

Article

Timing the Flames: Geostationary Satellite Detection of Diurnally Shifting Stubble Burning in Northwestern India

Hiren Jethva ^{1,2*}
¹ Morgan State University, GESTAR-II, Baltimore, MD, USA; hiren.t.jethva@nasa.gov
² NASA Goddard Space Flight Center, Greenbelt, MD, USA

* Correspondence: hiren.t.jethva@nasa.gov

Highlights

Stubble burning during post-monsoon in northwestern India produces massive levels of smoke pollution in the Indo-Gangetic Plain, leading to hazardous air quality and posing serious health risks. Two decades of observations from NASA and NOAA polar-orbiting satellites have shown a strong correlation between the increasing trends in fires and aerosol loading, which evidently changed during 2022–2025. Time-resolved geostationary observations of fires and smoke hotspots detected from AMI sensor on the GEOKOMPSAT-2A satellite revealed a diurnal shift in peak stubble burning times from the usual 1–2 PM to 4–5 PM local time. This temporal shift in burning pattern in northwestern India has disrupted the long-term, consistent monitoring of fire activities from NASA–NOAA satellite sensors.

What are the main findings?

- The long-term association between crop fire activities and smoke air pollution monitored from widely used NASA–NOAA satellite sensor has been disrupted by temporal shift in the peak stubble burning activities from early to late afternoon.
- Hourly detection of fires and smoke hotspots from GK2A–AMI geostationary observations unambiguously confirms this diurnal shift in crop burning pattern in northwestern India.

What are the implications of the main findings?

- Models forecast of the regional air quality that essentially relies on standard NASA–NOAA satellite fire detections are affected.
- While the NASA–NOAA satellite sensors have provided nearly two-decade long record of fires and air pollution globally, the utilization of time-resolved geostationary observations is deemed necessary for capturing the full extent of fire activities.

Abstract

Post-monsoon open-field stubble burning in northwestern (NW) India—a key agricultural region known as the “breadbasket”—is a longstanding practice to clear fields. Satellite observations spanning over two decades have revealed significant upward trends in crop production, vegetative greenness, and the frequency of post-harvest fires, with the latter contributing to hazardous air quality during the peak burning season (mid-October to mid-November). Since 2022, thermal anomaly data from Aqua–MODIS and SNPP–VIIRS sensors have shown a sharp decline in reported fire events—an observation that

Academic Editor: Firstname Last-name

Received: date

Revised: date

Accepted: date

Published: date

Copyright: © 2026 by the authors. Submitted for possible open access publication under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

contrasts starkly with a concurrent rise in regional aerosol loading detected from space. This apparent discrepancy became particularly pronounced in 2024–2025, prompting a closer examination using high temporal resolution imagery from the Advanced Meteorological Imager (AMI) on the geostationary satellite GEO-KOMPSAT-2A. These observations revealed a clear spike in fire-related signal occurring around and after 4:00 PM local time outside the typical noon to 2:00 PM detection window of MODIS and VIIRS. A fire detection algorithm exploiting the fire-sensitive, shortwave infrared 3.8 μm signal and its contrast to 11.2 μm infrared observations is designed to adopt AMI observations and applied to its multiyear observations (2019–2025). The resulting fire dataset unambiguously shows a gradual shift in stubble burning activity toward the late afternoon hours beginning 2022, that goes underreported by polar-orbiting satellites. The orbital drift of NASA’s MODIS sensor on Aqua platform allows detection of some of the gradually shifting fires during afternoon hours, albeit MODIS still misses a large number of fires occurring around and after 4 pm. AMI’s relatively coarse spatial resolution (~ 4 km), a consequence of its slant viewing geometry over NW India, imposes inherent limitations in quantifying the full extent of fire occurrences. The temporal shift in fire activity complicates operational air quality forecasting and underestimates emissions, which currently assimilate satellite fire detections predominantly captured during early afternoon overpasses of MODIS and VIIRS. Intense stubble burning and resulting air pollution highlight the need for effective crop residue management practices for mitigating the frequency of open biomass burning, thereby reducing episodic degradation of air quality and its associated public health and economic impacts.

Keywords: Post-monsoon stubble burning, northwestern India, Geostationary fire observations, diurnal shift in fire activities, MODIS, VIIRS, GK2A-AMI

1. Introduction

The “Green Revolution” introduced in mid 1960s in India brought a tremendous success in upscaling the crop yield and total productivity, particularly in staple food grains such as wheat, rice, and other crop varieties. Use of technology adaptation, high-yielding seed varieties, mechanized agricultural machinery, pesticides, fertilizers, expanded acreage, and a dual cropping system have played an instrumental role toward achieving this goal, which made India a self-sufficient and even an exporter of major grains [1,2]. The northwestern (NW) Indian states of Punjab and Haryana—the hotspots of agricultural revolution, have shown multifold increase in rice and wheat crop productivity over last several decades [3]. For instance, the data compiled from the Unified Portal for Agricultural Statistics of Department of Agriculture and Farmers Welfare (<https://upag.gov.in>) shows that the state of Punjab has seen more than fifteen-fold increase in rice crop production—from <1 million-tons in late 1960s to 12–14 million tons over the years 2016–2025. During 2002–2016, the rice crop production has increased from ~ 9 million-tons to ~ 13 million—a net increase in the productivity by 25% [4].

The two-crop rotation system introduced in northern India, as part of modern agricultural practices, involves growing wheat during the winter season (December through February) and rice during the monsoon season (May/June through September). Each crop-growing season is followed by a harvesting period lasting several weeks. One of the significant changes in agricultural practices over the past two to three decades has been the mechanization of harvesting, specifically the use of automatic combine harvesters. While

this has reduced the need for human labor, it has resulted in a considerable amount of crop residue remaining in the ground. Due to the increasing cost of manual labor, the lack of affordable region-wide crop residue removal mechanisms, and the limited time available to prepare the land for the next seasonal crop, farmers often resort to burning the residue in open fields [5]. The intensive burning of rice straw over a period of 3–4 weeks from mid-October to mid-November results in significant emissions of air pollutants, including harmful trace gases and particulate matter (aerosols), affecting both the source regions and downwind areas of the densely populated Indo-Gangetic Plain (IGP). These burning activities and their detrimental impact on regional air quality degradation have been extensively characterized through long-term satellite observations, ground data, and model results in numerous studies [6,7,8,9,10].

Between 2002 to 2016, fire detection data obtained from the Aqua-MODIS sensor revealed a significant increase in the post-monsoon crop fire activities, with a net ~60% rise in fire counts. This upward trend in fires coincided with a 25% increase in rice crop production and a 21% enhancement in the vegetation index (NDVI) [9]. The escalation in fire incidents, hence emissions of aerosols, resulted in a nearly 43% rise in the aerosol optical depth over the Indo-Gangetic Plain (IGP) region. Simultaneously, the ground-level particulate matter (PM_{2.5}) downwind at the US Embassy site in New Delhi also showed a marked upward trend of 60%. A substantial increase in rice crop production implies the generation of proportionate amounts of residue or leftover, which is estimated to be 1.5–2.25 times the actual crop amounts [5,11]. Increasing agricultural fire activities suggests greater availability of crop residue subjected to burning, and the generation of agricultural waste is proportional to the crop production amounts, which in turn is linked to NDVI measured from space. NDVI has been used widely to track and monitor crop growth and amounts, making it a critical parameter for monitoring crop growth and estimating crop amounts. Fire statistics detected from space indicate the frequency of burning incidences on the ground.

Based upon this hypothesis, a linear regression model was developed that blends these seemingly connected variables in a simple relationship correlating the MODIS NDVI measurements during pre-burning period—an indicator of crop amounts, with seasonally accumulated fire counts observed during the burning period (October and November)—a precursor of air pollution events [9]. The NDVI-fires relationship demonstrated the potential for predicting seasonal fire activities well in advance by examining the regional mean NDVI values prior to the onset of the burning season. An evaluation of the proposed prediction model, involving comparison of the predicted seasonal fire activity against the actual detection of active fires for the post-monsoon burning seasons of 2017–2021, showed efficient predictions of seasonal fire activity with an accuracy exceeding 90% or an error margin up to 10% [12].

In this paper, first, the evaluation of the fire prediction model for the post-monsoon burning seasons over NW India has been extended to more recent years 2022–2025. Second, the differences between the actual and predicted fire occurrences are examined in conjunction with the satellite-derived AOD over IGP region and vegetation indices for investigating the long-term correlation or lack thereof (Section 3). Third, the time-resolved observations of active fires from geostationary satellite sensor are introduced for examining the hourly evolution of fires over NW India (Section 4). The major findings, limitations and challenges involved in the derived fire statistics, and future implications of the presented work are discussed in Section 5.

2. Satellite Datasets

Several satellite-based datasets, including those representing fires, aerosols, and vegetation dynamics, are utilized to examine the stubble burning activities in NW India. This section provides a brief description of each of these datasets.

2.1. Thermal Anomalies/Active Fires Products from MODIS and VIIRS

The Thermal Anomalies/Fire algorithm of Moderate Resolution Imaging Spectroradiometer (MODIS) detects active fire pixels over land at a spatial resolution of 1 by 1 km². Fire detection is performed using a contextual algorithm that leverages the strong mid-infrared radiation emitted by active fires. A comprehensive description of the MODIS fire detection algorithm is presented in [13,14], and the Algorithm Theoretical Basis Document (ATBD) can be accessed at: http://modis-fire.umd.edu/files/atbd_mod14.pdf. In this study, the near-real time version of the MODIS Thermal Anomalies/Fire 5-Min L2 Swath 1-km data (Collection 6.1) from the Aqua platform (MYD14), obtained via NASA's Fire Information for Resource Management System (FIRMS) <https://earthdata.nasa.gov/earth-observation-data/near-real-time/firms> is utilized [15]. To ensure data quality and minimize false positives, only fire detections flagged with confidence levels in the 'nominal' (30–80%) and 'high' (80–100%) categories, as defined in the MODIS Collection 6 Fire User Guide, are included in the present analysis.

Since its launch in 2012, the Visible Infrared Imaging Radiometer Suite (VIIRS) onboard the Suomi National Polar-orbiting Partnership (Suomi-NPP or S-NPP) satellite has provided continuity in global remote sensing of atmospheric and land surface parameters, including thermal anomalies. VIIRS detects active fires at a nominal spatial resolution of 375 meters, representing a substantial enhancement over MODIS, which operates at 1-km resolution for fire detection. The higher spatial resolution of VIIRS enables improved sensitivity to smaller and lower-intensity fire events that may remain undetected by MODIS, thereby offering a more detailed characterization of fire activity at finer spatial scales. The S-NPP/VIIRS near-real time active fire detection product, VNP14IMGTDL_NRT, available during the post-monsoon stubble burning season was accessed from FIRMS [16]. In line with the MODIS fire detection confidence flags, VIIRS thermal anomaly data with confidence levels 'nominal' and 'high' classes were considered.

2.2. MODIS NDVI Product

The Normalized Difference Vegetation Index (NDVI) quantifies the contrast between the reflectance in the red and NIR bands. The increased greenness of the cropland due to the matured crops and/or greater cultivated area produces marked difference between the reflectance in the red and NIR bands, resulting in larger NDVI values. Numerous studies have shown that NDVI offers a practical approach to estimate crop production as it directly relates to the potential photosynthesis activities and various stages of crop growth.

Two different sets of NDVI have been used in this study. First, the MODIS standard vegetation indices produced on 16-day intervals and at multiple spatial resolutions are derived from atmospherically corrected surface reflectance in the red (670 nm) and near-infrared (860 nm) wavelength bands. The Aqua/MODIS Collection 006 monthly, Level 3 global NDVI dataset (MYD13C2) consists of cloud-free spatial composites of the gridded 16-day 1-km product (MYD13A2) and provided on a monthly scale as a Level 3 product projected on 0.05° grids [17]. The dataset was accessed from NASA's EarthData data holding at <https://www.earthdata.nasa.gov/data/catalog/lpcloud-myd13c2-061>. This dataset was used to calculate the area-averaged NDVI over NW India for the prediction of totality

of seasonal fire statistics for the years 2022–2025 based on a linear regression model developed by [4] and further revised in [12].

