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Spatio-Temporal Dynamics of Tropospheric Pollutants and Land Surface Temperature over Andhra Pradesh, India: A Google Earth Engine-Based Satellite Remote Sensing Study (2020–2024)

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Abstract

Air quality monitoring is the need of the hour in Andhra Pradesh, owing to the accelerated pace of urbanization and industrial growth in certain areas. This study undertakes a detailed spatio-temporal evaluation of six major air pollutants-carbon monoxide (CO), sulfur dioxide (SO_2), nitrogen dioxide (NO_2), ozone (O_3), particulate matter (PM2.5 and PM10) along with Land Surface Temperature (LST) across the state for the period 2020–2024. In the current study a multi-sensor suite of satellite data was processed and analyzed using the Google Earth Engine (GEE) cloud platform, which includes Sentinel-5P for trace gases, MODIS-derived Aerosol Optical Depth (AOD) for particulate matter, and Landsat 8 for LST.

The results reveal persistent pollution hotspots concentrated in the industrial corridors of Visakhapatnam-Kakinada and the urban agglomerations of Vijayawada and Tirupati, particularly for NO_2 and PM2.5. Temporal analysis indicates a significant reduction in NO_2 during the 2020 COVID-19 lockdown, followed by a gradual rebound in later years. High-resolution LST analysis distinctly delineated the Urban Heat Island (UHI) effect in major cities. A key contribution of this work is the development and application of a multi-level threat classification framework, which translates raw concentration data into an intuitive risk assessment map for each parameter. This research validates a scalable, multi-sensor approach for environmental surveillance and provides actionable, data-driven insights to support evidence-based air quality management and sustainable urban planning.

Keywords: Air Quality; Google Earth Engine; Remote Sensing; Andhra Pradesh; Sentinel-5P; PM2.5; Land Surface Temperature; Spatio-Temporal Analysis

1. Introduction

Air pollution has emerged as one of the most critical environmental issues of the present century, exerting profound impacts on human health and ecosystem stability globally. The World Health Organization (WHO) attributes millions of premature deaths annually to exposure to polluted air, with the majority occurring in low- and middle-income nations [1][2][3].India, undergoing profound economic and demographic transformation, is at the forefront of this crisis. Its cities frequently rank among the most polluted globally, prompting nationwide initiatives like the National Clean Air Programme (NCAP) aimed at curbing emissions [4]. However, the effectiveness of such programs depends on the availability of accurate, granular, and continuous environmental data, which remains a significant challenge.

The state of Andhra Pradesh, characterized by its extensive coastline, strategically located ports, and rapidly growing industrial and urban hubs, represents a significant case for examining the interplay between economic development

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and environmental sustainability. The region's complex emission landscape arises from multiple sources such as large-scale industries in the Visakhapatnam-Kakinada corridor, dense vehicular traffic in expanding cities like Vijayawada and Tirupati, thermal power plants, and agricultural activities [5]. Understanding the spatial distribution and temporal behavior of air pollutants in such a dynamic and varied environment is essential for mitigating public health risks and steering the region towards a sustainable future.

Traditional air quality assessment has mainly depended on ground-based monitoring stations. While providing highly accurate data, their sparse distribution and high operational costs render them incapable of capturing the comprehensive spatio-temporal heterogeneity of air pollution across a large state like Andhra Pradesh [6]. This data gap creates significant uncertainties in exposure assessment and hinders the ability to pinpoint and regulate diffuse and transboundary pollution sources. Satellite-based remote sensing offers a powerful and complementary approach, providing consistent and geographically extensive observations of the Earth's atmosphere.

The development of sophisticated satellite instruments, including the Tropospheric Monitoring Instrument (TROPOMI) aboard Sentinel-5P for detecting trace gases and the Moderate Resolution Imaging Spectroradiometer (MODIS) for aerosol monitoring, has significantly advanced space-based air quality observation [7][8]. Nevertheless, the immense data volumes, often at the petabyte scale, produced by these missions pose substantial computational challenges. The Google Earth Engine (GEE) platform addresses this limitation by offering a cloud-based infrastructure equipped with parallel processing capabilities and seamless access to extensive geospatial datasets[9]. This framework empowers researchers to perform comprehensive, long-term, and large-area environmental assessments that were once computationally unfeasible.

This study makes use of the Google Earth Engine (GEE) platform to integrate multi-sensor satellite datasets, including Sentinel-5P, MODIS, and Landsat 8, for a comprehensive environmental assessment of Andhra Pradesh during the period 2020–2024. The work goes beyond conventional monitoring by establishing an integrated framework that not only maps pollutant concentrations but also categorizes them into clear threat levels. The core objectives of this paper are to: (1) carry out a detailed spatio-temporal analysis of six major pollutants along with high-resolution Land Surface Temperature (LST); (2) identify persistent pollution hotspots and temporal trends, including the impact of the COVID-19 lockdown; (3) utilize high-resolution Landsat 8 data for a precise delineation of the Urban Heat Island effect; and (4) develop a novel threat-level classification system to translate complex scientific data into actionable insights for policymakers and the general public.

