Estimating Hourly Full-Coverage PM2.5 Concentrations Based On MODIS Data Over The Northeast of Thailand.

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Abstract

Particulate matter (PM_{2.5}) pollutants are a significant health issue with impacts on human health; however, monitoring of PM_{2.5} is very limited in developing countries. Satellite remote sensing can expand spatial coverage, potentially enhancing our ability in a specific area for estimating PM_{2.5}; however, some have reported poor predictive performance. An innovative combination of MODIS AOD was developed to fulfill all missing aerosol optical depth (AOD) data obtained from the Moderate Resolution Imaging Spectroradiometer (MODIS). Therefore, hourly PM_{2.5} concentrations were obtained in Northeastern Thailand. A Linear mixed-effects (LME) model was used to predict location-specific hourly PM_{2.5} levels. Hourly PM_{2.5} concentrations measured at 20 PM_{2.5} monitoring sites and 10-fold cross-validation were addressed for model validation. The observed and predicted concentrations suggested that LME obtained from MODIS AOD data and other factors are a potentially useful predictor of hourly PM_{2.5} concentrations ($R^2 > 0.70$), providing more detailed spatial information for local scales studies. Interestingly, PM_{2.5} along the Mekong River area was observed higher than in the plain area. The finding can infer that the monsoon wind brings polluted air into the province from sources outside the region. The results will be helpful to analyze air pollution-related health studies.

1. Introduction

PM_{2.5} has become a severe environmental and health issue in Thailand, a significant component of air pollution (Kumharn and Hanprasert 2016; Kumharn et al. 2020; Roberts et al. 2019; Xiao et al. 2020; Xing et al. 2016). The Northeast of Thailand is also facing this problem. This region consists of 20 provinces, Thailand's most significant part. Many sections in this region have suffered from severe PM_{2.5} pollution in recent years. Both pollution areas and levels are increasing gradually. Therefore, PM_{2.5} data is required for assessing the impacts of air quality on human health. However, PM_{2.5} observations lack adequate ground-based monitoring due to budget limitations. As satellite remote sensing can provide data with extensive spatial coverage, satellite-derived Aerosol optical depth (AOD) data can be used to derive surface PM_{2.5} concentrations. PM_{2.5} can be obtained from the association of AOD-PM_{2.5}. To date, several studies have investigated AOD-PM_{2.5} with other meteorological factors obtained from satellite data (the Moderate Resolution Imaging Spectroradiometer (MODIS), giving more accurate predictions of PM_{2.5} (Guo et al. 2017; Kong et al. 2016; Ma et al. 2016; Unnithan and Gnanappazham 2020). However, most studies in AOD-PM_{2.5} have only been carried out in a few areas in Thailand (Kanabkaew 2013; Tsai et al. 2000). So far, very little attention has been paid to the role of estimating PM_{2.5} using satellite remote sensing by MODIS Terra and Aqua covering Thailand. Additionally, the limitation of cloud cover leads to missing AOD data, mainly in the rainy season.

Therefore, this study focused on an innovative combination of MODIS AODs data for filling missing data. Satellite AODs data were retrieved using the MODIS AODs Terra and Aqua Daily Level-3 Data $1^\circ \times 1^\circ$ resolution products (MOD20 for Terra and MYD20 for Aqua) with MOD04 L2 and MOD08 M3 (<https://ladsweb.modaps.eosdis.nasa.gov/search/order/1>) for fulfilling all missing values. Therefore, hourly surface PM_{2.5} concentrations using satellite based AOD data must be sufficient and continuous for prediction. Previous research has established the quantitative association between satellite AOD and ground based PM_{2.5} using the LME model (Mhawish et al. 2020; Stowell et al. 2020; Wang et al. 2019; Zhang et al. 2019). Recently, LME has widely been used to establish the PM_{2.5}-AOD relationship with other meteorological factors. Therefore, the LME model was applied to satellite AODs with climate variables and other parameters for predicting the hourly PM_{2.5} concentration in a full-coverage spatial distribution in Northeast Thailand.

2 Data And Methodology

This study is focused on the Northeast of Thailand located on the Khorat Plateau, bordered by the Mekong River (along with Laos–Thailand border) to the north and east, by Cambodia to the southeast, and the Sankamphaeng Range south of Nakhon Ratchasima. It is separated from northern and central Thailand by the Phetchabun Mountains to the west. This region is naturally a high level plain called northeast plateau. Northeastern Thailand covers 167,718 km² with a population of 21,305,000. To calibrate the MODIS value predicted, AODs data, PM_{2.5}, are sampled at 20 stations, as shown in Figure 1. The calibration was performed independently for each monitoring site. A single hourly AOD–PM_{2.5} relationship obtained from 20 monitoring stations was established. The predicted hourly PM_{2.5} concentration from this method was validated independently.

