EES 502 Term Paper

Assessing the Relationship Between Forest Fires and $PM_{2.5}$ Levels in India

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Abstract: *Forest fires in India, exacerbated by climate change and land use changes, significantly contribute to air quality degradation through elevated PM2.5 levels, posing severe health and environmental risks. This study investigates the spatial and temporal relationships between forest fires and PM2.5 concentrations across Central India, Northeast India, and the Northern (Himalayan) region, using high-resolution satellite datasets from the Fire Information for Resource Management System (FIRMS) spanning 2003–2023 and the Local-Global Health Air Pollution version 2 (LGHAP v2) dataset spanning 2017–2021, respectively. Through time-series analysis, correlation heatmaps, spatial correlation, and Granger causality tests, the research reveals pronounced regional variations. Northeast India exhibits strong positive correlations and significant causality at lags 1 and 5, driven by shifting cultivation, while Central India shows localised PM2.5 hotspots in southern Chhattisgarh but negligible region-wide correlations due to non-fire pollution sources. The Northern Himalayan region displays no clear fire-PM2.5 link, attributed to minimal fire activity and rapid pollutant dispersal. These findings highlight the need for region-specific fire management and air quality strategies under frameworks like the National Clean Air Programme (NCAP). The study highlights the public health risks of fire-related PM2.5, particularly its long-range transport to urban centers, and advocates for future research integrating meteorological data and aerosol transport models to enhance predictive capabilities and inform targeted interventions.*

Introduction

Forest fires in India have become an escalating environmental concern, driven by a confluence of climate change, rising temperatures, and shifting land use patterns. These fires not only threaten biodiversity and ecosystems but also contribute significantly to air quality degradation, with far-reaching implications for public health and environmental stability. Among the pollutants released during forest fires, particulate matter with a diameter of 2.5 micrometres or less ($PM_{2.5}$) stands out as a particularly hazardous component due to its ability to penetrate deep into the respiratory system and exerts both immediate and long-term effects on human health and the environment (Cohen et al., 2017). While the direct link between forest fires and $PM_{2.5}$ levels is well-documented in specific regional studies, a broader, nationwide statistical analysis of how fire characteristics and other variables interact to influence $PM_{2.5}$ concentrations remains a critical knowledge gap. This study seeks to address this gap by providing a comprehensive, data-driven investigation of the spatial and temporal dynamics of $PM_{2.5}$ pollution associated with forest fires across India, offering insights that can inform air quality management, public health policies, and climate mitigation strategies.

$PM_{2.5}$ is considered one of the most dangerous forms of air pollution due to its microscopic size and chemical composition, which includes a mix of sulphate, nitrate, ammonium, organic carbon, elemental carbon, and metals (Pope & Dockery, 2006). From a health perspective, exposure to $PM_{2.5}$ is associated with a range of adverse outcomes, including respiratory diseases such as asthma and chronic obstructive pulmonary disease (COPD), cardiovascular conditions like heart attacks and strokes, and increased risk of premature mortality (Lelieveld et al., 2015). Vulnerable populations, such as children, the elderly, and individuals with pre-existing health conditions, are particularly at risk. According to the Global Burden of Disease study, air pollution, with $PM_{2.5}$ as a major contributor, was responsible for approximately 4.2 million deaths globally in 2019, with a significant proportion occurring in South Asia, including India (Health Effects Institute, 2020). Beyond acute health effects, long-term exposure to $PM_{2.5}$ has been linked to reduced lung function, cognitive impairment, and even adverse birth outcomes, highlighting its role as a silent but pervasive public health crisis (Gupta et al., 2018).

The environmental impacts of $PM_{2.5}$ are equally concerning. These fine particles can alter atmospheric chemistry by scattering and absorbing solar radiation, leading to changes in regional climate patterns, such as increased temperatures and altered precipitation (Ramanathan et al., 2007). $PM_{2.5}$ also contributes to the formation of regional haze, reducing visibility and affecting ecosystems by depositing on soil and water bodies, where it can disrupt nutrient cycles and harm aquatic and terrestrial life (Seinfeld & Pandis, 2016). In forested regions, the deposition of $PM_{2.5}$ can further stress vegetation, making trees more susceptible to disease, pests, and additional fire risk, creating a vicious cycle of environmental degradation (Pye et al., 2015). Moreover, $PM_{2.5}$ emissions from fires interact with greenhouse gases, exacerbating climate change by enhancing the greenhouse effect and contributing to global warming, which in turn fuels more frequent and intense wildfires (IPCC, 2021).

In India, where air quality is already a major concern due to industrial emissions, vehicular pollution, and biomass burning, forest fires add an additional layer of complexity. The country's diverse geography, ranging from the Himalayan foothills to the tropical rainforests of the Western Ghats, creates varying fire regimes and pollution patterns that require nuanced analysis. This knowledge gap limits the ability to predict pollution episodes, assess their impacts, and develop effective mitigation strategies. By focusing on a nationwide analysis, this study aims to fill this void, providing a robust framework for understanding how forest fires contribute to $PM_{2.5}$ levels and their subsequent health and environmental consequences.

The urgency of this research is underscored by India's commitment to improving air quality and mitigating climate change under international frameworks such as the Paris Agreement and national policies like the National Clean Air Programme (NCAP) (MoEFCC, 2019). Effective management of forest fire-induced $PM_{2.5}$ pollution requires not only identifying high-risk areas and seasons but also quantifying the statistical relationships between forest fires and pollutant levels. This study proposes to achieve this by leveraging advanced data sources, including satellite-based fire detection systems and high-resolution air quality models, to create a comprehensive dataset and employ statistical and geospatial analyses to map trends and hotspots. The expected outcomes will enhance our understanding of the environmental and health impacts of forest fires, inform evidence-based policies, and contribute to sustainable fire and air quality management strategies across India, ultimately supporting efforts to safeguard public health, protect ecosystems, and address the broader challenges of climate change.

Literature Review

Forest fires in India have become a critical environmental concern, significantly contributing to air quality degradation, particularly through elevated levels of particulate matter with a diameter of 2.5 micrometres or less ($PM_{2.5}$). $PM_{2.5}$ is a major public health threat due to its ability to penetrate deep into the lungs and enter the bloodstream, exacerbating respiratory and cardiovascular diseases. The relationship between forest fires and $PM_{2.5}$ levels across India's diverse ecological zones, including Eastern, Central, and Himalayan regions, and the Indo-Gangetic Plain (IGP), has garnered increasing attention in recent research. By examining regional patterns, climatic drivers, advanced methodologies, and persistent research gaps, this review aims to provide a comprehensive foundation for the project "Assessing the Relationship

Between Forest Fires and $PM_{2.5}$ Levels in India," offering insights that can guide data collection, statistical analysis, and policy formulation.

In Eastern India, the Similipal forest fire of March 2021 stands out as a pivotal case study, illustrating the acute vulnerability of the region's ecosystems to wildfires. Singh et al. (2021) documented a 56.21% increase in aerosol optical depth (AOD) and significant $PM_{2.5}$ spikes directly correlated with fire counts, emphasizing the immediate threat to air quality and public health in an area traditionally understudied compared to northern India. The study highlighted how smoke plumes from these fires not only elevated $PM_{2.5}$ concentrations but also extended their impact to downwind urban centres, exacerbating respiratory and cardiovascular risks for local populations. This event highlights the need for event-specific analyses to capture the rapid dynamics of $PM_{2.5}$ emissions and their health consequences, particularly in regions with limited baseline data.