2. Literature review

The review synthesizes recent scientific literature to establish the context for the present study. It examines the current status in three key areas: advanced satellite remote sensing techniques for monitoring air quality, recent applications of these approaches within the Indian context, and the growing role of cloud computing platforms such as Google Earth Engine in enabling multi-sensor data integration.

2.1. Advances in Satellite-Based Air Quality Monitoring

Over the past five years, atmospheric data from space have improved dramatically in both quality and resolution. A major advancement has been the launch of the TROPOMI instrument aboard Sentinel-5P, which has provided unprecedented spatial detail. This capability enabled studies such as that of Griffin et al., who were able to map industrial and urban NO_2 plumes with sufficient precision to attribute emissions to individual facilities—an achievement not possible with earlier sensors [10]. At the same time, methodologies for estimating ground-level fine particulate matter (PM2.5) from satellite-derived Aerosol Optical Depth (AOD) have become increasingly advanced. Notably, van Donkelaar et al. enhanced these estimates by combining satellite observations with global chemical transport models and ground-based measurements, producing more accurate and chemically detailed PM2.5 datasets worldwide [11]. Advances have also been made in the study of urban microclimates through high-resolution thermal sensors. For instance, Chakraborty and Lee (2019) developed a simplified algorithm using Landsat imagery to characterize Surface Urban Heat Islands at the global scale, illustrating the strong potential of modern satellite data for assessing the thermal consequences of urbanization [12].

2.2. Recent Air Quality Studies in the Indian Context

With its significant air quality challenges, India has been the focus of numerous recent remote sensing studies. A comprehensive analysis by Jaganathan et al. (2021) utilized satellite-based observations to map the spatio-temporal variability of PM2.5 across the entire country, identifying the Indo-Gangetic Plain and eastern industrial zones as persistent hotspots [13]. The COVID-19 pandemic provided a unique opportunity to study the effects of drastic emission reductions. The work of Sharma et al. (2020) was pivotal in using TROPOMI and MODIS data to quantify the sharp decline in NO_2 and PM2.5 over major Indian cities during the 2020 lockdown, confirming the dominant role of traffic and industry in urban pollution [14]. Beyond urban emissions, researchers like Kuttippurath et al. (2020) have utilized the satellite data to track long-range transport of pollutants from agricultural biomass burning, demonstrating its significant contribution to seasonal air quality degradation across large parts of the country [15].

