International Journal of Advanced Research and Multidisciplinary Trends (IJARMT)
An International Open Access, Peer-Reviewed Refereed Journal
Impact Factor: 6.4 Website: https://ijarmt.com ISSN No.: 3048-9458

Optimizing Remote Sensing Workflows for Stubble Burning Detection Using Google Earth Engine and Cloud-Based Geospatial Analysis

Nidhi Kundu
PhD CSE, OM Sterling Global University Hisar, Haryana INDIA

R.S. Hooda
Retired Chief Scientist, HARSAC

Sandeep Kumar
Assistant professor Dept.CSE, OM Sterling Global University Hisar

Abstract

Agriculture is a cornerstone of India's economy, particularly in the Indo-Gangetic Plains (IGP). However, the rise in mechanized harvesting has led to increased crop residue, with many farmers resorting to stubble burning as a quick and economical solution for field clearance. This practice remains prevalent due to inadequate residue management infrastructure and limited alternatives, despite regulatory efforts and awareness campaigns. This study leverages satellite data from NASA's Terra and Aqua platforms to estimate burnt areas in the IGP from 2000 to 2020, focusing on key states including Bihar, Haryana, Punjab, Uttar Pradesh, and West Bengal. The methodology involves mapping spatial and temporal patterns to identify stubble-burning hotspots, seasonal trends, and peak fire activity. Monthly quantification of cropland burning provides insights into seasonal peaks, while integrating satellite-derived data with agricultural statistics enhances the accuracy of fire estimates and sheds light on the influence of farming practices on burning trends. The analysis reveals that stubble burning is strongly correlated with the Rabi and Kharif crop cycles, with the highest incidences occurring during harvest periods—specifically in April, May, September, and November. Punjab and Haryana are identified as the most affected regions. While stubble burning peaked between 2013 and 2015, recent years have seen a gradual decline, likely due to increased regulatory measures and growing environmental awareness. These findings underscore the critical need for sustained interventions to mitigate the environmental and health impacts of stubble burning and promote sustainable agricultural practices.

Key words: Stubble Burning, Indo-Gangetic Plains, Satellite Data, Temporal Analysis, Spatial Patterns.

1. Introduction

1.1 Background

Stubble burning—the deliberate burning of crop residue following harvest—is a significant environmental and public health issue, particularly in northern India. Seasonal increases in agricultural fire incidents in states like Punjab and Haryana are major contributors to the declining air quality in the Indo-Gangetic Plain. Traditional ground-based monitoring techniques face challenges due to the scale and timeliness constraints of such large-area analyses. Effective surveillance necessitates the use of remote sensing and cloud-based technologies. This study leverages multi-source satellite data to explore the effective detection, tracking, and analysis of stubble burning events using Google Earth Engine (GEE), a cloud-based geospatial analysis platform. An effective and complementary process for examining environmental consequences, such as burnt areas, particulate matter (PM), and related health implications, over a broad area of interest (AOI), like five states, is offered by combining Google Earth Engine (GEE) and ArcGIS. Because it provides access to a large library of satellite and atmospheric datasets (such as MODIS, Sentinel, Landsat, and TROPOMI) without requiring local downloads, GEE is especially well-suited for this task. It is perfect for evaluating particulate matter levels over time and identifying burned regions using indices like NBR or BAI since it enables cloud-based processing of large-scale raster data. Time-series analysis, trend identification, and atmospheric composition monitoring are all included into GEE, allowing for quick, scalable calculations that would be challenging or time-consuming on a desktop computer. ArcGIS, on the other hand, is superior at creating maps, integrating datasets for interpretation at the local level, and conducting spatial analysis. Results (such raster maps of burned areas or PM concentration) are exported from GEE and imported into ArcGIS for additional analysis. Pollutant exposure was tied to health data, comprehensive and publication-quality maps were created, and zonal statisticsis used in ArcGIS to quantify impacts by state. Using GEE for data processing and ArcGIS for detailed analysis and mapping helped in handling large data easily and get clear, useful results.

