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RESEARCH ARTICLE

Chir pine forest and pre-monsoon drought determine spatial, and temporal patterns of forest fires in Uttarakhand Himalaya

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Abstract

Associated with farming practices (between 300 and 2000 m elevations), human-ignited small, and patchy surface forest fires occur almost every year in Uttarakhand (between 28°43`– 31°27` N and 77°34`– 81°02`E; area 51,125 km^2), a Himalayan state of India. Using fire incidence data of 19 years (2002–2020) generated by MODIS, we analysed the factors which drive temporal and spatial patterns of fire in the region. The fire incidence data were organized by 24 forest divisions, the unit of state forest management and administration. The standardized regression model showed that pre-monsoon temperature (March to May or mid-June), proportional area of the forest division under chir pine (*Pinus roxburghii*) forest (positive effect), and pre-monsoon and winter precipitation (negative effect) accounted for 56% of the variance in fire incidence density (FID). The pre-monsoon temperature (warmer) and precipitation (lower) were significantly different in 2009, 2012, 2016 and 2019, the years with high FID (average 54.9 fire/100 km^2) than the rest of years with low FID (average 20.9 fire/100 km^2). During the two decades of warming, high FID (> 30 incidence per year /100 km^2) occurred after every three to four years, and fire peaks tended to increase with time. The study suggests that effective fire management can be attained by improving pre-monsoon precipitation forecasting and targeting forest compartments with a higher occurrence of chir pine and fire-vulnerable oaks. Furthermore, since fires are human-ignited, periodical analysis of changes in population distribution and communities' dependence on forests would need to be conducted.

Keywords Chir pine (*Pinus roxburghii*) · Fire driving factors · Fire seasonality · Himalayas · Pre-monsoon drought · Surface forest fires

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Introduction

Fire-prone ecosystems cover about 40% of the land surface of the planet (Chapin et al. 2002), globally accounting for 32% of carbon monoxide release, 10% of total methane emission and 86% of soot release (Lavorel et al. 2007). Riding heat waves, fires have increased recently in several parts of the world because of climatic warming (Chen et al. 2019 and current reports). For example, the 2019-20 Australian bush fire season came at the end of the second hottest year on record. The consequences of forest fire escalation include biodiversity loss (Pérez-Cabello et al. 2012), forest carbon depletion (Arnett et al. 2015), and decline in soil fertility (Bae et al. 2019). Estimates on forest fires for the Himalayas are rather sketchy and fragmented. Consequently, developing forest fire management practices are challenging. Fire is a part of agricultural practices in many parts of the world including the Himalayas, particularly at forests-agrarian interfaces (Viedma et al. 2018).

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Globally, only 4% of fires are because of natural factors like lightning (Hirschberger 2016), and in India nearly all of fire incidences associated with vegetation are human-induced (Singh et al. 2014). Incidence of fire at forest-agrarian and forests-urban interfaces is influenced by forest composition and resultant fuel attributes, climate and weather conditions, topography, and cultural traits (Westerling et al. 2006; Urbieta et al. 2015; Viedma et al. 2018). Of the total forest area of India, 64.3% is fire-prone, mostly because of humans (FSI 2019). Human activity can play a key role in determining a fire regime at a regional level (Ye et al. 2017). In Himalayas, humans ignite forest fires as well as restrict them by collecting litter from the forest floor (this reduces fuel) (Ye et al. 2017; Negi 2019).

In Uttarakhand Himalaya, forest fire is common in foothills (< 500 m elevation) and subtropical elevations (600–2000 m) where *Shorea robusta* (sal, a dipterocarp) and *Pinus roxburghii* (chir pine), respectively are major forest forming species (Singh and Singh 1992). Climate change is likely to escalate forest fires by intensifying pre-monsoon (March-May) drought (Wester et al. 2019). Like several Himalayan regions, Uttarakhand is warming at a higher rate than global average rate (Banerjee et al. 2021). The black carbon released from forest fires is being recognised as a major air polluter and a major contributor to glacier melt (Ramanathan and Carmichael 2008). During April 2021, when forest fire peaked, Dehradun, a city at the foothills of the Western Himalaya had the BC concentration in air close to that of Delhi (Gogoi et al. 2021). In recent years, data on forest fire incidences have become more reliable in Uttarakhand with the development of MODIS (Moderate Resolution Imaging Spectroradiometers) for fire detection.

The main objectives of the present study are (i) to characterize the seasonal periodicity and spatial pattern of forest fires across the forest divisions of Uttarakhand Himalaya, and (ii) to identify the driving factors by analysing data on fire incidences compiled from MODIS for about two decades from 2002 to 2020. The analysis is in relation to multiple factors, such as the area under fire-prone forest types, pre-monsoon drought and temperature, population and cultural factors and timing of litterfall. Though forest fire in the region is a human-ignited phenomenon, we hypothesize that it is influenced to a great extent by forest composition, and pre-monsoon drought. Being the most fire tolerant species in Uttarakhand, chir pine (*P. roxburghii*) is likely to be a major determiner of the spatial distribution of fire occurrence.

Materials and methods

The study area

The study on forest fires of Uttarakhand, a Himalayan state of India (between 28°43`– 31°27`N and 77°34`– 81°02`E; area 51,125 km^2), was based on forest divisions (a forest division, is a unit containing several forest types demarcated for administrative and management purposes by State Forest Department (SFD)) of Uttarakhand state of Indian Himalaya. The rainfall pattern of the region is characterized by a typical monsoon season (mid-June to mid-September), which accounts for about three-fourths of the annual rainfall (average for Uttarakhand is ~ 1500 mm). In Uttarakhand, warming rate has increased recently, for example during 2000–2007 temperature increased at the rate of 0.043 °C/yr (Banerjee et al. 2021).

