A Review of Research in Estimation and Dispersion of Particulate Matter Using Remote Sensing Data in Southeast Asia

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Abstract
Air pollution is a major challenge for the global population nowadays, while the most deleterious effects in terms of human health (cardiovascular diseases, asthma) are detected in the densely populated and highly polluted regions of south and east Asia. This study provides a comprehensive review of scientific articles dealing with particulate matter (PM) estimations from space in the climate sensitive and polluted southeast Asian (SEA) region. PM monitoring from space over this region is a challenging task due to high aerosol burden, mostly attributed to biomass-burning smoke from extensive forest, agricultural and peat fires, outside cooking and increasing urban/industrial emissions due to growing population, urbanization and industrialization. Several satellite sensors onboard polar-orbiting and geostationary satellites are reviewed, as well as influencing factors (meteorological variables, gaseous pollutants, topographic characteristics), algorithms and statistical techniques that are synergistically implemented for assessment of surface pollution (i.e. PM concentrations) from space-borne remote-sensing applications. Furthermore, current review highlights the potential of implementing Machine Learning (ML) and Deep Learning (DL) models and advanced computational techniques for developing air pollution prediction in hotspot regions of Asia (mainly), opening a new era in PM simulations and providing support to policymakers and stakeholders to design new effective pollution control strategies for attaining sustainable development goals under the challenge of climate change. International collaboration in the fields of remote sensing applications, maintenance of ground-based pollution networks and development of new ML models between researchers from various countries is especially important for future perspectives and innovations in PM estimations from space.

Keywords: Air Pollution, Machine Learning, Particulate Matter, Remote Sensing, Southeast Asia

1. Introduction

Air pollution has been recognized as one of the most pressing environmental and public health challenges in recent decades, with particulate matter (PM) identified as a key pollutant driving morbidity and mortality worldwide [1][2][3] and [4]. The Sustainable Development Goals (SDGs) Agenda has made serious efforts to highlight global development challenges including the issue of mitigation of air pollution that affects several other sectors of social life and prosperity. Consequently, people around the world consider air pollution as a major threat for their health and well-being with multiple impacts on human health, economy and atmospheric environment [5][6] and [7]. Particulate matter, particularly particles with aerodynamic diameters less than 10 μm (PM_{10}) and 2.5 μm ($PM_{2.5}$), can

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penetrate deep into the respiratory system and lungs causing respiratory illness, cardiovascular diseases, asthma and premature deaths [8][9][10] and [11]. Air pollution in urban agglomerations around the world has been increasing in recent years [12] and [13], while global assessments estimate that millions of premature deaths each year are attributable to chronic exposure to elevated $PM_{2.5}$ concentrations, especially in the developing world, underlining the urgent need for accurate, spatially comprehensive monitoring frameworks for mapping air pollution at fine temporal and spatial scales [14][15][16] and [17]. However, estimations and forecasts of air pollution in urban and rural areas are really challenging due to high spatio-temporal variability of aerosols and pollutants, the scarce monitoring networks and the uncertainties in measurements and model input data.

Traditionally, PM monitoring relies on ground-based air quality stations that provide measurements of high-accuracy and temporal resolution (minutes to hours) at specific locations, mostly established in urban areas or at certain pollution hotspots. However, in many low- and middle-income regions, including much of Southeast Asia (SEA), such stations are limited in number and unevenly distributed due to high installation and maintenance costs [18][19] and [20]. This sparse network limits the ability to capture spatial heterogeneity and to provide timely, region-wide assessments of air quality. Similar difficulties in PM monitoring due to sparse networks exist throughout the world, even in Europe [21] and [22]. Remote sensing has emerged as a complementary solution in this issue, offering broad spatial and temporal coverage through satellite-derived products such as aerosol optical depth (AOD), meteorological data, and atmospheric pollutant gases. These data, combined with meteorological and land-use variables, allow researchers to estimate ground-level PM over large regions where direct measurements are not feasible [23] and [24].

Recent advances in computational techniques have established a new era in PM simulations and forecasting [25] and [26]. Several Machine Learning (ML) approaches including Random Forests (RF), Gradient Boosting Machines (GBM), Support Vector Machines (SVM), and deep learning (DL) frameworks can capture complex nonlinear relationships between AOD, meteorological variables, topographic characteristics and PM concentrations, outperforming many traditional statistical models in terms of accuracy and robustness in PM estimations [27][28][29][30][31][32] and [33]. These models are particularly valuable in regions with complex emission sources and limited ground data, as they can integrate multi-source datasets and improve spatial–temporal prediction performance of PM concentrations and other air pollutants [34][35][36] and [37].

Focusing on Southeast Asian (SEA) region is crucial because it represents one of the world's most dynamic yet environmentally vulnerable areas. SEA countries such as Malaysia, Burma, Thailand, Indonesia, Laos, Cambodia, Vietnam, and the Philippines are undergoing rapid urbanization and industrialization during the last decades, while also experiencing extensive agricultural burning, forest and peat fires, and frequent transboundary haze events [38][39][40] and [41]. Biomass burning is the largest pollution source in the region releasing large amounts of organic and inorganic aerosols, Black Carbon, and their gaseous precursors [42] and [43]. These pollutants are transported to the downwind countries that lie in the main pathway of the Southeast Asian pollution outflow, thus creating persistent haze and smog conditions during the dry season [44] and [45]. In the years 1997 and 2015 severe transboundary haze episodes, largely originating from peatland and forest fires in Indonesia, caused serious air quality deterioration across the region, leading to widespread health impacts and economic losses [39][46] and [47]. These recurring pollution events illustrate the urgent need for high-resolution, region-wide air quality data to support early warning systems, public health advisories, and regional policy initiatives such as the ASEAN Agreement on Transboundary Haze Pollution (https://hazeportal.asean.org/action/asean-agreement-on-transboundary-haze-pollution/).

