Application of Geographic Information System for PM2.5 Risk Assessment in Din Daeng District, Bangkok

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ABSTRACT

Air pollution from particulate matter smaller than 2.5 microns (PM2.5) is a global concern. In Din Daeng District, Bangkok, PM2.5 levels frequently exceed Thailand's air quality standards from January to April in every year due to traffic pollution and temperature inversions. Furthermore, climate change is expected to exacerbate the inversion phenomenon, significantly elevating risks to vulnerable populations, including children, the elderly, and individuals with respiratory and cardiovascular conditions. This study employs Geographic Information System (GIS) technology to create risk maps for PM2.5, aiding local governments in developing strategies to mitigate its impact. Data on PM2.5 concentrations, building footprints, and the distribution of vulnerable populations were collected and analysed for risks using Weighted Linear Combination (WLC) with assigned scores based on expert inputs. According to the assigned scores, people vulnerability is the most critical factor in assessing PM2.5 risk with a score of 45.00%, followed by PM2.5 concentration (33.33%) and population density (21.67%). Because of different patterns of population distribution in the area, the study also reveals that risk levels are higher during the day than at night, with 11.20% of the population at the highest risk during daytime, compared to 1.11% at night under worst case scenario. The study recommends different mitigation measures based on the time of day and suggests three actionable strategies: 1) distributing PM2.5 masks to all children monthly, 2) installing outdoor PM2.5 monitoring devices, and 3) constructing PM2.5 pollution control rooms for use when pollution levels exceed standards. The first two measures are short-term actions that local governments can implement immediately, while the third requires long-term investment and is particularly effective for protecting vulnerable groups.

Keyword: PM2.5/ Geographical Information System/ Risk assessment

1. INTRODUCTION

Air pollution, particularly Particulate Matter with a diameter of less than 2.5 microns (PM2.5), poses a significant threat to human health, especially for vulnerable groups in densely populated urban areas [1,2,3]. Exposure to high PM2.5 concentrations can severely impact respiratory and cardiovascular systems, increasing mortality risk [4,5]. Air pollution is closely linked to meteorological conditions; hence, climate change affects PM2.5 concentrations by altering patterns of precipitation, atmospheric circulation, temperature, radiation, and ventilation. These changes raise concerns about the intensity and frequency of PM2.5 events [6,7,8]. Consequently, assessing PM2.5 exposure has become a critical focus for governments and researchers [5,9]. Therefore, research on PM2.5 risk mapping is essential for helping national and local governments develop effective measures to mitigate its impact, particularly in urban areas.

Risk assessment is complex, relying on mathematical models to estimate the likelihood and intensity of specific events at particular locations [10]. Historically, spatial risk assessment was challenging due to the lack of advanced Geographic Information Systems (GIS), limited access to high-quality spatial data, and computational constraints that hindered accurate modeling of spatial distribution and risk intensity. However, advancements in GIS technology and improved access to high-quality spatial data, such as building footprints, have significantly enhanced the accuracy of urban

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population distribution analysis, which is crucial for risk assessment. The successful application of GIS in risk assessments has been demonstrated in numerous studies [11,12,13].

This study focuses on Din Daeng District, a densely populated urban area in the northern part of Bangkok, Thailand, to demonstrate the application of GIS for PM2.5 risk assessment. The district consistently experiences high PM2.5 concentrations between January and April each year [14,15]. In addition, this study proposes PM2.5 impact mitigation measures based on field surveys. The goal is to provide the local government of Din Daeng District with high-resolution PM2.5 risk maps to inform appropriate responses and actions to combat air pollution.

2. METHODOLOGY

2.1 Study area

Din Daeng District, located in the Bangkok Metropolitan Area, covers a total area of 8.35 km², comprising Din Daeng Subdistrict (3.73 km²) and Ratchadaphisek Subdistrict (4.62 km²), as shown in Figure 1. According to the Department of Provincial Administration, in 2023, the district had 109,802 registered residents and 64,834 households. Din Daeng is considered a key economic area in Bangkok due to its high concentration of department stores, condominiums, offices, government agencies, and schools, which attract people from nearby districts and provinces. The latent population is estimated to add an additional 75% to the registered population in the area [16]. Pollution Control Department reported that in 2021, there were 101 days, and in 2022, there were 91 days when the monitored PM2.5 concentrations exceeded Thailand's air quality standards [17].

