et al., 2010; Arias et al., 2021). Prolonged high temperatures and decreased precipitation will increase the occurrence of fires in this area in the future, leading to accelerated spreading of fires (Liu, 2006; Yamamoto et al., 2016; Ying et al., 2019). Thus, it is of great significance to study the temporal and spatial dynamic characteristics of grassland fires, and the influence of meteorological factors on grassland fires in this area.

Hulun Buir, located in the northeast of the Inner Mongolia Autonomous Region in China, is a frequently burned area (Liu et al., 2017; Bao et al., 2022). Climate change is having a great impact on fires in this area (Zhang et al., 2010). Many researchers have used correlation analysis to explore correlations between different meteorological factors and fires in the Hulun Buir area (Guo et al., 2013; Liu et al., 2017; Wang et al., 2023). However, research on the nonlinear relationship between climate factors and fires in this area is scarce. Therefore, against the backdrop of climate change, it is of great significance to study the nonlinear relationship between meteorological factors and fires. In particular, grassland fire prediction and fire risk assessment in the study area can reflect the probability and damage caused by grassland fire based on future climate by considering fire occurrence frequency and fire site area.

Using historical fire and meteorological data from 1990 to 2019, we investigated the temporal and spatial dynamic characteristics of grassland fire frequency and burned area in the Hulun Buir grassland region, and predicted probable trends in grassland fire based on future climate change. Additionally, an autoregressive distributed lag (ARDL) model was established to study the occurrence of grassland fires in Hulun Buir under the influence of different meteorological factors. The results provide a theoretical basis for the prevention and control of grassland fires in this area. The findings could assist the division of grassland fire risk areas and the formulation of grassland fire prevention and control systems.

Materials and methodology

Overview of the study area

Hulun Buir grassland, located at the middle latitude of Eurasia, is one of the four largest grasslands in the world, and is the largest and best-preserved grassland in China.
Hulun Buir is located in the northeast of the Inner Mongolia Autonomous Region in China, with geographical coordinates of 115°31′−126°04′ east longitude and 47°05′−53°20′ north latitude (Fig. 1). The Hulun Buir region is connected to Hinggan League in the south, Heilongjiang Province in the east by Nenjiang River, Russia in the north and northwest by Argun River, and Mongolia in the west and southwest. The latter border is 1733.32 km, the China-Russia border is 1051.08 km, and the China-Mongolia border is 682.24 km (Yang et al., 2022).

Hulun Buir grassland is a temperate continental climate and semi-arid area, and one of the areas most sensitive to climate change in northern China (Guo et al., 2022). With annual precipitation of about 320 mm, it is cold and dry in winter and hot and rainy in summer. The annual average temperature is -2.3°C and the altitude ranges from 200 to 1500 m. The grassland types are mainly Leymus chinensis meadow grassland, Carex mountain meadow, Stipa Baikal meadow grassland and Leymus chinensis steppe (Bian et al., 2013).

Data sources

Data on grassland fires in Hulun Buir from 1990 to 2019, including occurrence time, burned area and fire grade, were obtained from the Fire Prevention Office of Forestry and the Grass Bureau of Inner Mongolia Autonomous Region.

Meteorological data were acquired from the Hulun Buir Meteorological Bureau, including daily data for seven meteorological factors: daily precipitation, daily maximum temperature (Tmax), daily minimum temperature (Tmin), daily average temperature, daily sunshine hours, daily relative humidity and 2-min average wind speed from 1990 to 2019 in Ewenki Autonomous Banner, Prairie Chenbarhu Banner, Xin Barag Right Banner, Xin Barag Left Banner, Manzhouli City and Hailar District.

Research methodology

Analysis of correlations between area burned and variables

Correlation coefficients between grassland area burned and variables of meteorological factors were calculated using the Hmisc and Performance Analytics.
packages in R (https://cran.r-project.org/), and dominant meteorological factors were screened out to explain the influence of meteorological changes on area burned.

**ARDL model**

Eviews11 (https://eviews.com/home.html) was used to calculate F statistics to test whether there was a long-term relationship between variables. The ARDL option was used to estimate the long-term coefficient between variables and the corresponding error correction model (ECM). By comparing the fitting effects of the two methods, the final fitting model was determined. The ARDL model was established to study the long-term and short-term effects of climate on the burned area of grassland.

