# The Application of Google Earth Engine on PM2.5 Estimation and its Distribution Pattern in Saraburi Province, Thailand

**Rirugchart, P.,[1] Losiri, C.[2*] and Sitthi, A.[3]**
Department of Geography, Faculty of Social Sciences, Srinakharinwirot University, Watthana, Bangkok, Thailand, E-mail: pattara.rirugchart@g.swu.ac.th,[1] chudech@g.swu.ac.th[2*] asamaporn@g.swu.ac.th[3]
**Corresponding Author*

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**Abstract**
*In 2019, air pollution in Thailand caused 41,000 deaths, with Saraburi province identified as an area of concern for air pollution monitoring. From 2020 to 2022, there were consistently reported cases of respiratory diseases caused by prolonged exposure to air pollution in this province. Moreover, the number of air quality monitoring stations in Saraburi is insufficient for accurate future predictions of particulate matter levels. Therefore, this research aims to estimate PM2.5 concentrations from Aerosol Optical Depth (AOD) and meteorological data and study the spatial distribution patterns of PM2.5 in Saraburi Province. The estimation of PM2.5 levels is conducted using AOD data combined with meteorological data through a Multiple Linear Regression (MLR) method. The estimated values are then used to analyze the distribution patterns of PM2.5. The study found that in 2018, the average monthly PM2.5 concentration ranged from 0 to 74.1 µg/m³, with high-value clustering (hot spots) covering approximately 421.43 km², or 12.04% of the provincial area. In 2019, the average monthly PM2.5 concentration ranged from 0 to 41.4 µg/m³, with hot spots covering approximately 509.29 km², or 14.55% of the provincial area. In 2020, the average monthly PM2.5 concentration ranged from 0 to 50.0 µg/m³, with hot spots covering approximately 648.37 km², or 18.53% of the provincial area. In 2021, the average monthly PM2.5 concentration ranged from 0 to 55.3 µg/m³, with hot spots covering approximately 562.93 km², or 16.09% of the provincial area. In 2022, the average monthly PM2.5 concentration ranged from 0 to 57.3 µg/m³, with hot spots covering approximately 615.97 km², or 18% of the provincial area. The most of high-value clusters were in the western part of the province, where agricultural activities are prevalent, contributing to higher PM2.5 levels. In contrast, low-value clusters (cold spots) were primarily found in the eastern part of the province, which is largely forested.*

**Keywords:** AOD, Getis-Ord Gi*, MLR, Moran's I, PM2.5

## 1. Introduction

Air pollution is one of the leading risk factors for human mortality. According to a report by Our World in Data, in 2017, air pollution caused 6.56 million deaths worldwide. Air pollution originates from both natural sources and human activities. It can be categorized into two groups: particulate matter and gases. Fine particulate matter (PM2.5) is a significant air pollutant because it can remain suspended in the air for long periods, travel far from its source, and easily penetrate the human body. In 2015, The Global Burden of Disease (GBD) reported that long-term exposure to PM2.5 resulted in 4.2 million deaths, with 59% of these occurring in South and East Asia [1]. In 2005, Southeast Asian countries were found to have the worst air quality globally. In 2006, the WHO published air quality guidelines, identifying air pollution, particularly PM2.5, as a major threat to human health.

In Thailand, PM2.5 levels exceed standards during the late winter to early summer or seasonal transitions. During late winter, high-pressure systems or cold air masses from China periodically cover the upper part of Thailand, strengthening the northeast monsoon, leading to lower temperatures and cold weather. However, when the high-pressure systems weaken, the northeast monsoon also weakens or becomes calm, combined with temperature inversion at lower levels, resulting in low levels of particulate matter dispersion. Poor air circulation leads to the accumulation of dust, fog, and smoke in the atmosphere. Increased particulate matter in Thailand affects health, economy, and society.

A study by the Health Effects Institute reported that in 2019, air pollution was the seventh leading cause of death in the country, with 41,000 deaths. PM2.5 is the most impactful air pollutant on health. Research in Thailand assessing the economic and social impacts of air pollution found that in 2020, the economic and social impacts of PM2.5 amounted to 1.67 trillion baht, or 10.63% of the gross domestic product [2]. This indicates that PM2.5 impacts not only public health but also the economy, society, and national development.

Saraburi province is an area under air pollution surveillance. Particulate matter in Saraburi originates from diesel engine vehicles, open burning, industrial factories, and quarrying industries. Temperature inversion during late winter each year leads to poor air circulation, resulting in increased particulate matter in the atmosphere. Public health data from Saraburi province from 2020-2022 shows 336,036 respiratory disease cases [3], reflecting continuous exposure to air pollution annually. Saraburi has only two air quality monitoring stations, insufficient for predicting future particulate matter concentrations.

Currently, remote sensing technology is used to explore the Earth, monitor natural resources and environmental changes, and track global climate and air quality. Data from remote sensing devices or sensors on satellites or unmanned aerial vehicles can be analyzed spatially and temporally. Research in Thailand and abroad has studied PM2.5 concentration measurements using Aerosol Optical Depth (AOD). AOD affects atmospheric aerosols and is crucial for determining PM2.5 concentrations. The AOD data with a spatial resolution of 1 $km^2$ from the MAIAC algorithm of MODIS was compared with MYD04 data with a spatial resolution of 10 $km^2$ to assess the relationship and suitability for estimating PM2.5 using 84 ground monitoring stations in the UK [4]. In Thailand, the AOD from the Himawari 8 satellite was utilized to estimate PM2.5 in northern Thailand using Principal Component Analysis - General Regression Neural Network (PCA - GRNN) and Multiple Linear Regression (MLR) compared with ground monitoring stations [5]. Moreover, a study utilized AOD data from MODIS sensors with the MAIAC algorithm on the combined Aqua and Terra platform, using the MCD19A2 product processed by NASA. The data was analyzed alongside meteorological data to predict PM2.5 concentrations in Bangkok and its vicinity [6]. These studies applied remote sensing technology to various research areas to understand spatial patterns better. Therefore, the researcher recognizes the importance of this study, as Saraburi lacks researchers to study the area. Most research focuses on PM2.5 issues in major cities like Bangkok and Chiang Mai.

This study aims to estimate PM2.5 from AOD and meteorological data and study PM2.5 distribution patterns. The researcher hopes this study will guide PM2.5 monitoring when ground stations are insufficient or non-functional, allowing the government and private sectors to plan and develop policies to address PM2.5 issues, improving air quality and living conditions for the public in the future.

## 2. Study Area

The study area is Saraburi Province, located in central Thailand, covering approximately 3,576.49 $km^2$. The topography of Saraburi Province consists of about 60% lowland, which is part of the Chao Phraya River Basin, covering the western, central, and southern parts of the province. The northern and northeastern areas are characterized by flat terrain interspersed with hills, accounting for about 40% of the province, as shown in Figure 1. The climate of Saraburi Province is divided into three seasons: winter, summer, and rainy season. Winter lasts from mid-October to mid-February, during which cool and dry winds influenced by the northeast monsoon prevail, resulting in cool to cold weather. Summer spans from mid-February to mid-May, influenced by winds from the south and southeast, leading to generally hot and humid conditions. The rainy season extends from mid-May to mid-October, influenced by the southwest monsoon, which brings moisture from the Indian Ocean to Thailand. Additionally, a low-pressure trough passes over northern Thailand almost throughout the season, resulting in widespread rainfall. The average annual temperature in Saraburi Province is 28-29°C, with the highest temperatures reaching 33-34°C and the lowest temperatures ranging from 23-24°C.

## 3. Data and Methodology

### *3.1 Data*

To analyze the spatial distribution of PM2.5 in Saraburi province, the data is detailed and listed as shown in Table 1.

#### *3.1.1 AOD*

Aerosol Optical Depth (AOD) measures the transmission of solar radiation through aerosol particles to the Earth’s surface. These particles may include dust, smoke, and pollutants dispersed in the atmosphere. AOD data is collected using the Google Earth Engine platform with the MCD19A2 product, which includes data from the Terra satellite at 10:30 AM and the Aqua satellite at 1:30 PM Thai time. Both satellites orbit the Earth, recording global data every 1-2 days.

