Environ Monit Assess (2019) 191(Suppl 3): 791
https://doi.org/10.1007/s10661-019-7695-6

Identification and characterization of spatio-temporal hotspots of forest fires in South Asia

C. Sudhakar Reddy · Natalia Grace Bird · S. Sreelakshmi · T. Maya Manikandan · Mahbooba Asra · P. Hari Krishna · C. S. Jha · P. V. N. Rao · P. G. Diwakar

Received: 6 December 2018 / Accepted: 24 July 2019

Abstract Forest fire is considered as one of the major threats to global biodiversity and a significant source of greenhouse gas emissions. Rising temperatures, weather conditions, and topography promote the incidences of fire due to human ignition in South Asia. Because of its synoptic, multi-spectral, and multi-temporal nature, remote sensing data can be a state of art technology for forest fire management. This study focuses on the spatio-temporal patterns of forest fires and identifying hotspots using the novel geospatial technique "emerging hotspot analysis tool" in South Asia. Daily MODIS active fire locations data of 15 years (2003–2017) has been aggregated in order to characterize fire frequency, fire density, and hotspots. A total of 522,348 active fire points have been used to analyze risk of fires across the forest types. Maximum number of forest fires in South Asia was occurring during the January to May. Spatial analysis identified areas of frequent burning and high fire density in South Asian countries. In South Asia, 51% of forest grid cells were affected by fires in 15 years. Highest number of fire incidences was recorded in tropical moist deciduous forest and tropical dry deciduous forest. The emerging hotspots analysis indicates prevalence of sporadic hotspots, followed by historical hotspots, consecutive hotspots, and persistent hotspots in South Asia. Of the seven South Asian countries, Bangladesh has highest emerging hotspot area (34.2%) in forests, followed by 32.2% in India and 29.5% in Nepal. Study results offer critical insights in delineation of fire vulnerable forest landscapes which will stand as a valuable input for strengthening management of fires in South Asia.

Keywords Forest · Frequency · Density · Emerging · Hotspots, MODIS

This article is part of the Topical Collection on *Terrestrial and Ocean Dynamics: India Perspective*

Electronic supplementary material The online version of this article (https://doi.org/10.1007/s10661-019-7695-6) contains supplementary material, which is available to authorized users.

C. S. Reddy (✉) · N. G. Bird · S. Sreelakshmi · T. M. Manikandan · M. Asra · P. H. Krishna · C. S. Jha · P. V. N. Rao
National Remote Sensing Centre, Indian Space Research Organisation, Balanagar, Hyderabad, Telangana 500 037, India
e-mail: drsudhakarreddy@gmail.com

N. G. Bird
Centre for Spatial Information Technology, Institute of Science and Technology, Jawaharlal Nehru Technological University, Hyderabad, Telangana 500 085, India

S. Sreelakshmi
Indian Institute of Information Technology and Management, Thiruvananthapuram, Kerala 695 581, India

P. H. Krishna
Arid Zone Regional Centre, Botanical Survey of India, Jodhpur, Rajasthan 342 008, India

P. G. Diwakar
Indian Space Research Organisation, Antariksh Bhavan, New BEL Road, Bengaluru, Karnataka 560 231, India

Introduction

Fires occurring over millions of hectares worldwide every year have a major contribution in the processes of deforestation, forest degradation, emissions of trace gases and aerosols, fragmentation, invasion of alien species, and loss of biodiversity (Holdsworth and Uhl 1997). The extent of fires depends on various factors such as the frequency of human disturbances and the climate of the region (Narendran 2001). Irrespective of causes of fires, burning leads to greenhouse gas emissions which have direct influence on atmospheric chemistry and causing ecological damage and economic losses. In tropical deciduous forests, certain species and vegetation communities have developed as a response to fires (Dawson et al. 2002). The fire regime is used to describe fire frequency, density, intensity, and date of occurrence in a given ecosystem or region (Dwyer et al. 2000). Forest fires can be grouped into surface fires, ground fires, underground fires, and crown fires depending upon their nature and size. Surface fire is the most common forest fire in South Asia that burn undergrowth and dead material along the forest floor. Forest fires in South Asia are mostly anthropogenic which includes preparing a land for shifting cultivation, deforestation, controlled burning, to promote new flush of grasses, collection of minor forest produce, and fire wood burning. Shifting cultivation is the major cause of fire in north east India and Bangladesh (Satendra and Kaushik 2012; Reddy et al. 2017a).

Research in tropics was focused on the interactions and synergies between multiple disturbances (Peres et al. 2006). *Lantana camara* is an invasive alien species which has several characteristics that give it an advantage under conditions of frequent fire. It resprouts on being burnt and its seeds are dispersed by birds and animals enabling it to readily germinate following a disturbance. Fire *Lantana* hypothesis indicates that there is a positive feedback between fire incidences and invasion by lantana, leading to a fire *Lantana* cycle that can have damaging consequences for forest ecosystems. Studies confirm that *Lantana camara* is favored by fire disturbance (Hiremath and Sundaram 2005). There is a need to focus on studies related to monitoring and management of fires and their impact on the forests. The fires in Asia are mostly related to rise in temperature and decline in rainfall along with changes in land use (IPCC 2007).

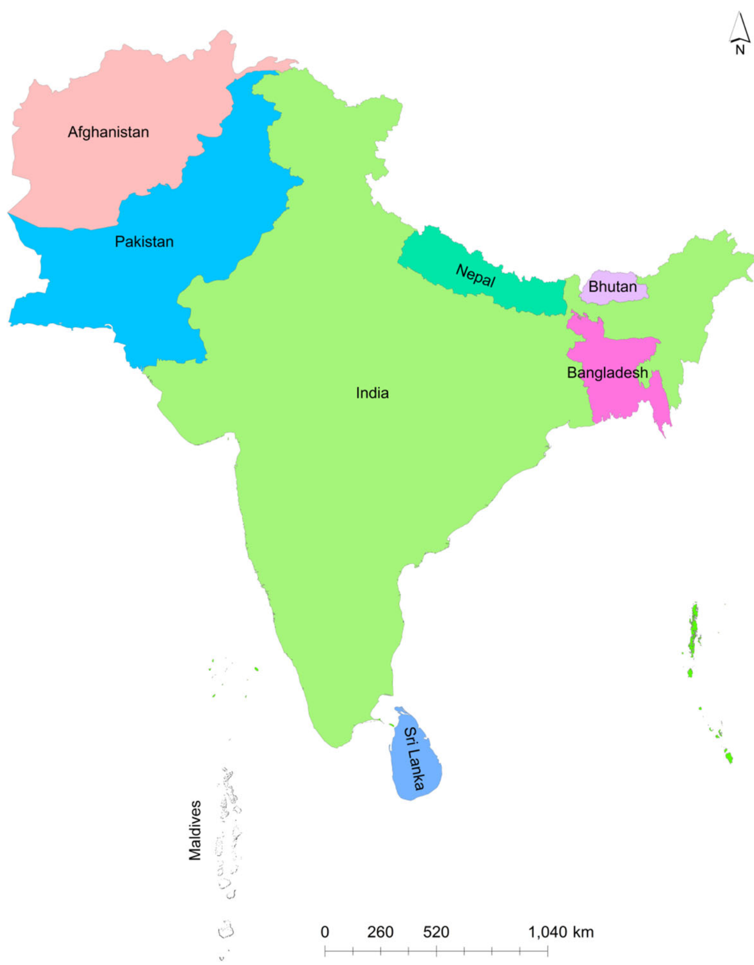
Satellite remote sensing provides comparatively less expensive and verifiable means of obtaining spatial coverage of a large or remote area with important environmental data (Kerr and Ostrovskym 2003). The space-borne sensors with short revisit times and high accuracy measurements make it possible to detect and monitor forest fires (Pausas and Keeley 2009). The applications of remote sensing data for monitoring and supporting implementation of the sustainable development goals, targets, and indicators are being explored and encouraged by the United Nations. Spatial pattern analysis has the potential to support in quick and reliable identification of priority areas for management intervention. Spatial statistics can assist in identifying spatio-temporal trends in the context of forest conservation (Harris et al. 2017). Statistical machine learning methods can provide a mathematically rigorous way of describing sampling and model error, estimating and predicting outcomes of interest and relationships between variables, and quantifying the uncertainty (Holloway and Mengersen 2018).

