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Satellite-Based Assessment of Air Pollution in Southern Districts of Tamil Nadu Using Sentinel-5P and Google Earth Engine: A Comparative Study

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ABSTRACT

This study investigates the spatial distribution of key air pollutants—NO_2, SO_2, CO, and surface O_3—across three southern districts of Tamil Nadu, India: Tuticorin, Tirunelveli, and Kanniyakumari, for the period April 2024 to March 2025. Pollutant data were derived from the Copernicus Sentinel-5P satellite and analyzed using the Google Earth Engine (GEE) platform to map annual variations and identify pollution patterns. The results showed that Tuticorin experienced the highest pollutant levels due to its dense industrial and port activities, followed by Tirunelveli, where urban growth and traffic contributed to moderate concentrations. Kanniyakumari, characterized by its coastal setting and minimal industrialization, recorded the lowest levels. Satellite-derived data were further compared with ground-based measurements from TNPCB and AQI India for validation. The novelty of this work lies in its use of satellite-based atmospheric observations and cloud computing (GEE) for air quality analysis in southern Tamil Nadu, a region where such remote sensing studies remain limited.

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INTRODUCTION

Air pollution remains one of the most pressing environmental challenges of our time, affecting human health, ecosystems, and climate stability (Koul, 2021; Rahman, 2025; Han, 2025; Singh, 2025). Pollutants such as nitrogen dioxide (NO_2), sulfur dioxide (SO_2), carbon monoxide (CO), and surface ozone (O_3) contribute to respiratory and cardiovascular diseases, long-term chronic conditions, and complex atmospheric interactions that drive greenhouse gas formation and aerosol generation (Shima, 2025; Aguilar-Gomez, 2025; Tortorella, 2024). The issue is particularly acute in rapidly urbanizing and industrializing regions, where emissions from vehicles, factories, and energy production continue to rise (Rybalova, 2022; Zamee, 2024; Lopez, 2025). In southern Tamil Nadu, districts like Tuticorin, Tirunelveli, and Kanniyakumari are experiencing rapid industrial and population growth, increasing transportation, and expanding urbanization (Soundranayagam, 2011; Queen Annes, 2019). Tuticorin, with its major industrial facilities and busy seaport, is especially vulnerable to elevated pollution levels (Verma, R.L., 2023). While ground-based monitoring stations provide valuable data (Karuppaswamy, 2022; Puttaswamy, 2022; Muniraja, 2023), their limited coverage often fails to capture spatial and

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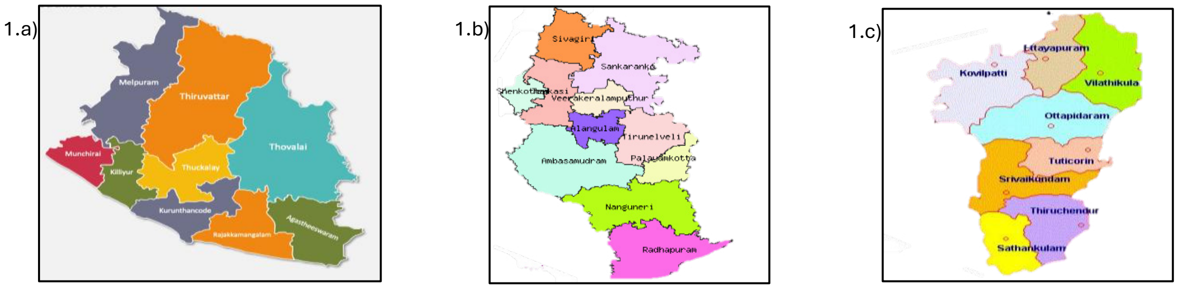


Fig. 1a,1b,1c. Map of the study area showing the geographical boundaries of Tuticorin, Tirunelveli, and Kanniyakumari districts in southern Tamil Nadu.

temporal variations, particularly in rural or less urbanized areas.

Recent studies have leveraged Sentinel-5P and other satellite platforms to monitor regional air quality. For instance, Muniraja et al. (2023) examined statewide variations during COVID-19 lockdowns, Behera et al. (2022) used Sentinel-5P to track changes in NO_2 and SO_2 across broad Indian regions, and Shah (2024) applied satellite data to multi-year monitoring of multiple pollutants in Pune City, highlighting the potential of satellite observations to complement ground measurements. Building on these approaches, this study applies Sentinel-5P data for a full year (1 April 2024 to 1 March 2025) to Tuticorin, Tirunelveli, and Kanniyakumari, processed via Google Earth Engine (GEE). This allows fine-scale spatial and temporal analysis of pollutant trends, identification of hotspots, and assessment of seasonal variability—capabilities not previously explored in this specific region. By integrating advanced satellite technology with cloud-based data processing, this work provides a scalable, accurate framework for understanding air pollution dynamics, supporting informed policy decisions, regional planning, and serving as a model for other under-monitored areas.