2.1 AOD data

The MODIS aerosol product monitors the ambient AOD over the oceans globally and the continents. Daily Level-2 data are produced at the spatial resolution of 0.25, 0.5, and 1.0 km (36 spectral channels between 0.41 and 14.23µm) with a viewing swath of 2330 km. Aerosol products were produced in both ocean and land (Kaufman et al. 1997). MODIS AOD collection 6.1 has been used in this work with a spatial resolution of 1°×1°retrieved (<http://disc.sci.gsfc.nasa.gov/giovanni> website).

2.2. Meteorological factors and land use data

Meteorological factors with horizontal resolutions of 1–30 km were retrieved from the Weather Research *and* Forecasting (WRF), which is a mesoscale meteorological model developed by the National Centers for Environmental Prediction (NCEP) and the National Center for Atmospheric Research (NCAR). Meteorological factors comprised the relative humidity (RH), temperature (TEM), wind speed (WS), and boundary layer height (BLH). The normalized difference vegetation index (NDVI), with a spatial resolution of 1 km, was downloaded from the EOSDIS website (<https://search.earthdata.nasa.gov>). All data were processed at 10 km, corresponding to the spatial resolution of the MODIS AOD data.

2.3 Ground-based PM_{2.5} data

An hourly basis of PM_{2.5} data was collected from the pollution control department and climate change data center of Chiang Mai University. To calibrate the MODIS AODs data, PM_{2.5} was sampled at 20 stations from 1 January 2020 through 31 December 2020. The calibration was performed independently for each station. A single hourly AOD–PM_{2.5} relationship was established using all parameters obtained from the 20 monitoring stations.

2.4 Statistical model

2.4.1. Model Description

Meteorological factors and land use greatly influence local daily AOD and hourly PM_{2.5} concentrations. To Estimate PM_{2.5}, the LME was applied (Ma et al. 2016; Shtein et al. 2020; Xiao et al. 2017; Zhang et al. 2020). The model included meteorological parameters and land-use data to evaluate the accuracy more accurately in different regions (Mhawish et al. 2020; Sahu et al. 2020; Wang et al. 2019). Each province is separately on the underlying geology, traffic volume, human populations, and elevation (ELEV). Therefore, this study added those parameters to improve the accuracy of PM_{2.5} estimates in each province. The LME model using MODIS AODs, meteorological factors, ad NDVI can be expressed as Equation (1).

$$PM2.5_{sd} = (\beta_0 + \mu_{0h}) + (\beta_1 + \mu_{1h}) \times AOD_{sh} + (\beta_2 + \mu_{2h})Tem_{sh} + (\beta_3 + \mu_{3h})RH_{sh} + (\beta_4 + \mu_{4h})WS_{sh} + (\beta_5 + \mu_{5h})BLH_{sh} + (\beta_6 + \mu_{6d})NDVI_{sM} + \varepsilon_r \quad (1)$$

where $PM2.5_{sd}$ is the ground-based $PM2.5$ ($\mu g/m^3$) at sites (s) on an hour of the day (h); β and μ_h (an hour of the day -specific) are the fixed and random intercepts, respectively; AOD_{sh} represents the MODIS and MISR AODs at sites on the day; and β_1 and μ_{1h} (an hour of the day-specific) are the fixed and random slopes of AOD, respectively. Tem_{sh} ($^{\circ}C$), RH_{sh} (%), WS_{sh} (m/s), and BLH_{sh} (m) are the climate variables at sites on an hour of the day; $\beta_2 \sim \beta_5$ and $\mu_2 \sim \mu_5$ are the fixed slopes and random day-specific slopes, respectively; $NDVI_{sd}$ (unitless) represents at sites in a month (M) at the site; β_6 and μ_{6M} are the fixed slopes and random month-specific slope, respectively; and ε represents the residual error.