Detailed review on the use of thermal channels for active fire detection is available in literature (Giglio et al. 2006). Chuvieco et al. (2010) prepared a spatial framework for fire risk assessment using remote sensing and geospatial techniques. Earth observation applications represent a unique platform to observe and assess how risks have evolved over the years are widely applied to disaster risk reduction. At a global level, operational fire monitoring systems are based on MODIS (Moderate-Resolution Imaging Spectroradiometer) sensor data. Near real-time monitoring of forest fires in India is being carried out by National Remote Sensing Centre and Forest Survey of India using MODIS active fire data. Over the past two decades, the increased human activities led to the rise of carbon in atmosphere (Reddy et al. 2017a). The total CO_2 emissions from forest fires in India were estimated as 98.11 Tg during 2014 (Reddy et al. 2017b). A critical issue is that without a clear understanding of the distribution and dynamics of forest fires, effective forest management is difficult (Goldammer and de Ronde 2004). Andela et al. (2017) analyzed long-term trends in burned area from 1998 to 2015 using the Global Fire Emissions Database version 4 product and found that global burned area declined by $24.3 \pm 8.8\%$ over the past 18 years. Spatial association between different forest types and the occurrence of fire incidences at different time periods can provide possible outcome for fire management. With the current trend of forest fires in

South Asia, there is a need to generate a spatial database for research and management-oriented requirements.

Harris et al. (2017) used emerging hotspot analysis tool to determine hotspots of forest loss. Bass (2017) analyzed significant spatial clusters of "hotspots" of manatee mortality in Florida and the temporal patterns of these hotspots using the emerging hotspot analysis. There have been no published work using emerging hotspot analysis tool to determine hotspots of forest fires. This study attempted to prepare a spatial database on distribution of forest fire hotspots using emerging hotspots analysis tool in South Asian countries. This work attempted to integrate satellite derived fire locations over a period of 15 years in order to characterize the spatio-temporal distribution of fire hotspots in South Asia. This study generated the patterns of forest fires across the forest types of South Asia. South Asia comprises the eight countries—India, Bangladesh, Bhutan, Nepal, Pakistan, Afghanistan, Sri Lanka, and Maldives (Fig. 1). It is covering a geographical area of 5,135,270 km^2. The Himalayas, separating South Asia from East Asia along the border of China's region of Tibet, are the highest mountains in the world and the dominant physical feature of the northern rim of South Asia. Other countries that share the Himalayas include Nepal, Bhutan, India, and Pakistan. On the opposite side of the Himalayas are two island countries off the coast of southern India. In South Asia, agricultural land is predominant constituting 43% of the total geographical area followed by barren land (19.9%) and forests (14.7%) (Reddy et al. 2018a). The study in South Asia has demonstrated the conservation priorities by identifying key habitats based on ecological principles, remote sensing, and geospatial techniques (Reddy et al. 2018b).

Fig. 1 Map of study area showing South Asian countries



Materials and methods

Data used

Input data consists of forest cover and forest types of South Asian countries (Reddy et al. 2018a; Fig. 2) and MODIS active fire detections data (https://firms.modaps.eosdis.nasa.gov/). The Resourcesat-2 AWiFS-based spatial database of forest cover and forest types were resampled to 1 km to match with the MODIS resolution. Active fire data from the MODIS instrument on NASA's Terra and Aqua satellites starting from 2003 to 2017 was used. MODIS fire observations are made four times every day from the Terra (10:30 h and 22:30 h) and Aqua (01:30 h and 13:30 h) satellites. The MODIS active fire detections consisted of a set of shape

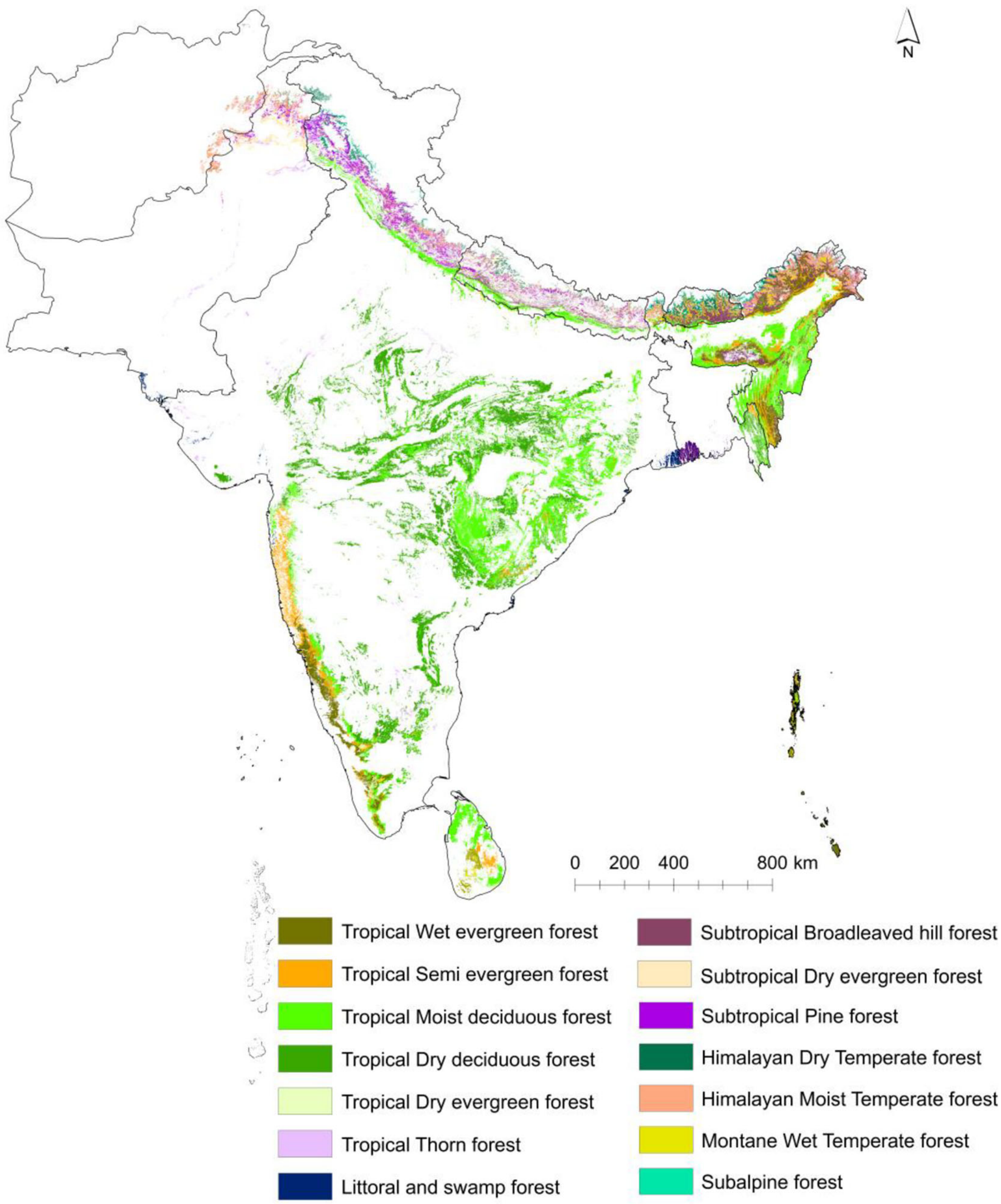


Fig. 2 Forest type map of South Asia (Source: Reddy et al. 2018a)

files with one record per active fire. Information related to each active fire included location (latitude and longitude), date, time, confidence level, and the type of satellite involved (Terra or Aqua). The location of fire corresponds to the center of a 1 × 1 km fire pixel representing one or more fire incidences occurring within the pixel area. The MODIS fire products were downloaded from NASA Fire Information for Resource Management System (FIRMS) data from January 2003 to December 2017 (https://firms.modaps.eosdis.nasa.gov/).

