Frontiers in Health Informatics
ISSN-Online: 2676-7104
www.healthinformaticsjournal.com
2024; Vol 13: Issue 8
Open Access

Application of the CMAQ Model to Assess the Vertical Distribution of PM2.5 Pollution in the Hanoi Area

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Cite this paper as: Duy An Dam, Thi Thanh Huong Chu, Thi Thu Trang Phung, Van Linh Le, Nguyen Quoc Phi, Hong Hiep Nguyen, Quang Lam Nguyen, Thi Thanh Binh Do, Khanh Vy Vu, Dam Vu Van(2024). Application of the CMAQ Model to Assess the Vertical Distribution of PM2.5 Pollution in the Hanoi Area. *Frontiers in Health Informatics*, *13 (8) 2817-2829*

Abstract

The study applies the CMAQ model, and combine with the WRF model, to analyze the vertical distribution of PM2.5 pollution in Hanoi, Vietnam, highlighting the city's severe air quality challenges. Simulations show a significant decline in PM2.5 concentrations with altitude, ranging from 50–84 µg/m³ at 30 meters to 34–40 µg/m³ at 320 meters, with urban hotspots exceeding Vietnam's air quality standard of 50 µg/m³ and the WHO guideline of 25 µg/m³. Seasonal analysis reveals higher concentrations from autumn to winter due to temperature inversions and low mixing heights, which trap pollutants near the ground. Despite capturing these trends, the model exhibited substantial errors, including a Mean Absolute Percentage Error of 63%, a Mean Absolute Error of 18 µg/m³, and an RMSE of 377 µg/m³, indicating challenges in incorporating local meteorology, urban architecture, and vegetation effects. The findings underscore the importance of integrating localized data and improved modeling to enhance the accuracy of PM2.5 predictions and inform effective air quality management and urban planning strategies in Hanoi.

1. Introduction:

1.1. Overview of Studies on PM2.5 Particulate Matter

Fine particulate matter PM2.5, defined as airborne particles with an aerodynamic diameter of 2.5 micrometers or smaller, is a hazardous component of air pollution in both urban and rural areas worldwide (Cohen et al., 2017; Manisalidis, 2020). Due to its ability to penetrate deeply into the respiratory and circulatory systems, PM2.5 has been closely linked to a wide range of adverse health effects, including respiratory and cardiovascular diseases, cancer, and even neurological issues (Brook et al., 2010; Pope & Dockery, 2006; World Health Organization, 2021).

As a result, understanding the sources, composition, spatial and temporal distribution of PM2.5, as well as its impacts on health and the environment, is of utmost importance and has garnered significant attention from the scientific community in recent years (Apte et al., 2018; Burnett et al., 2018; Lelieveld et al., 2019). Recent studies continue to emphasize the role of PM2.5 as a leading environmental risk factor for global public health (Koulova et al., 2014; GBD 2019 Diseases & Injuries Collaborators, 2020; Vohra et al., 2021).

Recent studies on PM2.5 have focused on various critical aspects. Some research has delved into identifying and analyzing the diverse sources of PM2.5 emissions, including anthropogenic sources (such as traffic, industry, and fossil fuel combustion) and natural sources (such as wildfires and desert dust) (Crippa et al., 2019; Zhang et al., 2018;

Lalchandani et al., 2021). Advanced methods, such as isotope analysis and atmospheric chemical modeling, are increasingly being used to trace the origins and track the transport of PM2.5 particles (Qiao et al., 2018; Li et al., 2024; Li et al., 2020). Moreover, climate change has been documented to significantly influence the concentration and composition of PM2.5 in many regions worldwide (Fiore et al., 2015; Demain et al., 2018), driving studies on the interactions between air pollution and climate change.

