Stubble (Crop Residue) Burning Detection Through Satellite Images Using Geospatial Foundation Model: *A Case Study in Punjab, India*

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Abstract

Stubble burning is a significant environmental challenge globally, with widespread implications for air quality, greenhouse gases emission, soil degradation and health issues. This practice is particularly prevalent in agricultural regions across the world, though its impacts are notably severe in the northern India. This proposed work focuses on improving the detection of stubble (crop residue) burning in Punjab (India), using geospatial foundation model. This study leverages series of satellite images where stubble burning incidents have been documented. By refining the model to incorporate local environmental factors, this study aims to improve the accuracy of stubble burning detection, thereby contributing to a scalable solution for real-time monitoring and intervention in crop residue burning practices worldwide.

1 Introduction

Stubble (Crop residue) [1], [2] burning is a widespread practice in agricultural regions across the world [3]–[6] particularly in Punjab, northern India (Figure 1)[7]–[9], where it is predominantly used to rapidly clear crop residues during the months of October and November. Despite its convenience for farmers, this practice has severe environmental consequences, including deteriorating air quality, soil degradation, and adverse health effects across northern India [10]–[13], including New Delhi [14]–[16]. Total emissions of carbon dioxide (CO_2) sulfur dioxide (SO_2), nitric oxide (NO_x), carbon monoxide (CO), $PM_{2.5}$, PM_{10} etc. from crop residue burning are quantified by [17] using statistical models combined with satellite observations and sensors. A Detailed study on the impact of stubble burning on climate change is provided in [18], [19], while satellite-based methods have been used

Tackling Climate Change with Machine Learning: workshop at NeurIPS 2024.

to monitor and detect stubble burning [20]–[22]. Similarly, in [23] Sentinel-2 data and Random Forest classifiers were used to map stubble burning, demonstrating the potential of integrating spectral indices such as NDVI [24] and NBR [25]. However, these methods often lack regional adaptability and precision, limiting their overall effectiveness. Recent advancements in remote sensing and machine learning have led to more accurate detection and monitoring of stubble burning. [26], [27]) A CNN-based deep learning framework was used to monitor active fire locations with high-resolution satellite imagery, significantly improving burn scar detection accuracy compared to traditional methods [28]. Fine-tuning pre-trained Earth observation models for regional applications enhances performance, achieving state-of-the-art results in land cover classification [29]. Transfer learning and adaptive strategies, as explored by [30], [31], are crucial for effectively fine-tuning geospatial models.This study aligns with these goals by fine-tuning the Prithvi-100m geospatial foundation model [32], [33] for the Punjab region to enhance stubble burning detection, utilizing a dataset of 1,500 coordinate points to improve regional specificity and detection accuracy. The Prithvi-100m-burn-scars model [34], further fine-tuned on the extensive HLS Burn Scar Scenes dataset [35], marks a significant advancement in burn scar detection. By leveraging this model on high-resolution satellite images [36] and a customized regional dataset (Punjab, India), stubble burning detection methods can be tailored to local environmental conditions. The proposed approach aims to offer a scalable solution for real-time monitoring and intervention in stubble burning practices worldwide. Accurate monitoring of stubble burning can significantly aid in crop residue management and reduce its environmental consequences, as discussed in [37]–[39].

2 Dataset and Preprocessing

The dataset [1] consists of 1,500 data points (latitude, longitude, date of observation) from Punjab, India, representing locations where active fires or stubble burning incidents were reported, as shown in Figure 2. Manual polygonization can be used to annotate fields on satellite images for the corresponding stubble burning observation dates. The recommended geospatial foundation model requires six bands (blue, green, red, narrow NIR, SWIR 1, and SWIR 2) compatible with Sentinel-2 (20m resolution) and a 5- to 6-day revisit time.

