Forest fire monitoring using spatial-statistical and Geo-spatial analysis of factors determining forest fire in Margalla Hills, Islamabad, Pakistan

Aqil Tariq, Hong Shu, Saima Siddiqui, B. G. Mousa, Iqra Munir, Adel Nasri, Hassan Waqas, Linlin Lu and Muhammad Fahad Baqae

State Key Laboratory of Information Engineering in Surveying, Mapping and Remote Sensing (LIESMARS), Wuhan University, Wuhan, China; Department of Geography, University of the Punjab, Lahore, Punjab, Pakistan; Faculty of Engineering, Al-Azhar University, Cairo, Egypt; National Engineering Research Center for Geographic Information System (NERGIS), School of Geography, China University of Geosciences, Wuhan, China; Key Laboratory of Digital Earth Science, Aerospace Information Research Institute, Chinese Academy of Sciences, Beijing, China

ABSTRACT
The objective of this study is to adopt a methodology for analyzing spatial patterns of danger of forest fire at Margalla Hills, Islamabad, Pakistan. The work is concentrated on burnt areas using Landsat data and to classify forest fire severity with different parameters (climatic, vegetation, topography and human activities). In addition to these four variables, the extent of the burned areas was measured. Statistical analysis at each fire scene was used to measure the effect on the variables. To calculate the fire severity ratio correlated to each variable, logistic and stepwise regressions were used. The results showed that the burned areas have increased at a rate of 25.848 ha/day ($R^2 = 0.98$) if the number of total days since the start of fire has increased. As a result, forest density, distance to roads, average quarterly maximum temperature and average quarterly mean wind speed were highly correlated with the fire severity. Only average quarterly maximum temperature and forest density affected the size of the burnt areas. Prediction maps indicate that 53% of forests are in the very low severity level (0.25–0.45), 25% in the low level (0.45–0.65) and 22% in high and very high levels (>0.65).

1. Introduction
Forest fires appear unavoidable in the natural world and they play a vital role in the regeneration of flora and the change of ecosystems. Nonetheless, unregulated forest fires may have detrimental environmental and local impacts. These fires are not only
harmful for property and human life but also endanger ecosystem permanency. There has been a growing increase in the amount and intensity of forest fires across the world over the last decade. This phenomenon raises public concern about the environmental and socio-economic impacts of forest fires.

According to a 2015 report by the Ministry of Climate Change and Capital Development Authority (CDA), Islamabad, Pakistan has a forest cover of around 5.2% of its geographical region (Islamabad CC 2015). Due to climate change and increased human economic activity, forest fires in this country in recent years have become a major environmental disaster that has burned large quantities of natural resources, destroyed the soil and caused air pollution (Schoennagel et al. 2004; Krebs et al. 2010). In addition to the altering human activities in land use, prolonged dry weather with unusually high temperature raises the number of fires across a significant part of Islamabad. Due to major effect of forest fires on habitats and forest fire prevention, socio-economic conditions and suppression have become a shared concern of researchers and governments around the world. In order to develop successful fire prevention and suppression plans, regional-scale maps of fire susceptibility need to be created (Hastie et al. 2009; Jung et al. 2013). These maps not only promote the appropriate distribution of resources required for fire prevention and suppression but also provide considerable support for land use planning tasks (Parks et al. 2011; Valdez et al. 2017).

Recent developments in the RS (remote sensing) and GIS (geographic information system) have tremendously assisted the task of developing maps of forest fire susceptibility (Khalid and Saeed Ahmad 2015; Castelli et al. 2015). GIS allows for the easy execution of the tasks of recording, evaluating, handling and displaying geographic data. The forest fire threat in an area can be evaluated taking into account several inducing factors including vegetation, climate, human activities and topography. The spatial associations between those variables and the regional historical fire record can be used to create data-driven models that perform accurate predictions of fire susceptibility for all areas of the world. Researchers have focused on the contribution of vegetation type and continuity, fire environment and topographic factors that influence the fire spread rate and period of favourable conditions and human involvement in fire suppression and extinguisher (Viegas et al. 1999; Samanta et al. 2011; Calkin et al. 2014). These developments have fuelled studies that generate forest fire risk maps in several regions in recent years, with major advancements in RS and GIS science, and the inference ability of machine learning helps greatly to estimate the spatial extent of forest fires (Satir et al. 2016).

Previous studies have analysed factors influencing long-term forest fire, burning threat and risk in Asia mostly at the local level and also at the national level (Pew and Larsen 2001; Bonazountas et al. 2007; Duane and Brotons 2018). They used various statistical approaches, simulations and algorithms to assess the impact of climatic and environmental influences. For example, in northeast Iran’s Golestan forest region, (Ricotta and Di Vito 2014) used a stepwise and regression statistical model to establish integrate between wildfire incidence and wild forest managing variables with strong association (more than 70%) between lower forest roads and fire period, barrier and forest organization frequency quarry plans (Mohammadi et al. 2014). In the Mediterranean region, forest fires represent an extremely serious environmental issue.
An estimated average of 600–800 (thousand hectares) per year is burned by more than 5,000 fires. The area is comparable to that of the island of Corsica and corresponds to 1.3% to 1.7% of the total Mediterranean forest. We analysed the fire management practices and accomplishments of Galicia, Spain in the past. It adds that 37% of the fires in Galicia were of unknown origin in the 1998–2002 period (Fernandes 2008). In Southwest China, Yunnan has suffered a large number of forest fires in recent decades. There was an average of 2674 fire incidents per year between 1951 and 2000, with an annual average of 111.85 million km² of burned areas and an annual average casualty involving the death of dozens of people, resulting in an average economic loss of more than $10 million annually directly related to forest fires in Yunnan province (Chen et al. 2014). 13% of bushfires every year are intentional and 37% are suspicious, according to Australia’s National Centre for Research in Bushfire and Arson (Walsh et al. 2007; Shao et al. 2016, 2020; Zhang et al. 2019).