Study area

The study focuses on three southern districts of Tamil Nadu—Tuticorin, Tirunelveli, and Kanniyakumari—located between 8.0°N–9.5°N latitude and 77.0°E–78.5°E longitude. These districts differ in geography, development, and environmental characteristics, providing an ideal setting to examine variations in air quality**.**

- **Tuticorin (8.6°N–9.2°N):** Located along the southeastern coast, Tuticorin is a major industrial hub with thermal power plants, chemical industries, and a busy port. Industrial and vehicular emissions drive high pollution levels. The climate is hot and dry, with temperatures ranging from 25–35°C, and rainfall mainly during the northeast monsoon (October–December).
- **Tirunelveli (8.2°N–9.0°N):** Positioned inland, Tirunelveli features a mix of urban settlements, agricultural areas, and the foothills of the Western Ghats. Rapid urban expansion, growing traffic, and construction contribute to moderate pollution. The district experiences a tropical climate with rainfall during both monsoons, affecting pollutant dispersion and deposition.
- **Kanniyakumari (8.0°N–8.4°N):** As the southernmost district of mainland India, Kanniyakumari has extensive coastal terrain, green cover, and minimal industrial activity. Pollution arises primarily from vehicles and seasonal tourism. Warm, humid conditions, strong coastal winds, and heavy monsoonal rainfall support effective pollutant dispersion, maintaining relatively good air quality.
- **Rationale for Site Selection:** These districts were selected for their contrasting characteristics—industrial Tuticorin, semi-urban Tirunelveli, and largely non-industrial Kanniyakumari—offering a clear gradient of pollution sources, land use, and population

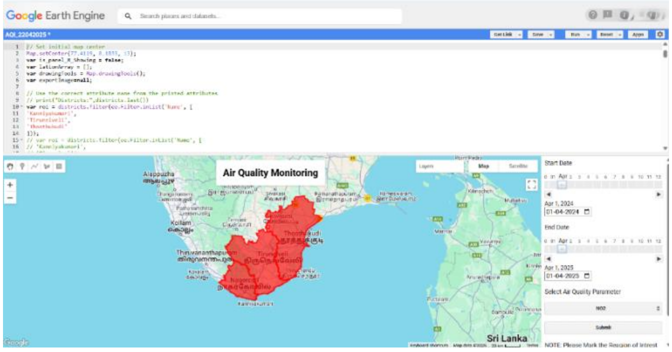


Fig. 2. Screenshot of the Google Earth Engine Interface

density. Their geographic proximity ensures consistent satellite coverage, facilitating reliable comparison of air quality trends across the region.

Methodology

Copernicus Sentinel-5P Satellite data

This study utilized data from the **Copernicus Sentinel-5 Precursor (Sentinel-5P)** satellite, part of the European Union's Copernicus Earth Observation Program. Launched by the European Space Agency in 2017, Sentinel-5P carries the **TROPOMI (Tropospheric Monitoring Instrument)** sensor, which provides daily, high-resolution measurements of key atmospheric pollutants including NO_2, SO_2, CO, and O_3 (Schneising et al., 2023). TROPOMI captures data at a spatial resolution of approximately **7 × 3.5 km**, suitable for analyzing pollution patterns across both urban and semi-urban regions. It measures **vertical column densities**, representing the total atmospheric concentration of pollutants from the Earth's surface to the upper atmosphere (Xia et al., 2021). This makes Sentinel-5P a consistent and reliable source for studying spatial and temporal variations in air quality, especially in regions with limited ground monitoring infrastructure.

Google Earth Engine (GEE)

Data processing and extraction were performed using Google Earth Engine (GEE), a cloud-based platform for large-scale geospatial analysis (Ashwini, 2024; Kurbucz, 2025). GEE hosts the full Sentinel-5P archive and provides tools for rapid filtering, aggregation, and visualization. For this study, GEE was used to access Sentinel-5P pollutant datasets (NO_2, SO_2, CO, O_3), apply Quality Assurance (QA) filtering, define district boundaries, compute daily and monthly averages, and generate time series and pollutant distribution maps. This approach significantly reduced processing time while enabling efficient analysis of a full year of high-resolution satellite data.

Tools used

In addition to GEE, **QGIS** and **Python** were employed to enhance spatial and analytical accuracy.

- **QGIS (Quantum Geographic Information System)** was used to prepare spatial boundaries for Tuticorin, Tirunelveli, and Kanniyakumari using official shapefiles from open-data sources (Albut, 2024). The shapefiles were clipped, projected, and exported as GeoJSON for compatibility with GEE. QGIS also supported post-processing by overlaying pollutant maps, annotating features, and producing high-resolution visual outputs for reporting (Markieta, 2014).
- **Python** was used to analyze the exported datasets, clean and organize time-series data, and

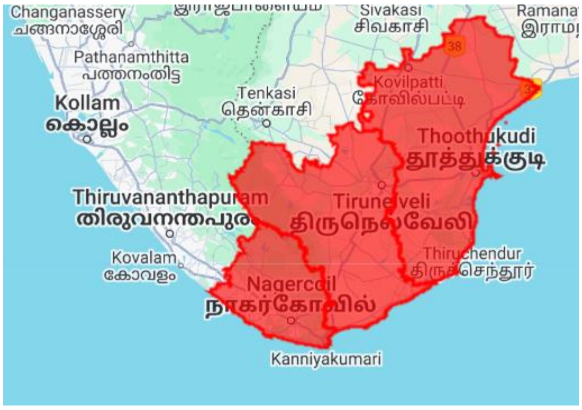


Fig. 3. Boundary of selected study area obtained through digitization in QGIS, used as input for further geospatial analysis

Table 1. Descriptive statistics of air pollutant concentrations (ppb) across the three districts.