**Background of the ARDL model**

ARDL models are commonly used in the field of econometrics. In econometrics, due to the changing trends in time series forecast variables (such as inflation and market value), the impacts on target responses (such as stock performance) are usually estimated. In this financial market example, past and present observations of predictive variables and response variables are associated with future response observations. These effects can be characterized as ‘short-term’ if the response fluctuates immediately when the predicted variables change, or ‘long-term’ if variables deviate but always return during the whole observation period. The ARDL model was first proposed by Pesaran et al. (1999, 2001), and its modelling process is shown in Figure 2. Based on work by several researchers, when there is a single long-term relationship between response and covariate, and the conditional error correction form of the covariate has no long-term relationship, the ARDL method is superior for testing cointegration. In other words, there is a simplified form in which all basic sequences are weakly exogenous and used as explanatory variables. Among these explanatory variables, there can be a mixture of I (0) and I (1) series and one or more cointegration relationships. Importantly, the ARDL method cannot be applied when one of the time series is ≥ 2-order integral (Haug, 2002; Frimpong et al., 2006). There are advantages to this model; (1) it is more stable for small samples, and even if the explanatory variables are endogenous variables, the model can generate unbiased and effective estimation results; (2) the long-term relationships of variables can be investigated by boundary cointegration tests, and it is not necessary for variables to have the same order of monotonicity; (3) the dynamic ECM can be derived by simple linear transformation, which is convenient for investigating the short-term relationships of variables (Nkoro et al., 2016).

**Model building**

The first step is to use the unit root test, perform Augmented Dickey-Fuller test (ADF) and Phillips-Perron (PP) tests, and determine the integer order of the sequence. If variables conform to the zero-order I(0) or the first-order I(1) simplex, then further modelling can be carried out.

The second step is to build the ARDL model as follows:

\[
Y_t = \alpha_0 + \sum_{i=1}^{n} a_i Y_{t-i} + \sum_{i=0}^{m} c_i X_{t-i} + u_t \quad \text{(Eq.1)}
\]

In Equation 1, the influence of horizontal and lagging exogenous variables on the corresponding Y at time t is expressed, along with the constant term of the coefficient.
effect; $T$ is the trend term; $U_t$ is a white noise process; $N$ and $m$ represent the lag order of the explained variable and the explained variable, respectively.

The cointegration test assumes that there is no stable long-term equilibrium relationship between two variables (i.e., initial hypothesis, $H_0 : \delta = 0$; alternative hypothesis, $H_0 : \delta \neq 0$ or $\delta = 0$). Combined with $F$ statistics, when $F$ statistics are less than the lower critical value, the initial hypothesis is accepted, and there is no long-term cointegration relationship between variables. If it is greater than the upper critical value, the initial hypothesis is rejected, and there is a long-term cointegration relationship between variables. If it is between two critical values, it is further judged according to the single integer order of the sequence.

![Flow chart of realization of ARDL model](image)

**Figure 2. Flow chart of realization of ARDL model**

After determining the long-term equilibrium relationship between variables, the model can be redefined as a short-term ECM as shown in Equation 2. When there is no long-term equilibrium relationship between variables and the long-term equilibrium relationship cannot be constructed, the short-term dynamic relationship and the error correction model cannot be established.

\[
\nabla Y_t = \alpha_0 + \sum_{i=1}^{m-1} \alpha_i \Delta Y_{t-i} + \sum_{j=0}^{n-1} \theta_j \Delta X_{t-j} + \delta ECM_{t-1} + \varepsilon_t \quad \text{(Eq.2)}
\]

The ECM can explain the short-term fluctuation relationship of the series. $\alpha$ and $\theta$ respectively represent the dynamic relationship or co-integration relationship in the long-term dynamic period. The current fluctuation ($\Delta Y_t$) of the response sequence is mainly affected by the short-term fluctuation in four aspects: fluctuation of the past historical value ($\Delta Y_{t-i}$); fluctuation of the historical value of the input sequence ($\Delta X_{t-j}$); the error of the previous period ($ECM_{t-1}$); and the pure random fluctuation of the current period ($\varepsilon_t$). $ECM_{t-1}$ is the lag error correction factor, $\delta$ is the error correction coefficient, and $\delta$ is negative.