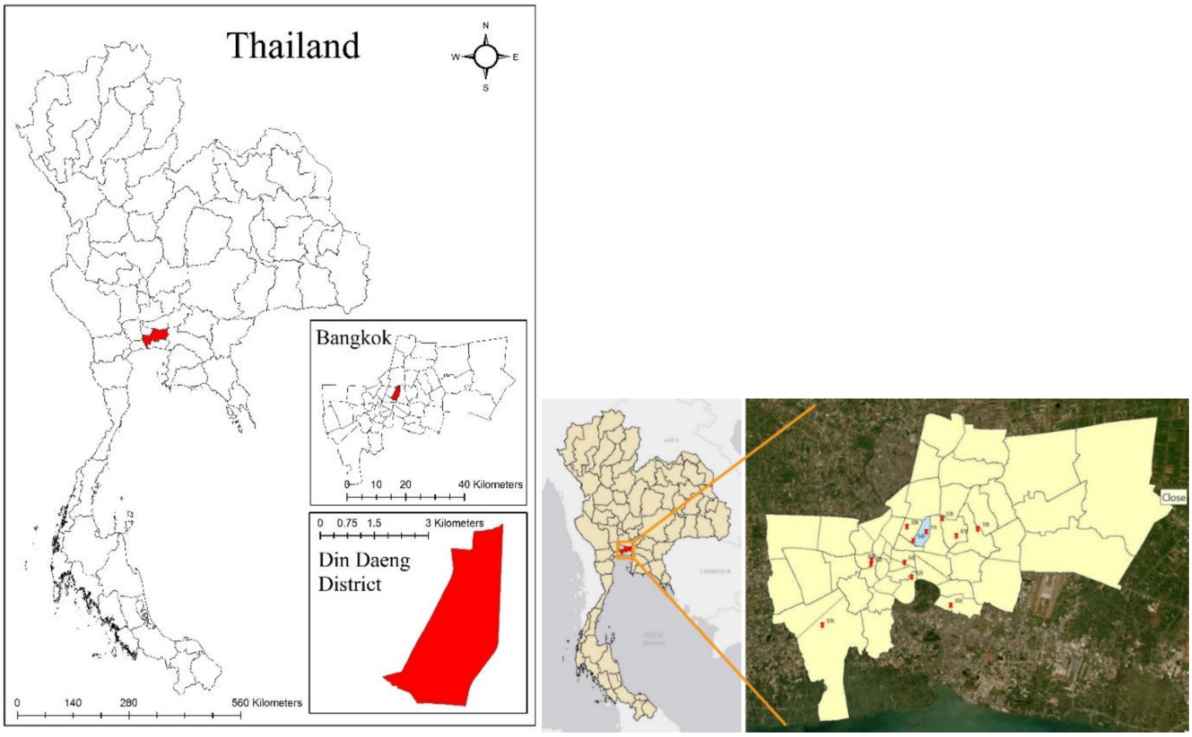

Figure 1. Location of Din Daeng District and 12 air quality monitoring stations in Bangkok

2.2 Development of PM2.5 risk map

The methodological flow is illustrated in Figure 2. PM2.5 risk is determined by three factors: PM2.5 concentration, population density, and vulnerability. All maps were generated using ArcGIS Version 10.8 (ESRI), grided into 20 m x 20 m.