Moving to Central India, where dry deciduous forests dominate, Kumar et al. (2021) analyzed fire activity from 2001 to 2020, revealing a dramatic increase—doubling or tripling—in fire frequency during warmer months. This surge in fire intensity has led to substantial $PM_{2.5}$ emissions, challenging air quality standards in densely populated and agriculturally significant areas. The study linked these trends to climatic warming, which dries out vegetation and extends fire seasons, resulting in persistent $PM_{2.5}$ pollution that accumulates over time. Additional research by Mishra and Pandey (2022) further detailed how these emissions interact with local meteorological conditions, such as low wind speeds, to create stagnant pollution pockets, amplifying exposure risks for rural and semi-urban communities. This regional analysis highlights the necessity of integrating fire dynamics with climatic variables to predict and mitigate $PM_{2.5}$ impacts effectively.

The Himalayan region presents a unique set of challenges due to its ecological sensitivity and altitudinal variability. In the Western Himalayas, Sharma et al. (2022) found that forest fire emissions contribute significantly to $PM_{2.5}$ increases, but precipitation acts as a natural mitigant, reducing pollutant levels post-fire through wet deposition. This mechanism contrasts with other regions, where dry conditions prolong $PM_{2.5}$ persistence. Conversely, in the Central Himalayas, particularly Uttarakhand, Pandey et al. (2023) reported a staggering rise in fire events—from 922 to 41,600 over two decades—driven by rising temperatures, drought, and human activities like deforestation. These fires generate dense smoke plumes that elevate regional $PM_{2.5}$ levels, threatening ecologically critical zones that regulate India's climate and water resources. A related study by Thakur et al. (2024) used satellite imagery to map these plumes, revealing their transboundary impact on neighbouring regions, including Nepal, and underscoring the need for cross-regional cooperation in air quality management.

In the Indo-Gangetic Plain (IGP), already burdened by industrial and agricultural pollution, forest fires exacerbate $PM_{2.5}$ levels, particularly during the post-monsoon season. Patel et al. (2023) documented a 116% rise in AOD and corresponding $PM_{2.5}$ concentrations, attributing this increase to enhanced wind speeds that disperse fire-related pollutants over vast areas. This dispersion amplifies exposure risks for millions of residents, compounding existing air quality challenges and necessitating integrated monitoring systems that account for both fire and meteorological factors. Additional research by Singh and Rao (2023) explored how seasonal agricultural burning in the IGP interacts with forest fires, creating synergistic $PM_{2.5}$ peaks that overwhelm local air quality infrastructure, further highlighting the region's vulnerability.

Climate change emerges as a central driver of these trends, influencing fire regimes, meteorological conditions, and $PM_{2.5}$ emissions across India. Das et al. (2023) modelled future fire weather danger, predicting a 60% increase in severe fire days in dry forests, which would likely elevate $PM_{2.5}$ outputs due to intensified combustion and prolonged fire seasons. In humid forests, however, higher moisture levels may suppress fire risk, resulting in lower $PM_{2.5}$ emissions, as noted by Rao and Kumar (2024). These contrasting regional responses underscore the complexity of climate-fire-pollution interactions, requiring predictive models that incorporate both local and global climatic variables. Temperature increases and drought conditions, particularly in the Central Himalayas, show strong statistical correlations with elevated $PM_{2.5}$ levels from fire smoke, while in the IGP, post-monsoon wind patterns enhance pollutant dispersal, extending their atmospheric residence time and amplifying downwind impacts (Pandey et al., 2023; Patel et al., 2023).

Methodological advancements have significantly improved our understanding of these dynamics. Geospatial machine learning, as applied by Joshi et al. (2024), has been used to quantify $PM_{2.5}$ and volatile organic compound (VOC) emissions from specific fire events, such as the 2021 Almora fires in Uttarakhand. These analyses revealed high VOC levels that interact with $PM_{2.5}$ to form secondary aerosols, complicating air quality dynamics and necessitating more nuanced pollution models. Nationally, Gupta et al. (2023) mapped spatial clustering of fire impacts in Central and Northeastern India from 2005 to 2022, identifying $PM_{2.5}$ as a key pollutant linked to ecological degradation, health outcomes, and even potential infectious disease risks, such as anthrax outbreaks. These studies demonstrate the power of integrating satellite data, statistical modelling, and machine learning to enhance the resolution and accuracy of $PM_{2.5}$ assessments.

Despite these advancements, significant research gaps persist, particularly in statistical and data-driven analyses across India's Northeast, Central, and Northern regions. One major limitation is the lack of high-resolution, region-specific datasets that integrate long-term forest fire occurrences with corresponding $PM_{2.5}$ measurements. To overcome this, we are utilizing high-resolution $PM_{2.5}$ data from the LGHAP v2 dataset, a global gap-free 1-km resolution dataset of daily $PM_{2.5}$ concentrations since 2000, which ensures detailed spatial and temporal coverage to enhance the accuracy and granularity of our analysis (Bai et al., 2024)

While Eastern and Central India have received attention for $PM_{2.5}$ spikes during fire events, data for Northeast and Himalayan areas remain sparse, limiting the development of robust statistical models (Li et al., 2023). For instance, the Northeast's dense forest cover and unique fire ecology are poorly understood in terms of $PM_{2.5}$ contributions, while the Northern regions, including parts of the Himalayas, lack consistent time-series data to track seasonal and long-term trends.

Another gap lies in the application of advanced analytical techniques. Many studies depend on basic statistical approaches, such as simple correlations or descriptive statistics, which limit their ability to capture the complex interactions between forest fires and $PM_{2.5}$ levels. More sophisticated methods, including time-series analysis, or spatial modelling, could provide deeper insights into these dynamics, helping to uncover patterns such as the geographic distribution of fire and pollution hotspots or seasonal variations across different regions. For instance, the spatial and temporal relationships in less-studied areas, including Northeast, Central, and Northern India, remain poorly understood, which restricts the development of predictive models and comprehensive impact assessments. Moreover, a broader regional perspective, as highlighted by recent analyses (e.g., Li et al., 2023), indicates that India's challenges with fire-related $PM_{2.5}$ are part of a larger Asian pattern influenced by factors like population density, land use practices, and climatic conditions. This comparative context suggests opportunities for India to learn from global best practices, such as adopting cutting-edge monitoring technologies and fostering regional cooperation, to enhance its strategies for managing air quality and fire risks.

This expanded review identifies key trends, such as regional variability in $PM_{2.5}$ impacts, the critical role of climate change, and the potential of advanced methodologies, while emphasizing persistent gaps in data availability, methodological sophistication, and regional coverage. These insights provide a robust foundation for the project, guiding its objectives to develop comprehensive datasets, quantify statistical relationships, map spatial and temporal patterns, and inform evidence-based strategies to mitigate the health and environmental burdens of forest fire-induced $PM_{2.5}$ pollution in India. By addressing these gaps, the project aims to contribute not only to national efforts but also to global knowledge on wildfire management and air quality, paving the way for sustainable environmental and public health policies.

Study Area

This study is situated within the broader geographical context of India, a nation characterised by significant ecological, climatic, and topographic diversity. While the analysis incorporates pan-India satellite datasets to establish spatial and temporal patterns of $PM_{2.5}$ pollution and fire activity, the core focus is on selected regions that are particularly fire-prone and environmentally sensitive. These include (i) the **central Indian states** of *Madhya Pradesh* and *Chhattisgarh*, (ii) the **northern Himalayan states** of *Uttarakhand* and *Himachal Pradesh*, and (iii) the **North Eastern region**, comprising *Arunachal Pradesh*, *Assam*, *Manipur*, *Meghalaya*, *Mizoram*, *Nagaland*, and *Tripura* (excluding *Sikkim*).

These regions were selected due to their high forest cover, recurring fire incidents, and vulnerability to pollution-related health and ecological impacts. **Central India**, especially Madhya Pradesh and Chhattisgarh, is known for its extensive dry deciduous forests and tribal populations dependent on forest resources. These landscapes often experience large-scale fires during the pre-monsoon period, driven by agricultural burning, leaf litter ignition, and dry climatic conditions. In **northern India**, Uttarakhand and Himachal Pradesh are part of the Himalayan ecosystem, where fire risks are heightened by steep terrain, chir pine dominance, and increasing anthropogenic disturbances. The combination of elevation-driven meteorology and forest fires in these regions contributes significantly to episodic air pollution and $PM_{2.5}$ accumulation, both locally and in adjacent valleys.

