

Issue Brief | October 2026

Beyond Single Sources

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**Fusing Open and Commercial Satellite
Data for Monitoring Crop Residue
Burning in India**





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In 2017, India burnt about 24 per cent of the crop residue generated.

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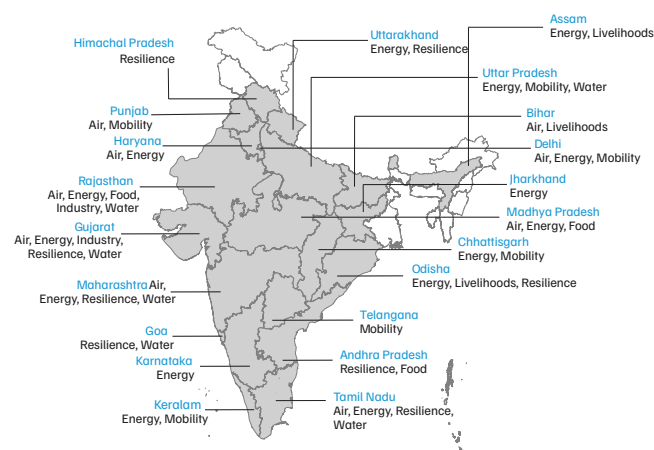
NATIONAL/INTERNATIONAL

2011 | National Water Resources Framework
2014 | 175 GW renewables target
2015 | International Solar Alliance
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2017 | Saubhagya Scheme
2019 | India Cooling Action Plan
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2022 | Mission LiFE
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2022 | E-waste (Management) Rules
2023 | G20 Green Development Pact
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2025 | Rajya Sabha Guidelines on Crop Residue Burning
2025 | India's Carbon Credit Trading Scheme (CCTS)
2025 | IFSCA's Framework for Transition Bonds
2026 | Disaster Risk Index for 16th Finance Commission
2026 | India's NDC 3.0
2026 | India's Scenarios towards Viksit Bharat and Net Zero

STATE

2022 | Rajasthan Organic Farming Mission
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2023 | Uttarakhand Solar Policy
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2026 | Uttarakhand Mukhyamantri Saur Swarojgar Yojana
2024-26 | Directives of Commission on Air Quality Management
Net Zero Roadmaps (BH, GJ, TN, UK)
Agroforestry Roadmaps (AS, MH, OD)
140+ Heat Action Plans (GJ, MH, OD, TN)
Treated Used Water Reuse Plans (MH, UP)
Flood Risk Mitigation Plans (GJ, MH)

21 STATES SUPPORTED





Crop residue burning releases greenhouse gases, damages soil, causes air pollution, and places a significant burden on both the environment and human health.

Contents

Section	Pg
Executive summary	1
1. Introduction	4
2. Data and methodology	6
2.1 Data	6
2.2 Methodology	8
2.3 Testing and validation	12
3. Results and discussion	14
3.1 Burn Area Index separates burnt and unburnt pixels accurately in PlanetScope images	14
3.2 Combining commercial satellite and Sentinel-2 imagery helps in improving the monitoring of farm fires	15
4. Limitations	20
5. Recommendations	23
Acronyms	24
References	25

Executive summary

Globally, crop residue burning (CRB) is a major environmental and public health concern. It releases greenhouse gases and particulate matter and also degrades soil quality and health (Vadrevu et al. 2019; Tawfeeq et al. 2025). Despite its harmful impacts, it remains a widely adopted post-harvest field-clearing practice in both developed and developing countries, with 450 million tonnes of crop residue burnt every year (CCAC 2023). In India, CRB is a national-scale problem and a major source of air pollution in northern Indian cities. For instance, it contributes as much as 35–40 per cent to Delhi's particulate matter 2.5 (PM_{2.5}) on peak burning days in late October and early November (Govardhan et al. 2023).

India has committed substantial public resources to the effort – roughly INR 4,200 crore during 2018–26 – through schemes such as the *Central Sector Scheme for Promotion of Agricultural Mechanisation for In-Situ Management of Crop Residue* (MoAFW 2026) and the *National Policy on Biofuels*. Evaluating whether such interventions are working and determining where to direct efforts next require accurate monitoring of the situation on the ground. Such monitoring underpins enforcement, targeted action, and course correction.

There are two satellite-based methods for monitoring these fires, but both have structural limitations. The first method is based on active fire counts detected by polar-orbiting satellites. Currently, the Commission for Air Quality Management in National Capital Region and Adjoining Areas (CAQM) follows a fire count-based protocol developed by the Indian Space Research Organisation (ISRO) to monitor CRB. These satellites have a coarser spatial resolution of 375 m and 1 km and revisit the same region once or twice a day, potentially missing small, short-lived fires that occur outside their narrow overpass windows (Schroeder et al. 2014). The underestimation has increased as peak burning has shifted to the evening, outside the satellite overpass windows (Singh et al. 2025a, 2025b).

The second monitoring method estimates burnt area using remote sensing (Giglio et al. 2006). In Indian conditions, the overall accuracy of the burnt area method using Sentinel-2 imagery is about 75 per cent, with a true positive rate (TPR) of 59 per cent (Ignatious et al.

2025). However, the Sentinel-2 constellation generally revisits the same area only once every five days, missing the fields burnt and subsequently managed (ploughing / tilling) in the interim (Ignatious et al. 2025). Moreover, cloud cover and other atmospheric conditions, along with smoke from fires, could obscure detections.

This study asks a practical question: can this gap be narrowed by combining the imagery India already relies on with complementary commercial data? We propose a method that combines openly available Sentinel-2 imagery with commercial multispectral imagery from Planet Labs to improve CRB estimates.

Data and methodology

We used openly available Sentinel-2 (Level-2A) and commercially available PlanetScope (Level-3B, Surface Reflectance) data. As mentioned above, the Sentinel-2 constellation generally revisits the same region every five days. However, certain strips on Earth's surface are revisited every other day or every third day. A portion of eastern Punjab spanning 9,700 sq km lies in one such strip. The region of interest (ROI) of this study lies within this region. We obtained Sentinel-2 images (using Google Earth Engine) between 23 October and 7 November 2024 for this ROI. We then procured PlanetScope images for the region to fill the observation gap between Sentinel-2 passes. Our objective was to estimate the extent of daily burning over two to three consecutive days during the peak CRB period.

We then followed the threshold-based approach discussed in Ignatious et al. (2025) to compute burnt area on Sentinel-2 images. Extending the approach for PlanetScope imagery, we extracted pixels of burnt and unburnt fields and analysed spectral indices – Simple Ratio (SR), Normalised Difference Vegetation Index (NDVI), Char Index (CI), Burn Area Index (BAI) and Bare Soil Index (BSol). BAI and CI could potentially differentiate between the two categories, and we defined four test thresholds for them. We tested these indices and thresholds across 14 randomly selected villages and computed performance metrics such as accuracy, TPR, false positive rate (FPR), and false negative rate (FNR), among others, to identify the best-performing threshold.

Key findings

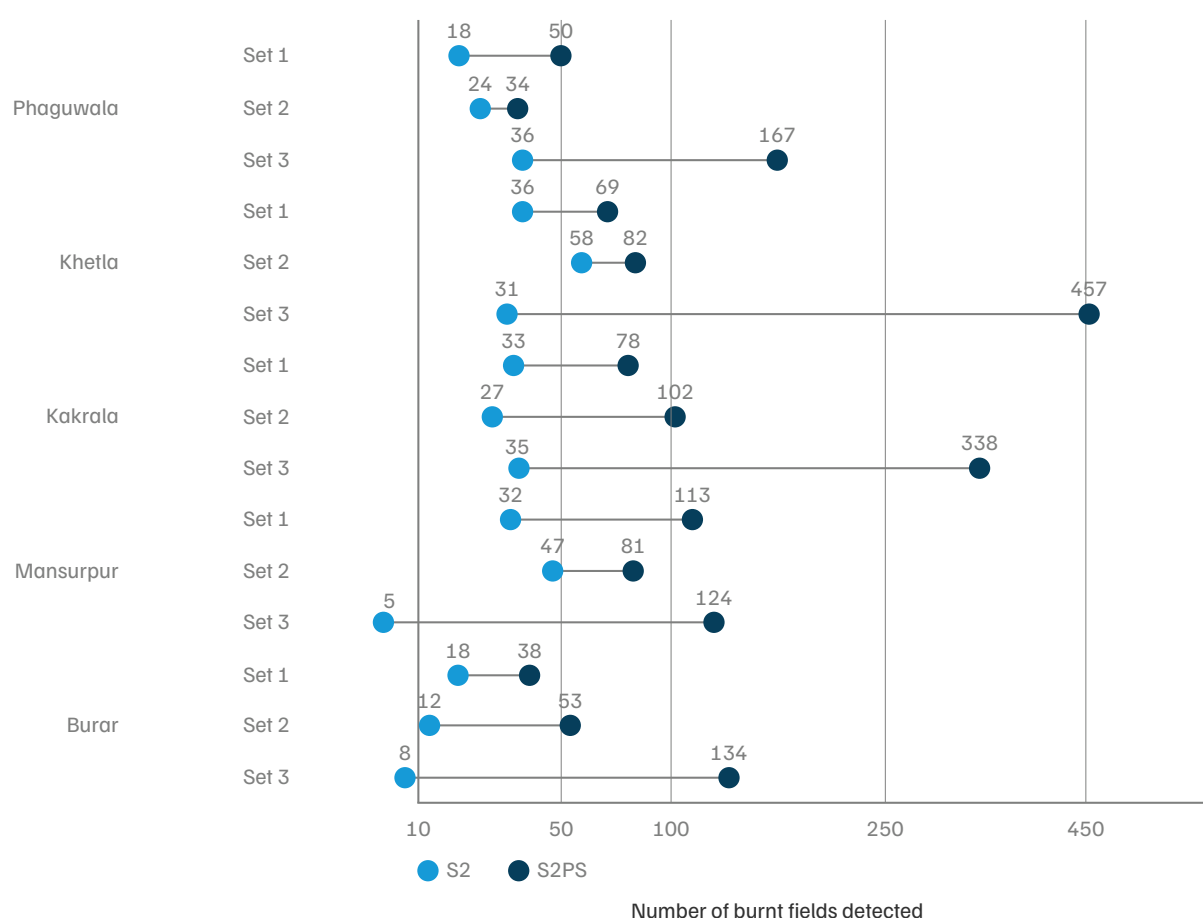
- The BAI has an overall accuracy of 82 per cent and correctly classifies 54 per cent of burnt pixels in PlanetScope images. Setting BAI between the 1st and 95th percentiles outperformed the other test thresholds. It misclassifies only 0.23 per cent of actual unburnt pixels as burnt. Table ES1 shows the performance metrics of the thresholds tested in this study.
- The algorithm developed using PlanetScope images in tandem with Sentinel-2 increased the number of burnt land parcels detected by two to five times compared with Sentinel-2 alone. Figure ES1 shows the number of fields detected using the algorithm across five randomly selected villages. This implies that combining commercial and openly available satellite imagery can improve CRB detection.