Due to sparse ground-based monitoring network in SEA region, satellite remote sensing seems to be the most appropriate technique for air pollution studies providing large snap-shots of aerosols and gaseous pollutants [48] and [49]. However, due to extensive cloud cover over the region, especially during the wet monsoon season, large parts of the SEA still face difficulties in satellite monitoring and assessment of air pollution from space [26]. Geostationary satellites over the region, such as Himawari-8 and the Geostationary Environment Monitoring Spectrometer (GEMS), opened new windows for high temporal resolution monitoring of air pollution over the region [26] and [50], while such satellite-based approaches have become increasingly available nowadays. This increase in satellite applications has given rise to studies dealing with estimations of PM concentrations from space, using traditional and advanced computational techniques.

Despite the recognized importance and necessity for accurate PM data in SEA, existing studies remain scattered, employing diverse data inputs, modeling approaches, and validation metrics. While numerous case studies have been conducted at city or national scales, there have been limited studies of methodological evolution, modelling framework comparison, and predictor integration strategies under the region's monsoon-driven and biomass-burning dominated conditions. These gaps make it challenging to assess model robustness, and regional research disparities across SEA [26]. By contrast, a large body of studies has been carried out in countries such as China and India, which rank among the top global contributors to PM research [51] and [52]. Therefore, a comprehensive, region-specific critical synthesis is necessary for the SEA region to evaluate current progress of research, identify methodological and geographic gaps, and provide a structured roadmap for future research in the field of PM predictions and forecasting. This review addresses this need by systematically examining studies conducted between 2000 and June 2025, focusing on estimates of $PM_{2.5}$ and PM_{10} concentrations from satellite remote sensing data in Southeast Asia. The study also emphasizes on the integration of machine learning (ML) techniques, which have become increasingly prevalent in recent years, and highlights methodological advancements, challenges, and opportunities for improving air quality assessment in this critical region.

2. Methodology

In this study, a systematic search was conducted in two major scientific databases namely Web of Science (WOS) and Scopus aiming to retrieve peer-reviewed journal articles related to particulate matter ($PM_{2.5}$ and PM_{10}) estimation using remote sensing applications and techniques in Southeast Asia. The search was performed on 1st July 2025 and included publications from 2000 to June 2025, aiming to capture both foundational and recent advances. Therefore, previous studies dealing with this issue in SEA region and neighboring polluted nations like India and China are not included in the Table list presented here. The following keywords were used in combination, adapted to the syntax of each database:

("Remote sensing" OR "satellite data") AND ("$PM_{2.5}$" OR "PM_{10}" OR "particulate matter" OR "AOD" OR "aerosol optical depth") AND ("Southeast Asia" OR "Malaysia" OR "Indonesia" OR "Thailand" OR "Singapore" OR "Vietnam" OR "Philippines" OR "Myanmar" OR "Cambodia" OR "Brunei" OR "Laos")

In Scopus database, these keywords were searched within the Title, Abstract, and Keywords fields. Whilst, in WOS, the search was conducted under the Topic category, which encompasses Title, Abstract, Author, and Keywords. All records retrieved from both databases were exported into a reference management system and duplicate entries were carefully removed. The remaining articles were subjected to a two-stage screening process. First, titles and abstracts were screened to exclude studies that were clearly irrelevant, such as those not conducted in Southeast Asia or not involving the estimation of particulate matter through remote sensing techniques but just analyze surface measurements. Second, full-text articles of the remaining records were assessed in detail to determine their eligibility based on predefined criteria. Only studies that estimated $PM_{2.5}$ or PM_{10} using satellite-based or remotely sensed data, conducted within the Southeast Asian region, and published in English as peer-reviewed journal articles were included. Review articles, conference proceedings, book chapters, and editorials were also excluded, or those lacking sufficient methodological detail to ensure robustness. More specifically, a total of 487 records were identified from the Web of Science (N = 275) and Scopus (N = 212) databases. After removing 150 duplicates, 337 records were screened, and 256 were excluded. 81 full-text articles were assessed for eligibility, while 40 of them were excluded for reasons including (i) study location outside Southeast Asia (N = 9), (ii) not accessible full text (N = 2), (iii) review articles (N = 3), and (iv) conference proceedings (N = 26). Finally, 41 articles were included in the current review list. The entire process of identification, screening, and inclusion is summarized in the PRISMA flow diagram (Figure 1).

3. Results and Discussion

3.1 Modelling Approaches and Trends

The distribution of studies estimating particulate matter based on satellite remote-sensing applications and techniques in SEA has evolved considerably over the past two decades and the number of published articles presents an increasing trend [51]. As shown in Figure 2, the early period (2004–2010) featured only a small number of studies, all of which employed geostatistical approaches. Between 2011 and 2015, the research activity remained limited, with only a slight increase in the use of geostatistical approaches but little adoption of more advanced techniques.

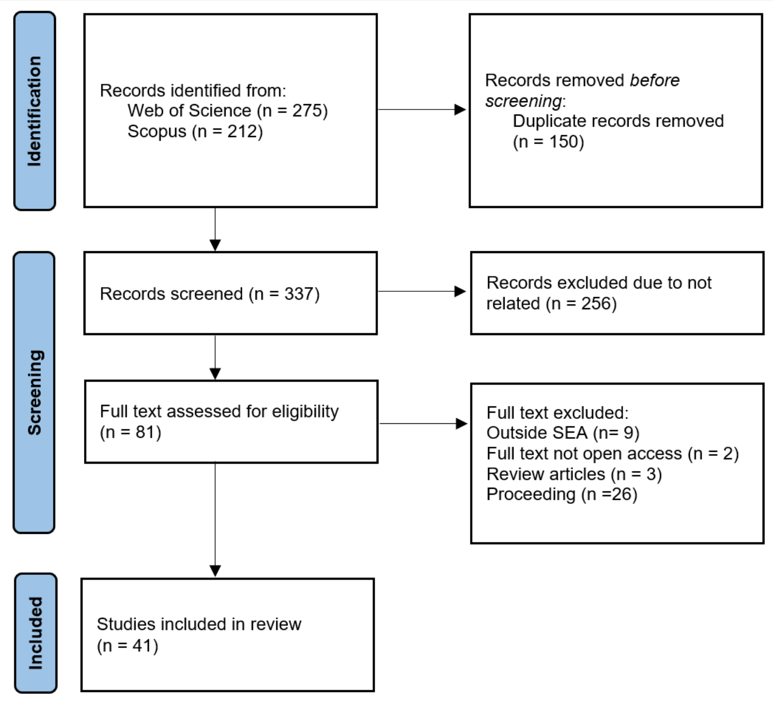

Figure 1: Flowchart of the systematic literature review process followed in this study

