A CFD-Based Air Quality Dispersion Modeling for Urban Areas using OpenFOAM

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KEY WORDS: air quality, air pollution, $PM_{2.5}$, urban area, 3D modeling, computational fluid dynamics, dispersion model

ABSTRACT:

Air pollution in urban areas posed a significant threat to public health and environmental sustainability. This research addressed the urgent need for accurate air quality monitoring systems in urban environments, focusing on the University of the Philippines-Diliman as the study area. The study used 3D modeling and Computational Fluid Dynamics (CFD) to simulate and assess air quality dispersion in the urban setting of the Campus. The research objectives included: (a) developing a 3D model of the Campus using LiDAR and geospatial techniques, (b) modeling the three-dimensional $PM_{2.5}$ dispersion in the area using CFD, and (c) validating the effectiveness of the CFD-based $PM_{2.5}$ dispersion model using on-ground air quality monitoring data. The LiDAR and GIS datasets, including Digital Terrain Models, Digital Surface Models, orthophotos, building footprints, and road networks, were utilized to create the 3D campus model. Meteorological data (wind speed, direction, cloudiness, solar irradiation), and emission parameters (pollutant sources and concentrations) were integrated into the model for CFD simulations. SimFlow, an OpenFOAM-based software, facilitated the dispersion modeling process. The study's results revealed the impact of urban factors on $PM_{2.5}$ dispersion, highlighting challenges in areas with restricted air movement due to buildings and narrow streets. Discrepancies between model predictions and on-ground measurements suggested the influence of unaccounted local factors. Nevertheless, the model demonstrated its utility in capturing general $PM_{2.5}$ trends. In conclusion, the combination of 3D modeling and CFD simulation proved to be a robust approach for urban air quality monitoring. While improvements were needed to address local influences, this research provided a foundation for better air quality comprehension and urban management, essential for achieving sustainable cities and climate action goals.

1. INTRODUCTION

1.1 Background

Air pollution poses a significant global threat, impacting health, the environment, agriculture, and economies, particularly in urban regions. In 2022, IQ Air reported that the Philippines maintained a moderate air quality index of 58. In Quezon City, $PM_{2.5}$ levels, one of the primary air pollutants in the area, measured at 15 µg/m³, three times the safe threshold set by the World Health Organization (WHO).

Recognizing this global issue, the Philippines must enhance its air quality monitoring, particularly in urban areas. Existing systems lack robustness, requiring further research on the health and environmental impacts of air pollution. This study aims to contribute on the improvement of air quality assessment in urban areas by incorporating 3D modeling and Computational Fluid Dynamics (CFD) in modeling the dispersion of air pollutants over an area. These innovative methods offer advantages over traditional approaches, allowing for spatial variability analysis and simulation of various influencing factors like traffic, industry, and weather.

This study strives to contribute to effective urban air quality monitoring by creating a 3D model using Light Detection and Ranging (LiDAR) data and Geographic Information System (GIS) techniques. This model will serve as the foundation for a CFD-based air quality dispersion model, enabling us to simulate pollutant transport and identify high-pollution areas. Furthermore, it also addresses gaps in urban air quality research resulting from limited on-ground monitoring and conventional assessment methods.

1.2 Research Objectives

This study aims to develop air quality monitoring and assessment by integrating 3D modeling and Computational Fluid Dynamics (CFD) to simulate air pollutant dispersion within urban areas. The primary objective is to construct a comprehensive three-dimensional model for simulating the air pollutant dispersion in an urban setting. Furthermore, this research strives to accomplish the following specific goals: (a) develop a 3D model of the UP Diliman Campus employing LiDAR and geospatial techniques, (b) simulate three-dimensional $PM_{2.5}$ dispersion in the region using CFD modeling, and (c) assess the reliability of the CFD-based $PM_{2.5}$ dispersion model by comparing it with real-world air quality monitoring data. By achieving these objectives, this study not only contributes to enhanced air quality management but also contributes to fostering sustainable and resilient urban environments while combating the worsening case of air pollution in the country.

1.3 Scope and Limitations

The study generally aims to develop CFD-based air quality dispersion model for assessing air quality and pollutant concentrations in a specific urban area. The model incorporates a 3D representation of the terrain, buildings, infrastructure, and traffic data within the area. It includes atmospheric components essential for simulating pollutant distribution. The CFD model not only assesses air quality but also identifies areas requiring pollution mitigation measures, contributing to raising awareness about air quality issues.

The study area, located in one of Quezon City's highly urbanized and diverse areas, University of the Philippines-Diliman Campus, serves as a representative sample of the city,

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encompassing diverse land uses including academic buildings, residential areas, and open spaces.
To build the 3D model, LiDAR data was used to provide the spatial information, including digital terrain and surface models and building footprints. ArcGIS and AutoCAD software were utilized for the 3D model construction. Air pollutant data, specifically hourly $PM_{2.5}$ concentration data, were sourced from Satellite missions. Emission sources for pollutant dispersion calculations were primarily linear mobile sources, particularly vehicles on the campus roads. Annual Average Daily Traffic (AADT) data from DPWH helped estimate vehicle-induced pollutant emissions.