The **North Eastern region of India**, comprising seven sister states (excluding Sikkim), is another fire-vulnerable zone characterized by complex terrain, rich biodiversity, and traditional land use practices such as jhum (shifting) cultivation. Seasonal forest fires are common, particularly during the dry winter and spring months. Despite being ecologically sensitive and home to numerous indigenous communities, this region remains underrepresented in national-scale studies on air pollution and fire impacts.

Though the core analysis is limited to these specific states, the use of nationwide datasets allows for contextualising localised patterns within the larger air quality scenario of India. The spatial heterogeneity in vegetation types, population distribution, and meteorological conditions, such as wind speed, humidity, and precipitation, makes this sub-national approach both necessary and insightful for uncovering region-specific relationships.

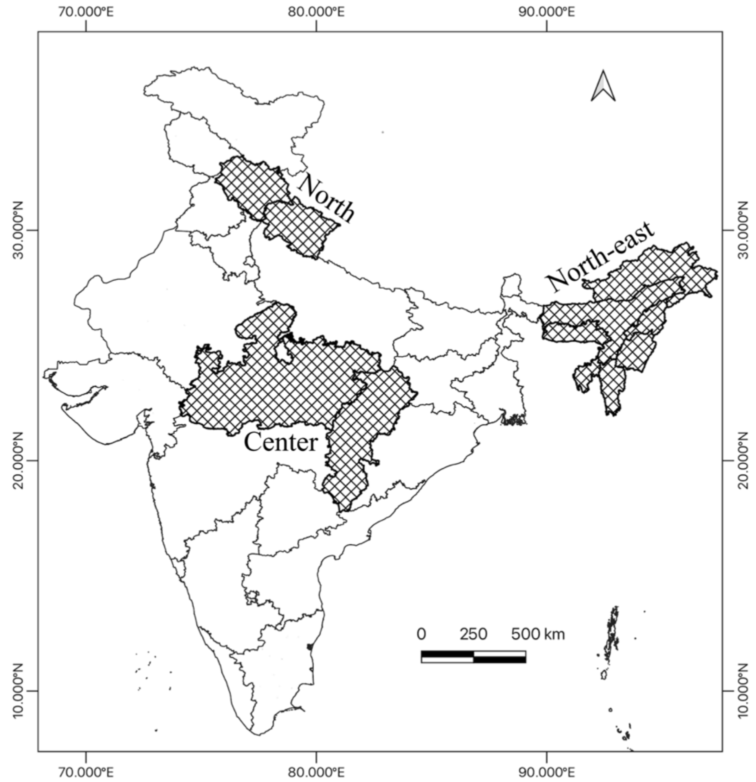

Figure 1: The shaded region is the study area of this study. The study is further divided into three sub-regions which are “Center”, “North-east” and “North”. The regions are annotated on the figure.

Furthermore, these regions align with several key policy and ecological priorities. Many of them fall within the ambit of the National Action Plan on Forest Fires (NAPFF) and contribute to the objectives of the National Clean Air Programme (NCAP). By focusing on regions with both high forest fire incidence and population exposure to pollution, this study aims to generate evidence that is both scientifically robust and policy-relevant. The findings are expected to inform not only regional air quality and health risk assessments but also broader national strategies for forest fire mitigation and environmental management.

Materials and Methods

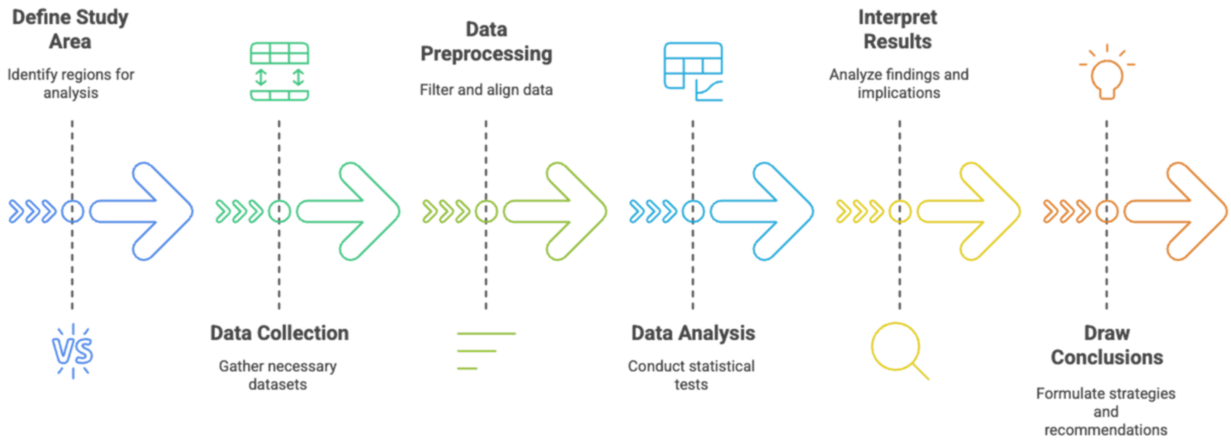

Figure 2: Flow chart of the study highlighting the main steps and over flow

Dataset

This study draws upon high-resolution, satellite-based datasets covering the entire Indian subcontinent to explore the spatio-temporal relationship between forest fire activity and $PM_{2.5}$ concentrations, with focused analysis on selected regions. While the study area is regionally focused, the datasets were downloaded at a pan-India scale to ensure consistency, accuracy, and the potential for future nationwide analysis.

1. **FIRMS Active Fire Data (MODIS, 2003–2023)** Active forest fire data were obtained from NASA's Fire Information for Resource Management System (FIRMS), based on the Moderate Resolution Imaging Spectroradiometer (MODIS) instruments onboard the Terra and Aqua satellites. Data were downloaded for the full extent of India, spanning a 21-year period from 2003 to 2023. The dataset provides daily global fire detections at 1-km resolution, with associated fire radiative power (FRP), acquisition time, and confidence scores.
2. **$PM_{2.5}$ Concentration Data (LGHAP v2, 2017–2021)** $PM_{2.5}$ concentration data were sourced from the Local-Global Health Air Pollution (LGHAP v2) dataset, which offers daily surface $PM_{2.5}$ values at 1-km resolution globally. The dataset integrates satellite-derived aerosol optical depth (AOD), ground-based monitoring data, and chemical transport models using machine learning algorithms. For this study, data were downloaded for India for the period 2017 to 2021. The five-year temporal window was selected to balance temporal coverage with computational efficiency, given the high spatial resolution and volume of data. The

$PM_{2.5}$ values were geospatially aligned with fire events to quantify the pollution impact of forest fires.

3. **Land Use and Land Cover Data (2005)**
To provide ecological and land management context, the study incorporates Land Use and Land Cover (LULC) data for India in 2005, derived from Landsat and IRS satellite imagery. The dataset, classified according to the International Geosphere-Biosphere Programme (IGBP) scheme, was developed through a combination of supervised classification, visual interpretation, and ground truth validation (Roy et al., 2015; Meiyappan et al., 2016). It offers a 100-m resolution map of India's land cover with a minimum mapping unit of 2.5 hectares. The 2005 LULC map was used to examine the dominant land cover types in fire-prone regions and assess how land cover may influence both fire occurrence and pollutant accumulation.

All datasets were pre-processed to ensure uniform spatial resolution, projection, and format. Fire detections were aggregated to common spatial grids and temporally synchronized with corresponding $PM_{2.5}$ values for further statistical and geospatial analysis. The integration of LULC data enabled the classification of fire-prone zones based on landscape characteristics, adding ecological depth to the pollution analysis. Together, these datasets establish a robust foundation for exploring the relationship between forest fires and $PM_{2.5}$ levels in India.

