

# **GeoHealth**

# RESEARCH ARTICLE

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## **Special Section:**

Fire in the Earth System

#### **Key Points:**

- Compared to 2001–2005, central India domain forest fire activity during 2006–2020 doubled in forest fire season and tripled in non-fire season
- Role of persistent warmer temperatures and multiple climate extremes in increasing forest fire activity over central India is highlighted
- Deciduous forests of Jagdalpur-Gadchiroli Range and Indravati National Park are extremely fire prone and fires are of high intensity

#### **Supporting Information:**

Supporting Information may be found in the online version of this article.

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# **Investigation of Forest Fire Activity Changes Over the Central India Domain Using Satellite Observations During 2001–2020**

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**Abstract** Recurrent and large forest fires negatively impact ecosystem, air quality, and human health. Moderate Resolution Imaging Spectroradiometer fire product is used to identify forest fires over central India domain, an extremely fire prone region. The study finds that from 2001 to 2020, ~70% of yearly forest fires over the region occurred during March (1,857.5 counts/month) and April (922.8 counts/month). Some years such as 2009, 2012, and 2017 show anomalously high forest fires. The role of persistent warmer temperatures and multiple climate extremes in increasing forest fire activity over central India is comprehensively investigated. Warmer period from 2006 to 2020 showed doubling and tripling of forest fire activity during forest fire (February-June; FMAMJ) and non-fire (July-January; JASONDJ) seasons, respectively. From 2015 JASONDJ to 2018 FMAMJ, central India experienced a severe heatwave, a rare drought and an extremely strong El Niño, the combined effect of which is linked to increased forest fires. Further, the study assesses quinquennial spatiotemporal changes in forest fire characteristics such as fire count density and average fire intensity. Deciduous forests of Jagdalpur-Gadchiroli Range and Indravati National Park in Chhattisgarh state are particularly fire prone (>61 fire counts/grid) during FMAMJ and many forest fires are of high intensity (>45 MW). Statistical associations link high near surface air temperature and low precipitation during FMAMJ to significantly high soil temperature, low soil moisture content, low evapotranspiration and low normalized difference vegetation index. This creates a significantly drier environment, conducive for high forest fire activity in the region.

Plain Language Summary Forest fire activity is strongly related to three factors-availability of combustible fuels, climate and weather forcing, and ignition agents (natural or anthropogenic). Under a warming climate, many studies suggest a significant increase in forest fires. Forest fire activity is already found to be significantly increasing in many regions for example, California and the Arctic. In India, most studies focus on either the forest fires in Himalayas or Jhum-cultivation led forest fire activity. However, central India which has a high forest fire activity goes neglected. The present study investigates the forest fire activity changes in central India domain over a period of 20 years using satellite observations. Compared to 2001–2005, forest fire activity during 2006–2020 doubled in the forest fire season and tripled in the non-fire season. In central India domain, forest fires are also found to increase under periods of persistent warmer temperatures and under simultaneous multiple climate extremes for example, severe drought, strong El Niño and intense heatwave. Further, some dense deciduous forests of the region are found to be extremely fire prone, and are identified. Significantly high soil temperature, low soil moisture content, low evapotranspiration and low vegetation index dries out the environment, and high forest fire activity occurs.

# 1. Introduction

Forest fire is an increasingly common phenomenon that affects almost all forest types and biomes on earth, largely causing global to regional changes in the air quality, radiation budget, land-atmosphere interactions, nutrient cycles, and ecological balance (Bowman et al., 2011; Cochrane, 2009; Giglio et al., 2016). Recurrent fires also pose considerable threat to nearby residents who often suffer from cardiovascular and respiratory diseases such as asthma, chronic bronchitis, and emphysema. In cases of massive forest fires, people are forced to evacuate or permanently relocate their homes. High fatalities of residents, firefighters, and fauna, severe air pollution ranging from few to thousands of kilometers, and huge economy losses from property damages, national park closures,

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Formal analysis: Madhavi Jain, Pallavi Saxena, Som Sharma, Saurabh Sonwani Investigation: Madhavi Jain, Pallavi Saxena, Som Sharma, Saurabh Sonwani Methodology: Saurabh Sonwani Software: Madhavi Jain, Pallavi Saxena, Som Sharma, Saurabh Sonwani Supervision: Saurabh Sonwani Validation: Madhavi Jain, Pallavi Saxena, Som Sharma

Visualization: Som Sharma, Saurabh

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Sonwani Writing – review & editing: Madhavi Jain, Pallavi Saxena, Som Sharma, Saurabh Sonwani tourism and recreational activity curbs, highway blocks, air travel diversions etc. are some of the major losses incurred from large scale, recurrent forest fires.

Fire incidences strongly depend on fuel type, climate-weather patterns, availability of ignition agents, and level of human interference (Flannigan et al., 2005, 2016). Globally, it is recognized that ~80% of forest fires are anthropogenic in nature (FAO, 2007). In India, ~50% of the forest areas are classified as fire prone and >95% of forest fires are of anthropogenic origin (Babu et al., 2016; Forest Survey of India [FSI], 2020; Satendra & Kaushik, 2014). In tropical countries such as India, forest fire is regularly used as a tool to make land available for agriculture, whether for shifting (Jhum) cultivation or permanent conversion to cropland (Ahmad et al., 2018; Chakma & Nahar, 2012; Crutzen & Andreae, 1990). Accidental and intentional fires caused by negligently discarded cigarette butts, campfires, debris burning, and acts of arson are also important forest fire ignition agents (Babu et al., 2016; Forest Survey of India [FSI], 2019; Sevinc et al., 2020). Given favorable weather conditions these anthropogenic fires can quickly become uncontrolled and spread to wide areas of the forest, ultimately turning into a large-scale disaster (Lamat et al., 2021). The occurrence, frequency, and intensity of forest fires is also linked to changing weather and climatic conditions such as warmer temperature, precipitation deficits, increased number of dry days, and El Niño-Southern Oscillation (ENSO) events. El Niño years are characterized by above normal temperatures and reduced precipitation across the tropics (Chen et al., 2017; National Oceanic and Atmospheric Administration [NOAA], 2021) and can lead to an increase in fire incidences, burnt area and pollutant emissions from fire activity (Larkin & Harrison, 2005). Similarly, severe and prolonged regional heatwaves take away moisture from the atmosphere and the soil, along with drying out timber, fire wood, understory shrubs, and forest floor grasses, which can significantly increase the likelihood of droughts and forest fires (Jain, 2021; Littell et al., 2016; Prasad et al., 2008; Whitman et al., 2019). Lightning strikes, such as those witnessed in the 2020 California fires, can also act as a major natural fire ignition agent in dry forests (Cattau et al., 2020; Li et al., 2020).