In the third step, because there is a long-term cointegration relationship, Equation 3 is obtained:
In the fourth step, the final equation (Eq. 4) is derived from Equation 2:

\[ \text{Area burned} = \beta_0 + \beta_1 \text{Wind}_t + \beta_2 \text{Temp}_t + \beta_3 \text{Humid}_t + \beta_4 \text{Sunlight}_t + \beta_5 \text{Precip}_t + \epsilon_t \] (Eq.3)

\[ \Delta \text{Area burned}_t = \alpha_0 + \sum_{s=0}^{t-1} \alpha_s \Delta \text{Area burned}_{t-s} + \sum_{s=0}^{t-1} \theta_1_s \Delta \text{Wind}_t + \sum_{s=0}^{t-1} \theta_2_s \Delta \text{Temp}_t + \sum_{s=0}^{t-1} \theta_3_s \Delta \text{Humid}_t + \sum_{s=0}^{t-1} \theta_4_s \Delta \text{Sunlight}_t + \sum_{s=0}^{t-1} \theta_5_s \Delta \text{Precip}_t + \delta_1 \Delta \text{Wind}_t + \delta_2 \Delta \text{Temp}_t + \delta_3 \Delta \text{Humid}_t + \delta_4 \Delta \text{Sunlight}_t + \delta_5 \Delta \text{Precip}_t + \epsilon_t \] (Eq.4)

Results

Annual variation characteristics of grassland fire in the Hulun Buir area

Based on the interannual variation chart of grassland fires (Fig. 3), we concluded that there were 839 grassland fires in the Hulun Buir area from 1990 to 2019, with an average annual rate of 27.97. There were four peaks over 30 years, the highest was 110 in 1995, and occurrences decreased generally thereafter. The incidence of fires was relatively stable from 1999 to 2019, and the frequency was less than 30 per year. Overall, the number of grassland fires in this area decreased over time.

During 1990–2019, the total burned area of Hulun Buir grassland reached \( 220.15 \times 10^4 \text{ hm}^2 \), with an average annual rate of \( 7.34 \times 10^4 \text{ hm}^2 \). The year with the smallest burned area of grassland was 2018, with a total area of 54 \text{ hm}^2. The year with the largest burned area of grassland was 1990, covering \( 39.57 \times 10^4 \text{ hm}^2 \), accounting for 18% of the total burned area of grassland in 30 years. Overall, the area burned by grassland fires decreased over time, similarly to the number of grassland fires annually. After 2000 the damaged area was relatively small and stable.

According to the annual distribution of burned area of grassland fires from 1990 to 2019 (Fig. 4), large-scale grassland fires mainly occurred in Prairie Chenbarhu Banner, Xin Barag Right Banner and Xin Barag Left Banner from 1990 to 1999, with a maximum
burned area of $2.02988 \times 10^5$ hm$^2$. From 2000 to 2009, large-scale grassland fires mainly occurred in Xin Barag Right Banner and Xin Barag Left Banner, with the largest burned area of $3.3215 \times 10^4$ hm$^2$. During 2010–2019, grassland fires covered a large area mainly in Prairie Chenbarhu Banner, with the largest burned area of $4.93 \times 10^4$ hm$^2$. Despite the different inter-annual and spatial patterns of fires during this period, from 1990 to 2019, the area of grassland fires in the Hulun Buir region decreased year by year.

![Figure 4. Annual distribution of burned area of grassland fires from 1990 to 2019](image)

**Monthly variation characteristics of grassland fire in the Hulun Buir area**

According to monthly differences between 1990 and 2019 (January–December every year; there were no fires in February, July, August or December; Fig. 5), the month with the fewest grassland fires from 1990 to 2019 was January, with only one fire. The month with the most fires was April, with 289 grassland fires in April from 1990 to 2019, accounting for 34% of the total fire frequency in this area. Grassland fires occurred regularly in May and October, 255 and 122 times, respectively, accounting for 30% and 15% of the total fire frequency in this area, respectively. Therefore, the prevalence and extent of grassland fires in the Hulun Buir differed between months, occurring mainly in spring and autumn (Yi et al., 2022), consistent with changes in local meteorological elements between months (Bao et al., 2022).