These datasets were integrated into the 3D urban model to create a CFD-based air quality dispersion model capable of monitoring and assessing air quality. SimFlow, an Open-source Field Operation and Manipulation (OpenFOAM)-based CFD modeling software, was employed for simulating urban atmospheric layers, with customized components tailored for urban boundary layer research focused on air quality and climate.

2. LITERATURE REVIEW

2.1 3D Modeling

As the technology continues to evolve, 3D modeling has become a vital resource for a variety of applications. A paper on the techniques and applications of 3D city modeling (Singh et.al, 2013) discussed how 3D modeling became one of the most researched topics at the present and how it can be a useful tool in different fields of study. One of the most important applications of 3D modeling is in the field of urban planning. 3D models can be used to visualize and analyze urban areas aiding in the development of the city.

The applications of 3D city models are rapidly expanding and gaining significance in today's urban studies, however, there is a deficiency of free-of-cost and high-resolution 3D city models available for use. A study on the reliable creation of 3D city models from open data (Girindran, et.al., 2020) aimed to create a methodology for generating 3D city models from open-source 2D building footprints in conjunction with open-source satellite-based elevation datasets. The results of the study show that the proposed methodology is a capable approach for generating 3D city models from open-source data. Despite the limitations, it had a significant contribution to the field of 3D city modeling.

2.2 Air Quality Monitoring

At present, there are different air quality monitoring technologies that are being used. These include stationary low-cost sensors, mobile air quality sensors, reference-grade monitors, and satellite monitors. These air quality monitoring systems are responsible for sampling and monitoring a wide range of particulates and gaseous pollutants, as well as analyzing and assessing the extent and trend of the pollutants present in the area throughout the years. However, there is still a sparse distribution of air quality monitoring stations available for use in the country which results in a lack of comprehensive and sufficient air quality information available, especially in urban areas.

A research study focusing on roadside pollutant mapping by integrating GIS techniques and air dispersion modeling (Ramos and Blanco, 2022) was conducted to monitor the behaviour of air pollutants in Baguio City. The study used the Line-source Gaussian dispersion model as a screening and regulatory model in predicting PM concentrations from motor vehicles and roadway intersections. This model is widely used in air quality monitoring studies as it provides accurate and reliable air pollution data from manageable and simple computational methods. The integration of dispersion and geostatistical modeling methods improved their estimation of PM10 concentrations within the major roads in the area. However, the method used in their study focused solely on near roadside areas and is only applicable to be used in monitoring air quality in that specific area. This can be further improved by considering additional geometric parameters such as building footprints and canopy heights to be able to monitor the air quality in areas near tall establishments and areas with high vegetation.

In a study conducted to assess the air quality in Pamplona City, Spain (Rivas et.al., 2019), they created a CFD dispersion model to measure the spatial representativeness of the current network of air quality monitoring stations in the city as well as to compute the impact of NO2 concentrations on the health of the residents. The numerical simulations they used were based on a steady-state Reynolds-Averaged Naver-Strokes (RANS) approach. The pollutants were assumed to be emitted by the traffic close to the ground and proportional to its Annual Average Daily Traffic (AADT). The final average concentration maps were computed as the weighted sum of the simulated scenarios assuming that the pollutant concentration solely depends on emission sources and wind speed and direction.

The methodology and techniques used in those studies were incorporated in this study to simulate the dispersion of air pollutants in UP Diliman on a 3D scale.

3. METHODOLOGY

3.1 Research Design

The procedures and techniques used to achieve the objectives of this study are divided into three stages: Data Acquisition, the 3D Modeling of the area, and the Air Dispersion Modeling. The flowchart for this study is shown in Figure 1.