The 24,303 km^2 state forests (45.4% of the total geographical area, FSI 2019) are managed under 33 forest divisions ranging in area from 47 km^2 to 2390 km^2 with about 50% of divisions falling within 500–1000 km^2 area (Uttarakhand Forest Statistics 2018). Since in forest divisions of protected areas (9 forest divisions) fires are regulated by SFD, we did not consider them for the present investigation. From the stand point of forest type, three forest divisions were chir pine (*Pinus roxburghii*)-dominated (Almora, Bageshwar and Tons), one was largely banj-oak (*Quercus leucotrichophora*)-dominated, nine had both chir pine and banj-oak forests, three had largely sal (*S. robusta*) and one had chir pine and sal as prominent forest types (Uttarakhand Forest Statistics 2018). Among the others, the forest divisions of foothills and plains (referred to as Tarai or moist plains) in the south included the early successional community of *Acacia catechu-Dalbergia sissoo* on freshly deposited sand along the rivers, and several mixed deciduous and evergreen broadleaved forest types. Between 1000 and 2000 m elevation range chir pine and banj oak form mono-dominants as well as mixed stands. In higher elevation, above 2500 m fires were rare because of moist forests and the absence of human settlements. In higher elevation areas (> 2500 m), sub-alpine forests consisting of silver firs (*Abies* spp.), blue pine (*P. wallichiana*), and spruce (*Picea smithiana*) were common.

Fire has promoted the regional domination of chir pine at the expense of broadleaf oak forests (Singh and Singh 1992; Semwal and Mehta 1996), and the ban on tree cutting above 1000 m elevation since 1981 further favoured chir pine, as branches of oak continued to be cut for fodder and firewood (Thadani 1999), while chir pine trees were generally saved. However, resin tapping and fire combine to cause mortality of chir pine trees (Fulé et al. 2021). One of the major purposes to ignite forest fires is to increase the availability and quality of grasses for feeding domestic animals (Brandis 1897; Goldammer 1993; Schmerbeck and Seeland 2007; Kohli 2010). Prescribed burning has been used by the forest managers to promote even-aged young stands of *P. roxburghii* and *S. robusta* at the expense of other tree species (Troup 1921; Singh and Singh 1992).

Data source and measurements

We obtained fire data for 24 study forest divisions (excluding wildlife sanctuaries, national parks and civil soyam forest divisions) from MODIS fire data product (MCD14ML) provided by Fire Information for Resource Management Systems (FIRMS). MODIS fire observations are made four times every day from Terra (1030 and 2230 h) and Aqua (0130 and 1330 h) satellites. Forest Survey of India (FSI) screens forest fires by clipping the MODIS data to include lands under forest department management. The data obtained contained records of ignition coordinates, and date of occurrence. MODIS specifies the location of the fire at the time of satellite pass. The location of fire corresponded to the centre of a 1×1 km fire pixel representing one or more fire incidences occurring within the pixel area. MODIS could detect fires as small as 50 m^2, depending on the intensity of the fire and its visibility from space.

Climate variables affect fuel accumulation and moisture which largely determine the time, location and occurrence probability of forest fires (Oliveira et al. 2012). In this study, the climate variables included annual and seasonal variables of precipitation, temperature, and relative humidity. Data for precipitation, relative humidity and temperature were obtained from 'NASA' 'POWER' (Prediction of Worldwide Energy Resource) global meteorology, surface solar energy and climatology data 'API' (https://power.larc.nasa.gov/data-access-viewer/).

For vegetation variable, we used area under different forest types for all Himalayan states provided in FSI (2019). Socioeconomic variables affect the probability of forest fire occurrence by affecting human activities. For example, human travel and collection of fuel and fodder and other NTFPs in or around forests will increase the probability of fire occurrence.

Analysis of spatial and seasonal patterns of forest fires

Year-to-year trends in active fire locations per state from 2002 to 2020 were assessed using the MCD14ML data product. Regression analysis was performed to estimate fire incidence patterns by months, season, and year in all studied forest divisions from the period 2002 to 2020. The number of fire detections for each year from 2002 to 2020 was analysed in terms of detections per unit forest area in the state forest divisions. To calculate fire interval time or fire frequency, we considered two fire levels (i) moderate fire level with more than 30 fire incidence/100 km^2 (fire incidence density, FID_{30}), and (ii) severe fire level with more than 100 fire incidence /100 km^2 (fire incidence density, FID_{100}). The forest divisions with FID below 30 fire incidence /100 km^2 were categorized as low fire divisions.

Statistical analysis was performed to evaluate how pre-monsoon (March to May or mid-June) temperature or precipitation influenced the severity of fire season. Correlation between forest area and fire incidence density; precipitation and number of fire incidences during pre-monsoon season; and fire incidence density for all studied forest divisions was developed in SPSS.

A total of 17 variables (total forest area, area under pine, sal, oak and other forests; winter, pre-monsoon, monsoon, and autumn temperature; winter, pre-monsoon, monsoon, and autumn precipitation; winter, pre-monsoon, monsoon, and autumn relative humidity; forest road density), grouped into climate, forest type and socioeconomic categories were selected as the initial forest fire driving factors. Standardized Regression Model was applied to identify the forest fire driving factors among the selected variables and their corresponding impacts on forest fire occurrence in 24 forest divisions of Uttarakhand by using stepwise regression through SPSS. Various statistical parameters were estimated for the developed model. This is considered the best approach for estimation of a continuous variable (Oza et al. 1989).

Results

The fire incidences varied widely, both temporally and spatially in Uttarakhand. On average across the study forest divisions and the period (19 years from 2002 to 2020), 176.40 ± 27.68 fire incidences per forest division occurred annually. In total in the 19 study years there occurred 80,440 fire incidences in Uttarakhand, ranging annually from 475 to 2020 (the COVID-19 affected year) to 10,091 in 2016. Across the divisions, the cumulative fire incidences during 2002–2020, ranged from 449 in Kalsi division to 7,919 in Almora division, and the yearly average of fire incidence was from 19.8 to 420.5 per division.

