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Original Research

Trend and Association Between Particulate Matters and Meteorological Factors: A Prospect for Prediction of $PM_{2.5}$ in Southern Thailand

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Abstract

Particulate matter (PM) concentration in southern Thailand has increased significantly due to open crop burning within the southeast Asian sub-region. This study aimed to explore the trend and relationship between PM and meteorological features in southern Thailand. Also, estimate the $PM_{2.5}$ when monitoring sites measure PM_{10}. Data on PM concentration and meteorological features were taken from air monitoring stations within southern Thailand from 2012 to 2021. Descriptive statistics were used to explore the data, and then a spline model was used to examine the trends and seasonal patterns of PM concentration and meteorological features. A scatter plot matrix and correlation analysis were used to assess the relation between PM and meteorological features. Machine learning models were used to predict $PM_{2.5}$ concentration. The highest annual average concentration of $PM_{2.5}$ and PM_{10} in southern Thailand was 18.9±8.24 μg/m^3 and 36.3±14.2 μg/m^3 in Songkhla Province, and the lowest concentration of $PM_{2.5}$ and PM_{10} was 13.9±7.65 μg/m^3 and 27.5±12.2 μg/m^3 at Phuket. The Multiple

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Linear Regression (MLR) and Artifical Neural Network (ANN) almost perform best for the prediction of $PM_{2.5}$ at each station, with 13.6% average Mean Absoulte Percentage Error (MAPE). Songkhla and Phuket need significant attention from local government officials and policymakers. $PM_{2.5}$ can be better predicted using the MLR model when it has missing values at some stations. The results help scientists and policymakers to better understand the condition and find the best possible solution to overcome the health issue that arises due to exposure.

Keywords: particulate matter, meteorological factors, trend, machine learning, southern Thailand

Introduction

Air quality is a significant element in climate change and causes environmental and public health problems. Globally, particulate matter (PM) concentrations with a diameter of less than 2.5 µm ($PM_{2.5}$) or less than 10 µm (PM_{10}) have become an environmental problem and have generated increased attention [1]. Therefore, PM has received much attention in many countries. Previous studies indicated the tendency to increase air pollutant concentration trends in developed and developing countries [2-4]. $PM_{2.5}$ had a significantly increasing trend in Southeast Asian countries like Bangladesh, Myanmar, Laos, and Thailand [3]. The largest source of particulate pollution in Southeast Asia is open crop residue burning. When more dust and gases are released into the air, it significantly impacts the air quality in the areas, which is particularly bad in the dry season [5].

Different studies have identified various factors associated with PM concentration at specific locations. Meteorological features such as wind speed, temperature, and relative humidity significantly affect PM concentration in different areas in Thailand [6-8]. Vehicular traffic and vegetation cover are also significant features associated with PM concentration [9, 10]. Previous studies have extensively discussed methods for modeling, predicting, and forecasting PM concentrations.

Major cities in Thailand have experienced a significant increase in air pollutant concentration over the last few years [11]. Air pollution problems have been more severe, particularly within the Bangkok metropolitan area and the northern parts of Thailand [12, 13]. The intensity and frequency of haze outbreaks have increased in the north of Thailand due to rapid changes in settlement planning [7-14]. The concentration of $PM_{2.5}$ and PM_{10} in northern Thailand usually exceeds WHO standards during the dry seasons [15]. The hourly records of PM exceed the accepted standards of the NAAQ and the WHO [9].

The southern part of Thailand lies between the Gulf of Thailand to the east and the Andaman Sea to the west. Due to tourist activities, the region has become an important economic hub for Thailand. The south of Thailand has seasonally been under hazy conditions caused by smoke from open burning and forest fires from within the country and other neighboring countries. PM concentration in southern Thailand was higher in 2015 than in subsequent years, mostly due to transboundary atmospheric aerosol transportation [16]. Many studies have established a significant relationship between PM concentration and adverse health outcomes (see, e.g., [17, 18]). The concentration of PM in the southern part of Thailand has historically been below the national average concentration, although recent findings indicate a gradually increasing trend in PM concentration over the southern region. However, very few studies have been conducted in recent years to explore the trends of PM concentration and meteorological factors and their associations within the southern region.

Moreover, predicting $PM_{2.5}$ is also very important, as these are very small particles and are sometimes not measured by devices. Many researchers develop time series-based machine learning models for predicting $PM_{2.5}$ (see, e.g., [19-22]). Which are computationally extensive and need historical data to predict. Predicting $PM_{2.5}$ using other correlated available pollutants and meteorology variables can reduce the computational cost and massive data collection.

Therefore, this study aimed to:

– Analyze the trends of PM concentration and meteorological factors in southern Thailand.
– Explore the association between PM concentration and meteorological factors in southern Thailand.
– Recommend the most accurate models for predicting $PM_{2.5}$ concentration in cases where $PM_{2.5}$ is unavailable at certain monitoring locations, but PM_{10} and other meteorological factors are available.