District		NO_2 (ppb)	SO_2 (ppb)	Surface O_3 (ppb)	CO (ppb)
Kanniyakumari	Average	3.56	1.21	23.58	647.98
	Maximum	8.63	22.86	25.18	951.19
	Minimum	0.01	0.00	21.48	401.95
	Standard Deviation	1.56	2.27	0.90	125.16
Tirunelveli	Average	4.36	1.19	23.59	645.22
	Maximum	11.43	22.90	25.24	951.19
	Minimum	0.31	0.01	21.18	377.90
	Standard Deviation	1.65	2.09	0.94	120.58
Tuticorin	Average	6.32	1.23	23.63	675.10
	Maximum	24.38	23.24	25.38	918.34
	Minimum	0.47	0.00	21.33	467.44
	Standard Deviation	2.72	2.10	0.94	121.17

generate visualizations such as trend plots and comparative graphs. It helped interpret spatial and temporal variations, complementing the outputs from GEE and QGIS.

Data extraction and processing

The workflow began with defining district boundaries in GEE using shapefiles prepared in QGIS. Sentinel-5P datasets for NO_2, SO_2, CO, and O_3 were then loaded for the study period (April 1, 2024 – March 1, 2025). Data were filtered using QA thresholds (e.g., >0.75 for NO_2) to remove low-quality readings and cloud-contaminated pixels. Monthly average concentrations were computed for each pollutant and spatially averaged across district extents, ensuring uniform data representation. The processed results were visualized as charts and maps in GEE and later exported as CSV and GeoTIFF files for refinement in Python and QGIS. This integrated approach enabled a comprehensive, year-long assessment of air pollution trends across the three districts, supporting spatial comparison and pollutant pattern interpretation.

RESULTS AND DISCUSSIONS

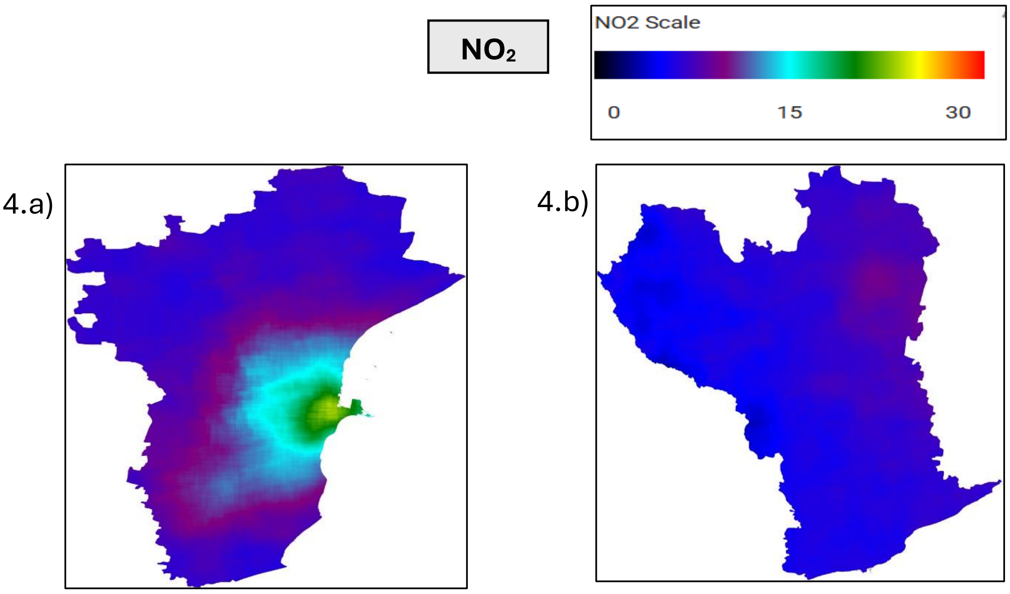
Descriptive and Inferential Statistical Analysis

A descriptive analysis was performed to examine the distribution and variability of major air pollutants—NO_2, SO_2, CO, and surface O_3—across Tuticorin, Tirunelveli, and Kanniyakumari from April 2024 to March 2025. The yearly mean concentrations derived from Sentinel-5P data are summarized in Table 1. These summaries provided insight into pollution intensity and variability throughout the year.

To determine whether these inter-district differences were statistically significant, a one-way ANOVA was performed for each pollutant. Results indicated that NO_2 ($p = 0.021$) and CO ($p = 0.034$) varied significantly among districts, confirming Tuticorin's elevated pollution levels. However, SO_2 ($p = 0.118$) showed no significant variation, suggesting relatively uniform distribution, possibly influenced by regional atmospheric mixing. A Pearson correlation analysis further explored pollutant interrelationships (Table 2). Strong positive correlations between NO_2–CO ($r = 0.83$) and NO_2–SO_2 ($r = 0.68$) highlight shared sources such as vehicular

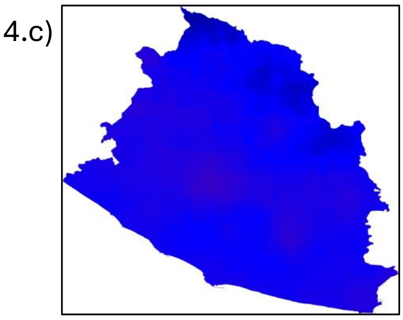
Table 2. Correlation Matrix of Major Pollutants

Pollutant	**NO_2**	**SO_2**	**CO**	**CH_4**	**O_3**
NO_2	1.00	0.68	0.83	0.41	–0.42
SO_2	0.68	1.00	0.59	0.38	–0.31
CO	0.83	0.59	1.00	0.47	–0.38
O_3	–0.42	–0.31	–0.38	–0.22	1.00



Tuticorin

Tirunelveli



Kanniyakumari

Fig. 4a, 4b, 4c. Spatial distribution of nitrogen dioxide (NO_2) concentrations across Tuticorin, Tirunelveli, and Kanniyakumari districts from April 2024 to March 2025, as extracted from Sentinel-5P data using Google Earth Engine.

and industrial combustion. Conversely, O_3 showed weak negative correlations with primary pollutants ($r = -0.42$ with NO_2 and $r = -0.38$ with CO), reflecting its secondary formation through photochemical reactions involving these precursors under sunlight.