2.5 Model Validation

The 10-fold cross-validation (CV) method was used to test for the overfitting of the model. The agreements between the predicted $PM2.5$ concentrations from the 10-fold CV and the measured $PM2.5$ concentrations were evaluated using the coefficient (R^2), mean prediction error (MPE), and root-mean-square error (RMSE). Relative prediction error (RPE) was also applied. RPE is defined as the RMSE divided by the observed intake values in the independent datasets and expressed as a percentage. The RPE is calculated as:

$$RPE = \frac{RMSE}{PM2.5} \times 100$$

$$MBE = \frac{1}{N} \sum_{i=1}^N |predicted_i - observed_i|$$

3 Results And Discussion

3.1 Validation of MODIS AOD

The correlation coefficient (R^2), mean absolute error (MAE), RMSE, and relative mean bias (RMB) were used to evaluate the accuracy of the MODIS AOD. Figure 2 shows the scatterplots and statistical parameters between the MODIS AOD and AERONET AOD. MODIS the MYD04 AOD extracted from the MODIS office products ("AOD_550_Dark_Target_Deep_Blue_Combined" as DT and DB). There are 3 AERONET AOD monitoring networks in the Northeast: Ubon Ratchathani, Nong Khai, and Mukdahan. Nong Khai and Muldahan is a new station that has been operated in 2020 with the presence of missing data in the rainy season. Therefore, AERONET AODs in Ubon Ratchathani were compared with satellite data. The result of AOD is a lower RMSE (0.65-0.67) and MAE (0.52-0.54), respectively, indicating little aerosol estimation uncertainty.

3.2 Descriptive statistics

The $PM2.5$ concentrations in the Northeast of Thailand were measured at the 20 monitoring sites from January 2020 to December 2020. Mean $PM2.5$ AOD, TEM, RH, WS, BLH, and NDVI values for each site are shown in Table 1. As shown in Table 1, the highest annual average concentrations of $PM2.5$ were found in Nong Khai ($37 \mu g/m^3$) compared with Buriram ($16 \mu g/m^3$). This result may be explained by the fact that Nong Khai is Thailand's border town to Laos, where high-level radiation hot spots have been found in the dry season. Another possible explanation for this is that these results are due to $PM2.5$ of the neighboring countries (Amnuaylojaroen et al. 2020; Chansuebsri et al. 2022; Kanabkaew et al. 2019; Ma et al. 2019). The average $PM2.5$ across 20 monitoring sites is $30 \mu g/m^3$, and

the overall mean AOD is 0.39. Mean meteorological variables (TEM, RH, and WS) are 26°C, 79%, and 11.23 m/s, respectively. BLH and NDVI are 496 m and 0.52, respectively.

3.3 PM2.5 model

This section developed the LME model using parameters, including AOD, TEM, RH, WS, BLH, and NDVI. TEM, RH, WS, and BHL data for each hour and NVDI data for each day during the month were obtained by linear interpolation. The fixed intercept and the slopes ($\beta_1 \sim \beta_5$ in Equation (1)) of each predictor for the LME model are shown in Table 2. For most variables (AOD, TEM, RH, and BLH), the results in Table 2 show that their effects on PM2.5 are most significant at the $\alpha = 0.05$ level except WS and NDVI. The LME of intercept and slope (AOD) are also statistically significant at most stations, while the random effects of intercept and slope (AOD) vary considerably by day. This supports our hypothesis that parameters influence the relationship between PM2.5 and run daily. Therefore, it is possible to perform daily calibrations using data from the multiple PM2.5 monitoring sites. The positive β values indicate a positive relationship between AOD and PM2.5 concentrations, and the most positive β values are found with WS and BLH. Negative β values shown for TEM, RH, and NDVI negatively correlate with PM2.5 concentrations. As shown in Table 2, for AOD, WS, and BLH, the coefficients are positively associated with PM2.5 concentrations increased with an increase in these parameters. In contrast, TEM, RH, and NDVI are negatively correlated with PM2.5 concentrations. In general, high wind speed results in the transport of pollution from other areas and, thus, more significant concentrations, while low wind speed leads to accumulation (Rasheed et al. 2015; Zhang et al. 2018). Table 3 presents the site-specific comparisons between the measured and predicted PM2.5 concentrations in the LME for all spatial sites (mean % Precision = 24%, Range = 15 to 30%). As it can be seen, both the model fit result in high R^2 , slopes close to 1 and intercepts close to 0, indicating a good agreement between the measured and predicted concentrations. In the LME, the % precision ranged from 15% ($3 \mu\text{g}/\text{m}^3$) in Surin to 30% ($10 \mu\text{g}/\text{m}^3$) in Maha Srakham with the mean value of 24% ($7 \mu\text{g}/\text{m}^3$). Regarding the measures of R^2 and precision values, our model presented considerably higher R^2 (0.93) and lower Precision (15%, $3 \mu\text{g}/\text{m}^3$). Interestingly, PM2.5 along the Mekong River area was observed generally higher than that in plain area. Overall, the performance of the LME to predict surface level hourly PM2.5 concentrations was improved. These performance tests suggest that the LME can be used to produce concentration data sets reliable for both time-series and cross-sectional health effect studies.

