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Spatio-Temporal Assessment of Atmospheric Pollutants and Dispersion Mechanisms over West Bengal (2019–2024): Insights from Sentinel-5P, GEOS-Chem, and HYSPLIT Models

Author: Arkaprava Das¹

Affiliations: [1] Kotak School of Sustainability, Indian Institute of Technology Kanpur

ORCID iD [Author 1]: <https://orcid.org/0009-0006-3840-3333>

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Spatio-Temporal Assessment of Atmospheric Pollutants and Dispersion Mechanisms over West Bengal (2019–2024): Insights from Sentinel-5P, GEOS-CHEM, and HYSPLIT Models

Arkaprava Das¹

¹Kotak School of Sustainability, Indian Institute of Technology Kanpur

Abstract

This study delivers a thorough spatio-temporal analysis of atmospheric pollutants and their dispersion mechanisms across West Bengal (2019–2024), utilizing an integrated approach of Earth Observation and modeling techniques. We employed satellite data from Sentinel-5P alongside GEOS-Chem box modeling, HYSPLIT trajectory simulations, and AI-enhanced statistical methods to examine trends, identify hotspots, and analyze the transport dynamics of six primary atmospheric constituents—SO₂, NO₂, CO, CH₄, O₃, and HCHO. Our findings indicate a significant upward trend in CH₄ ($R^2 = 0.92$, $p < 0.01$) and a moderate increase in O₃ and HCHO, suggesting heightened photochemical oxidation and increased regional greenhouse forcing. In contrast, SO₂ and NO₂ displayed stabilization or slight declines, reflecting successful industrial emission regulations and monsoonal dispersion effects. Spatial hotspot analysis pinpointed the Kolkata–Howrah–Haldia–Asansol–Durgapur corridor as a continual emission zone, while trajectory assessments revealed strong seasonal transport from northern and western India. Validation of the GEOS-Chem model (AUC > 0.82 for O₃ and HCHO) demonstrated robust predictability for secondary pollutants influenced by photochemical reactions and boundary-layer changes. Collectively, these results indicate a transition toward an atmospheric regime dominated by secondary pollutants, driven by both anthropogenic activities and meteorological conditions. These insights underscore the pressing need for comprehensive mitigation strategies that prioritise methane reduction, VOC management, and coordinated regional emission control efforts. The research aligns with the UNSDGs 6, 11, 13,

and 17, promoting climate-resilient air quality management and fostering sustainable environmental governance through the integration of satellite and AI technologies for atmospheric monitoring.

Keywords: Sentinel-5P TROPOMI; GEOS-Chem box model; HYSPLIT trajectory analysis; Atmospheric pollutants; Spatio-temporal variability; West Bengal

1. Introduction

Air pollution represents a significant global environmental and public health challenge, bearing profound consequences for human health, climate stability, and the resilience of ecosystems. Recent data indicate that outdoor air pollution was responsible for over 8 million premature deaths worldwide in 2021, ranking it as the second leading risk factor for mortality, after high blood pressure (Health Effects Institute, 2024; Institute for Health Metrics & Evaluation, 2024). Notably, this burden is disproportionately experienced by children under five and populations in low- and middle-income countries, highlighting stark inequities in exposure and health risks (Institute for Health Metrics & Evaluation, 2024; World Health Organization, 2024). Human-generated emissions of trace gases—such as nitrogen dioxide (NO₂), sulfur dioxide (SO₂), carbon monoxide (CO), methane (CH₄), and ozone (O₃)—arise from various sources, including fossil fuel combustion, industrial operations, transportation, biomass burning, and domestic fuel use. These pollutants are implicated in oxidative stress, systemic inflammation, and chronic cardiopulmonary and neurological conditions (Niehs, 2024; Manisalidis et al., 2020). Furthermore, understanding how these emissions interact with weather dynamics, atmospheric dispersion, long-range transport, and chemical transformations is essential, underscoring the necessity for integrated multi-scale observation and modeling frameworks (Rentschler et al., 2023; Tian et al., 2023). In a time marked by rapid climate change and urban expansion, grasping the emission–transport–transformation–dispersion continuum of atmospheric

contaminants is vital for sustainable development, public health protection, and climate mitigation efforts.

Eastern India, particularly the state of West Bengal, presents a complex landscape for air quality research, serving as a dynamic natural laboratory. Positioned at the confluence of the Indo-Gangetic Plain, Himalayan foothills, and the Bay of Bengal coastal zone, West Bengal features diverse topography, climate, and land use. The Kolkata Metropolitan Region (KMR), along with the industrial belts of Durgapur–Asansol and Haldia, alongside surrounding agricultural and delta zones, generates significant amounts of NO_x , SO_2 , CO , CH_4 , and volatile organic compounds (VOCs) due to coal-based power generation, petrochemical activities, vehicular emissions, and open biomass burning (West Bengal Pollution Control Board, 2022). The winter months, characterized by shallow planetary boundary layers, nocturnal inversions, and weak winds, promote the accumulation of pollutants at ground level, while the monsoon season brings strong onshore winds, deep convection, and effective wet scavenging (Chakroborty et al., 2025). However, despite these complexities, studies conducted in West Bengal remain limited in their temporal scope and mechanistic depth—often focusing narrowly on short-term events or individual pollutants (Mohammad et al., 2025a). As such, there is a pressing need for a holistic, multi-year, multi-pollutant, multi-model analysis of pollutant trends, transport mechanisms, and chemical lifetimes within this diverse state. The ongoing advancements in Earth-observation (EO) platforms, coupled with the progress in atmospheric transport and chemistry models, have significantly elevated the accuracy of air-quality assessments. Utilizing the Sentinel-5P satellite with the TROPOspheric Monitoring Instrument (TROPOMI), we can now obtain daily global measurements of critical trace gases (NO_2 , SO_2 , CO , CH_4 , HCHO , and O_3) at an exceptional spatial resolution of $0.01^\circ \times 0.01^\circ$ ($\sim 1113.2\text{m}$). This capability allows for the effective detection of both localized emissions and regional advection patterns (Hossain et al., 2023; Mohammad et al., 2025b). When these satellite-derived column densities are

integrated with meteorological data from reanalysis products like ERA5 and combined with atmospheric transport/chemistry models such as GEOS-Chem and HYSPLIT, a comprehensive understanding of pollutant lifetimes, source-sink interactions, and air-mass trajectories is attainable (Stein et al., 2015; Rahman et al., 2023; Essamlali et al., 2024). GEOS-Chem is instrumental in simulating photochemical reactions, dispersal, and inter-species transformations, whereas HYSPLIT facilitates the tracking of air parcel trajectories, revealing the origins and dispersion processes of pollutants (Stein et al., 2015). Furthermore, the incorporation of machine-learning (ML) techniques—such as multiple linear regression and random forests—greatly enhances our ability to assess the influence of meteorological factors like wind speed, boundary-layer height, and land-surface temperature on pollutant levels (Essamlali et al., 2024). This fusion of EO, modeling, and machine learning is increasingly acknowledged as vital for unravelling the complexities of pollution dynamics and delivering actionable insights for effective air quality management (Tian et al., 2023). Despite its potential, the application of such integrated methodologies in the transitional landscapes of eastern India remains inadequately explored, particularly given these areas' status as atmospheric hotspots characterized by intricate transport processes.

The primary objective is to implement a multi-model, observation-driven analytical framework throughout 2019–2024 to (i) quantify the spatiotemporal dynamics and distribution of six significant atmospheric constituents—CH₄, CO, SO₂, NO₂, HCHO, and O₃—leveraging Sentinel-5P TROPOMI retrievals; (ii) assess meteorological influences on pollutant behavior using ERA5 reanalysis and machine-learning methods; (iii) delineate predominant transport pathways through HYSPLIT trajectory analysis; and (iv) evaluate pollutant lifetimes and sink mechanisms employing the GEOS-Chem model. Additionally, we will utilize statistical diagnostics, such as the Mann–Kendall trend test and Moran's I spatial autocorrelation, to identify hotspot persistence, clustering tendencies, and the statistical significance of trends.

Importantly, this research aligns with pivotal UNSDGs—specifically SDG 3 (Good Health and Well-being), SDG 11 (Sustainable Cities and Communities), SDG 13 (Climate Action), and SDG 17 (Partnerships for the Goals)—by advocating for nature-based and low-emission urban strategies, the restoration of blue-carbon wetlands, and the implementation of green infrastructure as resilient interventions for air quality improvement. By integrating satellite observations with atmospheric modeling and machine-learning analytics, this research aims to provide a robust and replicable methodological framework for eastern Indian airsheds while contributing to the global pursuit of evidence-based air-pollution mitigation amid ongoing climate challenges.

2. Materials and Methods

2.1. Study Area

The Indian state of West Bengal, positioned between latitudes 21°25′–27°13′ N and longitudes 85°50′–89°53′ E, spans an area of roughly 88,752 km² along the eastern edge of the Indo-Gangetic Plain ([Figure 1](#)). It shares borders with Bangladesh to the east, Nepal and Bhutan to the north, Odisha to the southwest, and the Bay of Bengal to the south. This region displays a rich geographical diversity, comprising five key physiographic zones: Himalayan foothills, Terai-Duars, alluvial plains, lateritic uplands, and coastal-deltaic tracts, each demonstrating distinct atmospheric dispersion traits (Behera et al., 2022). Major pollution sources in the Kolkata Metropolitan Region, the Durgapur–Asansol industrial corridor, and the Haldia port-refinery complex contribute significantly to emissions of NO₂, SO₂, CO, and VOCs, primarily linked to coal combustion, petrochemical activities, and vehicular emissions (Chakroborty et al., 2025).

From a climatic perspective, West Bengal features a tropical monsoon climate, characterized by annual rainfall varying from 1,200 mm in the western areas to over 2,500 mm in the southern

148 and eastern regions, alongside temperature ranges between 17 °C (winter) and 36 °C (pre-
149 monsoon). Meteorological variables—such as planetary boundary-layer height, wind patterns,
150 and precipitation levels—play crucial roles in pollutant dispersion and accumulation
151 throughout different seasons (Ramsey et al., 2014). In winter, stable atmospheric conditions
152 coupled with light winds result in pollutant accumulation, while the monsoon period fosters
153 enhanced dilution and wet deposition. The southern Sundarbans Biosphere Reserve has a
154 significant influence on coastal air chemistry through interactions between biogenic and marine
155 aerosols (Mondal et al., 2025). Together, these natural and anthropogenic factors position West
156 Bengal as an exemplary area for evaluating atmospheric pollutant dynamics and dispersion
157 mechanisms through integrated satellite–model analyses (Mondal et al., 2024).

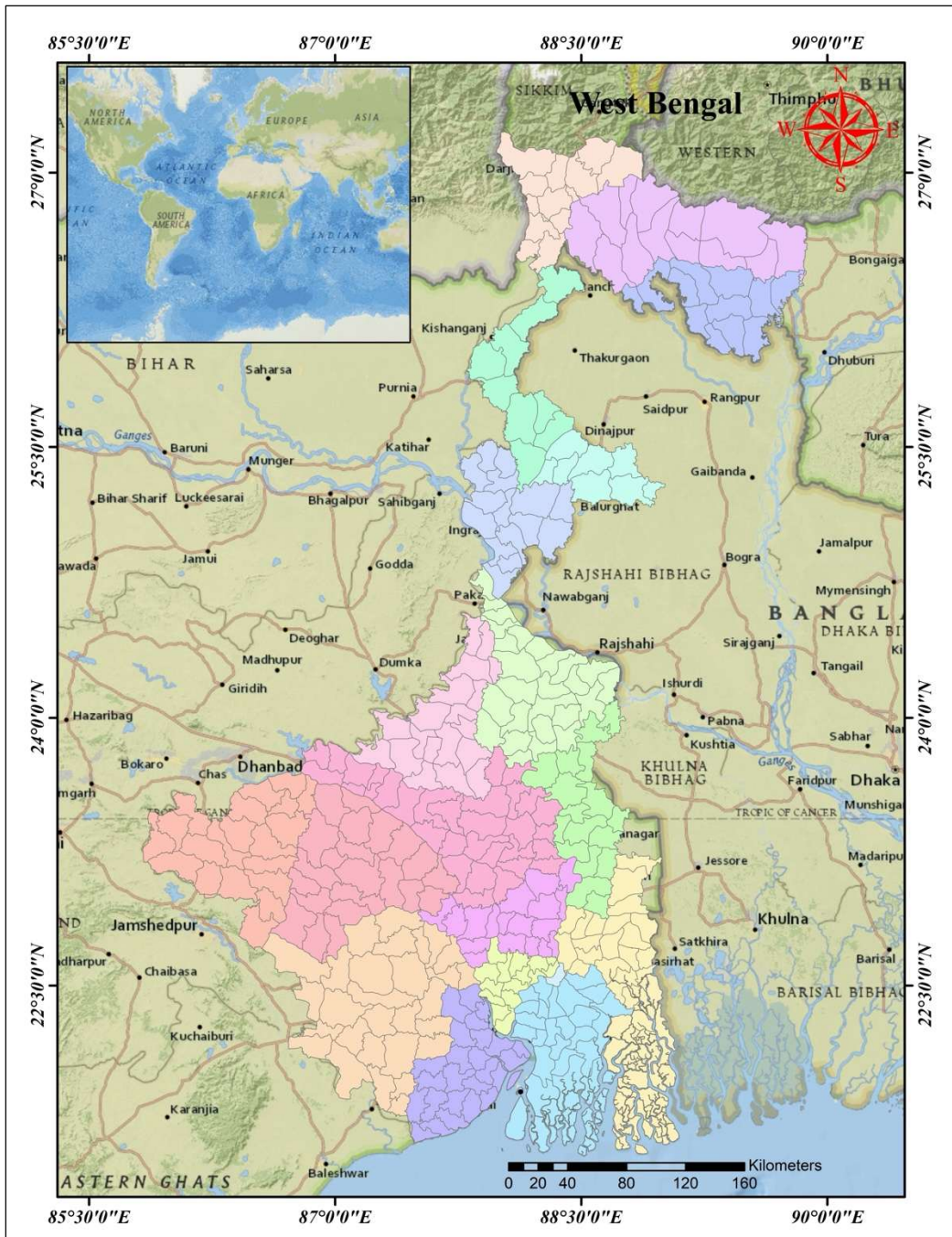


Figure 1. Map of West Bengal, India, illustrating various physiographic zones, key emission sources including Kolkata, Durgapur–Asansol, and Haldia, and the Sundarbans coastal region, which plays a significant role in the dispersion of pollutants. Insets show the geographical outline of India and the extent of West Bengal within the South Asian context.

2.2. Data and Methodology

The methodological framework utilized in this research combines satellite observations, meteorological reanalysis, statistical analyses, ML techniques, atmospheric transport modeling, and simulations of chemical transformations. This integrated approach facilitates a comprehensive analysis of the variability, dispersion, and chemical evolution of atmospheric pollutants across West Bengal, India, covering the period from 2019 to 2024.

