Determinants of PM2.5 Concentration in DKI Jakarta Province: A VAR Model Approach

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ABSTRACT – Air pollution in the DKI Jakarta Province is a serious issue as it is related to public health and environmental concerns. Therefore, this research aims to analyze the causality of PM2.5 concentration with meteorological factors such as air temperature, humidity, rainfall, and wind speed. The data source used is from the MERRA-2 satellite, which provides information at a spatial resolution of 0.5° × 0.625°. The data covers the period from January 1, 1980, to November 1, 2023, with hourly time intervals. The research variables involve PM2.5 concentration as the response variable, as well as predictor variables such as air temperature, humidity, rainfall, and wind speed. The analytical method employed is the Vector Autoregressive (VAR) approach, as all variables are stationary at the level. The constructed VAR model tends to indicate that meteorological variables have a low explanatory power for PM2.5 concentration, while changes in PM2.5 concentration itself have sustained impacts in both the short and long term. This suggests that the fluctuations in PM2.5 concentration in DKI Jakarta Province are not significantly influenced by meteorological factors.

Keywords– PM2.5, Jakarta, Vector Autoregressive, MERRA-2.

I. INTRODUCTION

Air pollution, according to Government Regulation No. 41 of 1999, refers to substances, energy, and/or other components that enter or are introduced into the ambient air due to human activities, resulting in a deterioration of ambient air quality and the impairment of its functions [1]. There are many types of air pollutants that are of concern according to the WHO, including Particulate Matter (PM), carbon monoxide, nitrogen dioxide, ozone, and sulfur dioxide [2]–[4]. Air pollution can lead to allergies, diseases, and even loss of life in humans. Furthermore, air pollution can result in the deterioration of other living organisms, namely the degradation of habitats for animals and plants. Environmental damage and degradation can also occur, such as acid rain, climate change, and ozone layer depletion. Therefore, air quality is one of the serious issues that needs attention as it is a crucial factor for human health and environmental sustainability.

PM2.5 is a type of small particle that can be inhaled and can have negative impacts on human health due to its very small size, allowing it to penetrate deeper into the respiratory system. The components of PM2.5 consist of elements such as Al, As, Br, Ca, Cl, Cr, Fr, K, Mg, Mn, Na, Pb, Ti, Zn, sulfate ions, nitrate ions, and ammonium ions [5]. PM2.5 can originate from natural factors such as sandstorms, forest fires, airborne dust, as well as anthropogenic sources like home cooking activities and smoking [6]. There are several factors that influence PM2.5 pollution, such as vehicle emissions, fuel usage, dust, and meteorological factors like relative humidity, surface pressure, wind speed, and air temperature [6]. PM2.5 causes various detrimental health problems such as asthma, respiratory inflammation, decreased lung function, and cancer [5].

From 2001 to 2019, there was an increase in the annual average concentration of PM2.5 in DKI Jakarta [7]. A research on the impact of air pollution in Jakarta, Indonesia, found that more than 10.5 million people in Jakarta are at significant risk due to air pollution [8]. According to air quality index monitoring data from IQAir, air pollution is predicted to cause 13,000 deaths in Jakarta during 2023 and result in approximately US$3.4 billion in losses in Jakarta during the same period [9]. This amount is equivalent to IDR 51.95 trillion (US$1 = Rp 15,280). Air pollution is a significant factor that causes diseases and deaths, including cancer, heart disease, and lung disease.

Respiratory effects can be caused by PM2.5. Research indicates that long-term exposure to PM2.5 can increase the risk of respiratory disease-related mortality, such as asthma, respiratory inflammation, and decreased lung function [10], [11]. PM2.5 also induces cardiovascular effects, such as an increased risk of heart attacks, heart rhythm disturbances, and coronary heart disease [12], [13]. Exposure to PM2.5 has also been linked to various other health impacts, including an increased risk of diabetes, decreased lung function, and an elevated risk of lung cancer [10], [14]. Therefore, the risk of premature death will increase due to exposure to PM2.5, especially for children, the elderly, and individuals with heart or lung diseases.

Therefore, controlling PM2.5 exposure is crucial to protect public health. Solutions to address air pollution in Jakarta involve emission control. Measures taken to reduce pollutant concentrations in the air and reduce emissions from pollution sources include controlling the number of motor vehicles and actively monitoring industrial activities. Additionally, efforts to improve public transportation by promoting its use and reducing private vehicle usage can contribute to reducing exhaust emissions. Another solution that can be implemented is increasing urban greenery. Urban greening and tree planting can help absorb pollutants from the air and improve air quality.

This research utilizes several meteorological variables, namely temperature, humidity, rainfall, and wind speed, to analyze the meteorological impacts on PM2.5 concentration in DKI Jakarta. Through this research, an analysis of air quality changes can also be conducted. The sensitivity of PM2.5 concentration to meteorological variables needs to be understood as a consideration in developing emission control strategies. It is essential for policymakers to comprehend the influence of meteorological condition changes on the effectiveness of emission control strategy plans in achieving air quality control objectives.

Research related to the relationship between meteorological variables and PM2.5 concentration has been conducted several times. A research that analyzed the influence of meteorological variables on PM2.5 concentration was once conducted in Jakarta using the Convergent Cross Mapping (CCM) method [15]. The results of the research indicate that meteorological variables influence local PM2.5 concentrations in the Jakarta area, but their effects vary across different seasons. Research in China shows that the relationship between meteorological variables and PM2.5 concentration exhibits spatial and seasonal variations [16]. Another research in China yielded results indicating that the influence of meteorological variables on PM2.5 concentration exhibits significant seasonal and regional variations [17]. In other words, changes in meteorological conditions have varying effects on PM2.5 concentrations in different regions. Several studies have also concluded that meteorological variables and climate or weather changes can influence PM2.5 concentrations [18], [19].

Vector Autoregressive (VAR) is a statistical model in time series analysis used to model the relationships between two or more variables that influence each other over time. This model is an extension of univariate autoregression (AR) models. In the VAR model, all variables are treated symmetrically as endogenous variables or variables whose values are determined by the model. To avoid simultaneous bias problems, each endogenous variable is a function of lagged values of all endogenous variables. PM2.5 concentration in a region is influenced by temperature, humidity, rainfall, and wind speed, making it suitable for the formulation of a VAR model.

The use of VAR method has been employed in several studies. A research conducted in Bangladesh mentioned that the VAR model used was stable and normal in analyzing the causality of six exogenous variables [20]. The results of the research explain that the VAR model can elucidate the influence of dependent variables on independent variables, Granger Causality can demonstrate bidirectional causality, and Impulse Response Functions (IRF) can provide an overview of the explanatory power of each independent variable. The utilization of the VAR method, which includes Granger Causality and IRF, has also been conducted in research in China to understand the relationships between PM2.5, PM10, SO2, CO, and NO2 [21]. The research demonstrates that Granger Causality can elucidate cause-and-effect relationships, and the results of Impulse Response Functions (IRF) can indicate short-term relationships between variables.

Regarding the air pollution issue in Jakarta, this research is conducted with the aim of (1) providing a general overview of PM2.5 and meteorological variables such as temperature, humidity, rainfall, and wind speed, and (2) analyzing the influence of meteorological variables including air temperature, humidity, rainfall, and wind speed on PM2.5 concentration. These values are expected to be used as considerations in determining policies for prevention and mitigation of the negative impacts of PM2.5 concentration.

