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Research

Effects of the COVID-19 lockdown in Hubei, China: cessation of incense burning reduces regional landscape fire

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ABSTRACT. Both anthropogenic and climatic factors are important determinants of landscape fire. Because the two groups of factors are intertwined and often act simultaneously, dissecting their effects on landscape fire is challenging. We used the COVID-19 lockdown event in Hubei, in which all immediate influences of anthropogenic factors were effectively removed, to quantify the effects of anthropogenic factors on landscape fire occurrence. We hypothesized that outdoor incense burning is the main causal factor of landscape fire. To test the hypothesis, we used random forest algorithm to model fire occurrence, including fire frequency, total area burned, and area of forest burned, for the lockdown period. We then estimated the differences between historical, simulated, and observed values of landscape fire and used the differences to represent the effects of anthropogenic activities on landscape fire. Our results showed that during the lockdown, landscape fire frequency was reduced by 77%, total area burned by 80%, and area of forest burned by 63%. By month, fire frequency decreased the most in April (85%), followed by February (80%), coinciding with the Qingming and Spring Festivals of 2020. The cessation of outdoor incense burning during the festival season was likely to be the most important factor that decreased fire occurrence, confirming our hypothesis about the causal relationship between outdoor incense-burning and landscape fire. Thus, educational programs encouraging people to stop outdoor incense burning during the festival season could reduce the occurrence of landscape fire.

Key Words: *anthropogenic effects; COVID-19; landscape fire; lockdown; Qingming festival; random forests*

INTRODUCTION

Worldwide, anthropogenic factors have exerted an ever-increasing influence on landscape fire frequency, duration, and severity, which were previously related only to climatic conditions (FAO 2007, Vanniere et al. 2008). Researchers try to model landscape fire occurrence by taking into account both anthropogenic and climatic factors. One of the difficulties is dissecting the effects of these groups of factors, as they are intertwined and often act simultaneously, causing compound effects that are difficult to distinguish. Further, neither anthropogenic nor climatic factors are controllable at a regional scale. Thus far, we can only control climatic factors in laboratory settings or at a micro-scale. In contrast, the establishment of nature reserves and national parks in many countries allows us to control anthropogenic activity on a local scale, but controlling anthropogenic activity on a regional scale is socially unacceptable and economically unaffordable. Therefore, studies identifying the effects of these groups of factors on fire at the regional scale could yield substantial insight into the fire regimes and help ascertain the causal factors of fire under changing climatic and socioeconomic conditions.

The breakout of a human respiratory disease in Wuhan, Hubei Province, China in late December 2019 and the subsequent lockdown of the whole of Hubei Province has created a unique opportunity to dissect the effects of anthropogenic factors on landscape fire at a regional scale from that of the climatic factors. The respiratory disease in Wuhan was caused by a novel coronavirus subsequently designated as COVID-19 by the World Health Organization (https://covid19.who.int/). COVID-19 has now been reported in nearly all countries of the world and has had substantial effects on the world economy and environment.

In Hubei, a state of emergency was declared on 23 January 2020 and the whole province was placed under an unprecedentedly strict lockdown. The lockdown was lifted on 30 April 2020. During the lockdown, all highways were blocked. In Wuhan, a city of 11 million people and the capital of Hubei Provence, the streets were empty except for a few vehicles in use for essential services. In rural areas of the province, villagers were directed to stay within the village or at home, if possible. As a result, most of the outdoor farming activities were halted. Acting out of fear of the new disease, many villagers chose to block all access to the village and stayed indoors, thus effectively stopping travel between villages. Anecdotal evidence indicated that during the lockdown, pig farms were unattended for a prolonged period, which contributed to the shortage of pork supplies in the market in the months following the lifting of the lockdown. Hence, the lockdown of Hubei, from the metropolitan to the most remote areas of the west, was the most complete in recorded history.

Two factors contributed to the completeness of the lockdown. First, there were the strictest directives from governments at all levels, starting from the provincial government down to the local village administration committees, prohibiting all outdoor activities. Second, there was a deep-rooted psychological fear by the Chinese populous of any severe epidemic disease. In Chinese folklore, severe epidemics are called *wçn yì* (瘟疫), meaning plague of countrywide proportion, and are usually associated with the disappearance of the whole population. Thus, during the lockdown period, all activities, including social and economic, came to a near-complete halt, for regulatory and voluntary reasons.

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Emerging evidence suggests that COVID-19 lockdowns implemented by many countries around the world to combat the spread of the pandemic had unintended environmental consequences, negative and positive. For example, in much of China, the countrywide lockdowns—started at various times, for various durations, and at different levels of restrictions for different regions—are associated with improvements in local air quality as road traffic and industrial activity were reduced or halted (Le et al. 2020, Liu et al. 2020). In other parts of the world, the lockdowns decreased the level of air pollutants such as particulate matter, nitrogen dioxide, and sulfur dioxide, but increased the level of tropospheric ozone (Marinello et al. 2021). In India, the lockdown has reduced night-time land surface temperature by 2–5 °C in major cities (Lele et al. 2021).

