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Examining the effects of forest fire on terrestrial carbon emission and ecosystem production in India using remote sensing approaches

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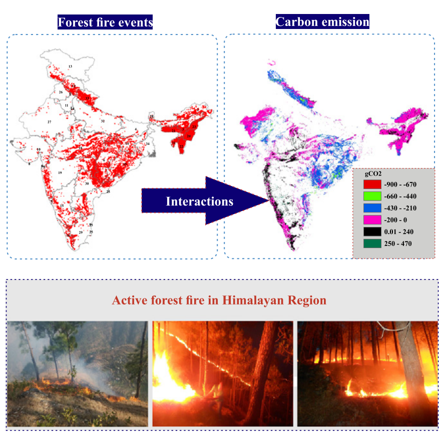
HIGHLIGHTS

- Impact of forest fire on ecosystem productivity and greenhouse gas emission is evaluated.
- Two ecosystem models have been utilized to assess the impact of forest fire on NPP.
- A new approach delta indices/delta NPP is proposed to delineate burn scars efficiently.
- The burn indices can precisely predict forest fires and associated GHG emissions.
- Forest fires have significant impact on greenhouse gas emission and ecosystem production.

GRAPHICAL ABSTRACT



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ABSTRACT

Remote sensing techniques are effectively used for measuring the overall loss of terrestrial ecosystem productivity and biodiversity due to forest fires. The current research focuses on assessing the impacts of forest fires on terrestrial ecosystem productivity in India during 2003–2017. Spatiotemporal changes of satellite remote sensing derived burn indices were estimated for both fire and normal years to analyze the association between forest fires and ecosystem productivity. Two Light Use Efficiency (LUE) models were used to quantify the terrestrial

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Net Primary Productivity (NPP) of the forest ecosystem using the open-source and freely available remotely sensed data. A novel approach (delta NPP/delta burn indices) is developed to quantify the effects of forest fires on terrestrial carbon emission and ecosystem production. During 2003–2017, the forest fire intensity was found to be very high (>2000) across the eastern Himalayan hilly region, which is mostly covered by dense forest and thereby highly susceptible to wildfires. Scattered patches of intense forest fires were also detected in the lower Himalayan and central Indian states. The spatial correlation between the burn indices and NPP were mainly negative (−0.01 to −0.89) for the fire-prone states as compared to the other neighbouring regions. Additionally, the linear approximation between the burn indices and NPP showed a positive relation (0.01 to 0.63), suggesting a moderate to high impact of the forest fires on the ecosystem production and terrestrial carbon emission. The present approach has the potential to quantify the loss of ecosystem productivity due to forest fires.

1. Introduction

According to the Intergovernmental Panel on Climate Change (IPCC, 2006; IPCC, 2014), forest degradation and associated biomass burning could be, in part, be responsible for the increases of greenhouse gas (GHG) into the atmosphere. The IPCC report (2014) has estimated that the annual GHG emissions caused by agricultural production were 5.0–5.8 $GtCO_2eq$/yr during 2000–2010, while the annual global GHG emissions due to land use land cover (LULC) changes were accounted as 4.3–5.5 $GtCO_2eq$/yr. Also, GHG flux caused by LULC change and forest degradation can lead to substantial changes in atmospheric chemistry in the long run (Smith et al., 2014).

Forest fire is one of the primary causative natural drivers of biodiversity loss (Pérez-Cabello et al., 2012), depletion of terrestrial ecosystem productivity and exhaustion of forest carbon stocks (Amiro et al., 2000; Amiro et al., 2001), decline in soil fertility and subsequent crop production (Cerdà, 1998), escalation of air pollutants (Bae et al., 2019; Yin et al., 2019), water quantity and quality (Venkatesh et al., 2020), and increase in the magnitude of landslide susceptibility (Jaboyedoff et al., 2018). These unfavourable consequences incurred by forest fires often take place over large areas and sometimes may last for years or decades (Pellegrini et al., 2018; Taylor et al., 2014). Therefore, a large-scale investigation is needed to calculate the degree of sensitivity between forest fire burn intensity and ecosystem production (Wang and Zhang, 2020; Kirchmeier-Young et al., 2019; Zheng et al., 2016).

During 2003–2017, a total of 520,861 active forest fire events were detected over the varying forest ecosystems in India, which are mainly concentrated over the dense evergreen and deciduous forest in eastern Himalayan states and lower Himalayan states (Table. S1). According to the report of Forest Survey of India (FSI), nearly 54.40%, 7.49%, and 2.41% of the forest cover in India are exposed to occasional fires, moderately frequent fires, and high incidence levels, respectively. Several studies were carried out in various environmental and climatic setups across India to demonstrate the effects of forest fires on natural ecosystem functioning. For example, Venkatesh et al. (2020) studied the impact of forest fires on the water balance and found that due to this forest fires and associated vegetation losses, the annual runoff increased by 25% compared to the normal (less-fire) year, which made the watershed prone to flooding. This effect has been widely demonstrated also in other areas of the world, such as southern Europe (Van Eck et al., 2016; Cerdà et al., 2017) and the USA (Cerdà and Robichaud, 2009). Using the Weather Research and Forecasting model coupled with chemistry (WRF-Chem) and in-situ observations in western Himalaya, Yesobu et al., 2020 observed sharp increases of CO, NOx, and O_3 by 52%, 52%, and 11% respectively during the high fire activity period.

This study further advances the earlier effort by proposing a novel analysis of the effects of forest fires on ecosystem production and terrestrial carbon emissions for different forest ecosystems of India using spatially explicit remote sensing data products and auxiliary information. This study evaluated the dynamics of terrestrial ecosystem productivity and vegetation phenological patterns using open-source and freely available remotely sensed data. This choice was made to guarantee a wide replicability of the proposed framework. The description of the data used in this study is given in Table. 1. This study proposed an approach (i.e., ΔNPP/Δburn indices) to quantify the effects of forest fires on terrestrial carbon emissions and ecosystems using several indicators [Soil Adjusted Vegetation Index (SAVI), Normalized Burn Ratio (NBR), Normalized Difference Moisture Index (NDMI), Modified Soil Adjusted Vegetation Index (MSAVI2), Land Surface Water Index (LSWI), and Land Surface Temperature (LST)]. The current research also assesses (1) the association between burn indices and NPP during normal (2003–2017) and fire (2009) years, (2) spatiotemporal dynamics of NPP during normal and fire years, and (3) impacts of forest fires on terrestrial ecosystem productivity and carbon emissions.

2. Materials and methods

2.1. Forest fires in India

Forest fires are now becoming a serious environmental concern not only in India but in many other countries across the globe due to the changing climate and associated local and regional warming (Taylor and Alexander, 2018; Littell et al., 2016; Zhang-Turpeinen et al., 2020; Vachula et al., 2020). Additionally, forest fires are now becoming a principal cause of forest degradation in India, especially in the dry deciduous forested region (Madhya Pradesh, Odisha, and Chhattisgarh), where the seasonal (April/May) forest burning is a common phenomenon due to abundant fuel load and low moisture content in soil (Chandra and Kumar Bhardwaj, 2015). However, in the north-eastern region of India, forest fires are mainly associated with traditional practices of shifting cultivation (local name *Jhum*) (Puri et al., 2011). Satellite remotely sensed data is the only reliable source of forest fire assessment in India, as comprehensive statistical data on active forest fire loss is weak (Roy, 2003). Additionally, Roy, 2003 and Kale et al. (2017) have asserted that about 90% of the forest fires in India are human-made, which demonstrates the necessity of proper prevention measures and creation of forest fire vulnerable zones for averting the ever-growing problems of forest fires on the natural environment. The other causative factors that could be responsible for forest fires are categorized in three major groups: (i) natural (ii) human deliberation, and (iii) unintentionally/accidental human interference (Jaiswal et al., 2002).