Fire incidence density

Year-to-year difference

The average annual fire incidence density (incidence per 100 km^2 forest area, FID), across the forest divisions was significantly more in the years: 2016 (67.4/100 km^2), 2012

(58.9/100 km^2), 2009/2008 (51/100 km^2 and 45.5/100 km^2), and 2019 (42.2/100 km^2) than in the rest of years (3.2 to 37/100 km^2) (Fig. 1). The averages of four high fire years and that of the rest of 15 years were significantly different ($t(5) = 5.41$; $p < 0.01$).

Time interval of fire recurrence

The time interval (years) between two successive FID_{30} years (30 or more fire incidence /100 km^2) across the divisions, on average ranged from 0 (no gap year i.e., fire of FID_{30} in successive years) to 3 year, with an average of 1.7 year (Table 1). The number of years with FID_{30} was high in Tarai West (15 out of 19 years) and Almora (12 out of 19 years), though the yearly mean FID was distinctly lower in it (44.5/100 km^2) compared to that in Almora (68.1/100 km^2), while in 7 divisions, FID_{30}, was very infrequent or absent. They included divisions of high altitude with moist temperate forests and of the plains/foothills with substantial urban surroundings or cropland plantations of eucalypts, and poplars, such as Tarai East. In them either humans were absent or did not depend on forests for biomass on day-to-day basis. In only 8 of the 24 forest divisions, the FID was > 100 in any of the years. The time interval between two successive years of FID_{100} ranged from 0 to 14 years, with an average of 4.9 years for divisions experiencing FID_{100} (Table 1).

Categories of forest divisions on the basis of fire incidence density

The 24 study Forest Divisions were divisible into four groups on the basis of average FID ($FID_{average}$) across 19 years (Fig. 2) and in five groups on the basis of peak annual FID (FID_{peak}) among study years (Fig. 3). Generally, a forest division fell within similar categories in the two classifications. For example, the low category of $FID_{average}$ included 11 divisions, of which 10 were also included in the low category FID_{peak}. They included the subalpine divisions as well as those of plains with thick urban surroundings like Dehradun and Haridwar.

In high fire incidence divisions, chir pine forest was dominant in two divisions (Almora, 69% and Bageshwar, 75.6%), Haldwani had largely sal forest (70.7%), and the rest of four divisions had both chir pine and banj oak forests. Division with moderate FID varied in forest types. Among all forest divisions, Almora topped in both the forest incidence classifications.

The highest FID in 19 study years in forest division gives an idea of fire severity that can occur. It was relatively high,

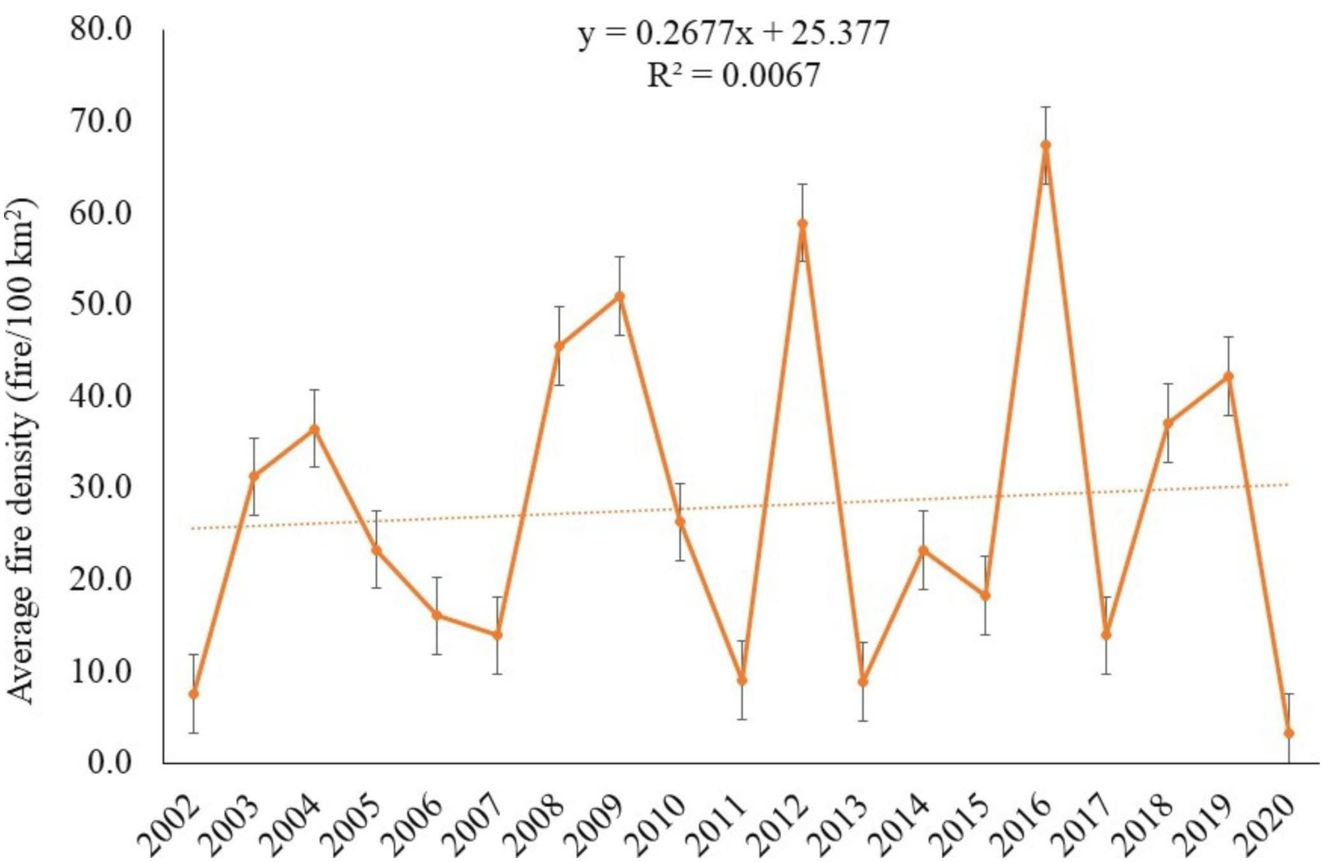


Fig. 1 Annual average fire incidence density across the 24 study forest divisions of Uttarakhand during 2002–2020

