Satellite Imagery-Based PM_{10} Air Parameter Analysis in Makassar Metropolitan City

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Abstract. *Air pollution caused by particulate matter (PM_{10}) remains a pressing environmental issue in major urban centers, particularly in Makassar City, where rapid population growth and the increasing number of vehicles significantly contribute to deteriorating air quality. Conventional monitoring methods are constrained by the limited coverage of Air Quality Monitoring Stations, which fail to capture the spatial variability of pollutants. This study applies remote sensing techniques using Landsat 8 Operational Land Imager (OLI) data to estimate PM_{10} concentrations across Makassar. Two established algorithms were implemented: Othman (2010), which utilizes visible bands (Blue, Green, Red), and Mozafari (2019), which employs coastal/aerosol, green, and red bands combined with the Normalized Difference Vegetation Index (NDVI) to account for vegetation effects. Data preprocessing, atmospheric correction, and algorithmic modeling were performed on the Google Earth Engine platform. Spatial analysis revealed elevated concentrations along major road corridors and commercial–industrial areas, particularly on 6/2 divided and 4/2 divided roads, where traffic volumes are highest. In contrast, residential and green spaces exhibited relatively lower values, confirming the influence of land use and road type on particulate distribution. The integration of remote sensing with GIS-based analysis successfully highlights pollution hotspots, demonstrating the potential of satellite-based monitoring as a complementary tool to conventional air quality networks.*

Keywords: Landsat 8, Makassar City, Air Quality, Remote Sensing, PM_{10}

Introduction

Air pollution has emerged as one of the most pressing environmental issues in urban centers across Indonesia. In Makassar, a metropolitan hub in Eastern Indonesia, the increasing number of motorized vehicles has significantly contributed to ambient air degradation, particularly with the rise of airborne particulate matter (PM_{10}). These fine particles, with diameters less than 10 micrometers, are capable of penetrating deep into the respiratory system, posing serious public health risks. As reported by the South Sulawesi Samsat Office, more than 2 million registered motorized vehicles operate within the city, a figure that directly correlates with elevated pollutant emissions.

Despite its severity, PM_{10} monitoring efforts remain constrained due to the limited number of Air Quality Monitoring Stations (AQMS) available. Indonesia, with only 68 stations nationally, lags behind regional counterparts like Malaysia and Thailand. In South Sulawesi, AQMS coverage is confined to two locations—Makassar and Maros—which fails to represent the spatial variability of air pollution across the city. Conventional ground-based monitoring alone is therefore inadequate for spatially continuous assessments.

As a solution, satellite-based remote sensing has become a promising alternative for large-scale and temporal air quality monitoring. Landsat 8 OLI/TIRS, operated by NASA, offers multispectral imagery with sufficient resolution (30 m) and temporal revisit cycles to estimate PM_{10} concentrations when coupled with appropriate atmospheric correction and empirical modeling techniques. Previous studies by Othman (2010) and Mozafari (2019) have demonstrated that spectral reflectance data derived from Landsat imagery can be used to construct regression-based models for estimating airborne particulate concentrations with notable accuracy.

Based on this context, this study aims to evaluate the reliability of satellite-based PM_{10} estimations in Makassar City by comparing them against direct field measurements. The research addresses the following key questions: (1) What are the actual PM_{10} concentration levels across different urban zones in Makassar based on ground-based measurements? (2) How accurately can satellite-derived models (Othman and Mozafari algorithms) estimate PM_{10} concentrations? and (3) What is the level of agreement between satellite estimations and field data? The overarching goal is to validate remote sensing as a viable method for air quality monitoring in urban environments with limited AQMS infrastructure.

Literature Riview

Particulate matter (PM_{10}) has long been recognized as one of the most critical pollutants affecting urban air quality. Numerous studies have linked PM_{10} exposure to respiratory illnesses, cardiovascular problems, and decreased life expectancy (Winatama et al., 2023). In developing cities, the primary sources of PM_{10} are vehicular emissions, industrial activities, and urban construction (Gunawan et al., 2018). Previous studies in Indonesian metropolitan areas consistently revealed that road traffic density is the dominant contributor to particulate concentrations exceeding the national air quality standards (Roza et al., 2015; Zulkifli et al., 2022).