Among the major forest types of India, the dry deciduous broadleaved forests are found to be highly susceptible to forest fires compared to others. This could be due to the lack of soil moisture, especially during autumn and dry pre-monsoon periods (5–6 dry months), which is featured by a high level of surface and air temperature and low moisture content in the air, and abundant fuel loads composed in the substrate. The spatial distribution of MODIS active forest events are predominantly concentrated over the central and east-central states of India (Odisha, Chhattisgarh, and Madhya Pradesh). These regions are mostly covered with deciduous forests and are highly susceptible to seasonal forest fires. The Chir Pine forests distributed in the hilly Himalayan states are also found to be highly vulnerable to forest fires (Joseph et al., 2009). The present study has considered all forest types of India,

Table 1
Description of datasets used in this study.

Dataset	Acquisition period	Description	Data source	Spatial scale	Temporal scale
MODIS					
MOD11A1	2003–2017	LST, Emissivity	NASA	1 km	Daily
MOD09A1	2003–2017	Surface reflectance	NASA	500 m	8 day
MOD17A2	2003–2017	GPP	NASA	500 m	8 day
MOD09Q1	2003–2017	Surface reflectance	NASA	230 m	8 day
MCD14DL	2003–2017	Active fire products	NASA	1 km	24, 48 h and 7 days
LULC					
ESA-CCI	2015	Land Use Land Cover	ESA	300 m	Yearly
Climate					
TerraClimate	2003–2017	Monthly climatology	http://www.climatologylab.org/terraclimate.html	~4 km	Monthly

including mosaic natural vegetation, evergreen broadleaved, deciduous broadleaved, evergreen needleleaved, deciduous needleleaved, mixed leaf type, tree and shrub, mosaic herbaceous cover, shrubland, grassland, and sparse vegetation cover, for evaluating the impact of forest fire on overall ecosystem production and GHG emissions in India (Fig. 1).

2.2. Methods

2.2.1. Estimation of land surface temperature (LST)

In this study, MODIS 1 km level-3 LST and emissivity product (MOD11A1) Version 6 obtained from the USGS[1] were used to estimate monthly and annual average LST for normal (2003–2017) and fire (2009) years, respectively (Table 1). Google Earth Engine (GEE) (Gorelick et al., 2017) was utilized in this study as a cloud computing platform to calculate monthly and annual LST values for the entire study period. At first, the weekly LST was estimated using the thermal bands of the data products. The monthly LST values were then aggregated to estimate annual average LST for each reference year. The quality of the pixels was tested through the quality assurance information associated with the data.

2.2.2. Estimation of burn indices

The level 3 (500 m gridded, 8-days) with 1–7 spectral band surface reflectance products (MOD09A1)[2] Version 6 were used to derive the burn indices for the forest fire disturbance analysis (Arnett et al., 2015). A defined scale factor equal to 0.0001 for bands 1–7 was used to retrieve the actual pixel information. A total of six burn indices, including SAVI, NBR, NDMI, MSAVI2, LSWI, and LST, were considered in this study for mapping burn scars in normal and fire years. Computation of these burn indices was done in the GEE. The selected burn indicators were extracted using expressions provided in Appendix A.

2.2.3. Quantification of net primary productivity (NPP) and carbon emission

In order to have reliable estimates of NPP (unit: gC m^{-2} $year^{-1}$), two different ecosystem models were used in the current research. Necessary information corresponding to the selected models for NPP estimation is described as follows, whereas the mathematical concept is provided in Appendix A.

2.2.3.1. Vegetation Photosynthesis Model (VPM). The VPM (Xiao et al., 2004) is based on the conceptual partitioning of non-photosynthetic vegetation (NPV; mostly senescent foliage, branches, and stems) and photosynthetic vegetation (PAV; mostly chloroplast) within the leaf and canopy. This model is driven by temperature stress scalar, moisture stress scalar, and age of phenology, respectively (Appendix A).

2.2.3.2. Carnegie-Ames-Stanford Approach (CASA). The CASA model (Potter et al., 1993) was used to estimate terrestrial NPP by utilizing satellite imagery information and climatic measurement across various eco-regions. The net photosynthetic radiation (PAR; unit: MJ m^{-2} $year^{-1}$), biophysical dynamics (NDVI), and different climatic and environmental stress regulators control the NPP of a biome (T_{s1}, T_{s2}, W_s) (Potter et al., 1993) (Appendix A).

2.2.4. Quantification of greenhouse gas emissions

The spatiotemporal emissions of the major greenhouse components (C, CO_2, CH_4, N_2O, NO_x, and particulate matter) were estimated through NPP. NPP assesses the environmental impact of forest fires and associated loss of natural resources in a highly enriched ecosystem.

2.2.4.1. Release of carbon. The IPCC guidelines for national greenhouse inventories (IPCC, 1997; 2006) were followed when calculating GHG emissions under forest fires, as given below:

$$C = \Delta Biomass \times 0.9 \times 0.45 \quad (1)$$

where, C (g C) is the amount of carbon released due to forest fires; *ΔBiomass* is the change in biomass between normal and fire years; the value of 0.9 represents the fraction of biomass oxidized on site and the value of 0.45 represents the actual carbon content (IPCC, 2006; Yan et al., 2009; Meinshausen et al., 2009).

The amounts of gaseous carbon (gCO_2, CH_4, CO) compound emissions were retrieved as follows:

$$E_j = \varepsilon_j \times \delta_j \times C \quad (2)$$

where, ε_j is the fraction of the total carbon emitted as compound j, and δ_j is the fraction of the passage from the emission of carbons to the emission of the specific compound. The ε_j and δ_j value sets for CO_2, CH_4, CO are considered as 0.888, 0.012, 0.1 and 3.67, 1.33, 2.33, respectively (IPCC, 1997; 2006; Yan et al., 2009; Meinshausen et al., 2009).

2.2.4.2. Release of nitrogen compounds. Emissions of nitrogen compounds (g NO_2, NO_x) were quantified as follows:

$$N = \gamma^* C \quad (3)$$

$$E_j = \varepsilon_j \times \delta_j \times N \quad (4)$$

where, γ^* is the proportion of emitted Carbon and Nitrogen, the value sets for the coefficients ε_j and δ_j for NO_2 and NO_x are specified as 0.007, 0.012 and 1.57, 2.14, respectively (IPCC, 1997; 2006; Yan et al., 2009; Meinshausen et al., 2009).

