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Application of the Gaussian Plume Model to Simulate Industrial Air Pollutant Dispersion

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Abstract

The Gaussian Plume Model is one of the most used and recognized mathematical methods for estimating the dispersion of air pollutants emitted from industrial stacks or other point sources into the atmosphere. This model is predicated on the idea that pollutants disperse in both dimensions horizontally and vertically like a Gaussian (or normal) distribution curve, subject to various atmospheric and source-related influences. In this regard, the model is used to replicate the patterns of pollutant concentrations for various emission rates, stack design parameters, and meteorological conditions. Primary parameters used in the study are wind speed, emission height, atmospheric stability class, and the pollutant release rate. These factors are crucial in defining how the pollutants are dispersed, diluted, and deposited in lower areas from the point of emission. With actual, or even hypothetical, meteorological data, the model creates spatial concentration patterns for various ground-level receptor locations. Simulation output analysis makes it possible to identify the concentration zones, which in geo-eco and human risk assessment are essential. Such output data is required for comparison to national and international air quality standards for evaluating compliance and

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for taking appropriate mitigation action. The model can also aid in the planning and management of industrial site selection, pollution control technology implementation, and the formulation of regulatory frameworks in environmental technology. In a cost-efficient manner, the Gaussian Plume Model together with other meteorological models, explain and predict with scientific rigor the movement of airborne contaminants. This understanding helps in planning how to reduce the contaminants and the damage their discharges may cause to the environment.

Keywords:

Gaussian plume model, air pollution, industrial emissions, pollutant dispersion, atmospheric stability, wind speed, environmental impact.

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Introduction

Industrial activities rank among the highest sources of air pollution (Abdel-Rahman, 2008). They release particulate matter (PM), sulphur dioxide (So2), nitrogen oxides (Nox), and volatile organic compounds (VOCs) (Selamat, 2019). These pollutants can greatly impact air quality, public health, ecosystems, and the climate (Khan & Hassan, 2021). Their release and subsequent behavior and movement, particularly for sound environmental governance and regulatory compliance, requires tracking (Nayak, 2024). An effective way to do this is through atmospheric dispersion modelling, which predicts, in relation to time and distance, the movement, dissipation, and possible deposition sites of the pollutants (Shakir et al., 2024; Baggyalakshmi et al., 2023).

Atmospheric dispersion models predict the dispersal and dilution of pollutants from specific sources. These sources are usually classified as point sources, which include emissions from industrial chimneys; line sources, such as highways; and area sources, like construction sites. Out of many models available, the Gaussian Plume Model is among the most favored because of its simplicity, low computational burden, and accuracy in steady state conditions (Pokhrel & Lee, 2019; Banerjee et al., 2011).

According to the Gaussian Plume Model theory, it is assumed that the concentration of pollutants spreads horizontally and vertically from the point of emission following a Gaussian distribution or a bell-shaped curve (Gibson et al., 2013). This model includes the most important parameters such as the emission rate, wind speed, stack height, and atmospheric stability class. The stability class, or turbulence within the atmosphere, affects how pollutants spread. For instance, stable atmospheric conditions are more likely to trap pollutants near the surface, while unstable conditions are more likely to allow pollutants to be quickly diluted and mixed.

The model is effective in estimating concentration of pollutants at several locations downstream from the emission point, which helps tracking pollution concentration and establishing appropriate limits for air quality standards (Modi et al., 2013). In the case of industrial applications, the model assists in estimating the environmental effects of particular plants, the enforcement levels of pollution abatement policies, and developing pollution control strategies (Salih et al., 2025; Dixit & Subramaniam, 2025).

This article applies the Gaussian Plume Model to examine the dispersion of pollutants from industrial stacks under varying weather conditions. This research focuses on the influence of wind speed, the stack's height, emission parameters, atmospheric stability, and other weather conditions on pollutants dispersion (Grigoras et al., 2012). The results include spatial concentration profiles which serve the purposes of air quality management, urban development, and the ecologically sustainable functioning of industries (Rao et al., 2021). These simulations aid the modelling and refining of strategies to control emissions and comply with the legal requirements, protect public health, and sustain the ecological balance.