Methodology

Spatial analysis

During the period from 2003 to 2017, MODIS-based active fire detections with confidence levels of 1–100% were included in the analysis. The forest cover and forest type data for South Asia was used to analyze forest fires (Reddy et al. 2018a). In order to characterize fire regimes (fire frequency and fire density), daily MODIS data on active fire locations were aggregated into 5 km × 5 km grid cells. The fire points detected across the forests has been used to estimate emerging hotspots. The framework outlined here determines the spatial and temporal distribution of forest fires.

Emerging hotspot analysis

Hotspot analysis has been used across disciplines to describe a region or value that is higher relative to its surroundings (Getis and Ord 1992; Harris et al. 2017). In this study, hotspot is defined as an area that exhibits statistically significant clustering in the spatial pattern of fire occurrences. Emerging hot spot analysis has been performed at a regional scale (South Asia). Emerging hotspot analysis uses NETCDF (Network Common data Form) file as an input and analyze the bins over the years. The input data is converted into a netCDF data cube structure by aggregating forest fire points in each country into space time bins (ARCGIS 2016). All the bins in NetCDF cube are associated with z-score and p values for each bin. Space time cube is created to summarize a set of points into NetCDF data structures by using space time bins, points data is converted into bins and counts over the year are evaluated. Space time cube bins are represented in x and y directions in time (t). The time step is the time slice or specific time range that the model will aggregate together into a bin (ARCGIS 2016). The time slice was set as end time analysis which is done only for locations with data with at least one point count is greater for at least one time step. End time performs analysis based on the final year data with correspondence to the other year's data; a space time cube is generated which is used as an input for emerging hotspot analysis. According to the specified distances the Getis-Ord GI* is run, if a bin has higher value in each year then it is said to be significantly hotspot, if the bin value in each year is decreasing is said to be a Cold spot (Bass 2017).

According to the time of occurrences in each bin, "emerging hotspot analysis" tool was used to identify statistically significant trends in data such as New, Intensifying, Diminishing, and Sporadic Hotspots. As neighborhood size increases, hot spots become larger and fewer; smaller neighborhood sizes capture more localized trends, inevitably in an element of subjectivity in choosing an appropriate value for neighborhood distance in a field (Harris et al. 2017). Emerging hotspot analysis was run at a neighborhood distance of 5 km. In polygon analysis mask, shape file of South Asia forest was used to avoid identification of hotspots or coldspots in non-forest landscapes. The sign of the z-score indicates if the trend in bin values increases (positive z-score) or decreases (negative z-score). Statistically significant trends have a small p value. Using the calculated hotspot z-score and p value for each bin and the trend z-score and p value, the emerging hotspot analysis tool classifies each location into one of 17 categories (Zhu and Newsam 2016).

The emerging hot spot analysis tool uses the Mann-Kendall statistic to test whether a statistically significant temporal trend exists through each bin's time series of z-scores resulting from the Getis-Ord Gi* statistic. The cluster and trend results from the Getis-Ord Gi* and Mann-Kendall statistics are then used to categorize each bin.

$$Gi^* = \frac{\sum_{j=1}^{n} W_{i,j}x_j - \overline{X}\sum_{j=1}^{n} W_{i,j}}{S\sqrt{\frac{n\sum_{j=1}^{n} W_{i,j}^2 - \left(\sum_{j=1}^{n} W_{i,j}\right)^2}{n-1}}}$$

where x_j is the attribute value for the feature j; $w_{i,j}$ is the spatial weight between feature, i, j; and n is equal to the total number of features.

$$\overline{X} = \frac{\sum_{j=1}^{n} x_j}{n}, \quad S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - \left(\overline{X}\right)^2}$$

Gi^* is a z-score and no further calculations is required.

To be classified into consecutive category, there has to be a consecutive and continuous run of multiple 2-year intervals that occur at the end of the time series and indicates that these areas have relatively recently become hotspots. An oscillating hotspot indicates a location that includes time steps as both hotspots and coldspots, with the final time step being a statistically significant hotspot and less than 90% of the 2-year time step intervals being statistically significant hotspots (Bass 2017). Definitions of hotspots are provided in Table 1.

Results and discussion

Seasonal and annual patterns of forest fires

From 2003 to 2017, a total of 522,348 forest fire occurrences were recorded by MODIS sensors in South Asia. Most of the forest fires occur in South Asia during the pre-monsoon season (January–May) when the weather is hotter and drier (Fig. 3, Table 2). The period of the year in which burning occurs in a given forest is referred to as the fire season. However, low levels of fire activity which may take place throughout the year. To overcome the effect of fire activity in all months, threshold of > 2% fire count based on 15 years data is considered. In India, start of fire season is from January and end of season is May (Table 3). In Afghanistan, fire incidences were more between May and December. In Bhutan, the start of fire season is from December and end of season in May. The fire season in Bangladesh is from March to April. Pakistan had shown different kind of fire pattern, which starts mostly from October and ends in July. In Sri Lanka, fire season is distributed over March to October.

In India, fire incidences were highest in the month of March followed by April from 2003 to 2017. From 2003 to 2017, fire occurrences have no specific trend. The state-wise decadal analysis indicates that from 2003 to 2017, Mizoram has the highest forest fire incidence that is, $n = 64{,}530$ followed by Assam ($n = 40{,}495$), Manipur ($n = 37{,}009$), Madhya Pradesh ($n = 34{,}104$), and Odisha ($n = 34{,}103$). In 2017, Madhya Pradesh has highest fires $n = 4178$, followed by Chhattisgarh ($n = 3781$), Odisha ($n = 2901$), Maharashtra ($n = 2506$), Mizoram ($n = 1843$), Assam ($n = 1766$), Telangana ($n = 1427$), Andhra

Table 1 Definitions of each emerging hotspot category

Hotspot category	Definition
Intensifying	A location that has been a statistically significant hot spot for 90% of the time step intervals, including the final time step. In addition, the intensity of clustering of high counts in each time step is increasing overall and that increase is statistically significant.
Persistent	A location that has been a statistically significant hot spot for 90% of the time step intervals with no discernible trend indicating an increase or decrease in the intensity of clustering over time
Oscillating	A statistically significant hot spot for the final time step interval that has a history of also being a statistically significant cold spot during a prior time step. Less than 90% of the time step intervals have been statistically significant hot spots.
Sporadic	A location that is an on-again then off-again hot spot. Less than 90% of the time step intervals have been statistically significant hot spots and none of the time step intervals have been statistically significant cold spots.
New	A location that is a statistically significant hot spot for the final time step and has never been a statistically significant hot spot before
Diminishing	A location that has been a statistically significant hot spot for 90% of the time step intervals, including the final time step. In addition, the intensity of clustering in each time step is decreasing overall and that decrease is statistically significant.
Historical	The most recent time period is not hot, but at least 90% of the time step intervals have been statistically significant hot spots.
Consecutive	A location with a single uninterrupted run of statistically significant hot spot bins in the final time step intervals. The location has never been a statistically significant hot spot prior to the final hot spot run and less than 90% of all bins are statistically significant hot spots.

