International Journal Software Engineering and Computer Science (IJSECS)
6 (2), 2026, 853-867
Published Online August 2026 in IJSECS (http://www.journal.lembagakita.com/index.php/ijsecs)
P-ISSN: 2776-4869, E-ISSN: 2776-3242. DOI: https://doi.org/10.35870/ijsecs.v6i2.7488.

RESEARCH ARTICLE **Open Access**

Nationwide PM2.5 Concentration Prediction in Indonesia Using GRU, GRU-Attention, and BiGRU-Attention Models with Sentinel-5P and ERA5-Land Data

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Received: June 9, 2026; Accepted: July 28, 2026; Published: August 1, 2026.

Abstract: Fine particulate matter (PM2.5) pollution has become a serious public health and environmental concern in Indonesia, yet ground-based monitoring stations remain limited and unevenly distributed across the archipelago, restricting comprehensive spatial assessment of pollutant concentrations. This study aimed to develop and comparatively evaluate three deep learning architectures, namely Gated Recurrent Unit (GRU), GRU with Additive Attention (GRU-Attention), and Bidirectional GRU with Additive Attention (BiGRU-Attention), for predicting daily PM2.5 concentrations in Indonesia by integrating Sentinel-5P satellite atmospheric chemistry products and ERA5-Land meteorological reanalysis data. The dataset combined PM2.5 ground-truth measurements from 26 BMKG monitoring stations covering the period 2020–2025, five Sentinel-5P pollutant variables and four ERA5-Land meteorological variables, producing 35,842 cleaned observations and seventeen engineered features. All variables were spatially and temporally aligned, normalized using RobustScaler with log1p target transformation, and reshaped into seven-day sequences using a stratified-station train, validation, and test split with proportions of 70%, 15%, and 15%. The results showed that BiGRU-Attention achieved the best performance with R^2 of 0.8302, RMSE of 7.4720 μg/m³, MAE of 4.8368 μg/m³, and MAPE of 26.7009%, outperforming GRU-Attention and the baseline GRU. This MAPE is higher than typical single-city PM2.5 models but is consistent with national-scale studies, where low-concentration observations inflate percentage-based errors. The best model was subsequently applied to produce a national daily PM2.5 distribution map, which can help identify regional PM2.5 hotspots, prioritize locations for additional monitoring infrastructure, and inform targeted air quality interventions in regions where ground-based coverage remains sparse.

Keywords: PM2.5; Deep Learning; GRU; ERA5-Land; Sentinel-5P.

1. Introduction

Air pollution is one of the most pressing global environmental issues affecting human health, ecosystems, and climate change. Among the various air quality indicators, fine particulate matter with an aerodynamic diameter of less than or equal to 2.5 micrometers (PM2.5) is of primary concern because its particles can penetrate the respiratory system down to the alveoli. Exposure to PM2.5 has been associated with increased morbidity and mortality from cardiovascular diseases, respiratory disorders, and lung cancer (WHO, 2021). According to recent reports, more than 90% of the world's population is still exposed to PM2.5 concentrations above the World Health Organization safe threshold, indicating the urgency of this issue at the global scale. A similar condition is observed in Indonesia, particularly in metropolitan areas such as Jakarta, Medan, and Surabaya, where daily PM2.5 concentrations frequently exceed 35 μg/m³ during the dry season due to a combination of transportation emissions, industrial activities, and forest fires (BMKG, 2025). Although the Meteorological, Climatological, and Geophysical Agency (BMKG) has developed a ground-based monitoring system, the distribution of observation stations remains limited and uneven across the country, making comprehensive spatial analysis of PM2.5 variation difficult. Therefore, an approach capable of estimating PM2.5 concentrations broadly, continuously, and efficiently is required.

Over the past decade, remote sensing has emerged as a potential alternative data source to expand air quality monitoring coverage, particularly in regions with limited ground-based stations. The Sentinel-5 Precursor (Sentinel-5P) satellite, equipped with the TROPOspheric Monitoring Instrument (TROPOMI), provides daily atmospheric observations at high spatial resolution, including key parameters such as nitrogen dioxide (NO_2), sulfur dioxide (SO_2), carbon monoxide (CO), ozone (O_3), and the Absorbing Aerosol Index (AAI), which represent anthropogenic activities and atmospheric processes closely linked to the formation of fine particulates (Mazza *et al.*, 2025). Several studies have demonstrated that Sentinel-5P products can be effectively used as predictor variables for PM2.5 modeling at regional and national scales (Wang *et al.*, 2021; Hassaan *et al.*, 2023). However, since Sentinel-5P does not directly measure PM2.5, integration with meteorological data becomes a crucial component to improve estimation reliability. The ERA5-Land reanalysis dataset developed by the European Centre for Medium-Range Weather Forecasts (ECMWF) provides high-resolution meteorological variables such as air temperature, dew-point temperature, surface pressure, and wind components, which play important roles in the dispersion, deposition, and chemical transformation of aerosols in the atmosphere (Muñoz-Sabater *et al.*, 2021).

Although statistical and conventional machine learning models have been widely used, these approaches have limitations in capturing the highly non-linear interactions and short-term temporal fluctuations that characterize atmospheric pollutant behavior, particularly when multiple heterogeneous data sources, such as satellite-derived atmospheric chemistry products and meteorological reanalysis, must be fused into a single predictive framework. This has driven the use of deep learning architectures based on time series, particularly the Gated Recurrent Unit (GRU) and attention-based variants, as more adaptive alternatives for learning complex spatio-temporal relationships from multi-source data (Huang & Qian, 2023). GRU, as a simpler variant of Long Short-Term Memory (LSTM), provides a strong foundation due to its ability to handle the vanishing gradient problem of standard Recurrent Neural Networks (RNN) using only two gates (reset gate and update gate), making it effective in capturing non-linear temporal dynamics in air quality data (Zhou *et al.*, 2019; Cho *et al.*, 2014). GRU has been successfully applied to PM2.5 prediction in Beijing (Zhou *et al.*, 2019) and air pollution modeling in Jakarta (Yudiskara *et al.*, 2023), and has been shown to outperform CNN and XGBoost in comparative PM2.5 forecasting studies (Saikumar *et al.*, 2025).