Research on the health impacts of PM2.5 remains a focal area. Large-scale epidemiological studies continue to provide evidence linking both long-term and short-term PM2.5 exposure to cardiovascular diseases, respiratory disorders, diabetes, and neurological conditions (Shen et al., 2024; Chen et al., 2017; Andersen et al., 2022). Notably, recent studies have concentrated on vulnerable populations such as children, the elderly, and individuals with pre-existing health conditions (Guarnieri & Balmes, 2014; Newby et al., 2015; Yang et al., 2020). Furthermore, research on biological mechanisms is shedding light on how PM2.5 induces damage at cellular and molecular levels, paving the way for new directions in developing interventions and preventive measures (Shukla, 2019; Xia et al., 2006).

Monitoring and modeling PM2.5 concentrations across various spatial and temporal scales are crucial for assessing population exposure and formulating effective policies. Air quality monitoring networks, combined with satellite data and advanced modeling techniques, have provided deeper insights into the variability of PM2.5 (Hammer et al., 2020; van Donkelaar et al., 2015; Wei et al., 2021). Atmospheric chemical and statistical models are increasingly refined to forecast PM2.5 concentrations and evaluate the effectiveness of pollution control measures (Geng et al., 2021; Han et al., 2025). The development of low-cost sensors also offers opportunities for high-resolution PM2.5 monitoring at local levels (Karagulian, 2019).

1.2. Overview of Studies on Vertical Distribution of PM2.5 (Including Modeling)

In recent years, many studies have focused on the vertical distribution of PM2.5 concentrations to elucidate the three-dimensional variation of this pollutant and the factors influencing these changes. Early studies on the vertical distribution of PM2.5 primarily relied on in-situ measurements using aircraft, balloons, or observation towers (McKendry, I., 2003; Liu et al., 2020). However, these methods are often limited in spatial and temporal coverage and entail high deployment costs.

The development of remote sensing techniques, particularly the use of LiDAR and satellite sensors, has provided valuable tools for observing the vertical distribution of PM2.5 over broader areas (Li et al., 2017; Hidy et al., 2009). Despite their advantages, remote sensing data often require complex algorithms to infer PM2.5 concentrations from measured parameters and can be affected by factors such as cloud cover and atmospheric conditions (Chu et al., 2013; van Donkelaar et al., 2010).

The use of numerical models to simulate the vertical distribution of PM2.5 has become increasingly common and plays a crucial role in complementing and expanding the understanding gained from experimental measurements. These models can simulate the complex physical and chemical processes governing the distribution of PM2.5 in the atmosphere, including emissions, transport, chemical transformation, and deposition (Arimoto et al., 2006).

Chemical transport models (CTMs) such as WRF-Chem (Weather Research & Forecasting model coupled with Chemistry) (Grell et al., 2005), GEOS-Chem (Goddard Earth Observing System Chemistry) (Bey et al., 2001), and CMAQ (Community Multiscale Air Quality) (Byun & Schere, 2006; Appel et al., 2021) are widely used to simulate PM2.5 concentrations in the vertical dimension. These models solve conservation equations for mass, momentum, and energy to simulate the transport and chemical transformation of pollutants, including PM2.5, in the three-dimensional atmosphere.

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Trajectory models, such as HYSPLIT (Hybrid Single-Particle Lagrangian Integrated Trajectory) (Stein et al., 2015; Rolph et al., 2017), are used to track the pathways of air masses and estimate the origins of PM2.5 at a specific location. While these models do not directly simulate PM2.5 concentrations in the vertical dimension, they can provide indirect information on the vertical transport of PM2.5, especially when combined with observational data or simulations from CTMs.

1.3. Overview of Studies on the Vertical Distribution of PM2.5 in Hanoi

Hanoi, the capital of Vietnam, has attracted significant attention from the scientific community regarding air quality and air pollution issues, particularly PM2.5 concentrations. Numerous studies have been conducted to assess PM2.5 pollution levels, identify sources, and propose solutions to mitigate air pollution in Hanoi (Hien et al., 2002; Hien et al., 2011; Cohen et al., 2005).