4. Discussion

All parameters are essential for modeling PM2.5 in Northern Thailand in this study. Understanding specific associations is especially important, where several cities experience some of the worst air quality in the country. Several factors may contribute to overall PM2.5 model performance (Ma et al. 2016; Wang et al. 2019). For instance, high wind speeds have been shown to contribute to PM2.5 concentrations (Chen et al. 2020; Li et al. 2017). WS can also vary significantly in the Northeast, reaching the lowest wind speeds in the winter months (Kumharn et al. 2020). In terms of RH, a similar pattern emerges with annual RH overall increasing (Paengkaew et al. 2020), and TEM is also a spatially variation and increase across the Northeast (Uttamang et al. 2018). AOD is an optical measurement of the abundance of fine particles in the air, and significant positive associations have been shown between PM2.5 and AOD. However, AOD coverage can vary between provinces and could contribute to differences found in β -values and model performance. In most provinces, the temperature has a significant negative relationship with PM2.5 concentrations. Our model results also show associations between PM2.5 and other covariates, including RH, WS, NDVI, and BLH. The small negative β -values found for BLH suggest a slightly negative relationship with PM2.5 concentrations, and RH significantly differs from one location to another. An additional negative association was found between NDVI and PM2.5. Since NDVI is described as land in use for agriculture, this parameter may account

for a portion of the PM concentrations in the air. Positive associations were shown for WS and BLH. A positive association for WS may be explained that WS brings polluted air into the province from sources outside the region, especially at higher wind speeds. The BLH, often a strong predictor in PM_{2.5} models. Generally, higher BLH is associated with lower PM_{2.5} concentrations because of more significant vertical mixing. However, the research results are opposite to existing literature due to the impact of BLH on air pollution levels, assuming that the air pollution is not caused by local emissions (Lou et al. 2019; Miao et al. 2019). In addition, it shows that the correlation coefficient between PM_{2.5} concentration and BLH is relatively low, which can contribute to less importance seen in the model diagnostics.

As mentioned earlier, the winter months experienced the maximum PM_{2.5} concentrations (Kumharn and Hanprasert 2016; Kumharn et al. 2020). This is likely due to temperature inversion, and the amount of PM_{2.5} brought into the country from neighboring countries. In addition, the fuel sources during these months are extremely dry, and winds bring higher temperatures (during daytime) and lower humidity to the surrounding atmosphere. Thus, high WS provides a driving force for dust generation and entrainment. Consequently, the occurrence of the high WS may be associated with increased PM concentrations in the winter months due to prolonged fire seasons driven by these seasonal winds. In addition, the northeast monsoon brings dry and cold air from China to most areas of Thailand in the winter months, and the monsoon winds blow towards land. As a result, PM_{2.5} in provinces next to the river was higher than in other areas. According to this data, we can infer that the wind brings polluted air into the province from sources outside the region. Taken together, this study is to develop MODIS data to estimate hourly PM_{2.5} concentrations in Northern Thailand, providing more information on ground based hourly PM_{2.5} with potential health risks due to elevated pollutant exposures. Therefore, the association between satellite AOD with other parameters and ground-level PM_{2.5} concentrations is utilized. The LME model can be applied to generalizable dust-prone areas in Thailand. Furthermore, AODs that were missing due to cloud cover or other surface albedo issues were fulfilled by MOD04 L2 and MOD08 M3. Our goal was to provide MODIS AOD with other factors to enhance ground hourly PM_{2.5} estimations over Northeastern Thailand.

5. Conclusions

Satellite AOD data have been increasingly used for PM_{2.5} air pollution studies. Remote sensing technologies have a great potential to expand current ground-level PM_{2.5} monitoring networks. To date, the application of satellite data to health effect studies has been limited primarily due to the insufficient power of AOD to predict PM_{2.5} and the high frequency of non-retrieval days. In this work, all missing AOD was fulfilled, which made it possible to determine the temporal and spatial patterns of PM_{2.5} in a large study domain comprising northern Thailand. Finally, satellite technologies will provide more acceptable spatial and temporal resolutions and more accurate retrievals. In addition, the advanced capability of differentiating by aerosol types in satellite technologies will further contribute to health effect studies investigating health implications. Since satellite data are readily available, the PM_{2.5} model can predict cost-effectively. Our method will help to examine the associations between subject-specific exposures to PM_{2.5} and their health effects.

