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Forest fire dynamics in India (2005–2022): Unveiling climatic Impacts, spatial Patterns, and interface with anthrax incidence

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ABSTRACT

The comprehensive analysis of forest fires in India from 2005 to 2022 underscores the urgent need for national-scale management and conservation efforts. Using kriging techniques, significant hotspots were identified, revealing a substantial increase in forest fire incidents in Mizoram by 2022, averaging 2614.78 ± 1519.36 occurrences. The study highlights the direct influence of climate conditions on forest fire occurrences, with significant positive correlations found with average and maximum temperatures. Furthermore, the impact of forest fires on anthrax dynamics in Orissa, Jharkhand, and Andhra Pradesh was examined, illustrating the ecological disruptions' implications for livestock and public health. This study advocates for interdisciplinary collaboration and tailored strategies to proactively manage forest fires, safeguard biodiversity, and ensure community well-being.

1. Introduction

India possesses merely one per cent of the global primary forests, characterized as native, natural and undisturbed forest ecosystems devoid of human activities. The escalation of anthropogenic activities worldwide, including agriculture, urbanization, and industrialization, driven by the burgeoning global population, poses a significant threat to both primary and secondary forest ecosystems (Parashar and Biswas, 2003; Cobb and Metz, 2017). Among the myriad of challenges faced by forest ecosystems, forest fires stand out, with a noticeable increase in frequency and intensity globally (Robinne et al., 2018), affecting around (1 %) of all forested areas annually. Fires affect forest ecosystems in two ways: high-intensity fire disturbances severely harm the equilibrium of forest ecosystems and cause the degradation of forest ecosystems; low-intensity fires help prevent major fires, preserve biodiversity, and promote natural regeneration (Liu et al., 2024).

1.1. Climate change and forest fires

The relationship between climate and forest fires has garnered attention within the scientific community, categorizing studies into two regimes: fuel-limited and flammability-limited. These regimes highlight the critical role of climatic conditions in preconditioning fuels in the months to years preceding the fire season. Global warming is anticipated to alter temperature and precipitation patterns worldwide, with climate and fire scientists predicting an increase in wildfire activity as the planet warms (Abatzoglou and Kolden, 2013). The impacts of climate change on wildfires are expected to become more severe, driven by the frequency of extreme weather events (Keith et al., 2009). These climate changes have the potential to significantly affect wildfire frequency, size, and intensity, leading to higher fire risks, longer fire seasons, and more severe consequences. The resulting hazards and vulnerabilities include microclimate alteration, floods, infrastructure destruction, economic losses, and human casualties. Post-wildfire conditions may accelerate other environmental disturbances, causing modified vegetation patterns, land degradation, desertification, and disruptions in the hydrological cycle. Even seemingly small climate changes can trigger catastrophic shifts in ecosystems when human exploitation compromises their resilience (SCBD, 2001; Forbes et al., 2011). Furthermore, carbon emissions and other greenhouse gases from wildfires create feedback loops on the climate, forming a cycle where more fires lead to increased emissions, creating conditions conducive to further wildfires (Abatzoglou and Kolden, 2013).

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1.2. Indian forests

India's remarkable biodiversity, covering over one-fifth of its territory, is home to approximately 173,000 forest villages inhabited mainly by tribal communities, that rely heavily on forest resources for sustenance (Kishwan et al., 2009). These communities significantly contribute to government revenue through the extraction of minor forest products, emphasizing the delicate balance between human livelihoods and sustainable forest use. The classification of dense, moderately dense, and open forest types, outlined by the Food and Agriculture Organization and the United Nations Framework Convention on Climate Change, relies on criteria such as canopy cover and tree height. According to the Forest Survey of India (FSI) 2021 report, India's total forest and tree cover stands at 80.9 million hectares, accounting for 24.62 per cent of the country's geographical area, showing an increase of 2,261 sq. km compared to 2019. This represents a two per cent contribution to the global forested area and one per cent to global primary forests. The country's forests, diverse in nature, comprise 18 distinct types grouped into five major categories based on dominant vegetation, including tropical evergreen, tropical deciduous, tropical thorn, montane, and swamp forests, as outlined by the FAO in 2015.

1.3. Forest fires in India

Forest fires in India are a pressing concern, particularly in regions like Madhya Pradesh, Odisha, and Chhattisgarh, where dry deciduous forests are prevalent. These fires, occurring mainly in April and May, are fueled by substantial vegetation and reduced soil moisture. Traditional practices like Jhumming contribute to forest fires in northeastern India. Satellite data is crucial due to limited statistical information on fire incidents. Human activities cause around 90 per cent of forest fires in India, necessitating robust prevention strategies. Forest fires are classified into natural and human factors, with understanding these factors vital for mitigation. Dry deciduous broadleaved forests are especially susceptible, notably during dry pre-monsoon periods. MODIS data reveals concentrated fire events in central and east-central India, while Chir Pine forests in the Himalayas are also vulnerable (Chandra and Kumar Bhardwaj, 2015; Puri et al., 2011; Roy, 2003; Kale et al., 2017; Jaiswal et al., 2002; Sannigrahi et al., 2020; Joseph et al., 2009). Recent literature underscores the significant impact of climate change on forest fire dynamics. Mina et al. (2023) highlight the interaction between climatic factors and fire intensity in the central Himalayas, while Yashwant (2023) links the surge in forest fires to climate change, affecting biodiversity and carbon emissions. Mohanty and Mithal (2022) report a tenfold increase in fire incidents over the past two decades, emphasizing the need for improved management practices. Barik and Baidya Roy (2023) project significant changes in fire weather regimes due to climate variations, and Sewak et al. (2022) review the increasing frequency and intensity of fires, detailing contributing climatic factors and socioeconomic impacts. These insights provide a comprehensive understanding of the interplay between forest fires and climate change.

1.4. Forest fire points

"Forest fire points" are specific locations where forest fires have been detected or are actively burning, playing a crucial role in environmental conservation, disaster management, and public safety in India. The Indian landscape, rich in forest cover and biodiversity, is prone to recurrent forest fires due to various factors such as changing climatic patterns and human activities. Understanding these dynamics is essential for timely response, resource allocation, and policymaking. Kumar et al. (2019) used GIS analysis to classify forest areas based on their susceptibility to fires, identifying categories from extremely fire-prone to less fire-prone. The Forest Survey of India (FSI) 2021 reports that about 10.66 per cent of India's forest cover is in extremely to very highly fire-prone zones, with states like Mizoram, Tripura, Meghalaya, and Manipur showing the highest fire tendencies. Approximately 65 per cent of India's deciduous forests are susceptible to fires, resulting in an annual economic loss of around $104 million (Ashutosh et al., 2019). India aims to increase its forest cover to 33 per cent by 2030, as outlined in its Intended Nationally Determined Contributions (INDC) plan. However, the rising frequency of forest fires poses a potential impediment to these goals, highlighting the urgent need for comprehensive and sustainable fire management strategies (Dogra et al., 2018).

1.5. Flame ignition factors

While numerous studies in developed countries have explored the relationship between forest fires and environmental parameters, our research addresses a significant gap by providing a detailed analysis of forest fire regimes in India using 18 years of data. We integrate data from the Forest Survey of India (FSI) spanning from 2005 to 2022 with meteorological factors such as minimum temperature (Tmin), maximum temperature (Tmax), average temperature (Tav), relative humidity (RH), wind speed (WS), Normalized Difference Vegetation Index (NDVI), elevation, and population density. These data are sourced from reputable agencies like the Climatic Research Unit (CRU), the National Oceanic and Atmospheric Administration (NOAA), and the Moderate Resolution Imaging Spectroradiometer (MODIS). Utilizing Geographic Information System (GIS) methodologies with spatial resolutions ranging from 0.25° x 0.25° to 2.0° x 2.0°, our approach provides a comprehensive analysis of forest fire dynamics. The insights gained are intended to support evidence-based policy decisions for effective forest fire management.

1.6. Anthrax and forest fire points

Anthrax, a zoonotic disease with persistent global health threats, is caused by *Bacillus anthracis*, a resilient, soil-borne bacterium. Surviving for extended periods under favourable conditions, *B. anthracis* infects hosts rapidly, particularly when soil pH and concentrations of organic calcium, potassium, and zinc are conducive. Grazing animals inadvertently encounter spores when grazing close to the soil surface or congregating in limited areas during water scarcity (Sushma et al., 2021; Suresh et al., 2022). Spores, resilient to extreme environmental conditions, persist despite heat, cold, desiccation, chemicals, and irradiation, with anthrax incidence varying by soil type and climate (Suresh et al., 2023). Our study investigates the intertwined relationship between anthrax outbreaks and forest fires, recognizing their potential interconnectedness. By exploring how forest fires can indirectly influence anthrax dynamics through habitat disruption and altered wildlife behaviour, we aim to better understand the complex interplay between ecological disturbances and disease dynamics.

The primary objectives of this study are to identify forest fire hotspots across districts in India at a national scale, analyze their spatial variations using Kriging interpolation techniques, and investigate the relationship between forest fires and various fire-related indices through statistical methods such as Kendall's tau (τ) test and Bland-Altman Analysis. Additionally, the study aims to explore the impact of forest fires on anthrax occurrences in Jharkhand, Orissa, and Andhra Pradesh—states with the highest frequency of anthrax attacks. By accomplishing these objectives, the study aims to provide an integrated assessment of forest fires and climate in India.

2. Material and methods

2.1. Study area

The study covers India, extending 3,287,263 km2 between latitudes 6° 44′ N and 35° 30′ N, and longitudes 68° 07′ E and 97° 25′ E. With forest cover comprising 24.62 % of its land area, as defined by the Forest Survey of India (FSI) with a canopy density exceeding 10 %, India's forests are predominantly tropical dry and moist deciduous, covering 68 % of the total forested area (Champion and Seth, 1968; Reddy et al., 2015).

The study examines forest coverage and historical fire hotspots across India (Fig. 1). Fig. 1 presents fire data aggregated at the district level, which enhances the analysis of fire patterns about meteorological and climatic factors by detailing how fire occurrences vary across different environmental conditions.

2.2. Forest fire points trends in India from 2005 to 2022

Forest fire data from 2005 to 2022 was analyzed by converting district-level fire events into percentages relative to the total number of forest fires in India, with 100 % representing the national baseline. This approach, which examines monthly data from January to June, reveals the temporal and spatial patterns of forest fires. The study covered 36 states and 732 districts, involving the creation of a comprehensive dataset and applying spatial analysis techniques, including variogram modelling, to assess distribution and clustering.

Fig. 2 illustrates a marked increase in forest fire events over the period. Beginning with 8,430 fires in 2005, the number fluctuated but exhibited an overall upward trend. Significant peaks occurred in 2010, 2012, 2017, 2019, 2021, and 2022, with the highest recorded at 104,500 events in 2021. This upward trajectory highlights a growing incidence of forest fires, underscoring the need for enhanced forest management and fire prevention strategies.