2.3. The Synergy of GEE and Multi-Sensor Data Fusion

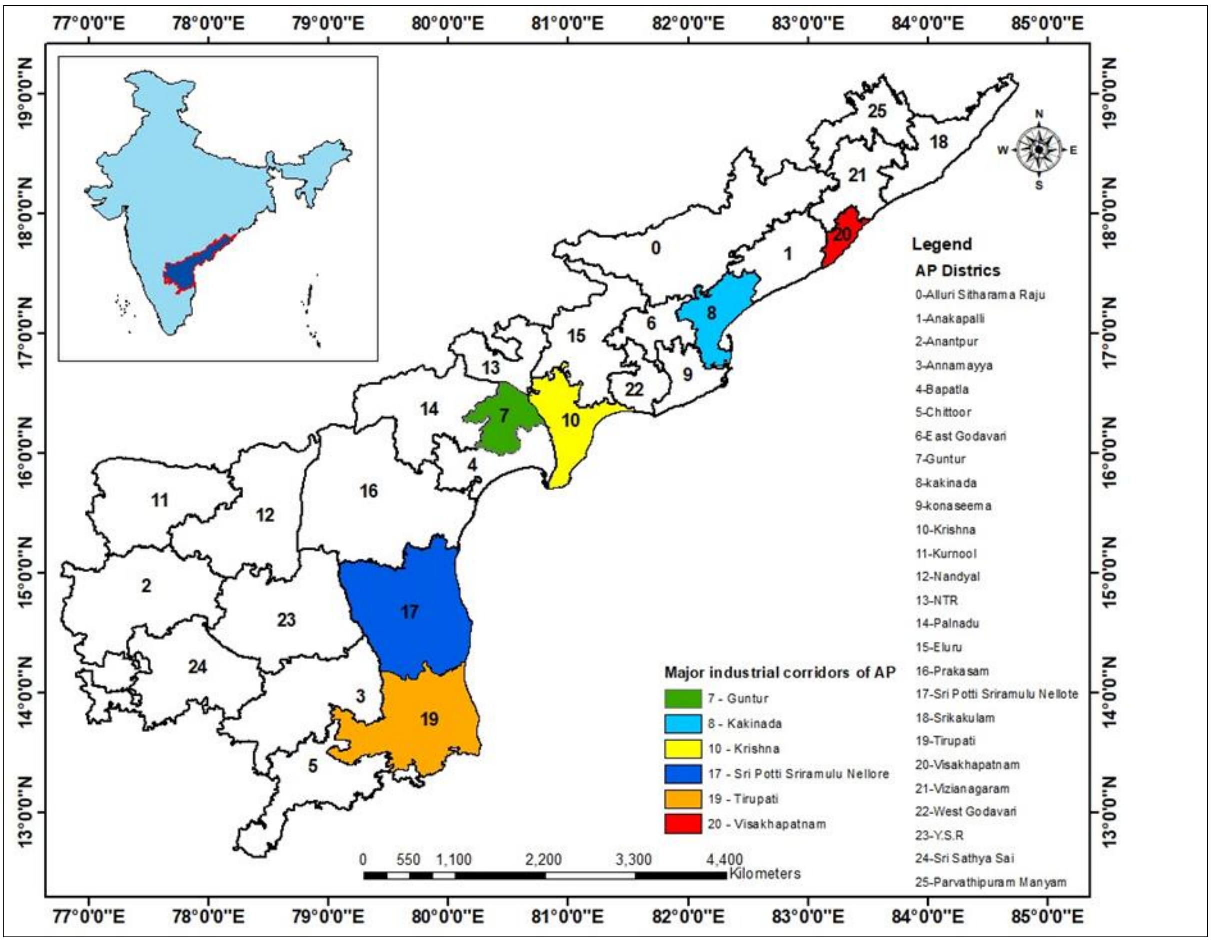
The vast volume of data generated by modern satellites necessitates powerful computational tools. Google Earth Engine (GEE) has emerged as a critical platform in this regard. A comprehensive review by Amani et al. (2020) highlighted the rapid expansion of GEE applications across diverse large-scale environmental studies, emphasizing its role in making petabyte-scale geospatial analysis broadly accessible [16]. Current methodological advances are now moving towards the integration of data from multiple sensors to create more holistic and accurate environmental insights. For instance, Xue et al. demonstrated the value of integrating satellite observations with chemical transport models and ground-based data to produce improved air quality estimates [17]. However, as noted in a recent review by Yassine et.al., there remains a need for studies that develop and validate integrated frameworks for integrating different types of satellite data (e.g., thermal, aerosol, and trace gas) for regional-scale risk assessment [18]. Addressing this gap, the present study develops a unified workflow within GEE to integrate datasets from Landsat 8, MODIS, and Sentinel-5P, thereby offering a multi-dimensional evaluation of environmental quality in Andhra Pradesh.

3. Materials and Methods

This section outlines the analytical framework, datasets, and processing methods applied for the spatio-temporal assessment of air quality and Land Surface Temperature (LST) in Andhra Pradesh. The complete workflow was executed using the Google Earth Engine (GEE) cloud-computing platform.

3.1. Study Area

The study was conducted over the state of Andhra Pradesh, located on the southeastern coast of India (Figure1). Covering an area of 162,975 km^2, the state features a diverse geology and geography, including the Eastern Ghat Mobile Belt, the fertile deltas of the Krishna and Godavari rivers, and a coastline of 974 km. The region is characterized by a tropical climate and is home to a population of approximately 50 million people. Its rapidly growing economy is driven by agriculture, aquaculture, and a expanding industrial sector concentrated in key urban centers and corridors, such as industrial corridor of Visakhapatnam, the commercial hub of Vijayawada, and the temple city of Tirupati. This blend of dense urban agglomerations, industrial zones, and extensive agricultural lands creates a complex and dynamic emissions landscape, making it an ideal region for this study.



(Source: https://onlinemaps.surveyofindia.gov.in/FreeMapSpecification.aspx)

Figure 1 Map of the study area, Andhra Pradesh, showing state boundaries, major cities, and key industrial regions

3.2. Satellite Datasets

A multi-sensor approach was adopted, utilizing data from three different satellite missions to ensure comprehensive coverage of all parameters. All datasets were accessed directly from the GEE data catalogue for the five-year period from January 1, 2020, to December 31, 2024. The specific data products are detailed in Table 1.

Table 1 Satellite Datasets Used in This Study

Parameter	Satellite/Sensor	GEE Product ID	Key Band(s)
NO_2, SO_2, CO, O_3	Sentinel-5P/TROPOMI	COPERNICUS/S5P/NRTI/L3	tropospheric_NO2_xxx, SO2_xxx, CO_xxx, O3_xxx
PM2.5, PM10	MODIS/Terra and Aqua	MODIS/061/MCD19A2_GRANULES	Optical_Depth_047
LST	Landsat 8/OLI and TIRS	LANDSAT/LC08/C02/T1_L2	ST_B10

3.3. Data Processing and Analysis in GEE

The GEE platform was used for all data acquisition, preprocessing, analysis, and visualization. A custom script was developed to automate the workflow for each parameter.