Table 1 Average annual and peak fire incidence density along with average number of years between two successive fire years of forest divisions in different FID classes

Forest divisions	Average Fire incidence density (fire/100 km^2)	Average number of years (between two fire years)		Peak fire incidence density (number per 100 km^2)
		With FID 30–100	With FID > 100	
Very high fire incidence density (> 60 fire/100 km^2)				
Tarai Central	64.33	14 (0.3)	3 (1)	117.29 (2006)
Almora	68.10	9 (1)	3 (5)	242.8 (2012)
High fire incidence density (41–60 fire/100 km^2)				
Narendra Nagar	43.13	6 (2)	3 (4)	143.46 (2016)
Haldwani	43.54	6 (1)	3 (5)	161.8 (2016)
Tarai West	44.49	15 (0.2)	NA	89.93 (2005)
Nainital	44.54	7 (2)	2 (7)	174.33 (2016)
Lansdowne	45.34	7 (1)	2 (7)	133.82 (2016)
Garhwal	49.25	3 (5)	5 (2)	149.51 (2018)
Moderate fire incidence density (21–40 fire/100 km^2)				
Ramnagar	22.07	6 (2)	NA	53.35 (2010)
Tarai East	23.04	5 (3)	NA	44.77 (2016)
Bageshwar	27.47	8 (1)	NA	97.67 (2012)
Tons	28.15	7 (1)	NA	81.82 (2009)
Champawat	35.14	6 (2)	2 (8)	104.69 (2019)
Low fire incidence density (< 20 fire/100 km^2)				
Pithoragarh	5.33	NA	NA	10.18 (2016)
Uttarkashi	6.87	NA	NA	22.42 (2009)
Upper Yamuna	8.38	1 (7)	NA	41.53 (2009)
Dehradun	9.26	1 (8)	NA	30.49 (2010)
Kalsi	10.13	1 (1)	NA	39.45 (2003)
Mussorie	13.09	3 (4)	NA	46.57 (2009)
Haridwar	13.29	1 (6)	NA	44.79 (2008)
Badrinath	14.38	2 (5)	NA	45.53 (2009)
Chakrata	17.15	4 (3)	NA	70.17 (2009)
Tehri	17.33	4 (4)	NA	48.58 (2009)
Rudraprayag	19.51	6 (2)	NA	51.61 (2009)

between 128 and 243/100 km^2 in six divisions (Fig. 3). In 19 of the 24 study forest divisions, the year 2016 was among the four top fire incidence years, and in 6 divisions it was the year of highest FID. Year 2016 was listed as high fire incidence year with an average density of 67.4/100 km^2 (Fig. 1). The year 2009 was the next prominent fire year in 14 divisions and it occurred as major (top four) fire year in 8 divisions. Of the three top fire affected forest divisions in which FID exceeded 150/100 km^2 in one or more years, two had chir pine forest as major forest type, and the remaining one had sal as major forest type. Forest divisions with banj oak (an evergreen oak generally occurring from 1000 to 2000 m) dominance like Mussorie had low fire incidence density (13.1/100 km^2).

On an average, the pre-monsoon precipitation was significantly lower in high fire years (2009, 2012, 2016 and 2019) than in low fire years (other of the study period) ($t(359) = 10.28$; $p < 0.01$).

Fire seasonality and peak month of fire incidence

The fire ignition can occur only when enough litter has accumulated on forest floor as well as conditions are dry. That is why most of the fires occurred from March to May but varied within this period across the forest divisions as following:

A prominent May FID peak with a secondary peak in April. It included Almora (Fig. S1 X), the division of the highest FID as well as three more divisions had moderate to low FID (Fig. S1 N,I,J); a prominent April peak with a secondary peak in May in 3 divisions (Fig. S1 T,Q,K); equally prominent April and May peaks (in four divisions, Fig. S1 R,E,F,B); one clear-cut April peak (in Lansdowne having high FID and high fire peak, Fig. S1 U); and several peaks staggered over a relatively long period from February to June (Fig. S1 S and W).

However, even within a division, the peak fire month varied from year to year, largely because of pre-monsoon rain storms. For example, in the year 2016, the April was the month of high FID peak, as burning was suppressed