2.3. Data collection, sources, pre-processing and analysis

We utilized forest fire count datasets from 2005 to 2022, provided by the Forest Survey of India (FSI), which offers downloadable data. FSI conducts systematic analyses of forest fire events across India using data from the Moderate Resolution Imaging Spectroradiometer (MODIS) satellite system, in collaboration with NASA and the University of Maryland's Geography Department. The MODIS-based active fire points are refined by FSI to exclude non-forest areas using existing forest cover

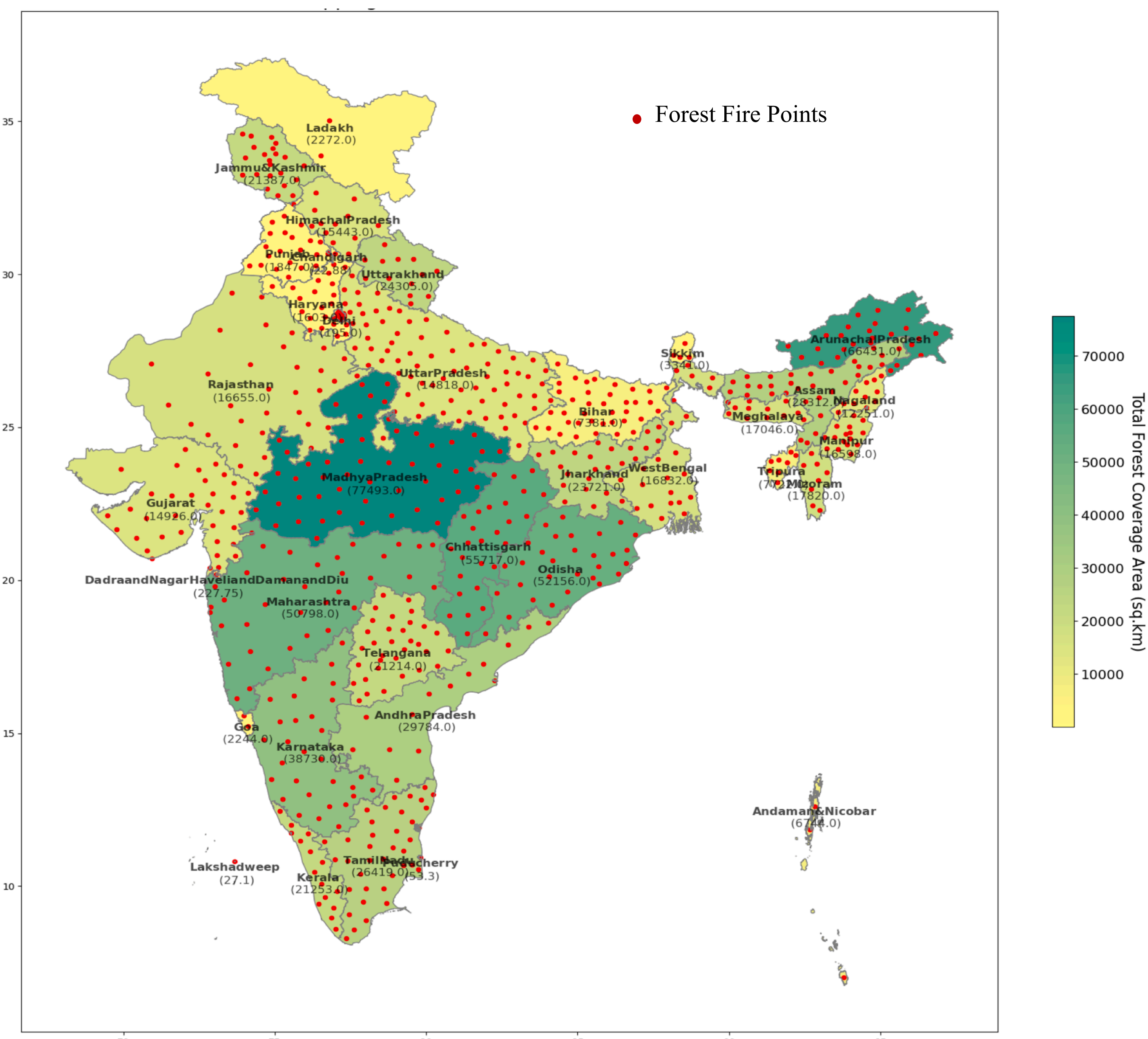

Fig. 1. Map illustrating forest coverage and historical hotspots of forest fires across India.

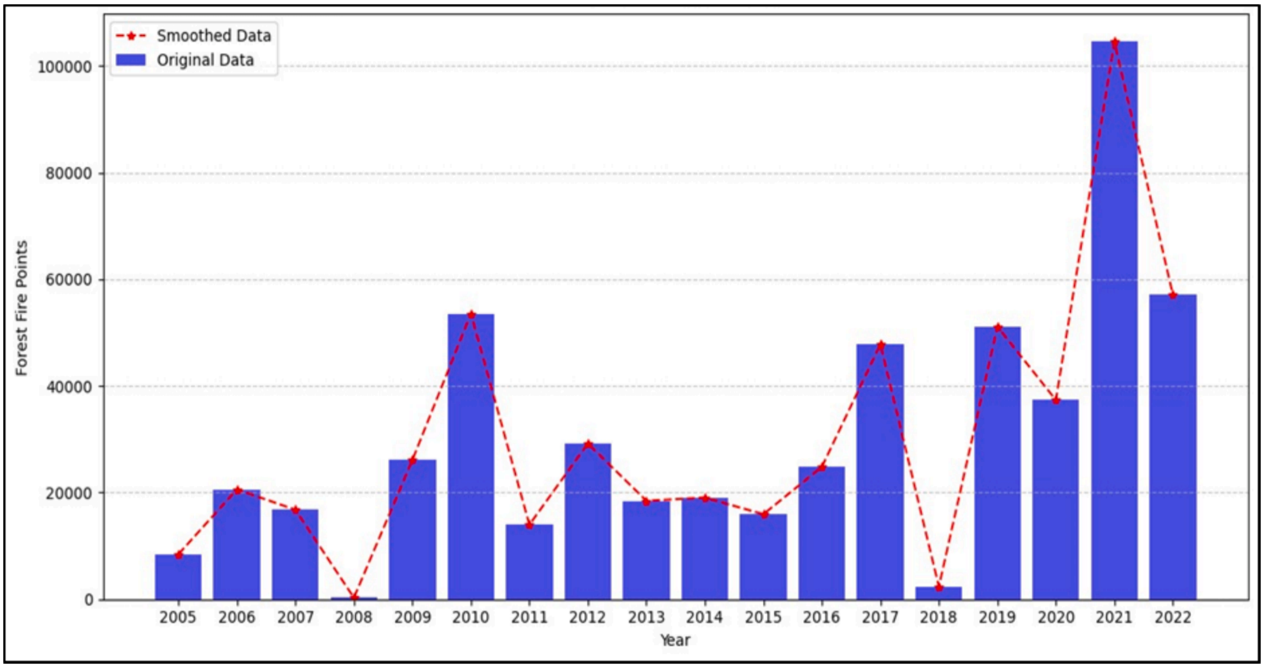

Fig. 2. Temporal trends in forest fire points (FFP) across India from 2005 to 2022, showing annual variations and patterns.

information. We acquired the geographical coordinates (latitude and longitude) of fire incidents in MS Excel format from the FSI website, which were converted into point shape files using ARC/GIS software. The dates associated with these fire points were extracted into day, month, and year columns. The study then focused on generating district-wise forest fire hotspots across India at the national level, identifying areas with the highest frequency of fires relative to the total number of forest fire events during the study period.

2.3.1. *Kriging*

Kriging is a spatial interpolation technique used to estimate variable values across a continuous area based on sampled data points. In this study, ordinary kriging, a common method, assumes a constant mean unless otherwise justified. The procedure involves fitting a variogram to determine the spatial covariance structure and using this information to interpolate values for unsampled locations. To address the non-normal distribution of forest fire count data, a logarithmic transformation is applied before kriging analysis. This transformation helps the data approximate a normal distribution, making it more suitable for kriging. Kriging is particularly useful for analyzing and predicting spatial patterns affected by human activities.

2.3.1.1. Variogram, nugget, sill and range. A variogram is a tool used to analyze spatial correlation by plotting the semi-variance (gamma-value), which measures the average squared difference between data pairs, against the distance or "lag" between them. The "experimental" variogram represents observed values, while the "theoretical" or "model" variogram shows the best-fitting distributional model. Key components of the variogram include the nugget, sill, and range. The nugget reflects small-scale variability or measurement error, the sill represents the maximum variability at large distances, and the range indicates the distance at which spatial correlation diminishes. By fitting models such as Gaussian, spherical, or exponential to the data, the variogram helps quantify spatial correlation and select the most appropriate model using statistical measures like Root Mean Square Error (RMSE).

Spherical model:

$$\widehat{y}(h) = C_0 + C\left[1.5\frac{h}{a} - \left(\frac{h}{a}\right)^3\right],\ if\ 0 \leq h \leq a. \tag{1}$$

Exponential model:

$$\widehat{y}(h) = C_0 + C\left[1 - exp\left\{-\frac{h}{a}\right\}\right]\ for\ h \geq 0 \tag{2}$$

Gaussian model:

$$\widehat{y}(h) = C_0 + C\left[1 - exp\left\{-\frac{h^2}{a^2}\right\}\right]\ for\ h \geq 0 \tag{3}$$

Where C is sill, a is nugget, h is lag values.

While various statistical methods, such as Root Mean Square Error (RMSE), least-squares, maximum likelihood, and Bayesian approaches, can aid in selecting the optimal variogram model, the final choice relies on user judgment. The best-fitting variogram model was determined based on RMSE values, which indicate how well the model fits the data. Different variogram models were assessed for the forest fire points (FFP) values.

Ordinary kriging was selected for interpolation due to its effectiveness in producing smooth estimates without needing additional data and its capacity to provide predictions with associated uncertainty. The chosen variogram model guided the ordinary kriging process, ensuring an accurate representation of spatial relationships. The interpolated results were visualized using shapefiles created in R, while the kriging calculations were performed in Python with libraries such as Pandas, NumPy, GeoPandas, and Matplotlib. This approach ensured precise spatial interpolation of forest fire points.

2.3.2. *Environmental features and data engineering*

To analyze the correlation between district climatology and forest fire points in India, we utilized climate data from 2005 to 2022. Forest fire point (FFP) data, with near real-time monitoring at a 1 km^2 resolution, was sourced from the Forest Survey of India and MODIS. Temperature data (minimum, maximum, average) were obtained from the Climatic Research Unit (CRU) at a 0.5° x 0.5° resolution. Relative humidity (RH) and wind speed (WS) data were provided by NOAA at a 2.0°

x 2.0° resolution. The Normalized Difference Vegetation Index (NDVI) data came from MODIS with a 0.25° x 0.25° resolution. Elevation data were retrieved from DIVA-GIS, and population density data were sourced from Earth Data and the Census of India (Table 1).

Statistical analyses, including correlation tests, will be employed to quantify relationships between environmental variables and forest fire points. This approach aims to provide insights into environmental monitoring and management strategies. Monthly averages of climate attributes and forest fire events for the study area will be analyzed using Kendall's tau (τ) correlation test.

The correlation test aimed to identify significant relationships (P≤0.05) between climate variables and forest fire incidents. Kendall's tau (τ) was calculated using the formula:

$$\tau = \frac{\sum A - \sum B}{\sum A + \sum B} \tag{4}$$

A represents concordant pairs, B represents discordant pairs, n is the number of observations, and Z is the Z-statistic. The Kendall's tau value ranges between −1 and 1, with 0 indicating no relation and 1 representing a perfect positive relation.

In addition, the significance level (1) was assessed to provide a statistical measure of the correlation's strength:

Table 1
Thematic layers of factors used and sources of data.

Parameters	Data Source	Temporal Resolution	Spatial Resolution
Forest Fire Points (FFP)	Forest Survey of India Near real-time monitoring of Forest Fire based on MODIS https://fsiforestfire.gov.in/index.php	Monthly	MODIS (1 km X 1 km)
Minimum Temperature (Tmin)	Climatic Research Unit (CRU) websitehttps://crudata.uea.ac.uk/cru/data/hrg/cru_ts_4.07/cruts.2304141047.v4.07/	Monthly	0.5° x 0.5°
Maximum Temperature (Tmax)	Climatic Research Unit (CRU) websitehttps://crudata.uea.ac.uk/cru/data/hrg/cru_ts_4.07/cruts.2304141047.v4.07/	Monthly	0.5° x 0.5°
Average Temperature (Tav)	Climatic Research Unit (CRU) websitehttps://crudata.uea.ac.uk/cru/data/hrg/cru_ts_4.07/cruts.2304141047.v4.07/	Monthly	0.5° x 0.5°
Relative Humidity (RH)	National Oceanic and Atmospheric Administration (NOAA) https://psl.noaa.gov/data/gridded/data.20thC.html	Monthly	2.0° x 2.0° – 222 km
Wind Speed (WS)	National Oceanic and Atmospheric Administration (NOAA) https://psl.noaa.gov/data/gridded/data.20thC.html	Monthly	2.0° x 2.0° – 222 km
Normalized Difference Vegetation Index (NDVI)	MODIS website (https://ladsweb.modaps.eosdis.nasa.gov/)	Monthly	0.25° x 0.25° –27.75 km
Elevation	DIVA-GIS https://www.diva-gis.org/Data	–	0.8 km X 0.8 km at the equator
Population density	Earth data (https://cmr.earthdata.nasa.gov/search/concepts/C1871832077-SEDAC.html) and Census of India (https://censusindia.gov.in/census.website/)	–	1 km X 1 km

$$\sum A + \sum B = \frac{n(n-1)}{2} \tag{5}$$

Moreover, the Kendall's tau test statistic (Z) was calculated to evaluate the deviation of the observed Kendall's tau from the expected value under the null hypothesis:

$$Z = \frac{3^{*}\tau^{*}\sqrt{n(n-1)}}{\sqrt{2(2n+5)}} \tag{6}$$

After conducting Kendall's tau tests, maps were created using ArcGIS Pro (https://www.esri.com/en-us/arcgis/products/arcgis-pro/) to visualize population density and elevation of forest fire points. Elevation data, derived from digital elevation models (DEMs), reveals how terrain height affects fire behaviour through factors such as slope and drainage. Population density, especially in northeast India where slash-and-burn agriculture is common, correlates significantly with forest fire incidents. Increased population growth leads to shorter fallow periods, heightening fire risk. The analysis included meteorological variables—minimum, maximum, and average temperatures, relative humidity, wind speed, and Normalized Difference Vegetation Index (NDVI)—along with elevation and population density. Temperature, relative humidity, wind speed, and NDVI were found to have the most significant relationships with forest fires in India.