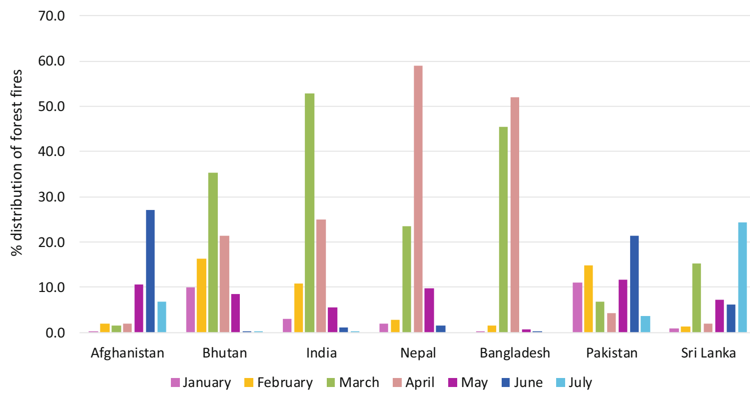


Fig. 3 Distribution of forest fire occurrences in South Asian countries for the months of January to July (2003–2017)

Pradesh ($n = 1360$), and Manipur (1235). High monthly fire incidences were recorded in June for Afghanistan and Pakistan. In contrast to it, Bangladesh and Nepal affected by high number of fire incidences in April. March and April are the peak fire months in most parts of the South Asian region, with the exception of some areas in the Himalayas.

Among the seven countries, India shows highest number (88.1%) of forest fire locations from 2003 to 2017 (Table 3). The year 2009 shows highest fire occurrences in the study period with contribution of 9.9% followed by 2012 (8.7%). The number of fires noticed in this study was extremely high for the 2009. In 2009, the annual mean temperature was 25.6 °C. By the records of meteorological department, 2009 was one of the 12 hottest years in 108 years since 1901 (IMD 2009). In the year 2016, more fires were occurred in Nepal. Distribution of forest fires in South Asian countries (2003–2017) is given in Figs. 4 and 5. Yearly high fire occurrences were noticed in 2016 ($n = 474$) in Pakistan. Annual rate of deforestation in this country was estimated as 2.1% by World Bank in 2009. In 2000, a study revealed that 1.27% out of 3.950 million ha, that is, 49,986 ha area was affected by forest fires (FAO 2009).

Fire frequency

Fire frequency analysis has been carried out at 5 × 5 km grid level. In this analysis, fire frequency describes the number of times the fire returned during the period of 15 years (2003 to 2017). From 2003 to 2017, grid-wise analysis indicates a greater number of fires were sporadic in nature. Of the 15 years, frequency analysis indicates 1–9-year fire-affected forest grid cells in

Table 2 Month-wise cumulative forest fire locations in South Asian countries: 2003–2017 (values are in percentage)

Month	Afghanistan	Bhutan	India	Nepal	Bangladesh	Pakistan	Sri Lanka	South Asia
January	0.2	10.1	2.9	1.9	0.3	11.1	1.0	2.8
February	1.9	16.3	10.9	2.7	1.4	14.7	1.4	10.0
March	1.5	35.2	52.8	23.5	45.4	6.9	15.2	50.2
April	1.9	21.3	24.9	59.0	52.1	4.2	1.9	27.4
May	10.5	8.5	5.4	9.7	0.7	11.7	7.1	5.4
June	27.2	0.3	1.1	1.4	0.0	21.4	6.2	1.4
July	6.7	0.3	0.1	0.0	0.0	3.6	23.2	0.2
August	2.5	0.3	0.0	0.0	0.0	0.6	21.9	0.3
September	10.9	0.8	0.0	0.0	0.0	0.9	14.0	0.2
October	19.9	0.7	0.2	0.0	0.0	5.1	7.1	0.3
November	10.3	1.7	0.5	0.3	0.1	8.5	1.0	0.5
December	6.5	4.5	1.1	1.5	0.1	11.3	0.0	1.2
Total	100.0	100.0	100.0	100.0	100.0	100.0	100.0	100.0

Table 3 Forest fire incidences in South Asian countries: 2003–2017

Country	Afghanistan	Bangladesh	Bhutan	India	Nepal	Pakistan	Sri Lanka	Total	% of total fires
2003	4	1825	131	25,401	1153	57	323	28,894	5.5
2004	42	1799	176	32,923	1378	181	424	36,923	7.1
2005	55	2262	193	25,612	1309	252	354	30,037	5.8
2006	138	2426	282	31,950	995	214	298	36,303	6.9
2007	16	2456	300	33,307	731	268	210	37,288	7.1
2008	29	1824	187	27,392	1542	319	218	31,511	6
2009	11	2332	331	45,839	2289	463	412	51,677	9.9
2010	5	1696	361	35,705	1774	233	181	39,955	7.6
2011	37	1570	213	26,266	1103	98	291	29,578	5.7
2012	17	2058	381	40,135	2076	392	388	45,447	8.7
2013	20	1849	189	24,827	1459	99	257	28,700	5.5
2014	31	1685	315	26,787	1810	199	342	31,169	6
2015	5	889	232	22,612	463	178	148	24,527	4.7
2016	13	1073	185	31,873	4128	474	295	38,041	7.3
2017	102	795	200	29,525	1231	287	158	32,298	6.2
Total	525	26,539	3676	460,154	23,441	3714	4299	522,348	100
Mean	35	1769.3	245.1	30,676.9	1562.7	247.6	286.6	34,823.2	6.7
Std dev	38.1	522.4	76.7	6319.5	857.7	125.2	89.6	8029.2	1.4

Afghanistan. Of the 841 fire-affected grid cells, 57 (64%) shown fire in once in 15 years, whereas about 115 (14%) forest grid cells were affected by fires continuously during the period 2003 to 2017 for Bangladesh. No fires were found in 765 grids which were mostly covered by mangroves. Fire frequency analysis for Bhutan indicates number of grids affected by fire once in 15 years are 215 (36%). About 845 (59%) forest grid cells were not affected by the fire in Bhutan. In Nepal, 1836 (42%) forest grid cells were not affected by fire. Highest number of grid cells (30%) shows fires affected once in 15 years (785). There are 31 grid cells (1%) were affected by fires continuously during 15 years period in Nepal.

No fires were detected in 47% of forest grid cells of India. Fire frequency analysis for Pakistan shows 390 grid cells (47%) were affected by fires in once in 15 years. Number of forest grid cells that were not affected by fires was 71% in Pakistan. Of the 2039 forest grid cells, 316 shows fire incidences once in 15 years in Sri Lanka during the period of 2003 to 2017. One-time fire-affected grid cells were more in number in all South Asian countries. Fire frequency map for South Asia is given in Fig. 6. The map legend gives the fire frequency

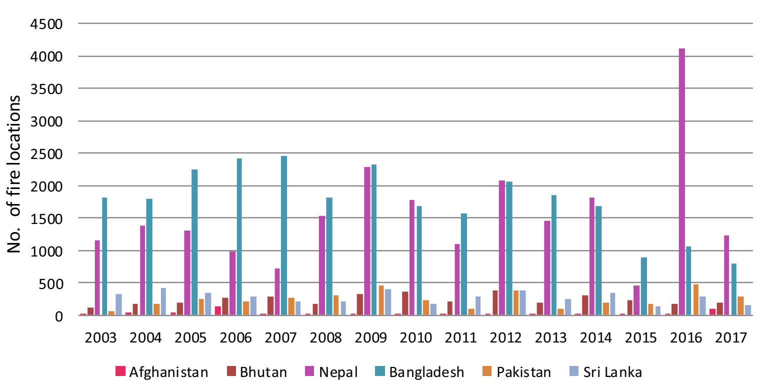


Fig. 4 Distribution of forest fires in South Asian countries (2003–2017)

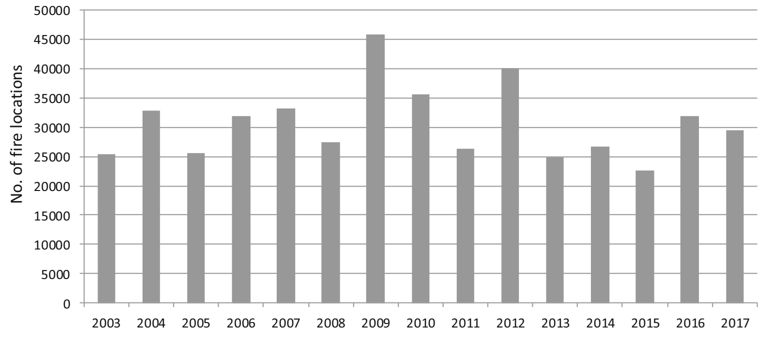


Fig. 5 Distribution of forest fires in India (2003–2017)

and affected number of grid cells (provided in the parenthesis). Spatial analysis indicates 8891 grids were affected by fires only once in 15 years in South Asia. The number of grids affected by fires for 2 years is 5311 grids. Among the forest fire-affected grid cells, 1054 (3%) were affected by fires throughout the study period.