Table ES1. Threshold 3 (T3) performs better in most metrics and has the highest accuracy

Metric	T1 (Between the 10th and 90th percentiles of BAI values of burnt fields)	T2 (Between the 5th and 95th percentiles of BAI values of burnt fields)	T3 (Between the 1st and 95th percentiles of BAI values of burnt fields)	T4 (Less than or equal to the 99th percentile of CI values of burnt fields)
Accuracy	0.6835	0.7581	0.8162	0.7258
True positive rate (TPR)	0.2079	0.3953	0.5433	0.3736
False positive rate (FPR)	0.0001	0.0006	0.0023	0.0400
False negative rate (FNR)	0.7921	0.6047	0.4567	0.6264
F1 score	0.3442	0.5663	0.7025	0.5211
Matthews correlation coefficient (MCC)	0.3687	0.5297	0.6414	0.4317
Cohen's kappa (k)	0.2395	0.4391	0.5855	0.3685

Source: Authors' analysis

Figure ES1. The inclusion of PlanetScope images in tandem with Sentinel-2 images improved the detection of burnt land parcels by two to five times compared to using Sentinel-2 alone



Source: Authors' analysis

Abbreviations: S2: scenario 1; S2PS: scenario 2.

Note: Axis uses a square-root scale to keep small and large counts both readable

Recommendations

Our analysis shows that combining commercial and openly available satellite imagery improves CRB detection. Therefore, to improve CRB monitoring in India, we recommend the following.

- The CAQM should revise the existing CRB monitoring protocol to include burnt area estimates alongside fire counts, adopting a hybrid approach that combines openly available Sentinel-2 imagery with commercial imagery to better detect CRB.**
- India should leverage its existing space ecosystem for continuous CRB monitoring.** In the long run, India should have its own constellation for environmental monitoring and reduce reliance on international satellites. Public–private partnerships, such as the recent one between the Indian National Space Promotion and Authorization Centre (IN-SPACe) and Pixxel (The Hindu 2025), can enable Indian authorities to use indigenous data to improve CRB monitoring.

1. Introduction

Crop residue burning (CRB) is a global concern with wide-ranging impacts on the climate, the environment, and public health. It releases vast amounts of greenhouse gases (GHGs), degrades soil health, and affects air quality at local and regional levels (Vadrevu et al. 2019; Tawfeeq et al. 2025). Despite these concerns, it is one of the most prevalent methods of clearing crop residue globally. Countries such as Thailand, Indonesia, and the Philippines burn more than 45 per cent of the rice straw generated (Reddington 2022). Even in highly developed countries such as the United States, CRB accounts for about 20 per cent of the particulate matter 2.5 (PM_{2.5}) emissions (Pinakana et al. 2024).

In 2017, India burnt about 24 per cent of the crop residue generated (Lin and Begho 2022) and registered a ~75 per cent rise in GHG emissions from CRB between 2011 and 2020 (Deshpande et al. 2023). It is also a major source of pollution in the Indo-Gangetic Plains (IGP), with the northwestern states being the primary contributors (Lan et al. 2022; Lin and Begho 2022). The major crops burnt are the paddy and wheat. For instance, Punjab and Haryana together burnt nearly 51 per cent of the paddy-cropped area in 2022 (Ambulkar et al. 2025). Although farmers burn wheat and paddy residue, paddy residue burning has a larger impact on air pollution. This is because the kharif harvest coincides with the early winter months when the meteorological conditions are unfavourable for the dispersion of pollutants (Xavier et al. 2026). During the kharif peak burning period, stubble burning can contribute as much as 35–40 per cent to Delhi's daily PM_{2.5} during late October and early November (Govardhan et al. 2023).

Although the National Green Tribunal (NGT) prohibited CRB in 2015 (MoAFW 2019), and central and state governments have introduced various schemes and policies to support farmers, burning continues. Therefore, monitoring the extent of the practice is essential for better enforcement, targeted action, and policy course correction, among other things.

While monitoring CRB through extensive field surveys is perhaps the most accurate method, it is resource-intensive and challenging. Therefore, satellite-based monitoring is the most widely adopted method (Walker 2024). There are two satellite-based methods of CRB monitoring: active fire counting and burnt area estimation (Giglio et al. 2006; Schroeder et al. 2014; Vadrevu et al. 2019).

Active fire counting

Satellite-borne sensors such as the Visible Infrared Imaging Radiometer Suite (VIIRS) and Moderate Resolution Imaging Spectroradiometer (MODIS) detect fire incidents based on thermal anomalies. However, their coarse spatial resolutions (1 km for MODIS and 375 m for VIIRS) and limited revisits (four observations a day combined from MODIS and VIIRS) result in many missed fires.

The Commission for Air Quality Management in National Capital Region and Adjoining Areas (CAQM) uses fire counts to track CRB, based on a protocol developed by the Indian Space Research Organisation (ISRO) (CAQM 2021). However, a recent study by the Council on Energy, Environment and Water (CEEW) found that in one instance in 2020, the sensors detected only 7 such incidents compared to 169 actual fire incidents over two consecutive days over a 74 sq km area in Sangrur, Punjab (Ignatious et al. 2025). Moreover, ISRO's study based on observations from the Indian National Satellite – 3rd Generation Second Repeat (INSAT-3DS) showed a temporal shift in burning timings over Punjab (Singh et al. 2025a). Another study corroborated this using observations from the Meteosat Second Generation Spinning Enhanced Visible and Infrared Imager (MSG-SEVIRI) between 2020 and 2024. It noted a shift in peak burning time from 1.30 p.m.¹ in 2020 to 5 p.m. in 2024, well past the overpass time of the fire-counting satellites (Singh et al. 2025b). Noting the emerging shift in burning times, the CAQM ordered state governments to intensify patrolling during evening hours (CAQM 2025). Recent studies demonstrate the utility of geostationary satellites such as INSAT-3DS and Tropospheric Emissions: Monitoring of Pollution (TEMPO) in tracking burning incidents that instruments such as MODIS, VIIRS, and the Tropospheric Monitoring Instrument (TROPOMI) aboard polar-orbiting satellites otherwise miss (Singh et al. 2025a; Zhu et al. 2026). However, we cannot identify individual burning farms from their data because of their coarse spatial resolution of a few kilometres.

¹ All times mentioned are in Indian Standard Time.

Burnt area estimation

Another method is estimating burnt area. By applying context-specific algorithms to multispectral satellite data, one can identify char signatures left after burning and estimate their area, and thus estimate the extent of CRB. Several studies have explored this method for CRB estimation using the openly available multispectral imagery from Sentinel-2 (Ignatious et al. 2025; Gulati et al. 2023; Ambulkar et al. 2025). A recent CEEW study found the best burnt-area estimation methods to be 75 per cent accurate in Indian conditions, highlighting Sentinel-2's low temporal resolution as the major challenge. While it showed that the burnt area method correctly classified 59 per cent of burnt pixels, it noted that many fields go undetected because farmers burn and clear them within five days, the general revisit time of Sentinel-2. Therefore, to continuously track CRB incidents,

the study recommended fusing commercial and openly available multispectral satellite imagery (Ignatious et al. 2025). But how effective is such a method in improving CRB detection?

In this study, we propose a methodology of combining commercial satellite data from Planet Labs with Sentinel-2 data to improve CRB detection. We chose PlanetScope imagery since it has a long archive available since 2014 (analysis-ready formats since 2017) over India, enabling retrospective estimation of CRB over the last few years. Previous studies have used PlanetScope imagery alone to map burnt areas (Dabral and Vadrevu 2025; Walker et al. 2022), for ground-truthing, and to track interventions (Deshpande et al. 2022; Chen et al. 2022; Jack et al. 2025). But a recent study used a combination of PlanetScope and Sentinel-2 data for monitoring CRB at smallholder farms at sub-field scale in India (Konkathi et al. 2026).



Crop residue burning contributes as much as 35–40 per cent to Delhi's particulate matter 2.5 (PM_{2.5}) on peak burning days in late October and early November

2. Data and methodology

We combined multispectral satellite imagery from Sentinel-2 and PlanetScope and developed a hybrid algorithm to estimate the extent of CRB. We also assessed how much it improves the detection of CRB incidents compared with using Sentinel-2 imagery alone. In this section, we explain in detail the data and methodology used in this study.

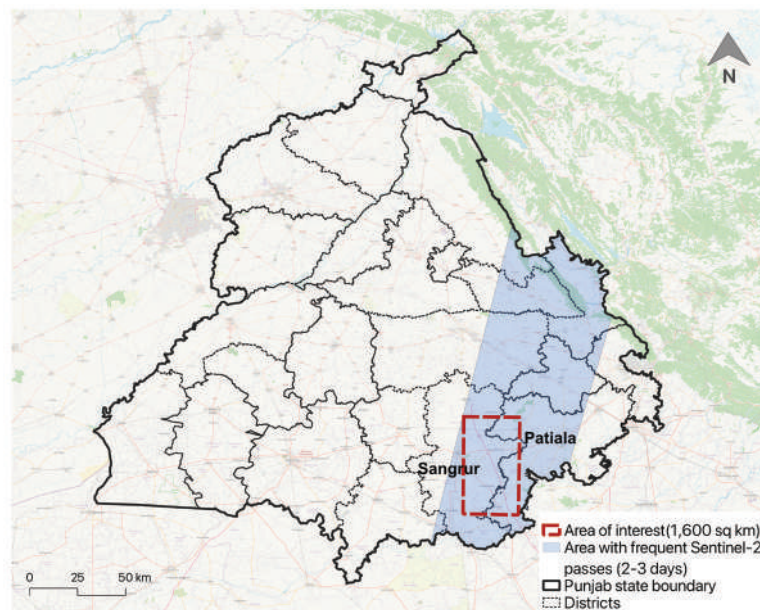
The limited temporal resolution of freely available satellite data, such as that from Sentinel-2, is a major challenge for remote sensing-based monitoring of crop residue burning.

2.1 Data

The Sentinel-2 constellation generally revisits the same region every five days. However, the constellation revisits certain strips of land on Earth every other or every third day. We identified a 9,700 sq km region in eastern Punjab that lies within one such strip. Annexure 1 explains this

region in detail. We defined a 1,600 sq km area in this region, over Sangrur and Patiala districts, as the region of interest (ROI) for this study. Figure 1 shows the selected ROI.