Some studies have focused on evaluating the distribution of PM2.5 concentrations spatially and temporally. The study by Hai et al. (2013) showed that PM2.5 concentrations in Hanoi fluctuate seasonally, with the highest concentrations in winter and the lowest in summer. This result is consistent with earlier research by Hien et al. (2002). Furthermore, the study by Thuy et al. (2018) indicated that PM2.5 concentrations tend to be higher in the central city area and decrease as one moves away from the center. This can be explained by the high traffic density and the influence of industrial activities concentrated in the areas surrounding the city center (Thuy et al., 2018).

Other studies have focused on evaluating the vertical distribution of PM2.5 concentrations in Hanoi. The study by Ly et al. (2021) used the WRF-Chem model to simulate the vertical distribution of PM2.5 in the atmosphere. The results showed that PM2.5 concentrations decrease with height, with the highest concentrations found in the lower layers near the ground, and gradually decreasing as height increases. The study also indicated that mixing height and temperature inversion significantly affect the vertical distribution of PM2.5. Specifically, low mixing height and temperature inversion reduce the vertical dispersion of PM2.5, leading to its accumulation in the lower layers near the ground (Ly et al., 2021).

The study by Thi Thuy Trinh et al. (2019) investigated the impact of temperature inversion on air pollutant concentrations in Hanoi, Vietnam, during the 2011–2015 period. The study also assessed the relationship between temperature inversion and health issues caused by air pollution. Temperature inversion occurred most frequently from November to March. Data from monitoring stations showed a significant increase in concentrations of NO2, SO2, PM10, and PM2.5 during periods of strong temperature inversion.

From previous studies on the vertical distribution of PM2.5 in Hanoi, it is evident that researching and developing methods and models to assess PM2.5 by height is highly necessary. Although studies such as those by Ly et al. (2021) and Thi Thuy Trinh et al. (2019) have provided initial insights into the vertical distribution of PM2.5 and the influence of meteorological factors, there are still certain limitations. Existing models mainly rely on numerical simulations that have not been fully validated by vertical measurement data. Therefore, integrating field survey data will help verify and calibrate existing models, enabling a more accurate assessment of the impact of meteorological factors, such as temperature inversion, on the vertical distribution of PM2.5.

2. Research Methodology

WRF Model, CMAQ Model, Building Rooftop Measurements

2.1. Model Structure

In this study, the WRF (Weather Research & Forecasting) model and the CMAQ (Community Multiscale Air Quality) model are used to simulate PM2.5 concentrations in the vertical dimension. The WRF model is an advanced numerical weather prediction system developed by the U.S. National Center for Atmospheric Research (NCAR), widely used in meteorological and air quality research (Skamarock et al., 2008). The CMAQ model is a multiscale air quality model developed by the U.S. Environmental Protection Agency (US EPA) to simulate the dispersion, transport, and chemical transformation of pollutants in the atmosphere (Byun & Schere, 2006).

The WRF model provides meteorological conditions such as wind, temperature, pressure, and humidity in three-dimensional space, which are crucial inputs for the CMAQ model to calculate the dispersion and transformation of pollutants in the air. According to Pleim et al. (2014), the WRF-CMAQ combination has been proven effective in simulating PM2.5 concentrations in different atmospheric layers, especially in urban areas with complex meteorological conditions. Similarly, the study by Liu et al. (2021) showed that the WRF-CMAQ model helps recreate the vertical structure of PM2.5 in detail, providing essential information for assessing air pollution levels at different heights.