In this study, we describe the spatial pattern of forest fire and factors influencing the occurrence of fire on a large scale and model the probability of occurrence of fire in Pakistan where this phenomenon is repeated. The calculation of the incidence of fire at this scale may provide guidance for the preparation and execution of fire prevention actions, in particular the strategy of forestry managing plans adapted to different environmental situations. In this study, we assess and compare the relative contribution of climate, vegetation, topography and human activity to the incidence, scale and burnt area of fire in northern Punjab, Pakistan. Pakistan is filled with a

Figure 1. Geographical location of study area, red points referring to the spatial distribution of most forest fire occurrence area.
range of edaphic, physiographic, climatic and wildlife differences (Department BIF 1927; Tanvir and Mujtaba 2006; Abidi et al. 2013; Khalid and Saeed Ahmad 2015). Many fires are scattered across a zone of roughly 11,603 hectares. From 2002 to 2011, 75% of the forest fires last for about 1–4 h and 15% for 4–8 h (Khalid and Saeed Ahmad 2015). The main aim of this research is to identify the spatiotemporal changes in burnt area using Landsat 7 (ETM+ [enhanced thematic mapper plus]) and 8 (OLI/TIRS [operational land imager/thermal infra-red sensor]) data. We used modelling and predicting the fire ignition and size distribution daily and yearly. The geospatial techniques were used to identify burned areas and compare forest fire aspects with various variables including climate, vegetation conditions, topography and human activities from 2005 to 2018. Statistical analysis was used to identify the susceptibility of forest fires dependent on the important effect on fire severity dynamics in the forests of Margalla Hills, Islamabad, Pakistan.

2. Materials and methods

2.1. Study area

This study was conducted in Margalla Hills, Islamabad, capital of Pakistan (33°043′N and 72°055′E; Figure 1). Margalla Hills are situated on the north-eastern part of the Islamabad Capital Territory, Pakistan (Shah et al. 2021). Among Pakistan’s naturally significant safe areas, Margalla National Park contains a scrub tree environment associated with biodiversity. It is located on the north-eastern side of Islamabad, Punjab and occupies nearly 15,883 hectares. This study area extends to the hills of Murree in the east and the Wah Cement Industries in the west. In the west and northwest, it is surrounded by the capital border beyond which the Haripur district Khyber Pakhtun Khwa (KPK) is located (Khalid and Saeed Ahmad 2015). The natural climate is subtropical with mild summers and winters. The average maximum summer temperature of the region is 34.3°C and the average annual rainfall is 1200 mm per year with less snow fall in winter (Ibrar Shin and Ajab Khan 2000). There is no industrial operation

| Year | Number of fires | Duration (cumulative no. of days) | Cumulative days of fire occurrence | Field survey generate map data | Cumulative burnt area (field survey data) | Burnt area (percentage) |
|------|-----------------|----------------------------------|-----------------------------------|------------------------------|------------------------------------------|-------------------------|
| 2005 | 22              | 23                               | 23                                | 2630.63                      | 2630.63                                  | 15.58                   |
| 2006 | 12              | 9                                | 32                                | 1023.53                      | 3654.17                                  | 6.17                    |
| 2007 | 23              | 21                               | 53                                | 2430.36                      | 6084.53                                  | 16.08                   |
| 2008 | 33              | 23                               | 76                                | 2760.35                      | 8844.88                                  | 21.90                   |
| 2009 | 22              | 20                               | 96                                | 1911.34                      | 10,756.23                                | 13.34                   |
| 2010 | 11              | 8                                | 104                               | 972.21                       | 11,728.44                                | 5.81                    |
| 2011 | 15              | 25                               | 129                               | 358.46                       | 12,086.90                                | 2.12                    |
| 2012 | 19              | 33                               | 162                               | 254.82                       | 12,341.72                                | 1.47                    |
| 2013 | 26              | 37                               | 199                               | 987.54                       | 13,329.27                                | 6.40                    |
| 2014 | 36              | 38                               | 237                               | 3051.34                      | 16,380.61                                | 19.78                   |
| 2015 | 23              | 36                               | 273                               | 3125.55                      | 19,506.17                                | 20.62                   |
| 2016 | 22              | 18                               | 291                               | 315.54                       | 19,821.71                                | 2.20                    |
| 2017 | 17              | 26                               | 317                               | 2935.93                      | 22,757.65                                | 21.14                   |
| 2018 | 18              | 20                               | 337                               | 1491.63                      | 24,249.28                                | 9.80                    |
to clear trees and the population density level is very small, i.e. less than 15 people per km² in the study area (Khalid and Saeed Ahmad 2015; Tariq and Shu 2020).

Each year, Margalla Hills experience fire incidents mainly in the Chir pine (*Pinus roxburghii* Sarg.) owing to their dry indicators as a litter over the field having raisin in it and is often named as ‘hot wood’. Incidents of fire arise because of two primary causes, i.e. normal and anthropogenic behaviour. Rock weathering, lightening and hot environment are the normal means of forest fire rising and spreading in the area, while human presence and disturbance in the woodland region and cause of woodland vegetation burning fall in second place based on reports of fire incidents (Brooks and Lusk 2008; Iqbal et al. 2013; Collen et al. 2015).

### 2.2. Forest fire occurrence data

The geo-database of forest fire is founded on a data archive, covering completely recorded forest fires during various field surveys conducted from 15 June 2005 to 12 July 2018 (14 consecutive years) (Table 1). Forest fire occurrence and field survey data are obtained from CDA, Islamabad. A total number of 299 fires were recorded in the Margalla Hills, 30 of which were lightning-ignited as indicated in Figure 1. Small patches origins of the fire are mostly unknown. Each fire statement included numerous variables such as location of the explosion, time, day of ignition, finally burned area, environment and approximate reason. All these forest fires erupted in May, June and July showing that summer is the main fire season in the study area.

### 2.3. Ancillary data

The main source of digital data correlated to all variables influencing the forest area was the CDA, Islamabad Pakistan. The maps are two-dimensional (2D) and three-dimensional (3D) data and topographic maps. Meteorological data including precipitation, humidity, mean daily wind speed, mean daily maximum and minimum temperature were obtained from Pakistan Meteorological Department (PMD), Islamabad, Pakistan. ArcGIS 10.6 was used to perform both digital data analysis and spatial modelling. A geodatabase was created for residential areas, boundary lines, paved/unpaved, forest road and residential road network. All spatial data are available at a scale of 1:20,000, as a representation of universal transverse Mercator (UTM), zone 43 and as WGS84 Datum.