Key Contributions

- **Implementation of Gaussian plume model -** Carried out simulations of industrial air pollution dispersal with temperature variations, changes in source parameters, and source location, confirming the model's applicability in environmental assessments.
- **Inclusion of emission parameters -** Added emission source, atmospheric stability classes, wind speed, and effective stack height to the model for better forecast precision.
- **Validation Through Comparison -** Utilizing field data, the concentration of the pollutant was validated against the model predictions and was found to be in adequate agreement ($R^2 = 0.87$), thus confirming the model validity.
- **High-Exposure Areas Determination -** Calculated and illustrated concentration isopleths for spatial and contour concentration maps to determine the areas with the highest concentration of pollutants, especially in the proximity of 1 km from the source.
- **Insights for Planning and Policy -** Issued recommendations for the creation of buffer zones, more stringent emission limits, and better compliance with the legislation.

This research focuses on the use of the Gaussian Plume Model for simulating the dispersion of industrial air pollutants and evaluates the consequences for the environment. The Abstract provides a comprehensive description for the air quality management purpose of the study, while its methodology and importance are discussed in the Introduction alongside industrial emission contexts, dispersion in the atmosphere, and the strengths of the Gaussian Plume Model. The Literature Survey covers the model's theoretical literature, its history, use and limitations, contemporary improvements, and additional literature. The methodology describes a definite system which includes, but is not limited to, data gathering, classifying atmospheric stability, determining the effective stack height, and computing simulations. The results and discussion section focuses on the dispersion patterns and concentration-distance relationships, model validation results, and the contour maps and field data comparison. The results of the study are integrated in figures and tables with the model, the simulation's workflow, and the quantitative results which are represented in an architecture diagram, and a flowchart, and concentration comparison data. The conclusion, alongside the results of the study, mentions high exposure zones, emission control and compliance, regulatory needs, buffer zones, and model accuracy while emphasizing on the predictive strengths the Gaussian system provides.

Literature Survey

The earlier work concerning atmospheric dispersion laid the groundwork for the development of the Gaussian plume model which was further refined by Sutton, Gifford, Pasquill, and others for engineering use (Liang et al., 2023). Its fundamental version assumes mean wind and release of the pollutant in a steady-state manner with the concentration of the pollutant following a Gaussian distribution (normal distribution) in both the crosswind and vertical directions an assumption which made the model useful and popular for point-source dispersion problems (Al-Rashid & Greaves, 2025).

Pasquill Gifford's stability classes (A-F) are still used to define atmospheric turbulence in Gaussian formulations. These empirical stability classes connect meteorological parameters, such as wind speed, solar insolation, cloud cover, or temperature lapse, to the dispersion coefficients utilized in the model. Despite being straightforward and popular, researchers warn that the Pasquill scheme misclassifies stability in some environments, and that using more objective meteorological preprocessors, such as AERMET, enhances consistency in the model inputs (Sadulla, 2024).

Turner's Workbook of Atmospheric Dispersion Estimates and the accompanying guidance documents from the EPA created lookup tables, example calculations, and recommended procedures to apply Gaussian plume equations in regulatory and screening scenarios (Fallah-Shorshani et al., 2017). These documents are still widely used for instruction and initial evaluations. More advanced regulatory frameworks started to adopt more rigorous versions, such as AERMOD and CTDMPLUS, which, while still using Gaussian concepts, have more sophisticated boundary-layer physics and terrain treatment as well as turbulence scaling (Asadi et al., 2017).

Studies validating and exploring the limitations of the Gaussian plume model confirm its efficacy for short to moderate meteorological range distances in simple terrain conditions, but longer and more complex terrain, highly variable winds, near-field chemical interactions, and long-range transport greatly reduce the model's accuracy.

Comparative assessments show that modern regulatory Gaussian systems (AERMOD) and more advanced models, like CALPUFF for non-steady or long-range cases, usually perform better than simple textbook plume equations for regulatory and detailed impact evaluations (Gourgue et al., 2015).