[1] Website: https://lpdaac.usgs.gov/dataset_discovery/modis/modis_products_table/mod11a1_v006
[2] Link: https://lpdaac.usgs.gov/dataset_discovery/modis/modis_products_table/mod09a1_v006

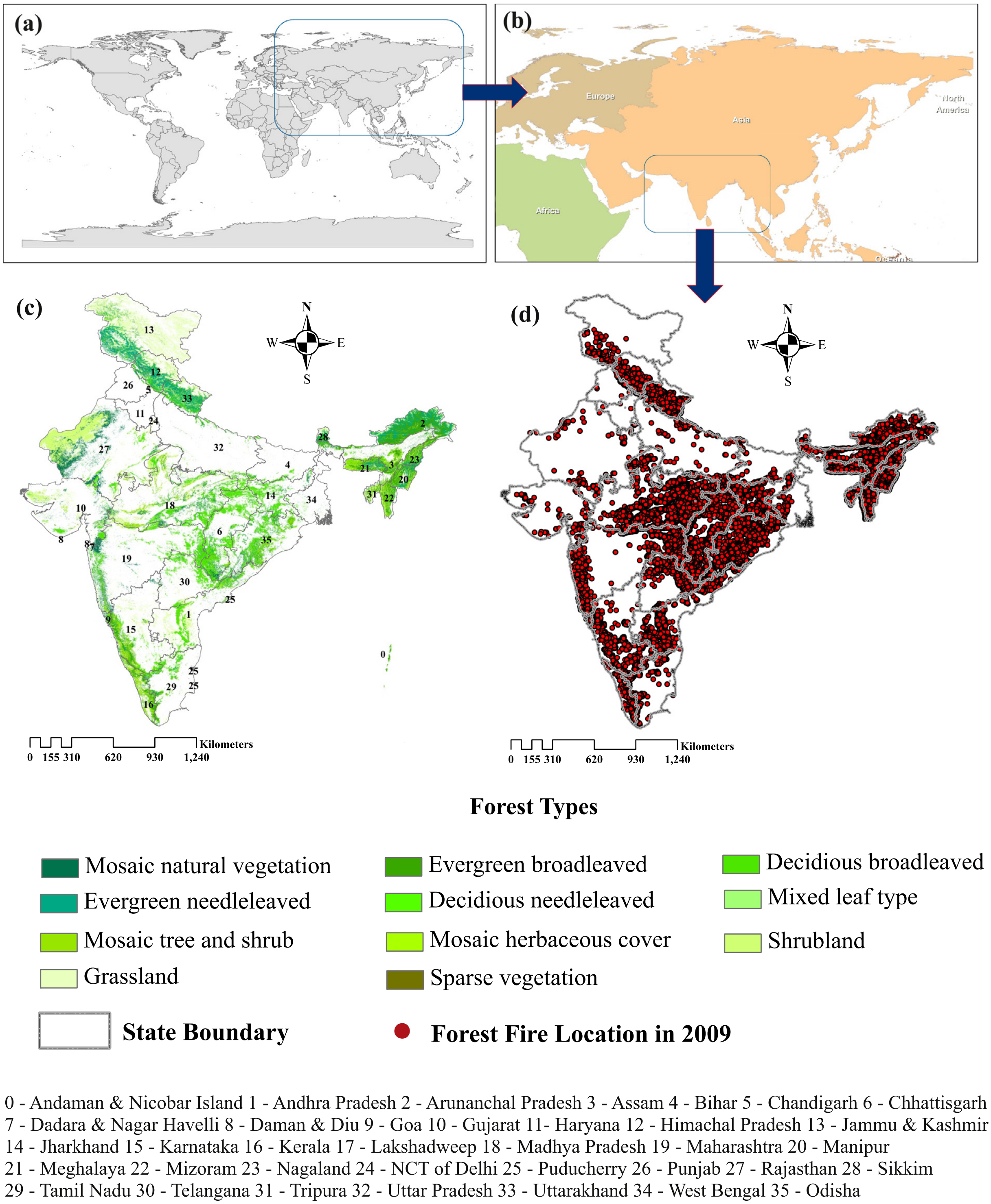


Fig. 1. Location of the study area (a)World boundary, (b) Asian subcontinent, (c) Major forest types of India, and (d) Forest fire locations in 2009.

2.2.5. Experimental design

This study explicitly focused on the fire impacts on ecosystem production and carbon emissions in India. The European Space Agency Climate Change Initiative (ESA-CCI) 300 m spatial explicit LULC data for 2015 was utilized to segregate different forest cover types from the other land cover classes. A total of 11 forest cover classes, including mosaic natural vegetation, evergreen broadleaved, deciduous broadleaved, evergreen needleleaved, deciduous needleleaved, mixed leaf type, mosaic tree and shrub, mosaic herbaceous cover, shrubland, grassland, and sparse vegetation covers, were taken into account for depicting the spatial extent of forest cover across the country. The required climate variables were collected from TerraClimate (Abatzoglou et al., 2018). The recode and subsequent categorization of forest covers were performed in ArcGIS 10.7. Subsequently, the active forest fire events over the forest ecosystems were identified from MODIS active forest fire products. 15 years (2003–2017) of forest fire data were collected to examine the temporal-spatial characteristics of forest fire events in India and its historical trends over the period. During 2003–2017, a total of 520,861 active forest fire events were recorded across the forest ecosystems in India. Additionally, the maximum number of forest fire events was recorded in 2009 (50,753), followed by 2012 (45,083), 2010 (39,455), and 2007 (37,424). The minimum fire events were recorded in 2015 (26,694). Given the estimates of annual forest fire events in each reference year, the year 2009 was chosen as "forest fire year," and the remaining years (2003–2017) were considered as "normal" years (forest fires not as frequently occurred as in 2009 reference year).

The final NPP output was used in the current study to evaluate the rates of change in NPP, corresponding to a particular index (Eqs. (5)–(11)). They were used to identify the sensitivity between NPP and the selected burn indices, thereby making them understandable to the readers. All the required input variables were rescaled into a uniform spatial resolution using bilinear interpolation method for the subsequent analysis. The resampling and interpolation were performed in ArcGIS 10.7. The linear association between the six burn indices (SAVI, NBR, NDMI, MSAVI2, LSWI, and LST) and NPP were evaluated using the 2d kernel density analysis, performed in Spyder (an IDE for python scripting). The forest fire intensity (FFI) in fire and normal years were computed using kernel and point density tools available in ArcGIS 10.7. Later, the spatial correlation between the response (NPP) and explanatory variables (burn indices) was carried out to assess the spatial interaction between forest burning and changes in NPP. A higher correlation means a higher association between the model parameters and NPP, and vice versa. The ArcPy python module was used for computing the pixel-wise correlation. Pearson correlation coefficient analysis was performed using the PerformanceAnalytics package in the R statistical software to analyze relationships between NPP and the selected burn indices. Additionally, overall air quality and concentration of SO_2 and NO_2 compounds in India were computed on GEE using Sentinel 5p satellite data products. A total of 43,740 sample points (the filtered active fire locations, shown in Fig. 1) were utilized for analysis. Table 1 describes the data type, data source, spatial, and temporal extent of the data set used in the present research.

$$\Delta NPP = NPP_{prefire} - NPP_{fire} \tag{5}$$

$$\Delta(NPP/NBR) = \frac{\Delta NPP}{\Delta NBR} \tag{6}$$

$$\Delta(NPP/SAVI) = \frac{\Delta NPP}{\Delta SAVI} \tag{7}$$

$$\Delta(NPP/NMDI) = \frac{\Delta NPP}{\Delta NMDI} \tag{8}$$

$$\Delta(NPP/LSWI) = \frac{\Delta NPP}{\Delta LSWI} \tag{9}$$

$$\Delta(NPP/LST) = \frac{\Delta NPP}{\Delta LST} \tag{10}$$

$$\Delta(NPP/MSAVI) = \frac{\Delta NPP}{\Delta MSAVI} \tag{11}$$

where, ΔNPP is the NPP (gC m^{-2} $month^{-1}$) difference between the normal and fire years. Subsequently, the spatial coherence of the two ecosystem models (CASA & VPM) and sensitivity between burn indices and NPP were evaluated using standard model validation technique (Ma et al., 2014).

$$R^2 = 1 - \frac{\sum (x_i - y_i)^2}{\sum {y_i}^2 - \frac{{y_i}^2}{N}} \tag{12}$$

where, R^2 is the coefficient of determination, x and y are explanatory and response variables of the i^{th} month, respectively, $N$is the total number of samples.