The analysis based on decadal time scale satellite data reveals that 59.6% area of total vegetation cover has been affected by varied rate of frequency of forest fires in Similipal biosphere reserve. Grid-wise analysis shows that 26% grids are having very high disturbance regimes due to repeated fires in the 10 years. The percentage of grids affected by fire in 9 years is estimated at 15.3% followed by 9% in 8 years, 8.2% in 7 years, and 6.6% in 6 years in Similipal biosphere reserve (Saranya et al. 2014). The total cumulative area of 46.6% of total vegetation cover was affected by fires in Nilgiri biosphere reserve from the year 1973 to 2014. The decadal monitoring (2005–2014) has indicated a gradual decline of forest fires over the Nilgiri biosphere reserve. The analysis based on fire-affected grids shows that the frequency grids of 1–5 times were occupying 67.6% followed by 6 times (8.4%), 7 times (7.6%), 8 times (6.2%), 9 times (5.2%), 10 times (3.1%), 11 times

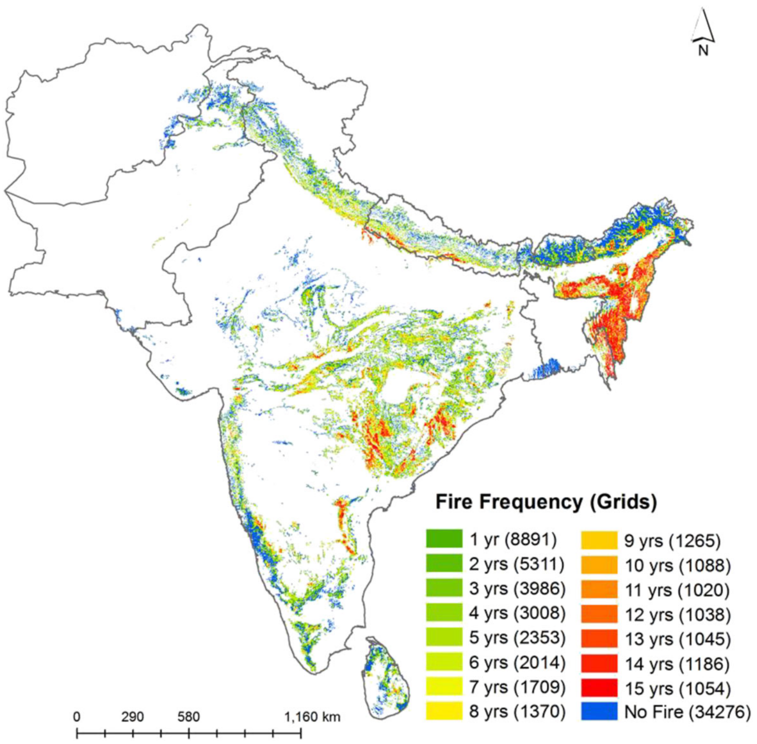


Fig. 6 Forest fire frequency map of South Asia (2003–2017)

(1.3%), 12 times (0.4%), 13 times (0.1%), and 14 times (0.1%) (Reddy et al. 2018c).

Fire density

Fire density analysis has been carried out at 5 × 5 km grid level. At regional level in South Asia, totally 51% of forest grid cells were affected by fires from 2003 to 2017 (Fig. 7). Among the fire-affected grid cells 72% were affected by low fire count (1–13). Fire count analysis indicates 10% of forest grid cells were affected by fire in Afghanistan. In Bangladesh, 445 grid cells have shown less (1–37) fire counts. Fire data for Bangladesh indicates 50% of forest grids affected by fires. Fire density data for Bhutan shows total 41% of forest grid cells were affected by fires. About 53% of grid cells were affected by fires in India. In Nepal, 58% of forest grid cells were affected by fires. Total forest grid cells affected by fires are 830 (29%) in Pakistan. A total of 886 forest grid cells (43%) affected by fires in Sri Lanka. Fire density maps provides the grid cell wise total number of fire occurrences (Fig. 8). The analysis of cumulative fire occurrences from 2001 to 2017 detected the strongest geographic hotspots in North East India.

Forest type wise analysis

There are 13 types of fire prone forests in South Asia, i.e., dry deciduous forest, dry evergreen forest, moist deciduous forest, Himalayan dry temperate forest, Himalayan moist temperate forest, wet evergreen forest, semi-evergreen forest, sub-alpine forest, subtropical broad-leaved forest, subtropical dry evergreen forest, subtropical pine forest, thorn forest, and Montane wet temperate forest. Among the forest types, moist deciduous forest ($n = 174{,}331$) was affected by highest fires followed by dry deciduous forest ($n = 112{,}722$) and semi-evergreen forest ($n = 53{,}726$) (Tables 4 and 5).

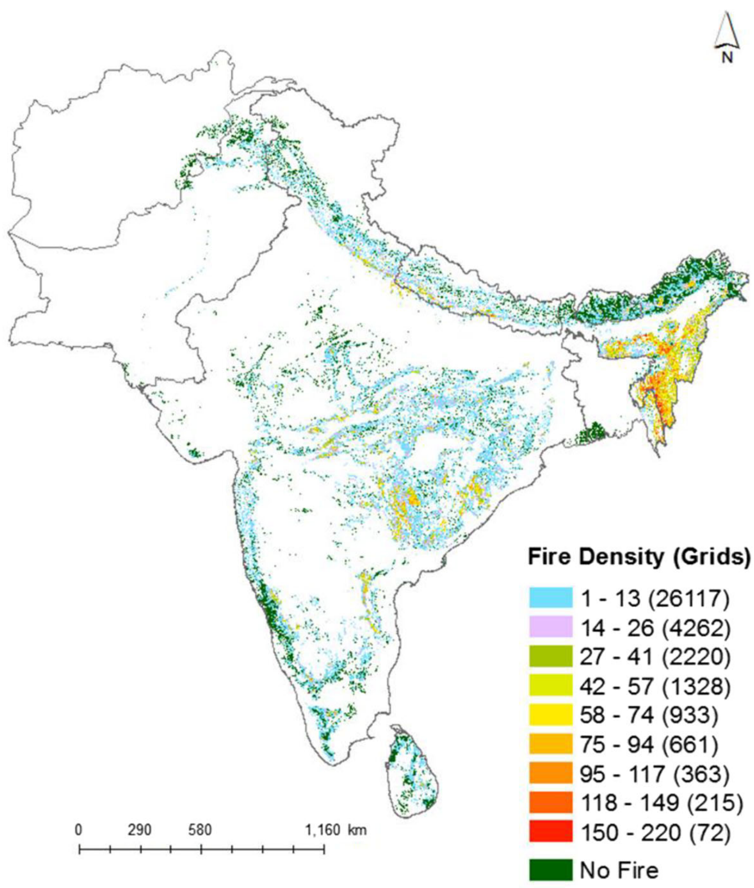


Fig. 7 Forest fire density map of South Asia (2003–2017)