II. LITERATURE REVIEW

A. The Influence of Temperature on PM2.5

Temperature has a positive correlation with PM concentration. Temperature is linked to solar radiation, and as solar radiation increases, the temperature also rises. This can lead to the vertical lifting of air masses, causing the ascent of water vapor and air pollutants, including particulate matter, present within it into the atmosphere [22]. Research in Delhi indicates an exponential increase in PM2.5 concentration with decreasing temperature. The research also reveals a negative correlation between temperature and PM2.5 concentration, which is attributed to several factors such as motor vehicles and factories [23]. Furthermore, a research in China identified temperature as the dominant influencing factor in monitoring PM2.5 concentrations [24].

B. The Influence of Humidity on PM2.5

Humidity has a significant influence on PM2.5 concentration. A research in Delhi found a strong negative correlation between PM2.5 concentration and air temperature under high humidity conditions, specifically when the relative humidity is above 50%. Furthermore, it was also found that PM2.5 concentration correlates positively with humidity [23]. Another research found that humidification is a method that can accelerate the rate of PM2.5 deposition [25]. As particle size increases and pollutant concentrations rise, the influence of humidity on PM2.5 concentration becomes more significant. Furthermore, the research indicates that increased humidity leads to the agglomeration of fine PM, forming larger PM particles. Humidification is beneficial in preventing PM from entering the human respiratory system, thereby reducing the impact of PM on the human body.

C. The Influence of Rainfall on PM2.5

Rainfall factor influences the concentration of PM2.5. A research found that rainfall has a significant effect in reducing PM2.5 concentrations in several regions in China [14]. This research indicates that the reduction effect on PM2.5 concentration by rainfall varies depending on the intensity of rainfall and the previous air pollution levels. Another research found that PM2.5 concentrations tend to decrease after rainfall occurs. This research also demonstrates that the average PM2.5 concentration decreases by 20.99% one hour after rainfall compared to pre-rainfall conditions [26]. A research in China elucidates that various types of rainfall have an impact on the concentration of PM2.5 [14], [27].

D. The Influence of Wind Speed on PM2.5

A research found that wind speed has an influence on the concentration of PM2.5 in Hong Kong [28]. Winds from the north during the winter increase the concentration of PM2.5, while winds from the south during the summer reduce the concentration of PM2.5. Another research found a negative correlation between wind speed and PM2.5 concentration. This research indicates that PM2.5 concentration tends to decrease with an increase in wind speed [29]. Furthermore, a research also found the influence of wind speed on PM2.5 concentration in Delhi. This research indicates a negative correlation between PM2.5 concentration and wind speed, where PM2.5 concentration tends to decrease with increasing wind speed [23].

III. METHODOLOGY

This research is conducted with the objective of examining the impact of meteorological variables, including air temperature, surface humidity, precipitation, and wind speed, on the concentration of PM2.5 in DKI Jakarta Province. The research process, spanning from the data collection to VAR model estimation and analysis, is delineated in the flowchart shown in the Figure 1.

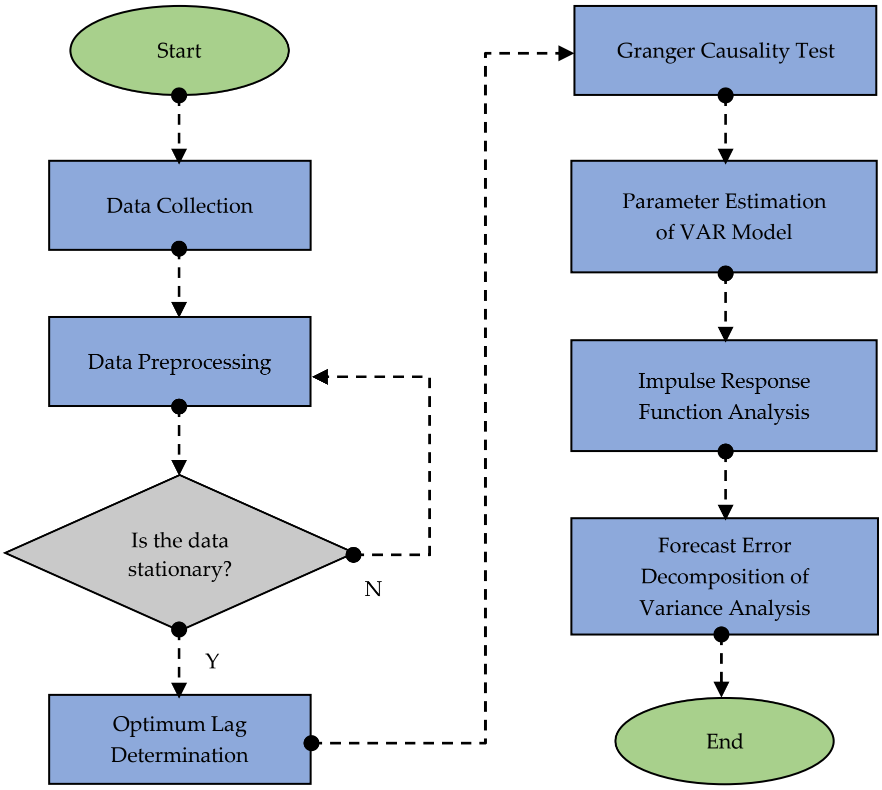
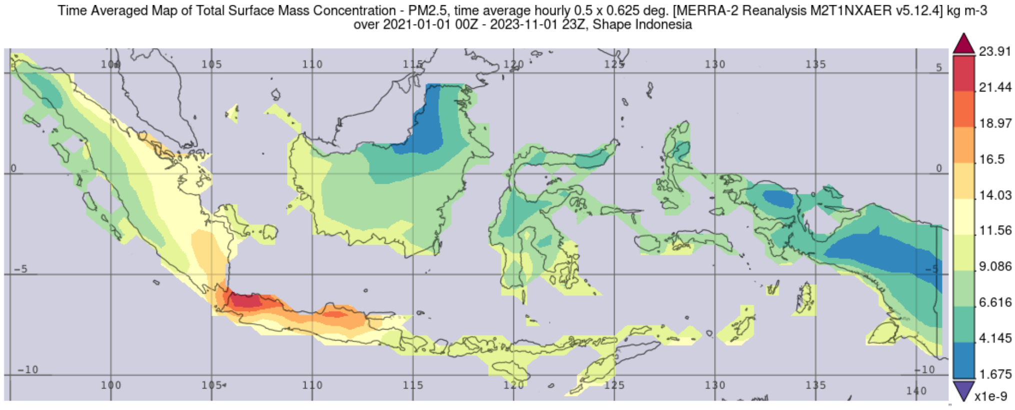