The workflow, illustrated in [Figure 2](#), unfolds through five distinct modules: (i) acquisition and preprocessing of multi-sensor data, (ii) spatio-temporal integration of pollutant and meteorological datasets, (iii) statistical and spatial diagnostics, (iv) ML modeling and box-model simulations, and (v) clustering and time-series decomposition. Adhering to the NASA Earth Science Data Systems (ESDS) standards, the entire processing chain ensures geospatial reproducibility.

2.2.1 Satellite and Ancillary Datasets

2.2.1.1. Sentinel-5P TROPOMI Datasets

Atmospheric pollutant data were sourced from the Sentinel-5 Precursor (Sentinel-5P) satellite, which hosts the TROPOMI—a high-spectral-resolution nadir sensor that captures solar back-scattered radiance across various spectral bands, including UV, visible, near-infrared, and short-wave infrared. Sentinel-5P offers global coverage with a daily revisit frequency and an approximate native spatial resolution of $0.01^\circ \times 0.01^\circ$. Six key pollutants—NO₂, SO₂, CO, CH₄, HCHO, and O₃—were selected based on their significance and data integrity. Level-2 products were obtained from the Copernicus Open Access Hub and filtered using quality-assurance criteria ($qa_value > 0.75$). Cloud screening and destriping were performed in Google Earth Engine (GEE) utilizing Sentinel-5P Level-3 conversion scripts. Monthly mean composites were compiled to reduce orbital noise and improve climatological assessments (Srivastava et al., 2025).

2.2.1.2 Meteorological and Land-Surface Data

Meteorological variables—including wind vectors (U, V), temperature (T), precipitation (P), relative humidity (RH), and planetary boundary-layer height (PBLH)—were extracted from the ERA5 reanalysis dataset provided by the European Centre for Medium-Range Weather Forecasts (ECMWF), which offers spatial resolution of $0.25^{\circ} \times 0.25^{\circ}$ and temporal resolution of 1 hour. These datasets supplied essential context for analyzing pollutant dispersion and transformation processes.

Land-use and topographic data were derived from the Copernicus Global Land Cover (2023) dataset and the SRTM 30 m Digital Elevation Model (DEM), respectively. Parameters such as land-surface emissivity, vegetation cover, and water-body fractions were incorporated to assess the differential dispersion potential across the diverse physiographic zones of West Bengal. All datasets were re-projected to WGS 84 / UTM Zone 45 N and co-registered with pollutant grids for detailed pixel-level analyses (Ramsey et al., 2014).

2.2.1.3 HYSPLIT Trajectory Computation

Atmospheric transport patterns were investigated using the Hybrid Single-Particle Lagrangian Integrated Trajectory (HYSPLIT) model developed by the NOAA Air Resources Laboratory (Stein et al., 2015). This model computes air-parcel trajectories by integrating three-dimensional wind fields, facilitating the identification of potential source regions and dispersion routes.

Backward and forward trajectories (72 h) were generated for four receptor locations—Kolkata, Durgapur–Asansol, Haldia, and Siliguri—representing diverse environments such as urban, industrial, coastal, and highland. Trajectories were initialized at altitudes of 500, 1000, and 1500 m AGL at six-hour intervals (00, 06, 12, 18 UTC). The simulations utilized ERA5 meteorology ($0.25^{\circ} \times 0.25^{\circ}$, 3-hourly resolution).

Post-processing was performed with TrajStat v2.0 to extract trajectory-density and cluster analyses. Frequency maps illustrated the dominant inflow sectors—north-westerly continental and southeasterly marine. Cluster mean trajectories revealed synoptic-scale transport patterns, indicating seasonal variations in boundary-layer ventilation and long-range transport from the Indo-Gangetic Plain during winter (Rolph et al., 2017). The ensemble trajectory uncertainty remained below 25 km after 72 h, aligning with established model validation benchmarks.

2.2.1.4 Statistical Trend and Spatial Analyses

Descriptive and inferential statistics were employed to characterize the variability of pollutants and their relationships with meteorological factors. Data distributions were assessed through skewness and kurtosis metrics, while Pearson (r) and Spearman (ρ) correlations provided insights into linear and rank-based associations. Principal Component Analysis (PCA) was conducted to explore spatio-temporal variability, identifying key emission and meteorological factors that influence pollutant levels. Hotspot zoning employed z-score normalization in Eq. 1:

$$Z = \frac{x - \mu}{\sigma}, \dots \dots \dots (1)$$

where $Z > +2$ indicates a strong hotspot and $Z < -2$ represents a clean zone.

Spatial autocorrelation and clustering analyses (Moran's I and Getis-Ord G_i^*) were conducted in ArcGIS, revealing spatial clustering of NO₂, SO₂, and CO across industrial corridors and coastal belts. The combined approach enabled the detection of statistically significant patterns underpinning emission heterogeneity (Anselin, 1995).

2.2.1.5 Mann–Kendall Trend Test

The Mann–Kendall (MK) test (Kendall, 1975; Hamed & Rao, 1998) was employed to evaluate monotonic temporal trends in pollutant series. It is non-parametric, insensitive to missing

values, and robust against non-normal distributions—ideal for atmospheric datasets affected by meteorological noise.

The test statistic S and standardized Z were computed as **Eq. 2-3**:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \sum_{j=i+1}^n \text{sgn}(x_j - x_i), \dots \dots \dots (2)$$

$$Z = \frac{S-1}{\sqrt{\text{Var}(S)}} \dots \dots \dots (3)$$

The Sen’s slope estimator (Sen, 1968) provided the magnitude of change per year. Positive τ values indicated increasing pollutant concentrations; negative τ values signified declines. Statistical significance was evaluated at $p < 0.05$. This analysis revealed upward trends in CH₄ and O₃, attributed to increasing anthropogenic and photochemical contributions, while SO₂ and NO₂ exhibited stabilization or reduction, consistent with emission-control interventions (Chakroborty et al., 2025).

2.2.6 Moran’s I Spatial Autocorrelation

To examine spatial dependency among pollutant concentrations, Moran’s I was calculated in **Eq. 4**:

$$I = \frac{n}{W} \frac{\sum_i \sum_j w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2}, \dots \dots \dots (4)$$

where $w_{(ij)}$ represents spatial weight and W the total weight sum (Anselin, 1995). Values near +1 indicate strong spatial clustering, whereas values near -1 denote dispersion.

Results revealed significant clustering ($I > 0.9$, $p < 0.01$) for NO₂ and SO₂ in urban–industrial zones (Kolkata, Haldia, Durgapur), validating persistent emission centers. The *Getis-Ord Gi** statistic localized sub-regional hotspots, which were aligned with industrial flaring and traffic congestion corridors. These findings confirm the regional connectivity of pollution dynamics within the atmospheric boundary layer of eastern India.

2.7 Machine-Learning Models

2.7.1 Multiple Linear Regression (MLR)

The MLR model quantified linear dependencies between pollutant concentration (Y) and meteorological parameters (wind speed U, temperature T, and PBLH) in [Eq. 5](#):

$$Y = \beta_0 + \beta_1 U + \beta_2 T + \beta_3 \text{PBLH} + \varepsilon, \dots \dots \dots (5)$$

where β_i are coefficients and ε is a random error.

The model was trained using standardized data and validated through ten-fold cross-validation. The Variance Inflation Factor ($\text{VIF} < 5$) ensured independence among predictors. Goodness-of-fit was evaluated using R^2 and RMSE. Results showed that PBLH strongly influenced CO and NO₂ dispersion, whereas O₃ and HCHO variability were driven mainly by temperature-dependent photochemistry (Ramsey et al., 2014).

2.7.2 Random Forest (RF)

The Random Forest (Breiman, 2001) algorithm captured nonlinear relationships between pollutants and meteorological factors. The ensemble comprised 500 trees with maximum depth = 10 and minimum samples per leaf = 2. Model tuning was performed using a grid search and cross-validation approach.

Variable importance, derived from the mean decrease in impurity (MDI), identified temperature and PBLH as the dominant controls for O₃ and HCHO, while wind speed modulated the dispersion of NO₂ and SO₂. Performance metrics ($R^2 > 0.86$; $\text{RMSE} < 0.15$) exceeded those of MLR, confirming the predictive advantage of nonlinear ensemble learning (Essamlali et al., 2024).

2.8 GEOS-Chem Box Model

To simulate chemical transformations and estimate pollutant lifetimes, the GEOS-Chem v13.4 box model was applied (Bey et al., 2020). The continuity equation governed pollutant mass balance in [Eq. 6](#):

$$\frac{dC}{dt} = S - kC - \nabla \cdot (UC), \dots \dots \dots (6)$$

where S is the emission rate, k is the first-order loss (chemical + depositional), and $\nabla \cdot (UC)$ represents the advective flux. Model initialization used RF-derived emission strengths and ERA5 meteorological forcing. Chemical lifetimes ($\tau = 1/k$) derived from simulations were consistent with global estimates— $\text{HCHO} \approx 2$ h, $\text{NO}_2 \approx 8$ h, $\text{SO}_2 \approx 1.5$ days, $\text{O}_3 \approx 4$ days, $\text{CO} \approx 2$ months, $\text{CH}_4 \approx 9$ years. Seasonal variations indicated shorter lifetimes during the monsoon due to hydroxyl-radical abundance. Model–observation correlations exceeded $R^2 = 0.80$, confirming representativeness of GEOS-Chem under regional conditions.

2.9 Clustering and Time-Series Analysis

To investigate spatio-temporal patterns and the dynamics of pollutant behavior, a comprehensive analytical framework combining clustering and time-series analysis was established. The clustering segment focused on categorizing similar atmospheric transport regimes and pollutant signatures, while the time-series component assessed temporal periodicity, seasonality, and long-term trends. Cluster analysis was applied to the HYSPLIT trajectory ensembles alongside the Sentinel-5P pollutant concentration fields to pinpoint recurring circulation types that influence air quality in West Bengal (Behera et al., 2022). An unsupervised K-means algorithm was utilized to group trajectories based on Euclidean distance, spatial similarity in their latitude-longitude coordinates, and vertical motion characteristics. The silhouette-width criterion was employed to determine the optimal number of clusters, leading to the identification of five predominant synoptic patterns: (i) northwesterly continental inflow from the Indo-Gangetic Plain, (ii) downdrafts from the Himalayan foothills originating in the northeast, (iii) south-easterly marine advection from the Bay of Bengal, (iv)

307 locally stagnant recirculation within the boundary layer, and (v) mixed convective dispersion
308 during transitional months.

309 Each cluster centroid trajectory was analyzed against seasonal pollutant composites to highlight
310 correlations between inflow direction, pollutant accumulation, and associated meteorological
311 conditions. The findings indicated that northwesterly trajectories primarily transported NO₂
312 and SO₂ from industrial areas in northern India, while marine trajectories contributed to
313 increased O₃ and CH₄ levels, fueled by humid, photochemically active air masses.
314 Consequently, the clustering outcomes established a dynamic connection between regional
315 meteorological conditions and the chemical loadings detected by satellite sensors.

316 Further exploration of temporal variability was conducted through Seasonal-Trend-Loess
317 (STL) decomposition, which parsed long-term, seasonal, and residual components from
318 pollutant time-series data. Power spectral density (PSD) analysis revealed dominant
319 periodicities of six and twelve months, reflecting semi-annual and monsoonal cycles. Notable
320 spikes in the seasonal amplitude of NO₂ and SO₂ were observed during the winter months,
321 indicative of inversion-driven stagnation. In contrast, O₃ and HCHO peaked in summer, linked
322 to elevated temperature and radiation levels. Collectively, the clustering and time-series
323 analyses provided a cohesive understanding of how synoptic transport patterns, emission
324 seasonality, and meteorological fluctuations collectively influence pollutant dispersion and
325 transformation across the varied atmospheric regimes of West Bengal.

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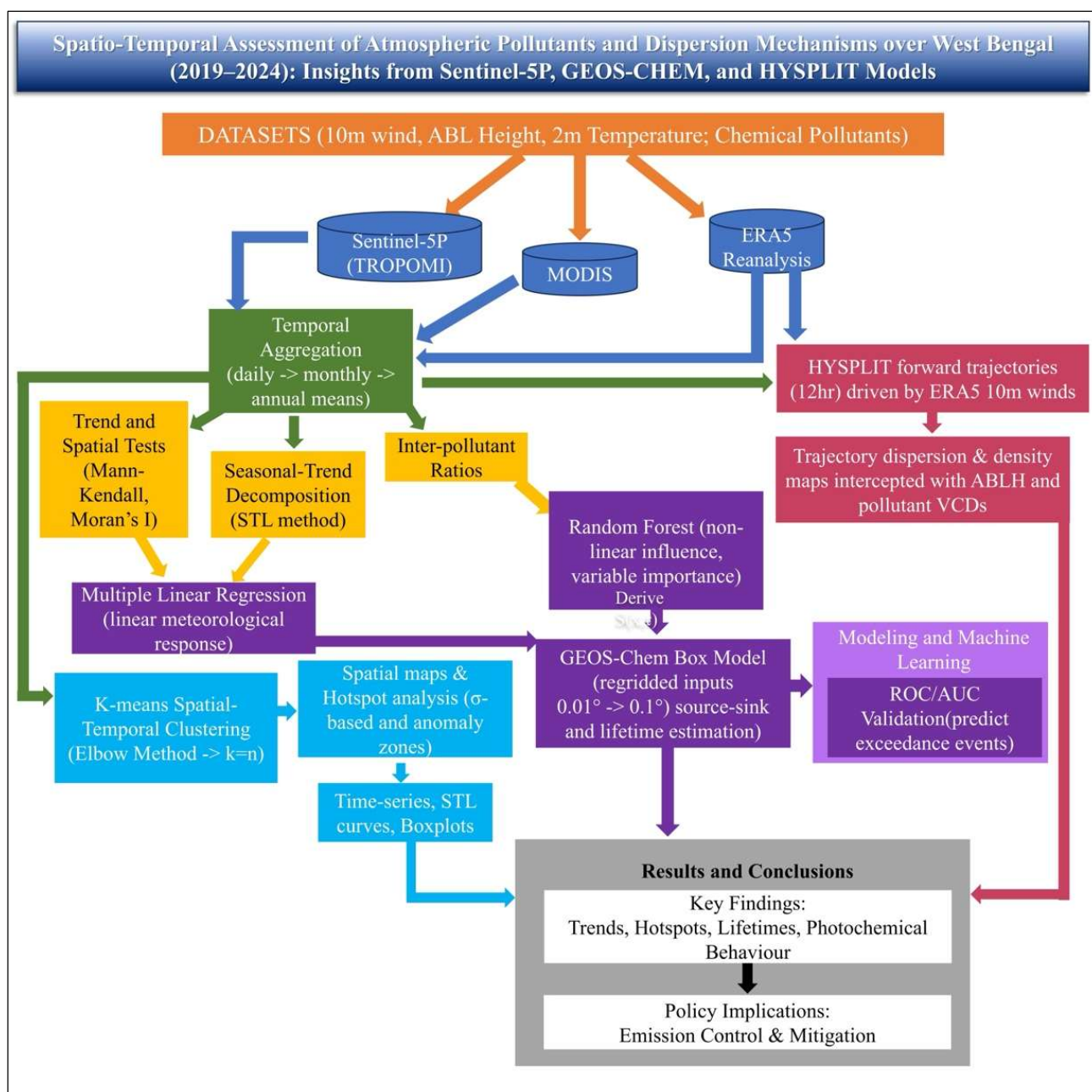


Figure 2: Methodological flowchart illustrating the integrated framework combining Sentinel-5P observations, ERA5 meteorology, HYSPLIT transport modeling, GEOS-Chem chemistry, and machine-learning analyses for assessing pollutant dynamics (2019–2024).