Statements And Declarations

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Competing Interests

"The authors have no relevant financial or non-financial interests to disclose."

Author Contributions

"All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by [Wilawan Kumharn], [Oradee Pilahome], [Wichaya Ninsawan], [Yuttapichai Jankondee]. The first draft of the manuscript was written by [Wilawan Kumharn] and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript."

Data Availability

"The datasets generated during and/or analyzed during the current study are not publicly available due to privacy and ethical concerns, neither the data nor the source of the data can be made available but are available from the corresponding author on reasonable request."

References

1. Amnuaylojaroen T, Inkom J, Janta R, Surapipith V (2020) Long Range Transport of Southeast Asian PM2.5 Pollution to Northern Thailand during High Biomass Burning Episodes Sustainability 12:10049
2. Chansuebsri S, Kraisitnitikul P, Wiriya W, Chantara S (2022) Fresh and aged PM2.5 and their ion composition in rural and urban atmospheres of Northern Thailand in relation to source identification Chemosphere 286:131803 doi:<https://doi.org/10.1016/j.chemosphere.2021.131803>
3. Chen Z et al. (2020) Influence of meteorological conditions on PM2.5 concentrations across China: A review of methodology and mechanism Environment International 139:105558 doi:<https://doi.org/10.1016/j.envint.2020.105558>
4. Guo J et al. (2017) Impact of diurnal variability and meteorological factors on the PM2.5 - AOD relationship: Implications for PM2.5 remote sensing Environmental Pollution 221:94-104 doi:<https://doi.org/10.1016/j.envpol.2016.11.043>
5. Kanabkaew T (2013) Prediction of Hourly Particulate Matter Concentrations in Chiangmai, Thailand Using MODIS Aerosol Optical Depth and Ground-Based Meteorological Data EnvironmentAsia 6:65-70 doi:10.14456/ea.2013.20
6. Kanabkaew T, Mekbungwan P, Raksakietisak S, Kanchanasut K (2019) Detection of PM2.5 plume movement from IoT ground level monitoring data Environmental Pollution 252:543-552 doi:<https://doi.org/10.1016/j.envpol.2019.05.082>
7. Kaufman YJ, Tanré D, Remer LA, Vermote EF, Chu A, Holben BN (1997) Operational remote sensing of tropospheric aerosol over land from EOS moderate resolution imaging spectroradiometer Journal of Geophysical Research: Atmospheres 102:17051-17067 doi:<https://doi.org/10.1029/96JD03988>
8. Kong L, Xin J, Zhang W, Wang Y (2016) The empirical correlations between PM2.5, PM10 and AOD in the Beijing metropolitan region and the PM2.5, PM10 distributions retrieved by MODIS Environmental Pollution 216:350-

