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EXTENT AND MAGNITUDE OF INDUSTRIAL STACK EMISSIONS ON AMBIENT PARTICULATE CONCENTRATIONS

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ABSTRACT: Management of ambient PM2.5 concentrations require understanding of their source contribution for the effective controlling of emission. This study is aimed to evaluate the performance of air quality dispersion model (AERMOD) in predicting ambient ground level PM2.5 and PM10 concentrations emitted from the largest industrial estate in Thailand as a demonstration case. Emission data in this study comprised of 247 industrial stacks were used together with local terrain features and meteorological data in 2018 for the analysis. Evaluation of model performance was accomplished by statistical comparison between observed and modeled PM2.5 and PM10 concentrations. Results from statistical analysis indicated that predicted PM2.5 and PM10 concentrations data were lower than those measured ground level concentrations. This under-estimated prediction reveals less contribution of emission from industrial stacks towards ambient particulate concentrations. It also highlights the competence of current total particulate (all size) emission standard in controlling ambient particulate pollution (PM2.5 and PM10) particularly from industrial stack emission sources.

Keywords: AERMOD, CBPF, Maptaphut, PM2.5, PM10

1. INTRODUCTION

Recently, they are great concerns on particulate pollution with focusing on fine particulate matter e.g. PM2.5 and PM10. The association between inhalation exposures to ambient fine particulate (PM2.5) and health impacts are well recognized and documented in many researches [1-7]. Particulate consists of solid and liquid phases. It is emitted directly from natural and anthropogenic activities. The secondary particulate can also be formed as a product of chemical transformation in the air [8].

Identification of emission sources and quantification of their contributions to the ambient concentration of pollutants has been a major focus of air quality research [9]. However, a big constraint on explanation of the source-receptor relationship of particulate pollution are due to different of the size of PM measured from the sources and at the receptors. Typically, PM emitted from the point sources are measured as total suspended particulate (all-size). For example, in Thailand, it is measured according to the US.EPA method 5 (isokinetic measurement). In contrast, the ambient particulate matters are measured according to their size i.e. PM2.5, PM10. This fact leads to limitation in evaluating the contribution of PM emitted from the source to the size-specific PM in the environment.

This study presents the method to determine the choices to predict ambient PM2.5 and PM10 concentrations emitted as PM from the industrial point sources. Three different tiers, are tested and evaluated for their abilities in using existing available emission data in predicting PM2.5 and PM10 ambient concentrations. To serve this objective, comprehensive analysis was conducted in the Maptaphut industrial complex where both PM emission and ambient PM2.5 and PM10 concentrations are well reported and documented. The study area is the largest industrial complex in Thailand [10]. It is located in the Eastern region of the country (about 179 km from Bangkok). There are five industrial estates and the seaport. The industrial complex is homed to petroleum refinery, petrochemical industry, coal-fired power plant (coal and natural gas fired), metal industry, gas separation plant. Concern on environmental deterioration has been raised in this industrial complex, particularly with the issue related to air pollution. At present, this area has been set up as the pilot area to implement the concept of area-based management by considering both the individual emission limit of each point source as well as its area-based carrying capacity. Sulfur dioxide (SO_2) and nitrogen dioxide (NO_2) are selected conventional pollutants in this implementation. Currently, the ambient concentrations of SO_2 and NO_2 measured in the vicinity of this industrial complex are within their ambient air quality standards. Performance of the model was comprehensively assessed by comparing predicted data with intensively measured data from continuous ambient air quality monitoring stations located in the vicinity of the industrial area.

2. RESEARCH SIGNIFICANCE

Emission standard of particulate matter are usually designated as total dust (all size) which make difficulty in determining the extent and magnitude of PM2.5 and PM10 contribution from the industrial source. This study comprehensively evaluated the contribution of industrial emission toward PM 2.5 and PM10 ambient concentrations under the worst case assumption (all emitted dust are PM2.5 and PM10). Finding of this research is very much useful to be used and be supported to describe the source contribution of particulate matter particularly when a need of controlling PM2.5 and PM10 are raised and focused to the industrial stack source.