3.3.1. Tropospheric Trace Gases (NO_2, SO_2, CO, O_3)

For each of the four trace gases, the corresponding Sentinel-5P TROPOMI Level-3 Near Real-Time (NRTI) Image Collection was utilized. For each year in the study period, the collection was filtered by date and bounded to the Andhra Pradesh Area of Interest (AoI). A function was mapped over the collection to clip each image to the AoI boundary. Finally, the mean () reducer was applied to the annual image stack to generate a single, cloud-free composite image representing the mean tropospheric column concentration for that year.

3.3.2. Particulate Matter Estimation (PM2.5 and PM10)

Ground-level PM concentrations were estimated from satellite-retrieved Aerosol Optical Depth (AOD), a widely validated technique. The analysis employed the daily MODIS MCD19A2 Version 6.1 product, which provides AOD at a 1 km resolution. The Optical_Depth_047 band was selected for this purpose. The annual mean AOD was calculated for each year. Subsequently, PM concentrations were derived using an empirical linear regression model as follows:

$$PM_{2.5}(\mu g/m^3) = 165.69 \times AOD + 8.7597 \qquad (1)$$

$$PM_{10}(\mu g/m^3) = 195.7 \times AOD + 14.5 \qquad (2)$$

These conversion factors were applied to the annual mean AOD maps to generate the final PM2.5 and PM10 concentration maps.

3.3.3. Land Surface Temperature (LST)

To achieve a high level of spatial detail for urban climate analysis, LST was derived from the Landsat 8 Collection 2: Tier 1 Level-2 science product. The thermal infrared band ST_B10 was selected for extraction. Following the official documentation, a scaling factor of 0.00341802 and an offset of 149 were applied to convert the raw digital numbers to Kelvin. This was further converted to degrees Celsius by subtracting 273.15. The annual mean LST was then calculated by averaging all available cloud-masked scenes for each year.

3.4. Spatio-Temporal Analysis and Threat Classification

In this analysis, two primary analytical methods were employed

- Spatio-Temporal Mapping: The generated annual mean maps for each of the seven parameters were used to visually and quantitatively analyze the spatial distribution of pollution and LST, identify persistent hotspots, and observe year-on-year changes.
- Threat Level Classification: To translate continuous concentration data into a practical risk assessment tool, a threat classification framework was developed. Using a custom function in Google Earth Engine (GEE), pixel values from the 2024 mean concentration maps were reclassified into three categories: Low (1), Medium (2), and High (3). The thresholds for this classification were based on established guidelines (e.g., WHO Air Quality Guidelines for PM2.5) and an analysis of the data distribution for other parameters. This method provides an intuitive visualization of areas facing the most significant environmental stress.

3.5. Methodological Workflow

The overall workflow, from data acquisition to final analysis, is illustrated in the flowchart below (Figure 2). The framework is designed to be a reproducible and scalable process entirely within the Google Earth Engine environment.