9. Kumharn W, Hanprasert K (2016) Aerosol optical properties in ultraviolet ranges and respiratory diseases in Thailand *Atmospheric Environment* 142:221-228 doi:<https://doi.org/10.1016/j.atmosenv.2016.07.046>
10. Kumharn W, Janjai S, Irie H, Pilahome O (2020) Aerosol size distribution using Thailand ground-based instruments and climate variables *Theoretical and Applied Climatology* 142:599-611 doi:10.1007/s00704-020-03328-8
11. Li X, Feng YJ, Liang HY (2017) The Impact of Meteorological Factors on PM_{2.5} Variations in Hong Kong *IOP Conference Series: Earth and Environmental Science* 78:012003 doi:10.1088/1755-1315/78/1/012003
12. Lou M et al. (2019) On the Relationship Between Aerosol and Boundary Layer Height in Summer in China Under Different Thermodynamic Conditions *Earth and Space Science* 6:887-901 doi:<https://doi.org/10.1029/2019EA000620>
13. Ma X, Wang J, Yu F, Jia H, Hu Y (2016) Can MODIS AOD be employed to derive PM_{2.5} in Beijing-Tianjin-Hebei over China? *Atmospheric Research* 181:250-256 doi:<https://doi.org/10.1016/j.atmosres.2016.06.018>
14. Ma Y et al. (2019) Long-term variations of the PM_{2.5} concentration identified by MODIS in the tropical rain forest, Southeast Asia *Atmospheric Research* 219:140-152 doi:<https://doi.org/10.1016/j.atmosres.2018.12.024>
15. Mhawish A, Banerjee T, Sorek-Hamer M, Bilal M, Lyapustin AI, Chatfield R, Broday DM (2020) Estimation of High-Resolution PM_{2.5} over the Indo-Gangetic Plain by Fusion of Satellite Data, Meteorology, and Land Use Variables *Environmental Science & Technology* 54:7891-7900 doi:10.1021/acs.est.0c01769
16. Miao Y et al. (2019) Interaction Between Planetary Boundary Layer and PM_{2.5} Pollution in Megacities in China: a Review *Current Pollution Reports* 5:261-271 doi:10.1007/s40726-019-00124-5
17. Paengkaew W, Limsakul A, Junggoth R, Pitaksanurat S (2020) Variability and Trend of Heat Index in Thailand during 1975-2017 and Their Relationships with Some Demographic-Health Variables *EnvironmentAsia* 13:26-40 doi:10.14456/ea.2020.3
18. Rasheed A, Aneja VP, Ayyer A, Rafique U (2015) Measurement and Analysis of Fine Particulate Matter (PM_{2.5}) in Urban Areas of Pakistan *Aerosol and Air Quality Research* 15:426-439 doi:10.4209/aaqr.2014.10.0269
19. Roberts S et al. (2019) Exploration of NO₂ and PM_{2.5} air pollution and mental health problems using high-resolution data in London-based children from a UK longitudinal cohort study *Psychiatry Research* 272:8-17 doi:<https://doi.org/10.1016/j.psychres.2018.12.050>
20. Sahu SK et al. (2020) Estimating ground level PM_{2.5} concentrations and associated health risk in India using satellite based AOD and WRF predicted meteorological parameters *Chemosphere* 255:126969 doi:<https://doi.org/10.1016/j.chemosphere.2020.126969>
21. Shtein A et al. (2020) Estimating Daily PM_{2.5} and PM₁₀ over Italy Using an Ensemble Model *Environmental Science & Technology* 54:120-128 doi:10.1021/acs.est.9b04279
22. Stowell J et al. (2020) Estimating PM_{2.5} in Southern California using satellite data: Factors that affect model performance *Environmental Research Letters* 15 doi:10.1088/1748-9326/ab9334
23. Tsai F, Smith K, Vichit-Vadakan N, Ostro B, Chestnut L, Kungskulniti N (2000) Indoor/outdoor PM₁₀ and PM_{2.5} in Bangkok, Thailand *Journal of exposure analysis and environmental epidemiology* 10:15-26 doi:10.1038/sj.jea.7500071
24. Unnithan SLK, Gnanappazham L (2020) Spatiotemporal mixed effects modeling for the estimation of PM_{2.5} from MODIS AOD over the Indian subcontinent *GIScience & Remote Sensing* 57:159-173 doi:10.1080/15481603.2020.1712101

25. Uttamang P, Aneja VP, Hanna AF (2018) Assessment of gaseous criteria pollutants in the Bangkok Metropolitan Region, Thailand *Atmos Chem Phys* 18:12581-12593 doi:10.5194/acp-18-12581-2018
26. Wang H, Li J, Peng Y, Zhang M, Che H, Zhang X (2019) The impacts of the meteorology features on PM_{2.5} levels during a severe haze episode in central-east China *Atmospheric Environment* 197:177-189 doi:https://doi.org/10.1016/j.atmosenv.2018.10.001
27. Xiao Q, Wang Y, Chang HH, Meng X, Geng G, Lyapustin A, Liu Y (2017) Full-coverage high-resolution daily PM_{2.5} estimation using MAIAC AOD in the Yangtze River Delta of China *Remote Sensing of Environment* 199:437-446 doi:https://doi.org/10.1016/j.rse.2017.07.023
28. Xiao Z, Xie X, Lin X, Xie J, Chen J, Shi Y, Chen Y (2020) The spatio-temporal characteristics of aerosol optical thickness as well as the relationship with PM_{2.5} in Xiamen city, China *Environmental Monitoring and Assessment* 192:676 doi:10.1007/s10661-020-08622-6
29. Xing Y-F, Xu Y-H, Shi M-H, Lian Y-X (2016) The impact of PM_{2.5} on the human respiratory system *J Thorac Dis* 8:E69-E74 doi:10.3978/j.issn.2072-1439.2016.01.19
30. Zhang K, de Leeuw G, Yang Z, Chen X, Su X, Jiao J (2019) Estimating Spatio-Temporal Variations of PM_{2.5} Concentrations Using VIIRS-Derived AOD in the Guanzhong Basin, China *Remote Sensing* 11:2679
31. Zhang X et al. (2018) Enhancement of PM_{2.5} Concentrations by Aerosol-Meteorology Interactions Over China *Journal of Geophysical Research: Atmospheres* 123:1179-1194 doi:https://doi.org/10.1002/2017JD027524
32. Zhang Y, Wang W, Ma Y, Wu L, Xu W, Li J (2020) Improvement in hourly PM_{2.5} estimations for the Beijing-Tianjin-Hebei region by introducing an aerosol modeling product from MASINGAR *Environmental Pollution* 264:114691 doi:https://doi.org/10.1016/j.envpol.2020.114691

Tables

Table 1. Mean PM_{2.5} concentrations ($\mu\text{g}/\text{m}^3$) observed and climate conditions at the 20 monitoring sites in 2020.