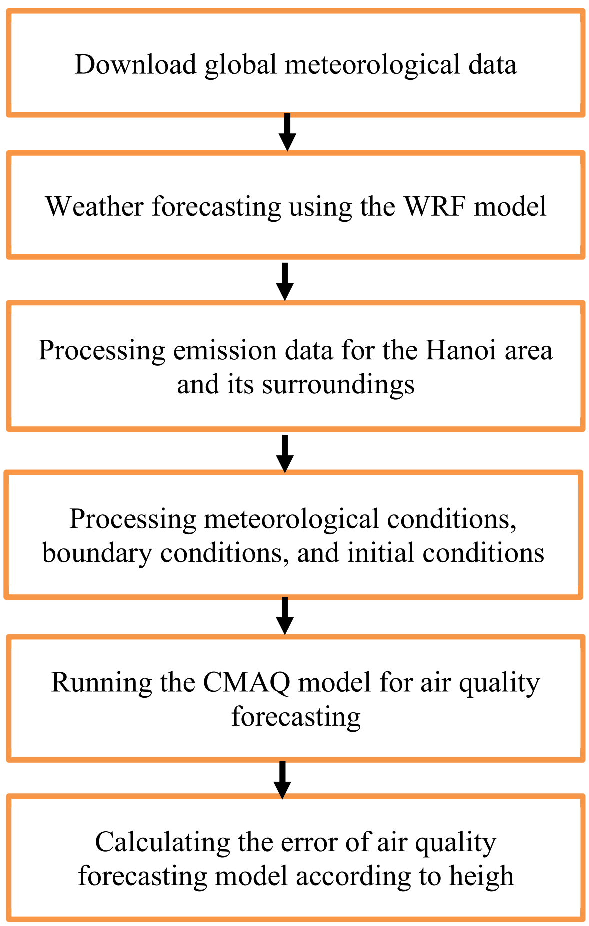

Figure 1: Flowchart of Calculation Steps

We calculated PM2.5 concentrations using the CMAQ model version 5.0.2. The Meteorology-Chemistry Interface Processor (MCIP) version 4.2 was applied to adjust the results from the Weather Research and Forecasting (WRF) model version 3.8.1 to ensure compatibility with the CMAQ grid system. The model domain consists of 80×80 grid cells with a resolution of 3 km×3 km per cell, covering the domain of the WRF model. Emission data for the study area was derived from the project "Research on the Construction of Air Pollutant Emission Maps for Forecasting and Air Pollution Control in the Key Economic Region of the Northern Region" (Hồ Quốc Bằng, 2022), with emission data outside the study area sourced from EDGAR v8.1 (Crippa et al., 2024). Emission data for model validation was collected from two monitoring campaigns at two different locations (details available in our paper: Dam et al., 2024).

CMAQ calculates vertical mixing due to turbulence using Kz theory and the Bulk Richardson number [30]. The baseline value of Kz in the CMAQ model, represented by $Kz_{\min}$ is set to 1,0 $m^2.s^{-1}$. However, since version 4.6, CMAQ has used the KZMIN option, incorporating the effect of land cover, as described by the following equation:

$$Kz_{min} = KZL + (KZU - KZL) \times UFRAC \quad (1)$$

$$UFRAC = 0.01 \times PURB \quad (2)$$

where:

- KZL and KZU are constant values with values of 0.01 and 1.0, respectively.
- UFRAC (Urban Fraction) represents the urban land cover fraction, calculated as the urban fraction PURB (ranging from 0% to 100%) as shown in Equation (2).
- Therefore, Kz_{min}in CMAQ ranges from 0.01 to 2.0, depending on the model version and UFRAC.

In the study, we conducted experiments with an average value of Kz_{min} of 1.0 to predict the $PM_{2.5}$ concentration.

2.2. Data

As mentioned above, the PM2.5 concentration in Hanoi shows significant seasonal variation, reflecting the complex interaction between emission sources and the characteristic meteorological conditions of the region. Studies have shown that PM2.5 concentrations tend to be higher during the autumn to early spring months (from August to March the following year) (Nghiem, 2021; Oanh et al., 2006; Bui et al., 2022; Hai et al., 2013; Chifflet et al., 2024). Therefore, we conducted predictions for two time points corresponding to our two observation periods (Dam et al., 2024). The locations of the monitoring points are shown in Figure 1.