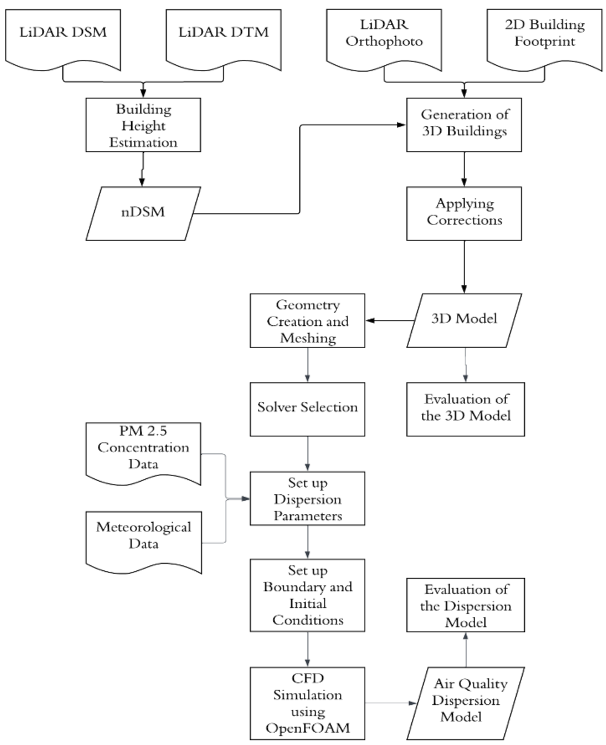


Figure 1. Methodological Flowchart

3.2 Data Acquisition

Table 1 provides a summary of the datasets employed in the 3D modeling and air quality dispersion modeling conducted within the UP Diliman Campus. The table includes details about the data sources and, when applicable, their spatial resolutions. These datasets were utilized to develop a comprehensive 3D representation of the buildings located within the Campus. Additionally, they were employed in the creation of a dispersion model to simulate the movement and spread of air pollutants, specifically focusing on $PM_{2.5}$ particles.

Table 1. Datasets

Data set	Resolution (m)	Source
Orthophoto	1 x 1	NAMRIA
Terrain Models		
Digital Terrain Model	1 x 1	NAMRIA
Digital Surface Model	1 x 1	NAMRIA
2D Features		
Building Footprint		Open Street Map
Road Network		Open Street Map
Meteorological Data		
Wind Speed	2.5 x 2.5	PAG-ASA
Solar Irradiation	2.5 x 2.5	GRASS GIS
Emission Parameters		
Average Daily Traffic		DPWH
$PM_{2.5}$ Concentration	30 x 30	Sentinel 5P
Data		On-Ground Monitoring Stations

3.3 3D Modeling of the Campus

The 3D modeling phase covers a complex process of extracting crucial geospatial datasets from LiDAR data to construct 3D representations of buildings at the UP Diliman campus. This procedure requires various datasets and tools. In this study, ArcGIS and the 3D Base Maps task are utilized, which comprises three stages: the estimation of building heights, the extraction of 3D building features, and the refinement of the 3D building model.

3.3.1 Estimation of Building Features: The Normalized Digital Surface Model (nDSM) is a derivative elevation product representing the building heights on the area above the ground. It can be used to estimate the height of buildings by measuring the difference between the highest point of the building and the ground surface. In this study, the nDSM was derived from the LiDAR DSM and DTM retrieved from NAMRIA. The estimated height of each building was applied to extract an accurate representation of the buildings for the creation of the 3D model in the area. The estimated heights are calculated using Equation 1,

$$H_{nDSM} = H_{DSM} - H_{DTM} , \quad (1)$$

where H_{nDSM} = Estimated Building Height
H_{DTM} = Ground Elevation
H_{DSM} = Peak Elevation

3.3.2 Extraction of 3D Building Features: To use the 2D building footprints in the extraction of the 3D building features from the LiDAR datasets, the footprint needs to be properly segmented first. The segmented building footprint dataset is created to identify the areas of high elevation that are likely to be buildings. This was done through the segmentation toolbar under the ArcGIS 3D base maps task using elevation data from the DSM, DTM, and nDSM. The segmentation of the building footprint was done before the extraction of the 3D building features to improve the efficiency of the extraction process.

The extraction of 3D buildings was performed using the Create Buildings tool within the 3D Base Maps task. This extraction process required several essential datasets: segmented 2D building footprints for identifying building features, DSM for elevation data, DTM for ground elevation information, and nDSM for normalized elevation data and building heights.

The extracted 3D building polygons were in LoD2, representing fundamental external structure of the buildings. However, these extracted data are still in 2D polygon state. To convert them into 3D feature classes, the Fuse 2D Features tool was employed to merge the 2D building polygons into a 3D building feature class. This output feature class contained data on 3D coordinates and heights for each building.

3.3.3 Refinement of the 3D Building Model: After extracting the 3D Building features using ArcGIS, the data was converted into a drawing file and imported to AutoCAD. The 3D building features were further refined to improve its accuracy. In this process, the accuracy of the 3D model was checked by comparing them to ground-truth data. In this case, the LiDAR orthophoto was used for the comparison.

The refined 3D building features were used to create a more realistic air quality dispersion model. The 3D environment would be able to capture the complex flow of air around the buildings, which has a significant impact on the dispersion of air pollutants. The refinement of 3D building features is an important step in the creation of accurate air quality dispersion models which leads to better decision-making on air quality management.

3.4 Air Quality Dispersion Modeling

In this study, CFD was employed to simulate air quality dispersion across the complete 3D urban environment of UP Diliman Campus, encompassing various elements such as street canyons, open areas, and buildings of varying heights. The simulation was executed using OpenFOAM via the SimFlow software.

