International Conference on Business Research
University of Moratuwa, Sri Lanka
December 8, 2025

https://doi.org/10.31705/ICBR.2025.23

ANALYSIS OF SEASONAL AND SPATIAL PATTERNS OF PM2.5 IN SRI LANKA USING SATELLITE-DERIVED DATA

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ABSTRACT

Sparse ground monitoring and limited reliable evidence for policy hinder air quality management in Sri Lanka. This study employs satellite-derived PM2.5 data from the Global High Air Pollutants (GHAP) product for 2017–2022 using Google Earth Engine and Python, aggregating the data to analyse the temporal dynamics of the pollutant distribution at national and provincial levels. The results show a significant monsoon-driven seasonal cycle—highest concentration in January–March and lowest concentration during the mid-year Southwest monsoon, with a late-year rebound—and persistent spatial disparities, with the Western Province (especially the Colombo urban area) consistently elevated relative to the central highlands. An exploratory weekday analysis for 1 January–31 December 2022 indicates workweek increases that peak mid-to-late week and relax on weekends, underscoring anthropogenic influences. These findings provide a baseline climatology of PM2.5 for Sri Lanka, highlight periods and regions of greatest concern, and motivate targeted weekday traffic/industrial controls in urban hubs.

Keywords: PM2.5, Remote Sensing, Seasonal Patterns, Satellite-Derived Data, Sri Lanka

1. Introduction

Air pollution remains a critical global challenge, disproportionately affecting economically disadvantaged regions with limited monitoring capacity [1]. Fine particulate matter (PM2.5) can penetrate deep into the lungs and enter bloodstream, leading to respiratory and cardiovascular diseases, reduced labor productivity, and premature mortality [2, 3]. Developing countries such as Sri Lanka possess only a limited number of ground-based stations capable of continuously monitoring PM2.5 levels.

The lack of dense, high-resolution monitoring data constrains policymakers' ability to design effective interventions [4].

Satellite-derived datasets provide a valuable alternative for air-quality monitoring in regions with sparse or inconsistent ground observations. Aerosol Optical Depth (AOD) products retrieved from sensors such as MODIS [5], VIIRS [6], and MAIAC [7] have been widely used to infer surface-level PM2.5 concentrations. Recent global datasets, most notably the GHAP 1-km PM2.5 product combine satellite AOD, reanalysis variables, chemical transport model outputs, and machine-learning frameworks to produce gapless, high-accuracy global PM 2.5 estimates [8].

To overcome these limitations, satellite-derived datasets provide a valuable alternative for assessing air quality in regions with sparse ground monitoring [7, 11]. This study aims to establish a satellite-derived baseline for Sri Lanka to improve understanding of PM2.5 pollution dynamics and their temporal variability. Specifically, the study seeks to:

- Identify and characterize the seasonal variability of PM2.5 concentrations across Sri Lanka from 2017 to 2022.
- Examine spatial disparities among provinces and between key urban and rural regions.
- Investigate weekday–weekend contrasts to capture anthropogenic influences on PM2.5 levels.
- Provide a foundation for future satellite-based PM2.5 forecasting and inform evidence-based policy design.

Monsoonal circulation and dry-season conditions strongly influence PM2.5 dynamics across South Asia. For instance, concentrations typically peak during the dry winter months in northern India due to limited dispersion, while monsoon rainfall suppresses levels through wet deposition [9]. In Sri Lanka, Colombo and its surrounding urbanized areas have recorded elevated PM2.5 levels, primarily from traffic emissions and biomass burning [4].

Recent advancements in machine learning and data-fusion techniques have further enhanced the accuracy of satellite-based air-quality estimation. Neural-network and data-assimilation frameworks have demonstrated superior predictive performance compared to traditional regression models [8,13]. These freely available, high-resolution satellite-derived methodologies are particularly valuable for Sri Lanka, where open-access indicators can mitigate the absence of dense ground-monitoring networks [9,8,13].