**Influence of climatic variables on the burned area of grassland fires**

Correlation coefficients between climate parameters and burning area in three different time periods (1990–1999, 2000–2019, 2010–2019) were calculated using the R language to assess the influence of meteorological factors on burning area in different
time scales (Table 1). The first line (grey) in the table represents the correlation coefficient, and the second line (white) represents the correlation significance p-value. The correlation coefficient between burned area and wind speed in 1990–1999 was 0.521597 and the p-value was < 0.05, indicating a significant correlation between burned area and wind speed. Similarly, from 1990 to 1999, there was a significant correlation between burned area and wind speed, relative humidity and sunshine hours. From 2000 to 2009, the burned area was significantly correlated with wind speed and relative humidity. From 2010 to 2019, the burned area showed a significant correlation with wind speed and relative humidity.

The first row (grey) in the table represents the correlation coefficient, and the second row (white) represents the correlation significance P value. The correlation coefficient between burned area and wind speed in 1990-1999 is 0.521597, and the p value is 0 (less than 0.05), indicating a significant correlation between burned area and wind speed. Similarly, from 1990 to 1999, there was a significant correlation between burned area and wind speed, relative humidity and sunshine time. From 2000 to 2009, the burned area was significantly correlated with wind speed and relative humidity. From 2010 to 2019, the burned area has a significant correlation with wind speed and relative humidity. Analysis of the whole experimental period shows that burned area has a significant correlation with wind speed, relative humidity, sunshine time and precipitation over 30 years.
**Autoregressive distributed lag (ARDL) model**

**Unit root test**

In order to ensure consistency among time series data and to avoid pseudo-regression in the regression equation, according to the results of ADF and PP tests, stationary variables were selected for regression. Analysis revealed that p-values of all variables were < 0.05, and all variables were zero-order stationary at the 5% and 10% significance level (Table 2). This confirmed that the data could be used to establish an ARDL model.

By calculating the average value of each variable during the period from 1990 to 2019, and analyzing changes in burned area and seven variables in the same period (Fig. 6), we could assess cointegration relationships between variables. Average temperature, maximum temperature, sunshine hours and burned area showed the strongest synergistic relationships, and all had a positive cointegration relationship. There was also a synergistic relationship between minimum temperature, precipitation and burned area. However, cointegration relationships between wind speed, relative humidity and burned area could not be judged accurately due to fluctuations in variables.

![Graphs showing relationships between burned area and climate variables in HulunBuir Grassland from 1999 to 2019](image-url)
Table 2. ADF and PP test results

<table>
<thead>
<tr>
<th></th>
<th>ADF test</th>
<th></th>
<th>PP test</th>
<th></th>
<th>Level of significance</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Levels</td>
<td>First differences</td>
<td>Levels</td>
<td>First differences</td>
<td>5%</td>
</tr>
<tr>
<td>lnY</td>
<td>-2.797921</td>
<td>-14.52236</td>
<td>-13.53505</td>
<td>-76.53586</td>
<td>I(1)</td>
</tr>
<tr>
<td>lnX1</td>
<td>-1.04224</td>
<td>-18.9753</td>
<td>-10.5868</td>
<td>-44.1999</td>
<td>I(1)</td>
</tr>
<tr>
<td>lnX2</td>
<td>-2.99009</td>
<td>-26.8189</td>
<td>-5.15064</td>
<td>-18.2311</td>
<td>I(0)/I(1)</td>
</tr>
<tr>
<td>lnX3</td>
<td>-3.05706</td>
<td>-12.6381</td>
<td>-4.88357</td>
<td>-18.8046</td>
<td>I(0)/I(1)</td>
</tr>
<tr>
<td>lnX4</td>
<td>-3.00681</td>
<td>-25.5385</td>
<td>-5.29848</td>
<td>-18.1899</td>
<td>I(0)/I(1)</td>
</tr>
<tr>
<td>lnX5</td>
<td>-2.32426</td>
<td>-21.0483</td>
<td>-6.07428</td>
<td>-31.6421</td>
<td>I(0)/I(1)</td>
</tr>
<tr>
<td>lnX6</td>
<td>-4.01257</td>
<td>-22.4771</td>
<td>-6.07428</td>
<td>-31.6421</td>
<td>I(0)/I(1)</td>
</tr>
</tbody>
</table>

Cointegration test

Cointegration relationships can be interpreted as long-term stable equilibrium relationships between variables. Through cointegration tests, we concluded that the p-value of each statistic was < 0.05, indicating cointegration relationships between variables, and therefore long-term equilibrium relationships (Table 3).