Figure 1. Region of interest selected in this study



Source: Authors' analysis

We then extracted harmonised Sentinel-2 (Level-2A) data using Google Earth Engine (GEE) at 10 m resolution for the peak burning period, 23 October to 7 November 2024. We obtained high-resolution PlanetScope satellite images (Level-3B, Surface Reflectance) at 3 m resolution from Planet Labs for days without Sentinel-2 passes. We resampled the PlanetScope images to 10 m to match

the Sentinel-2 resolution. By combining Sentinel-2 and PlanetScope imagery, we created three image sets. These sets ensure consecutive coverage over three or four days, allowing us to estimate the extent of new burning each day by comparing it with the previous day. Table 1 lists the sets, image sources, and corresponding dates.

Table 1. Selected dates and image sources

Image set	Image date	Image source
Set 1	23 October 2024	Sentinel-2
	24 October 2024	PlanetScope
	25 October 2024	Sentinel-2
Set 2	28 October 2024	Sentinel-2
	29 October 2024	PlanetScope
	30 October 2024	Sentinel-2
Set 3	4 November 2024	Sentinel-2
	5 November 2024	PlanetScope
	6 November 2024	PlanetScope
	7 November 2024	Sentinel-2

Source: Authors' analysis

We used the crop layer from the 2024 land use land cover (LULC) dataset from the Environmental Systems Research Institute (ESRI) (ESRI, n.d.). We masked this layer with the road network data from OpenStreetMap to remove road pixels that overlap with crops.

We used the farm boundaries from the Google Agricultural Landscape Understanding (ALU) dataset to delineate farms (Dua et al. 2026). We selected the

fields tagged with very high confidence (95 per cent) and added a 10 m buffer (contracted) at the edges to avoid overlap between the field polygons. We excluded polygons smaller than 400 sq m from our field analysis. Figure 2 shows the sample fields from the ALU dataset. We used this dataset in Section 3.2 only to count freshly burnt fields; it does not play a role in the burnt area algorithm.

Figure 2. Field boundaries obtained from Google Agricultural Landscape Understanding (ALU)



Source: Authors' analysis of Dua et al. 2026

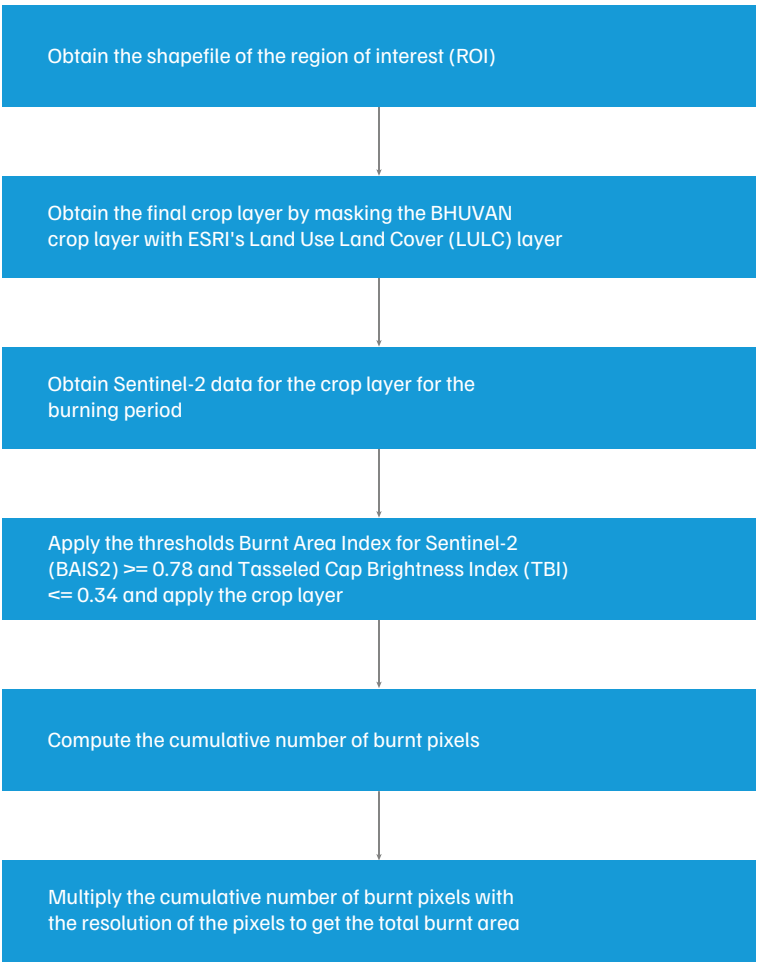
2.2 Methodology

We developed a hybrid burnt-area algorithm by combining multispectral imagery from Sentinel-2 satellites with PlanetScope imagery. The method detects burnt areas from both sources separately and combines them to generate insights.

For burnt-area detection from Sentinel-2 imagery, we used the algorithm described in an earlier study

(Ignatious et al. 2025). The algorithm uses a threshold-based approach that combines two spectral indices – the Burnt Area Index for Sentinel-2 (BAIS2) and the Tasseled Cap Brightness Index (TBI). Figure 3 summarises the methodology for detecting burnt areas using the Sentinel-2 imagery.

Figure 3. Methodology for computing burnt area using Sentinel-2 imagery



Source: Ignatious, Sneha Maria, Rishikesh P, and Mohammad Rafiuddin. 2025. Monitoring Crop Residue Burning Better: Moving Beyond Fire Counts. Council on Energy, Environment and Water.

The spectral bands and their characteristics differ between PlanetScope and Sentinel-2 images. Annexure 2 provides a comparison. While PlanetScope multispectral imagery contains eight different bands, only six (coastal blue, blue, green, red, red edge and near infrared) are comparable to those in Sentinel-2.

We tested five different indices mentioned in Walker et al. (2022) to identify burn areas using PlanetScope images. Although they used a machine learning (ML) approach to detect burnt areas, they calculated the Simple Ratio (SR), Normalised Difference Vegetation Index (NDVI), Char Index (CI), Burn Area Index (BAI) and Bare Soil Index (BSol) for PlanetScope images over the fields in Bathinda and Faridkot districts of Punjab and identified the indices

that could effectively distinguish between burnt and unburnt fields. Annexure 3 explains the indices and their formulae in detail.

For this, we first identified three sets of fields through visual interpretation – newly burnt, green unburnt and golden-yellow unburnt – on the PlanetScope image of 24 October 2024, the image selected for ‘training’. While unburnt fields appeared visibly green or golden-yellow, newly burnt fields appeared visibly black in the 24 October image and golden-yellow in the previous day’s Sentinel-2 image. Figure 4 shows examples of newly burnt fields marked, and Figure 5 shows the green and golden-yellow fields identified in the training data.

Figure 4. The fields that appeared golden-yellow on day 1 and black on day 2 are marked as ‘burnt’

**a) Unburnt field on 23 October 2024
from Sentinel-2**



**b) Burnt field on 24 October 2024
from PlanetScope**



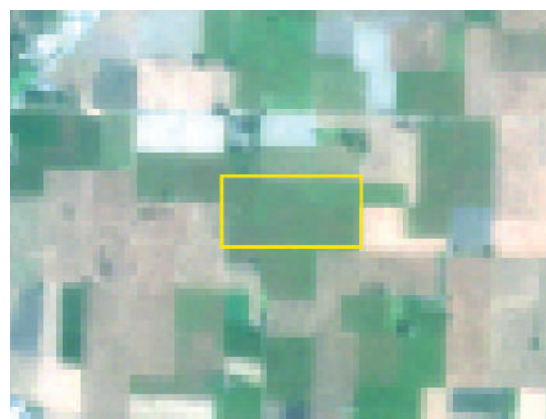
Source: Authors' analysis of Sentinel-2 and PlanetScope images of 23 and 24 October, respectively

Figure 5. Unburnt fields appeared golden-yellow or green on high-resolution PlanetScope images

**a) Golden-yellow unburnt field identified
on high-resolution PlanetScope image**



**b) Green unburnt field identified on high-
resolution PlanetScope image**

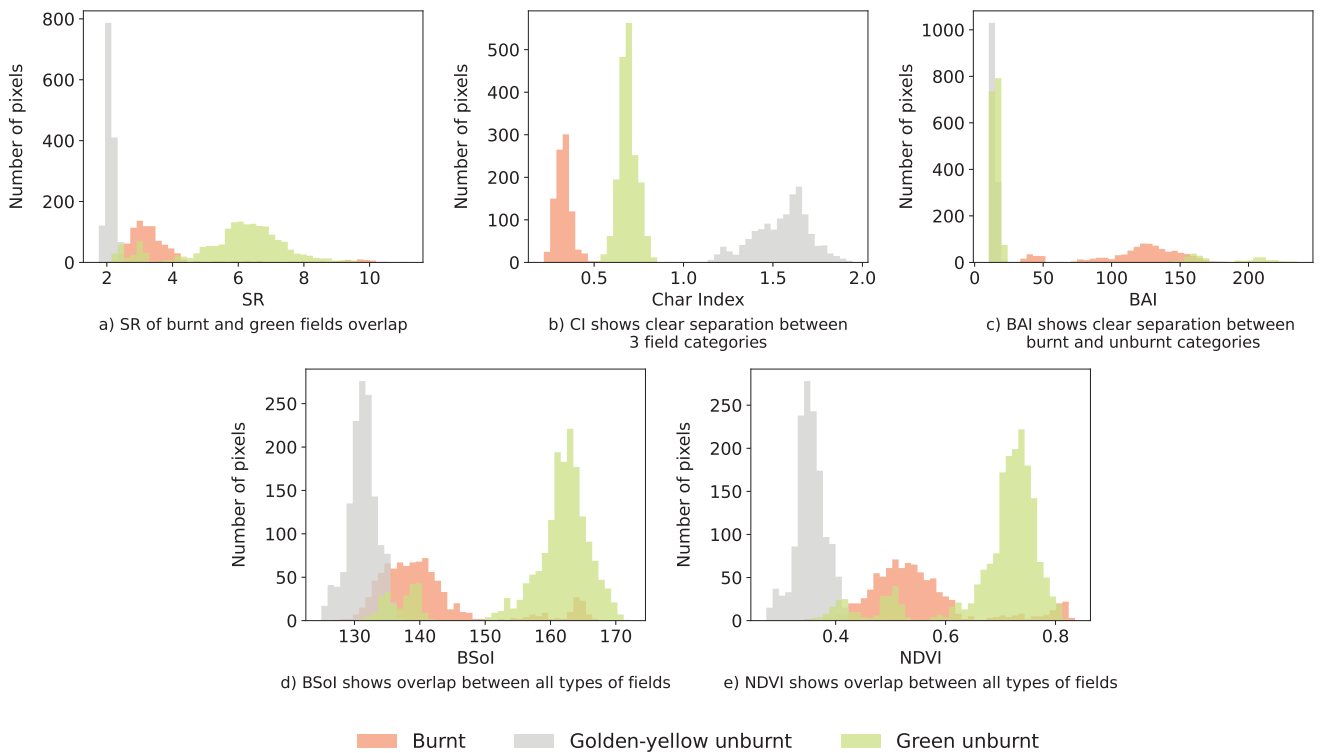


Source: Authors' analysis of PlanetScope images

To extract the pixel-level data from the marked fields, we followed the approach described in Ignatious et al. (2025). We drew polygons within each field to include only pixels that fall within the field, avoiding the edges. Edge pixels could contain information from two different fields belonging to two different categories (Ignatious et al. 2025). We then extracted pixels at a 10 m resolution

(the same as Sentinel-2) from the PlanetScope image for all three field categories. This included 919 burnt pixels, 1,839 unburnt green pixels, and 1,385 unburnt golden-yellow pixels. We computed the five indices for the three field categories. Figure 6 shows the resulting histograms for each index.