Conventional PM_{10} monitoring relies on ground-based Air Quality Monitoring Stations (AQMS) and gravimetric methods, which provide accurate but spatially limited observations. Indonesia currently operates only a small number of AQMS units compared to its geographic extent, which creates significant data gaps in spatial coverage (Sulistyo et al., 2024). This limitation underscores the importance of developing complementary methods to extend air quality assessments across wider areas.

Landsat 8, operated by NASA and USGS since 2013, has been widely used for environmental monitoring due to its Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS), which provide 30 m spatial resolution and a 16-day revisit cycle. The visible bands, particularly blue, green, and red, are sensitive to atmospheric scattering and have been successfully applied for estimating aerosol and PM_{10} concentrations (Lin et al., 2019; Mozafari, 2019). Compared to coarse-resolution sensors such as MODIS, Landsat 8 enables more detailed spatial analysis of urban air pollution, making it suitable for localized monitoring in cities like Makassar.

Remote sensing has increasingly been employed as an alternative to enhance spatiotemporal monitoring of air pollutants. The United States Geological Survey (USGS, 2012) has emphasized the utility of multispectral sensors such as Landsat 8 OLI/TIRS in deriving aerosol and particulate-related indices. Several international studies have demonstrated the feasibility of estimating particulate matter using satellite-derived reflectance. Othman (2010), for instance, developed a regression-based model for arid regions that showed strong correlations between spectral bands and measured PM_{10} concentrations. Similarly, Mozafari (2019) applied an alternative model using OLI images in Tehran, demonstrating improved accuracy through multi-band integration.

In the Southeast Asian context, remote sensing applications for air quality have been explored in countries like Malaysia and Thailand, where spatial models successfully complemented limited ground stations (Nguyen et al., 2015). However, in Indonesia, research remains limited to specific case studies, such as coal-fired power plant areas (Dede et al., 2020) or single metropolitan settings, leaving a gap in systematic assessments across diverse urban landscapes.

From this review, it is evident that satellite-based methods offer promising potential in bridging the monitoring gap for PM_{10} in Indonesian cities. Yet, localized calibration and validation remain essential to account for urban morphology, emission sources, and atmospheric conditions. This study builds upon previous empirical models (Othman, 2010; Mozafari, 2019) while focusing on Makassar as a case study to validate the applicability of remote sensing for PM_{10} estimation in an urban tropical environment.

Methodology

This study was designed as a remote sensing–based analysis without direct field measurements. The research framework focuses on the application of Landsat 8 imagery and established empirical algorithms (Othman, 2010; Mozafari, 2019) to estimate spatial variations of PM_{10} across Makassar City. A total of 30 sampling points were selected to represent different road classifications and land-use types. The selection prioritized areas with high levels of human activity, especially those associated with transportation, trade, and service zones, which are considered the primary contributors to urban air pollution. These points were distributed across five road types—6/2 divided, 4/2 divided, 4/1 undivided, 2/2 undivided, and 2/1 undivided—allowing the analysis to capture variations in traffic intensity and emission sources.