We attempted to quantify the effects of the lockdown on landscape fire (hereafter simply "fire") in Hubei Province. Unlike other regions, such as parts of southern Europe (Ganteaume et al. 2013, Calvino-Cancela and Canizo-Novelle 2018), much of North and South America (Johnson 1992, Lewis et al. 2011, Westerling 2016, Aragao et al. 2018), and most parts of Australia and Africa (N'Dri et al. 2018, D'Onofrio et al. 2020, Kramer 2020), where a hot, dry climate dominates the summer months and summer fires are common, Hubei has a monsoonal, wet summer and a relatively dry winter and spring, with the majority of fires occurring in the winter and spring months. In southeast Asia, where rainfall is usually high, climate factors play a lesser role in forest fire occurrence; most of the forest fires are related to intentional burning to clear land for plantation crops such as pulpwood, rubber, and palm oil (Hamilton et al. 2000, Fuller and Murphy 2006, Tacconi 2016). In Hubei, apart from climatic factors, two types of anthropogenic activities have been suggested as major contributors to fires in the province (Yue C., Fire Prevention and Control Bureau of Hubei, *personal communication*). First, like in other parts of China (Wu et al. 2014, Ye et al. 2017, Zeng et al. 2020), fire is used in Hubei as a long-established management tool for burning crop residues and clearing excessive vegetation around cropland. Second, as is the case in the rest of China, outdoor incense burning is still commonly practiced in Hubei at the memorial ceremonies during the traditional Spring Festival, which usually falls in January or February, and Qingming Festival, a lunar calendar–based festival that usually falls in late March or early April (Ye et al. 2017, Yin et al. 2018). The majority of fires in Hubei (inclusive of forest fires, agricultural fires, and grass/shrubland fires) typically occur between late November and April each year, a period that has been officially designated as the fire season of the province by the Fire Prevention and Control Bureau of Hubei, the provincial authority for fire services. The lockdown period, January–April, coincided with that of the official fire season in the province.

Our aim in this study was to use the lockdown event as a surrogate for a controlled experiment in which all immediate anthropogenic influences on fire were removed to quantify the effects of anthropogenic activities on fire occurrence during the 2020 fire season in Hubei. As outdoor incense burning and associated activities such as fireworks (hereafter simply "outdoor incense burning") are commonly practiced during the Spring and Qingming Festivals, and fire occurrence was usually the highest during these periods, there have been suggestions that these fires are related to the incense-burning activities. We therefore hypothesized that outdoor incense burning is the main causal factor of fire during the January–April fire season, with the prediction that the effects of lockdown, which effectively ceased all outdoor incense-burning activities, should be the highest in February and April as the Spring and the Qingming Festivals of 2020 fall in February and April, respectively.

To test this hypothesis, we first used the random forests (RF) algorithm (Breiman 2001) to build the predictive model of fire occurrence for Hubei based on climatic and fire occurrence data for 2011–2019. Using the RF model, we then simulated fire occurrence, including fire frequency, total area burned, and area of forest burned, for the 2020 fire season based on the climatic condition of the period and estimated the differences between the model simulated and the observed values for this period. We used the estimated differences to represent the effects of lockdown on fire occurrence.

METHODS

Geographic context

Hubei Province is located in Central China (Fig. 1). The total area of the province is 186,000 km², with forest coverage of 40% (http://www.lknet.ac.cn). The major forest types include subtropical evergreen broadleaf forest, evergreen and deciduous broadleaf mixed forest, and evergreen coniferous forest. The provincial climate is dominated by the monsoonal atmospheric circulation, and temperature is in the lower range of the subtropical region with a prolonged wet season during summer–autumn (May–October) and a prolonged cold and dry winter–spring (December–April; Fig. 2). The average annual rainfall is c. 1200 mm, with average monthly rainfall of c. 140 mm in the wet summer–autumn months and c. 60 mm in the dry winter–spring months (Fig. 2). According to the Fire Prevention and Control Bureau of Hubei, the dry and cold winter–spring is the high fire-risk period and the official fire season is declared to be November–April. Given that the temperature is low during this period, most of the fires are usually small in scale (average total area burned per fire of 4.4 ha and average area of forest burned per fire of 0.9 ha) and of low intensity. Nonetheless, the high number of fires reported each year still pose a serious threat to the safety of people, the health of the economy, and the ecology of agriculture and forest ecosystems.

Fire occurrence and climatic data

Fire occurrence data, including fire frequency, area burned, and area of forest burned, for Hubei Province from 2011 to 2019 were obtained from the Fire Prevention and Control Bureau of Hubei. The data were maintained by the bureau based on a network of fire surveillance in the province supplemented with data from remote-sensing satellites (MODIS Terra, MODIS Aqua; data available from http://www.gscloud.cn). Fire occurrence records from before 2010 were available from the bureau, but these records were incomplete and imprecise, so they were not used for the present analysis. Meteorological data for all 27 meteorological stations of Hubei (Fig. 1) for the same period were obtained from the China Meteorological Data Network (http://data.cma.cn). In all, climatic data were obtained for seven variables: atmospheric pressure, temperature (TEM), relative humidity (RHU), precipitation (PRE), wind speed, sunshine hours, and ground-

Fig. 1. Map of Hubei, China, showing distribution of forested vegetation and distribution of meteorological stations (red dots) from which data were obtained and used for model development. Total area of the province is 186,000 km², forest cover is 39.6%, with the majority of the forests located in the west and northeast.