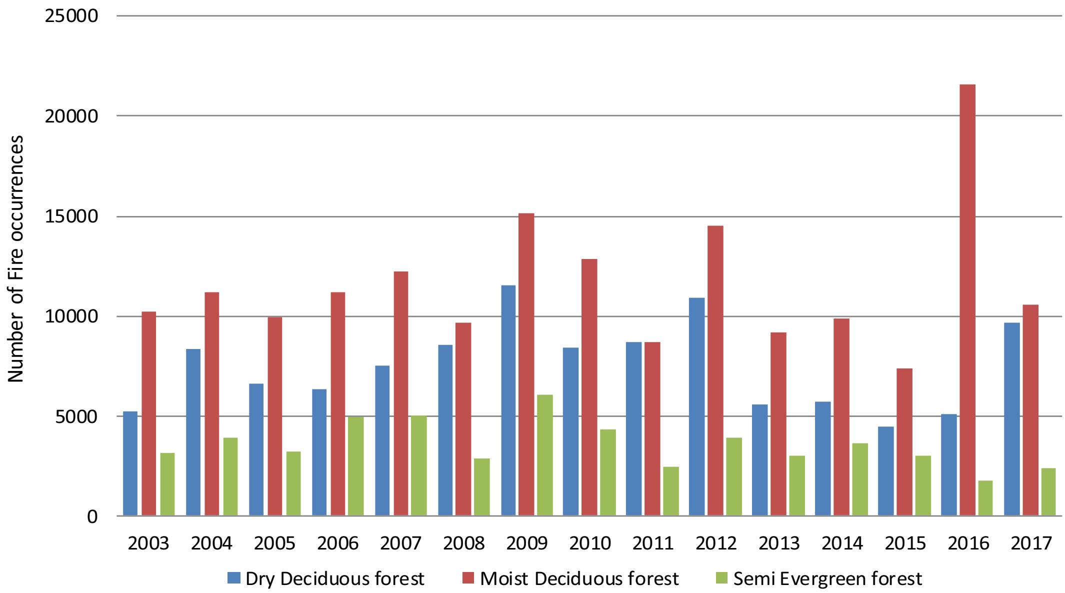


Fig. 8 Annual fire incidences across major fire vulnerable forest types: 2003–2017

Forest fires occurred during the period 2003 to 2017 in dry deciduous forest, moist deciduous forest, and semi-evergreen forest are given in Fig. 8. The forest types in Afghanistan are Himalayan dry temperate forest, Himalayan moist temperate forest, subtropical pine forest, and subtropical dry evergreen forest. During the period 2003 to 2017, Himalayan moist temperate forest shows a greater number of fires $n = 480$ and thus became vulnerable forest type. Forest types in Bangladesh are tropical moist deciduous forest, tropical semi-evergreen forest, and tropical dry deciduous forest. Dry deciduous forest is more vulnerable to forest fires ($n = 15{,}880$) in Bangladesh. Himalayan dry temperate forest, subtropical pine forest, Montane wet temperate forest, Himalayan moist temperate forest, sub-alpine forest, subtropical broad-leaved forest, and moist deciduous forest are the major forest types in Bhutan. Subtropical broad-leaved hill forest ($n = 2669$) is found to have the highest

Table 4 Annual fire incidences across forest types of South Asia (2003–2011)

Forest type	2003	2004	2005	2006	2007	2008	2009	2010	2011
Dry deciduous forest	5245	8385	6631	6348	7540	8566	11,551	8397	8679
Dry evergreen forest	698	899	700	950	845	720	1154	941	761
Moist deciduous forest	10,257	11,221	9952	11,173	12,233	9641	15,124	12,870	8665
Himalayan dry temperate forest	596	739	574	718	649	662	1072	788	536
Himalayan moist temperate forest	646	921	678	949	732	734	1396	900	689
Montane wet temperate forest	683	882	658	768	719	674	1323	910	611
Semi-evergreen forest	3168	3911	3204	4943	4996	2908	6030	4334	2484
Sub-alpine forest	1365	1754	1392	1690	1555	1468	2460	1878	1378
Subtropical broad-leaved hill forest	1188	1526	1127	1666	1455	1355	2195	1779	1298
Subtropical dry evergreen forest	619	928	712	834	839	620	1254	863	619
Subtropical pine forest	812	1102	820	977	932	833	1598	1088	735
Thorn forest	1489	1946	1495	1886	1760	1475	2738	1987	1428
Wet evergreen forest	2128	2709	2094	3401	3033	1855	3782	3220	1695
Total	28,894	36,923	30,037	36,303	37,288	31,511	51,677	39,955	29,578

Table 5 Annual fire incidences across forest types of South Asia (2012–2017)

Forest type	2012	2013	2014	2015	2016	2017	Total	% of fires (2003–2017)	Mean (2003–2017)	Std dev (2003–2017)
Dry deciduous forest	10,929	5551	5719	4471	5074	9636	112,722	21.6	7514.8	2171.9
Dry evergreen forest	1069	799	731	729	437	745	12,178	2.3	811.9	173.8
Moist deciduous forest	14,539	9193	9896	7385	21,582	10,600	174,331	33.4	11,622.1	3458.6
Himalayan dry temperate forest	903	608	650	495	752	534	10,276	2.0	685.1	152.8
Himalayan moist temperate forest	1083	773	810	616	852	806	12,585	2.4	839.0	199.4
Montane wet temperate forest	1059	675	791	541	700	592	11,586	2.2	772.4	203.0
Semi-evergreen forest	3917	3040	3617	3019	1770	2385	53,726	10.3	3581.7	1131.8
Sub-alpine forest	2209	1481	1628	1267	1203	1327	24,055	4.6	1603.7	353.0
Subtropical broad-leaved hill forest	2043	1436	1591	1259	1671	1193	22,782	4.4	1518.8	313.2
Subtropical dry evergreen forest	1206	604	726	560	580	719	11,683	2.2	778.9	215.4
Subtropical pine forest	1520	772	984	645	893	770	14,481	2.8	965.4	272.8
Thorn forest	2559	1495	1741	1290	1288	1436	26,013	5.0	1734.2	434.4
Wet evergreen forest	2411	2273	2285	2250	1239	1555	35,930	6.9	2395.3	714.9
Total	45,447	28,700	31,169	24,527	38,041	32,298	522,348		34,823.2	7101.6

number of forest fires and lowest for subtropical pine forest, $n = 15$ fires were occurred. Moist deciduous forest shows fire record of $n = 406$ in Bhutan (Table 6).

All major types of forests in India, i.e., dry deciduous forest, moist deciduous forest, dry evergreen forest, Montane wet temperate forest, Himalayan dry temperate forest, Himalayan moist temperate forest, semi-evergreen forest, sub-alpine forest, sub-tropical broad-leaved hill forest, wet evergreen forest, subtropical pine forest, thorn forest, and subtropical dry evergreen forest were affected by fires. Among the forest types, moist deciduous forest has witnessed highest number of fires ($n = 155{,}195$) followed by dry deciduous forest ($n = 96{,}842$) and semi-evergreen forest ($n = 49{,}975$).

Table 6 Summary of fire incidences across forest types of South Asian countries (2003–2017)

Forest type	Afghanistan	Bangladesh	Bhutan	India	Nepal	Pakistan	Sri Lanka	Total
Dry deciduous forest		15,880		96,842				112,722
Dry evergreen forest				12,138			40	12,178
Moist deciduous forest		8156	406	155,195	8156		2418	174,331
Himalayan dry temperate forest	2		209	7802	2251	12		10,276
Himalayan moist temperate forest	480		86	9198	2313	508		12,585
Montane wet temperate forest			204	9310	2047		25	11,586
Semi-evergreen forest		2503		49,975			1248	53,726
Sub-alpine forest				21,680	2350	25		24,055
Subtropical broad-leaved hill forest			2669	15,790	4323			22,782
Subtropical dry evergreen forest	19			10,099		1565		11,683
Subtropical pine forest	24		102	12,116	2001	238		14,481
Thorn forest				24,647		1366		26,013
Wet evergreen forest				35,362			568	35,930
Total	525	26,539	3676	460,154	23,441	3714	4299	522,348

Himalayan dry temperate forest ($n = 7802$) has represented with the lowest fire occurrences in India. Nepal has seven types of forest viz. Himalayan dry temperate forest, Himalayan moist temperate forest, sub-alpine forest, Montane wet temperate forest, subtropical broadleaved forest, moist deciduous forest, and subtropical pine forest. Moist deciduous forest has the highest number of forest fire ($n = 8156$) and subtropical broadleaved hill forest ($n = 4323$). Montane wet temperate forest has the lowest number of fires ($n = 2047$). Himalayan dry temperate forest, thorn forest, Himalayan moist temperate forest, sub-alpine forest, subtropical pine forest, and subtropical dry evergreen forest were the forest types in Pakistan. Subtropical dry evergreen forest ($n = 1565$) has the highest forest fire incidences followed by thorn forest ($n = 1366$) and Himalayan moist temperate forest ($n = 508$). There are the five types of inland forests in Sri Lanka, i.e., wet evergreen forest, dry evergreen forest, moist deciduous forest, semi-evergreen forest, and Montane wet temperate forest. Moist deciduous forest has highest number of forest fire count ($n = 2418$) followed by semi-evergreen forest ($n = 1248$). Least number of fire occurrences was observed in Montane wet temperate forest ($n = 25$).