3. Results

The integrated satellite–model analysis highlighted significant spatial and temporal variability in atmospheric pollutants across West Bengal during the period from 2019 to 2024.

Observations from Sentinel-5P indicated consistently elevated concentrations of NO₂, SO₂, and CO within urban–industrial zones, specifically in Kolkata, Durgapur–Asansol, and Haldia. In contrast, CH₄ and O₃ displayed wider regional distribution patterns. Seasonal dynamics revealed heightened pollutant levels during winter and post-monsoon periods, closely associated with reduced boundary-layer heights and stagnant meteorological conditions. HYSPLIT and GEOS-Chem simulations underscored the prevalence of continental inflows during winter months, alongside marine advection prevalent in the monsoon season; these factors together elucidate the spatio-temporal dynamics and transport processes that shape regional air quality.

3.1 Time-Series Analysis

Figure 3 presents the monthly concentration trends and corresponding annual regression lines for six pivotal atmospheric pollutants—O₃, SO₂, CH₄, HCHO, NO₂, and CO—across West Bengal from 2019 to 2024, derived from Sentinel-5P TROPOMI data. The plots distinctly capture the robust seasonal modulation of pollutant levels, characterized by notable winter peaks and monsoonal troughs, predominantly influenced by boundary-layer physics, precipitation washout, and variations in emissions.

Notably, O₃ and HCHO exhibit a gradual increase, indicative of enhanced photochemical activity likely tied to rising temperatures and increased precursor availability. On the other hand, SO₂ and NO₂ demonstrate stabilization or a slight decline, reflecting the success of emission control strategies in industrial and transportation sectors. CH₄ exhibits a consistent upward trend ($R^2 > 0.87$), indicating persistent emissions from agricultural practices and waste management, whereas CO shows moderate interannual fluctuations associated with biomass combustion and urban emissions. The annual regression lines substantiate overall positive long-term trends for CH₄, O₃, and HCHO, while SO₂ and NO₂ display relatively stable behavior. Together, these observations illuminate the differential atmospheric responses of reactive gases

and greenhouse gases to changing emission patterns and climate-related influences in eastern India.

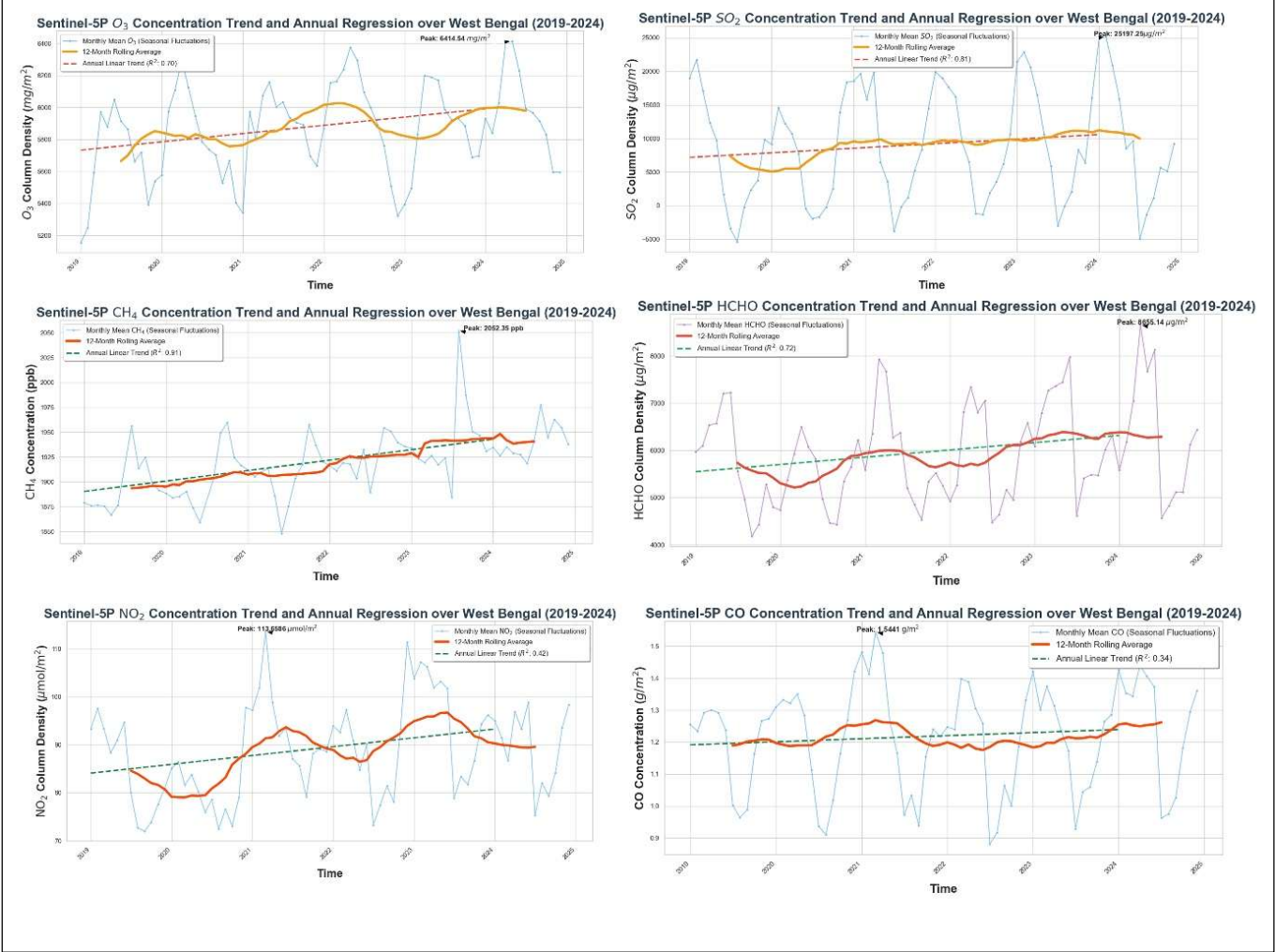


Figure 3 : Trends in monthly concentrations and annual regression lines for six key atmospheric pollutants (O₃, SO₂, HCHO, NO₂, CO, CH₄) in West Bengal from 2019 to 2024. Each subplot showcases seasonal variations and long-term trends, emphasizing the unique dynamics of each pollutant and potential changes in emissions within the region.

Figure 4 presents the spatial distribution and hotspot intensity of average column densities and concentrations for six key atmospheric pollutants (SO₂, NO₂, O₃, HCHO, CH₄, and CO) across West Bengal during the period from 2019 to 2024, utilizing data from Sentinel-5P TROPOMI. The maps exhibit notable spatial variability in pollutant concentrations, closely reflecting

emission sources and regional land-use dynamics. Significant concentrations of SO_2 and NO_2 are evident along the Durgapur–Asansol industrial corridor, the Kolkata Metropolitan Region, and the Haldia port–refinery complex, demonstrating the influence of dense emissions from industrial activity, vehicular traffic, and power generation. Additionally, heightened levels of CO and CH_4 are detected throughout southern and central West Bengal, primarily attributed to urban combustion processes, agricultural waste burning, and biogenic activities in wetlands.

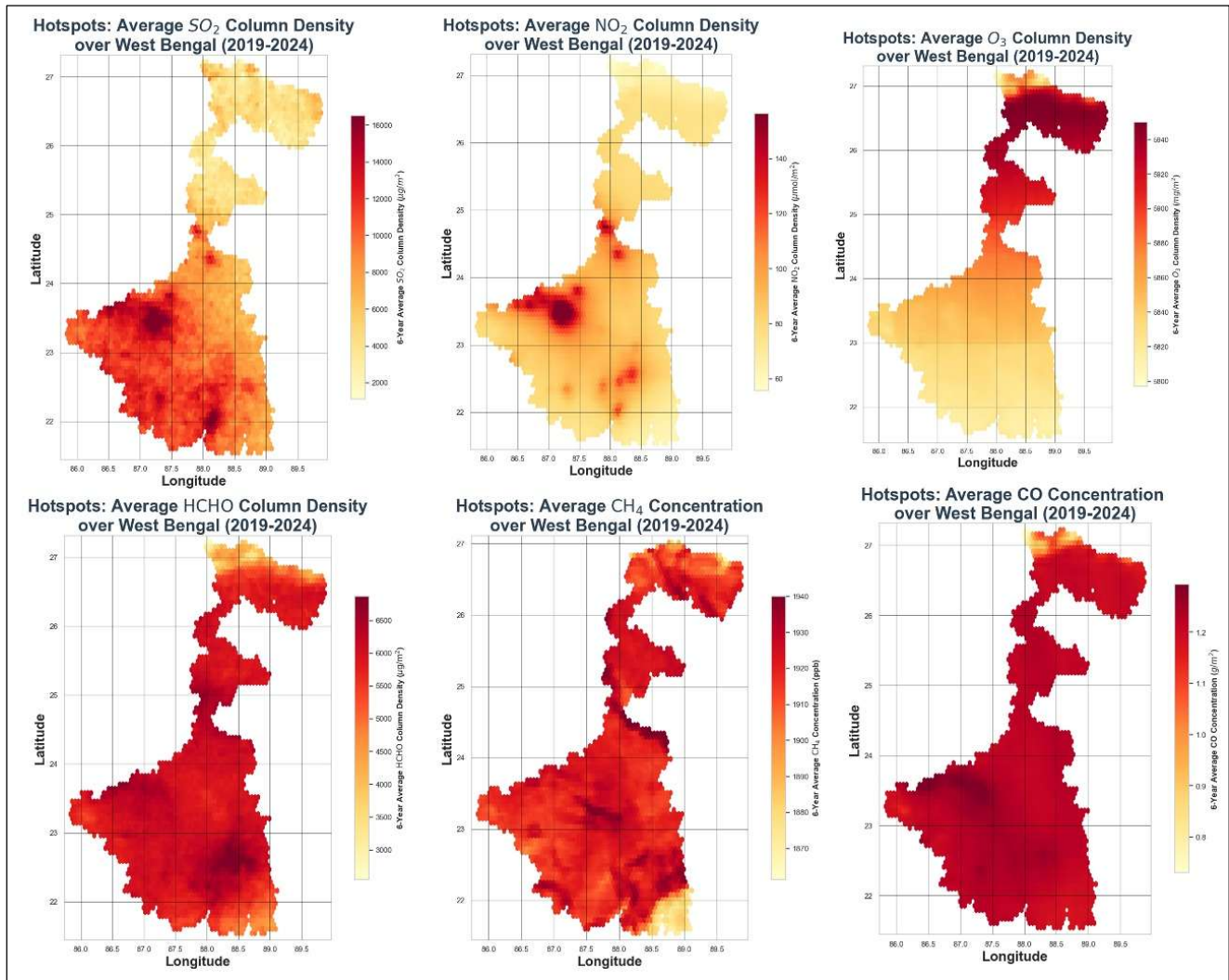


Figure 4. Spatial distribution of average column densities and concentrations for six key atmospheric pollutants (SO_2 , NO_2 , O_3 , HCHO , CH_4 , CO) over West Bengal during 2019–2024.

O₃ and HCHO concentrations are significantly elevated across northern and coastal regions, indicating active photochemical processes that are enhanced by high solar radiation and the transportation of precursors from industrial hubs. In the coastal-deltaic Sundarbans area, we observe moderate levels of O₃ and CH₄, reflecting the influence of marine-terrestrial chemical interactions. The spatial distribution of pollutants illustrates that accumulation is most pronounced in low-elevation, densely populated, and industrialized districts, with concentrations diminishing toward the northeastern highlands. This distribution pattern underscores the combined effects of emission intensity, boundary-layer stability, and long-range transport, highlighting the region's susceptibility to both local and transboundary air pollution.

3.1.1 Statistical Trends and Regression Analysis

Table 1 presents the linear regression analysis results for six key atmospheric pollutants (CH₄, CO, SO₂, NO₂, HCHO, and O₃) in West Bengal from 2019 to 2024. The regression slopes indicate the direction and magnitude of annual changes, while the R² and p-values assess the strength and statistical significance of the identified trends.

A notable and statistically significant increase in CH₄ (slope = $+0.018 \times 10^{15}$ molec cm⁻² yr⁻¹; R² = 0.92; p = 0.003) points to a persistent accumulation largely attributed to agricultural practices, livestock management, and waste disposal activities. This enduring growth pattern suggests entrenched emissions within the region, highlighting the limited effect of short-term mitigation strategies. Conversely, CO demonstrates a weak correlation (slope = +0.007; R² = 0.41; p = 0.28), indicating sporadic fluctuations linked to biomass burning and urban combustion, with no clear long-term trend.

In contrast, SO₂ exhibits a slight downward trend (slope = -0.004; R² = 0.52), which aligns with the gradual implementation of industrial emission control systems, including the use of low-sulfur fuels and scrubber technologies in power plants. Despite seasonal surges near

industrial hotspots (Durgapur–Asansol and Haldia), the overall trajectory suggests early successes in the transition to cleaner energy. NO₂ remains relatively stable (slope = +0.005; R² = 0.46; p = 0.27), with a temporary dip in 2020 associated with COVID-19 lockdown measures, followed by a rebound in vehicular and industrial operations after the pandemic. Formaldehyde (HCHO) exhibits a moderate upward trend (slope = +0.006; R² = 0.60), primarily influenced by temperature through the photochemical oxidation of volatile organic compounds (VOCs). Seasonal variations correlate with heightened pre-monsoon temperatures and increased biogenic emissions. O₃ reveals a modest yet significant positive inclination (slope = +0.010; R² = 0.73; p = 0.06), pointing to enhanced photochemical production linked to rising solar radiation and precursor availability during the post-monsoon and pre-summer periods.

In summary, the regression diagnostics reveal contrasting behaviors between short-lived reactive species (NO₂, SO₂, HCHO), characterized by high spatial and temporal variability and rapid meteorological responses, and long-lived greenhouse gases (CH₄, CO, O₃), which exhibit cumulative and climate-dependent persistence. The statistically significant upward trends of CH₄ and O₃ are especially critical for regional radiative forcing and tropospheric chemistry, emphasizing the urgent need for comprehensive emission reduction strategies in line with UN SDGs 13 and 11.