Material and Methods

Study Area and Data Source

The study area consists of five main provinces of southern Thailand that have air pollution and weather stations. In 2022, the population of southern Thailand was 9.49 million with an area of 70,715 Km^2. These provinces in southern Thailand stations include Surat Thani, Phuket, Songkhla, Narathiwat, and Yala. Hourly data on $PM_{2.5}$ and PM_{10} concentrations and meteorological factors including wind speed, temperature, relative humidity, and atmospheric pressure were obtained from the Pollution Control Department of Thailand. The locations of air pollution monitoring stations are shown in Fig. 1. The hourly data of air pollutant concentration and meteorological factors were taken from each station from 1 January

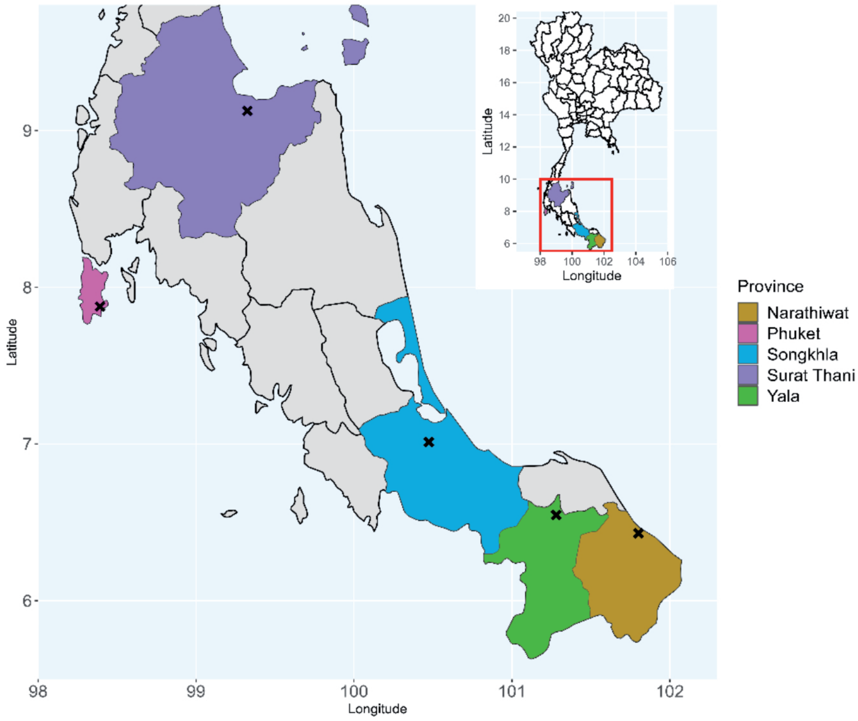

Fig. 1. The locations of the monitoring stations in the South of Thailand area.

2012 to 31 December 2021 and aggregated into daily data.

Statistical Analysis and Modeling

The obtained data were preprocessed before analysis. We identified the outliers, and also missing values were imputed using multiple imputations, which were less than 15% in each station and for each variable. After pre-processing, we plot each PM and meteorological factor and fit a cubic spline model to understand the trend and pattern. Then we used a scatter plot matrix with a Pearson correlation coefficient. A scatter plot was used to investigate the linear relationship between these variables, and then correlation was considered to evaluate the strength of that linear relationship among variables. Finally, we compare the machine learning models to predict $PM_{2.5}$ when the station measures PM_{10} and has meteorological factors. Data for each station were split into training and testing sets at a ratio of 80:20. The first 80% of observations were used to train the models. Then the predictive performance of these models was assessed on 20% of the observation of test data using root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE). The flowchart of the study is presented in Fig. 2. All statistical analysis was performed using R programming. The details of the used models are as follows:

The cubic spline function was used to examine the seasonal patterns and trends in particulate matter variables by dividing the whole range into knots. The cubic spline model is as follows:

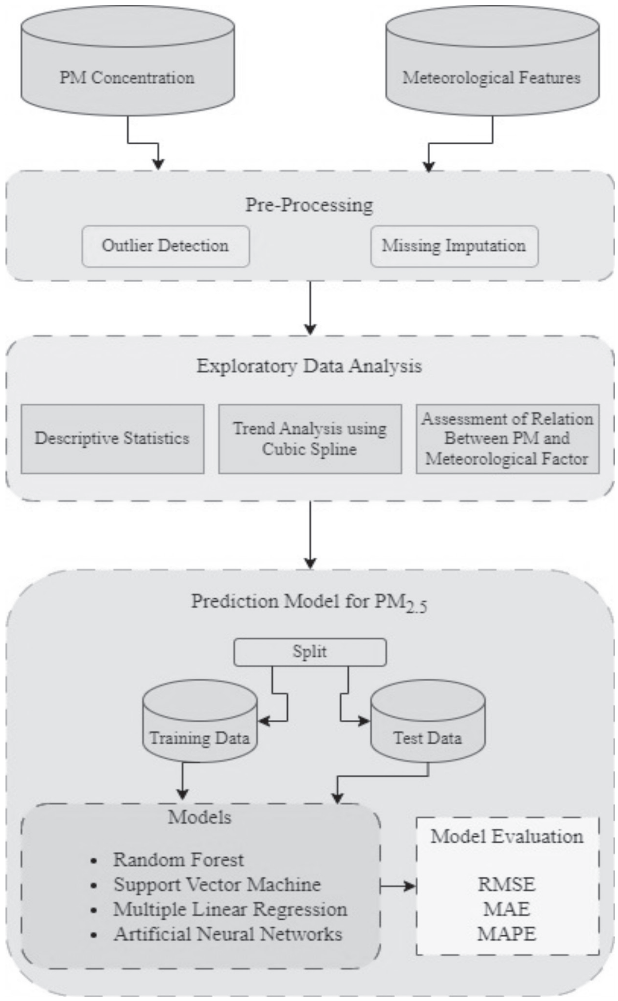

Fig. 2. Flowchart of the Study.

