Natural Hazards (2022) 114:3529–3544
https://doi.org/10.1007/s11069-022-05530-5

ORIGINAL PAPER

Hotspot and trend analysis of forest fires and its relation to climatic factors in the western Himalayas

Sunil Kumar[1,2] · **Amit Kumar**[1]

Received: 10 November 2021 / Accepted: 27 July 2022 / Published online: 13 August 2022

Abstract

Forest fire is one of the main issues of forest ecosystems around the world which has resulted in loss of biodiversity, forest degradation, soil erosion, and greenhouse gas emission. Ironically, the information on the forest fire regime and its pattern are still lacking in the Himalayan region. In this study, Moderate-Resolution Imaging Spectroradiometer active fire data products from 2001 to 2020 have been analysed for understanding the forest fire trends and its hotspots patterns during the active fire season (February to June). About 1347 average fire counts/year were recorded in six natural vegetations with the highest number of fires observed during the year 2012 ($n=3096$) and minimum in 2011 ($n=210$). Mann–Kendall trends analysis for the spatial and temporal pattern of fires indicated that there is a significant increase of forest fires towards higher elevation. Forest fire hotspot analysis using fire radiative power, fire frequency, and fire density showed that Uttarakhand is the most forest fire-prone state as compared to other north-western Himalayan states. It is also revealed that the May month has a higher number of fire counts and the evergreen needle forests have higher fire frequencies amongst the forest types. The forest fires were found to be more influenced by land surface temperature as compared to rainfall. The outcomes in this study on the temporal and spatial patterns for forest fire can be used for forest fire modelling.

Keywords Forest fire · Fire frequency · Fire density · Hotspot · Mann–Kendall trend · MODIS · Himalayas · Burnt area

1 Introduction

Forest fire is a major threat to forest ecosystems around the world. Though it is a natural process to retune the forest flora, it has been observed that forest fire incidences have increased due to changing climatic conditions. It has created deteriorating effects

✉ Amit Kumar
amitkr@ihbt.res.in

1 RS-GIS Laboratory, Environmental Technology Division, CSIR-Institute of Himalayan Bioresource Technology, Palampur, Himachal Pradesh 176061, India

2 Academy of Scientific and Innovative Research (AcSIR), CSIR-HRDC Campus Ghaziabad, Ghaziabad, Uttar Pradesh 201002, India

such as biodiversity loss, forest degradation, soil erosion, imbalanced atmospheric pattern, and global warming due to loss of carbon from the forests in the atmosphere. Thus, forest fires have become a serious environmental and ecological concern (Littell et al. 2016; Vachula et al. 2020; Zhang-Turpeinen et al. 2020). Globally, the total carbon emission from fires has been estimated as 3.53 Pg. per annum (Van Der Werf et al. 2004), which is 25–35% of the total net carbon dioxide emission (FAO 2012).

Forest fire incidences have increased in India during last two decades particularly in the Himalayan regions (Vadrevu et al. 2019) leading to forest degradations (Dobriyal and Bijalwan 2017). Fires are frequent in these regions and have been shifted to the higher altitudes due to changing climatic conditions. Most of the Himalayan forest fires are considered as manmade (Rogers et al. 2020). Sometimes villagers deliberately burn the forests for the need of fodder in the next monsoon season which grow above the burnt locations. These fires are also due to mistakes when peoples throw cigarettes or shepherds leave fires alive after their cooking. The rich floral diversities of western Himalayan forests are under threat due to such fires. These fires are seasonal and have been reported mainly during February to June (Bahuguna and Singh 2002). The Chir pine (*Pinus roxburghii*) forests at the foothills are prone to fires. Several endangered and indigenous species of this forest are under threat due to recurrent fires (Negi 2019; Semwal and Mehta 1996). Information on spatial and temporal fire occurrences is prerequisite to understand the effect of forest fires on flora and environment. Ironically this information like fire frequency, fire seasonality, fire regime, fire hot spot, fire susceptible zones, vegetation under forest fire, etc., are presently lacking in the western Himalayan region. The present study thus intends to harness the potential of the Geographic Information System (GIS) and Remote Sensing (RS) techniques for the derivation of the above information. We have analysed the temporal patterns and trends of forest fires in western Himalaya for the year 2001 to 2020. Seasonality of forest fires within the fire seasons was also examined concerning land use class and fire radiative power (FRP) of forest fire occurrences points. The cluster and hotspot analysis have been done to understand the spatial distribution of forest fires.

Fire regime addresses a variety of fire parameters such as fire type, its intensity, its severity, fire size, its spatial pattern, and fire seasonality (Akther and Hassan 2011; Gill and Allan 2008; Swetnam and Brown 2010). This is the consequence of relations between biotic and abiotic factors (Duncan and Schmalzer 2004). A fire regime is considered as dynamic as it is affected by climatic conditions and human involvements (Leone et al. 2003). In the present context, an unadulterated natural fire regime may not be present and thus understanding the fire regime for space and time becomes imperative (Duncan et al. 2009). Temporal and spatial characteristics of fire regimes can be computed from forest fire statistical records (Kasischke et al. 2003). Regions having randomly distributed higher concentration of fire clusters are known as hotspot.

Available information on forest fires regime is insufficient in the Himalayan region. About 37,300 Km^2 per annum forest area is affected by forest fires (Bahuguna 1999), which results in a loss of approximately USD 110 million (MoEF 1999). Fires in the western Himalayan region are seasonal and generally occur during the dry season (February to June). The climatic conditions, topographical factors, vegetation type, and socioeconomic factors play a major role in fire frequencies and intensities.

In the present study, Moderate-resolution Imaging Spectroradiometer (MODIS) active fire point data have been used to analyse forest fires in the western Himalaya in terms of trend of increase or decrease in fires, most vulnerable forest types, shifting of forest fires to higher elevations, specific time for high fire events in a season, influence of land surface temperature and rainfall on forest fires, regions having higher fire frequencies, fire density, and hotspots. The answers to these will help in forest fire management and mitigation.