The CFD simulation of air quality dispersion at UP Diliman Campus involved several stages. Initially, the 3D campus geometry was generated using LiDAR data and geospatial techniques. This geometry was subsequently imported into OpenFOAM, where boundary conditions were defined. These boundary conditions encompassed inflow and outflow specifications, as well as surface roughness details for buildings and other surfaces. Following the specification of boundary conditions, the CFD simulation was executed, taking several hours to complete. The simulation results were saved in a post-processing format and utilized for visualizing air quality dispersion within the campus, as discussed in subsequent sections.

3.4.1 Geometry Creation and Meshing: The AutoCAD-generated 3D building model was imported into SimFlow for simulation. A box geometry matching the 3D model's dimensions (1140 m x 880 m x 60 m) was created to refine the geometry.

The 3D computational mesh (1400 m x 1200 m x 200 m) was created to encompass the study area, ensuring comprehensive coverage and detailed simulation around buildings.

The input raster data used had varying spatial resolutions which could cause inaccuracies in the simulation. To minimize this problem, mesh alignment was done. Further refinement of the coarse mesh involved increasing cell density to 1 m x 1 m x 1 m cell size, enhancing alignment with fine details from input data. However, this precision improvement also increased the computational demands, slowing down the simulation process.

The simulation area dimensions were carefully chosen to facilitate comprehensive air quality dispersion simulation, particularly around buildings and roads, while accommodating computational resource requirements, including simulation and emission parameters.

3.4.2 Solver Selection: The CFD modeling solver used in this study was a steady state incompressible SimpleFOAM solver for Reynolds-Averaged Navier-Stokes (RANS) equation model with a renormalization group (RNG) k-ε turbulence closure scheme. The RANS equation model is a mathematical model widely used to simulate turbulent flows with a set of equations that describe the average flow field.

The choice of the RANS equation model with the RNG k-ε model for the $PM_{2.5}$ dispersion modeling is motivated by several factors, including its capability to capture turbulent flow behaviour, its computational efficiency, and its established reliability in simulating atmospheric pollution phenomena (Idrissi et.al., 2018). The model has been extensively validated and utilized in various studies related to air pollution and dispersion modeling, providing a robust foundation for its application in $PM_{2.5}$ dispersion simulations.

OpenFOAM has an available simulation tool that allows turbulence parametrization to simulate the airflow in an urban environment. It also has an aerosol module and kinetic pre-processor interface that aid the model in representing the vertical and horizontal distribution of air pollutant emission in an area. The atmospheric suitability classes identified from the meteorological data were integrated in the interface. This allows a more accurate assessment of air pollutant concentration in the simulation domain.

3.4.3 Setting-up Dispersion Parameters and Boundary Conditions: In SimFlow, the setup of CFD-based simulations requires the incorporation of dispersion parameters and boundary conditions. The datasets containing these parameters and conditions were imported into the simulation software for precise calculations.

For the boundary conditions for this study, the -x and +x axes of the mesh were designated as the inlet and outlet, respectively, for the air flow within the study area. The dispersion parameters, on the other hand, determine how air pollutants behave in simulations. These parameters encompass various factors, such as the emission rate of air pollutants, the speed of the wind, and the intensity of solar irradiation.

The vehicular emission rates on the road segments for which AADT values and vehicle population data are available were calculated using Equation 2 adopted from the UP National Center for Transportation Studies (UP NCTS) (Vergel and Tiglao, 2013),

$$E_v = \sum (v_i D_i)\, EF_i, \tag{2}$$

where E = Mass Emission of the Vehicles per Day
i = Vehicle Category
v = Number of Vehicles
D = Distance travelled by the vehicle per day in km
EF = Mass Emission Factor

3.5 Evaluation and Validation of the Models

A thorough comparison was made between the output of the models and the available actual and observed data. The evaluation process involved rigorous statistical analyses to compare the model outputs with actual and observed data. These analyses allowed for an in-depth examination of the models' performance in replicating real-world phenomena.

Through this comprehensive evaluation, the study aimed to provide a comprehensive understanding of the strengths and limitations of the models. By determining the suitability of the model for capturing and simulating complex real-world scenarios effectively, future studies can use this to enhance the performance, refine the methodologies, and improve the overall reliability of the models.

3.5.1 Evaluation of the 3D Model: The evaluation of the 3D models included comparing them with real-world building heights, a critical step for assessing accuracy. However, due to limited data on actual building heights, a standardized assumption was made, considering each floor as 4 meters high, providing a fundamental benchmark.

In addition to assumption-based comparisons, statistical methods like mean absolute error (MAE) and root mean square error (RMSE) were employed to quantitatively evaluate the overall modeling performance. These measures offer insights into deviations, aiding in assessing modeling accuracy and precision

By utilizing these evaluation techniques, the study aimed to confirm the fidelity of the 3D models, acknowledging data limitations. Standardized assumptions and statistical measures provided a systematic approach to assess modeling performance despite data constraints.