1.2 Challenges in Detection

Conventional satellite data analysis methods for large-scale and time-sensitive environmental monitoring tasks, such as detecting stubble burning, are severely limited by several issues. Traditional workflows often rely on desktop-based GIS software, which requires substantial local storage and processing power to handle and process massive amounts of satellite imagery. Tasks like downloading data, applying preprocessing steps (e.g., cloud masking and mosaicking), and performing classification are usually manual and time-consuming, leading to delayed analysis and reduced scalability. Moreover, real-time or near-real-time monitoring is not feasible due to data latency and download limitations, which frequently impede access to current satellite data. The ability to extract precise and timely insights from satellite imagery is further constrained by the lack of automation and integration with sophisticated machine learning models. To address these challenges, cloud-based platforms like Google Earth Engine (GEE) enable scalable, real-time geospatial analysis with high temporal and spatial resolution. If the same work were done using only ArcGIS with MODIS data, several challenges would arise. One of the main issues is the difficulty in handling large volumes of data, as MODIS datasets are extensive and would need to be manually downloaded and stored locally, consuming significant disk space and time.

Processing such data for a large area like five states would also require high computing power, which a typical desktop setup might struggle to provide. Additionally, ArcGIS does not offer direct access to satellite data archives like Google Earth Engine does, so users would need to

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search for, download, and preprocess each dataset manually, including tasks like mosaicking, clipping, and filtering. This process can be very time-consuming and prone to errors. Automating these tasks for multiple dates or regions is also more complex in ArcGIS, as it lacks the cloud-based scripting capabilities that GEE offers. Furthermore, integrating atmospheric data such as PM2.5 levels would be more difficult, since ArcGIS does not provide easy access to global atmospheric datasets. Overall, using only ArcGIS for this kind of large-scale analysis would be less efficient, more labor-intensive, and technically demanding.

2. Study Area and Datasets

2.1 Study Area

The Indo-Gangetic Plains encompass approximately 700,000 km² (270,000 square miles) and span parts of northern India, including states such as Punjab, Haryana, Uttar Pradesh, Bihar, Jharkhand, and West Bengal Although the study considers 5 states for coding section to display Haryana is the only state shown. This is done so that results for Haryana may be compared with other studies for verification.the study is carried out state wise for better reporting and bounding box of Haryana is shown. When to consider other states the bounding box latitude and longitudes needs to be replaced. The study is conducted on a state-wise basis for improved reporting, and the bounding box for Haryana is currently shown. To consider other states, the latitude and longitude values of the bounding box must be updated accordingly. Study area that is used in the complete study is shown in Figure 1.