To enhance performance by leveraging historical context, GRU was further developed into Bidirectional GRU (BiGRU), which processes time series data in both forward and backward directions, enabling more comprehensive temporal dependency capture. Subbiah *et al.* (2024) demonstrated that integrating BiGRU with feature selection effectively predicts PM2.5 concentrations by extracting bidirectional temporal patterns. However, even within a short historical window, not all preceding days and features contribute equally to the current PM2.5 concentration; GRU and BiGRU models therefore still face limitations in differentiating the most relevant information from less informative time steps, motivating integration of the attention mechanism to enhance model focus on the most influential features and time steps (Bahdanau *et al.*, 2015; Vaswani *et al.*, 2017). The combination of BiGRU with attention has been shown to outperform conventional models in various time-series domains (Song *et al.*, 2022).

The fundamental limitation of existing air quality estimation in archipelagic regions like Indonesia lies in the high spatial variability of local microclimates and the non-linear coupling between atmospheric chemical precursors and meteorological dynamics, conditions that conventional spatial interpolation methods and unidirectional sequential models are not designed to capture. Despite this potential, the application of deep learning models integrating multi-source satellite data and meteorological reanalysis remains very limited in Indonesia, although this tropical region exhibits high meteorological variability, strong convective dynamics, and uneven distribution of PM2.5 monitoring stations. This gap highlights the urgency of developing models that can not only process heterogeneous data but also effectively capture the complex temporal dependencies characteristic of Indonesian tropical atmospheric dynamics. The novelty of this study lies in the comparative evaluation of three GRU-based deep learning architectures (GRU, GRU-Attention, and BiGRU-Attention) that integrate Sentinel-5P atmospheric chemistry products with ERA5-Land meteorological reanalysis data at the national scale of Indonesia, an approach that has not yet been explored at this scope. The study aims to (1) develop and analyze the performance of GRU, GRU-Attention, and BiGRU-Attention models for predicting PM2.5 concentrations in Indonesia; (2) identify the best-performing model based on R^2, RMSE, MAE, and MAPE evaluation metrics; and (3) apply the best model to generate a national spatial distribution map of PM2.5 to support data-driven air quality management.

2. Related Work

2.1 Deep Learning Approaches for PM2.5 Prediction

Recent studies have shown the effectiveness of recurrent neural network variants for PM2.5 forecasting. GRU-based architectures have consistently outperformed conventional RNN and machine learning baselines for PM2.5 forecasting across diverse urban contexts, including Beijing (Zhou *et al.*, 2019) and Jakarta (Yudiskara *et al.*, 2023), as well as in multi-sensor comparative settings evaluated against CNN and XGBoost baselines (Saikumar *et al.*, 2025). Building on this foundation, bidirectional extensions have been shown to further improve accuracy by capturing temporal dependencies in both directions, as demonstrated for PM2.5 prediction in Delhi and Amaravathi (Subbiah *et al.*, 2024), for particulate concentration estimation from urban sensors (Xu *et al.*, 2022), and for carbon monoxide prediction in Yogyakarta (Ordiyasa *et al.*, 2024). Although these studies confirm the strength of GRU-based models, most were conducted at the city scale with limited integration of satellite-derived chemistry variables.

2.2 Satellite and Reanalysis Data for Air Quality Prediction

Satellite-based remote sensing combined with meteorological reanalysis has become an increasingly important approach for spatial air quality estimation. Across different geographic contexts, satellite-derived atmospheric chemistry products have proven effective for spatial air quality estimation, particularly when combined with meteorological variables, as shown in global model reviews (Xu *et al.*, 2021), Sentinel-5P-based mapping in the Nile Delta (Hassaan *et al.*, 2023), and seasonal pollutant pattern analysis in Saudi Arabia (Anwer *et al.*, 2025). More directly relevant to the present study, the combination of Sentinel-5P and ERA5-Land has been shown to capture spatial and temporal PM2.5 dynamics at regional and national scales (Mamić & Gašparović, 2023), and has also been applied within the Indonesian context, although Rahman *et al.* (2025) remained limited to city-level coverage in Jakarta. Hanami *et al.* (2025) further investigated spatio-temporal pollutant changes across four Sumatra provinces using Sentinel-5P imagery. However, these Indonesia-focused studies remain confined to city- or regional-level analysis and do not extend to a national-scale, multi-station evaluation that integrates both satellite chemistry products and meteorological reanalysis within a unified deep learning framework.

2.3 Attention Mechanism in Time Series Modeling

The attention mechanism, originally introduced for neural machine translation and later popularized through the transformer architecture, allows models to adaptively assign different weights to each input element rather than relying on a single fixed representation (Bahdanau *et al.*, 2015; Vaswani *et al.*, 2017). Within air quality forecasting specifically, attention-augmented GRU variants have outperformed conventional sequential baselines, whether combined with Grey Relational Analysis for feature weighting (Qing, 2023) or implemented as a self-weighted ensemble that reduced prediction error by approximately 20% (Huang & Qian, 2023). More directly relevant to the architecture adopted in this study, Song *et al.* (2022) demonstrated that BiGRU combined with attention outperformed operational numerical models in tropical cyclone trajectory prediction, indicating strong generalization capability of this specific combination beyond air quality applications. However, the application of attention-augmented bidirectional architectures specifically to PM2.5 prediction using multi-source satellite and reanalysis data remains largely unexplored, particularly within the Indonesian context.

2.4 Research Positioning

Numerous studies have explored PM2.5 estimation using satellite data and deep learning, providing the methodological foundation for this research. Table 1 summarizes key related studies organized by method, data, and performance.

Table 1. Summary of Key Related Studies on PM2.5 Prediction

Author/Year	Method	Dataset	Performance	Relevance
Zhou *et al.* (2019)	GRU	Beijing ground obs.	High accuracy	GRU baseline for PM2.5 prediction
Wang *et al.* (2021)	LSTM + Meteorology	China ground obs.	$R^2 = 0.92$	Integration of meteorological variables
Xu *et al.* (2021)	Review / ML models	Satellite + ground	—	Importance of meteorology in satellite-based PM2.5
Muthukumar *et al.* (2022)	CNN-LSTM	Satellite + ground	$R^2 = 0.92$	Satellite + meteorology integration with DL
Xu *et al.* (2022)	BiGRU	Urban sensors	Improved RMSE	Bidirectional temporal modeling for PM2.5
Song *et al.* (2022)	BiGRU-Attention	Satellite	Outperforms LSTM	BiGRU + attention for time series prediction
Mamić & Gašparović (2023)	RF, XGBoost	Sentinel-5P	National scale $R^2 > 0.80$	Sentinel-5P for national PM estimation
Kim *et al.* (2023)	LSTM, GRU, BiLSTM	Ground obs.	GRU best 24h	GRU superiority over LSTM variants
Huang & Qian (2023)	Self-weighted GRU	Urban sensors	RMSE −20%	GRU ensemble for PM2.5 prediction
Subbiah *et al.* (2024)	BiGRU + feature sel.	India ground obs.	High accuracy	BiGRU for bidirectional PM2.5 modeling
Rahman *et al.* (2025)	Random Forest	Sentinel-5P + ERA5	$R^2 = 0.79$	Sentinel-5P + ERA5-Land for Indonesia PM2.5
Mazza *et al.* (2025)	CNN + Sentinel-5P	Sentinel-5P	High-res maps	Sentinel-5P-based PM2.5 retrieval via DL
Saikumar *et al.* (2025)	GRU, CNN, XGBoost	Multi-sensor	GRU: 98.56%	GRU superiority over CNN and XGBoost