$$S(t) = a + bt + \sum_{i=1}^{k} C_i (t - t_i)^3 \quad (1)$$

where $S(t)$ is the spline function for $PM_{2.5}$ at time t. a, b, C_k are parameters in the model and k indicates the number of knots.

Multiple Linear Regression (MLR) is a simple predictive approach that establishes a linear relationship between a continuous variable (e.g., $PM_{2.5}$ concentration) and multiple determinants. The MLR is defined as follows:

$$Y_t = \beta_0 + \sum_{i=1}^{p} \beta_i X_i \quad (2)$$

where, Y_t is the variable of interest, β_0 is the intercept, and ach β_i represents the coefficient of each determinant X_i.

The Support Vector Machine (SVM) was initially developed as a classification algorithm by Vapnik and Cortes [23]. However, the introduction of support vector regressors allowed SVM to be applied to numeric data. The SVM applies the kernel function to create a map of data in higher dimensional space for regression analysis [24]. The SVM model can be written as:

$$f(x) = w.x + \sigma \quad (3)$$

where $x \in X$ represents a vector of independent variables, $w \in X$ are weighting parameters each $x \in X$ and σ indicates the distance between each hyperplane and the observed factor.

Random forest (RF) is a supervised learning algorithm that combines decision trees to create a forest based on bagging [25]. It uses the bagging technique to select variables' random samples as the model calibration training dataset [26]. Decision trees in the forest are created using a random selection of features. Each decision tree is used to predict the training data, and the average from all decision trees is chosen as the predicted outcome.

The development of Artificial Neural Networks (ANN) is based on the human brain and the connections between neurons [27]. ANN consists of an input layer, hidden layers, and an output layer. In ANN, one input layer is mainly responsible for input parameters, one or more hidden layers, and one output layer. The networks generally have a learning system based on examples that incorporate new ones. The error estimation of the learning system is backward-spread, and the learning process is continuous. After sufficient learning is achieved, the networks are used to make predictions based on input data.

Results and Discussion

The descriptive statistics include mean, standard deviation (SD), median, maximum, and minimum of daily air pollutant concentrations and meteorological features at each station presented in Table 1. Songkhla has the maximum average exposure of $PM_{2.5}$ and PM_{10}, which were 18.2±8.24 μg/m^3 and 36.3±14.2 μg/m^3, respectively. While the minimum exposure of $PM_{2.5}$ and PM_{10} was 13.9±6.42 μg/m^3 and 27.5±12.2 μg/m^3 in Phuket. Average levels of meteorological features varied across the southern region of Thailand. The overall average temperature in Southern Thailand was 28.9ºC in Phuket and 28.6ºC in Songkhla. The daily concentrations of PM and meteorological factors for all five monitoring stations are shown in Fig. 3. A preliminary assessment of air pollutant concentration at the five monitoring stations indicated varying characteristics in each province. We observed significant variability in the concentration of $PM_{2.5}$ and PM_{10} at the Songkhla, Narathiwat, Surat Thani, and Phuket stations. PM concentration in Surat Thani province showed significant annual variability, with high pollutant levels in December and January. The daily concentrations of $PM_{2.5}$ and PM_{10} in Phuket were consistent with Surat Thani province. The cubic spline model (indicated with a red curve) was used to examine the seasonal patterns and trends in PM concentration. The spline function showed significant seasonal variability in $PM_{2.5}$ and PM_{10} concentration. Phuket has an increasing trend of both PM concentrations. Similarly, variability and trends can be seen in wind speed and atmospheric pressure in each region, while temperature has a strong seasonal pattern in each region.

The relation between PM constraints and meteorological features was determined using a scatter plot and Pearson correlation analysis in Fig. 4. The diagonal presents the histogram of each series. Lower diagonals present the scatter plot to examine the linear or non-linear relation between variables, and the upper diagonal presents the Pearson correlation coefficient with significance present with steric signs. Scatter plots and correlation measures show that both PM concentrations are positively, strongly, and linearly related. Temperature is positive but very weaker related to PM in Songkhla, Phuket, and Narathiwat. Windspeed has a negative relation with PM in Songkhla but is positively related to Yala and Surat Thani. Relative humidity is negatively associated with PM concentrations at all stations, so it can decrease the concentration of PM in the air. Higher atmospheric pressure accumulates more particles so positively associated with PM concentrations except in Narathiwat.