Second, the 1-km NDVI daily dataset reported in the MODIS/Terra+Aqua BRDF Model Parameters Daily L3 Global 1km SIN Grid V061 product (MCD19A3D) [18] was used to investigate the temporal evolution of the greenness of the cropland from harvest to post-harvest period. the Multi-angle Implementation of Atmospheric Correction (MAIAC) MCD19A3D product provides gap-filled NDVI values at 1-km spatial resolution over cloud-free and low aerosol pixels.

Additionally, the MODIS MCD19A1 product (Version 6.1) [19] delivering land surface bidirectional reflectance factor (BRF) dataset is used to calculate the Normalized Burn Ratio (NBR)—an indicator of land surface conditions from greenness to burned pixels. The MCD19A1 Terra+Aqua Level 2 gridded product is derived utilizing the MAIAC algorithm and offers cloud-free, atmospherically corrected (gases and aerosols) surface reflectance at 1 km spatial resolution in MODIS bands 1–12, including 0.86 μm (band 2) and 2.1 μm (band 7) wavelength bands used for calculating NBR.

2.3. MODIS MAIAC Aerosol Optical Depth Product

The MAIAC algorithm utilizes time series analysis to retrieve aerosol optical depth (AOD) and surface bidirectional reflectance factor (BRF) from MODIS observations over both dark vegetated and bright reflective surfaces. To detect smoke aerosols from biomass burning, MAIAC applies a dedicated "smoke test" that distinguishes thick smoke layers from clouds. To isolate thick smoke produced from biomass burning activities, MAIAC incorporates a dedicated "smoke test" designed to differentiate heavy smoke plumes from clouds. This discrimination leverages the enhanced spectral absorption observed at 0.412 μm relative to the 0.47–0.67 μm range, attributable to increased multiple scattering and elevated absorption by organic carbon species characteristic of biomass combustion emissions. Previous validation studies of MAIAC using ground-based AERONET direct AOD measurements at the Kanpur site situated in the center of IGP revealed a reasonable agreement with an RMSE and a correlation of 0.23 and 0.86, respectively, suggesting sufficient accuracy of MAIAC aerosol product used to derive long-term trends in AOD over northern India. In this study, the MAIAC AOD retrievals at 1 km spatial resolution from the standard MODIS Level 2 product (MCD19A2 V6.1) [20], with relaxed quality assurance (QA) thresholds is used to enable detection under extreme aerosol loading conditions caused by the intense stubble burning in northern India.

2.4. GEO-KOMPSAT-2A (GK2A) Advanced Meteorological Imager (AMI) Observations

GK2A is a new generation geostationary (GEO) meteorological satellite from Korea Meteorological Agency (KMA) launched on December 5, 2018, started operation at parking location 128.2°E longitude on July 25, 2019. GK2A carries an advanced, multispectral (a total of 16 channels spanning 0.47 μm to 13.21 μm spectral range) AMI sensor with significantly higher spatial resolution (0.5 to 1 km for the visible channels and 2 km for near-infrared and infrared channels at sub-satellite point), more spectral channels, and faster image update rate than its predecessor instrument of Communication Ocean, and Meteorological Satellite (COMS). AMI captures images of Earth's hemisphere in all 16 channels at a 10-minute interval. A detailed description of the GK2A-AMI sensor, technical specifications, its in-orbit test and performance validation are given in [21].

Of the particular interest to the present study, the measurements acquired in the fire-sensitive, shortwave infrared 3.8 μm channel and infrared 11.2 μm channels are used for

developing a research algorithm for detecting active fires and associated smoke hotspots over NW India region. First, the raw count data ('image_pixel_values') measured by AMI is the respective two channels ('sw038' and 'ir112') are converted to radiance using their pre-defined gain and offset values as follows:

$$Radiance = (Radiance * R_{gain}) + R_{offset} \quad (1)$$

Where, $Bandbits$, R_{gain} , and R_{offset} are the bits, gain, and offset of the two channels, respectively. The $Radiance$ values are then used to calculate effective temperature, T_{eff} , followed by brightness temperature using spectral coefficient as follows:

$$T_{eff} = \frac{C3_{spect}}{\log(\frac{C2_{spect}}{Radiance} + 1)} \quad (2)$$

$$T_b = C9_{spect} + C10_{spect} * T_{eff} + C11_{spect} * T_{eff}^2 \quad (3)$$

The effective or brightness temperature is defined as the temperature of a black body that would emit the same total electromagnetic radiation or energy at specific wavelength measured by satellite sensor. The gain, offset, spectral coefficients, and Level 1b data processing sample codes in FORTRAN90 language used for converting counts to brightness temperature for the two respective channels were obtained from https://nmisc.kma.go.kr/upload/resource/data/gk2a/20190509_sample_code_ifort.zip placed under GK2A-AMI's information webpage at: <https://nmisc.kma.go.kr/enhome/html/base/cmm/selectPage.do?page=static.gk2ami-cro.gk2aMicro&ref=vksdr.com> Note that the coefficients denoted in Eq. (2) and (3) are labeled in the same sequential order they appear in the sample code.

The brightness temperature, T_b , in Kelvin are calculated for both 0.38 μm and 11.2 μm spectral bands. Additionally, AMI's Level 2 cloud mask product (*gk2a_ami_le2_cld_fd020ge*) is used to identify cloud-free pixels. The cloud mask product reports indices '0', '1', and '2' representing confident clouds, probable clouds, and clear pixels, respectively. A close examination of the cloud mask images alongside temporally collocated true-color RGB images from MODIS and VIIRS show that AMI's cloud product tends to classify fire hotspots and heavy smoke pixels as probably cloudy (index '1'). Because such thermal hotspots are the subject matter of the present study, the probably cloudy pixels are treated as 'cloud-free' in this study. These datasets, along with geolocation coordinates, were extracted for the NW Indian states of Punjab and Haryana using an appropriate shapefiles boundary. The multiyear GK2A-AMI dataset was obtained from the National Meteorological Satellite Center of Korea Meteorological Administration: <https://nmisc.kma.go.kr/enhome/html/main/main.do> using its API functionality.

3. Long-term Fire Trends, Aerosol Loading, and Vegetation Indices

3.1. Evaluation of Fire Prediction Model

Figure 1 displays the cumulative fire counts for the post-monsoon season (October 1 through November 30) derived from a) Suomi-NPP/VIIRS and b) Aqua-MODIS near real-time fire products for the years 2016–2025. The fire data for the most recent years 2022–2025, displayed as solid lines, show a gradual, drastic decline in total fire activities compared to previous years in both MODIS and VIIRS fire datasets over NW India. For

instance, the seasonal fire counts detected from Aqua-MODIS in 2022, 2023, 2024, and 2025 were lower by 20%, 39%, 67%, and 71% relative to the 2016–2021 averaged counts. Because of its enhanced fire detection at higher spatial resolution (375 m), VIIRS detects multi-fold more fires than those from relatively coarser 1 km detection of MODIS [12].

The linear regression fire prediction model developed using the 2002–2016 long-term fires vs. NDVI relationship [9,12], as displayed in Figure 2, starts showing increasingly positive biases (i.e., predicted fire counts > actual fire counts) in the predicted seasonal fires, yielding errors of 19%, 68%, 222%, and 233% for the years 2022, 2023, 2024, and 2025, respectively. In other words, the actual fire counts observed from Aqua-MODIS at the end of burning season found to be substantially lower than the model predicted fire counts. Given the high efficacy of the prediction model demonstrated for the previous years (2017–2021), such large prediction errors in fire activities encountered during more recent years raised an alarm.

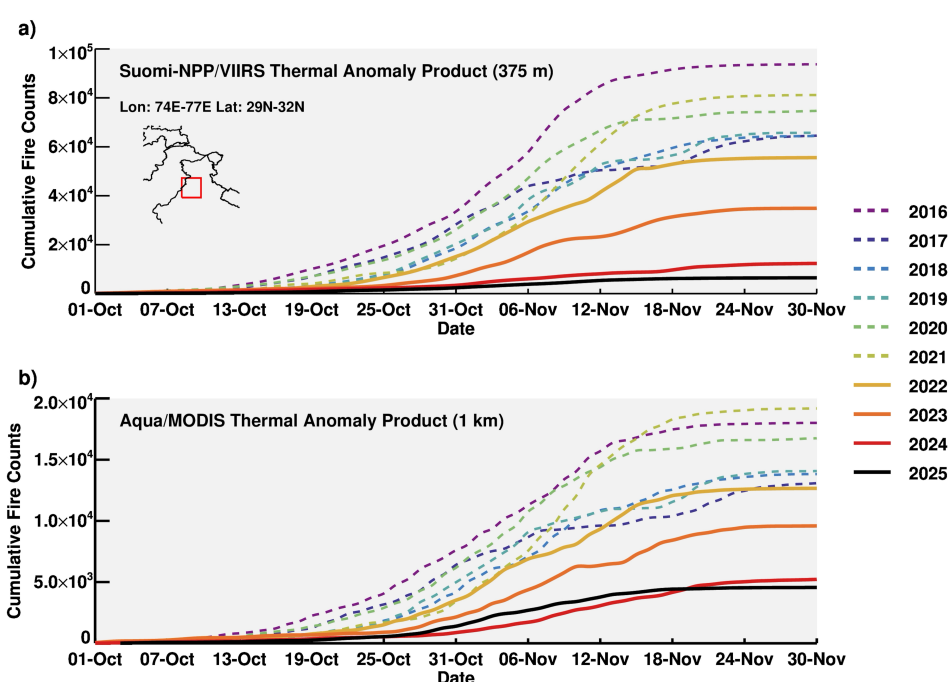


Figure 1 Cumulative fire counts by detection date from (a) Suomi-NPP/VIIRS and (b) Aqua/MODIS sensors over northwestern Indian subcontinent (red box in map) for the post-monsoon crop residue burning seasons (October–November) of 2016–2025. Near real-time thermal anomaly/fire detection data available for this period from each sensor were used.

The seasonal mean aerosol optical depth (470 nm) retrieved from MODIS's MAIAC algorithm over IGP, as depicted in Figure 3, shows an overall increasing trend in region-wide aerosol loading during the period 2022–2025. A sharp decline in crop fire activities in combined Punjab and Haryana, where most crop fires are concentrated across northern India during post-monsoon, and simultaneous increase in aerosol amounts over the length and breadth of IGP are contradictory and counter intuitive.

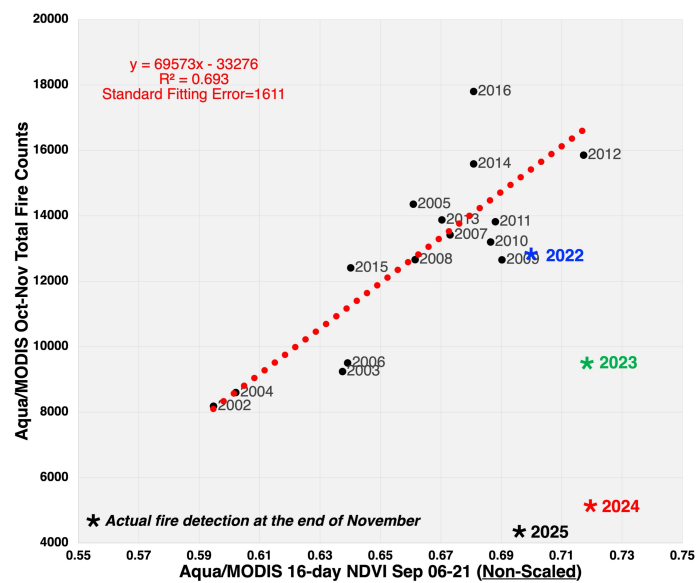


Figure 2 Relationship between pre-burning season NDVI and post-monsoon total fire counts over NW India derived based on multi-year (2002–2016) Aqua/MODIS datasets. Black-filled circles represent individual years used in the linear regression (red dotted line), with regression statistics shown in the top-left corner. Color-coded asterisk symbols are actual values of NDVI, and total fire counts observed for the years 2022–2025 not used in the regression.