The PM2.5 concentration map was created using the Inverse Distance Weighting (IDW) technique with data from 12 Pollution Control Department (PCD) air quality monitoring stations in Bangkok as shown in Figure 1 [18]. Daily PM2.5 concentration data from 1 January 2023 to 31 March

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2023, were used to produce spatial distribution maps at the 50th, 95th, and 99th percentiles. The population distribution maps were based on building footprints in the Din Daeng District in 2022, sourced from the Department of City Planning and Urban Development under the Bangkok Metropolitan Administration (BMA). The maps were divided into daytime and nighttime to reflect different settlement patterns: during the day, people are assumed to reside in non-residential buildings such as offices, schools, and government buildings, while at night, they reside in residential buildings including hotels. Daytime population density was calculated by summing the surveyed census data from 2020 with the commuter population [16], then dividing by the total non-residential building area. Nighttime population density was calculated by summing the surveyed census data from 2020 with the estimated non-registered population in the area [16], then dividing by the total residential building area. The gridded population for each building was determined by multiplying the population density by the floor area (number of floors multiplied by the building area), then dividing by 400 (as a grid size is 20 m x 20 m). The vulnerability map shows the locations of nurseries, schools, hospitals, and nursing homes, along with the number of occupants, as collected during field surveys.

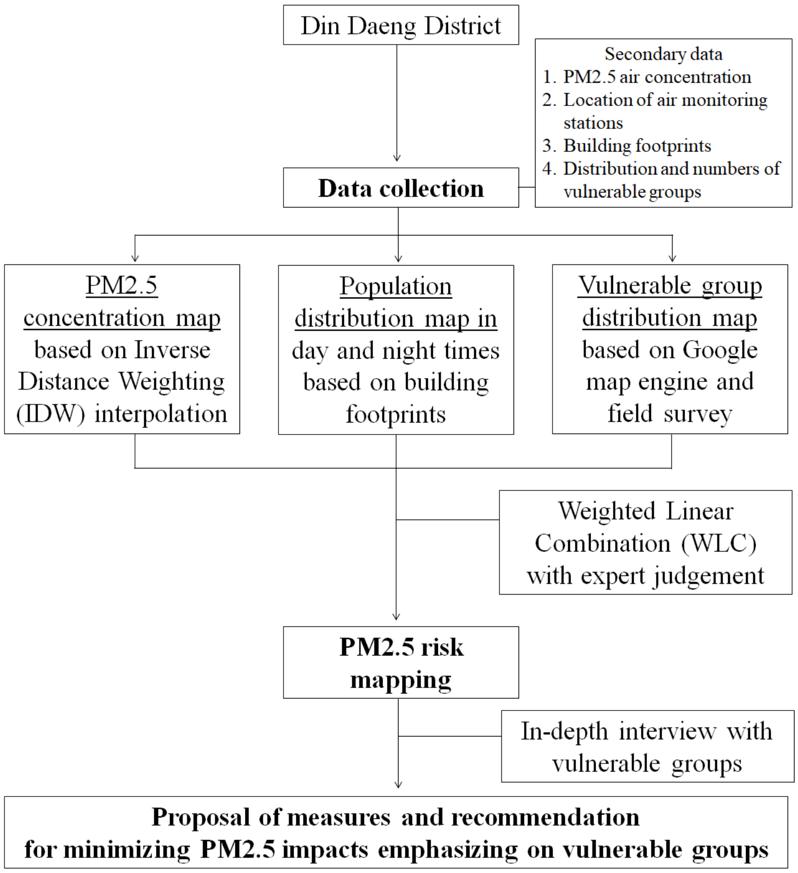

Figure 2. Methodological flow

A Weighted Linear Combination (WLC) method was applied to calculate PM2.5 risks, incorporating PM2.5 concentration, population distribution, and vulnerability factors. These factors were weighted to a total score of 100 by three academic experts in the fields of air pollution, population studies, and health. The selection criteria for experts include relevant academic backgrounds and extensive journal publications in the fields especially in Bangkok area. Similarly, spatial values across the three maps were converted to ordinal values based on expert judgment. All maps were then rasterized, and PM2.5 risks were calculated using the equation below:

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$$\mathrm{Aij} = \frac{\sum_{i=1}^{n} \mathrm{WjXij}}{\sum_{j=1}^{k} \mathrm{Wj\,Yj}}$$

Where; A_j=risk score of grid I; W_j=weighting based on expert judgement for factor j; X_{ji}=ordinal value of factor j at grid i; Y_j=maximum ordinal value of factor j. The risk scores are categorized into "very low", "low", "medium", "high" and "very high" and the definitions are summarized in Table 1.