The performance of RF, SVM, MLR, and ANN for predicting $PM_{2.5}$ was evaluated and presented in Fig. 5 for each station with different evaluation measures. Each graph presents the observed $PM_{2.5}$, which is test data, and the predicted values using each model along with

Table 1. Descriptive Statistics of Daily PM Concentration and Meteorological Features.

	Surat Thani	Phuket	Songkhla	Narathiwat	Yala
$PM_{2.5}$ ($\mu g/m^3$)					
Mean±SD	16.9±6.25	13.9±6.42	18.2±8.24	15.8±6.73	15.8±6.79
Median [Min-Max]	15.9 [4.42-73.0]	12.9 [3.04-83.4]	16.5 [4.96-162]	14.7 [2.42-72.4]	14.9 [2.17-84.1]
PM_{10} ($\mu g/m^3$)					
Mean±SD	33.0±11.1	27.5±12.2	36.3±14.2	29.0±11.5	30.6±11.7
Median [Min-Max]	31.2 [8.17-136]	26.2 [5.17-172]	34.3 [8.13-322]	28.0 [5.42-172]	28.8 [9.04-135]
Wind Speed (*knot*)					
Mean±SD	0.926±0.39	1.34±0.635	1.34±0.481	0.877±0.479	0.897±0.286
Median [Min-Max]	0.838 [0.19-3.86]	1.21 [0.23-5.13]	1.29 [0.08-4.50]	0.829 [0.054-4.65]	0.892 [0.171-2.48]
Temperature (ºC)					
Mean±SD	27.7±1.75	28.9±1.25	28.6±2.10	27.4±1.54	27.4±1.46
Median [Min-Max]	27.7 [21.9-41.8]	29.0 [24.2-32.4]	28.6 [21.4-43.6]	27.5 [21.5-31.3]	27.4 [20.0-34.9]
Relative Humidity (*%*)					
Mean±SD	79.5±7.80	72.4±7.99	73.8±7.39	74.8±8.50	75.0±9.64
Median [Min-Max]	79.0 [0.21-100]	73.1 [45.3-96.9]	73.6 [48.0-99.9]	74.6 [43.1-99.0]	76.7 [31.0-99.0]
Atmospheric Pressure (*hPa*)					
Mean±SD	755±1.94	757±1.32	756±3.17	755±3.21	756±1.48
Median [Min-Max]	754 [728-762]	757 [752-761]	755 [736-771]	755 [724-760]	756 [727-760]