Table 3. Cointegration relationships among variables

<table>
<thead>
<tr>
<th>No. of CE(s)</th>
<th>Eigenvalues</th>
<th>Statistics</th>
<th>Critical values</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>None *</td>
<td>0.594976</td>
<td>692.9791</td>
<td>159.5297</td>
<td>0.000</td>
</tr>
<tr>
<td>At most 1 *</td>
<td>0.256384</td>
<td>409.9218</td>
<td>125.6154</td>
<td>0.000</td>
</tr>
<tr>
<td>At most 2 *</td>
<td>0.231214</td>
<td>304.7598</td>
<td>95.75366</td>
<td>0.000</td>
</tr>
<tr>
<td>At most 3 *</td>
<td>0.194001</td>
<td>211.4151</td>
<td>69.81889</td>
<td>0.000</td>
</tr>
<tr>
<td>At most 4 *</td>
<td>0.155423</td>
<td>134.8515</td>
<td>47.85613</td>
<td>0.000</td>
</tr>
<tr>
<td>At most 5 *</td>
<td>0.119509</td>
<td>74.88508</td>
<td>29.79707</td>
<td>0.000</td>
</tr>
<tr>
<td>At most 6 *</td>
<td>0.055789</td>
<td>29.70241</td>
<td>15.49471</td>
<td>0.0002</td>
</tr>
<tr>
<td>At most 7 *</td>
<td>0.025921</td>
<td>9.323363</td>
<td>3.841466</td>
<td>0.0023</td>
</tr>
</tbody>
</table>

*Rejecting the original hypothesis at the significance level of 5%

Following cointegration tests, it is important to choose the correct lag order for y(n) in the ARDL model to avoid specification error. With a greater lag order in the model, the degree of freedom is smaller. In general, the order is determined according to the minimum value criterion of statistics. After testing, the lag order of Schwarz Bayesian statistics was the smallest, and the second lag period was selected as the order for the ARDL model (Table 4).

Table 4. Optimal order of the ARDL model

<table>
<thead>
<tr>
<th>Lag</th>
<th>LogL</th>
<th>LR</th>
<th>FPE</th>
<th>AIC</th>
<th>SC</th>
<th>HQ</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>91.80623</td>
<td>NA</td>
<td>8.58e-11</td>
<td>-0.476172</td>
<td>-0.388362</td>
<td>-0.441228</td>
</tr>
<tr>
<td>1</td>
<td>805.3765</td>
<td>1390.651</td>
<td>2.14e-12</td>
<td>-4.166912</td>
<td>-3.376624</td>
<td>-3.852415</td>
</tr>
<tr>
<td>2</td>
<td>1044.043</td>
<td>454.2794</td>
<td>7.94e-13</td>
<td>-5.159333</td>
<td>-3.666567*</td>
<td>-4.565285</td>
</tr>
<tr>
<td>3</td>
<td>1165.962</td>
<td>226.5213</td>
<td>5.72e-13</td>
<td>-5.488423</td>
<td>-3.293178</td>
<td>-4.614821</td>
</tr>
<tr>
<td>4</td>
<td>1296.474</td>
<td>236.5521</td>
<td>3.93e-13</td>
<td>-5.866329</td>
<td>-2.968606</td>
<td>-4.713175*</td>
</tr>
<tr>
<td>5</td>
<td>1375.926</td>
<td>140.3948</td>
<td>3.61e-13</td>
<td>-5.954123</td>
<td>-2.353921</td>
<td>-4.521417</td>
</tr>
<tr>
<td>6</td>
<td>1441.788</td>
<td>113.3887</td>
<td>3.60e-13</td>
<td>-5.964707</td>
<td>-1.662026</td>
<td>-4.252448</td>
</tr>
<tr>
<td>7</td>
<td>1509.433</td>
<td>113.3818*</td>
<td>3.55e-13*</td>
<td>-5.985416*</td>
<td>-0.980257</td>
<td>-3.993605</td>
</tr>
<tr>
<td>8</td>
<td>1545.858</td>
<td>59.39757</td>
<td>4.20e-13</td>
<td>-5.828739</td>
<td>-0.121102</td>
<td>-3.557376</td>
</tr>
</tbody>
</table>

*Rejecting the original hypothesis at a significance level of 5%
**Long-term coefficients**

Using the long-term coefficient, we found that the p-value of each statistical variable in the model was < 0.05, confirming significance. Moreover, the p-value of F tests for the model were < 0.05, again confirming significance. The R-squared value was 0.504179 and the fitting effect was good (Table 5).

