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RESEARCH ARTICLE

Model for Measuring the Dispersion Distance of PM2.5 from Combustion of Agricultural Residues

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Abstract

Air pollution caused by fine particulate matter (PM2.5) is a major environmental and public health concern, particularly in Northern Thailand. Agricultural residue burning is a primary contributor to PM2.5 pollution in Nakhon Sawan Province, Thailand, where rice and sugarcane cultivation generate substantial biomass waste. This study develops a dispersion model based on the Gaussian Plume Model to analyze PM2.5 spread from burning sites, aiding pollution forecasting and management. The methodology comprises three steps: (1) calculating PM2.5 emission rates, (2) predicting dispersion using meteorological data, and (3) visualizing results through concentration graphs and geospatial mapping. The model evaluates PM2.5 dispersion under different wind speeds (light, moderate, and strong) and atmospheric stability conditions. Simulated results indicate that PM2.5 concentrations peak near the source and decrease along the x-axis. Under light breeze conditions, the PM2.5 concentration at 125 meters is 0.00245 $\mu g/m^3$, decreasing to nearly zero at 1,000 meters. Stronger winds enhance dispersion, reducing concentrations more rapidly. The findings confirm the model's effectiveness in estimating PM2.5 dispersion and emphasize the influence of meteorological factors on pollutant distribution. Future improvements should incorporate geographical factors, additional emission sources, and regional accumulation effects for improved accuracy. The model provides a foundation for policymakers to develop air pollution mitigation strategies that promote public health and environmental sustainability.

1. Introduction

PM2.5 is a particulate matter that significantly contributes to air pollution and currently has the most substantial impact on human health. PM2.5 can be produced from various sources, such as emissions from vehicle engines, forest fires, and the burning of agricultural waste. According to air quality monitoring by the Pollution Control Department in Northern Thailand, six provinces have recorded pollution levels exceeding the standard: Chiang Rai, Chiang Mai, Lampang, Lamphun, Phrae, and Nan (Pollution Control Department, 2019). In Nakhon Sawan province, pollution levels exceeded the standard by 11–20% throughout the year (Air Quality and Noise Management Bureau, Pollution Control Department, 2020).

The predominant factor contributing to elevated pollution levels in Nakhon Sawan province is the open burning of agricultural residues following harvest. Approximately 49% of the province's agricultural land is allocated to rice and sugarcane cultivation, both of which generate significant residual biomass. Post-harvest residue management practices primarily involve either plowing the biomass into the soil or burning it to prepare for the subsequent planting season. When farmers opt for burning, particularly during periods of stagnant atmospheric conditions with minimal wind, the accumulation of fine particulate matter (PM2.5) in the air significantly increases. This practice is a major contributor to pollution levels that frequently exceed established air quality standards (Wongwaitayakool, 2018).

Due to the issue of air pollution accumulation ex-

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ceeding standard levels caused by the burning of agricultural waste, the researcher is interested in developing a model to measure the dispersion distance of PM2.5 from burning agricultural areas. This model aims to serve as a crucial tool in applying knowledge gained from studying the factors affecting the dispersion distance of PM2.5. It will be used to forecast the accumulation of PM2.5 and to plan for the prevention, control, and management of such events.

2. Literature Review

Traditional atmospheric dispersion modeling has been extensively used to understand how pollutants like PM2.5 spread in various environments. One of the most common models, the Gaussian Plume Model (GPM), provides a mathematically simple yet effective tool to simulate pollutant behavior under assumptions of steady-state emissions and homogeneous atmospheric conditions. Lotrecchiano et al. (2020) applied the GPM to simulate fire-related pollutant dispersion and found the model's predictions to be reliable when multiple monitoring stations were used to validate concentration levels. Abdel-Rahman (2008) also verified the usefulness of the Gaussian Plume approach for near-ground pollutant emissions, emphasizing its sensitivity to wind speed, atmospheric stability, and emission height.

Another important study by Yang et al. (2020) modified the GPM for predicting ammonia and PM dispersion from poultry farms. Their version incorporated field-specific assumptions such as steady emission sources, constant wind speed, and uniform distribution. Their findings confirmed that while GPM assumptions limit real-world accuracy, its predictions aligned well with field measurements when environmental parameters were tightly controlled. This affirmed its applicability for rural agricultural settings.

In contrast, AERMOD, developed by the U.S. EPA and used by Alemayehu and Hackett (2015), introduces additional complexity by integrating boundary layer meteorology and terrain data. Their application showed that both PM2.5 and SO2 dispersion patterns could be simulated more accurately within regulatory limits. AERMOD's strength lies in its ability to model variable meteorological profiles, although it requires more extensive input data than GPM.