3. METHODOLOGY

3.1 Model Configuration

The AERMOD version 9.9.0 dispersion model was used in this study. It is a steady-state air dispersion model used as a regulatory model in Thailand. The horizontal and vertical distribution of air concentration are simulated through the Gaussian dispersion. The model is preferred to apply in predicting ground level concentrations of air pollutants for a short-range (< 50 km from the source) [11]. In this study the modeling domain was configured to cover an area of 12.5 × 12.5 km^2 with the finest horizontal and vertical grid spacing of 100 m. Study domain was centered at 12.616325°N, 101.263349°E. Topographical characteristics of the study domain were derived from the Shuttle Radar Topography Mission (SRTM3). Emissions of total dust from industrial point sources were derived from the Maptaphut emission database of the year 2020 reported to the Office of Natural Resources and Environmental Policy and Planning [12]. These data consisted of geographical coordinates, stack height (m), stack diameter (m), exhausted temperature (K), stack exit velocity (m/s) and total dust emission rate (g/s) of each stack. Totally, there were 247 stacks used as emission input in this analysis. Spatial distribution of emission sources is illustrated in Figure 1.

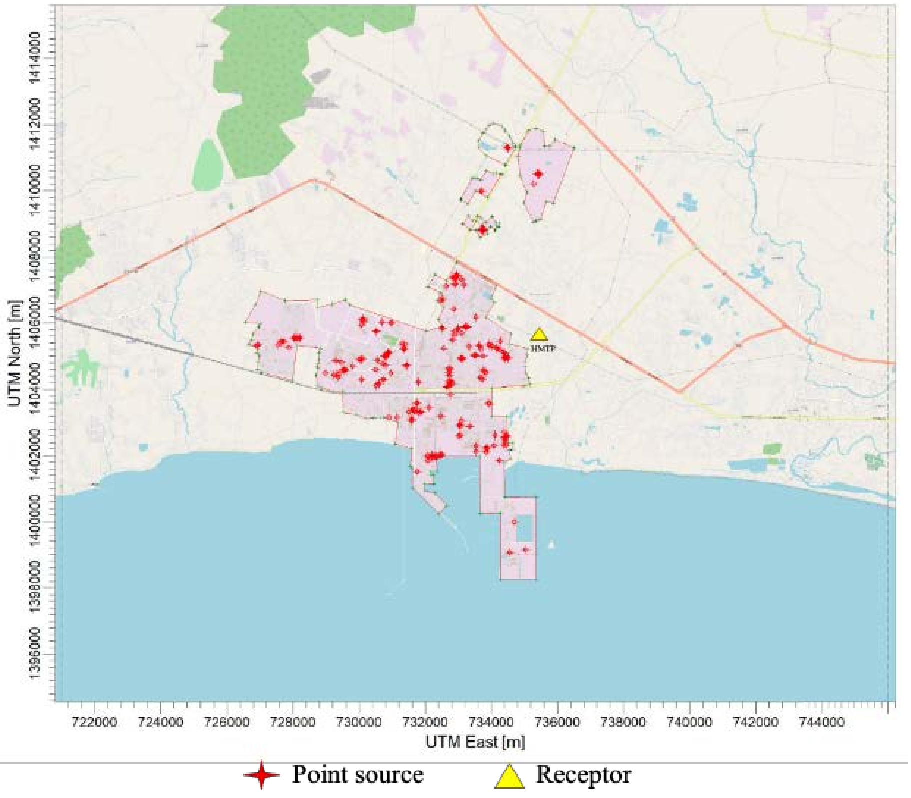


Fig 1. Study domain

The upper air characteristics in this study were obtained from the simulation of the weather research forecast (WRF) model while the surface meteorological features were obtained from the 10 meters' height meteorological tower located within the study domain. Data were prepared on the hourly basis covering the year 2018 (1st January – 31st December 2018). These data were prepared as the AERMET format. For the model verification purpose, AERMOD was simulated during the period from August – October 2018 with regards to availability of measured ambient PM2.5 and PM10 concentrations. The wind rose during this period was generated using the WRPLOT feature within the AERMET module of AERMOD (Figure 2).