Data pre-processing

The preprocessing stage was a critical component of this study, aimed at transforming raw satellite-derived datasets into a format suitable for spatial and temporal analysis. The forest fire dataset, acquired from the NASA Fire Information for Resource Management System (FIRMS), was originally in point data format, with each fire detection geolocated to a 1 km resolution grid cell. This high-resolution dataset recorded the precise coordinates and timestamps of every active fire detected via MODIS sensors, providing rich temporal granularity from 2003 to 2023. Only the points with a confidence level of more than 30% were retained to maintain the quality of forest fire points considered for the study. The 1 km resolution is excellent for fire detection and monitoring, but it posed challenges for integration with air quality data in the context of broader-scale statistical analysis.

The $PM_{2.5}$ dataset, sourced from the LGHAP v2 product, was available as gap-filled global daily estimates at a 1 km resolution for the years 2017 to 2021. While this fine resolution is valuable for air quality monitoring, its direct use alongside the 1 km fire data was limited in analytical scope. For any given 1 km cell and day, the probability of a fire occurrence aligning precisely with a $PM_{2.5}$ value was very low, leading to sparse overlaps in space-time. Consequently, the dataset was ill-suited for statistical correlation or regression analyses at this resolution, as the limited fire occurrences per $PM_{2.5}$ cell would yield weak or non-significant relationships.

To address this issue, a spatial coarsening strategy was employed. The $PM_{2.5}$ data were aggregated from a 1 km to a 10 km resolution by averaging the $PM_{2.5}$ values within each 10 km × 10 km grid cell for each day. This spatial transformation allowed for a more meaningful representation of regional air quality, smoothing out local variability and better capturing pollution signals influenced by multiple fire events. In tandem with this, the forest fire point data were also gridded to the same 10 km resolution. Each fire detection was assigned to its corresponding 10 km cell based on spatial coordinates, and the total number of fire detections per grid cell was computed for each day, resulting in a daily fire count dataset at 10 km scale. This harmonised preprocessing ensured that both $PM_{2.5}$ concentrations and fire occurrences were spatially and temporally aligned, with one daily value per 10 km grid cell for each variable. The choice of a 10 km resolution struck a balance between preserving spatial detail and aggregating sufficient data points for robust statistical analysis.

This gridded dataset enabled the application of correlation analyses, spatial mapping, and seasonal trend detection in subsequent stages of the research. By establishing a common analytical scale, the preprocessing workflow not only facilitated compatibility between heterogeneous datasets but also enhanced the reliability and interpretability of the results. This foundation was critical in advancing the study's objective of quantifying the relationship between forest fire activity and $PM_{2.5}$ levels across diverse ecological and geographic regions of India.

Results

Forest Fire Time Analysis

1. Monthly Time-Series Analysis

This section presents a time series analysis of monthly forest fire counts across three study regions using 22 years of satellite data. The analysis is illustrated in Fig. 2 through a time series plot showing fire counts, with February to May highlighted, peak months marked, and regional trends summarised.

The February–May period, highlighted with a shaded region in the time series plot, consistently captures the majority of forest fire activity across all three regions, reflecting the critical influence of India’s pre-monsoon dry season. During these months, climatic conditions—characterized by high temperatures, low humidity, and minimal rainfall—create a tinderbox environment where dry vegetation, such as fallen leaves, twigs, and grasses, becomes highly flammable. Human activities further amplify fire incidence during February–May, with practices such as agricultural burning, forest clearing, and accidental ignitions peaking as communities prepare land or engage in seasonal activities (Reddy et al., 2017; FSI, 2021).

Regionally, Central India shows a pronounced April peak in fire counts for 17 out of 22 years, driven by its tropical dry deciduous forests, which accumulate extensive dry biomass during the prolonged February–May dry season. High temperatures and low moisture, combined with widespread slash-and-burn agriculture in Madhya Pradesh and Chhattisgarh, make April particularly fire-prone, as farmers clear land for cultivation. In the North Eastern region, March dominates as the peak month for 18 out of 22 years, fuelled by a shorter February–April dry season and the practice of slash-and-burn agriculture in valleys (Dhar et al., 2023). Here, evergreen and semi-evergreen forests, along with grasslands, dry out rapidly in March, and community-led burns for agricultural land preparation trigger widespread fires (FSI, 2021)

Ramakrishnan, 1992). The Northern Himalayan region, peaking in April for 8 out of 22 years, exhibits greater variability due to its complex topography and microclimates. Pine and oak forests accumulate dry needles and leaves from February to May, while human activities—such as forest clearing for grazing or accidental fires from tourism—heighten risks, though annual climatic shifts like early rains can alter peak timing (Sharma et al., 2017).

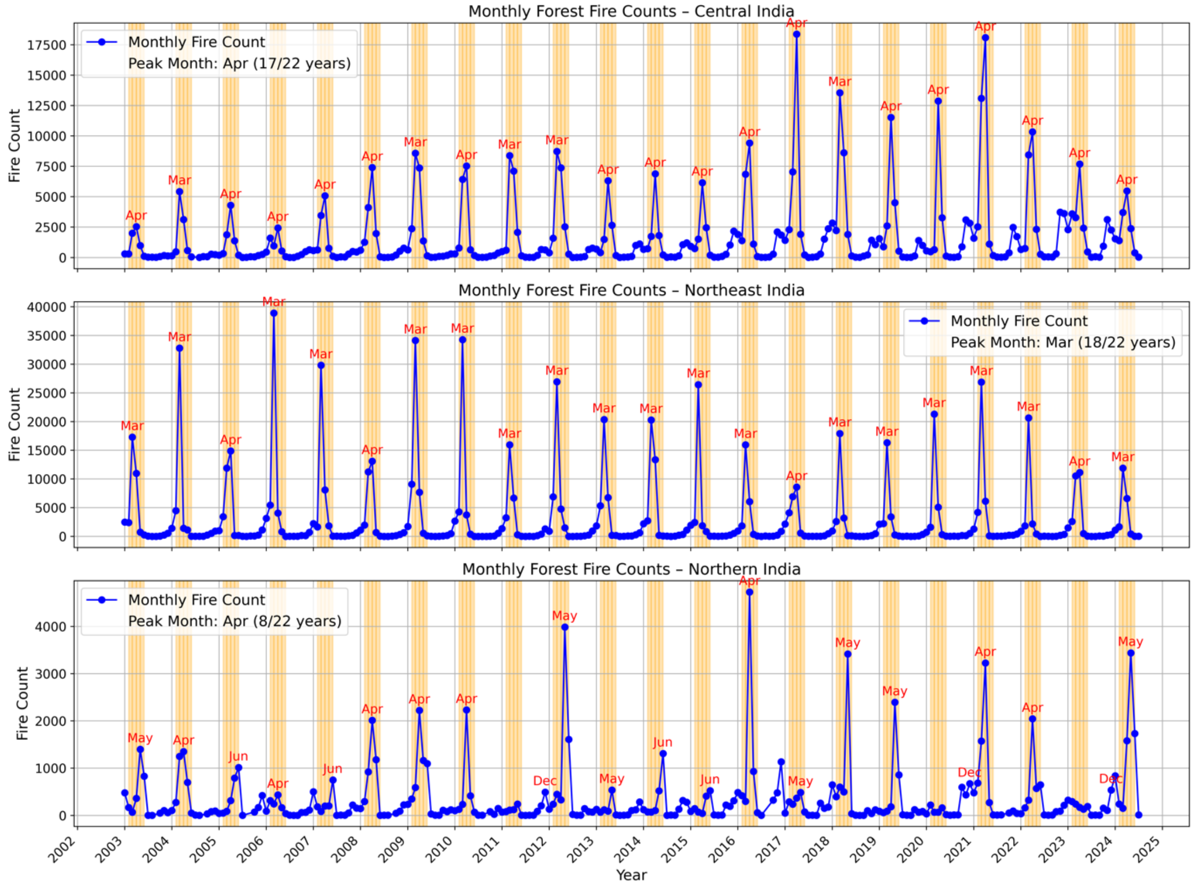

Figure 3: Time series plot illustrating the monthly forest fire counts three study regions: Central India, North-eastern India, and Northern India. The months of February through May are highlighted with a yellow shaded region. The blue line with filled circles represents the time series of forest fire counts. The month with the highest count in each year is labelled in red above the respective point. The peak month, defined as the month with the highest occurrence of forest fire counts, along with the number of times it has been the peak month, is indicated in the legend.