Recent innovations have explored the integration of remote sensing data and machine learning. Li et al. (2015) combined satellite imagery with Random Forest regression models to estimate surface PM2.5 concentrations across large spatial extents. This hybrid model significantly improved spatial resolution and prediction accuracy ($R^2 = 0.98$), especially in areas lacking monitoring infrastructure. However, its reliance on large, labeled datasets and computational resources limits its applicability in small-scale agricultural settings.

Zhang et al. (2018) proposed a weather-integrated GPM that dynamically adjusted model parameters based on real-time meteorological inputs. This improvement increased temporal precision in PM2.5 forecasts while maintaining the model's core simplicity. It bridges the gap between static Gaussian models and dynamic hybrid systems.

More advanced approaches include hybrid AI models. For instance, Wu et al. (2023) introduced CEEMDAN-PE-GWO-VMD-BiLSTM-AT, a deep learning framework capable of capturing nonlinear relationships in time-series PM2.5 data. Similarly, Ma et al. (2024) employed Graph Convolutional Networks (GCNs) to model the spatial-temporal correlation of emissions across urban environments. GCNs adapt well to irregular spatial distributions and are highly suitable for dense cities but are computationally intensive.

Li and Wu (2024) utilized LSTM networks to track PM2.5 variability across multiple stations in China, demonstrating effectiveness for time-series forecasting in data-rich environments. Huang (2016) proposed a hybrid ARIMA-SVM model to overcome the limitations of linear models in predicting pollutant trends. Tırınk (2025) used ensemble learning methods (e.g., XGBoost, LightGBM) on air pollution datasets to outperform conventional dispersion models. Qin et al. (2019) applied convolutional neural networks (CNNs) on spatial grids to assess fine-grained pollutant diffusion. Meanwhile, Feng et al. (2022) developed a transfer learning approach to adapt trained PM2.5 models from urban to suburban environments with minimal labeled data.

Based on the comprehensive literature review, the existing pollution dispersion models can be broadly categorized into several groups. Each approach presents distinct strengths and limitations depending on its underlying methodology and data requirements. The following table summarizes a qualitative comparison of these models, highlighting their respective advantages, challenges, and suitable application contexts. This classification aims to provide a clearer understanding of how the proposed GPM fits within the spectrum of available modeling techniques, as shown in Table 1.

Collectively, these studies highlight a continuum of modeling approaches ranging from empirical models such as the GPM to advanced AI-based systems. While sophisticated machine learning frameworks offer high accuracy, they often require extensive data and computational resources. In contrast, this study adopts a GPM-based approach that is physically grounded and computationally efficient, making it well-suited for rural agricultural settings where data availability may be limited. This model aims to strike a balance between practicality and accuracy, providing a reliable tool to support local air quality forecasting and inform evidence-based environmental management strategies.

Table 1. Comparative overview of PM2.5 dispersion modeling approaches.

Model	Strengths	Limitations	Suitable Applications
GPM	- Physically based, simple, and fast to implement. - Requires relatively minimal input data (e.g., wind speed, emission rate).	- Assumes steady-state emissions and homogeneous atmospheric conditions. - Not suitable for complex terrain or highly variable meteorological conditions.	- Suitable for rural areas or scenarios with stable sources and weather conditions.
AERMOD	- Incorporates terrain and detailed meteorological data. - Models atmospheric boundary layer changes effectively.	- Requires extensive input data and computational resources.	- Suitable for urban or complex terrain environmental impact assessments.
Machine Learning Models (LSTM, RF, GCN, etc.)	- High accuracy when trained with large, comprehensive datasets. - Can capture complex nonlinear relationships.	- Requires large labeled datasets and high computational power. - May lack clear physical interpretability.	- Suitable for long-term forecasting and dense urban areas with rich monitoring data.
Hybrid Models (AI + Physics-based)	- Combines strengths of physical and data-driven approaches.	- Complex and data-intensive.	- Used when high accuracy is needed across diverse environmental conditions.

3. Methodology

The methodology of this research is divided into three steps: Step 1 involves calculating the emission rate of PM2.5 into the air; Step 2 involves forecasting the dispersion of PM2.5 in the air; and Step 3 involves presenting the model results, as shown in Fig. 1.