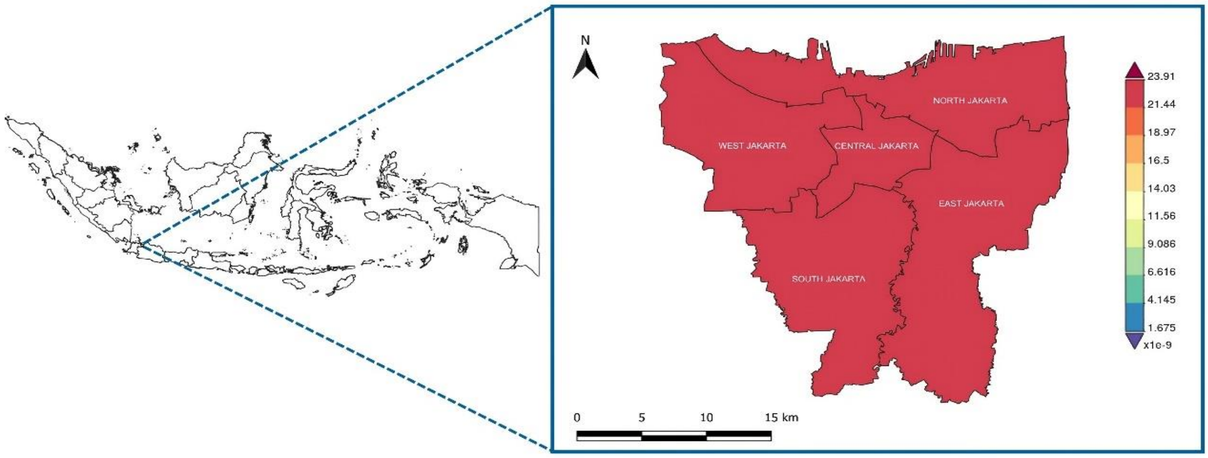
Figure 1 Flowchart of methodology

A. Study Area

DKI Jakarta Province is located between 6°12' South Latitude and 106°48' East Longitude. This province is a low-lying area with land area of 662.33 km^2 and average elevation of 7 meters above sea level. Based on its geographical position, the province is bordered by West Java Province from south to the east and shares boundaries with Banten Province to the west. On the northern side, DKI Jakarta extends along the coast from west to the east for a length of 35 km, serving as the estuary for 9 rivers and 2 canals [30].



(a)



(b)

Figure 2 **(a)** Spatial distribution of PM2.5 concentrations in Indonesia and **(b)** area averaged of PM2.5 concentrations in DKI Jakarta Province during the period of 2021-2023

According to Figure 2a, it is evident that the northern regions of Java Island, particularly in the DKI Jakarta Province and its vicinity, display elevated concentrations of PM2.5 in comparison to other geographical areas. Satellite data derived from the Modern-Era Retrospective Analysis for Research and Applications (MERRA-2) further indicates that the average aggregate PM2.5 concentration in the DKI Jakarta Province over the past three years amounts to 23.9074 μgram/m^3, surpassing the designated threshold for favorable conditions (0 – 15 μgram/m^3) as shown in Figure 2b. Consequently, this research is specifically oriented towards the DKI Jakarta Province, encompassing East Jakarta, North Jakarta, South Jakarta, Central Jakarta, and West Jakarta.

B. Data and Variables

This research utilizes meteorological variables, including air temperature, surface humidity, precipitation, and wind speed, to investigate their impact on PM2.5 concentrations in the DKI Jakarta Province. The data is derived from the MERRA-2 satellite, covering the period from January 1, 1980, to November 1, 2023, with hourly intervals. The initial observation values for each variable represent aggregated averages over specific areas. Details regarding the number of observations and units for the variables employed in this research can be found in Table 1.

MERRA-2 constitutes a satellite equipped with a long-term reanalysis model developed by the Global Modeling and Assimilation Office (GMAO) at NASA, as outlined by Gelaro et al. [31]. This satellite is instrumental in furnishing a spectrum of meteorological and aerosol parameters spanning from the year 1980 to the present. The MERRA-2 model incorporates the atmospheric model from the Goddard Earth Observing System (GEOS) and employs the Grid Point Statistical Interpolation (GSI) scheme. Operating at a spatial resolution of 0.5° × 0.625°, the model comprises 72 vertical pressure layers extending from the surface to 0.01 hPa. Furthermore, it integrates a three-dimensional variational data assimilation algorithm, refreshed at six-hour intervals for analysis, as detailed by Sayeed et al. [32].

Table 1 Research variables

Variable	Name	Units	Obs.
Y	PM2.5 Concentrations	kg/m³	384,263
X1	Wind speed	m/s	384,263
X2	Air temperature	C	384,263
X3	Surface humidity	-	384,264
X4	Precipitation	mm/hour	384,264

The data was sourced from the MERRA-2 satellite at a spatial resolution of 0.5° × 0.625°. Specifically, each satellite data pixel represents an area of approximately 50 km × 65 km. Considering the constraints in resolution and the geographical extent of the study site, the examination of PM2.5 concentrations in DKI Jakarta was conducted at the provincial level. In addition to the inherent low resolution, the data obtained from the MERRA-2 satellite is constrained by the absence of daily period data. Research conducted by Xu et al. underscores the significant day-to-day fluctuations in PM2.5 concentrations [33]. To capture data variations more effectively, this study concentrated its analytical efforts on daily periods. Before conducting the analysis, a data preprocessing stage was implemented to aggregate hourly data into daily periods. The outcomes of the preprocessing stage reveal a total of 16,009 daily period data points for each observed variable.

C. Stationarity Test

A stationarity test was conducted on the aggregated daily data before employing the VAR model for analysis. According to Basuki & Prawoto, a time series is deemed stationary if it lacks unit roots. In this research, the Augmented Dickey Fuller (ADF) test was utilized to ascertain the stationarity of the data [34]. Detection of unit roots involves comparing the t-statistics against the Critical Value MacKinnon. A dataset is identified as stationary when the absolute value of t-statistics exceeds the Critical Value MacKinnon or when the significance value is less than α = 0.05 [35]. The equation model applied in the ADF test is explicated as follows:

$$\Delta Y_t = \beta_1 + \beta_2 t + \delta Y_{t-1} + \alpha_i \sum_{i=1}^{m} \Delta Y_{t-i} + e_t \quad (1)$$

m is the lag length.

D. Optimum Lag Determination

Following the application of the ADF test to assess stationarity, the identification of the optimal lag length for model formulation ensued. In the context of VAR modeling, the determination of both short and long spans or lags is a pivotal phase. A model with an excessively short lag may pose interpretability challenges, while an overly extended lag may result in inefficiency [34]. In this research, the selection of the optimal lag relied on three criteria: Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC), and Hannan-Quinn Information Criterion (HQ). The mathematical expressions employed for computing these criteria are explicated as follows:

$$AIC = -2\left(\frac{1}{T}\right) + 2(k + l) \quad (2)$$

$$SIC = -2\left(\frac{1}{T}\right) + k\left(\frac{log\ (T)}{T}\right) \quad (3)$$

c

$$HQ = -2\left(\frac{1}{T}\right) + 2k\left(\frac{log\ (T)}{T}\right) \quad (4)$$

l is the sum square residual, T is the number of observations, and k is the number of parameters.