2.3.3. *Spatial cluster analysis*

Multi-distance spatial-clustering analysis (Ripley's K-function), a well-established method, has found broad application in analysing the spatial relationship among multiple point patterns. It characterizes the distribution pattern of landscapes by treating them as points in space, mapping their distribution and assessing spatial arrangements based on this map (Guo et al., 2015; Stoyan and Penttinen 2020). In our investigation, Ripley's K function was employed to evaluate the spatial distribution of forest fires in India. The Ripley's K(r) function is defined as:

$$K(r) = A\sum_{i=1}^{n}\sum_{j=1}^{n}\frac{r_{ij}(r)}{n^2}\left(i,j=1,2,\cdots,n,i\neq j,r_{ij}\leq r\right) \tag{7}$$

where n is the number of fire points; d is the distance scale; *rij* is the distance between fire points *i* and *j*; and A is the area of the study area.

To make the results more reliable and stable, the square root of *K(r)/π* is introduced to correct the function, resulting in the *L(r)* function with the following equation.

$L(r) = \sqrt{\frac{K(r)}{\pi}} - \mathrm{r}$ (8).

When *L(r)* exceeds the expected value, it indicates an aggregated distribution of fire spots, whereas a value below the expected suggests a discrete distribution. Statistical significance in spatial aggregation occurs when *L(r)* surpasses the upper packet traces, while significance in spatial discreteness arises when *L(r)* falls below the lower packet traces.

2.3.4. *Bland-Altman analysis*

For the Bland-Altman analysis of forest fire points in India from 2005 to 2022, data was collected systematically to assess forest fire occurrences. Pairwise comparisons were conducted between the following years: 2005 and 2011, 2012 and 2016, 2017 and 2022, and 2005 and 2022. The analysis involved calculating the mean difference in forest fire points for each year pair and determining the lower and upper limits of agreement. Bland-Altman plots were then generated, with the mean difference on the y-axis and the average number of forest fire points for each pair on the x-axis. This approach facilitated the assessment of agreement and variability in forest fire data over the selected years.

2.3.5. *Impact of forest fire on anthrax*

The analysis of the impact of forest fires on anthrax involved three key steps: data acquisition, visualization, and spatial analysis. Initially, data from 2005 to 2022 was sourced from the OIE, state animal husbandry departments, and NADRES. Trends in “Anthrax attacks,” “Anthrax outbreaks,” and “Forest fires” were examined using line plots generated in R. Correlation analysis between forest fire points and anthrax occurrences was conducted in MS Excel for the states of Orissa, Jharkhand, and Andhra Pradesh. Kriging interpolation, detailed in Section 2.3.1, was used to create heat maps showing forest fire hotspots, while distance plots were developed to illustrate the impact of these hotspots on anthrax cases. In these plots, circles were drawn around high and low forest fire points, with black circles indicating high and white circles indicating low forest fire points. This approach provided a detailed exploration of the relationship between forest fires and anthrax, offering valuable insights for public health and wildlife conservation strategies.

2.4. Tools and software

The study employed ArcGIS 10.3 for spatial analysis and visualization, R for statistical and correlation analysis, and Python for data processing. These tools collectively enabled a comprehensive examination of forest fire dynamics and their impact on anthrax outbreaks.

3. Results

3.1. Overall forest fire assessment

From 2005 to 2022, forest fire assessments across Indian states and Union territories revealed significant spatial and temporal variations. Madhya Pradesh reported the highest average incidents per year (3360.17 ± 4631.8), followed by Maharashtra (2543.72 ± 2770.31) and Odisha (2640.67 ± 2374.78). West Bengal experienced an average of 190.17 ± 180.56 incidents annually, peaking in 2017. Jharkhand showed significant variability, averaging 554.5 ± 552.07 incidents, especially in 2016. Karnataka averaged 704.33 ± 492.93 incidents, peaking in 2018. Kerala maintained consistent moderate incidents, averaging 129.17 ± 125.46 annually.

Over the 18-year study period, a total of 524,741 forest fire points were recorded, highlighting the substantial national impact. Andaman and Nicobar averaged 10.22 ± 22.36 incidents, indicating occasional low-impact events. Chandigarh, Daman Diu, and Delhi recorded minimal incidents. Haryana averaged 31.11 ± 45.27 incidents annually, while states like Chandigarh, Lakshadweep and Puducherry had minimal to zero incidents (Table 2; Fig. 2).

In 2005, the data indicated relatively low fire incidents in several states. West Bengal had 31 incidents, while Madhya Pradesh, Maharashtra, and Odisha recorded 893, 521, and 1125 incidents, respectively. Minimal incidents were observed in Andaman and Nicobar, Chandigarh, Daman and Diu, Delhi, Haryana, Lakshadweep, and Puducherry. By 2022, a marked increase in incidents was evident. Madhya Pradesh experienced a significant surge, peaking at 18,912 incidents, while Maharashtra and Odisha also witnessed notable spikes. Mizoram recorded the highest average incidents (2614.78 ± 1519.36) for the year. West Bengal saw a substantial rise to 729 incidents. Other states like Lakshadweep consistently reported minimal to no incidents, demonstrating regional disparities (Fig. 3) this comprehensive analysis underscores the heterogeneous nature of forest fire occurrences, emphasizing the need for region-specific mitigation strategies and increased awareness.

3.2. Kriging

The geostatistical analysis uncovered valuable insights into the spatial and temporal dynamics of forest fire points in India. Utilizing variogram modelling, the spherical model emerged as the optimal fit, highlighting a distinct range of spatial autocorrelation in forest fire occurrences across districts. The successful minimization of Root Mean Square Error further validated the model’s accuracy, enhancing the reliability of the findings. Beyond academic contributions, these results hold practical significance for crafting effective management strategies and policy interventions, offering a foundational understanding of the spatial intricacies of forest fire occurrences for future research and targeted mitigation efforts. In our study, we assessed three variogram models—Spherical, Gaussian, and Exponential—using metrics such as Partial Sill, Full Sill, Range, Nugget, RMSE, and MSE. The Spherical model outperformed the others, with a Partial and Full Sill of 0.3966, a Range of 1.8539, and an exceptionally low Nugget of 5.9744e-10, indicating its superior ability to capture spatial dependence. With the lowest RMSE (0.0316) and MSE (0.0010), the Spherical model proved.

to be the most effective in modelling and predicting spatial variability, making it the preferred choice for our analysis (Table 3).

The kriging results shed light on the diverse spatial patterns of forest fire incidents across Indian states and Union Territories. Mizoram, a pronounced hotspot, is predicted to witness a significant number of forest fire points, aligning with observed high-frequency incidents. Similarly, states like Maharashtra, Chhattisgarh, and Madhya Pradesh demonstrate substantial predicted forest fire points, reflecting their historical prominence in such occurrences. Zooming in at the district level reveals specific areas of concern, such as Pune and Nagpur in Maharashtra, Bastar in Chhattisgarh, Hoshangabad and Balaghat in Madhya Pradesh. The associated numbers underscore the urgency for targeted mitigation efforts, emphasizing the need for state-specific strategies in forest fire management. This kriging-based analysis provides a nuanced perspective, guiding effective interventions at both state and district levels in addressing the spatial distribution of forest fire incidents (Fig. 4).

3.3. Environmental attributes and forest fires

Across various Indian districts, meteorological trends depict significant patterns over the years. Maximum temperatures have consistently risen, with an increase observed from 30.19 °C in 2005 to 30.45 °C in 2022, indicating a warming climate trend.

Similarly, minimum temperatures have also shown a steady increase, ranging from 18.76 °C to 19.10 °C over the same period. Wind speeds exhibit fluctuations without a clear trend, maintaining an average of around 2.9 to 3.0 m per second throughout the years. Relative humidity levels have remained relatively stable, hovering around 60 to 65 per cent over the years. However, the Normalized Difference Vegetation Index (NDVI) has displayed a positive trend, with values increasing from 0.45 in 2005 to 0.51 in 2022, suggesting improved vegetation health and coverage. Overall, the data indicates a warming climate with stable humidity levels and potential vegetation enhancement across Indian districts (Fig. 5.).

In our extensive analysis spanning from 2005 to 2022, we thoroughly investigated the relationship between climate attributes and forest fire incidents in the district of India. Referencing Table 4, we utilized Kendall’s tau (τ) correlation coefficients to examine the connections between the number of forest fires and crucial climate variables, specifically maximum temperature, minimum temperature, average temperature, NDVI, relative humidity and wind speed. and the values for Tmax, Tmin, Tav, NDVI, RH, WS, and elevation were + 0.4545, +0.4474, +0.4568, +0.4504, −0.4497, +0.4523, and + 0.4383, respectively. Significant positive correlations were evident for Tav ($\tau = +0.4568$, $P \leq 0.001$) and Tmax ($\tau = +0.4545$, $P \leq 0.05$). Although correlations were identified for Tmin, NDVI, RH and WS, they did not reach statistical significance ($P > 0.05$). Elevation showed a highly significant correlation with forest fire incidents ($\tau = 0.4383$, $P \leq 0.001$).

Regression analyses revealed varying degrees of association between meteorological variables and forest fire points. A statistically significant relationship was observed between Tmin and forest fire points, with the model explaining 41.42 % of the variability (multiple R=0.6436). Both the intercept and Tmin coefficients were significant (p-values < 0.05). In

Table 2
Number of forest fires per year, from 2005 to 2022, in each state of India, during our review of climate attributes and their effects on forest fire between 2005 and 2022. Total fire incidents per year and average number of incidents per state (±standard deviation; SD) are also given.

State/UTs	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	Average ± SD
West Bengal	31	166	6	1	100	227	196	115	117	116	138	142	431	10	317	218	729	363	190.17 ± 180.56
Andaman & Nicobar	0	1	6	1	0	7	0	12	9	96	1	24	0	1	6	15	2	3	10.22 ± 22.36
Chandigarh	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0.06 ± 0.24
Daman and Diu	0	0	1	0	0	0	0	1	3	1	0	0	0	0	0	1	3	1	0.61 ± 0.98
Delhi	0	0	0	0	0	1	0	0	0	0	0	2	6	0	2	3	5	6	1.39 ± 2.17
Haryana	7	11	14	1	20	30	4	42	5	5	6	43	198	10	16	49	46	53	31.11 ± 45.27
Jharkhand	146	550	140	0	431	1318	188	307	554	202	457	740	1474	23	456	132	2031	832	554.5 ± 552.07
Karnataka	355	634	416	172	597	435	372	711	606	424	294	831	1990	117	1427	751	1293	1253	704.33 ± 492.93
Kerala	83	55	131	6	168	105	11	224	98	114	91	165	559	2	204	172	63	74	129.17 ± 125.46
Lakshadweep	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0 ± 0
Madhya Pradesh	893	1102	863	43	2850	2390	1462	3061	753	534	294	2675	5133	149	6536	3051	18,912	9782	3360.17 ± 4631.8
Maharashtra	521	1011	1241	6	2252	1796	887	3316	1433	702	722	1874	5364	232	5448	2475	11,132	5375	2543.72 ± 2770.31
Puducherry	0	0	0	0	0	0	0	0	0	0	0	0	8	0	0	0	1	0	0.5 ± 1.89
Tamil Nadu	195	108	122	3	277	149	33	262	89	284	97	113	441	4	1153	294	300	218	230.11 ± 258.81
Chhattisgarh	789	844	1756	1	2850	2849	1063	3443	1531	1018	1272	2808	5204	36	3386	980	7409	4695	2329.67 ± 1959.55
Telangana	269	544	695	0	1204	651	307	1170	860	911	985	1095	3336	52	2822	2635	6661	3490	1538.17 ± 1679.06
Andhra Pradesh	813	1033	1235	0	1244	1188	812	1382	1283	1546	1141	1758	4037	18	4316	2688	7410	4191	2005.28 ± 1870.09
Goa	3	9	1	0	2	0	3	0	4	3	0	10	37	2	11	10	11	8	6.33 ± 8.7
Himachal Pradesh	9	8	48	1	168	125	11	243	34	32	22	199	327	13	223	284	818	1108	204.06 ± 300.25
Punjab	21	37	18	2	39	56	10	83	36	20	7	45	397	996	45	107	305	100	129.11 ± 240.54
Rajasthan	14	48	53	1	95	118	86	82	75	52	90	66	273	22	366	455	530	282	150.44 ± 159.44
Gujarat	131	207	100	0	181	180	99	146	179	75	116	262	530	46	318	323	698	362	219.61 ± 175.67
Uttarakhand	143	163	222	2	629	859	91	1254	119	379	207	1501	1186	139	7286	1538	9154	5322	1677.44 ± 2696.53
Uttar Pradesh	234	252	303	0	370	738	200	558	237	218	130	691	1225	126	955	707	2916	1503	631.28 ± 701.19
Sikkim	0	7	0	0	1	5	1	2	0	0	3	0	16	0	9	7	20	8	4.39 ± 5.9
Assam	181	1335	903	3	1891	2514	1323	2167	1610	2535	1655	1766	2008	23	1708	3094	3510	2365	1699.5 ± 979.06
Arunachal Pradesh	79	523	632	16	779	582	523	508	501	535	358	292	779	44	580	729	1138	1149	541.5 ± 318.19
Nagaland	107	1195	850	18	981	1646	944	897	845	886	722	678	1034	41	766	1329	1784	1374	894.28 ± 491.63
Manipur	293	1679	1222	1	1484	2487	1273	1506	1302	1774	1286	1105	1255	24	2397	4304	5625	2609	1757 ± 1395.74
Mizoram	1511	4510	2740	1	3441	4675	1691	2218	2258	2189	2468	1318	2122	3	3360	3825	5852	2884	2614.78 ± 1519.36
Tripura	325	1412	780	0	711	1127	634	1233	589	1160	476	346	616	1	1508	2066	2327	439	875 ± 650.46
Meghalaya	56	1289	500	0	1009	1743	879	910	804	1124	1374	967	1749	24	1565	2058	2362	1623	1113.11 ± 684.25
Bihar	67	123	84	0	143	398	80	196	273	140	45	321	386	4	283	68	760	306	204.28 ± 188.39
Ladakh	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0.06 ± 0.24
Jammu and Kashmir	29	81	92	4	115	31	8	123	23	74	13	217	0	7	167	341	248	1312	160.28 ± 303.24
Odisha	1125	1652	1593	0	2077	2510	780	3022	2221	1905	1463	2763	5652	206	3473	2637	10,445	4008	2640.67 ± 2374.78
Total	8430	20,589	16,767	283	26,109	30,940	13,971	29,194	18,451	19,054	15,933	24,817	47,774	2375	51,109	37,346	104,500	57,099	29152.28 ± 23820.93