Step 1: Calculating the Emission Rate of PM2.5 into the Air

In this model, the calculation area is defined as 1 Thai Rai (40 meters × 40 meters). The PM2.5 pollutant quantity is based on the mass of dry rice straw Junpen et al. (2018), as shown in Equation 1.

$$Q_{PM2.5} = M \times EF_{PM2.5} \tag{1}$$

where $Q_{PM2.5}$ is the emission rate of PM2.5 pollutants (milligrams/second), M is the mass of dry rice straw (grams dry mass/rai), and $EF_{PM2.5}$ is the emission factor of PM2.5 pollutants (seconds/Thai rai).

Step 2: Forecasting the Dispersion of PM2.5 in the Air

This research uses data from agricultural burning in Tambon Nong Bua, Amphoe Nong Bua, Nakhon Sawan Province (Office of Agricultural Economics, Ministry of Agriculture and Cooperatives, 2020). The calculation of PM2.5 concentration includes horizontal test distances, wind speed, atmospheric stability, and the height of the area (Yang et al., 2020). The horizontal test distances are set at 125 meters intervals from the burning point up to 1,000 meters. Wind speed is categorized into three levels:

- **Light breeze:** smoke rises straight up, wind speed of 0.44 meters/second.
- **Moderate breeze:** dust disperses, wind speed of 5.78 meters/second.
- **Strong breeze:** large branches sway, wind speed of 11.11 meters/second (National Oceanic and Atmospheric Administration (NOAA), 2020).

For atmospheric stability, levels B (moderately unstable) and D (neutral) are used (U.S. Environmental Protection Agency, 1995), representing the worst-case scenarios for air pollution accumulation at the selected wind speeds. The calculations using the GPM (Colls, 2002) can be expressed as follows:

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

$$\sigma_y = 465.11628\, x \, \tan(\Theta) \tag{3}$$

$$\Theta = 0.017453293\,[c - d\ln(x)] \tag{4}$$

$$\sigma_z = a\, x^b \tag{5}$$

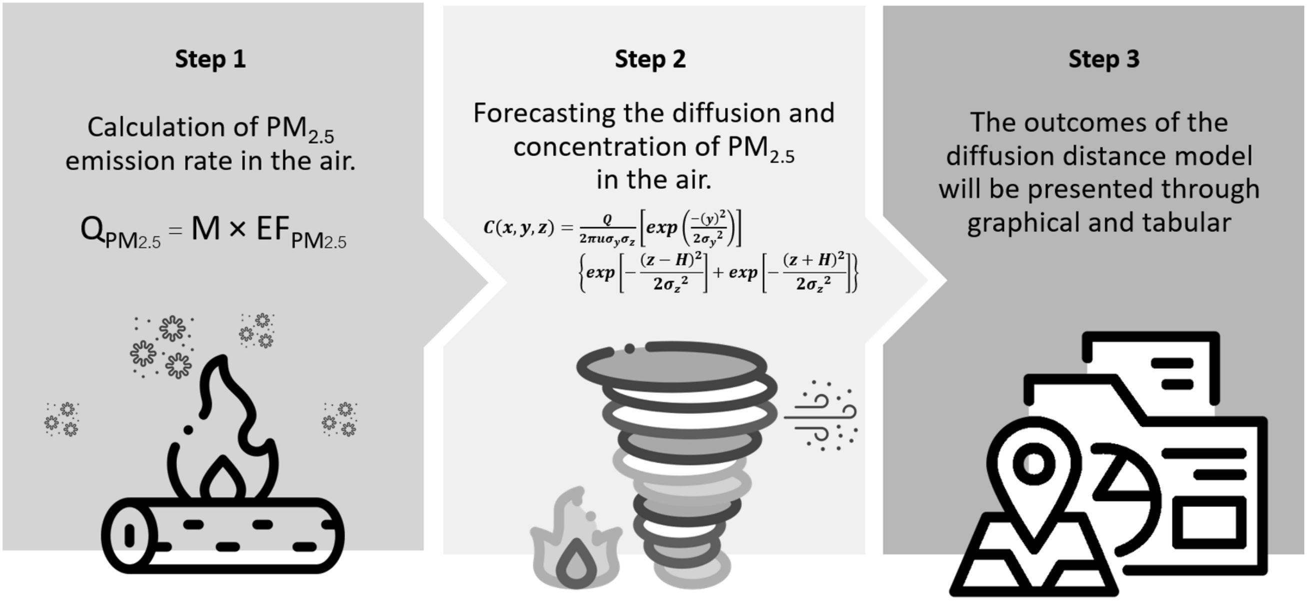

Figure 1. Methodology framework.