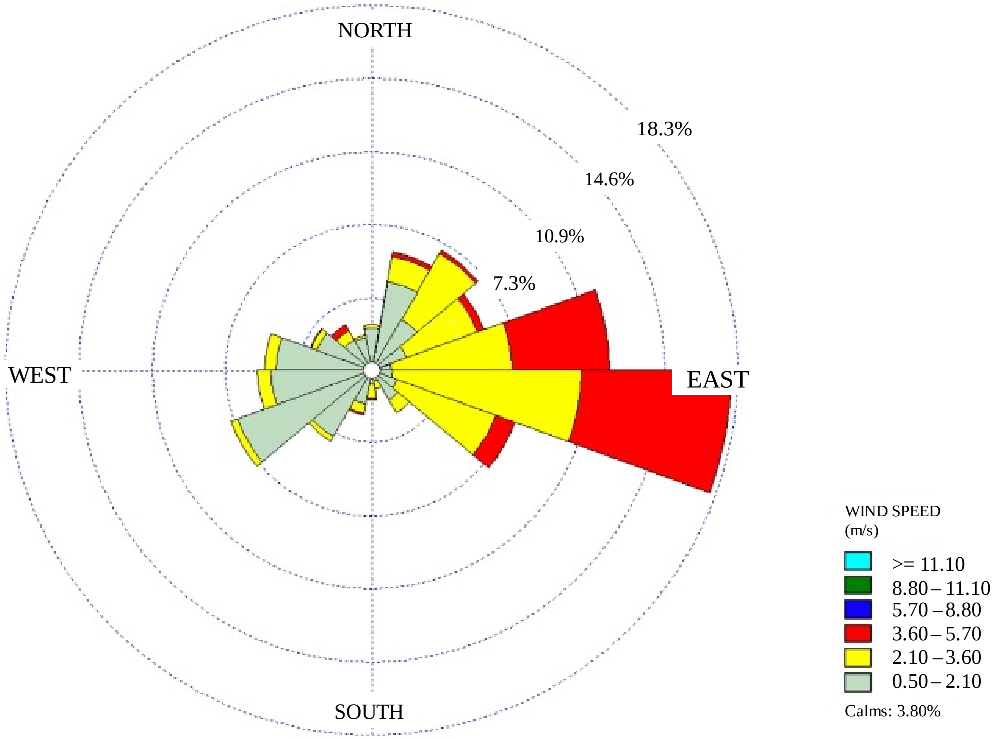


Fig 2. Wind rose in August – October 2018

3.2 Ambient PM2.5 and PM10

Monitoring data of ambient PM2.5 and PM10 used in this study was chosen from the station at the health promotion hospital Maptaphut (HMTP) taking into consideration the highest number of available data. PM2.5 and PM10 ambient monitoring data during the period from 1st August – 31st October 2018 were selected for model evaluation due to availability (completeness) of measured data from monitoring station.

3.3 Model Performance Evaluation

Evaluation of model performance was accomplished by statistical comparison between observed and modeled PM2.5 and PM10 concentrations covering the period from 1st August – 31st October 2018. Statistical tools used to serve this purpose were Observed Mean (Omean), Predicted Mean (Pmean), Observed Standard Deviation (Ostd), Predicted Standard Deviation (Pstd), Pearson correlation coefficient (r^2), Root Mean Square Error (RMSE), Index of Agreement (IOA), Fractional Bias (Fb), Fraction Variance (Fs) and the Robust Highest Concentration (RHC). Hourly predicted results were compared with those measured PM2.5 and PM10 concentrations. Statistical indicators used in this evaluation were followed the previous studies by [13 & 14] and as shown in Equations (1) - (10).

$$O_{mean} = \frac{1}{N}\sum_{i=1}^{N} O_i \qquad \text{(Eq.1)}$$

$$P_{mean} = \frac{1}{N}\sum_{i=1}^{N} P_i \qquad \text{(Eq. 2)}$$

$$O_{std} = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(O_i - O_{mean})^2} \qquad \text{(Eq. 3)}$$

$$P_{std} = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(P_i - P_{mean})^2} \qquad \text{(Eq. 4)}$$