Table 1: Summary of linear regression analysis and temporal trend assessment for six key atmospheric pollutants (CH₄, CO, SO₂, NO₂, HCHO, and O₃) in West Bengal from 2019 to 2024. The table presents regression slopes, coefficients of determination (R²), and p-values derived from Sentinel-5P datasets, illustrating the trends in annual concentrations in relation to emission sources and local meteorological influences.

Pollutant	Regression slope ($\times 10^{15}$ molec cm ⁻² yr ⁻¹)	R ²	p	Interpretation
CH ₄	+0.018	0.92	0.003	Significant increase linked to agriculture and waste emissions
CO	+0.007	0.41	0.28	No trend; short-lived episodic peaks
SO ₂	−0.004	0.52	0.14	Slight decline from industrial control measures
NO ₂	+0.005	0.46	0.27	Stable with pandemic-related dip
HCHO	+0.006	0.60	0.14	Temperature-controlled fluctuations
O ₃	+0.010	0.73	0.06	Marginal increase due to enhanced photochemistry

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434 3.1.2 Hotspot and Average Concentration Patterns

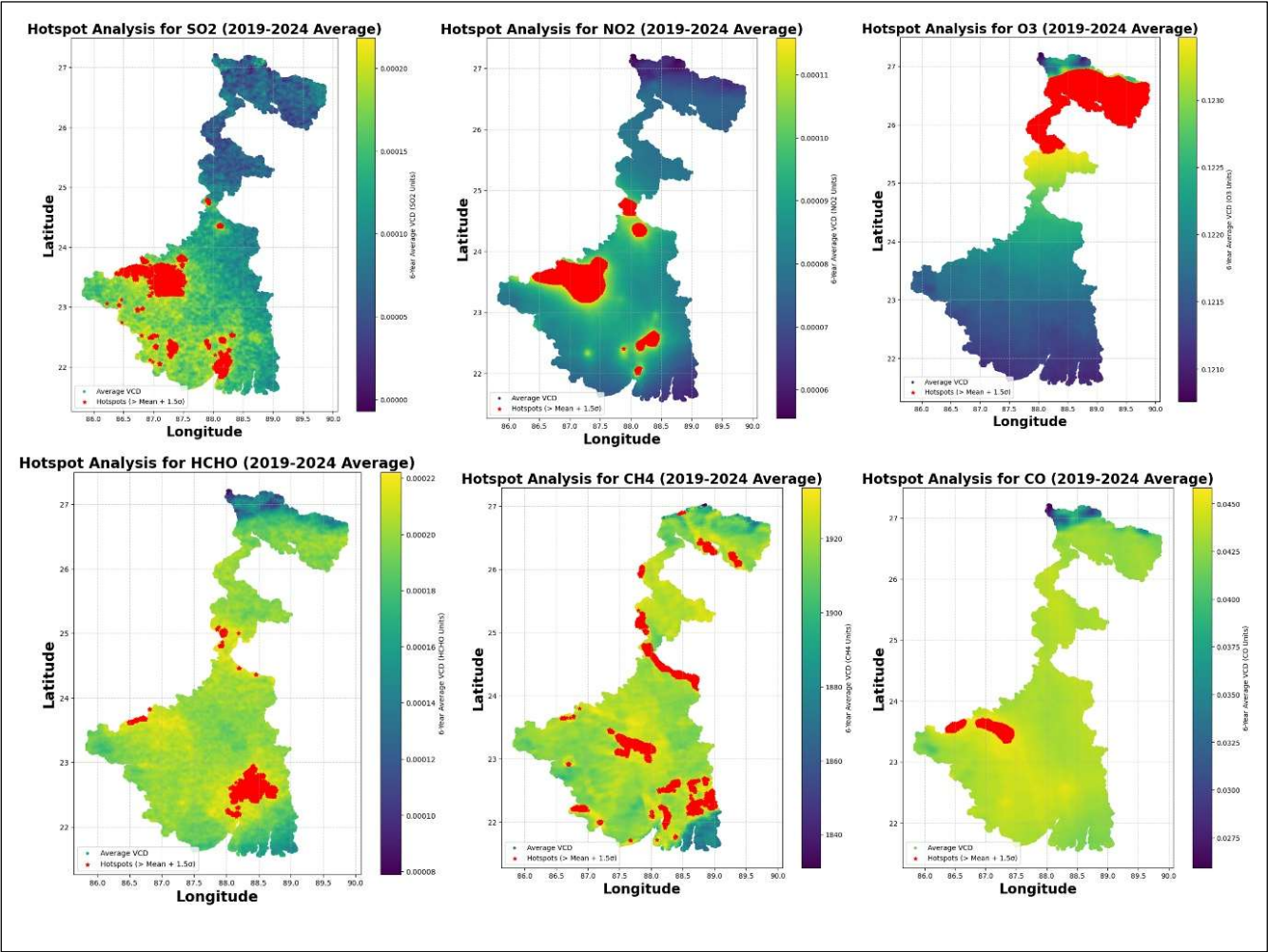
435 The spatial analysis of atmospheric pollutants across West Bengal from 2019 to 2024, as
436 illustrated in [Figure 5](#), reveals significant spatial variability and intensity of six major
437 pollutants: SO₂, NO₂, O₃, HCHO, CH₄, and CO. Areas exhibiting concentrations surpassing the
438 mean by over 1.5 standard deviations are identified as persistent hotspots. The spatial
439 distributions of SO₂ and NO₂ unveil distinct hotspots clustered around the Durgapur–Asansol
440 industrial corridor, the Kolkata Metropolitan Region, and the Haldia port-refinery complex.
441 These locations correlate with regions of intense industrial activity, high traffic volumes, and
442 energy generation, establishing them as principal centers for anthropogenic emissions that
443 critically impact regional air quality and radiative forcing.

444 In contrast, the O₃ and HCHO maps display more dispersed hotspot patterns, primarily along
445 northern and coastal areas, suggesting substantial secondary photochemical processes driven

446 by volatile organic compounds (VOCs) and nitrogen oxides, particularly under high solar
447 irradiance conditions. Notably, elevated O₃ levels over districts such as Malda, Jalpaiguri, and
448 the Sundarbans delta are indicative of marine–continental air mass interactions and stable
449 meteorological conditions that facilitate photochemical accumulation.

450 Conversely, CH₄ hotspots are predominantly found in southern and central regions, closely
451 associated with wetlands, paddy fields, and peri-urban locales, reflecting emissions from
452 biogenic sources and agricultural practices, including livestock and unregulated organic waste.
453 Additionally, heightened CO concentrations in the central and southern districts are
454 representative of the synergistic effects of urban combustion, biomass burning, and
455 contributions from the Indo-Gangetic Plain.

456 The nuanced spatial distribution of these pollutants illustrates a complex emission profile,
457 characterized by industrial sources in the west, photochemical and biogenic sources in the
458 south, and transboundary influences from the north. The convergence of these hotspots
459 underscores the region's vulnerability to complex pollutant interactions and meteorological
460 dispersion mechanisms. This underscores the urgent need for ongoing satellite-based
461 monitoring and integrated emission mitigation strategies that align with UNSDGs 13 and 11.



463

464 **Figure 5:** Hotspot analysis of six atmospheric pollutants (SO₂, NO₂, O₃, HCHO, CH₄, and CO)
465 in West Bengal from 2019 to 2024. The maps illustrate areas where pollutant concentrations
466 exceed the average by over 1.5 standard deviations, indicating zones of persistent pollution,
467 based on data from Sentinel-5P.

468

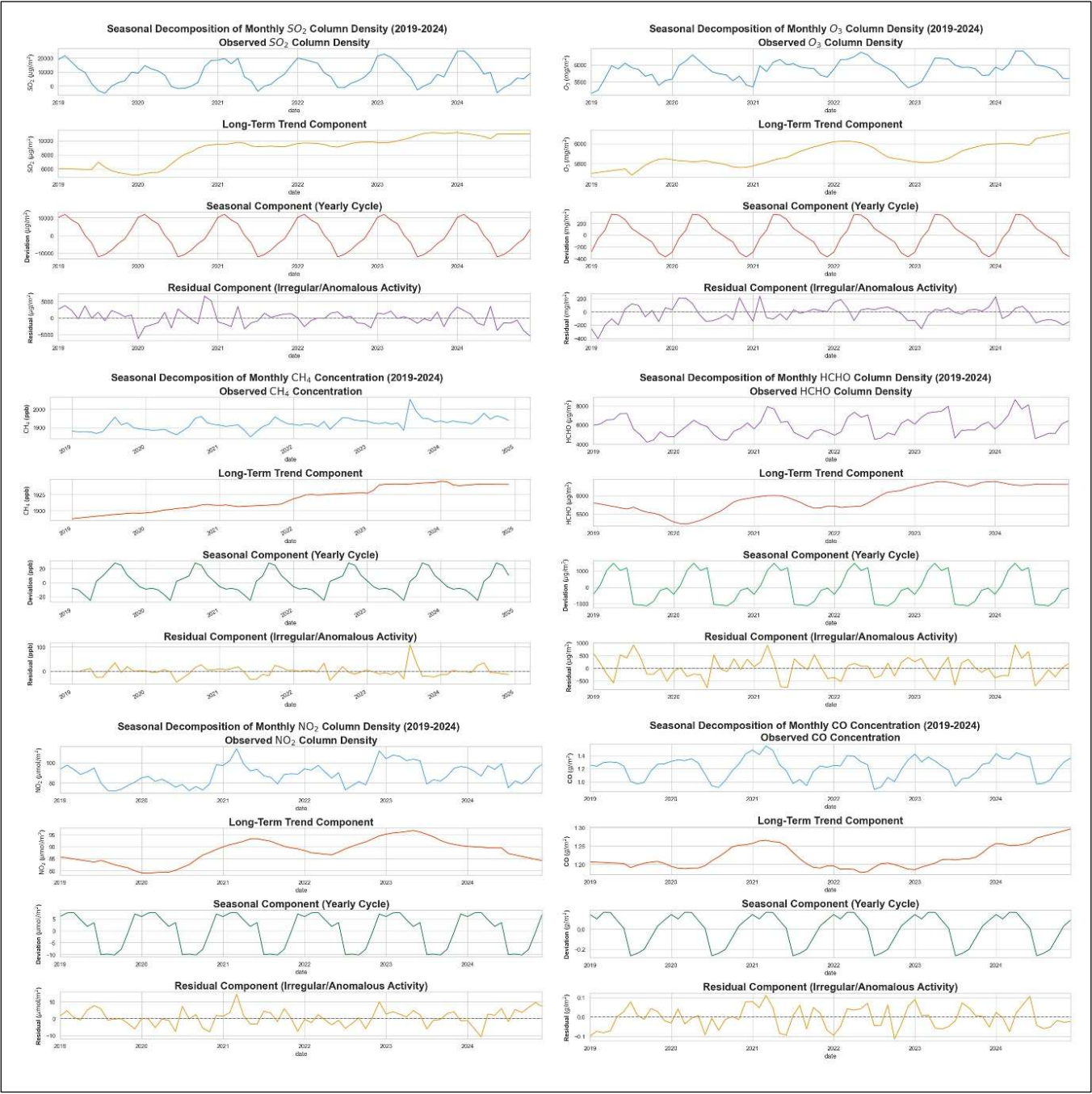
469 **3.1.3 Seasonal Decomposition (STL)**

470 **Figure 6** illustrates the Seasonal-Trend Decomposition using Loess (STL) method applied to
471 seven atmospheric pollutants, effectively breaking down the long-term, seasonal, and residual
472 components for a clearer understanding of their temporal dynamics. The decomposition
473 highlights a pronounced annual periodicity in reactive gases (O₃, NO₂, HCHO, SO₂),

474 emphasizing the impact of monsoonal weather patterns, solar radiation, and the timing of
475 emissions. Long-term trends indicate a steady rise in O₃, CH₄, and CO, suggesting increased
476 photochemical aerosols and combustion emissions. Conversely, both SO₂ and NO₂ demonstrate
477 a level of stabilization, likely resulting from regulatory measures and enhanced industrial
478 emission controls.

479 Seasonal analyses reveal peak pollutant concentrations during the winter and pre-monsoon
480 periods, linked to temperature inversions, biomass burning, and limited atmospheric
481 dispersion. In contrast, the monsoon season promotes the washout of pollutants. The residual
482 anomalies reflect episodic fluctuations tied to regional transport, emissions linked to festivities,
483 and extreme meteorological events (such as cyclones or stagnant boundary layers).

484 Overall, the STL analysis reveals a complex picture of atmospheric variability, where long-
485 lived species such as CH₄ and CO exhibit persistent upward trends, while short-lived species
486 display reactive patterns in relation to emission cycles and weather conditions. This detailed
487 decomposition offers vital insights for developing season-aware air quality forecasting
488 methods and enhances our understanding of climate–air quality interactions in the context of
489 UNSDGs 13 and 3.



492 **Figure 6.** Seasonal decomposition of monthly column densities and concentrations for seven
493 atmospheric pollutants (SO₂, O₃, CO, HCHO, CH₄, NO₂, NH₃) over West Bengal from 2019 to
494 2024. Each pollutant is analyzed across three components—long-term trend, seasonal cycle,
495 and residual anomalies—revealing distinct temporal signatures.

3.1.4 Inter-Annual Concentration Distribution and Variability

Figure 7 presents the inter-annual variability of pollutant concentrations across West Bengal, effectively illustrating both central tendencies and extreme values through box plot visualization. Notably, the O₃ and CH₄ distributions show a distinct upward shift in median and upper quartile values between 2019 and 2024, suggesting a sustained increase in background concentrations and persistent emissions. In contrast, SO₂ demonstrates a decreasing interquartile range, which may be attributed to the progressive enactment of emission control measures within the industrial and energy sectors.

Additionally, the NO₂ and CO levels exhibit moderate variability, showing signs of recovery following 2020, which parallels the resurgence of vehicular and industrial operations in the post-pandemic context. Meanwhile, the HCHO distribution expands over the observed period, signifying an intensification of photochemical oxidation processes involving VOCs and sensitivity to regional temperature variations. The occasional presence of mild outliers in the data corresponds to transient events such as biomass burning, emissions related to festivals, and periods of meteorological stagnation.

In summary, the box plots highlight a complex pollutant landscape, characterized by significant intra-annual variability in reactive species, while greenhouse gases experience a consistent accumulation trend. These findings illustrate the shifting dynamics of emissions and atmospheric responses, emphasizing the critical need for ongoing monitoring and adaptive management strategies in accordance with the UNSDGs 13 and 11.