3. Results

3.1. Associations between forest fire intensity, burn indices and ecosystem production

Fig. 2 shows spatial distribution of the FFI in fire (2009) and normal (2003–2017) years. In both the fire and normal years, FFI is found to be very high in the eastern Himalayan region (Assam, Meghalaya, Manipur, Nagaland, Arunachal Pradesh), central dry region (Madhya Pradesh, Odisha, Chattisgarh), and lower Himalayan region (Himachal Pradesh, Uttarakhand). These regions are predominantly covered with dense deciduous forests and thereby highly prone to wildfires. Additionally, the high distribution of forest fires is also perfectly corroborated with the existence of active forest fire events detected over the forested ecosystem during the study period.

The relationships between the burn indices and NPP are evaluated so that the ecosystem's productivity can be linked to these burn indices (Fig. 3). Fig. 3 depicts spatial association and sensitivity between the burn indices and NPP during the study period (2003–2017). Among all the burn indices, high spatial coherences are observed between SAVI and NPP (Fig. 3f), NBR and NPP (Fig. 3d), NMDI, and NPP (Fig. 3e), and LST and NPP (Fig. 3a). Among the model pairs, the association between LST and NPP is found negative (r between −0.33 and −0.66), whereas the rest of the model pairs produced positive associations with NPP. Considering the spatial nature of the correlation estimates, all the burn indices exhibit moderate to strong negative associations with NPP over the regions occupied by deciduous forest, thus making these regions highly susceptible to recurring forest burning (Figs. 3, S1, S2, S3, S4, S5).

The linear associations between selected burn indices and NPP of the fire year are analyzed for two ecosystem models, CASA and VPM (Fig. 4). For the CASA model, all of the burn indices, except LST, are positively associated with NPP. Among the six indices, the highest coefficient of determination value is estimated for LSWI (=0.63), NDMI (=0.63), and NBR (=0.63), followed by MSAVI2 (R^2 = 0.58), SAVI (=0.58), and LST (=0.27) (Fig. 4). For VPM model, the highest coefficient of determination values are accounted for MSAVI2 (=0.45), SAVI (=0.44), NBR (=0.33), LSWI (=0.32), NDMI (=0.32), respectively (Fig. 4). Additionally, a trivial association is found between LST and VPM NPP (=0.001). The mean values of the burn indices and NPP are found significantly lower than that of the average year (Table. 2), which suggests a substantial impact of forest fire on vegetation health, soil moisture, and surface warming.

The correlation matrix among the burn indices and NPP exhibits synergic and trade-off interactions between forest burning and degradation of ecosystem productivity (Fig. 5). The statistical significance of the parameter estimates at three probability levels exhibits the state of coordination between forest fire led biodiversity degradation and resultant trade-offs on essential regulatory and supporting ecosystem services, including carbon sequestration and GHG regulation, which are considered and evaluated in this research. In addition, the spatial nature and association between the burn indices and NPP are computed with a ΔIndex/ΔNPP approach (Figs. S4, S5, S6, S7). Higher ΔIndex/ΔNPP values exhibit closer spatial linkages between the response and control variables. High ΔIndex/ΔNPP values are mostly concentrated over the regions with high FFI (Fig. S7). This highlights the usefulness of the satellite burn indices in explaining spatially explicit categorization of forest fire vulnerable zones.

3.2. Impact of forest fire on carbon sequestration and GHG emissions

The carbon emission and sequestration are quantified for each state of India using the output of NPP (Fig. 6). The emission and sequestration of carbon compounds are closely linked with the distribution of active fire events and vegetation types. Very high to high carbon emissions were found in the eastern Himalayan states, western desert region,

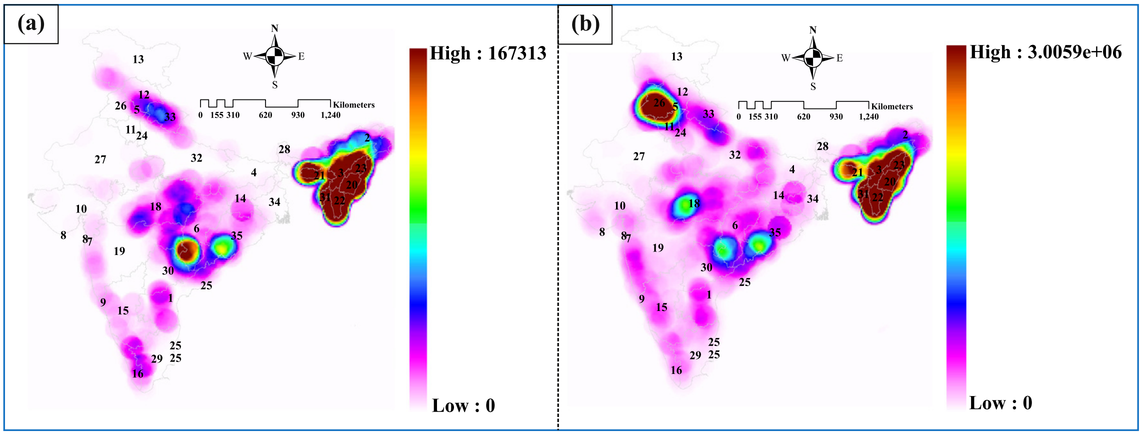


Fig. 2. (a, b) Forest Fire Intensity (FFI) estimated using point and kernel density (a) for 2009 and (b) for entire study period (2003–2017).

and lower Himalayan region. The high rate of gaseous carbon emission due to forest fires and associated mortalities thus poses a potentially serious threat to the forest communities of the country.

The discharge of nitrogen and other GHG compounds follows a similar trend as carbon in the mentioned states (Figs. S8, S9; Table. S2). Among the 33 administrative regions, the maximum total emissions of carbon and nitrogen compounds are observed in Odisha, Rajasthan, Chattisgarh, Andhra Pradesh, Madhya Pradesh, Telengana, and Uttarakhand states, accounting for high biomass and resulted in forest cover loss due to large number forest fire events in 2009. In contrast, only two states/central territories act as the sequester of greenhouse compounds.