Studies relying solely on conventional machine learning, such as Random Forest and XGBoost, demonstrate strong baseline performance but have limited capacity to model long-range temporal dependencies inherent in atmospheric time series (Mamić & Gašparović, 2023; Rahman *et al.*, 2025). More importantly, none of the studies reviewed in this section, including those conducted within Indonesia (Yudiskara *et al.*, 2023; Rahman *et al.*, 2025; Hanami *et al.*, 2025), were designed to address the specific characteristics of the Indonesian setting: an archipelagic geography with highly uneven and sparse ground-monitoring coverage, pronounced tropical meteorological variability, and recurring seasonal biomass-burning episodes that drive sharp, short-lived PM2.5 spikes largely absent from temperate urban contexts such as Beijing or Seoul. Existing Indonesian-focused studies were restricted to a single city (Jakarta) or a limited set of provinces (Sumatra), relying on either ground observations or satellite data alone, without a systematic multi-station, national-scale evaluation. This combination of sparse spatial coverage and high event-driven variability limits the direct transferability of prior GRU- and attention-based architectures developed for denser, more homogeneous monitoring networks, motivating the national-scale, multi-source approach adopted in this study.

Deep learning architectures, particularly GRU-based models, address this limitation through gating mechanisms that effectively retain relevant historical information (Zhou *et al.*, 2019; Kim *et al.*, 2023). The integration of attention mechanisms further enhances model selectivity by adaptively weighting the most informative time steps (Song *et al.*, 2022; Huang & Qian, 2023). Despite these advances, no study has systematically compared GRU, GRU-Attention, and BiGRU-Attention architectures in the context of integrated Sentinel-5P and ERA5-Land data for PM2.5 prediction at the national scale of Indonesia, a tropical archipelago with high meteorological variability and sparse monitoring networks. This study fills that gap by systematically comparing all three architectures under identical preprocessing, sequence configuration, and evaluation protocols, and by applying the best-performing model to generate a daily spatial distribution map covering the entire Indonesian archipelago.

3. Methodology

This study developed daily PM2.5 prediction models for Indonesia by integrating ground observation, satellite, and meteorological reanalysis data using a deep learning approach. The overall research framework, illustrated in Figure 1, comprises six main stages: data collection, preprocessing, feature engineering, model development, performance evaluation, and spatial mapping. All experiments were conducted using PyTorch on a CUDA-enabled GPU environment.

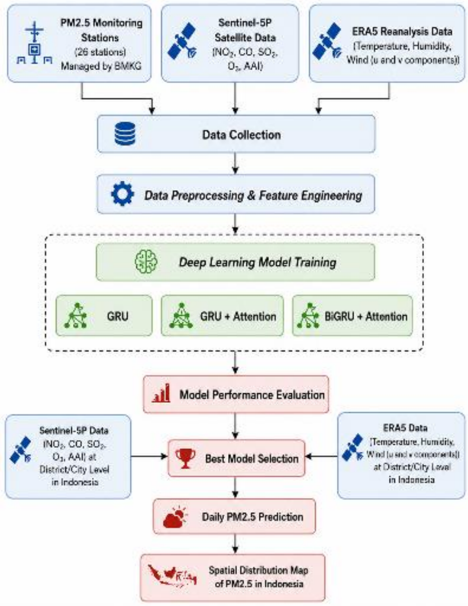

Figure 1. Overall Research Framework

3.1 Data Sources

Three primary data sources were used in this study. PM2.5 ground-truth measurements were obtained from 26 BMKG monitoring stations across Indonesia covering the period 2020 to 2025, including timestamp, PM2.5 concentration, station name, and geographic coordinates. Sentinel-5P satellite products were accessed through the Google Earth Engine (GEE) API, providing five atmospheric chemistry variables: nitrogen dioxide (NO_2), sulfur dioxide (SO_2), carbon monoxide (CO), ozone (O_3), and the Absorbing Aerosol Index (AAI). ERA5-Land meteorological reanalysis data were retrieved from the ECMWF/ERA5_LAND/HOURLY collection on GEE, including 2-meter air temperature, 2-meter dew-point temperature, and 10-meter zonal (u) and meridional (v) wind components. Because Sentinel-5P and ERA5-Land data are gridded while PM2.5 data are point-based, bilinear interpolation was applied to extract grid values at each BMKG station location.

3.2 Data Preprocessing and Feature Engineering

After spatial and temporal alignment, the three data sources were merged using an inner join based on timestamp and location, yielding 40,666 initial rows. Records containing missing or invalid predictor values were removed. Missing PM2.5 values were handled using linear interpolation only when the gap was a single day; longer gaps were excluded to avoid biasing temporal patterns. The final cleaned dataset comprised 35,842 observations. Feature engineering was performed to enrich the model's representation of spatial, temporal, and meteorological characteristics. Relative humidity (RH) was derived from air temperature and dew-point temperature using the Magnus formula. Wind speed was calculated from the zonal and meridional wind components, while wind direction was decomposed into cyclical sine and cosine components to preserve its circular nature. To capture seasonal patterns, cyclical temporal features (sin_month, cos_month, sin_doy, cos_doy) were added. The original u and v wind components were then dropped to avoid redundancy with the derived features. All predictor features were scaled using RobustScaler to mitigate the influence of outliers, and the PM2.5 target was transformed using the log1p function to reduce skewness. The final configuration consisted of seventeen input features covering spatial, atmospheric chemistry, meteorological, and temporal information. After scaling, the data were arranged into time-series sequences using a sliding-window technique with a sequence length of seven days, meaning the model used historical information from days (t−6) to t to predict PM2.5 at day t. The dataset was split using stratified-station sampling with proportions of 70% for training (5,918 sequences), 15% for validation (1,269 sequences), and 15% for testing (1,269 sequences), ensuring that each station was represented in every subset.