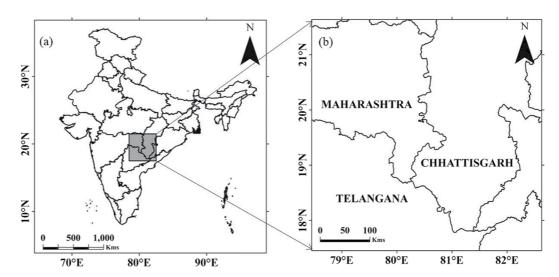
In India, land clearance activities and frequent droughts have engendered enormous, unrestrained vegetation fires that have burned down many large areas of forest and agricultural land (Reddy et al., 2017; Vadrevu et al., 2006). Moreover, crop residue burning after harvest is an extensively practiced activity by farmers in India (Sarkar et al., 2018; Saxena et al., 2021) and can become a forest fire hazard. Forest fire incidences in turn cause further land degradation, worsen local to regional scale environmental health, release trapped carbon dioxide (CO<sub>2</sub>) back into the atmosphere and significantly contribute to global warming (Flannigan et al., 2000; Henderson et al., 2011). While some forest fires benefit the ecosystem by clearing away snag trees and forest floor debris, recycling nutrients back to the soil, opening up canopy, and promoting healthier subsequent forest generation, in most cases however, frequent, uncontrolled, and massive fires are immensely harmful to the ecosystem (Bond & Keeley, 2005; Meyn et al., 2007; North et al., 2012; Reddy et al., 2017). Several studies also highlight that forest fires can be responsible for soil erosion and can affect the water quality (Hewelke et al., 2020; Massman et al., 2003). Thus, forest fires significantly affect the forest structure, ecological processes as well as hydrological and biogeochemical cycles (Bond & Keeley, 2005; Massman et al., 2003; Turner, 1989).

Forest fires also emit large quantities of particulate matter (PM) and black carbon (BC) as well as trace gases for example,  $CO_2$ , carbon monoxide (CO), methane (CH<sub>4</sub>), hydrocarbons, and oxides of nitrogen (NO<sub>x</sub>) and frequent fires can alter atmospheric chemistry (Bibi et al., 2017; Crutzen & Andreae, 1990; Ribeiro-Kumara et al., 2020). Globally, biomass burning contributes to 20%–30% of  $CO_2$  emissions and hydrocarbons, CO and  $NO_x$ , 42% of BC, and 74% of primary organic carbon (Andreae, 1991; Bond et al., 2004; Saxena et al., 2021). Moreover, over India, Reddy et al. (2017) estimated that 67.83, 4.47, 0.29, 0.01, and 0.07 Tg/yr of  $CO_2$ , CO, CH<sub>4</sub>,  $NO_x$ , and  $N_2O$ , respectively were emitted from protected area forests (such as national parks, sanctuaries, conservation and community reserves) in the year 2014. Several studies also highlight that aerosol loading is the highest during the forest fire season (Mitchell et al., 2014; Saxena et al., 2021; Tosca et al., 2013). This is of particular importance in countries such as India, where aerosol load is already significantly high due to air pollution and dust (Dey et al., 2004; Sonwani & Kulshrestha, 2019; Sonwani & Saxena, 2021). In such circumstances, a high forest fire activity can worsen the already poor air quality in India and significantly impact human health.

Satellite observation based thermal anomalies and active fire data sets are a convenient, easily accessible, and a reliable tool to provide long-term continental to local scale fire information and to continuously monitor forest fires over various parts of the world (Giglio et al., 2009, 2016; Jain, 2021; Kale et al., 2017; Littell et al., 2016; Yang et al., 2021). Even though attention towards the impact of forest fires in the tropics has greatly increased over the past few decades (Goldammer & Price, 1998; Saxena et al., 2021; Vadrevu et al., 2006), research on

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**Figure 1.** (a) Geographical location of central India domain (shaded in gray) within the Indian boundary and (b) an enlarged view of the study area showing Chhattisgarh, Maharashtra, and Telangana states.

causes of forest fires in India along with their ecological, climatic and human health impacts is still limited. The fire season in the Indian subcontinent is spread over the dry months from February till June (FMAMJ), whereas remaining months of the year (JASONDJ) show little to no fire activity and are considered as the non-fire season (FSI, 2020; Kale et al., 2017). Forests in India are of diverse types, but much focus remains on either Himalayan forest fires (Babu et al., 2016; Banerjee, 2021; Chandra, 2005; Kumar, Rajeevan, et al., 2013; Kumar, Sheikh, et al., 2013) or on forest fires caused by the practice of Jhum-cultivation in north-east India (Ahmad et al., 2018; Lamat et al., 2021; Puri et al., 2011). However, central India, an extremely fire prone region often goes neglected.

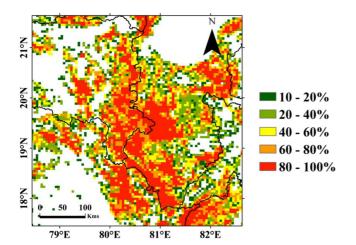
Therefore, the present study intends to fill this research gap by investigating the long-term forest fire activity changes from 2001 to 2020 over central Indian forests. The main objectives of the present study are: (1) to prepare a 20-year climatology of satellite derived forest fire activity during both forest fire and non-fire seasons, (2) to investigate in-depth the impact of climate and atmospheric extremes in causing anomalous forest fire activity events, (3) to assess quinquennial spatiotemporal changes in forest fire characteristics viz., fire count density and average fire intensity, and (4) to find statistical associations between various meteorological and environmental variables during forest fire season over central India.

# 2. Study Area

The study area is selected on the basis of Forest Survey of India (2020) report on the state of Indian forests. The report identifies central India, that is, parts of Chhattisgarh, Odisha, Telangana, and Maharashtra states that form an extremely forest fire prone region. Therefore, central India domain (latitude: 17.5°–21.5°N and longitude: 78.5°–82.5°E) as shown in Figure 1, is selected for the present study. Figure 1 also shows the location of the study area within the larger Indian administrative boundary. Central India has broad leaf deciduous trees as the dominant forest type and experiences a tropical climate with the mean annual temperature >24°C and the mean annual precipitation ranging from 10 to 20 cm (Reddy et al., 2015).

Most deciduous forests of India shed their leaves by the end of January and a considerable dry leaf litter is available for ignition during the forest fire season (Reddy et al., 2017). Agriculture and cultivation activities are the dominant land uses adjacent to the central Indian forests. Small rural and tribal settlements also exist in the vicinity. Some important municipal towns and cities in the study area are: Bijapur, Dantewada and Jagdalpur in Chhattisgarh, Gadchiroli, Chandrapur and Nagpur in Maharashtra, and Asifabad, Mancherial and Warangal in Telangana.

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**Figure 2.** ISRO forest fraction cover (%) data set at 5 km spatial resolution (Reddy et al., 2016) extracted over central India domain (latitude:  $17.5^{\circ}$ –  $21.5^{\circ}$ N and longitude:  $78.5^{\circ}$ – $82.5^{\circ}$ E).