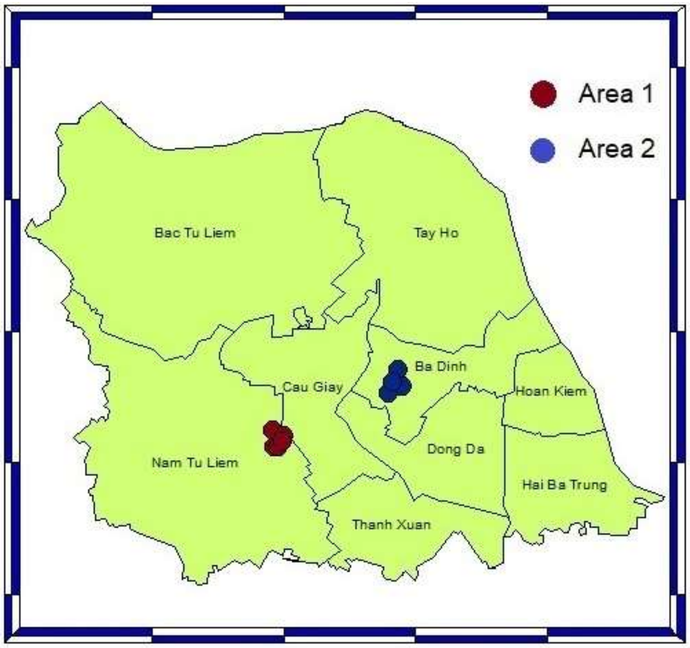

Figure 2: Locations of the monitoring points

2.3. Error calculation

To evaluate the performance of the PM2.5 vertical distribution forecasting model in Hanoi, we employed common error metrics, including Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE). These metrics allow us to accurately and comprehensively compare the forecasted results with measured data. MAPE is one of the most widely used indicators for assessing forecast model performance. It is calculated based on the absolute difference between the forecasted and actual values, divided by the actual values, and then multiplied by 100 to express it as a percentage (Hyndman & Koehler, 2006). The formula for MAPE is as follows:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{\widehat{y_i} - y_i}{y_i}\right| \times 100$$

Where y_i represents the actual value, $\widehat{y_i}$ is the forecasted value, and n is the number of samples..

MAE is another metric used to assess the mean absolute error between forecasted and actual values. It is calculated by taking the absolute difference between forecasted and actual values and then computing the average of these errors (Willmott & Matsuura, 2005). The formula for MAE is as follows:

$$MAE = \frac{1}{n}\sum_{j=1}^{n}|\widehat{y_i} - y_i|$$

RMSE is a metric that evaluates the standard deviation of errors, calculated by taking the square root of the mean of the squared errors (Chai & Draxler, 2014). The formula for RMSE is as follows:

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

All three metrics MAPE, MAE, and RMSE are widely used for evaluating the performance of air pollution forecasting models (Seinfeld & Pandis, 2016; Zhang et al., 2012). Utilizing these metrics in combination allows for a comprehensive assessment of the forecasting model's performance.