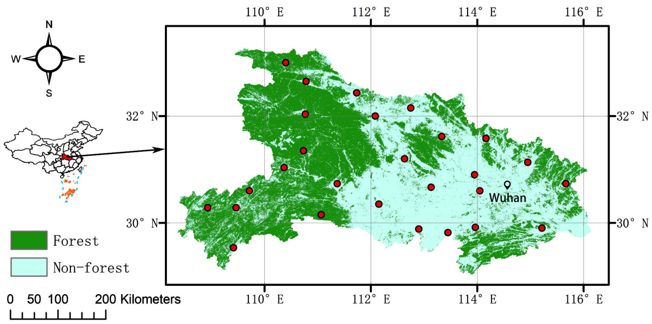
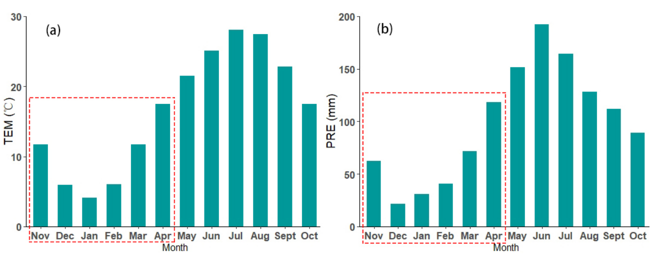


Fig. 2. Monthly mean temperature (a) and precipitation (b) of Hubei Province, China, based on records of the 27 meteorological stations from 2011–2019. The region is dominated by a typical subtropical humid monsoon climate with cold and dry winter-spring (Dec–Apr) and hot and wet summer-autumn (May–Oct). November–April has been declared as the fire season of the province (dashed rectangle) by the Fire Prevention and Control Bureau of Hubei.



level temperature. The monthly averages were then calculated for each of the seven variables. R package *mice* was used for all missing data imputation (R Core Team 2020). Briefly, the package creates multiple imputations (replacement values) for multivariate missing data. This method is based on fully conditional specification, where each incomplete variable is imputed by a separate model. The summary statistics for the climatic variables are presented in Table 1. In addition, month of the year (MTH) was included as the eighth variable of the models. MTH was a composite variable comprising both the anthropogenic and climatic elements. It has been speculated that the high fire occurrences during January to April are related to anthropogenic activities rather than to the climatic conditions of the period. The inclusion of MTH in the model was therefore to help take into consideration the effects of anthropogenic factors.

Random forests algorithm

We used an RF algorithm to build the fire occurrence prediction models for (1) monthly fire frequency, (2) monthly area burned, and (3) monthly area of forest burned. RF is a machine learning method and is first introduced by Breiman (2001). The method is based on a decision tree classifier and can be used both for classification tasks and for regression analysis. Compared to many of the statistical modeling methods, which require certain conditions to be met between model variables (e.g., independence, homoscedasticity, and normal distributions of errors), RF is more flexible in its approach for studies comprised of a large number of correlated variables with complex interactions between them and can fit complex models without presupposing forms of functions (e.g., linear, exponential, and logistic). In addition, RF is able to avoid the overfitting problem common to many other machine learning methods through the use of bootstrap aggregation. Since its introduction, RF has been used in studies of many different disciplines including fire forecasting (Wu et al. 2014), generating useful results.

Table 1. Seven meteorological parameters used in the random forest modeling.

Variables	Mean ± SE	Range
PRS (hPa)	989±0.75	976–1004
TEM (°C)	16.6±0.8	1.13–29.5
RHU (%)	75.2±0.5	61.4–86.5
PRE (mm)	98.6±6.6	3.2–373
WIN (m/s)	1.7±0.0	1.13–2.18
SSD (hour)	4.5±0.2	0.89–7.95
GST (°C)	18.8±0.9	2.32–33.9

PRS, atmospheric pressure; TEM, temperature; RHU, relative humidity; PRE, precipitation; WIN, wind speed; SSD, sunshine; GST, ground level temperature.

Relative importance of model variables

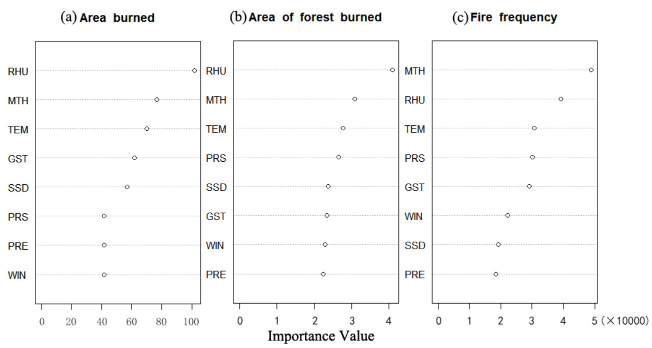
To rank individual variables of the RF models, we used the importance values of variables based on the strength of their relationship to fire occurrence at the regional scales. In RF, the importance value of a variable is estimated by considering the degree to which prediction errors increase when data for that variable are permuted while all others are left unchanged (R Core Team 2020). We used the increase in node purity from the RF model as the indicator for the importance value of individual variables and computed 10 repetitions. For each model repetition, we identified variables that were predictive of the outcome based on their importance values. Only those variables that were identified in seven or more repetitions were considered important and were included in the final model. The final RF models contained all eight environmental variables.