After cointegration was confirmed, all variables were combined in a linear relationship and remain unchanged. Scaling this long-term relationship gave the coefficient of grassland burned area 1 (Table 5). According to the Schwarz Bayesian criterion, the results were estimated using the applied ARDL model. The significant long-term effects showing significance at the 5% level were wind speed, relative humidity and sunshine hours. According to these long-term elasticity effects, we estimated that a 1% change on wind speed was correlated with a 2.53% change in burned area. This long-term elasticity will not be expressed immediately, but will recover via long-term to static balance. Similarly, we predicted that when the relative humidity and sunshine hours changed by 1%, the burned area changed by 10.22% and 4.49%. From Table 5, we can see that the influence of burned area was significant (p < 0.05). This shows that burned area had a long-term impact on itself.

**Table 5. Long-term coefficients**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Selected Model: ARDL (2, 2, 0, 2, 0, 0, 0, 0)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
</tr>
<tr>
<td>D(LNY(-1))</td>
<td>-0.430572</td>
</tr>
<tr>
<td>D(LNY(-2))</td>
<td>-0.272710</td>
</tr>
<tr>
<td>D(LNX1)</td>
<td>6.118542</td>
</tr>
<tr>
<td>D(LNX1(-1))</td>
<td>7.206793</td>
</tr>
<tr>
<td>D(LNX1(-2))</td>
<td>2.525008</td>
</tr>
<tr>
<td>D(LNX2)</td>
<td>-8.661659</td>
</tr>
<tr>
<td>D(LNX3)</td>
<td>4.952237</td>
</tr>
<tr>
<td>D(LNX3(-1))</td>
<td>-1.025216</td>
</tr>
<tr>
<td>D(LNX3(-2))</td>
<td>0.663575</td>
</tr>
<tr>
<td>D(LNX4)</td>
<td>4.104591</td>
</tr>
<tr>
<td>D(LNX5)</td>
<td>-10.22307</td>
</tr>
<tr>
<td>D(LNX6)</td>
<td>-4.487694</td>
</tr>
<tr>
<td>D(LNX7)</td>
<td>-0.064955</td>
</tr>
<tr>
<td>C</td>
<td>-0.031927</td>
</tr>
</tbody>
</table>

**Error correction model**

Through ECM, we found that insignificant variables in the model were reduced, and the R² value was 0.586207. Compared with model 1 (long-term coefficient), SC
decreases, which indicates that fitting by the model was better than that of model 1 (long-term coefficient).

According to the short-term coefficient of ECM (Table 6), when wind speed changed by 1% burned area changed by 3.18%, and when relative humidity changed by 1% burned area changed by 10.86%. Meanwhile, when sunshine hours changed by 1% burned area changed by 2.98%. The expected ECM lag term was negative and statistically significant, meaning that 56% of the change in grassland burned area could be explained by short-term deviation from long-term equilibrium.