Figure 1: Stubble burning in rice field

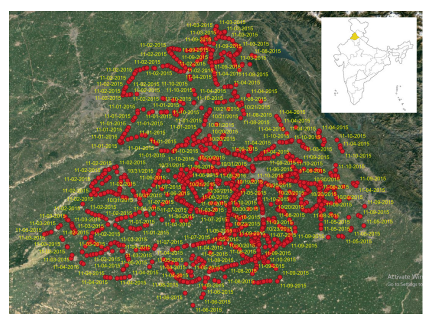

Figure 2: 1,500 Ground truth data points

Sentinel-2 (L2A) products [40] offer freely accessible surface reflectance data, making them a cost-effective alternative to commercial datasets like PlanetScope. While Sentinel-2 has a lower spatial resolution (10 meters) and a 5-day revisit time compared to PlanetScope's higher resolution (around 3 meters) and daily revisit capability, its free and open access is invaluable for large-scale and long-term monitoring. To correct atmospheric effects in our 2015 data, recorded before Sentinel-2 L2A products became available in 2018, we applied the Sen2Cor processor [41] to the Level-1C data. This process removes aerosols, water vapor, and other noise. Additionally, Min-Max normalization [42] is used to scale reflectance values, addressing variations in illumination, sensor angles, and atmospheric conditions, thereby improving model robustness and generalization across diverse regions and timeframes.

[1] Someone gathered it with the assistance of local resources and chose to remain anonymous.

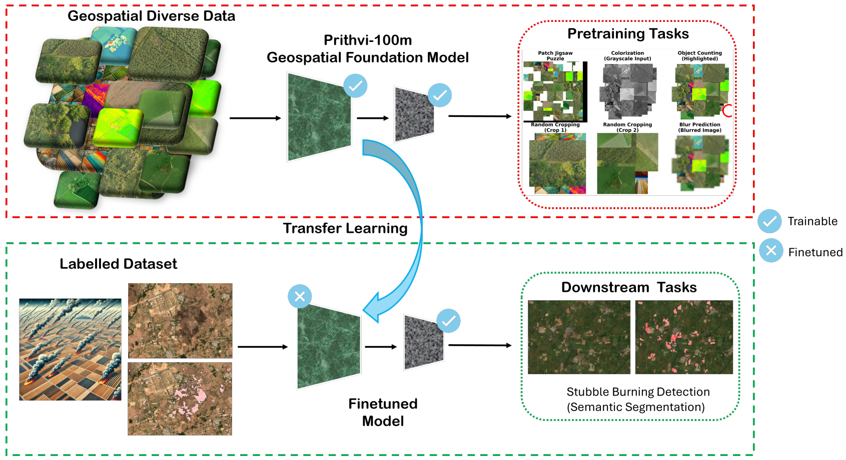

Figure 3: Fine-tuning of geospatial foundation model

3 Proposed Method

In this study, we aim to fine-tune the Prithvi-100m geospatial foundation model, pre-trained on diverse remote sensing images, for stubble burning detection.While the baseline remote sensing index method provides valuable insights, it is prone to false positives, often mistaking dark pixels or patches on the ground for stubble burning areas when they might actually be regions where bio-char or ashes have been applied. To address this, we propose a fine-tuned geospatial foundation model specifically designed to detect actual stubble burning areas, thereby reducing false positives and enhancing detection accuracy.The model uses a Vision Transformer (ViT) architecture [43] with a self-supervised encoder [44], employing a Masked Auto-Encoder (MAE) [45] learning strategy and a Mean Squared Error (MSE) loss function [46]. It leverages spatial attention across multiple patches and temporal attention within each patch.

To begin the fine-tuning process, we will apply standard data augmentation techniques, such as rotation, random cropping, flips, spectral perturbations, and patch jigsaw puzzles, to enhance training diversity and prevent over-fitting. Next, we will adapt the Prithvi-100m model using our stubble burning dataset, optimizing it for effective burn scar detection. The fine-tuned model will then be rigorously evaluated against unseen data to validate its performance. The workflow of fine-tuning the Prithvi-100m geospatial foundation model is shown in Figure 3.