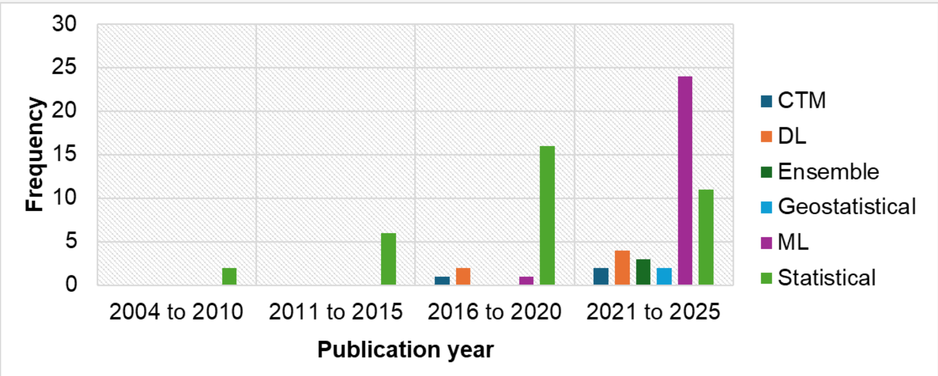

Figure 2: Frequency of PM estimation methods reported in studies published between 2004 and 2025 referring to the SEA region

A significant growth in publication records was observed during 2016–2020, with geostatistical approaches still predominant, while a few studies began incorporating chemical transport model (CTM) approaches, as well as emerging machine learning (ML) and deep learning (DL) models in $PM_{2.5}$ and PM_{10} estimations, opening a new era for PM prediction in SEA region.

The most recent period, from 2021 to June 2025, reflects both growth in number of studies and in diversification of techniques. Machine learning has become the most widely applied approach for PM simulations, while statistical and geostatistical methods remain in use alongside less frequent but increasingly important applications of CTM, DL, and ensemble approaches. Overall, these trends highlight the growing sophistication of PM estimation research in SEA, moving from simple regression toward complex data-driven approaches that integrate multiple parameters and data sources. This reflects not only the growing scientific interest for such studies, but also the need for advanced computational techniques aiming to attain more accurate, robust and quick results with goal of near real-time estimation of PM concentrations at large spatial domains [26]. The details of the reviewed studies and the approaches used are summarized in Table 1.

Table 1: Summary of studies dealing on particulate matter (PM) estimation in Southeast Asia using remote sensing (Continue next page)