2 Study area

The western Himalaya is the study area which consists of Ladakh, Jammu & Kashmir, Himachal Pradesh, and Uttarakhand regions of India. It ranges from 72.5 to 80.9°E longitude to 28.8°N-37.0°N latitude covering 2,10,561 km^2 geographical area. The altitude ranges from 186 to 8246 m AMSL, which increases in north-east direction (Fig. 1). Different kinds of forest types are found in this region owing to its diversified elevation gradients. The major vegetation types are evergreen broadleaf forest, deciduous broadleaf forest, evergreen needle leaf forest, mixed forest, shrubland, and grassland (Roy et al. 2016). Foothills are most vulnerable to forest fires which are frequent during February to June due to weather conditions favouring fires such as high temperature, prolonged dry spell, and forest type dominant of flammable *Pinus roxburghii*.

3 Datasets and methodology

3.1 Active fires and fire radiative power (FRP)

Daily MODIS C6 fire dataset has been used to understand the forest fires, which were downloaded from NASA FIRMS website (Fire Information for Resource Management System (FIRMS), 2016. https://earthdata.nasa.gov) for the period 2001 to 2020. These datasets provide geographical locations of fire point centres representing 1*1 km area

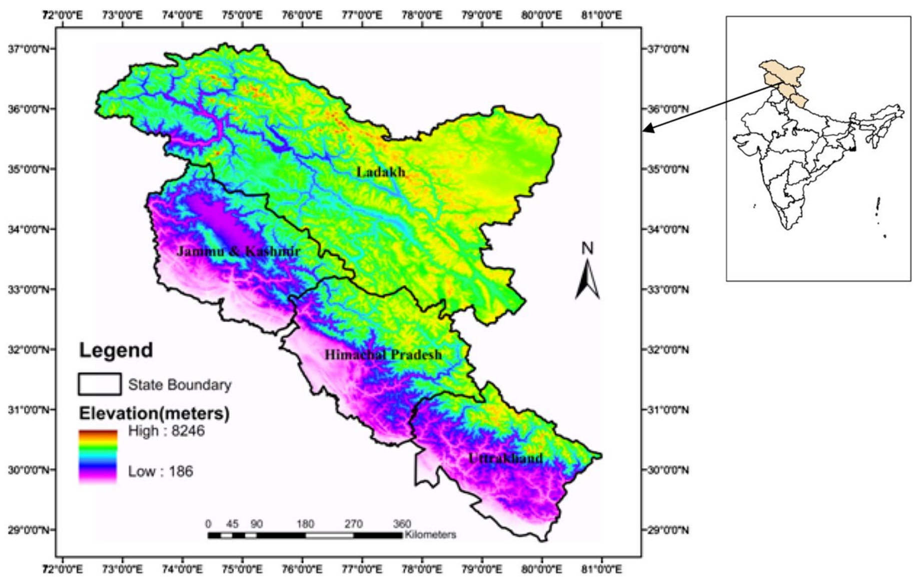


Fig. 1 Elevation map of study area

with date and time of its occurrence. The FRP datasets are quantitative radiant heat emissions normally used for the approximation of fire intensities. FRP values recorded in MODIS C6 active fire products determine the fire energy emitted per unit time in megawatts (MW) unit and are calculated by the formula given by (Kaufman et al. 1998) and later modified by (Giglio et al., 2018) as follows:

$$\mathrm{FRP} = A_s\beta\left(T_f^8 - T_b^8\right) \tag{1}$$

where T_f is the brightness temperature of fire pixel at 4 μm, T_b represents mean brightness temperature at 4 μm of the background window. The actual pixel area of MODIS is derived at the viewpoint of scan 's' and the β the coefficient equal to 4.34 * $10^{-19}\mathrm{Wm}^{-2}\mathrm{K}^8$ specific to the spectral response at 4 μm.

All together 24,946 such fire points were overlaid on natural vegetations of the study area and the non-forested regions were discarded from the analyses. Six vegetation classes such as evergreen needle leaf forest, deciduous broadleaf forest, shrubland, evergreen broadleaf forest, mixed forest, and grassland were used for the analysis.

3.2 Vegetation types and elevation data

We have used open source decadal land use/land cover (LULC) raster data of 100 m resolution for the year 2005 (Roy et al. 2016). It was calibrated with the ground-truthing points for more accuracy. LULC data extracted for the western Himalayan region has 14 classes (Supplementary datasheet Figure 1).

The open source 30 m SRTM elevation data (https://earthdata.nasa.gov) was used for the extraction of elevation values for the fire points using Arc Map software (ESRI, USA).

The 1*1 km grid MOD11C3 MODIS Land Surface Temperature (LST) and 0.25 degree * 0.25 degree Tropical Rainfall Measuring Mission TRMM_3B43 rainfall data (https://modis.gsfc.nasa.gov) were used to retrieve monthly temperature and rainfall for the fire season from the year 2001 to 2020.

3.3 Methodology

We have used nonparametric seasonal Mann–Kendall statistical analysis for understanding the pattern of forest fires in the study area during the year 2001 to 2020. This test doesn't require a normally distributed sample and is less influenced by outliers because it depends on the sign of the variables and not on its values (Gilbert 1988). Mann–Kendall positive value determines an inclining trend whereas its negative value indicates declining trend.

The Getis-OrdGi* hotspot analysis technique was utilized for the detection of forest fire hotspots in the present study. Gi* statistics consider every aspect of fire occurrence points under analysis in the perspective to their neighbour values (Scott and Warmerdam 2005). Gi* statistics calculate significant grids with high values surrounded by several high values grids. The high fire incidence grids are though important but may not be statistically significant hotspot. The native total of an attribute and its surrounding was evaluated consequently to the total of all attribute. The hotspot examination using Gi* statistics is computed as follows:

$$G_i^* = \frac{\sum_{j=1}^{n} W_{ij}x_j}{\sum_{j=1}^{n} x_j} \tag{2}$$

where G_i^* is the spatial subordination statistics of fire occurrence i over n incidents. The expression x_j describes the scale of the variable x at incident j over every n and w_{ij} describes the load value of the incidence i and j which characterize their spatial inter-association. The result of the G_i^* statistic provides a z-score of every character in the dataset. The higher positive z-score indicates more powerful grouping of high values (hot spot), and statistically negative lower z-scores indicates a stronger grouping of small values (cold spot).