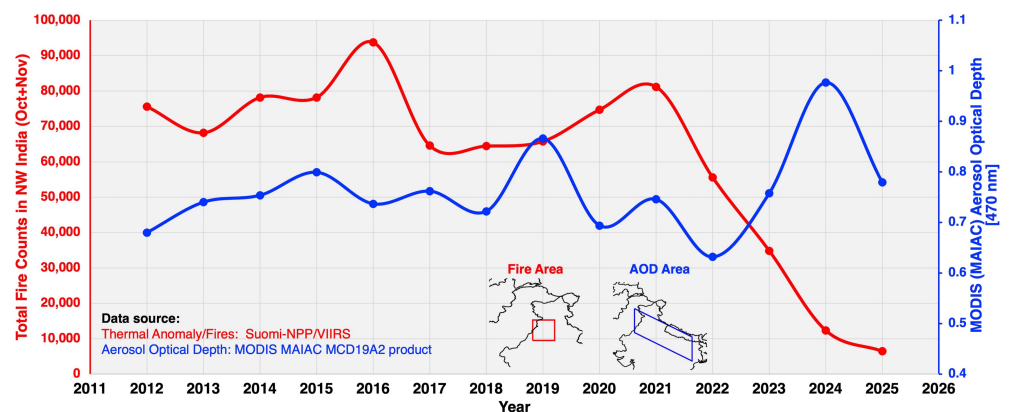


Figure 3 Time-series of seasonal total fire counts over greater Punjab and Haryana regions (red box) and total column aerosol optical depth at 550 nm over the Indo-Gangetic Plain (IGP, blue box). The thermal anomalies/fires data at a native spatial resolution of 375 meters were accessed from Suomi-NPP/VIIRS, whereas AOD dataset was derived from the MAIAC algorithm applied to the combined Terra + Aqua-MODIS observations.

3.2. Vegetation Indices

To further investigate these contrasting trends in fire sources and aerosol loading, satellite-derived vegetation indices are examined. The health of vegetative surfaces, maturity stages of crops, and burned areas are often identified using different vegetation indices measured from satellite sensors. Vegetation and burned area indices have been widely used by the wildfire and agricultural communities for monitoring and tracking the health and progression of vegetated areas, harvesting practices, and estimating burned areas. Two commonly used such indices are NDVI—Nondimensional Vegetation Index

and NBR—Normalized Burn Ratio. NDVI is calculated using the atmospherically corrected surface reflectance in the red band (around 670 nm) and near-Infrared band (around 860 nm) as follows:

$$NDVI = \frac{\rho_{RED} - \rho_{NIR}}{\rho_{RED} + \rho_{NIR}} \quad (4)$$

Where, ρ_{RED} and ρ_{NIR} are the surface reflectance in the red (around 670 nm) and NIR (around 860 nm) spectral bands, respectively. NBR is a fire-sensitive index derived from the pair of surface reflectance at near- and shortwave-infrared measurements using the following simple formulation:

$$NBR = \frac{\rho_{NIR} - \rho_{SWIR}}{\rho_{NIR} + \rho_{SWIR}} \quad (5)$$

Where, ρ_{NIR} and ρ_{SWIR} are the surface reflectance in the NIR and SWIR (around 2.1 μm) spectral bands, respectively. Healthy, unburned or undamaged vegetated surfaces are characterized by high reflectance in NIR and low in SWIR parts of the spectrum, whereas burned areas show an opposite behavior: low NIR and high SWIR reflectance. NBR values typically range from -1 to 1. Decreasing NBR values indicate increasing damage to vegetation cover often resulting from fire, presence of ash from burned vegetation, and the increasing exposure of bare, dry soils and rocky areas. On the other hand, NBR values in the range 0 to 1 represent increasingly healthy, undamaged vegetation only lightly burned or not at all affected by fire. NBR, along with other burn indices, calculated from spectral reflectance measurements from high spatial resolution sensors, such as Landsat 8/9 (30 m) and Sentinel-2 (10 m), have been effectively used for mapping pre- and post-fire changes, burn severity, and quantifying burned areas [22,23,24].

The MCD19A3D product (Version 6.1) of MODIS Terra and Aqua combined reports NDVI at 1 km resolution sinusoidal grid on a daily basis over cloud-free areas. NDVI is calculated from the atmospherically corrected spectral surface reflectance in the red and NIR bands derived from the Multi-angle Implementation of Atmospheric Correction (MAIAC) algorithm. The MCD19A1 product (Version 6.1) of MODIS derived from MAIAC algorithm provides atmospherically corrected surface reflectance in seven spectral bands from visible to SWIR at 1 km sinusoidal grid on daily scale. Here, NBR was calculated using the surface reflectance in red (band 2) and SWIR (band 7) bands. NDVI and NBR datasets derived from MODIS are used to track the progression of burning activities in Punjab. Figure 4 shows the temporal variations of area-averaged, 3-day running mean of (a) NDVI and (b) NBR during 2019-2025 crop burning months of October and November for Punjab. Also shown are the 5th and 95th percentile of all data collected over the entire state. Both indices show much higher values at the beginning of burning season with NDVI in the range 0.7-0.75 and NBR at ~ 0.6, indicating healthy, mature cropland. As the stubble burning activities advance and intensify during the later and earlier halves of October and November, respectively, both indices show a near-linear decline in their magnitudes, reaching ~0.4 and ~0.2, on average, around November 10. Then onwards, both NDVI and NBR remained near-stable towards the end of the burning period.

The fire detection data from MODIS and VIIRS showed a drastic decline in stubble burning incidences during 2022-2025. If these observations accurately reflected the full extent of stubble burning, it would be anticipated that the NDVI and NBR metrics should also have responded proportionately in their temporal behavior. Under a scenario of reduced burning activities, both NDVI and NBR should reflect considerably higher

values than those typically observed during previous years. Contrary to this expectation, both vegetation indices exhibited similar behaviors between 2019–2025, with minimal interannual variations. These findings, combined with rising levels of aerosols in IGP during 2022–2025, cast a doubt on whether the fire statistics and their recent trends derived from both MODIS and VIIRS fully capture the extent of crop fire activities in NW India. This discrepancy prompted an exploration beyond the widely used polar orbiting sensors to investigate temporal evolution of fire activities using GK2A-AMI geostationary platform.

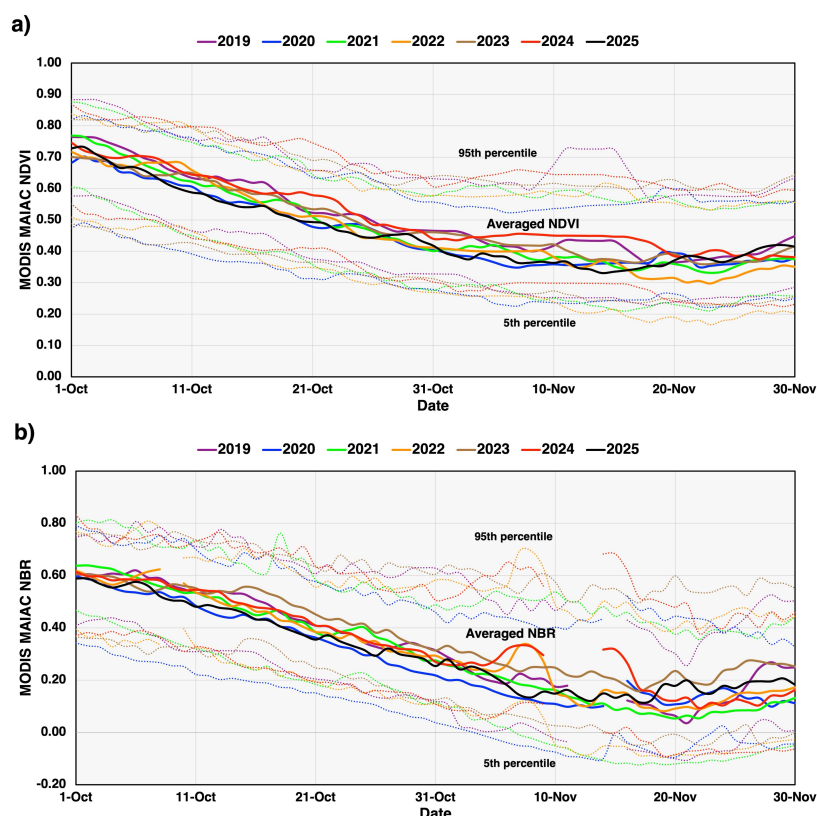


Figure 4 Temporal variations of NDVI and NBR derived from MODIS MAIAC aerosol algorithm applied to MODIS on Terra and Aqua platforms over NW India for the post-monsoon season of 2019 through 2025. Solid and dotted lines represent mean and 5th/95th percentile values, respectively.

4. Time-resolved Active Fire Detection from GK2A-AMI Geostationary Satellite

4.1. Visual Analysis of Images

An investigation of near real-time images from AMI sensor aboard GK2A geostationary satellite began during 2024 post-monsoon burning season. Figure 5 displays the true-color RGB images captured by AMI on Nov 01, 2024 (top panel) and Nov 07, 2025 (middle panel) at 1:30 PM Indian Standard Time (IST) (left) and 4:00 PM IST (right). The near-real time true-color and spectral brightness temperature images captured by GK2A-AMI sensor are readily available from CIRA RAMMB web portal <https://slider.cira.colostate.edu/>. A striking difference in the RGB image between the two timeframes, i.e., early and late afternoon, is the enhanced brightening effect of the scene in the late afternoon at

4 PM. This phenomenon is attributed to strong forward scattering (i.e., the sun and satellite are in the opposite direction) caused by the fine-mode carbonaceous aerosols emitted from stubble burning.

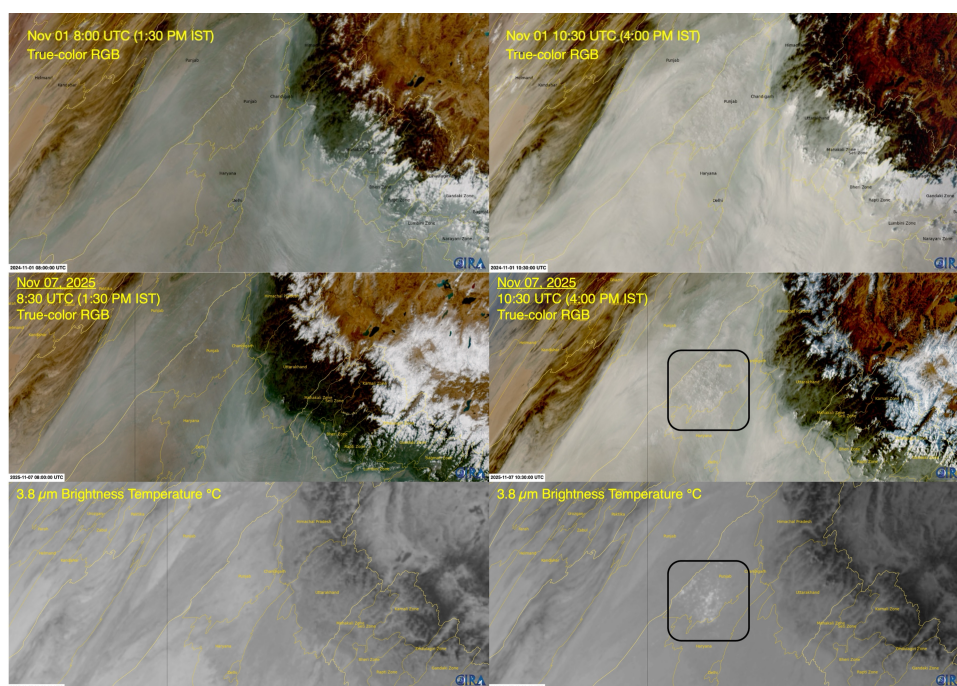


Figure 5 (Top and middle) True-color RGB images of northwestern Indian subcontinent captured by the GK2A-AMI sensor on November 1, 2024, and November 7, 2025, at 1:30 PM IST (left) and 4:00 PM IST (right). The corresponding image of 3.8 μm brightness temperature for November 7, 2025, are shown in the bottom two panels.

Another marked difference between the two timeframes is the extensive presence of spotty smoke clouds in the state of Punjab seen at 4 PM IST, which are mostly absent in the 1:30 PM timeframe—a typical time window when the polar orbiting MODIS and VIIRS sensors pass over the region. The bottom two panels show the corresponding 3.8 μm brightness temperature (in Celsius) images captured on November 7, 2025. The 3.8 μm band is fire-sensitive shortwave infrared spectral region primarily used for detecting active fires. Enhancements in the brightness temperature, specifically over the Indian state of Punjab, compared to the surrounding backgrounds in the 4 PM timeframe observations are indicative of the intense stubble burning activities. Numerous such images captured during the post-monsoon stubble burning seasons of 2024 and 2025 revealed a consistent pattern of enhanced brightness temperature during late afternoon hours in the state of Punjab, India.