Study area	Parameters	Output	Method	R/R^2	Accuracy	Reference
Peninsular, Malaysia	AVHRR data, NO_2, SO_2, O_3, CO and API	PM_{10}	MLR	$R^2 = 0.958$	RMSE = 17.83 μg m^{-3}	[56]
Penang Island, Malaysia	AOD derived from handheld spectroradiometer	PM_{10}	Linear	R = 0.81	RMSE = 0.054 μg m^{-3}	[76]
Klang Valley, Malaysia	MODIS Terra AOD	PM_{10}	NLCC	NLCC = 0.10 – 0.62	$p = 0.08 – 0.80$	[77]
Kuala Lumpur, Malaysia	MODIS Terra AOD	PM_{10}	NLCC	$R^2 = 0.359$	-	[55]
Peninsular, Malaysia	MODIS Terra AOD	PM_{10}	MEM	R = 0.88	RMSE = 7.32 μg m^{-3}	[78]
Iskandar, Malaysia	MODIS Terra AOD, Land use	PM_{10}	Linear	-	-	[79]
Malaysia	MODIS Terra AOD, RH, TEMP, K index	PM_{10}	MLR ANN	$R^2 = 0.66$ $R^2 = 0.71$	RMSE = 12.39 μg m^{-3} RMSE = 11.61 μg m^{-3}	[18]
East Coast Peninsular Malaysia	AT, RH, WS, radiation, MSLP, rainfall, CO, NO_2, and SO_2	PM_{10}	MLR MLP RBF	$R^2 = 0.594$-0.706 $R^2 = 0.691 – 0.794$ $R^2 = 0.827 – 0.929$	VIF = 1.077 – 1.926 RMSE = 8.49 – 9.57 μg m^{-3} RMSE = 9.19 - 4.08 μg m^{-3}	[80]
Malaysia	Himawari-8 AOD, NO_2, SO_2, O_3, CO, WS, WD, TEMP, RH	$PM_{2.5}$	SVR RF	$R^2 = 0.66$ $R^2 = 0.62$	RMSE = 12.11 μg m^{-3} RMSE = 11.40 μg m^{-3}	[81]
Selangor, Malaysia	slope, road density, SAVI, NDVI, BU, LST, EV, WS	PM_{10}	 RF KNN NB		Precision: 0.99 0.98 0.92	[82]
Johor, Malaysia	AOD from Landsat 8 OLI	PM_{10}	MLR	$R^2 = 0.91$	RMSE = 20.67 μg m^{-3}	[83]
East Malaysia	MODIS Terra AOD	PM_{10}	Linear	$R^2 = 0.92$	-	[84]
Malaysia	Himawari-8 and VIIRS AOD, NO_2, SO_2, O_3, CO	$PM_{2.5}$	SVR RF XGBoost	$R^2 = 0.56$ $R^2 = 0.64$ $R^2 = 0.59$	RMSE = 14.02 μg m^{-3} RMSE = 12.17 μg m^{-3} RMSE = 12.24 μg m^{-3}	[26]
Chiangmai, Thailand	MODIS Terra AOD	PM_{10} $PM_{2.5}$	Linear MLR	$R^2 = 0.21 – 0.22$ $R^2 = 0.71 – 0.77$	$p < 0.01$	[57]
Northern, Thailand	MODIS Terra and Aqua AOD	$PM_{2.5}$	Cubic S-curve Quadratic Log Linear Power Exponential	$R^2 = 0.77$ $R^2 = 0.76$ $R^2 = 0.76$ $R^2 = 0.76$ $R^2 = 0.75$ $R^2 = 0.74$ $R^2 = 0.65$	Cubic validation = 83.33%	[85]
Northern, Thailand	MODIS Terra and Aqua AOD	PM_{10}	Linear	R = 0.64 – 0.74	$p < 0.001$	[58]
Northern, Thailand	MODIS Terra AOD	PM_{10}	Linear regression	$R^2 = 0.971 – 0.986$	-	[86]
Northern Thailand	MAIAC AOD, MODIS surface reflectance	$PM_{2.5}$	Linear regression	R = 0.39 – 0.78 R = 0.39 – 0.86	Prediction efficiency: 1.7 – 58.8 % 10.8 – 27.2 %	[87]
Chiang Mai and Bangkok, Thailand	NO_2, SO_2, CO, HCHO, O_3, AI, DEM	$PM_{2.5}$	IDW OK RF RFK	$R^2 = 0.84$ $R^2 = 0.90$ $R^2 = 0.88$ $R^2 = 0.77$	RMSE = 5.4 μg m^{-3} RMSE = 4.267 μg m^{-3} RMSE = 5.57 μg m^{-3} RMSE = 7.11 μg m^{-3}	[67]
Thailand	AOD, LST, NDVI, EV	$PM_{2.5}$	MLR RF XGBoost SVM	$R^2 = 0.51$ $R^2 = 0.95$ $R^2 = 0.62$ $R^2 = 0.61$	RMSE = 18.28 μg m^{-3} RMSE = 5.58 μg m^{-3} RMSE = 14.74 μg m^{-3} RMSE = 15.32 μg m^{-3}	[68]
Northern Thailand	MODIS Terra and Aqua AOD, TEMP, RH, WS, PBLH, fire hotspot, NDVI	$PM_{2.5}$	RF	$R^2 = 0.80$	RMSE = 14.30 μg m^{-3}	[88]
Thailand	MAIAC and Himawari-8 AOD, Pressure, TEMP, WS, rainfall	$PM_{2.5}$	XGBoost	$R^2 = 0.20 – 0.91$	RMSE = 7.07 – 36.93 μg m^{-3}	[50]
Thailand	NO_2, SO_2, O_3, CO, HCHO, land cover, RH, lat, long, EV, TEMP, evaporation, pressure, dew point, wind component, precipitation	$PM_{2.5}$	SVM RF CatBoost XGBoost LigthGBM TabNet	$R^2 = 0.821$ $R^2 = 0.829$ $R^2 = 0.857$ $R^2 = 0.867$ $R^2 = 0.868$ $R^2 = 0.873$	RMSE = 10.96 μg m^{-3} RMSE = 10.70 μg m^{-3} RMSE = 9.78 μg m^{-3} RMSE = 9.44 μg m^{-3} RMSE = 9.42 μg m^{-3} RMSE = 9.22 μg m^{-3}	[69]
Bangkok, Thailand	Merra-2 AOD, TEMP, RH, pressure, WS, WD, rainfall and fire counts	PM_{10}	MLR	$R^2 = 0.37 – 0.41$	-	[89]

Table 1: Summary of studies dealing on particulate matter (PM) estimation in Southeast Asia using remote sensing (Continue from previous page)

Study area	Parameters	Output	Method	R/R^2	Accuracy	Reference
Northern, Thailand	MODIS Terra and Aqua AOD, min max TEMP, WS, RH, air pressure, OBB	$PM_{2.5}$	MLP-ANN	R = 0.78	RMSE = 0.0313 μg m^{-3}	[40]
Thailand	MODIS Terra and Aqua AOD, LST, NDVI, EV, time, WOY	$PM_{2.5}$	Log-Linear Regression	R^2 =53.8%	RMSE = 22.2 μg m^{-3}	[90]
Northeastern, Thailand	MODIS AOD, RH, TEMP, WS, BLH, NDVI	$PM_{2.5}$	LME	R^2 > 0.70	RMSE = 3 - 10 μg m^{-3}	[62]
Thailand	MODIS AOD	$PM_{2.5}$	WRF-Chem	R = 5/55	RMSE = 12 μg m^{-3}	[60]
Greater Bangkok	Fengyun-4A AOD, TEMP, radiation, RH, pressure, wind component, cloud cover, MSLP, BLH, fire counts, NDVI, terrain, population density	$PM_{2.5}$	RF ADB GB XGBoost SEM	R = 0.74 R = 0.75 R = 0.73 R = 0.71 R = 0.84	RMSE = 12.9 μg m^{-3} RMSE = 12.9 μg m^{-3} RMSE = 13.2 μg m^{-3} RMSE = 13.8 μg m^{-3} RMSE = 10.4 μg m^{-3}	[23]
Northern Thailand	MODIS AOD, DNB from Suomi NPP, DEM, Atmospheric pressure, WS, WD, rainfall, land use, TEMP, RH and land slope	$PM_{2.5}$	MLR	R = 0.999 R = 0.238	p < 0.00000000000000022 p = 0.0594	[91]
Vietnam	MODIS Terra and Aqua AOD, TEMP, pressure, radiation, WS, RH	$PM_{2.5}$	MLR	R^2 = 0.411	RMSE = 20.299 μg m^{-3}	[92]
Hanoi, Vietnam	MAIAC AOD, PBLH	$PM_{2.5}$	GAM CTM	R^2 = 0.63 R^2 = 0.69	RMSE = 21 μg m^{-3} RMSE = 18 μg m^{-3}	[93]
Hanoi, Vietnam	AOD from Landsat 8 OLI with different atmospheric correction methods	PM_{10}	MLR	R^2 = 0.311 R^2 = 0.400 R^2 = 0.919	RMSE = 36.61 μg m^{-3} RMSE = 37.43 μg m^{-3} RMSE = 13.74 μg m^{-3}	[94]
Ho Chi Minh, Vietnam	MODIS AOD	$PM_{2.5}$	Linear regression	R = 0.89	RMSE = 8.063 μg m^{-3}	[95]
Vietnam	MODIS and VIIRS AOD, TEMP, RH, Pressure, WS, WD, BLH, NDVI, population density and road map	$PM_{2.5}$	MEM	R^2 = 0.75	RMSE = 11.76 μg m^{-3}	[96]
Sumatera, Indonesia	MODIS Terra AOD	PM_{10}	Linear	R = 0.49 – 0.89	RMSE = 23.8 – 789 μg m^{-3}	[97]
Jakarta, Indonesia	Residential area, NDVI, TEMP, RH	$PM_{2.5}$	LUR	R^2 = 0.56	RMSE = 8.19 μg m^{-3}	[98]
Sumatra, Indonesia	Fire inventory, meteorological data	$PM_{2.5}$	WRF–Chem	R = 0.71	RMSE = 159.87 μg m^{-3}	[61]
Jakarta, Indonesia	TEMP, dew point, RH, precipitation, pressure, WS, WD	$PM_{2.5}$	LSTM	R = 0.78 R = 0.71	RMSE = 18.53 μg m^{-3} RMSE = 19.40 μg m^{-3}	[73]
Mekong River, Basin	MAIAC AOD, BLH, RH, TEMP, pressure, precipitation, WD, WS.	$PM_{2.5}$	CNN LightGBM Stacking	R^2 = 0.62 R^2 = 0.70 R^2 = 0.72	RMSE = 11.88 μg m^{-3} RMSE = 10.55 μg m^{-3} RMSE = 10.21 μg m^{-3}	[72]
SEA	MODIS Terra and Aqua AOD, Angstrom exponent	$PM_{2.5}$	Linear regression	R^2 = 0.69 – 0.85 R^2 = 0.33 – 0.39	-	[99]