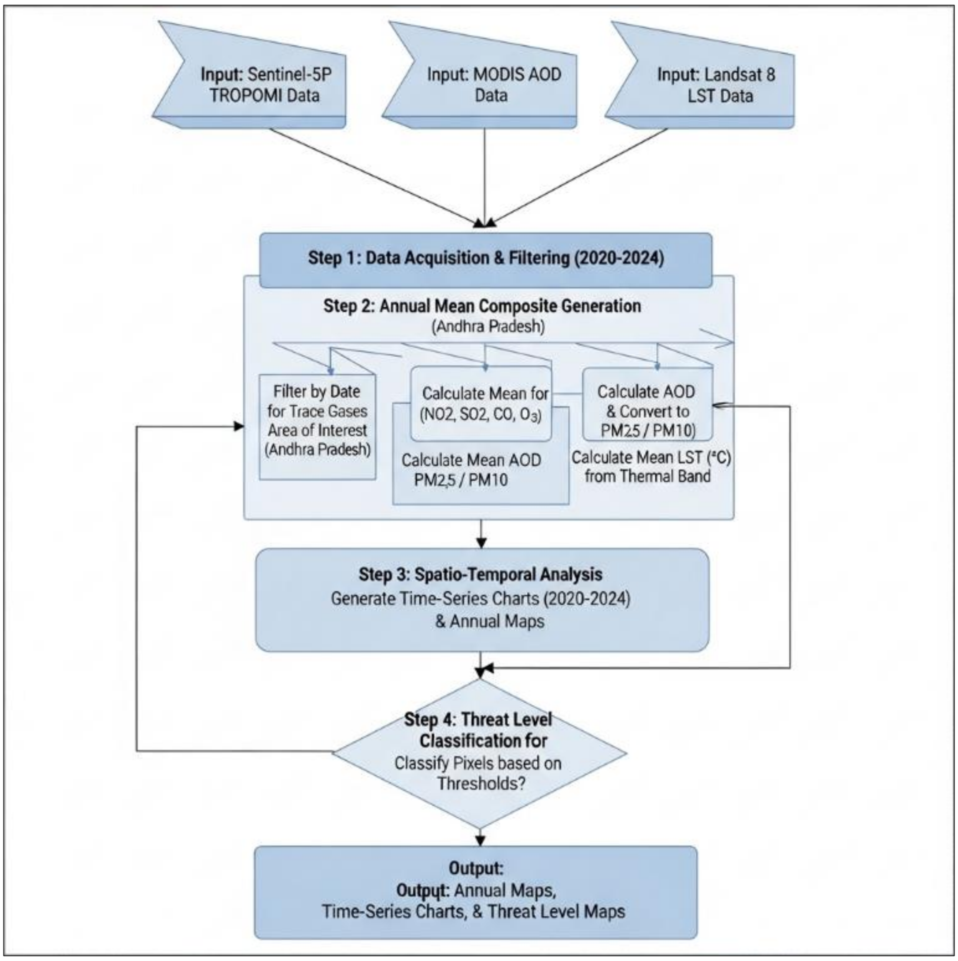


Figure 2 Methodological flowchart illustrating the key stages of the study

4. Results

The spatio-temporal patterns of the six target air pollutants and Land Surface Temperature (LST) across Andhra Pradesh for the study period of 2020–2024 are presented here. The results are derived from the GEE-based analysis of Sentinel-5P, MODIS, and Landsat 8 satellite data.

4.1. Spatio-Temporal Distribution of Tropospheric Pollutants

The annual mean distributions of tropospheric trace gases revealed distinct and persistent spatial patterns.

4.1.1. Nitrogen Dioxide (NO_2)

As shown in the annual maps (Figure 3), NO_2 concentrations were consistently highest over major urban and industrial centers. Prominent hotspots were identified over the Visakhapatnam metropolitan area, the Vijayawada-Guntur urban corridor, and the industrial zones near Tirupati and Kurnool. Temporally, a marked decrease in NO_2 levels was observed across all hotspots in 2020, followed by a progressive rebound in the subsequent years, with 2023 and 2024 levels approaching or exceeding those of the pre-lockdown period.

4.1.2. Sulfur Dioxide (SO_2)

Unlike the more diffuse NO_2, SO_2 concentrations were highly localized into distinct plumes originating from specific point sources. The most significant hotspots were identified near major thermal power plants (e.g., in Nellore district) and the industrial refinery complex in Visakhapatnam. The intensity of these plumes showed minor annual fluctuations but remained geographically fixed throughout the five-year period.

4.1.3. Carbon Monoxide (CO) and Ozone (O_3)

CO exhibited a more diffuse spatial pattern than NO_2 or SO_2, with moderately elevated levels across the state, indicating contributions from a mix of sources including vehicular emissions and biomass burning. Conversely, tropospheric O_3 concentrations were generally lower over the primary NO_2 hotspots and higher in the surrounding suburban and rural areas, particularly downwind of major cities.