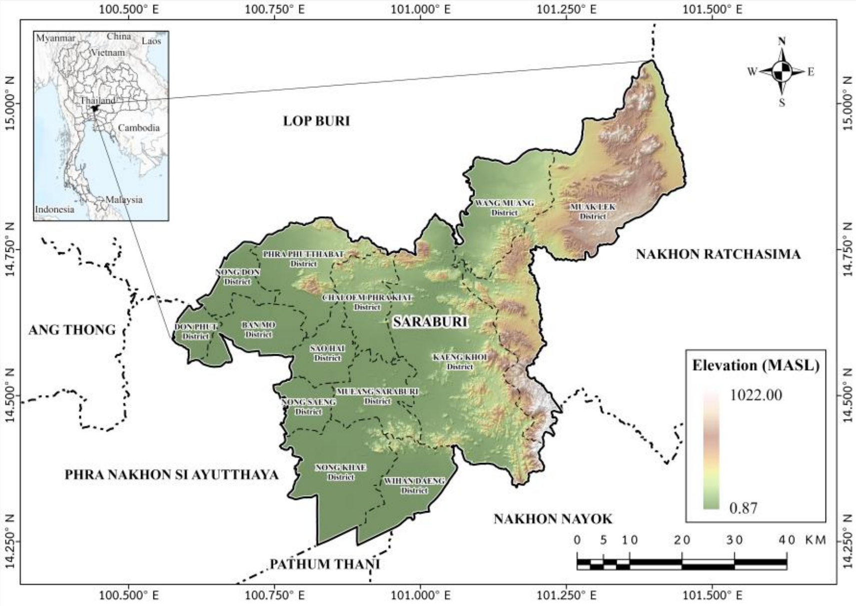


**Figure 1:** Saraburi province, Thailand

**Table 1:** Data used in the study

| Data Set | Variable | Data Source | Unit | Temporal Data | Spatial Data |
|---|---|---|---|---|---|
| Satellite Data | Aerosol Optical Depth (AOD) | MODIS | None | Daily (2018-2022) | Pixel 1 x 1 km |
| Meteorological Data | Air Temperature | ECMWF | Degrees Celsius | Daily (2018-2022) | Pixel 0.125° x 0.125° |
| | Relative Humidity | ECMWF | Percentage | Daily (2018-2022) | Pixel 0.125° x 0.125° |
| | Wind Speed | ECMWF | m/s | Daily (2018-2022) | Pixel 0.125° x 0.125° |
| Ground-based PM2.5 Data | Particulate Matter less than 2.5 microns (PM2.5) | Pollution Control Department (Thailand) | µg/m³ | Daily (2018-2022) | - |

Terra and Aqua use the MODIS sensor system, which has 36 spectral bands ranging from 0.41 to 14.28 µg/m³. Currently, the Multiangle Implementation Atmospheric Correction (MAIAC) algorithm, with a spatial resolution of 1 km, is used.

*3.1.2 Meteorological data*

Meteorological data is a factor related to the concentration of fine particulate matter (PM2.5) in Thailand. To estimate and track trends in PM2.5 changes, meteorological data is necessary to improve the accuracy of the model results. The meteorological data variables used to estimate PM2.5 include air temperature, relative humidity, and wind speed. This study uses Google Earth Engine to collect ERA5 climate data from the European Centre for Medium-Range Weather Forecasts (ECMWF). ERA5 is a reanalysis model that uses weather data from global monitoring stations to create spatial data with a resolution of 0.125° x 0.125°. Google Earth Engine currently provides ERA5 data on an hourly, daily, and monthly basis with a spatial resolution of 11.132 km. Since the spatial resolutions of the data differ, the researcher uses the AOD resolution as a basis for rescaling to a uniform spatial resolution of 1 km. Bicubic interpolation, an image processing technique, is used to improve the size or scale of the image by estimating new pixels based on 4x4 neighboring pixels, resulting in increased image resolution [7].

*3.1.3 PM2.5 data from ground stations*

PM2.5 data is collected using Multiple Linear Regression (MLR) to derive equations for estimating PM2.5 concentrations in Saraburi Province. Data is sourced from two air quality monitoring stations of the Pollution Control Department in Saraburi Province: 1) Station 24t located at Na Phra Lan Police Station, Na Phra Lan Subdistrict, Chaloem Phra Kiat District, Saraburi Province, and 2) Station 25t located at Phra Lak Fire Station, Pak Phriao Subdistrict, Mueang Saraburi District, Saraburi Province. Additionally, data is collected from six neighboring province stations: 1) Station 20t at

Bangkok University, Rangsit Campus, Khlong Nueng Subdistrict, Khlong Luang District, Pathum Thani Province, 2) Station 21t at Ayutthaya Wittayalai School, Pratu Chai Subdistrict, Phra Nakhon Si Ayutthaya District, Phra Nakhon Si Ayutthaya Province, 3) Station 47t at Phon Saen Pumping Station, Nai Mueang Subdistrict, Mueang Nakhon Ratchasima District, Nakhon Ratchasima Province, 4) Station 77t at Ban Bu Yai Bai Community Hall, Tha Tum Subdistrict, Si Maha Phot District, Prachin Buri Province, 5) Station 99t at Lopburi Meteorological Station, Thale Chup Son Subdistrict, Mueang Lopburi District, Lopburi Province, and 6) Station o66 at Chalerm Phrakiat Water Park, Yan Sue Subdistrict, Mueang Ang Thong District, Ang Thong Province. In total, data is collected from eight stations, as shown in Figure 2.

*3.2 Methodology*

This research is divided into two parts according to its objectives: estimating PM2.5 from AOD and meteorological data and studying the distribution patterns of PM2.5. The preliminary steps are explained in Figure 3.

*3.2.1 Estimation of PM2.5*

To estimate fine particulate matter (PM2.5), the researcher used the Multiple Linear Regression (MLR) method, which is commonly used to estimate values related to PM2.5. This regression analysis method finds the linear relationship between the dependent variable and two or more independent variables using Equation 1 [6].

$$PM2.5 = a_0 + a_1 AOD + a_2 T + a_3 WS + a_4 RH \qquad \text{Equation 1}$$

Where:

$PM2.5$ = Fine particulate matter (PM2.5)
$a_0$ = y-intercept
$a_1, a_2, a_3, a_4$ = Regression coefficients of the independent variables
$AOD$ = Aerosol Optical Depth
$T$ = Air temperature
$WS$ = Wind speed
$RH$ = Relative humidity

Using Google Earth Engine to collect independent variables, including AOD and meteorological data such as air temperature, relative humidity, and wind speed, all of which are daily data. Data is collected from the locations of the eight air quality monitoring stations over five years (2018-2022) and exported in CSV table format to find the relationship between the independent variables and the dependent variable, PM2.5, from ground stations. Microsoft Excel's Regression function in Data Analysis is used to create the MLR equation. Once the equation for estimating PM2.5 for the study area is known, it is applied in Google Earth Engine, exporting spatial data in Raster file format to map PM2.5. The risk levels of PM2.5 are determined according to Thailand's air quality standards. PM2.5 between 0 – 15.0 μg/m³ Very good, meaning everyone can live normally. PM2.5 between 15.1 – 25.0 μg/m³ Good, meaning at-risk groups should monitor for symptoms like frequent coughing, difficulty breathing, wheezing, chest tightness, chest pain, palpitations, nausea, unusual fatigue, or dizziness.