4. Discussion

4.1. Associations between geographical factors, climate change, and forest fire events

In the tropical climate zones, forest fires usually occur during the prolonged dry summer, when the mean atmospheric temperature often exceeds the normal level. A detailed LULC map with actual forest fire locations and estimated forest fire intensities of different districts in India suggest that all of the high fire intensity zones are predominantly situated in the deciduous forest region (Fig. 1). Conversely, in the lower Himalayan and eastern Himalayan hilly regions, the occurrence of high fire intensity at the low altitude (≤1500 m above MSL) can be attributed to plant species (e.g., *Pinus roxburghii, Quercus leucotrichophora*), and proximity to the villages that make these areas susceptible to anthropogenic interferences (e.g., clearance of forest cover, stimulating grazing intensity, dispersing plant communities and dismantling plant functional traits, changing ignition patterns, etc.) (Bowman et al., 2011; Balch et al., 2017; Sharma et al., 2017; Kumar and Ram, 2005). Moreover, the high inflammability of the igniting material of the Pine forest depends on low moisture content, and the high ambient temperature has increased the dryness of fuel loads lying on forested strand promoting high-density forest fires in the summertime (Sharma et al., 2011). Abundance of dry leaves in forest strand and windward face of the surface topography could be a plausible reason for gaining a relatively higher proportion of available surface energy to trigger the acute forest fires in the hilly forested region in India.

There are several factors responsible for rising surface and air temperatures in the study region. The weather record of the last century reveals a sharp increase in average and maximum air temperature in India (Srivastava et al., 2017; Ross et al., 2018). This has enhanced the moisture deficit conditions in the forested region in the early summer (Jha et al., 2016; Sharma et al., 2017). The observations in the last 20 years by Joseph et al. (2009) show that the increasing intensity and spread of forest fires in Asian countries were largely related to rises in temperature and declines in precipitation in combination with increasing intensity of land uses. The weak Westerlies (contributed substantially to the total annual rainfall in lower Himalayan and western region) and associated below-average winter precipitation is also responsible for catastrophe fire event that occurred in 2016 in Uttarakhand (Sati and Juyal, 2016). The late monsoon precipitation is of utmost crucial importance for sustaining soil moisture and preventing fire intensities, especially in summer times (Jha et al., 2016; Sati and Juyal, 2016). Additionally, the lower Himalayan foothill forested regions are experiencing increased unusual winter forest fire incidents. These might indicate the acute dryness of litter and biomass of the forested strand, which acts as the fuel of forest burns and accelerates the spread of forest ignition (Sati and Juyal, 2016). Considering the causal factors of forest fire in the Western Ghats region, it was found that most of the big fire events in this region were associated with anomalies of monsoon. When the climatic conditions were homogenous, vegetation cover would become a crucial factor for detecting the forest fire (Renard et al., 2012). The climate coupled with slope and gradient of landscape could influence the spreading of fumes, as the slope enhances the chances of fire spreading by increasing the fire ignition (Jaiswal et al., 2002). Apart from the natural factors, human-induced climate change could also be an important determinator of wildfire events for not only in India, but it is evident across the world, including Canada, UK, USA, and many other European countries (Kirchmeier-Young et al., 2019). Kirchmeier-Young et al. (2019) have reported that about 1.2 million Ha forest area was burned in British Columbia (Canada) due to the extreme forest fire in 2017. Having inspected the main causes of these unusual forest fire events, the human-induced climate change was found to be the most critical factor (Kirchmeier-Young et al., 2019).

The present study has observed a drastic change in NPP between the fire and normal years in India. Such changes might have resulted from the lack of surface moisture and temperature limiting conditions that prevail in this region. The extreme surface and temperature limiting conditions may have triggered the functional changes in leaf foliage and wide-scale tree mortality (Chuvieco et al., 2004; Bartsch et al., 2009). The phenological disturbance is mostly associated with light use efficiency and absorbed/fractional photosynthetic capacity of plants (Xiao et al., 2004). It favors temperature and moisture limiting conditions in an ecosystem that is detrimental to ideal photosynthesis and plant respiration (Yuan et al., 2015). Additionally, seasonality and intensity of forest fire (crown, surface, and ground fires) have significantly controlled phenological state and crown fuel structure, load, and moisture content of a forest by determining the seed or vegetation reproductive capacity and hence dismantle the native ecosystem structure and function meticulously (Flannigan et al., 2000). The season factors, therefore, can