Parameter: AT (ambient temperature); AOD (Aerosol Optical Depth); TEMP (Air Temperature); RH (Relative Humidity); WS (Wind Speed); WD (Wind Direction); LST (Land Surface Temperature); EV (Elevation); BLH (Boundary Layer Height); NDVI (Normalized Difference Vegetation Index); MSLP (Mean Sea Level Pressure); OBB (Open Burning Emission); DNB (Day–Night Band); WOY (Week of Year); BU (Built-Up Index); AI (Aerosol Index); DEM (Digital Elevation Model); API (Air Pollution Index); AVHRR (Advanced Very High-Resolution Radiometer); MODIS (Moderate Resolution Imaging Spectroradiometer); MAIAC (Multi-Angle Implementation of Atmospheric Correction). **Method:** MLR (Multiple Linear Regression); MEM (Mixed Effect Model); MLP (Multilayer Perceptron); RBF (Radial Basis Function); RF (Random Forest); XGBoost (Extreme Gradient Boosting); SVM (Support Vector Machine); LME (Linear Mixed Effects Model); ANN (Artificial Neural Network); SVR (Support Vector Regression); IDW (Inverse Distance Weighting); OK (Ordinary Kriging); RFK (Random Forest Kriging); NLCC (Non-Linear Correlation Coefficient); LUR (Land Use Regression); KNN (K-Nearest Neighbour); NB (Naïve Bayes); ADB (Adaptive Boosting); GB (Gradient Boosting); SEM (Stacked Ensemble Model); CNN (Convolutional Neural Network); LightGBM (Light Gradient Boosting Machine); CTM (Chemical Transport Model); GAM (Generalized Additive Model); MLP-ANN (Multilayer Perceptron Artificial Neural Network); LSTM (Long Short-Term Memory Network).

Initial studies during the 2000s relied on linear regression and multiple linear regression (MLR) methods, using satellite-derived AOD as the key predictor of PM [53] and [54]. These approaches offered straightforward interpretability and demonstrated the potential of satellite data for air quality assessment in countries such as Malaysia and Thailand [55][56][57] and [58]. Geostatistical approaches, including inverse distance weighting (IDW), kriging, and Land Use Regression (LUR), have improved spatial interpolation near the monitoring sites but remain limited in capturing the dynamic atmospheric conditions. Those techniques showed satisfactory potential for PM estimations; however, they relied heavily on in-situ data, which are often scarce across large areas [59], particularly in the SEA region.

Chemical Transport Models (CTM), such as Goddard Earth Observing System-Chem (GEOS-Chem) and the Community Multiscale Air Quality Modeling System (CMAQ), simulate air pollutant concentrations based on assimilating meteorological datasets, emission inventories, physical and chemical algorithms to estimate atmospheric constituents. These models provide interpretability based on atmospheric science; however, their application in Southeast Asia remains limited, with only a few studies attempting to use CTMs for PM estimations [60][61] and [62]. According to [63], CTM is hard to implement in developing countries due to the lack of chemical and physical information on aerosols and gaseous pollutants, updated emission inventories and transformation processes.

Since 2016, ML approaches have rapidly gained traction in Southeast Asia, driven by advances in computing power and the growing availability of multi-source datasets (see Table 1). Methods such as Random Forest (RF), Support Vector Regression (SVR), Gradient Boosting (XGBoost, LightGBM), and Artificial Neural Networks (ANN/MLP) have consistently outperformed traditional regression techniques by capturing nonlinear interactions among AOD, meteorological parameters, trace gases and spatial features, with large applications over the globe [25][64][65] and [66]. Studies across the SEA region report notable improvements in simulation accuracy when these diverse variables are integrated [26][67][68] and [69]. In this respect, ML demonstrates a stronger capacity to capture complex relationships between PM and other parameters; however, they require large volumes of training data [17], which shows a particular challenge in SEA, were frequent cloud cover and missing satellite retrievals limit data availability. Furthermore, the results from a recent study dealing with $PM_{2.5}$ estimations in Malaysian cities using ML techniques revealed an accuracy of 97.7% from the RF model, outperforming those from ANN (61.14%) and LSTM (61.77%), helping to mitigate the adverse pollution effects [70]. In another study, three ML algorithms (decision tree, boosted regression tree and random forest) were applied for PM_{10} predictions in Kota Bharu, Malaysia, with the RF model outperforming others with an accuracy of 98.37% and sensitivity of 97.19% [71]. More recently, deep learning (DL) approaches, including Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, have been adopted in countries such as Vietnam, Malaysia and Indonesia to better capture the spatio-temporal dependencies of PM variability [72][73] and [74].