For comparative analysis, we will compare this model with the baseline, the fine-tuned Prithvi-100m-burn-scars model (Overall accuracy 0.96) [47] on the HLS Burn Scar Scenes dataset [35] and also with the Skysense FM model [48] as well. The models will be tested on a common validation set to assess their effectiveness in detecting burn scars or stubble burning. Performance will be evaluated using standard metrics, including precision, recall, F1-score, and the area under the ROC curve (AUC-ROC), providing a comprehensive assessment of the model's ability to detect stubble burning incidents accurately while minimizing false positives and negatives. This approach highlights that while the foundational model offers a strong base, task-specific fine-tuning is essential for optimizing performance in targeted applications like stubble burning detection. Details on the baseline model and geospatial foundation model are in Appendix.

4 Conclusion & Pathways to Climate Impact

This proposal outlines a method for fine-tuning the Prithvi-100m geospatial foundation model to detect stubble burning incidents in Punjab, India. By customizing the model to account for regional environmental conditions and using a localized dataset, this work aims to enhance the accuracy and effectiveness of stubble burning detection. The improved model is expected to offer greater precision and reliability in monitoring stubble burning across diverse agricultural landscapes globally , paving the way for scalable applications to mitigate air pollution. Stubble burning, a common agricultural practice, significantly impacts air quality by emitting large quantities of greenhouse gases (GHG).

Effective monitoring of these events allows for more targeted interventions and policy measures to reduce emissions and promote sustainable farming practices. Ultimately, this study aims to provide policymakers and civil society with a tool to monitor and regulate stubble burning globally. It supports climate action (SDG 13) by reducing GHG emissions, addresses land degradation (SDG 15), and promotes responsible consumption and production in agriculture (SDG 12).

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A Appendix

Here we will provide further details on the baseline model and geospatial foundation model used in this study.

A.1 Baseline Model

Previously, we conducted baseline work on stubble burning detection using traditional remote sensing methods, leveraging spectral indices such as NDVI (Normalized Difference Vegetation Index) and NBR (Normalized Burn Ratio) on small ground truth patches we collected. We analyzed this approach using data from Sentinel, Planet, and various active fire products for the area of interest. This section provides an overview of the baseline data, the methods employed, and the preliminary results obtained from our earlier analysis.

A.1.1 Baseline Data

For the baseline work, remote sensing data was collected following a stubble burning incident on May 9, 2023. The dataset includes high-resolution PlanetScope satellite imagery with 8 spectral bands at a 3-meter resolution, captured daily from May 1 to May 20, 2023. Additionally, Sentinel-2 satellite imagery, providing 13 spectral bands at a 10-meter resolution (2A data product), was acquired on four distinct dates within the same period (Figure 4). Furthermore, NASA's active fire products were utilized to gather data on active fires across the Punjab region during the 2022 Kharif season, offering a broader spatial resolution of 500 meters.

Planet images available at a daily frequency. Higher spatial resolution leads to better identification of burn areas. Burn incidents become indistinguishable within 2 days of burning as shown in Figure 5. However, Sentinel-2 satellite imagery is freely available but on interval of 5-6 days. Infrared spectral bands (SWIR) are available which are directly correlated with fire.

Daily monitoring of fire incidents is conducted at low spatial resolution using NASA satellite instruments, specifically MODIS and VIIRS. The MODIS instrument captures data four times each day, providing direct detection of fire events at a lower spatial resolution of 1 kilometer. This data is typically available with a latency of 2 to 3 hours. Similarly, VIIRS collects data once a day, offering direct detection of fires with an improved spatial resolution of 375 meters. Like MODIS, the data from VIIRS is also available with a latency of 2 to 3 hours. These tools are critical for consistent and timely monitoring of fire events over large areas.