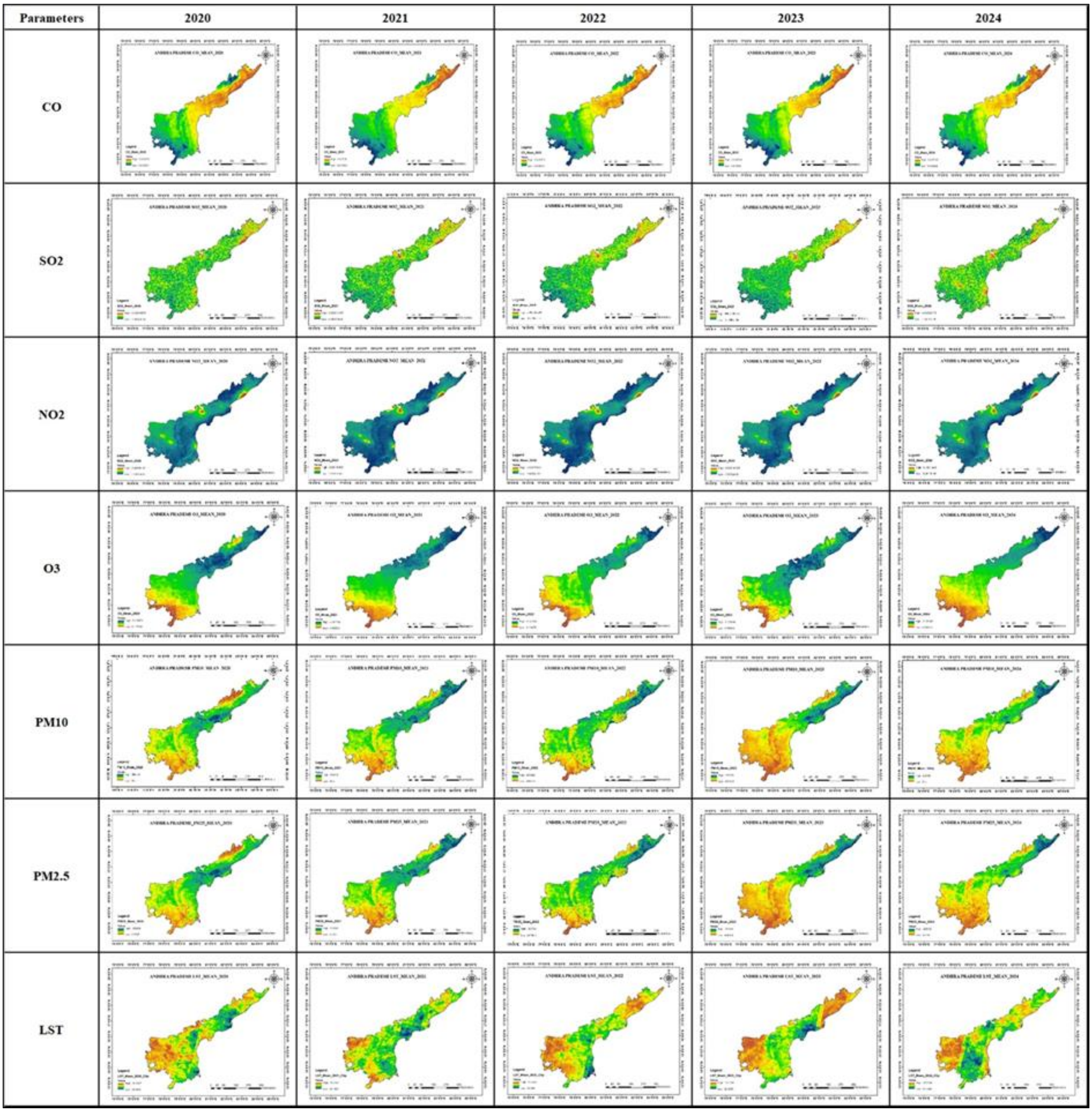


Figure 3 Spatio-temporal maps of annual mean concentrations for NO_2, SO_2, CO, O_3, PM2.5, PM10, and LST over Andhra Pradesh from 2020 to 2024

4.2. Spatio-Temporal Distribution of Particulate Matter

The particulate matter maps (Figure 3) derived from MODIS AOD showed widespread pollution, particularly in populous regions.

4.2.1. PM2.5 and PM10

Both fine and coarse particulate matter were found in high concentrations along the entire coastal belt, which hosts the majority of the state's population and industrial activity. The highest levels were consistently observed in the Visakhapatnam-Kakinada industrial corridor and the Krishna-Guntur region. Temporal trends did not show the sharp 2020 dip seen in NO_2, indicating more complex and diverse emission sources.

4.3. High-Resolution Land Surface Temperature (LST)

The analysis of Landsat 8 thermal data provided a detailed view of the region's surface temperature dynamics. A prominent Urban Heat Island (UHI) effect was clearly visible, with all major cities Visakhapatnam, Vijayawada, Guntur, Tirupati, and Nellore acting as distinct heat islands. These urban cores consistently registered annual mean LST values several degrees Celsius higher than their surrounding vegetated and rural areas. The spatial extent of these high-temperature zones showed a marginal but noticeable expansion over the five-year study period.

4.4. State-Wide Temporal Trends

The time-series charts generated from the state-wide mean of each parameter provide a clear overview of the temporal trends from 2020 to 2024 (Figure 4). The most significant trend was observed for NO_2, which showed a sharp decline from 2020 to 2021, followed by a steady increase through 2024. PM2.5 and PM10 exhibited inter-annual variability, with a slight overall increasing trend post-2021. LST also showed a marginal but consistent year-on-year increase in the state-wide average.