Overall, these findings underscore the spatial heterogeneity of air pollution across the three districts and the interconnected nature of primary and secondary pollutants. The statistical results not only validate the observed emission patterns but also emphasize the need for district-specific air quality management strategies.

Spatial patterns and visual interpretations

Nitrogen Dioxide (NO_2): Nitrogen dioxide (NO_2) is a major urban pollutant emitted primarily from vehicles, industrial combustion, and power generation. It plays a key role in atmospheric chemistry, contributing to tropospheric ozone and secondary particulate formation (Ferreira, 2025; Zahara, 2025), and poses significant health risks by irritating the respiratory system, aggravating asthma, and increasing susceptibility to infections(Verma, 2023).

In this study, NO_2 concentrations varied spatially and seasonally across three southern districts of Tamil Nadu. Tuticorin recorded the highest annual mean (6.31 ppb), reflecting its industrial base, including thermal power plants, chemical and fertilizer units, and heavy port traffic. Tirunelveli showed moderate levels (4.35 ppb), with urban hotspots near city centers

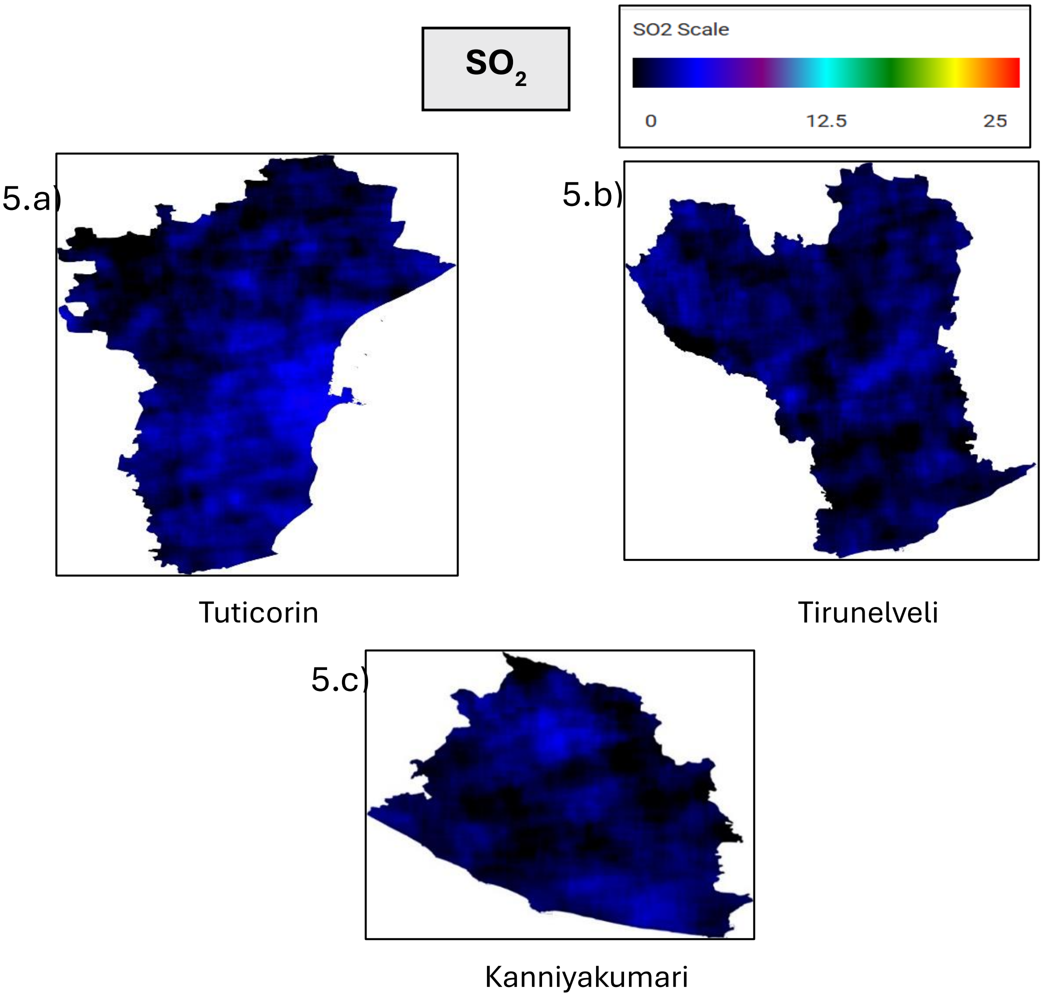


Fig. 5a, 5b, 5c. Spatial distribution of sulfur dioxide (SO_2) concentrations across Tuticorin, Tirunelveli, and Kanniyakumari districts from April 2024 to March 2025, as extracted from Sentinel-5P data using Google Earth Engine.

and highways due to growing vehicular and commercial activity. Kanniyakumari, being more rural and less industrialized, had lower levels (3.56 ppb), although temporary increases occurred during the tourist season (December–March).Seasonal analysis revealed winter peaks (December–February) caused by low atmospheric mixing and temperature inversions, monsoon declines (June–September) from rainfall-induced washout, and moderate summer levels (March–May) influenced by photochemical activity and stagnant air masses. These spatial and seasonal patterns highlight the combined effects of industrial emissions, traffic, and meteorology. Tuticorin's persistently high NO_2 emphasizes the need for targeted emission controls, while Tirunelveli and Kanniyakumari provide useful baselines for regional air quality assessment.