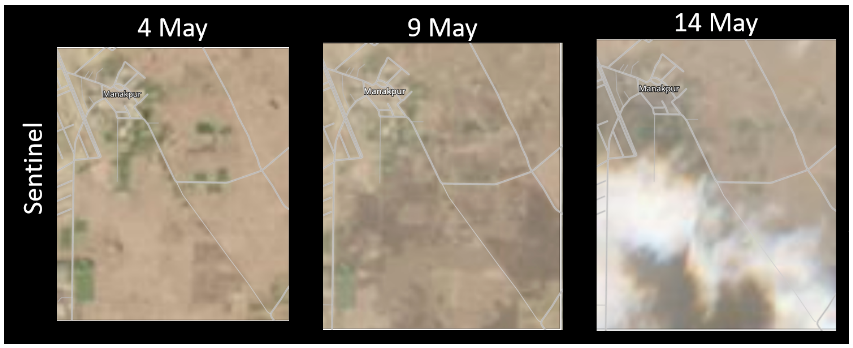

Figure 4: Temporal sentinel imagery of burn area (May 2023)

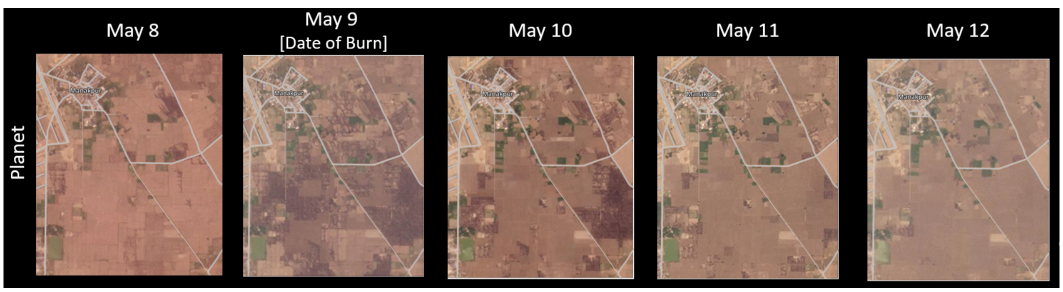

Figure 5: Temporal planet imagery of burn area (May 2023)

A.1.2 Baseline Method

We conducted an analysis by comparing Planet and Sentinel imagery, along with active fire products, to alert authorities and calculate the last burn index using Sentinel imagery. Figure 6 illustrates the baseline method for detecting fire-affected areas using remote sensing data. The process begins with two types of input data: active fire detection from MODIS/VIIRS and other remote sensing datasets. These inputs are processed to generate visual representations of the affected regions, marked by red circles. The processed images are then analyzed using various indices, including the Char Index, Burn Area Index, Bare Soil Index, NBR (Normalized Burn Ratio), and others such as MIRBI (Mid-Infrared Burn Index) and BSI (Burn Severity Index), to assess the extent and impact of the burn. The outputs from these indices are subsequently used in a time-series change detection analysis to monitor changes over time. The final result is visualized, indicating the spatial distribution of detected changes (marked by red and blue triangles), which aids in identifying patterns and understanding the impact of burning over time.

A.1.3 Preliminary Results

Combining MODIS, Sentinel, and Planet imagery significantly enhances the accuracy of fire detection, building on methodologies proposed in prior studies. This integrated approach not only improves detection precision but also facilitates the timely issuance of alerts to authorities, enabling prompt action. In Figure 7, the first image, dated October 5, 2022, depicts the area before any burning activity, showing a relatively uniform landscape. The second image, from October 16, 2022, shows the aftermath of stubble burning, with darker patches clearly indicating fire-affected areas. The third image, labeled 'Burn Area Mask' and also dated October 16, 2022, precisely highlights the locations impacted by the burning. The pink mask effectively outlines the burn areas, providing an