# 3. Data and Methods

# 3.1. Forest Fraction Cover

Forest fraction cover ( $5 \times 5$  km) data set over India (Reddy et al., 2016) is available at ISRO's Bhuvan portal (https://bhuvan.nrsc.gov.in/home/index.php) in geoTIFF format for 3 years—1930, 1975, and 2013. For each 5 km grid cell this data set estimates the percentage of land (0%–100%) falling under the forest category of land use. Reddy et al. (2017) define forest as land >1 ha in area, with dominant native tree species and having 5 m minimum stand height as well as >10% crown canopy cover. For the present study, forest fraction cover for 2013 was extracted for the central India domain (latitude:  $17.5^{\circ}$ –21.5°N and longitude:  $78.5^{\circ}$ –82.5°E) using ArcGIS version 10.6 (Figure 2). Forest fraction cover <10% was excluded.

#### 3.2. MODIS Fire Product Data Set

The Moderate Resolution Imaging Spectroradiometer (MODIS) collection 6 algorithm developed by Giglio et al. (2016) identifies potential fires using dynamic day and night time temperature thresholds. The MODIS fire product (1  $\times$  1 km; https://firms.modaps.eosdis.nasa.gov/download/) has been used

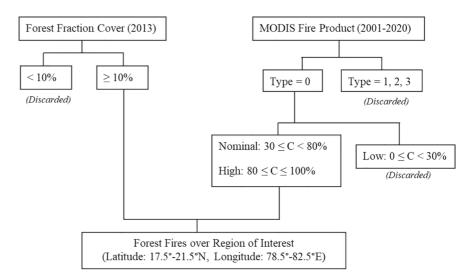
as a standard data set by researchers for identifying forest and wild fires, biomass and crop residue burning hotspots, active volcano fires, and offshore fires at varying spatial and temporal scales (Giglio et al., 2009; Roy et al., 2005; Saxena et al., 2021; Tansey et al., 2008; Yang et al., 2021; Yin et al., 2019). This data is of point vector type and each inferred fire hotspot is flagged as 0 for presumed vegetation fire, 1 for active volcano, 2 for fires from other static land source, and 3 for offshore fires. Moreover, to gauge the quality of data, each fire pixel is assigned a detection confidence level viz., <30% for low-confidence fires, 30%–80% for nominal-confidence fires, and  $\geq 80\%$  for high-confidence fires (Giglio et al., 2018).

For the present study, fires over a 20-year period, from January 2001 to December 2020, over central India domain (Figure 1) were selected. Of these, only the fires flagged as type 0 (i.e., presumed vegetation fire) were considered. To eliminate the risk of falsely flagged fire events, low-confidence fires (i.e., confidence level <30%) were discarded from the data set (Giglio et al., 2018) and only the fires with nominal to high confidence level were retained. Further, to ensure that the fires were selected exclusively over forested regions of central India domain, the forest fraction cover ( $\geq$ 10%) data set (Figure 2) was masked over the 2001–2020 MODIS active fires data set (confidence level  $\geq$ 30%, fire type = 0). This way, any fires that were either (a) potentially falsely flagged, or (b) were burning over predominant agricultural areas, or (c) those categorized as other than vegetation fires were effectively discarded. The methodology flowchart scheme is provided in Figure 3. Along with thermal anomalies, the MODIS active fires data set also provides the fire radiative power (FRP) for each fire pixel. FRP estimates the pixel-integrated radiant heat output (in MW) generated through fires and is useful in distinguishing high, medium, and low intensity fires (Saxena et al., 2021).

# 3.3. Fire Count Anomaly and Quinquennial Spatiotemporal Analysis

Monthly active fire counts from 2001 to 2020 were estimated in the present study. Based on Kale et al. (2017), the MODIS data set (fire counts and FRP) was divided into two periods viz., forest fire season (FMAMJ) and non-fire season (JASONDJ) for the 20-year study period. Fire count anomalies were calculated for FMAMJ and JASONDJ seasons in each year. Further, to analyze the spatiotemporal changes in forest fire counts and FRP, the 20-year seasonal (FMAMJ and JASONDJ) data was grouped into four quinquennial time frames viz., 2001–2005, 2006–2010, 2011–2015, and lastly 2016–2020. The point vector MODIS fire counts and FRP for all quinquennial time frames were remapped into  $0.1^{\circ} \times 0.1^{\circ}$  grids using fishnet tool in ArcGIS version 10.6. This fishnet tool remapping method helps to estimate the forest fire density, average FRP and locate the areas vulnerable to high intensity fires in central Indian forests.

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**Figure 3.** Flowchart showing methodology scheme adopted for the study. Confidence level of MODIS fire pixels is denoted by C in the flowchart.

# 3.4. Meteorological and Environmental Variables

Regional fires are closely associated to changes in the land variables for example, normalized difference vegetation index (NDVI), soil temperature, soil moisture and atmospheric variables for example, BC emission, air temperature, and precipitation. Therefore, in the present study, monthly means of near surface air temperature, precipitation, soil temperature (0–10 cm), soil moisture content (0–10 cm), evapotranspiration, NDVI, BC, and CO emissions for 20-year study period (2001–2020) were used to find statistical associations exclusively over FMAMJ. Model and observational data sets were downloaded from NASA Giovanni data portal (https://giovanni.gsfc.nasa.gov/giovanni/). Details about the data set source, spatial resolution, time coverage and parameter units for each variable is provided in Table 1. Pearson correlation was estimated for these variables and monthly forest fire counts, exclusively for FMAMJ and over a smaller domain (latitude: 18.5°–20°N and longitude: 79.5°–81.5°E) that showed high fire activity.

# 4. Results and Discussion

# 4.1. Forest Fire Climatology

Monthly fire counts are estimated over the study region from January 2001 till December 2020 (Table 2). The 20-year climatology suggests that forest fire activity in central India domain is the least during July and August (1.1–1.3 mean fire counts/month). Within the entire period of Indian summer monsoon (ISM), central India receives maximum rainfall in the months of July and August (Goswami et al., 2020). Forest fire activity is strongly

Table 1           Details of Various Meteorological and Environmental Variables Selected for the Study									
Variable	Source	Spatial resolution (in degree)	Time coverage	Units					
Near surface air temperature	GLDAS Model (GLDAS_NOAH025_M v2.1)	$0.25 \times 0.25$	01/2001-2011/2020	K					
Precipitation	GPM (GPM_3IMERGM v06)	$0.1 \times 0.1$	01/2001-2011/2020	mm/day					
Soil temperature (0–10 cm)	GLDAS Model (GLDAS_NOAH025_M v2.1)	$0.25 \times 0.25$	01/2001-2011/2020	K					
Soil moisture content (0-10 cm)	GLDAS Model (GLDAS_NOAH025_M v2.1)	$0.25 \times 0.25$	01/2001-2011/2020	kg/m <sup>2</sup>					
Evapotranspiration	GLDAS Model (GLDAS_NOAH025_M v2.1)	$0.25 \times 0.25$	01/2001-2011/2020	kg/m²/s					
NDVI	MODIS-Terra	$0.05 \times 0.05$	01/2001-2012/2020	Unitless					
BC emission	MERRA-2 Model (M2TMNXADG v5.12.4)	$0.5 \times 0.625$	01/2001-2012/2020	kg/m²/s					
CO emission	MERRA-2 Model (M2TMNXCHM v5.12.4)	$0.5 \times 0.625$	01/2001-2012/2020	kg/m²/s					