GK2A-AMI provides high-frequency (i.e., 10-minute interval), full-disc hemispherical spectral observations, including in the 3.8 μm and 11.2 μm bands that can be used to identify active fires [25]. An unambiguous 3.8 μm signal occurring in the late afternoon during more recent years over the study region underscored the necessity of developing a research-level algorithm for deriving a multi-year record of diurnal fire statistics, which is described in the subsequent section. It is emphasized here that the primary objective of the proposed algorithm is to investigate the diurnal variations in fire occurrences over NW India, rather than creating an official Level 2 product for the full-disc observations.

4.2. Fire Detection Algorithm

The proposed algorithm of detecting fire and smoke hotspots essentially relies on the two fundamental measurements acquired in the 3.8 μm and 11.2 μm spectral bands. The enhancement of thermal radiation in the 3.8 μm band is caused by increasing temperature associated with the burning conditions, whereas the 11.2 μm signal, which is mostly unaffected by burning, aids in providing a contrast. Although AMI make observations of full disc at a 10-minute interval, hourly measurements are considered here for the ease of data download and reducing processing time. First, the brightness temperature measurements are analyzed for the selected dates of different years (2019–2025) aligning with peak stubble burning period. Figure 6 shows the hourly maps of normalized brightness temperature difference (ΔT_b) between 3.8 μm and 11.2 μm channels of the GK2A-AMI for these selected dates of years 2019–2025 over NW India. ΔT_b values for the respective hourly timeframe data are normalized relative to the averaged values derived from the 09–11 IST hours observations as follows:

$$\Delta T_b(t) = T_b^{3.8} - T_b^{11.2} \quad (6)$$

$$\Delta T_b(t)_{norm} = \Delta T_b(t) - \Delta T_b(09 - 11 \text{ IST})_{avg} \quad (7)$$

Where, $\Delta T_b(t)$ is difference in brightness temperature between 3.8 μm and 11.2 μm , $\Delta T_b(09 - 11)_{avg}$ is averaged brightness temperature difference calculated from 09–11 IST hourly observations, and $\Delta T_b(t)_{norm}$ is the normalized brightness temperature for hourly timeframes between 12–18 IST. The primary purpose to perform such normalization is to reduce the background surface effects as much as possible, particularly over the non-burning hot surfaces (semi-arid or arid surfaces) identified along the southern borders of the two states, which may be detected as fire hotspot due to its higher temperature.

The hourly maps of normalized $\Delta T_b(t)_{norm}$ for the selected dates of 2019–2021 show distinct enhancements, particularly in the state of Punjab, which first start appearing at 12 IST, further intensify during early afternoon, and diminish during early evening hours. A visual comparison of these maps with fire hotspots detection from S-NPP/VIIRS on NASA's Worldview visualization platform (<https://worldview.earthdata.nasa.gov/>) for the same dates revealed an excellent spatial correlation—suggesting that $\Delta T_b(t)_{norm}$ enhancements are a strong indicator of the active fires. Starting in 2022, the time window of enhanced $\Delta T_b(t)_{norm}$ signal is pushed later by an hour or more, occurring between 14–17 IST. This indicates a delayed start of burning activities, which became more pronounced in 2024 and 2025 with maximum contrast observed at 16 and 17 IST hours. Similar maps (not shown here) for additional days during the peak burning period demonstrated consistent pattern between 2019–2025.

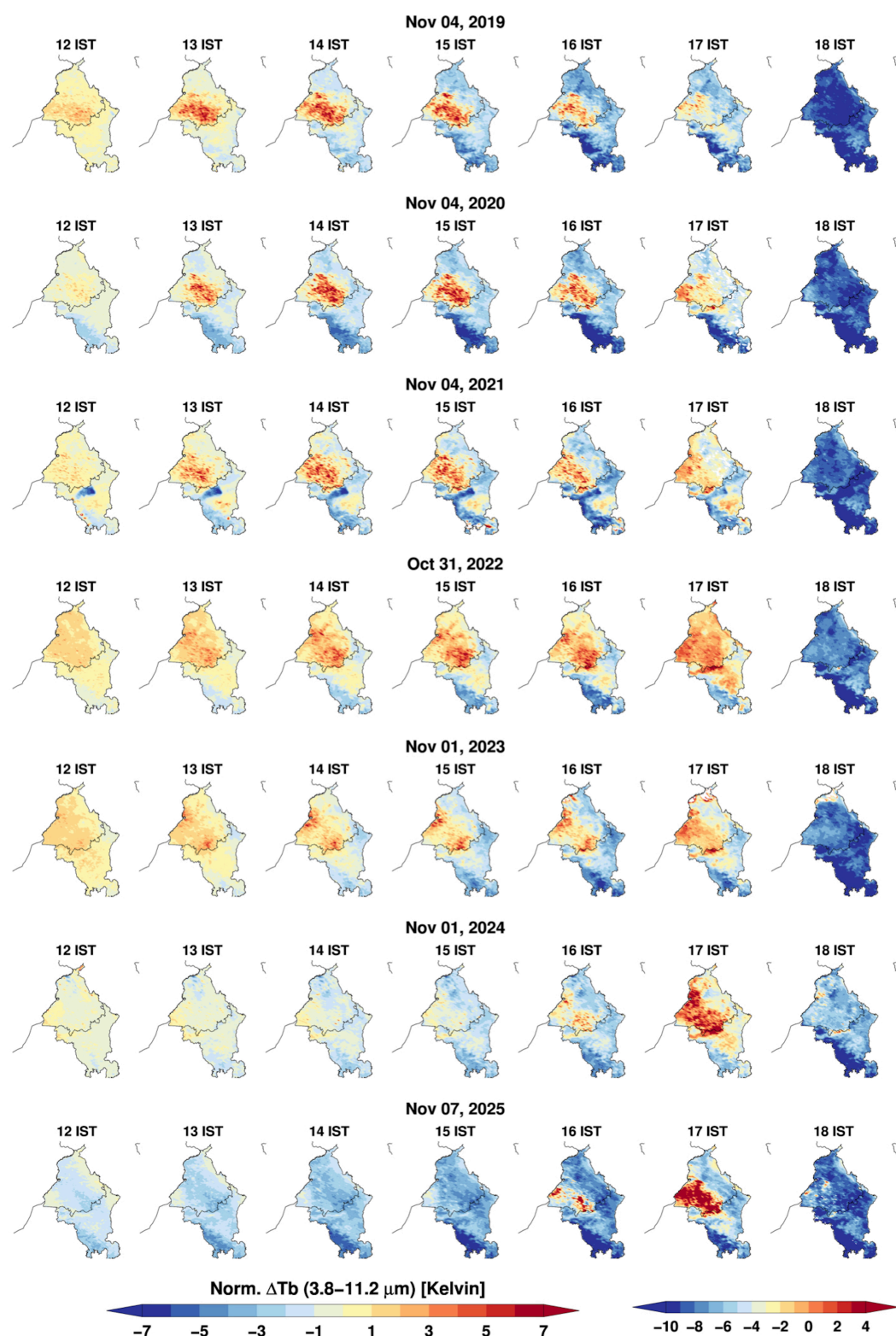


Figure 6 Hourly maps of normalized brightness temperature difference (ΔT_b) between 3.8 μm and 11.2 μm channels of the GK2A-AMI sensors for selected dates of years 2019–2025 over NW India. ΔT_b values for the respective hourly timeframe data are normalized relative to the averaged values derived from the 9–11 IST hours observations. Maps for 17:00 and 18:00 IST hours (rightmost column) are shown with different color scale range (–10 K to 4 K).

Table 1 Dynamic, hour-dependent normalized brightness temperature conditions and respective confidence flags for detecting active fires from GK2A-AMI observations.

Local Hour [IST]	$\Delta T_b(t)_{norm}$ Conditions	T_b Thresholds	Confidence Flag ¹
		[in degree K] 3.8 μ m & 11.2 μ m	
12-14	$3.0 < \Delta T_b(t)_{norm} \leq 4.0$	303 K & 293 K	1 (low)
	$4.0 < \Delta T_b(t)_{norm} \leq 5.0$		2 (nominal)
	$\Delta T_b(t)_{norm} > 5.0$		3 (high)
15-16	$2.5 < \Delta T_b(t)_{norm} \leq 3.5$	301 K & 291 K	1
	$3.5 < \Delta T_b(t)_{norm} \leq 4.5$	299 K & 289 K	2
	$\Delta T_b(t)_{norm} > 4.5$		3
17	$2.0 < \Delta T_b(t)_{norm} \leq 3.0$	297 K & 288 K	1
	$3.0 < \Delta T_b(t)_{norm} \leq 4.0$		2
	$\Delta T_b(t)_{norm} > 4.0$		3
18	$-4.0 < \Delta T_b(t)_{norm} \leq -3.0$	295 K & 287 K	1
	$-3.0 < \Delta T_b(t)_{norm} \leq -2.0$		2
	$\Delta T_b(t)_{norm} > -2.0$		3

¹ Confidence Flag Interpretation: 1=low, 2=nominal, 3=high

A thorough examination of many such images of hourly normalized brightness temperature differences, in conjunction with its correlation to the near collocated VIIRS thermal anomaly/fire detection data provided dynamic, time-dependent thresholds and ranges of $\Delta T_b(t)_{norm}$ for identifying the fire and/or possibly hot smoke pixels. Table 1 lists these ranges and thresholds, including the absolute brightness temperatures in both bands used for enhanced cloud screening, for different hourly timeframes adopted for detecting fire hotspots from GK2A-AMI observations. Each valid fire pixel is assigned with a corresponding confidence level: low (1), or nominal (2), or high (3), which reflects the observed $\Delta T_b(t)_{norm}$ conditions. Fire pixels flagged with lower (higher) confidence level are associated with relatively smaller (larger) enhancement in $\Delta T_b(t)_{norm}$. Although AMI makes measurements of full disc at every 10 minutes, hourly observations are used here for the ease of computation and data handling with an aim to evaluate the temporal fire behavior from noon (12 IST) to evening hours (18 IST). Also, note that though AMI's native subsatellite pixel resolutions ~ 2 km, it scans NW Indian region at a slant viewing angle. This viewing geometry results in stretching of the pixel at ground, making pixel resolution of ~3.8 km over the study region.

Figure 7 presents the first set of fire detection maps for the same selected dates as depicted in Figure 6. Fire pixels identified at all three confidence levels (low, nominal, and high) are shown as color-coded dots. Consistent with the observations made in the normalized brightness temperature difference maps (Figure 6), the majority of fires in 2019, 2020, and 2021 are observed to occur between 13-16 IST time window. This was effectively captured by the polar orbiting MODIS and VIIRS sensors during their respective pass over the region between 1 PM-2 PM local time (data not shown here). In the subsequent and more recent years, there was a noticeable shift in the onset of crop burning, which appeared to be shifted by an hour later in 2022 and 2023 and further delayed to 4-5 PM hours in 2024 and 2025.

Figure 8 presents the fire data for the selected dates, represented as hourly fractions of total fires accumulated between 12:00 and 16:00 IST, plotted against individual hours.

The fractional approach to the hourly fire data removes the absolute number of fires observed on these specific dates, enabling a direct comparison of the hourly progression of fire activities. The diurnal pattern of fire activities demonstrates a gradual shift: from early afternoon during the years 2019–2021, to between 15:00–16:00 IST in 2022 and 2023, and finally to between 16:00–18:00 IST in 2024–2025. At this point, these results provided a strong hint of delayed burning pattern, i.e., from usual early afternoon to late afternoon, over NW India. To further verify and expand the scope of investigation, the proposed fire detection scheme was consistently applied to the two month-long, i.e., October 1st to November 30th, post-monsoon fire seasons of 2019 through 2025. The derived multi-year record of fire observations is discussed in the subsequent section.

4.3. Collocation of GK2A-AMI and SNPP-VIIRS Active Fire Dataset

The spatiotemporal collocation of GK2A-AMI fire dataset with that available from SNPP-VIIRS high resolution (375 m) detection was performed to investigate their spatial coherency and identifying false positive rates in AMI fire detection. The VIIRS near real-time fire detection product (VNP14IMGTDL_NRT) was collocated with the derived GK2A-AMI fire hotspots in space and time for the post-monsoon burning seasons of for years 2020, 2021, and 2022. VIIRS on SNPP passes over the region around 1:40 pm local time. AMI fire observations corresponding to 2 pm timeframe were selected for temporal collocation due to its high probability of capturing active fires detected by VIIRS just about 20 minutes before. Spatial collocation was performed by identifying VIIRS pixels within $0.04^\circ \times 0.04^\circ$ (~4 km) grid box centered at each AMI pixel longitude and latitude coordinates. Fire pixels in both datasets flagged with “nominal” and “high” confidence levels were considered.