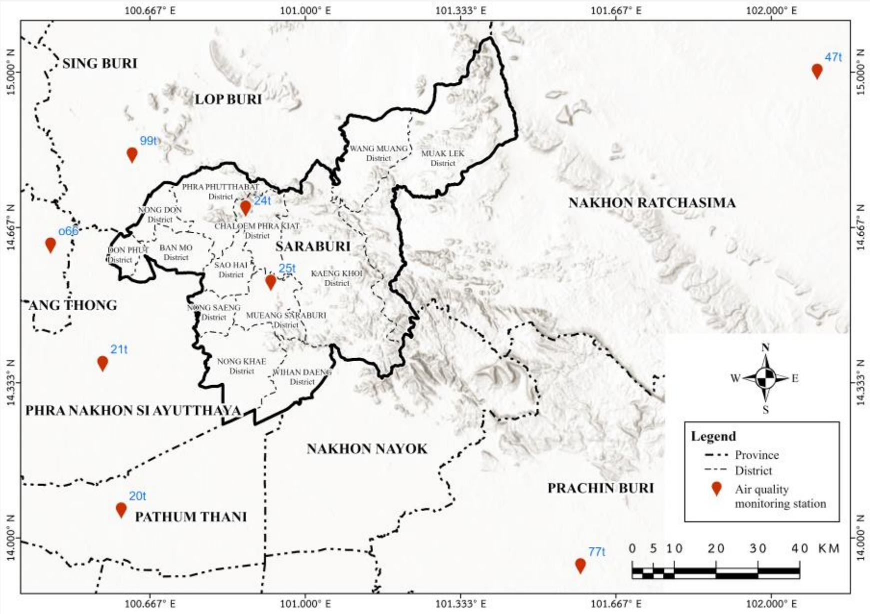


**Figure 2:** Locations of air quality monitoring stations in Saraburi Province and neighboring provinces

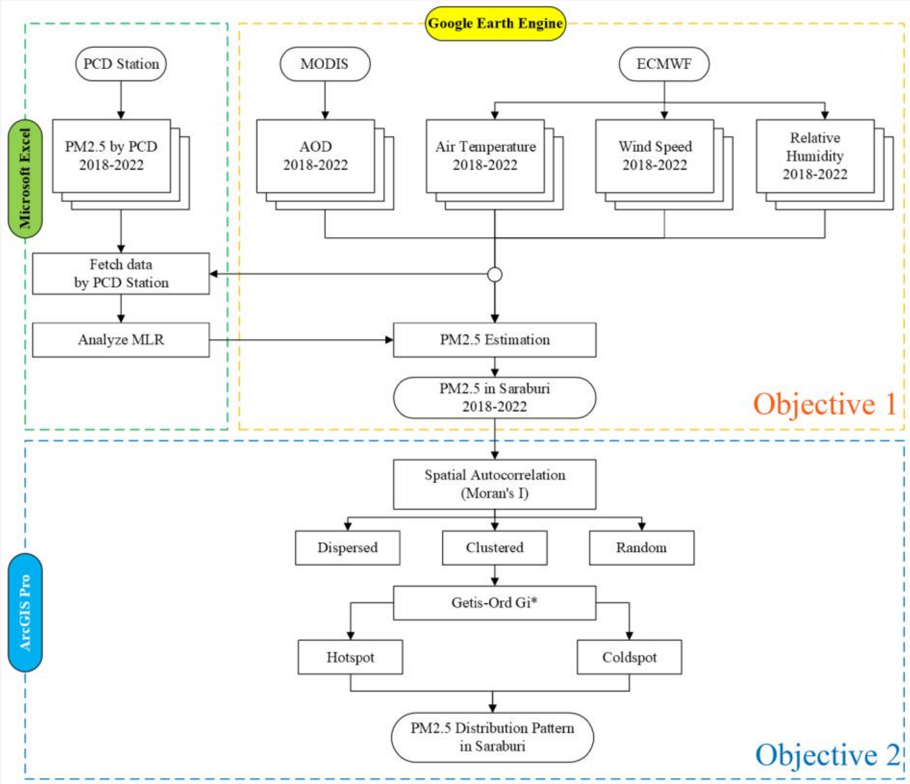


**Figure 3:** Study workflow

PM2.5 between 25.1 – 37.5 μg/m³ Moderate, meaning everyone should reduce outdoor activities or strenuous exercise. At-risk groups should use protective equipment like PM2.5 masks when going outside and consult a doctor if symptoms occur. PM2.5 between 37.6 – 75.0 μg/m³ Unhealthy for sensitive groups, meaning everyone should use protective equipment when going outside, limit outdoor activities or strenuous exercise, and monitor for symptoms. At-risk groups should avoid strenuous outdoor activities, follow medical advice, and see a doctor if symptoms occur. PM2.5 above 75.1 μg/m³ Unhealthy, meaning everyone should avoid outdoor activities. If necessary, use protective equipment and see a doctor if symptoms occur. Those with chronic diseases should stay in safe areas, prepare necessary medications and equipment, and strictly follow medical advice [8].

*3.2.2 Google Earth Engine*

Google Earth Engine (GEE) is a freely available public domain tool that has revolutionized geospatial analysis. Launched in 2010 [9][10] and [11], GEE provides a cloud-based platform for accessing, processing, and visualizing massive datasets of satellite imagery and other geospatial data [12]. This has fostered its widespread use across diverse disciplines like remote sensing, ecology, hydrology, agriculture, and urban planning. A key strength of GEE is its substantial catalog of freely available, multi-temporal satellite imagery from various sensors like Landsat, MODIS, and Sentinel [13] and [14]. The platform seamlessly integrates numerous other geospatial datasets as well, including land cover maps, elevation models, and climate data. This comprehensive toolkit empowers researchers with a vast array of resources for their studies [15] and [16]. Due to its convenience, speed, and cost-effectiveness in data storage and processing, the researcher used GEE for data collection and preliminary analysis.

*3.2.3 Analysis of PM2.5 distribution patterns*

The analysis of PM2.5 distribution patterns involves spatial autocorrelation analysis (Moran’s I), which examines the spatial characteristics of the data, such as clustering, dispersion, or randomness. Moran’s I compares the values at different locations, weighted by a matrix of each point, and can be calculated using Equation 2 [17].

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}\left(x_i - \bar{x}\right)\left(x_j - \bar{x}\right)}{W\sum\left(x_i - \bar{x}\right)^2}$$

Equation 2

Where:

$I$ = Global Moran's I spatial autocorrelation index
$x_i$ = Observed value at location $i$
$x_j$ = Observed value at location $j$ near location $i$
$\overline{x}$ = Mean of observed values
$n$ = The number of locations
$w_{ij}$ = Spatial weight between locations $i$ and $j$
$W$ = Sum of spatial weights

This research uses ArcGIS for spatial statistical analysis to determine the distribution patterns. Values close to 1 indicate clustering of PM2.5, values close to -1 indicate dispersion, and values close to 0 indicate randomness. If clustering is detected, Getis-Ord Gi* analysis is used to identify hot spots (high values) and cold spots (low values) of PM2.5 [18], as shown in Equation 3.

$$Gi^* = \frac{\sum_j w_{ij}(d)x_j}{\sum_j x_j}$$

Equation 3

Where:

$Gi^*$ = Getis-Ord Gi*
$W_{ij}(d)$ = the weighted value of the distance $d$ which equals 1 if $d$ is within the area $j$, and equals 0 if $d$ is outside the area $j$
$x_i$ = The observed value of the area $i$
$\sum_j x_i$ = The sum of all observed values

The results provide statistical data and maps that clarify the spatial context of each area, identifying regions with PM2.5 clustering, which can be designated as surveillance areas in the future.

## 4. Results and Discussion

### *4.1 Estimation of PM2.5*

Using Google Earth Engine, daily AOD data from Terra and Aqua satellites with MODIS sensors and daily meteorological data (air temperature, wind speed, and relative humidity) from ECMWF were collected as independent variables. The relationship between PM2.5 from ground stations (dependent variable) was analyzed over five years (2018-2022) in Saraburi Province as shown in Table 2. The results of the multiple linear regression analysis indicate that the four independent variables, which are AOD, air temperature, relative humidity, and wind speed, significantly predict or estimate changes in the dependent variable (PM2.5), as the P-values for all four variables are less than 0.05. The $R^2$ value is 0.438, explaining the proportion of variance in PM2.5, with an RMSE of 12.945 µg/m³. The PM2.5 estimation equation can be constructed as shown in Equation 4. The relationship between the estimated PM2.5 and the PM2.5 from ground monitoring stations is shown in Figure 4.