Figure 6. Burn Area Index (BAI) and Char Index (CI) show potential separation between the burnt and the unburnt pixels



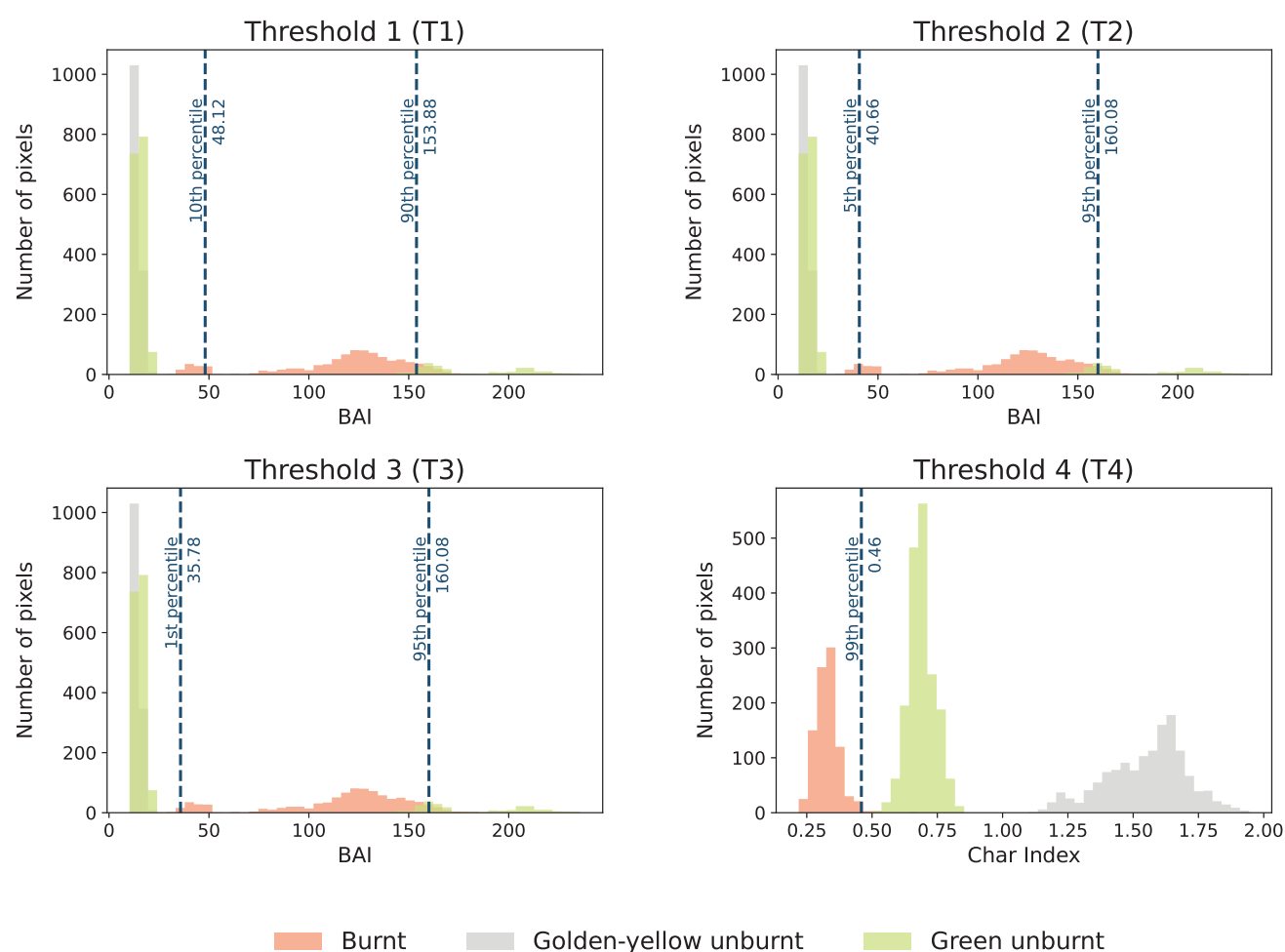
Source: Authors' analysis

Abbreviations: BSol: Bare Soil Index; NDVI: Normalised Difference Vegetation Index; SR: Simple Ratio.

The histogram analysis showed that BAI and CI can potentially distinguish between burnt and unburnt pixels in PlanetScope images. However, the BAI values of green pixels overlap with the upper bound of burnt pixel values, and the BAI of golden-yellow pixels lies close to the lower bound of burnt pixel values, whereas the CI values of green pixels lie close to the lower bound of burnt pixel

values. Therefore, we defined the BAI thresholds capping at both ends and the CI thresholds capping only at the upper bound value. Table 2 lists the four thresholds identified: Threshold 1 (T1), Threshold 2 (T2), Threshold 3 (T3), and Threshold 4 (T4). Figure 7 illustrates these thresholds, and Table 3 lists their corresponding values.

Figure 7. Test thresholds identified for the Burn Area Index (BAI) and Char Index (CI) used in this study



Source: Authors' analysis

Table 2. Identified thresholds used for testing in the study

Threshold	Description
Threshold 1 (T1)	Between the 10th and 90th percentiles of BAI values of burnt fields
Threshold 2 (T2)	Between the 5th and 95th percentiles of BAI values of burnt fields
Threshold 3 (T3)	Between the 1st and 95th percentiles of BAI values of burnt fields
Threshold 4 (T4)	Less than or equal to the 99th percentile of CI values of burnt fields

Source: Authors' analysis

From the training dataset, we identified these threshold values and summarised them in Table 3.

Table 3. Identified threshold values

Threshold	Value
Threshold 1 (T1)	48.12 <= BAI <= 153.88
Threshold 2 (T2)	40.66 <= BAI <= 160.08
Threshold 3 (T3)	35.78 <= BAI <= 160.08
Threshold 4 (T4)	CI <= 0.46

Source: Authors’ analysis

We then tested the performance of these thresholds by applying them to the PlanetScope image of 5 November 2024.

2.3 Testing and validation

To test the algorithm’s ability to distinguish between burnt and unburnt pixels, we applied T1, T2, T3, and T4 to 14 randomly selected villages out of 328 in the ROI on the PlanetScope image of 5 November 2024. We marked a total of 858 fields (through visual interpretation), including 346 burnt fields and 512 unburnt fields (golden-yellow unburnt: 280; green unburnt: 232).

Annexure 4 lists the villages selected for testing. We masked the images with a crop and a road network layer to isolate crop pixels. We computed the accuracy, true positive rate (TPR), false positive rate (FPR), false negative rate (FNR), F1 score, Matthews correlation coefficient (MCC), and Cohen’s kappa (k). Table 4 describes the confusion matrix, and Table 5 presents the metrics and their formulae.

Table 4. The confusion matrix used for computing performance metrics

		Observed	
		Number of burnt pixels	Number of unburnt pixels
Detected	Number of burnt pixels	True positive (TP)	False positive (FP)
	Number of unburnt pixels	False negative (FN)	True negative (TN)

where,

- True positives are the burnt pixels correctly detected as burnt by the algorithm.
- False positives are the unburnt pixels incorrectly classified as burnt.
- False negatives are the burnt pixels incorrectly classified as unburnt.
- True negatives are the unburnt pixels correctly classified as unburnt.

Source: Authors’ compilation

Table 5. List of performance metrics used in the study

Metric	Description	Formula	Range of values
Accuracy	The algorithm's ability to correctly detect burnt and unburnt pixels	$(TP + TN) / (TP + FP + FN + TN)$	0–1
True positive rate (TPR)	The algorithm's ability to correctly classify a burnt pixel as burnt	$TP / (TP + FN)$	0–1 Higher is better
False positive rate (FPR)	The algorithm's tendency to detect an unburnt pixel as burnt	$FP / (FP + TN)$	0–1 Lower is better
False negative rate (FNR)	The algorithm's tendency to classify a burnt pixel as unburnt	$FN / (TP + FN)$	0–1 Lower is better
F1 score	How well the algorithm identifies a burnt pixel	$2TP / (2TP + FP + FN)$	0–1 Higher is better
Matthews correlation coefficient (MCC)	The algorithm's ability to correctly classify burnt and unburnt pixels	$\frac{(TP \times TN - FP \times FN)}{\sqrt{((TP + FN) \times (TP + FP) \times (TN + FP) \times (TN + FN))}}$	–1–1 Higher is better
Cohen's kappa (k)	Similar to MCC; uses all four metrics - TP, FP, FN, TN	$P_0 = \frac{TP + TN}{TP + TN + FN + FP}$ $P_e = \frac{((TP + FN) \times (TP + FP)) + ((FN + TN) \times (FP + TN))}{(TP + TN + FN + FP)^2}$	–1–1 Higher is better

Source: Authors' compilation

To understand if using PlanetScope and Sentinel-2 imagery together improves CRB detection, we compare the number of fields detected under two scenarios: using Sentinel-2 alone and the other using PlanetScope images in tandem with Sentinel-2 images.

3. Results and discussion

In this section, we present the extent to which combining commercial satellite images with openly available Sentinel-2 images can help improve CRB monitoring.

3.1 Burn Area Index separates burnt and unburnt pixels accurately in PlanetScope images

We applied the thresholds T1, T2, T3, and T4 identified in Section 2.2 to the PlanetScope image of 5 November 2024, our ‘testing’ image, to detect burnt pixels. Table 6 presents the confusion matrices, and Table 7 presents the performance metrics for these thresholds.

T3 performs better than the other thresholds on all metrics except FPR. It has an accuracy of 0.82 and a TPR of 0.54. The F1 score and MCC are 0.70 and 0.64, respectively, while the FNR is 0.46. The k value is also the highest at 0.59. Therefore, we chose T3 as the threshold for identifying burnt areas in PlanetScope imagery using BAI.