The hotspot investigation was carried out in 5*5 Km^2 grids in which the mean of annual sum of FRP were aggregated for each grid for the year 2001–2020. The Getis-OrdGi* hotspot analysis identified the hotspot and coldspots of forest fires in the area of investigation. The Inverse Distance Weighted (IDW) interpolation technique has produced a smooth and continuous surface of hotspot for the forest fire, which was further classified into 5 distinct classes of hotspots.

Fire density and fire frequency analyses were executed in 5*5 km^2 grids, which were intersected with six different classes of natural vegetation types and total fire count during the year 2001 to 2020. Fire frequency explains the number of occasions of forest fires in the last 20 years (2001–2020). The state-wise and forest type-wise (six natural vegetation types) burned area, fire counts, fire frequency, fire density and hotspots were analysed with the help of intersect tools in ArcGIS software. Monthly land surface temperature and rainfall data were used for the correlation of above parameters with monthly fire incidence during the fire season.

4 Results

MODIS fire data showed the average fire count per year as 1347. It was highest in the year 2012 ($n=3096$) and lowest in 2011 ($n=210$).Though the recorded fire incidences shows its increasing trends but are statistically insignificant. The fire season in the western Himalayan region extends from February to June with its peak in May. The evergreen needle leaf forests had the highest forest fire intensity (57.07%) followed by deciduous broadleaf forest (24.44%), shrubland (8.9%), evergreen broadleaf forest (4.47%), mixed forests (4.15%), and grassland (0.9%) during the year 2001 to 2020. Man-Kendall trends analysis (Mann–Kendall statistic $S=66$) at mean elevation in fire season during 2000–2020 showed significant shifting of fire incidences towards the higher elevation (Fig. 2).

Month-wise, the highest number of fire count occurred during the month of May ($n=9883$) followed by in April ($n=6629$), June ($n=5315$), March ($n=1999$) and February ($n=1119$) (Fig. 3). The rise in the temperature during the summer season has lead to increased fire incidences and precipitations resulting due to the onset of monsoon period during the last days of June have reduced the fire incidences during this month. State-wise monthly fire counts of Uttarakhand, Himachal Pradesh, Jammu & Kashmir, and Ladakh are shown in Table 1 of Supplementary datasheet.

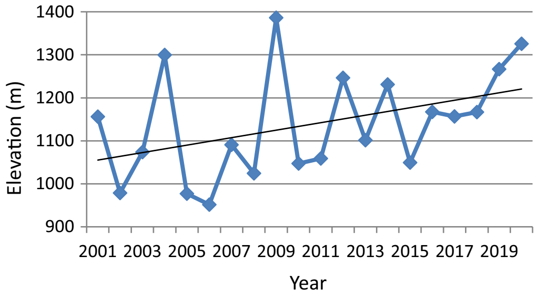


Fig. 2 Mean elevation ranges of fire points reported during 2000–2020

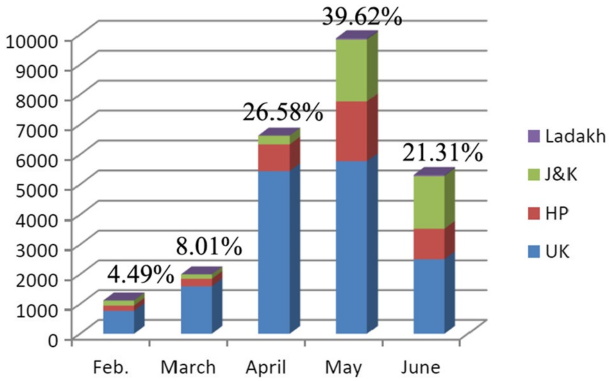


Fig. 3 Month-wise fire counts in the western Himalayas during 2001 to 2020

4.1 Relation with land surface temperature and rainfall

The highest value of fire counts was recorded in the year 2012 ($n=3096$) followed by in year 2009 ($n=3025$) and 2016 ($n=2934$) in which mean land surface temperature was 27.90 °C, 26.76 °C, 28.21 °C and rainfall was 31.38 mm, 44.65 mm, 61.00 mm, respectively. The lowest number of fire counts were recorded during 2011 ($n=210$) followed by in 2020 ($n=215$) and 2001 ($n=285$) in which mean land surface temperature was 25.25 °C, 23.94 °C, 26.51 °C and rainfall was 70.77 mm, 78.58 mm, 35.44 mm, respectively (Fig. 4). The forest fire was observed to increase with increase in mean monthly temperature, while it was found to decrease with rainfall (Fig. 5).

4.2 Forest types and fire counts

The highest number of fires was observed in the deciduous broadleaf forest in the year 2016 ($n=875$) and it was lowest in the year 2020 ($n=22$). In evergreen broadleaf forest highest fire points were observed in the year 2009 ($n=175$) and the least in the year 2011 ($n=11$). In the evergreen needle leaf forest, the highest fire counts were found in the year 2012 ($n=2067$) and the lowest in the year 2001 ($n=81$). In the mixed forests, the maximum number of fire counts was observed in the year 2012 ($n=156$) and the lowest in the year 2011 ($n=2$). In the shrubland, the highest fire point counts were recorded in the year 2018 ($n=293$) and the least in the year 2011 ($n=24$). The grassland had maximum fire

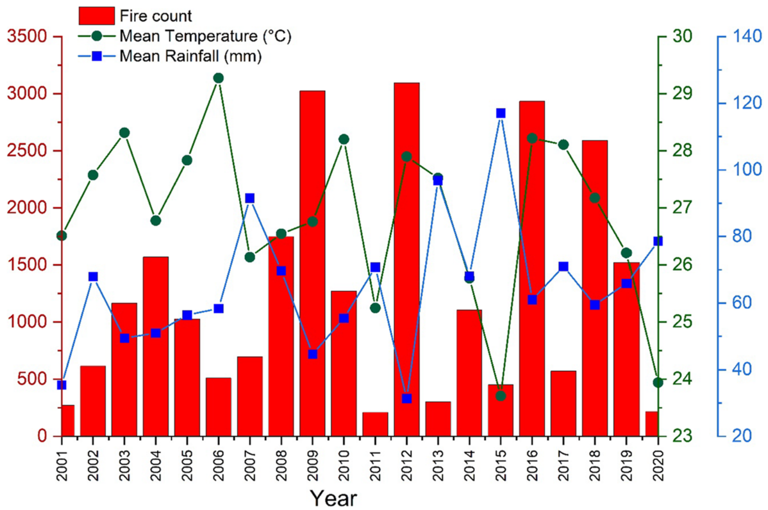


Fig. 4 Trends of fires depicted along with the mean temperature and rainfall during the year 2001 to 2020