2. Literature Review

Research across South Asia consistently demonstrates strong seasonal patterns in PM2.5 concentrations linked to monsoonal dynamics. Concentrations typically peak during the dry winter months due to limited atmospheric mixing, whereas monsoon rainfall reduces PM2.5 via wet deposition [9]. In Sri Lanka, studies remain limited by the scarcity of ground-based monitoring stations; however, available evidence indicates increasing PM2.5 burdens in Colombo and surrounding regions, largely attributed to vehicular emissions and biomass burning [4]. These studies, while informative, are geographically narrow and highlight the need for broader nationwide assessment.

Satellite-based remote sensing has emerged as a practical solution for air-quality monitoring in regions with sparse observational infrastructure. MODIS AOD [5], VIIRS AOD [6], and MAIAC AOD [7] provide essential inputs for estimating surface PM2.5. Integrating these observations with chemical transport models enhances spatial continuity and improves estimation accuracy, particularly in regions with complex atmospheric regimes [11]. Studies across South Asia show that satellite-derived PM2.5 effectively captures seasonal and inter-annual variation, enabling region-wide exposure analysis [9], [12].

Recent global datasets such as the GHAP PM2.5 product extend this capability by generating daily, gapless, 1 km-resolution PM2.5 using advanced machine-learning and data-fusion frameworks [8]. These datasets outperform traditional regression-based approaches and provide high-fidelity PM2.5 information in countries lacking ground-monitoring networks. Such advances enable more comprehensive exposure assessments, facilitate long-term trend analysis, and support policy-relevant decision-making in data-scarce environments [10], [13].

3. Methodology

3.1. Data Sources

This study employed the Global High Air Pollutants (GHAP) PM2.5 dataset, which provides daily global estimates of PM2.5 concentrations at a 1 km spatial resolution across all terrestrial regions for the period January 2017 to December 2022. The dataset reports PM2.5 concentrations in micrograms per cubic meter (μg/m^3) and represents the first gapless global PM2.5 product developed under the GHAP framework by Wei et al. [11]. The theoretical basis of GHAP is grounded in the well-established association between satellite-derived Aerosol

Optical Depth (AOD) and ground-level PM2.5 concentrations. AOD provides a column-integrated measure of atmospheric aerosols, which, when combined with meteorological variables (e.g., temperature, humidity, boundary-layer height) and chemical transport model outputs, enables accurate estimation of surface PM2.5 levels [5].

The GHAP modeling system integrates multiple satellite sensors (such as MODIS, MAIAC, and VIIRS AOD products), reanalysis data, and ground-based observations through advanced machine learning and big-data fusion techniques. It utilizes an ensemble-learning framework that demonstrates high predictive accuracy, with a cross-validation R^2 of 0.91 and a root mean square error (RMSE) of 9.20 $\mu g/m^3$ at the daily scale [12]. GHAP provides spatiotemporally continuous PM2.5 estimates daily (GHAP_D1K_PM25), monthly (GHAP_M1K_PM25), and annual (GHAP_Y1K_PM25) resolutions. The dataset is openly accessible via the Google Earth Engine (GEE) platform and is distributed under a Creative Commons Attribution 4.0 License, curated for GEE access by Samapriya Roy [10].

3.2. Tools and Environment

Data extraction and analysis were conducted in Google Colab using the GEE Python library, supported by the geemap and xee packages for data access and visualization. Key Python libraries included xee and xarray for handling multidimensional raster data, matplotlib for data visualization, and geemap for interactive inspection and visualization of spatial datasets. GEE facilitated access to PM2.5 datasets at multiple temporal resolutions, including daily, monthly, quarterly, and yearly.

