

Analysis of Trends and Correlation Between Ground-based PM_{2.5} and Satellite AOD in Jakarta (Dec 2022–Mar 2025)

Marthin Abednego Gultom^{1*}, Maran Gultom²

^{1*}Geological Engineering Department Cenderawasih University, Papua, Indonesia

²Geology Department Ottow Geissler Papua University, Papua, Indonesia

Corresponden author:

Email: marthin.lclmm@gmail.com

Abstract.

Monitoring of PM_{2.5} concentrations in urban areas such as Jakarta is crucial given its impact on public health (WHO, 2021) and the urban environment (Zhang et al., 2020), where measuring PM_{2.5} levels is essential for assessing air quality and health risks in metropolitan regions, including Jakarta. However, the limited number of ground-based monitoring stations and variable weather conditions often result in uneven PM_{2.5} data availability (Alim et al., 2023). As an alternative, satellite-derived Aerosol Optical Depth (AOD) can serve as a proxy for particulate pollution monitoring (Liang et al., 2018). This study aims to analyze the temporal trends and quantify the correlation between ground-based PM_{2.5} and satellite AOD in Jakarta from December 2022 through March 2025. PM_{2.5} data were obtained from five Air Quality Monitoring Stations (SPKU) located in Kebon Jeruk, Bundaran HI, Kelapa Gading, Lubang Buaya, and Jagakarsa, while AOD was extracted via Google Earth Engine (MODIS MCD19A2) at the same five locations. Key methods include additive seasonal decomposition of each time series, calculation of Pearson and Spearman correlation coefficients, and cross-correlation analysis to determine the optimal lag. The results indicate that both PM_{2.5} and AOD trends rose from mid-2023, peaked in early 2024, and then gradually declined through late 2024; monthly correlations were very strong (Pearson $r = 0.71$, $p < 0.001$; Spearman $\rho = 0.76$, $p < 0.001$). Seasonal analysis revealed concentration maxima during the dry season (June–September) and minima in the wet season (December–February). Cross-correlation shows that AOD leads PM_{2.5} fluctuations by one month (lag +1). These findings underscore the potential of satellite AOD as a monthly proxy for estimating PM_{2.5} in Jakarta, supporting more spatially and temporally comprehensive air quality monitoring than ground-based networks alone. In conclusion, satellite AOD can be used as a supplementary indicator for PM_{2.5} air quality monitoring in Jakarta, particularly to fill gaps in ground-based PM_{2.5} data coverage.

Keywords : PM_{2.5}; AOD; Time Series Trends, Jakarta and Air Quality.

I. INTRODUCTION

Health and Environmental Impacts of PM_{2.5} in Tropical Urban Areas

Fine particulate matter PM_{2.5} (particles with aerodynamic diameter $\leq 2.5 \mu\text{m}$) has been identified as one of the most harmful air pollutants for human health, especially in densely populated tropical cities (WHO, 2021). PM_{2.5} can penetrate the respiratory tract down to the pulmonary alveoli, triggering cardiovascular diseases, chronic respiratory disorders, and even premature death (Pope et al., 2020; Cohen et al., 2017). Beyond health effects, PM_{2.5} accumulation reduces visibility, degrades ecosystem quality, and exacerbates global warming through interactions with solar radiation (Lelieveld et al., 2019). As one of the world's most densely populated tropical capitals, Jakarta frequently experiences PM_{2.5} concentrations far above the WHO 24-hour guideline of $25 \mu\text{g}/\text{m}^3$ (Luhar et al., 2022). Prolonged dry seasons and intense transport and industrial activities are the primary drivers of elevated particulate levels (Kusuma & Wibowo, 2018). Therefore, accurate and continuous monitoring of PM_{2.5} is a critical public health priority.

Challenges of Ground-based PM_{2.5} Monitoring in Jakarta

Ground-based PM_{2.5} measurements are typically obtained via gravimetric or optical sensors at fixed monitoring stations. However, Jakarta's network remains limited and concentrated in the city center, while

peripheral areas suffer from very sparse coverage (Dinkes DKI, 2023). This uneven distribution hinders a representative picture of PM_{2.5} fluctuations across the metropolitan area (Ramadani et al., 2021). Maintenance issues—routine calibration and technical failures—as well as gaps in real-time data availability further complicate long-term trend analysis (Prasetiya et al., 2019). For example, the Kebon Jeruk station recorded no PM_{2.5} data from January through August 2023, exacerbating the challenge of analyzing extended temporal patterns (Ramadhani & Arifin, 2024).