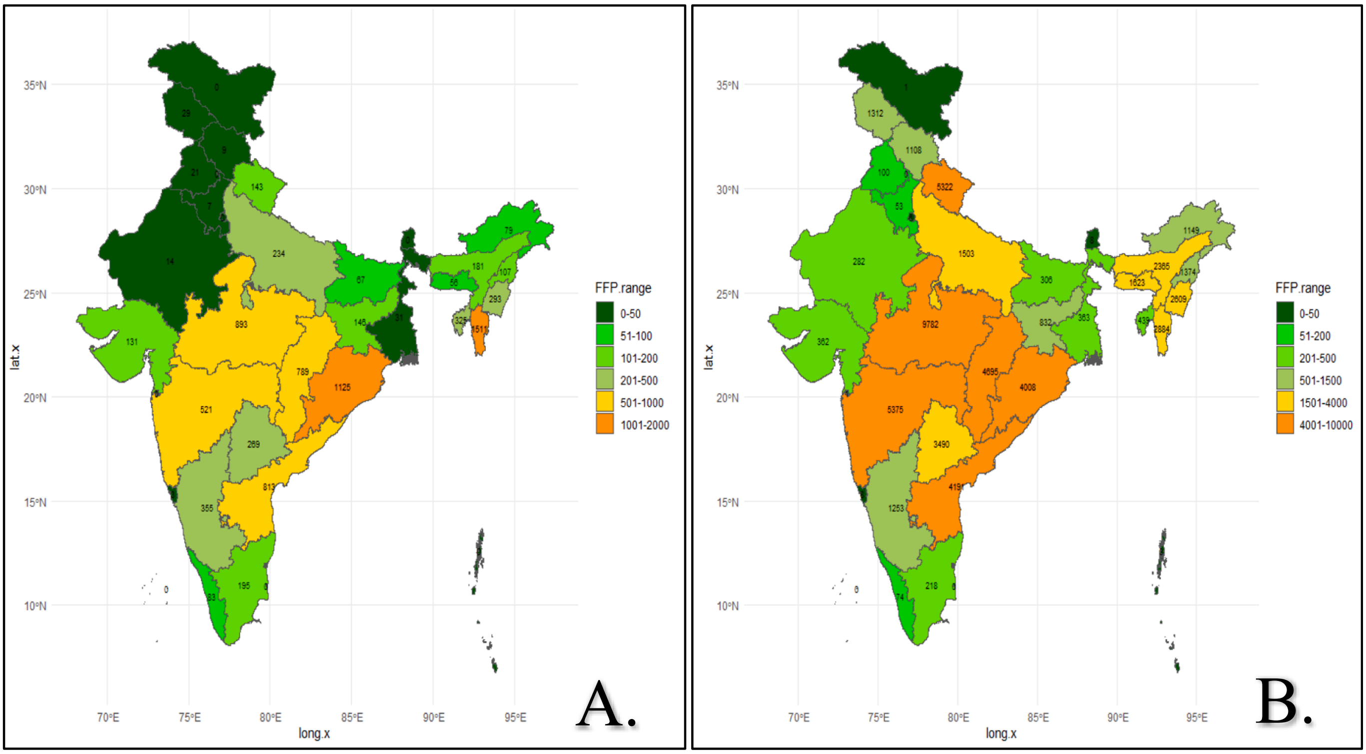

Fig. 3. A comparison of fire incident data from the beginning (2005) and the end (2022) of the period of our review of climate attributes and their effects on forest fire points in the Indian states. Heat maps of forest fire points for A. year 2005 and B. year 2022.

Table 3
Kriging Performance Assessment for Forest Fire Points: Variogram Model Comparison.

Variogram Model	Partial Sill	Full Sill	Range	Nugget	RMSE	MSE
Spherical	0.3966	0.3966	1.8539	5.9744e-10	0.0316	0.0010
Gaussian	0.3966	0.3966	1.5133	1.4472e-09	0.0557	0.0031
Exponential	0.2981	0.3966	1.9897	0.0986	0.0475	0.0023

contrast, Tmax and WS showed weak and statistically insignificant relationships, with low R-squared values of 0.0079 and 0.0388, respectively, indicating that these models fail to provide reliable predictions. The analysis of Tav indicated a moderately significant association, with a multiple R of 0.4041 and an R-squared value of 0.1633, suggesting that 16.33 per cent of the variability in forest fire points can be explained by Tav. The analysis involving NDVI revealed a strong and highly significant relationship, explaining 54 % of the variability, with both intercept and NDVI coefficient being statistically significant. Regarding elevation, the regression model showed a weak relationship with forest fire points, with an R-squared value of 0.03879 (Fig. 6). However, Elevation (Fig. 7A), acting as a linchpin, unveils temperature gradients influencing ignition likelihood, delineates vegetation shifts impacting fuel dynamics and unravels topographical configurations shaping fire behaviour. This suggests that while elevation may influence fire susceptibility through other mechanisms, it alone does not strongly predict the number of forest fire incidents.

Population density is one of the main reasons behind the number of fire incidents in a forested landscape. In northeast India, forest fires are primarily caused by shifting cultivation, i.e., slash-and-burn agriculture. Past research has discussed that rapid population growth promotes a short fallow cycle in shifting cultivation in northeast India. Many other studies worldwide have also highlighted the importance of population density in forest fire monitoring and mapping (Fig. 7B). Human activities, intensified by India's population growth from 88.89 crore in 1991 to an estimated 1.43 billion in 2023, significantly impact forest fires. Practices like land clearing for agriculture, deliberate fires, and farming-related activities contribute to fires, exacerbated by urbanization, where population reached 35.87 per cent in 2022. Shifting cultivation, particularly prevalent in northeast India, heightens fire risks, as seen in slash-and-burn practices. Rapid population growth in these areas shortens fallow cycles, escalating risks. Additionally, CO_2 emissions hit 2,423,951.40 kilotons in 2019, with oil consumption peaking at 5,185 thousand barrels per day in 2022, exacerbating dry conditions conducive to fires. Road density, rising from 1.4 to over 1.9 thousand kilometres per thousand square kilometres from 2012 to 2019, aids firefighting access but also increases human-induced fire risks, complicating forest fire dynamics in India. These findings underscore the importance of Tmin and NDVI as significant predictors of forest fire occurrences, while Tmax, WS, and elevation are less significant.

3.4. Fire spatial distribution

The analysis of multi-distance spatial clustering unveiled compelling findings regarding the distribution of forest fires across Indian districts. Across the years 2005, 2013, 2022 and the cumulative period from 2005 to 2022, the observed L(r) values consistently surpassed both the expected values and the upper packet traces (Fig. 8). This signifies a robust spatial aggregation distribution of forest fires during these periods. As per the principles of this analysis, when L(r) exceeds the expected value, it indicates an aggregated distribution of fire spots, with statistical significance being established if L(r) surpasses the upper packet traces. Conversely, if L(r) falls below the expected value, it suggests a discrete distribution, with statistical significance denoted by L(r) values smaller than the lower packet traces. Thus, the observed pattern of forest fires in India not only displayed a clear spatial aggregation but also demonstrated statistically significant clustering, highlighting the importance of spatial analysis in understanding fire dynamics.

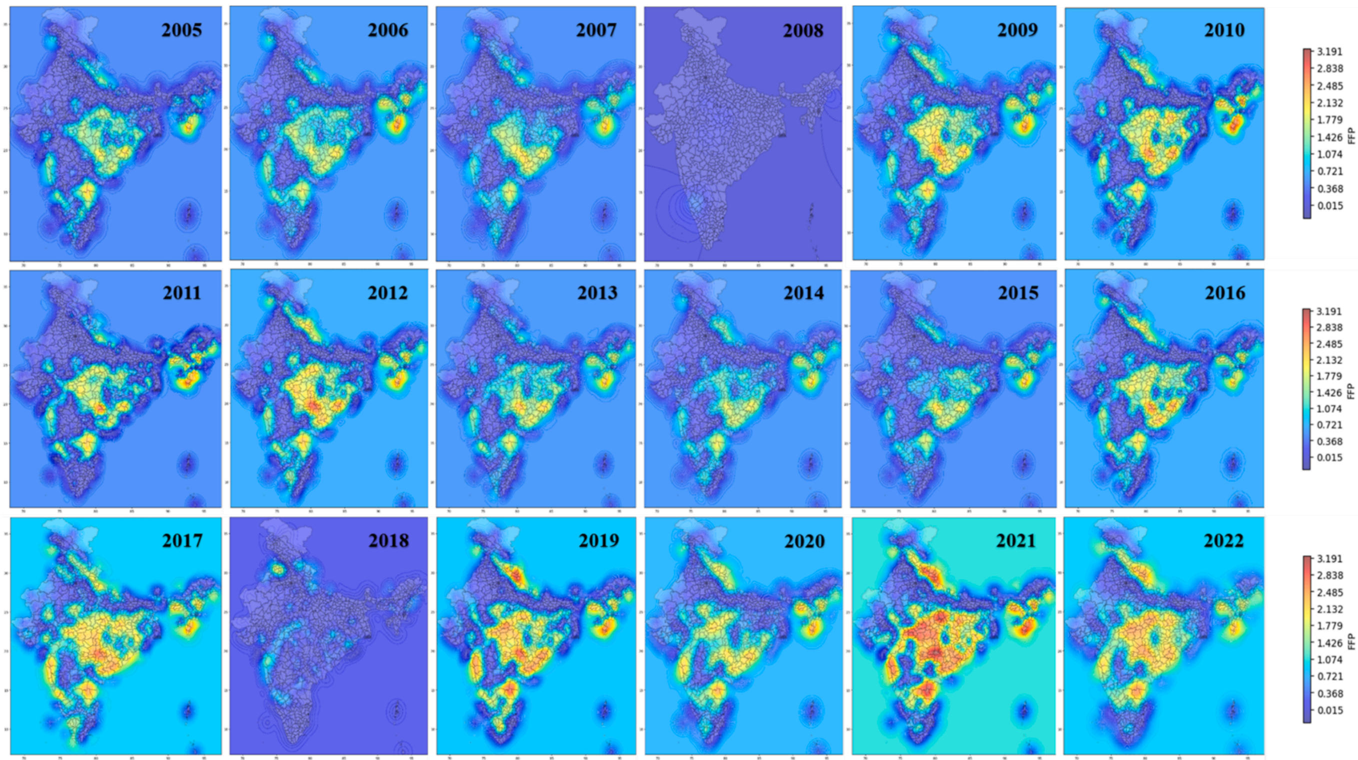

Fig. 4. Geostatistical Mastery – Kriging Analysis Unveiling Forest Fire Dynamics (2005–2022) in Indian Districts, Illuminated with Heat maps.