2. Yearly Time-Series Analysis

This section conducts a yearly time series analysis of forest fire counts across three ecologically sensitive regions in India—Central India, the North Eastern region and the Himalayan region in the North using 22 years of satellite data. The analysis is visualized in Figure 3, where annual fire counts are plotted with blue markers, and a red dashed linear trend line, accompanied by its equation and R^2 value, illustrates the long-term direction and strength of fire activity trends in each region.

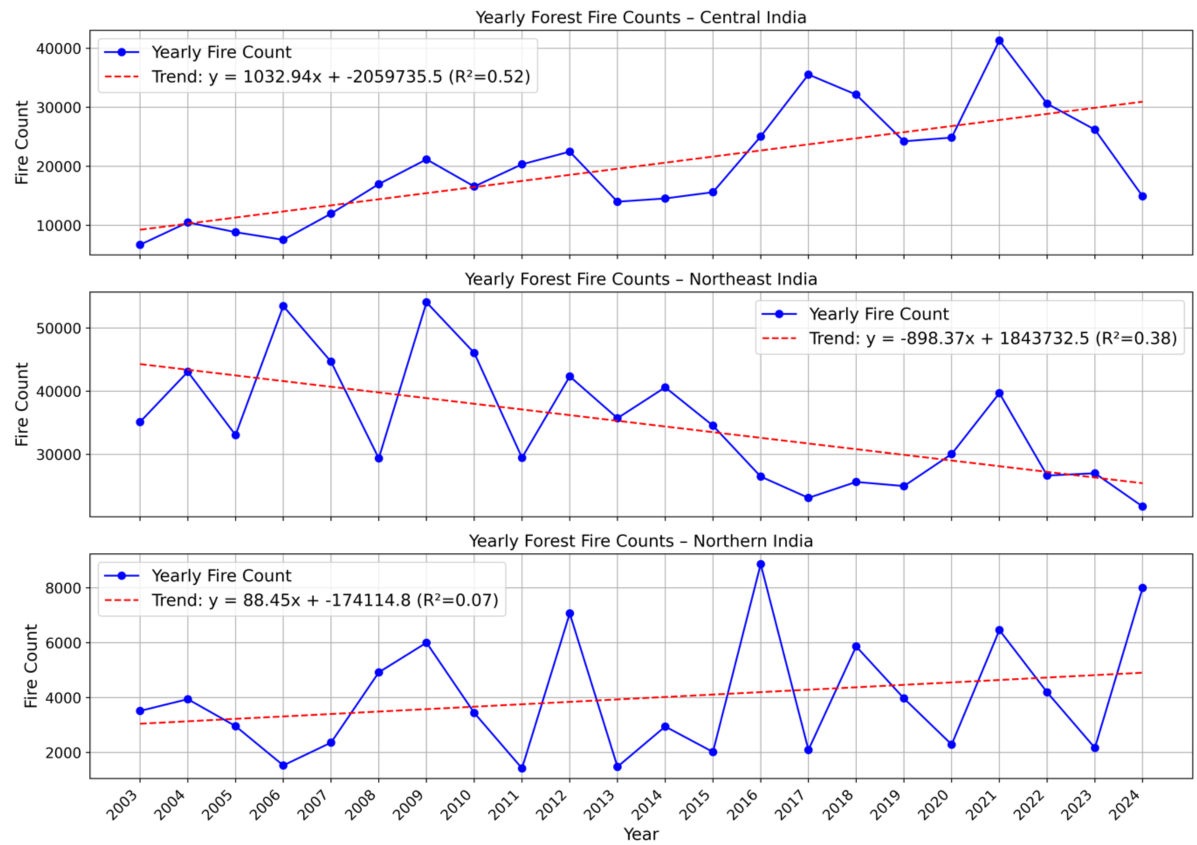

Figure 4: Time series plots of yearly forest fire counts for three study regions: Central India, North-eastern India, and Northern India. For each region, the blue markers represent the actual annual fire counts, while the red dashed line shows the linear trend, with the equation and R^2 value provided in the legend. The titles of each subplot indicate the respective study region.

The linear trend analysis reveals distinct patterns across the three regions. In Central India, the trend line ($y = 1032.94x + -2059735.5$, $R^2 = 0.52$) indicates a moderate positive trend in yearly fire counts, suggesting an increase in fire activity over the 22-year period. This upward trajectory aligns with increasing anthropogenic pressures, such as expanding agricultural burning (Sahu et al., 2021) and forest clearing for development in Madhya Pradesh and Chhattisgarh, coupled with climatic shifts that prolonged dry seasons. The R^2 value of 0.52 reflects a reasonable fit, indicating that about half of the variability in fire counts can be explained by the linear trend, though other factors like interannual climate variability likely contribute to fluctuations.

In contrast, the North Eastern region shows a negative trend ($y = -898.37x + 1843732.5$, $R^2 = 0.38$), suggesting a decline in fire counts over time. This downward trend may reflect changes in land-use practices, such as reduced reliance on shifting cultivation (jhum) due to policy interventions like the New Land Use Policy [NLUP] 2011, Forest Policy 1988, and Jhum Land

Regulation 1948. governments have made consistent efforts to terminate shifting cultivation and replace it with high revenue-generating settled agriculture. However, the R^2 value of 0.38 indicates a weaker fit, implying that the linear model captures only a portion of the variability, possibly due to erratic fire patterns influenced by local weather or inconsistent fire management practices (FSI, 2021).

The Northern Himalayan region exhibits a slightly positive trend ($y = 88.45x + -174114.8$, $R^2 = 0.07$), but the low R^2 value suggests a very weak linear relationship. This minimal trend and poor fit likely stem from the region's high interannual variability, driven by complex topography, fluctuating monsoon patterns, and sporadic human-induced fires from tourism or grazing activities in Uttarakhand and Himachal Pradesh (Bhandari et al., 2012). The weak trend highlights the challenge of modelling fire activity in this region with a simple linear approach, as climatic and anthropogenic factors create inconsistent patterns.

The yearly trends highlight regional differences in fire dynamics. Central India's increasing fire counts signal a need for enhanced fire prevention, such as controlled burns or stricter land-use regulations (Srivastava & Garg, 2013). The North Eastern region's decline suggests potential benefits from sustainable agricultural shifts, though monitoring remains crucial given the moderate R^2. The Northern Himalayan region's weak trend calls for adaptive management strategies to address its variability, such as real-time fire detection systems.

Correlation Analysis

This section examines the correlation between $PM_{2.5}$ concentrations and forest fire counts. The analysis aims to assess the relationship between fire activity and air pollution, focusing on $PM_{2.5}$ as a key indicator of fire-related emissions.