3. Results and Conclusions

3.1. Forecast Map of PM2.5 Pollution Distribution by Height

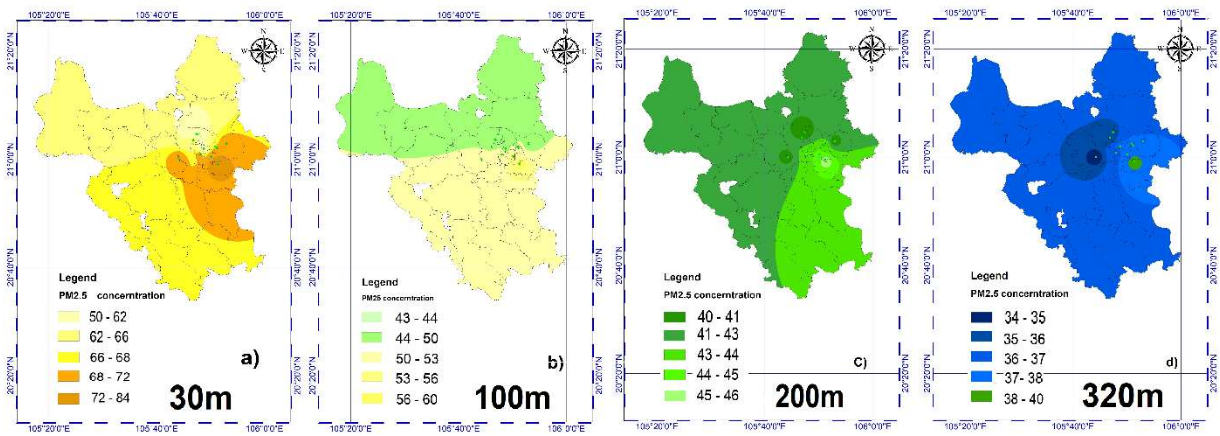

Figure 3: Distribution of PM2.5 concentration as forecast by height in Hanoi, Vietnam

Figure 3 presents the simulated 24-hour average concentrations of fine particulate matter (PM2.5) in Hanoi from August to October 2023 at heights of 30 m, 100 m, 200 m, and 320 m. The variations in PM2.5 concentrations are illustrated through color bands on the map, showing a clear decrease in concentration with increasing height. At 30 m, PM2.5 concentrations were the highest, ranging from 50 to 84 µg/m³, with significant hotspots in central areas, particularly the southeastern region. This high concentration is primarily attributed to dense industrial activities and heavy traffic in these areas. At 100 m, PM2.5 levels decreased to 43–60 µg/m³, though the central region still exhibited higher concentrations compared to other areas.

The decline in PM2.5 concentrations continued at 200 m, ranging from 40 to 46 µg/m³, where the distribution became more uniform, reflecting a reduced influence of surface emission sources. At 320 m, concentrations were at their lowest, between 34 and 40 µg/m³, with significantly reduced levels even in central areas. Compared to the National Technical Regulation on Ambient Air Quality (QCVN 05/2023), which sets a 24-hour average PM2.5 limit of 50 µg/m³, concentrations at 30 m citywide and at 100 m in the central and southern areas exceeded this threshold. Additionally, all height levels exceeded the WHO-recommended limit of 25 µg/m³ for 24-hour average PM2.5 concentrations, highlighting the severity of air pollution in Hanoi.

3.2. Error Calculation and Accuracy Assessment of the Forecast Model

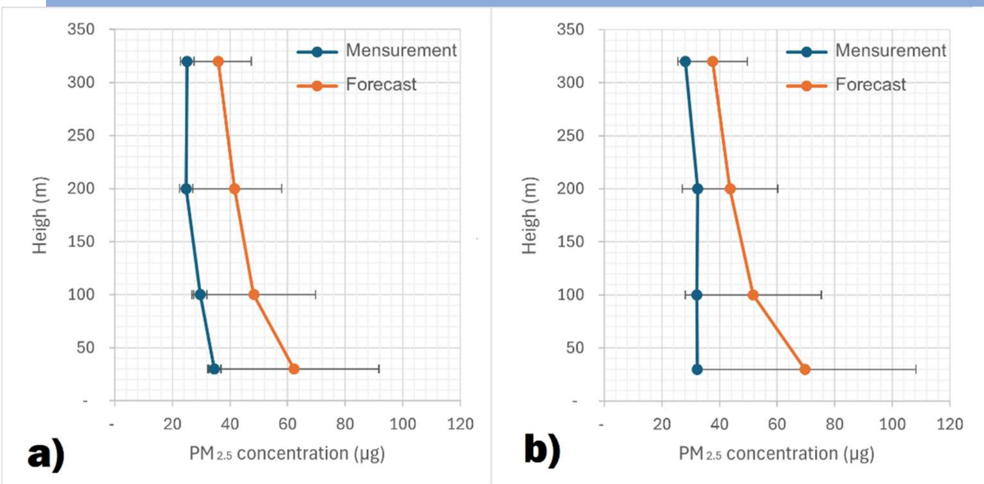

Figure 4: Comparison of predicted and measured PM2.5 concentration in areas 1 and 2 of Hanoi from August to October 2023 by height