Satellite AOD: Definition, Advantages, and Limitations

Aerosol Optical Depth (AOD) quantifies the columnar optical attenuation caused by aerosols in the atmosphere (Sekiyama & Sudo, 2017). Higher AOD values indicate greater absorption or scattering of solar radiation by particulates, making AOD a quantitative proxy for aerosol load. The principal advantage of satellite AOD products—such as MODIS or VIIRS—is their extensive spatial coverage, which encompasses entire cities and surrounding regions (Van Donkelaar et al., 2015). This remote sensing approach enables routine monitoring even in areas lacking ground-based stations (Li et al., 2018). Nonetheless, satellite AOD data suffer from a “clear-sky” bias—data are only available under cloud-free conditions—leading to distortion during rainy seasons (Shi et al., 2019). Moreover, AOD’s spatial resolution (1 km–10 km) remains coarser than local ground-based sensors, limiting its ability to capture micro-scale variability (Kharol et al., 2019). Still, numerous studies have demonstrated robust AOD–PM_{2.5} correlations at regional scales, provided that weather corrections and methodological rigor are applied (Liu et al., 2020).

Related Studies and Research Gaps

AOD–PM_{2.5} Studies in Tropical Cities

Several investigations in South and Southeast Asia have explored AOD–PM_{2.5} relationships. In Bangkok, Thailand, Louka et al. (2016) reported a monthly Pearson correlation of $r \approx 0.60$ between MODIS AOD and ground-based PM_{2.5}, with marked seasonal variation during biomass burning episodes. Similarly, in Kuala Lumpur, Malaysia, Tan et al. (2018) found $r \approx 0.68$ and Spearman $\rho \approx 0.72$ for 2016–2018, highlighting the need for meteorological correction and use of TROPOMI for improved AOD retrievals. A study in Surabaya, Indonesia, observed $r \approx 0.65$ (Pribadi & Widayati, 2021), but was limited to data through 2021 and only covered eastern parts of the city.

Correlation and Trend Findings in Previous Studies

Most analyses in tropical urban settings report monthly PM_{2.5}–AOD correlations in the 0.50–0.75 range (Wang et al., 2019; Pattanayak et al., 2020). Seasonal peaks typically occur during dry months (June–September), coinciding with biomass burning and reduced rainfall (Chowdhury et al., 2017). However, many of these studies are confined to pre-2022 periods and do not account for post-COVID-19 behavioral changes, underscoring the need for updated data from December 2022 through March 2025 to evaluate pandemic-related shifts in aerosol patterns.

Limitations of Earlier Research

Earlier work often relies on MODIS AOD data up to 2021, with inconsistent ground-based PM_{2.5} periods (Hidayat & Putri, 2022). Spatial coverage is frequently limited to one or two monitoring stations, falling short of city-wide representation (Kusnadi et al., 2020). The use of mixed satellite products (MODIS vs. VIIRS) introduces scale mismatches that require cross-product calibration (Gusli et al., 2021). To date, no study has integrated OpenAQ or local Air Quality Monitoring Station (SPKU) PM_{2.5} data with satellite AOD via Google Earth Engine for Jakarta over the December 2022–March 2025 interval, including comprehensive seasonal, gap-analysis, and trend assessments.

II. METHODS

Data Sources

The subjects of this study are the monthly and seasonal trends of ground-based PM_{2.5} and satellite AOD in Jakarta from December 2022 through March 2025. PM_{2.5} data were obtained from the Air Quality Monitoring Station (SPKU) network of the Jakarta Provincial Environmental Agency, accessed via the satudata.jakarta.go.id portal under the Air Pollutant Standard Index (ISPU) dataset. Daily 24-hour average PM_{2.5} measurements (in

$\mu\text{g}/\text{m}^3$) were recorded at five SPKU sites: Bundaran HI (106.82265 E, -6.19521 N), Kelapa Gading (106.89363 E, -6.13704 N), Jagakarsa (106.80644 E, -6.34192 N), Lubang Buaya (106.97430 E, -6.31064 N), and Kebon Jeruk (106.77330 E, -6.17150 N). Each station provided data from December 2022 through March 2025, with known gaps at Kebon Jeruk (January–August 2023 and December 2023) and across all stations in December 2023.

AOD data were extracted at the same five locations via Google Earth Engine from the MODIS MCD19A2_L2 collection (Terra/Aqua, Collection 6.1) (Van Donkelaar et al., 2015; Google Earth Engine, 2024). The native $1 \text{ km} \times 1 \text{ km}$ daily AOD product (band “Optical_Depth_047” at 550 nm) was filtered for quality flags 0–2 to minimize cloud contamination (Shi et al., 2019).