Table 1. Risk score categorization

Risk level	Risk score	Definition
Very low	0.00-0.20	Carrying out activities or operations does not necessarily require risk management or further control improvements.
Low	0.21-0.40	Carrying out activities or operations does not necessarily require additional risk management. However, activities or operations involving vulnerable groups should reduce outdoor activities, and risk management should be consistently maintained to ensure that adequate risk controls are still in place.
Medium	0.41-0.60	Carrying out activities or operations should reduce outdoor activities. For activities or operations involving vulnerable groups, wearing dust masks is recommended. At this level of risk, information on air pollution and self-protection methods should be communicated to the public.
High	0.61-0.80	Activities or operations during this period may be considered for cancellation as appropriate until the risk is reduced. If going outdoors is necessary, wearing a dust mask is recommended. At this level of risk, information about air pollution conditions and self-protection methods should be communicated to the public.
Very high	0.81-1.00	Activities currently underway cannot continue until the risk is reduced. If the risk cannot be mitigated, the activity must be halted or suspended. At this level of risk, information about air pollution conditions and self-protection methods should be communicated to the public.

2.3 Proposal of PM2.5 impact minimization measure

Field surveys were conducted in March 2024 for face-to-face interviews with vulnerable groups in Din Daeng District. Response to time with PM2.5 concentration exceeding the air quality standards and expected support from local governments were inquired. Costs of implementing the expected support is estimated following Thailand market prices as of 30 April 2024.

3. RESULTS AND DISCUSSION

3.1 PM2.5 risk map

Figure 3 shows PM2.5 concentration maps at the 50th, 95th, and 99th percentiles. According to Thailand's air quality standards, ambient PM2.5 concentrations should not exceed 37.5 µg/m³ over a 24-hour period or 15 µg/m³ annually. The ranges of minimum and maximum concentrations at the 50th, 95th, and 99th percentiles were 29.0-37.0 µg/m³, 63.4-72.5 µg/m³, and 77.11-91.33 µg/m³, respectively. Figure 4 illustrates the population distribution maps for daytime and nighttime. During the day, people are assumed to be at their workplaces, leading to minimal population dispersion but high density in outer areas along the main roads. At night, people return to their residences, resulting in greater population dispersion across all residential zones. From these maps, considering different population patterns between daytime and nighttime can overcome shortcomings of remote sensing as described in the previous study [19]. As for the vulnerable group map shown in Figure 5, these groups tend to cluster on the west side, which accounts for 75% of all vulnerable buildings, while the Ratchadaphisek Subdistrict accounts for the remaining 25%.

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The weighting and criteria for ordinal conversion values determined by experts for PM2.5 concentration, population distribution, and vulnerability are presented in Table 2 and Table 3, respectively. The weighting scores show that vulnerable groups (45.00%) are the most significant factor influencing PM2.5 risk, followed by PM2.5 concentration (33.33%) and population distribution (21.67%). Older adults are positively and strongly associated with natural mortality due to short-term exposure to PM2.5 [20, 21]. Additionally, high population density significantly increases the risk of PM2.5 due to pollution centralization and congestion effects [22, 23].