The spatiotemporal collocated AMI-VIIRS dataset reveals an excellent agreement with VIIRS, where only about 1.6%, 4%, and 4% of AMI fire dataset for the years 2020, 2021, and 2022, respectively, had false positives with no VIIRS fire detection within or in the vicinity of collocated AMI pixel. Figure 9 illustrates the probability distribution function and cumulative distribution fire radiative power (FRP) (in megawatts) of VIIRS fire pixels collocated to AMI for post-monsoon seasons of 2020 (blue), 2021 (orange), and 2022 (green). The distributions of collocated dataset show a wide range of FRP with about 50% and 80% of the AMI’s fire data were contained within FRP up to 100 MW and 150 MW, respectively.

Lowering brightness temperature thresholds used for cloud screening (Table 1) by 2° K in both bands resulted in somewhat higher false positive rates of about 2%, 6%, and 10% in the respective years. On the other hand, increasing brightness temperature threshold by $+2^\circ$ provided quite smaller fraction of total pixels with false positives of about 1%, 2.5% and 2% in the respective years. The accumulated number of derived fire hotspots was, however, significantly larger in the former scenario than those obtained in the stricter latter scenario (see section 4.5, Figure 12).

Based on the AMI-VIIRS collocated dataset, a near-optimum absolute threshold values of brightness temperature in both bands were selected, as tabulated in Table 1, that provides a good trade-off between accuracy and statistics of fire detection from AMI.

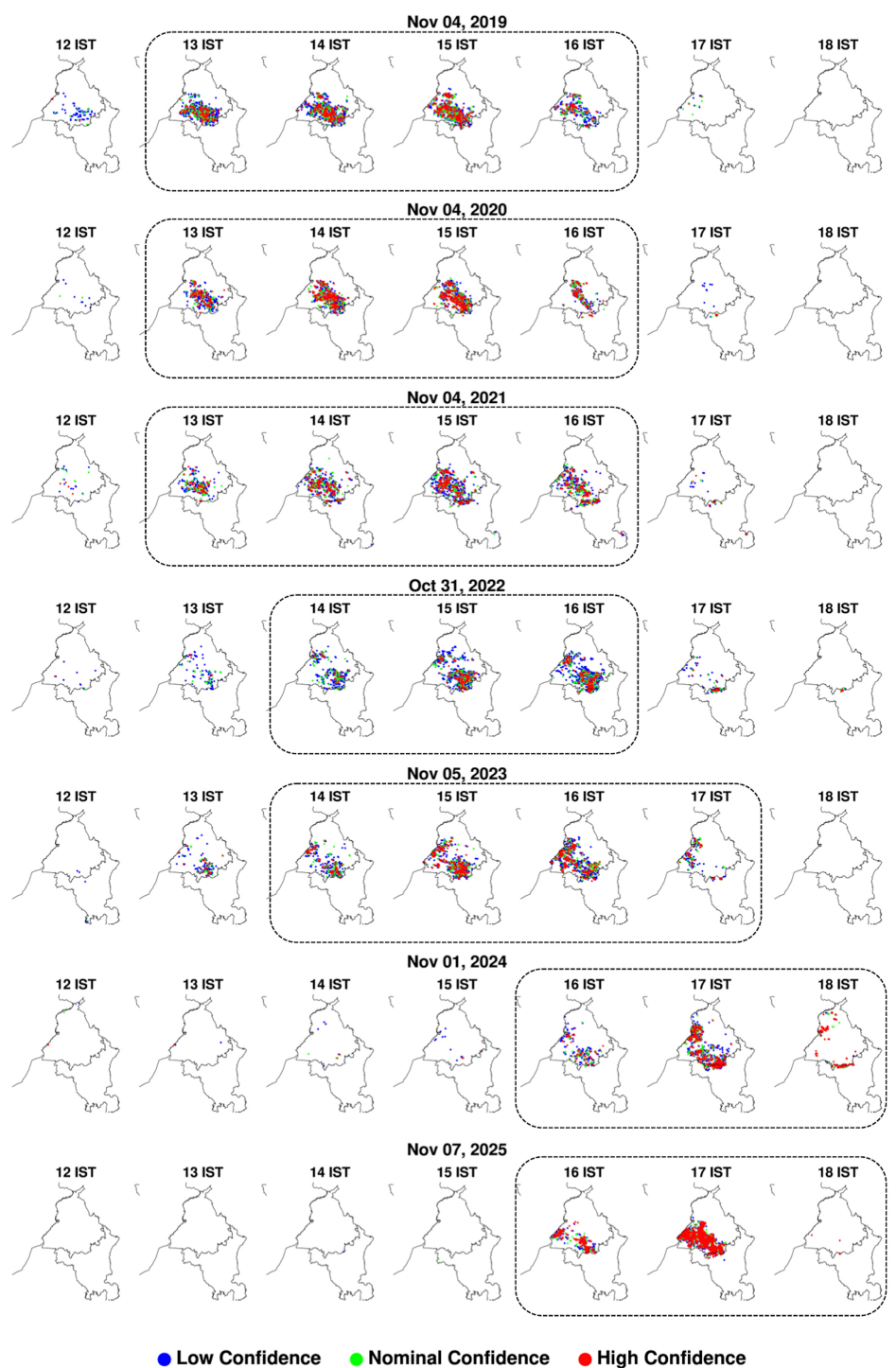


Figure 7 Hourly maps of probable fire hotspots and smoke pixels over NW India inferred from GK2A-AMI data for selected dates of years 2019 and 2025. Color dots represent confidence level (low, nominal, and high) of fire detection. Hourly timeframes with majority of fire occurrence are marked with dotted rectangular boxes for the respective years.

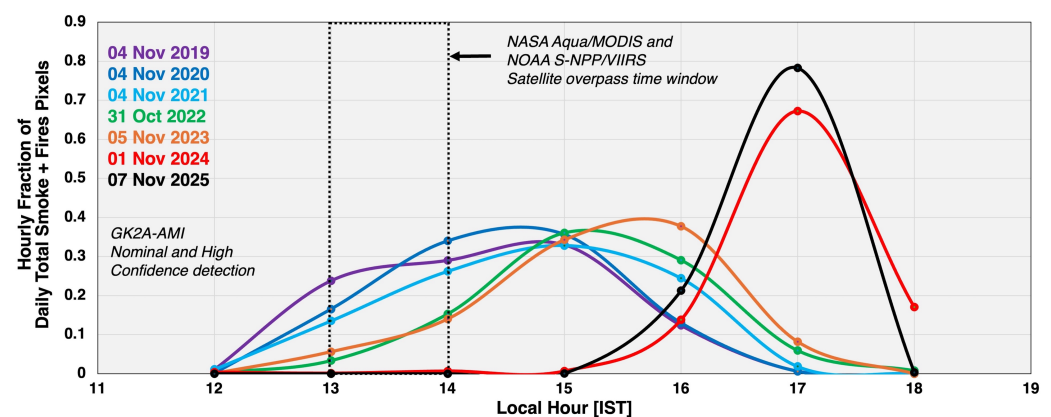


Figure 8 Hourly evolution of fire and smoke pixel statistics inferred from GK2A-AMI brightness temperature data for the selected dates of years 2019–2025. Values on the y-axis represent the fractional fires/smoke statistics relative to the total number of fire pixels detected between 12:00 and 18:00 IST. Nominal and high confidence level data are used. The dotted rectangle indicates the typical pass over time window of MODIS and VIIRS sensors on Aqua and Suomi-NPP platforms.

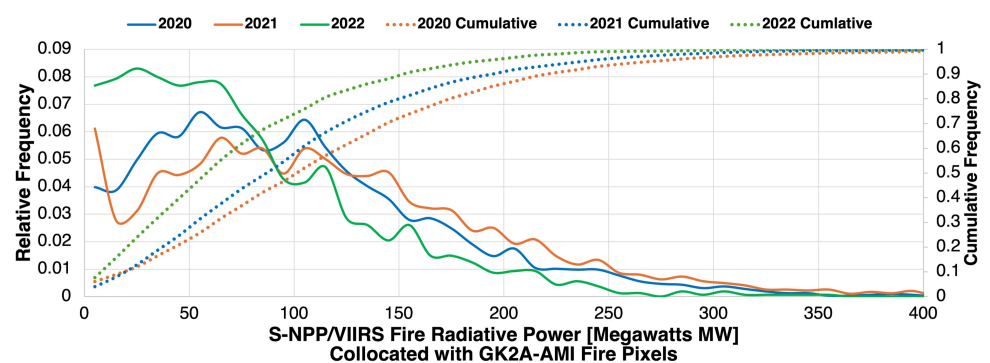


Figure 9 Probability distribution function (solid lines) and cumulative distribution (dotted lines) of fire radiative power [MW] of SNPP-VIIRS pixels collocated to AMI fire pixels for post-monsoon seasons of 2020 (blue), 2021 (orange), and 2022 (green).

4.4. Multi-year Hourly Record of Fires from GK2A-AMI over NW India

Figure 10 shows the gridded (0.10° by 0.10°) hourly maps (12 IST – 18 IST) of total, accumulated fire hotspots for the post-monsoon burning season across Punjab and Haryana for years 2019 through 2025. Each grid is color-coded according to the respective total fire counts. Fire pixels identified with confidence level ‘2’ (nominal) and ‘3’ high) are included. It should be noted that the fire detection algorithm is applied to GK2A-AMI observations for each hourly timeframe independently. As these fires typically last for several hours, fire hotspots detected in one timeframe are possibly observed in subsequent timeframe observations.

The spatial extent and density of fire counts vary by years. For instance, the 2021 fire season is observed as the most active with the maximum number of fire counts occurring predominantly between 13 IST to 17 IST. This finding aligns well with the highest fire counts detected by MODIS and 2nd highest, after 2016, by VIIRS (see Figure 1)—both pass over the region between 13–14 IST. However, it is important to note that fires ignited after the polar orbiting MODIS/VIIRS sensors’ overpass times are missed in their respective fire detection datasets. Secondly, a salient feature relevant to the present investigation, is the

systematic and gradual delay in the onset of fires, especially in the state of Punjab. Starting in the fire season of 2022, the major stubble burning activities commenced approximately an hour later than in the previous year. In the more recent years of 2023–2025, the timings of peak burning were further delayed, with the majority of fire occurrences distributed during the 14–17 IST time window, with largest density of fires observed at 15 and 17 IST hours.

