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Wildfire ignition in the forests of southeast China: Identifying drivers and spatial distribution to predict wildfire likelihood

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Understanding the spatial distribution and driving factors of forest fire facilitates local forest fire management planning and optimization of resource allocation for fire prevention geographically. In this study, we analyzed the spatial pattern and drivers of forest fire in Fujian province, southeastern China, during 2000–2008 using Ripley's *K*-function and logistic regression (LR) model. The likelihood of fire occurrence was mapped based on the resultant model. The data regarding fire ignitions, weather conditions, vegetation, topography, infrastructure, and socioeconomic factors were extracted from ArcGIS environment. The study revealed that fire ignition was mainly clustered in space due to the comprehensive influence of different factors. Elevation, daily precipitation, and daily relative humidity were negatively associated with fire ignitions, whereas distance to settlement, population density, and per capita gross domestic product (GDP) impacted fire occurrence positively. The spatial distribution of fire occurrence likelihood was highly variable in Fujian: high fire likelihood was prevalent in the northern and southeastern parts of Fujian, whereas it was relatively low in the western province. Fire risk may be underestimated in some areas of Fujian according to the spatial patterns of the model residual, which should be paid more attention to in the forest fire management practice.

1. Introduction

Forest fire is an important ecological factor, which has a significant impact on forest regeneration and succession (Podur, Martell, & Csillag, 2003), and from economic and safety perspectives, results in a loss of forest resources and threatens the safety of human life and property (Flannigan, Stocks, & Wotton, 2000). Forest fires mainly fall into two categories: human-ignited or *anthropogenic* fires, versus fires that are not a direct consequence of human action – *naturally induced* fire. Worldwide, human activities are responsible for most wildfire ignitions – for example, more than 95% of all fires in southern Europe (San-Miguel-Ayanz & Camiá, 2009), and 60% in Alaska over the period of 1950–2005 were anthropogenic (Todd & Jewkes, 2006). The causes of forest fires differ between South and North China: in Daxing'an Mountains, in the north, fires were identified as originating equally from humans as by lightning (Guo et al. 2015), while in southern regions, the majority of fires were attributable to human activity. In the southeastern province of Fujian, human-caused forest fires reached 95% in the past decade (He, Liu, Zhao, & Zhou, 2013).

Understanding spatial distribution and primary factors that influence fire occurrence is crucial for forest management and allocation of fire prevention and suppression resources. For example, fire towers, inspection stations, fire patrols and firebreaks should be allocated around fire-prone zones, which can reduce economic expense and improve the efficiency of forest fire management. In the past decades, numerous studies have been conducted to identify spatial patterns and drivers of fire occurrence (Hu & Zhou, 2014; Martínez, Vega-Garcia, & Chuvieco, 2009; Syphard et al. 2008; Zhang, Zhang, Li, Xu, & Zhou, 2013). This early research tended to consider primarily meteorological factors. More recent research has begun to include a comprehensive analysis of vegetation, terrain, human activity, socioeconomic influences, and other biophysical and ecological factors (Chas-Amil, Prestemon, McClean,

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& Touza, 2015; Fry & Stephens, 2006; Romero-Calcerrada, Barrio-Parra, Millington, & Novillo, 2010). Findings from these studies have revealed the essentiality of considering different types of potential influences, in order to identify key variables or driving factors (Catry, Rego, Bação, & Moreira, 2009; Loboda & Csiszar, 2007; Martínez et al. 2009; Nunes et al. 2005; Syphard et al. 2008).

Forest fire prediction research is a developing field in China, and has focused mainly on the Chinese boreal forest in northern China. Fujian, located southeast of China, is one of China's four major forest management regions, ranking the highest in terms of forest coverage. It is also an area with a high annual forest fire incidence. Although increased fire prevention efforts have reduced the number of annual forest fires in recent years in Fujian, the total area of forest burned has increased (He et al. 2013). Despite these increases, compared to the northern forest regions in China, studies focused on forest fire drivers and forecasting in Fujian province are insufficient to inform forest fire management in this region. For example, only a few variables have been used so far to perform fire danger classification and fire forecasting, and methods of analysis have not been especially sophisticated (He et al. 2013), which may miss out on important nuances, such as anthropogenic influences or interactions among variables. Research has shown that forest fire occurrence, especially anthropogenic forest fire, was affected by many factors (Oliveira, Oehler, San-Miguel-Ayanz, Camia, & Pereira, 2012; Zhang, Zhang, & Zhou, 2010) in which socioeconomic indicators and human activity were found to be indispensable considerations; nonetheless, these indicators have not been considered in the fire-prediction studies of Fujian. In the past decades, forest-related socio-economic activities, including tourism, have become potentially meaningful influences in Fujian due to the abundance of forest resources and increasing interest in these types of activities. This has the potential to increase the complexity of relationships between fire occurrence and local factors affecting risk of ignition, as well as the unique spatial distribution of fire occurrence.