3.3. Study Area

The study area encompassed the entire territory of Sri Lanka. Administrative boundaries were obtained from the FAO GAUL 2015 Level 2 dataset via GEE. The region of interest (ROI) was defined as the union of all Sri Lankan districts. The ROI was visualized using geemap to ensure complete spatial coverage (Figure 1). The provinces were mapped according to GAUL codes in Table 1.

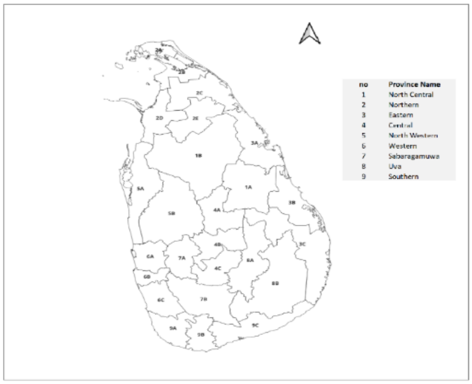

Figure 1. Sri Lanka and Its Nine Provinces based on GAUL, with District-Level Subcodes (e.g., 1A, 1B)

Table 1: Sri Lankan Provinces Using GAUL Codes

Gaul code	Province
2736	Western
2737	Central
2738	Southern
2739	Northern
2740	Eastern
2741	Northwestern
2742	North Central
2743	Uva
2744	Sabaragamuwa

3.4. Data Processing

Daily PM2.5 images were processed to compute mean concentrations for each day from 1 January to 31 December 2022, capturing short-term temporal variability. Each day was assigned a day-of-week index (0 = Monday, 6 = Sunday) to calculate weekday-specific averages and examine weekly patterns. Monthly PM2.5 images were aggregated to assess longer-term temporal variability and seasonal trends. National monthly averages over the period 2017–2022 were calculated to establish a long-term climatology, with 95% confidence intervals (95% CI) quantifying statistical uncertainty (Figures 2 and 4). For provincial-level comparisons, min–max scaling was applied independently to each month, normalizing values while retaining seasonal patterns (Figure 3).

Quarterly and yearly PM2.5 composites were generated to examine broader temporal patterns. Monthly images were assigned to their respective year and quarter and averaged within each quarter to produce quarterly composites. Provincial mean PM2.5 concentrations were computed using GAUL Level 1 geometries, exported as a Pandas data frame, standardized, and aggregated by province and quarter across all year to analyze seasonal and inter-provincial variability. Yearly averages were obtained by averaging across all spatial pixels and time points for each year, and spatial maps of annual mean PM2.5 were generated to visualize inter-annual variability.

4. Results and Discussion

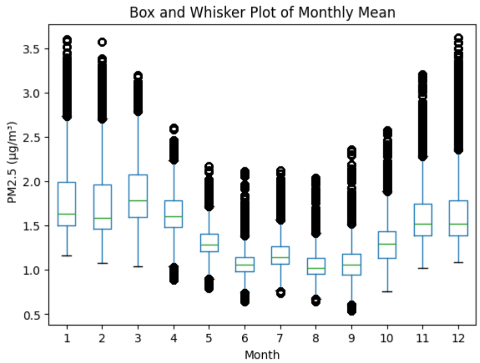

Figure 2: Box-and-Whisker Plot of the Monthly Average PM2.5 (Unscaled)

Figure 2 illustrates the temporal variability of PM2.5 concentrations throughout the year, showing the overall monthly averages for Sri Lanka computed from 2017 to 2022. The highest values occur between January and March, followed by a gradual decline from April onward, reaching the lowest levels between May and August. Concentration then begins to rise again from September through December, forming a secondary peak toward the end of the year.