**Table 2:** Results of multiple linear regression analysis

| | Coefficients | Standard Error | t Stat | P-value |
|---|---|---|---|---|
| Intercept | 101.252 | 3.985 | 25.406 | 0.00 |
| AOD | 28.969 | 0.973 | 29.770 | 0.00 |
| Air temperature | -0.844 | 0.133 | -6.348 | 0.00 |
| Relative Humidity | -0.885 | 0.025 | -34.715 | 0.00 |
| Wind speed | 0.968 | 0.221 | 4.374 | 0.00 |
| Adjust R Squared = 0.437  R Square = 0.438  R = 0.662  RMSE = 12.945 | | | | |

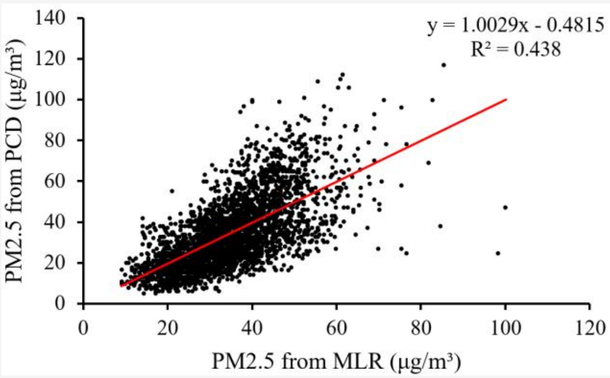


**Figure 4:** The correlation analysis between PM2.5 from the model and PCD monitoring stations during the period 2018-2022 across 8 stations (N = 3,108 observations)

For applying the MLR model to estimate PM2.5 in Saraburi Province, in 2018, the average monthly PM2.5 concentration ranged from 0-74.1 μg/m³. The highest PM2.5 levels exceeding the standard were in August, followed by May, June, March, and February, with values of 74.1 μg/m³, 68.5 μg/m³, 57.8 μg/m³, 48.4 μg/m³, and 40.1 μg/m³, respectively. February had the most extensive area exceeding the PM2.5 standard, covering approximately 146.95 km² or 4.20% of the province, as shown in Figure 5.

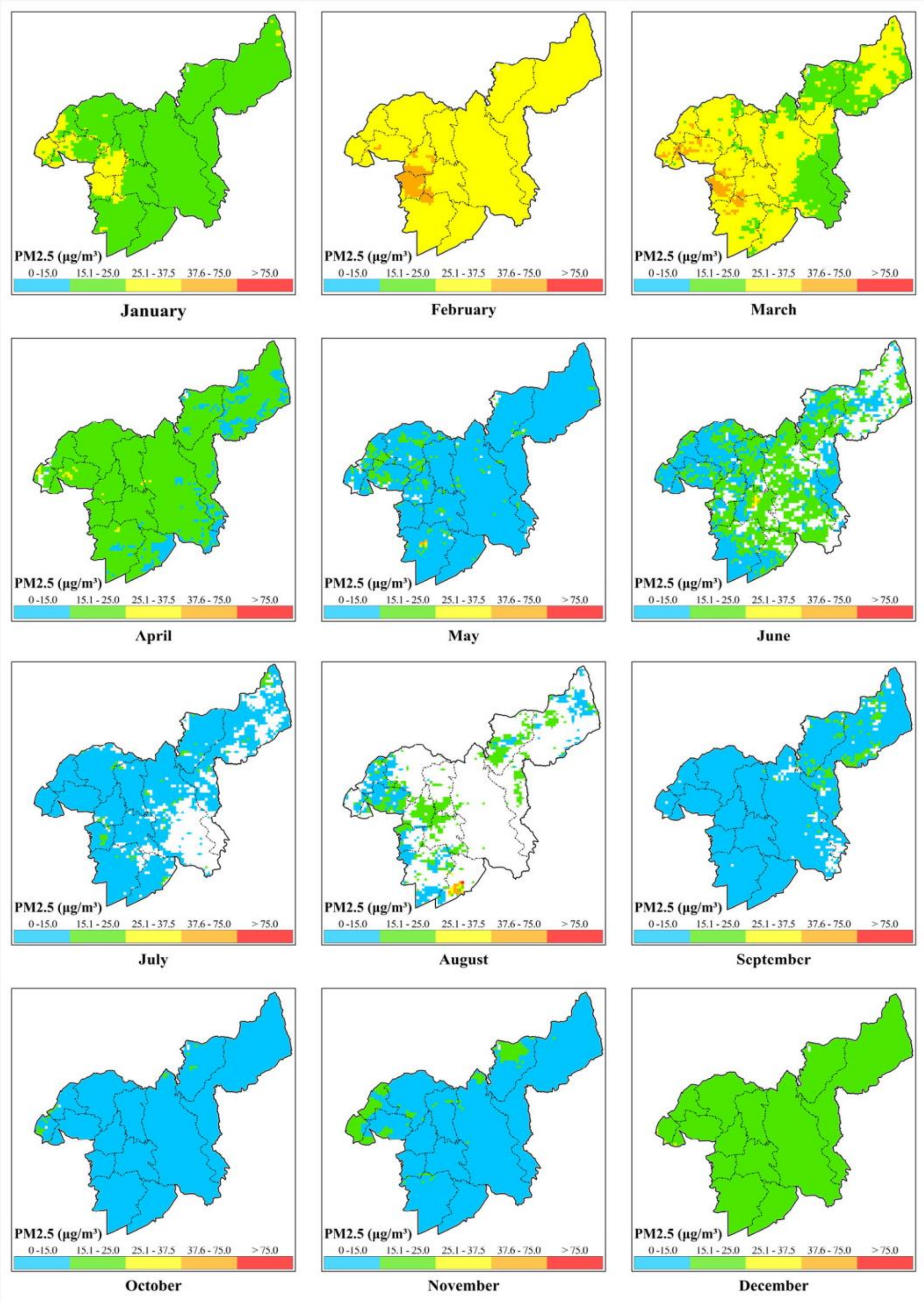


**Figure 5:** The concentration of PM2.5 dust in Saraburi Province in 2018

In 2019, the average monthly PM2.5 concentration ranged from 0-41.4 μg/m³. The highest PM2.5 levels exceeding the standard were in June, followed by April, with values of 41.4 μg/m³ and 39.6 μg/m³, respectively. April had the most extensive area exceeding the PM2.5 standard, covering approximately 2.91 km² or 0.08% of the province, as shown in Figure 6.