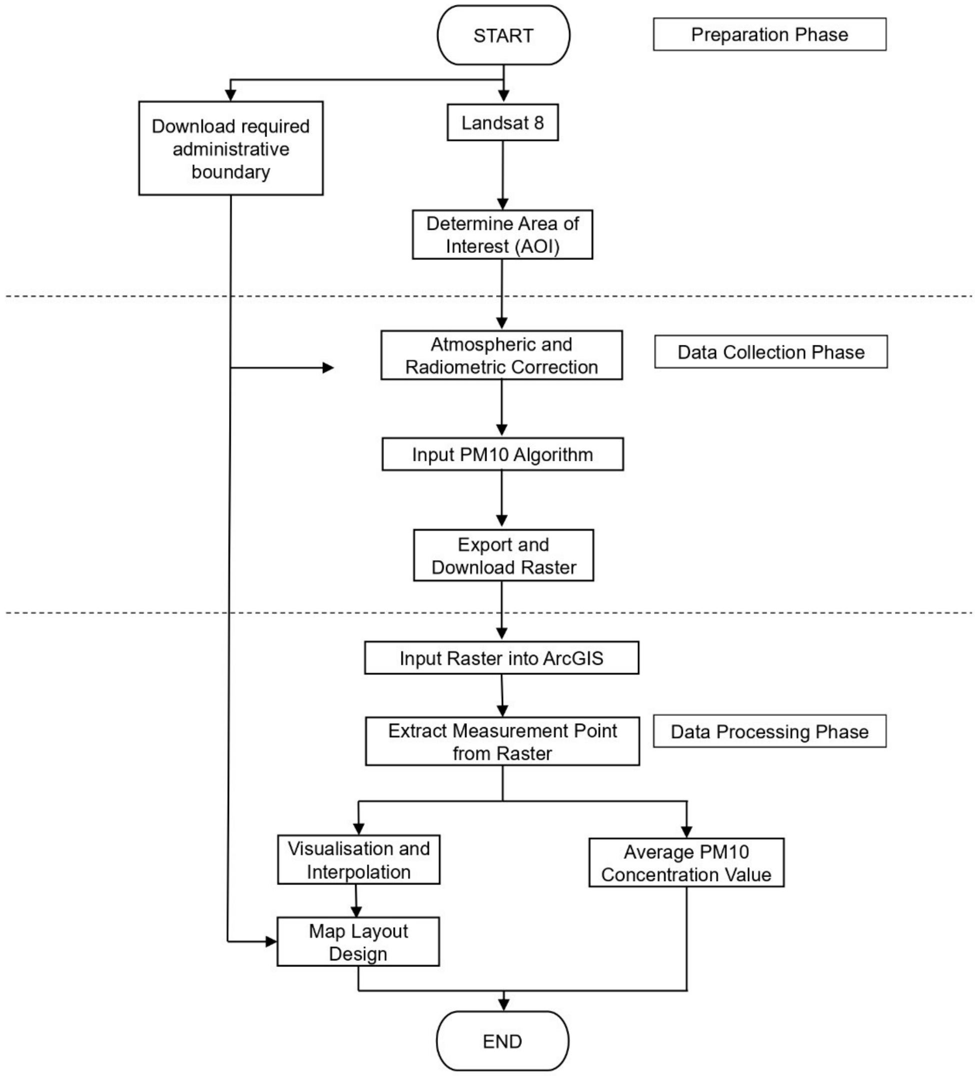


Figure 1 research flowchart

- Preparation Stage

The preparatory stage included determining the study area and identifying representative sampling points across Makassar City. A total of 30 sampling locations were selected using purposive sampling, with consideration of traffic intensity, land use, and road classification. Administrative boundary data and road network shapefiles were collected from the South Sulawesi GIS repository to support spatial analysis. Additionally, Landsat 8 OLI/TIRS imagery acquired on March 11, 2025 was downloaded from the USGS Earth Explorer and preprocessed using Google Earth Engine (GEE). The preprocessing involved radiometric and atmospheric correction, as well as cloud masking, to ensure reliable reflectance values.