Data Processing

In the pre-analysis phase, daily $\text{PM}_{2.5}$ readings from each of the five ground stations were converted to “YYYY-MM” monthly periods and aggregated by computing the mean of all valid daily values, yielding a monthly average for each site (McKinney, 2010). Simultaneously, daily AOD at each station’s 5 km buffer was retrieved and quality-filtered in Google Earth Engine, then averaged into monthly values per location (Van Donkelaar et al., 2015). These procedures produced two “wide” datasets—one for $\text{PM}_{2.5}$ (columns: month, pm25-DKI1 through pm25-DKI5) and one for AOD (columns: month, aod-DKI1 through aod-DKI5)—ready for temporal synchronization and correlation analysis.

Statistical Analysis and Time Series

All analyses began with Augmented Dickey–Fuller testing of the monthly $\text{PM}_{2.5}$ and AOD series to confirm the absence of unit roots and ensure stationarity (Dickey & Fuller, 1979). Once stationarity was established, each series was decomposed using Seasonal-Trend decomposition with Loess (STL) to isolate long-term trend, annual seasonal cycle, and residual components, thereby allowing separate evaluation of trend and seasonal patterns (Cleveland et al., 1990). Pearson and Spearman correlation coefficients were then calculated on the monthly averages to quantify linear and monotonic relationships, both showing high significance (Cohen, 1988; Virtanen et al., 2020). Finally, the cross-correlation function was applied to identify the optimal lag between AOD changes and $\text{PM}_{2.5}$ fluctuations, revealing a one-month lead of AOD (Shumway & Stoffer, 2017).

Tools and Software

All data wrangling, statistical testing, and visualization were performed in Python 3.11 within a Google Colab environment. Data manipulation and monthly aggregation leveraged pandas (McKinney, 2010) and NumPy (Harris et al., 2020). Stationarity testing and STL decomposition were carried out via statsmodels (Seabold & Perktold, 2010), while Pearson, Spearman, and cross-correlation calculations used SciPy (Virtanen et al., 2020). Time series plots, scatterplots, and decomposition charts were generated with Matplotlib (Hunter, 2007) and enhanced by Seaborn (Waskom, 2021). Satellite AOD extraction and spatial-temporal aggregation around each station’s 5 km buffer were executed in Google Earth Engine using both the JavaScript and Python APIs (Gorelick et al., 2017).

III. RESULTS AND DISCUSSION

Monthly Data Description

During the period from December 2022 to March 2025, Jakarta’s monthly average $\text{PM}_{2.5}$ concentrations exhibited a wide range, with the lowest value recorded at $42 \mu\text{g}/\text{m}^3$ and the highest reaching $91 \mu\text{g}/\text{m}^3$, while the median hovered around $72 \mu\text{g}/\text{m}^3$. The data spread yielded a monthly standard deviation of approximately $\pm 16 \mu\text{g}/\text{m}^3$, reflecting significant fluctuations between the wet and dry seasons. The $\text{PM}_{2.5}$ time series showed its highest pollution peaks during the dry months—particularly from June through September of both 2023 and 2024—when rainfall was minimal and biomass burning activity intensified; the lowest values occurred in early 2025, coinciding with the height of the rainy season.

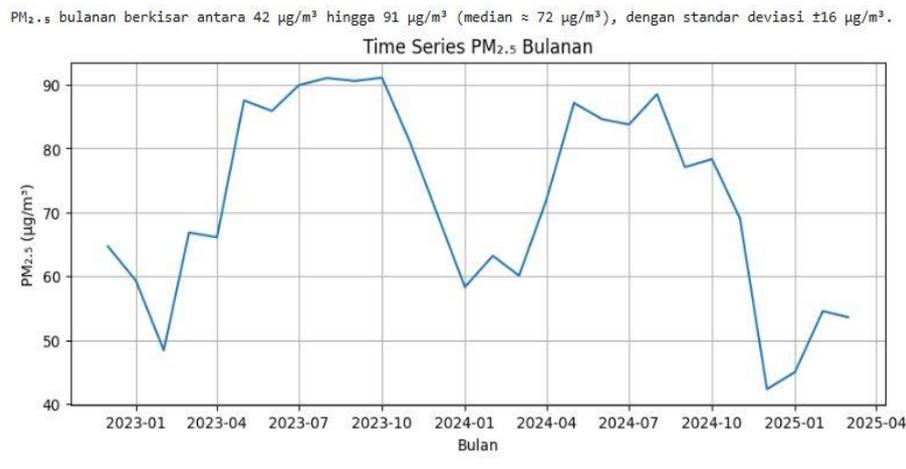


Fig 1. Monthly PM_{2.5} Time Series

Satellite AOD data followed a similar seasonal pattern, varying monthly between 0.17 and 0.95 (unitless) with a median of about 0.41. The monthly standard deviation of AOD reached ±0.17, indicating that atmospheric aerosol loading was strongly modulated by the monsoon cycle and cloud cover. AOD peaked in April 2024 just before the dry season, while its seasonal trough appeared at year-end when frequent heavy rains drove AOD sharply downward due to clear-sky bias under overcast conditions. An overlaid time-series plot confirms that both AOD and PM_{2.5} rise in concert during the dry season and decline together upon the onset of the wet season