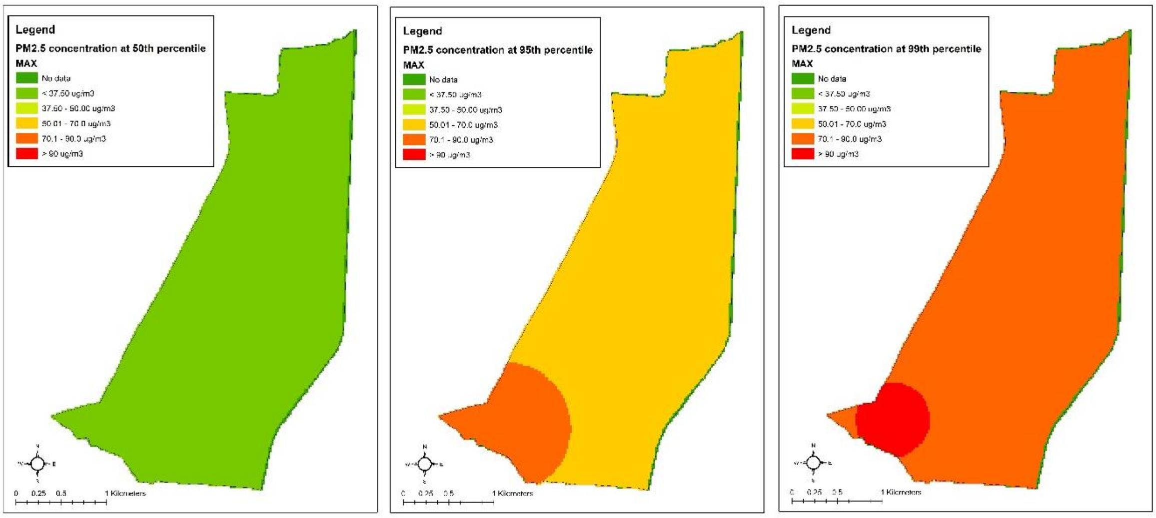

Figure 3. PM2.5 concentration maps at 50th percentile (left), 95th percentile (middle) and 99th percentile (right)

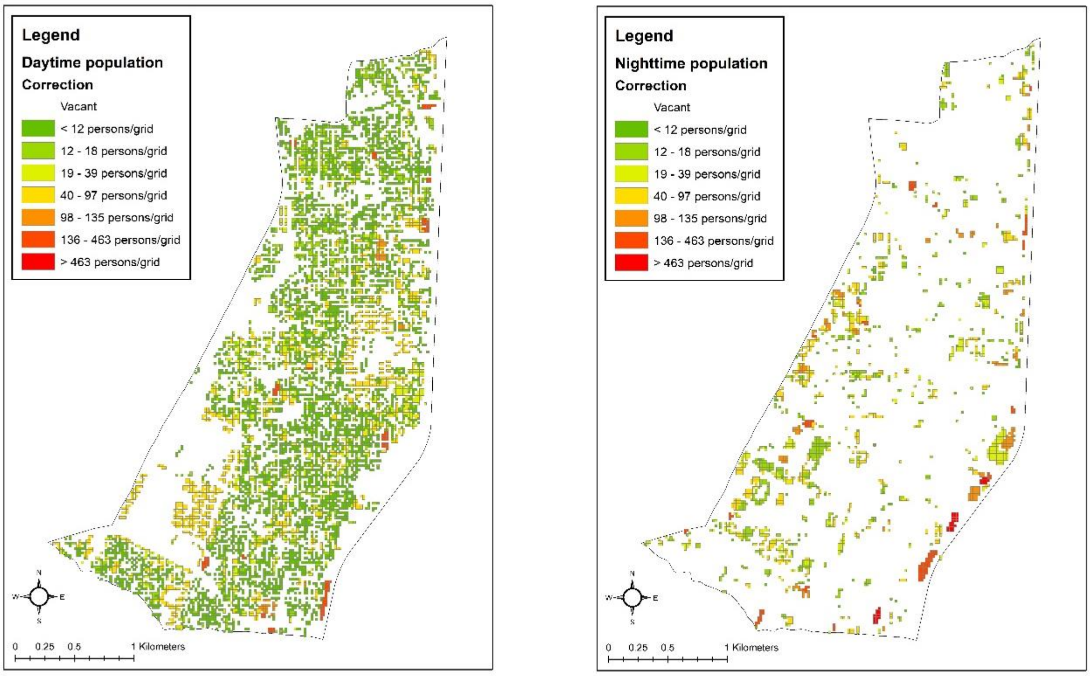

Figure 4. Population distribution in daytime (left) and night time (right)