Overall, the scientific research in SEA presents clear progression from the early regression and geostatistical approaches to more advanced CTM, ML, and DL models and techniques for PM estimations from space. Yet, the broader application of these models remains constrained by challenges such as limited interpretability, data imbalances between haze and non-haze periods, and difficulties in transferring models across the region's diverse environmental and emission contexts [75]. Addressing these limitations highlights the need for careful selection and integration of predictor parameters particularly AOD, meteorological variables, vertical aerosol profiles and trace gases to strengthen model robustness, enhance transferability, and overcome data limitations unique to SEA.

It should be noted that the performance metrics reported in Table 1 were derived from different study designs, spatial and temporal resolutions of satellite data, parameter selection and validation techniques. Therefore, direct numerical comparisons across studies should be approached with caution. The table is intended to illustrate methodological evolution and the range of reported modelling performance rather than to provide a strict benchmarking comparison. Despite these methodological differences, an overall progression toward improved predictive capability can be observed in more recent machine learning and ensemble-based approaches compared to earlier regression-based models.

3.2 Aerosol Optical Depth (AOD) as a Key Parameter

Aerosol Optical Depth (AOD) represents the attenuation of solar radiation into the atmospheric column by aerosols through scattering and absorption processes [100][101] and [102]. Ground-based networks such as the AErosol RObotic NETwork (AERONET) provide the most reliable long-term AOD observations that are frequently used as reference data for validating satellite retrievals [103] and [104]. The number of AERONET stations in Southeast Asia is about 20, while only two stations are established in Malaysia [19]. Although these datasets have been essential for validating the accuracy of satellite AOD products from MODIS (Moderate Resolution Imaging Spectroradiometer), Multi-angle Imaging SpectroRadiometer (MISR), Visible Infrared Imaging Radiometer Suite (VIIRS), and Himawari-8 [105][106] and [107], their sparse coverage limits direct application in regional PM monitoring. As a result, satellite-derived AOD has become indispensable for large-scale estimation of PM concentrations. Numerous studies have demonstrated a strong correlation between AOD and PM over the globe, making AOD a widely used predictor for estimating PM concentrations from satellite remote sensing [53][100] and [108]. In Southeast Asia, where ground-based air quality monitoring networks are rather limited, AOD serves as a crucial proxy to extend spatial coverage.

Satellite-based AOD products have evolved significantly over the last two decades [109]. MODIS, onboard Terra and Aqua satellites, remains the most widely used sensor due to its long temporal archives (since 2000) and broad spatial coverage allowing near-daily global earth observations [110][111] and [112]. MODIS AOD retrievals, especially when processed with the MAIAC (Multi-Angle Implementation of Atmospheric Correction) algorithm, provide fine spatial resolution (~1 km) and improved accuracy over heterogeneous surfaces, enabling better application over complex terrains [87][113] and [114]. The MISR instrument, also onboard Terra, offers multi-angle observations that improve retrievals over bright urban or land (desert) surfaces, though its use in SEA has been less frequent compared to MODIS [115] and [116]. More recently, the VIIRS sensor onboard Suomi-NPP satellite has been increasingly adopted as the successor to MODIS [117][118] and [119]. VIIRS was designed with specifications comparable to MODIS, including similar resolution, spectral channels, and AOD retrieval algorithms [120] and [121], while also providing higher-resolution AOD products (6 km) that improve its suitability for both regional assessments and finer-scale PM mapping, such as nationwide studies in Vietnam [96] and [122] and in Malaysia [123].

Geostationary platforms have further advanced the AOD-based PM estimations. Himawari-8, which carries the Advanced Himawari Imager (AHI) sensor, provides AOD retrievals at 10-minute temporal resolution across East and Southeast Asia [124][125] and [126]. This high-frequency observation increases the likelihood of obtaining cloud-free pixels, thereby improving data availability for PM estimation [127] and [128]. Validation against AERONET sites in Southeast Asia has demonstrated strong correlations, confirming the reliability of Himawari-8 AOD product and reinforcing its applicability for regional PM studies [124][127] and [129]. Moreover, [81] showed that Himawari-8 AOD, when integrated with meteorological data in machine learning techniques, achieved R^2 values of 0.62–0.66 for $PM_{2.5}$ estimations in Malaysia. This finding demonstrates the potential of Himawari-8 AOD for estimating PM concentrations in this region [130]. Whilst, the Chinese Fengyun-4A satellite has also shown potential, since [23] reported high accuracies (R^2 = 0.73–0.84) for hourly $PM_{2.5}$ predictions in Bangkok using Fengyun-4A AOD and ML models. Most recently, the launch of the Geostationary Environment Monitoring Spectrometer (GEMS) sensor aboard GEO-KOMPSAT-2B satellite in 2020 has opened new opportunities for air quality research in Asia. As the first geostationary sensor dedicated to atmospheric composition, GEMS provides hourly observations of AOD, along with key trace gases such as NO_2, SO_2, O_3, formaldehyde (HCHO) and glyoxal (CHOCHO), enabling integrated assessment of aerosols and their precursors [131]. Besides, [132] reported strong agreement between GEMS-derived AOD and AERONET observations in mainland Southeast Asia, particularly during the dry season (R^2 = 0.63–0.79). These findings render GEMS as a useful platform providing new data for monitoring aerosol pollution and supporting regional air quality assessment across Southeast Asia.