3.3 Model Architectures

Three deep learning architectures were developed and compared. The GRU model served as the baseline. It consists of a single GRU layer with a hidden size of 512, followed by Layer Normalization and a fully connected hidden layer with 256 neurons. The update gate (z_t) and reset gate (r_t) of GRU allow the model to retain relevant information from previous time steps while alleviating the vanishing gradient problem of standard RNNs (Cho *et al.*, 2014), as illustrated in Figure 2.

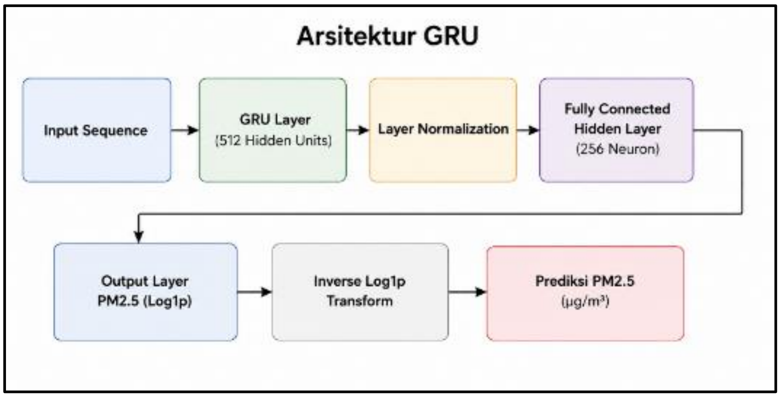

Figure 2. GRU Model Architecture

The GRU-Attention model extends the baseline by adding an Additive (Bahdanau) Attention mechanism on top of the GRU outputs at all time steps. The attention layer computes weights over each hidden state, producing a context vector that emphasizes the most relevant historical information for predicting PM2.5. The context vector is then passed to a fully connected layer with 256 neurons before producing the final prediction, as illustrated in Figure 3.

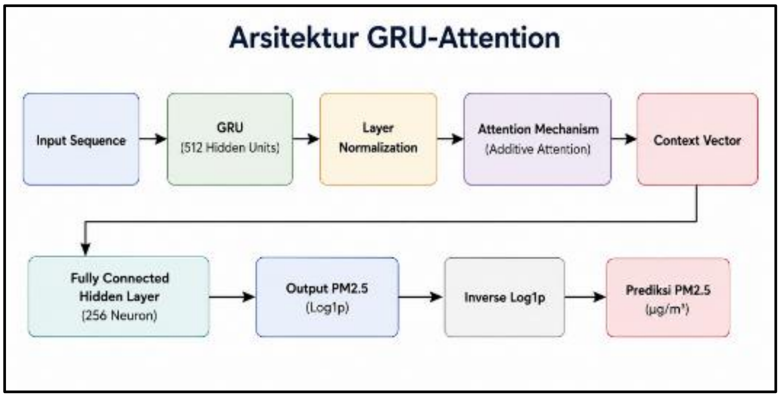

Figure 3. GRU-Attention Model Architecture

The BiGRU-Attention model combines bidirectional processing with the additive attention mechanism. A bidirectional GRU layer with a hidden size of 1,024 processes the input sequence in both forward and backward directions, yielding richer temporal representations. The attention layer is applied on top of the concatenated hidden states. This architecture is expected to capture temporal dependencies more comprehensively than unidirectional variants, as illustrated in Figure 4.

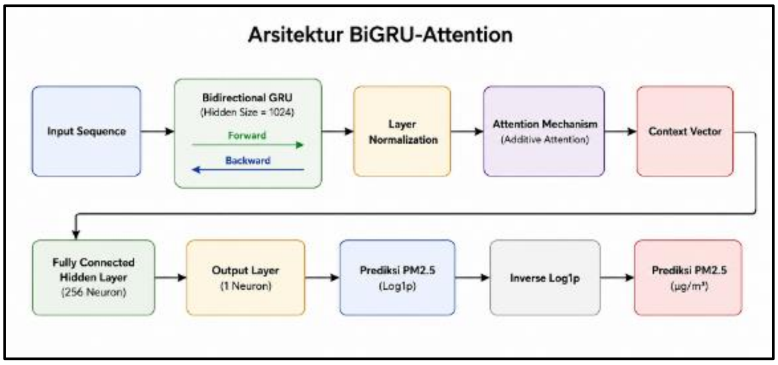

Figure 4. BiGRU-Attention Model Architecture

Hyperparameters for each architecture (hidden size, learning rate, and batch size) were determined through manual tuning rather than an automated search procedure. Approximately 1,000 training trials were conducted, in which parameter values were iteratively adjusted based on the resulting validation MSE: configurations that yielded improved validation performance were explored further around that region of the hyperparameter space, while less promising settings were discarded. This iterative, validation-guided process continued until no further improvement in validation MSE was observed, and the final configuration for each model, summarized in Table 2, corresponds to the best-performing combination identified through this search. A formal grid or random search was not adopted given the substantial computational cost of training three architectures with multi-seed ensembles; we acknowledge this as a limitation and note it as a direction for more systematic hyperparameter optimization in future work. All models were trained using the Mean Squared Error (MSE) loss function with the Adam optimizer. Training employed early stopping with a patience of 20 epochs, gradient clipping of 1.0, and the ReduceLROnPlateau scheduler. Ensemble averaging across multiple random seeds was used to enhance prediction stability. The final hyperparameter configurations of the three models are summarized in Table 2.

Table 2. Hyperparameter Configuration of the Three Model Architectures

Component	GRU	GRU-Attention	BiGRU-Attention
Input features	17	17	17
Sequence length	7 days	7 days	7 days
Target transform	log1p	log1p	log1p
Feature scaler	RobustScaler	RobustScaler	RobustScaler
Hidden size	512	512	1024
GRU layers	1	1	1 (bidirectional)
Layer normalization	Yes	Yes	Yes
FC hidden layer	256	256	256
Optimizer	Adam	Adam	Adam
Learning rate	0.0003	0.0003	0.0002
Batch size	32	64	64
Max epochs	200	400	200
Early stopping	20	20	20
Gradient clipping	1.0	1.0	1.0
Scheduler	ReduceLROnPlateau	ReduceLROnPlateau	ReduceLROnPlateau
Ensemble seeds	3 seeds	3 seeds	6 seeds

3.4 Evaluation Metrics

Model performance was evaluated using four standard regression metrics. The coefficient of determination (R^2) measures the proportion of PM2.5 variance explained by the model, with values closer to 1 indicating better fit. The Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) quantify the average prediction error in the original concentration units (μg/m³), with lower values indicating better performance. The Mean Absolute Percentage Error (MAPE) expresses the average error in percentage terms, providing scale-independent comparison. Evaluation was performed on the held-out test set that was not used during training or validation. The four evaluation metrics used in this study are mathematically defined as follows: the coefficient of determination is calculated using Equation (1), the Mean Absolute Error using Equation (2), the Root Mean Square Error using Equation (3), and the Mean Absolute Percentage Error using Equation (4).