The eight variables were ranked according to their relative contribution to fire occurrence (Fig. 3). The top three contributors were RHU, MTH, and TEM. The contribution of PRE to fire occurrence was not as high as expected and it ranked seventh for area burned, and eighth (the lowest) for fire frequency and area of forest burned (Fig. 3).

Model validation

As the data set was relatively small, containing records for only nine years, we used the leave-one-out cross-validation method for model validation (Meijer and Goeman 2013, Cheng et al. 2017). Briefly, when computing model parameters, for each sample in the dataset, all remaining sample data were used as training data for the model. This validation method makes use of all individuals in the training data set, thus maximizing the size of the training set and improving the accuracy of the prediction. This validation method has been successfully used in studies of multiple disciplines (Shao et al. 2016, Cheng et al. 2017, Mikshowsky et al. 2017).

Fig. 3. Dot charts of relative importance (increase in node purity) of eight environmental variables related to fire occurrence in Hubei, China: (a) area burned, (b) area of forest burned, and (c) fire frequency. PRS, atmospheric pressure; TEM, temperature; RHU, relative humidity; PRE, precipitation; MTH, month of the year; WIN, wind speed; SSD, sunshine hours; and GST, ground level temperature.



Model prediction accuracy is evaluated by the root mean square error (RMSE) and by the mean bias. As the sample data used in the prediction was not used in the cross-validation, RMSE can thus be used to evaluate the performance of the model: the smaller the RMSE value, the smaller the prediction error, and the better the fitting effect of the model. The mean bias represents the deviations between the mean forecast values of the model and the mean of the observations. The smaller the mean bias, the better the model predictive power. Model predictive power is also evaluated with the coefficient of determination (R^2). An R^2 value was calculated between the simulated value and the observed value for each of the modeled variables: fire frequency, area burned, and area of forest burned. R^2 values vary between 0 and 1. The closer the value is to 1, the stronger the explanatory value of the variable and the better the predictive power of the model.

For all three modeled variables, R^2 equaled 0.90 or higher, RMSE ranged from 37.7 to 225, and mean bias ranged from 24.1 to 118 (Table 2). The high R^2 values suggested the high predictive power of our RF models for all three modeled variables. The relatively high RMSE values were in part a reflection of the large variation of the variables being modeled. The mean bias of the three modeled variables was c. 50% or less than that of the RMSE, confirming the predictive power of the RF as suggested by the high R^2 values.

Quantifying the effects of anthropogenic activities on fire occurrence during the COVID-19 lockdown

To quantify the effects of anthropogenic activities on fire occurrence during the COVID-19 lockdown, we used an RF model to simulate fire occurrence in Hubei for the lockdown period (January–April 2020) based on the climatic data for the period. We then compared fire occurrence between the observed values, the historical averages, and the simulated values of the corresponding months. The discrepancies in fire occurrence values between the observed, the historical, and the simulated were then used to represent the effects of anthropogenic activities on fire during the COVID-19 lockdown.

Table 2. Coefficient of determination (R^2) and root mean square error (RMSE) of fire predictive models based on random forest algorithm.

Model	Median	Range	RMSE	R^2	Mean bias
Fire frequency (fires/month)	1.0	0–276	37.7	0.91	27.6
Area burned (ha)	3.8	0–1374	225	0.91	118
Area of forest burned (ha)	0.1	0–260	40.1	0.90	24.1

Statistical analysis

To determine the effects of outdoor incense burning on fire occurrence, we used a one-sample t-test to compare fire occurrence between the observed values and the corresponding historical values during the lockdown period. In addition, we compared fire occurrence between the simulated values and the historical values to determine if weather conditions during the lockdown period deviated from the long-term averages. Data were tested for normality and were log-transformed as needed, before testing. We considered differences with $p < 0.05$ to be significant. Unless otherwise mentioned, all analyses were conducted with *R statistical Package* (version 3.6.1) and the R-package *random ForestSRC* (version 2.9.3; R Core Team 2020).

RESULTS

Historical fire occurrence in Hubei Province

Fire occurrence in Hubei, including fire frequency, area burned, and area of forest burned, showed strong seasonal variation (Fig. 4). A total of 2658 fires were recorded over the 9 years. Most of the fires occurred during the winter–spring season (January–April, 92%) followed by September–December (7.4%), and May–August (0.6%). The average area burned per fire was the lowest in January–April and the highest in September–December (Table 3). The area burned and the area of forest burned showed similar seasonal patterns to that of the fire frequency (Fig. 4)

Weather conditions in Hubei Province during the COVID-19 lockdown

Weather conditions during the lockdown period were relatively normal with no extreme weather recorded. Of the seven climatic variables, RHU and TEM were identified by RF modeling as the most important contributors to fire occurrence in Hubei (Fig. 3). During the lockdown, RHU was higher than the historical average ($p < 0.05$) except in March (Fig. 5a), and TEM was higher than the historical average ($p < 0.05$, Fig. 5b) except in April, when it was lower than the historical average (Fig. 5b).