### 2.4. Remote sensing data and processing

We obtained Landsat 7 (ETM+) data for the years 2005–2012 and Landsat 8 (OLI + TIRS) data for the years 2013–2018. All available Landsat (ETM + OLI/TIRS) data between 2005 and 2018 (cloud cover 0–3%) was obtained from USGS-EROS (U.S. Geological Survey’s Earth Resources Observation and Science) (https://www.usgs.gov/). In Landsat 7 (ETM+), Scan lines were removed to enhance the image’s visualization using (plugin/extension) Landsat_gapfills.sav in Envi v_5.4. Scan lines are gaps that occurred due to the scan line corrector (SLC) mechanical failure of all
USGS Landsat 7 imagery collected after 31 May 2003. However, these items are also valuable and maintain the same radiometric and geometric corrections as the data obtained prior to the failure of the SLC. Interoperability between Envi v_5.4 and ArcMap 10.6 was very helpful when the scanning lines were eliminated. Envi v_5.4 has the option to calibrate multispectral bands at a time, which saves time relative to older models where calibration was performed independently on each band. In order for Envi v_5.4 to read the available bands in the folder and group them, the files must be in TIFF format. However, when scanning line removal feature is activated using Landsat_gapfill, the resulting band is an Envi file with emp. and .hdr extensions. Thus, the removal of the scan line was done on each band available in 2005–2013 data and the product for each band was exported as a TIFF file in the ArcMap 10.6 environment. Noise reduction, topography correction, radiometric calibration and atmospheric correction using a FLAASH module (Schläpfer and Richter 2015; U.S. Environmental Protection Agency 2016; Avtar et al. 2019; Luo and Ding 2019). Later, Landsat 7 and 8 images were used as inputs to generate normalized differentiated vegetation index (NDVI), normalized burn ratio (NBR) and delta normalized burn ratio (dNBR) images. From 2005 to 2018, Landsat images were used, one image from pre-fire and one from post-fire were analysed. Landsat ETM + and OLI/TIRS images with 08 bands were used to estimate pre- and post-fire burned area from 2005 to 2018. NDVI, NBR and dNBR areas were identified using ERDAS imagine 2016.

2.5. Burned area mapping

Burnt area analysis was done separately using Landsat 7 and Landsat 8 datasets, and all the pixels identified as burned were compiled into a composite image. Different burned area maps were created from the images acquired by Landsat sensors from May 2005 to July 2018. All maps were exported at same 30-m resolution.

We sampled top-of-atmosphere (TOA) images from ETM+ and OLI across the study area. While past studies had shown that surface reflection, data would remove differences due to atmospheric effects (Viegas 1998; Masek et al. 2006; Negi and Kumar 2016; Shao et al. 2019). At the time of test, not all of the sensors examined in this analysis had surface reflectance data stored in the USGS Earth Explorer, the primary objective of which was the application of this sample.

Hence, TOA correction methods were used; precisely, for Landsat ETM+ and OLI, radiometric correction to Level 1 TOA (Ouaidrari and Vermote 1999; Storey et al. 2014). Throughout ENVI 5.4, both data extraction and pre-processing of images (conversion of digital number [DN] to reflection) were performed. Stacking layers requires merging bands to create a single multispectral image. Analysis method was used to clip the area of study. Burned areas were marked by the disparity between each date and the base mosaic in the value of two satellite indices. For each year, two maps were created from ArcGIS 10.6 software, using Landsat images and exporting the maps. Because during a particular period, after obtaining two desired images (pre and post), an algorithm was performed on the satellite images to measure burned areas and also to match the ancillary data received by Islamabad, CDA (Lesmeister et al. 2019).
Three indices were used to measure burned area from Landsat data. The NDVI is the most frequently used band ratio in ecological science and widely used in range-land experiments, though with differing degrees of performance. NDVI is a plant predictor which was considered to be a valuable covariate in DSM (Mulder et al. 2011). This measure has values varying from −1 to 1 (Jensen and Lulla 1987). The typical green vegetation range is from 0.2 to 0.8. NDVI was further explained using Equation (1) (Escuin et al. 2008).

\[
\text{NDVI} = \frac{(\text{Band}^{\text{RED}} - \text{Band}^{\text{NIR}})}{(\text{Band}^{\text{RED}} + \text{Band}^{\text{NIR}})}
\]

where Band^{RED} denotes 0.63–0.69 μm wavelengths, and Band^{NIR} involves wavelengths of 0.76–0.86 μm. We required two images for the calculation of NBR following Equation (2) (Escuin et al. 2008). NBR was measured from an image shortly before burning, and a second NBR is estimated for an image just after burning.

\[
\text{NBR} = \frac{(\text{Band}^{\text{NIR}} - \text{Band}^{\text{SWIR}})}{(\text{Band}^{\text{NIR}} + \text{Band}^{\text{SWIR}})}
\]

where Band^{NIR} denotes 0.76–0.90 μm wavelengths, and Band^{SWIR} involves wavelengths of 2.09–2.35 μm. The dNBR was calculated using Equation (3) (Veraverbeke et al. 2010). The NBR was used for determining the severity of a fire. Burned frequency and severity are determined by differentiating between these two index layers:

\[
\text{dNBR} = (\text{NBR}^{\text{Pre–fire}} - \text{NBR}^{\text{Post–fire}})
\]

High values range of dNBR indicates more severe damage and negative range values suggest decreased vegetation productivity after-fire. ‘Non-processing zones’ contain portions of the background covered by fog or haze or wet areas. Normalized burn ratio – field survey data (NBR-FD) based on the field survey data was conducted by CDA, Islamabad and they also calculated burnt area after forest fire. Delta normalized burn ratio – field survey data (dNBR-FD) was extracted from pre- and post-fire field survey difference and both files (NBR and dNBR) were provided to us in the form of shape files of burned area. Processed satellite data and the CDA field data were grouped in two clusters. The first cluster shows calculated indices of NDVI, NBR and dNBR, and second cluster used ground field derived data including NBR-FD and dNBR-FD. Correlation matrices between Landsat image and CDA field data were estimated and all variables were performed in R software. Correlations having absolute values greater than 0.6 were tallied within the field and image categories were named by sensor type and strength of the Pearson correlation coefficient.

2.6. Spatial analysis

Environmental factors data were acquired from the ALOS-PALSAR Digital Elevation Model (DEM) with a 10 m utilizing surface analysis functions. The DEM was obtained at a spatial resolution of 12.5 m from synthetic aperture radar (SAR) data.
from the L-band. In this analysis, the DEM has been resampled (coarse gridded) to 30 m spatial resolution. Terrain attributes, i.e. slope, aspect, curvature plane, terrain position index (TPI) and topographic wetness index (TWI), were obtained from the DEM using SAGA-GIS. Forest density was estimated using Landsat images of 30 m spatial resolution. The NDVI, using sub-pixel classification and converted into 30 m² spatial resolution according to all RS data.

Various GIS and RS functions were used to model climatic factors (Radha Krishna Murthy 2004; Bhunia et al. 2011; Samanta et al. 2011). Mean daily meteorological data were gathered from the meteorological stations. All these data types were generalized to measure meteorological layers with a cell size of 30 m². To this aim, a multiple regression approach has been employed. Each variable was linked to the corresponding coordinates and elevation data, including mean maximum temperature, mean minimum temperature, mean relative humidity, wind speed and rainfall. To obtain the smallest discrepancy between observable data and negative simulated data, various configurations have been evaluated. X, Y coordinates and every cells’ middle Z values were obtained by developing a DTM (digital terrain model) array of 10 m². An algebraic equation was used by examining all variables of meteorology and then interpolated methods were used in the spatial analyst tool in Arc GIS 10.6 software package.