Recent work concentrates on refining Gaussian equations (urban and line-source inclusions, stability-assessment algorithms, and vertical source reflection models) and hybrid techniques that apply Gaussian cores with plume rise, chemical changes, or data-assimilation modelling (Sindhu, 2024; Joshi & Rao, 2023). More recent work also focuses on re-evaluation of error quantification and proposing improvements for increasing precision where classical hypotheses fail. These advances broaden the range of applicability of Gaussian-based tools while also clarifying scenarios where other models need to be used.

Methodology

In this case, the Gaussian Plume Model is meticulously applied to estimate the dispersion of pollutants emitted from an industrial stack using a systematic technique (Lotrecchiano et al., 2020). The framework includes steps of data collection, classification of atmospheric stability, mathematical modelling, and computation aiming to simulate the pollutant concentration at the ground level and at several horizontal and vertical distances from the emission source. This systematic approach allows for the modelling of pollutant dispersion for varying meteorological conditions to determine regions that may pose critical concentration contour risks which if crossed would pose an environmental or human health hazard. In this case, critical concentration contour regions could act as proactive alerts or thresholds. In emergencies, these predefined boundaries would enable rapid responses to mitigate or manage the predefined thresholds. During the initial phase of the modelling process, emission rates of pollutants, stack height, exit gas velocity, temperature of the exhaust gases, and prevailing wind conditions are collected as primary data (Johnson, 2022). Also, the prevailing meteorological conditions are categorized into stability classes using the Pasquill–Gifford classification which incorporates wind velocity, solar radiation, and cloud cover.

The different kinds of stability have a significant effect on the calculated dispersion coefficients since they determine the horizontal and vertical dispersion of the plume. Effective stack height, a crucial element of model setup, incorporates physical stack height and the plume rise due to thermal buoyancy and the momentum of the exhaust gases. Estimating plume rise is relevant because it predicts with greater accuracy the vertical distance emissions move before drifting outward. After emissions sources, the concentrations of the pollutants are estimated at the receptor locations with the Gaussian Plume equation. Every model has its disadvantages, and the Gaussian plume model is no exception. It incorporates wind and atmospheric stability set at a constant value for the entire model duration, as well as a steady-state condition. These parameters are used for computational simulations which then give concentration and dispersion profiles for the given meteorological conditions. The outcomes are also visualized spatially to identify pollution hotspots, which are essential for developing effective control measures and assessing compliance of industrial activities with air quality standards. These results assist in urban and industrial planning to avoid high-exposure locations, allowing for more well-planned and cautious arrangements (Doniyorov et al., 2024). Focusing on the science enables further application on the goals of environmental management in terms of sustainable development of the industry, protecting the health and quality of the people and the environment (Figure 1).