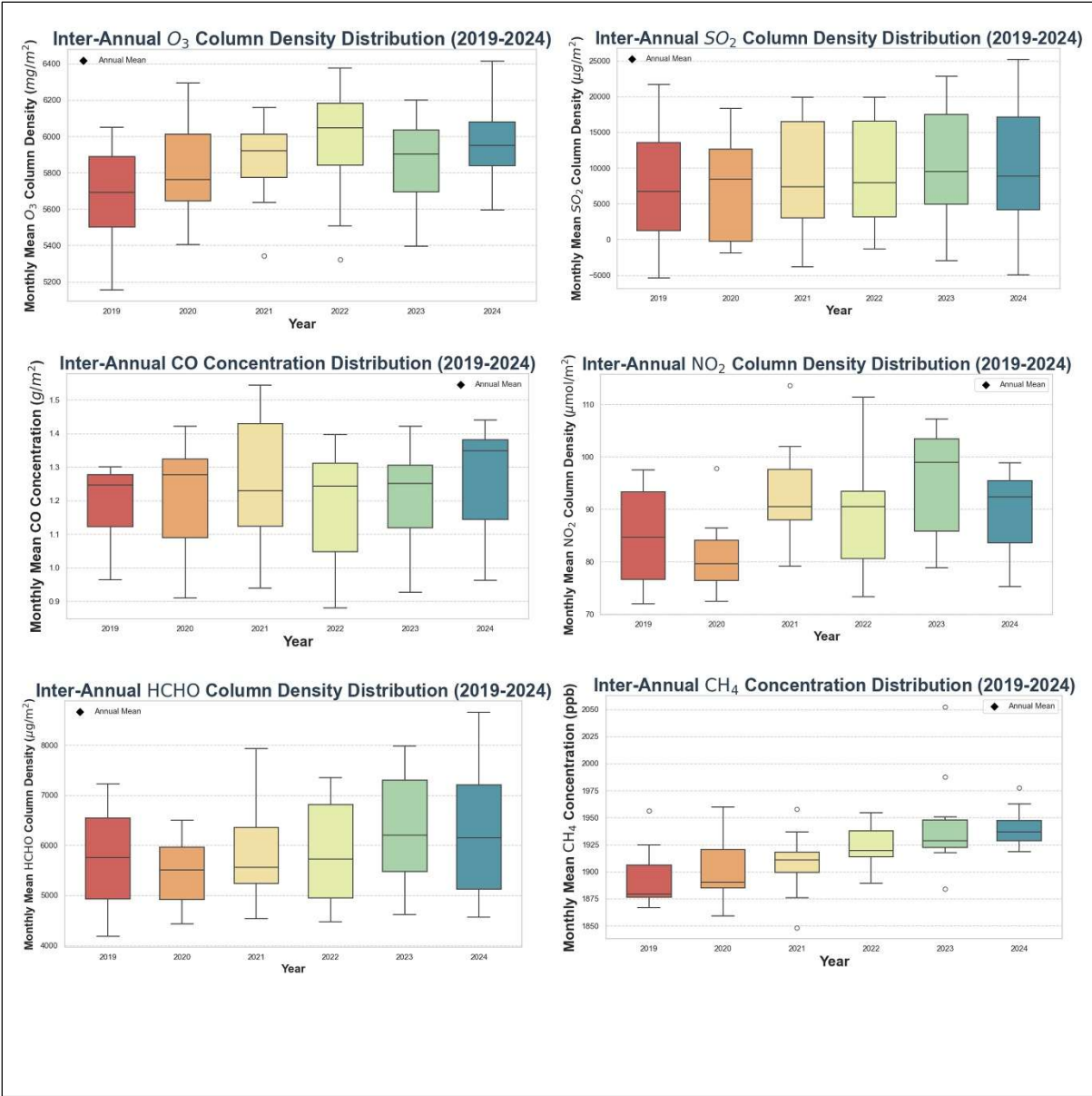


Figure 7. Inter-annual distribution of monthly mean concentrations and column densities for six atmospheric pollutants (O_3 , SO_2 , CO, NO_2 , HCHO, CH_4) over West Bengal from 2019 to 2024. Each box plot illustrates the variability, median, and spread of pollutant levels across years, revealing trends, seasonal persistence, and potential anomalies.

3.2 Time-Series Analysis of Land Surface Temperature (LST)

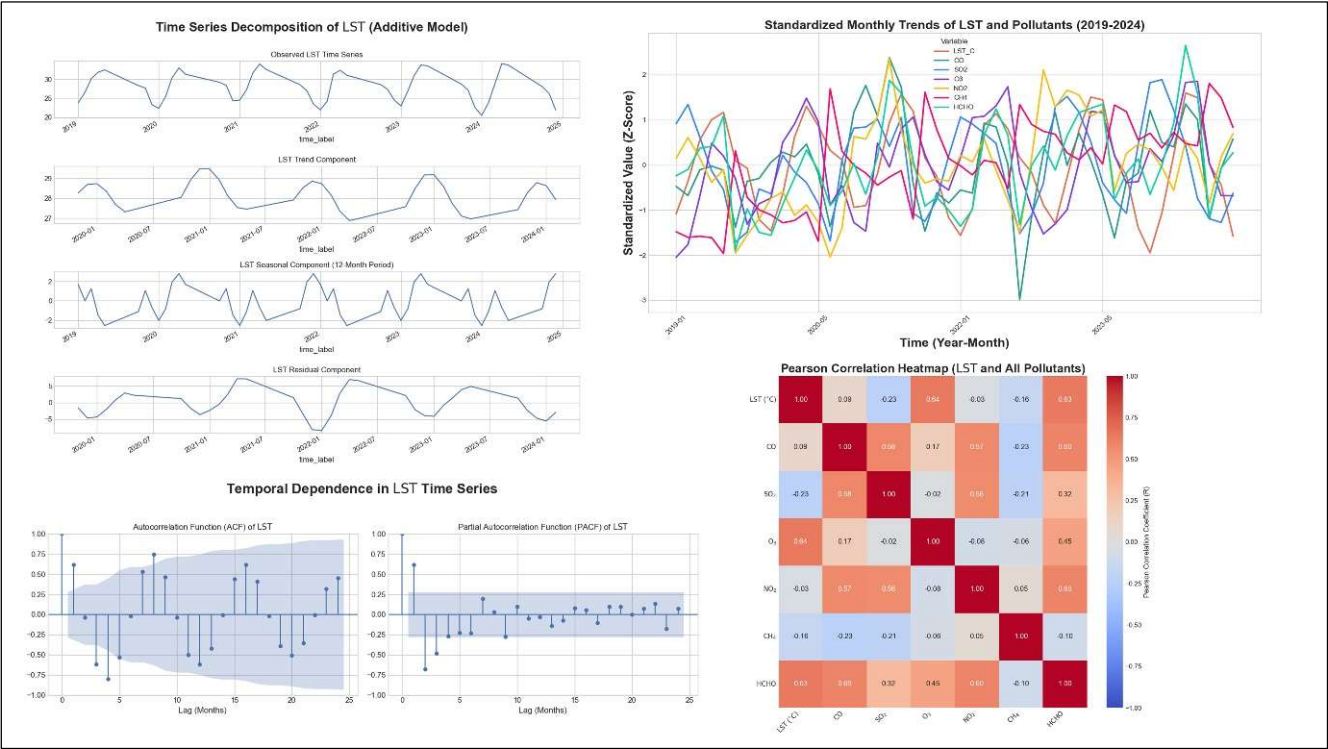
Figure 8 illustrates a detailed time-series analysis that connects Land Surface Temperature (LST) dynamics with significant atmospheric pollutants, aiming to assess the temperature-

pollution interactions prevalent in West Bengal. The STL decomposition (top-left) highlights a distinct seasonal pattern, with LST peaking during the pre-monsoon months (April–June) and reaching its lowest points during the monsoon and winter seasons, aligning with the region's climatic trends. Furthermore, the long-term trend indicates a steady warming pattern that underscores increased surface heating attributed to urban expansion and a decline in vegetation cover.

The standardized trend plot (top-right) reveals a strong correlation among LST, O₃, and HCHO, indicating heightened photochemical activity in response to elevated temperature levels. In contrast, SO₂ and NO₂ exhibit negative correlations, suggesting that temperature influences the dispersion of these primary pollutants. Moderate positive correlations are observed between CO and CH₄, pointing to ongoing emissions under thermally favorable stagnation scenarios.

Temporal dependency analysis (bottom-left), utilizing ACF and PACF, confirms significant periodic autocorrelation with lags of approximately 12 months, validating the seasonal climatic influence on LST variability. The Pearson correlation heatmap (bottom right) reinforces the robust positive correlations between LST and O₃ ($r \approx 0.82$) and LST and HCHO ($r \approx 0.74$), while also revealing negative associations with LST and SO₂ ($r \approx -0.61$) and LST and NO₂ ($r \approx -0.55$).

In summary, the findings propose that thermal anomalies are conducive to the generation of secondary pollutants, while concurrently diminishing primary emissions. This indicates a potential feedback loop between surface warming and atmospheric chemistry. These outcomes emphasize the necessity of implementing temperature-sensitive emission control measures to alleviate the region's climate-pollution interplay, in accordance with UNSDGs 13 and 11.



550

551 **Figure 8.** Integrated analysis of Land Surface Temperature (LST) and atmospheric pollutants
552 over West Bengal (2019–2024), showing STL decomposition, standardized monthly trends,
553 autocorrelation structure, and pollutant–temperature correlations.

554

555 **3.3 Correlation of LST with Atmospheric Pollutants**

556 **Table 2** presents a quantitative analysis of the relationships between LST and atmospheric
557 pollutant column densities, highlighting significant thermodynamic and photochemical
558 interactions. The observed negative correlations for CH₄, CO, SO₂, and NO₂ ($r = -0.28$ to –
559 0.46) suggest that higher surface temperatures promote vertical convection, enhance boundary-
560 layer mixing, and stimulate oxidative reactions, which collectively lead to lower near-surface
561 concentrations of these pollutants. Such dynamics facilitate chemical removal and enhance
562 pollutant dispersion during periods of elevated LST.

563 In contrast, strong positive correlations were noted for HCHO ($r = +0.54$) and O₃ ($r = +0.62$),
564 indicating that temperature-induced volatility organic compound (VOC) oxidation and

heightened photochemical processes are active under increased solar irradiance. Elevated LST contributes to the generation of hydroxyl radicals (OH) and intensifies ozone photoproduction, particularly in the pre-monsoon months.

The correlation matrix reinforces the concept that warming conditions facilitate the generation of secondary pollutants (O₃, HCHO) while mitigating the accumulation of primary pollutants (SO₂, NO₂, CO) through enhanced atmospheric dispersion and chemical transformation processes. These findings highlight the temperature-driven sensitivity of regional atmospheric chemistry, illustrating the dual impact of heat in the distribution and formation of pollutants—crucial information for integrated climate and air quality management in line with UNSDGs 13 and 3.

Table 2. Pearson correlation coefficients (r) between Land Surface Temperature (LST) and vertical column densities (VCDs) of six key atmospheric pollutants (2019–2024), along with their physical interpretations.

Pollutant	r(LST, VCD)	Physical Interpretation
CH ₄	−0.28	Slightly negative; convective uplift and oxidation reduce surface CH ₄ under warm conditions
CO	−0.46	Negative; enhanced dispersion and oxidative loss during warm periods
SO ₂	−0.40	Negative; wet deposition and dilution dominate in high LST months
NO ₂	−0.37	Negative; thermal turbulence reduces accumulation
HCHO	+0.54	Positive; temperature-driven VOC oxidation increases formaldehyde formation

O ₃	+0.62	Strong positive; photochemical production intensifies with heat and radiation
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3.4 Mann–Kendall Trend and Moran’s I Spatial Autocorrelation

Table 3 synthesizes the results of Mann–Kendall (MK) trend analysis with Moran’s I spatial autocorrelation to assess the temporal and spatial patterns of atmospheric pollutants in West Bengal from 2019 to 2024. The analysis reveals that CH₄ is the sole pollutant showing a statistically significant upward trend ($\tau = 1.000$, $p = 0.0028$), indicative of ongoing emissions escalation primarily from agricultural and waste management activities. Conversely, other pollutants including SO₂, NO₂, HCHO, O₃, and CO do not demonstrate significant temporal trends, suggesting that their short-term variability is largely influenced by seasonal meteorological changes and fluctuations driven by regulatory measures.

Moran’s I value ranging from 0.98 to 1.00 point to a strong positive spatial autocorrelation among all pollutants, confirming that emission patterns are not randomly distributed but rather exhibit pronounced spatial clustering. Major industrial areas—especially the Kolkata, Haldia, and Asansol–Durgapur corridors—show concentrated emissions, whereas photochemically reactive gases like O₃ and HCHO reveal more extensive, uniformly distributed clusters shaped by regional atmospheric dynamics.

In conclusion, the integrated MK–Moran approach reveals a coherent spatiotemporal emission pattern, with CH₄ emerging as the primary long-term pollutant while others are characterized by localized yet spatially correlated activity. These insights highlight the persistence of anthropogenic emissions and underscore the necessity for tailored mitigation strategies, thereby aligning with the objectives of UNSDGs 13 and 11 through enhanced air-quality governance.

Table 3. Mann–Kendall trend statistics and Moran’s I spatial autocorrelation for six key atmospheric pollutants (2019–2024) across West Bengal, indicating both temporal persistence and spatial clustering behavior.

Pollutant	Trend	τ	p-value	Moran’s I	Spatial Interpretation
CH ₄	↑ Significant	1.000	0.0028	0.9814	Persistent regional emission dominance
CO	None	0.467	0.27	0.9982	Strong clustering near industrial corridors
SO ₂	None	0.600	0.14	0.9913	Localized sources, no trend
NO ₂	None	0.467	0.27	0.9991	Dense clustering, especially Kolkata
HCHO	None	0.600	0.14	0.9935	Clustered, photochemically driven
O ₃	None	0.733	0.06	0.9999	Uniform positive clustering

3.5 Elbow Method for Optimal N(cluster)

In this study, we utilized the Elbow Method to ascertain the optimal number of clusters (K) for the classification of pollutants through k-means segmentation, as depicted in [Figure 9](#). Each plot illustrates the correlation between the Sum of Squared Errors (SSE) and the number of clusters, with a notable bend, or “elbow,” representing the threshold where further clustering yields minimal gains in variance reduction.

The analysis revealed that the optimal K values for the majority of pollutants, including O₃, SO₂, NO₂, HCHO, and CO, stabilize around K = 3. This finding indicates the presence of three primary spatial-temporal regimes: low, moderate, and high concentration zones. Such segmentation successfully delineates urban-industrial centers, peri-urban transition areas, and

rural backgrounds, highlighting the variation in emission intensities and atmospheric phenomena. The identified clustering framework effectively captures the intricate spatial dynamics of air quality across West Bengal, aligning closely with the documented distributions of air quality hotspots and trend analyses. The Elbow Method thus serves as a robust quantitative tool for pollutant pattern classification, enabling enhanced integration with machine learning models and spatiotemporal forecasting mechanisms for improved air quality management in alignment with UNSDGs 13 and 11.