Fig. 4. Landscape fire occurrence of Hubei Province, China, based on data from 2011–2019: (a) monthly fire frequency and (b) monthly area burned and monthly forest area burned.

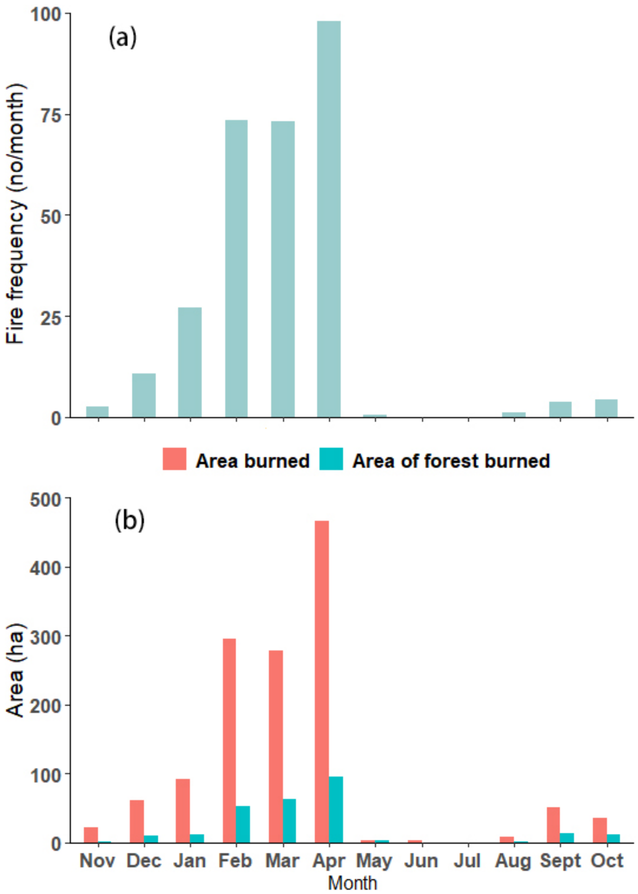


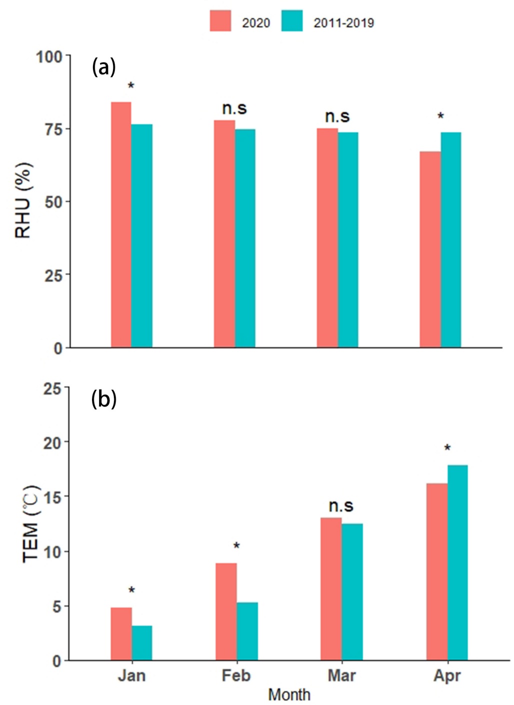
Table 3: Seasonal variation of landscape fire occurrence in Hubei, China during 2011-2019

Variables	Jan–April	May–Aug	Sept–Dec
Average precipitation (range; mm)	65.4 (14.7–174)	159 (68.8–374)	71.2 (3.2–203)
Average mean temperature (range; °C)	9.8 (1.2–18.3)	25.1 (20.5–29.5)	14.5 (4.2–24.3)
Total number of fires	2446	197	15
Average area burned per fire (ha)	4.1	7.7	9.7
Average area of forest burned per fire (ha)	0.8	1.7	2.9
Total area burned (ha)	10,183	1512	144
Total area of forest burned (ha)	2011	330	43

Fire occurrence in Hubei Province during the COVID-19 lockdown

The COVID-19 lockdown in Hubei extended from 23 January to 30 April 2020. During the lockdown period, the total observed number of fires was 46; the total area burned and total area of

Fig. 5. Comparison of RHU (a) and TEM (b) between the COVID-19 lockdown period and the corresponding months of 2011–2019. RHU and TEM were the most important meteorological variables for landscape fire occurrence of Hubei Province, China. RHU, relative humidity; TEM, temperature; asterisks above bars indicate significant difference from historical averages at P < 0.05; n.s., not significant.