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**Table 2** *Monthly Forest Fire Counts From 2001 to 2020 Occurring on Forest Fraction Cover ≥10% Over Central India Domain* 

	January	February	March	April	May	June	July	August	September	October	November	December	Total
2001	61	420	461	125	29	0	0	1	13	2	4	2	1,118
2002	6	96	382	240	68	1	0	0	5	11	5	19	833
2003	123	344	2,161	668	354	17	1	0	6	10	8	3	3,695
2004	11	48	1,633	793	194	13	0	0	19	4	15	23	2,753
2005	90	386	1,322	567	389	33	4	2	4	8	2	7	2,814
2006	67	701	672	679	88	24	1	0	3	6	5	8	2,254
2007	28	407	2,977	1,467	273	11	1	4	1	7	7	34	5,217
2008	214	348	1,016	880	793	16	4	0	5	16	14	36	3,342
2009	254	1,495	3,750	1,038	228	14	0	3	5	11	14	22	6,834
2010	77	574	2,262	692	146	35	0	3	4	5	11	16	3,825
2011	26	72	1,859	427	670	43	2	0	3	23	43	86	3,254
2012	111	1,947	4,944	444	258	20	0	1	5	9	3	50	7,792
2013	69	123	1,420	1,603	405	17	0	0	17	5	8	56	3,723
2014	41	280	1,006	1,161	217	31	0	5	2	19	15	80	2,857
2015	138	543	1,046	701	439	12	0	1	4	9	31	248	3,172
2016	297	1,185	1,983	1,382	240	8	0	1	3	6	22	119	5,246
2017	117	1,186	1,922	2,959	254	22	3	2	18	8	22	171	6,684
2018	348	988	4,256	445	341	8	0	0	8	16	29	49	6,488
2019	45	186	1,560	1,367	457	41	7	0	0	6	5	81	3,755
2020	43	71	519	819	194	18	3	0	2	4	18	158	1,849
Mean	108.3	570	1,857.5	922.8	301.8	19.2	1.3	1.1	6.3	9.2	14.0	63.4	3,875.2

*Note.* Only the fires having nominal to high confidence level ( $\geq$ 30%) and those of type = 0 (Biomass) are considered. Please note the considerably high fire counts (in bold) during some months or years in the table.

related to three factors: (a) availability of combustible fuels, (b) climate and weather forcing, and (c) natural or anthropogenic ignition agents (Chen et al., 2017; Flannigan et al., 2016; Li et al., 2020; Littell et al., 2016; Sevinc et al., 2020). Moist firewood and high soil moisture during monsoon greatly reduce the availability of combustible fuel (firewood), probability of fire ignition and also fire spread (Flannigan et al., 2016; Jensen et al., 2018; Wotton et al., 2010). Despite high lightning activity (a natural ignition agent) during pre-monsoon and monsoon seasons over the region (Nath et al., 2009), fire activity in ISM months viz., JJAS is suppressed naturally due to the presence of high fuel moisture. Fires caused due to human activities are also naturally curtailed during such conditions.

As rainfall activity decreases by the end of ISM, forest fire activity picks up. Mean forest fire counts increase by ~10 times from September (6.3 counts/month) to December (6.3.4 counts/month) and further increase to 108.3 counts/month in January (Table 2). This suggests that even during the non-fire season (JASONDJ), a considerable number of forest fires occur. This is particularly evident during December and January, when drier winter conditions persist. With the onset of forest fire period in February, central Indian forests show a dramatic increase in fire activity. Fire counts increase three times from the month of February (570 counts/month) to March (1,857.5 counts/month). Compared to March, fire activity in April is reduced to half (922.8 counts/month) and again considerably decreases in June (19.2 counts/month). From 2001 to 2020, about 70% of forest fires over the study region occur during 2 months—March and April. Warmer Indian landmass and associated high temperature during pre-monsoon, ample availability of dry firewood (shrubs, understory trees, and crown), and dry pre-monsoonal winds blowing over the region create a conducive environment for fires to ignite, spread faster and be of high intensity (Jain, 2021; Littell et al., 2016).

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Table 3
Yearly Forest Fire Counts and Fire Counts Anomaly for Forest Fire Season (FMAMJ) and Non-Fire Season (JASONDJ) From 2001 to 2020

	Fire	counts	Anomaly			
Year	FMAMJ	JASONDJ	FMAMJ	JASONDJ		
2001	1,035	28	-2,636.4	-173.1		
2002	787	163	-2,884.4	-38.1		
2003	3,544	39	-127.4	-162.1		
2004	2,681	151	-990.4	-50.1		
2005	2,697	94	-974.4	-107.1		
2006	2,164	51	-1,507.4	-150.1		
2007	5,135	268	1,463.5	66.9		
2008	3,053	329	-618.4	127.9		
2009	6,525	132	2,853.5	-69.1		
2010	3,709	65	37.6	-136.1		
2011	3,071	268	-600.4	66.9		
2012	7,613	137	3,941.6	-64.1		
2013	3,568	127	-103.4	-74.1		
2014	2,695	259	-976.4	57.9		
2015	2,741	590	-930.4	388.9		
2016	4,798	276	1,126.6	74.9		
2017	6,343	572	2,671.6	370.9		
2018	6,038	147	2,366.6	-54.1		
2019	3,611	142	-60.4	-59.1		
2020	1,621	185	-2,050.4	-16.1		
Total	73,429	4,023				
Mean	3,671.4	201.1				

 $\it Note.$  The considerably anomalous fire counts (in bold) during some seasons or years in the table.

It is a generally accepted notion that yearly variability in soil moisture conditions and drought events are linked to higher forest fire activity (Reddy et al., 2017; Jensen et al., 2018). Over central India, some years show an anomalously high or low forest fire activity. The yearly fire counts and computed anomalies for forest fire and non-fire season are provided in Table 3. In the last two decades, an increasing linear trend of fire counts during both FMAMJ and JASONDJ are observed (Figure 4a). However, an inter-annual and inter-seasonal variation is noted in the time series of fire counts. Majority of the years from 2001 to 2020 show an inverse inter-seasonal relationship of fire activity (Figure 4a). For years 2003, 2008, 2009, 2011, 2012, 2015, 2016, and 2019, which show a considerably high (low) fire counts during FMAMJ months, the succeeding JASONDJ months typically show a considerably low (high) fire counts. Similarly, inter-annual FMAMJ fire activity significantly decreases after a considerably high fire activity during the preceding FMAMJ year for example, 2003, 2007, 2009, 2012, and 2017 (Table 3, Figure 4a). Over central India domain, the forest fire season activity is observed to take anywhere from 1 to 3 years to peak again. This time allows the forests to rejuvenate, replenish the burnt firewood and restore its ecosystem after a particularly intense, wide-spread and anomalously high fire activity season (Bond & Keeley, 2005; Hewelke et al., 2020; North et al., 2012).