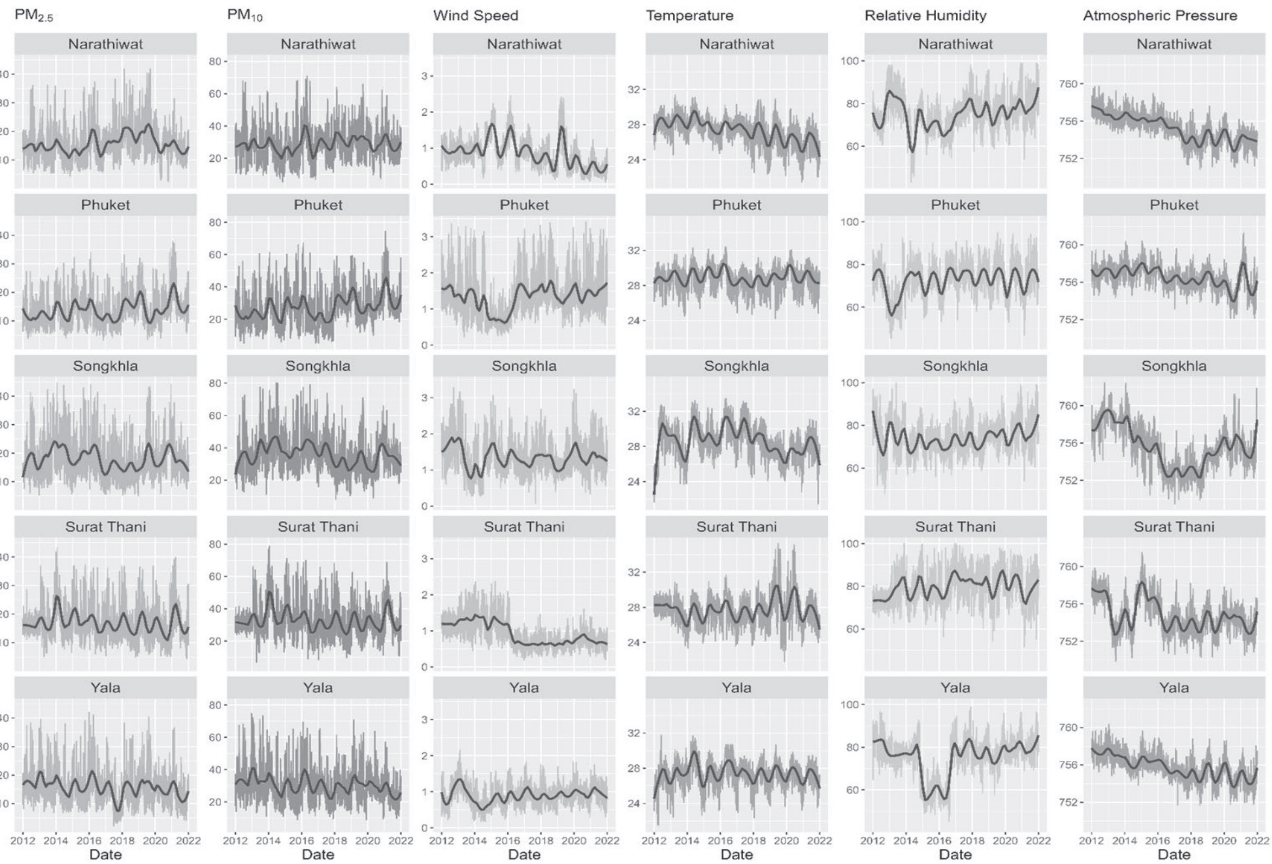

Fig. 3. PM Concentration and Meteorological features from five stations in Southern Thailand. The red line is the cubic spline fitted line.

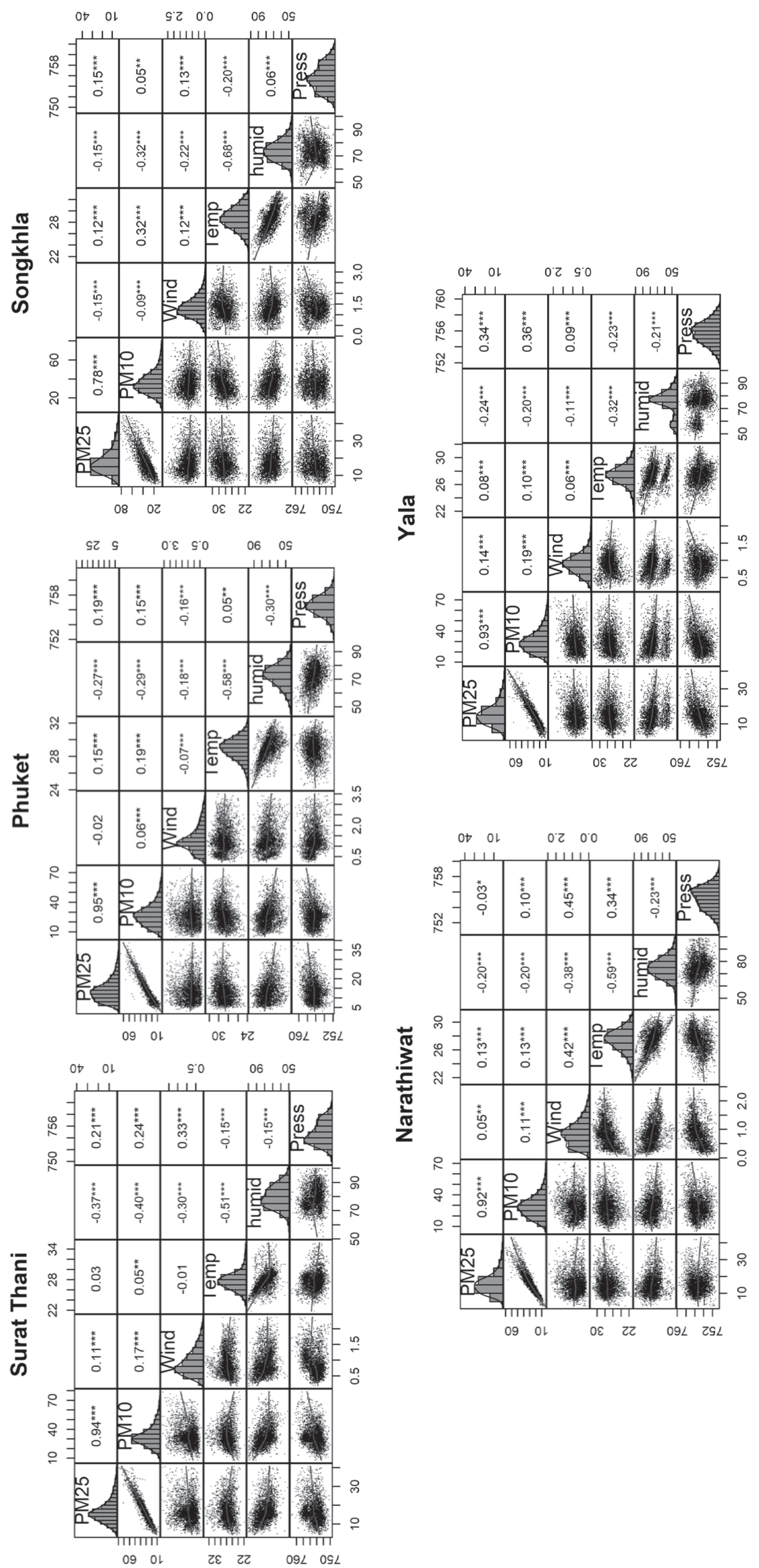

Fig. 4. Correlation between PM Concentration and Meteorological features from five stations in Southern Thailand.