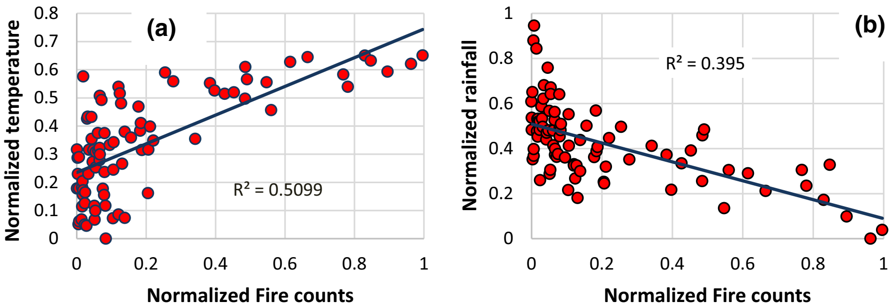


Fig. 5 Relationship of forest fires with **a** land surface temperature and **b** rainfall

counts in the year 2012 ($n=25$) and minimum in the year 2013 ($n=3$) (Supplementary datasheet Figure 2).

4.3 Burnt area and fire counts

The result shows that the burnt area was highest in the year 2012 (2327.52 km^2) annually and it was minimum in 2020 (99.32 km^2). This may be due to the COVID-19 restrictions imposed in India during 2020 which might have led to the lesser anthropogenic disturbance to the forest. State-wise burnt area is shown in (Table 1). The results of burnt area analysis has revealed that it was highest in the month of May followed by April, June, March, and February (Supplementary datasheets Figure 3). Month-wise highest burnt area was observed in the month of February 2006 (34.07 km^2), for March it was 2004 (245.48 km^2), and for April it was 2016 (1612.73 km^2). Similarly, for May the 2012 had highest observed burnt area (1770.88 km^2), and for June it was in the year 2016 (238.20 km^2) (supplementary datasheet Figure 4).

Table 1 Year-wise number of fire counts and burnt area (Km^2) statistics of different western Himalayan states during 2001 to 2020

Year	Uttarakhand		Himachal Pradesh		Jammu & Kashmir		Ladakh		Total	
	Fire counts	Burnt area	Fire counts	Burnt area	Fire counts	Burnt area	Fire counts	Burnt area	Fire counts	Burnt area
2001	140	90.27	34	1.27	68	37.92	43	0	285	129.46
2002	157	69.27	194	151.35	264	172.54	0	0	615	393.16
2003	803	1013.46	245	89.7	143	106.26	1	0	1192	1209.42
2004	1274	807.3	131	43.28	164	101.42	1	0	1570	952
2005	647	681.15	120	46.68	261	275.89	0	0	1028	1003.72
2006	286	149.83	46	16.42	177	118.09	1	0.17	510	284.51
2007	344	309.16	131	54.62	214	236.79	9	1.56	698	602.13
2008	1340	791.27	307	140.88	98	41.62	3	1.39	1748	975.16
2009	1733	1253.32	589	148.2	704	493.43	0	0	3026	1894.95
2010	903	695.38	270	54.02	100	88.25	0	0	1273	837.65
2011	123	42.72	16	3.49	70	62.79	1	0	210	109
2012	2023	1762.43	648	311.9	425	253.19	0	0	3096	2327.52
2013	155	70.5	71	18.63	78	102.99	0	0	304	192.12
2014	768	250.43	86	26.17	248	285.62	4	0	1106	562.22
2015	344	1064.22	66	16.53	41	3.03	1	0	452	1083.78
2016	2117	1586.69	433	268.39	384	418.24	0	0	2934	2273.32
2017	325	186.14	140	38.57	100	121.04	6	0	571	345.75
2018	1202	924.46	667	205.54	712	569.88	10	0	2591	1699.88
2019	1332	1381.66	98	17.95	93	119.7	0	0	1523	1519.31
2020	76	11.89	51	13.83	86	73.6	2	0	215	99.32

Highest number of fire counts was found in year 2012 ($n = 3096$) and lowest number of fire counts was observed in year 2011($n = 210$). The relationship between burn area and fire counts shows positive correlation and statistically significant ($r = 0.94$, $P < 0.05$) (Fig. 6).

4.4 Fire density

The 24.15% grid cell of natural vegetation was found affected by fire in which 373 (3.54%) grid cells were observed to possess more than 20 fire count. The 401 (3.81%) grid cells were affected by 11–20 fire counts, and 1767 (16.79%) grid cells were found to represent less than 10 fire counts during 2001–2020 (Fig. 7).

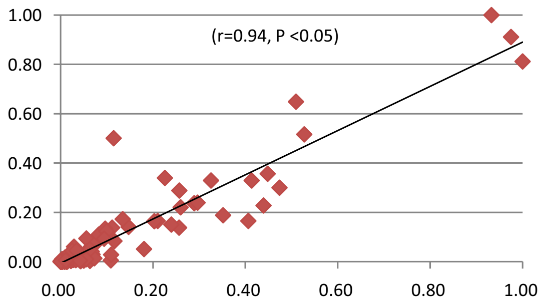
It was revealed that a total of 30 (0.65%), 764 (34.58%), 487 (24.12%), and 1260 (72.70%) grid cells were observed fire-affected in Ladakh, Himachal Pradesh, Jammu and Kashmir, and Uttarakhand states of western Himalaya, respectively. In Ladakh, 29 (96.66%) grid cells were affected by less than 10 fire counts and only 1 (3.33%) grid cell was observed to have 11–20 fire counts. In Himachal Pradesh, 39 (5.10%) grid cells were found to affected by more than 20 fire counts, 86 (11.25%) grid cells were found to have 11–20 fire counts and 639 (83.63%) grid cells were found to possess less than 10 fire counts. In Jammu and Kashmir, 61 (12.52%) grid cells were found to have more than 20 fire counts, 68 (13.96%) grid cells were found to possess 11–20 fire counts and 358 (73.51%) grid cells were found to have less than 10 fire counts. In Uttarakhand, 273 (21.66%) grid cells were found with more than 20 fire counts, 246 (19.52%) grid cells had 11–20 fire counts and 741 (58.80%) grid cells had less than 10 fire counts (Supplementary datasheet Table 2).