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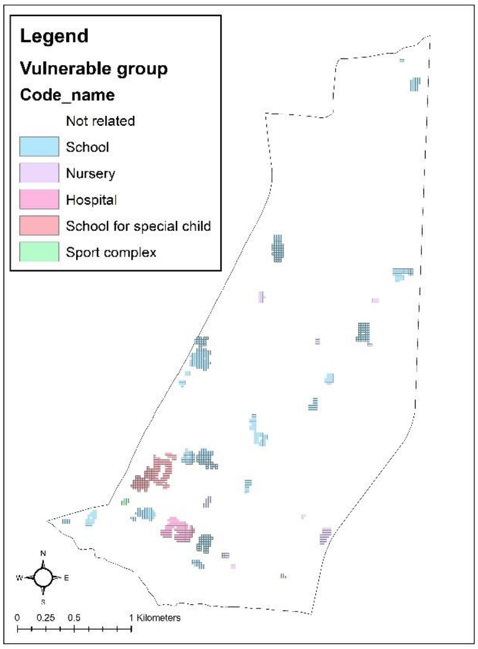

Figure 5. Location of vulnerable groups

Table 2. Weighting scores of PM2.5 risk factors by experts

PM2.5 Risk factor	Expert scoring			Average score
	Expert No.1	Expert No.2	Expert No.3	
PM2.5 concentration	40	30	40	33.33
Population density	30	10	25	21.67
Vulnerability	30	60	35	45
Total	100	100	100	100

Table 3. Criterion for ordinal conversion by experts

PM2.5 concentration		
PM2.5 concentration	Definition	Ordinal score
> 75.0 µg/m^3	Air quality affects health	5
37.6 – 75.0 µg/m^3	Air quality is likely to affect health	4
25.1 – 37.5 µg/m^3	Moderate air quality	3
15.0 – 25.0 µg/m^3	Good air quality	2
< 15 µg/m^3	Very good air quality	1
Population density		
Population Density	Definition	Ordinal score
> 50 person/m^2	Relatively high density	5
20.0 – 50.0 person/m^2	High density	4
10.0 – 20.0 person/m^2	Medium density	3
4.0 – 10.0 person/m^2	Low density	2
< 4 person/m^2	Very low density	1
Vulnerability		
Vulnerable group	Definition	Ordinal score
Young children (ages 0-5), elderly (60 years and above), and patients	High vulnerability	3
Primary school children (ages 6-12)	Medium vulnerability	2
Secondary school children (ages 13-18) and older	Low vulnerability	1

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PM2.5 risk maps are shown in Figure 6, and the affected population during daytime and nighttime is summarized in Table 4 and Table 5, respectively. The results indicate that, during the daytime, high-risk grids were predominantly located in areas with vulnerable groups, such as children, the elderly, and patients, who are at greater risk. Medium risk was the most common in scenarios with PM2.5 concentrations at the 50th percentile (85.38%) and 95th percentile (84.65%), while high risk was primarily observed in the 99th percentile scenario (82.56%). At nighttime, high-risk areas were identified in hotels and condominiums in the central part. Similarly, medium risk accounted for the majority in the 50th percentile (85.34%) and 95th percentile (95.78%) scenarios, while high risk was mainly observed in the 99th percentile scenario (72.93%). This detailed information can help local governments develop effective responses tailored to the different risk profiles of daytime and nighttime during periods of high PM2.5 concentration.