Then, various factors induced by anthropogenic activities were evaluated, comprising of the residential area, paved and unpaved/dirty roads. The distance from forest road maps was generated through connectivity and spread utilities (Cutler et al. 2007), while the kernel density function was applied to prepare the population density layer (Table 2).

### Table 2. List of climatic, vegetation, topography and human activities concerning the fire occurrence and its sources.

| Type of data          | Environmental covariates                                    | Sources   |
|-----------------------|-------------------------------------------------------------|-----------|
| Remote sensing        | Landsat 7                                                   | Landsat   |
|                       | Landsat 8                                                   | Landsat   |
| Forest density        | Normalized differentiate vegetation index (NDVI)            | Landsat   |
| DEM                   | Elevation (m)                                               | ALOSPALSR |
| Slope                 | Slope degree                                                | ALOSPALSR |
| Aspect                | Aspect degree                                               | ALOSPALSR |
| Plan curvature        | Direction of slope                                          | ALOSPALSR |
| TWI                   | Topographic wetness index (TWI)                             | ALOSPALSR |
| TPI                   | Terrain position index (TPI)                                | ALOSPALSR |
| Temperature           | Mean monthly quarterly temperature                           | PMD       |
| Precipitation         | Mean monthly quarterly precipitation                         | PMD       |
| Relative humidity     | Mean monthly quarterly and annual humidity                  | PMD       |
| Wind speed            | Mean monthly, quarterly and annual wind speed                | PMD       |
| Population density    | Population density (people/km²)                             | CDA       |
| Residential distance  | Distance to the residential (m)                             | OSM       |
| Paved road distance   | Distance to the paved road (m)                              | OSM       |
| Unpaved/dirty road    | Distance to the dirty road (m)                              | OSM       |
| Forest road distance  | Distance to the forest road (m)                             | OSM       |

2.7. Statistical analysis

The severity of forest fire was seen from the beginning to the end of the fire across the entire burned field. Total burned extents were assessed against duration (days).
The time for burning was calculated from this curve by applying a logistic function to the total burned areas as shown in Equation (4) (Abdi et al. 2018).

\[ G = \frac{F_x}{1 + \exp\left[a(t - b)\right]} \]  

where \( G \) = total burnt area versus duration (hours, time), \( F_x \) = maximum burned area, \( b = \) duration/time to reach 50% of all total burned areas, \( a = \) calculated by an iterative process of optimization to reduce the observed minus the predicted value. The periods for 5%, 10%, 90% and 95% were also calculated by interpolation and were referred to as A5, A10, A90 and A95, respectively.

The zonal statistics method was used to measure the mean values of climatic, vegetation, topography and human activities for each fire area. Therefore the stepwise multiple regression approach (Chou et al. 1993) was supported out to invent the association between predictors and dependent which was compiled in the R Package software. In the model, the dependent variables wildfire severity was connected with the four-factor variables (climatic, vegetation, topography and human activities). Variables with a greater correlation were added, and lower correlation variables were discarded. Ultimately, numerical models of susceptibility to forest fire were created. Spatial maps of susceptibility to forest fire were produced in a raster format. Later these maps were divided into three groups using the equal interval process.

3. Results and discussion

3.1. Burned area mapping

Figure 2 shows the dNBR maps of Margalla Hills in different distinguished colours from 2005 to 2018, respectively. It can be observed that delta normalized burned area
is concentrated in the eastern, central and southern areas and had been expanding from 2005 to 2018. The proportion of delta NBR increased from 1.4% to 21.9% in 2005–2018. dNBR areas are mainly located near residential and road network covered areas. However, no changes have been detected in the north and northwestern vegetative cover areas, since they are located in the mountains. Similarly, no case was reported near water bodies. NBR, dNBR, NBR-FD and dNBR-FD burn severity indices indicated higher proportion of significant correlation greater than 0.6 within the variables (Table 3). Comparison of NBR, NBR-FD, dNBR and dNBR-FD showed that dNBR worked in a general way. NBR correlation with field attributes immediate post-fire effects after capturing post-fire image as indicated by comparing the dNBR and NBR for various individual fires. dNBR produced better correlation after various weeks have elapsed since burning.

Table 3. Pearson correlation between satellite-derived and ground-based derived results.

|         | NBR  | dNBR | NBR-FD | dNBR-FD |
|---------|------|------|--------|---------|
| NBR     | 1.0000 | 0.0695 | 0.0344 | 0.9997  |
| dNBR    | 0.0695 | 1.0000 | 0.9874 | 0.0715  |
| NBR-FD  | 0.0344 | 0.9874 | 1.0000 | 0.0385  |
| dNBR-FD | 0.9997 | 0.0715 | 0.0385 | 1.0000  |

Figure 3. (a) Logistic regression comparison between burnt area and fire duration in the experimental region and (b) total days of incidence of fire against burnt region (total cumulative days).

Table 4. Stepwise regression results based on the factors affecting forest fire occurrence in the study area.

| Factors                                   | Sig.   | F      | R²   |
|-------------------------------------------|--------|--------|------|
| Fire durability                           |        |        |      |
| Forest density                            | 0.0030 | 11.32  | 81.27|
| Average warmest wind speed quarter (AWWQ) | 0.0432 | 5.01   | 59.81|
| Average warmest quarterly minimum temperature (AWQmiT) | 0.0210 | 21.93  | 55.46|
| Average warmest quarterly maximum temperature (AWQmaT) | 0.0023 | 24.64  | 58.23|
| Distance to roads                         | 0.0002 | 8.96   | 82.64|
| Topographic wetness index (TWI)           | 0.0001 | 5.34   | 44.59|
| Terrain position index (TPI)              | 0.0001 | 11.23  | 60.94|
| Burnt area                                |        |        |      |
| Average warmest quarter minimum temperature (AWQmiT) | 0.006  | 9.1    | 27.48|
| Average warmest quarter maximum temperature (AWQmaT) | 0.007  | 8.3    | 84.58|
| Forest density                            | 0.001  | 132.01 | 82.24|
| Population density                        | 0.002  | 4.34   | 78.34|
| Residential distance                      | 0.003  | 8.33   | 81.34|
3.2 Climatic, vegetation, topography and human activities concerning forest fire

Forest fires are a major contemporary challenge to valuable forest resources in the Margalla region, Islamabad. Nearly 25,812.36 hectares of forest area was burned during May 2005 to July 2018. The scale of the fire patches was estimated as 0.3–2523 hectares (Figure 2). In general, during less than a month, almost 7% of the trees were burned. Logistic model findings show that the burned areas have increased at a pace of 25.848 ha/day (Figure 3(a); $R^2 = 0.98$). Furthermore, the figures show that approximately 50% of the overall region was burned over a period of 25 days. The remaining 50% area was burned during the following 13 days period and 1707.3 ha/year (Figure 3(b); $R^2 = 0.97$). The rate the fire extent increased at the end of the period revealed that fire exploitation and prevention operations were unsuccessful.