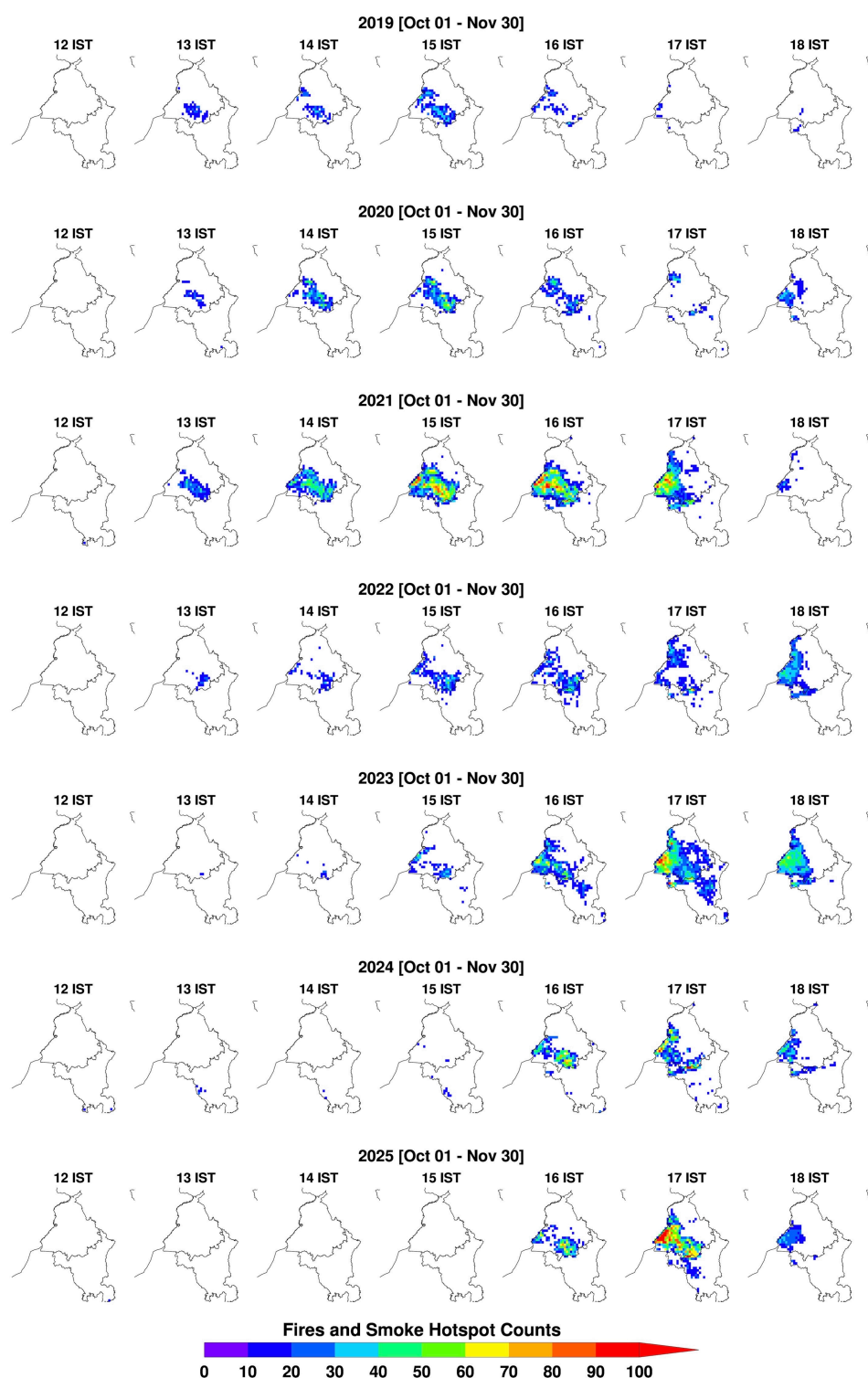


Figure 10 Hourly maps of gridded total fires and smoke hotspots detected from GK2A-AMI observations during post-monsoon months of October and November for the years 2019–2025. The fire detection data flagged with nominal ('2') and high ('3') confidence levels are used and uniformly gridded to 0.10° by 0.10° .

To further examine the diurnal patterns of crop fires on a state basis, the multi-year fire detection dataset is analyzed separately for Punjab and Haryana, as demonstrated in Figure 11. Only unique fires detected within individual hourly timeframes are considered in this analysis. Unique fires are defined as those observed at specific geolocation coordinates during a particular hourly interval and are not recounted even if detected again in subsequent hourly observations at the same location. The dataset encompasses fire hotspots for the entire post-monsoon season (October and November) from 2019 to 2025. Fires flagged with nominal and high confidence levels are included.

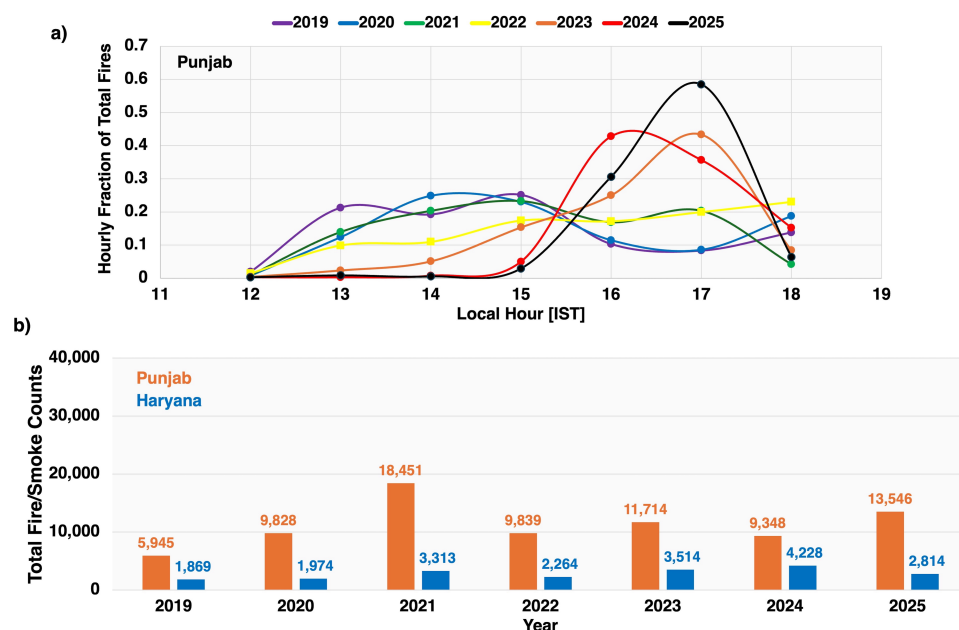


Figure 11 Year wise hourly fractional fires/smoke counts relative to the total number of hotspots for a) Punjab state of India. b) The total number of post-monsoon seasonal fire and smoke hotspots for Punjab and Haryana for 2019–2025 are shown as bar chart.

The top panel of Figure 11 (a) shows the hourly fraction of total fire counts plotted against hour for Punjab. Data for different years are depicted using different colors. In Punjab, the diurnal behavior of fire occurrences shows a gradual delay in the fire density to late afternoon hours, particularly during more recent years of 2023–2025.

The bottom panel of Figure 11 (b) displays the bar chart of total number of unique fire hotspots accumulated between 12–18 IST time interval for Punjab (orange) and Haryana (blue). As it can be seen that crop fire activities in Haryana show no significant trend with total fire counts remained mostly in the range 2000–4000 counts. In contrast, stubble burning incidences in Punjab were significantly higher than in Haryana, showing a strong upward trend from approximately 6,000–18,000 fire occurrences in 2019–2021—a roughly three-fold (300%) increase in fire activities. In the post-monsoon season of 2024, Punjab saw a significant decline of ~49% in fire activities compared to those observed in 2021—the most active year in fires in AMI's 7-year long record. This drastic reduction in fires in 2024 was followed by a substantial uptick of ~45% in stubble burning in 2025, which is comparable to the averaged fire counts observed during the active years 2021–2023.

4.5. Limitations and Challenges

The research-level algorithm for fire detection developed and presented in this study rely on 1) the normalization of early noon to evening brightness temperature difference data relative to those observed during morning hours, and 2) dynamic ranges of the brightness temperature difference. The normalization approach is adopted for removing surface related signal in the fire detection. Any variations caused by rapidly changing land surface temperature conditions that are not related to the fires may still lead to false positive or negative in the fire detection procedure. The native subsatellite pixel resolution of AMI sensor is ~2 km. However, the pixel size increases as a function of viewing zenith angle. For the study region of NW India observed within the field-of-view of the sensor, the pixel size becomes two-fold larger and estimated to be approximately ~4 km. On the other hand, MODIS and VIIRS sensors detect and report fire hotspots at much finer resolution of 1 km and 375 meters, respectively. For example, small-scale fires detected by MODIS/VIIRS may not produce sufficient radiative signal in the NIR 3.8 μm band at AMI's coarser resolution to be qualified as a fire pixel. Additionally, small- and large-scale fires identified in a single 4 km AMI pixel is considered as one fire pixel. For these reasons, the fire hotspots data derived from GK2A-AMI and presented in this study is expected to be underrepresented and cannot be directly compared to those identified by the high-resolution sensors.

The presence of clouds hinders the detection of fires on the ground. Clouds affect both the timeframe observations during 09-11 IST used in the normalization process and the spatiotemporal fire detection during 12-18 IST time window. The cloud screening relies on the GK2A-AMI Level 2 cloud product, which reports three classes of clouds: cloudy ('0'), probably cloudy ('1'), and clear ('2'). All three cloud classes show variability in geometric cloud fraction for different years with about 32%, 24%, 7%, 11%, 15%, 2%, and 5% of total pixels in Punjab were identified as cloudy for the years 2019 through 2025, respectively. These pixels were discarded in the fire detection procedure. The AMI cloud product misclassified many of fire pixels during peak burning hours as probably cloudy. These pixels were called back in the algorithm with strict thresholds in brightness temperature in both bands to retain fire pixels while rejecting water/ice clouds. These steps in the algorithm ensure that the effects of clouds and cloud shadows remain at minimal level.

To quantify the sensitivity of the fire detection statistics to the choice of brightness temperature thresholds used for cloud screening, two additional versions of fire datasets were derived for Punjab by perturbing the revised threshold values by $\pm 2^\circ\text{K}$ uniformly for each timeframe observations. The recalculated fire statistics for each year were compared against those derived in the original (revised in this report) dataset to quantify changes. Figure 12 summarizes the results of this sensitivity analysis.

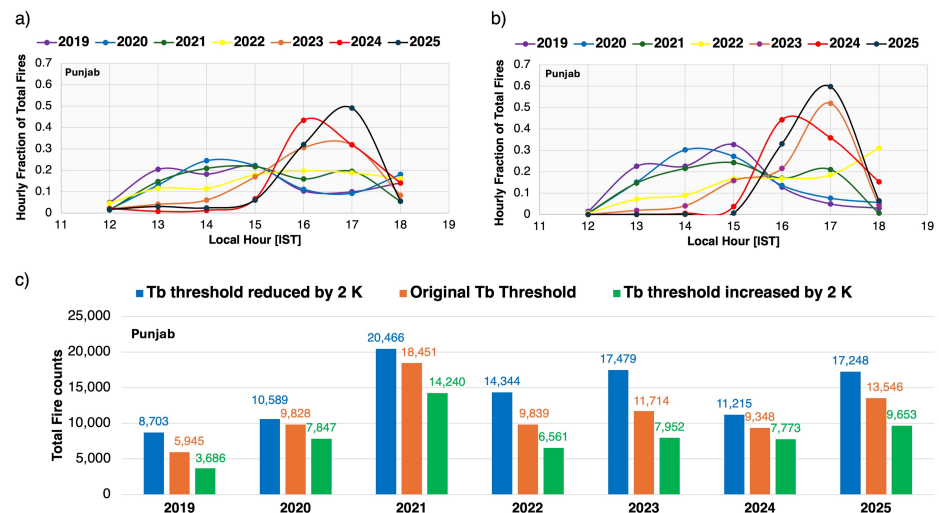


Figure 12 Year wise hourly fractional fires hotspot counts relative to the total number of hotspots for Punjab derived under two scenarios: a) absolute brightness temperature threshold for each timeframe is reduced by 2 K and b) absolute brightness temperature threshold for each timeframe is increased by 2 K. c) Year wise total fire counts derived under the original (orange) and two brightness temperature threshold scenarios (blue and green).

Under the relaxed cloud screening method, lowering the hour-dependent brightness temperature thresholds used for cloud screening by -2° K resulted in significantly higher fire counts for specific year. For example, fire counts for the years 2019, 2022, and 2023 were about 46%, 46%, and 49% larger compared to the original fire dataset. On the other hand, under the stricter cloud screening scenario, increasing brightness temperature thresholds by $+2^{\circ}$ K yields reduced fire counts in all years with percent decrease by -38%, -33%, and -32% for 2019, 2022, and 2023, respectively.

This sensitivity test demonstrated significant impacts of the choice of Tb thresholds on the absolute fire hotspots counts. Despite such pronounced effects, the inferred diurnal variations in hourly fractional fire counts remain largely unchanged, as illustrated in Figure 12 a) and b). In all three scenarios studied here, diurnal pattern of fires in Punjab unambiguously show a clear shift in the peak fire activities to later afternoon hours during post-monsoon seasons of 2023, 2024, and 2025.

It is emphasized here that the main objective of the present research was to investigate the diurnal changes in stubble burning activities, in terms of fire count detection, over NW India rather than deriving an official and accurate fires/thermal anomaly product. Some remaining false positive or negative fire detection is still possible in the derived dataset. However, given stringent thresholds in the measured brightness temperature differences adopted in fire detection algorithm, it is expected that such false detections should not alter the overall results presented in this paper.