3.5. Bland-Altman analysis

The Bland-Altman analysis of forest fire points in India, spanning from 2005 to 2022, reveals an intriguing trend of increasing forest fire occurrences over the years, contrary to the previously discussed decreases. Initially, the comparison between 2005 and 2010 might have suggested a decrease; however, revisiting the data with a focus on long-term trends indicates an overarching increase. For instance, while early analyses showed average decreases in forest fire points for specific intervals, a comprehensive examination across the entire timeframe highlights a notable escalation in incidents. This shift is particularly evident in the long-term analysis from 2005 to 2022, where an increase in forest fire points could be inferred from the broader context of environmental and climatic changes influencing forest fire frequencies and intensities.

In detail, Table 5′s statistical outcomes from the Bland-Altman analysis provide a nuanced view of the agreement in forest fire points over the selected years, with a focus now on interpreting these results in the context of increasing trends. The period between 2005 and 2010, initially observed as a decrease, sets the stage for a baseline in fire occurrences. Moving to the interval between 2011 and 2016, where a mean difference of −13.7800 was noted, the data can be reconsidered in light of increasing variability and outliers that suggest a rise in forest fire points when considering the broader environmental context. The subsequent analysis for 2017 to 2022, showing a mean difference of −15.2267, and the long-term comparison from 2005 to 2022, with a mean difference of −16.4453, further indicates a complex interplay of factors that, upon closer examination, may reveal an overall trend of increasing forest fire occurrences. The wide confidence intervals observed in these comparisons, such as −370.278 to 237.3876 for the long-term trend, suggest significant variability that could encompass both decreases and increases, with the latter becoming more pronounced when considering external factors like climate change, deforestation, and human activities contributing to the escalation of forest fires. The accompanying Bland-Altman plot (Fig. 9) visually underscores these statistical nuances, emphasizing the importance of robust interpretation and caution in the assessment of forest fire point agreement within the specified timeframe.

3.6. Impact of forest fire on anthrax

Over the years, time series patterns indicated an upward trend in anthrax attacks, marked by notable fluctuations in Forest Fires, particularly in 2017. Descriptive statistics for anthrax attacks included a mean of 403.56 and a standard deviation of 340.83 (Fig. 10). Our analysis uncovered a robust positive correlation ($r = 0.394$) between anthrax attacks and Forest Fires, suggesting a significant environmental influence on Anthrax occurrences. The correlation coefficient indicates a moderate positive relationship between forest fire points and anthrax occurrences across various districts in Andhra Pradesh, Jharkhand and Odisha.

Furthermore, the regression analysis confirms this relationship, with forest fire points emerging as a significant predictor ($p < 0.05$) of anthrax occurrences. The intercept of 1086.33 and the slope of 42.91 suggest that, on average, each additional forest fire point leads to an estimated increase of approximately 42.91 anthrax occurrences. Additionally, the coefficient of determination (R^2) value of 0.119 reveals that around 11.9 per cent of the variability in anthrax occurrences can be explained by variations in forest fire points. Overall, these findings underscore the substantial impact of forest fires on anthrax incidence, emphasizing the importance of considering environmental factors in anthrax management and prevention strategies (Fig. 11).

Analyzing historical data spanning from 2005 to 2022 reveals significant fire risk zones in Odisha, Jharkhand, and Andhra Pradesh. In Odisha, districts such as Koraput, Malkangiri and Rayagada consistently report high fire incidents, averaging around 2640.67 fires per year. Similarly, in Jharkhand, Latehar, Gumla, and Simdega stand out with an average of 554.5 fires annually. Meanwhile, in Andhra Pradesh, East Godavari, West Godavari and Visakhapatnam experience considerable fire risk, averaging approximately 2005.28 fires yearly. These regions,

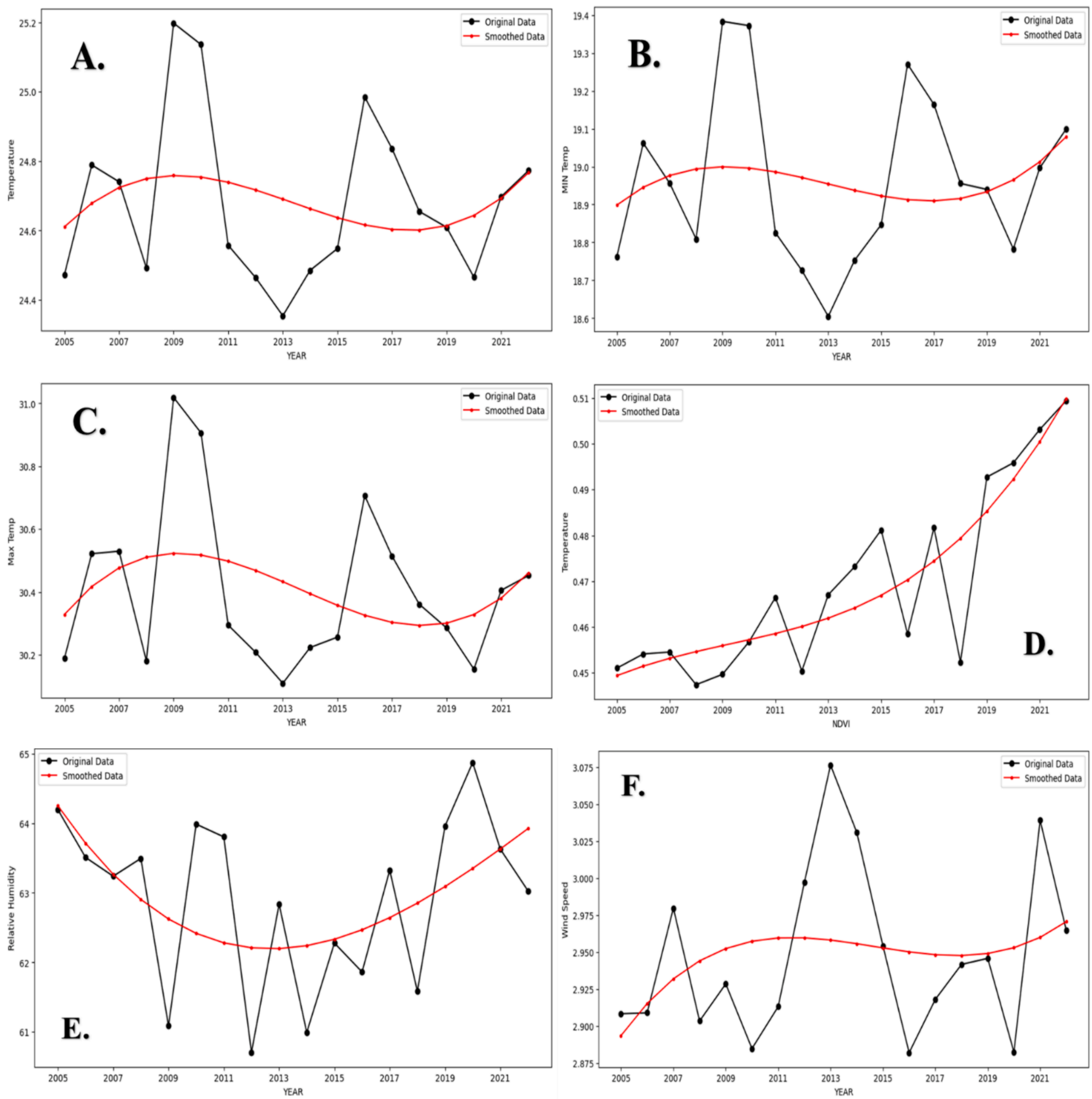

Fig. 5. Climatic Trend Analysis from 2005 to 2022 in Indian Districts. (A. Average Temperature, B. Minimum Temperature, C. Maximum Temperature, D. Normalized Difference Vegetation Index (NDVI), E. Relative Humidity (RH), F. Wind Speed (WS)).

characterized by dense forest cover and prone to fire incidents due to factors like dry vegetation and human activities, necessitate prioritizing fire prevention and management efforts to effectively mitigate associated risks (Fig. 12A).

Furthermore, a comprehensive analysis utilizing Kriging techniques identifies high-risk zones and potential anthrax hotspots in Andhra Pradesh, Jharkhand and Odisha. In Andhra Pradesh, coastal areas like Krishna, East Godavari, and Visakhapatnam districts exhibit elevated risk, with numerical values indicating higher probabilities of anthrax outbreaks. Similarly, forested regions such as the Seshachalam and Nallamala forests, along with areas with dense livestock populations in districts like Kurnool and Prakasam, are deemed high-risk. In Jharkhand, vulnerable areas include forested regions in Palamu and Latehar districts, tribal-dominated areas like Simdega district and locations near wildlife reserves such as Betla National Park. In Odisha, coastal plains including Ganjam, Puri, and Kendrapara districts, marshy and wetland areas, and grazing lands near forests in districts like Sundargarh and Mayurbhanj present significant anthrax risk. The numerical data derived from Kriging provide insights into the extent of vulnerability in these identified zones (Fig. 12B).

Analysis of the data from 2005 to 2022 reveals a notable correlation between forest fire occurrences and anthrax attacks, particularly evident in specific geographical areas. By plotting the distance from distinct points to both forest fire incidents and anthrax occurrences, a discernible

Table 4
Kendall's tau (τ) test and correlation of climate variables (relative humidity, RH; minimum temperature, T_{min}; maximum temperature, T_{max}; average temperature, T_{av}; and wind speed, WS; Normalized Difference Vegetation Index, NDVI; Elevation) to the forest fire incidents reviewed in our study of climate attributes and their effects on forest fire between 2005 and 2022, in the district of India. Z-statistics and P-values are also given. ** = P≤0.001, highly significant correlation; * = P≤0.05, significant correlation; ns = non-significant correlation.

Environmental Variable	Kendall's tau (τ)	Z-statistic	*P*-value	Concordant Pairs	Discordant Pairs
T_{min} (°C)	0.57705	3.3356	0.0008**	129	93
T_{max} (°C)	0.2287	2.5789	0.2008^{ns}	96	126
T_{av} (°C)	0.4013	2.3139	0.0206*	113	109
NDVI	0.4509	2.6234	0.0085*	118	104
RH (%)	0.1442	0.8339	0.4043^{ns}	81	141
WS (km h^{-1})	0.1372	1.1025	0.4534^{ns}	83	139
Elevation (mts)	0.4383	3.7576	0.0002**	123	99

trend emerges: as the distance from forest fire points increases, the frequency of anthrax attacks generally decreases. For instance, within the 0–100 km range from forest fire points, there are relatively fewer anthrax incidents observed. However, beyond the 100 km threshold, the incidence of anthrax gradually rises. This pattern suggests a potential link between forest fires and anthrax outbreaks, with areas closer to forest fire points showing heightened susceptibility to anthrax incidents. Areas closer to forest fire points tend to experience higher incidences of anthrax outbreaks, indicating a possible exacerbation of anthrax risk by forest fires. Conversely, closer proximity to reference points correlates with fewer incidents of both forest fires and anthrax attacks, suggesting lower susceptibility potentially due to factors like better surveillance or environmental conditions (Fig. 13). Certain districts in Andhra Pradesh, Jharkhand, and Odisha emerge as high-risk zones for anthrax outbreaks, coinciding with areas experiencing notable frequencies of forest fire incidents. For example, Visakhapatnam in Andhra Pradesh recorded 829 anthrax cases and 278 forest fire incidents, while Latehar in Jharkhand saw 1268 forest fire incidents alongside 190 anthrax cases. These regions are identified as potential hotspots for anthrax outbreaks based on historical data (Fig. 12C).