$$r^2 = \frac{N(\sum_{i=1}^{N} O_i P_i) - (\sum_{i=1}^{N} O_i)(\sum_{i=1}^{N} P_i)}{\sqrt{[N(\sum_{i=1}^{N} O_i^2) - (\sum_{i=1}^{N} O_i)^2][N(\sum_{i=1}^{N} P_i^2) - (\sum_{i=1}^{N} P_i)^2]}} \qquad \text{(Eq. 5)}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(P_i - O_i)^2} \qquad \text{(Eq. 6)}$$

$$IOA = 1 - \frac{\sum_{i=1}^{N}(P_i - O_i)^2}{\sum_{i=1}^{N}(| P_i - O_{mean} | + | O_i - O_{mean}} \qquad \text{(Eq. 7)}$$

$$\text{Fb} = 2\frac{(O_{mean} - P_{mean})}{(O_{mean} + P_{mean})} \qquad \text{(Eq. 8)}$$

$$\text{Fs} = 2\frac{(O_{std} - P_{std})}{(O_{std} + P_{std})} \qquad \text{(Eq. 9)}$$

$$\text{RHC} = C(R) + (\overline{C} - C(R))\ln(\frac{(3R-1)}{2})) \qquad \text{(Eq. 10)}$$

Where

O_i = Observed data
P_i = Predicted modeled data
$C(R)$ = the R^{th} highest concentration
$\overline{C}$ = the mean of the top R-1 concentrations

4. RESULTS AND DISCUSSION

4.1 PM2.5 and PM10 Concentrations

Predicted ground level concentrations of PM2.5 and PM10 at receptor were simulated from AERMOD model. Predicted data were on an hourly basis were compared with those measured data during the same period (1st August – 31st October 2018). Overall performances of the model were evaluated using fractional bias (Fb) and fractional variance (Fs). A closer to zero, a better of model performance is shown. The values can be varied between -2 and 2, with a negative value indicating over-prediction [15]. Statistical analysis of the model performances is presented in Table 2 and Table 3. As for overall performance, it was found that AERMOD under-estimated PM2.5 and PM10 concentrations measured at receptor point. Even though there is a good correlation between observed and predicted data ($r^2 \sim 0.8$), the index of agreement (IOA) is unacceptable for both PM2.5 and PM10 (IOA < 0.5). This can be explained by the fact that emission rates used to model PM2.5 and PM10 in this study were only from the point (stack) sources. However, ambient concentrations of particulate matter can also be contributed by other emission sources particularly mobile and on-site local sources. Even though there is a large difference between observed and predicted data, this study can answer our hypothesis on the influence as well as extent and magnitude of the dust emitted from the industrial sources on their potential contribution to the ambient particulate concentrations.

Table 2 Performance evaluation statistics for PM2.5 concentrations

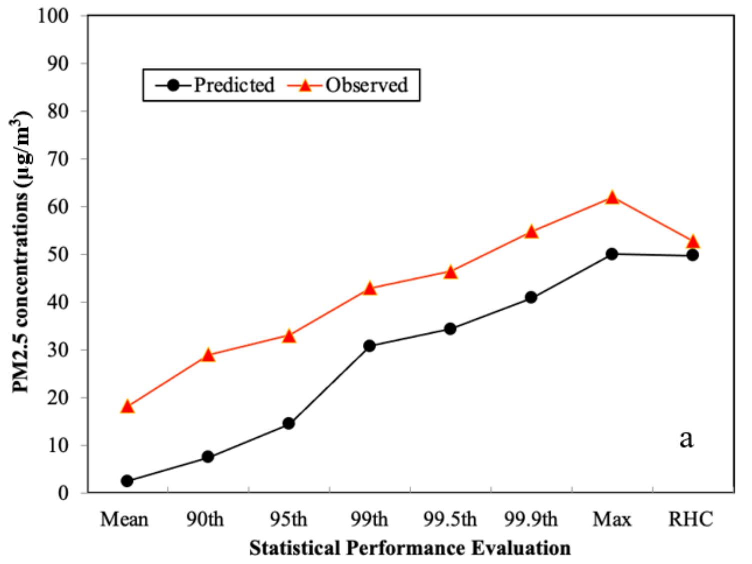
PM2.5	observed	predicted
No. of samples	2112	2112
Mean	18.20	2.46
S.D.	8.31	5.92
r^2	0.80	
RMSE	16.54	
IOA	0.50	
Fb	1.52	
Fs	0.34	
RHC	52.77	49.73