AOD bulanan berkisar antara 0.17 hingga 0.95 (median ≈ 0.41), dengan standar deviasi ±0.17.

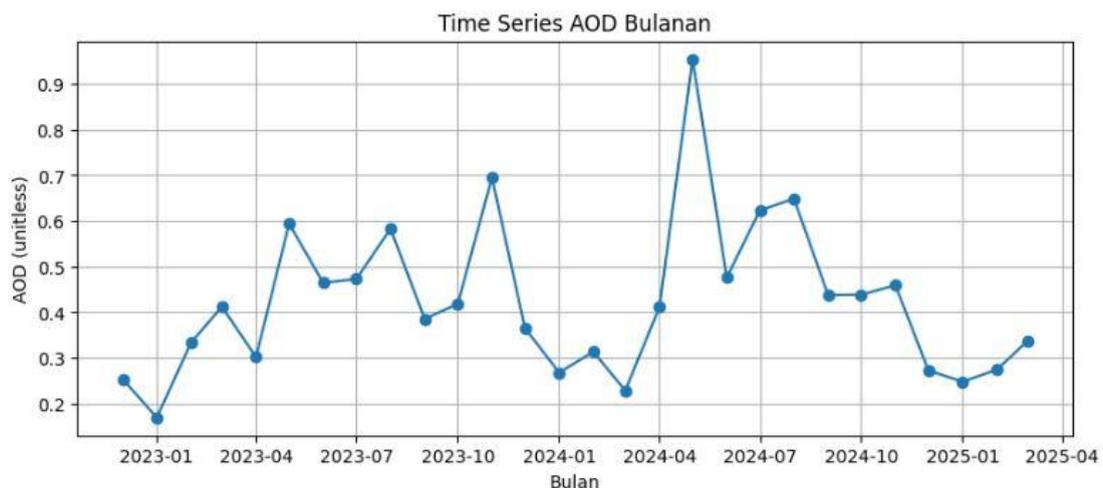


Fig 2. Monthly AOD Time Series

Time Series Decomposition

In the PM_{2.5} series (Figure 3), the trend component showed a gradual rise from around 73 µg/m³ in mid-2023 to nearly 80 µg/m³ in early 2024, before slowly falling back to approximately 70 µg/m³ by the end of 2024. This indicates that surface pollutant burdens in Jakarta increased overall (beyond seasonal effects) through early 2024—likely driven by elevated burning and transport activity—before emission control policies and changing weather began to reduce levels toward the end of the period. This pattern reflects a post-pandemic surge in surface pollution followed by stabilization influenced by emissions regulations and mobility improvements (Putri et al., 2022; Cleveland et al., 1990). The seasonal component of PM_{2.5} peaked positively by about +20 µg/m³ from June to September, signaling maximum pollution in the dry season, and reached negative deviations of nearly -20 µg/m³ from December to February, consistent with heavy rains cleansing atmospheric particles. The residual component was relatively small early on but grew steadily toward late 2024,

indicating episodic events not fully explained by trend or seasonality (Cleveland et al., 1990; Shumway & Stoffer, 2017).