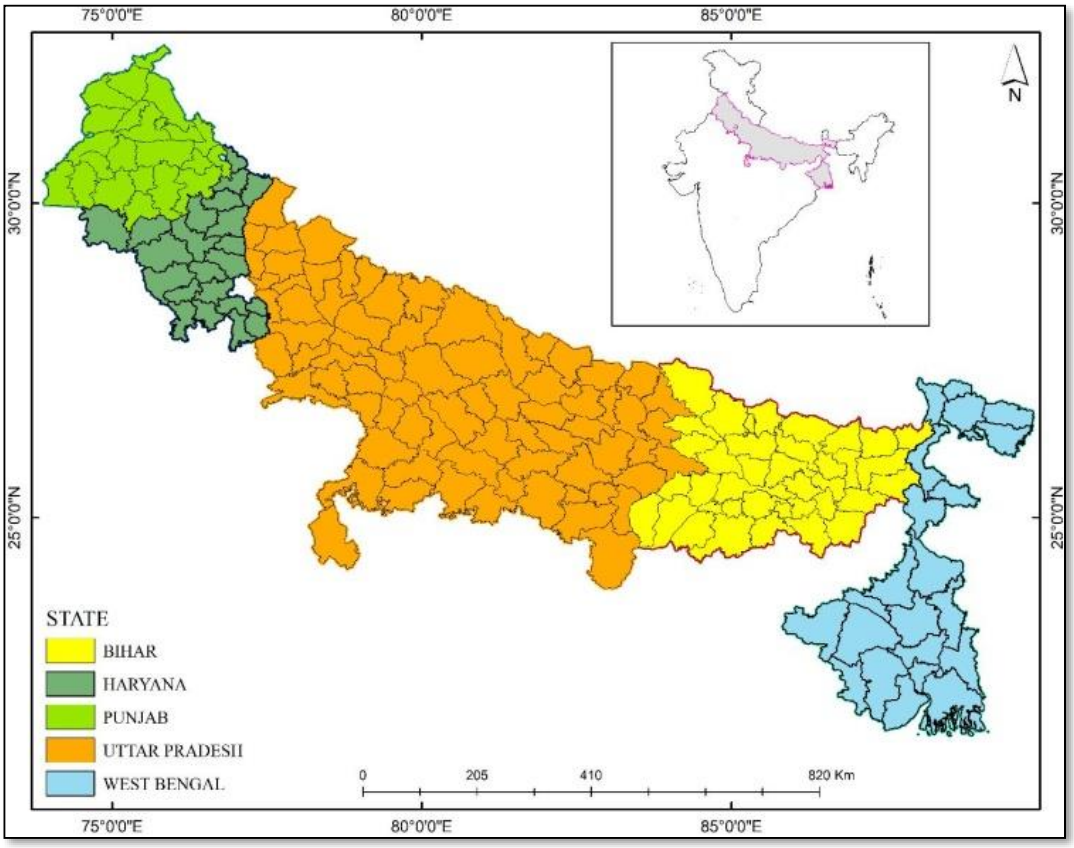

Figure 1

2.2 Satellite Datasets Used

This study utilizes seven primary satellite datasets to identify and track stubble burning activity across the Indo-Gangetic Plain:

- **Sentinel-2 MSI (Multispectral Instrument):** Provides high-resolution optical imagery with a spatial resolution of 10 to 20 meters and a revisit frequency of five days. This dataset is instrumental in detecting fine-scale changes in vegetation and burned areas.
- **MODIS (MOD14A1):** Offers daily global coverage at a 1-kilometer resolution. This thermal dataset is used for detecting thermal anomalies associated with active fires.
- **VIIRS (VNP14IMG):** Delivers enhanced thermal resolution at 375 meters with daily acquisition. This dataset complements MODIS by providing additional thermal anomaly detection capabilities.
- **Sentinel-5P (TROPOMI):** The dataset provides comprehensive atmospheric data, including key pollutants such as nitrogen dioxide (NO_2), sulfur dioxide (SO_2), carbon monoxide (CO), ozone (O_3), methane (CH_4), and the Aerosol Index. It offers a daily temporal resolution, allowing for consistent monitoring of short-term air quality variations. With a spatial resolution of approximately 7 km, it is well-suited for regional analysis. This makes the dataset particularly valuable for studying air pollution patterns, assessing environmental health risks, and supporting policy decisions related to atmospheric quality and climate change.
- **MODIS Aerosol Optical Depth (AOD):** is a widely used satellite-derived measure that serves as a reliable proxy for estimating particulate matter (PM2.5) levels in the atmosphere. The primary products used for AOD monitoring are MOD04_L2 from the Terra satellite and MYD04_L2 from Aqua, both offering consistent and complementary data. These products provide a spatial resolution of 10 km and daily temporal coverage, making them highly suitable for tracking air quality, analyzing pollution trends, and supporting climate and health studies across large regions.
- **CAMS (Copernicus Atmosphere Monitoring Service)** The Copernicus Atmosphere Monitoring Service (CAMS) provides global modeled data for a wide range of atmospheric pollutants, including PM2.5, PM10, and various gases. This data can be accessed and integrated into analysis workflows either through external API connections or via Earth Engine's STAC (SpatioTemporal Asset Catalog) integration. CAMS is particularly valuable for large-scale air quality monitoring and forecasting, offering consistent, spatially continuous data that complements satellite observation
- **MERRA-2 (NASA)** – MERRA-2, developed by NASA, is an atmospheric reanalysis dataset that provides PM2.5 and other key atmospheric variables. It is especially useful for analyzing long-term trends in air quality and climate due to its consistent, historical coverage and global scale.

All datasets were accessed and processed through Google Earth Engine.