Table 1 Field Data Locations

Point	Road Type	Measurement Location	Land Use	District	Coordinat X	Coordinat Y
1	6/2 D	Veteran Street	Trade and Service Zone	Makassar	119.4235877	-5.139477857
2		Central Park Indonesia	Mixed Zone	Tamalate	119.3980582	-5.148735504
3		MTOS Mall	Trade and Service Zone	Tamalanrea	119.4748838	-5.144292434
4		Perintis Kemerdekaan Street	Trade and Service Zone	Tamalanrea	119.4993053	-5.129157312
5		Panakkukang Mall	Trade and Service Zone	Panakkukang	119.4457089	-5.156465134
6		Heroes Cemetery	Trade and Service Zone	Panakkukang	119.4619042	-5.143785278
7		Nipah Mall	Trade and Service Zone	Panakkukang	119.4494929	-5.140062271
8		PLN Hertasning	Mixed Zone	Rappocini	119.4452273	-5.163728618
9	4/2 D	In front of toll gate	Public Service Zone	Ujung Tanah	119.4116132	-5.115785338
10		Central Market	Trade and Service Zone	Wajo	119.4135679	-5.130592906
11		Phipo Mall	Trade and Service Zone	Mariso	119.4041764	-5.154752192
12		TSM Mall	Trade and Service Zone	Tamalate	119.3951422	-5.162849106
13		Kima	Industrial Zone	Biringkanaya	119.5014343	-5.109536248
14		Ratu Indah Mall	Trade and Service Zone	Mamajang	119.4160831	-5.153083269
15		Primaya Hertasning	Trade and Service Zone	Rappocini	119.4562551	-5.175949197
16	4/1 UD	Raya Mosque	Trade and Service Zone	Bontoala	119.4198169	-5.131091713
17		Terong Market	Trade and Service Zone	Bontoala	119.4252232	-5.131588998
18		G. Bawakaraeng Street	Trade and Service Zone	Makassar	119.4182629	-5.13535782
19	2/2 UD	Paotere Port	Mixed Zone	Ujung Tanah	119.4210446	-5.112004308
20		In front of SMA 17 Makassar	Public Facility Zone	Tallo	119.4303212	-5.121004287
21		Teuku Umar Street	Trade and Service Zone	Tallo	119.4321569	-5.117567493
22		Daya New Market	Trade and Service Zone	Biringkanaya	119.5057735	-5.114464949
23		Toddopuli Raya Street	Trade and Service Zone	Manggala	119.455896	-5.162570548
24		Antang Raya Street	Trade and Service Zone	Manggala	119.478231	-5.157948029
25		Borong Raya Street	Trade and Service Zone	Manggala	119.4684456	-5.163900267
26		Rajawali Street	Trade and Service Zone	Mariso	119.4105079	-5.152053712
27	2/1 UD	Sulawesi Street	Trade and Service Zone	Wajo	119.4074245	-5.130030311
28		Losari Beach	Trade and Service Zone	Ujung Pandang	119.4078634	-5.143000995
29		Penghibur Street	Trade and Service Zone	Ujung Pandang	119.4054457	-5.137726862
30		Landak Lama Street	Trade and Service Zone	Mamajang	119.4184472	-5.162069086

Figure 2 image of field data location

- Data Collection Stage

The primary dataset was multispectral Landsat 8 imagery, focusing on Bands 1, 2, 3, and 4 due to their sensitivity to aerosol scattering and suitability for PM_{10} estimation. Secondary data included land-use classification (trade, service, industrial, mixed, public facilities, and residential zones) and road classification (6/2 divided, 4/2 divided, 4/1 undivided, 2/2 undivided, 2/1 undivided). In addition, vehicle registration statistics from the South Sulawesi Transportation Office and BPS were collected to provide contextual information for interpreting the relationship between PM_{10} concentrations, land use, and traffic density.

- Data Processing and Analysis

The methodology consisted of several sequential stages, outlined as follows:

1. Pre-processing of Satellite Data

   Radiometric and atmospheric corrections were applied to the Landsat 8 imagery using GEE functions to obtain surface reflectance values. A region of interest (ROI) was defined based on the Makassar city boundary, and cloud-masked composite images were generated to ensure spatial consistency with field measurement dates.

2. Estimation of PM_{10} Using Empirical Models

Two established regression models were applied for PM_{10} estimation:

- Othman (2010) model:

$$PM10=(396\times\rho B)+(253\times\rho G)-(194\times\rho R) \quad (1)$$

- Mozafari (2019) model:

$$PM10=-444\times \rho 1+1.766\times \rho G-1.664\times \rho R +78 \quad (2)$$

Where ρB, ρG, and ρR represent reflectance values of the blue, green, and red bands respectively. These models were implemented within GEE to generate raster layers representing estimated PM_{10} concentrations across Makassar.

3. **Spatial Analysis**

The resulting raster outputs were analyzed in ArcGIS, where estimated PM_{10} values were overlaid with land-use and road network maps. This facilitated the identification of pollution hotspots in relation to traffic corridors and functional zones.

4. **Interpretation**

The analysis examined PM_{10} patterns across the 30 selected points, with specific attention to differences between road types and land uses, supported by traffic volume data.