Table 6. Confusion matrices for thresholds T1, T2, T3 and T4

T1				T2			
Observed				Observed			
Detected		True	False	Detected		True	False
	True	5,056	4		True	9,615	21
	False	19,266	36,565		False	14,707	36,548
T3				T4			
Observed				Observed			
Detected		True	False	Detected		True	False
	True	13,215	84		True	9,087	1,464
	False	11,107	36,485		False	15,235	35,105

Source: Authors' analysis

Table 7. Threshold 3 (T3) performs better in most metrics and has the highest accuracy

Metric	T1	T2	T3	T4
Accuracy	0.6835	0.7581	0.8162	0.7258
True positive rate (TPR)	0.2079	0.3953	0.5433	0.3736
False positive rate (FPR)	0.0001	0.0006	0.0023	0.0400
False negative rate (FNR)	0.7921	0.6047	0.4567	0.6264
F1 score	0.3442	0.5663	0.7025	0.5211
Matthews correlation coefficient (MCC)	0.3687	0.5297	0.6414	0.4317
Cohen's kappa (k)	0.2395	0.4391	0.5855	0.3685

Source: Authors' analysis

3.2 Combining commercial satellite and Sentinel-2 imagery helps in improving the monitoring of farm fires

We tested two scenarios to establish the utility of fusing commercial and openly available satellite imagery for burnt area estimation. In the first scenario (S2), we estimated the burnt area using Sentinel-2 images alone;

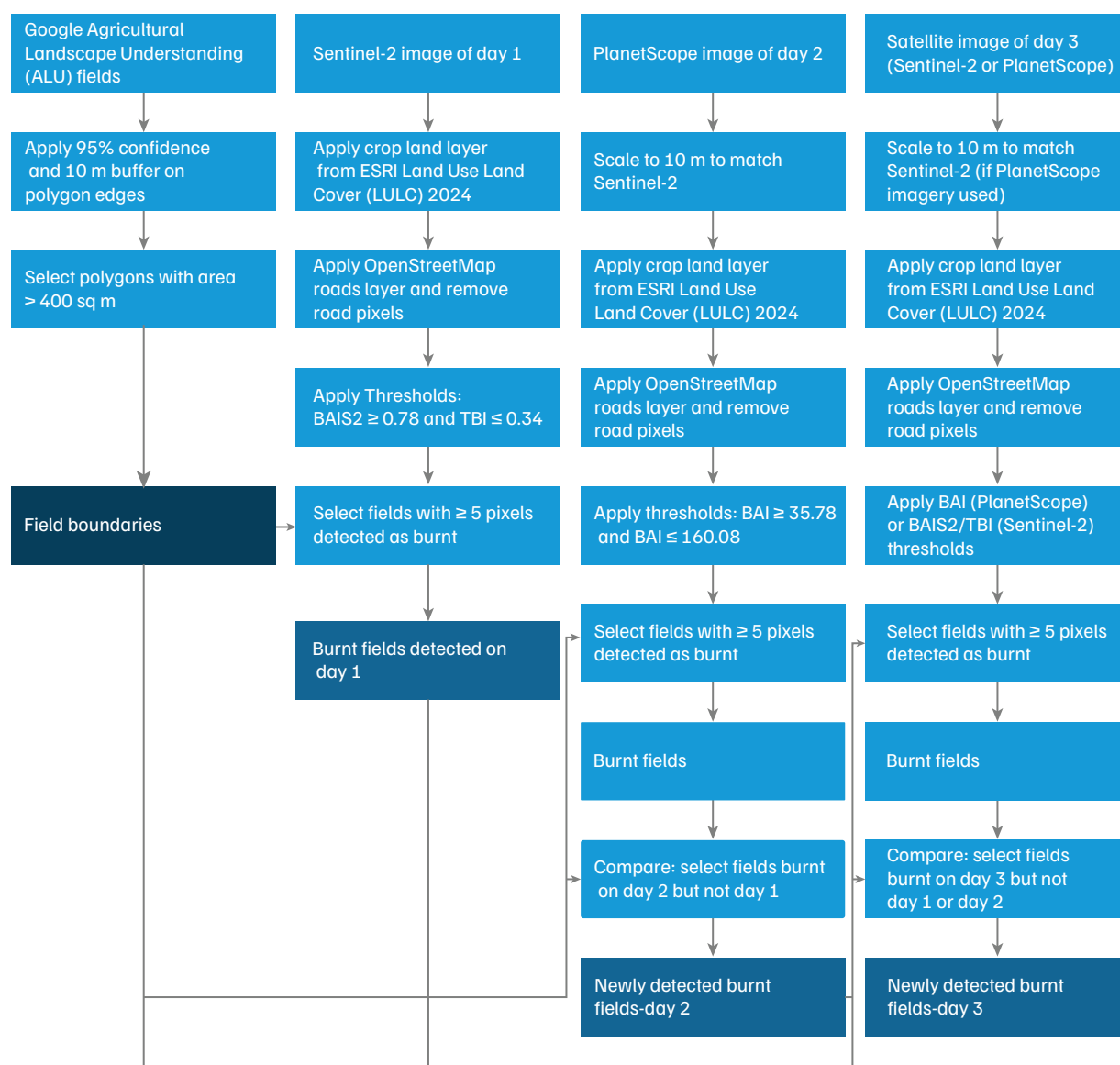
in the second scenario (S2PS), we complemented Sentinel-2 imagery with PlanetScope imagery. Table 8 summarises the two scenarios, and Figure 8 illustrates the methodology adopted. Our algorithm records fields that are unburnt on one day and burnt the next as freshly burnt. We applied the algorithm to five randomly selected villages, namely, Phaguwala, Kakrala, Khetla, Mansurpur, and Burar. Annexure 5 provides additional details on the villages. We marked a field/patch as burnt if the algorithm identified at least five burnt pixels (500 sq m) within it.

Table 8. Scenarios used to assess the performance of a continuous image series

Scenario	Description
Scenario 1 (S2)	When only Sentinel-2 images are available
Scenario 2 (S2PS)	When PlanetScope image(s) are available between Sentinel-2 passes

Source: Authors' analysis

Figure 8. Summary of the methodology adopted to identify burnt fields on consecutive days using a combination of commercial satellite images and openly available satellite imagery

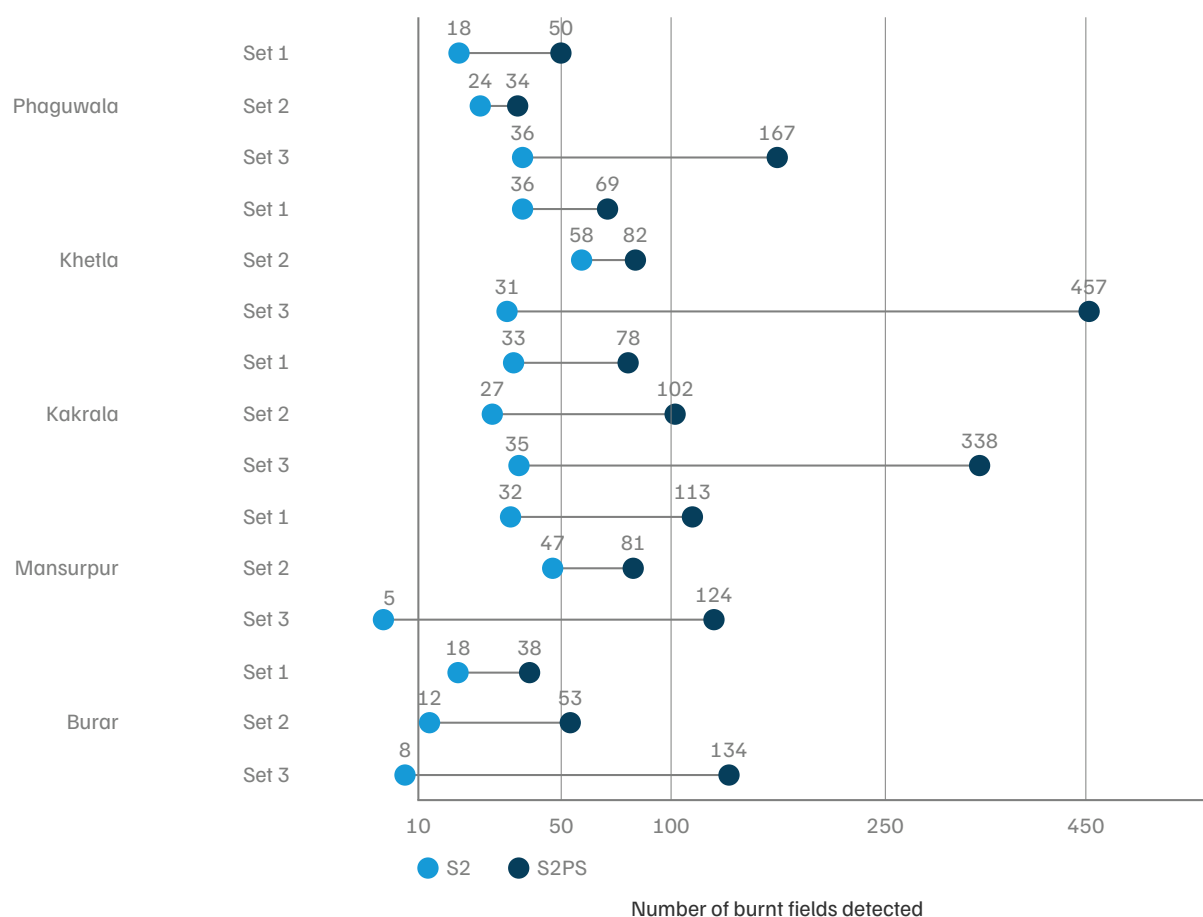


Source: Authors' analysis

We counted newly burnt fields from the second day of each set onwards, as first-day detections include all fields burnt since the start of the season (15 September). For example, the number of newly burnt fields in Set 1 includes the sum of newly detected fields only on

24 October 2024 and 25 October 2024. Figure 9 shows the number of fields detected in five selected villages in Scenarios 1 and 2. Figure 10 also shows the fields detected under these two scenarios in Phaguwala village for Set 3.

Figure 9. Including PlanetScope images in tandem with Sentinel-2 images detected 2–5 times more burnt land parcels than using Sentinel-2 alone



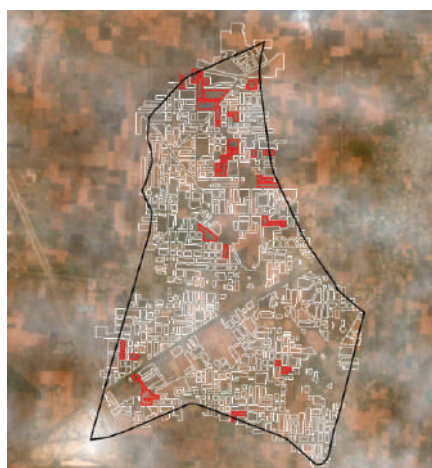
Source: Authors' analysis

Abbreviations: S2: scenario 1; S2PS: scenario 2.