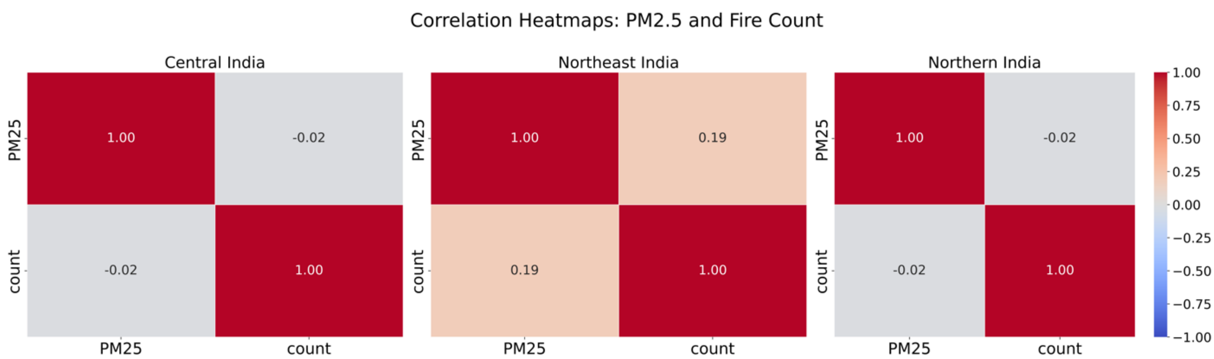

Figure 5: This figure presents correlation heatmaps illustrating the relationships between $PM_{2.5}$ concentrations and forest fire counts.

The correlation analysis reveals negligible associations in Central India and the Northern (Himalayan) region, with correlation coefficients of -0.02 for both. These near-zero values suggest that forest fire counts have little to no linear relationship with $PM_{2.5}$ levels in these regions. In Central India, characterised by dry deciduous forests, fires may produce significant $PM_{2.5}$, but other sources such as vehicular emissions, industrial activities, or dust—likely dominate air pollution patterns, diluting the fire-specific signal (Guttikunda & Calori, 2013). Similarly, in the Northern Himalayan region, the complex topography and variable wind patterns may disperse fire-related $PM_{2.5}$ rapidly, while urban pollution and biomass burning for heating could overshadow fire contributions. The negligible correlations indicate that $PM_{2.5}$ variability in these regions is driven by a mix of sources, with forest fires playing a limited role in the overall pollution profile.

In contrast, the North Eastern region shows a weak positive correlation of 0.20, suggesting a modest relationship between forest fires and $PM_{2.5}$ levels. This association likely stems from the region's reliance on shifting cultivation (jhum), which generates localized smoke and particulate matter during the fire-prone months of February to April (Ramakrishnan, 1992). The evergreen and semi-evergreen forests, combined with less industrialized landscapes compared to Central India, may allow fire-related $PM_{2.5}$ to contribute more noticeably to air quality. However, the correlation remains weak, indicating that other factors, such as seasonal meteorology or non-fire biomass burning, still influence $PM_{2.5}$ variability (FSI, 2021).

Given the negligible correlations in Central India and the Northern Himalayan region, and the weak correlation in the North Eastern region, a simple region-wide correlation analysis appears insufficient to capture the nuanced interactions between forest fires and $PM_{2.5}$. To address this, a spatial and regionalised correlation analysis is proposed. By examining correlations at finer spatial scales, which is grid-scale, this can better isolate fire-related $PM_{2.5}$ contributions from other pollution sources. Such an analysis could reveal localised hotspots where fires significantly impact air quality, informing targeted mitigation strategies.

Spatial Correlation Analysis

To further investigate the relationship between forest fires and $PM_{2.5}$ concentrations, a spatial correlation analysis was conducted at the grid scale, focusing exclusively on days with recorded fire activity. This approach isolates fire-related $PM_{2.5}$ contributions by filtering out non-fire days, enabling a more precise assessment of fire impacts on air quality. Correlation coefficients were calculated for each grid cell and plotted as contours on a map, with a land use/land cover (LULC) map alongside to contextualise the results.

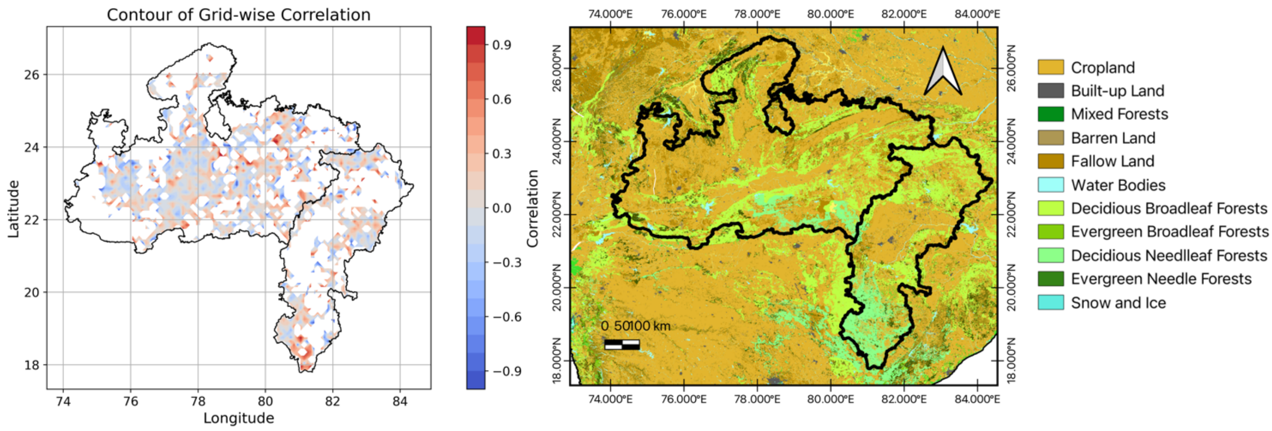

Figure 6: The left panel of the figure shows a contour map of grid-wise correlation coefficients between forest fire counts and $PM_{2.5}$ concentrations across Central India The values range from -1 to 1. The right panel illustrates the corresponding LULC map with a legend of its LULC categories on the right.

In Central India, the spatial correlation analysis reveals a complex and heterogeneous distribution of correlation coefficients, reflecting the region's diverse LULC patterns dominated by deciduous broadleaf and deciduous needleleaf forests. Across much of the region, areas with positive correlation are sparse and faintly distributed, suggesting that forest fires have a limited and inconsistent impact on $PM_{2.5}$ levels. Cropland-dominated areas exhibit predominantly negative correlations, indicating that $PM_{2.5}$ variability in these zones is likely driven by non-fire sources, such as agricultural residue burning, vehicular emissions, or dust, which may mask fire-related contributions (Guttikunda & Calori, 2013). This aligns with the negligible region-wide correlation (r = -0.02) reported earlier, where the irregular forest distribution and prevalence of other pollution sources dilute the fire-specific $PM_{2.5}$ signal. However, a distinct pattern emerges in southern Chhattisgarh, where a dense expanse of deciduous needleleaf forest coincides with a substantial area of high positive correlation. This hotspot, characterized by contiguous forest cover and fewer competing pollution sources, indicates that forest fires significantly elevate $PM_{2.5}$ concentrations during fire events. The strong correlation in this subregion suggests that fire-related emissions, amplified by the high biomass content of deciduous needleleaf forests, contribute substantially to local air pollution, with seasonal fires generating localized smoke plumes that are less dispersed due to relatively stable meteorological conditions (FSI, 2021).