where:

$C(x, y, z)$: pollutant concentration at position (x, y, z) (milligrams/cubic meter)
Q : emission rate of the pollutant (milligrams/second)
π : constant, 3.141
x : distance along the x-axis from the emission source (meters)
y : distance along the y-axis (meters), perpendicular to the x-axis
z : height above ground level (meters)
H : height of the emission source (meters), set to 0 since burning occurs at ground level
σ_y : horizontal dispersion coefficient (meters)
σ_z : vertical dispersion coefficient (meters)
Θ : angle perpendicular to the x-axis (radians)

The parameters a, b, c, and d are derived from atmospheric stability levels, corresponding to wind speed (meters/second) and the amount of sunlight or cloud cover. Equation 2 calculates the pollutant concentration at height z, determined by subtracting the elevation at the PM2.5 source from the elevation at the target point. The resulting value can be positive or negative.

Equations 3–4: σ_y is calculated using Θ, where the horizontal distance x is in kilometers.

- For light breeze conditions ($u = 0.44$ meters per second, stability level B): $c = 18.3330$, $d = 1.8096$.
- For moderate breeze conditions ($u = 5.78$ meters per second, stability level D): $c = 8.333$, $d = 0.72382$.
- For strong breeze conditions ($u = 11.11$ meters per second, stability level D): $c = 8.333$, $d = 0.72382$.

Equation 5: σ_z uses the horizontal distance x (in kilometers).

- **Light breeze** ($u = 0.44$ meters per second, stability level B):
  - Distance $<$ 200 meters: $a = 90.673$, $b = 0.93198$.
  - 210 meters $\leq$ Distance $\leq$ 400 meters: $a = 98.483$, $b = 0.98332$.
  - Distance $>$ 400 meters: $a = 109.300$, $b = 1.09710$.
- **Moderate breeze** ($u = 5.78$ m/s, stability level D):
  - Distance $<$ 300 meters: $a = 34.459$, $b = 0.86974$.
  - 310 meters $\leq$ Distance $\leq$ 1,000 meters: $a = 32.093$, $b = 0.81066$.
- **Strong breeze** ($u = 11.11$ meters per second, stability level D):
  - Distance $<$ 300 meters: $a = 34.459$, $b = 0.86974$.
  - 310 meters $\leq$ Distance $\leq$ 1,000 meters: $a = 32.093$, $b = 0.81066$.

Step 3: Displaying the Results of the Model

The results of the dispersion model will be presented in the form of graphs and tables using the GPM method. The concentration of PM2.5 from the source will be highest at the emission point and will decrease to near zero as the horizontal distance along the x-axis increases. The results will be displayed according to varying wind speeds and atmospheric stability levels. The calculated concentration of PM2.5 will be expressed in units of micrograms per cubic meter (μg/m^3).

4. Findings and Discussion

The simulation of PM2.5 dispersion using the GPM was conducted at distances of 125, 250, 375, 500, 675, 750, 875, and 1,000 meters from the source, assuming a constant emission rate of 399.667 milligrams per second. Under a light breeze, the initial concentration was 0.00245 micrograms per cubic meter, gradually decreasing to 0.00037 micrograms per cubic meter at 1,000 meters. For moderate wind conditions, the concentration started at 0.00095 micrograms per cubic meter and dropped to 6.46×10^{-5} micrograms per cubic meter, while under strong winds, it began at 0.00049 micrograms per cubic meter and fell to 3.36×10^{-5} micrograms per cubic meter. The highest concentration along the x-axis was observed at 675 meters.

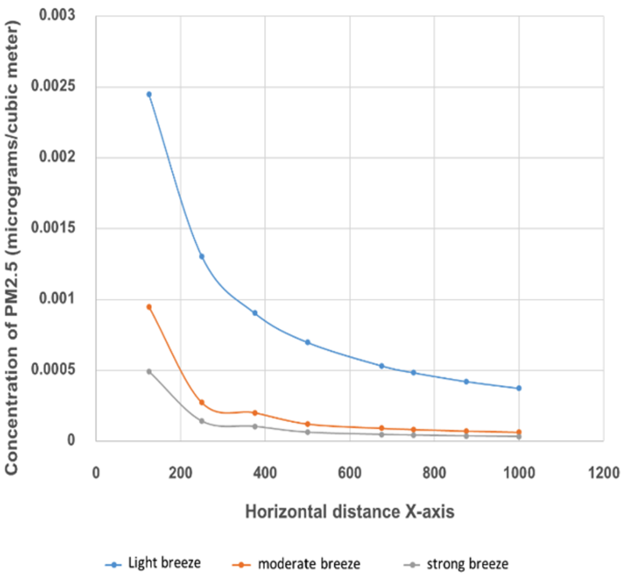

Figure 2. Concentration of PM2.5.