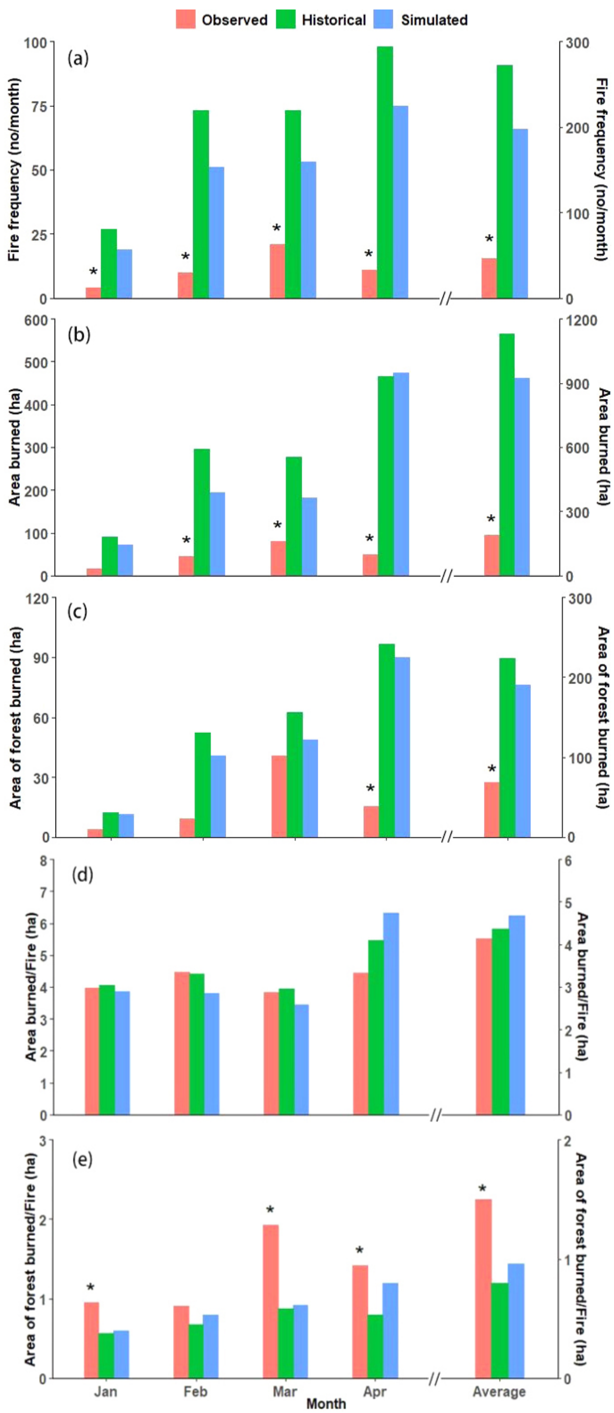


forest burned were 190 ha and 69 ha, respectively; the simulated values for the same period were 189 fires, and areas of 925 ha and 186 ha, respectively, and the historical averages (based on data for 2011–2019) were 271 fires, 1131 ha and 223 ha, respectively. The observed fire frequency was reduced by 77% (46 vs 190 fires) compared to the simulated value and by 83% compared to the historical average (46 vs 271 fires). Similarly, the observed area burned and area of forest burned was reduced by 80% and 63%, respectively, relative to the simulated values, and by 83% and 69%, respectively, relative to historical averages.

On a monthly basis, the observed fire frequency, area burned, and area of forest burned in February, March, and April were significantly lower than that of the historical averages (Fig. 6; one-sample t-tests, $p < 0.05$). The difference in fire frequency between values of the observed and the simulated was the greatest in April (85%) followed by February (80%), January (79%), and March (60%; Fig. 6a). The area burned and area of forest burned showed similar monthly patterns to that of fire frequency (Fig. 6b–c).

Importantly, the model-simulated fire frequency, area burned, area of forest burned, and area burned per fire during the lockdown period were not significantly different from that of historical averages (Fig. 6a–c, e; one-sample t-tests, $p > 0.05$),

Fig. 6. Landscape fire occurrence of Hubei Province during the COVID-19 lockdown, January–April, 2020: (a) fire frequency; (b) total area burned; (c) total area of forest burned; (d) area burned per fire; and (e) area of forest burned per fire. Historical, fire occurrence values for 2011–2019; Simulated, random forest model simulated fire occurrence values during the lockdown; Observed, observed fire occurrence values during the lockdown. For January–April, an asterisk above a bar indicates significant difference (vs historical value) at P < 0.05 (one-sample t-test).



suggesting that during the lockdown period, the effects of climatic conditions on fire were in line with that of the long-term averages, although RHU and TEM deviated a little from their long-term averages (Fig. 5). On the other hand, the observed area of forest burned per fire was significantly higher during the lockdown period than the historical averages (1.3 vs 0.7 ha, one-sample t-test, $p < 0.05$). The pattern was consistent across the four-month lockdown period except for February (Fig. 6e).

DISCUSSION

This study demonstrated that the COVID-19 lockdown, in which nearly all outdoor anthropogenic activities in Hubei virtually ceased at a regional scale from January to April 2020, reduced the number of fires by 77%, area burned by 80%, and area of forest burned by 63% in a period that coincides with the official high-risk fire season. These reductions are direct evidence that the majority of fires in the region have anthropogenic causes.

In particular, the greatest decrease in fire frequency and area burned was recorded in April and February (Fig. 6a–b). The 2020 Spring and Qingming Festivals fell in February and April, respectively, coinciding with the greatest decrease in fire frequency and area burned, when outdoor incense burning effectively ceased due to the lockdown. Thus, these results support our hypothesis that outdoor incense burning is responsible for most of the fires during this period.