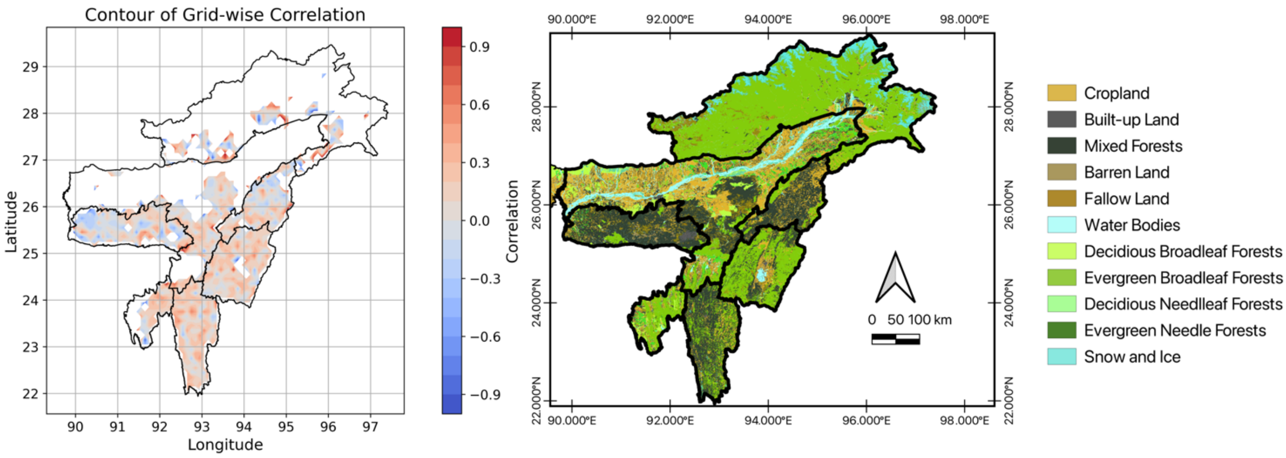

Figure 7: The left panel of the figure shows a contour map of grid-wise correlation coefficients between forest fire counts and $PM_{2.5}$ concentrations across northeast India The values range from -1 to 1. The right panel illustrates the corresponding LULC map with a legend of its LULC categories on the right.

In the North Eastern region, the forested region is characterized by a mix of evergreen broadleaf and evergreen needleleaf forests, except in Meghalaya, which is dominated by evergreen needleleaf forests, and Arunachal Pradesh, which primarily consists of evergreen broadleaf forests. Areas with mixed forest types exhibit a relatively uniform high positive correlation ($r > 0.5$), suggesting that forest fires in these zones consistently contribute to elevated $PM_{2.5}$ levels. This pattern is likely driven by the region's reliance on shifting cultivation, which generates significant smoke and particulate matter during the fire-prone months of February to April (Ramakrishnan, 1992) and the absence of anthropogenic sources. In Meghalaya, however, the correlation varies spatially: the eastern part shows positive correlations, while the western part exhibits negative correlations. In Arunachal Pradesh, the absence of significant fire activity, likely due to colder temperatures and high moisture content in evergreen broadleaf forests, results in negligible correlations (FSI, 2021). The uniform high correlations in mixed forest areas underscore the role of fire-prone evergreen forests in driving $PM_{2.5}$ levels, while the variability in Meghalaya and low fire activity in Arunachal Pradesh highlight the influence of local ecological and climatic factors.

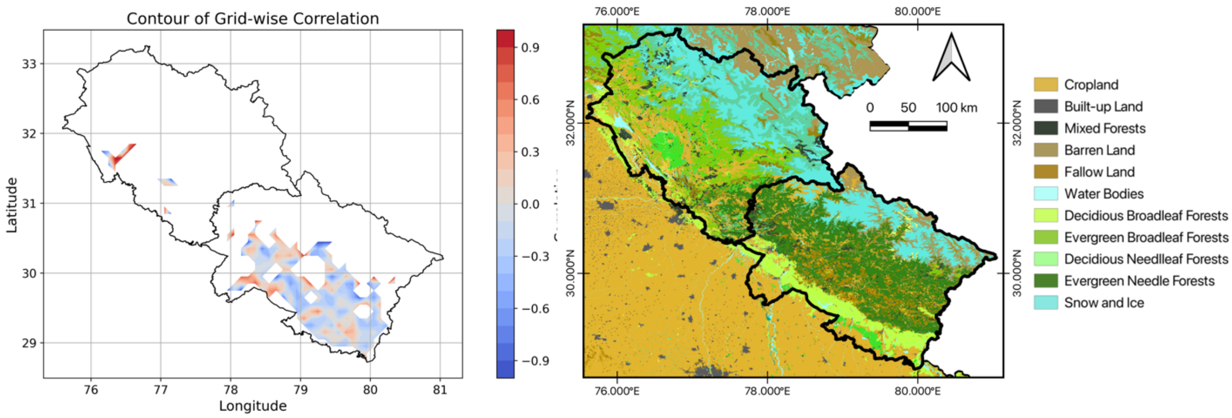

Figure 8: The left panel of the figure shows a contour map of grid-wise correlation coefficients between forest fire counts and $PM_{2.5}$ concentrations across north India (Himalayas). The values range from -1 to 1. The right panel illustrates the corresponding LULC map with a legend of its LULC categories on the right.

In the Northern Himalayan region, the spatial correlation analysis reveals no clear trend, with a mix of positive and negative correlations across the states of Himachal Pradesh and Uttarakhand. In Himachal Pradesh, fire activity is minimal, likely due to the predominance of high-altitude evergreen broadleaf forests and snow-covered areas, which limit fire occurrence (FSI, 2021). Consequently, correlations between forest fires and $PM_{2.5}$ are negligible, as other sources, such as urban pollution or biomass burning for heating, dominate air quality patterns. In Uttarakhand, the LULC transitions from deciduous broadleaf forests at lower elevations to evergreen needleleaf forests at mid-elevations, followed by snow-covered regions at higher altitudes. Despite the presence of fire-prone deciduous forests, the spatial correlation analysis shows no consistent pattern, with a mix of positive and negative correlations. This lack of trend may be attributed to complex topography and variable wind patterns, which rapidly disperse fire-related $PM_{2.5}$, combined with contributions from non-fire sources such as vehicular emissions and domestic fuelwood burning. The absence of a clear spatial trend in this region aligns with the negligible region-wide correlation ($r = -0.02$) reported earlier, indicating that forest fires play a limited role in $PM_{2.5}$ variability.

The spatial correlation analysis reveals significant regional variations in the relationship between forest fires and $PM_{2.5}$ concentrations, driven by differences in LULC, fire activity, and competing pollution sources. The findings discussed above emphasise the need for spatially explicit analyses to identify fire-driven $PM_{2.5}$ hotspots, such as southern Chhattisgarh and parts of the North Eastern region, where targeted fire management could effectively reduce air pollution. Future research should integrate temporal fire patterns, meteorological data, and source apportionment studies to further elucidate the complex interactions between forest fires and $PM_{2.5}$ across diverse regions (Sharma et al., 2010; FSI, 2021).

Granger Causality Test

The Granger causality test is a statistical method that determines whether one time series (e.g., forest fire counts) can predict another (e.g., $PM_{2.5}$ concentrations) by testing if past values of the first series improve the prediction of the second beyond the information in its own past values. The quantities derived from this test—F-statistics, p-values), chi² statistics play critical roles in determining the causal relationship. The F-statistic and chi² statistic assess the improvement in model fit when lagged fire counts are included, with higher values indicating a stronger potential causal effect, though significance hinges on the p-value. The p-value, thresholded at 0.05, determines whether the observed relationship is statistically significant, rejecting the null hypothesis of no causality when below this level. Together, these quantities shape the inference of causality, with significant results suggesting that past fire counts predict $PM_{2.5}$ levels, while non-significant outcomes point to other dominant factors.

To assess the causal relationship between forest fire counts and $PM_{2.5}$ concentrations, a Granger causality test was conducted across Central India, Northeast India, and Northern India, with lag orders ranging from 1 to 7. The test results, summarised in Table 1, include F-statistics, p-values, and chi-squared tests. A significance level of $p < 0.05$ was used to determine causality.

The Granger causality test evaluates whether past values of forest fire counts can predict $PM_{2.5}$ concentrations beyond the information already contained in past $PM_{2.5}$ values. In Central India, all lag orders from 1 to 7 yield p-values ranging from 0.1260 to 0.4150 across various test statistics, with the lowest p-value (0.1260) at lag 5. These results indicate no significant causal relationship ($p > 0.05$), suggesting that forest fires do not Granger-cause $PM_{2.5}$ concentrations in this region. This aligns with the earlier spatial correlation findings, where heterogeneous land use and non-fire pollution sources, such as industrial emissions and dust, likely dominate $PM_{2.5}$ variability.