# **4.2.** Impact of Climate and Atmospheric Extremes on Forest Fire Activity

Global climate and regional weather changes also play a key role in forest fire activity (Chen et al., 2017; Flannigan et al., 2000; Intergovernmental Panel on Climate Change [IPCC], 2018; Li et al., 2020). In India, 12 out of the 15 warmest years (recorded since 1901) have occurred during the recent one and half decade that is, 2006–2020 (India Meteorological Department [IMD], 2021). Moreover, the years 2017 (+0.54°C), 2016 (+0.71°C), 2015 (+0.42°C), 2010 (+0.54°C), and 2009 (+0.55°C) remain the five warmest years in India Meteorological Department (IMD) records. Between 2001 and 2005, the present study finds an average of ~2,149 and ~88 fire counts during FMAMJ and JASONDJ respectively. However, corresponding to a considerably warmer environment during 2006–2020, fire activity in central India is also found to dramatically increase. Compared to 2001–2005, in this

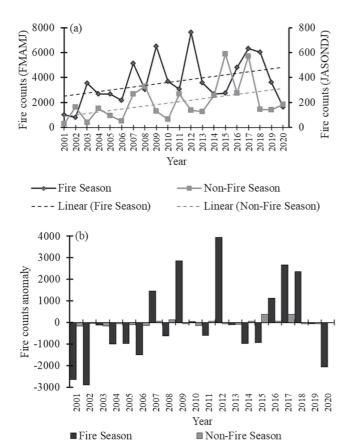
time period, the average fire counts are noted to nearly double ( $\sim$ 4,179) during FMAMJ and triple ( $\sim$ 250) during JASONDJ. This is an important finding of the present study. Lamat et al. (2021) also indicates toward the likelihood of an increase in forest fire activity under rising temperature.

Additionally, for India, the 2001–2010 decade had a +0.23°C temperature anomaly, while the 2011–2020 decade had an even higher temperature anomaly of +0.34°C, and is the warmest decade in Indian records (IMD, 2021). About 70% of the years from 2001 to 2010 show a negative fire count anomaly in FMAMJ (Figure 4b). Of this decade, excessively low (≤−1,000) and excessively high (≥+1,000) fire count anomalies were observed for five and two years, respectively. These figures changed to three and four years, respectively during 2011–2020 (Figure 4b), indicating an increasing fire activity trend over central India domain. The year 2020 is interesting as it recorded anomalously low forest fire activity during both FMAMJ and JASONDJ (Figures 4a and 4b). The Government of India imposed a national level stringent lockdown during 2020 to curb COVID-19 pandemic. This severely restricted activities and human movement. Paudel (2021) found that both human induced fires and FRP significantly decreased during COVID-19 imposed lockdown in Nepal, a neighboring country of India. The same reason could be attributed to the anomalous decrease in fire activity in central India domain during 2020.

Apart from regional weather changes, global scale events such as El Niño are linked to increased forest fires (Chen et al., 2017). Three month running means of sea surface temperature (SST) anomalies over Nino 3.4 region that is, Oceanic Nino Index (ONI) is an important index for ENSO. El Niño events having warmest SST

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**Figure 4.** (a) Forest fire counts and (b) fire counts anomaly observed during forest fire season (FMAMJ) and non-fire season (JASONDJ) from 2001 to 2020.

anomalies over the central equatorial Pacific region increase the likelihood of a drier pre-monsoon and a drought inducing subsidence over India (Kumar et al., 2006; Misra & Bhardwaj, 2020). Moreover, simultaneous multiple atmospheric extremes events for example, El Niño, drought and heat waves often result in severe compounding impacts and greatly increase the risk of forest fires (Jain, 2021). In India, since the ISM succeeds the forest fire season, a combination of factors such as a weak monsoon, severe heatwaves occurring in JJAS, and prolonged meteorological droughts are likely to impact not only the coming non-fire season but the succeeding forest fire season as well (FSI, 2019; Ghatak et al., 2017; Kale et al., 2017). A good example is the 2009 drought, one of the three major droughts faced by India, in the last 100 years (Acharya et al., 2011). A strong El Niño in the Pacific Ocean and a warmer Indian Ocean SST in 2009 resulted in a 48% deficit in June rainfall (and 23% below normal JJAS rainfall) over India (Acharya et al., 2011; Kumar, Rajeevan, et al., 2013; Kumar, Sheikh, et al., 2013). Uncertain ISM, government unpreparedness and a significantly warmer 2009 (+0.55°C temperature anomaly) further drove the country into a severe drought, especially over central India (Acharya et al., 2011; IMD, 2021). The present study finds that in 2001-2010 decade, the year 2009 had the highest fire count (6,525) as well as fire count anomaly (+2,853) over central India domain (Table 3, Figure 4). Similarly, the severe drought of 2002 was followed by an El Niño event in 2003. This coincides with higher fire activity observed from 2002 JASONDJ to 2003 FMAMJ (Table 3, Figure 4a). Reddy et al. (2017) also found high forest fire incidences during 2009 and 2012 in India.

Another remarkable period of substantially high fire activity is from 2015 JASONDJ to 2018 FMAMJ. With over 2,500 reported fatalities, the 2015 heat wave extending from Karachi (Pakistan) to Telangana (India) was one of the deadliest (Ghatak et al., 2017; Pattanaik et al., 2017; Wehner et al., 2016). Persistent dry atmospheric conditions, unusually clear skies, low rainfall, and enhanced localized heating of land surface during late May severely depleted soil moisture over central India (Ghatak et al., 2017). This further caused a