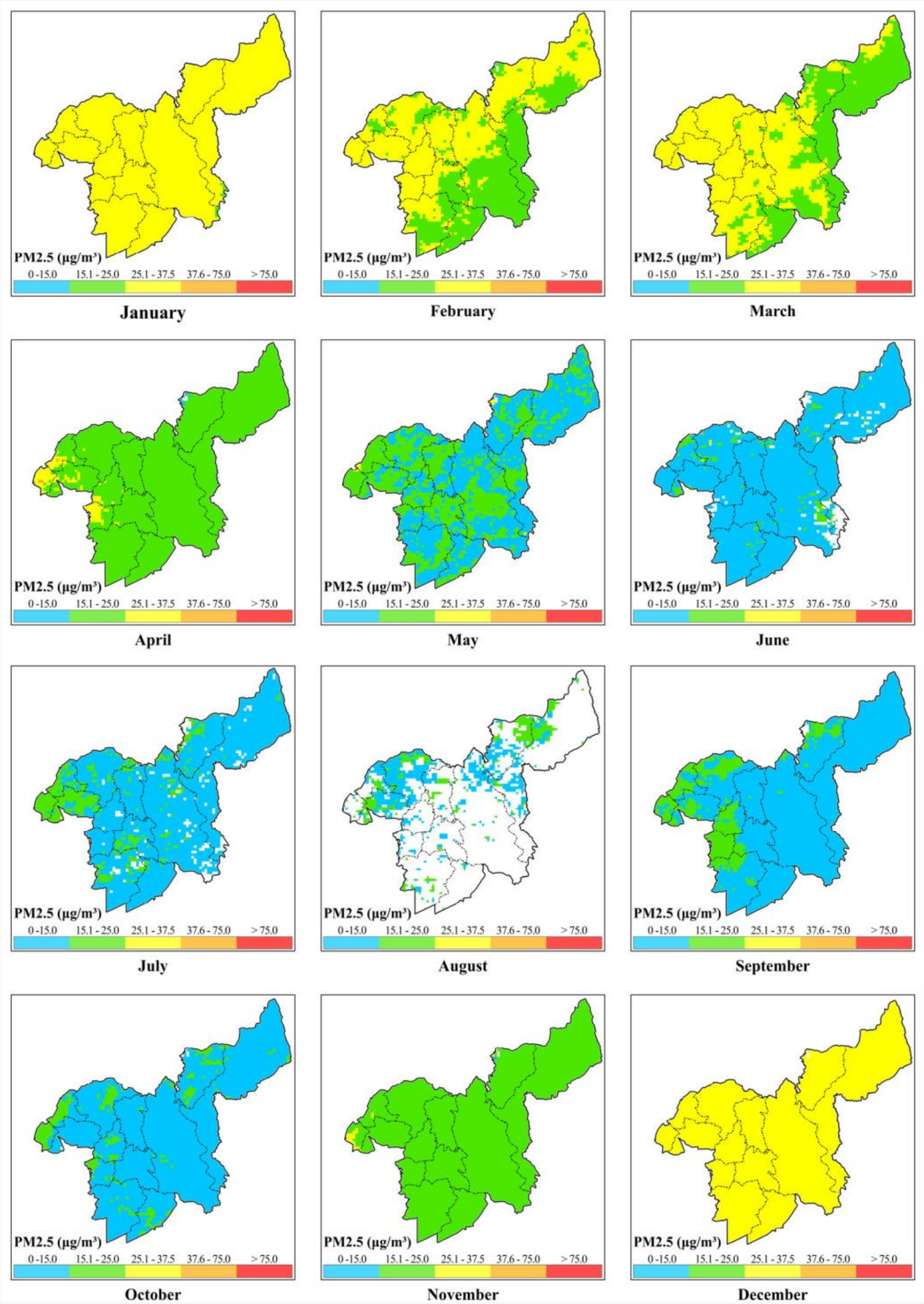


**Figure 6:** The concentration of PM2.5 in Saraburi Province in 2019


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In 2020, the average monthly PM2.5 concentration ranged from 0-50.0 μg/m³. The highest PM2.5 levels exceeding the standard were in February, followed by April, with values of 50.0 μg/m³ and 37.8 μg/m³, respectively. February had the most extensive area exceeding the PM2.5 standard, covering approximately 2,089.75 km² or 59.72% of the province, as shown in Figure 7.

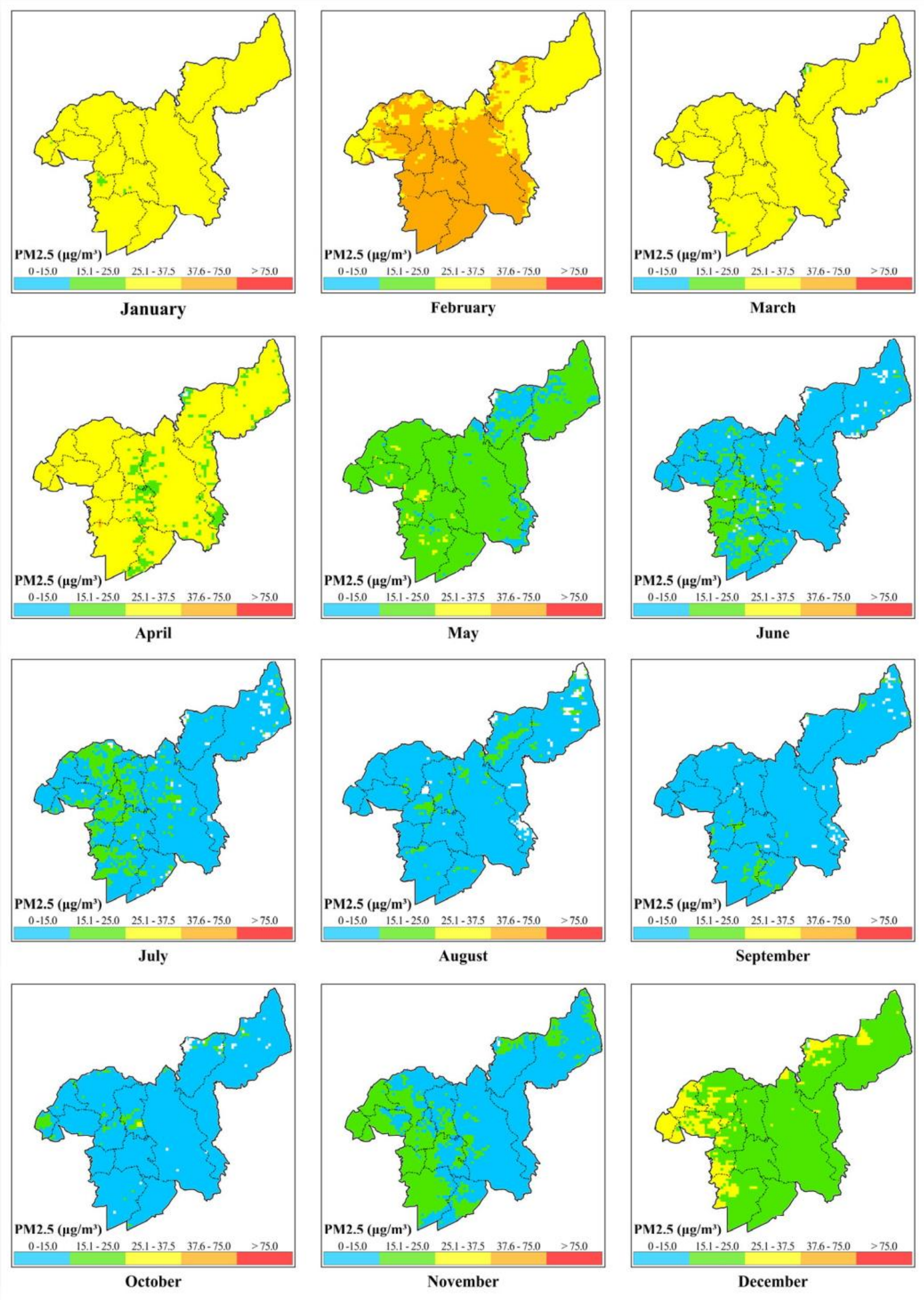


**Figure 7:** The concentration of PM2.5 in Saraburi Province in 2020


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In 2021, the average monthly PM2.5 concentration ranged from 0-55.3 μg/m³. The highest PM2.5 levels exceeding the standard were in May, followed by January, March, April, and February, with values of 55.3 μg/m³, 42.6 μg/m³, 41.1 μg/m³, 39.2 μg/m³, and 37.7 μg/m³, respectively. January had the most extensive area exceeding the PM2.5 standard, covering approximately 1,025.44 km² or 29.30% of the province, as shown in Figure 8.