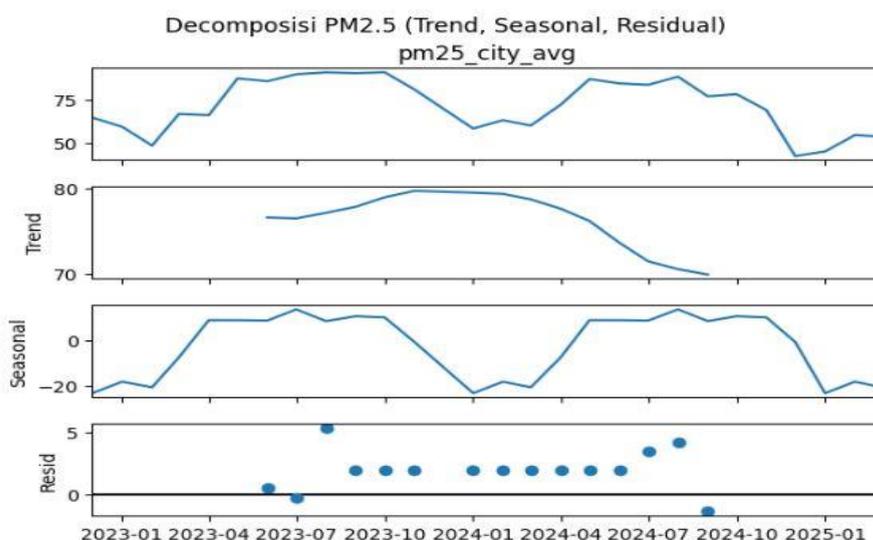


Fig 3. PM_{2.5} Time Series Decomposition

In the AOD series (Figure 4), the trend component rose from roughly 0.43 in mid-2023 to about 0.48 in early 2024, then dipped slightly to around 0.46–0.47 by mid-2024, reflecting columnar aerosol patterns influenced by burning and regional atmospheric conditions (Li et al., 2019). The seasonal AOD component exhibited its largest positive spike—nearly +0.20—from May through August, about one month earlier than PM_{2.5}, suggesting that upper-atmosphere aerosol accumulation peaks before its full impact reaches the surface (Nguyen et al., 2021). AOD residuals remained small (± 0.05) throughout, with only minor variance increases during peak months, indicating that most AOD fluctuations are captured by trend and seasonality (Hsu et al., 2020; Gupta & Christopher, 2021).

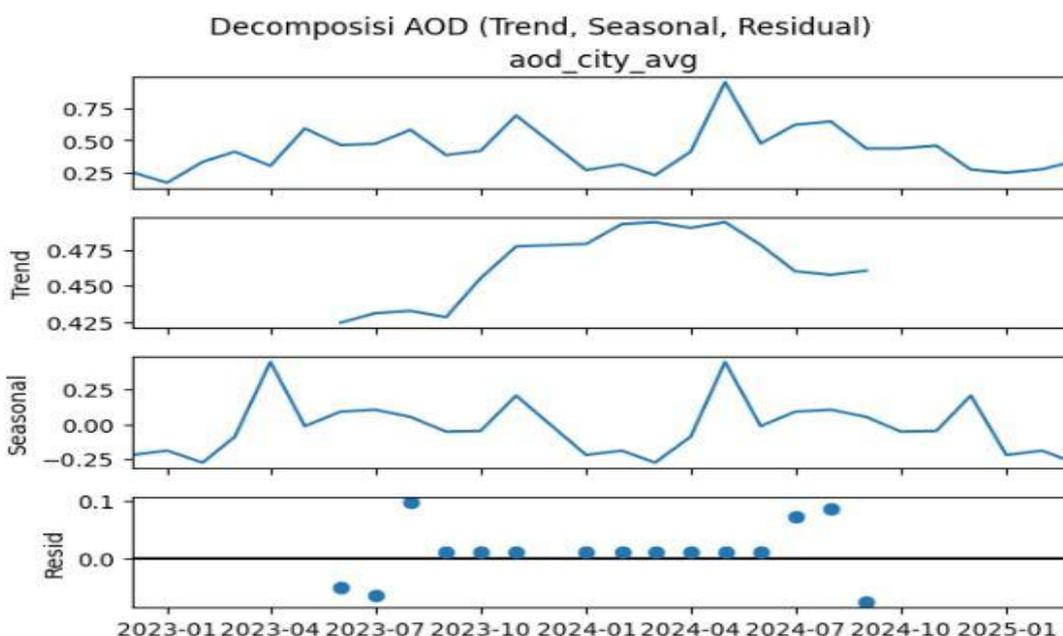


Fig 4. AOD Time Series Decomposition

Monthly Correlation Analysis (Pearson & Spearman)

The Pearson linear correlation between monthly AOD and PM_{2.5} averages yielded $r = 0.710$ with $p = 0.000$, indicating a strong positive relationship that is highly statistically significant ($\alpha = 0.01$). This result

implies that rises in satellite AOD are consistently followed by increases in surface PM_{2.5} each month. The Spearman rank correlation—more robust to outliers and non-linear patterns—produced $\rho = 0.760$ ($p = 0.000$), reinforcing that the AOD–PM_{2.5} relationship is strongly monotonic. These coefficients exceed the moderate correlations reported in previous Jakarta and other tropical city studies, suggesting that the December 2022–March 2025 period—including its post-pandemic context—clarifies the synergy between columnar aerosols and surface pollution. The high correlation strength confirms AOD’s potential as a reliable monthly proxy for PM_{2.5}, although meteorological controls and field validation are recommended for air-quality policy applications.