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \hat{y})^2} \tag{1}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | y_i - \hat{y}_i | \tag{2}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{3}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100\% \tag{4}$$

Where y_i denotes the i-th observed (actual) PM2.5 concentration, $\hat{y}_i$ denotes the i-th predicted concentration, $\bar{y}$ is the mean of all observed values, and n is the total number of observations. R^2 approaches 1 for a perfect fit; RMSE, MAE, and MAPE approach zero as the prediction error decreases. R^2 and MAPE are scale-independent, whereas RMSE and MAE are reported in μg/m³.

3.5 Spatial Mapping

After identifying the best-performing model, daily spatial PM2.5 maps were generated for the entire Indonesian archipelago. Sentinel-5P and ERA5-Land data were extracted for all district and city centroids in Indonesia, processed through the same preprocessing pipeline as the training data, and reshaped into seven-day sequences. The best model was then used to produce predicted PM2.5 concentrations at each location. The point predictions were visualized using ArcMap 10.4 to generate a national-scale spatial distribution map.

4. Result and Discussion

4.1 Results

Exploratory analysis of the integrated dataset revealed clear spatial variability in PM2.5 concentrations across the 26 BMKG stations. As shown in Figure 5, the Kemayoran3 station in Jakarta recorded the highest mean concentration at approximately 37 μg/m³, followed by Semarang, Medan2, Pesawaran, and Palembang3, with mean concentrations in the range of 21–24 μg/m³. In contrast, stations such as Singkawang, Kototabang2, Kotabaru, Palu, and Sorong exhibited average concentrations below 8 μg/m³. The temporal pattern in Figure 6 shows that daily average PM2.5 concentrations mostly ranged between 5 and 25 μg/m³, with a notable peak exceeding 50 μg/m³ in late 2023 to early 2024, suggesting the influence of meteorological and anthropogenic factors. Among the Sentinel-5P variables, AAI and O_3 displayed nearly normal distributions, while CO, NO_2, and SO_2 exhibited right-skewed distributions consistent with emission-driven sources. ERA5-Land variables showed stable temperature ranges of 300–305 K and humidity peaks around 70%, reflecting Indonesia's humid tropical climate.

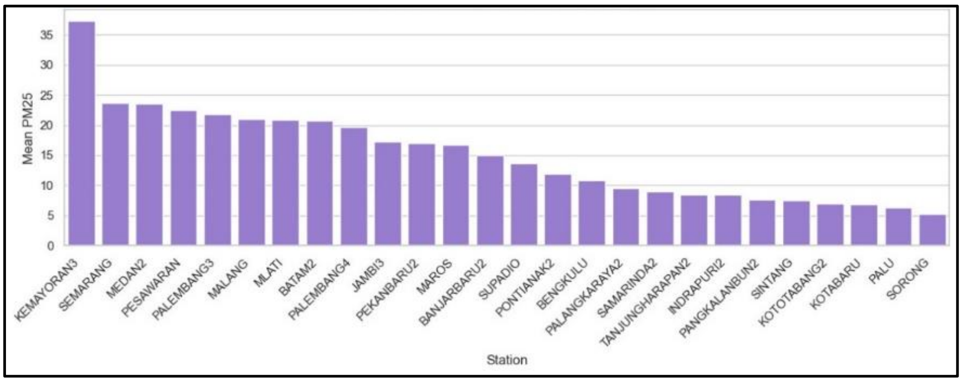

Figure 5. Per-station PM2.5 ranking

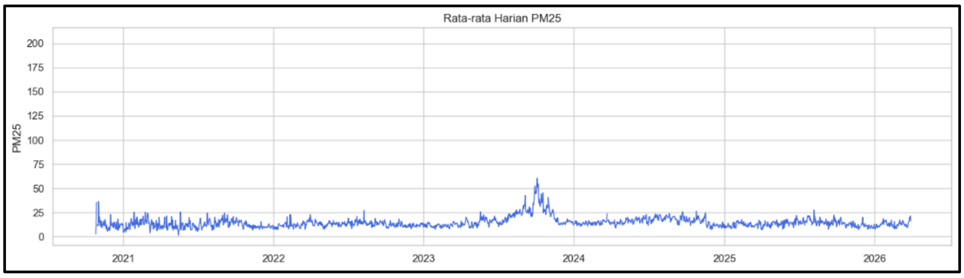

Figure 6. Daily average PM2.5 time series

All three models converged successfully on the validation set, with the training and validation loss curves showing stable convergence behavior, as illustrated in Figure 7. The baseline GRU model achieved its best validation MSE of 0.101416 at epoch 45, GRU-Attention reached 0.100288 at epoch 42, and BiGRU-Attention reached 0.106422 at epoch 19. The performance of the three models on the held-out test set is summarized in Table 3.