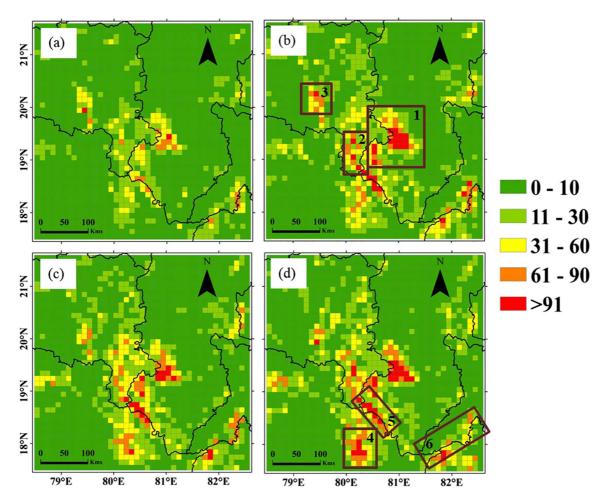
second temperature anomaly peak in June and daily maximum temperatures crossed 45°C for several days in a row at many places (Wehner et al., 2016). The region also experienced a rare drought of 5–100 years return period and negative anomalies (−0.35 to −0.04) of NDVI coincided with the severely affected central India domain (Sahana et al., 2020). Concurrently, the time from 2015 JJA to 2016 MAM experienced an extremely strong El Niño event, with ≥+2.5 ONI reported for some months (NOAA, 2021). Further, the years 2015, 2016, and 2017, some of the warmest in India's history, recorded +0.42°C, +0.71°C, and +0.54°C temperature anomaly, respectively (IMD, 2021). The combined impact of persistent warmer temperature over consecutive years, and multiple atmospheric extreme events viz., a severe heatwave, a rare drought and an extremely strong El Niño year proved disastrous for central Indian forests. The present study finds remarkably high forest fires during this period. In forest fire season of 2016, 2017, and 2018 the number of forest fire events were 4,798, 6,343, and 6,038, respectively, while 590 and 572 fires burnt during non-fire season of 2015 and 2017, all anomalously high numbers (Table 3). Warmer decades in the future are likely to accompany with precipitation deficits, frequent episodes of severe droughts, and severe heatwaves, which would cause persistent dry weather, deplete soil moisture, and lower forest NDVI (IPCC, 2018). Combined, such factors have the potential to increase forest fire activity in central India in the future during both FMAMJ and JASONDJ (FSI, 2019).

# 4.3. Quinquennial Spatiotemporal Forest Fire Changes

According to recent reports (FSI, 2019, 2020), central Indian forests fall in extremely to very highly fire prone categories. Quinquennial fire counts and FRP are mapped (0.1° × 0.1° grids) for central India for both FMAMJ (Figures 5 and 6) and JASONDJ (Figure S1 and S2 in Supporting Information S1). From these gridded spatiotemporal data sets, forest fire characterization viz., fire count density and average fire intensity is performed in order to isolate: (a) extremely to very highly fire prone areas, and (b) areas with medium to high intensity forest fires.

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**Figure 5.** Spatiotemporal patterns of forest fire counts during forest fire season (FMAMJ) in central India domain in (a) 2001–2005, (b) 2006–2010, (c) 2011–2015, and (d) 2016–2020. Regions of high fire activity are highlighted in dark red boxes in the figure. Box 1 – Jagdalpur-Gadchiroli Range, Mikabeli Range, and Indravati National Park in Chhattisgarh, Box 2 – Sundernagar Range in Maharashtra, Box 3 – Tadoba Andhari Tiger Reserve in Maharashtra, Box 4 – Medaram-Thadvai Forest Range in Telangana, Box 5 – Forest patches at Odisha-Telangana state border, and Box 6 – Alluri Sitarama Raju Forest area at the Odisha-Andhra Pradesh state border.

Each quinquennial time frame distinctly highlights hotspots of considerably high forest fire activity. Forest fire count density sharply increases from 2001–2005 (Figure 5a) to 2006–2010 (Figure 5b) time frame. High fire count density (>60 fire counts/grid) is frequently observed after 2005 (Figures 5b–5d). Within the central India domain (latitude: 17.5°–21.5°N and longitude: 78.5°–82.5°E), a smaller domain (latitude: 18.5°–20°N and longitude: 79.5°–81.5°E) is noted to be extremely fire prone during FMAMJ. Deciduous forests of Jagdalpur-Gadchiroli Range, Mikabeli Range and Indravati National Park in Chhattisgarh, Sundernagar Range and Tadoba Andhari Tiger Reserve in Maharashtra, Medaram-Thadvai Forest Range in Telangana and Alluri Sitarama Raju Forest area at the Odisha-Andhra Pradesh state border are identified as regions that are highly vulnerable to forest fires. Of these, the deciduous forest patches in Chhattisgarh are noted to be extremely fire prone and fire count density varies from very high (61–90 fire counts/grid) to extremely high (>91 fire counts/grid). One study estimates that just Indravati National Park in Chhattisgarh emitted 0.61 Tg/yr CO<sub>2</sub> in 2014 forest fires (Reddy et al., 2017). However, 2014 was an anomalously low fire activity year (Table 3) and average CO<sub>2</sub> emissions over Indravati National Park and by extension, central India domain would significantly exceed this estimate.

For successive quinquennial time frames viz., 2001–2005, 2006–2010, 2011–2015, and 2016–2020 in central India domain, 246.42, 3,203.46, 2340.99, and 3,942.72 km² forest area, respectively is estimated to fall under extremely fire prone category (>91 fire counts/grid) while 1,848.15, 4,681.98, 5,667.66, and 6,653.34 km² forest area, respectively is estimated to fall under highly fire prone category (61–90 fire counts/grid). Fire count density in the extremely fire prone areas of Chhattisgarh forests is observed to slightly decrease during the 2011–2015

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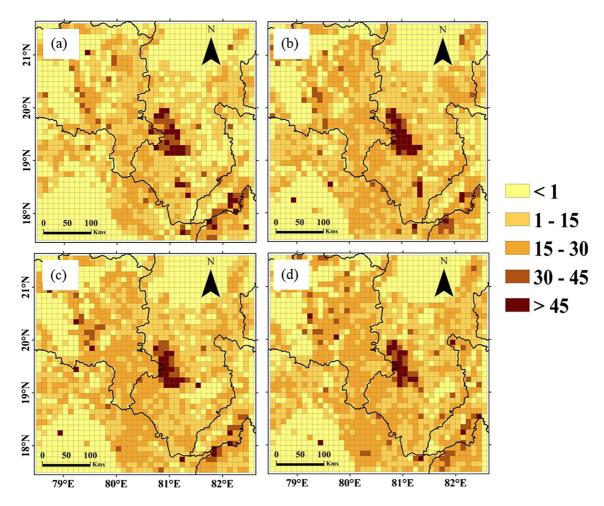


Figure 6. Spatiotemporal patterns of average fire radiative power (in MW) during forest fire season (FMAMJ) in central India domain in (a) 2001–2005, (b) 2006–2010, (c) 2011–2015, and (d) 2016–2020.

time period (Figure 5c), but is found to again increase in the following time period that is, 2016–2020 (Figure 5d). In contrast, fire prone hotspots identified in Telangana and Odisha-Andhra Pradesh state border show a very different temporal behavior. Unlike Chhattisgarh, fire count density in these patches is noted to continually increase with each time frame (Figures 5a–5d). Apart from this, different forest management policies in states, controlled fires by forest departments, forest clearing for logging and other land use activities for example, agriculture, mining, urbanization etc., and involvement of tribal people are some of the additional local factors which could possibly attribute to differing spatiotemporal forest fire characteristics (Babu et al., 2016; FSI, 2020).