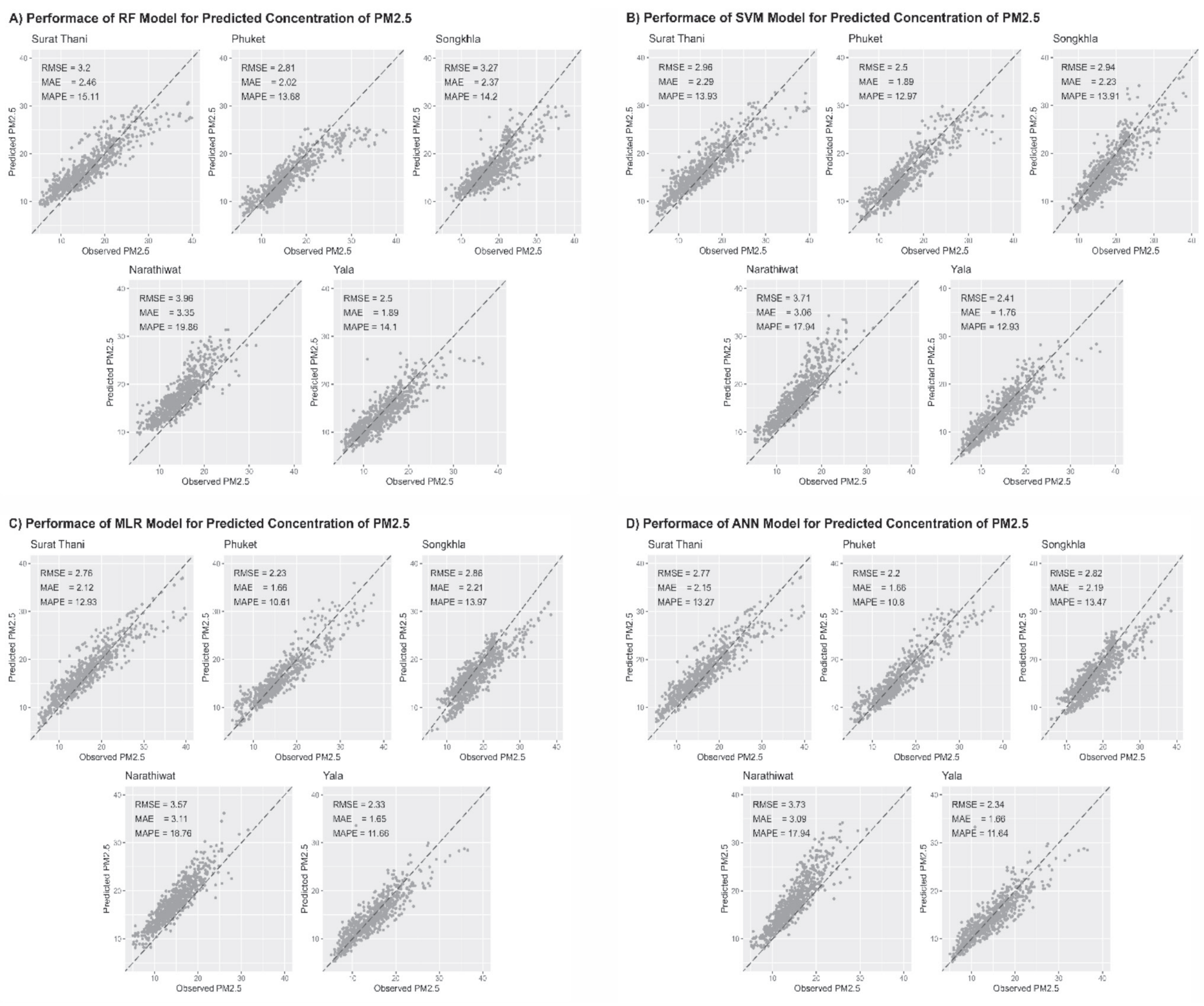

Fig. 5. Prediction Performance of $PM_{2.5}$ Concentration Using Different Machine Learning Models. A) RF Model. B) SVM Model. C) MLR Model. D) ANN Model. Performance Evaluations are based on Test Data.

RMSE, MAE, and MAPE. The results revealed that the MLR and ANN have almost the same and lowest values of RMSE, MAE, and MAPE measures for each station except Narathiwat, where SVM performs a bit better than other models. But if we compare the computational complexity and performance of all models, then MLR is the least complex, has good results, and is suggested to be used for predicting $PM_{2.5}$ in these regions.

This study has investigated the trends of $PM_{2.5}$ from five air quality monitoring stations in southern Thailand. The concentration of $PM_{2.5}$ was predicted at each station by combining PM_{10} with meteorological features, including atmospheric factors such as temperature, pressure, wind speed, and relative humidity, using three machine learning models (support vector machines, random forests, and artificial neural networks) and the multiple linear regression model. The present study has also predicted $PM_{2.5}$ at these stations using machine learning models and multiple linear regression.