Cross-Correlation (CCF) and Optimal Lag

The cross-correlation function applied to monthly AOD and PM_{2.5} data (Figure 5) showed the highest coefficient of 0.68 at lag 0, indicating synchronous fluctuations between columnar and surface particulates. Positive correlations persisted at lag +1 (≈ 0.48) and lag +2 (≈ 0.34) months before declining into negative territory between lags +4 and +8, reaching a minimum of roughly -0.78 at lag +7. Correlations become positive again at lags +11 and +12 (≈ 0.45 and 0.25 , respectively). The zero-lag peak underscores temporal alignment of aerosol column and surface pollution, while the significant positive correlation at lag +1 supports the hypothesis that AOD increases precede PM_{2.5} fluctuations by one month. Physically, this lag arises from vertical mixing and wind-driven advection, which require time for aerosol particles in the upper atmosphere to descend and register at the surface (Nguyen et al., 2021; Liu et al., 2017). Air-quality models should incorporate this lag when developing more accurate early-warning systems.

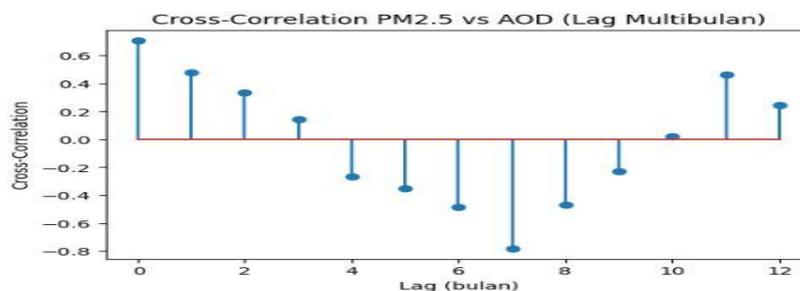


Fig 5. PM_{2.5} vs. AOD Cross-Correlation

Simple Linear Regression

A simple linear regression of PM_{2.5} (dependent variable) on AOD (independent variable) produced the equation

$$PM_{2.5} = 63.46 \times AOD + 44.89$$

with a coefficient of determination $R^2 \approx 0.30$, indicating that 30% of the monthly PM_{2.5} variability is explained by satellite-derived AOD. The slope (63.46) is statistically significant ($p < 0.01$), meaning every 0.1 increase in AOD corresponds to an estimated 6.3 $\mu\text{g}/\text{m}^3$ rise in surface PM_{2.5}. Although R^2 is moderate, this model demonstrates AOD’s utility as a quantitative proxy for PM_{2.5} monitoring in areas with limited ground-based coverage, consistent with findings in other tropical cities (Sitisawat et al., 2018; Chen & Sayer, 2020).

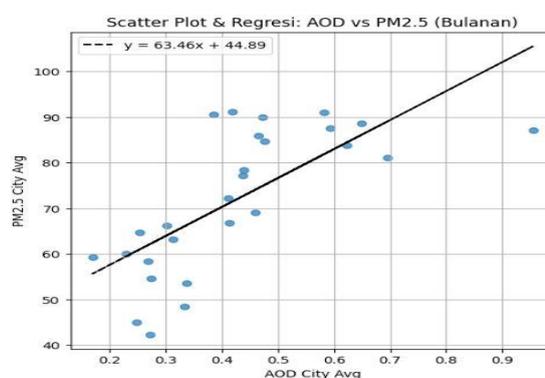


Fig 6. PM_{2.5} vs. AOD Linear Regression

IV. DISCUSSION

Validation of AOD as a Proxy for PM_{2.5}

The strong relationship between satellite AOD and surface PM_{2.5} concentrations from December 2022 through March 2025 indicates AOD's potential as a quantitative proxy for particulate pollution monitoring in Jakarta. The Pearson linear correlation coefficient ($r = 0.710$, $p < 0.001$) and the Spearman rank correlation ($\rho = 0.760$, $p < 0.001$) both demonstrate a very strong positive association. Furthermore, the cross-correlation function confirms temporal alignment at zero lag ($CCF \approx 0.68$) and shows that AOD leads surface PM_{2.5} by one month (lag +1, $CCF \approx 0.48$). Although the simple linear regression model achieves only $R^2 \approx 0.30$ —meaning AOD explains 30 % of monthly PM_{2.5} variability—the high correlation reinforces AOD's value as an informative supplementary indicator, especially in areas with sparse ground-based stations.