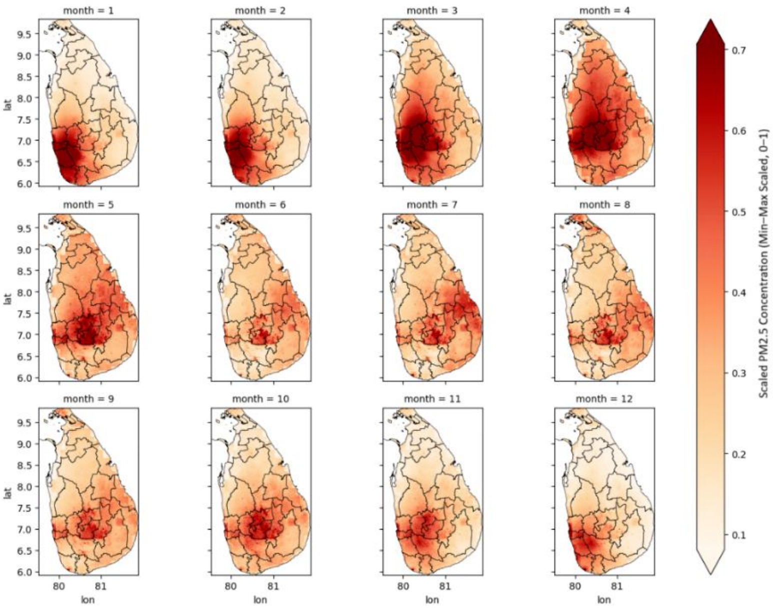

Figure 3: Monthly Average PM2.5 Distribution over Sri Lanka (2017–2022) based on Min–Max Scaled Concentrations for Each Month

In Figure 3, A clear spatial gradient is evident, with the highest concentrations in the western and southwestern regions, moderate values across the mid-country interior, and the lowest levels in the northern and eastern areas. This spatial structure remains consistent throughout the year, shaped by emission intensity, topography, and monsoon-driven dispersion. The Western and Sabaragamuwa Provinces (Colombo, Gampaha, Kalutara, Ratnapura, Kegalle) record the highest PM2.5 levels nationwide. Elevated values dominate from January to March, reflecting strong anthropogenic emissions and limited dispersion, followed by a marked decline during May–August with the southwest monsoon. Concentration rises slightly again toward the year's end.

The Central, Northwestern, and North Central Provinces (Kandy, Matale, Nuwara Eliya, Kurunegala, Puttalam, Anuradhapura, Polonnaruwa) show moderate pollution levels with clear seasonal variation—higher during dry months and lower during monsoon periods. Valleys such as Kandy and Ratnapura exhibit localized accumulation, whereas high-elevation zones like Nuwara Eliya remain consistently cleaner. In contrast, the Southern, Uva, Eastern, and Northern Provinces (Galle, Matara, Hambantota, Badulla, Monaragala, Ampara, Batticaloa, Trincomalee, Jaffna, Mannar, Kilinochchi, Vavuniya, Mullaitivu) maintain comparatively low PM2.5 concentrations year-round. Strong coastal ventilation and sparse industrial activity contribute to sustained air quality improvements, with only slight increases observed during the dry months.

Overall, Figure 3 highlights a persistent west-to-east and southwest-to-north decline in PM2.5 concentrations across Sri Lanka. The western and southwestern urban–industrial regions experience the highest values, while inland, northern, and coastal provinces remain cleaner, forming a stable spatial pattern over 2017–2022 that reflects the country's emission geography and climatic influences.

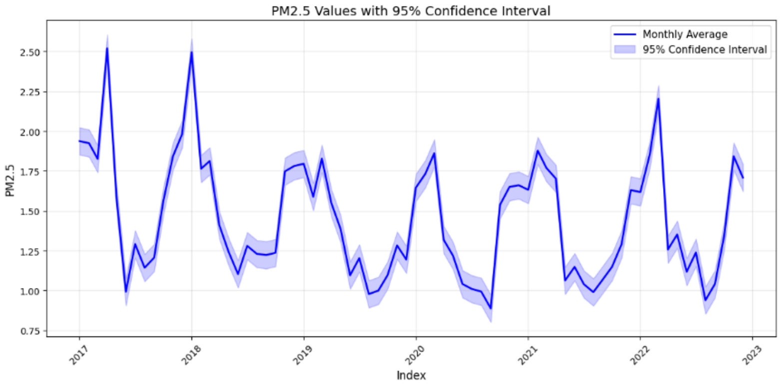

Figure 4: Long-Term Monthly Average PM2.5 (2017–2022)