4.6. Aqua's Orbital Drift and Fire Detection

Beginning in July 2021, Aqua satellite has been under free-drift mode through lowering its altitude, causing its mean local time to shift to later times in the day (<https://aqua.nasa.gov>). Over NW Indian fire region, Aqua's gradual drift resulted in the average pass over times during burning season as 1:44 pm, 1:53 pm, 2:05 pm, 2:32 pm, and 3:12 pm in 2021 through 2025, respectively. As a result of this drift, MODIS detected some of the fires occurring in the midafternoon hours and prior to 4 PM local time not monitored by VIIRS on Suomi-NPP platform flying earlier than MODIS.

The linear fire trends calculated individually from VIIRS and MODIS show that fire counts detected from VIIRS over NW India reduced, relative to 2021 levels, by 68%, 43%, 15%, and 8% in 2022, 2023, 2024, and 2025, respectively. On the other hand, MODIS on Aqua sees reduction in fire activities by 66%, 50%, 27% and 23% during the same period.

These discrepancies in declining trends in fires between VIIRS and MODIS, where Aqua-MODIS records noticeably lower fire trend relative to VIIRS could be attributed to Aqua's gradual orbital drift, enabling MODIS sensor to detect greater number of fires occurring post 1:30 PM local time that were missed by VIIRS. These observations serve as additional evidence and support the findings of shifting stubble fires to late afternoon times in NW India deduced from GK2A-AMI fire detection data. However, it is to be noted here that despite the delayed monitoring during drift period, MODIS currently still misses capturing peak fire activities occurring around and after the 4-PM local time over NW India.

The MAIAC aerosol algorithm applied to Aqua-MODIS (MCD19A2 product) and SNPP-VIIRS (VNP19A2 product) includes a unique capability for smoke detection via high quality cloud detection/mask that includes specialized thermal detection technique for identifying thermal hotspots or active fires based on modified MODIS Collection 6 standard active fire detection algorithm [14]. MAIAC identifies active fire hotspots by evaluating brightness temperature at 11 μm and its thermal contrasts against 4 μm and 12 μm bands along with using a combination of dynamic thermal thresholds (i.e., as a function of AOD) and relative spatial contrasts [25]. Note that the MAIAC fire detection data reported in MCD19A2 and VNP19A2 products are different than the standard thermal anomaly/fire products produced separately for MODIS and VIIRS sensors. Author takes advantage of MAIAC fire hotspots and co-retrieved AOD data over NW India for investigating their combined interannual trends from both sensors.

Figure 13 displays a bar chart of the normalized, fire pixels weighted seasonal AOD [470 nm] (October and November combined) for 2019 through 2025. The MAIAC AODs over and around (± 1 pixel) the fire pixel for each available observations during October and November were extracted. The seasonal fire pixel weighted AOD for each year was further normalized with respect to the maximum number of fire pixels detected during the fire season of 2021. The normalized or scaled seasonal AOD derived from both MODIS and VIIRS show a substantial increase during 2019-2021, followed by a gradual yet drastic declining scaled AOD during 2022-2025 in VIIRS data. AOD data from Aqua-MODIS also shows similar behavior, however, the rate of decline is noted significantly lower relative to that observed in VIIRS data. Different rates of declining AOD over and around fire pixels in NW India between the two sensors point to a likely possibility that time-drifting observations from MODIS on Aqua may have captured some of the gradually shifting fresh fires occurring post 1:30 pm and during mid-afternoon hours in the period 2022-2025 that are missed by VIIRS on SNPP satellite flying around 1:30 pm IST over the region.

While MODIS on Aqua continues to collect science quality data for climate monitoring during the drift period, it is estimated that mean local time of overpass will be shifted to ~3:50 PM local time by August 2026—a significant delay compared to its pre-drift ~1:30 PM time when Aqua was an integral platform of NASA's A-train satellite constellation. It is, therefore, expected that rapidly drifting Aqua-MODIS will likely see more fire occurrences in 2026 onwards, if the new fire pattern regime over Punjab persists.

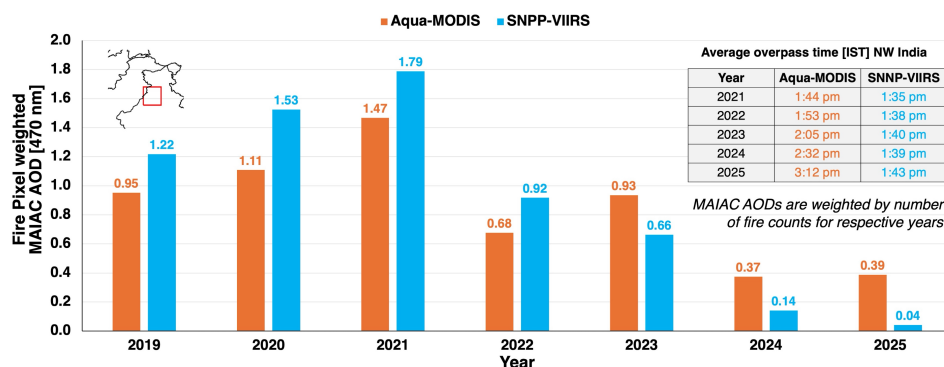


Figure 13 Normalized (scaled) fire pixel weighted aerosol optical depth [470 nm] dataset over NW India (red box in the inside map) derived from MAIAC algorithm applied to Aqua-MODIS (orange) and SNPP-VIIRS (blue). Table shown as an inset lists the average overpass time of the respective sensors for years 2021–2025.

Quantifying the fraction of fires missed by MODIS/VIIRS is a challenging task due to the lack of consistent measurements from geostationary sensors having similar characteristics (higher spatial resolution) around the times when peak fire activities occur. Comparing hourly fire hotspots detected from GK2A-AMI sensor with those from MODIS/VIIRS is complicated due to significant differences in their spatial resolution, i.e., AMI's ~4km coarser resolution ground footprint against MODIS/VIIRS high spatial resolution detection at 1 km and 375 m, respectively. However, a rough estimate can be made by looking at the interannual fire trends calculated from GK2A-AMI and MODIS/VIIRS. For instance, while AMI records ~45% increase in fire counts in 2025 relative to 2024 observations, VIIRS sees ~48% reduction in fire activities between 2024 and 2025. On a net sense, therefore, VIIRS missed ~64% fire detection in 2025. Similarly, MODIS missed detecting ~40% fires in 2025. In 2024, AMI records 20% lesser fire incidences compared to 2023 levels, whereas VIIRS and MODIS data showed ~65% and ~46% reduced frequency, respectively, leading to 56% and 32% missed fire detection in the respective datasets.

5. Discussion and Final Remarks

5.1. Major Findings

The hourly geostationary observations acquired from GK2A-AMI sensor in the 3.8 μm and 11.2 μm , along with AMI's cloud mask product, were used in a research-level fire detection algorithm for inferring the diurnal changes in the post-monsoon fire occurrences in NW India, including states of Punjab and Haryana. A dramatic decline in fire activities seen by the polar-orbiting MODIS and VIIRS sensors yet increasing regionwide aerosol loading and largely unchanged behavior of vegetation indices prompted to examining the time-resolved fire observations from geostationary platform. GK2A-AMI data was chosen for this study because of its readily available imagery and freely available observational dataset in near real-time.

The multi-year (2019–2025) AMI record of active fire hotspots detection over NW India revealed a gradual shift in the onset of fire activities: occurring between 13–14 IST during 2019–2021, delayed by an hour or so in 2022, and further pushed toward late afternoon and between 16–17 IST in 2023–2025. The polar-orbiting MODIS and VIIRS sensors on Aqua and Suomi-NPP platforms typically pass over the region between 13–14 IST, capturing the significant fire incidences before this temporal shift began in 2022. If the dramatic decline trends in fire occurrences beginning 2022 detected from MODIS and VIIRS were actual, it should be reflected in the surface property retrieval from space. However,

the vegetation indices, NDVI and NBR, derived from MODIS exhibited similar intraseasonal behavior with minimal spread over the period 2019–2025—suggesting the recent fire trends detected from MODIS/VIIRS are not representative of the totality of fire activities over the region.

The performance of the fire detection algorithm was tested under relaxed and stricter cloud screening methods. Under both scenarios, and despite significant differences in absolute number of fire counts between them, the diurnally shifting fire pattern remained unchanged, where both methods demonstrated late afternoon burning in Punjab during 2022–2025. Started in 2021, Aqua’s orbital drift resulted in MODIS to gradually shift its overpass time around 1:30 pm in 2021 to closer to 4 pm in 2025. This temporal drift allowed MODIS to detect some of the lately occurring fires over NW India that were not seen by VIIRS. As a result, the rate of decrease in fire activities calculated using MODIS fire dataset was noticeably lower than that derived from VIIRS—a supporting evidence corroborating similar findings deduced from GK2A-AMI geostationary observations.

Fire detection from coarser resolution measurements remains as a challenging problem. Specifically, handling sub-pixel cloud contamination and capturing small-scale fires are a difficult task. Small-scale fires are prevalent in the region where detection by even high-resolution sensors, such as MODIS and VIIRS, poses challenges. For example, an experimental hybrid MODIS-Landsat method (ModL2T) mapping area at 30-m spatial resolution resulted in $44 \pm 21\%$ higher burned area than the standard MODIS product (MCD64A1), and up to $105 \pm 52\%$ increase in dry matter emissions over GFEDv4s inventory [26].

5.2. Future Implications

Despite inherent uncertainties involved in the fire detection at AMI’s coarser spatial resolution, its high-frequency, time-resolved observations allow an inference of diurnal changes in fire activities, as demonstrated over NW India in this study. Future improvements to the presented algorithm are expected as AMI data are being understood better. For instance, a large solar zenith angle correction to reflectance was applied to GK2A-AMI data, which was not considered in the present study, for improving fire detection over China [27]. One of the future improvements can be mapping the high-resolution fire detections from MODIS and VIIRS to collocated AMI’s coarser resolution brightness temperature observations for understanding their relation, thereby improving different ranges of thresholds adopted in the current research algorithm.

The development of a research-based fire detection algorithm presented in this work opened possibilities for its application to other geostationary sensors looking at the Indian subcontinent. For example, INSAT-3DS imager of India’s ISRO space agency carries a total of 6 spectral bands, including 3.8–4.0 μm SWIR band and 10.2–11.2 μm and 11.5–12.5 μm thermal infrared bands—similar to the GK2A-AMI bands used in the present work. An active fire detection algorithm applied to INSAT-3DS over the NW India has been demonstrated confirming the late afternoon agricultural burning in Punjab and Haryana [28]—consistent with the findings of the present study obtained using GK2A-AMI observations.

The derived time-resolved fire detection data from geostationary GK2A-AMI is anticipated to improve the air quality forecast in the region. Currently, these forecast models predominantly rely on ingesting fire data, hence resulting emissions, from MODIS and VIIRS—both these standard sensors miss the peak fire activities occurring in the late afternoon. Consequently, the model forecast of air quality measures, such as PM_{2.5}, aerosol

optical depth, and trace gas concentrations, have been considerably underestimated compared to ground observations in recent years during the post-monsoon biomass burning season. By assimilating the fire detection data, and resulting emissions, from geostationary platforms into these models, it is expected that the accuracy of the air quality forecast will improve under the new crop fire regime.

The scope and application of the presented fire detection algorithm should be expanded additional regions and states within India to better understand the diurnal changes in fire pattern. This is important because the fire monitoring via MODIS and VIIRS has shown numerous fires in other states too, including Uttar Pradesh, Madhya Pradesh, Bihar, and southern/southeastern states. A subcontinent-wide application of the presented algorithm would provide comprehensive insights into temporal changes and interannual trends in crop fires, which are essential for estimating smoke emissions and assessing their adverse effects on air quality, health, and climate.

Finally, the detrimental effects of open-field crop burning over NW India on worsening regional air quality, public health, and economic activities have been well demonstrated in various studies. Both previous research and present analysis underscore an urgent need for an effective crop residue management system for mitigating the frequency of biomass burning, thereby reducing episodic degradation of air quality and its associated public health and economic impacts.

Supplementary Materials: No supplementary material is attached to the present manuscript.

Author Contributions: Conceptualization, H.J.; methodology, H.J.; data acquisition, H.J.; formal analysis, H.J.; investigation, H.J.; data curation, H.J.; writing—original draft preparation, H.J.; visualization, H.J.

Funding: This research received no external funding. The sole author pursued the present work out of his own research interest of long-term monitoring of agricultural fire activities over northwestern India.