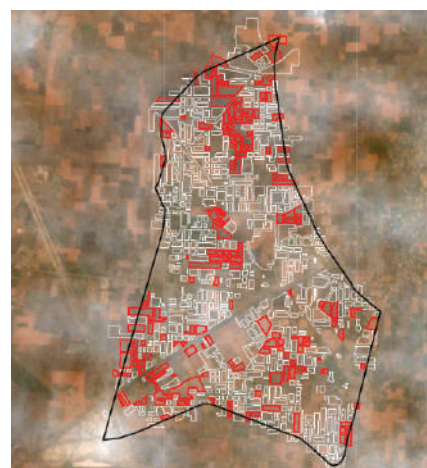
Note: Axis uses a square-root scale to keep small and large counts both readable

Figure 10. Including PlanetScope images in tandem with Sentinel-2 detected 4.6 times more burnt land parcels than using Sentinel-2 alone in Phaguwala

S2 – Fields detected only with Sentinel-2 images for Set 3



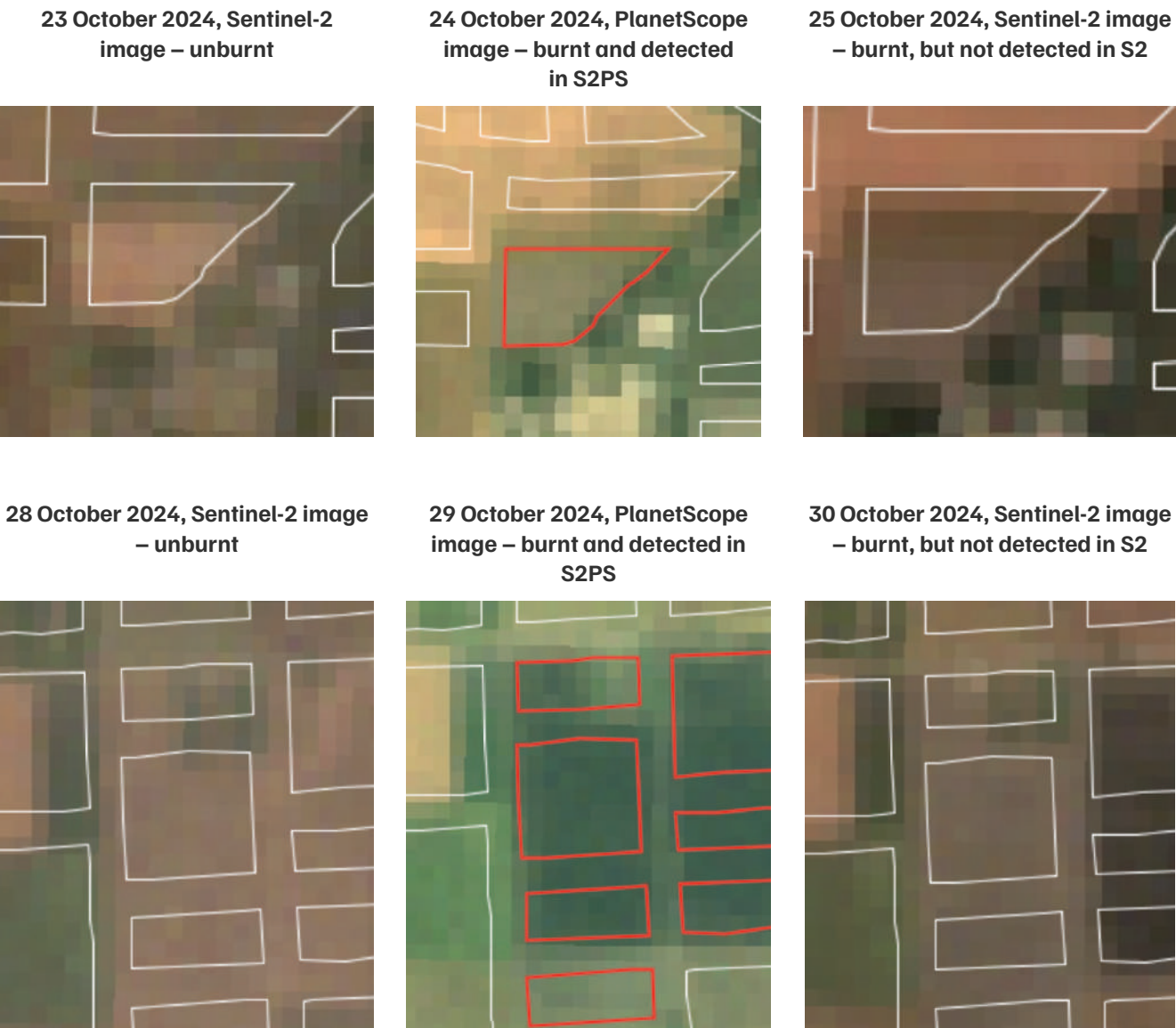
S2PS - Fields detected with PlanetScope images in tandem with Sentinel-2 images for set 3

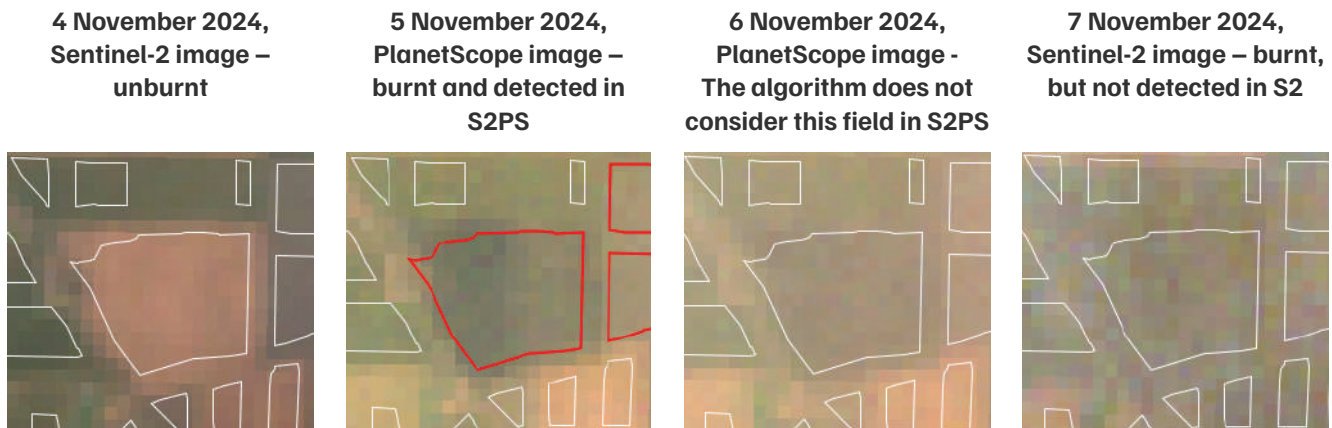


Source: Authors' analysis

Combining Sentinel-2 and PlanetScope imagery increased the number of detected burnt fields. The number of burnt land parcels detected in S2PS is two to five times higher than in S2. Figure 11 shows fields burnt between Sentinel-2 passes that PlanetScope detected, but the next Sentinel-2 pass did not. These fields belong to villages from a region with a Sentinel-2 revisit time of two to three days. In other regions, where the revisit period is five days, the underestimation could potentially be greater.

Figure 11. PlanetScope images in tandem with Sentinel-2 images improve the detection of burnt fields



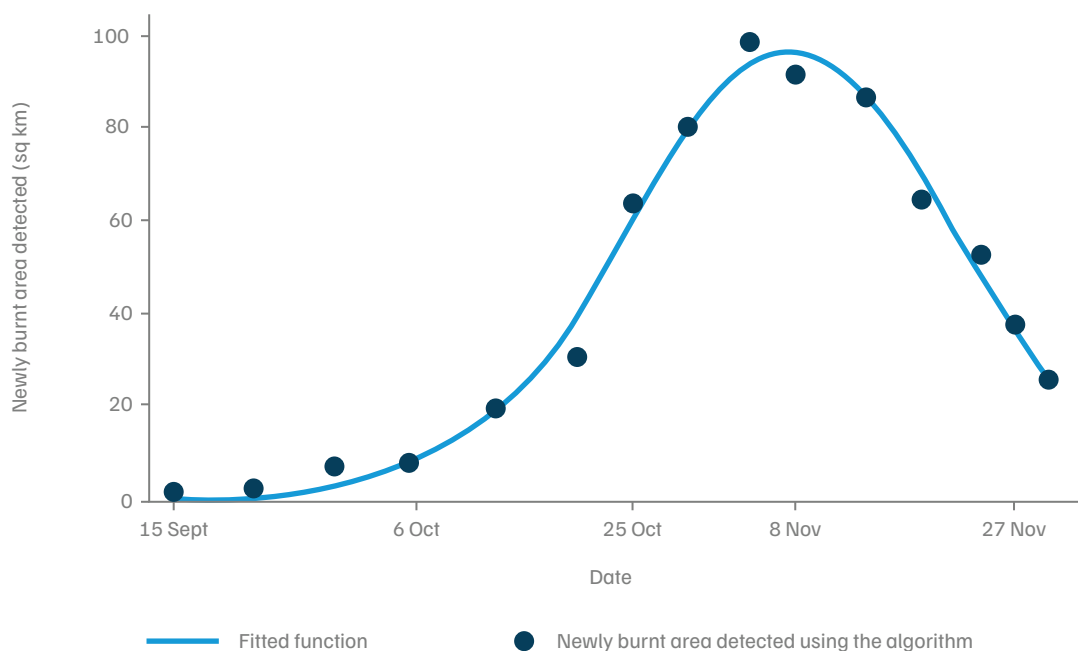


Source: Authors' analysis

Combining commercial and openly available satellite imagery increases the number of fire incidents detected and, in turn, improves daily estimates. However, large commercial datasets are expensive. Therefore, we propose a methodology that combines commercial and open imagery on select dates to estimate burning over an entire season. For instance, if we have commercial

satellite images for 15 dates before or after the Sentinel-2 pass, we can obtain newly burnt fields for 15 days of a season. From this, we can fit a function to estimate the newly burnt area for the whole season (Figure 12). We can then derive the cumulative burnt area from the newly burnt area.

Figure 12. Fitting a function to newly burnt areas from a few days during the season can help estimate the burnt area for the entire season



Source: Authors' analysis

Note: The values shown in this plot are illustrative and do not represent actual burnt area estimates.

4. Limitations

The algorithm developed for Sentinel-2 has an overall accuracy of 75 per cent (Ignatious et al. 2025), and the algorithm for PlanetScope 82 per cent. Therefore, the burnt area algorithm developed by combining Sentinel-2 and PlanetScope images has an overall accuracy of 75 per cent. It correctly detects about 54 per cent of actually burnt pixels. However, this satellite-based methodology has several limitations.

In this section, we discuss the key challenges encountered while applying this approach.