4.5 Fire frequency

The forest fires in the study area have been irregular. The maximum number of yearly repeated forest fires was 19 and we have classified the forest fire frequency into four categories, i.e., below 4 years, 5 to 8 years, 9 to 12 years, and greater than 12 years. Results indicate that 41 (0.397%) grid cells had more than 12 forest fire repetition, 270 (2.618%) grid cells underwent 9–12 forest fire repetitions, 659 (6.39%) grid cells were having a repetition of 5–8 forest fires, 1538 (14.917%) grid cells had less than 5 fire repetitions, and 7802 (75.674%) grid cells were remained unaffected by forest fires (Fig. 8).

State-wise Ladakh had 30 (0.66%) grid cells having below 5 forest fire repetitions. In Himachal Pradesh 602 (27.25%) grid cells were found to have less than 5 fire repetitions, 131 (5.93%) grid cells were found to have 5 to 8 fire repetitions, 29 (1.31%) grid cells

Fig. 6 Relationship of monthly forest fires counts with burnt area from 2001 to 2020



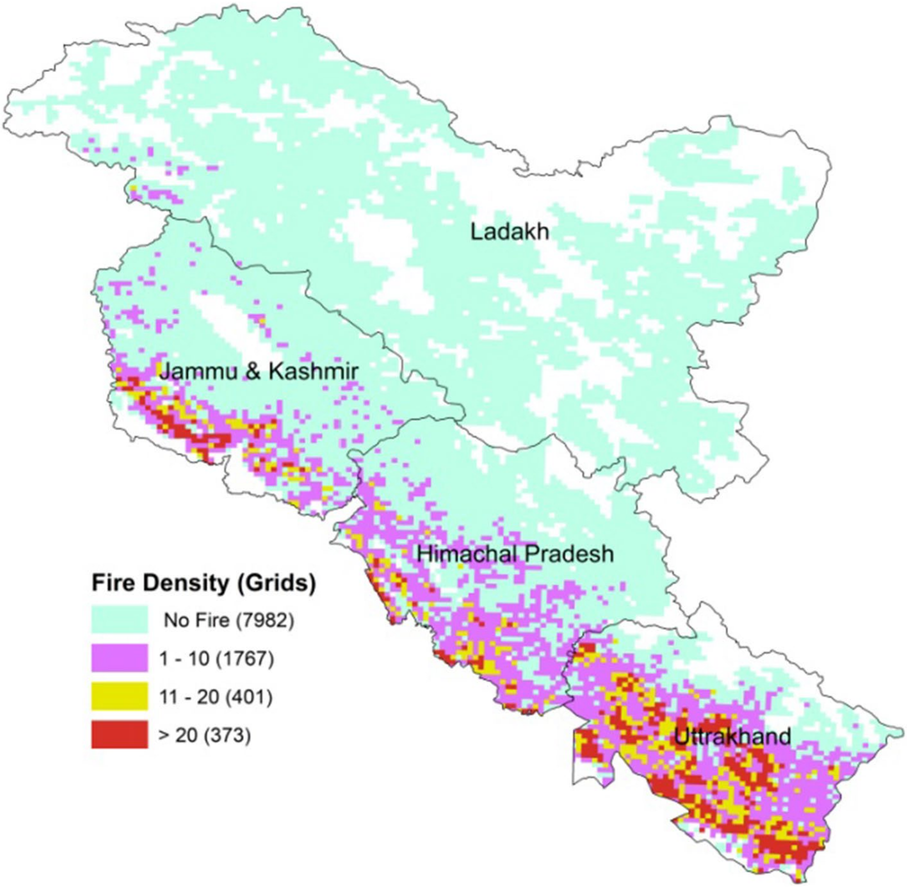


Fig. 7 Forest fire density map of western Himalaya (2001–2020)

were observed to have fire repetitions between 9 and 12 and 2 (0.09%) grid cells had above 12 forest fire repetition. In Uttarakhand, 604 (34.85%) grid cells had below 5 fire repetition, 433 (24.99%) grid cells were observed to have fire repetitions between 5 and 8, 200 (11.54%) grid cells had 9–12 fire repetition and 23 (1.33%) grid cells underwent above 12 forest fire repetitions. In Jammu and Kashmir, the 333 (16.49%) grid cells were found below 5 fire repetitions, 97 (4.80%) grid cells were observed to possess 5 to 8 fire repetitions, 41 (2.03%) grid cells had 9–12 fire repetitions, and 16 (0.79%) grid cells possess above 12 forest fire repetition (Supplementary datasheet Table 3).

4.6 Hot spot analysis

It was observed that sum of 491 grids show very high hotspot, 501 grids show high, 713 grids are in Medium, and 802 grids are under the low category during 2000–2020 (Fig. 9). State-wise results indicate the presence of very high category grids only in Uttarakhand $n=428$ (87.17%) followed by 63 (12.83%) grids in Jammu and Kashmir. The highest number of grids was found in Uttarakhand $n=367$ (73.25%) followed by in Jammu and