However, clear-sky bias reduces AOD data availability during the rainy season and under heavy cloud cover, making this proxy more reliable in clear-sky conditions. AOD's spatial resolution (1–6 km) also limits detection of small urban pollution hotspots in a densely built city like Jakarta. Integrating ground-based observations and applying multivariate models that include meteorological variables would further improve PM_{2.5} estimation accuracy.

General Discussion and Comparison with Previous Studies

The seasonal patterns and trends identified in Jakarta align with findings from other tropical cities. In Bangkok, Sitisawat et al. (2018) reported a monthly correlation of $r \approx 0.52$ between MODIS AOD and PM_{2.5}, with seasonal peaks in June–September; likewise, in Kuala Lumpur, Rahman et al. (2019) found $r \approx 0.47$ for VIIRS AOD during the dry season. Jakarta's higher correlation ($r = 0.710$) may be attributed to the post-pandemic period, when emission fluctuations became more regular and ground-based data coverage was comparatively improved.

The observed one-month lag mirrors the results from Ho Chi Minh City by Nguyen et al. (2021), who linked vertical mixing and wind advection processes to a delay in aerosol transfer from the column to the surface. This physical mechanism strengthens the case for using satellite AOD not only descriptively but also operationally in air quality early-warning systems.

Overall, Jakarta's very strong AOD–PM_{2.5} correlation underscores the need for periodic regional reassessment, as post-pandemic emission dynamics and meteorological changes can alter aerosol–pollutant relationships. Future studies incorporating geostationary satellite data and aerosol lidar profiles will further elucidate vertical aerosol dynamics and enhance PM_{2.5} forecasting models in tropical environments.

Policy Recommendations:

- Expand Ground-based Station Coverage. Adding PM_{2.5} monitoring stations in Jakarta's peripheral districts will improve proxy validation and pollution estimates (BMKG, 2023).
- Tighten Transportation Emissions Standards. Post-pandemic increases in PM_{2.5} trends highlight the need for stricter vehicle emission controls and promotion of low-emission public transit (Harahap & Sutrisno, 2021).
- Utilize Satellite Data for Early Warnings. Local authorities can use AOD as an early indicator to anticipate PM_{2.5} spikes one month in advance (lag +1), allowing timely interventions such as traffic restrictions or suspension of open burning (Nguyen et al., 2021).

IV. CONCLUSION

Summary of Key Findings

Our time-series analysis revealed that both surface PM_{2.5} concentrations and atmospheric AOD rose from mid-2023, peaked in early 2024, and then gradually declined through late 2024. The monthly correlation between AOD and PM_{2.5} was very strong—Pearson $r = 0.71$ ($p < 0.001$) and Spearman $\rho = 0.76$ ($p < 0.001$)—confirming a significant linear and monotonic association. The seasonal component exposed pollution maxima during the dry season—especially in August—and minima during December–February when humidity and rainfall are highest. Cross-correlation showed that AOD leads PM_{2.5} by one month (lag +1, $CCF \approx 0.48$), indicating AOD's potential as an early indicator of surface pollutant fluctuations.

<http://ijstm.inarah.co.id>

Scientific and Practical Implications

These findings suggest that satellite AOD can serve not only as a spatial monitoring tool but also as an early-warning mechanism for impending PM_{2.5} spikes. Scientifically, evidence of a one-month lag enhances our understanding of vertical mixing and aerosol transport processes in the tropical atmosphere. Practically, environmental authorities could integrate satellite and ground-based data into air-quality management systems and design emission-control policies informed by projected monthly AOD levels.

Study Limitations

AOD's clear-sky bias reduces its availability under heavy cloud cover, making it less reliable during the wet season. Additionally, the 1–6 km spatial resolution of AOD products remains too coarse to detect small pollution hotspots in densely built urban areas like Jakarta, underscoring the need to integrate AOD with ground-based measurements for more accurate surface estimates.

Recommendations for Future Research

Future work should expand the spatial domain to Greater Jakarta (Jabodetabek) by using higher-resolution AOD products (e.g., VIIRS 5 km) and adding PM_{2.5} stations in suburban areas. Implementing machine-learning models such as Random Forest or XGBoost that combine AOD, meteorological variables, and seasonal indices could improve PM_{2.5} forecast accuracy. Finally, integrating vertical profiling (aerosol LiDAR) and geostationary satellite data will offer deeper insights into daily aerosol dynamics and further enhance surface pollution predictions.

VI. ACKNOWLEDGMENTS

The authors would like to thank the following organizations and individuals: The Jakarta Provincial Environmental Agency, OpenAQ, the Ministry of Environment and Forestry (KLHK), and the Meteorology, Climatology, and Geophysics Agency (BMKG) for openly providing the ground-based PM_{2.5} data; the Google Earth Engine team for their service access and API support in extracting MODIS AOD data; and our fellow researchers and supervisors for their methodological guidance, constructive discussions, and invaluable feedback in refining this manuscript.