Table 5. Long-term estimates of climate parameters during the forest fire period (1990–2018).

| Climatic variables                                      | Average statistics for May, June and July | Long term 2005–2018 |
|----------------------------------------------------------|------------------------------------------|---------------------|
| Average warmest quarter minimum temperature (AWQmiT)     | 18.24                                    | 23.04               |
| Average warmest quarter maximum temperature (AWQmaT)     | 28.52                                    | 36.23               |
| Average warmest quarterly precipitation (AWQP)           | 98.23                                    | 116.22              |
| Average warmest wind speed quarter (AWWQ)               | 7.30                                     | 13.32               |
| Average warmest relative humidity quarter (AWRQ)         | 72.34                                    | 55.32               |
| Frequency of precipitation (day)                         | 11.23                                    | 4.79                |

Figure 4. Spatially overlapping of average warmest wind speed quarter and burnt areas.
The effects of the climatic, vegetation, topographic and human activities on frequency of forest fire occurrence are seen in Table 4 on stepwise regression. The initiation and spreading of a fire are primarily influenced by the surface fuels ‘water vapours, the trees’ moisture content and the wind direction. The litter quality content to be measured is given by different limitations, e.g. air temperature and rainfall (FAO 2009). Climatic variables were prepared for the fire amount in the Margalla Hills. During the study period from June 2005 to July 2018, the average warmest quarterly maximum temperature (AWQmaT) was observed at approximately 7.84 °C that is higher than the long-term AWQmaT from 1990 to 2018. Average warmest quarterly minimum temperature (AWQmiT) was approximately 4.80 °C higher than the long-term average AWQmiT from 1990 to 2018, average warmest quarterly precipitation (AWQP) was 17.99 mm lower than the long-term AWQP from 1990 to 2018, and average warmest relative humidity quarter (AWRQ) was almost 17% greater than the long-term AWRQ from 1990 to 2018. The average warmest wind speed quarter (AWWQ) was between 23.04 km/h from 2005 to 2018, which is 5.30 km/h less than that was during the long-term AWWQ from 1990 to 2018 (Table 4). Statistical results of climate factors indicate that daily AWQmiT, average warmest quarterly maximum temperature (AWQmaT) and AWWQ, mainly affected the time of forest fires in the research area ($R^2 = 0.59$). However, there were no meaningful correlations between the selected parameters and the severity of the fires.

Figure 5. Spatially overlapping of daily average warmest quarterly minimum temperature (AWQmiT) and burned areas.
Figure 4 demonstrates that the maximum patches of fire existed in the regions of AWWQ. Furthermore, our analysis indicated that AWQmiT of P = 0.210 and average warmest quarter maximum temperature (AWQmaT) of P = 0.0023 was affected by both the duration of fire and the spread of fire, more by the duration of fire than by the spread of fire in all fire patches (Table 5).

Figure 5 demonstrates that fires at low temperature had no correlation with burned areas. Low temperature did not have a correlation with other parameters. Fires occurring at maximum temperatures demonstrated more severe intensity than those occurring at minimum temperatures (Figure 6). Previous studies have suggested that the environment provides a major influence on the intensity of fire and the fire activity under severe climate change pressure (Parks et al. 2011; Seneviratne et al. 2012; Abidi et al. 2013; Tien Bui et al. 2019). In this study, AWQP, AWWQ and AWRQ displayed minor variations during wildfires and no major fire intensity impact. The findings of earlier studies suggest that the risk of forest fire incidence is strongly linked to the annual volume of precipitation (Zhang et al. 2011; Mohammadi et al. 2014). Moreover, road distance had a strong positive association with longevity of forest fire across all the variables. The decision coefficient ($R^2$) for the model to 82.34% as this element was applied to the regression model.

Figure 7 shows that the forest road network did follow forest road requirements in the study region. The density of road was 3.93 m/ha and coverage of the network of
road was detected in 32.98% of the research area. Thus, ideal road density can decline the incidence and fire period, since it is easier to reach fire-prone areas. In forest fire studies the proximity to a road density is a known significant factor (Zhang et al. 2011). An analysis of the destroyed woods found that the bulk of fire spots were in very low road intensity areas. It is, therefore, necessary to find optimum density of road (approximately 20 m/ha) and fair road network coverage (up to 65%) within forest zones (Lotfalian et al. 2016). Access roads enable fire engine movement and reduce the travel time for fire crews to get to forest fires. In such woods, paths may be substituted as main forest roads with low path width. Tracks are also essential for the safety of forest fires because they link to the road network and often serve as a firebreak. They require larger and easier movements to combat a fire within or at the outskirts of a forest (FAO 2009). Certain variables that were anthropogenically mediated showed no major impact on wildfire period (P –0.05). Spatial data (Figures 1 and 2) indicate that most wildfires happened in regions with small density of population and at a long distance from public highways. In some cases, average coverage of fire patches is less than 1 km from built-up areas and 1.34 km from civic highways. Some forest patches are located more than 2 km away from residential areas and approximately 1.5 km away from public highways.

Many parks and hiking trails are present in the study area. Human activities, e.g. mining, hiking, farming and timber harvesting could be related to fires. This indicates the need for specific studies into trends, seasonal arrangements and ranges of dissimilar forms of anthropogenic actions in fire-sensitive areas. The regression analysis

![Burned areas overlapping with and outside of the forest road network.](image)
indicates that forest composition has greatly influenced the intensity of fire in terms of environmental variables (Table 4). Forest density not only influenced the fire distribution ($R^2 = 0.82$) but also greatly increased fire patch length ($P < 0.001$).