E. Granger Causality Test

An examination of Granger causality is conducted on the observed variables before estimating parameter of the VAR model. The Granger causality test serves to identify the presence of causal relationships or consequential links between one variable and another. Essentially, this test is instrumental in determining whether a given dependent variable may be influenced by an independent variable, while reciprocally, the independent variable may assume the role of a dependent variable [36]. The equation model employed in the Granger causality test is delineated as follows:

$$Y_t = \sum_{i=1}^{m} \alpha_i Y_{t-i} + \sum_{i=1}^{m} \beta_i X_{t-i} + e_t \quad (5)$$

where m is the lag length, α_i is the coefficient of the ith lag on Y variable, and β_i is the coefficient of the ith lag on X variable.

F. Vector Autoregressive (VAR)

Christopher A. Sims originally introduced the VAR model for macroeconomic analysis in 1980 [37]. The VAR model constitutes a system of equations, representing all variable components as a linear function of a constant value and lags derived from variables within the system [38]. This research utilizes a VAR model to examine meteorological variables such as wind speed, air temperature, surface humidity, and rainfall, and investigate their impact with PM2.5 concentrations within the DKI Jakarta Province. The equation model employed in the VAR framework is articulated as follows:

$$Y_t = A_0 + A_1 Y_{t-1} + A_2 Y_{t-2} + \cdots + A_p Y_{t-p} + e_t \,, \quad \text{or} \tag{6}$$

$$Y_t = A_0 + \sum_{n=1}^{p} A_n Y_{t-n} + e_t \tag{7}$$

where A_0 is a vector of constant values or intercepts and A_n is a matrix of parameter values.

The parameters of the VAR model are deduced through the Ordinary Least Squares (OLS) method. As per Salsabila et al., OLS stands out as the most widely used method for VAR model estimation. OLS estimates parameters by minimizing the sum of squared errors within a model [39]. Additionally, Gujarati underscores the simplicity of the OLS method in model estimation, as it does not necessitate intricate separation with other variables [40]. In essence, OLS emerges as a straightforward and effective estimation approach in comparison to more intricate methods.

G. Impulse Response Function (IRF)

Following the estimation of the VAR model, an analysis of Impulse Response Functions (IRF) is undertaken to examine the influence of shocks on individual variables. The IRF analysis serves as a method to discern the response of an endogenous variable to perturbations in a specific variable. Through IRF analysis, the response to a one-standard-deviation independent change can be systematically assessed. Beyond scrutinizing shocks, this analysis also facilitates the exploration of the impact of disturbances equivalent to one standard error. Such disturbances represent innovations in one endogenous variable and their subsequent effects on other endogenous variables within the dynamic structure of the VAR model [41]–[44].

H. Forecast Error Decomposition of Variance (FEDV)

This research employs FEDV analysis in addition with IRF to assess the magnitude of the impact of shocks on individual variables. FEDV analysis, also known as Forecast Error Variance Decomposition, is a method utilized to dissect innovations in a variable concerning the constituent components of other variables within the VAR model. The information encapsulated in FEDV provides insights into the proportion of sequential movements induced by shocks [45]–[48]. Through the computation of the percentage of squared prediction errors for a variable resulting from innovations in other variables, the forecasting errors of said variable attributable to its own dynamics and those of other variables can be discerned [41].

IV. RESULTS AND DISCUSSIONS

In order to confirm the findings of previous studies that meteorological variables, which in this case are represented by surface humidity, air temperature, wind speed, and precipitation, have an influence on fluctuations in PM2.5 concentrations, especially in DKI Jakarta Province specifically, an in-depth exploration of the data used was first carried out. Figure 3 presents a time series graph of daily fluctuations of meteorological variables used to identify patterns, trends, and fluctuations in the data throughout the study period from 1980 to 2023. From Figure 3, it can be seen that the surface moisture level in DKI Jakarta Province from 1980 to 2023 fluctuates significantly throughout the period, with values ranging from about 0.015 to 0.025. These fluctuations may reflect seasonal variations or long-term climate change. Then for air temperature in DKI Jakarta Province from 1980 to 2023 is known to range between 25°C and 30°C. Although there were some temperature spikes above and below this range, there was no clear increasing or decreasing trend during the period. Furthermore, on the wind speed variable (in meters per second) in DKI Jakarta Province from 1980 to 2023, it can be seen that there are variations with significant fluctuations throughout the time period. There are some prominent peaks, indicating days with very high wind speeds. Although there are large variations in the data, there is no clear upward or downward trend in average wind speed over time. Finally, for the precipitation variable (in mm per hour) in DKI Jakarta Province from 1980 to 2023 it is known that there is significant variation throughout the period, with some notable peaks. While there are fluctuations, there is no clear trend of an overall increase or decrease in precipitation over this time period.