Table 3 Performance evaluation statistics for PM10 concentrations

PM10	observed	predicted
No. of samples	2112	2112
Mean	36.65	2.46
S.D.	12.43	5.92
r^2	0.79	
RMSE	35.25	
IOA	0.37	
Fb	1.75	
Fs	0.71	
RHC	88.26	49.73

Note: S.D.; Standard deviation, r^2; Correlation coefficient RMSE; Root mean square error, IOA; Index of agreement, Fb; Fractional bias, Fs; Fractional variance, RHC; Robust highest concentration

The ability of the model to predict extreme end concentrations (episode) of PM2.5 and PM10 were evaluated by comparing high end percentiles (90th, 95th, 99th, 99.5th, 99.9th), maximum and the robust highest concentration (RHC) of measured and predicted PM2.5 and PM10 data as illustrated in Figure 3. It was found that predicted PM2.5 and PM10 concentrations results were lower than measured data. However, under the assumption that all of the particulate emitted from the industrial stack sources were in the size of PM2.5, the gap between predicted and observed high end concentrations can be lower down. Hence, the study elucidates the possibility to apply this concept to evaluate ambient PM2.5 concentrations when the emission rates of specific size of particulate are not available since the concern on potential health impact can be assessed using the high-end concentration for the health conservative purpose.



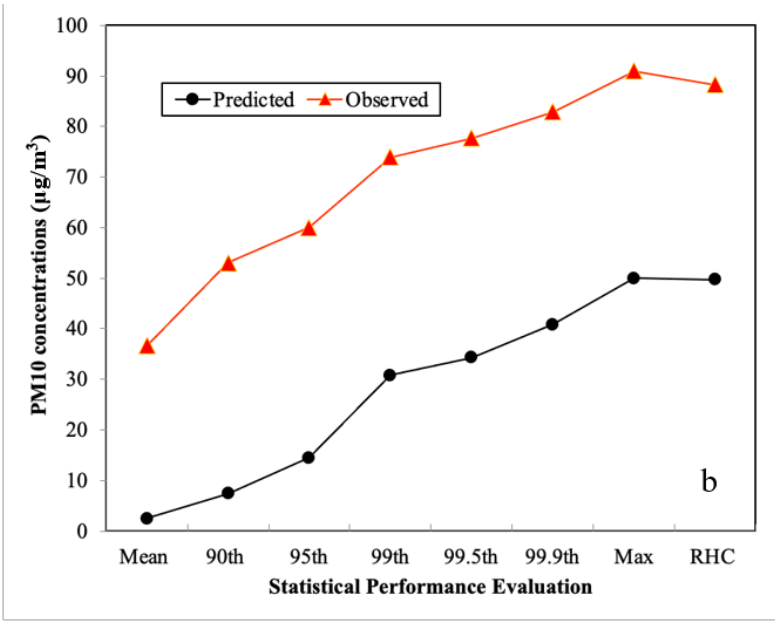


Fig 3. Mean, percentiles, maximum, and RHC for predicted and observed (a) PM2.5 and (b) PM10 concentrations

Figure 4 (a) illustrates spatial distribution of the highest 1-hour average concentration for each uniform Cartesian grid. High concentrations were occurred in the northwest direction of the emission sources due to the influence of the South Easterly wind. In order to evaluate whether these high concentrations were probably occurred only for couple hours, we also evaluate for the 98th percentile of the predicted data as shown in Figure 5 (b). The maximum and the 98th percentile of 1-hr average within the modeling domain were 171 and 46 µg/m^3, respectively. Therefore, the maximum concentration may be just occurred as a peak from unfavorable meteorological condition during the modeling periods. The results clearly indicated the affected areas located downwind from the major prevailing wind (Southeastern & Southwestern winds)