3.5.2 Evaluation of the CFD-Based Air Quality Dispersion Model: The study evaluated the CFD-based air quality dispersion model by comparing simulated hourly $PM_{2.5}$ concentration data with on-ground measurements from May 31, 2022, and August 3, 2022, representing summer and rainy seasons. However, on-ground $PM_{2.5}$ data was limited to Unioil Congressional 2 and Unioil West Avenue stations, which were distant from UP Diliman Campus, potentially introducing spatial discrepancies and limiting data accuracy.

Despite the spatial gap, these monitoring stations offered valuable insights into overall air quality. While they may not precisely represent the study area's pollutant concentrations, they provide contextual information and help identify general air pollution trends.

To address the spatial limitation, average hourly data from the dispersion model were calculated and compared with on-ground measurements. This allowed for the identification of relative differences and trends in $PM_{2.5}$ dispersion.

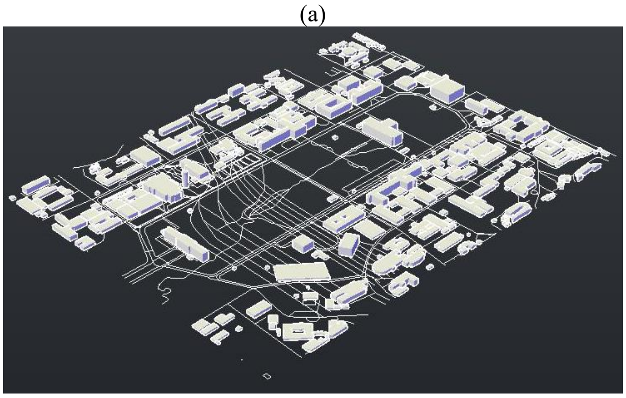
Statistical metrics like root mean square error (RMSE) and mean absolute error (MAE) were employed to assess the consistency between simulated and on-ground data. RMSE gauged model fit, while MAE measured errors between $PM_{2.5}$ values from the two datasets.

4. RESULTS AND DISCUSSION

4.1 3D Model of the Study Area

The created 3D model of the buildings in the study area is in LoD 2. Figure 2 show the 3D model of the buildings in ArcGIS (a) and AutoCAD (b)

(a)



(b)

Figure 2. 3D Model of the Buildings around UP Diliman Academic Oval in (a) ArcGIS and (b) AutoCAD

4.2 Air Quality Dispersion Model

The variation and trend in $PM_{2.5}$ concentration in an urban area throughout the day is a complex phenomenon that can be influenced by several factors, including the meteorological conditions within the area such as wind speed and solar irradiance and the topographical features. Human activities around the area may also be a contributor to the accumulation and dispersion of $PM_{2.5}$ in the area.

4.2.1 Simulation Results for May 2022 Data: $PM_{2.5}$ data from May 2022 was used in this study to test the effectiveness of the created dispersion model in simulating the behaviour of $PM_{2.5}$ in the area during the summer season. Figure 3 shows snapshots of the hourly dispersion of $PM_{2.5}$ concentration gathered from the model. The minimum and maximum $PM_{2.5}$ concentration values in the figures are 0.0 μg/m³ and 30.0 μg/m³, respectively.

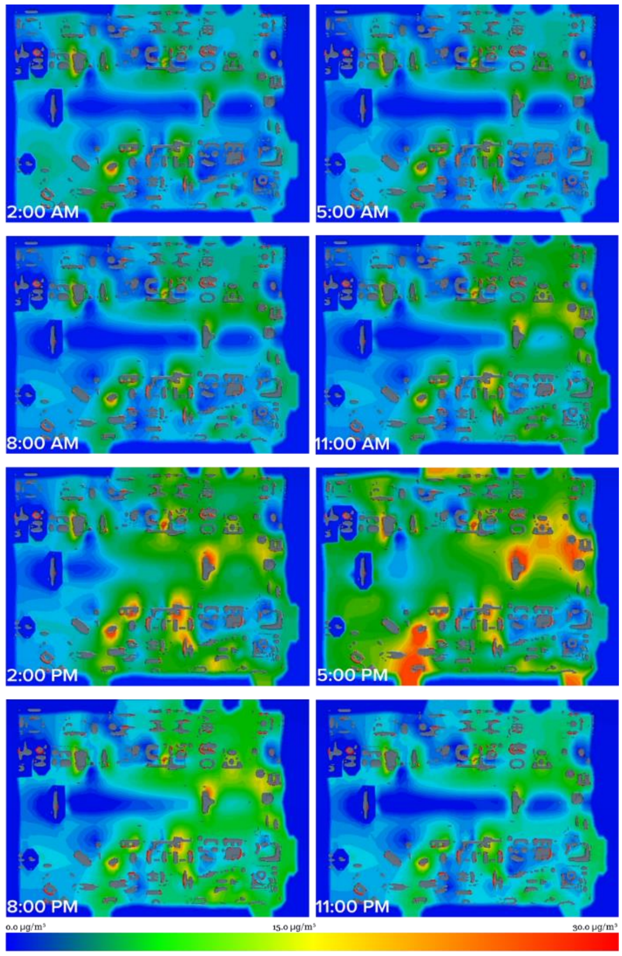


Figure 3. Simulation of the Dispersion of $PM_{2.5}$ in UPD Academic Oval for May 2022