3. Methodology

3.1 Google Earth Engine (GEE)

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Google Earth Engine is a cloud-based platform for geospatial analysis at the planetary scale. Although using JavaScript or Python APIs to process the multi-petabyte catalog of satellite imagery and geospatial datasets it hosts it can eliminate the need for local storage or computational infrastructure yet arcgis pro was used for detailed analysis and verification with ground data. By using Google Earth Engine (GEE) with datasets such as MODIS, VIIRS, Sentinel-5P (TROPOMI), MODIS Aerosol Optical Depth (AOD), CAMS (Copernicus Atmosphere Monitoring Service), and MERRA-2 (NASA), a wide range of outputs related to fire events, air pollution, and environmental health were generated. From MODIS and VIIRS, GEE was used to produce burnt area maps, detect active fire locations, and estimate fire intensity using fire radiative power. MODIS AOD provides aerosol concentration data that can serve as a proxy for PM2.5 levels, useful for identifying pollution trends and spatial patterns. Sentinel-5P offers daily measurements of key pollutants like nitrogen dioxide (NO_2), sulfur dioxide (SO_2), carbon monoxide (CO), ozone (O_3), and methane (CH_4), enabling detailed air quality monitoring. CAMS supplies modeled data on particulate matter (PM2.5 and PM10) and gases, allowing for both historical analysis and pollution forecasting. MERRA-2, a NASA reanalysis dataset, provides long-term data on PM levels and atmospheric conditions, supporting trend analysis and environmental health studies. GEE enables you to visualize these outputs as maps and time-

```
// ===========================================
// 1. Define AOI: Karnal district (buffered)
// ===========================================
var karnal = ee.FeatureCollection("FAO/GAUL_SIMPLIFIED_500m/2015/level2")
.filter(ee.Filter.eq('ADM0_NAME', 'India'))
.filter(ee.Filter.eq('ADM2_NAME', 'Karnal'))
.geometry();

var aoi = karnal.buffer(5000).bounds();

// Display AOI
Map.centerObject(aoi, 10);
Map.addLayer(aoi, {color: 'FF0000'}, 'Study Area');

// ===========================================
// 2. Add Indices: NDVI, NBR, NDMI, EVI, BSI
// ===========================================
function addIndices(img) {
var ndvi = img.normalizedDifference(['B8', 'B4']).rename('NDVI').toFloat();
var nbr = img.normalizedDifference(['B8', 'B12']).rename('NBR').toFloat();
var ndmi = img.normalizedDifference(['B8', 'B11']).rename('NDMI').toFloat();
var evi = img.expression(
'2.5 * (NIR - RED) / (NIR + 6 * RED - 7.5 * BLUE + 1)', {
'NIR': img.select('B8')
```

Figure 2

series charts, assess pollution exposure across different regions, analyze trends, and export results in formats such as GeoTIFFs or CSV files for further use in ArcGIS or reporting. The principal benefits for using GEE includes efficient processing of large datasets through cloud-native parallel computing and the ability to perform real-time analytics with interactive ualizations and access to extensive satellite archives. A sample coding of GEE workflow is shown in Figure 2. The study is carried on all major sattes having stubble burning incidences but for this particular section AOI is taken as Karnal Haryana where stubble burning is intensive and all the results could be checked for accuracy.

3.2 Preprocessing in GEE

1. Cloud Masking: For optical datasets (e.g., Sentinel-2), cloud pixels were removed using the QA60 band and built-in functions like mask Clouds ().
2. Temporal Filtering: Images from October–November for the years 2019–2023 were selected.
3. NDVI and NBR Calculation: Vegetation indices were computed to detect burned areas.
   - NDVI = (NIR − Red) / (NIR + Red)
   - NBR = (NIR − SWIR2) / (NIR + SWIR2)
4. Convert NO_2 to µmol/m²

$$NO_2\ (\mu mol/m^2) = NO_2\ \text{column} \times 1e5$$

5. Compute Exposure Index

$$\text{Exposure Index} = \sqrt{NO_2 \times PM2.5 \times \text{Population}}$$

3.3 Burn Area and Fire Detection

- Thermal Anomalies: To detect active fires, MODIS and VIIRS fire products were employed.
- Burned Area Mapping: Burned regions were identified using changes in NBR. Supervised Classification: Labeled samples of burned versus unburned pixels were used to apply the Random Forest classifier.