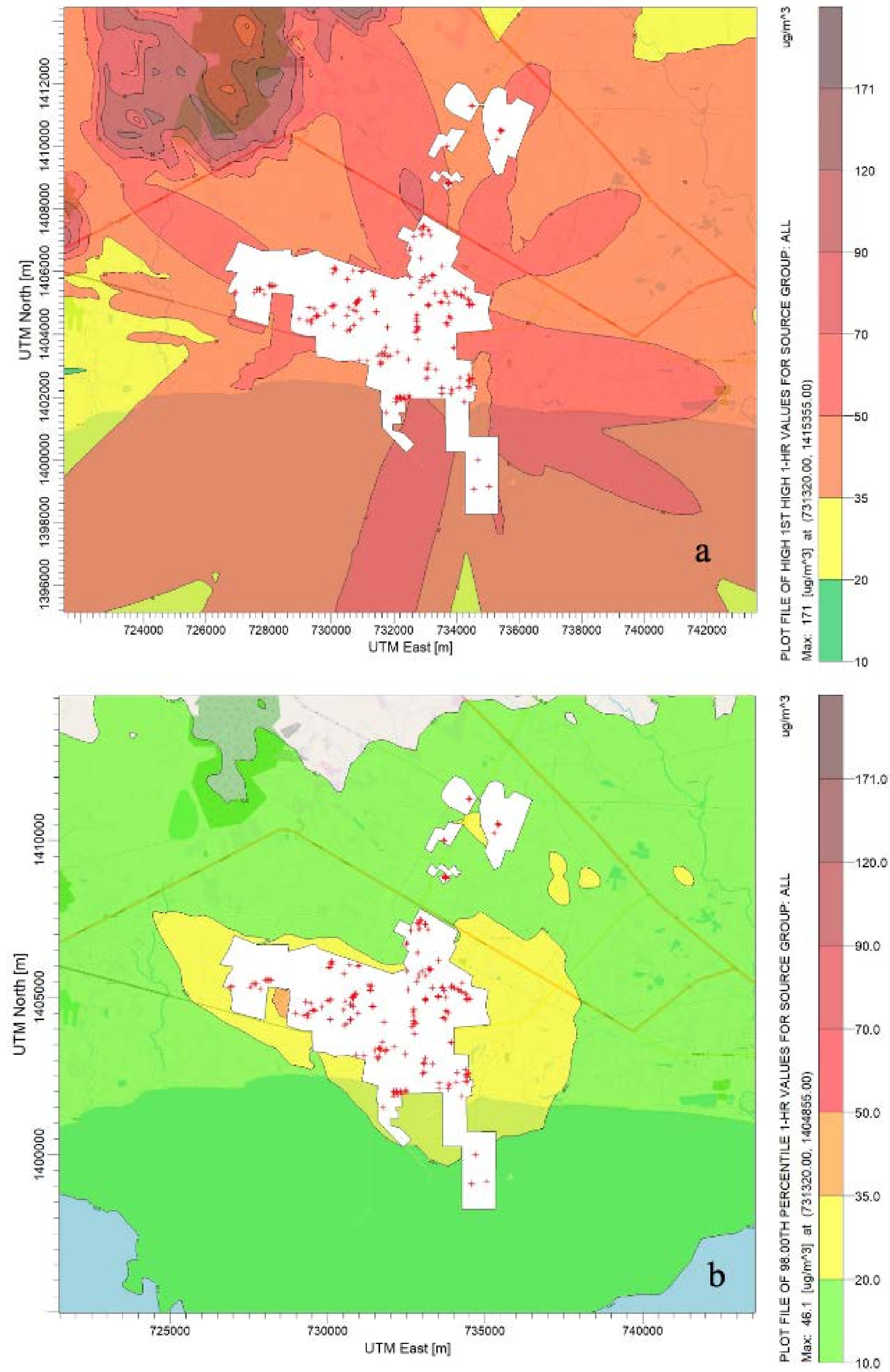


Fig 4. Plot file of PM2.5 concentrations (µg/m^3) (a) 1st highest 1-hr (b) 98th percentile of 1-hr