Sulfur Dioxide (SO_2): Sulfur dioxide (SO_2) is primarily emitted from the combustion of sulfur-rich fossil fuels, such as coal and oil, in power plants and industrial boilers (Wang, 2025). With a pungent odor and strong oxidizing potential, SO_2 poses risks to human health, particularly for children, the elderly, and individuals with asthma, and contributes to environmental issues like acid rain, soil degradation, corrosion, and aquatic acidification (Nurhisanah, 2022; Khalaf, 2024; Rifat, 2020).

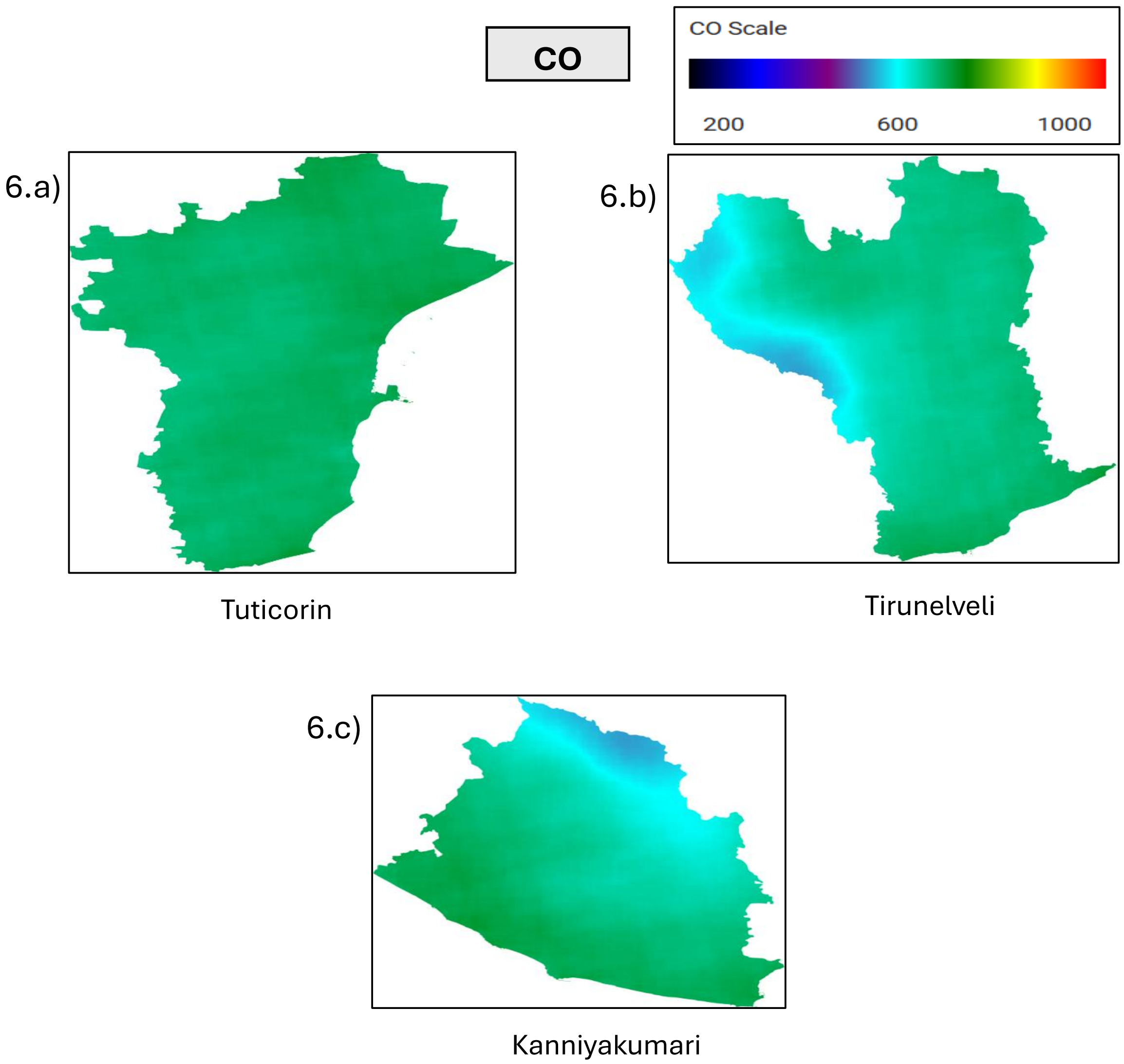


Fig. 6a, 6b,6c. Spatial distribution of carbon monoxide (CO) concentrations across Tuticorin, Tirunelveli, and Kanniyakumari districts from April 2024 to March 2025, as extracted from Sentinel-5P data using Google Earth Engine.

In this study, SO_2 levels were relatively uniform across the three districts, reflecting regional dispersion. Tuticorin recorded the highest mean concentration (1.23 ppb), consistent with its industrial activities, including coal-fired power plants, chemical industries, and fertilizer units. Kanniyakumari (1.21 ppb) slightly exceeded Tirunelveli (1.19 ppb), likely due to localized combustion from vehicles and domestic fuel use during peak tourist months. Tirunelveli's lower levels may result from limited industrialization and moderate vegetation cover, which aid pollutant dilution.