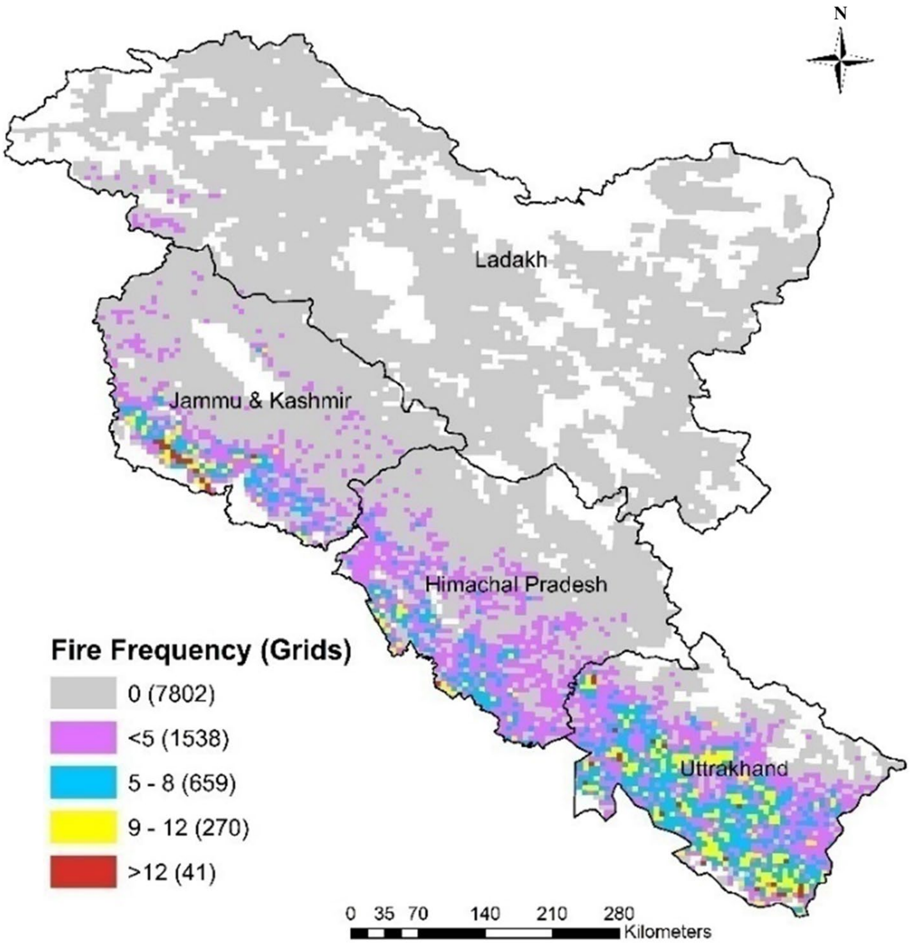


Fig. 8 Forest fire frequency map at 5*5 km^2 grid of western Himalaya (2001–2020)

Kashmir $n=80$ (15.97%), and in Himachal Pradesh $n=54$ (10.78%). Medium level hotspot grids were found highest in Himachal Pradesh $n=242$ (33.94%) followed by in Jammu and Kashmir $n=228$ (31.98%), Uttarakhand $n=222$ (31.14%) and Ladakh $n=21$ (2.95%). The 455 (56.73%), 235 (29.30%), 105 (13.09%), and 7 (0.87%) grids are present in Himachal Pradesh, Uttarakhand, Jammu, and Kashmir, and Ladakh, respectively (Table 2).

5 Discussion

Increase in the hotspots intensity results in the high rate of spread of forest fire and vice versa (Trollope 1981). The present study has also identified very high hotspot fire-sensitive regions where fire spread rates are high. These areas require more attention for proactive measures. Fire incidences were highest in the May month due to the increasing temperature and prolonged dry spells prevailing in the summer season. It is also influenced by the availability of sufficient amount of fuels on the forest floor in the form of litters. Litter fall

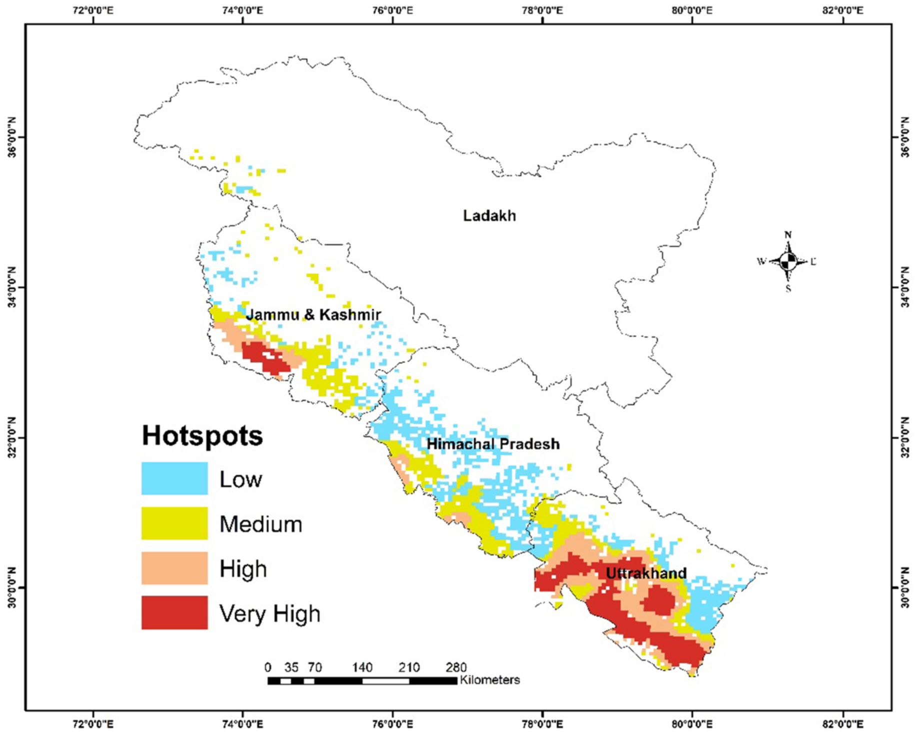


Fig. 9 Hotspot map of western Himalayas at 5*5 km^2 grid during 2001–2020

Table 2 Fire hotspots at 5*5 Km^2 grid cells in the western Himalayan states

State	Low (%)	Medium (%)	High (%)	Very high (%)
Ladakh	7 (0.87)	21 (2.95)	0 (0.00)	0 (0.00)
HP	455 (56.73)	242 (33.94)	54 (10.78)	0 (0.00)
UK	235 (29.30)	222 (31.14)	367 (73.25)	428 (87.17)
J&K	105 (13.09)	228 (31.98)	80 (15.97)	63 (12.83)
Total	802 (100.00)	713 (100.00)	501 (100.00)	491 (100.00)

in Chir pine forest starts to fall by the end of February, and its highest accumulation is found during April and May (Sharma et al. 2007). Consequently, from June onwards the fire incidences start declining due to onset of the monsoon. However, in our study we have observed that though the fire incidences were high in all the months of fire seasons, it could not be translated into corresponding burnt areas as most of these fires are surface fire in nature. Therefore, canopy remains unchanged or minute changes take place in the forest canopies between pre and post fire conditions and thus could not be detected by the burnt area satellite product which are generally coarse resolution. However, in the rare conditions these satellite products can detect active fires of 100–300 m size (Louis Giglio 2018). Although, in our study we could find significant correlation between number of fire incidences and burned area.