Results from the correlation analysis indicated a significant correlation between $PM_{2.5}$ and PM_{10} at each station. The significance of meteorological factors (temperature, relative humidity, wind speed, and atmospheric pressures) differed by location. Theoretically, a higher atmospheric water concentration in the atmosphere dissolves particulates such as fine particulates, reducing PM concentrations. Consequently, the present study found negative correlations between relative humidity, the concentration of PM_{10}, and $PM_{2.5}$ at all stations in Southern Thailand. These results agree with findings from studies within the Southeast Asia region [28, 29]. However, similar studies have reported a positive correlation between relative humidity and PM concentration. The effect of relative humidity on pollutants may vary due to the type of aerosols in different atmospheres [30]. High temperatures cause convection, which may lead to the dispersion of air pollutants. However, this study reports no correlation between temperature and PM concentrations across the stations. As these regions have tropical weather, therefore, the relatively stable temperature could mitigate any positive correlation with particulate matter. However, similar studies found a significant correlation between temperature and PM [31, 32]. The predictive accuracy of the MLR model for predicting $PM_{2.5}$ is higher than other machine learning models. This might be due to the nature of the relation between these variables being linear. The results are location-specific, indicating that geographical factors could affect the concentration and distribution of particulate matter. However, the methodology can be used in further research.

Conclusions

All the provinces have high exposure to PM concentration as compared to WHO. While Songkhla has very high exposure, Phuket has an increasing trend of PM concentration, which needs more attention from the government and stakeholders in making policies for the future. Humidity is negatively affecting PM concentration in all these regions, while atmospheric pressure causes more PM particles. For the stations where $PM_{2.5}$ is missed, it can be predicted using PM_{10} and other variables due to their significant relationship. Future studies can use this methodology for analyzing the pattern and predicting $PM_{2.5}$ in other countries and regions. Moreover, these results help local governments to make strategies and scientists to better understand the ground condition and suggest the best possible solution to policymakers that overcome the health issues that arise due to the exposure.

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Conflict of Interest

The authors declare no conflict of interest.

References

1. QU H., LU X., LIU L., YE Y. Effects of traffic and urban parks on PM_{10} and $PM_{2.5}$ mass concentrations. Energy Sources, Part A: Recovery, Utilization, and Environmental Effects. **45** (2), 5635, **2023**.
2. COLETTE A., GRANIER C., HODNEBROG Ø., JAKOBS H., MAURIZI A., NYIRI A., BESSAGNET B., D'ANGIOLA A., D'ISIDORO M., GAUSS M. Air quality trends in Europe over the past decade: a first multi-model assessment. Atmospheric Chemistry and Physics. **11** (22), 11657, **2011**.
3. SHI Y., MATSUNAGA T., YAMAGUCHI Y., LI Z., GU X., CHEN X. Long-term trends and spatial patterns of satellite-retrieved $PM_{2.5}$ concentrations in South and Southeast Asia from 1999 to 2014. Science of the Total Environment. **615**, 177, **2018**.
4. BHATTI U.A., NIZAMANI M.M., MENGXING H. Climate change threatens Pakistan's snow leopards. Science. **377** (6606), 585, **2022**.
5. CHUANG H.C., HSIAO T.C., WANG S.H., TSAY S.C., LIN N.H. Characterization of particulate matter profiling and alveolar deposition from biomass burning in Northern Thailand: The 7-SEAS study. Aerosol and Air Quality Research. **16** (11), 2897, **2016**.
6. PHUENGSAMRAN P., LALITAPORN P. Estimating particulate matter concentrations in central Thailand using satellite data. Thai Environmental Engineering Journal. **35** (3), 1, **2021**.
7. AMNUAYLOJAROEN T., MACATANGAY R.C., KHODMANEE S. Modeling the effect of VOCs from biomass burning emissions on ozone pollution in upper Southeast Asia. Heliyon. **5** (10), **2019**.
8. SAHANAVIN N., PRUEKSASIT T., TANTRAKARNAPA K. Relationship between PM10 and PM2.5 levels in high-traffic area determined using path analysis and linear regression. Journal of Environmental Sciences. **69**, 105, **2018**.
9. CHALERMPONG S., THAITHATKUL P., ANUCHITCHANCHAI O., SANGHATAWATANA P. Land use regression modeling for fine particulate matters in Bangkok, Thailand, using time-variant predictors: Effects of seasonal factors, open biomass burning, and traffic-related factors. Atmospheric Environment. **246**, 118128, **2021**.
10. GAUTAM S., BREMA J. Spatio-temporal variation in the concentration of atmospheric particulate matter: A study in fourth largest urban agglomeration in India. Environmental technology & innovation. **17**, 100546, **2020**.
11. BUYA S., LIM A., SAELIM R., MUSIKASUWAN S., CHOOSONG T., TANEEPANICHSKUL N. Impact of air pollution on cardiorespiratory morbidities in Southern Thailand. Clinical Epidemiology and Global Health. **25**, 101501, **2024**.
12. SAHANAVIN N., TANTRAKARNAPA K., PRUEKSASIT T. Ambient PM_{10} and $PM_{2.5}$ concentrations at different high traffic-related street configurations in Bangkok, Thailand. Southeast Asian J Trop Med Public Health. **47** (3), 528, **2016**.
13. SUKKHUM S., LIM A., INGVIYA T., SAELIM R. Seasonal patterns and trends of air pollution in the upper northern Thailand from 2004 to 2018. Aerosol and Air Quality Research. **22** (5), 210318, **2022**.
14. KHODMANEE S., AMNUAYLOJAROEN T. Impact of biomass burning on ozone, carbon monoxide, and nitrogen dioxide in Northern Thailand. Frontiers in Environmental Science. **9**, 641877, **2021**.
15. AMNUAYLOJAROEN T., PARASIN N., LIMSAKUL A. Health risk assessment of exposure near-future $PM_{2.5}$ in Northern Thailand. Air Quality, Atmosphere & Health. **15** (11), 1963, **2022**.
16. CHOMANEE J., THONGBOON K., TEKASAKUL S., FURUUCHI M., DEJCHANCHAIWONG R., TEKASAKUL P. Physicochemical and toxicological characteristics of nanoparticles in aerosols in southern