4.2 Bivariate Polar Plot Results

The conditional bivariate probability function (CBPF model) was applied to illustrate the magnitude of PM2.5 and PM10 concentrations with respect to wind characteristics (wind speed and wind direction). The CBPF diagram was plotted through the openair R package (open-source polar plot function). Hourly particulate concentrations were used together with measured wind speed and wind direction from the same monitoring station to draw the CBPF plot as illustrate in Figure 5. For better explanation and interpretation of the results, the air quality guideline regulated by New Zealand was applied. Detail of the guideline was presented elsewhere [16]. Results revealed that high concentrations of PM2.5 and PM10 were predominantly dispersed from southwest directions. These directions are situated by the industrial complex (about 1 kilometer away from southwest direction of HTMP monitoring station). Moreover, under the calm wind condition (wind speed < 0.5 m/s), concentrations of PM2.5 and PM10 were within alert category (66% - 100% from the ambient air quality standard). Considering that this monitoring site is located not too far the curbside of the road, the result revealed the influence of traffic emission to measured PM2.5 and PM10 concentrations at this site.

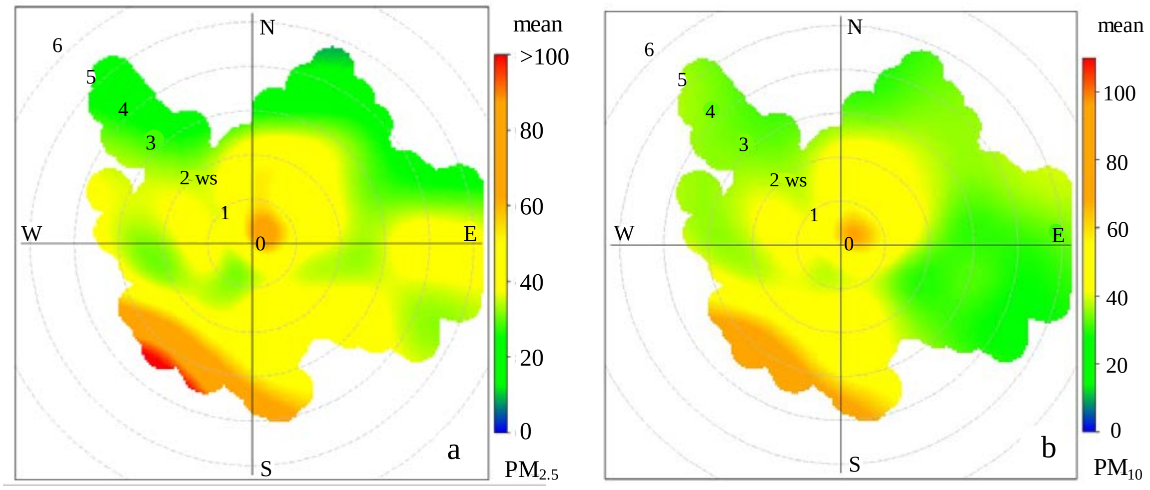


Fig 5. Bivariate polar plot of (a) PM2.5 and (b) PM10 concentration at HTMP monitoring station

Results from this study demonstrated that using AERMOD coupled with CBPF is success in identification of the potential PM2.5 and PM10 emission sources. AERMOD results showed that the predicted data from model was close to PM2.5 concentrations than PM10 concentrations at the interested receptor points. Taking into consideration that there are many industries located in both southwest directions from HMTP monitoring station, results from the bivariate polar plot clearly indicated that those emissions from southwest directions were greatly affected to high ambient concentrations measured at the receptors.

5. CONCLUSION

AERMOD air dispersion model was evaluated for its performance to predict ground level PM2.5 and PM10 concentrations. Study area was Maptaphut industrial area, Thailand. Total dust emission data comprised of 247 stacks located in the study domain. These emissions were assumed as constant value for each source over the simulated period. Predicted results were compared with those observed data and the performance of the model were statistically evaluated. Comparisons of modeled and observed results indicated that predicted PM2.5 and PM10 concentrations data were lower than those measured ground level concentrations (under prediction). The key finding from this study reveals that industrial stacks are not the major emission sources contributed to ambient PM2.5 and PM10 concentrations. This study also highlights that the current total dust (all size) emission standard is adequate in controlling ambient particulate (at every cut size) pollution. The effort in controlling of existing PM2.5 and PM10 ambient concentrations should be focused on other major contributing sources i.e. mobile sources, construction and open burning activities to reach the effective management of particulate pollution.

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