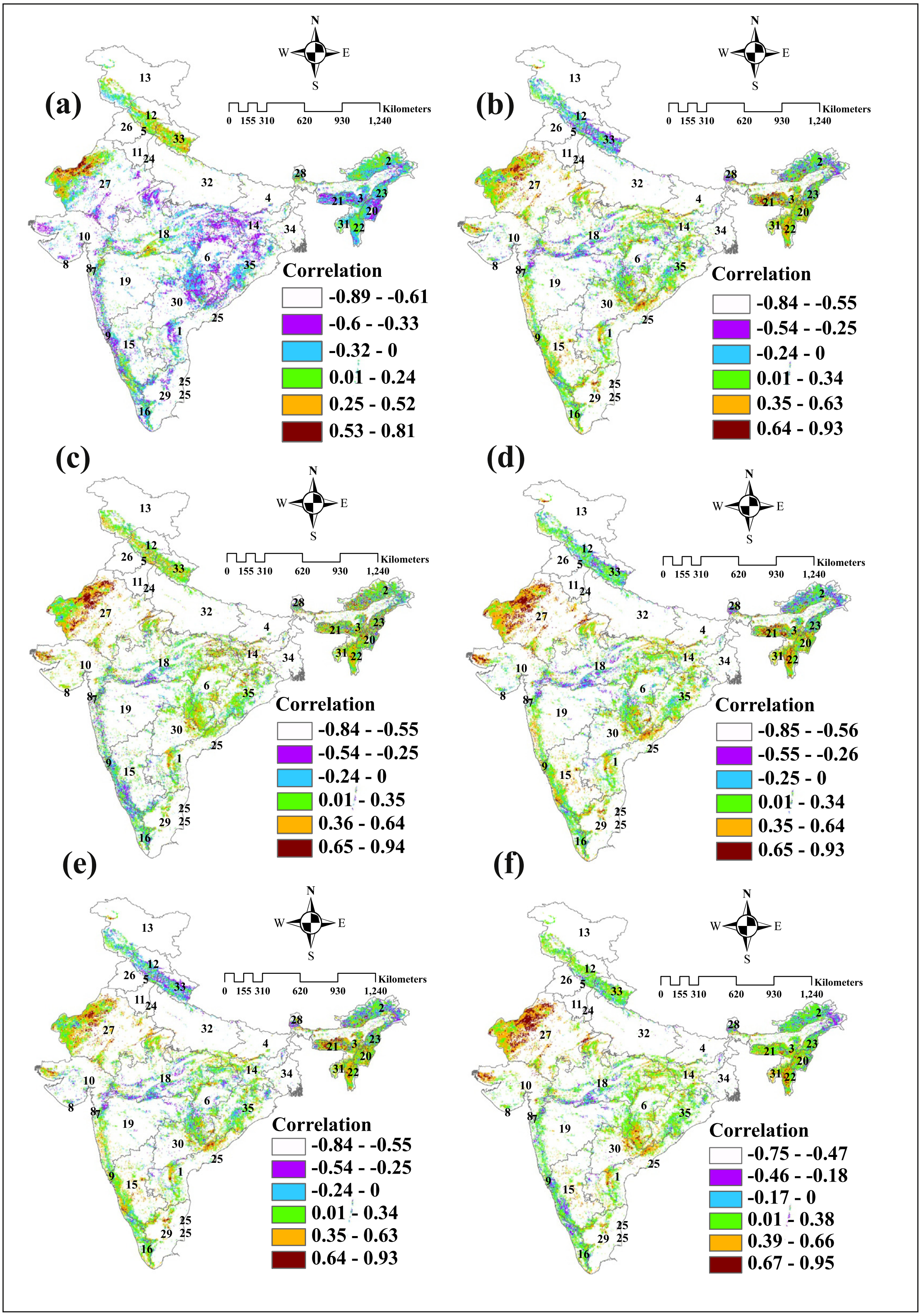
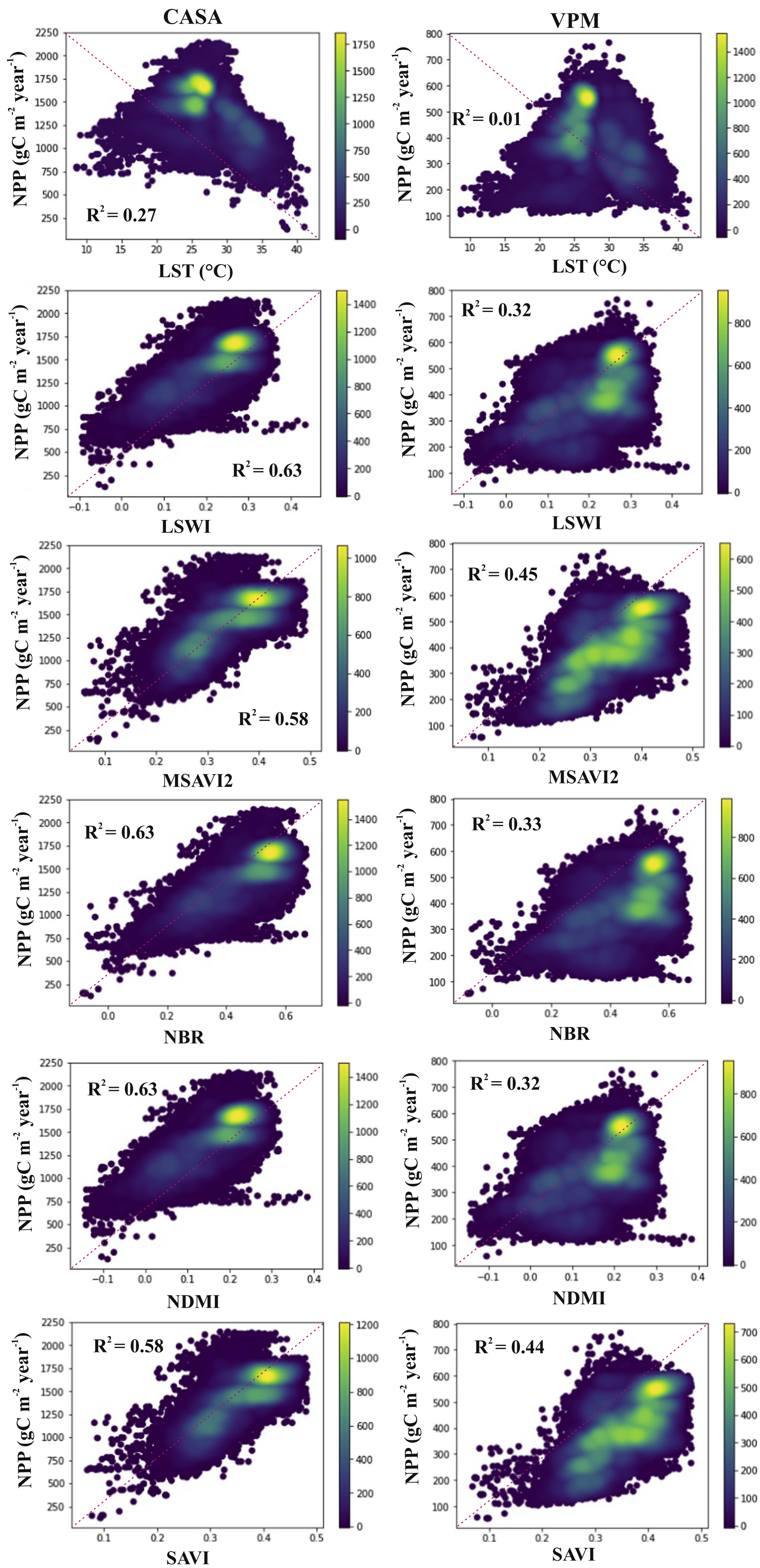


Fig. 3. Spatial correlation between the burn indices and NPP (a) LST & NPP, (b) LSWI & NPP, (c) MSAVI2 & NPP, (d) NBR & NPP, (e) NDMI & NPP, and (f) SAVI & NPP.

connect to the availability of deciduous cover, which would regulate the warming and cooling behavior of surface and ground fuel from direct sunlight, especially during the summertime (Hély et al., 2000). This could be a possible reason for the regular and recurring fire events happening over the large portions of the Himalayan and central dry regions in India, specifically in the states of Odisha, Chhattisgarh, Uttarakhand, Himachal Pradesh, Manipur, Nagaland, Mizoram, and Arunachala Pradesh. Nevertheless; it pursues special consideration from a researcher, ecologist, environmentalist, botanist, and biologist to vividly explore and investigate the fire behavior of this region to maintain the rich ecological and natural diversity of the Himalayan ecosystem.


CASA
VPM
NPP (gC m-2 year-1)
R² = 0.27
R² = 0.01
LST (°C)
R² = 0.63
R² = 0.32
LSWI
R² = 0.58
R² = 0.45
MSAVI2
R² = 0.63
R² = 0.33
NBR
R² = 0.63
R² = 0.32
NDMI
R² = 0.58
R² = 0.44
SAVI

4.2. Usability of satellite remote sensing burn indices in burn area mapping and wildfire analysis

Using the six burn indices, the association between forest fires and ecosystem production is explored in this study. All of the driving variables have shown positive influences on ecosystem production and terrestrial carbon emissions. Among the burn indices, soil moisture and vegetation-based variables are highly associated with forest burning and associated damages, compared to the other variables. SAVI and MSAVI2 are found more capable of explicitly defining the spatiality of forest fire locations. This is due to the addition of soil-adjustment factor (L) in its formula, which reduces the background attenuation from the soil and enhances the vegetation signal in the spectrum (Huete, 1988; Harris et al., 2011). The LST is also found as a good proxy for evaluating and identifying the burn scars across the regions in this study. A similar observation was made in the Iberian Peninsula, where maximizing the surface brightness temperature is found to be the most critical criterion for burn area delineation and mapping, instead of NDVI and other biophysical controls that cannot be directly used for burn scar delineation (Chuvieco et al., 2005). Among the selected vegetation and burn indices, SAVI, MSAVI2, and NBR are the most suitable and spatially coherent burn indicators, as they primarily provide more rigorous feasibility of burnt area mapping coupled with the field-based observations. Several studies have advocated the use of ΔNBR to produce spatially explicit burn area maps, often referred as Burn Area Reflectance Classification (BARC) for delineating post-fire scars as it is found reasonably correlated with the field-based burn scar assessment (Keeley, 2009; Roy et al., 2006). However, several noise factors such as atmospheric contaminations, aerosols, bidirectional reflectance variation, and clouds often perturb the remotely sensed post-fire measured reflectance, making the system insensitive to capture the post-fire changes and ultimately hindering the optimal use of these burn indices for describing physical shift of interest (Roy et al., 2006). The results exhibit a good coherence between the spatial and temporal distribution of the selected burn indices and the intensity of forest fires. Therefore, the normal (positive) relation between the burn indices with the intensity of forest fires, justified as the spatial agreement between the active fire locations and the difference in burn-indices, indicates the robust feasibility and practical applicability of satellite-based observation for the active fire distribution.