Thailand during recent haze episodes in lower southeast Asia. Journal of Environmental Sciences. **94**, 72, **2020**.

17. PAOIN K., UEDA K., VATHESATOGKIT P., INGVIYA T., BUYA S., DEJCHANCHAIWONG R., PHOSRI A., SEPOSO X.T., KITIYAKARA C., THONGMUNG N. Long-term air pollution exposure and decreased kidney function: A longitudinal cohort study in Bangkok Metropolitan Region, Thailand from 2002 to 2012. Chemosphere. **287**, 132117, **2022**.
18. PAOIN K., UEDA K., INGVIYA T., BUYA S., PHOSRI A., SEPOSO X.T., SEUBSMAN S.A., KELLY M., SLEIGH A., HONDA A. Long-term air pollution exposure and self-reported morbidity: A longitudinal analysis from the Thai cohort study (TCS). Environmental Research. **192**, 10330, **2021**.
19. BHATTI U.A., YAN Y., ZHOU M., ALI S., HUSSAIN A., QINGSONG H., YU Z., YUAN L. Time series analysis and forecasting of air pollution particulate matter ($PM_{2.5}$): an SARIMA and factor analysis approach. Ieee Access. **9**, 41019, **2021**.
20. HASNAIN A., HASHMI M.Z., KHAN S., BHATTI U.A., MIN X., YUE Y., HE Y., WEI G. Predicting ambient $PM_{2.5}$ concentrations via time series models in Anhui Province, China. Environmental Monitoring and Assessment. **196** (5), 487, **2024**.
21. ERDEN C. Genetic algorithm-based hyperparameter optimization of deep learning models for $PM_{2.5}$ time-series prediction. International Journal of Environmental Science and Technology. **20** (3), 2959, **2023**.
22. JIANG L., TAO Z., ZHU J., ZHANG J., CHEN H. Exploiting PSO-SVM and sample entropy in BEMD for the prediction of interval-valued time series and its application to daily $PM_{2.5}$ concentration forecasting. Applied Intelligence. **53** (7), 7599, **2023**.
23. CORTES C., VAPNIK V. Support-vector networks. Machine learning. **20**, 273, **1995**.
24. DRUCKER H., BURGES C., KAUFMAN L., SMOLA A., VAPNIK V. Support Vector Regression Machines Advances in neural information processing systems Volume 9, 155-161. Cambridge, MA: MIT Press, **1997**.
25. BREIMAN L. Random forests. Machine learning. **45**, 5, **2001**.
26. CHA G.W., MOON H.J., KIM Y.C. Comparison of random forest and gradient boosting machine models for predicting demolition waste based on small datasets and categorical variables. International Journal of Environmental Research and Public Health. **18** (16), 8530, **2021**.
27. JAIN A.K., MAO J., MOHIUDDIN K.M. Artificial neural networks: A tutorial. Computer. **29** (3), 31, **1996**.
28. SIRITHIAN D., THANATRAKOLSRI P. Relationships between meteorological and particulate matter concentrations ($PM_{2.5}$ and PM_{10}) during the haze period in urban and rural areas, northern thailand. Air, Soil and Water Research. **15**, 11786221221117264, **2022**.
29. DAHARI N., LATIF M.T., MUDA K., NORELYZA N. Influence of meteorological variables on suburban atmospheric $PM_{2.5}$ in the southern region of peninsular Malaysia. Aerosol and Air Quality Research. **20** (1), 14, **2020**.
30. ECK T.F., HOLBEN B., KIM J., BEYERSDORF A., CHOI M., LEE S., KOO J.-H., GILES D., SCHAFER J., SINYUK A. Influence of cloud, fog, and high relative humidity during pollution transport events in South Korea: Aerosol properties and $PM_{2.5}$ variability. Atmospheric Environment. **232**, 117530, **2020**.
31. SAWUT R., LI Y., KASIMU A., ABLAT X. Examining the spatially varying effects of climatic and environmental pollution factors on the NDVI based on their spatially heterogeneous relationships in Bohai Rim, China. Journal of Hydrology. **617**, 128815, **2023**.
32. WANG L., ZHAO B., ZHANG Y., HU H. Correlation between surface $PM_{2.5}$ and O_3 in eastern China during 2015-2019: Spatiotemporal variations and meteorological impacts. Atmospheric Environment. **294**, 119520, **2023**.