4. Discussion

4.1. Overall forest fire assessment

The forest fire assessment spanning 2005 to 2022, as revealed by the diverse patterns across Indian states and Union Territories, underscores the urgent need for strategic forest fire management and conservation measures on a nationwide scale. West Bengal experienced fluctuating incidents, peaking in 2017, while Mizoram recorded the highest average incidents by 2022, indicating a significant nationwide increase. The findings of this study, in line with existing literature (Wotton, 2009; Negi and Kumar, 2016; Sharma and Pant, 2017), emphasize the direct influence of climate conditions, such as heat waves and reduced rainfall, on forest fire incidents. Moreover, the discussion underscores the limited studies addressing the relationship between the monsoon season and forest fires in India, necessitating ongoing research to fill this knowledge gap. This comprehensive overview highlights the importance of interdisciplinary research, collaboration and the implementation of region-specific mitigation strategies to effectively address the diverse impacts of forest fires in the country (Kumar and Kumar, 2022). The shift in the average annual forest fire incidents from West Bengal in 2005 to Mizoram in 2022 illustrates the dynamic nature of forest fire occurrences, necessitating adaptive and nationwide approaches to forest fire management. The complex interplay of natural and anthropogenic factors, as identified by authors such as Wotton (2009), Negi and Kumar (2016) and Sharma and Pant (2017), underscores the multifaceted influences on forest fire incidents, ranging from temperature increases to low precipitation. The study's findings highlight the necessity for ongoing research and monitoring to develop effective prevention and management strategies, considering the diverse climatic and ecological conditions across the country. In conclusion, the discussion emphasizes the crucial role of interdisciplinary collaboration and the implementation of sustainable practices to mitigate the increasing threat of forest fires and preserve India's rich biodiversity and ecosystems (Yu et al., 2018).

4.2. Kriging

The geostatistical analysis conducted in this study, employing variogram modelling with the spherical model as the optimal fit, has revealed insightful spatial and temporal dynamics of forest fire points in India. The successful minimization of root mean square error has strengthened the model's accuracy, underlining its reliability in predicting and understanding forest fire occurrences across districts. The staggering total of 5,24,741 recorded forest fire points over the 18-year study period emphasize the significant national impact, making the findings crucial for crafting effective management strategies and policy interventions. Kriging results further identify specific hotspots and high-risk areas at both state and district levels, guiding targeted mitigation efforts. The study aligns with existing research on the importance of climate and weather conditions in forest fire occurrences, providing a nuanced perspective that contributes to informed decision-making for future research and proactive forest fire management. The cited authors, including Bessie and Johnson (1995),

Flannigan and Harrington (1988), Van Wagner (1987), Wang et al. (2016), Wotton et al. (2010), Tian et al. (2012) and Tapper et al. (1993) support and reinforce the study's findings.

4.3. Environmental attributes and forest fires

The extensive analysis conducted from 2005 to 2022 delved into the intricate relationship between climate attributes and forest fire incidents in India. Through the utilization of Kendall's tau correlation coefficients, significant positive correlations for average and maximum temperatures were identified, underlining their pivotal influence on forest fire occurrences. This finding resonates with prior research by Prasad et al. (2008a) and Sharma et al. (2012), which highlighted the critical role of temperature in biomass drying and wind speed in fire spread. Additionally, regression analyses unveiled diverse associations between meteorological variables and forest fire points, with notable factors such as NDVI and minimum temperature emerging as crucial predictors of fire incidents. The observed negative correlation between relative humidity and forest fires in the Indian district further underscores the regulatory role of climatological factors in fire risk assessments, emphasizing the importance of holistic fire management strategies. The negative correlation between relative humidity and forest fires supports previous research by Prasad et al. (2008b) and Saglam et al. (2008). In the context of climate change, insights from studies by Swetnam and Betancourt (1990) and Aldersley et al. (2011) were incorporated, highlighting the strong link between fire and climate. The vulnerability of dry deciduous forests in central India is emphasized, urging policy interventions to address future challenges. References to FAO (2001), Kumar and Jain (2011), Jhajharia et al. (2009) and Jain et al. (2013) provide a comprehensive backdrop, contributing to a nuanced

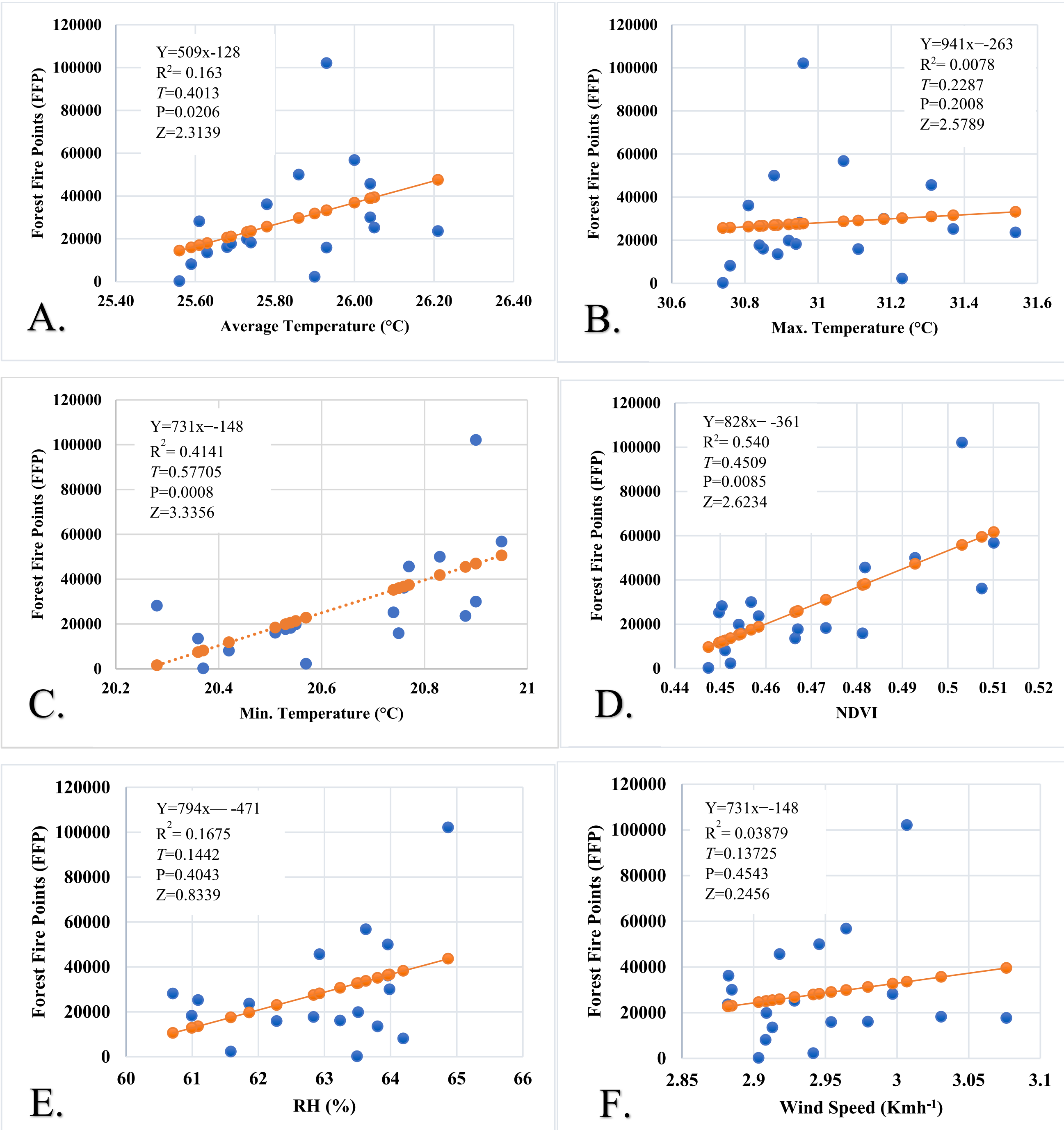

Fig. 6. Graphs depicting Kendall's tau (τ) values, correlation regression equations (y = mx + c; where m is the slope of the line relating y to x, and c is the y-intercept of that line; Orange line), R^2 values (coefficients of determination); P-values (≤0.05), and Z-statistics (±1.96) between forest fire incidents (orange dots) and climate attributes for India, during our review of climate attributes and their effects on forest fire between 2005 and 2022: **A.** correlation plot of several fire points and average temperature (Tavg; °C); **B** correlation plot of several fire points and maximum temperature (Tmax; °C); **C.** correlation plot of several fire points and minimum temperature (Tmin; °C); **D.** correlation plot of several fire points and normalized difference vegetation index (NDVI); **E.** correlation plot of number of fire incidents and relative humidity (RH; %) and **F.** correlation plot of number of fire points and wind speed (WS; kmh^{-1}). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

discussion on the implications of climate anomalies for forest fire events in India.

The consistent increase in NDVI data from 2005 to 2022, as found in our study, underscores the intricate relationship between vegetation dynamics, climate conditions, and forest fire occurrences in India. This trend is likely attributed to the concurrent increase in tree cover, cropping intensity, and the adoption of sapling methodologies, as highlighted by Kuttippurath and Kashyap (2023) which indicates a substantial rise in leaf area, with India adding 996,640 km2 of new green cover, these efforts potentially aid in reducing forest fire incidents. However, despite these mitigation efforts, forest fire occurrences persist, exacerbated by warmer temperatures, as shown in our various studies and efforts to increase NDVI may have positive effects on mitigating forest fires (Pragya et al., 2023; Das et al., 2023: Jodhani et al., 2024). A

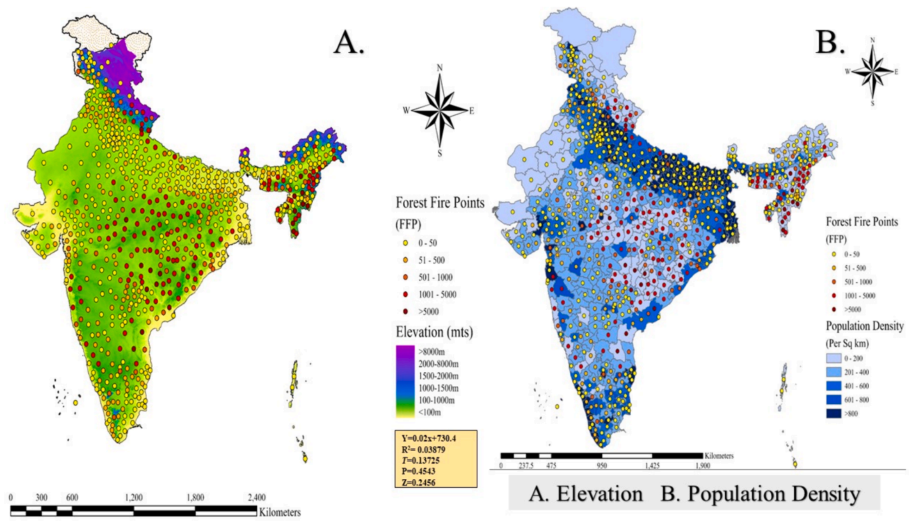

Fig. 7. Spatial variation of elevation and population density, interacting with forest fire points over the study area.