4.3. Effects of forest fires on ecosystem production, GHG emissions, and ecosystem services

Forest fires are the primary causative and natural drivers of biodiversity loss, depletion of terrestrial ecosystem productivity and forest carbon stocks, decline of soil fertility and subsequent crop production, escalation of air pollutants, and increase in the magnitude of landslide susceptibility (Amiro et al., 2000; Amiro et al., 2001; Verma and Jayakumar, 2012). In India, forest fires mainly occurred in the region with limited connectivity, rugged topography, and lack of available resources. Additionally, the majority of the population (apart from plain) of the forest fire-prone states of Lower Himalayan and Eastern Himalayan region solely depend on limited natural resources for fodder, medicinal plant, timber, and others primary activities, which catalyzes the environmental and ecological degradation of this region (Nandy et al., 2011).

NPP was used in this study as a proxy to assess the effects of forest fires on natural ecosystem production and terrestrial carbon emissions. The NPP is a widely used ecosystem indicator for evaluating the carbon sequestration capacity of the ecosystem (Li et al., 2016; Neumann and Smith, 2018). To understand the effect of wildfires on the carbon budget, the accurate measurement of fire intensity of each plant type and/or biome is essential because of the volatilization and redistribution of carbon due to active forest fires depends on type and intensity of fire (Wang et al., 2001).

This study observed that regions with higher forest fire events have higher NPP values and vice versa. Additionally, the changes in NPP between the fire and normal years are also found higher in the fire-prone regions. This can be attributed to the high forest fire intensity and associated forest cover losses due to recurring forest fire happing in these regions. A similar observation was made in the boreal forest region (Canada), where the measured CO_2 flux from eddy covariance and LUE modeled NPP showed that the forest fire had reduced the net downward fluxes of carbon; however, it (carbon flux) has increased 10–30 years after the fire event (Peng and Apps, 1999; Amiro et al., 2000; Amiro et al., 2003). The study by Amiro et al., 1999 on measuring the net carbon flux over the boreal forest revealed that fire disturbance disrupted the overall carbon cycle at the ecosystem level, and it would need 15 to 30 years following a fire event to reach the normal photosynthetic level, which appears to be a significant entity to any carbon balance model. However, several additional attributes, including the decomposition process and heterotrophic respiration, are required for efficient carbon budget and flux estimation. These approximations are not covered in this research and hence could be a future scope of this work. The mean NPP values of the high forest-fire-intensity regions show a drastic change in the forest fire year (2009), which can be attributed to significant biomass loss and resultant forest carbon stock due to forest fire (Gillett et al., 2004). These changes in total biomass could be linked to post-fire mortality and associated changes, as shown by de Vasconcelos et al. (2013) for South Western Brazilian Amazonia, which revealed a significant loss of total and above-ground biomass due to the increase of large-scale tree mortality after the first year (1.6×10^6 Mg and 1.4×10^6 Mg) and the fourth year (4.4×10^6 Mg and 3.7×10^6 Mg) of the fire event. The resultant emissions of total and above-ground carbon stock after the fire increased in the subsequent years (0.8×10^6 Mg C and 0.7×10^6 Mg C after the first year; 2.2×10^6 Mg C and 1.8×10^6 Mg C after the fourth year) depend on the balance between the rate of decomposition of dead tree and regeneration of fresh canopy in a given period (de Vasconcelos et al., 2013). Therefore, post-fire mortality assessment is highly recommended to gain real insights about the collective response/regeneration time of a plant community due to anomalous forest disturbances. The overall response can be ascribed to the acute biomass burning (Andreae, 2001), LULC changes in different eco-regions for biofuels (Searchinger et al., 2008), and severe deforestation and associated forest degradation (Van der Werf et al., 2009). The results echo the fact that reducing fossil fuel emissions to the atmosphere and undertaking fire control activities are essential elements for stabilizing atmospheric CO_2 concentration (Van der Werf et al., 2009).

Forest ecosystems of India play a significant role in the global terrestrial carbon balance, assimilating CO_2 from the atmosphere, storing carbon, and releasing greenhouse components to the atmosphere (Chen et al., 2019; de Vries et al., 2017; Meifang et al., 2017). The accelerated natural and human interventions have led frequent forest fires across India, which significantly dismantle the native ecosystem functions and pose a serious threat to its highly diverse and rich ecosystems. Conserving the biodiversity and natural resources of the forest ecosystems from any disruptive interventions and calamities should be the core of the policymaking for sustainable development of the region. Most of the mountainous societies thrive in close socio-ecological associations with nature while bearing with traditions, values, and faith weaved as the fundamental fabric of the indigenous cultures. These associations often appear to be fruitful to maintain fair forest management policies integrated with the active participation of local peoples through Joint Forest Management (JFM) and community-based forest management

Fig. 4. The 2d density scatter plot shows the association between burn indices and carbon sequestration. The coefficient of determination values represent the model strength and percent of variation explained by the independent variable.

Table 2
Student's *t*-test showing mean differences of the burn indices and NPP between fire and average year.

		Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference				
					Lower	Upper			
Pair 1	NPP_FIRE - Avg__NPP	−52.27	44.94	0.22	−52.70	−51.85	−242.285	43,384	0.000
Pair 2	LST_FIRE - Avg_LST	0.74	1.04	0.01	0.73	0.75	147.983	43,384	0.000
Pair 3	LSWI_FIRE - Avg_LSWI	−0.01	0.04	0.00	−0.01	−0.01	−80.099	43,384	0.000
Pair 4	MSAVI_FIRE - Avg_MSAVI	0.00	0.03	0.00	0.00	0.00	−22.289	43,384	0.000
Pair 5	NBR_FIRE - Avg_NBR	−0.02	0.06	0.00	−0.02	−0.02	−72.122	43,384	0.000
Pair 6	NDMI_FIRE - Avg_NDMI	−0.03	0.04	0.00	−0.03	−0.03	−188.956	43,384	0.000
Pair 7	SAVI_FIRE - Avg_SAVI	0.00	0.03	0.00	0.00	0.00	−26.851	43,384	0.000

(Anthwal et al., 2010; Bhattacharya et al., 2010). Moreover, the study by Sarin (2001) revealed that active involvement and empowering of women for managing and preserving local forest resources through integrated public participatory and citizen science-based approaches have an impeccable impact on formulating and regulating effective forest management policies. In the Himalayan region, the strong negative impacts of forest fire on ecosystem productivity, soil nutrient status (soil organic carbon, nitrogen, phosphorus, and potassium), and understorey vegetation structure can be controlled by educating local villagers about the adverse effects of active forest fire (both human-induced and natural) on their native ecosystems (Kumar et al., 2013).