The NDVI values range from minimum $-0.13$ to maximum $0.56$ (Figure 8). The high NDVI values are related to high density of forests. The high-density woods are distinguished by a dense tree crown system, where fire is expected to propagate as an aggressive crown burn, resulting in greater fuel accumulation and therefore increasing the intensity of burning (Duane et al. 2015; Duane 2018). Most of the forest fires occur in the dense forest areas of the Margalla Hills (Figure 6). Moreover, in woodland systems with high closing canopy, probability of crown fires is higher due to a rise in vertical and horizontal cohesion (Pourtaghi et al. 2015). Our analysis found no important association between fire intensity ($P = 0.06$) and topographic parameters (aspect, slope, TPI, TWI and plan curvature). Nevertheless, most fires happened in the eastern and southwestern parts. Nearly 52% of the fire-prone areas are located in the eastern part, as this area received less humidity and more sun radiation (Chuvieco et al. 2019). The average slope in the burned areas was less steep and estimated at approximately 44%. Various studies have found that as the slope increase, the gap and angle between fire and materials reduces which contributes to more severe intensity of fires (Finney and McAllister 2011; Lecina-Diaz et al. 2014; Werth et al. 2016). However, in our study area slope has not shown any major impact on the intensity of the fire.
Figure 9 illustrates that risk analysis of forest fire using critical fire resilience criteria classifies three threat levels by intensity. According to the analysis, 53% of forests are located in the very low-risk severity level (0.25–0.45), 25% are in the low-risk level (0.45–0.65) and 22% in the high and very high-risk level (>0.65). Table 4 indicates that the path to the forest road was the best predictor with a determination coefficient of 72.64% affecting the length of the forest fire. Our results indicate that in all the woods, average road density was around 3.23 m/ha, although in the fire areas this number was somewhat smaller, 2.14 m/ha (Figure 7).

Road density in the study region is far from the appropriate requirements, i.e. 20 m/ha. Due to the length of the fires, nearly 2/3 of the research region is in the medium and above threat range and it is impossible to establish a network of forest road of acceptable capacity and good coverage. Moreover, the results of the fire spread probability map displayed that the huge common (80%) of forests are situated at very low severity (69%), low severity (6%) and high and very high severity levels (5%) (Figure 10). Larger forest patches with longer burn periods seemed to locate in the remote extents of low road coverage that were situated mainly at higher elevations. Therefore, less road lines increase fuel cohesion and result in a less fractured region. As an outcome, bigger and lengthier fires occurred, especially in areas of minor road density and timid road network cover. Additionally, in ground-based activities, greater fires appeared in remote areas with limited visibility for firefighting teams (Pew and Larsen 2001; Holsinger et al. 2016). Lower road densities render it safer for the fire departments to reach gear and function as firebreaks in fire
suppression (Narayanaraj and Wimberly 2012; Ricotta et al. 2018). The major influencing factor in human-induced fires is the distance to the forest route. Greater road masses represent a greater degree of human operations and disturbances (Syphard et al. 2007, 2011). Their analysis offers innovative data on the correlation of climatic, vegetation, topography and human activities in the Margalla Hills and on the resilience of fire and fire spread over a brief period. While the intensity of fire is affected by environmental factors and high density of forest, roads of forest are the single biggest manipulating restriction for extending the time of a fire, mainly in complex elevated woods, comparatively lower density of road and lower road network cover.

4. Conclusion

Wildfires pose a significant danger to the Margalla Hills forests, Islamabad, Pakistan. Forest fires are major contemporary challenge to forest resources conservation in Margalla, Islamabad. Almost 25,812.36 ha forest area was burned from May 2005 to July 2018. The burned area was estimated using Landsat data and validated with field data. The scale of the fire patches was estimated as 0.3–2523 hectares. Our findings show that with increasing cumulative days after the start of forest fire the burned areas have increased in the months of May, June and July (2005–2018) at a pace of 25.848 ha/day. Average burned area was 1707.3 ha/year, that eventually increase burning around 7% of the overall forested region in less than a month. We investigated the variables affecting the length of these wildfires and their distribution.

Figure 10. Susceptibility map of spreading forest fires.
Many variables, such as weather conditions and human activities, fuel characteristics of fire management activities, and changes in land use and climate, affect fire behaviours. Climate change is considered among these factors to be a key factor attributable to forest fires. We compared the factors that affected the forest fire. The results showed that during this span of time, forest density had a significant relationship with fire activities. There was no strong correlation between topographic parameters (aspect, curvature of the plan and slope). We also found an intriguing connection between the severity of the fire and the mean daily temperature, whereas wind speed only had a significant influence on the duration of the fire. During the forest fire, there were no significant correlations between fire severity and other climatic factors (daily rainfall and humidity). Forest density had a major effect on the length and distribution of forest fires among the parameters of the study. While topographical factors (TPI, slope, aspect, TWI, and curvature of the plane) hardly take effect. Through spatial analysis, it is found that in certain areas with extensive forest coverage, such as the southwestern and eastern sections of our study location, major fires happened. We also observed an interesting association between fire intensity (fire spread and duration/time) and mean temperature, although wind direction only affected the length of fire substantially. During a forest fire, there were no important differences between the intensity of the fire and other environmental conditions (mean precipitation and humidity). Many forests in Pakistan have a low forest road network and therefore, it is difficult to reach the whole forest area. Spatial analyses found that most wildfires happened in less populated areas and at a long distance from public roads, but some anthropogenic behaviours could have influenced fire growth. In practice, RS and GIS is a useful technique for exploring forest fire and their distribution. By using various meteorological models to evaluate the impact of weather on forest region and the influence of urban heat island in Islamabad, this work can be further elaborated.

Acknowledgements

We are also thankful to Dr. Shazada Adnan, Pakistan Meteorological Department, Islamabad, Pakistan; they are providing all meteorological data related to this research. We also admire Dr. Muhammad Imran of Institute of Geoinformation and Earth Observation (IGEO), University of Arid Agriculture, Rawalpindi for their facilitation at various stages of the field campaign. We are highly thankful to the unspecified reviewers and editor of journal for their enthusiastic support and valuable suggestions during the review of the manuscript. All the authors would like to say thanks to Miss Merry and Stephen C. McClure for their enthusiastic support and valuable suggestions during the review of the manuscript.

Disclosure statement

The authors declare that there is no conflict of interest in this manuscript’s publication. Moreover, the writers have thoroughly addressed ethical issues, including plagiarism, informed consent, fraud, data manufacturing and/or falsification, dual publication and/or submission and redundancy.

Funding

This research was supported by the National Natural Science Foundation of China (No. 41871345) and the National Key Research and Development Program of China (Grant No. 2019YFE0127700).
Author contributions

A.T.: conceptualization, writing—review and editing, methodology, software, formal analysis, visualization, data curation, writing—original draft, investigation. H.S.: supervision, conceptualization, writing—review and editing, methodology, software, formal analysis, visualization, data curation, writing—original draft, investigation. S.S.: visualization, validation, investigation, writing—review and editing. B.G.M.: writing—review and editing. I.M.: writing—review and editing. L.L.: supervision, conceptualization, writing—review and editing, methodology, software, formal analysis, visualization, data curation, writing—original draft, investigation and funding. M.F.B.: visualization, validation, investigation. All authors have read and agreed to the published version of the manuscript.