Results and Discussion

A. Satellite-Based PM_{10} Estimations

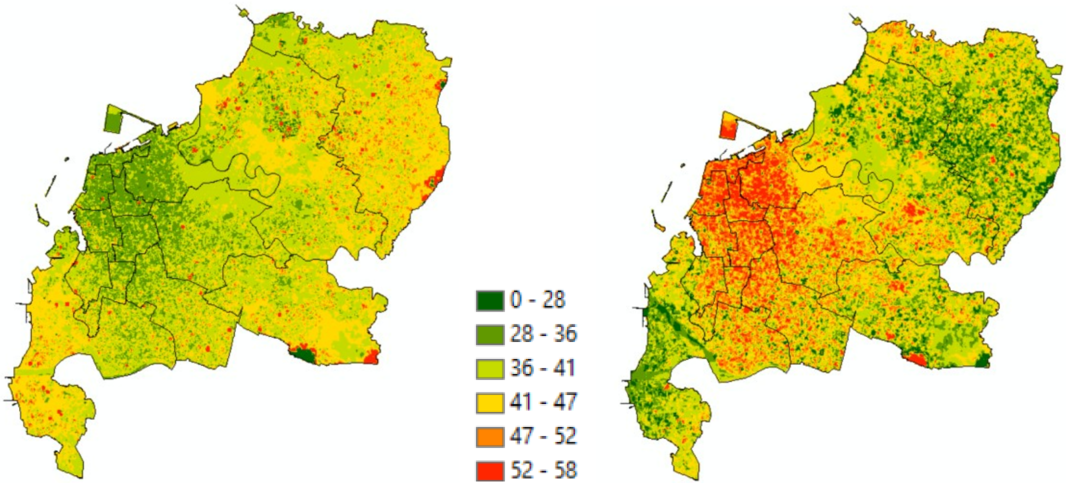
Table 2 Summary of PM_{10} Concentration Estimates

Road Type	Measurement Location	Othman	Mozafari
6/2 D	Veteran	35.4	49.2
	CPI	48.2	43.7
	MTOS	39.8	44.0
	BTP	46.6	32.9
	Mall Panakukang	39.7	43.9
	Taman Makam Pahlawan	37.8	44.0
	Mall Nipah	34.9	52.1
	PLN Hertasning	50.7	33.3
4/2 D	Depan pintu tol (Damkar & Pabrik terigu)	36.7	48.3
	Pasar sentral	44.9	35.4
	Mall Phipo	39.9	38.1
	TSM	41.4	34.5
	Kima	44.8	36.6
	Mall ratu indah	32.5	47.4

Road Type	Measurement Location	Othman	Mozafari
	Primaya hertasning	39.8	38.1
4/1 UD	Mesjid Raya	39.2	44.2
	Pasar terong	46.0	57.4
	Jl. G. Bawakaraeng	36.7	48.3
2/2 UD	Sekitar pelabuhan paotere	34.1	51.8
	Depan SMA 17 MKS	32.2	53.2
	Pertigaan galangan kapal (Sekitar mesjid)	33.3	51.9
	Pasar Baru Daya	44.2	31.3
	Perempatan todoppuli	33.9	47.8
	Perempatan jembatan pannara	35.0	45.5
	perempatan ujung bori	41.4	44.3
	Pasar Lelang Rajawali	39.6	41.3
2/1 UD	Jl. Sulawesi	36.7	48.1
	Pantai losari	36.3	48.7
	Depan dermaga kayu bangkoa	45.7	58.42
	Depan satu sama	42.4	40.2

The application of Othman (2010) and Mozafari (2019) algorithms to Landsat 8 OLI imagery provided spatially distributed estimations of PM_{10} concentrations across Makassar City. The Othman model, which utilizes visible bands (Blue–Band 2, Green–Band 3, Red–Band 4), generated values ranging from 32.5 - 50.7μg/m³. This approach captures aerosol scattering in the visible spectrum but often results in higher estimates in densely built-up areas.

In contrast, the Mozafari model, which integrates Coastal/Aerosol (Band 1), Green (Band 3), Red (Band 4), and the Normalized Difference Vegetation Index (NDVI), produced slightly lower but more consistent values, ranging from 31,3 - 58,4 μg/m³. The inclusion of NDVI reduces surface reflectance effects, particularly in heterogeneous urban landscapes.