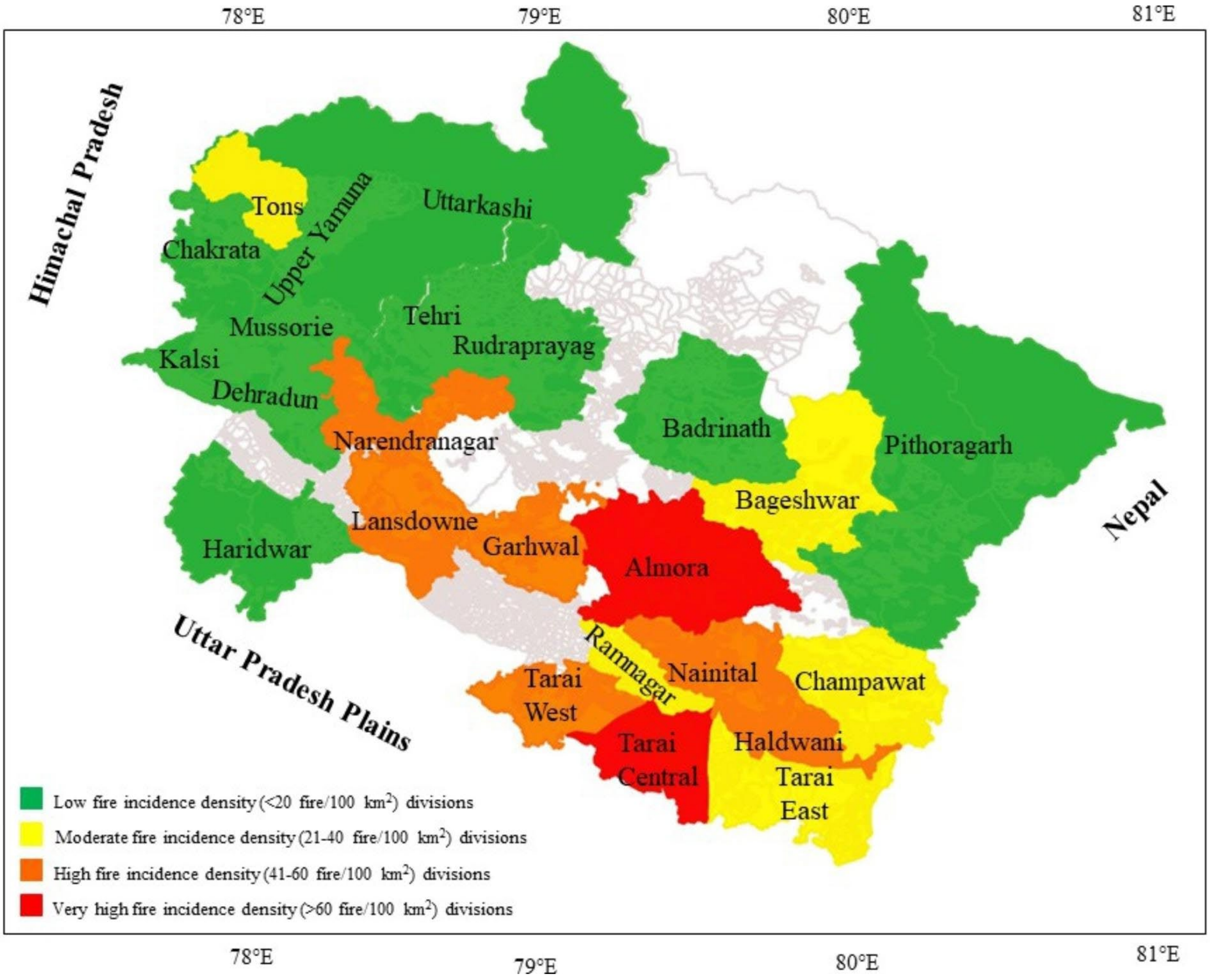


Fig. 2 Forest fire incidence density (FID) map of Uttarakhand. The FID is average number of fire incidences per year during 2002–2020. The different fire incidence density classes are categorized as: (i) low fire incidence density (< 20 fire/100 km^2) divisions (n = 11); (ii) moderate fire incidence density (21–40 fire/100 km^2) divisions (n = 5); (iii) high fire incidence density (41–60 fire/100 km^2) divisions (n = 6); and (iv) very high fire incidence density (> 60 fire/100 km^2) divisions (n = 2)

by rain in May (63.2 mm in May compared to 11.4 mm in April). On the other hand, in 2012 burning was negligible in April because it was wet (34.9 mm) and May which was dry (3.52 mm) and warm witnessed high FID peak (Fig. 4).

Analysis of driving factors of FID

Across the 19 study years, the Standardized Regression Model for fire incidence modelling with several contextual factors was statistically significant i.e. model provided a fit to the data with five factors: pre-monsoon temperature, proportional area under chir pine forest in the division, winter precipitation, pre-monsoon precipitation, and forest under other species. The model had low standard error with no auto-correlation in residuals (Durbin Watson, DW, statistics is approximately 2). The five factors explained 56% of the variation in fire incidence. It shows that fire incidence across forest divisions of Uttarakhand was strongly positively influenced by pre-monsoon temperature, and area under pine forests. The fire progression was adversely impacted by the presence of mixed vegetation, particularly when like *Syzygium cumini, Adina cordifolia, Anogeissus latifolia*, and other such moist habitat species. Pre-monsoon and winter precipitation were negatively correlated with fire incidence density. The model showed that with the increase of 1 standard deviation in the pre-monsoon temperature and area under chir pine forest across the forest divisions, the standard deviation in fire incidence would increase by 0.86 and 0.34, respectively. In contrast, with increase in 1 standard deviation in winter precipitation, pre-monsoon precipitation and forest area of other species than chir pine, the fire incidence would decrease by 0.25, 0.21 and 0.18 standard deviation, respectively.

$$\mathrm{FID} = 0.86\,\mathrm{PT} + 0.34\,\mathrm{APF} - -0.25\,\mathrm{WP} - -0.21\,\mathrm{PP} - -0.18\,\mathrm{AOF}$$
$$\left(\mathrm{Adj}\ R^2 = 0.56;\ \mathrm{SE} = 29.15;\ \mathrm{DW} = 1.98;\ \mathrm{ANOVA} = 100.68\ (0.00)\right)$$