Station	Lat	Long	PM2.5 ($\mu\text{g}/\text{m}^3$)	AOD (unitless)	TEM ($^{\circ}\text{C}$)	RH (%)	WS (m/s)	BLH (m)	NDVI (unitless)	EVEL (m)
Amnat Charoen	15.90	104.62	28	0.46	27	79	9.82	403	0.51	191
Bueng Kan	18.18	103.73	33	0.51	25	79	14.53	639	0.67	147
Buriram	14.94	103.10	16	0.17	25	83	7.51	444	0.63	183
Chaiyaphum	15.81	102.02	17	0.18	25	82	8.18	463	0.55	194
Kalasin	16.53	104.05	29	0.40	25	80	12.88	448	0.50	156
Khon Kaen	16.42	102.85	33	0.37	25	79	12.69	405	0.49	179
Loei	17.28	101.75	33	0.43	26	75	13.60	604	0.55	357
Maha Sarakham	15.84	103.37	34	0.42	27	82	9.56	379	0.48	145
Mukdahan	16.54	104.72	28	0.41	25	79	12.64	492	0.50	140
Nakhon Phanom	17.41	104.77	29	0.39	25	79	12.74	589	0.47	166
Nakhon Ratchasima	14.97	102.08	30	0.33	27	77	9.95	642	0.47	173
Nong Bua Lam Phu	17.20	102.44	32	0.42	25	73	12.92	567	0.54	407
Nong Khai	17.84	102.57	37	0.46	25	79	12.64	572	0.51	174
Roi Et	16.07	103.64	26	0.43	25	81	13.20	401	0.50	137
Sakhon Nakhon	17.62	103.96	29	0.43	25	79	12.65	551	0.50	175
Si Sa Ket	15.09	104.33	35	0.42	27	78	10.05	396	0.50	124
Surin	14.88	103.49	19	0.15	26	71	5.64	475	0.54	167
Ubon Ratchathani	15.12	104.89	31	0.46	27	80	10.31	495	0.56	113
Udon Thani	17.41	102.78	33	0.48	25	81	13.20	557	0.45	165
Yasothon	15.36	104.36	29	0.43	27	79	9.86	403	0.54	131

***independent variable is significant at the $\alpha = 0.001$ level

**independent variable is significant at the $\alpha = 0.01$ level

*Independent variable is significant at the $\alpha = 0.05$ level

Table 2. Fixed effect of the linear mixed-effects (LME) model used to predict the ground-level PM2.5 concentrations using the samples collected from 2020.