Figure 4 shows the composite monthly climatology of PM2.5 concentrations across Sri Lanka over the six-year period. The line represents the long-term monthly mean, and the shaded band indicates the 95% confidence interval. A clear seasonal cycle is evident: concentrations rise sharply to a peak in the early months of the year (January–March), followed by a decline to an annual minimum in mid-year (June–September). The amplitude of this cycle demonstrates the influence of seasonal drivers.

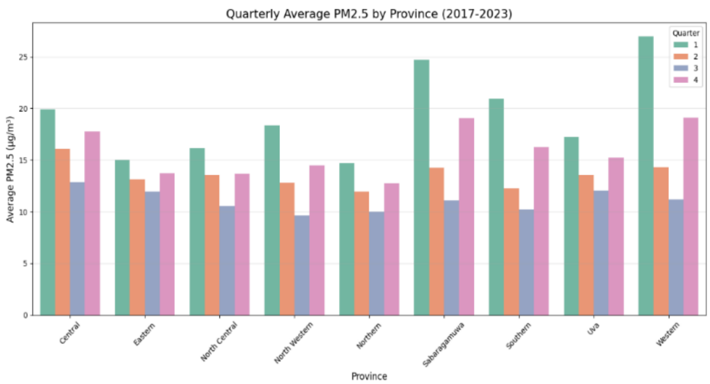

Figure 5: Spatial-Temporal Variability of PM2.5 Concentrations Across Sri Lankan Provinces

Figure 5 displays quarterly average PM2.5 concentrations across provinces using a bar chart. The analysis reveals heterogeneity both between provinces and across seasons. Western, Southern and Sabaragamuwa consistently show the highest levels, often exceeding 20 μg/m^3, particularly in the first (Q1) quarter. These elevated levels reflect persistent urban emissions in the Western Province and potential agricultural or dust-related contributions in the North Central region. Eastern and Northern provinces record relatively lower values. Across nearly all provinces, concentrations peak in Q1, indicating the strong influence of seasonal drivers.

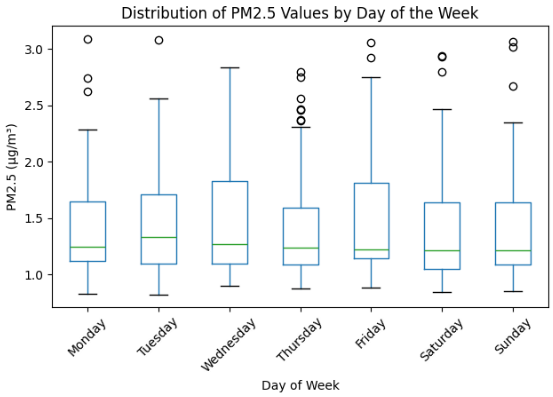

Figure 6: Distribution of PM2.5 Concentrations by Day of the Week (Monday–Sunday) from 1 January to 31 December 2022

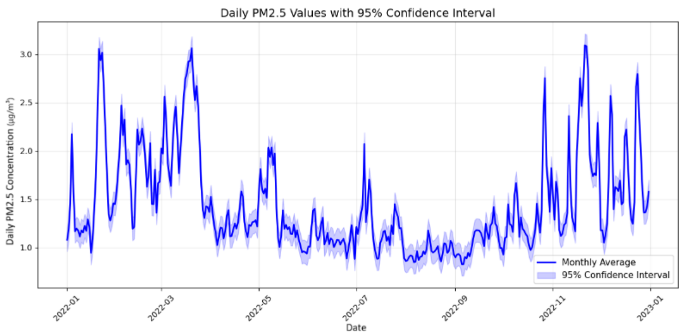

Figure 7: PM2.5 Daily Average Plot, 2022

Day-wise analysis of PM2.5 concentrations revealed a clear weekly pattern. Levels gradually increased over the workweek, peaking on Wednesdays and Fridays, followed by reductions during the weekend. This pattern highlights the influence of anthropogenic activities, including traffic and industrial operations, on air quality.