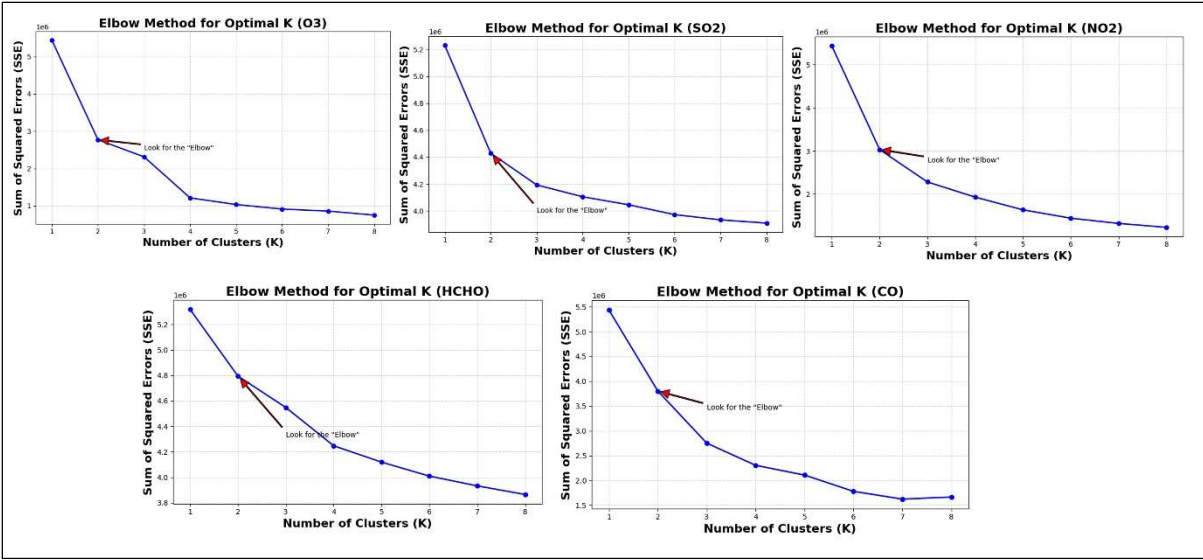


Figure 9. Plots of the Elbow method displaying the Sum of Squared Errors (SSE) in relation to varying cluster numbers (K) for six atmospheric pollutants (O₃, SO₂, NO₂, HCHO, CO, CH₄) across West Bengal. The curve illustrates the inflection point, or "elbow," indicating the optimal number of clusters for k-means segmentation.

3.6 Time-Series and Spatial Clustering

Figures 10 and 11 illustrate the spatio-temporal clustering dynamics of significant atmospheric pollutants, utilizing k-means segmentation on time-series data spanning 2019 to 2024. The temporal analysis presented in **Figure 10** highlights distinct annual cycles for the pollutants,

showcasing peak levels in pre-monsoon and winter months. These peaks can be attributed to heightened photochemical reactions, increased combustion activities, and greater atmospheric stability. Specifically, the SO₂ and NO₂ clusters exhibit pronounced spikes in heavily industrialized and urban regions, while O₃ and HCHO display more gradual fluctuations, which align with their photochemical formation processes. In contrast, CO is characterized by broader seasonal variations, indicating ongoing emission sources and extensive regional transport.

In terms of spatial distribution ([Figure 11](#)), the clustering distinctly differentiates the urban-industrial emission corridors (Durgapur–Asansol, Kolkata–Howrah, Haldia) from agro-bioactive and wetland-rich areas located to the south and east. Northern and coastal zones present a more diffuse pollutant landscape, indicative of the complex interactions between marine and continental air masses, as well as various atmospheric transport mechanisms.

The combined insights from both the time-series and spatial clustering analyses underscore the diverse behavioral patterns of pollutants, highlighting the significant spatial correlations between emission sources and meteorological factors. This holistic approach not only enhances the interpretability of satellite-derived air-quality information but also establishes a foundation for targeted mitigation strategies and adaptive policy frameworks in line with UNSDGs 13 and 11.

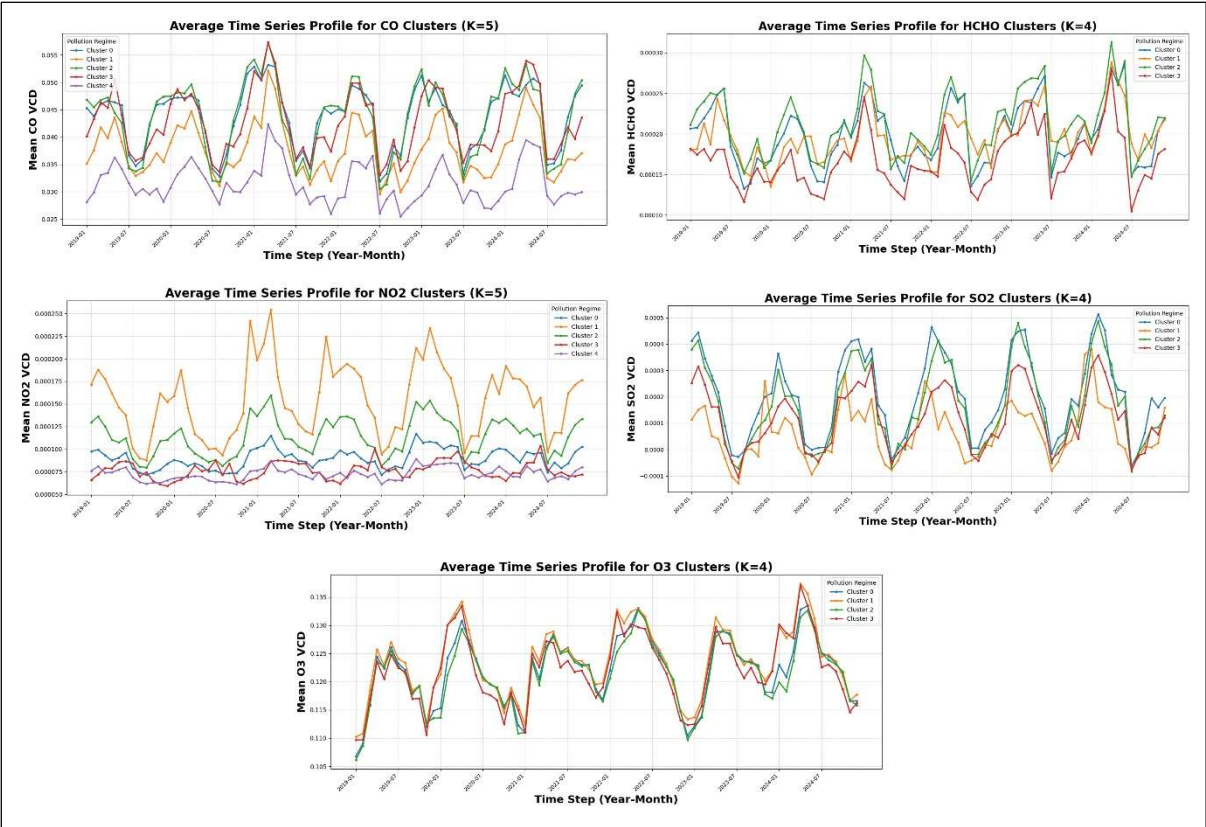


Figure 10. Average time-series profiles of clustered pollutant regimes for CO (K=5), HCHO (K=4), NO₂ (K=5), SO₂ (K=4), and O₃ (K=4) over West Bengal (2019–2024). Each line represents the mean vertical column density (VCD) of a cluster, illustrating distinctive seasonal oscillations, inter-annual variability, and emission-regime-specific trends.

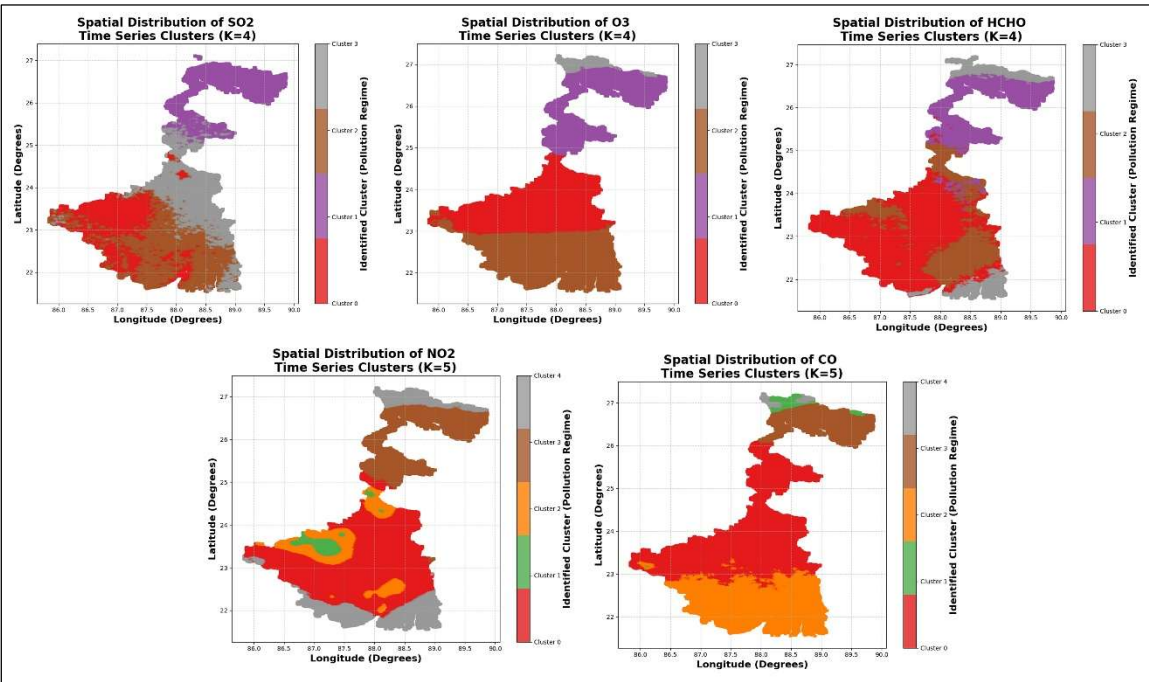


Figure 11. Spatial distribution of time-series clusters for five atmospheric pollutants—SO₂, O₃, HCHO (K=4), and NO₂, CO (K=5)—across West Bengal (2019–2024). Each map delineates unique pollution regimes derived from temporal clustering, highlighting spatial heterogeneity, emission dominance, and transport characteristics.

3.7 Hotspot Analysis with Respect to Sigma (σ)

The results outlined in [Table 4](#) provide a detailed overview of spatial concentration hotspots for primary atmospheric pollutants, determined using the σ (standard deviation) methodology. Notably, areas exhibiting values surpassing $+1\sigma$ from the mean are identified as statistically significant pollution hotspots. This analysis indicates a distinct spatial stability of emission centers across West Bengal, highlighting both human activities and natural factors influencing air quality.

Hotspots for NO₂ and CO are particularly prominent, covering 24% and 22% of the assessed areas, respectively. These hotspots are predominantly situated over urban centers such as Kolkata, Howrah, Asansol, and Bardhaman, indicating substantial emissions from vehicular traffic, industrial operations, and biomass combustion. In contrast, SO₂ hotspots are notably confined around Haldia and Durgapur, which correspond with the locations of refineries and thermal power plants. Furthermore, CH₄ hotspots are extensively found in the agro-wetland regions of Nadia and Murshidabad, closely associated with paddy farming and anaerobic processes occurring in wetlands. Conversely, HCHO and O₃ display hotspots driven by photochemical processes, particularly in the southern and coastal areas, suggesting the influence of secondary atmospheric formation dynamics.

In summary, this σ -based hotspot delineation approach successfully identifies consistent emission zones and captures seasonal variability, offering a quantitative basis for targeted

interventions in air quality management and climate-resilient policies aligned with the UNSDGs 11 and 13.

Table 4. Average percentage of hotspot areas, key districts, and main emission sources for six significant atmospheric pollutants (CH₄, CO, SO₂, NO₂, HCHO, and O₃) in West Bengal from 2019 to 2024. The σ -based (standard deviation) hotspot analysis reveals areas with pollutant concentrations exceeding $+1\sigma$ above the regional average, emphasizing consistent emission zones and their corresponding anthropogenic or natural origins.

Pollutant	Mean area of hotspots (%)	Persistent hotspot districts	Primary drivers
CH ₄	16	Nadia, Murshidabad, Malda	Paddy fields, wetlands
CO	22	Kolkata, Asansol	Transport and biomass combustion
SO ₂	18	Durgapur, Haldia	Power and refineries
NO ₂	24	Kolkata, Howrah, Bardhaman	Vehicular and industrial sources
HCHO	15	South 24 Parganas	Photochemical VOC oxidation
O ₃	12	Southern districts	Secondary formation zones

3.8 Ratio Analysis (All Four Diagnostic Ratios)

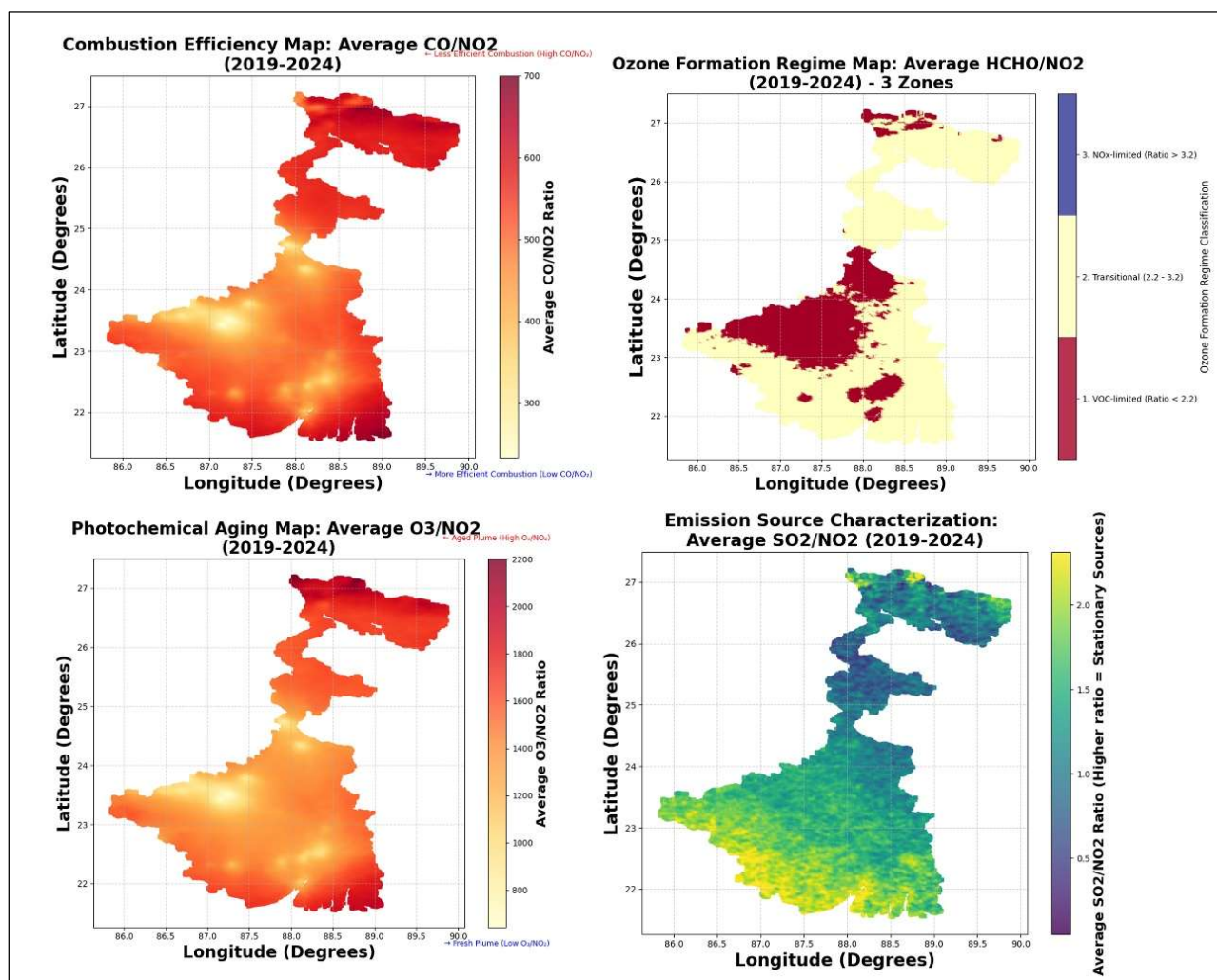
The results presented in **Figure 12** illustrate a detailed, ratio-based diagnostic framework that enhances our understanding of atmospheric chemistry, emission efficiency, and photochemical dynamics across West Bengal from 2019 to 2024. The CO/NO₂ ratio (top left) serves as an indicator of combustion efficiency, revealing that elevated ratios in the southern and central regions correlate with inefficient fuel combustion, primarily due to transport activities and

biomass burning practices. This finding highlights critical emission inefficiencies that warrant further investigation.