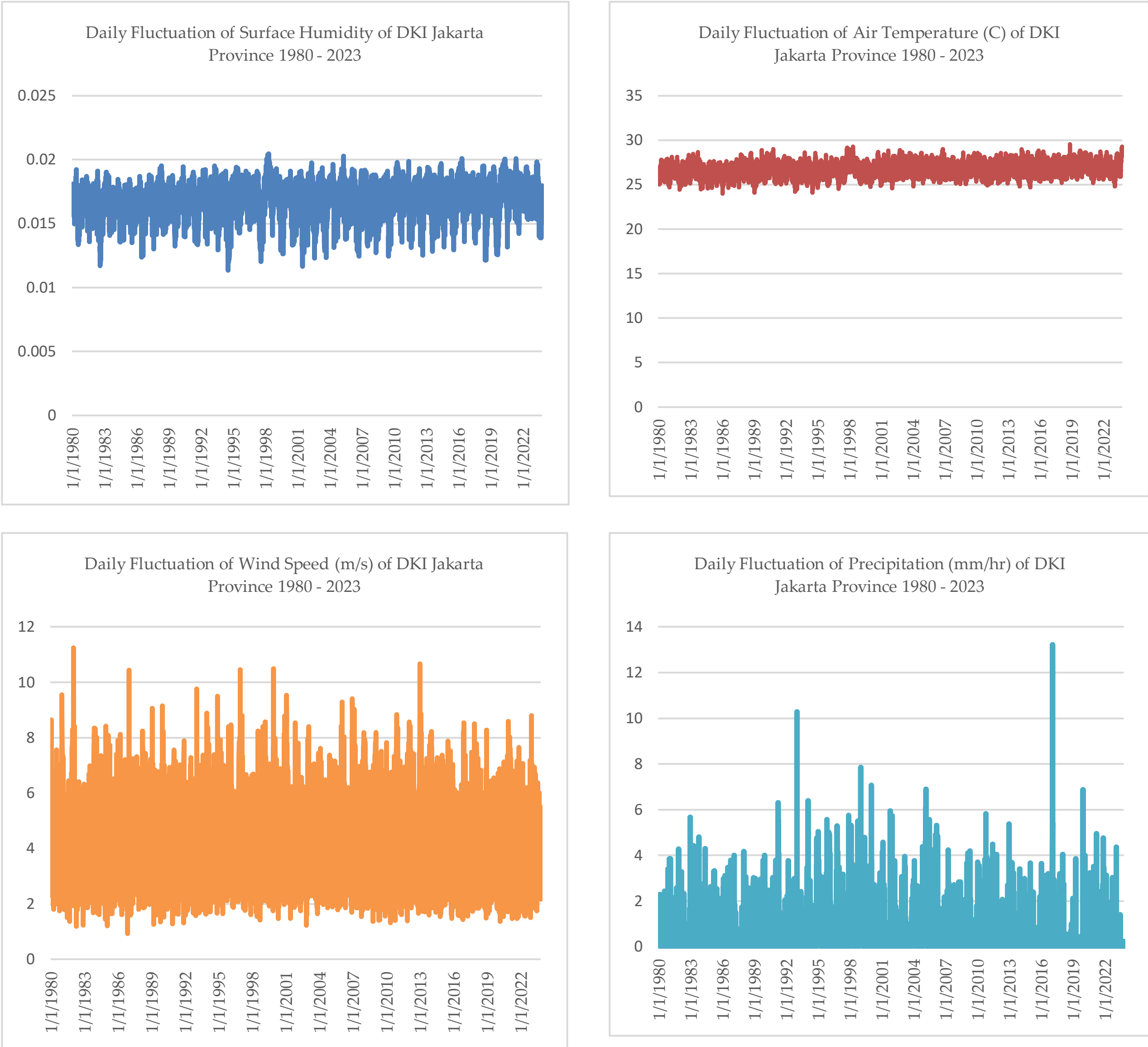


Figure 3 Daily fluctuations of meteorological variables of DKI Jakarta Province 1980 - 2023

To further identify the recent fluctuations of the meteorological variables used, Figure 4 is presented, covering the last year of the study period used, 2023. In Figure 4, it is clear that the surface moisture experienced significant fluctuations throughout 2023 with values ranging between 0.015 and 0.025, with some noticeable peaks and valleys. Although there are high daily variations, it can be seen that surface humidity in DKI Jakarta Province has a downward trend throughout the year. As for the air temperature variable, it can be seen that there are significant fluctuations, with some noticeable peaks and valleys throughout 2023. Although there is considerable daily variation, there is a clear upward trend in temperature from January to November, as shown by the trend line. Then on the wind speed variable, it can be seen that there are significant variations throughout 2023. There are several peaks that show a sharp increase in wind speed, but there are also times when the wind speed is relatively low. This indicates that weather conditions and wind circulation in Jakarta are very dynamic and can change rapidly with a downward trend. Finally, in the precipitation variable, it can be seen that there are several significant precipitation peaks, especially around March 2023. In general, the fluctuations show that precipitation varies from day to day, with some days experiencing a sharp increase in precipitation intensity but with a decreasing trend throughout 2023.

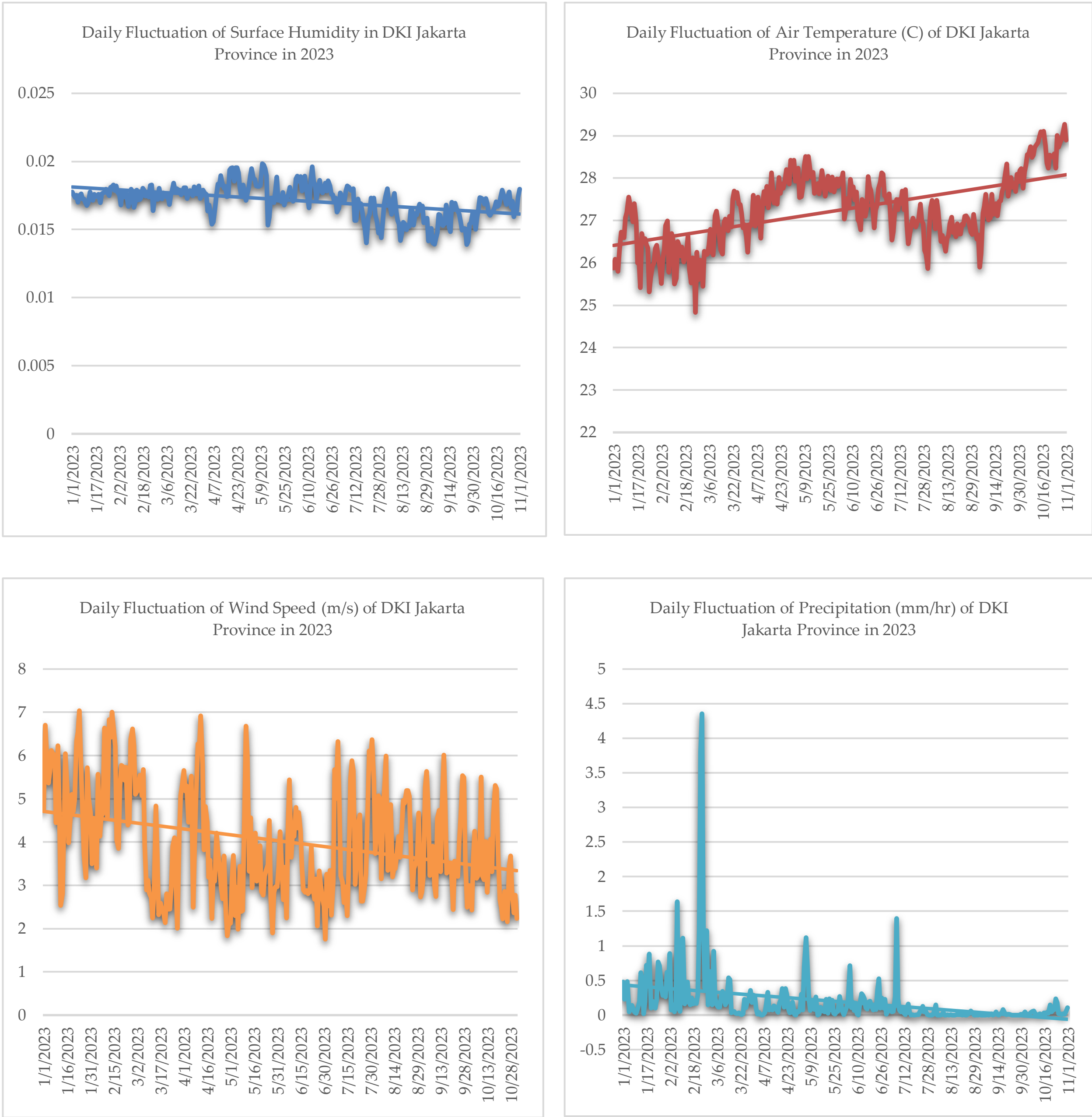
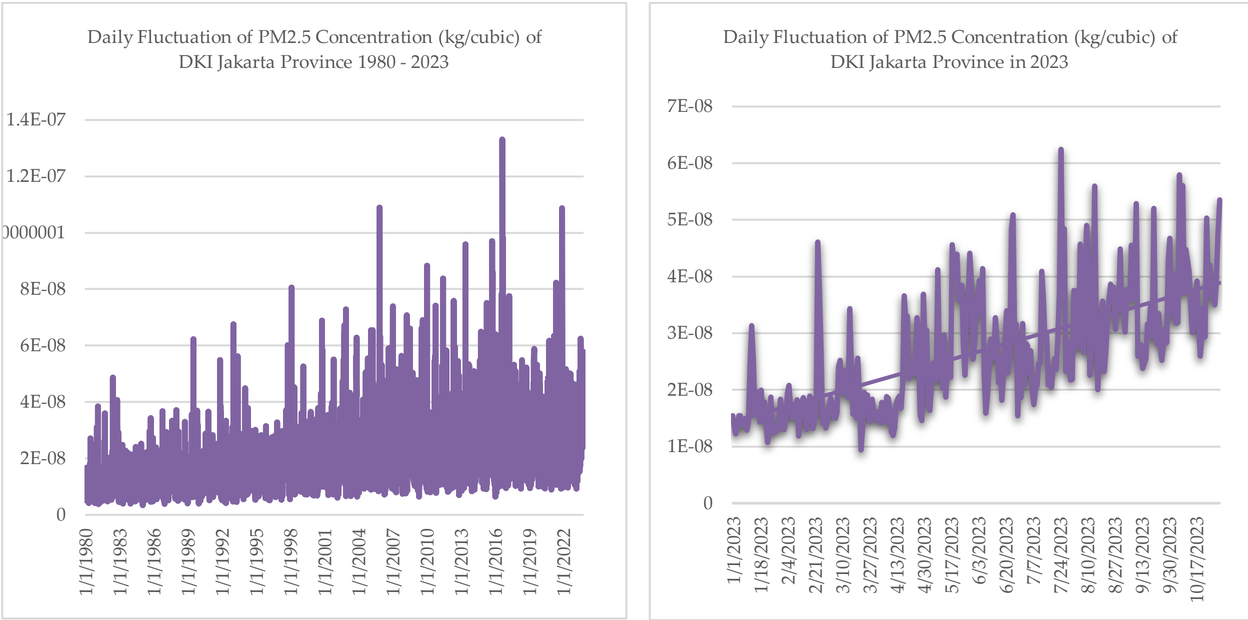