Similarly, FRP, a measure of radiative heat of each fire pixel (Giglio et al., 2009, 2016), is an important characteristic of fire intensity. Quinquennial spatiotemporal patterns of average FRP show that during FMAMJ, the Jagdalpur-Gadchiroli Range and Indravati National Park in Chhattisgarh are the only two major forests having high intensity fires (FRP > 45 MW; Figure 6). Both these ranges are composed of very dense deciduous forests (Figure 2). For the same fire count density in two grids, the average FRP can drastically vary, and is directly proportional to the amount of biomass burnt. Since dense forests typically have a higher biomass than either open or scrub forests, they have a significant likelihood of higher FRP during any forest fire occurrence. For successive quinquennial time frames viz., 2001–2005, 2006–2010, 2011–2015, and 2016–2020 in central India domain, 3,942.72, 4,065.93, 3,696.3, and 3,080.25 km² forest area, respectively is estimated to fall under high intensity fire (FRP > 45 MW) category, while 6,776.55, 6,037.29, 4,681.98, and 6,899.76 km² forest area, respectively is estimated to fall under medium intensity fire (30–45 MW) category. Furthermore, average FRP over the Chhattisgarh forest patch was highest during 2006–2010 time frame. However, this high FRP hotspot seems to be gradually caving inwards from 2001 to 2020 (Figures 6b–6d). This could indicate either (1) lesser biomass

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**Table 4**Pearson Correlation (r) Among Monthly Forest Fire Counts, Meteorological Variables, and Environmental Variables
During Forest Fire Season (FMAMJ) in the Fire Prone Region (Latitude: 18.5°–20°N and Longitude: 79.5°–81.5°E)
Within Central India Domain (Latitude: 17.5°–21.5°N and Longitude: 78.5°–82.5°E)

	FFC	AT	PREC	ST	SM	ET	NDVI	BC	CO
FFC	1	0.107	-0.364**	0.067	-0.521**	-0.558**	-0.519**	0.465**	0.443**
AT	0.107	1	0.012	0.993**	0.029	-0.041	-0.578**	0.032	0.003
PREC	-0.364**	0.012	1	0.043	0.899**	0.862**	0.414**	-0.252*	-0.250*
ST	0.067	0.993**	0.043	1	0.061	-0.020	-0.586**	0.063	0.034
SM	-0.521**	0.029	0.899**	0.061	1	0.957**	0.507**	-0.316**	-0.312**
ET	-0.558**	-0.041	0.862**	-0.020	0.957**	1	0.601**	-0.348**	-0.340**
NDVI	-0.519**	-0.578**	0.414**	-0.586**	0.507**	0.601**	1	-0.355**	-0.331**
BC	0.465**	0.032	-0.252*	0.063	-0.316**	-0.348**	-0.355**	1	0.999**
CO	0.443**	0.003	-0.250*	0.034	-0.312**	-0.340**	-0.331**	0.999**	1

*Note.* FFC, monthly forest fire counts; AT, near surface air temperature; PREC, precipitation; ST, soil temperature (0–10 cm); SM, soil moisture (0–10 cm); ET, evapotranspiration; NDVI, normalized difference vegetation index; BC, black carbon emission; CO, carbon monoxide emission. \*Correlation is significant at the 0.05 level (two-tailed). \*\*Correlation is significant at the 0.01 level (two-tailed).

availability that is, degradation of dense broad leaf deciduous forests, or (2) quicker fire extinguishment and better fire management practices, or both. In general, the remaining forests of central India domain show a temporally increasing (and spatially expanding) average FRP (Figures 6b–6d).

Forest fire characteristics greatly differ when forest fire season progresses to non-fire season. The spatiotemporal pattern of fire activity during JASOND is remarkably different than during FMAMJ. Almost all fire activity is limited to wildland urban interface that is, WUI (North et al., 2012) during JASOND. Deciduous forest patches near Nizamabad city and Medaram-Thadvai Forest Range in Telangana, Nawapara Forest Range in Chhattisgarh, isolated forests near Sitanadi Wildlife Sanctuary on the Chhattisgarh-Odisha state border, and Alluri Sitarama Raju Forest area at the Odisha-Andhra Pradesh state border are WUI's showing high fire activity (Figure S1 in Supporting Information S1). It is highlighted that the extremely fire prone area of Chhattisgarh viz., Jagdalpur-Gadchiroli Range and Indravati National Park shows little to no fire activity during JASOND. Average FRP remains lower during JASOND than in FMAMJ over the central India domain (Figure S2 in Supporting Information S1). Generally, lesser fuel is available for burning after the end of an intense forest fire season and meteorological conditions in JASOND are not so favorable for fire activity (Reddy et al., 2017). However, low intensity fires (10–30 MW) witnessed at WUI's could be ignited due to the intentional clearing of forest for agriculture, accidental fires due to crop residue burning, or land clearing for any commercial and urban development projects.

# 4.4. Associations Between Meteorological Variables and Forest Fires

Statistical associations based on Pearson correlation are studied (Table 4) among monthly forest fire counts and selected meteorological and environmental variables mentioned in Table 1. The analysis is performed exclusively during the high forest activity period that is, FMAMJ. For this analysis, only the smaller (inner) domain (latitude:  $18.5^{\circ}-20^{\circ}N$  and longitude:  $79.5^{\circ}-81.5^{\circ}E$ ) showing very high forest fire activity during FMAMJ is considered (detailed discussion provided in Section 4.3). Regional and climate extremes such as El Niño, heat waves, and droughts are linked to increased forest fires (Chen et al., 2017; IPCC, 2018; Jain, 2021). In turn, large forest fires can alter surrounding atmosphere through various meteorological feedbacks and environmental responses. In Table 4, forest fire counts show a significant but negative correlation with precipitation (r = -0.364,  $p \le 0.01$ ), soil moisture content at 0-10 cm soil layer (r = -0.521,  $p \le 0.01$ ), evapotranspiration (r = -0.558,  $p \le 0.01$ ) and NDVI (r = -0.519,  $p \le 0.01$ ) and a significant but positive correlation with BC (r = 0.465,  $p \le 0.01$ ) and CO (r = 0.443,  $p \le 0.01$ ) emissions. High forest fire counts directly imply a significant reduction in NDVI due to the burning of biomass, and also a significant decline of moisture due to the associated sub-surface to canopy water losses incurred during high fire activity.

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Near surface air temperature shows a strong, significant and positive correlation with soil temperature at 0–10 cm soil layer (r = 0.993,  $p \le 0.01$ ; Table 4). This implies that high temperatures prior to ISM significantly increase soil temperature in extremely fire prone central Indian forests. High soil temperature and near surface air temperature destroy plant roots and seeds, wilt understory shrubs and trees, desiccate leaves, twigs and organic matter, kill soil microorganisms, and alter the soil nutrient cycling (Flannigan et al., 2000; Littell et al., 2016; Vadrevu et al., 2006; Whitman et al., 2019). High air temperatures are also likely to significantly reduce NDVI (r = -0.578,  $p \le 0.01$ ; Table 4) in tall trees as well as the forest crown canopy, creating drier environment conducive for fire ignition. Moreover, in central India, most deciduous trees shed their leaves by the end of January and therefore dried grasses and dry leaf litter (i.e., combustible fuel) availability is significantly high during FMAMJ (Reddy et al., 2017).