The effect of forest fires on vegetation depends upon their ability to recover themselves before the next fire occurrence at the same place. This time interval gets reduced with the increasing frequency of fire occurrences. In general, in the high-frequency fire occurrence areas, the time of accumulation of fuel load is gets minimized and thus due to lesser fuel load, the frequency of forest fires get declined. During our field surveys, we have observed that surface fires prevail in the study region where litter act as fuel load which accumulates every year during the fire season. These produce burnt effects under the canopy and the high value of FRP which may grow up to the crown fire destroying tree species. Most of the high fire density and high fire frequency occurred in the evergreen needle leaf forest consisting of Chir pine (*Pinus roxburghii*) and is thus considered as one of the high-intensity fire regimes.

It was also found that there is an inclination of fire incidence with the increase in land surface temperature and it declined with the increase in rainfall but this relation is statically insignificant. Other variables may also play a significant role in producing the forest fires such as soil moisture content, anthropogenic interferences, topographical factors, phenology, etc. However, the mean temperature of fire season seems to be declined and rainfall shows increasing trends in the study region during 2001 to 2020. But highest fire count recorded in the year 2008, 2012, 2016 and 2018. This is due to the seasonal weather variations in the fire seasons of every year. The rainfall of the April and May declined and the temperature inclined causing highest fire incidences in the respected years (Supplementary datasheet Figure 5). The annual minimum burnt area was recorded in 2020 due to COVID 19 restriction. However, our statewise data showed that minimum burnt area recorded for Himachal Pradesh in year 2011 (3.49 Km^2) and in J&K in year 2015 (3.03 Km^2).

The results coincide with the findings of (Schwartz et al. 2015), who have also reported shifting of fires towards the high elevation due to the changing climatic conditions. The mean annual latitude and longitude of forest fire incidence indicate the increase of fire events towards the Uttarakhand state which represents low latitude and higher longitude regions of western Himalayas.

The results showed that trends of fire frequency, fire density and hotspots are higher in Uttarakhand. This may be due to the population growth which has put forest under anthropogenic pressure which is in agreement with the reported anthropogenic means of forest fires (Satendra and Kaushik 2014). Though it is considered that forest fires are also manmade but in those cases it was observed that suitable weather conditions are also important for the spread of fires. During 2001 to 2011, the population growth was reported as 29.86% in Uttarakhand, while in Himachal Pradesh and Jammu and Kashmir, it was 14.13% and 10.79% respectively (Census data India, 2011. https://censusindia.gov.in). The forest cover plays important role in forest fires. The forest cover has increased in all the states during 2001 to 2020. It is highest in the Himachal Pradesh (18.05%) followed by Jammu and Kashmir (4.63%) and Uttarakhand (4.49%). However, the very dense type of forest has increased highest in the Uttarakhand (65.44%) followed by Jammu and Kashmir (49.41%) and Himachal Pradesh (20.83%) (Forest Survey of India, 2003 and 2021) which could be another reasons of more forest fire incidences in Uttarakhand. The month-wise results shows the start of the fire season is February in Uttarakhand followed by March in Himachal Pradesh, April in Jammu and Kashmir, and May in Ladakh. It can be interpreted as forest fire season starts early in the low latitudes regions and later at the higher latitudes.

6 Conclusions

Forest fire intensity and density-related information derived in this study can be utilized for understanding of forest fires in the western Himalayan region. Evergreen needle leaf forests undergo the highest number of forest fire occurrences during the fire season. Uttarakhand was found as most fire-sensitive state. Increasing trends of forest fires towards the higher elevation as observed in this study can be further investigated in the perspective of changing climatic scenarios. Flash and surface forest fires commonly observed in this region affect a small area and could not be detected by the coarse resolution data used in this study. Future study may include high-resolution satellite sensors for more detailed results. The outcomes of this study on the temporal and spatial patterns for forest fire can be utilised for forest fire modelling. The relationship between the land surface temperature and rainfall with other fire affecting variables may be used for pre-fire prediction modelling to conserve the biodiversity. The region with higher fire density, fire frequency, and forest fire hotspots can be utilised for forest fire management at priority basis by forest managers.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s11069-022-05530-5.

Acknowledgements The authors are thankful to Dr. Sanjay Kumar, Director, CSIR-IHBT Palampur, for his support and providing the facility under CSIR project MLP-206. Author Sunil Kumar acknowledges the Council of Scientific and Industrial Research (CSIR), New Delhi, for providing SRF fellowship. We also thank research staff of the Environmental Technology division of CSIR-IHBT, Palampur, for their help during this research. We acknowledge NASA for providing access to MODIS active fire data. This is CSIR-IHBT Publication No 4872.

Funding The authors have not disclosed any funding.

Declarations

Conflict of interest The authors declare that they have no known competing financial interests or personal conflict that could have appeared to influence the work reported in this paper.

References

Akther MS, Hassan QK (2011) Remote sensing-based assessment of fire danger conditions over boreal forest. IEEE J Sel Top Appl Earth Obs Remote Sens 4:992–999. https://doi.org/10.1109/JSTARS.2011.2165940

Bahuguna VK, Singh S (2002) Fire situation in India. Int for Fire News 26:23–27

Bahuguna VK (1999) India: forest fire prevention and control strategies (IFFN No. 20)–GFMC 23–27

Census data India (2011) Ministry of home affairs, Government of India. https://censusindia.gov.in

Dobriyal MJR, Bijalwan A (2017) Forest fire in western himalayas of India: a review. New York Sci J 10:6. https://doi.org/10.7537/marsnys100617.06

Duncan BW, Schmalzer PA (2004) Anthropogenic influences on potential fire spread in a pyrogenic ecosystem of Florida. USA Landsc Ecol 19:153–165. https://doi.org/10.1023/B:LAND.0000021714.97148.ac