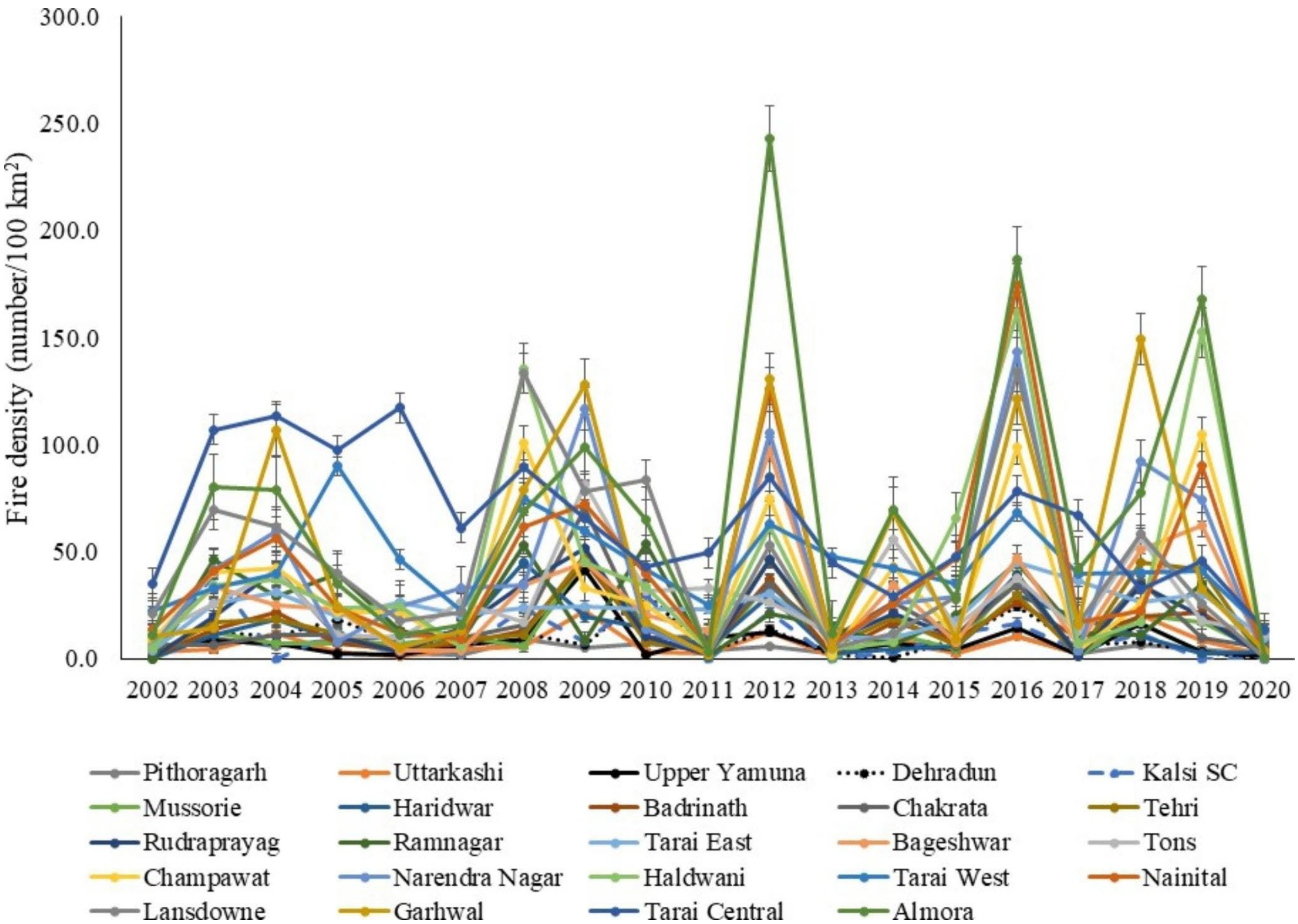


Fig. 3 Annual fire incidence density (FID) by forest divisions during 2002–2020

where; FID = Fire Incidence Density (fire/100 km^2); PT = Pre-monsoon temperature (°C); APF = Area under chir pine forest (km^2); WP = Winter precipitation (mm); PP = Pre-monsoon precipitation (mm); and AOF = Area under other forest species (km^2).

When we take average values of 19 years, the Standardized Regression Model for fire incidence was statistically significant, i.e., model provided a fit to the data with three independent contextual factors. The model has low standard error having no auto-correlation in residuals (Durbin Watson (DW) statistics is approximately 2). The model predicting fire incidence density fitted the data well, explaining 86% of the variation in fire incidence density in Uttarakhand. Area under pine forest and pre-monsoon temperature were the most important variables.

Discussion

Drivers of forest fires

As conceptualized in Fig. 5, human ignited forest fires in Uttarakhand are influenced by several biophysical and cultural drivers. These drivers are under a constant flux, resulting in a wide variation in fire incidence across the forest divisions, years and seasons of a year. In a broad term, while the spatial differentiation of fire incidence is largely determined by the percentage of area under chir pine forest, pre-monsoon is the time when it mostly occurs. During the pre-monsoon conditions are dry and warm, and fresh litter is deposited on forest floor. In contrast, during the monsoon (June-end to September-end), heat is accompanied by heavy rainfall and high humidity levels, which have opposite effect of heat on fire (Ma et al. 2020).

The expansion of chir pine, as being observed in Uttarakhand (Singh and Singh 1992; Das et al. 2021) is likely to intensify fire and increase the area affected, but the fire season would remain tied to pre-monsoon drought. In the