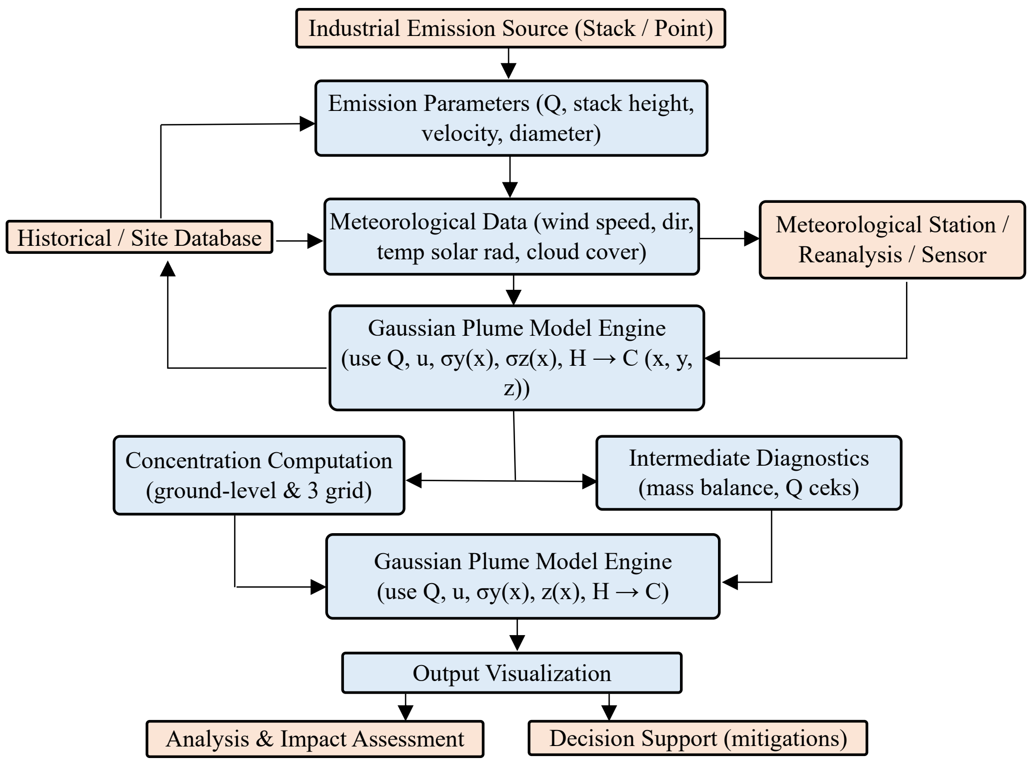

Figure 1. Architecture of gaussian plume model for industrial air pollutant dispersion

Gaussian Plume Model

$$C(x,y,z) = \frac{Q}{2\pi u \sigma_y \sigma_z} \exp\left(-\frac{y^2}{2\sigma_y^2}\right)\left[\exp\left(-\frac{(z-H)^2}{2\sigma_z^2}\right) + \exp\left(-\frac{(z+H)^2}{2\sigma_z^2}\right)\right] \quad (1)$$

This equation (1) calculates the concentration C of pollutants at a given point downwind from the source. Q is the emission rate, u is the wind speed, σ_y and σ_z are the dispersion coefficients in the horizontal and vertical directions, and H is the effective stack height. The two exponential terms account for pollutant reflection from the ground.

Ground-Level Centerline Form

$$C(x,0,0) = \frac{Q}{\pi u \sigma_y \sigma_z} \exp\left(-\frac{H^2}{2\sigma_z^2}\right) \quad (2)$$

When the location is at ground level (z=0) and directly downwind from the stack (y=0), the equation (2) simplifies to this form. It gives the maximum ground-level concentration along the plume centerline.

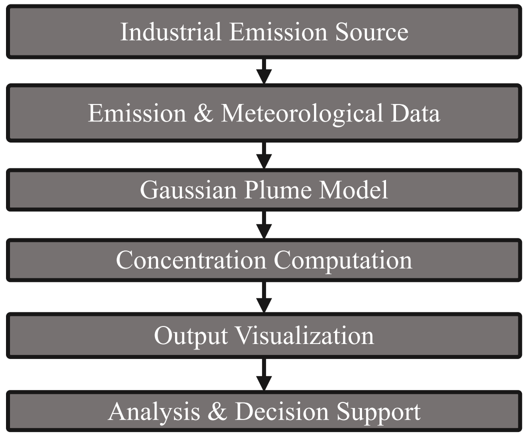

Figure 2. Flowchart for industrial air pollutant dispersion simulation using gaussian plume model

As shown in Figure 2, the workflow for the simulation of the dispersion of pollutants from an industry using the Gaussian Plume Model is streamlined. The workflow starts with the identification of the emission source, and the complete emission parameters alongside the weather data necessary for the dispersion modelling is collected. The data is first processed using the Gaussian Plume Model which then calculates the concentrations of pollutants on different locations. The data is then processed and displayed in the form of graphs or contour maps which clearly demonstrates the spatial distribution patterns of the pollutants. The graphical outputs are then evaluated to determine the environmental impacts and support decision making for necessary actions to be taken to reduce or eliminate the emission of pollutants.