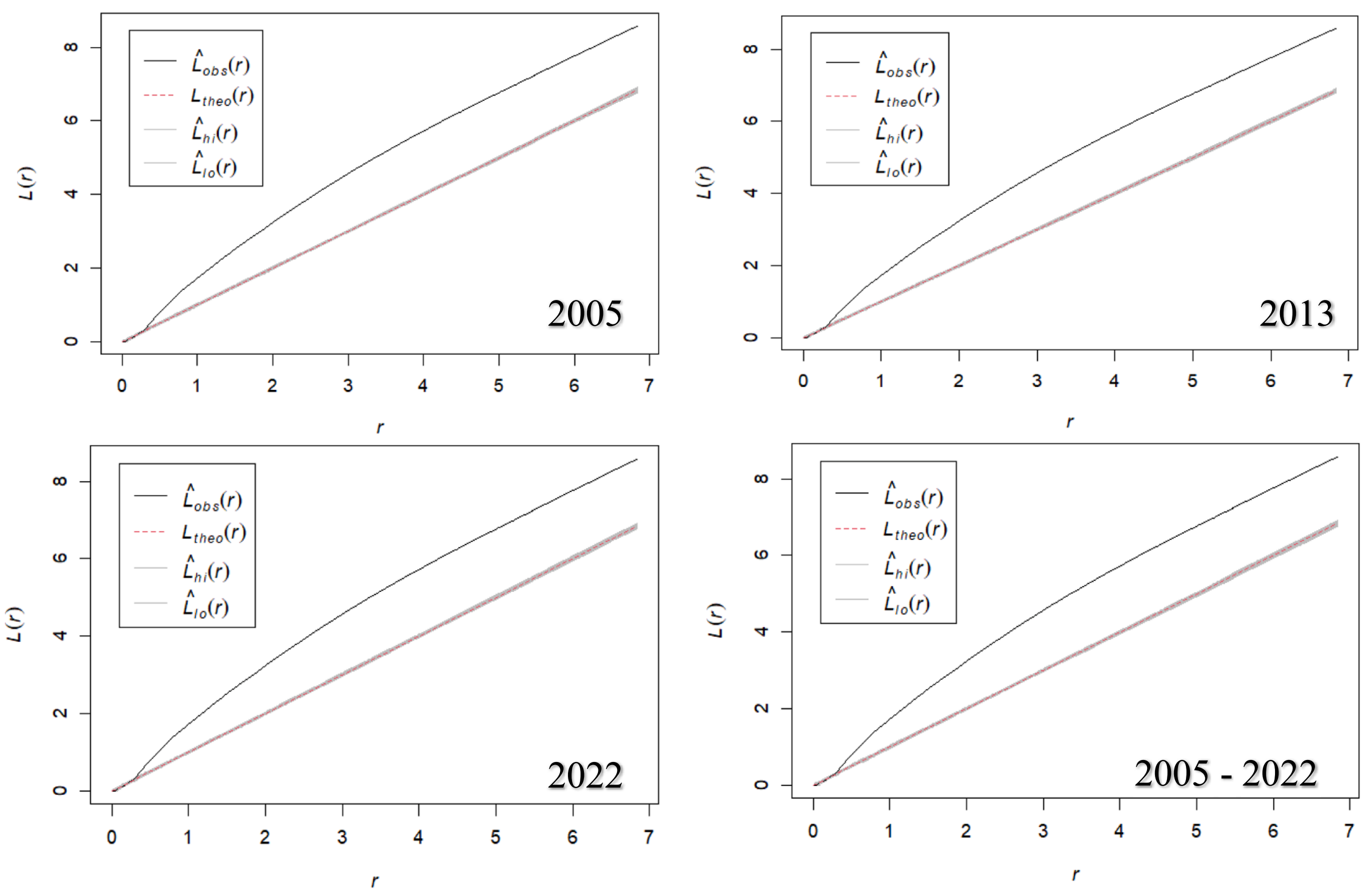

Fig. 8. Spatial distribution pattern of forest fire points in Indian districts during 2005, 2013, 2022 and Cumulative period from 2005 – 2022, respectively.

Table 5
Summary of Bland-Altman analysis for forest fire points in India (2005–2022).

Year	Mean difference	Lower limit	Upper limit
2005 with 2010	−29.8797	−238.3120	178.5524
2011 with 2016	−13.7800	−123.3352	95.7751
2017 with 2022	−15.2267	−248.4331	217.9795
2005 with 2022	−16.4453	−370.278	237.3876

decreasing trend in forest fires is usually apparent with rising elevations due to lower temperatures and higher humidity compared to regions at lower elevations (Chakraborty et al., 2014).

The increase in population density is one of the main reasons behind the number of fire incidents in forested landscapes in northeast India. Forest fires in this region are primarily caused by shifting cultivation, a practice known as slash-and-burn agriculture. Past research has shown that rapid population growth promotes shorter fallow cycles in shifting

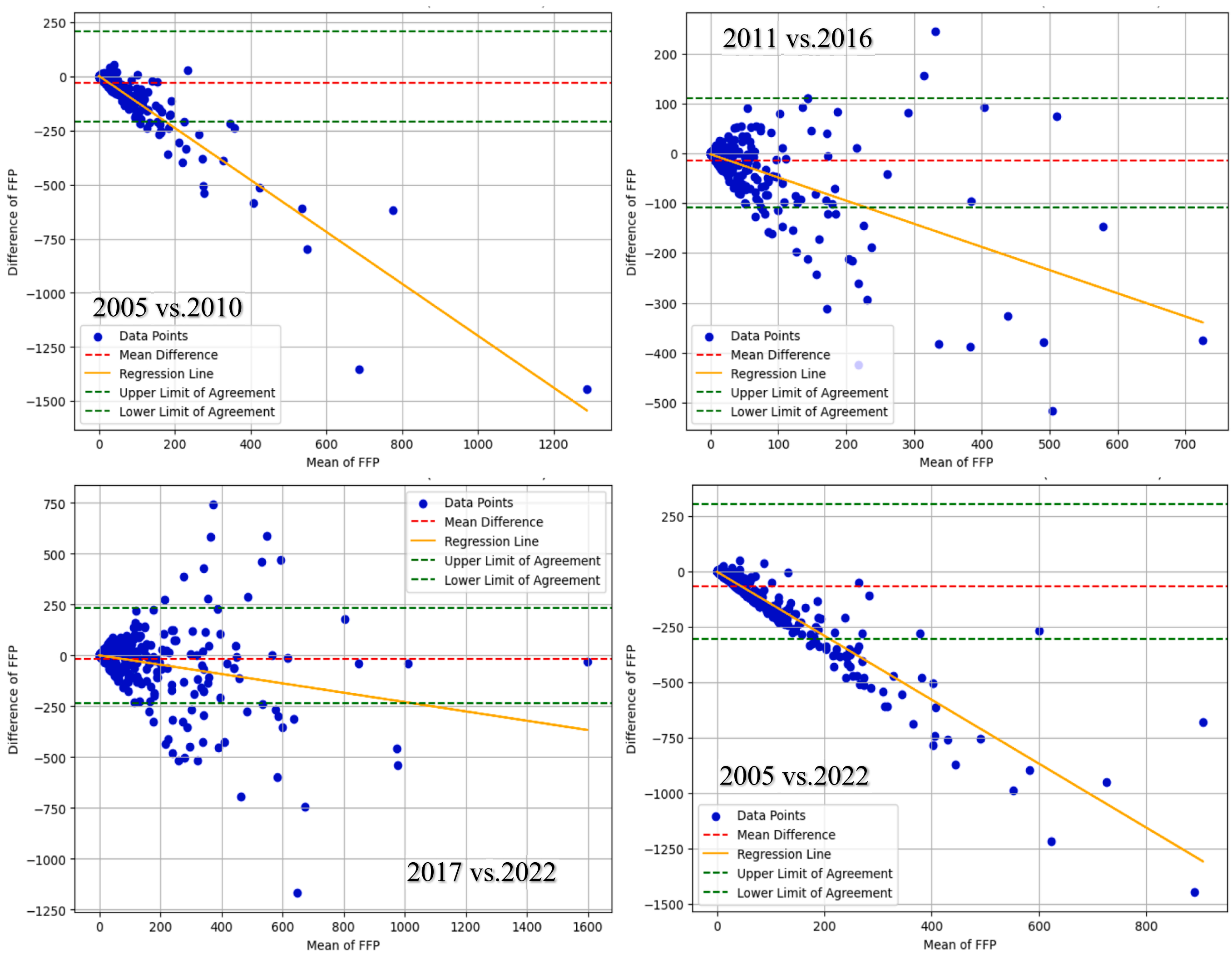

Fig. 9. Bland-Altman Plots Comparing Forest Fire Points in India for 2005 vs. 2010, 2011 vs. 2016, 2017 vs. 2022 and 2005 vs. 2022.

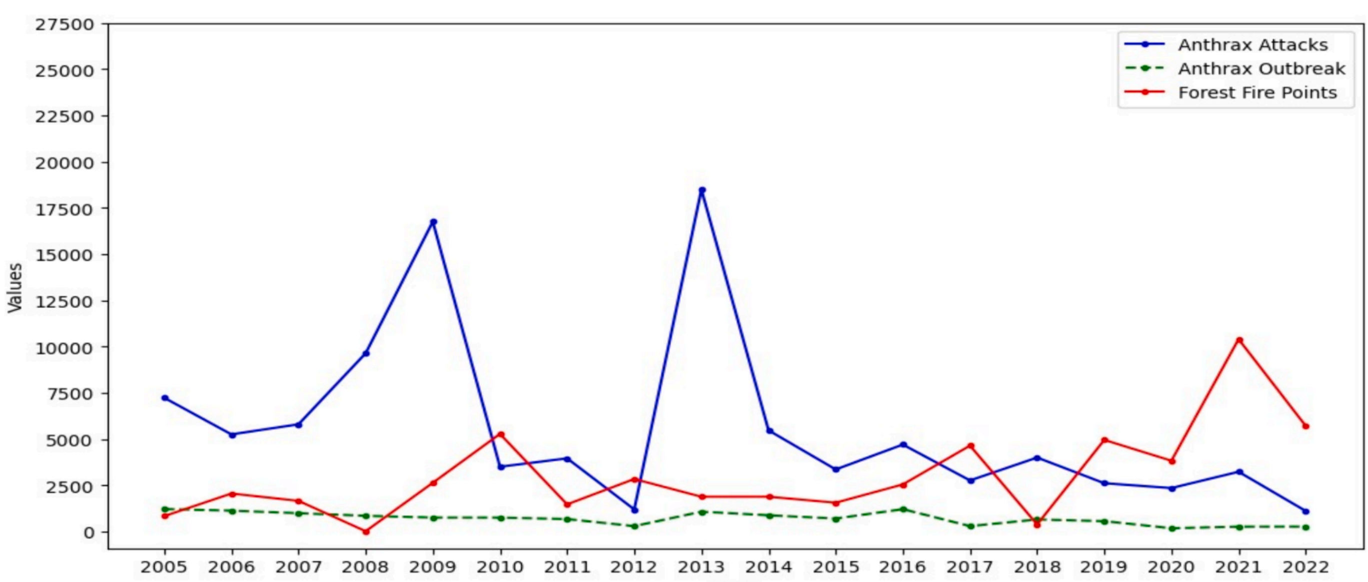

Fig. 10. Temporal Trends of Anthrax Attacks, Anthrax Outbreak and Forest Fires Over the Years (Adjustment factor of 10 was used for data visualization only, without changing the data frequency).

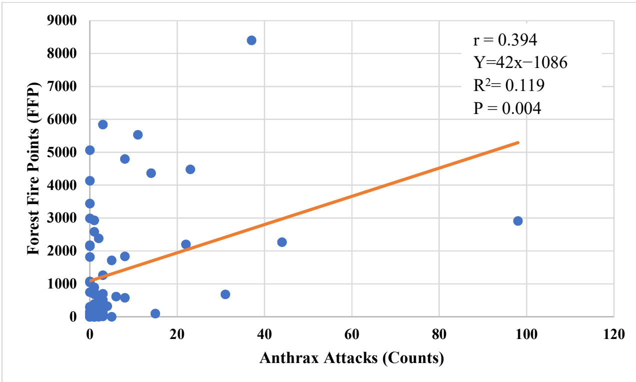

Fig. 11. Correlation and Regression Analysis: Impact of Forest Fire Points on Anthrax Occurrence in Andhra Pradesh, Jharkhand and Odisha Districts.

cultivation in northeast India. Studies from around the world have also highlighted the importance of population density in monitoring and mapping forest fires (Lamat et al., 2021; Borgohain et al., 2023). In Uttarakhand, trends of fire frequency, fire density, and hotspots are higher, which may be due to population growth putting anthropogenic pressure on forests, in agreement with the reported anthropogenic causes of forest fires in the region (Chakraborty et al., 2014).

4.4. Fire spatial distribution

Our research findings reveal significant insights into forest fire distribution across Indian districts, with observed *L(r)* values consistently surpassing expected values and upper packet traces from 2005 to 2022, indicating robust spatial aggregation. This underscores the importance of spatial analysis in comprehending fire dynamics. Subsequent studies on forest fire susceptibility in regions like the Indian Western Himalayas corroborate these findings, identifying vulnerability factors such as forest cover ratio, temperature, and settlement proximity (Pragya et al., 2023). Furthermore, research on the Western Himalayan region emphasizes increasing burn areas and the impact of climatic variables and human activities on fire occurrence, necessitating effective forest management (Somnath et al., 2020). In ecologically sensitive areas like the Western Ghats, machine learning techniques contribute to predicting fire susceptibility, and identifying key determinants such as land use and proximity to agricultural fields (Babu et al. 2024).

4.5. Bland-Altman analysis

The Bland-Altman analysis of forest fire points in India from 2005 to 2022 provides a nuanced perspective on the agreement in forest fire occurrences over consecutive years. Initially perceived as a decrease, the period between 2005 and 2010 establishes a baseline for fire occurrences, while subsequent intervals, such as 2011 to 2016 and 2017 to 2022, exhibit mean differences suggesting decreases but with increasing variability and outliers indicative of a rise when considering broader environmental contexts. The long-term comparison from 2005 to 2022 similarly hints at an overall trend of increasing forest fire occurrences, supported by a mean difference of −16.4453, albeit with wide confidence intervals (−370.278 to 237.3876) reflecting significant variability. External factors like climate change, deforestation and human activities likely contribute to this complexity, emphasizing the need for comprehensive understanding. These findings, supported by insights from Altman (1991), Altman (2007), Altman and Bland (1995), Altman and Bland (1986) and others, underscore the importance of robust interpretation and caution in assessing forest fire occurrences in India. The accompanying Bland-Altman plot (Fig. 4) visually reinforces these nuances, highlighting the necessity for thorough analysis in understanding forest fire trends over the specified years.