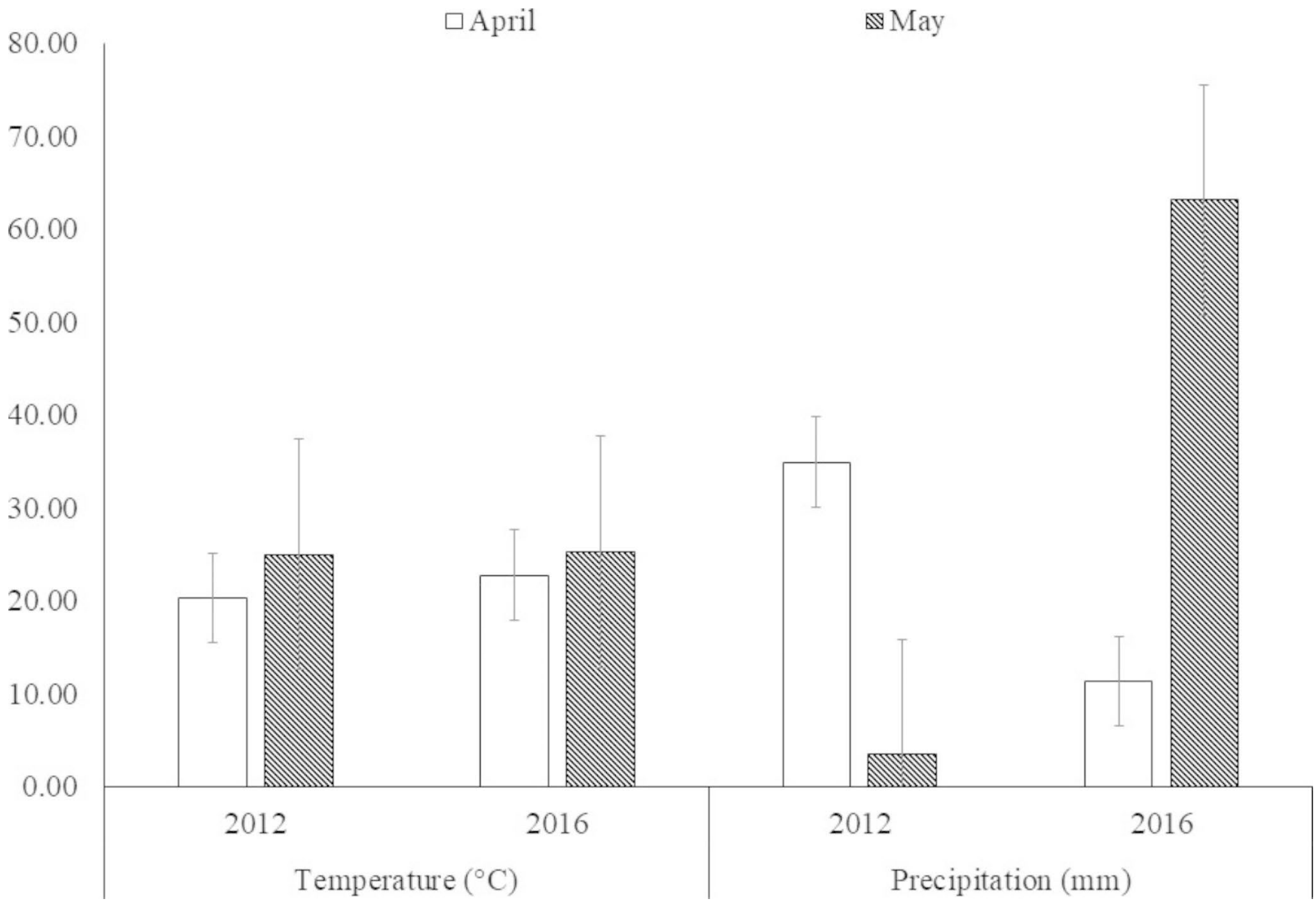
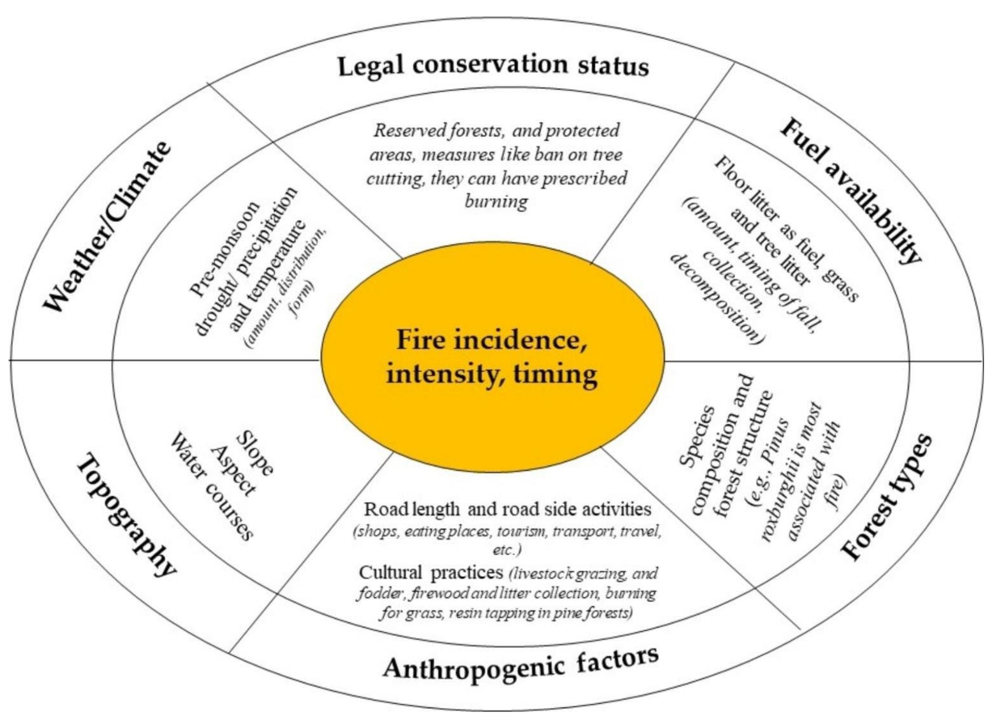


Fig. 4 A comparison between temperature and precipitation in April and May of two mega fire years (2012 and 2016)

Fig. 5 Major factors which determine the intensity and timing of forest fires in Central Himalaya. It is largely based on Uttarakhand state of India, but applies to an extent also to central and western Nepal, and western Himalayan states of India



forest divisions with chir pine and banj oak interfaces, the fire incidence may increase because of the conversion of banj oak forest into chir pine. For example, in Nainital and Almora divisions during about three decades banj oak forest lost 22.2% area from dense forest area and 29.2% from degraded open forest area largely because of biomass extraction by local communities and recurring fires. Chir pine is the main beneficiary of these changes in banj oak forests.