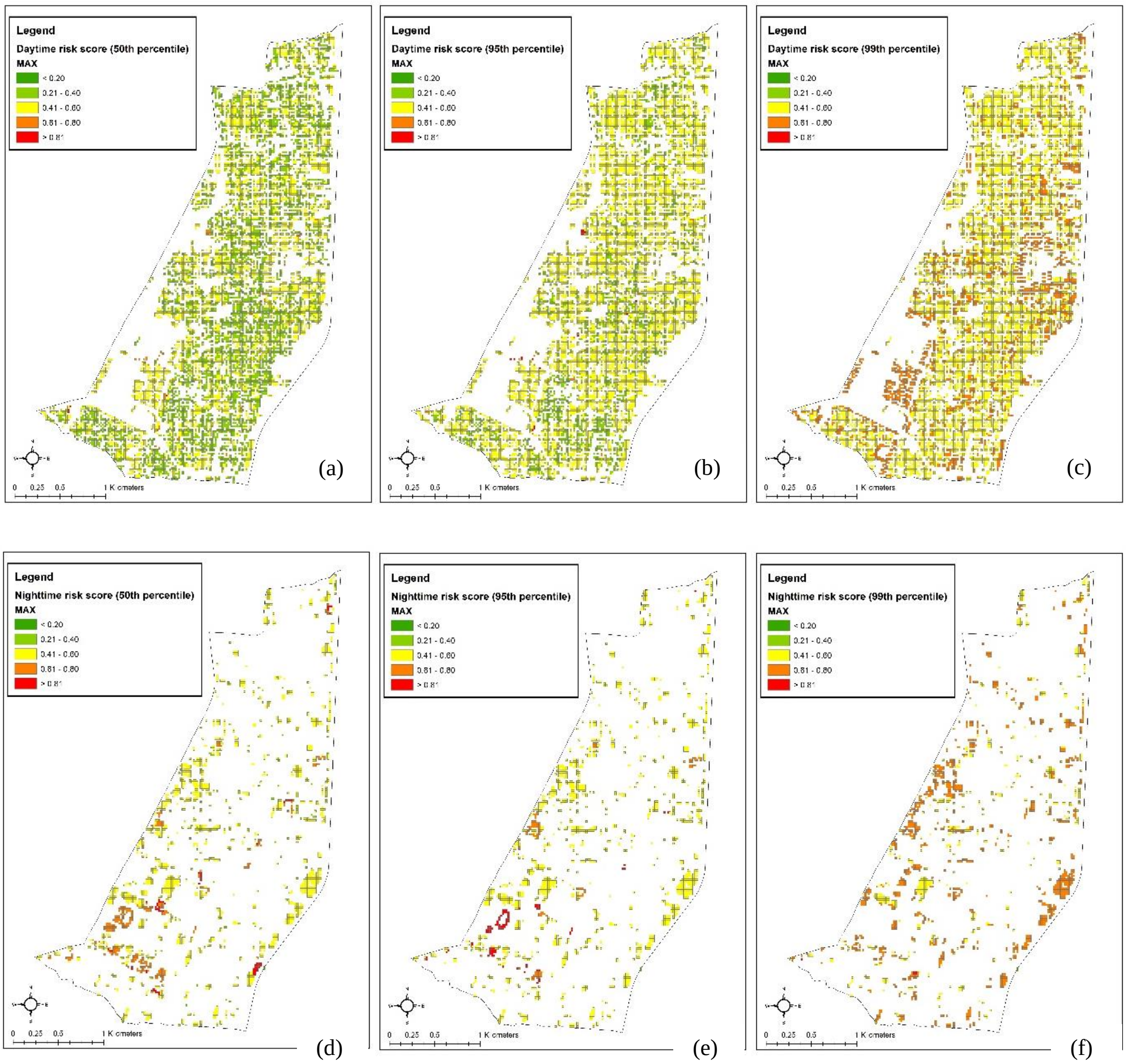

Figure 6. PM2.5 risk map: (a) Daytime at 50th percentile, (b) Daytime at 95th percentile, (c) Daytime at 99th percentile, (d) Night time at 50th percentile, (e) Night time at 95th percentile and (f) Night time at 99th percentile

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Table 4. Affected population in daytime