5. Conclusion

In this study, the impacts of forest fires on ecosystem production and terrestrial carbon emissions are evaluated using burn indices based on open source and freely available satellite remotely sensed data and ecosystem production models. Several burn indices (LST, NBR, LSWI, NDMI, SAVI, and MSAVI2) are incorporated for mapping the burn scars due to forest fire and their linkages with changes in NPP. In summary, fair associations are observed between the burn indices and NPP. These correlation values collectively indicate the coherence of forest burning with the loss in terrestrial NPP. Among the burn indices, the moisture indices, LSWI, NDMI, and SAVI, are found to be the most suitable and spatially coherent burn indicators. The ΔNPP and estimated forest fire events in each state of India are found correlated to each other. Maximum changes in biomass, CO_2, CO, CH_4, NO_2, NO_X, particulate matter were observed in the regions with high forest fire events, and they also exhibit a positive correlation with ΔNPP. The newly introduced approach (ΔNPP/Δburn-indices) exhibits a high potential of quantifying the loss in ecosystem productivity due to forest fires in different eco-regions in India. This approach can be replicated to other similar ecosystems for forest fire evaluation because it uses satellite data with worldwide coverage, which is freely available. In addition, the current approach also helps with an accurate delineation of burn areas using remotely sensed data, which can be used in broader aspects if more accurate field-based observations can be obtained. Therefore, the developed approach and similar approaches in this direction will be valuable for planning agencies, consultancies, and local governments in planning and managing different fire mitigation strategies across regions. A detail investigation (both quantitative and qualitative) is, therefore, essential for developing fire inventories for different plant functional types in the fire-prone regions to cope with ecological destructions and biodiversity losses due to forest fires.

Credit author statement

SS – Conceptualization; Data curation; Formal analysis.
FP - Conceptualization; Supervision; Writing - review & editing.
BB - Conceptualization; Supervision; Writing - review & editing.
ASB - Conceptualization; Writing - review & editing.
KS – Conceptualization, Writing - review & editing.
SC - Conceptualization; Data curation; Formal analysis;
PKJ - Writing - review & editing.
QZ - Writing - review & editing.
YW - Writing - review & editing.
SB - Conceptualization; Formal analysis;
AB - Conceptualization; Data curation; Formal analysis;
SH - Formal analysis; Visualization;
SK - Writing - review & editing.

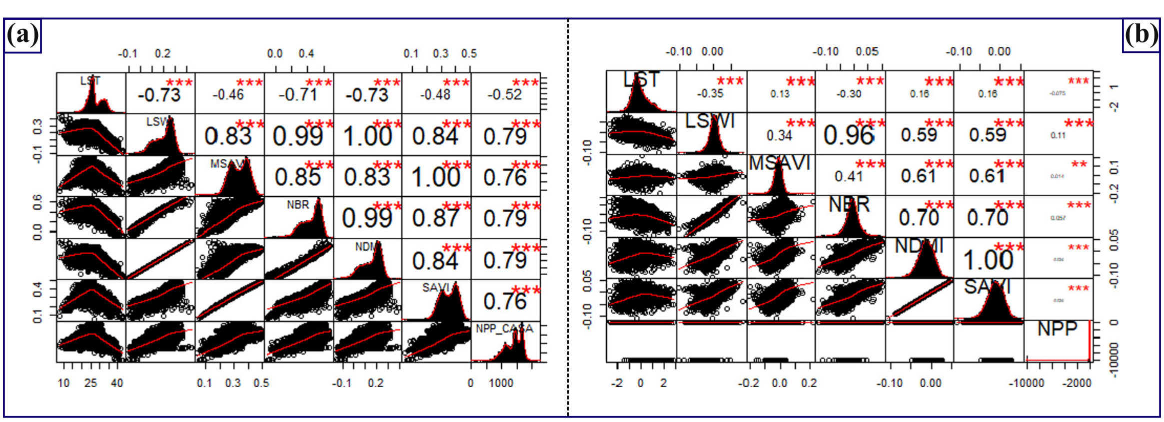


Fig. 5. Correlation matrix between (a) burn indices and NPP and (b) delta burn indices and NPP. The statistical significance of estimates were measured at $P = .0001$, $P = .001$, and $P = .005$ level.

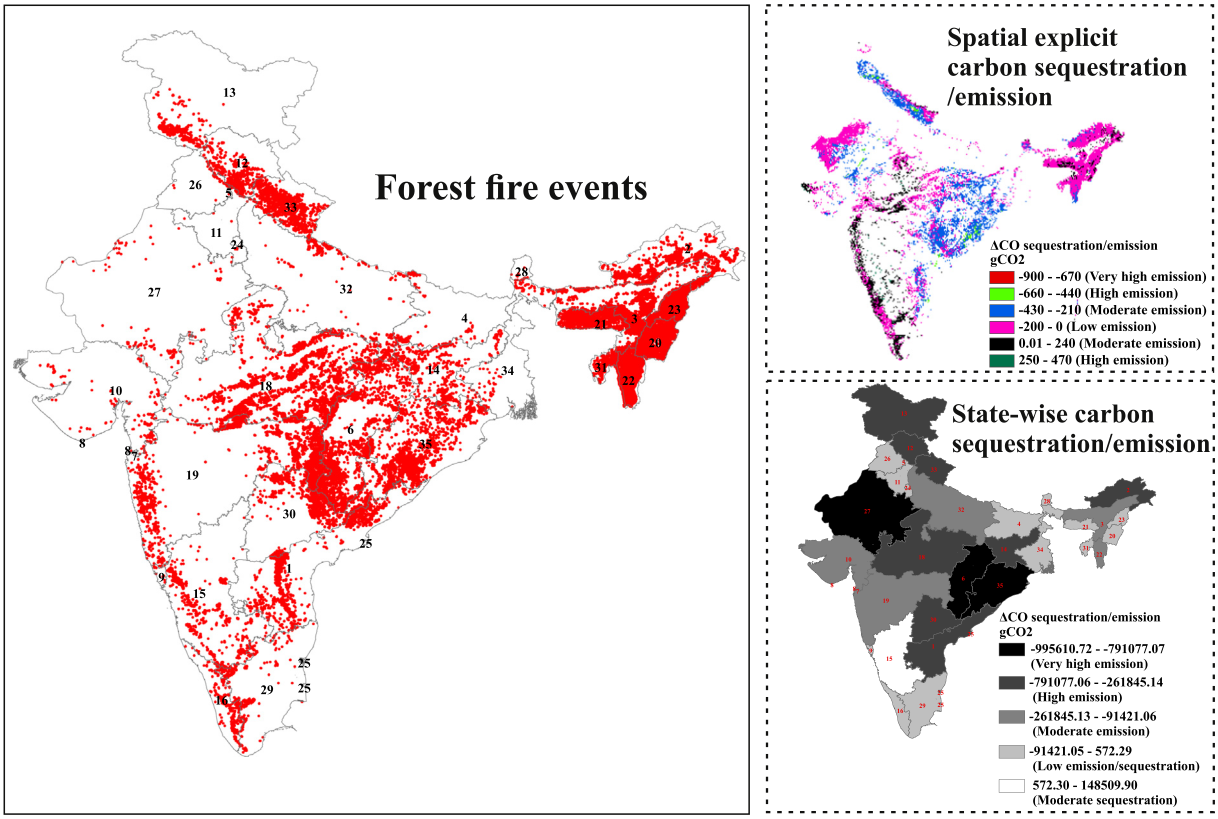


Fig. 6. Spatial distribution of forest fire events and spatial (in)explicit carbon emission/sequestration in 2009.

PSR - Data curation; Writing - review & editing.

Declaration of competing interest

The authors whose names are listed in this manuscript certify that they have involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2020.138331.

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