Figure 4 Daily fluctuations of meteorological variables of DKI Jakarta Province in 2023

Figure 5 specifically presents the daily fluctuations of the endogenous variable in this study, namely the concentration of PM2.5 in DKI Jakarta Province for the 43-year observation period, namely 1980 to 2023 and the one-year observation period, namely during 2023. Figure 5 shows that the level of air pollution represented by PM2.5 concentration fluctuates significantly from 1980 to 2023. In addition, there are also several high peaks that signify a drastic increase in fine particle concentrations, which may be caused by meteorological variables that are exogenous to the present study. As for the special observation period of 2023, it can be seen that the PM2.5 concentration variable has significant variations. There are several high peaks that show a sharp increase and an increasing trend during 2023 in the particle concentration and may be caused by meteorological variables such as surface humidity, air temperature, wind speed, and precipitation.



(a) **(b)**

Figure 5 **(a)** Daily fluctuation of PM2.5 concentration in DKI Jakarta Province 1980 - 2023 and **(b)** daily fluctuation of PM2.5 concentration of DKI Jakarta Province in 2023

A. *Stationarity Test*

The results of stationarity testing using the Augmented Dickey Fuller (ADF) test are presented in Table 2.

Table 2 Stationarity testing results using augmented dickey fuller

Variable	ADF (Level)		
	t-statistics ADF	Critical Value MacKinnon (5%)	Prob*
Precipitation	−16,094	−2.861	< 0.001
Wind Speed	−26.394	−2.861	< 0.001
Surface Humidity	−11.932	−2.861	< 0.001
PM2.5 Concentration	−7.653	−2.861	< 0.001
Air Temperature	−12.221	−2.861	< 0.001

In this case the data is said to be stationary if the absolute value of the ADF t-statistics is greater than the MacKinnon criterion value at the 5% significance level or the p-value obtained is smaller than the significance level used which is 0.05. So based on the values obtained in Table 2, it is known that all the variables used have been stationary at the level without having to do the differencing process.

B. *Optimum Lag Determination*

In order to optimize the Akaike Information Criterion (AIC), Schwarz Criterion (SC), and Hannan-Quinn Criterion (HQ) while considering the stability of the model, the selection of the optimum lag is based on tracking the lag that has the minimum AIC, SC, and HQ values. Table 3 presents the results of the optimal lag search. Table 3 shows that the smallest SC (-41.91706) value is located at the seventh lag, so the optimum lag value is seven.

Table 3 Optimum lag determination results

Lag	AIC	SC	HQ
0	−37.94161	−37.93921	−37.94082
1	−41.68456	−41.67014	−41.67979
2	−41.82919	−41.80277	−41.82045
3	−41.88391	−41.84547	−41.87119
4	−41.93696	−41.88651	−41.92027
5	−41.96925	−41.90680	−41.94860
6	−41.98515	−41.91068	−41.96052
7	**−42.00354**	**−41.91706** *	**−41.97494**
8	−42.00777	−41.90928	−41.97519

C. Granger Causality Test

The Granger Causality test is conducted to determine the causal relationship between each variable with each other. The existence of a causal relationship in the variables used in building the model indicates that the model built contains the right variables because each variable can become an endogenous variable so that it is suitable for the application of the vector autoregressive model. Table 4 shows the results of the Granger Causality test.

Table 4 Granger causality test results

Hipotesis Null	Obs	F-Statistics	p-value
Wind speed does not granger cause precipitation	16009	4.895	2×10^{-5}
Precipitation does not granger cause wind speed		11.416	2×10^{-14}
Surface humidity does not granger cause precipitation	16009	43.701	1×10^{-61}
Precipitation does not granger cause surface humidity		39.693	1×10^{-55}
PM2.5 concentration does not granger cause precipitation	16009	20.671	7×10^{-28}
Precipitation does not granger cause PM2.5 concentration		52.108	6×10^{-74}
Air temperature does not granger cause precipitation	16009	3.805	4×10^{-4}
Precipitation does not granger cause air temperature		39.573	2×10^{-55}
Surface humidity does not granger cause wind speed	16009	2.379	2×10^{-2}
Wind speed does not granger cause surface humidity		39.648	1×10^{-55}
PM2.5 concentration does not granger cause wind speed	16009	4.953	1×10^{-5}
Wind speed does not granger cause PM2.5 concentration		26.403	3×10^{-36}
Air temperature does not granger cause wind speed	16009	26.081	9×10^{-36}
Wind speed does not granger cause air temperature		4.124	2×10^{-4}
PM2.5 concentration does not granger cause surface humidity	16009	6.996	2×10^{-8}
Surface humidity does not granger cause PM2.5 concentration		11.898	3×10^{-15}
Air temperature does not granger cause surface humidity	16009	111.443	3×10^{-160}
Surface humidity does not granger cause air temperature		9.163	2×10^{-11}
Air temperature does not granger cause PM2.5 concentration	16009	28.178	8×10^{-39}
PM2.5 concentration does not granger cause air temperature		6.678	6×10^{-8}

Based on Table 4, it is known that the p-value for the entire null hypothesis stating the causal relationship between variables is partially smaller than the significance level used (0.05). Thus, it can be said that all variables used have a reciprocal (two-way) relationship. This condition indicates that the variables used in building the VAR model are appropriate because all variables can be positioned as endogenous variables including the PM2.5 concentration variable which is the specific endogenous or dependent variable in this study.

D. Parameter Estimation of Vector Autoregressive Model

In the process of estimating the parameters of the VAR model with PM2.5 concentration as the dependent variable, the method used is Ordinary Least Square. Then because the range of values of each variable used is quite large, the logarithmic transformation of all variables is carried out so that the resulting VAR model is simpler and easier to interpret. Consequently, the VAR model built will lead to the principle of elasticity. Table 5 presents the parameter coefficients of the VAR model constructed using the Ordinary Least Square method.