Table 1: Granger Causality Test Results for Forest Fires and $PM_{2.5}$

Lag	Central India		Northeast India		Northern India	
	SSR-based F Test (F, p)	SSR-based Chi2≤ Test (chi2≤, p)	SSR-based F Test (F, p)	SSR-based Chi2≤ Test (chi2≤, p, df)	SSR-based F Test (F, p)	SSR-based Chi2≤ Test (chi2≤, p)
1	F=0.8584, p=0.3546	Chi2≤=0.86 , p=0.3530	F=8.4481, p=0.0038	Chi2≤=8.50, p=0.0036	F=0.9794, p=0.3233	Chi2≤=0.99 , p=0.3195
2	F=1.2778, p=0.2794	Chi2≤=2.57 , p=0.2757	F=2.6770, p=0.0698	Chi2≤=5.40, p=0.0669	F=0.8845, p=0.4142	Chi2≤=1.80 , p=0.4056
3	F=1.1700, p=0.3204	Chi2≤=3.55 , p=0.3141	F=2.2611, p=0.0806	Chi2≤=6.88, p=0.0757	F=0.7512, p=0.5226	Chi2≤=2.31 , p=0.5091
4	F=0.9852, p=0.4150	Chi2≤=4.00 , p=0.4058	F=1.6170, p=0.1688	Chi2≤=6.59, p=0.1592	F=0.5645, p=0.6886	Chi2≤=2.34 , p=0.6731
5	F=1.7290, p=0.1260	Chi2≤=8.80 , p=0.1170	F=2.4545, p=0.0327	Chi2≤=12.5, p=0.0279	F=1.2908, p=0.2685	Chi2≤=6.75 , p=0.2398
6	F=1.5571, p=0.1574	Chi2≤=9.55 , p=0.1448	F=1.8577, p=0.0865	Chi2≤=11.4, p=0.0753	F=1.2884, p=0.2632	Chi2≤=8.15 , p=0.2269
7	F=1.4215, p=0.1938	Chi2≤=10.2 , p=0.1770,	F=1.7245, p=0.1012	Chi2≤=12.4, p=0.0864	F=1.1837, p=0.3129	Chi2≤=8.8, p=0.2659

In Northeast India, the test shows a significant causal effect at lag 1 ($p = 0.0038$) and lag 5 ($p = 0.0327$), with F-values of 8.4481 and 2.4545, respectively. This suggests that forest fire counts Granger-cause $PM_{2.5}$ concentrations, particularly with a one-lag and five-lag delay. At other lags (2-4 and 6-7), p-values range from 0.0698 to 0.1688, indicating weaker or non-significant causality.

In Northern India, p-values across all lag orders (1-7) range from 0.2632 to 0.6886, with no value below the 0.05 threshold, indicating no significant Granger causality. This result is consistent with the negligible spatial correlations and minimal fire activity in the Himalayan region, where complex topography and cold temperatures limit fire occurrence and disperse $PM_{2.5}$ rapidly (FSI, 2021).

The Granger causality analysis highlights regional differences in the temporal dynamics of fire-$PM_{2.5}$ relationships. Northeast India's significant causality at specific lags underscores the role of fire-prone land use practices, while the lack of causality in Central and Northern India reflects the dominance of non-fire sources and environmental constraints. These findings suggest that fire management strategies should focus on Northeast India, particularly during peak fire seasons, while broader pollution control measures are needed in Central and Northern India.

Discussion

This study examines the relationship between forest fires and PM2.5 concentrations across Central India, Northeast India, and the Northern Himalayan region, using high-resolution satellite data and statistical methods. The results reveal regional variations in fire activity and PM2.5 dynamics, offering insights for air quality management and policy.

Regional Variations in Fire-PM2.5 Relationships

In Northeast India, strong positive correlations in evergreen and mixed forest areas, coupled with Granger causality at lags 1 and 5, indicate that forest fires significantly drive PM2.5 levels during the February-April fire season. This is largely due to shifting cultivation, which produces substantial smoke in regions with limited industrial pollution, amplifying the fire-PM2.5 signal. Central India shows a complex pattern, with a PM2.5 hotspot in southern Chhattisgarh's deciduous forests, but negligible region-wide correlations ($r = -0.02$) and no causality, suggesting non-fire sources like agricultural burning and industrial emissions dominate (Guttikunda & Calori, 2013). The Northern Himalayan region exhibits no clear fire-PM2.5 link, with minimal fire activity in Himachal Pradesh and variable patterns in Uttarakhand due to rapid pollutant dispersal and urban pollution sources

Forest Fire-Induced PM2.5 Spikes and Long-Range Transport

Forest fires in dense forested areas, such as southern Chhattisgarh and Northeast India, cause significant PM2.5 spikes, driven by biomass combustion in deciduous and evergreen forests. These fine aerosols can travel hundreds of kilometers via wind patterns, potentially reaching urban centers like those in the Indo-Gangetic Plain, where they contribute to regional haze. In urban areas, fire-derived PM2.5 blends with local pollution, masking its origin but increasing health risks, including respiratory and cardiovascular diseases, especially for vulnerable populations. The transboundary nature of these aerosols, as seen in Himalayan fire plumes affecting Nepal, necessitates regional cooperation and advanced monitoring to manage their impacts.

Implications for Public Health and Environmental Management

The strong fire-PM2.5 link in Northeast India calls for targeted fire management to reduce exposure, particularly for indigenous communities, who face heightened risks of respiratory illnesses due to limited healthcare access. Central India's Chhattisgarh hotspot suggests localized fire management could improve air quality, but broader strategies are needed to address dominant non-fire sources. In the Northern Himalayas, where fires play a minor role, air quality efforts should prioritise urban pollution, while proactive fire prevention protects sensitive ecosystems amid rising climate-driven risks.

Methodological Contributions and Limitations

The use of LGHAP v2 PM2.5 and FIRMS fire data at 10 km resolution advances prior studies with coarser datasets, enabling robust correlation and causality analyses. Integrating land use/land cover data enriched ecological context. However, the 2017-2021 PM2.5 data limits long-term trend analysis, and 10 km resolution may obscure fine-scale variations. The Granger causality test's linearity assumption may miss complex dynamics, such as secondary aerosol formation, suggesting a need for advanced modelling. The focus on three regions limits generalizability to other fire-prone areas like the Western Ghats.

Future Research Directions

Future studies should incorporate meteorological data to assess wind and humidity effects on PM2.5 dispersal, particularly in the Himalayas. Source apportionment studies can clarify fire versus non-fire contributions in Central India. Tracking aerosol pathways with models like HYSPLIT can map long-range PM2.5 transport to urban areas, informing mitigation (Thakur et al., 2024). Predictive machine learning models for Northeast India could enable early warnings for PM2.5 episodes. Comparative studies with Asian fire-prone regions can foster global best practices for fire and air quality management (Li et al., 2023).

Conclusion

This study reveals significant regional variations in the relationship between forest fires and PM2.5 concentrations across India, with Northeast India showing a strong fire-PM2.5 link due to shifting cultivation, while Central and Northern India are dominated by non-fire pollution sources. The identification of PM2.5 spikes in dense forested areas, particularly in southern Chhattisgarh and Northeast India, and their potential to travel hundreds of kilometres to urban centres, underscores the hidden public health risks posed by fire-related aerosols, which can exacerbate respiratory and cardiovascular diseases in urban populations unaware of their origin

These findings highlight the need for region-specific fire management and air quality strategies aligned with the National Clean Air Programme (NCAP) and National Action Plan on Forest Fires (NAPFF). Future research should focus on tracking aerosol pathways using atmospheric transport models and integrating meteorological data to enhance predictive capabilities, supporting targeted interventions to mitigate the health and environmental impacts of forest fire-induced PM2.5 pollution across India and beyond

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