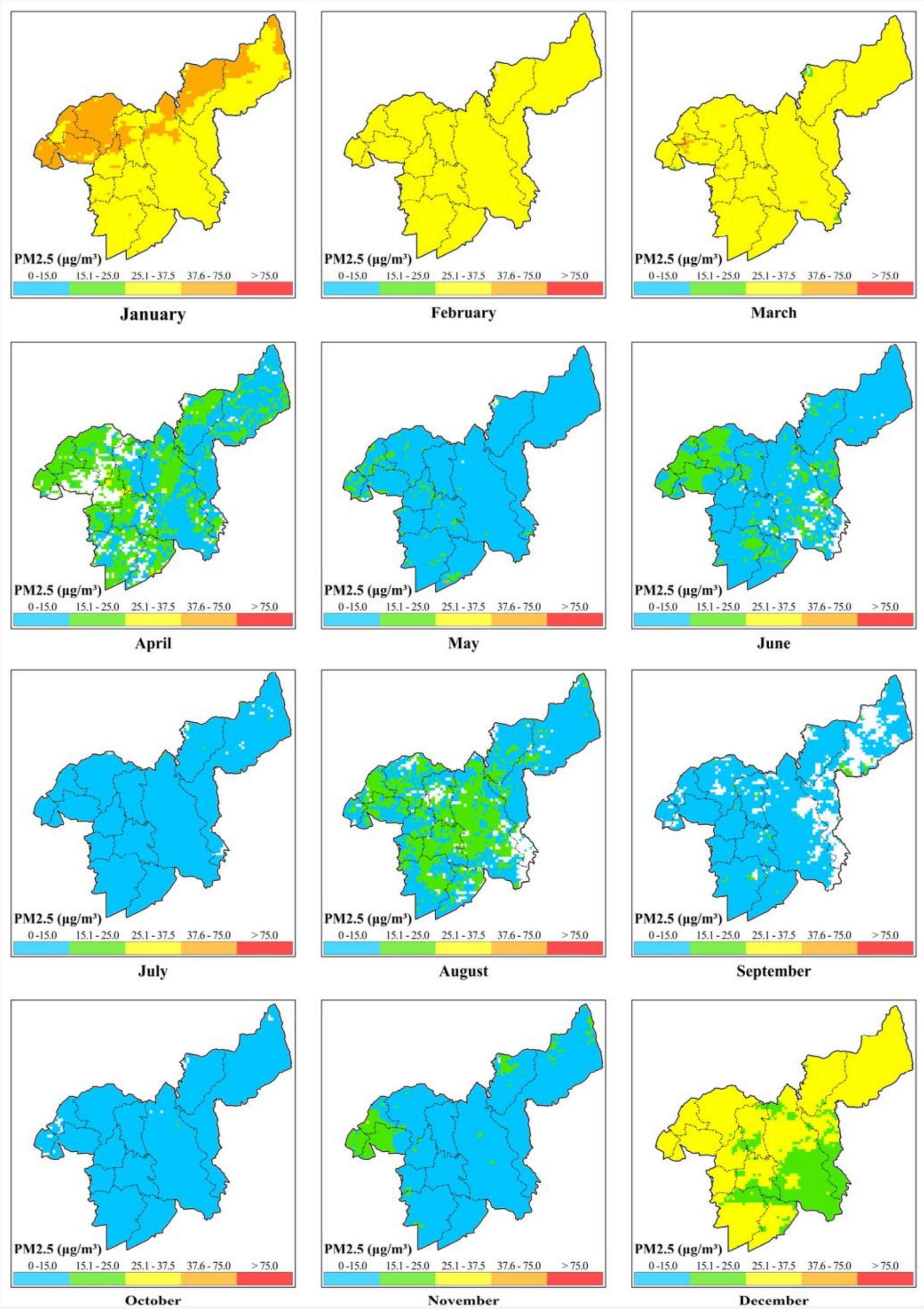


**Figure 8:** The concentration of PM2.5 in Saraburi Province in 2021


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In 2022, the average monthly PM2.5 concentration ranged from 0-57.3 µg/m³. The highest PM2.5 levels exceeding the standard were in May, followed by January, March, April, and February, with values of 57.3 µg/m³, 42.6 µg/m³, 41.1 µg/m³, 39.2 µg/m³, and 37.7 µg/m³, respectively. April had the most extensive area exceeding the PM2.5 standard, covering approximately 1,262.01 km² or 36.07% of the province, as shown in Figure 9.

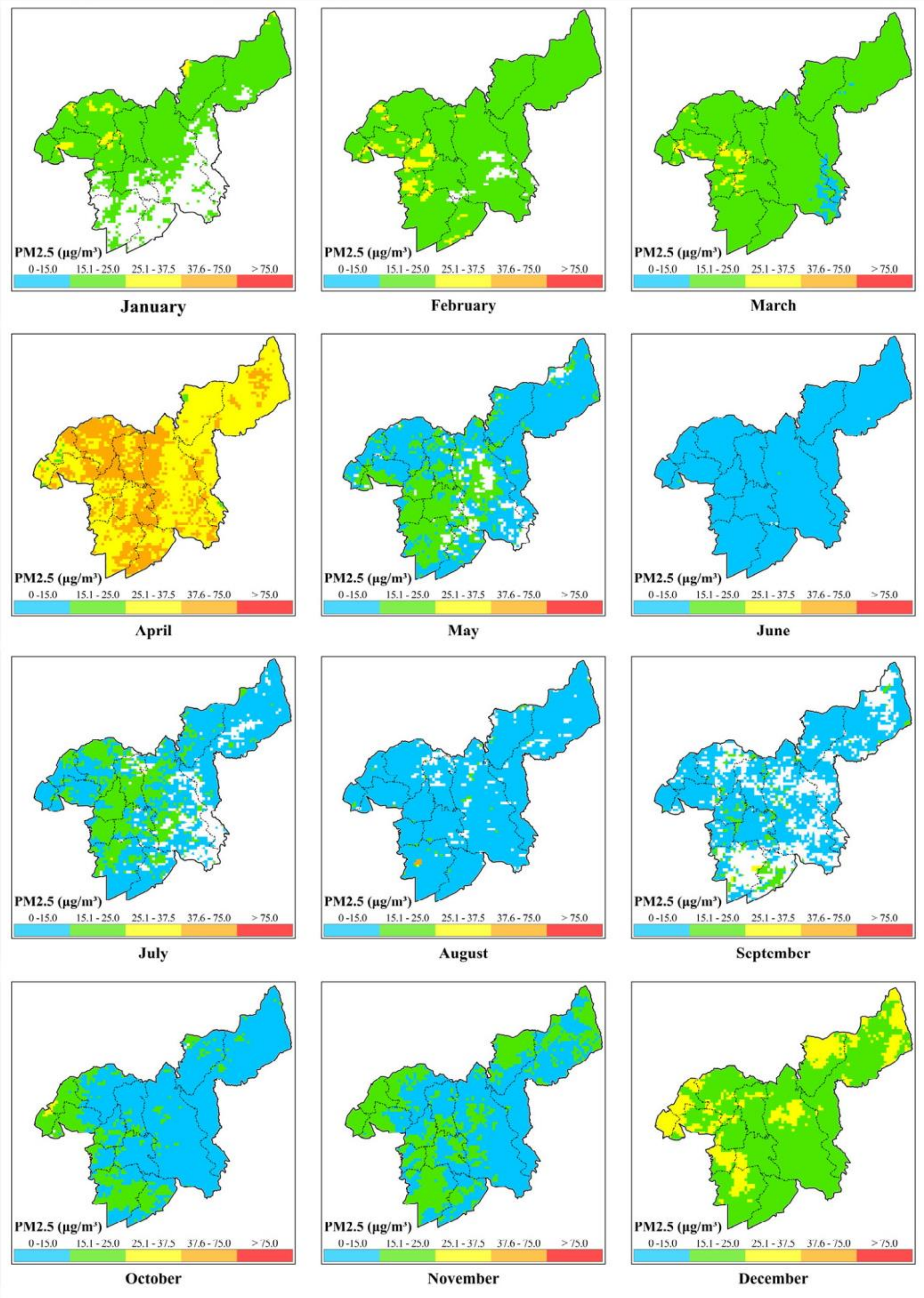


**Figure 9:** The concentration of PM2.5 in Saraburi Province in 2022


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*4.2 PM2.5 Distribution Patterns*

Analyzing the PM2.5 distribution patterns in Saraburi Province from 2018-2022 using Equation 4 and Spatial Autocorrelation (Moran's I) revealed that the Moran's index ranged from 0.39 to 0.99, indicating a clustered distribution pattern, as shown in Figure 10. Further analysis using Getis-Ord Gi* identified high-value clusters (Hot Spots) and low-value clusters (Cold Spots). In 2018, the highest PM2.5 levels exceeding the standard were in February, primarily in the western part of the province, covering agricultural areas. The most affected districts were Sao Hai, followed by Nong Saeng, Ban Mo, Nong Khae, Mueang Saraburi, Wihan Daeng, and Phra Phutthabat, covering approximately 421.43 km² or 12.04% of the province. Low-value clusters were mainly in the eastern part, covering forest areas, with the most affected districts being Muak Lek, followed by Kaeng Khoi, Wang Muang, Nong Don, Ban Mo, and Phra Phutthabat, covering approximately 346.99 km² or 9.92% of the province, as shown in Figure 11.