Of the forest types, deciduous forests show significantly high fire incidences. It is due to dry inflammable material in the form of grass and leaf litter was significantly higher in deciduous forests. Overall moist deciduous forest has 33.4% of fire count followed by dry deciduous forest (21.6%). Based on the 15 years MODIS fire data, forest types of the study area can be divided into three risk categories, i.e., high risk, moderate risk, and low risk. High-risk category (where high fire occurrences were recorded each year and those showed more than 20% of fire occurrences) includes moist deciduous forest and dry deciduous forest. The overall trends in fire activity shows semi-evergreen forest, wet evergreen forest, and thorn forests are among the moderate fire risk forests (5–20% of total fire count). Low-risk zone

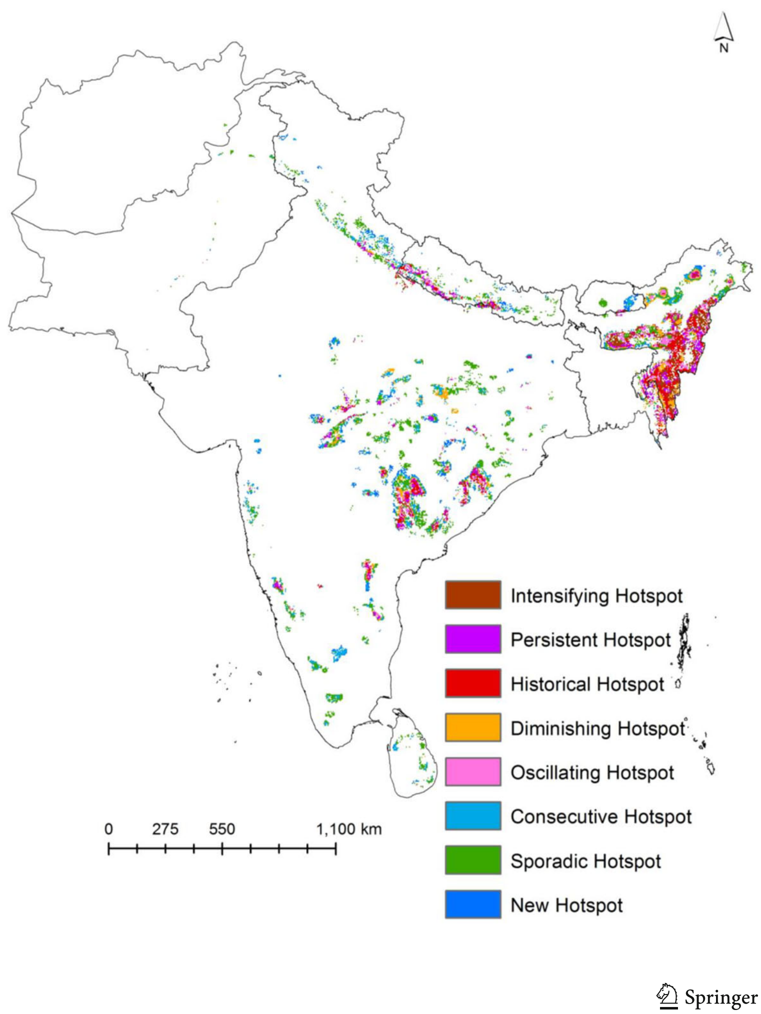


Fig. 9 Emerging fire hotspots in South Asia

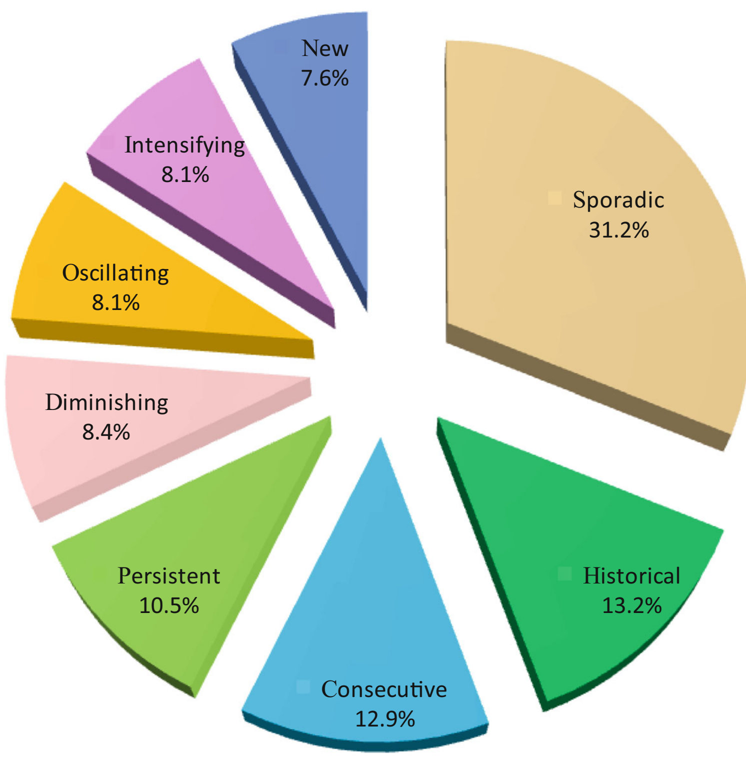
forest types (where minimal cases of fire occurrences were observed and those which had < 5% total fire count) are Montane dry temperate forest, subtropical dry evergreen forest, Montane wet temperate forest, tropical dry evergreen forest, Montane moist temperate forest, subtropical pine forest, subtropical broad-leaved forest, and sub-alpine forests (Table 6).

Emerging hotspot analysis

The emerging hotspot analysis tool categorizes each bin into distinct categories that cover a range of scenarios: one category of non-significance along with eight hotspot and eight coldspot categories. This study selected only eight hotspots, each representing a different temporal state. Emerging hotspot analysis determines hotspot categories by calculating the end time year vs all other years in this case 2003–2017 (Fig. 9). The emerging hotspots analysis indicates predominance of sporadic hotspots (31.2%), followed by historical hotspots (13.2%), consecutive hotspots (12.9%), persistent hotspots (10.5%), diminishing hotspots (8.4%), oscillating hotspots (8.1%), intensifying hotspots (8.1%), and new hotspots (7.6%) in South Asia (Fig. 10). Not emerging or non-significant hotspots occupying a 82.2% of the total area of hotspots. At national level 34.2% of forest area in Bangladesh is represented by fire hotspots, followed by 32.2% in India, 29.5% in Nepal, 14.4% in Sri Lanka, 14% in Bhutan, 4.4% in Pakistan, and 1.7% in Afghanistan.