Duncan BW, Shao G, Adrian FW (2009) Delineating a managed fire regime and exploring its relationship to the natural fire regime in East Central Florida, USA: a remote sensing and GIS approach. For Ecol Manage 258:132–145. https://doi.org/10.1016/j.foreco.2009.03.053

FAO (2012) The state of food and agriculture. Food and agriculture organization of the United Nations. ISBN 978–92–5–107317–9

Fire Information for Resource Management System (FIRMS) | Earthdata [WWW Document] (2016). URL https://earthdata.nasa.gov/earth-observation-data/near-real-time/firms

Forest Survey of India 2003 and 2021. Ministry of Environment Forest and Climate Change, Dehradun, Uttarakhand

Giglio L (2018) MODIS Collection 6 Active Fire Product User's Guide Revision B. University of Maryland

Giglio L, Schroeder W, Hall JV, Justice CO (2018) MODIS collection 6 active fire product user's guide revision B

Gilbert RO (1988) Statistical methods for environmental pollution monitoring. Biometrics 44:319. https://doi.org/10.2307/2531935

Gill AM, Allan G (2008) Large fires, fire effects and the fire-regime concept. Int J Wildl Fire 17:688–695. https://doi.org/10.1071/WF07145

https://earthdata.nasa.gov

Kasischke ES, Hewson JH, Stocks B, van der Werf G, Randerson J (2003) The use of ATSR active fire counts for estimating relative patterns of biomass burning-A study from the boreal forest region. Geophys Res Lett. https://doi.org/10.1029/2003GL017859

Kaufman YJ, Justice CO, Flynn LP, Kendall JD, Prins EM, Giglio L, Ward DE, Menzel WP, Setzer AW (1998) Potential global fire monitoring from EOS-MODIS. J Geophys Res Atmos 103:32215–32238. https://doi.org/10.1029/98JD01644

Leone A, Perrotta C, Maresca B (2003) Plant tolerance to heat stress: current strategies and new emergent insights. In: Sanità L, di Toppi B, Pawlik-Skowrońska, (eds) Abiotic stresses in plants. Springer, Dordrecht, pp 1–22. https://doi.org/10.1007/978-94-017-0255-3_1

Littell JS, Peterson DL, Riley KL, Liu Y, Luce CH (2016) A review of the relationships between drought and forest fire in the United States. Glob Chang Biol. https://doi.org/10.1111/gcb.13275

MoEF (1999) National forestry action plan. Ministry of Environment and Forests (MoEF), Government of India, New Delhi

Negi GC (2019) Forest fire in Uttarakhand: causes, consequences and remedial measures. Int J Ecol Environ Sci 45:31–37

Rogers BM, Balch JK, Goetz SJ, Lehmann CER, Turetsky M (2020) Focus on changing fire regimes: interactions with climate, ecosystems, and society. Environ Res Lett 15(3):030201. https://doi.org/10.1088/1748-9326/ab6d3a

Roy PS, Meiyappan P, Joshi PK, Kale MP, Srivastav VK, Srivasatava SK, Behera MD, Roy A, Sharma Y, Ramachandran RM, Bhavani P, Jain AK, Krishnamurthy, YVN (2016) Decadal land use and land cover classifications across India, 1985, 1995, 2005, https://doi.org/10.3334/ORNLDAAC/1336 [WWW Document]. ORNL DAAC, Oak Ridge, Tennessee, USA. URL https://daac.ornl.gov/cgi-bin/dsviewer.pl?ds_id=1336

Satendra, Kaushik AD (2014) Forest fire diaster management. National Institute of Disaster Management, Ministry of Home Affairs, New Delhi. ISBN-978-93-82571-09-4

Schwartz MW, Butt N, Dolanc CR, Holguin A, Moritz MA, North MP, Safford HD, Stephenson NL, Thorne JH, van Mantgem PJ (2015) Increasing elevation of fire in the Sierra Nevada and implications for forest change. Ecosphere 6(7):art121. https://doi.org/10.1890/ES15-00003.1

Scott L, Warmerdam N (2005) Extend crime analysis, with ArcGIS spatial statistics tools. Arc User. vol. 8, No. 2

Semwal RL, Mehta JP (1996) Ecology of forest fires in chir pine (*Pinus roxburghii* sarg.) Forests of garhwal himalaya. Curr Sci 70:426–427

Sharma JK, Sharma S (2007) Litter fall under different aged chir pine stands in shiwalik hills of Himachal Pradesh in North-western Himalayas. Indian Froster 133(8):1081–90

Swetnam TL, Brown PM (2010) Comparing selected fire regime condition class (FRCC) and LANDFIRE vegetation model results with tree-ring data. Int J Wild Fire. https://doi.org/10.1071/WF08001

Trollope WSW (1981) Recommended terms, definitions and units to be used in fire ecology in South Africa. Proc Annu Congr Grassl Soc S Afr 16:107–109. https://doi.org/10.1080/00725560.1981.9648931

Vachula RS, Huang Y, Russell JM, Abbott MB, Finkenbinder MS, O'Donnell JA (2020) Sedimentary biomarkers reaffirm human impacts on northern Beringian ecosystems during the Last Glacial period. Boreas 49:514–525. https://doi.org/10.1111/bor.12449

Vadrevu KP, Lasko K, Giglio L, Schroeder W, Biswas S, Justice C (2019) Trends in vegetation fires in South and Southeast Asian Countries. Sci Rep 9(1):1–13. https://doi.org/10.1038/s41598-019-43940-x

Van Der Werf GR, Randerson JT, Collatz GJ, Giglio L, Kasibhatla PS, Arellano AF, Olsen SC, Kasischke ES (2004) Continental-scale partitioning of fire emissions during the 1997 to 2001 El Niño/La Niña Period. Science 303:73–76. https://doi.org/10.1126/science.1090753

Zhang-Turpeinen H, Kivimäenpää M, Aaltonen H, Berninger F, Köster E, Köster K, Menyailo O, Prokushkin A, Pumpanen J (2020) Wildfire effects on BVOC emissions from boreal forest floor on permafrost soil in Siberia. Sci Total Environ 711:134851. https://doi.org/10.1016/j.scitotenv.2019.134851