Another important meteorological variable viz., precipitation shows a strong, significant and positive correlation with soil moisture content at 0–10 cm soil layer (r = 0.899,  $p \le 0.01$ ). Additionally, for precipitation, a strong, significant correlation exists with evapotranspiration (r = 0.862,  $p \le 0.01$ ) and a moderate but significant correlation exists with NDVI (r = 0.414,  $p \le 0.01$ ; Table 4). High soil moisture content is a significant deterrent of forest fire activity (Flannigan et al., 2016; Jensen et al., 2018; Wotton et al., 2010). However, during FMAMJ, chances of precipitation are very low and rainfall activity onsets at the end of the forest fire season. Thus, low precipitation, low soil moisture, resulting lower evapotranspiration and a reduced NDVI during FMAMJ create conducive conditions for the observed high forest fire activity.

Large fires occurring during FMAMJ in the extremely fire prone regions of the study area viz., inner domain are likely to emit more BC and CO due to the incomplete combustion of biomass/fuel (Bibi et al., 2017; Crutzen & Andreae, 1990). Forest fire counts shows a positive, moderate but a significant correlation with both BC and CO emissions (Table 4). Both evapotranspiration and NDVI are found to be inversely associated with BC and CO emissions (Table 4). A negative, moderate but significant correlation exists between BC and evapotranspiration  $(r = -0.348, p \le 0.01)$  as well as NDVI  $(r = -0.355, p \le 0.01)$ ; Saxena et al., 2021). Similarly, for CO a negative, moderate but significant correlation exists with evapotranspiration  $(r = -0.340, p \le 0.01)$  as well as NDVI  $(r = -0.331, p \le 0.01)$ . A near perfect correlation is found between BC and CO  $(r = 0.999, p \le 0.01)$ , mostly likely as they are emitted from the same source that is, forest fires. BC, CO and other emissions from forest fires such as PM, CO<sub>2</sub>, CH<sub>4</sub>, hydrocarbons, and nitrous oxides, significantly degrade regional air quality, atmospheric chemistry, and cause adverse effects on human health (Andreae et al., 1994; Bibi et al., 2017; Goel et al., 2021; Reid et al., 2005; Saxena & Sonwani, 2019, 2021; Sonwani & Kulshreshtha, 2016).

# 5. Conclusions

Forests in India are of diverse types but much focus remains on fires in Himalayas or shifting cultivation led fires in north-east India. However, central India forest fires often go neglected. The region is surrounded by important towns and cities in the states of Chhattisgarh, Maharashtra, and Telangana. Frequent and large fires would not only imbalance the forest ecosystem, but also affect the regional air quality via hazardous emissions, severely impacting the health of millions of people living in the area. The present study finds that from 2001 to 2020, about 70% of forest fires over central India domain occurred during 2 months March (1,857.5 counts/month) and April (922.8 counts/month). However, owing to warmer conditions in the Indian subcontinent from 2006 to 2020 (as compared to 2001–2005), a doubling and tripling of forest fire activity is noted in forest fire (FMAMJ) and non-fire (JASONDJ) seasons, respectively. The study further highlights the role of multiple simultaneous climate extremes for example, El Niño, heat waves, weak ISM, and droughts in causing anomalously high fire activity periods over central India. An example is the severe Indian drought of 2002 which was followed by the 2003 El Niño. The period from 2002 JASONDJ to 2003 FMAMJ, showed anomalously higher fire activity over central Indian forests. A series of events viz., a strong El Niño, warmer Indian Ocean SST, below normal JJAS rainfall, a significantly warmer 2009 and a severe drought caused extremely high forest fires in the study region during 2009 FMAMJ. Similarly, the anomalously high forest fires from 2015 JASONDJ to 2018 FMAMJ is attributed to the combined impact of persistent warmer temperature over consecutive years, and multiple extreme events viz., a severe heatwave, a rare drought and an extremely strong El Niño year. Forest fires during both FMAMJ and JASONDJ in central India are likely to increase with warmer decades in the future. Warmer climate causes precipitation deficits, frequent severe episodes of droughts and heatwaves, persistent dry weather, depleted soil moisture, and lower forest NDVI, all factors linked to high forest fire activity.

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Since central Indian forests are extremely to very highly fire prone, the present study mapped quinquennial fire counts and FRP on  $0.1^{\circ} \times 0.1^{\circ}$  grids to characterize the fire count density and average fire intensity. Deciduous forests of Jagdalpur-Gadchiroli Range, Mikabeli Range and Indravati National Park in Chhattisgarh are found to be particularly fire prone with many hotspots having >61 fire count density. During FMAMJ of 2001–2005, 2006–2010, 2011–2015, and 2016–2020 in central India domain, 246.42, 3,203.46, 2340.99, and 3,942.72 km<sup>2</sup> forest area, respectively is estimated to fall under extremely fire prone category (>91 fire counts/grid) while 3,942.72, 4,065.93, 3,696.3, and 3,080.25 km<sup>2</sup> forest area, respectively is estimated to fall under high intensity fire (FRP >#x000A0;45 MW). In central India, most deciduous trees shed their leaves by the end of January and therefore dried grasses and dry leaf litter availability is significantly high during FMAMJ. Statistical associations among monthly forest fire counts and various meteorological and environmental variables over a smaller but a high forest fire activity region are highlighted for FMAMJ. High forest fire counts decrease the soil moisture content, evapotranspiration, and NDVI and are associated with an increase in BC and CO emissions. High surface air temperatures prior to ISM significantly increase soil temperature and significantly reduce NDVI, creating a drier environment. Moreover, precipitation shows a significant positive correlation with soil moisture content, evapotranspiration and NDVI. During FMAMJ, chances of precipitation are very low. Thus, high near surface air low precipitation, low soil temperature and moisture, low evapotranspiration and low NDVI during FMAMJ create conducive conditions for high forest fire activity in central India domain. The study highlights the need for more such investigations over high forest fire activity regions of India, especially in the context of warmer future climates. The study will also benefit from development of longer climatology once more data becomes available. Deeper investigations are also needed to ascertain if warming climate is causing a shift in the forest fire season in India.

# **Conflict of Interest**

The authors declare no conflicts of interest relevant to this study.

# **Data Availability Statement**

The MODIS fire product data utilized for this study is open sourced and available at https://firms.modaps.eosdis.nasa.gov/download. Model and observational data sets used for Pearson correlation statistics are open sourced and are available at the NASA Giovanni data portal (https://giovanni.gsfc.nasa.gov/giovanni/).

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