3.4 Workflow Automation

The Google Earth Engine (GEE) script was designed to systematically analyze environmental conditions through a comprehensive workflow. First, it defines the study region as a AOI of rectangular box and sets the analysis period from October 1, 2019 to November 30, 2019.time line may be changed as per requirement by simply changing the dates. Sample shown in script is of time period of kharif season of 2019. The script then loads and preprocesses Sentinel-2 imagery; sentinel data of area of interest is considered and since burning is evaluated for only kharif season time period is taken accordingly. Only images with cloud cover less than 20% were taken to account and only spectral bands (NIR, Red, SWIR) relevant to stubble burning were taken to account for analysis. Key vegetation indices including NDVI (Normalized Difference Vegetation Index) and NBR (Normalized Burn Ratio) are computed for each image pre burning and post burning to assess crop health and burn severity. A composite of sentinel image is generated from the sentinel data of the area of intrest that is Karnal, Haryana.Although for complete study it is all major states observing stubble burning.

A threshold value of NBR that is retrieved from composite image is used to detect the threshold. For better understanding of work flow the NDVI and NBR layers are displayed on GEE itself. Script also utilizes (NO_2) data from Sentinel-5P for October 1 to December 31, 2023, converts the values from mol/m² to µmol/m² for better utilization. Additionally, the script accesses

PM2.5 concentration data from the CAMS Near-Real-Time dataset, computing mean values for the specified period and area. The script tries to integrate multiple data sources to analyze the environmental impact stubble burning. The Google Earth Engine (GEE) script retrieves surface-level PM2.5 data from the Copernicus Atmosphere Monitoring Service (CAMS) Near-Real-Time (NRT) dataset, which is provided by the European Centre for Medium-Range Weather Forecasts (ECMWF). The CAMS and NRT data sets offers global air quality information and provide useful insights on realtime monitoring. The script filters the PM2.5 data based as desired in the study. After filtering the PM2.5 data the scripts clips it to the AOI used in the study. The final output represents the average PM2.5 concentration in (µg/m³).

WorldPop 2020 gridded population data is used to add demographic information to the environmental analysis. It accesses the dataset representing people per pixel for the year 2020.For confirming spatial alignment in Karnal the script calculated mean population and clips it from AOI.the result of this provides a raster where each pixel value correspondes to average no of people per pixcel which facilitate pollution and health risk assessments integration. Furthermore, the Exposure Index is computed as a composite metric designed to assess potential health risk zones by integrating environmental pollution with the population density of an area. Using the principle that higher pollution levels in more densely populated areas pose a greater public health concern the script identifies high risk zones. The index is calculated using a specific formula that combines the pollution data with population density, thereby highlighting areas where the risk to public health is elevated. This mathematical relationship ensures that areas with both high pollution and high population density are flagged as high-risk zones, making it a useful tool for urban health planning, environmental monitoring, and policy prioritization.

A normalization is done for Exposure Index for visual interpretation and comparison. Exposure Index values are divide by 100,000 that scales down the data while preserving relative differences.the results achieved are than clamped between 0 and 1 so that all values lying outside the range are limited to minimum and maximum. This ExposureNorm, allows for consistent visualization across regions and helps highlight areas with relatively higher pollution exposure when displayed using a color gradient. Additionally, the script also identifies areas where PM2.5 concentrations are more than 10 µg/m³, which is the World Health Organization's recommended safe limit for fine particulate matter exposure. To accomplish this, condition is applied i.e (PM2.5 > 10) across the image. This condition creates a binary mask that highlights only the pixels satisfying this condition. These high-exposure zones are then visualized on the map using a red color, making them easily distinguishable. This process aids in pinpointing regions where air quality may pose health risks, thereby supporting targeted environmental assessments and public health interventions. The script calculates the average NO_2 and PM2.5 values over the entire Area of Interest (AOI) using the reduce Region () function in Google Earth Engine. This function summarizes the pixel values of an image over a specified region using a statistical reducer.

Finally, the script generates several output layers that are exported as GeoTIFF files to Google Drive for further analysis or visualization. The snippet of script in Figure 2 analyzes fire impact and vegetation change within a user-defined area of interest (AOI) using Sentinel-2 satellite imagery for the year 2024. It calculates pre- and post-fire vegetation indices—NDVI (Normalized Difference Vegetation Index) and NBR (Normalized Burn Ratio)—for September and December, respectively. Cloudy pixels are masked to improve data quality. The difference in NDVI (NDVI_diff) highlights vegetation loss, while the difference in NBR (dNBR) is used to assess burn severity. The script classifies burn severity into five categories, flags areas with significant NDVI drop, estimates the number of burned pixels, and finally exports all key layers—including pre/post NDVI, NBR, NDVI_diff, dNBR, and burn severity classes—to Google Drive as GeoTIFF files.