Station	β_0 (Intercept)	β_1 (AOD)	β_2 (Tem)	β_3 (RH)	β_4 (WS)	β_5 (BLH)	β_6 (NDVI)	RMSE($\mu\text{g}/\text{m}^3$)
Amnat Charoen	67.34 ^{***}	20.67 ^{***}	-1.04 ^{***}	-0.10 ^{***}	-0.21	0.03 ^{**}	-33.80 ^{***}	9.95
Bueng Kan	59.24	14.49 ^{***}	0.39 ^{***}	0.09 ^{***}	0.05	0.03 ^{***}	-98.11	11.41
Buriram	84.46 ^{***}	22.95 [*]	-1.19 ^{***}	-0.16 ^{***}	0.47 ^{***}	-0.02 [*]	-40.50 [*]	5.50
Chaiyaphum	114.19 ^{***}	2.53	-2.00 ^{***}	-0.27 ^{***}	0.28	-0.03 ^{**}	-14.37	6.41
Kalasin	73.23 ^{***}	13.18	-0.41	-0.32 ^{***}	0.30	0.00	-33.04	11.20
Khon Kaen	78.65	33.28 ^{**}	-1.08 ^{***}	0.38 ^{***}	-0.28	0.05	-151.96	13.48
Loei	129.97 ^{***}	16.36 ^{***}	-2.75 ^{***}	-0.43 ^{***}	0.02	0.04 ^{***}	-43.94	11.39
Maha Sarakham	55.55 [*]	36.64 ^{***}	-2.14 ^{***}	-0.06	0.29 [*]	0.09 ^{***}	-14.28 ^{***}	14.97
Mukdahan	77.90 ^{***}	13.64 ^{***}	-0.65 ^{***}	-0.09 ^{**}	-0.18 ^{**}	0.03 ^{**}	-82.53 [*]	10.71
Nakhon Phanom	141.57 ^{***}	11.21 ^{**}	-0.86 ^{***}	-0.26 ^{***}	-0.05	-0.01	147.92 [*]	11.02
Nakhon Ratchasima	44.59 [*]	11.95	0.96 ^{***}	0.39 ^{***}	-0.08	-0.02 [*]	-131.12 ^{**}	9.37
Nong Bua Lam Phu	22.06	21.37 ^{***}	0.16	0.27 ^{***}	-0.46 ^{***}	0.05 ^{***}	-78.61 ^{***}	10.17
Nong Khai	59.75 [*]	9.71 ^{**}	-1.20 ^{***}	0.18 ^{***}	-0.28 ^{**}	0.05 ^{***}	-64.65	12.54
Roi Et	21.23	12.38 [*]	0.55 ^{***}	0.19 ^{***}	0.04	0.02	-76.56	11.62
Sakhon Nakhon	133.92 ^{***}	24.72 ^{**}	-2.07 ^{***}	-0.28 ^{***}	-0.27 ^{***}	0.00	-72.39 [*]	9.37
Si Sa Ket	192.90 ^{***}	20.13 ^{**}	-2.28 ^{***}	-0.45 ^{***}	0.66 ^{***}	-0.02	-147.58 [*]	12.70
Surin	84.28 [*]	16.73	-1.61 ^{***}	-0.32 ^{**}	0.32	-0.03	11.34	4.29
Ubon Ratchathani	131.27 ^{***}	6.20	-1.76 ^{***}	-0.17 ^{***}	0.01	0.01	-90.34	11.83
Udon Thani	36.45	12.90 ^{***}	-0.82 ^{***}	-0.15 ^{***}	-0.39 ^{***}	0.07 ^{***}	-16.63	10.48
Yasothon	101.74 ^{***}	22.89 ^{***}	-1.56 ^{***}	-0.22 ^{***}	-0.06	0.02 [*]	-53.36	10.48

***independent variable is significant at the $\alpha = 0.001$ level

**independent variable is significant at the $\alpha = 0.01$ level

*Independent variable is significant at the $\alpha = 0.05$ level

Table 3. PM_{2.5} concentrations ($\mu\text{g}/\text{m}^3$) were observed at the 20 monitoring sites in 2020.

Station	PM2.5 _{measured}	PM2.5 _{predicted}	Bias	R ²	PRE	MPE(μg/m ³)	P-values
Amnat Charoen	28	28	0	0.80	25	7	***
Bueng Kan	33	34	1	0.82	23	8	***
Buriram	16	16	0	0.83	24	4	*
Chaiyaphum	17	18	1	0.76	26	5	***
Kalasin	29	29	0	0.75	27	8	*
Khon Kaen	33	33	0	0.85	26	8	***
Loei	33	33	0	0.87	23	7	***
Maha Sarakham	34	34	0	0.80	30	10	*
Mukdahan	28	28	0	0.81	24	7	***
Nakhon Phanom	29	29	0	0.76	26	8	***
Nakhon Ratchasima	33	33	0	0.81	21	6	*
Nong Bua Lam Phu	32	32	0	0.83	21	7	***
Nong Khai	37	37	0	0.80	24	9	***
Roi Et	26	26	0	0.81	29	7	***
Sakhon Nakhon	29	29	0	0.83	22	6	***
Si Sa Ket	35	35	0	0.73	26	9	*
Surin	29	19	0	0.93	15	3	***
Ubon Ratchathani	31	31	0	0.80	25	8	***
Udon Thani	33	33	0	0.84	23	7	***
Yasothon	29	29	0	0.79	25	7	**

***independent variable is significant at the α = 0.001 level

**independent variable is significant at the α = 0.01 level

*Independent variable is significant at the α = 0.05 level

Bias = PM2.5_{measured} - PM2.5_{predicted}

Figures

Figure 1

The PM_{2.5} concentrations in the Northeast of Thailand were measured at the 20 monitoring sites.

Figure 2

Scatterplots and statistical parameters of) aerosol optical depth (AOD). The dashed line represents, and the black solid line represents the 1:1 line, and both lines represent the fitted linear regression line.