- **Identification and categorisation of fields:** Categorising fields is challenging, even with high-resolution images. For instance, in some cases, the dark green colour of the field appears black in the image and vice versa. Figure 13 shows one such example.
- **Exclusion of harvested and tilled fields in the training dataset:** Identifying fields managed through zero-burn practices is challenging using high-resolution images. It would require field verification. Therefore, we did not include the harvested and tilled fields in the unburnt category in the training data. Ideally, the unburnt set should have included fields that are unburnt but tilled, green, or freshly harvested (Walker 2024).
- **Inclusion of only a single image each for the training and testing datasets:** The training and testing fields used in the study were based on a single day's images due to the limited availability of PlanetScope images. Atmospheric conditions can vary during the burning season. As a result, image properties, including reflectance values, can change. Therefore, the training set should ideally include fields marked on images from different dates to account for seasonal changes.

Figure 13. Categorisation of fields is challenging, even when using high-resolution satellite images



Source: PlanetScope image

- **Cost:** Commercial satellite data are expensive (Konkathi et al. 2026). The price of high-resolution images per sq km could be as high as INR 250. This implies that it would cost about INR 1.2 crore (~ USD 130,000) to procure PlanetScope imagery for the entire state of Punjab for one day.
- **Field boundaries:** While Google's ALU is one of the few datasets that have attempted to digitise

field boundaries in India, it has limitations. Sometimes, a single patch is divided into multiple boundaries. Overlapping patches can result in different field types (unburnt, burnt, partially burnt, completely burnt) within a single polygon (Figure 14). As a result, a single burnt field covered by more than one polygon might get marked as burnt more than once by the algorithm.

Figure 14. ALU field boundaries vary in size, and a single boundary can contain different field types

a) Different field types included in a single polygon



b) The polygons are of different sizes



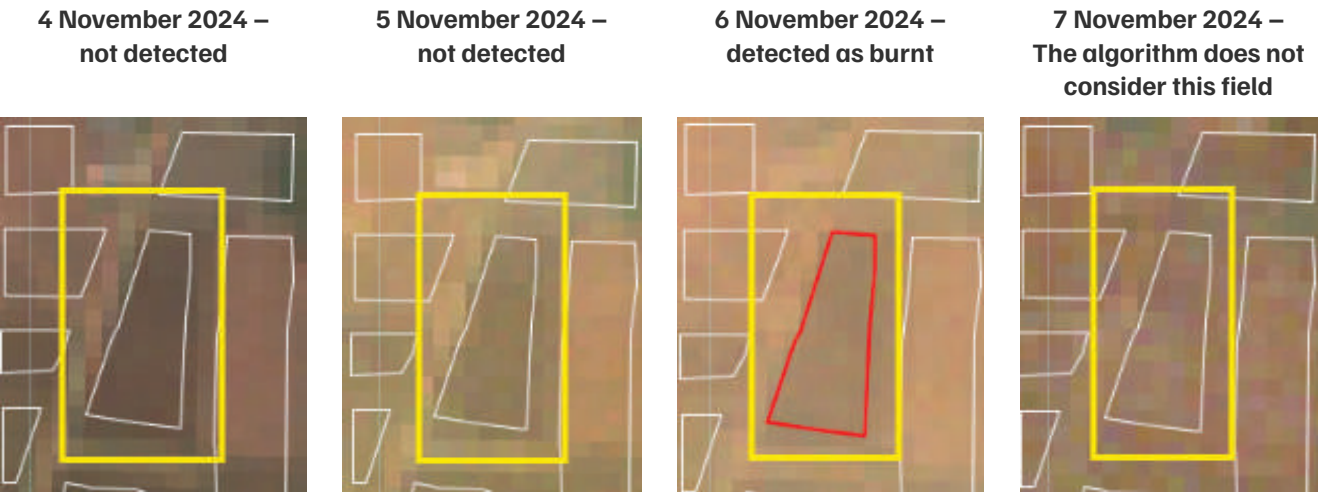
Source: Authors' analysis

Note: White polygons are ALU field boundaries, and the fields inside the yellow box are sample polygons that include two field types in a single polygon.

- **Detection of fields burnt several days ago as newly burnt fields:** The burnt fields identified by the algorithm on a particular day might not actually be newly/freshly burnt fields. In some cases, burnt fields not detected in the previous day's Sentinel-2 or PlanetScope images may be detected in a PlanetScope image on a later day.

This may be due to atmospheric conditions on a particular day that influence spectral values. For instance, Figure 15 shows a field that appears burnt on the Sentinel-2 image of 4 November but is not detected by the algorithm on that day or on the PlanetScope image of the next day. However, the algorithm detected it on 6 November.

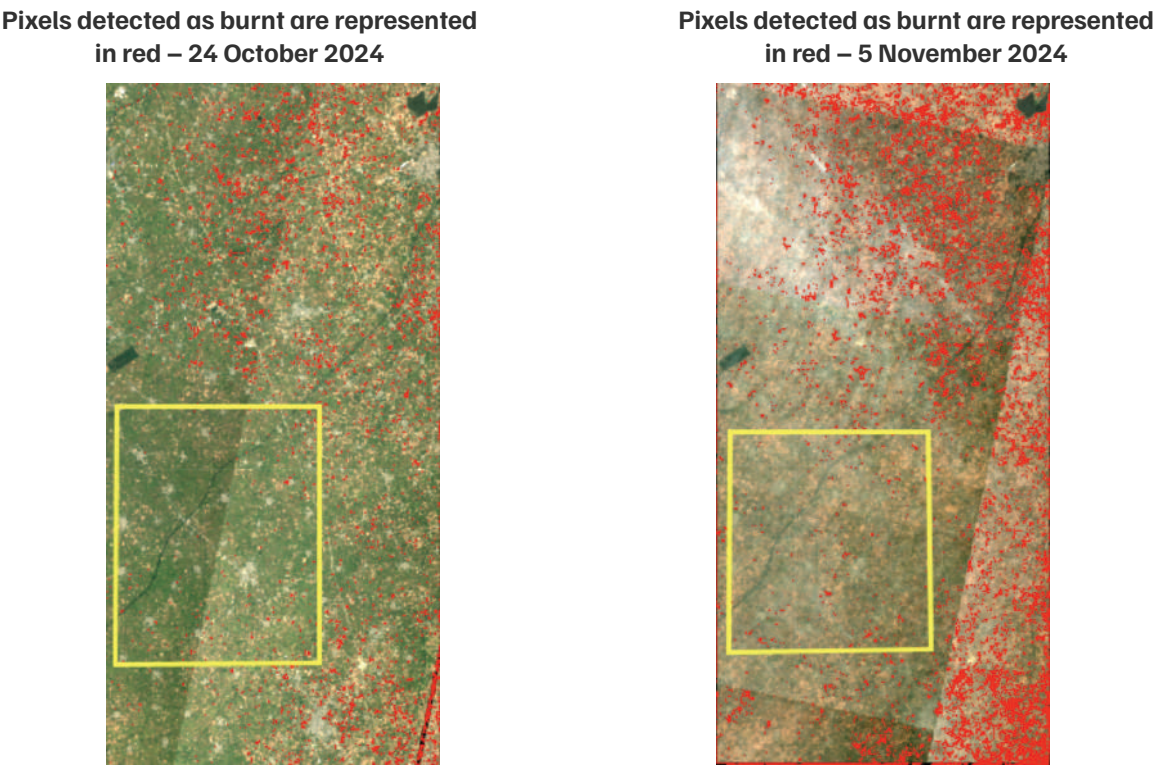
Figure 15. The algorithm misses a field visibly burnt on 4 November, but detects it only on 6 November



Source: Authors’ analysis

- **Tile-to-tile variation in detection:** Despite procuring harmonised PlanetScope imagery², detection extent varied across tiles³, as shown in Figure 16. It shows the burnt pixels detected on the PlanetScope image of 24 October and 5 November 2024. The region within the yellow polygon has much sparser detection than the rest of the image.

Figure 16. Detection of burnt pixels varies across the PlanetScope image



Source: Authors’ analysis

² Radiometrically harmonised imagery to match the Sentinel-2 imagery
³ PlanetScope tiles over region of interest can differ slightly since they are captured at slightly different times

5. Recommendations

Our analysis shows that combining commercial and openly available satellite imagery improves CRB detection. While the current approach relies on threshold-based methods, it could potentially be improved by using ML and artificial intelligence (AI) methods. Although the current approach combines multispectral imagery from Sentinel-2 and PlanetScope, it can be applied to imagery from other sources. Therefore, to improve CRB detection, we recommend:

- **The CAQM should revise the CRB monitoring protocol** to include burnt areas, in addition to fire counts. The current protocol, which relies on fire counts alone, does not represent burning on the ground, as MODIS and VIIRS do not capture farm fires set after their overpass time. The CAQM should therefore adopt an approach that combines openly available Sentinel-2 imagery with commercial imagery to better detect CRB. Improving CRB detection would also improve the emission inventories feeding into air quality models, such as those powering Delhi's Air Quality Early Warning System (AQEWS) (Ignatious et al. 2025).
- **India should leverage its existing space ecosystem for continuous data for CRB monitoring.** While PlanetScope imagery has been available since 2014 (analysis-ready formats since 2017), data restrictions pose risks, such as the recent US restriction on satellite imagery in West Asia (BBC 2026). Therefore, India should explore using and relying on its own constellation. The recent public-private partnership between the Indian National Space Promotion and Authorization Centre (IN-SPACe) and Pixxel aims to launch 12 earth observation (EO) satellites over the next five years (The Hindu 2025). Indian authorities like the CAQM should leverage data from these sources, alongside other openly available and commercial imagery, to improve CRB monitoring.

Our proposed methodology, which estimates the burnt area using a combination of PlanetScope and Sentinel-2 imagery, has an overall accuracy of about 75 per cent, with a TPR of 54 per cent. This method can complement the fire counts obtained from MODIS and VIIRS to provide a better estimate of CRB in India.