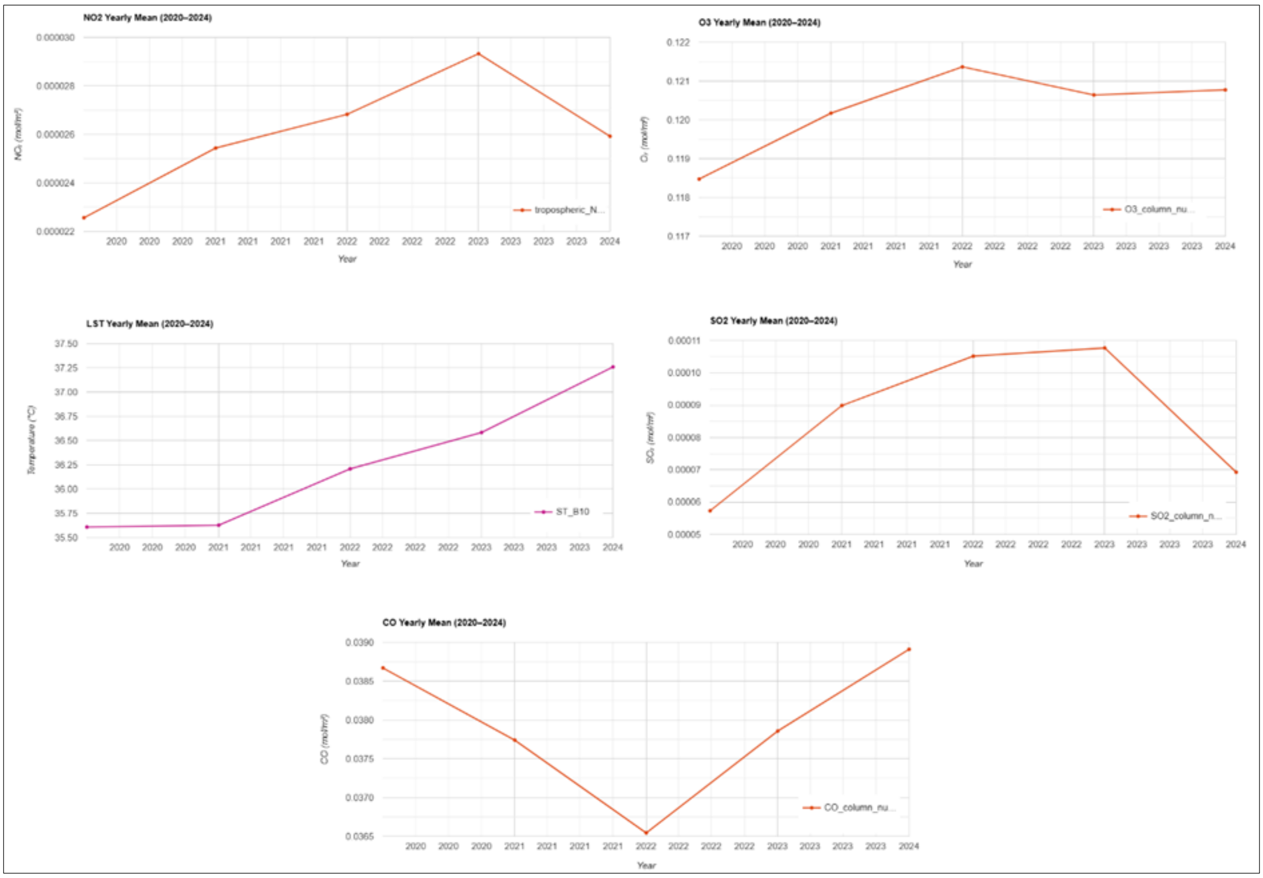


Figure 4 Time-series plots showing the annual state-wide mean concentration for each pollutant and LST from 2020 to 2024

5. Discussion

This study used a multi-sensor satellite approach within Google Earth Engine to conduct a comprehensive spatio-temporal assessment of air quality and LST across Andhra Pradesh. The results presented in the previous section provide a robust, data-driven overview of the region's environmental status. This section interprets these findings, discusses their alignment with existing literature, and explores their broader implications for policy and future research.

5.1. Interpretation of Key Findings

The spatial analysis consistently identified the industrial-urban corridors, particularly the Visakhapatnam-Kakinada belt and the Vijayawada-Guntur metropolitan region, as persistent hotspots for NO_2 and PM2.5. This is directly attributable to the high density of anthropogenic activities, including industrial emissions, heavy vehicular traffic, and energy production, which are concentrated in these zones. The localized nature of SO_2 plumes further corroborates this, as they spatially align with known point sources like thermal power plants and refineries.

The temporal trends observed provide a unique insight into the drivers of air pollution in the region. The sharp decline in NO_2 concentrations during 2020 serves as a large-scale "natural experiment," confirming the overwhelming contribution of the transportation and industrial sectors to ambient NO_2 levels. The subsequent rebound to pre-pandemic levels by 2023–2024 underscores the challenge of decoupling economic activity from emissions. In contrast, the comparatively smaller change in PM2.5 during the lockdown suggests a more complex emission profile, with significant contributions from sources that were less affected by the restrictions, such as domestic solid fuel combustion, dust, and the formation of secondary aerosols.