Table 5 Model parameter coefficients of ordinary least square estimation results

Parameter	Coefficient of Estimation Results	Parameter	Coefficient of Estimation Results
Constant	−3.5416	Log(precipitation (-2))	−0.0062
Log(wind speed (-1))	0.0922	Log(precipitation (-5))	−0.0039
Log(wind speed (-3))	0.0988	Log(PM2.5 (-1))	0.5272
Log(air temperature (-1))	1.4458	Log(PM2.5 (-2))	0.0368
Log(air temperature (-4))	−0.4364	Log(PM2.5 (-3))	0.0527
Log(surface humidity (-1))	0.2173	Log(PM2.5 (-4))	0.0709
Log(surface humidity (-3))	−0.2199	Log(PM2.5 (-5))	0.0521
Log(surface humidity (-6))	0.1922	Log(PM2.5 (-6))	0.0328
Log(precipitation (-1))	−0.0127	Log(PM2.5 (-7))	0.0902

Based on Table 5, the VAR model equation for PM2.5 concentration as the dependent variable can be written as follows:

$$\begin{aligned}\log(Y_t) = {} & -3{,}5416 + 0{,}0922\log(X_{1_{t-1}}) + 0.0988\log(X_{1_{t-3}}) + 1.4458\log(X_{2_{t-1}}) - 0.4364\log(X_{2_{t-4}}) \\ & + 0.2173\log(X_{3_{t-1}}) - 0.2199\log(X_{3_{t-3}}) + 0.1922\log(X_{3_{t-6}}) - 0.0127\log(X_{4_{t-1}}) \\ & - 0.0062\log(X_{4_{t-2}}) - 0.0039\log(X_{4_{t-5}}) + 0.5272\log(Y_{t-1}) + 0.0368\log(Y_{t-2}) \\ & + 0.0527\log(Y_{t-3}) + 0.0709\log(Y_{t-4}) + 0.0521\log(Y_{t-5}) + 0.0328\log(Y_{t-6}) \\ & + 0.0902\log(Y_{t-7})\end{aligned} \quad (8)$$

Equation(8) above can be interpreted that changes in PM2.5 concentrations in DKI Jakarta Province every day are influenced by wind speed the day before (increasing PM2.5 concentrations by 0.092%), wind speed three days before (increasing PM2.5 concentrations by 0.098%), air temperature the day before (increasing PM2.5 concentrations by 1.445%), air temperature four days before (decreasing PM2.5 concentrations by 0.436%), surface humidity the day before (increasing PM2. 5 concentrations by 0.217%), surface humidity three days before (decreased PM2.5 concentration by 0.219%), surface humidity six days before (increased PM2.5 concentration by 0.192%), rainfall one day before (decreased PM2.5 concentration by 0.012%), rainfall two days before (decreased PM2. 5 concentration by 0.006%), rainfall five days before (decreased PM2.5 concentration by 0.003%), PM2.5 concentration one day before (increased PM2.5 concentration by 0.527%), PM2.5 concentration two days before (increased PM2.5 concentration by 0.036%), PM2.5 concentration three days before (increasing PM2.5 concentration by 0.052%), PM2.5 concentration four days before (increasing PM2.5 concentration by 0.070%), PM2.5 concentration five days before (increasing PM2.5 concentration by 0.052%), PM2.5 concentration six days before (increasing PM2.5 concentration by 0.032%), PM2.5 concentration seven days before (increasing PM2.5 concentration by 0.090%).

E. Impulse Response Function (IRF) and Forecast Error Decomposition of Variance (FEDVs) Analysis

The results of the IRF are depicted in Figure 6. In the IRF, for the endogenous variable (PM2.5 concentration), any shock to the exogenous variable causes an impulse response close to zero, indicating the stability of the constructed VAR model. The response of the change in PM2.5 concentration due to a shock to the change in rainfall is almost zero (slight variation in the initial path and thereafter, no change in the time path). The same conclusion applies to changes in wind speed, changes in surface humidity, and changes in air temperature, indicating the weak explanatory power of these exogenous variables. In the case of PM2.5 concentration changes alone, we observe a negative trend, with a drastic drop from 25% to about 5% in the early stages, and after more than 60 days, the shocks are close to zero. The attention to the negative trend in the impulse response of PM2.5 concentration to changes in itself is an interesting finding. The drastic drop initially, followed by a slow approach to zero after more than 60 days, illustrates that the impact of changes in PM2.5 concentration in earlier days on changes in later days tends to be stronger and last longer. This suggests a cumulative effect that needs to be considered in understanding the dynamics of air quality. Therefore, the impulse response function summarizes that the impact of changes in PM2.5 concentrations in previous days on changes in PM2.5 concentrations in subsequent days tends to be stronger and last longer than other explanatory variables.