As shown in Fig. 2, PM2.5 concentrations decrease with increasing distance from the source under varying wind speeds.

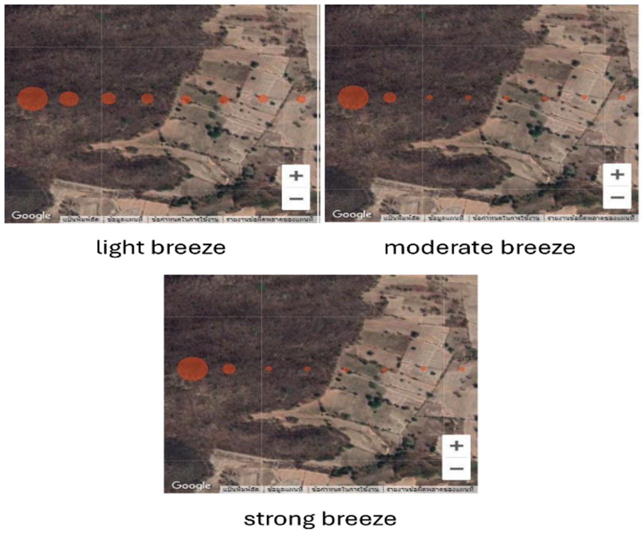

Figure 3. Results on Google Map.

Fig. 3 illustrates the spatial distribution of PM2.5 concentrations on Google Maps within the study area, highlighting that dust concentration changes least over time under light breeze conditions and most rapidly under strong breeze conditions. These measurements correspond to coordinates 15.85902 latitude and 100.6547 longitude.

The findings from this study are particularly valuable for local policymakers and rural environmental management authorities. By utilizing readily available meteorological data, the model allows local governments to estimate PM2.5 dispersion patterns and identify high-risk areas during agricultural burning periods. This enables the implementation of targeted interventions such as temporary burning restrictions, localized public health advisories, and the promotion of alternative biomass management practices. Its low data requirements and computational simplicity make the model highly suitable for rural contexts, where access to advanced monitoring technologies is often limited. Consequently, this study provides a practical and cost-effective tool to support evidence-based decision-making and strengthen air quality management in agricultural communities.

5. Conclusion

This study developed a Gaussian Plume Model to estimate the dispersion distance of PM2.5 emitted from agricultural residue burning in Nakhon Sawan Province, Thailand. The findings emphasize the critical role of meteorological conditions, particularly wind speed and atmospheric stability, in influencing pollutant dispersion patterns. While the model demonstrates practical applicability for forecasting PM2.5 spread in rural agricultural settings, it also faces limitations, such as the exclusion of complex terrain effects and other pollution sources, which may affect prediction accuracy. Despite these challenges, the model provides a valuable foundation for local authorities to better understand and manage air quality risks associated with agricultural burning. Future work should focus on addressing these limitations through incorporation of geographical factors, additional emission sources, and validation with field measurements. Ultimately, this research contributes to the ongoing efforts to develop accessible and effective tools that support evidence-based policies aimed at reducing PM2.5 exposure and protecting public health in rural communities.

In future research, it is essential to incorporate detailed geographical factors into the dispersion model to better reflect the influence of terrain, land use, and elevation on the spread of PM2.5 pollutants. Including such spatial characteristics will allow for more accurate predictions of pollutant behavior across complex rural landscapes. Additionally, the model should be expanded to consider multiple sources of PM2.5 emissions beyond agricultural residue burning, such as those originating from vehicles, industrial facilities, and other anthropogenic activities within and around the study area. Accounting for these diverse emission sources will provide a more comprehensive understanding of air pollution dynamics and cumulative impacts on local air quality. Furthermore, future work should address the accumulation and interaction of PM2.5 from neighboring regions, as pollutant transport across boundaries can significantly influence concentration levels and exposure risks. By integrating these factors, the model's overall accuracy and relevance to real-world conditions will be greatly enhanced, thereby improving its utility as a decision-support tool for environmental management and public health protection.

Declaration of AI Use

The authors declare that AI tools were used only to assist in language refinement and content organization. All AI-generated outputs were carefully reviewed and validated by the authors to ensure factual accuracy, originality, and compliance with ethical publication standards.

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