Despite these advancements, several limitations constrain the use of AOD for PM estimation in SEA. A major challenge is the significant data loss (or data contamination) due to cloud cover, especially during the monsoon season, which often leads to substantial observational gaps. Such missing data reduces temporal continuity and may bias short-term PM estimates if pollution episodes occur during cloudy conditions. Although geostationary platforms, such as Himawari-8, mitigate this issue by offering high-frequency observations, missing data remains a critical limit. To address this issue, several gap-filling approaches have been developed, including multi-source AOD fusion, interpolation, multi-variable AOD estimation and combine applications [100]. AOD from Himawari-8 and VIIRS was fused to generate seamless $PM_{2.5}$ maps across Malaysia, highlighting the growing importance of reconstructing continuous AOD fields to support reliable PM modelling in regions frequently affected by cloud cover [26].

It is also important to note that AOD alone cannot fully explain the variability of ground-level PM concentrations, as it represents the total columnar aerosol burden rather than surface conditions [53] and [133]. The strength of the AOD - PM relationship is influenced by meteorological factors such as relative humidity (RH), temperature (TEMP) and wind, as well as ancillary variables like land surface temperature, vegetation indices, and fire hotspots (see studies in Table 1). In addition, the vertical profiles of these factors, along with elevated aerosol layers, further affect the relationship between AOD

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and PM. As summarized in Table 1, several studies in Southeast Asia have demonstrated that integrating AOD with meteorological and ancillary parameters leads to significant improvements in PM estimation accuracy. These findings highlight the need for multi-parameter approaches, which will be further discussed in Section 3.3.

3.3 Meteorological and Ancillary Parameters

Although AOD remains the key parameter for satellite-based PM estimations, using it alone often limits the prediction accuracy, since it represents the total atmospheric column aerosol burden rather than surface-level concentrations. The geometric change of the vertical aerosol profile further complicates the relationship between AOD and $PM_{2.5}$ [100]. The AOD–PM relationship is also highly sensitive to meteorological conditions and emission sources, which vary across regions and seasons. According to [134] the meteorological conditions influence the emissions, transport, removal, and chemical transformations of atmospheric pollutants, shaping their complex diurnal, seasonal and interannual variations. There are several attempts that have been made to estimate PM concentrations involving meteorological variables, yet the relationships among influencing parameters remain not fully understood [30][135][136][137][138][139][140] and [141].

In SEA region, the seasonally-changing meteorological variables highlight the need for multi-parameter approaches. The region is situated in the tropics and is strongly influenced by the monsoon season, which governs the seasonal variability of wind, rainfall, and humidity. During the southwest monsoon (May–September), large-scale biomass burning from slash and burn activities in Indonesia releases substantial amounts of aerosols and gaseous precursors [42] and [142]. Prevailing southwesterly winds then transport these pollutants along the main pathway of the Southeast Asian outflow, affecting downwind countries such as Malaysia, Singapore, and southern Thailand [44]. This makes wind direction and speed critical parameters for modelling transboundary haze events that highly affect the regional (rural and urban) pollution levels. In contrast, the northeast monsoon (November–March) brings heavy rainfall and persistent cloud cover across much of the SEA region. While rainfall acts as an efficient removal mechanism for atmospheric particles [143] and [144] cloud cover reduces the availability of satellite retrievals, presenting challenges for remote sensing–based PM monitoring, simulation and forecasting.

As shown in Figure 3, temperature (TEMP), wind speed (WS), relative humidity (RH), pressure, planetary boundary layer height (PBLH) and rainfall are among the most frequently used predictors for PM estimations in SEA studies. Temperature influences both boundary layer dynamics and atmospheric chemistry, with higher temperatures enhancing photochemical reactions and vertical mixing that affect PM concentrations at the ground [145]. In fact, temperature strongly influences the efficiency of photochemical processes, leading to ozone formation and driving the production of secondary aerosols that contribute to particulate matter [146][147] and [148].

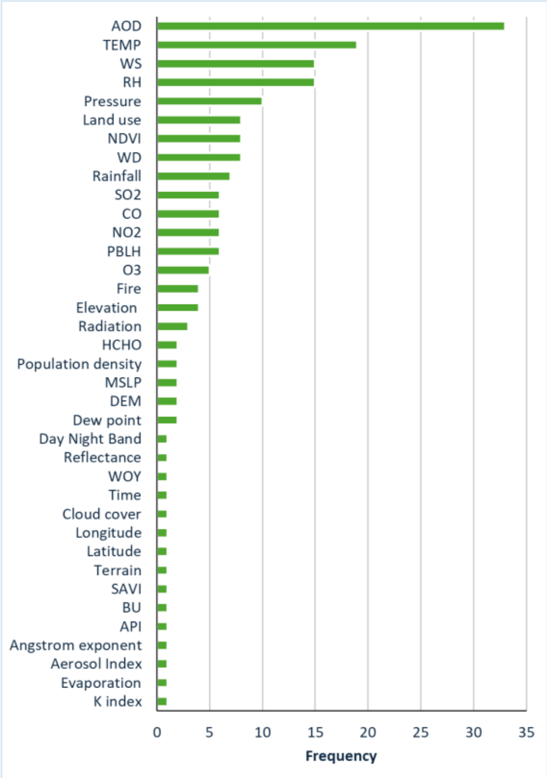

Figure 3: Frequency of parameters used in PM estimation studies based on remote-sensing and ML techniques in the SEA region

Pressure, though less commonly discussed, provides insights into atmospheric stability and large-scale circulation patterns that affect pollutant dispersion in SEA region. Besides that, atmospheric pressure has been found to correlate positively with $PM_{2.5}$ and PM_{10} concentrations, as higher pressure obstructs the upward dispersion of particulate matter, leading to its accumulation near the surface [149]. In addition, relative humidity (RH) is consistently high in SEA and plays a crucial role in aerosol hygroscopic growth, altering scattering properties [150] and [151], modulating chemical speciation [152], wet removal processes [153] and weakening the direct relationship between AOD and ground-level PM.