(a) (b)

Figure 3 PM_{10} Concentration Visualization Map (a) Othman (b) Mozafari

When compared with Air Quality Monitoring Station (AQMS) data, which recorded PM_{10} concentrations between 3.69–14.15 µg/m³ with an average of 7.23 µg/m³ during the observation period, both satellite-based models showed substantially higher estimates. This discrepancy reflects the difference in measurement approaches: AQMS data represents localized point measurements under controlled conditions, while satellite-derived estimates capture broader atmospheric scattering across mixed land covers and anthropogenic sources. Similar patterns have been reported in previous studies, where remote sensing tends to overestimate PM_{10} compared to ground-based measurements due to atmospheric and surface reflectance effects. Nevertheless, the spatial detail provided by satellite-based estimations offers valuable insights into the distribution of pollution hotspots, complementing the limited coverage of AQMS networks.

B. Phenomenon of PM_{10} Based on Land Use and Road

1) Land use

Overlaying PM_{10} concentration maps with land-use data revealed that the highest concentrations were associated with trade and service zones (e.g., Panakkukang Mall, Nipah Mall, Central Market) and industrial zones (e.g., Kima Industrial Estate). These areas exhibited higher satellite-derived concentrations due to intense vehicular movement and industrial activities. In contrast, public service facilities and mixed-use areas showed moderate values, while green and open spaces recorded the lowest levels. These findings are consistent with studies in other Indonesian cities, where urban land use strongly correlates with PM_{10} variability.

2) Road Type

Analysis by road classification showed distinct variations in estimated PM_{10} levels (see Table of 30 locations). On 6/2 divided roads, concentrations reached up to 50.7 µg/m³ (Othman) and 52.1 µg/m³ (Mozafari), reflecting their role as major transport arteries with high traffic intensity. 4/2 divided roads (e.g., TSM, Mall Ratu Indah) also recorded elevated values between 32.5–46.0 µg/m³ (Othman) and 35.4–57.4 µg/m³ (Mozafari). On 4/1 undivided and 2/2 undivided roads, PM_{10} levels were moderate but still significant, particularly near markets and ports where emissions from commercial activities combine with traffic. Finally, 2/1 undivided roads (e.g., Losari Beach, Kayu Bangkoa Pier) showed relatively lower values, though localized peaks occurred in areas with high tourism and coastal activity.

Supporting data from the South Sulawesi Traffic Directorate (2024) reported more than 2.09 million registered vehicles in Makassar, dominated by motorcycles (1.63 million units), followed by passenger cars (349,973 units), trucks (100,111 units), and buses (3,161 units). This high vehicle density explains the concentration of PM_{10} along major road corridors, validating the remote sensing results.

Conclusion and Recommendation

This study demonstrated the applicability of Landsat 8 imagery for estimating PM_{10} concentrations in Makassar City using the Othman (2010) and Mozafari (2019) algorithms. The Othman model, based on visible bands (2, 3, and 4), produced higher concentration values ranging from 22–58.9 µg/m³, while the Mozafari model, which incorporates coastal/aerosol (Band 1), green (Band 3), red (Band 4), and NDVI, yielded slightly lower and more stable estimates of 16–57.6 µg/m³. Both models consistently identified pollution hotspots along major transport corridors, commercial districts, and industrial areas, with lower values observed in residential and green spaces.

When compared to AQMS data (3.69–14.15 µg/m³; average 7.23 µg/m³), the satellite-based estimations were considerably higher. This discrepancy reflects the broader spatial coverage and atmospheric sensitivity of satellite data compared to localized ground measurements. Nevertheless, the spatial analysis confirmed strong relationships between PM_{10} levels, land use, and road types, with the highest concentrations occurring on 6/2 divided and 4/2 divided roads that experience high traffic volumes.

Overall, the findings indicate that satellite-based remote sensing provides a reliable approach to map PM_{10} distribution and pollution hotspots in urban environments where ground monitoring remains limited.

Recommendations:

- Environmental agencies should integrate satellite-based estimation tools into existing air quality monitoring systems to improve spatial coverage and early detection.
- Future research should explore the incorporation of other satellite sensors (e.g., Sentinel-5P, MODIS) and machine learning techniques for improved PM_{10} prediction accuracy.
- The influence of meteorological parameters and temporal variations should be examined to better understand seasonal pollution patterns.

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