In Figure 3, the relationship between wind speed, solar irradiance, and $PM_{2.5}$ concentration is evident. During the morning hours, high wind speeds and abundant solar irradiance promote efficient $PM_{2.5}$ dispersion, resulting in lower concentrations. Wind aids pollutant dilution, and solar irradiance enhances atmospheric mixing.

A shift occurs in the late afternoon. Wind speed decreases, hindering dispersion efficiency. Reduced solar irradiance further limits atmospheric mixing, leading to concentration hotspots and $PM_{2.5}$ peaks. During nighttime, despite lower wind speeds and reduced solar irradiance, $PM_{2.5}$ dispersion accelerates, suggesting other additional factors may have influenced the nighttime dispersion.

The concentration hotspots are found near Quirino Avenue, T.M. Kalaw Street, and Osmeña Avenue which highlight the influence of local factors, such as traffic patterns and human activities, on the spatial distribution of $PM_{2.5}$. The presence of busy roads, university facilities, and student gathering areas intensifies the emission sources and leads to elevated levels of $PM_{2.5}$ in these specific locations.

These findings highlight the complex nature of $PM_{2.5}$ dispersion and the need to consider multiple factors when analyzing and interpreting the data.

4.2.2 Simulation Results for August 2022: $PM_{2.5}$ data from August 2022 was used in this study to test the effectiveness of the created dispersion model in simulating the behaviour of $PM_{2.5}$ in the area during the rainy season. Figure 4 shows snapshots of the hourly dispersion of $PM_{2.5}$ concentration gathered from the model. The minimum and maximum $PM_{2.5}$ concentration values in the figures are 0.0 µg/m³ and 30.0 µg/m³, respectively.

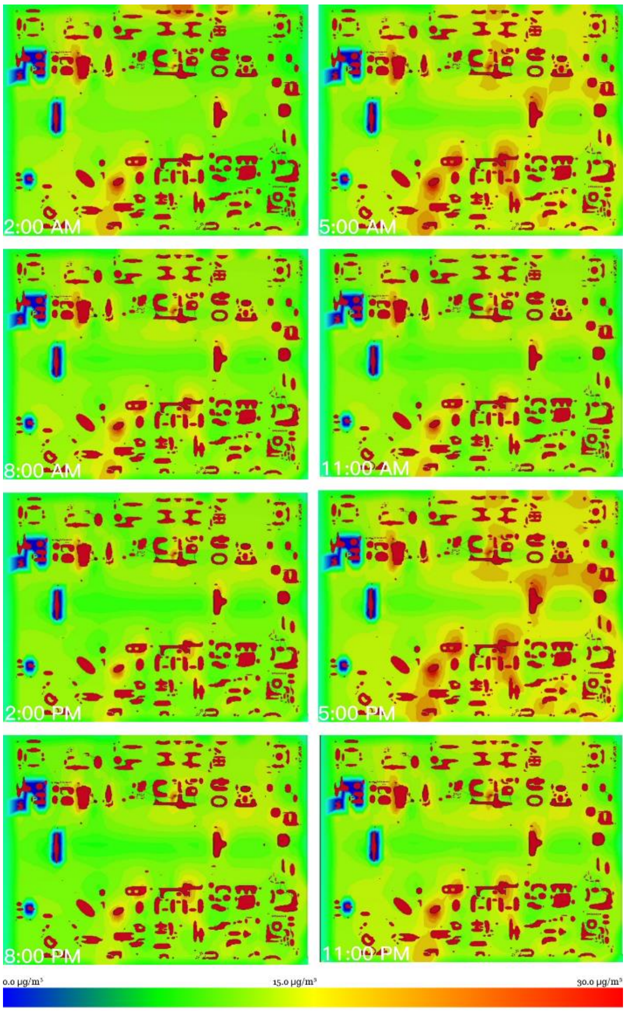


Figure 4. Simulation of the Dispersion of $PM_{2.5}$ in UPD Academic Oval for August 2022

Figure 4 illustrate the hourly variations in $PM_{2.5}$ concentrations in the area. The pattern appears relatively unpredictable compared to the previous simulation.