ORCID

Aqil Tariq http://orcid.org/0000-0003-1196-1248
Hong Shu http://orcid.org/0000-0003-2108-1797
Saima Siddiqui http://orcid.org/0000-0003-3020-0233
B. G. Mousa http://orcid.org/0000-0003-1009-6459
Iqra Munir http://orcid.org/0000-0002-8714-6269
Adel Nasri http://orcid.org/0000-0001-6491-5291
Hassan Waqas http://orcid.org/0000-0002-1837-9341
Linlin Lu http://orcid.org/0000-0003-1647-1950
Muhammad Fahad Baqa http://orcid.org/0000-0002-4165-6802

Data availability statement

We would like to pay special and heart whelming thanks to USGS (https://earthexplorer.usgs.gov/) department for providing us Landsat 7 (ETM+) and 8 (OLI/TIRS) data and CDA, Islamabad, Pakistan for digital and all ancillary data. The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to legal restrictions, some data cannot be made publicly available. Data are from the CDA, Islamabad, Pakistan.

References

Abdi O, Kamkar B, Shirvani Z, Da Silva SJ, Buchroithner MF. 2018. Spatial-statistical analysis of factors determining forest fires: a case study from Golestan, Northeast Iran. Geomat Nat Haz Risk. 9(1):267–280.
Abidi A, Ifrah S, Noor J. 2013. Economic analysis of forest management in Pakistan—a case study of Changa Mange and Murree Forest. Munich Personal RePEc Archive. http://mpra.ub.uni-muenchen.de/28086/.
Avtar R, Sahu N, Aggarwal AK, Chakraborty S, Kharrazi A, Yunus AP, Dou J, Kurniawan TA. 2019. Exploring renewable energy resources using remote sensing and GIS—a review. Resources. 8(149):23.
Bhunia GS, Dikhit MR, Kesari S, Sahoo GC, Das P. 2011. Role of remote sensing, geographic bioinformatics system and bioinformatics in kala-azar epidemiology. J Biomed Res. 25(6):373–384.
Bonazountas M, Kallidromitou D, Kassomenos P, Passas N. 2007. A decision support system for managing forest fire casualties. J Environ Manage. 84(4):412–418.
Brooks M, Lusk M. 2008. Fire management and invasive plants. Arlington (VA): U.S. Fish and Wildlife Service.
Calkin DE, Cohen JD, Finney MA, Thompson MP. 2014. How risk management can prevent future wildfire disasters in the wildland-urban interface. Proc Natl Acad Sci USA. 111(2):746–751.

Castelli M, Vanneschi L, Popović A. 2015. Predicting burned areas of forest fires: an artificial intelligence approach. Fire Ecol. 11(1):106–118.

Chen F, Niu S, Tong X, Zhao J, Sun Y, He T. 2014. The impact of precipitation regimes on forest fires in Yunnan Province, Southwest China. Sci World J. 2014:1–9.

Chou YH, Minnich RA, Chase RA. 1993. Mapping probability of fire occurrence in San Jacinto Mountains, California, USA. Environ Manage. 17(1):129–140.

Chuvieco E, Mouillot F, van der Werf GR, San Miguel J, Tanase M, Koutsias N, García M, Yebra M, Padilla M, Gitas I, et al. 2019. Remote sensing of environment historical background and current developments for mapping burned area from satellite Earth observation. Remote Sens Environ. 225:45–64.

Collen B, Kock R, Heinrich M, Smith L, Mace G. 2015. Biodiversity and ecosystems. In: Waage J, Yap C, editors. Thinking beyond sectors for sustainable development. London: Ubiquity Press; p. 3–10. https://www.ubiquitypress.com/site/chapters/10.5334/bao.a/.

Cutler R, Lawler J, Thomas Edwards J, Beard KH, Cutler A, Hess KT, Gibson J. 2007. Random forests for classification in ecology. Ecology. 88(11):2783–2792.

Department BIF. 1927. The Forest Act, 1927. Islamabad.

Duane A. 2018. Assessing global change impacts on fire regimes in Mediterranean ecosystems. [Barcelona]. http://hdl.handle.net/10803/664057

Duane A, Brotons L. 2018. Synoptic weather conditions and changing fire regimes in a Mediterranean environment. Agric For Meteorol. 253–254(January):190–202.

Duane A, Piqué M, Castellnou M, Brotons L. 2015. Predictive modelling of fire occurrences from different fire spread patterns in Mediterranean landscapes. Int J Wildland Fire. 24(3):407–418.

Escuin S, Navarro R, Fernández P. 2008. Fire severity assessment by using NBR (normalized burn ratio) and NDVI (normalized difference vegetation index) derived from LANDSAT TM/ETM images. Int J Remote Sens. 29(4):1053–1073.

FAO. 2009. International handbook on forest fire protection – technical guide for the countries of the Mediterranean basin. 1–163. http://www.fao.org/forestry/27221-06293a5348df37bc8b14e24472df64810.pdf.

Fernandes PAM. 2008. Forest fires in Galicia (Spain): the outcome of unbalanced fire management. J For Econ. 14(3):155–157.

Finney MA, McAllister SS. 2011. A review of fire interactions and mass fires. J Combust. 2011:1–14.

Hastie, T., Tibshirani, R., & Friedman, J. H. (2009). The elements of statistical learning: data mining, inference, and prediction. 2nd ed. New York: Springer.

Holsinger L, Parks SA, Miller C. 2016. Weather, fuels, and topography impede wildland fire spread in western US landscapes. For Ecol Manage. 380:59–69.

Ibrar Shin M, Ajab Khan M. 2000. Vegetation comparison of sacred, reserved and unreserved sites of Rumli village at Margalla Hills National Park, Islamabad. Pak J Biol Sci. 3(10):1681–1683.

Iqbal MF, Riaz KM, Malik AH. 2013. Land use change detection in the limestone exploitation area of Margalla Hills National Park (MHNIP), Islamabad, Pakistan using geo-spatial techniques. J Himal Earth Sci. 46(1):89–98.

Government of Pakistan M of climate change, Islamabad. 2015. Year book 2015–16. 1st ed. Islamabad, Pakistan.

Jensen JR, Lulla K. 1987. Introductory digital image processing: a remote sensing perspective. Geocarto Int. 2(1):65–66. https://www.wildfirelessons.net/HigherLogic/System/DownloadDocumentFile.ashx?DocumentFileKey=9f94b4ed-d5f2-45b8-b198-5677d430e3ae.

Jung J, Kim C, Jayakumar S, Kim S, Han S, Kim DH, Heo J. 2013. Forest fire risk mapping of Kolli Hills, India, considering subjectivity and inconsistency issues. Nat Hazards. 65(3):2129–2146.