A notable finding is the spatial distribution of tropospheric ozone (O_3), which was often lower in the most polluted urban cores and higher in downwind, less-developed areas. This apparent paradox is well-explained by atmospheric chemistry: in urban centers with high NO_2 emissions, O_3 is rapidly depleted through titration by nitric oxide (NO). As the polluted air mass moves to suburban and rural areas where NO levels are lower, volatile organic compounds (VOCs) and sunlight drive the photochemical production of O_3, leading to elevated concentrations away from the primary emission sources [19].

Finally, the high-resolution LST data from Landsat 8 clearly delineated the Urban Heat Island (UHI) effect in all major cities. The spatial congruence of elevated LST and high pollutant concentrations points to a potential synergistic relationship. The UHI can alter local atmospheric circulation, leading to air stagnation and trapping pollutants, while higher temperatures can also accelerate the chemical reactions that form harmful secondary pollutants like ozone [20].

5.2. Comparison with Existing Literature

The findings of this study are largely consistent with the wider literature on air quality in India. The identification of urban and industrial centers as the primary drivers of pollution aligns with national-scale studies [13]. The magnitude of the NO_2 reduction during the 2020 COVID-19 lockdown is comparable to that observed in other major Indian metropolitan areas, as reported by Sharma et al. (2020), reinforcing the value of this period as a benchmark for assessing the impact of anthropogenic emissions [21][22]. Further, the study demonstrates the effectiveness of Google Earth Engine for regional-scale, multi-sensor environmental assessments, supporting conclusions from comprehensive reviews regarding the platform's capabilities [9].

5.3. Policy Implications and Significance

The results of this study have significant implications for environmental governance in Andhra Pradesh.

5.3.1. Targeted Interventions

The high-resolution hotspot maps and the "Threat Level" classification provide a clear, evidence-based tool for policymakers to prioritize interventions, deploy mobile monitoring units, and enforce emission standards in the most critically affected areas.

5.3.2. Integrated Urban Planning

The demonstrated link between the UHI effect and air pollution hotspots underscores the need for integrated urban and environmental planning. Policies promoting green infrastructure, cool roofs, and sustainable transport can simultaneously mitigate urban heat and improve air quality.

5.3.3. Cost-Effective Monitoring

This study validates a robust, low-cost framework for continuous, state-wide air quality surveillance. This approach can supplement the existing ground-based network and provide crucial data for regions that are currently unmonitored.

Limitations and Future Directions

While this study provides valuable insights, certain limitations must be acknowledged. First, satellite instruments measure column-integrated concentrations, which may not perfectly correlate with ground-level conditions where human exposure occurs, although our conversion to surface concentration mitigates this for gaseous pollutants. Second, the linear conversion of AOD to PM mass concentration is an approximation; future work could refine this using geographically weighted regression or machine learning models that incorporate meteorological parameters.

Future research should focus on validating these satellite-derived findings with a dense network of low-cost ground sensors. Additionally, the high-resolution pollution maps generated in this study can be used as inputs for health impact assessments to quantify the disease burden attributable to air pollution in Andhra Pradesh.

6. Conclusion

This research successfully developed and implemented a comprehensive, multi-sensor framework on the Google Earth Engine platform to conduct a five-year spatio-temporal analysis of air quality and Land Surface Temperature across Andhra Pradesh. The findings conclusively demonstrate that the synergistic use of Sentinel-5P, MODIS, and Landsat 8 data provides a robust and scalable method for identifying persistent pollution hotspots, analyzing temporal trends, and delineating urban heat islands with high fidelity. The development of a threat-level classification system further translates complex satellite data into an intuitive, policy-relevant tool for risk assessment.

The primary contribution of this work is the validation of a cost-effective and replicable methodology for continuous environmental surveillance in regions with limited ground-based monitoring infrastructure. This approach enables a critical paradigm shift from sparse, reactive monitoring to a holistic, proactive strategy for environmental management. The insights generated from this study offer a crucial evidence base for policymakers in Andhra Pradesh to formulate targeted interventions, promote sustainable urban and industrial development, and ultimately safeguard public health against the adverse effects of environmental degradation. Future work should focus on integrating these findings with ground-level data to develop high-resolution exposure models for health impact assessments.

Compliance with ethical standards

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Disclosure of conflict of interest

No conflict of interest to be disclosed.

Author's Contributions

- Author 1 was responsible for data compilation, result analysis, and manuscript preparation.
- Author 2 was responsible for algorithm development and implementation in GEE, as well as result analysis.
- Author 3 was responsible for satellite data acquisition, result analysis, and figure preparation.

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