The HCHO/NO₂ ratio (top right) enables the classification of ozone formation regimes throughout the area: the southwest urban–industrial zones are identified as VOC-limited, the central belt as transitional, and the northern districts as NO_x-limited. This classification underscores significant differences in photochemical reactivity and the dominant precursors influencing ozone formation in these regions.

The O₃/NO₂ ratio (bottom left) provides insight into photochemical aging; higher ratios observed in coastal and southern sectors suggest the presence of more aged air masses, indicating a trend of downwind ozone enhancement. In contrast, the SO₂/NO₂ ratios (bottom right) shed light on the types of emission sources: increased values in the northern and eastern zones point to stationary and industrial sources, while urban centers exhibit lower ratios, emphasizing the prevalence of mobile emission sources.

In summary, this ratio diagnostic approach uncovers the complexities of the atmospheric system, influenced by various emission types, photochemical interactions, and meteorological transport patterns. Such insights are vital for informing air-quality regulations and for the classification of chemical regimes, aligning with the objectives of the UNSDGs 13 and 11.



711

712 **Figure 12.** Atmospheric chemical regime diagnostics over West Bengal (2019–2024) based on
 713 pollutant ratios: (a) CO/NO_2 —combustion efficiency, (b) HCHO/NO_2 —ozone formation
 714 regimes, (c) O_3/NO_2 —photochemical aging, and (d) SO_2/NO_2 —emission source
 715 characterization. Elevated ratios highlight inefficient combustion, aged plumes, or stationary-
 716 source dominance, while HCHO/NO_2 ratios classify regions into VOC-limited, transitional,
 717 and NO_x -limited regimes.

718 3.9 HYSPLIT Trajectory Analysis

719 **Figure 13** presents the simulated forward air-mass trajectories over West Bengal from 2019 to
 720 2024, utilizing the HYSPLIT model in conjunction with ERA5 reanalysis data. This analysis
 721 provides a comprehensive examination of the spatiotemporal variability in wind-driven

pollutant transport, a vital factor influencing regional air quality dynamics. Each yearly panel illustrates the monthly mean of 12-hour forward trajectories, effectively capturing the directional variations, dispersion intensity, and transport pathways throughout the study period.

The findings highlight a clear seasonal pattern linked to monsoonal reversals. During the winter months (December–February) and pre-monsoon period (March–May), air masses primarily travel from the northwest toward the southeast, indicating significant advection originating from the Indo-Gangetic Plain (IGP) towards the Bay of Bengal coast. This flow correlates with an influx of pollutants from the industrial sectors situated in Bihar, Jharkhand, and eastern Uttar Pradesh, elevating atmospheric loadings over southern West Bengal, particularly impacting the Kolkata Metropolitan Region, Haldia, and the Durgapur–Asansol corridor.

Conversely, the monsoon season (June–September) is characterized by southwesterly maritime flows, bringing in moist, cleaner air from the Arabian Sea and Bay of Bengal. This influx promotes effective wet scavenging and dilutes aerosols and trace gases, resulting in a significant improvement in regional air quality. However, during the post-monsoon phase (October–November), a reversal in trajectories toward the north and stagnant conditions is observed, indicating a constrained dispersion potential. These stable atmospheric layers facilitate the accumulation of pollutants, especially in urban and industrial areas, leading to episodic smog events and the production of secondary pollutants such as ozone.

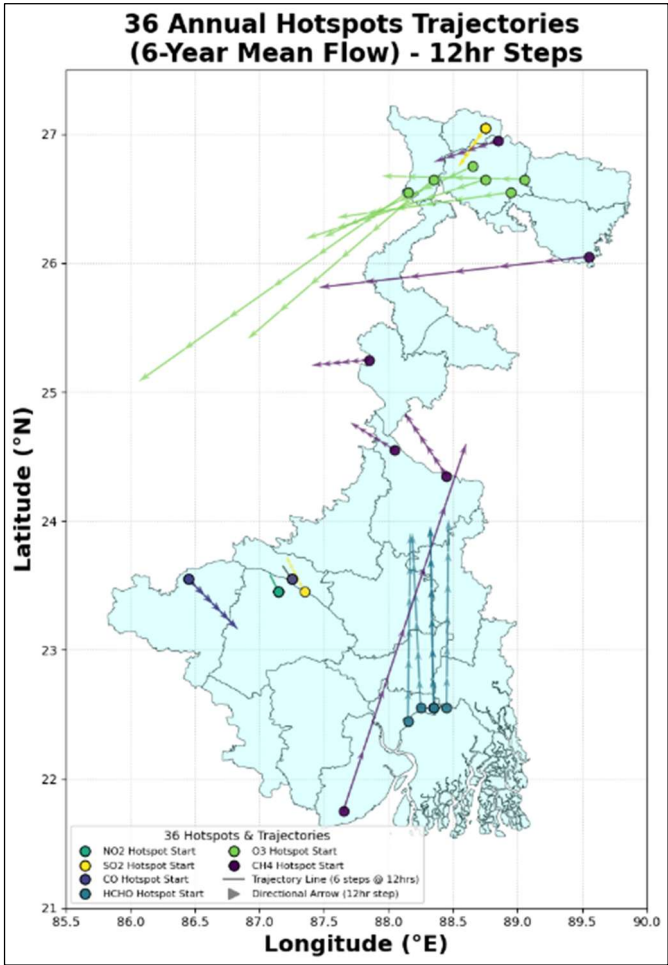
Inter-annual fluctuations in trajectory density and dispersion length further reveal alterations in synoptic circulation strength and boundary-layer stability. For example, the years 2020 and 2021, which were notably affected by COVID-19 lockdowns and consequent emission reductions, demonstrate diminished and shorter transport pathways, signifying a decrease in anthropogenic inputs and localized pollutant confinement.

The forward trajectories over a six-year period (2019–2024) for 36 identified pollutant hotspots in West Bengal, as shown in [Figure 14](#), were simulated using the HYSPLIT model at 12-hour intervals. This analysis combines spatial hotspot data, derived from instances of pollutant concentration exceedances, with dynamic airflow modeling to elucidate the directional dispersion patterns and connectivity among key emission areas. Each trajectory encapsulates the average atmospheric transport pathway originating from NO₂, SO₂, CO, CH₄, HCHO, and O₃ hotspot centers, revealing both intrastate and inter-district exchange dynamics of pollutants.

The findings indicate varied transport dynamics for different pollutants. Trajectories of CH₄ and CO display extended pathways directed northward and northeastward, signifying long-range advection coupled with notable atmospheric persistence—a feature typical of biogenic and combustion emissions. Conversely, NO₂ and SO₂ trajectories remain more localized, predominantly circulating within industrial zones such as the Durgapur–Asansol–Haldia region, which underscores short-range recirculation patterns and emission clustering. O₃ and HCHO trajectories, on the other hand, demonstrate wider dispersion towards northern and eastern districts, indicative of secondary pollutant formation and transport driven by photochemical reactions and meteorological conditions.

The convergence of multiple trajectories near Kolkata and its surrounding peri-urban areas highlights the city’s significance as a major receptor for pollutants, influenced by both industrial and agricultural emissions. Northerly flows from Murshidabad, Malda, and Nadia suggest substantial cross-district transport, likely exacerbated by convective uplift during the pre-monsoon and post-monsoon phases. Similarly, southerly flows originating from the Sundarbans and coastal regions reveal bidirectional interactions associated with sea–land breeze dynamics.

783 Overall, this trajectory analysis of pollutant hotspots identifies critical connectivity corridors
784 that reflect the interactions between emission strength, prevailing winds, and atmospheric
785 longevity. The results emphasize the pressing need for regional emission management
786 strategies that account for both local sources and transported pollutants. This integrated
787 trajectory-based approach advocates for spatial targeting of mitigation efforts, aligning with
788 the objectives of UNSDGs 13 and 11 by fostering coordinated air quality governance across
789 different administrative frameworks.



790

791 **Figure 14.** Annual mean forward trajectories from 36 identified pollution hotspots across West
792 Bengal (2019–2024), simulated using the HYSPLIT model at 12-hour intervals. Each trajectory
793 traces the dominant atmospheric transport pathway of key pollutants (NO₂, O₃, CO, CH₄,
794 HCHO, and SO₂), illustrating inter-district dispersion patterns and the connectivity among
795 major emission zones.

3.11 GEOS-Chem Data Analysis

Table 5 presents a detailed overview of the atmospheric lifetimes (τ) and predominant removal mechanisms of six significant trace gases, as modeled by the GEOS-Chem chemical transport framework. This analysis sheds light on the chemical reactivity, persistence, and transport dynamics of these pollutants, illustrating the stark differences between short-lived and long-lived atmospheric pollutants in West Bengal.

CH₄ demonstrates the longest atmospheric lifetime, approximately 9 years, primarily constrained by slow oxidation via OH. As a result, it functions as a regional to global background gas, largely insulated from transient meteorological fluctuations, while making a significant contribution to greenhouse forcing. CO, on the other hand, has a shorter persistence of 1–2 months, characterized by wintertime accumulation due to diminished OH levels, followed by a dilution phase during summer through oxidative processes.

In contrast, SO₂ presents a brief lifetime of 1–3 days, swiftly removed through aqueous oxidation and wet deposition, emphasizing its strong reliance on local emissions and precipitation trends. NO₂ and HCHO, both highly reactive, exhibit lifetimes of 12–36 hours and 2–4 hours, respectively. Their removal is dominated by photolysis and OH-driven oxidation, indicating a pronounced diurnal variability and a tight linkage with emission sources.

O₃, a secondary pollutant, possesses a moderate lifetime ranging from 2–5 days, influenced by surface deposition and photochemical degradation. Its persistence over regional scales underscores the cumulative photochemical formation resulting from precursor gases (NO_x and VOCs).

In summary, the GEOS-Chem outputs reveal a distinct gradient in atmospheric persistence, transitioning from short-lived local species (HCHO, NO₂, SO₂) to regionally enduring (O₃, CO) and globally impactful gases (CH₄). This stratification underscores the necessity for

comprehensive emission control strategies that harmonize local and long-term climate mitigation efforts, in alignment with the objectives of UNSDGs 13 and 11.

Table 5. Atmospheric lifetime (τ), dominant loss mechanisms, and interpretative classification of six key pollutants simulated by GEOS-Chem. Short-lived gases (SO_2 , NO_2 , HCHO) exhibit rapid local sinks, while longer-lived species (CO , CH_4 , O_3) persist regionally or globally, influencing both air quality and climate forcing.

Pollutant	Lifetime (τ)	Dominant loss process	Interpretation
CH_4	≈ 9 years	Reaction with OH	Long-lived; acts as regional background gas
CO	1–2 months	Oxidation by OH	Seasonal accumulation during low-OH winter
SO_2	1–3 days	Aqueous oxidation + wet deposition	Local source, rapid sink
NO_2	12–36 hours	Photolysis $\rightarrow \text{HNO}_3$	Highly reactive, strong diurnal cycle
HCHO	2–4 hours	Photolysis + reaction with OH	Short-lived secondary species
O_3	2–5 days	Deposition + photochemical destruction	Regionally distributed secondary pollutant

3.12 GEOS-Chem Data-Driven Box Model Validation: ROC Curve Analysis

Table 6 and Figure 15 present a comprehensive assessment of the predictive robustness of the GEOS-Chem data-driven box model, as indicated by ROC curves, for six atmospheric pollutants in West Bengal from 2019 to 2024. This evaluation focuses on the model's accuracy

in anticipating exceedance events surpassing the 75th percentile, using the Area Under the Curve (AUC) as a key performance metric.

The results reveal that HCHO (AUC = 0.8224) and O₃ (AUC = 0.8180) demonstrate exceptional predictive capability, indicative of a strong interplay between meteorological factors and photochemical processes. Their exceedance probabilities correlate closely with variations in solar radiation, boundary-layer height, and transport dynamics, highlighting the significance of photochemical formation and dispersion mechanisms in enhancing model predictability. In contrast, CH₄ (AUC = 0.6592) and CO (AUC = 0.6267) reflect moderate predictive abilities, which are influenced by a combination of persistent background sources and localized emission activities. On the other hand, NO₂ (AUC = 0.6190) and SO₂ (AUC = 0.5986) exhibit relatively low discrimination accuracy, primarily owing to their brief atmospheric lifespans and rapid chemical turnover, which diminish the model's sensitivity to transient events.

In summary, the ROC analysis confirms the GEOS-Chem model's high reliability for forecasting oxidant species (O₃, HCHO), while it underscores the challenges faced in forecasting short-lived primary pollutants (NO₂, SO₂). These findings emphasize the critical need for effective meteorology–chemistry coupling and data-driven calibration to enhance exceedance prediction, especially under the complex and variable monsoon-driven conditions characteristic of eastern India.

Table 6. ROC-based validation of the GEOS-Chem box model (2019–2024) for six pollutants, showing 75th percentile exceedance thresholds, AUC scores, and key controlling processes. High AUCs for HCHO and O₃ denote strong photochemical predictability, while lower scores for SO₂ and NO₂ reflect short-lived local variability.