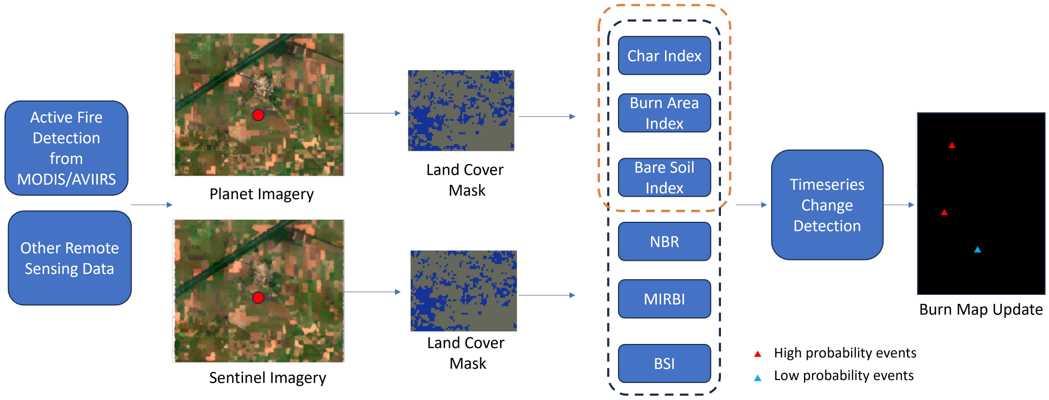

Figure 6: Workflow of baseline method using traditional remote sensing indices

accurate assessment of the extent of stubble burning. Similarly, the method successfully detected stubble-burnt patches in another region, as shown in Figure 8. This visual analysis is crucial for monitoring agricultural practices and assessing their environmental impact.

Figure 7: Masked burnt area occurred on 16^{th} Oct, 2022

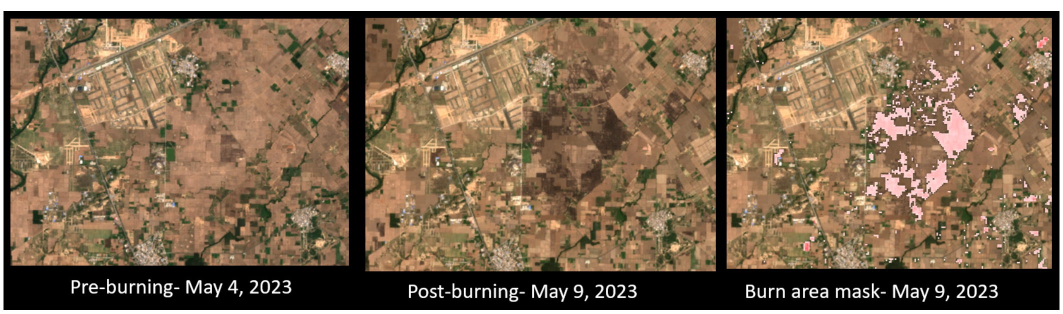

Figure 8: Masked burnt area occurred on 9^{th} May, 2023

A.1.4 Limitation of baseline method and other techniques

Remote sensing (RS) spectral index-based method track the spectral differences between two images- normal and burned. It is merely a difference of temporal changes in pixel that may be due to any reason. Some of the RS based indices to detect burning are- MNDFI (Modified normalized difference fire index), BAI (Burning Area Index), NBR (Normalized Burning Ratio).

Simple Models (CNN, RCNN etc.) can be used but not promising in case of limited training data. It may also not detect temporal or positional relation. It may not deal with data from different sensors of different resolution, for different local conditions. Whereas, Foundational models are trained on diverse data from different sources and sensors.