Data Availability Statement:

The thermal anomaly/fire data acquired by Aqua-MODIS and Suomi-NPP-VIIRS are available from NASA's Fire Information for Resource Management System (FIRMS) portal: <https://earthdata.nasa.gov/earth-observation-data/near-real-time/firms>.

The following datasets used in the present research can be directly accessed from NASA's EarthData data holding repository.

- The Aqua/MODIS Collection 006 monthly, Level 3 global NDVI dataset (MYD13C2): <https://www.earthdata.nasa.gov/data/catalog/lpcloud-myd13c2-061>.
- The MODIS/Terra+Aqua BRDF Model Parameters Daily L3 Global 1km SIN Grid V061 product (MCD19A3D): <https://www.earthdata.nasa.gov/data/catalog/lpcloud-mcd19a3d-061>.
- The MODIS/Terra+Aqua Land Surface BRDF Daily L2G Global 500m and 1km SIN Grid V061 dataset: <https://www.earthdata.nasa.gov/data/catalog/lpcloud-mcd19a1-061>.

- The MODIS/Terra+Aqua Land Aerosol Optical Depth Daily L2G Global 1km SIN Grid V061 product: <https://www.earthdata.nasa.gov/data/catalog/lpcloud-mcd19a2-061>.

The GEO-KOMPSAT-2A Advanced Meteorological Imager dataset can be obtained from the National Meteorological Satellite Center of Korea Meteorological Administration: <https://nmssc.kma.go.kr/enhome/html/main/main.do>.

The thermal anomaly/fire hotspot dataset for the Indian states of Punjab and Haryana derived from GK2A-AMI observations and presented in this paper will be freely accessible at Zenodo data repository after the review process.

Acknowledgments: The lead author thank the National Meteorological Satellite Center of Korea Meteorological Administration for making the GK2A-AMI observational dataset freely available to the users. The author also acknowledges NASA's EarthData data repository for freely distributing vegetation indices, aerosol optical depth used in the present research. Acknowledgements are due to the NASA's Fire Information for Resource Management System (FIRMS)—a part of NASA's Land, Atmosphere Near real-time Capability for Earth observations (LANCE) and NASA's Earth Science Data and Information System (ESDIS), for distributing active fire datasets from both MODIS and VIIRS in near real-time. Acknowledgements are also due to the OMI TLCF computational system used for data storing, processing, analysis, and graphics preparation.

Conflicts of Interest: The authors declare no conflicts of interest. The author emphasizes that the presented research work does not intend to defame the farmers of Punjab and Haryana states of India. The research work was conducted independently in the absence of any influence from individuals or agencies.

Abbreviations

The following abbreviations are used in this manuscript:

GK2A	GEO-KOMPSAT-2A
NASA	National Aeronautics and Space Administration
NOAA	National Oceanic and Atmospheric Administration
AMI	Advanced Meteorological Imager
MODIS	Moderate Resolution Imaging Spectroradiometer
VIIRS	Visible Infrared Imaging Radiometer Suite
NDVI	Nondimensional Vegetation Index
NBR	Normalized Burn Ratio
AOD	Aerosol Optical Depth
IGP	Indo-Gangetic Plain
IST	Indian Standard Time

References

1. Parayil, G. The Green Revolution in India: A Case Study of Technological Change. *Technol. Cult.* **1992**, *33*(4), 737-756. doi: [10.2307/3106588](https://doi.org/10.2307/3106588).
2. Pingali, P. Green Revolution: Impacts, limits, and the path ahead. *Proc. Natl. Acad. Sci.* **2012**, *109*(31), 12302-12308. doi: [10.1073/pnas.0912953109](https://doi.org/10.1073/pnas.0912953109).
3. Duxbury, J. M. Long-term yield trends in the rice-wheat cropping system. *J. Crop Prod.* **2001**, *3*(2), 27-52. doi: [10.1300/J144v03n02_02](https://doi.org/10.1300/J144v03n02_02).
4. Jethva, H.; Torres, O.; Field, R. D.; Lyapustin, A.; Gautam, R.; and Kayetha, V. Connecting crop productivity, residue fires, and air quality over northern India. *Sci. Rep.* **2019**, *9*, 16594. doi: [10.1038/s41598-019-52799-x](https://doi.org/10.1038/s41598-019-52799-x).
5. Badarinath, K. V. S.; Kiran Chand, T. R.; and Krishna Prasad, V. Agriculture crop residue burning in the indo-gangetic plains: A study using irs-P6 AWiFS satellite data. *Curr. Sci.* **2006**, *91*(8), 1085-1089, <https://www.currentscience.ac.in/Volumes/91/08/1085.pdf>.
6. Kaskaoutis, D. G.; Kumar, S.; Sharma, D.; Singh, R. P.; Kharol, S. K.; Sharma, M. et al. Effects of crop residue burning on aerosol properties, plume characteristics, and long-range transport over northern India. *J. Geophys. Res. Atmos.* **2014**, *119*, 5424-5444. doi: [10.1002/2013JD021357](https://doi.org/10.1002/2013JD021357).
7. Cusworth, D. H.; Mickley, L. J.; Sulprizio, M. P.; Liu, T.; Marlier, M. E.; DeFries, R. S. et al. Quantifying the influence of agricultural fires in northwest India on urban air pollution in Delhi, India. *Environ. Res. Lett.* **2018**, *13*(4), 044018. doi: [10.1088/1748-9326/aab303](https://doi.org/10.1088/1748-9326/aab303).
8. Jethva, H.; Chand, D.; Torres, O.; Gupta, P.; Lyapustin, A.; and Patadia, F. Agricultural burning and air quality over northern India: A synergistic analysis using NASA's A-train satellite data and ground measurements. *Aerosol Air Qual. Res.* **2018**, *18*, 1756-1773. doi: [10.4209/aaqr.2017.12.0583](https://doi.org/10.4209/aaqr.2017.12.0583).
9. Jethva, H.; Torres, O.; Field, R. D.; Lyapustin, A.; Gautam, R.; and Kayetha, V. Connecting crop productivity, residue fires, and air quality over northern India. *Sci. Rep.* **2019**, *9*, 16594. doi: [10.1038/s41598-019-52799-x](https://doi.org/10.1038/s41598-019-52799-x).
10. Liu, T.; Mickley, L. J.; Gautam, R.; Singh, M. K.; DeFries, R. S.; and Marlier, M. E. Detection of delay in post-monsoon agricultural burning across Punjab, India: Potential drivers and consequences for air quality. *Environ. Res. Lett.* **2021**, *16*, 014014. doi: [10.1088/1748-9326/abcc28](https://doi.org/10.1088/1748-9326/abcc28).
11. Gupta, P. K.; Sahai, S.; Singh, N.; Dixit, C. K.; Singh, D. P.; Sharma, C., et al. Residue burning in rice-wheat cropping system: Causes and implications. *Curr. Sci.* **2004**, *87*(12), 1713-1717.
12. Jethva, H. Assessing predictability of post-monsoon crop residue fires in Northwestern India. *Front. Earth Sci.* **2022**, *10*:1047278. doi: [10.3389/feart.2022.1047278](https://doi.org/10.3389/feart.2022.1047278).
13. Giglio, L.; Descloitres, J.; Justice, C. O.; and Kaufman, Y. An enhanced contextual fire detection algorithm for MODIS. *Rem. Sens. Environ.* **2003**, *87*, 273-282, doi: [10.1016/S0034-4257\(03\)00184-6](https://doi.org/10.1016/S0034-4257(03)00184-6).
14. Giglio, L.; Schroeder, W.; and Justice, C. O. The collection 6 MODIS active fire detection algorithm and fire products. *Rem. Sens. Environ.* **2016**, *78*, 31-41. doi: [10.1016/j.rse.2016.02.054](https://doi.org/10.1016/j.rse.2016.02.054).
15. MODIS Science Team. *MODIS/Aqua Thermal Anomalies/Fire 5-Min L2 Swath 1km NRT* [Data set]. **2021**. NASA LANCE MODIS at the MODAPS. doi: <https://doi.org/10.5067/MODIS/MYD14.NRT.061>. Date Accessed: 2026-02-22.
16. NASA VIIRS Land Science Team. *VIIRS (S-NPP) I Band 375 m Active Fire Product NRT (Vector data)* [Data set]. **2020**. NASA LANCE MODIS at the MODAPS. doi: https://doi.org/10.5067/FIRMS/VIIRS/VNP14IMGT_NRT.002. Date Accessed: 2026-02-22.
17. Didan, K. *MODIS/Aqua Vegetation Indices Monthly L3 Global 0.05Deg CMG V061* [Data set]. **2021**. NASA Land Processes Distributed Active Archive Center. doi: <https://doi.org/10.5067/MODIS/MYD13C2.061>. Date Accessed: 2026-02-22.
18. Lyapustin, A.; Wang, Y. *MODIS/Terra+Aqua BRDF Model Parameters Daily L3 Global 1km SIN Grid V061* [Data set]. **2022**. NASA Land Processes Distributed Active Archive Center. doi: <https://doi.org/10.5067/MODIS/MCD19A3D.061>. Date Accessed: 2026-02-22.
19. Lyapustin, A.; Wang, Y. *MODIS/Terra+Aqua Land Surface BRDF Daily L2G Global 500m and 1km SIN Grid V061* [Data set]. **2022**. NASA Land Processes Distributed Active Archive Center. doi: <https://doi.org/10.5067/MODIS/MCD19A1.061>. Date Accessed: 2026-02-22.
20. Lyapustin, A.; Wang, Y. *MODIS/Terra+Aqua Land Aerosol Optical Depth Daily L2G Global 1km SIN Grid V061* [Data set]. **2022**. NASA Land Processes Distributed Active Archive Center. doi: <https://doi.org/10.5067/MODIS/MCD19A2.061>. Date Accessed: 2026-02-22.
21. Kim, D.; Gu, M.; Oh, T.-H.; Kim, E.-K.; Yang, H.-J. Introduction of the Advanced Meteorological Imager of Geo-Kompsat-2a: In-Orbit Tests and Performance Validation. *Remote Sens.* **2021**, *13*, 1303. doi: [10.3390/rs13071303](https://doi.org/10.3390/rs13071303).

22. Singh, D; Kindu, N; Ghosh, S. Mapping rice residues burning and generated pollutants using Sentinel-2 data over northern part of India. *Rem. Sen. Appl. Soc. Env.* **2021**, 100486. doi: 10.1016/j.rsase.2021.100486. 971
23. Deshpande, M. V.; Pillai, D.; Jain, M. Agricultural burned area detection using an integrated approach utilizing multi spectral instrument based fire and vegetation indices from Sentinel-2 satellite. *MethodsX.* **2022**, 9:101741. doi: 10.1016/j.mex.2022.101741. 972
24. Mohammad, L.; Bandyopadhyay, J.; Sk, R.; Mondal, I.; Nguyen, T. T.; Lama, G. F. C.; Anh, D. T. Estimation of agricultural burned affected area using NDVI and dNBR satellite-based empirical models. *J Environ Manage.* **2023**, 343:118226. doi: 10.1016/j.jenvman.2023.118226. 973
25. Lyapustin, A.; Wang, Y.; Korkin, S.; and Huang, D. MODIS Collection 6 MAIAC algorithm, *Atmos. Meas. Tech.* **2018**, 11, 5741–5765, doi: <https://doi.org/10.5194/amt-11-5741-2018>. 974
26. Liu, T.; Marlier, M. E.; Karambelas, A.; Jain, M.; Singh, S.; Singh, M. K.; Gautam, R.; and DeFries, R.S. Missing emissions from post-monsoon agricultural fires in northwestern India: regional limitations of MODIS burned area and active fire products. **2019**. *Environ. Res. Commun.*, 1(1), 011007, doi: 10.1088/2515-7620/ab056c. 975
27. Chen, J.; Zheng, W.; Wu, S.; Liu, C.; Yan, H. Fire Monitoring Algorithm and Its Application on the Geo-Kompsat-2A Geostationary Meteorological Satellite. *Remote Sens.* **2022**, 14, 2655. <https://doi.org/10.3390/rs14112655>. 976
28. Singh, N.; Pradhan, R.; Shukla, B. P.; Pandya, M. R., and Sharma, R. Active Fire Detection using Indian Geostationary Satellite INSAT-3DS. *Remote Sens. Earth Syst. Sci.* **2025**, 8, 1014–1027. <https://doi.org/10.1007/s41976-025-00233-4>. 977

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content. 978