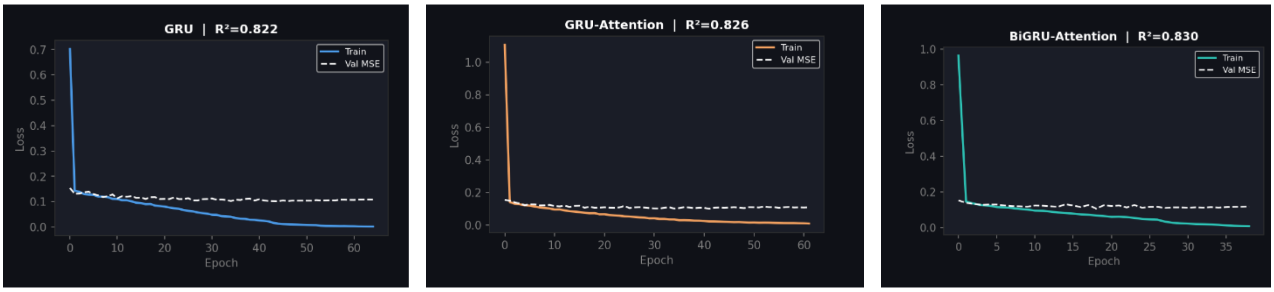

Figure 7. Training and validation loss curves for the three models

Table 3. Performance Comparison of GRU, GRU-Attention, and BiGRU-Attention on the Test Set

Model	R^2	RMSE (µg/m³)	MAE (µg/m³)	MAPE (%)
GRU	0.8215	7.6614	4.9872	27.5098
GRU-Attention	0.8261	7.5617	4.9386	26.9122
BiGRU-Attention	0.8302	7.4720	4.8368	26.7009

The baseline GRU model achieved an R^2 of 0.8215, with RMSE of 7.6614 µg/m³, MAE of 4.9872 µg/m³, and MAPE of 27.5098%, indicating that the model captured temporal associations between atmospheric pollutants, meteorological variables, and PM2.5 concentrations. Adding the attention mechanism to GRU increased R^2 to 0.8261 and reduced RMSE to 7.5617 µg/m³, MAE to 4.9386 µg/m³, and MAPE to 26.9122%. The best performance was achieved by BiGRU-Attention, which produced the highest R^2 of 0.8302 and the lowest RMSE of 7.4720 µg/m³, MAE of 4.8368 µg/m³, and MAPE of 26.7009%. As shown in Figure 8, the scatter plots of predicted versus actual values for all three models show that most points are concentrated near the diagonal line, although deviations tend to increase at higher PM2.5 concentrations, which is a known challenge for regression models trained on right-skewed pollutant data.

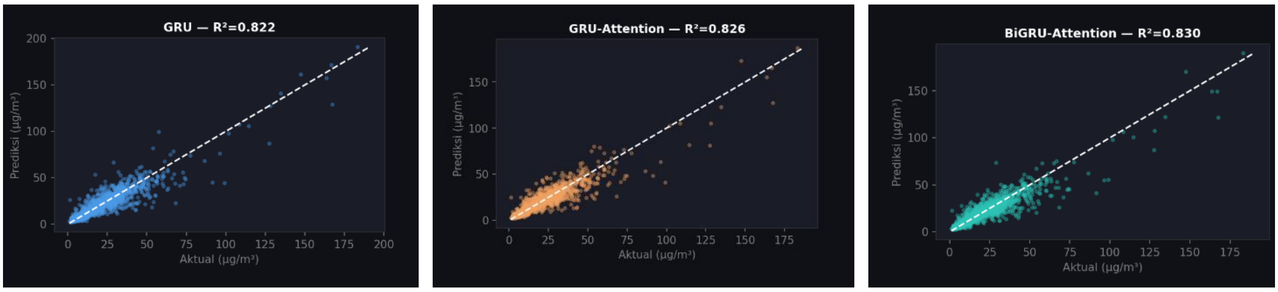

Figure 8. Scatter plots of actual vs. predicted PM2.5 for the three models

To evaluate whether the performance improvement achieved by BiGRU-Attention over the baseline GRU reflects a genuine effect rather than random variation, a Wilcoxon signed-rank test was conducted on the paired absolute errors of the two models across the same 1,269 test sequences. The results indicated a statistically significant difference between the models ($W = 377127$, $p = 0.048$), suggesting that the observed performance gain is unlikely to be attributable to chance alone. Although the improvement in aggregate evaluation metrics is relatively small, the statistical evidence indicates a consistent advantage of the bidirectional attention-based architecture over the unidirectional GRU baseline. Nevertheless, given that the p-value is only marginally below the conventional significance threshold ($\alpha = 0.05$), the magnitude of the observed effect should be interpreted with caution. These findings suggest that the proposed architecture provides a measurable, albeit modest, improvement in predictive performance. To complement the correlation-based evaluation presented in Figure 8, Figure 9 illustrates the temporal tracking performance of the three models at the Malang station over a continuous four-month period from 18 June to 21 October 2025. All three architectures adequately captured the overall trend and short-term fluctuations of the observed PM2.5 concentrations, with BiGRU-Attention showing closer agreement with local peaks than the baseline GRU model. Larger deviations were nonetheless observed during periods of rapid concentration change, such as in late July and mid-August, consistent with the models' reduced sensitivity to abrupt, short-term spikes discussed in the limitations paragraph. This illustration used a continuous temporal holdout period rather than the stratified-station split used to derive the quantitative metrics reported in Table 3, because visualizing daily tracking behavior requires chronologically ordered data; therefore, the resulting error magnitudes are broadly consistent with, though not numerically identical to, those presented in Table 3.

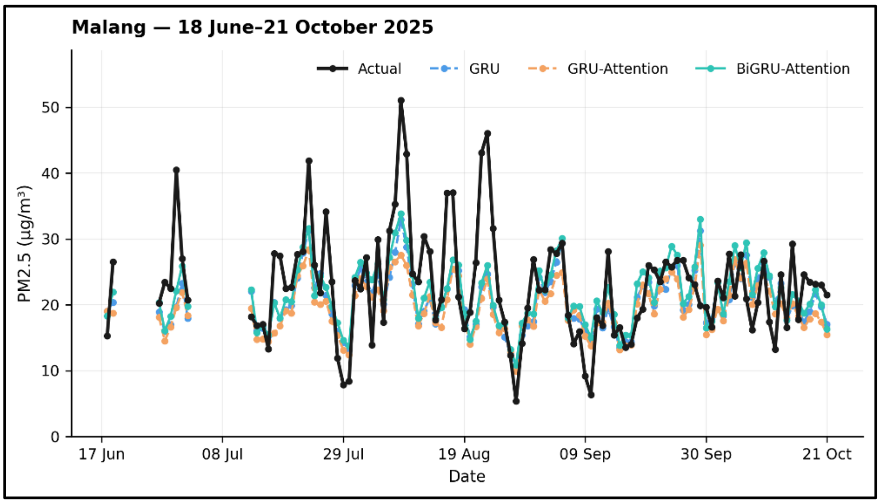

Figure 9. Observed versus predicted PM2.5 concentrations for Malang over a continuous four-month period (18 June–21 October 2025)