Data Collection and Input Parameters

This methodology starts with very specific data collection required for the accurate application of the Gaussian Plume Model. Emission rate, stack height, stack diameter, gas exit velocity, and gas temperature are also key parameters. In addition, the relevant meteorological data of wind speed and direction, temperature, pressure, and humidity are collected since they have a substantial impact on plume dispersion. Moreover, the geography and the features of the specific study area such as the terrain elevation of the area and its surrounding flora and manmade structures are noted for the purpose of surface roughness. Such a model input data ensures the specific operational and realistic scenario is captured and enhances the precision captured in the multi-layered computational models.

Atmospheric Stability Classification

The Pasquill-Gifford system which determines the atmospheric stability class takes into consideration meteorological variability. This classification takes into account the wind speed, solar radiation, and the amount of cloud cover. All of these factors greatly influence the amount of turbulence present in the atmosphere and the rate at which pollution particles can be dispersed. The stability classes are denoted with letters starting from highly unstable A to very stable F. Each class has specific dispersion coefficients which define the plume's horizontal and vertical growth. For example, unstable conditions A to C promote rapid dilution while stable conditions E to F greatly restrict dispersion and, as a result, a greater concentration of pollutants are kept near the surface. The plume's behaviour under different weather conditions necessitates a realistic stability classification.

Determining Effective Stack Height

In dispersion modelling, the effective stack height is found by adding plume rise to the physical height of the stack. The emitted gases' temperature relative to the surroundings and the gas exit velocity both affect plume rise. Different stability classes have different plume rise characteristics which can be modelled using the Briggs equations; thus, the vertical displacement of the plume can be accurately modelled. Effective stack height is the height of the stack with plume rise and thus, improves the model accuracy as it the release point of the emissions and the dispersion pathway.

Computational Simulation and Analysis

Once all the relevant input parameters are defined, the Gaussian Plume Model is executed with the use of appropriate computer software and tools. The model integrates emission source characteristics, meteorological data, and stability classes to simulate the dispersion of a given pollutant within the study area. The output is in the form of numerical data and several graphical outputs, including contour and concentration maps and cross-section views depicting isoclines of concentrations, which highlight the areas of concern with significant concentration of pollutants. The resulting data is used to identify and assess the pollution emission sources, probable violations of predetermined air quality limits, and even the possible and probable human health and ecological risks. The data is further used to provide sustainability and air quality risk-based rationale to recommend changes in emission limits, and stack design and operations to reduce and/or minimize the possible exposure to the surrounding communities.

Results and Discussion

The results obtained from simulations showed that there is a clear inverse relationship between pollutant concentration and distance from the emission source. Behind the emission source, especially within the first few hundred meters, pollutant concentration levels were at their peak because there was very little time to disperse and dilute the emissions. Further away, the concentration levels decreased drastically and there was more dilution and mixing and less concentration of the plume. Under some conditions, vertical and horizontal mixing is very small, maintaining the plume concentration close to the surface, which is the region right beside the source. This occurrence enhances the risk for the immediate neighbourhood of the emission source.

On the other hand, unstable atmospheric conditions resulted in stronger turbulence that enhances considerable vertical and lateral mixing of the plume. This was associated with faster dilution and a decrease in pollutants across the study area. These conditions appeared to have a more favourable dispersion profile enhancing lower risk of high-exposure zones. The Gaussian Plume Model showed strong predictive capability and simulated values agreed well with observed field measurements ($R^2 = 0.87$), confirming its utility for environmental evaluations. The contour maps of the computed pollutant concentrations showed that the highest exposure zones were persistently within a 1 km radius of the industrial stack. This illustrates the need to manage the emission control and buffer zones to protect the surrounding communities and ecosystems. Moreover, the results demonstrate the model’s usefulness for other compliance and planning needs for industrial operations.