Seasonal analysis showed higher SO_2 concentrations in winter (December–February) due to atmospheric trapping from low mixing heights and temperature inversions, and lower levels during the monsoon (June–September) owing to wet deposition and atmospheric cleansing. Despite small numerical differences, these variations are environmentally significant, influencing local acid deposition and respiratory health outcomes.

Carbon monoxide (CO): Carbon monoxide (CO) is a colorless, odorless, and toxic gas produced by incomplete combustion of carbon-based fuels such as petrol, diesel, wood, and coal. CO binds with hemoglobin, reducing oxygen transport to vital organs, and prolonged exposure—even at moderate levels—can cause dizziness, fatigue, and cognitive impairment (Yina, 2025; Szponar, 2025). In this study, CO concentrations showed clear spatial variability across the districts. Tuticorin recorded the highest average (675.10 ppb), reflecting its industrial landscape with power plants, petrochemical facilities, port operations, and heavy vehicular traffic. Tirunelveli had slightly lower levels (645.22 ppb), influenced by urban traffic and commercial expansion along key transport corridors. Kanniyakumari, though less industrialized, exhibited

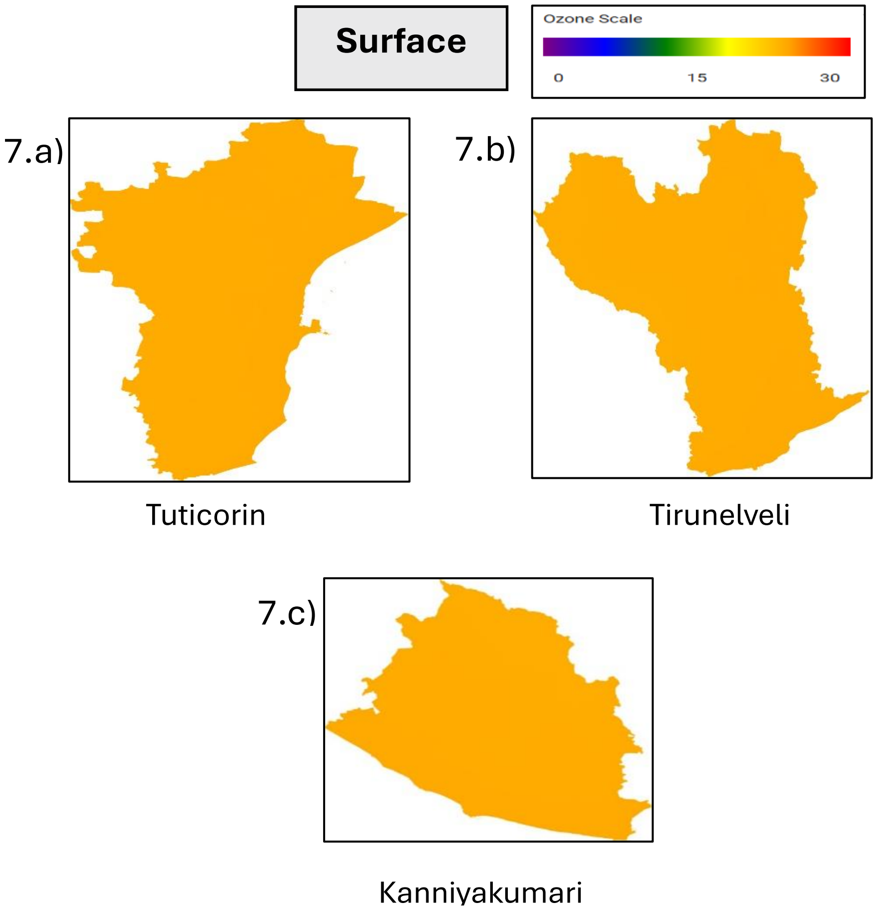


Fig. 7a,7b, 7c. Spatial distribution of surface ozone concentrations across Tuticorin, Tirunelveli, and Kanniyakumari districts from April 2024 to March 2025, as extracted from Sentinel-5P data using Google Earth Engine.

a comparable mean (647.98 ppb), likely due to seasonal tourism-related vehicle activity during December–March.

Seasonally, CO peaked in winter when cooler temperatures and lower boundary-layer mixing restricted dispersion, declined during the monsoon with enhanced atmospheric ventilation, and remained moderate in summer due to photochemical oxidation into CO_2. These patterns underscore the combined impact of industrial and transport emissions on regional CO levels. Tuticorin's persistently high concentrations highlight the need for targeted emission control, while emerging urban trends in Tirunelveli and Kanniyakumari warrant early mitigation efforts.

- **Surface Ozone (O_3)**: Surface ozone is a secondary pollutant formed through photochemical reactions of NO_2 and volatile organic compounds (VOCs) under sunlight. Unlike stratospheric ozone, which protects against UV radiation, ground-level ozone is harmful, causing respiratory issues and crop damage (Kawichai, 2025; Gopikrishnan, 2025). In this study, O_3 concentrations were nearly uniform across the three districts: Tuticorin (23.63 ppb), Tirunelveli (23.59 ppb), and Kanniyakumari (23.58 ppb). This uniformity reflects its regional formation through atmospheric chemistry rather than direct local emissions, highlighting the limitation of satellite monitoring in capturing near-surface ozone. Meteorological factors, including wind patterns, atmospheric mixing, and solar intensity, further influence ozone dispersion and accumulation. Previous ground-based measurements recorded higher maxima (up to 51.28 ppb in Kanniyakumari; Sharma, 2016), indicating that satellite data (Sentinel-5P) may underestimate surface-level ozone, which is most relevant for human health. This underscores the importance of combining satellite observations with local ground monitoring for accurate assessment.