The script retrieves Sentinel-5P satellite data to compute the mean NO_2 column number density, expressed in µmol/m². This pollutant is associated with vehicle and industrial emissions. Elevated NO_2 levels are closely associated with respiratory issues, such as asthma and lung inflammation, and contribute to the formation of other pollutants like ground-level ozone and fine particulate matter (PM2.5). In the context of environmental and public health monitoring, this band serves as a key indicator of urban air quality and pollution exposure. Simultaneously, it accesses CAMS (ECMWF atmospheric composition) data to extract surface-level PM2.5 concentrations in µg/m³—these are fine particulate matter known to cause respiratory and cardiovascular problems.

In addition, the script incorporates WorldPop 2020 population data to evaluate human exposure to pollution. Using this, it computes an Exposure Index, which is derived as the square root of the product of NO_2, PM2.5, and population density, then normalized between 0 and 1. This index helps identify areas where pollution levels overlap with high population density, thus signaling potential public health risk zones. Asnapshot of working environment is shown in Figure 3.

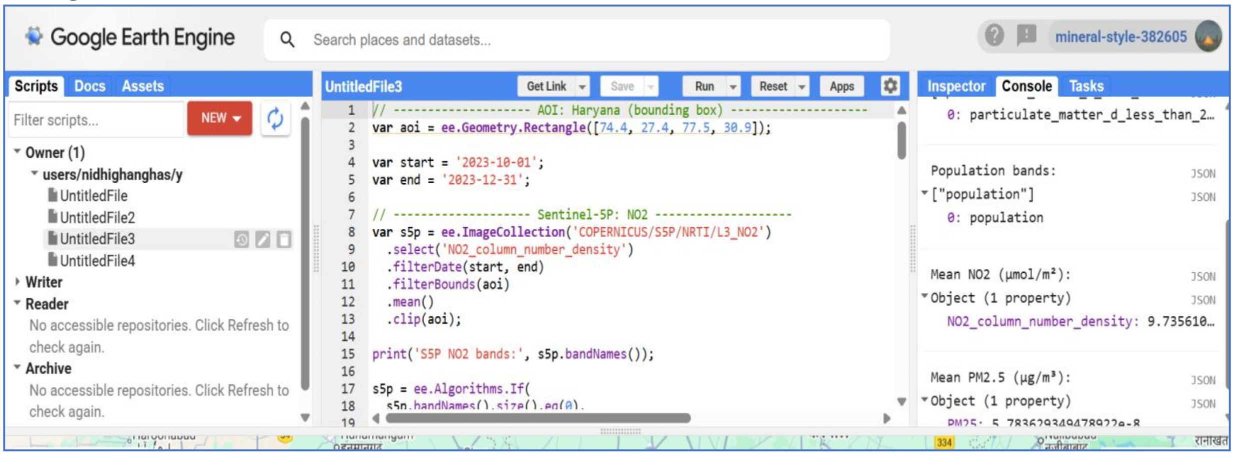

Figure 3

Google Earth Engine is utilized as a cloud-based, deterministic spatial analysis platform. It offered a extremely powerful platform for large-scale geospatial computations and environmental monitoring. Google earth Engine Supports Random Forest Algorithm, for machine learning it can contribute a lot. Google earth cloud may be utilized for deep learning concepts in Stubble burning which supports tenser flow.