A.2 Geospatial Foundation Model

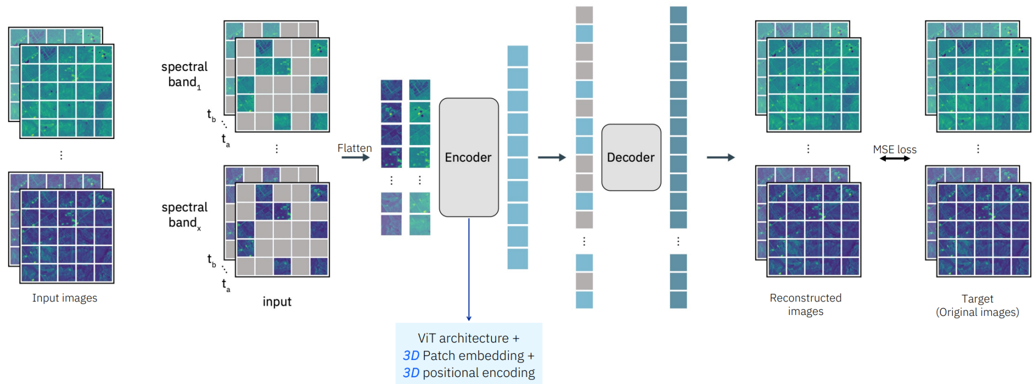

Figure 9: The mask auto-encoder structure for pretraining Prithvi model on large scale multi-temporal and multi-spectral satellite images [33].

Foundation models, trained on diverse datasets, are adapt at capturing temporal and spatial relationships, making them highly effective for complex tasks like stubble detection. Fine-tuning these models with smaller, labeled datasets further enhances their accuracy. However, many farmers burn stubble at night to avoid detection, making optical imagery alone insufficient. To address this, we need to fine-tune the foundation model on a diverse range of data collected from multiple sensors. This data should include optical and radar imagery, providing robust day/night coverage and mitigating issues like cloud and noise interference. Such multi-modal data fusion cannot be effectively handled by simple deep learning models. Instead, we require a foundation model trained on diverse datasets with varying resolutions and sensor types. For this purpose, we selected the PRITHVI-100M geospatial foundation model, which is specifically trained on three timestamps of Harmonized Landsat Sentinel (HLS) data.

The PRITHVI-100M model represents a state-of-the-art approach to analyzing high-resolution satellite imagery using advanced machine learning techniques. Built on the Vision Transformer (ViT) architecture, it incorporates 3D patch embedding and 3D positional encoding to process multispectral and temporal satellite data effectively. The model employs a self-supervised learning strategy based on a masked auto-encoder (MAE). During training, multispectral images captured over various time intervals and spectral bands are divided into smaller patches, which are flattened and processed by the model. Its encoder-decoder structure generates a latent representation of the input, which is used to reconstruct the original image. The training process is guided by a Mean Squared Error (MSE) loss function to minimize reconstruction errors (Figure 9). The MAE learning strategy, which involves masking certain patches during training, forces the model to learn underlying data patterns by reconstructing the missing patches. This improves its ability to generalize and enhances its robustness across applications like land cover classification, change detection, and environmental monitoring.

In this work, we fine-tune the PRITHVI-100M model on our dataset, using a Swin-B backbone and a state-of-the-art U-Net regressor [49]. Unlike simpler models that struggle to integrate diverse data types effectively, foundation models like PRITHVI-100M can leverage cross-modal learning to capture nuanced relationships between different modalities. This capability significantly enhances the accuracy and robustness of distinguishing stubble burning from other land disturbances.

PRITHVI-100M is particularly suitable for this task as it is trained on diverse earth observation data across three timestamps, making it well-suited for change detection tasks. Additionally, it utilizes six-band Harmonized Landsat Sentinel (HLS) data, including SWIR1 and SWIR2 bands. These bands are highly effective in capturing the burning ratio, as demonstrated in the baseline method.

Overall, PRITHVI-100M represents a significant advancement in geospatial data analysis by combining ViT, 3D positional encoding, and MAE learning to deliver robust and scalable performance on large-scale satellite imagery. After fine-tuning the model, the results will be validated against the baseline method. However, challenges like detecting minor fires persist, underscoring the need for further refinements.