Outdoor incense burning is a Chinese tradition to commemorate ancestors and has long been practiced during the Spring and Qingming Festivals in rural China. During the festivals, incense is burned at the sites of ancestor graves, which are usually scattered in vegetated areas. As a part of the incense-burning activities, firecrackers and even fireworks are ignited and paper money for the dead (stacks of printed paper or plain paper) are burned. All these activities can have unintended consequences: igniting uncontrolled fires.

Apart from anthropogenic activities, the strong seasonality of fire occurrence suggests that climatic factors play an important role in determining the fire regime of Hubei. Among the seven climatic variables, it is interesting that relative humidity and temperature were the most important contributors to fire occurrence while precipitation had a lesser influence (Fig. 3; Table 4). Both relative humidity and temperature were negatively correlated with fire occurrence (Table 4). This is in strong contrast to other regions such as Australia, Europe, and North America, where summer fire regimes dominate, high temperature and low precipitation are often the most important climatic variables affecting fire frequency, scales, and intensity (Littell et al. 2009, Ganteaume et al. 2013, Aragao et al. 2018, Kramer 2020). The weak negative correlation between temperature and fire occurrence is interesting and is more of a reflection of the winter fire regimes in Hubei. Most of the fires occur in the winter months when temperatures are low, and almost no fires occur in summer months when temperatures are high (Fig. 4). Factors other than temperature are more likely the major contributors to the fire occurrence in Hubei.

The strong negative influence of relative humidity on fire occurrence (Table 4) is probably a reflection of its close correlation with soil moisture. Soil moisture has been an important variable

Table 4. Pearson correlation coefficient between fire occurrence and the seven climatic variables used in the random forest modeling.

	Fire frequency	Area burned	Area of forest burned
Variable			
PRS	0.20*	0.18	0.14
TEM	-0.29*	-0.23*	-0.18
RHU	-0.42*	-0.49*	-0.43*
PRE	-0.22*	-0.25*	-0.21*
WIN	0.13	0.16	0.16
SSD	-0.08	0.01	0.01
GST	-0.29*	-0.22*	-0.17

Please refer to Table 1 for variable information. *P < 0.05.

in landscape fire occurrence (Ganteaume et al. 2013, Westerling 2016). Simulation studies suggest that soil moisture (both surface and in-depth) is highly positively correlated with air humidity (Rao and Rakesh 2019, Yang et al. 2019). Most of the landscape fires in Hubei are surface fires, i.e., burning is restricted to the ground level with the understory-layer vegetation and the litter layer making up the bulk of the fuel load. When the humidity rises, so does the moisture content of the soil surface layer; the risk of fire is lowered as it is difficult to burn materials with high moisture content. We did not include soil moisture in our modeling due to unavailability of data in our study region. On the other hand, the low influence of precipitation on fire occurrence may have been affected by anthropogenic activities, which are responsible for much of the fire occurrence. For instance, precipitation in the January to April period is similar to that in the August to December period (Table 3), yet 92% of the fires occur during the January to April period vs 7.4% during the August to December period. This discrepancy in fire occurrence between the two periods is strongly affected by anthropogenic activities and is unlikely precipitation-related.

Of the 8 variables used for our modeling, MTH is the only variable that is categorical and related to anthropogenic activities. Its inclusion has greatly increased the predictive power of the model, reflecting the importance of anthropogenic activities to fire occurrences in the study region. Most of the fires occur during January to April, a period known to be associated with high anthropogenic fire-causal activities, as discussed.

Temperature has been an important determinant for landscape fire (Westerling 2016, Kramer 2020). The lockdown has been reported to decrease the land-surface temperature by 2–5 °C for major cities in India (Lele et al. 2021). This type of temperature decrease is probably the reversal of heat island effects, which are typically restricted to cities where the level of anthropogenic activities is much higher than in rural areas. While the actual effects of anthropogenic activities on the temperature in rural areas during the lockdown are unknown, we expect they would be much weaker than those reported in the cities. As most landscape fires occur in rural areas, the effects of any anthropogenic activity–related temperature change on fire occurrence should, therefore, be minimal.

A notable observation is that the area of forest burned per fire during the lockdown period was substantially larger than that of the long-term average of the region (Fig. 6e). Two factors may have contributed to this increase: (1) substantially reduced fire suppressing response by the local fire services during the lockdown as many services, including government fire services, were affected; and (2) fires ignited by non-anthropogenic events are often larger in scale than those ignited by the former. In the latter case, fires ignited by anthropogenic activities, intentionally or accidentally, are usually located close to roads and infrastructure and can be suppressed relatively quickly by fire services or even those responsible for starting the fire. In contrast, fires ignited by non-anthropogenic events are usually located in more remote areas and take longer for the fire service to respond, resulting in larger areas burned per fire.

In other parts of the world, although the COVID-19 lockdowns were less strict or shorter than in Hubei, they also caused substantial changes in fire incidence and severity. For instance, in India, the lockdown (25 March to 15 April 2020) reduced forest fire frequency by 55% in 10 fire-prone states (Lele et al. 2021). In contrast, the lockdown in Colombia increased the number of forest fires, which was caused by the lapse of government control and the subsequent increase in activities of the armed groups in the region during the COVID-19 pandemic period (Amador-Jimenez et al. 2020). In both cases, changes in fire occurrence were caused by the change in anthropogenic activities during the lockdown.