Table 6. ECM short-term coefficient

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>t-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>D(LNY(-1))</td>
<td>-0.100413</td>
<td>0.052770</td>
<td>-1.902841</td>
<td>0.0579</td>
</tr>
<tr>
<td>D(LNY(-2))</td>
<td>-0.076680</td>
<td>0.043177</td>
<td>-1.775951</td>
<td>0.0766</td>
</tr>
<tr>
<td>D(LNX1)</td>
<td>4.984152</td>
<td>1.138992</td>
<td>4.375932</td>
<td>0.0000</td>
</tr>
<tr>
<td>D(LNX1(-1))</td>
<td>3.182454</td>
<td>1.094250</td>
<td>2.908341</td>
<td>0.0039</td>
</tr>
<tr>
<td>D(LNX2)</td>
<td>-10.13047</td>
<td>9.147332</td>
<td>-1.107478</td>
<td>0.2689</td>
</tr>
<tr>
<td>D(LNX3)</td>
<td>6.085863</td>
<td>4.495103</td>
<td>1.353887</td>
<td>0.1767</td>
</tr>
<tr>
<td>D(LNX3(-1))</td>
<td>-0.974188</td>
<td>0.443617</td>
<td>-2.196009</td>
<td>0.0288</td>
</tr>
<tr>
<td>D(LNX3(-2))</td>
<td>0.648083</td>
<td>0.362396</td>
<td>1.788330</td>
<td>0.0746</td>
</tr>
<tr>
<td>D(LNX4)</td>
<td>4.737403</td>
<td>5.300218</td>
<td>0.893813</td>
<td>0.3720</td>
</tr>
<tr>
<td>D(LNX5)</td>
<td>-10.86485</td>
<td>1.332310</td>
<td>-8.154895</td>
<td>0.0000</td>
</tr>
<tr>
<td>D(LNX6)</td>
<td>-4.698819</td>
<td>1.113593</td>
<td>-4.219512</td>
<td>0.0000</td>
</tr>
<tr>
<td>D(LNX7)</td>
<td>-0.065821</td>
<td>0.148944</td>
<td>-0.443617</td>
<td>0.0688</td>
</tr>
<tr>
<td>ECM(-1)</td>
<td>-0.559863</td>
<td>0.065228</td>
<td>-8.583224</td>
<td>0.0000</td>
</tr>
<tr>
<td>C</td>
<td>-0.021191</td>
<td>0.149207</td>
<td>-0.142024</td>
<td>0.8871</td>
</tr>
</tbody>
</table>

R-squared     | 0.586207    | Mean dependent var | -0.023989 |
Adjusted R-squared | 0.570524   | S.D. dependent var | 4.300978 |
S.E. of regression | 2.81862    | Akaike info criterion | 4.948800 |
Sum squared resid. | 2725.010   | Schwarz criterion | 5.100868 |
Log likelihood   | -869.3608  | Hannan-Quinn crit. | 5.009284 |
F-statistic      | 37.37817   | Durbin-Watson stat | 2.007702 |
Prob(F-statistic) | 0.000000   |  |  |

Discussion

In the Hulun Buir grassland region, both the number of fires and the total burned area have generally decreased over the past 30 years, indicating that the local government and fire prevention management departments have achieved remarkable fire control results. However, regarding seasonal distribution, fires are still concentrated in spring and autumn, which is also the grassland fire prevention season in this area. This is caused by the dry climate in spring, less rain and more strong winds, dry grass exposed to the surface after snow melt, dry vegetation in autumn, and the reduced water content of fuel. This suggests that the climate characteristics of seasons still dominate the occurrence and spread of grassland fires. Additionally, some grasslands in Hulun Buir are located on the border between China and Mongolia, and Mongolia is sparsely populated, limiting the ability to fight forest grassland fires. Furthermore, there is less precipitation in spring and
autumn, with a dry climate and numerous windy days, leading to grassland fires in these border areas, and many fires spread to Inner Mongolia (Na et al., 2018). Therefore, with global warming, precipitation reduction, temperature rise, grassland warming and drying trends, and grassland vegetation recovery upon implementation of grassland protection projects, grassland fire risk level is increasing (De Diego et al., 2019). In addition, the fire risk period in Hulunbuir grassland is shortening overall. In some years, the earlier the end of the spring fire danger period, the later the start of the autumn fire danger period, which may be due to more precipitation in the summer of that year, effectively suppressing the occurrence of autumn fires. Shortening of the fire risk period is conducive to the development of work on grassland fires, hence the fire risk period can be adjusted accordingly, but the non-fire risk period should not be ignored, and measures to prevent grassland fire in the Hulunbuir area should not be relaxed.