Khalid N, Saeed Ahmad S. 2015. Monitoring forest cover change of Margalla Hills over a period of two decades (1992–2011): a spatiotemporal perspective. J Ecosyst Ecography. 6(1):1–8.
Krebs P, Pezzatti GB, Mazzoleni S, Talbot LM, Conedera M. 2010. Fire regime: history and definition of a key concept in disturbance ecology. Theory Biosci. 129(1):53–69.

Lecina-Diaz J, Alvarez A, Retana J. 2014. Extreme fire severity patterns in topographic, convective and wind-driven historical wildfires of Mediterranean pine forests. PLoS One. 9(1):e85127.

Lesmeister DB, Sovern SG, Davis RJ, Bell DM, Gregory MJ, Vogeler JC. 2019. Mixed-severity wildfire and habitat of an old-forest obligate. Ecosphere. 10(4):e02696.

Lotfalian M, Khosrozadeh S, Hosseini SA, Kazemi M, Zare N. 2016. Determination of forest skid trail density in Caspian forests, Iran. J For Sci. 62(2):80–87.

Luo Z, Ding S. 2019. Object detection in remote sensing images based on GaN. ACM Int Conf Proceeding Ser. 57(6):499–503.

Lesmeister DB, Sovern SG, Davis RJ, Bell DM, Gregory MJ, Vogeler JC. 2019. Mixed-severity wildfire and habitat of an old-forest obligate. Ecosphere. 10(4):e02696.

Lotfalian M, Khosrozadeh S, Hosseini SA, Kazemi M, Zare N. 2016. Determination of forest skid trail density in Caspian forests, Iran. J For Sci. 62(2):80–87.

Luo Z, Ding S. 2019. Object detection in remote sensing images based on GaN. ACM Int Conf Proceeding Ser. 57(6):499–503.

Lesmeister DB, Sovern SG, Davis RJ, Bell DM, Gregory MJ, Vogeler JC. 2019. Mixed-severity wildfire and habitat of an old-forest obligate. Ecosphere. 10(4):e02696.

Lotfalian M, Khosrozadeh S, Hosseini SA, Kazemi M, Zare N. 2016. Determination of forest skid trail density in Caspian forests, Iran. J For Sci. 62(2):80–87.

Luo Z, Ding S. 2019. Object detection in remote sensing images based on GaN. ACM Int Conf Proceeding Ser. 57(6):499–503.
Working Groups I and II of the Intergovernmental Panel on Climate Change (IPCC). Cambridge, UK/New York, NY: Cambridge University Press; p. 109–230.

Shah A, Ali K, Nizami SM. 2021. Four decadal urban land degradation in Pakistan a case study of capital city islamabad during 1979–2019. Environ Sustain Indic [Internet]. 10(October 2020):100108. https://doi.org/10.1016/j.indic.2021.100108

Shao Z, Cai J, Fu P, Hu L, Liu T. 2019. Deep learning-based fusion of Landsat-8 and Sentinel-2 images for a harmonized surface reflectance product. Remote Sens Environ. 235:111425.

Shao Z, Fu H, Fu P, Yin L. 2016. Mapping urban impervious surface by fusing optical and SAR data at the decision level. Remote Sens. 8(11):1–21.

Shao Z, Wu W, Guo S. 2020. IHS-GTF: a fusion method for optical and synthetic aperture radar data. Remote Sens. 12(17):1–20.

Storey J, Choate M, Lee K. 2014. Landsat 8 operational land imager on-orbit geometric calibration and performance. Remote Sens. 6(11):11127–11152.

Syphard AD, Keeley JE, Brennan TJ. 2011. Comparing the role of fuel breaks across southern California national forests. For Ecol Manage. 261(11):2038–2048.

Syphard AD, Radoloff VC, Keeley JE, Hawbaker TJ, Clayton MK, Stewart SI, Hammer RB. 2007. Human influence on California fire regimes. Ecol Appl. 17(5):1388–1402.

Tanvir MS, Muitaba IM. 2006. Neural network based correlations for estimating temperature elevation for seawater in MSF desalination process. Desalination. 195(1–3):251–272.

Tariq A, Shu H. 2020. CA-Markov chain analysis of seasonal land surface temperature and land use landcover change using optical multi-temporal satellite data of Faisalabad, Pakistan. Remote Sens. 12(20):3402–3423.

Tien Bui D, Hoang N-D, Samui P. 2019. Spatial pattern analysis and prediction of forest fire using new machine learning approach of multivariate adaptive regression splines and differential flower pollination optimization: a case study at Lao Cai province (Viet Nam). J Environ Manage. 237:476–487. https://linkinghub.elsevier.com/retrieve/pii/S0301479719301239.

U.S. Environmental Protection Agency. 2016. Quality Assurance Guidance Document 2.12. https://www3.epa.gov/ttnamti1/files/ambient/pm25/qa/m212.pdf.

Valdez MC, Chang KT, Chen CF, Chiang SH, Santos JL. 2017. Modelling the spatial variability of wildfire susceptibility in Honduras using remote sensing and geographical information systems. Geomat Nat Hazards Risk. 8(2):876–892.

Veraverbeke S, Lhermitte S, Verstraeten WW, Goossens R. 2010. The temporal dimension of differenced normalized burn ratio (dNBR) fire/burn severity studies: the case of the large 2007 Peloponnese wildfires in Greece. Remote Sens Environ. 114(11):2548–2563.

Viegas DX. 1998. Forest fire propagation. Philos Trans R Soc A Math Phys Eng Sci. 356(1748):2907–2928.

Viegas DX, Bovio G, Ferreira A, Nosenzo A, Sol B. 1999. Comparative study of various methods of fire danger evaluation in southern Europe. Int J Wildland Fire. 9(4):235.

Walsh DJ, Rumba KE, Parsons M, Thackway R. 2007. Reporting fire in Australia’s forests and vegetation. Canberra: Bureau of Rural Sciences.

Werth PA, Potter BE, Alexander ME, Clements CB, Cruz MG, Finney MA, Forthofer JM, Goodrick SL, Hoffman C, Jolly WM, et al. 2016. Synthesis of knowledge of extreme fire behavior: volume 2 for fire behavior specialists, researchers, and meteorologists. Gen. Tech. Rep. No. PNW-GTR-891. Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Research Station. p. 258.

Zhang H, Ning X, Shao Z, Wang H. 2019. Spatiotemporal pattern analysis of China’s cities based on high-resolution imagery from 2000 to 2015. ISPRS Int J Geo-Inf. 8(5):241.

Zhang JH, Yao FM, Liu C, Yang LM, Boken VK. 2011. Detection, emission estimation and risk prediction of forest fires in China using satellite sensors and simulation models in the past three decades – an overview. Int J Environ Res Public Health. 8(8):3156–3178.