In 2019, the highest PM2.5 levels exceeding the standard were in April, primarily in the western part of the province, covering agricultural areas. The most affected districts were Ban Mo, followed by Nong Saeng, Nong Don, Phra Phutthabat, Don Phut, Nong Khae, Mueang Saraburi, Wihan Daeng, and Phra Phutthabat, covering approximately 509.29 km² or 14.55% of the province. Low-value clusters were mainly in the eastern part, covering forest areas, with the most affected districts being Muak Lek, followed by Kaeng Khoi, Wang Muang, Nong Don, Ban Mo, and Phra Phutthabat, covering approximately 344.05 km² or 9.83% of the province, as shown in Figure 12.

In 2020, the highest PM2.5 levels exceeding the standard were in February, primarily in the southern part of the province, covering agricultural areas. The most affected districts were Kaeng Khoi, followed by Wihan Daeng, Nong Khae, Mueang Saraburi, Muak Lek, Chalerm Phra Kiat, and Sao Hai, covering approximately 648.37 km² or 18.53% of the province. Low-value clusters were mainly in the eastern part, covering forest areas, with the most affected districts being Muak Lek, followed by Wang Muang, Don Phut, Kaeng Khoi, Chalerm Phra Kiat, Phra Phutthabat, Nong Don, and Ban Mo, covering approximately 444.27 km² or 12.70% of the province, as shown in Figure 13.

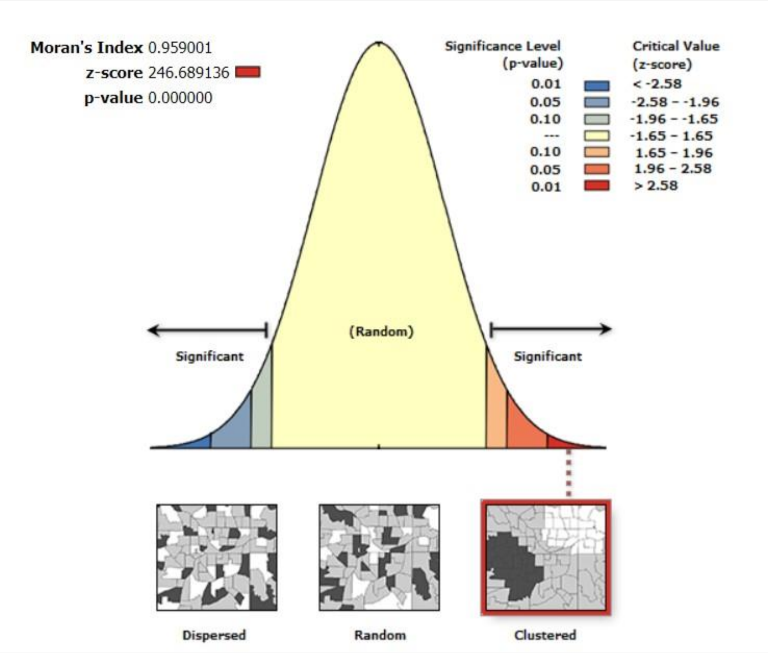


**Figure 10:** Example of spatial Autocorrelation (Moran's I) analysis results for PM2.5 dust data in Saraburi Province in January 2018


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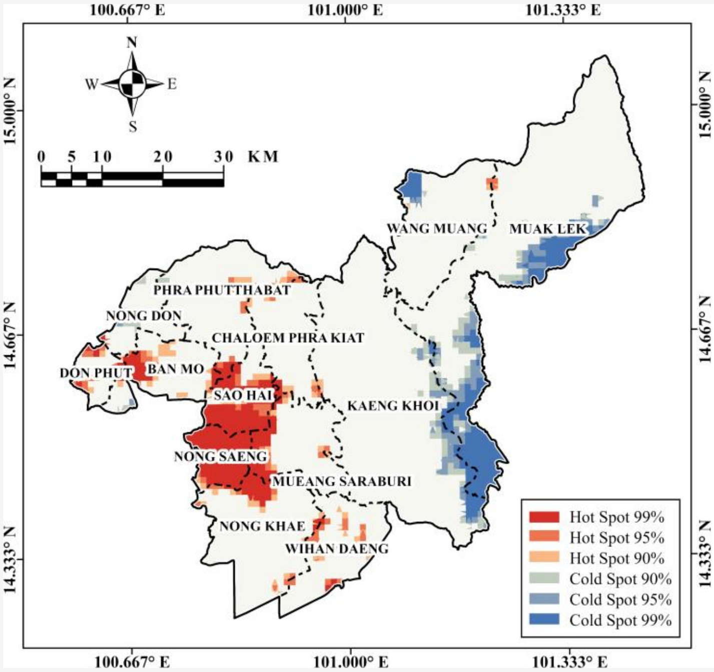


**Figure 11:** Distribution pattern of PM2.5 data in Saraburi Province in February 2018

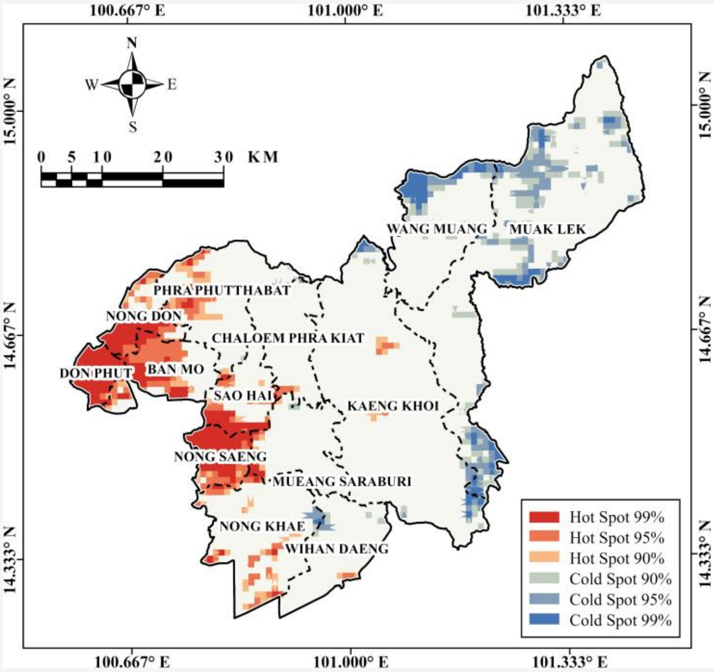


**Figure 12:** Distribution pattern of PM2.5 data in Saraburi Province in April 2019

In 2021, the highest PM2.5 levels exceeding the standard were in January, primarily in the northern part of the province, covering agricultural areas. The most affected districts were Wang Muang, followed by Phra Phutthabat, Ban Mo, Muak Lek, Nong Don, Don Phut, Kaeng Khoi, Chalerm Phra Kiat, and Sao Hai, covering approximately 562.93 km² or 16.09% of the province. Low-value clusters were mainly in the eastern part, covering forest areas, with the most affected districts being Kaeng Khoi, followed by Muak Lek, Wihan Daeng, Mueang Saraburi, Wang Muang, and Nong Khae, covering approximately 369.83 km² or 10.57% of the province, as shown in Figure 14.