Afghanistan has 100% of fire hotspot area under sporadic category. Nepal represents 35.3% of hotspot area under sporadic category, followed by persistent hotspots (17.6%), historical hotspots (14.3%), oscillating hotspots (13.7%), consecutive hotspots (10.6%), new hotspots (5.5%) and diminishing hotspots (2.2%), and intensifying hotspots (0.7%). Pakistan represents 77.5% of area in sporadic hotspots, followed by consecutive hotspots (15%), historical hotspots (5%), and oscillating hotspots (2.5%). In Bangladesh, persistent hotspots are highest (23.8%), followed by diminishing hotspots (22.7%), historical hotspots (20.4%), intensifying hotspots (7.7%), sporadic hotspots (4.6%), consecutive hotspots (2.2%), and new hotspots (0.9%). Bhutan represents 33.6% of new hotspots, followed by 32% in sporadic hotspots, 25% in consecutive hotspots, 3.5% in oscillating hotspots, 3.1% in historical hotspots, 1.6% in persistent hotspots, 0.7% in diminishing hotspots, and

Fig. 10 Distribution of forest fire hotspots in South Asia



0.5% in intensifying hotspots. Permagats state mainly has persistent and historical hotspots. Sarpang and Zhemgang have persistent hotspots in Bhutan. Sri Lanka has 66.1% of sporadic hotspot area followed by 28.3% in consecutive hotspots, 4.2% in new hotspot, 0.8% in oscillating hotspots, and 0.6% in diminishing hotspots. India has all categories of hotspots. Sporadic fire hotspots were seen highest (29.8%) in India followed by historical hotspots (14.5%), consecutive hotspots (12.1%), persistent hotspots (10.3%), diminishing hotspots (9.2%), oscillating hotspots (8.1%), and least were new hotspots at 7%.

At regional level, highest concentration of fire hotspots are found in North East India, followed by central India. Based on state-wise analysis of India, Madhya Pradesh and Chhattisgarh have highest emerging hotspot area followed by Odisha, Maharashtra, Arunachal Pradesh, Assam, Mizoram, Manipur, Meghalaya, Nagaland, Andhra Pradesh, Uttarakhand, Telangana, Karnataka, Jharkhand, Tamil Nadu, Tripura,

Table 7 State-wise percentage distribution of emerging hotspots in India (2003–2017)

State	Consecutive hotspot	Diminishing hotspot	Historical hotspot	Intensifying hotspot	New hotspot	Oscillating hotspot	Persistent hotspot	Sporadic hotspot
Andhra Pradesh	13.9	7.3	11.3	0.3	7.6	9.5	9.4	40.6
Arunachal Pradesh	18.6	17.4	4.5	2.9	5.7	10.3	2.9	37.7
Assam	3.2	15.4	17.0	13.9	0.9	17.0	11.0	21.7
Bihar	6.1	0.9	10.1	0.9	8.1	3.0	15.6	55.3
Chhattisgarh	14.6	12.2	10.2	1.4	13.3	6.4	8.1	33.7
Goa	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Gujarat	40.0	0.0	0.0	0.0	60.0	0.0	0.0	0.0
Haryana	19.5	0.0	0.0	0.0	0.0	0.0	0.0	80.5
Himachal Pradesh	23.5	0.0	0.0	0.0	1.0	0.0	0.0	75.6
Jammu & Kashmir	18.1	0.0	0.0	1.3	40.1	1.3	0.0	39.1
Jharkhand	15.4	0.0	0.5	1.5	7.2	3.0	2.0	70.5
Karnataka	34.9	2.6	4.8	0.0	6.4	3.9	8.4	39.1
Kerala	24.2	0.0	0.0	0.0	0.0	0.0	0.0	75.8
Madhya Pradesh	21.3	8.6	4.3	0.5	13.0	2.8	9.0	40.5
Maharashtra	16.7	9.8	4.7	0.1	16.4	3.9	4.7	43.6
Manipur	0.0	5.5	35.3	26.7	0.0	8.7	22.7	1.1
Meghalaya	5.5	5.9	7.6	26.4	3.7	15.3	13.4	22.1
Mizoram	0.0	17.0	36.7	28.4	0.0	5.8	12.1	0.0
Nagaland	0.0	2.2	30.3	37.7	0.0	10.4	15.6	3.8
Odisha	9.9	6.7	14.1	2.6	7.0	8.7	12.1	39.0
Punjab	17.9	0.0	0.0	0.0	0.0	0.0	3.9	78.2
Rajasthan	5.7	0.0	0.0	0.0	49.9	0.0	0.0	44.5
Sikkim	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Tamil Nadu	35.1	0.0	0.0	0.0	4.3	0.0	0.0	60.6
Telangana	17.2	5.5	17.5	2.1	11.7	9.4	14.5	22.1
Tripura	3.2	9.6	33.4	3.9	0.0	17.8	22.9	9.2
Uttar Pradesh	13.5	2.5	20.3	4.1	2.1	6.2	8.0	43.5
Uttarakhand	25.3	4.0	2.9	0.7	13.7	2.8	11.4	39.0
West Bengal	17.1	0.0	0.0	0.0	0.0	0.0	0.0	82.9

Uttar Pradesh, Bihar, Himachal Pradesh, Jammu & Kashmir, Kerala, Gujarat, Punjab, Haryana, West Bengal, and Rajasthan. The concentration of intensifying hotspot is high in Nagaland, followed by Mizoram, Manipur, Meghalaya, and Assam. Historical hotspots are widely distributed in Mizoram, Manipur, Nagaland, and Assam. At state level, sporadic hotspots are widespread in West Bengal, Haryana, Punjab, Kerala, Himachal Pradesh, Jharkhand, and Tamil Nadu. Persistent hotspots are found mostly in Tripura, Manipur, Bihar, and Telangana (Table 7). The detectability of a fire depends on the flame size but the surface heterogeneity, clouds, heavy smoke, and sun glint and other abiotic factors in all affect the detectability of fires (Matin et al. 2017).

Harris et al. (2017) studied sensitivity to neighborhood size, or the distance over which each point is compared to all others. As neighborhood size increases, hotspots will become larger and fewer, smaller neighborhood sizes capture more localized trends. There is certainly an element of subjectivity in selecting a suitable value for neighborhood distance. Emerging hotspot results for three different spatial domains within the Democratic Republic of Congo has been carried out at local (neighborhood distance, 11.3 km), subnational (neighborhood distance, 24 km), and national (neighborhood distance, 45.3 km) levels. In the present study, neighborhood distance of 5 km has been used to cover more localized trends and high number of emerging hotspots in South Asia for conservation prioritization of forests.

Global Forest Watch Fires is a dynamic online forest monitoring and fire alert system that provides near real-time information (https://fires.globalforestwatch.org/). NASA's Fire Information for Resource Management System (FIRMS) provides near real-time tools for managing global wildland fires (https://earthdata.nasa.gov/firms). The European Forest Fire Information System (EFFIS) provides the services in the European Union countries with updated and reliable information on wildland fires (http://effis.jrc.ec.europa.eu/). Near real-time monitoring of fires in India is carried out by National Remote Sensing Centre (NRSC) and Forest Survey of India (FSI) using MODIS and Suomi NPP VIIRS fire alerts. The processed signals on active forest fire hotspots are being transmitted to State Forest Departments (https://bhuvan.nrsc.gov.in/; http://117.239.115.41/smsalerts/).

Conclusions

The study attempted to give insight in the use of remote sensing and geospatial techniques for fire management. In this work, historical fire data based on MODIS was used to identify the spatial and temporal distribution of forest fires in South Asia. The information generated from time series satellite data for the last 15 years was summarized using spatial statistics tool "emerging hotspots analysis." Due to the coarse resolution, multiple fire incidences within one-pixel area are reported as a single incidence. The present work would be useful in studies related to ecological modeling and would greatly contribute to biodiversity conservation. The overall trends in fire activity shows deciduous forests are among the fire dominated regions. Spatial information generated in this study is useful for effective forest fire management in South Asia.

Acknowledgments This work has been carried out as part of ISRO's National Carbon Project. We thank ISRO-DOS Geosphere Biosphere Programme for the financial support. We are grateful to Shri Santanu Chowdhury, Director, NRSC, Hyderabad and Dr. V.K. Dadhwal, Project Director, National Carbon Project and Director, Indian Institute of Space Science and Technology, Thiruvananthapuram, for suggestions and encouragement. We are grateful to NASA for providing access to the MODIS data.

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