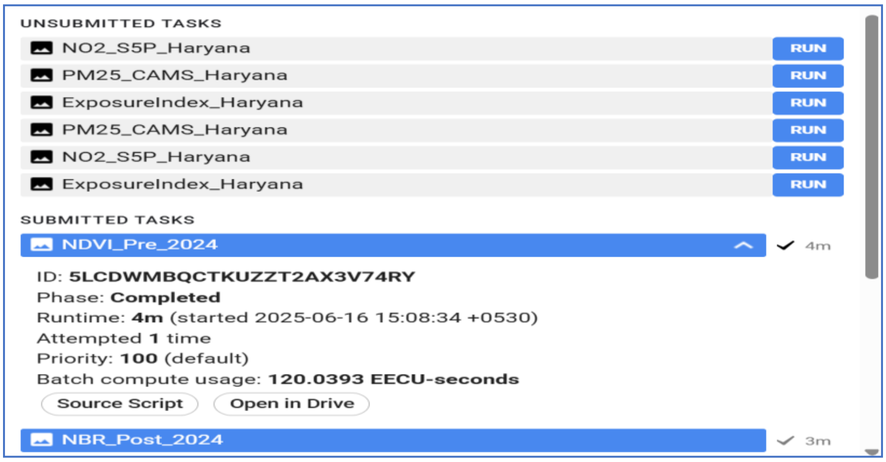

Figure 4

3.5 Advantages of the GEE-Based Workflow

This system offers cloud-native execution, eliminating the need for local infrastructure and ensuring seamless accessibility from anywhere. With massive data availability, users can tap into extensive archives, including Sentinel, MODIS, and VIIRS, enabling comprehensive historical and real-time analysis. The platform supports real-time processing, delivering instant output generation for time-sensitive applications. Its scalability across regions allows vast areas, such as the Indo-Gangetic Plain, to be processed within minutes, making large-scale environmental monitoring efficient. Additionally, visual and spatial outputs enhance interpretation, providing policymakers with clear, actionable insights for informed decision-making. For conducting state-wide or regional environmental health assessments (like NO_2/PM2.5 exposure across Punjab, Haryana, UP, Bihar, and West Bengal), GEE offers an unmatched combination of speed, scalability, and simplicity—making it the preferred platform over ArcGIS for cloud-enabled remote sensing and geospatial analysis. Google Earth Engine (GEE) offers several advantages over ArcGIS, especially when working across a very large region such as the Indo-Gangetic Plain (IGP) spanning multiple states. GEE provides direct access to a vast global data catalog, eliminating the need for manual downloads, which is often required in ArcGIS workflows. For large areas of interest, GEE excels due to its cloud-based processing capabilities, whereas ArcGIS is constrained by the performance limits of local machines. Automation in GEE is straightforward using JavaScript, enabling scalable and repeatable analyses, while ArcGIS typically relies on Python scripting or ModelBuilder, which can be more cumbersome. In terms of collaboration, GEE allows easy sharing of scripts and results through simple URLs, whereas ArcGIS requires more complex setups unless using ArcGIS Online. Furthermore, GEE is free for research and educational use, making it highly accessible, while ArcGIS requires expensive licenses. Lastly, GEE supports integration of near real-time datasets, which is more limited in standard ArcGIS environments.

4. Results and Discussion

4.1 Burn Detection Accuracy

The classification achieved an overall accuracy of 80–90% when validated against VIIRS fire points and field reports. A high correlation ($R^2 = 0.87$) was found between detected burn areas and known stubble burning hotspots. Final result of the study when all states are taken in account shows the excess risk which clearly indicates NCR cleary in high health risk zone. By dynamically identifying the worst impact areas of the health impact index, the analysis provides a robust and spatially explicit delineation of zones with elevated environmental health risks. These findings underscore the critical need for targeted interventions and policy measures in the NCR to mitigate the adverse effects of pollution and environmental degradation on public health. The use of this script ensures that the spatial patterns of risk are both accurate and reproducible, supporting informed decision-making in environmental health

4.2 Performance

Performing the same environmental health impact analysis across five states using traditional desktop GIS software like QGIS or ArcGIS Pro can be significantly time-consuming, often taking anywhere from 30 minutes to several hours depending on the resolution of the data, the number of raster layers involved, and the processing power of the local machine. High-resolution datasets and complex raster operations can stretch processing time to several hours, especially when handling large geographic extents such as multiple states. In contrast, the adoption of Google Earth Engine (GEE) as the primary processing platform brought significant performance and scalability advantages to this study. Through parallel processing, GEE enabled the execution of complex geospatial operations at speeds up to 50 times faster than traditional desktop environments, dramatically reducing analysis time. Its capability for real-time monitoring allowed near-instant access to updated satellite imagery across vast regions, which is critical for timely detection and response—particularly during peak stubble burning seasons. Furthermore, GEE supports automated batch processing, allowing consistent and repeatable analyses over multiple years without manual intervention. This automation not only improves workflow efficiency but also enhances the reproducibility and reliability of results, making GEE a superior choice for large-scale, time-sensitive environmental health studies.

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