Figure 4 compares the predicted and measured 24-hour average PM2.5 concentrations for Areas 1 and 2 in Hanoi during August to October 2023 across various heights, as outlined in Figure 3. The data reveals a clear decrease in PM2.5 concentrations with increasing height, a trend consistently represented in both graphs. At 30 m, concentrations were highest, ranging from 50 to 84 µg/m³, but declined to 43–60 µg/m³ at 100 m. This decreasing pattern persisted at 200 m (40–46 µg/m³) and was most pronounced at 320 m, with the lowest values recorded at 34–40 µg/m³.

Figure 4a shows the predicted and measured concentrations in Area 1, highlighting significant discrepancies between the two datasets. A similar pattern was observed in Figure 4b for Area 2. While the model effectively captured the overall trend of decreasing PM2.5 concentration with height, its accuracy in predicting specific concentrations in these areas was limited. This limitation is evidenced by high error metrics: a Mean Absolute Percentage Error (MAPE) of 63%, a Mean Absolute Error (MAE) of 18 µg/m³, and a Root Mean Square Error (RMSE) of 377 µg/m³. These values reflect substantial deviations, with the MAPE indicating an average prediction error of 63%, the MAE representing a significant bias given Hanoi's PM2.5 levels, and the RMSE pointing to large dispersion and extreme deviations in the model's predictions. The graphical analysis further underscores these discrepancies, revealing a tendency for the model to overestimate PM2.5 concentrations at most heights, particularly at 30 m, 200 m, and 300 m. The pronounced divergence between predicted and measured values suggests that the model failed to adequately account for factors influencing PM2.5 dispersion, such as topography, urban architecture, and vegetation. Meteorological conditions, identified as a critical factor, were inadequately represented, contributing significantly to the model's predictive inaccuracies in three-dimensional space.

5. Conclusion

The study revealed that PM2.5 concentrations in Hanoi decrease with altitude, ranging from 50–84 µg/m³ at 30 meters to 34–40 µg/m³ at 320 meters, with urban hotspots exceeding Vietnam's air quality standard and WHO guidelines. Seasonal patterns indicated higher PM2.5 levels in autumn and winter, driven by temperature inversions and low mixing heights. While the CMAQ model effectively captured these trends, it exhibited significant errors, including a Mean Absolute Percentage Error (MAPE) of 63%, highlighting challenges in accurately predicting pollutant levels.

The study have some limitations in incorporating localized factors, such as detailed urban architecture, vegetation effects, and topographical influences, leading to substantial prediction errors. Validation issues arose from insufficient vertical measurement data, which hindered the accurate calibration of the model. Furthermore, the model's representation of transient emission sources and temporal variations was limited, affecting its ability to capture the complex dynamics of PM2.5 distribution fully.

In future research, the team intends to integrate high-resolution urban datasets and field-measured vertical profiles to enhance the model accurately. Additionally, the scope of the study will be expanded to encompass other regions, with a focus on real-time monitoring of results. Furthermore, air quality data will be systematically linked with health studies to provide comprehensive insights, facilitating improved air quality management and the development of effective mitigation strategies.

6. Acknowledgements

The authors would like to thank the Global Change and Sustainable Development Research Institute for supporting this research. Additionally, the authors acknowledge the project titled "Research on the Scientific Basis and Practical Application of Lidar to Forecast Air Pollution Distribution by Height: Pilot Application for Typical Areas in Hanoi" for providing the essential data utilized in this study.

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