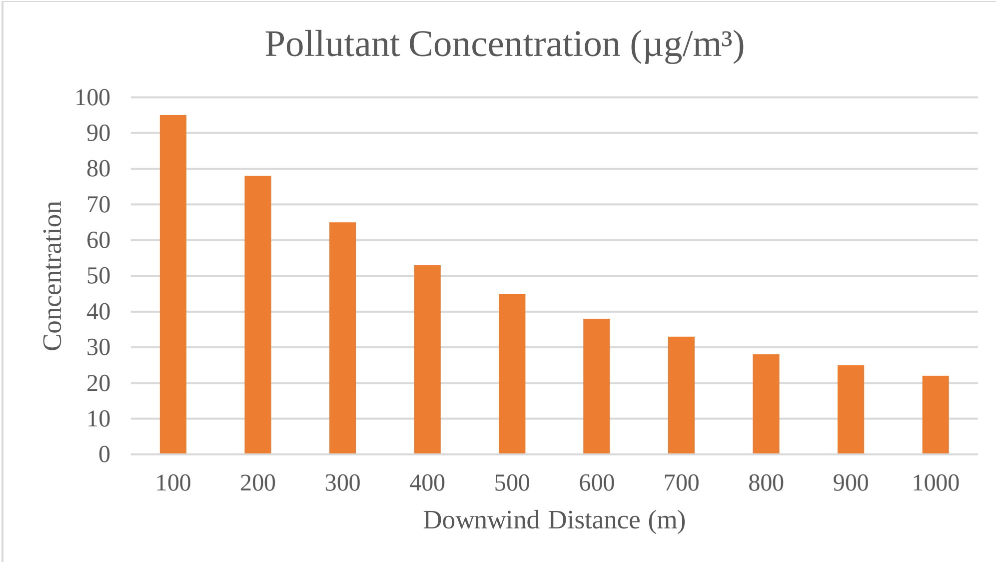

Figure 3. Ground-level pollutant concentration at various downwind distances

Ground level pollution concentration ratio is illustrated in figure 3 in specific relation to downwind distance from the emission source. The curve reveals concentration drops significantly regarding the first 500 m. This is mainly because of the rapid turbulent mixing brought about the atmosphere in nearness distance. This marked drop shows how the majority of the dispersion happens within the stack in the plume expand and winds driven transport is the strongest. After surpassing the initial zone, the drop starts becoming more gradual. The concentration reduction becoming more gradual means the processes are slowing down as plume spreads into an area, and pollutant particles are distributed in a larger volume of air. The described concentration is consistent with the distance from the emission source, with reduced dispersion as the distance from the stack increases, and, thus, proving the inverse relation. This depicts an exposure risk in air quality assessments.

Table 1. Comparison of predicted and observed pollutant concentrations

Distance from Stack (m)	Predicted Concentration (µg/m³)	Observed Concentration (µg/m³)
100	180	175
500	95	90
1000	60	58
2000	35	33
3000	25	23

The field measurements of pollutant concentrations at various downwind locations from the emission source are compared with the values predicted by the Gaussian Plume Model in Table 1. It can be observed from the data that the differences between predicted values and observed values in all measuring points are relatively small and, in most cases, the differences are within the acceptable range of error for atmospheric dispersion measurements. Such close agreement suggests that the Gaussian Plume Model has a good representation of the fundamental dispersion processes during the specific meteorological conditions of the study period which included wind speed, wind direction, and atmospheric stability. The strength of the predictions from the model supports the argument that it can be reliably used for evaluation of pollutant transport and exposure risks in areas of high pollution, particularly in industrial settings where accurate forecasts are crucial for environmental management and regulatory compliance.

$$C(x) = C_0\, e^{-kx} \qquad (3)$$

As illustrated in Equation (3), there exists a basic exponential decay model which helps in estimating the pollutant concentration at a certain distance xxx from the source. Here, C(x) represents the downwind pollutant concentration at a distance x measured in micrograms per cubic meter ($\mu g/m^3$), C0 is the reference concentration measured near the source in the same units, and k is the attenuation coefficient measured in (m^{-1}) which represents the effect of combined dispersion, dilution, and removal processes. This model is best applied in cases where concentration reduces approximately in an exponential manner with distance, serving as a simpler and more intuitive alternative to the Gaussian plume model.