A comparison between two super fire years, 2012 and 2016, explains the critical role of pre-monsoon rainstorms in the landscape flammability. In 2012 there were few fire incidents during April because of frequent rain (35 mm) and FID peaked in May which was dry. Since litter fall largely occurs during March-end and most of April (Singh and Singh 1992), fire rarely occurs before that. In contrast, in 2016 fires peaked in April, as it was dry and warm, and they were suppressed in May because of rain (63.21 mm).

Fire incidence in Uttarakhand is relatively high. The highest incidence of 10,091 fires in 2016 in Uttarakhand, is considerably more than the highest reported for Arunachal (777 in 2009), a state with a larger forest area and affected by shifting agriculture (Ahmad et al. 2018). In fact, Uttarakhand has much more forest fire incidence than any other Himalayan state other than Mizoram of the Eastern Himalayas. Apart from cultural traits, vegetation composition seems to account for it. Among the Himalayan regions, the chir pine occupies more area in Uttarakhand than any other state (Singh et al. 2021).

Wider implication of forest fire for the region

Studies generally have shown that fire induces the growth of grasses in pine forests and that is the main reason of fire ignition by farmers (Fulé et al. 2021). There is a scarcity of fodder for livestock, which has been an integral part of Uttarakhand's subsistence farming since the time immemorial (Fig. 5). However, other anthropogenic factors also contribute to forest fires. For example, the presence of workers for pine resin tapping is common during the period, and its role in fire ignition cannot be ignored.

Decrease in livestock density hence in free grazing, and breaking down of age-old day-to-day human-forest interactions are some of the major consequences of rural depopulation (Mamgain and Reddy 2017). In recent years, abandonment of agriculture and migration of people (Mamgain and Reddy 2017) from rural mountain areas have increased rapidly. From 2012 to 2017 population of cattle and goats decreased by ~75%. This, in combination with decrease in free grazing can be considered a major change in the rural landscapes. However, these changes in forest and local people relationship have not been accompanied by decrease in forest fire incidences. Possibly, it is the part of the past legacy that will take time to diminish. Even if changes that have occurred in the attitude of people, may not be reflected, as a forest fire does not take more than a few individuals to ignite.

The rapid climatic warming in Himalayas (Wester et al. 2019) is likely to accelerate forest fire incidences. The depletion of soil moisture during pre-monsoon months reflects it (Singh et al. 2018).

Fire incidence rapidly declines above 2000 m in evergreen oak forests often with Lauraceous undercanopy. However, oaks particularly *Q. leucotrichophora* often occur along with chir pine both as mixed and separate adjacent stands, south slope aspect and the ridge tops being under chir pine and northern slopes hill bases under oaks (Singh and Singh 1992). Since the ban on tree cutting in 1981, while chir pine stands were largely saved, banj oak continued to be degraded because of lopping of its branches for fodder and firewood. Fire spreading from chir pine forest stands to banj oak forest stands further aggravated the degradation of banj oak forests. With increased light availability chir pine rapidly colonizes the degraded oak forests, resulting in its range expansion. Sal with thick bark and ability to establish seedlings on burnt sites (Troup 1921) is another major gainer of small surface fires regime. Patches of savanna like vegetation have developed around sal forests because of frequent fires. Though MODIS data as maintained by the FSI do not shed light on the significance of invasive species like *Lantana camara*, they too increase fire spread (Negi 2019).

Management implications

Since pre-monsoon drought and the proportion of chir-pine forests in a forest division determine fire incidences, the preparation for fire management can be made effective by improving the prediction of pre-monsoon precipitation or its absence. While managing forest fires, focus should be on forest compartments with higher percentage of chir pine surrounded by fire-vulnerably oaks occur more. There should be a long term plan with definite yearly targets, rather than reacting to fire incidences as a seasonally crisis. It may be clear that small patchy forest fires are required to avoid disastrous big fires so there is a need to practice controlled fires based on research. This may warrant a policy decision and community level involvement.

It may be pointed out that population distribution in the mountains and dependence of local communities on forests on day-to-day basis are rapidly changing. For example, because of the reduced grazing, herbaceous litter may increase and provide a larger fuel mass for fires even during winters. These changes and their impact on fire regimes should be closely monitored for improving fire management. The role of local forest institutions, like Van Panchayats might need to be examined in view of social changes occurring in the region.

It may be emphasized that MODIS data have played important role in understanding the spatial and temporal distribution of fire, however, more data collection on varied parameters and research are needed in view of rapidly changing climate and social factors.

Conclusions

Our analysis of MODIS data on fire leads to the conclusion (i) that chir pine forest is the major determiner of the spatial distribution of fire incidence, (ii) that the timing of forest fire is largely driven by the dry pre-monsoon months and litterfall (source of fuel for fire), and the need of the local farmers for new growth of grasses, and (iii) that at the forest division level fire events surge after every three to four years, which could be predicted with the improved pre-monsoon weather forecasting. People are used to igniting fire but as burnt area expands and fire incidences decrease. Because of this social feedback the fire season is generally less than 40–45 days, and it could be further shortened by promoting awareness and community involvement.

It is important to examine why human-ignited fire continues unabated, despite the weakened linkage between forest and farming in several areas with the increasing agriculture abandonment, migration and depopulation. Because of the decrease in cultivation, woody species and exotics like *L. camara* and *Ageratina adenophora* have increased. Though, it can be speculated that because of increased conflicts between human and wildlife, farmers tend to keep areas around households open by burning hide-outs likely to be used by wild animals such as boars, and porcupines, which often damage crops. Fire management should be far more research based than it has been. For example, almost nothing is known about species vulnerability at community level, based on bark thickness and other adaptation traits.

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