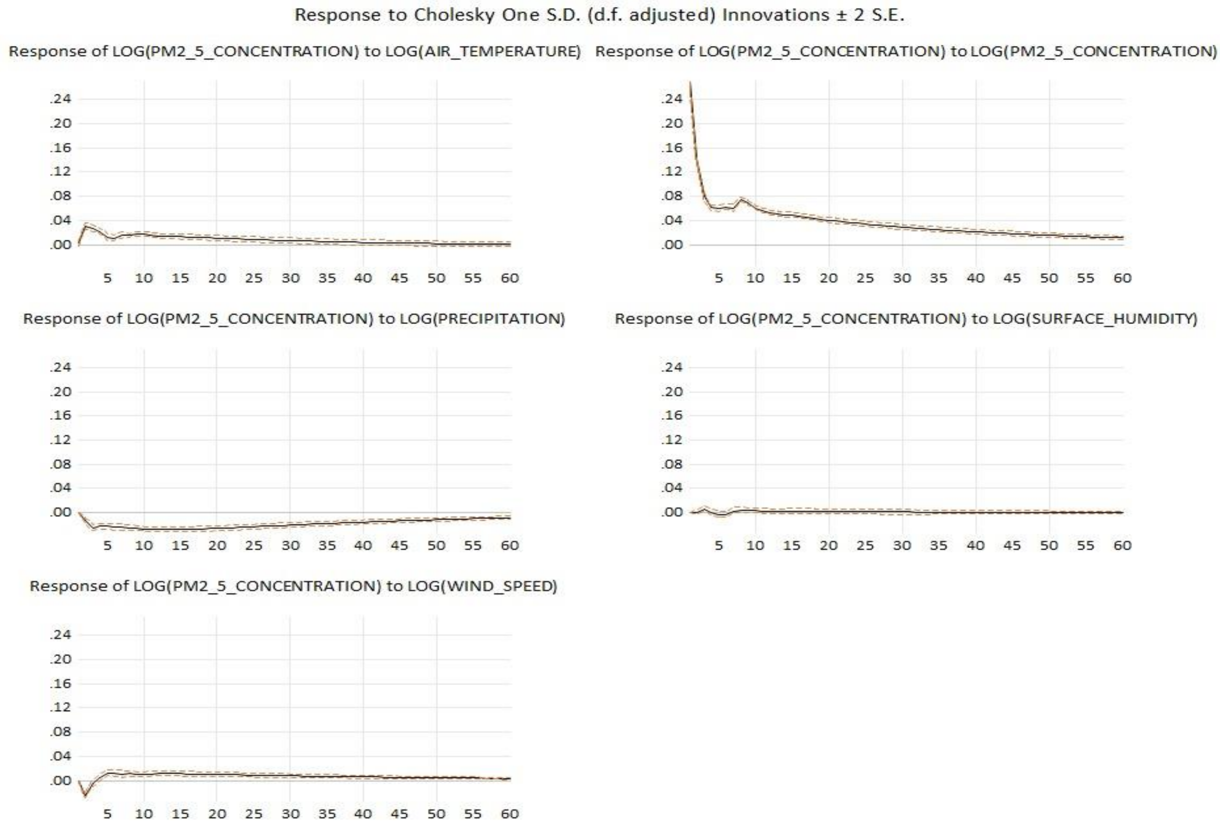


Figure 6 Impulse response function (IRF) analysis

The results of the FEDV visualization are presented in Figure 7. In this case, the Variance Decomposition (VDC) is calculated over a 200-day forecast horizon to determine how much of the forecast error variance for the variables in the model can be explained by the contributions to each explanatory variable. The change in PM2.5 concentration in DKI Jakarta Province is influenced by the shock itself, which is 94.63% on the second day, which then gradually decreases to 88.14% in the next 200 days (see Figure 7). Thus, in the long run, the influence of the PM2.5 concentration variable shocks themselves will continue to decrease. The VDC results also reveal the explanatory power of the other exogenous variables. Within a period of 10 days (short term), the variables of rainfall, wind speed, surface humidity, PM2.5 concentration, and air temperature can explain 3.12%; 1.99%; 0.64%; 93.14%; and 1.09% of the variation in the growth of PM2.5 concentration in DKI Jakarta Province. Therefore, in the short term, the variation in the growth of PM2.5 concentration in DKI Jakarta Province can be better explained successively by the PM2.5 concentration itself, followed by rainfall, and wind speed. Meanwhile, for 200 days (long term), the contribution of rainfall, wind speed, surface humidity, PM2.5 concentration, and air temperature to explain the variation in PM2.5 concentration growth is 8.61%; 1.72%; 0.47%; 88.14%; and 1.07%. Therefore, we can conclude that PM2.5 concentration has the maximum explanatory power to explain the growth of PM2.5 concentration in DKI Jakarta Province, both in the short and long term. In addition, it is also known that wind speed, surface humidity, and air temperature have better explanatory power in the short-term when compared to the long-term perspective while rainfall has better explanatory power in the long-term when compared to the short-term perspective to explain the variation in PM2.5 concentration growth in DKI Jakarta Province.

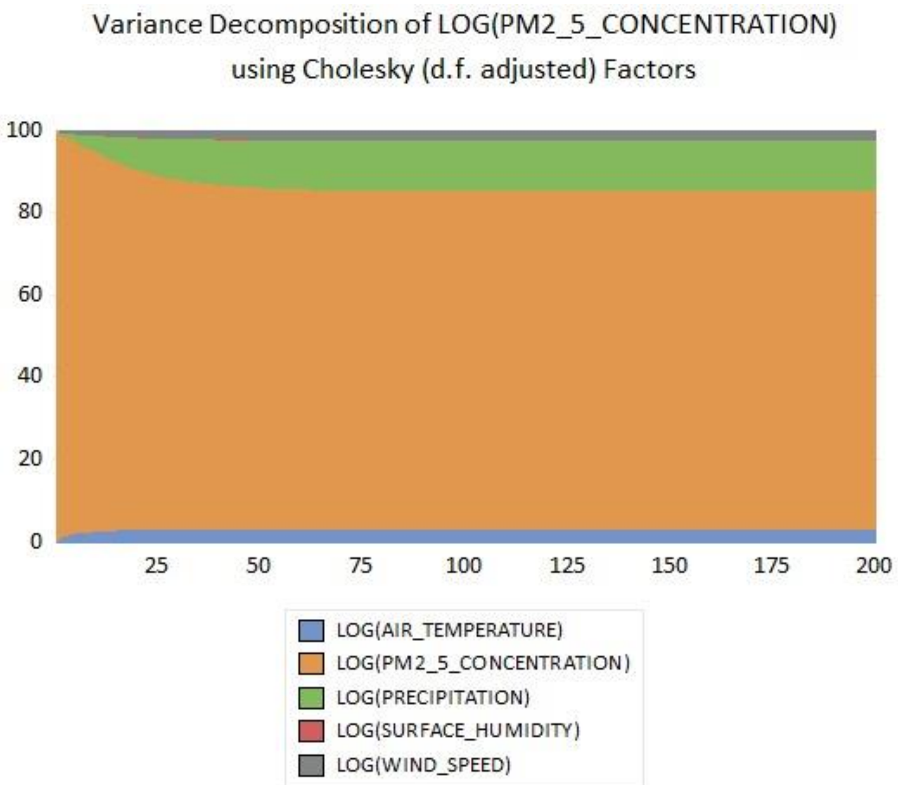


Figure 7 Forecast error decomposition of variance (FEDVs) analysis

With this finding, it can be said that the constructed VAR model has a tendency to show that meteorological variables have low explanatory power on PM2.5 concentrations, while changes in PM2.5 concentrations themselves can have a sustained impact in the short and long term. These findings tend to contradict the results of studies conducted by Vaishali, (2023) and Zhao (2016), who respectively found that meteorological variables such as surface humidity, air temperature, wind speed, and precipitation have a significant influence on decline and growth. This could be due to the different geographical conditions of the research locus and the possibility of other variables apart from the meteorological side that have a significant influence specifically on PM2.5 concentrations in DKI Jakarta Province.

V. CONCLUSIONS

Changes or growth in PM2.5 concentrations in DKI Jakarta when viewed from a meteorological aspect are influenced by wind speed the day before, wind speed three days before, air temperature the day before, air temperature four days before, surface humidity the day before, surface humidity three days before, surface humidity six days before, rainfall the day before, rainfall two days before, rainfall five days before, and PM2.5 concentrations the day, two days, three days, four days, five days, six days, and seven days before. However, the constructed VAR model shows that the meteorological variables, which in this case are surface humidity, air temperature, wind speed, and rainfall, have low explanatory power on PM2.5 concentrations. This finding is based on the IRF and FEDVs analysis which shows that the variable with the greatest explanatory power for fluctuations in PM2.5 concentrations in DKI Jakarta Province is the PM2.5 concentration variable itself, followed by the rainfall variable, then the wind speed variable, the surface humidity variable, and finally the air temperature variable. Based on these findings, in order to reduce PM2.5 concentrations in DKI Jakarta Province which tend to continue to increase, the DKI Jakarta government is advised to explore variables outside of meteorological elements before formulating policies aimed at improving air quality. The exploration process can be collaborated with expert researchers to develop a more comprehensive model by considering additional factors that can affect air quality, such as industrial activity, transportation, and land use. In addition, spatial analysis can also be conducted by observing differences in air pollution in various regions in DKI Jakarta, and more detailed temporal analysis to understand the seasonal and long-term trends of PM2.5 concentrations in DKI Jakarta Province more deeply.

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