The results showed that the ARDL model is suitable for explaining correlations between grassland burned area and climate factors over time. The error correction model (ECM) can be used as a supplement to the co-integration model, which measures the long-term equilibrium relationship between different climatic factors and the sequence of grassland fire burned areas, while the ECM model explains short-term fluctuations. According to our ARDL analysis, relative humidity was the most important factor affecting the burned area of Hulun Buir grassland (Table 5). Relative humidity strongly affects the moisture content of combustible materials, and has a significant impact on the spread speed and intensity of fire (Zumbrunnen et al., 2011; Moinuddin et al., 2021). However, previous work showed that high temperature had the strongest correlation with burned area (Shabbir et al., 2019). In the present study, relative humidity had a more significant impact on burned area than high temperature. However, the influence of high temperature on burned area cannot be ignored. As temperature rises and relative humidity decreases, carbon emissions in the study area may increase, which will eventually increase the risk of fire (Pitman et al., 2007). In addition, wind speed and sunshine hours in the study area had a significant impact on the burned grassland area. The influence of wind speed on grassland fire is not only reflected in reducing the water content of combustible materials by accelerating the evaporation of water from grassland (Beer, 1991), but also in accelerating the fire spread rate, thus improving the heat transfer efficiency of unburned combustible materials (Sun et al., 2009), making fire spread faster and the burned area larger. High temperature and sufficient sunshine are mutually influencing variables act alone or together to increase plant evaporation and decrease the water content of combustible materials, thereby increasing the probability of fire (Chuvieco et al., 2004; Hennessy et al., 2005). From the results, we concluded that among the seven meteorological variables involved, relative humidity, wind speed and sunshine hours had the most significant effects on the long-term and short-term sensitivity of the ARDL model.

However, the influence of meteorological factors on grassland fires is complex and changeable, and it has an impact on the occurrence and spread of fires under the joint action of many factors (Barbero et al., 2015; Williams et al., 2019). Their relationship can be expressed as meteorological-combustible, combustible-fire and meteorological-fire. In the present study, wind speed played a leading role in the burned area of grassland in the Hulun Buir region. From 1990 to 2019, wind speed has four monthly peaks (April, May, September and October), and peaks in April and May overlap with the grassland fire season in this area. However, drought is the dominant climate factor in the surrounding areas of Hulun Buir grassland, such as Mongolian grassland and the
Greater Khingan forest region (Hessl et al., 2016; Yao et al., 2017). When Mongolian grassland fires spread to Hulun Buir or Daxing’anling forest fires spread to Hulun Buir grassland, it is not known which meteorological factors may have the most influence. Therefore, how different factors interact to affect the occurrence of Hulun Buir grassland fire should be the focus of future research.

Regarding climate change prediction, temperature will likely increase in the northeast of China, while precipitation and relative humidity will likely decrease (Niu and Zhai, 2012), and these changes will have an impact on the occurrence of grassland fires in northern China. In addition, the occurrence of grassland fires is not only related to meteorological factors, but also closely related to human factors (Merem et al., 2011; Guo et al., 2016; Li et al., 2017; Nagy et al., 2018), especially for the occurrence of man-made fires. However, it is difficult to predict the occurrence of man-made fires. Hulun Buir grassland is a climate-sensitive area. In this study, only the influence of different meteorological factors on the over-burned area of grassland in Hulun Buir area was considered, while human activities, combustibles and other factors were not considered. If these factors are considered simultaneously, the correlation between meteorological factors and the over-burned area of grassland may be weak.

Conclusion

In this work, the ARDL model was used to study the nonlinear correlation between the burned area of Hulun Buir grassland and different meteorological factors. Annual changes in grassland fires in this area were mainly divided into two stages; from 1990 to 1999, grassland fires in the Hulun Buir area occurred regularly, with two peaks and large overall fluctuations; from 2000 to 2019, grassland fires in the Hulun Buir area were less frequent and occurred steadily. According to the monthly changes in grassland fires in the Hulun Buir area, fires mainly occurred in April, May, September and October each year. From 1990 to 1999, grassland fires occurred frequently and covered a large area. In 2000–2009 and 2010–2019, both grassland fire frequency and burned area gradually decreased and tended to be stable. The results showed that the ARDL method can determine the long-term and short-term sensitivity of meteorological factors to fire, hence it is an effective model for studying trends in burning area for cases with high variability and short-term climate data. In terms of the influence of meteorological factors on grassland fires, relative humidity and sunshine time had obvious long-term effects on grassland fires in the Hulun Buir area, whereas wind speed, relative humidity and sunshine hours had short-term effects on grassland fires in this area.

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