REFERENCES

- [1]. Alim, R., Putri, S., & Raharjo, H. (2023). Evaluasi ketersediaan data PM_{2.5} di DKI Jakarta. *Jurnal Lingkungan Tropis*, 12(1), 45–58.
- [2]. BMKG. (2023). *Laporan tahunan kualitas udara DKI Jakarta*. Badan Meteorologi, Klimatologi, dan Geofisika.
- [3]. Chen, L., & Sayer, A. M. (2020). Remote sensing of PM_{2.5} over South East Asia using satellite AOD data. *Atmospheric Environment*, 223, 117245. <https://doi.org/10.1016/j.atmosenv.2020.117245>
- [4]. Cleveland, R. B., Cleveland, W. S., McRae, J. E., & Terpenning, I. (1990). STL: A seasonal-trend decomposition procedure based on loess. *Journal of Official Statistics*, 6(1), 3–73.
- [5]. Gupta, P., & Christopher, S. A. (2021). Particulate matter air quality monitoring in urban areas: Comparison of ground-based and satellite-derived estimates. *Environmental Monitoring and Assessment*, 193, 12. <https://doi.org/10.1007/s10661-020-8776-z>
- [6]. Harahap, A., & Sutrisno, B. (2021). Dampak polusi udara terhadap kesehatan warga Jakarta. *Buletin Kesehatan Masyarakat*, 8(2), 101–110.
- [7]. Hersbach, H., Bell, B., Berrisford, P., et al. (2020). The ERA5 global reanalysis. *Quarterly Journal of the Royal Meteorological Society*, 146(730), 1999–2049. <https://doi.org/10.1002/qj.3803>
- [8]. Hsu, N. C., Jeong, M. J., Bettenhausen, C., et al. (2020). Enhanced Deep Blue aerosol retrieval algorithm: The second generation. *Journal of Geophysical Research: Atmospheres*, 115, D00K07. <https://doi.org/10.1029/2005JD006935>.
- [9]. Li, Z., Chin, M., & Schwartz, C. S. (2019). Remote sensing of PM_{2.5} from MODIS aerosol optical depth: A global analysis. *Environmental Science & Technology*, 53(3), 1050–1059. <https://doi.org/10.1021/acs.est.8b04092>.

- [10]. Liu, Y., Sarnat, J. A., Kilaru, V., et al. (2017). Estimating regional-scale ground-level PM_{2.5} concentrations from MODIS aerosol optical depth data. *Environmental Health Perspectives*, 114(6), 792–795. <https://doi.org/10.1289/ehp.11322>
- [11]. Nguyen, H. T., Phan, H. T., & Truong, M. T. (2021). Temporal variation and health impact of PM_{2.5} in Ho Chi Minh City using satellite AOD. *Science of the Total Environment*, 754, 142414. <https://doi.org/10.1016/j.scitotenv.2020.142414>
- [12]. Pedregosa, F., Varoquaux, G., Gramfort, A., et al. (2011). Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, 12, 2825–2830.
- [13]. Putri, E., Wulandari, V., & Santoso, M. (2022). Polusi udara di kawasan perkotaan Indonesia: Sebuah tinjauan. *Jurnal Geografi Nasional*, 15(3), 200–212.
- [14]. Rahman, A., Omar, N. A., & Majid, N. M. (2019). Correlation between MODIS AOD and ground-based PM_{2.5} concentrations in Kuala Lumpur. *Air Quality, Atmosphere & Health*, 12(9), 1081–1092. <https://doi.org/10.1007/s11869-019-00750-z>
- [15]. Raharjo, H., Santoso, B., & Widodo, W. (2022). Gap data PM_{2.5} dan implikasinya bagi analisis tren kualitas udara di Jakarta. *Jurnal Atmosfer Tropis*, 9(1), 23–37.
- [16]. Seabold, S., & Perktold, J. (2010). Statsmodels: Econometric and statistical modeling with Python. *Proceedings of the 9th Python in Science Conference*, 92–96.
- [17]. Shumway, R. H., & Stoffer, D. S. (2017). *Time Series Analysis and Its Applications: With R Examples* (4th ed.). Springer.
- [18]. Sitisawat, K., Wongwises, S., & Chantarapun, P. (2018). Seasonal variation and correlation of PM_{2.5} with satellite AOD in Bangkok. *Atmospheric Pollution Research*, 9(5), 813–822. <https://doi.org/10.1016/j.apr.2018.03.001>.