Heatmaps and Spatial-Seasonal Trends

Heatmaps illustrated district-wise and seasonal pollutant patterns. Tuticorin consistently exhibited higher NO_2 and CO levels due to its industrial density, thermal power plants, and port-related traffic, while elevated SO_2 reflected combustion emissions from industrial sources. Tirunelveli showed moderate pollutant levels, with localized hotspots near urban settlements and highways, indicating growing vehicular and commercial activity. Kanniyakumari displayed lower and more uniform pollutant concentrations, aided by limited industrialization, higher vegetation cover, and strong coastal winds that enhance pollutant dispersion. Surface ozone remained relatively uniform across all districts, consistent with its secondary formation and dependence on precursors and meteorological conditions. These spatial and seasonal patterns emphasize the interplay between anthropogenic activity, land use, and atmospheric dynamics in shaping air quality. Even within a geographically connected region, differences in industrialization, urban density, and meteorology lead to distinct pollution profiles, affecting both environmental quality and public health.

Significance of Satellite-Based Monitoring and Ground Data Comparison

Satellite-based monitoring provides a powerful alternative to traditional ground networks, especially in regions with sparse air quality stations. In this study, Sentinel-5P data processed through the Google Earth Engine (GEE) platform enabled large-scale, high-resolution pollution assessment across southern Tamil Nadu. This approach addressed data gaps common in semi-urban and rural areas and allowed district-wise comparison of pollutants using consistent, uniform datasets. To validate the Sentinel-5P observations, ground-level air quality data were obtained from the Tamil Nadu Pollution Control Board (TNPCB) for Tirunelveli and Tuticorin, and from the AQI India platform for Kanniyakumari, covering April 2024–March 2025. Sentinel-5P reported average concentrations of NO_2 (3.56–6.32 ppb), SO_2 (1.19–1.23 ppb), O_3 (23.58–23.63 ppb), and CO (645–675 ppb), while ground data indicated slightly higher values—NO_2 (8–12 ppb), SO_2 (2–3 ppb), CO (700–950 ppb), and O_3 (25–28 ppb). Primary pollutants such as NO_2 and CO were higher in ground observations since these gases accumulate near emission

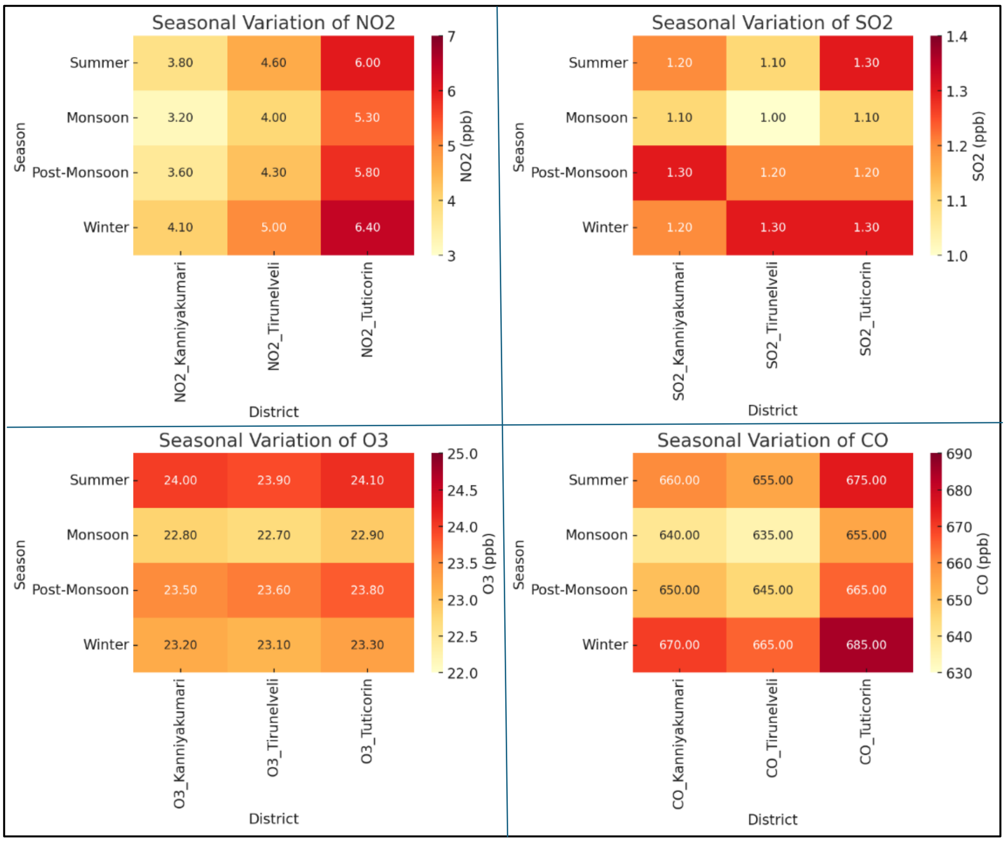


Fig. 8. Seasonal variation in major air pollutants — Nitrogen Dioxide (NO_2), Sulfur Dioxide (SO_2), Surface Ozone (O_3), and Carbon Monoxide (CO) — across Kanniyakumari, Tirunelveli, and Tuticorin districts of southern Tamil Nadu during April 2024–March 2025.

sources like vehicles and industries, whereas the satellite sensor captures broader atmospheric columns. The TROPOMI sensor aboard Sentinel-5P measures total column concentrations over a 5.5 × 3.5 km^2 grid, integrating signals from multiple atmospheric layers, while ground sensors provide direct surface readings that better represent human exposure. Consequently, satellite data tend to underestimate surface-level concentrations but offer valuable insights into regional patterns and spatial gradients.