Risk score category	Affected population impacted by PM2.5 at different percentiles in daytime		
	50	95	99
Very low	50 (0.04%)	0 (0%)	0 (0%)
Low	511 (0.37%)	70 (0.05%)	50 (0.04%)
Medium	116,768 (85.38%)	115,775 (84.65%)	8,478 (6.20%)
High	11,615 (8.49%)	5,773 (4.22%)	112,915 (82.56%)
Very high	7,824 (5.72%)	15,151 (11.08%)	15,325 (11.20%)
Total	136,768 (100%)	136,768 (100%)	136,768 (100%)

Table 5. Affected population in nighttime

Risk score category	Affected population impacted by PM2.5 at different percentiles in nighttime		
	50	95	99
Very low	9 (0.01%)	9 (0.01%)	9 (0.01%)
Low	21,865 (13.42%)	4,770 (2.93%)	0 (0.00%)
Medium	138,972 (85.34%)	155,972 (95.78%)	42,263 (25.95%)
High	1,704 (1.05%)	355 (0.22%)	118,765 (72.93%)
Very high	290 (0.18%)	1,734 (1.06%)	1,803 (1.11%)
Total	162,840 (100%)	162,840 (100%)	162,840 (100%)

3.2 PM2.5 impact minimization measure

Based on the interviews, three measures supported by local governments were proposed by vulnerable groups in the study area: Measure (1) is the monthly distribution of PM2.5 masks to all children (43.75% of total respondents), Measure (2) is the construction of PM2.5 pollution control rooms to be used when pollution levels exceed standards (37.50% of total respondents), and Measure (3) is the installation of outdoor PM2.5 monitoring devices (18.75% of total respondents). Respirator face masks, as a personal-level intervention, can effectively reduce ambient particle concentrations by 68.1% [24]. However, caution should be exercised when using N95 masks, as they can increase the workload on the metabolic system, particularly for pregnant workers, potentially causing dizziness and hypoxia [25]. Furthermore, ventilation and air conditioning systems in buildings or rooms can effectively control indoor PM2.5 concentrations. For example, the China Academy of Building Research has developed the T/CECS 586-2019 standard, titled "Technical Specification for Pollution Control of Fine Particulate Matter (PM2.5) in Buildings," under the China Engineering Construction Standardization Association [26]. In Thailand, the adoption of PM2.5 pollution control rooms is still relatively limited and primarily implemented by the national government due to the high investment costs, which are not feasible for private uses. Regarding outdoor PM2.5 monitoring devices, several low-cost sensors have recently been introduced to the market. This suggests that, initially, the government can easily provide these devices to vulnerable groups to enhance awareness, encourage timely responses, and prompt action when PM2.5 concentrations are high. A successful example of a participatory urban sensing framework for PM2.5 monitoring can be observed in Taiwan [27]. Currently, the ground-based monitoring devices called DustBoy, initiated by the National Research Council of Thailand (NRCT), are widely used across several provinces in Thailand. However, their intelligent application in urban areas is still under investigation [28].

When considering their application for vulnerable groups, the estimated annual cost for Measure (1) is 67,126,055 Baht, for Measure (2) is 7,035,750 Baht, and for Measure (3) is 160,072 Baht, based on current Thailand market prices. However, integrating all three measures is recommended: Measure (1) offers a short-term solution, Measure (3) facilitates immediate action during peak pollution levels, and Measure (2) should be considered for medium-to-long-term implementation.

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4. CONCLUSIONS

This study demonstrates the successful application of GIS for PM2.5 risk assessment. The primary factors influencing PM2.5 risk are receptor vulnerability, PM2.5 concentration, and population density, with vulnerability being the most significant factor. Notably, there is a considerable difference in population distribution between daytime and nighttime, underscoring the need for tailored implementation strategies throughout the day. To ensure the proposed measures are practical and effective, it is recommended to conduct interviews with local governments. Short-term plans include providing N95 masks and installing additional PM2.5 monitoring devices to facilitate timely responses and actions. The construction of PM2.5 pollution control rooms is considered a long-term plan due to its high investment costs.

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