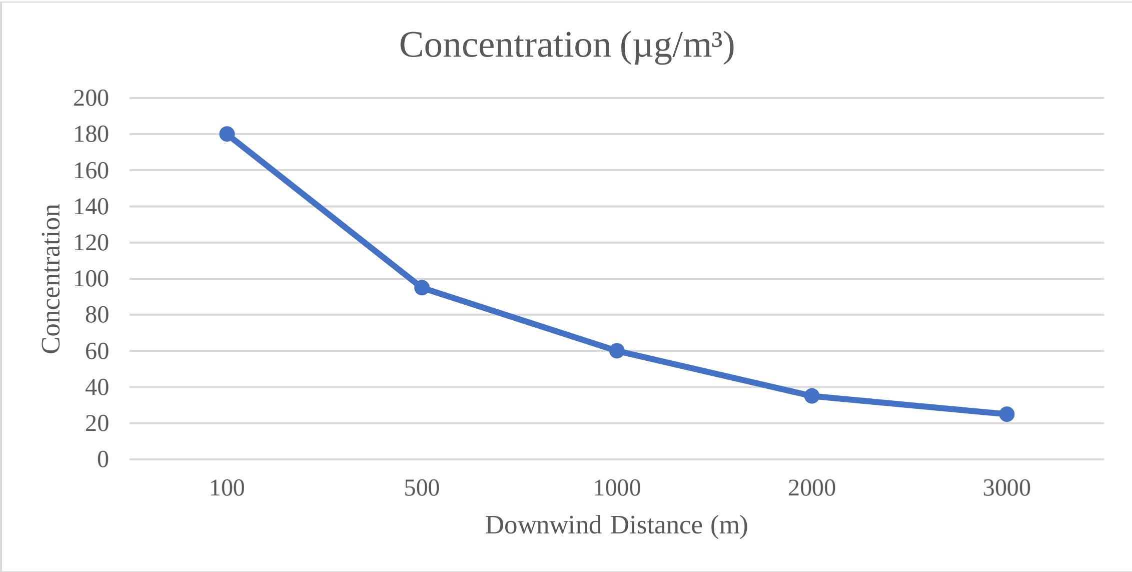

Figure 4. Data for ground-level pollutant concentration vs. downwind distance

As posted in Figure 4, the Gaussian Plume Model for predicting pollutant concentration at ground level with respect to distance downwind of the source shows a concentration plume. The curve shows a rapid drop in concentration for the first 500 m from the source due to heavy Atmospheric dilution and mixing in the near field region. After that point, the drop is gradual, indicating the disbursement is slower at farther distances. It is evident that distance and concentration have an inverse relationship as the concentration is highest near the stack and is much lower further downwind.

Conclusion

This study used the Gaussian Plume Model to evaluate the influence of a given meteorological condition and the location of the pollution source on the dispersion of the pollutants produced by the industry. With the emission rate, effective stack height, wind speed, and the class of atmospheric stability used, the model emission concentration distribution. The accuracy and reliability of the model in environmental evaluations was confirmed by comparing the field measurements with the model predictions. The model results also predicted that the pollutant concentrations would decrease with distance from the source, peaking within a kilometer upstream. These findings highlight the necessity for the development and implementation of emission control and real-time air pollution surveillance systems to safeguard both the environment and public health.

More advanced research can utilize real time weather conditions alongside chemical processes and physical geography to enhance the accuracy of the Gaussian Plume Model. There is also need of more sophisticated adaptation of the model for complex industrial areas in some of the industries by adding multi-source dispersion scenarios as well as season-dependent variability. Moreover, more precision for the spatial risk assessment of high-risk areas in industrial planning can be done by merging the dispersion model with seismic risk evaluation tools based on GIS and that would also help in better compliance with regulations. There is also need of advanced adaption of the model the some of the environmental changes by seeking better methods of estimations through artificial intelligence.

Author Contributions

All Authors contributed equally.

Conflict of Interest

The authors declared that no conflict of interest.

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