Sentinel-5P ensures consistent daily global coverage, which supports long-term regional analyses even in under-monitored areas. Ground stations, though temporally detailed with hourly data, are geographically limited and prone to occasional data gaps. For secondary pollutants like ozone, ground-based measurements captured greater variability (25–28 ppb) compared to the satellite's near-uniform readings (~23–24 ppb). This difference arises because satellites detect ozone mainly in upper atmospheric layers, while ground sensors record concentrations within the boundary layer where health impacts occur. Environmental factors such as humidity, cloud cover, and boundary-layer dynamics can further influence measurement accuracy. Overall, this comparison demonstrates the complementary roles of both methods: satellite data are ideal for identifying large-scale pollution patterns, whereas ground observations remain essential for understanding near-surface air quality and population exposure. Integrating both approaches offers a more complete and reliable assessment of air quality in southern Tamil Nadu.

Limitations and Future scope

Although this study provides a comprehensive annual assessment of air quality across southern Tamil Nadu, certain limitations highlight opportunities for refinement. Incorporating meteorological factors such as wind speed, humidity, temperature, and boundary-layer height would enhance understanding of pollutant dispersion and formation, particularly for secondary pollutants like surface ozone. Including these parameters could clarify how atmospheric conditions influence spatial and temporal variations in pollutant concentrations. Ground-truth validation using continuous station-based data would also strengthen the reliability of satellite-derived results. Since Sentinel-5P measures total column concentrations, integrating surface-level monitoring can help correct potential discrepancies and improve model accuracy. Despite these constraints, the study demonstrates the strength of combining remote sensing with cloud-based platforms like Google Earth Engine for effective air quality monitoring in regions with limited ground infrastructure. Future research could extend this approach by developing integrated air quality models that merge satellite and ground data for real-time tracking and predictive analysis. The insights from this work can guide policymakers in formulating targeted pollution control strategies. Industrial corridors in Tuticorin and traffic-heavy zones in Tirunelveli, for instance, can be prioritized for emission reduction, while the relatively clean environment in Kanniyakumari may serve as a model for sustainable regional planning. Expanding future studies to include meteorological linkages, seasonal variability, and socio-economic factors would further enhance the practical relevance of this research for environmental management and policy development.

CONCLUSIONS

This study provides a detailed analysis of NO_2, SO_2, CO, and surface O_3 across three southern districts of Tamil Nadu using Sentinel-5P satellite data and Google Earth Engine (GEE). Tuticorin consistently exhibited the highest pollution levels, followed by Tirunelveli, while Kanniyakumari showed comparatively lower concentrations.

Spatial and seasonal patterns reflect both anthropogenic and natural influences. Tuticorin's elevated NO_2 and CO levels stem from dense industrial activities, including thermal power plants, chemical factories, and port operations, supplemented by vehicular emissions. Tirunelveli, with moderate industrialization, experienced moderate pollution due to increasing urbanization and traffic along highways and city centers. Kanniyakumari benefited from lower population density, minimal industrial presence, agricultural land use, and coastal winds, which facilitated pollutant dispersion, although short-term peaks were observed during peak tourism seasons. Natural factors such as coastal breezes, water bodies, and vegetation further contributed to the dilution of pollutants, especially in Kanniyakumari. However, satellite-based assessments have limitations for secondary pollutants like surface ozone, as Sentinel-5P primarily measures upper-atmosphere concentrations, potentially underestimating surface-level exposure. Integrating local ground-based monitoring is essential for a more accurate assessment of pollutants affecting human health. Overall, this study demonstrates the value of combining high-resolution satellite data with cloud-based platforms like GEE to reveal spatial and contextual variations in air quality. The results highlight the need for district-specific pollution mitigation strategies that consider local emission sources, land use, population density, and meteorological factors. This approach provides a scalable framework for monitoring air quality in under-studied or data-scarce regions.

ABBREVIATIONS

- NO_2 - Nitrogen Dioxide
- SO_2 - Sulfur Dioxide
- O_3 - Ozone
- CO - Carbon monoxide

- GEE - Google Earth Engine
- ESA - European Space Agency
- VOCs -Volatile Organic Compounds
- QA - Quality Assurance
- QGIS - Quantum Geographic Information System
- CSV - Comma- Separated Values
- TROPOMI - Tropospheric Monitoring Instrument
- GeoTIFF - Georeferenced Tagged Image File Format
- GeoJSON - Geographic JavaScript Object Notation

GRANT SUPPORT DETAILS

The present research did not receive any financial support.

CONFLICT OF INTEREST

The authors declare that there is not any conflict of interests regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/ or falsification, double publication and/or submission, and redundancy has been completely observed by the authors.

LIFE SCIENCE REPORTING

No life science threat was practiced in this research.

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