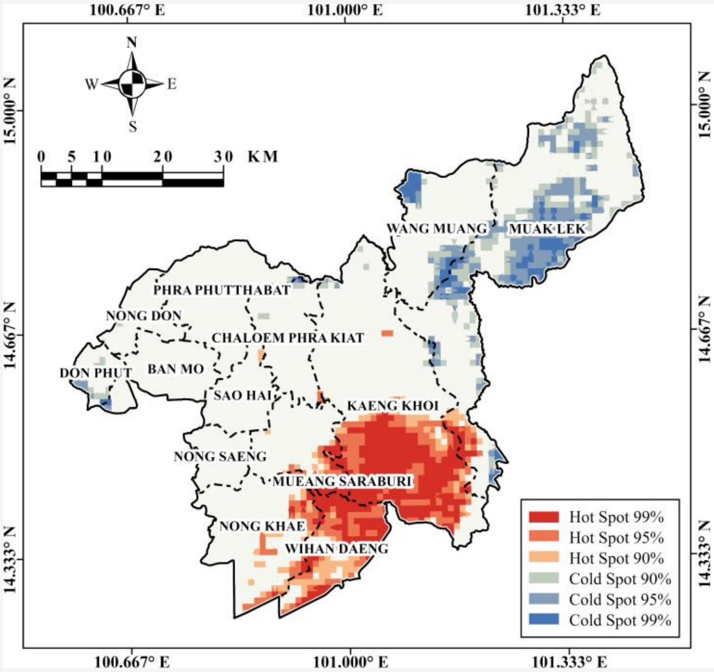


**Figure 13:** Distribution pattern of PM2.5 data in Saraburi Province in February 2020

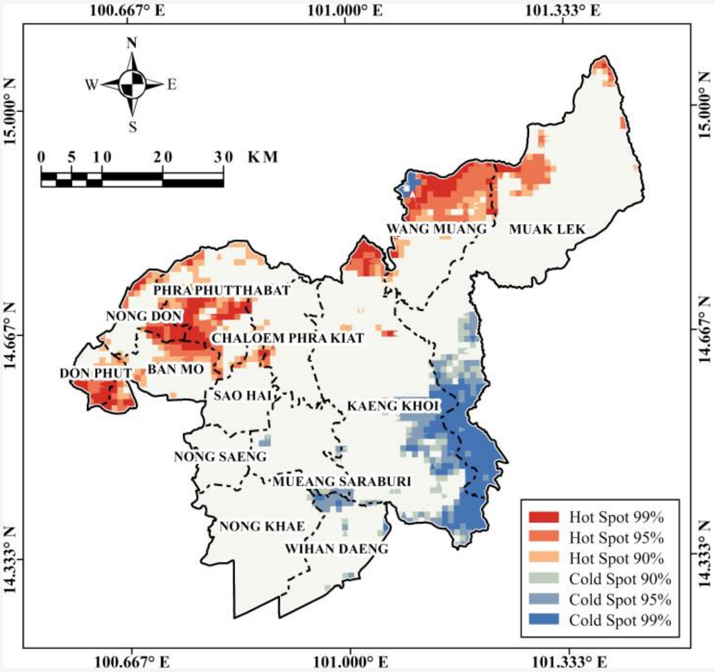


**Figure 14:** Distribution pattern of PM2.5 data in Saraburi Province in January 2021

In 2022, the highest PM2.5 levels exceeding the standard were in April, primarily in the central part of the province, covering agricultural areas. The most affected districts were Kaeng Khoi, followed by Phra Phutthabat, Chalerm Phra Kiat, Mueang Saraburi, Wihan Daeng, Nong Khae, Sao Hai, Ban Mo, Nong Don, Muak Lek, and Don Phut, covering approximately 615.97 km² or 0.18% of the province. Low-value clusters were mainly in the eastern part, covering forest areas, with the most affected districts being Muak Lek, followed by Wang Muang, Kaeng Khoi, Muak Lek, Nong Don, Don Phut, Nong Khae, Ban Mo, Wihan Daeng, Nong Saeng, Mueang Saraburi, Sao Hai, and Chalerm Phra Kiat, covering approximately 513.19 km² or 14.67% of the province, as shown in Figure 15.

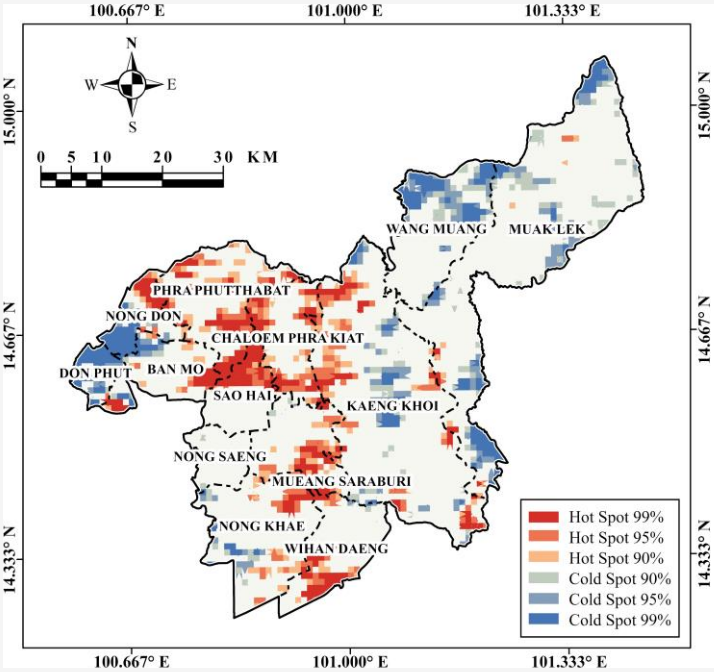


**Figure 15:** Distribution pattern of PM2.5 data in Saraburi Province in April 2022

## 5. Conclusion

This research focuses on estimating PM2.5 levels using Aerosol Optical Depth (AOD) data combined with meteorological data through the Multiple Linear Regression (MLR) method to develop an equation for estimating PM2.5 concentrations in Saraburi province over a five-year period (2018-2022). The results of the PM2.5 estimation and the correlation analysis between the modeled PM2.5 and the observed PM2.5 from ground monitoring stations (PCD) indicate that the model achieves an $R^2$ value of 0.438 and an RMSE of 12.945 µg/m³. This reflects a moderate level of correlation, demonstrating the model's potential for estimating PM2.5 concentrations effectively. The trends indicate that PM2.5 levels exceeding the standard in Saraburi province typically occur between January and April, as well as May and August, which corresponds to seasonal transitions. These patterns align with changes in meteorological data, leading to lower mixing heights and reduced air circulation, which in turn causes the accumulation of particulate matter, fog, and smoke in the atmosphere.

The analysis of PM2.5 distribution patterns in Saraburi Province revealed that airborne particulate matter tends to cluster. Without wind to disperse the particles, they form clusters. High-value clusters (Hot Spots) were mainly found in the western part of the province, where agricultural activities such as burning crop residues, waste, or construction debris are common, leading to high PM2.5 levels. Low-value clusters (Cold Spots) were primarily in the eastern part, where forest areas can absorb pollutants through leaves and bark, reducing PM2.5 levels. This study utilized the MLR method to estimate PM2.5 levels by incorporating satellite data and remote sensing technology for spatial analysis, compensating for the lack of ground-based data for forecasting PM2.5 issues. If the model is applied to other regions, it is important to consider the RMSE, as it affects the accuracy of PM2.5 estimates compared to ground stations. In this study, the RMSE is 12.945 µg/m³, indicating a moderate correlation. Future research may include additional meteorological variables such as rainfall data or other factors like DEM, NDVI, and hotspots to improve the accuracy of the MLR model. Extending the study period to 10 or 20 years would also provide clearer insights into the long-term accumulation of PM2.5.

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