India should leverage its existing space ecosystem for continuous data for CRB monitoring

Acronyms

AI	artificial intelligence	LULC	land use land cover
ALU	Agricultural Landscape Understanding	MCC	Matthews correlation coefficient
AQEWS	Air Quality Early Warning System	ML	machine learning
BAI	Burn Area Index	MODIS	Moderate Resolution Imaging Spectroradiometer
BAIS2	Burnt Area Index for Sentinel-2	MSG-SVIRI	Meteosat Second Generation Spinning Enhanced Visible and Infrared Imager
BSol	Bare Soil Index	NDVI	Normalised Difference Vegetation Index
CAQM	Commission for Air Quality Management in National Capital Region and Adjoining Areas	NGT	National Green Tribunal
CEEW	Council on Energy, Environment and Water	PM2.5	particulate matter with a diameter of 2.5 micrometres or less
CI	Char Index	ROI	region of interest
CRB	crop residue burning	S2	scenario 1
EO	earth observation	S2PS	scenario 2
ESRI	Environmental Systems Research Institute	sq km	square kilometres
FN	false negative	sq m	square metres
FNR	false negative rate	SR	Simple Ratio
FP	false positive	T1	threshold 1
FPR	false positive rate	T2	threshold 2
GEE	Google Earth Engine	T3	threshold 3
GHG	greenhouse gases	T4	threshold 4
IGP	Indo-Gangetic Plains	TBI	Tasseled Cap Brightness Index
INR	Indian rupee	TEMPO	Tropospheric Emissions: Monitoring of Pollution
INSAT-3DS	Indian National Satellite – 3rd Generation Second Repeat	TN	true negative
IN-SPACe	Indian National Space Promotion and Authorization Centre	TP	true positive
ISRO	Indian Space Research Organisation	TPR	true positive rate
k	Cohen's kappa	TROPOMI	Tropospheric Monitoring Instrument
		USD	United States dollar
		VIIRS	Visible Infrared Imaging Radiometer Suite

References

- Ambulkar, Rupal, Gaurav Govardhan, Srujan Gavhale, et al. 2025. "Crop Residue Burning in North-Western India: Emission Estimation and Uncertainty Quantification." *Journal of Geophysical Research: Atmospheres* 130 (4): e2024JD042198. <https://doi.org/10.1029/2024JD042198>.
- BBC (British Broadcasting Corporation). 2026. "Concerns after Satellite Provider Restricts Iran Images Following US Pressure." *British Broadcasting Corporation*, April 11. <https://www.bbc.com/news/articles/c5y721yqe6ro>.
- CAQM (Commission for Air Quality Management). 2021. "CAQM Direction." Commission for Air Quality Management, August 16.
- CAQM (Commission for Air Quality Management). 2025. "CAQM Direction 2025." Commission for Air Quality Management.
- CCAC. 2023. "Indian Agricultural Residue Potential to Supplement Energy Sector." Climate and Clean Air Coalition, August 29. <https://www.ccacoalition.org/news/indian-agricultural-residue-potential-supplement-energy-sector>.
- Chen, Jinxi, Rong Li, Minghui Tao, et al. 2022. "Overview of the Performance of Satellite Fire Products in China: Uncertainties and Challenges." *Atmospheric Environment* 268 (January): 118838. <https://doi.org/10.1016/j.atmosenv.2021.118838>.
- Dabral, Shubhangi, and Krishna Prasad Vadrevu. 2025. "Evaluation of Deep Learning Algorithms for Mapping Burnt Areas in an Agricultural Landscape." In *Remote Sensing of Land Cover and Land Use Changes in South and Southeast Asia, Volume 1*. CRC Press.
- Deshpande, Monish Vijay, Nitish Kumar, Dhanyalekshmi Pillai, Vijesh V. Krishna, and Meha Jain. 2023. "Greenhouse Gas Emissions from Agricultural Residue Burning Have Increased by 75 % since 2011 across India." *Science of The Total Environment* 904 (December): 166944. <https://doi.org/10.1016/j.scitotenv.2023.166944>.
- Deshpande, Monish Vijay, Dhanyalekshmi Pillai, and Meha Jain. 2022. "Detecting and Quantifying Residue Burning in Smallholder Systems: An Integrated Approach Using Sentinel-2 Data." *International Journal of Applied Earth Observation and Geoinformation* 108 (April): 102761. <https://doi.org/10.1016/j.jag.2022.102761>.
- Dua, Radhika, Aditi Agarwal, Aishwarya Jayagopal, et al. 2026. "Agricultural Landscape Understanding at Country-Scale." *arXiv:2411.05359*. Preprint, arXiv, June 1. <https://doi.org/10.48550/arXiv.2411.05359>.
- ESRI. n.d. "Esri | Sentinel-2 Land Cover Explorer." Accessed October 5, 2026. <https://livingatlas.arcgis.com/landcoverexplorer/>.
- Giglio, L., G. R. van der Werf, J. T. Randerson, G. J. Collatz, and P. Kasibhatla. 2006. "Global Estimation of Burned Area Using MODIS Active Fire Observations." *Atmospheric Chemistry and Physics* 6 (4): 957–74. <https://doi.org/10.5194/acp-6-957-2006>.
- Govardhan, Gaurav, Rupal Ambulkar, Santosh Kulkarni, et al. 2023. "Stubble-Burning Activities in North-Western India in 2021: Contribution to Air Pollution in Delhi." *Heliyon* 9 (6). <https://doi.org/10.1016/j.heliyon.2023.e16939>.
- Gulati, Bhavneet, Raghu Sharma, Shruti Kanga, et al. 2023. "Unraveling the Relationship Between Stubble Burning and Air Quality Degradation in Punjab: A Temporal and Spatial Analysis (2019–2022)." *Journal of Climate Change* 9 (2): 43–53. <https://doi.org/10.3233/JCC230014>.
- Ignatious, Sneha Maria, Rishikesh P, and Mohammad Rafiuddin. 2025. *Monitoring Crop Residue Burning Better: Moving Beyond Fire Counts*. Council on Energy, Environment and Water. <https://www.ceew.in/publications/how-can-satellite-borne-remote-sensing-capture-crop-burning-and-farm-fires>.
- Jack, B. Kelsey, Seema Jayachandran, Namrata Kala, and Rohini Pande. 2025. "Money (Not) to Burn: Payments for Ecosystem Services to Reduce Crop Residue Burning." *American Economic Review: Insights* 7 (1): 39–55. <https://doi.org/10.1257/aeri.20230431>.
- Konkathi, Preethi, Nathan Torbick, Ishan Ajmera, Michele Reba, and Joanne V. Hall. 2026. *Monitoring Crop Residue Burning in Smallholder Farms at Sub-Field Scale Using High-Resolution Satellite Imagery*. Nos. EGU26-15156. EGU26. Copernicus Meetings. <https://doi.org/10.5194/egusphere-egu26-15156>.
- Lan, Ruoyu, Sebastian D. Eastham, Tianjia Liu, Leslie K. Norford, and Steven R. H. Barrett. 2022. "Air Quality Impacts of Crop Residue Burning in India and Mitigation Alternatives." *Nature Communications* 13 (1): 6537. <https://doi.org/10.1038/s41467-022-34093-z>.
- Lin, Muyang, and Toritseju Begho. 2022. "Crop Residue Burning in South Asia: A Review of the Scale, Effect, and Solutions with a Focus on Reducing Reactive Nitrogen Losses." *Journal of Environmental Management* 314 (July): 115104. <https://doi.org/10.1016/j.jenvman.2022.115104>.
- MoAFW (Ministry of Agriculture and Farmers' Welfare). 2019. "NGT." Ministry of Agriculture and Farmers' Welfare, June 21. <https://www.pib.gov.in/newsite/PrintRelease.aspx?relid=190615®=48&lang=2>.
- MoAFW. 2026. "Union Agriculture Minister Shri Shivraj Singh Chouhan and Union Environment, Forest and Climate Change Minister Shri Bhupender Yadav Chair High-Level Meeting on Permanent Solution for Stubble Management." June 16. <https://www.pib.gov.in/www.pib.gov.in/Pressreleaseshare.aspx?PRID=2273815>.
- Pinakana, Sai Deepak, Amit U. Raysoni, Alqamah Sayeed, et al. 2024. "Review of Agricultural Biomass Burning and Its Impact on Air Quality in the Continental United States of America." *Environmental Advances* 16 (July): 100546. <https://doi.org/10.1016/j.envadv.2024.100546>.

- Reddington, Carly. 2022. *Air Pollution and Greenhouse Gas Emissions from the Agricultural Sector in South and Southeast Asia*. Economic and Social Commission for Asia and the Pacific. <https://un-csam.org/sites/default/files/2023-08/Air%20Pollution%20and%20GHG%20Emissions%20from%20Agri%20in%20SA%20and%20SEA.pdf>.
- Schroeder, Wilfrid, Patricia Oliva, Louis Giglio, and Ivan A. Csizsar. 2014. "The New VIIRS 375 m Active Fire Detection Data Product: Algorithm Description and Initial Assessment." *Remote Sensing of Environment* 143 (March): 85–96. <https://doi.org/10.1016/j.rse.2013.12.008>.
- Singh, Nimisha, Rohit Pradhan, Bipasha Paul Shukla, Mehul R. Pandya, and Rashmi Sharma. 2025a. "Active Fire Detection Using Indian Geostationary Satellite INSAT-3DS." *Remote Sensing in Earth Systems Sciences* 8 (3): 1014–27. <https://doi.org/10.1007/s41976-025-00233-4>.
- Singh, Nimisha, Rohit Pradhan, Bipasha Paul Shukla, and Mehul R. Pandya. 2025b. *Evidence of Shift in Stubble Burning Timing over Northwest India from Geostationary Satellite Observations*. November 25.
- Tawfeeq, Wena Shafeeq, Hastyar Hama Rashid Najmuldeen, Mohammed Hassan, Hassan Hussein Hama Amin, Ghafoor Ahmed Mam Rasul, and Nidhi Chaudhary. 2025. "Impact of Crop Residue Burning on Soil Properties, Microbial Activity, and CO₂ Emissions." *Applied and Environmental Soil Science* 2025 (January): 6423454. <https://doi.org/10.1155/aess/6423454>.
- The Hindu. 2025. "PixxelSpace India-Led Consortium to Establish India's First Commercial Earth Observation Satellite Constellation." *The Hindu*, August 12. <https://www.thehindu.com/sci-tech/science/pixxelspace-india-led-consortium-to-establish-indias-first-commercial-earth-observation-satellite-constellation/article69924236.ece>.
- Vadrevu, Krishna Prasad, Kristofer Lasko, Louis Giglio, Wilfrid Schroeder, Sumalika Biswas, and Chris Justice. 2019. "Trends in Vegetation Fires in South and Southeast Asian Countries." *Scientific Reports* 9 (1): 7422. <https://doi.org/10.1038/s41598-019-43940-x>.
- Walker, Kendra. 2024. "Overcoming Common Pitfalls to Improve the Accuracy of Crop Residue Burning Measurement Based on Remote Sensing Data." *Remote Sensing* 16 (2): 342. <https://doi.org/10.3390/rs16020342>.
- Walker, Kendra, Ben Moscona, Kelsey Jack, et al. 2022. "Detecting Crop Burning in India Using Satellite Data." arXiv:2209.10148. Preprint, arXiv, September 21. <https://doi.org/10.48550/arXiv.2209.10148>.
- Xavier, Evita Merin, Sneha Maria Ignatious, and Mohammad Rafiuddin. 2026. "How Kharif Farm Fires Hit Delhi Harder than Rabi Fires." Council on Energy, Environment and Water (blog), May 25. <https://www.ceew.in/blogs/how-kharif-farm-fires-hit-delhi-harder-rabi-fires>.
- Zhu, Qindan, Tianjia Liu, and Makoto Kelp. 2026. *Capturing Time-Resolved Prescribed Fire Emissions with TEMPO Special Observations*. Earth ArXiv, July 2. <https://eartharxiv.org/repository/view/13813/>.



India generates around 754 million tonnes of crop residue annually, of which 228 million tonnes are surplus.

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