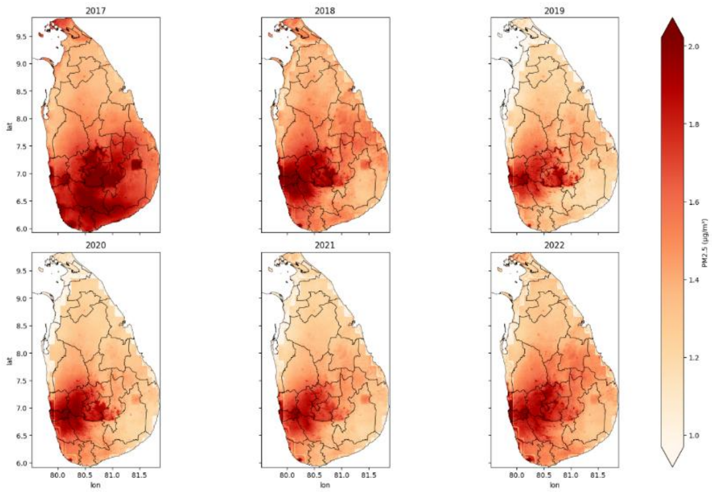

Figure 8: Annual Average PM2.5 for Each Year from 2017 to 2022

Figure 8 presents spatial maps of annual mean PM2.5 for each year of the study period. The highest values occurred in 2017, followed by a smaller peak in 2018. The lowest concentrations were recorded in 2019, after which levels gradually increased through 2022. The observed year-to-year variability may be influenced by multiple factors, including meteorological conditions such as rainfall and large-scale events like the COVID-19 lockdown in 2020. However, these aspects were not directly analyzed in this study and could be explored in future research.

5. Conclusion and Implications

Analysis of satellite-derived PM2.5 concentrations across Sri Lanka for 2017–2022 reveals a pronounced monsoon-driven seasonal cycle, significant west–east spatial disparities, with persistently elevated levels in the Western Province, and a weekday–weekend pattern associated with anthropogenic activity. Interpretation of these results is constrained by the limited density of ground-based monitoring stations, potential under-representation of local pollution hotspots, and episodic meteorological or regional events that may perturb typical patterns. Nevertheless, the findings provide actionable insights, supporting targeted weekday emission controls in urban hubs, motivating expansion of monitoring networks, and promoting integration of additional satellite and meteorological indicators to inform policy.

An exploratory analytical approach was adopted to characterize the spatiotemporal variability of PM2.5, which is particularly justified in contexts with sparse monitoring infrastructure and complex interactions between meteorology and human activities. This approach establishes a baseline climatology, highlighting daily, monthly, quarterly, and annual patterns, as well as weekday–weekend variations, thereby identifying periods and regions of elevated exposure. These insights are critical for guiding future predictive modeling, informing the selection of relevant covariates, temporal resolutions, and spatial aggregation strategies. Subsequent work will incorporate additional satellite-derived and meteorological variables (e.g. aerosol optical depth, NO_2, precipitation, wind) and develop machine-learning forecasts (e.g. NARX), while expanded ground-based monitoring is to enhance model validation, improve predictive accuracy, and strengthen evidence-based decision-making.

Acknowledgement

Institutional support provided by the University of Moratuwa is gratefully acknowledged. Appreciation is also extended to the global research community for the open-source datasets, software tools, and technical documentation that facilitated this work.

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