A study on the effects of rain and snow on the air quality index, $PM_{2.5}$ levels, and dry deposition flux of PCDD/Fs (Tian et al., 2021) explored the impact of precipitation on air quality and found that rainfall significantly affects $PM_{2.5}$ concentrations. Before precipitation, $PM_{2.5}$ levels tend to be highest. During rainfall, levels decrease as rain washes pollutants from the atmosphere. Post-precipitation, $PM_{2.5}$ concentrations gradually rise again. These findings highlight precipitation's role in $PM_{2.5}$ dispersion dynamics and the resulting variations in the simulation.

Figure 4 also indicates a broader dispersion pattern compared to the previous simulation. Concentration hotspots appear along Quirino Avenue, T.M. Kalaw Street, near Palma Hall to the Science Complex, and along Osmeña Avenue, particularly near the Main Library, Melchor Hall, and the University Theatre.

Despite rain-induced dispersion, $PM_{2.5}$ particles accumulate in certain areas due to factors like local emission sources (e.g., traffic), ongoing pollutant release during and after rain, complex airflow patterns, and local meteorological conditions.

Rain effectively cleanses the atmosphere, reducing airborne pollutant concentrations based on rainfall intensity and duration. However, $PM_{2.5}$ levels can still be influenced by various factors during rain, such as local emissions and meteorological conditions. Rainfall improves air quality but may not eliminate $PM_{2.5}$ entirely, necessitating a comprehensive understanding of the interplay between rainfall, emissions, and meteorology for effective air pollution mitigation during rainy periods.

4.3 Evaluation and Validation of the Results

The evaluation process in this study encompassed two key aspects: the assessment of the accuracy of the generated 3D building models and the evaluation of the air quality simulation results.

4.3.1 Evaluation of the 3D Buildings: Table 2 presents a comprehensive comparison between the heights of selected buildings as depicted in the model and their real-life counterparts. It is important to note that this comparison was made under the assumption that each floor of the buildings had a standard height of four (4) meters

Table 2. Comparison of Building Heights

Name	No. of Floors	Height (m)		Diff.
		Model	Actual	
Junio Hall	4	16	16	0
Gonzalez Hall	6	24	24	0
Malcolm Hall	5	20	20	0
Quezon Hall	5	20	20	0
Vargas Museum	3	16	12	4
College of Arts and Letters	5	20	20	0
Bocobo Hall	4	20	16	4
Benitez Hall	3	10	12	-2
Palma Hall	4	20	16	4
Melchor Hall	5	20	20	0
Abelardo Hall	2	8	8	0
Villamor Hall	4	16	16	0
Vinzons Hall	5	20	20	0
Carillon Tower	-	40	39.6	0.4
UP Film Institute	3	16	12	4
Mean Absolute Error				1.235 m
Root Mean Square Error				2.131 m

The relatively low values obtained reflect a high level of agreement between the modelled and actual building heights and indicate the accuracy and reliability of the modeling approach used in the study. This indicates the accuracy and reliability of the methodology used in this study, specifically the 3D Basemaps tool in ArcGIS that involved extracting the normalized Digital Surface Model (nDSM) from the LiDAR Digital Surface Model (DSM) and Digital Terrain Model (DTM) layers.

4.3.2 Evaluation of the Dispersion Models: Figures 5 and 6 show the comparison between the on-ground $PM_{2.5}$ data and the simulated $PM_{2.5}$ data from the air quality dispersion model from the May 31 and August 3, 2022, respectively.

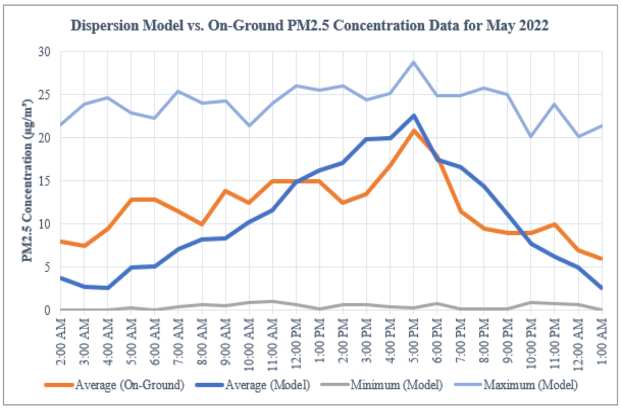


Figure 5. Dispersion Model vs. On-Ground $PM_{2.5}$ Concentration Data for May 2022