4.6. Impact of forest fire on anthrax

Our analysis reveals a robust positive correlation ($r = 0.394$) between anthrax outbreaks and forest fires in Odisha, Jharkhand and Andhra Pradesh, with significant annual fluctuations. Using Kriging techniques, we identified potential anthrax hotspots in forested regions and areas with dense livestock populations, indicating higher probabilities of outbreaks. Previous studies support this hypothesis, showing that forest fires impact soil bacterial communities and correlate with anthrax occurrences (Smith et al., 2008; Singh et al., 2021). Forest fires alter soil bacterial diversity, especially after high-intensity fires, indirectly influencing *Bacillus anthracis* dynamics by changing ecological conditions conducive to its proliferation. This correlation highlights the significant environmental role in disease dynamics, with post-fire ecosystem disruptions affecting herbivore populations critical to anthrax ecology (Mysterud et al., 2008; Hugh-Jones et al., 2012). Changes in vegetation post-fires can alter herbivore foraging behaviour, increasing exposure to anthrax spores (Turnbull et al., 2004). Wildlife displacement after fires can spread spores to new areas (Blackburn et al., 2007), and the viability of anthrax spores is influenced by fire-induced heat (Dragon and Rennie, 2001). Increased human-wildlife interaction post-fire raises the risk of anthrax transmission to humans (Alexander, 2012).

The impact of wildfires on anthrax prevalence lies in their influence on spore dissemination, emphasizing the necessity of targeted surveillance and response in areas at high risk. Anthrax spore survival and longevity are intricately linked to soil properties and climatic conditions, which can be altered by wildfires. This complex relationship between forest fires and anthrax involves nuanced ecological interactions, with profound implications for wildlife disease dynamics. Our research aligns with previous studies, affirming a significant correlation between forest fires and the distribution of anthrax risk. Local environmental dynamics, such as permafrost thawing and climatic conditions, play pivotal roles in shaping anthrax distribution and outbreaks, as evidenced in regions like Western Uganda (Driciru et al., 2020). Wildfires have the potential to alter animal susceptibility and exposure to infection, thereby shaping disease patterns. Changes in biogenic volatile organic compound (BVOC) emissions from forest floors post-fire could potentially impact the transmission of diseases like anthrax over considerable distances (Albery et al., 2021). The 2016 Siberian anthrax outbreak, attributed to permafrost thawing, serves as a stark illustration of how environmental changes can reactivate dormant spores (Ezhova et al., 2021). Additionally, wildfires exert an influence on microbial life in the aero biome, consequently altering pathogen dispersal across ecosystems (Kobziar et al., 2022). Following a wildfire, short-term alterations in small mammal communities may occur, potentially heightening the prevalence of zoonotic pathogens such as PUUV (Ecke et al., 2019). These findings underscore the necessity for comprehensive research into how fires impact the spread of anthrax. Spatial autocorrelation analysis reveals the clustering of anthrax outbreaks, providing insights into their connection with environmental events such as forest fires. Understanding these relationships enables effective resource allocation to mitigate anthrax in fire-prone regions.

While the study offers valuable insights into forest fire occurrences and their implications in India, it has notable limitations. Data reliance may introduce biases or inaccuracies due to varying quality and completeness. Kriging techniques used for hotspot identification are subject to assumptions and uncertainties that may affect accuracy. Focusing on Jharkhand, Orissa, and Andhra Pradesh limits generalizability to other regions with different conditions. Additionally, the temporal scope from 2005 to 2022 may not fully capture long-term trends or shifts. Addressing data source reliability and limitations is crucial for a robust interpretation and identifying areas for future research.

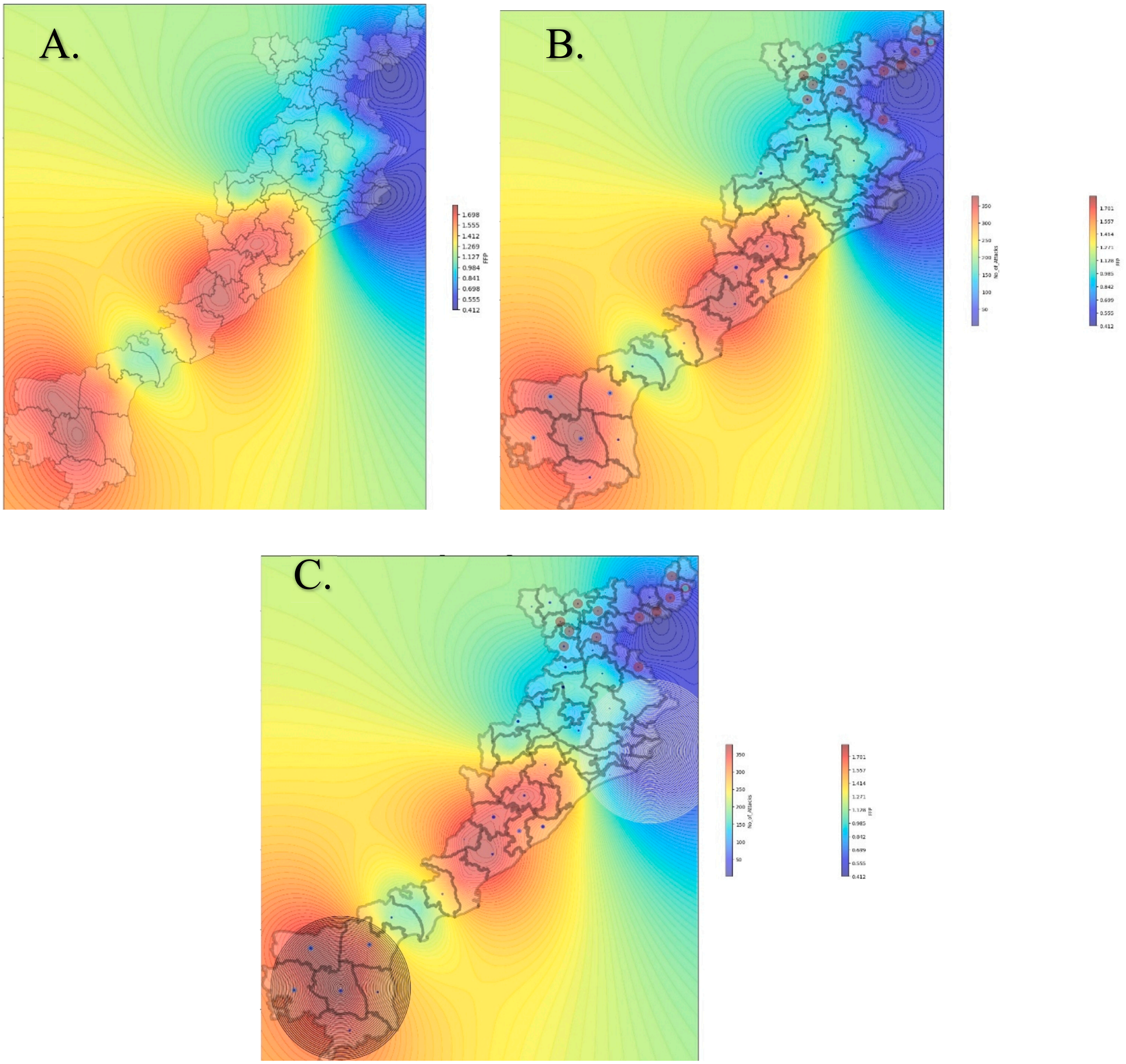

Fig. 12. Mapping Forest Fire Occurrences and Anthrax Outbreaks: **A.** Forest Fire Incidents **B.** Anthrax Attacks on FFP **C.** Distance Plotting of FFP and Anthrax Attack in Orissa, AP, and Jharkhand.

5. Conclusion

In conclusion, the analysis from 2005 to 2022 underscores the urgent need for comprehensive forest fire management in India. Using Kriging techniques to identify hotspots and analyze trends allows for targeted mitigation efforts. Understanding the relationship between climate factors, particularly temperature, and forest fires is crucial for effective prevention and management strategies. Bland-Altman analysis emphasizes the need for continuous monitoring to track trends and adapt responses. The study also highlights the link between forest fires and anthrax dynamics, underlining the interconnectedness of ecological disruptions and public health risks. Practical implications include developing targeted forest management policies for high-risk areas, implementing robust monitoring systems, and formulating public health strategies to address disease outbreaks related to forest fires. These integrated approaches will help India mitigate fire impacts, protect ecosystems, and benefit communities, farmers, and researchers.

6. Future research directions

This study reveals a notable increase in forest fire hotspots and their correlation with rising temperatures in India, along with impacts on anthrax dynamics in specific states. Future research should extend the temporal and spatial scope, enhance data accuracy, investigate interactions between diverse climate factors and fire dynamics, and explore broader health impacts beyond anthrax.

CRediT authorship contribution statement

N. Sagar: Conceptualization, Data curation, Methodology, Validation, Visualization, Writing – original draft, Writing – review & editing. **K.P. Suresh:** Conceptualization, Data curation, Methodology,

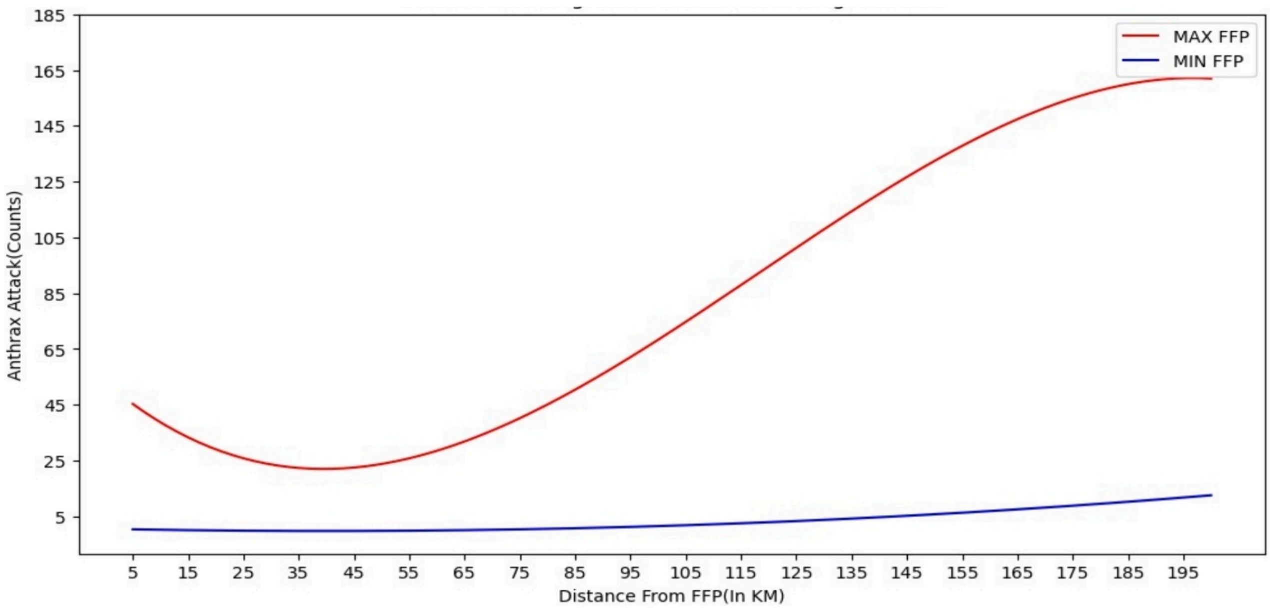

Fig. 13. Line graph illustrating the spatial relationship between anthrax incidence and Forest Fire Points (FFP) occurrence in Orissa, Andhra Pradesh and Jharkhand.

Validation, Visualization, Writing – original draft, Writing – review & editing. **Y.B. Naveesh:** Writing – review & editing, Methodology, Investigation, Data curation. **C.A. Archana:** Writing – review & editing. **D. Hemadri:** Writing – review & editing. **S.S. Patil:** Writing – review & editing. **V.P. Archana:** Data curation, Writing – review & editing. **R. Raaga:** Data curation, Formal analysis, Writing – review & editing. **A.S. Nandan:** Data curation, Formal analysis. **A.J. Chethan:** Data curation, Formal analysis.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: K P Suresh reports financial support was provided by The Pennsylvania State University. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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