The best-performing model, BiGRU-Attention, was applied to predict daily PM2.5 concentrations for 30 April 2026 across all district and city centroids in Indonesia using the corresponding seven-day input window from 24 to 30 April 2026. The resulting map of predicted PM2.5 distribution across Indonesia on 30 April 2026, shown in Figure 10, revealed clear spatial heterogeneity. Most of Kalimantan, Sulawesi, Maluku, and Papua exhibited concentrations in the range of 0–15 μg/m³, while parts of Sumatra ranged between 10 and 25 μg/m³. The highest concentrations were observed in Java, particularly in the Jakarta metropolitan area, where values exceeded 35 μg/m³. The date of 30 April 2026 was selected based on data availability for demonstration purposes rather than to represent a specific pollution episode. For context, the predicted concentrations in the Greater Jakarta area on this date (39.62–45.45 μg/m³) were moderately above the historical average of the highest-concentration station in the dataset (Kemayoran3, approximately 37 μg/m³), yet still within the range observed during the 2020–2025 training period, which included peaks exceeding 50 μg/m³. This indicates that the selected date represents a plausible, moderately elevated day for the Jakarta metropolitan area rather than an extreme or atypical event, illustrating the model's general inference capability rather than a specific pollution episode.

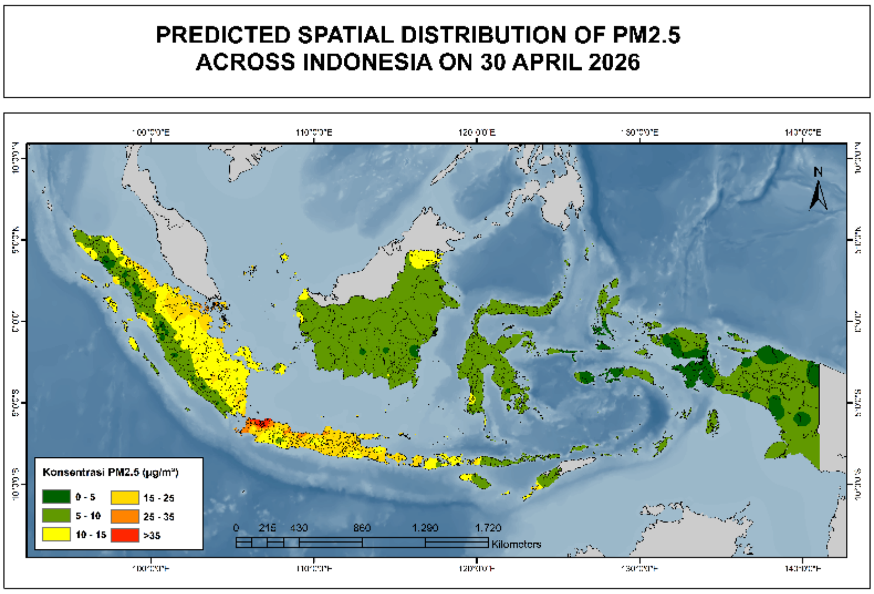

Figure 10. Predicted spatial distribution of PM2.5 across Indonesia on 30 April 2026

Table 4. Ten Locations with the Highest Predicted PM2.5 Concentration on 30 April 2026

No.	Location	PM2.5 (μg/m³)
1	Kota Jakarta Selatan	45.45
2	Kota Jakarta Barat	45.32
3	Kota Jakarta Timur	44.98
4	Kota Jakarta Pusat	43.36

5	Kota Tangerang Selatan	41.83
6	Kota Serang	41.79
7	Kabupaten Tangerang	41.79
8	Kota Bekasi	41.41
9	Kota Depok	39.75
10	Kota Tangerang	39.62

Table 4 lists the ten locations with the highest predicted concentrations on 30 April 2026. All locations were in Java, primarily within the Greater Jakarta metropolitan area, with values ranging from 39.62 to 45.45 μg/m³, substantially higher than most other regions of Indonesia.

4.2 Discussion

The baseline GRU achieved an R^2 of 0.8215 and RMSE of 7.6614 μg/m³, indicating that the model explained approximately 82.15% of the variation in PM2.5 concentrations based on Sentinel-5P and ERA5-Land variables. This performance is related to the gating mechanism of GRU, which retains relevant information from previous time steps while filtering less informative signals. The seven-day sequence length provides a balance between historical information richness and model complexity, allowing the model to capture short- to medium-term temporal patterns associated with PM2.5 dynamics (Cho *et al.*, 2014; Hu *et al.*, 2023). Adding the attention mechanism to GRU improved R^2 from 0.8215 to 0.8261 and reduced RMSE from 7.6614 to 7.5617 μg/m³. This improvement reflects the attention mechanism's ability to identify relevant temporal information for PM2.5 prediction. Whereas standard GRU relies primarily on the final hidden state, attention assigns different weights to all hidden states, enabling the model to focus on time steps with stronger relevance to the current PM2.5 value (Bahdanau *et al.*, 2015; Vaswani *et al.*, 2017). For atmospheric data with complex temporal dependencies, this adaptive weighting helps the model retain informative features throughout the sequence rather than depending solely on the last step.

BiGRU-Attention achieved the best results among the three architectures, suggesting that combining bidirectional processing with attention provides advantages in modeling complex PM2.5 dynamics. Whereas GRU processes data only in the forward direction, BiGRU processes information forward and backward, producing a richer temporal representation (Tao *et al.*, 2019; Song *et al.*, 2022). The attention mechanism further enables the model to select informative hidden states from the bidirectional representation. This combination is particularly relevant to air quality data, where PM2.5 concentrations are influenced by atmospheric processes that may develop gradually over several days.

Although the performance gain of BiGRU-Attention over the baseline GRU was statistically significant, its magnitude remained modest. This result may be explained by two factors. Within a relatively short seven-day input window, the benefits of bidirectional context and attention-based weighting may partially overlap, because both mechanisms emphasize informative time steps. Once the attention layer has learned to prioritize relevant days, the additional backward-pass information captured by the bidirectional structure may offer comparatively limited incremental value. In addition, the predictive ceiling of the current feature set may already be approached, because fire-related variables such as MODIS fire counts and boundary-layer height, both of which are known to drive sharp, short-lived PM2.5 spikes in Indonesia, were not included as predictors. Without these variables, architectural refinement alone may not substantially reduce residual prediction error attributable to unmodeled atmospheric processes. This interpretation is consistent with the future work directions in Section 5, which recommend incorporating predictors that capture vertical and fire-driven atmospheric dynamics.