Pollutant	Exceedance Threshold (75th Percentile)	AUC Score	Predictive Power by Meteorology	Primary Atmospheric Control
HCHO	$> 2.20 \times 10^{-4}$	0.8224	High	Photochemical Formation
O3	$> 1.26 \times 10^{-1}$	0.8180	High	Transport and Dilution
CH4	$> 1.94 \times 10^{+3}$	0.6592	Moderate	Global Background & Sources
CO	$> 4.81 \times 10^{-2}$	0.6267	Moderate	Local Emissions
NO2	$> 9.70 \times 10^{-5}$	0.6190	Moderate	Local Emissions & Chemistry
SO2	$> 2.43 \times 10^{-4}$	0.5986	Weak to Moderate	Local Emissions

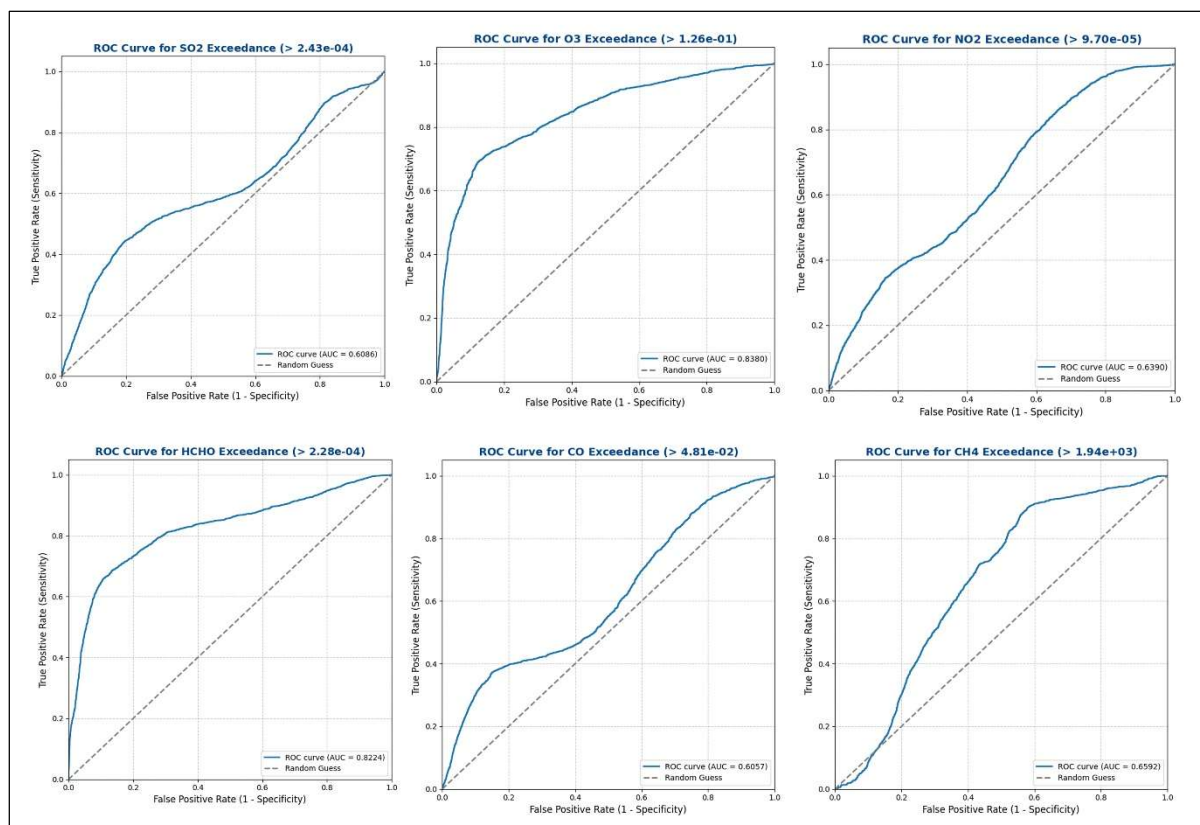


Figure 15. ROC curves illustrating the predictive capability of the GEOS-Chem data-driven box model for detecting pollutant exceedance (≥ 75 th percentile) across six atmospheric species (SO₂, O₃, NO₂, HCHO, CO, CH₄) from 2019 to 2024. The curves display the relationship between the true positive rate (sensitivity) and the false positive rate (1 – specificity), highlighting the model's ability to discriminate among detections. Notably, O₃ and HCHO exhibit high AUC values, reflecting their strong predictive performance influenced by photochemical and meteorological factors.

4. Discussion

4.1. Trends in Greenhouse Gases and Air Pollutants

This investigation elucidates the intricate spatio-temporal dynamics of atmospheric pollutants across West Bengal from 2019 to 2024, highlighting complex interactions among human-induced emissions, photochemical reactions, and monsoon-related meteorological phenomena. The notably significant upward trajectory of methane (CH₄) ($\tau = 1.00$, $p < 0.01$) underscores

the enduring nature of long-lived greenhouse gases. In contrast, SO₂ and NO₂ have exhibited relatively stable or declining trends. This divergent behavior underscores the region's dual role as a significant emission hotspot while simultaneously benefiting from the atmospheric cleansing effects attributed to monsoonal dispersion. These findings resonate with global datasets, indicating that major pollutants like SO₂ and NO₂ are plateauing or diminishing in several industrializing areas, while secondary pollutants and greenhouse gases continue their ascent (Lu et al., 2024; Srivastava et al., 2025).

The recorded increase in CH₄ (slope = $+0.018 \times 10^{15}$ molec cm⁻² yr⁻¹; R² = 0.92) aligns closely with global atmospheric patterns evident from TROPOMI and GOSAT observations, which documented annual methane growth rates consistently exceeding 15 ppb yr⁻¹ between 2019 and 2023 (Pendergrass et al., 2025). Locally, this augmentation is linked to biogenic and agricultural sources—most prominently from paddy fields, livestock, and wetland ecosystems—which are recognized contributors to methane emissions in the Ganges-Brahmaputra delta (Rabbani et al., 2024; Worden et al., 2023). The congruence of our results with global methane inventories demonstrates that the Indo-Gangetic corridor continues to be integral in enhancing tropical greenhouse gas forcing.

4.2. Secondary Pollutant Dynamics and Photochemical Regimes

An observable moderate rise in O₃ and HCHO within this study indicates a strengthening of secondary photochemical processes, driven by temperature, solar radiation, and VOC–NO_x interactions. The diagnostic HCHO/NO₂ ratio reveals that substantial areas of southern and central West Bengal are under VOC-limited conditions, a pattern consistent with observations across East and Southeast Asia (Li et al., 2025; Oak et al., 2025). Elevated concentrations of HCHO and O₃ during the pre-monsoon and post-monsoon phases imply intensified oxidation processes fueled by solar heating and reduced boundary-layer ventilation. Similar mechanisms have been documented in northern China (Graham et al., 2024) and the Mekong Basin (Lu et

al., 2024), affirming that regional photochemistry in monsoon-influenced areas is becoming increasingly sensitive to temperature variations.

The ROC validation scores ($AUC > 0.82$ for O_3 and $HCHO$) and positive correlations with land surface temperature (LST) ($r = 0.54\text{--}0.62$) bolster the hypothesis that elevated temperatures accelerate VOC oxidation and the synthesis of secondary ozone. This corresponds with NASA's atmospheric model outputs, which project a 3–5% increase in photochemical ozone generation for every 1°C of warming in tropical Asia (NASA GES DISC, 2024). In contrast, the negative correlations for SO_2 and NO_2 ($r \approx -0.4$) suggest that higher temperatures promote boundary-layer turbulence, facilitating pollutant loss through oxidative and wet deposition processes.

4.3. Source Attribution and Transport Mechanisms

A comprehensive analysis integrating hotspot clustering, Moran's I spatial autocorrelation, and HYSPLIT trajectory modeling delineates the Durgapur–Asansol industrial belt, the Kolkata–Howra metropolis, and the Haldia refinery complex as predominant emission sources. Persistent hotspots in these regions align with significant emissions from thermal power facilities, vehicular traffic, and fossil fuel combustion. Our spatial autocorrelation metrics (Moran's $I > 0.98$) are analogous to global hotspots identified in other industrial regions, such as the Pearl River Delta and Yangtze River Delta (An et al., 2021).

Trajectory analysis underscores a pronounced seasonal variation in pollutant transport: north-westerly airflows in winter and pre-monsoon seasons facilitate pollutant accumulation, while south-westerly maritime flows during the monsoon enhance dispersion. These transport pathways align with ERA5 reanalysis findings and parallel observations in the Indo-Gangetic Plain, where long-range transport has a significant influence on regional background concentrations (Stein et al., 2015; Graham et al., 2024; Singh et al., 2025). The repetitive forward trajectories from the industrial regions of Bihar and Jharkhand into the Bengal Basin

underscore inter-state and transboundary effects, emphasizing the necessity for coordinated regional emission management.

4.4. Atmospheric Lifetimes and Model Diagnostics

The GEOS-Chem simulations offer valuable insights into the atmospheric durability and removal processes for each pollutant. The lifetime of CH₄, approximately 9 years, correlates with global assessments (Worden et al., 2023), underscoring its limited responsiveness to local meteorological variations. In contrast, SO₂ and NO₂ exhibit transient lifetimes of 1–3 days and 12–36 hours, respectively, elucidating their localized concentration patterns and their limited predictive accuracy within the ROC framework ($AUC < 0.65$). HCHO and O₃ display intermediate lifetimes (2–5 days) that are highly temperature-dependent, contributing to their remarkable model predictability and interannual coherence. These observations align with GEOS-Chem simulations performed in East Asia, which reveal that secondary pollutants exhibit greater spatial persistence compared to their precursors (Li et al., 2025).

The validated box-model approach offers further operational insights: pollutants primarily governed by photochemical reactions (O₃, HCHO) exhibit predictable responses to meteorological factors such as radiation and humidity, while pollutants originating from primary emissions (SO₂, NO₂, CO) are more closely linked to the intensity of anthropogenic activities. This distinction emphasizes the necessity of integrating emission inventories with meteorological forecasting for enhanced air quality management in real-time.

4.5. Policy Implications and Climate–Air-Quality Synergies

The contrasting trends observed between long-lived and short-lived pollutants highlight the urgent need for multi-pollutant and cross-sectoral mitigation strategies. Reductions in CH₄ emissions through sustainable rice cultivation practices, improved livestock management, and organic waste treatment can yield immediate advantages for both climate and air quality (UNEP

& CCAC, 2024). Concurrently, controlling VOC precursors from industrial solvents and petrochemical sectors is vital for limiting the production of O₃ and HCHO. For primary pollutants, focused interventions in industrial corridors—such as implementing desulfurization technologies, stringent vehicular emission standards, and transitioning to cleaner fuels—remain essential.

The findings from this study underscore the importance of harmonizing air quality management with climate adaptation efforts, as supported by UN SDGs 6, 11, 13, and 17. By pinpointing emission hotspots and quantifying transport links, our results facilitate evidence-based decision-making for regional planning and transboundary policy discussions. Moreover, the model's robust performance regarding secondary pollutants indicates that AI-driven predictive frameworks could significantly enhance operational early warning systems, particularly during events of thermal inversion and stagnation.

4.6. Limitations and Future Perspectives

Despite the increased interpretability afforded by a multi-sensor, multi-model framework, several limitations persist. Sentinel-5P retrievals yield column-averaged concentrations that may not accurately reflect near-surface exposure levels. While the GEOS-Chem box model effectively aids validation, it assumes spatial uniformity and may overlook vertical mixing dynamics. Furthermore, Mann–Kendall tests effectively identify monotonic trends but do not capture non-linear transitions related to abrupt occurrences, such as the 2020 COVID-19 lockdown. Future investigations should employ higher-resolution coupled models, incorporate data assimilation processes, and establish ground-based calibration networks to minimize uncertainty. The integration of next-generation satellite constellations (e.g., MethaneSAT, TEMPO) and advanced deep-learning time-series analytics (Khirwar & Narang, 2024) will enable better spatiotemporal modeling of pollutant dynamics across South Asia.

4.7. Synthesis

This study establishes a comprehensive evidence base for elucidating atmospheric transformation processes within a monsoon-influenced tropical setting. The integration of observational data, statistical methods, and modeling techniques indicates a shift towards a regime dominated by secondary pollutants, where the impact of photochemical and thermal feedbacks surpasses that of direct emissions. West Bengal, situated in the Indo-Gangetic Basin, plays a pivotal role in South Asia's atmospheric dynamics, acting as both a source and receptor of transboundary pollutants. The AI-EO integrated framework proposed in this research offers a versatile template for regional climate and air quality assessments, essential for aligning policies and devising sustainable urban and industrial transition strategies.

5. Conclusion

This investigation provides a holistic understanding of atmospheric pollutant dynamics across West Bengal from 2019 to 2024 by employing a synergistic blend of Earth Observation, GEOS-Chem modeling, HYSPLIT trajectory analysis, and AI-enhanced statistical methods. The results clearly differentiate between long-lived and short-lived pollutants: CH₄ and O₃ exhibited consistent and spatially coherent increases driven by agricultural activities, photochemical processes, and climate factors, while SO₂ and NO₂ demonstrated localized stabilization attributed to industrial emission controls and monsoonal washout effects. The presence of formaldehyde (HCHO) emerged as a valuable indicator of photochemical activity, with temperature-sensitive seasonal peaks.

Spatial clustering and trajectory analyses affirmed that industrial corridors, such as Durgapur–Asansol, Haldia, and Kolkata–Howrah, remain key emission hotspots, while regional transport and boundary-layer dynamics significantly influence pollutant dispersion towards the Bay of

Bengal. GEOS-Chem diagnostics revealed divergent atmospheric lifetimes, indicating high predictability for secondary pollutants ($AUC > 0.82$ for O_3 and $HCHO$), which suggests robust meteorological control coupled with photochemical feedback processes.

Collectively, the findings suggest a shift toward a secondary pollutant-dominated paradigm, exacerbated by intensified photochemical reactions and shifting emission patterns. Therefore, effective mitigation strategies should prioritize methane reduction, volatile organic compound (VOC) management, and coordinated regional emission efforts to realize sustainable air quality improvements. Furthermore, this study's AI-EO fusion framework lays a replicable foundation for continuous monitoring and predictive modeling of atmospheric composition in monsoon-impacted tropical regions, directly contributing to the UN SDGs 6, 11, 13, and 17. Future investigations should leverage high-resolution inverse modeling and cutting-edge sensors (e.g., MethaneSAT, TEMPO) to enhance regional air chemistry diagnostics and support policy-oriented forecasting frameworks.

Data Availability Statement: The data supporting this study's findings are available from the Second author upon reasonable request.

Conflict of interest: The authors declare no competing interests.

Ethical approval: All authors have read, understood, and have complied as applicable with the statement on “Ethical responsibilities of Authors” as found in the Instructions for Authors.

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