The objectives of the present research are to (1) identify the spatial distribution of fire ignitions in Fujian, China, (2) understand the comprehensive and individual effects of ignition factors on fire occurrence, and (3) produce spatially explicit statistical models and maps predicting patterns of fire ignitions in Fujian, China, using a combination of biophysical and human variables. Results can provide the necessary guidance for local forest fire management in terms of fire resource allocation, reducing the economic burden of fighting fires, and improving the efficiency of forest management strategies in the forests of southeastern China. Findings from this case study also have the potential to be implemented in other areas of southeastern China, which have many shared variables, such as fire frequency, climate conditions, forest resources, and socioeconomic factors.

2. Materials and methods

2.1. Study area

Fujian is a province in southeastern China (Fig. 1a). The total land area of Fujian is 124,000 km^2, which accounts for 1.3% of China's total land area. The climate of Fujian is warm, humid subtropical monsoon, which is affected by the monsoon circulation and topography. Average annual rainfall is 1400–2000 mm, and average temperature 17–21 °C. The current forest coverage of Fujian is around 66%. Dominant tree species include *Pinus massoniana* Lamb., *Cunninghamia lanceolata*, *Casuarina equisetifolia* L., *Phyllostachys heterocycla*, and others.

Fujian has a relatively high forest fire frequency compared to other regions in China that have high forest coverage such as Chinese boreal forest. The fire season is from approximately September 15 until April 30 of the following calendar year. From 1951 to 1998, forest fires occurred on average 1385 times annually and more than 95% fires are caused by human activities (Zheng et al. 2001).

2.2. Spatial distribution analysis

K-function proposed by Ripley (1976) is a useful tool to describe how the interaction or spatial dependence between events varies through space. Ripley's *K*-function is defined as follows:

$$K(d) = \frac{1}{\lambda} E \text{ (number of other events within d distance of an arbitrary event)}$$

where λ is the density (number per unit area) of events, and $E(\bullet)$ is the expectation operator. It has been widely used in spatial point pattern analysis and spatial point process modeling (Dissing & Verbyla, 2003; Podur et al. 2003). Theoretically, for a homogeneous Poisson process, known as "complete spatial randomness" (CSR), $K(d) = \pi d^2$. For $d \geq 0$, Ripley's *K*-function can be used as a formal statistic to test the null hypothesis of CSR. The values of $K(d)$ less than πd^2 indicate regularity, whereas aggregation is indicated when $K(d)$ is greater than πd^2. There are three basic edge correction methods for Ripley's *K*-function and we used "The guard area correction" in this study. SpPack software was used to perform the *K*-function (Perry, 2004), and confidence envelopes were set to 95%, based on 499 replicates.

2.3. LR model

In recent years, many scholars have used LR to predict and analyze forest fire occurrence (Chang et al. 2013; Martínez et al. 2009; Oliveira et al. 2012; Rodrigues, de al Riva, & Fotheringham, 2014; Saefuddin, Setiabudi, & Fitrianto, 2012; Vega Garcia, Woodard, Titus, Adamowicz, & Lee, 1995). In the analysis, forest fire occurrence was assigned a value of 1 ($y = 1$), while "zero occurrence" was 0 ($y = 0$). Furthermore, we assumed that the probability of occurrence of forest fire ($y = 1$) was *P*, and the probability of no forest fires ($y = 0$) was $(1 - P)$. This allowed us to use LR to model the probability of occurrence of forest fire in association with each variable. The specific expression was

$$\ln\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_m x_m \quad (1)$$

The formula for estimating the probability of forest fire occurrence converted using *Logit* was

$$p = 1 \Big/ \left(1 + e^{-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_m x_m)}\right) \quad (2)$$

In Eq. (2), *P* is the probability of forest fire occurrence, *m* is the number of covariates, is $(\beta_1, \beta_2, \ldots \beta_\mathrm{m})$ is the correlation coefficients for each variable using the LR model, and $(x_1, x_2, \ldots, x_m)$ are the respective variables which influenced the occurrence of forest fires.

2.3.1. Dependent variable

Binomial LR model requires that the data are in a binomial distribution. A certain percentage of random points (non-fire points) were created to satisfy the requirements of the binomial LR model. The forest fire data used in this study were Fujian 2000–2008 satellite fire point data provided by the Forestry Science Data Center (http://www.cfsdc.org/indexAction.action?classId=1). There were 13,185 forest fires that occurred in Fujian during 2000–2008. Data points also provided the geographic coordinates, time, and other information of the forest fires. There was