The substantial decrease in fire occurrence associated with the lockdown has two implications. First, as urbanization in China continues and the rural population becomes smaller, anthropogenic activity–related fires will reduce. Since the 1980s, China has experienced a rapid expansion of the urban population. The percentage of the rural population in China decreased from 82% in 1978 to 74% in 2000, and to 44% in 2015 (http://www.stats.gov.cn/english/). In Hubei, the proportion of the rural population is comparable with that of the national average, with 39% of its 59 million people living in rural areas in 2020. As the rural population decreases, so will its effects on fire. The effects of population size on fire occurrence are evident from a fire study in Heilongjiang, northeast China (Wu et al. 2014). Population density is substantially lower in Heilongjiang than in Hubei (82 vs 317 people/km²; http://www.stats.gov.cn/english/), anthropogenic activities in Heilongjiang are responsible for igniting only 52% of fires, which is substantially lower than in Hubei (77% in the present study). In European countries, anthropogenic activities are responsible for 50% to 90% of forest fires (Ganteaume et al. 2013, Parente et al. 2018). This wide variation in the proportion of anthropogenic activity–related fires is also closely related to population density. In areas where population density is high, the proportion of anthropogenic activity–related fires is close to 90% whereas in remote and less populated areas, the proportion is close to 50%. Second, as the majority of fires are related to anthropogenic activities, educational programs on fire risk of certain activities, such as burning of crop residues and outdoor incense burning during the Spring and Qingming Festivals in rural areas, can be an effective measure to reduce fire occurrence.

While the present study has captured the short-term effects of anthropogenic activities on fire, it did not address their long-term impact. In the short term, anthropogenic activities may affect fire occurrence by directly causing, controlling, and suppressing fires.

In the long term, they may impact on fire by modifying the flammability of landscapes through changes in land use and land cover, contributing to global warming through the burning of fossil fuels, and causing changes in drought and flood patterns at regional and continental scales. In Australia, Europe, and North and South America, studies have shown that global warming and change in rainfall and drought patterns attributable to anthropogenic activities have greatly exacerbated the duration, scale, and intensity of fires at local and regional scales (Ganteaume et al. 2013, Calvino-Cancela and Canizo-Novelle 2018, Marengo et al. 2018, Kramer 2020).

Another limitation of the present study is that we did not assess the spatial variation in climatic conditions and in fire occurrence within the study region. Instead, we treated Hubei as a whole. We were partly constrained by the available fire occurrence data, which did not provide enough detail on individual fire locations. As climatic conditions, vegetation, and socioeconomic conditions are likely to vary spatially within Hubei, models that capture this spatial variation may be able to forecast the spatial variation of fire occurrence more accurately. However, as the emphasis of the present study was to quantify the effects of anthropogenic activities on fire occurrence in Hubei as a whole, our approach is appropriate, and the results offer useful insight into the changes in fire regimes and allow us to identify the main causal factors of fire during the 2020 COVID-19 lockdown when the influence of anthropogenic activities was effectively removed from the system.

CONCLUSION

In conclusion, we have shown that the effective removal of anthropogenic influence during the COVID-19 lockdown in Hubei decreased fire frequency by 77%, area burned by 80%, and area of forest burned by 63%. These decreases represent the short-term influence of anthropogenic factors on fire occurrence. Outdoor incense burning (or its absence) during the Spring and the Qingming Festivals is likely the most important activity that contributed to the decreases during the lockdown.

The current study was undertaken on an opportunistic basis, using the COVID-19 lockdown event as a surrogate for a controlled experiment with all immediate anthropogenic influences on fire removed. While it is generally believed that the high incidents of fire occurrence during January and April in Hubei, and in other similar contexts in China, are anthropogenic activity–related, it has been difficult to establish the quantitative relationship between the two. Part of the difficulty was due to the unwillingness of people to report the actual causes of fires for fear of persecution. Lighting a landscape fire is a criminal offense and incurs heavy penalties, including jail sentences. In the fire occurrence data used for the present study, the causes of many of the fire events were recorded as unknown or undetermined. Thus, the results of the present study are direct evidence that the majority of landscape fires are related to anthropogenic activities, particularly outdoor incense burning. Outdoor incense burning is still commonly practiced in rural areas of China. While it may not be possible to ban such a practice outright in the foreseeable future, educational programs encouraging people to modify or take necessary fire-preventing precautions will greatly decrease fire occurrence in Hubei and in other similar contexts in China.

Responses to this article can be read online at:
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Author Contributions:

QX: methodology, data analysis, and manuscript drafting; WM, JT, WZ, TM, and WP: methodology, data processing, and analysis; YZ: conception, methodology, and manuscript drafting. All authors contributed to the writing and editing of the manuscript and approved the final version of the manuscript.

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Data Availability:

Data supporting the findings of this study are available at Dryad https://doi.org/10.5061/dryad.1c59zw3x2.

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