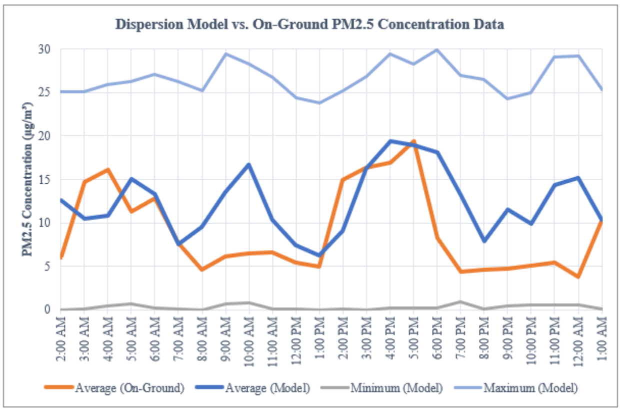


Figure 6. Dispersion Model vs. On-Ground $PM_{2.5}$ Concentration Data for August 2022

The results indicate that the dispersion model successfully accounted for the key factors influencing the spatial distribution of $PM_{2.5}$ in urban areas. It accurately simulated the general patterns and trends observed in the measured data obtained from on-ground monitoring stations.

The dispersion model was able to capture the main factors that affect the distribution of $PM_{2.5}$ in urban areas but not all the localized sources of pollution which cause spikes in $PM_{2.5}$ concentration that on-ground monitoring stations can handle.

Despite these limitations, the created dispersion model remains a valuable tool for simulating $PM_{2.5}$ and gaining insights into the general spatial distribution of $PM_{2.5}$ concentration. It serves as a foundation for further refinement and can contribute to better understanding and management of air quality, particularly in urban environments.

5. CONCLUSIONS

The research findings suggest that combining 3D modeling and CFD methods is a reliable approach for creating air quality simulation models. A 3D model provides a realistic representation of the physical world, while CFD methods solve fluid flow equations in this 3D environment. This combination offers a powerful tool for understanding and predicting physical system behaviour, particularly air quality dispersion.

Additionally, the study successfully met its specific objectives. It developed a 3D model of UP Diliman Campus using LiDAR and geospatial techniques, focusing on the academic oval area. The study also effectively modelled $PM_{2.5}$ dispersion in 3D space using Computational Fluid Dynamics (CFD), considering various factors like topography and meteorology. This CFD-based model provides a comprehensive air quality dispersion model, tracking and predicting $PM_{2.5}$ concentration levels and identifying hotspots, especially in urban areas. Furthermore, the model's validation through a comparative analysis with on-ground air quality data confirmed its accuracy.

These achievements demonstrate the feasibility of using 3D modeling and CFD methods for $PM_{2.5}$ dispersion modeling in complex urban environments. These findings can enhance air quality management in urban areas. They contribute to the field of air quality research, improving our understanding of air pollution and aiding in the development and implementation of urban air quality management strategies.

However, it's crucial to acknowledge that air quality dispersion models have limitations, influenced by factors like data accuracy, model complexity, and available computational resources. Therefore, using such models requires caution and an awareness of their constraints.

REFERENCES

Girindran, R., Boyd, D. S., Rosser, J., Vijayan, D., Long, G., & Robinson, D. 2020. On the reliable generation of 3D city models from open data. *Urban Science*, 4(4), 47.

Idrissi, M.S., Lakhal, F.A., Salah, N.B., & Chrigui, M. 2018. CFD Modeling of Air Pollution Dispersion in Complex Urban Area. In: Haddar, M., Chaari, F., Benamara, A., Chouchane, M., Karra, C., Aifaoui, N. (eds) Design and Modeling of Mechanical Systems—III. CMSM 2017. *Lecture Notes in Mechanical Engineering*. doi.org/10.1007/978-3-319-66697-6_117

Singh, S.P., Jain, K., & Mandla, V.R. 2013. Virtual 3D City modeling: Techniques and Applications. *ISPRS – International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*. XL-2/W2. 10.5194/isprsarchives-XL-2-W2-73-2013.

Ramos, R.V., & Blanco, A.C. 2022. Integrated GIS and air dispersion modeling approach for roadside pollutant mapping: a case study in Baguio City, Philippines. *Spatial Information Research*, 30(3), 371-383.

Rivas, E., Santiago, J. L., Lechón, Y., Martín, F., Ariño, A., Pons, J. J., & Santamaría, J. M. 2019. CFD modeling of air quality in Pamplona City (Spain): Assessment, stations spatial representativeness and health impacts valuation. *Science of the Total Environment*, 649, 1362-1380.

Tian, X., Cui, K., Sheu, H.L., Hsieh, Y.K., & Yu, F. 2021. Effects of Rain and Snow on the Air Quality Index, $PM_{2.5}$ Levels, and Dry Deposition Flux of PCDD/Fs. *Aerosol Air Qual. Res*. 21, 210158. doi.org/10.4209/aaqr.210158

Vergel, K.B.N., & Tiglao, N.C.C. 2013. Estimation of emissions and fuel consumption of sustainable transport measures in Metro Manila. *Philippine Engineering Journal*, 34(1), 31–46

World Health Organization, n.d. Air Pollution Data Portal. URL https://www.who.int/data/gho/data/themes/air-pollution.