Beyond architectural advantages, the performance of BiGRU-Attention can also be interpreted in relation to the meteorological predictors used in the model. Wind speed governs the horizontal dispersion and dilution of locally emitted pollutants, so periods of low wind speed are typically associated with pollutant accumulation near emission sources (Chen *et al.*, 2020). Relative humidity influences the hygroscopic growth of aerosol particles, which can increase particulate mass concentration under humid tropical conditions. The bidirectional attention structure may help the model capture temporal patterns associated with stagnant-wind and high-humidity conditions, allowing it to represent meteorological states linked to elevated PM2.5 levels in urban hotspots such as Jakarta, even though no explicit boundary-layer height variable was included in this study. A key contribution of this study is the integration of Sentinel-5P remote sensing data with ERA5-Land meteorological reanalysis within a deep learning framework. Sentinel-5P provides information on atmospheric pollutants such as CO, NO_2, SO_2, O_3, and AAI, which have direct or indirect relationships with PM2.5 formation and transformation. ERA5-Land complements these variables with meteorological information that influences dispersion, deposition, and accumulation processes, including air temperature, relative humidity, dew-point temperature, and wind speed. The integration of these sources produces a more comprehensive representation than using historical PM2.5 data alone, allowing the model to capture associations related to physical and chemical factors involved in fine particulate formation. These findings reinforce the potential of satellite and reanalysis data as alternative inputs to support air quality monitoring in regions with limited ground stations (Rahman *et al.*, 2025; Fania *et al.*, 2024).

When compared explicitly, the BiGRU-Attention model developed in this study achieved a higher R^2 (0.8302) than the Random Forest model reported by Rahman *et al.* (2025) for Jakarta using the same Sentinel-5P and ERA5-Land data sources (R^2 = 0.79), despite extending the spatial scope from a single city to a national, multi-station evaluation across 26 BMKG stations. This suggests that the improvement may reflect not only the deep learning architecture itself but also the generalization of the satellite–reanalysis fusion approach beyond the city-scale setting in which it was previously validated. A similar numerical comparison with GRU-based studies conducted elsewhere in Indonesia, such as Yudiskara *et al.* (2023) in Jakarta, is constrained by the absence of reported quantitative metrics such as R^2 and RMSE in that study; nonetheless, the present results are consistent with that work's qualitative conclusion that GRU-based architectures are suitable for Indonesian air quality data.

The spatial distribution pattern produced by BiGRU-Attention on 30 April 2026 showed higher concentrations on Java than in other regions, consistent with known PM2.5 characteristics in Indonesia, where concentrations tend to cluster in highly urbanized and economically active areas. The ten locations with the highest predicted concentrations were all within or near the Greater Jakarta metropolitan area, where transportation, industrial activity, and energy consumption are high. Conversely, most of Kalimantan, Sulawesi, Maluku, and Papua showed lower concentrations, generally below 10 μg/m³, aligning with the global pattern that PM2.5 is higher in heavily urbanized regions and lower in less populated areas (Hammer *et al.*, 2020). The use of NO_2, SO_2, CO, O_3, and AAI as predictors is also scientifically relevant, since these gases are related to atmospheric processes involved in the formation of secondary aerosols, which constitute a major component of PM2.5.

Several limitations should be acknowledged. Although BiGRU-Attention performed best, all models showed larger prediction errors at higher PM2.5 concentrations, suggesting limited representation of extreme pollution events in the training data. This systematic underestimation at high concentrations carries a practical risk because the model is least reliable during severe pollution episodes, such as fire-driven haze events, when accurate concentration estimates are most critical for public health warnings and protective action. Users applying this model for operational air quality alerts should therefore treat high-concentration predictions with caution, for example by supplementing model outputs with conservative safety margins or cross-validation against available ground observations during such episodes, rather than relying on point estimates alone. The use of 26 BMKG stations, while geographically diverse, still constrains the spatial coverage of the ground-truth data, especially in eastern Indonesia. In addition, the daily temporal resolution may not capture sub-daily emission peaks driven by traffic, industrial activity, or biomass burning events. Fire-related variables such as MODIS fire counts and boundary-layer height were also not included, although these predictors could further improve estimation accuracy in fire-prone regions.

5. Conclusion and Recommendations

This study developed and comparatively evaluated three GRU-based deep learning architectures, namely GRU, GRU-Attention, and BiGRU-Attention, for predicting daily PM2.5 concentrations in Indonesia by integrating Sentinel-5P satellite atmospheric chemistry data and ERA5-Land meteorological reanalysis. Among the three architectures, BiGRU-Attention achieved the best performance, with an R^2 of 0.8302, RMSE of 7.4720 μg/m³, MAE of 4.8368 μg/m³, and MAPE of 26.7009%, outperforming both GRU-Attention and the baseline GRU.

The main contribution of this work lies in the comprehensive comparative evaluation of GRU-based architectures with attention mechanisms in the context of multi-source data integration, namely Sentinel-5P and ERA5-Land, at the national scale of Indonesia, an approach that has not been previously reported at this geographic scope. The BiGRU-Attention model was successfully applied to generate a national spatial distribution map of daily PM2.5, capable of estimating concentrations in regions without ground-based monitoring stations. These results highlight the potential of combining remote sensing, meteorological reanalysis, and bidirectional attention-based deep learning to support data-driven air quality monitoring and policy formulation in Indonesia. However, given the model's MAPE of 26.7% and the limitations discussed in the preceding discussion, including underestimation at high pollution concentrations and the exclusion of fire-related predictors, this approach should currently be regarded as a complementary tool that supports, rather than fully substitutes for, ground-based air quality monitoring networks.

Future research may benefit from incorporating Aerosol Optical Depth and Planetary Boundary Layer Height to capture vertical atmospheric dynamics not represented by the current surface-level predictors, along with MODIS fire count data to improve accuracy during fire-driven pollution episodes. Beyond predictor enrichment, more advanced architectures such as Transformer-based models, Temporal Convolutional

Networks (TCN), or hybrid graph neural networks could be explored to improve the modeling of spatial dependencies among stations. Increasing the spatial and temporal resolution of the output maps, for example to sub-district level or hourly resolution, would also enable more detailed local-scale analysis. Ultimately, deploying the model within a real-time monitoring dashboard could translate this research into a practical decision-support tool for environmental policy and public health protection.

Acknowledgment

The authors would like to express their sincere gratitude to Universitas Pamulang (UNPAM) for the institutional support provided during this research. We also extend our deepest appreciation to the Meteorological, Climatological, and Geophysical Agency (BMKG) for providing the essential PM2.5 ground-truth data that made this study possible.

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