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The planetary boundary layer (PBL) is another commonly used parameter, as it plays a key role in shaping the vertical and horizontal distribution of aerosols, highly affecting the aerosol concentrations near the ground and their diurnal variability [154][155][156] and [157]. Subsequently, the relationship between PM concentrations and PBLH has been widely studied, revealing that it's strongly influenced by seasonal variations, geographical location, local circulation and prevailing wind patterns [158]. As a complement to Table 1, Figure 3 shows the frequency of parameters used in PM estimation studies across Southeast Asia, with temperature, wind speed, RH, pressure, land use and NDVI to exhibit the higher frequencies after AOD.

On the other hand, gaseous pollutants such as NO_2, SO_2, O_3, and CO also appear with moderate frequency in PM simulation studies, as they represent both direct emissions from combustion sources and precursors for secondary aerosol formation [67][74] and [159]. The inclusion of these gases helps capture the atmospheric chemistry component of PM variability that is not directly represented by AOD. Whilst CO is often emitted alongside PM during incomplete combustion, it has been used as a proxy for anthropogenic activity and biomass burning intensity [160] and [161]. Trace gas products namely NO_2, SO_2, CO, O_3, HCHO from Sentinel-5P together with AI and digital elevation model (DEM) were intergrated [67], which resulted in significantly improved $PM_{2.5}$ estimation accuracy in Thailand, highlighting the potential of gases pollutants integration in regional modelling. In Malaysia, [26] also found that incorporating NO_2, SO_2, CO, O_3, together with Himawari-8 and VIIRS AODs allowed for gap-filling and seamless nationwide $PM_{2.5}$ mapping, thereby overcoming challenges associated with missing data due to cloud cover.

Furthermore, spatial features such as land use and vegetation indices are moderately used to characterize land cover, biomass density and surface reflectance, all of which influence aerosol emissions and satellite AOD retrievals [162]. Among the geographical features, land cover type, geographic coordinates, and elevation have been shown to sequentially demonstrate their respective importance in improving PM estimation accuracy [69]. Elevation and DEM further provide important context for PM modelling in regions with complex terrain, as topography modulates pollutant dispersion and accumulation. In Thailand, [68] demonstrated that integrating MODIS AOD with NDVI, LST and elevation substantially improved $PM_{2.5}$ estimation ($R^2 = 0.95$; RMSE = 5.58 $\mu g\ m^{-3}$), highlighting the importance of incorporating spatial features into PM modelling. In addition, emission inventories and human activity proxies are also integrated into PM estimation models to capture the influence of biomass burning, urban emissions and anthropogenic activity [96] and [163]. The fire hotspot datasets serve as direct proxies for episodic fire emissions, complementing AOD in capturing haze-related pollution events [47]. Whilst road density was used to represent traffic-related emissions and urban development that contributed to PM concentrations [164][165][166][167] and [168] and population density serves as a surrogate for anthropogenic activity and potential exposure [82][96] and [169].

In addition to the commonly used parameters, several less frequent variables such as aerosol optical and radiative properties, including the Ångström exponent, aerosol index, absorbing fraction and surface reflectance have also been used as parameters for improving the PM retrieval accuracy [99]. While these parameters appear with low frequency compared to AOD and meteorological variables (Figure 3), they highlight promising pathways for further exploration in future studies, although their use in Southeast Asia remains limited.

3.4 Source-Specific PM Estimation in SEA

Air pollution in SEA is strongly influenced by diverse emission contexts, including large-scale biomass burning, rapid urbanization, and agricultural activities [170] and [171]. While Sections 3.1–3.3 examined modelling techniques and ancillary parameters, it is equally important to synthesize how these approaches perform under different dominant emission regimes. The complex mixture of natural and anthropogenic sources across SEA creates regionally heterogeneous PM characteristics, which directly affect satellite retrieval performance and modelling accuracy.

Biomass burning, especially large-scale waste combustion and land-clearing practices in Sumatra and Kalimantan, constitutes a dominant source of particulate emissions in Southeast Asia [26]. Evidence indicates that such activities may contribute as much as 90% to PM species in mainland SEA and are responsible for roughly 40–60% of haze events observed in major cities [170] and [172]. These events are characterized by extremely high aerosol loading, strong vertical mixing variability, and long-range transport driven by monsoonal circulation. During the southwest monsoon season, prevailing winds transport smoke plumes toward Malaysia, Singapore, and southern Thailand, generating severe transboundary haze episodes [39] and [42]. Several studies incorporated fire hotspot data, open biomass burning (OBB) emissions, AI, and trace gases (CO, NO_2, SO_2, HCHO) to better capture the chemical and transport

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dynamics associated with haze events [67][69] and [131]. ML approaches, particularly Random Forest and boosting algorithms, have demonstrated improved performance during burning episodes by capturing nonlinear relationships between AOD, meteorological variables, and fire activity indicators [26][81] and [123]. However, modelling under haze conditions presents specific challenges, including data imbalance between extreme pollution days and background conditions, as well as cloud contamination during transitional monsoon periods.

Chemical transport models (CTMs) such as WRF-Chem have also been applied in Indonesia and Thailand to simulate fire-driven PM variability [60] and [61]. While CTMs offer physically interpretable results and incorporate emission inventories, their accuracy depends heavily on the reliability of biomass burning inventories, which remain uncertain in SEA. Overall, biomass-burning-dominated regions benefit most from integrated multi-parameter frameworks combining AOD, fire hotspots, meteorological data, and gaseous precursors, highlighting the need for dynamic, season-aware modelling strategies. In contrast to episodic haze events, urban PM pollution in SEA is primarily associated with traffic emissions, industrial activities, construction, and residential combustion. Major metropolitan areas such as Bangkok, Kuala Lumpur, Hanoi, Ho Chi Minh City, and Jakarta exhibit complex emission mixtures and high population exposure. Urban-focused studies frequently incorporate land-use variables, built-up indices, road density, population density, and elevation as proxies for anthropogenic activity. Land Use Regression (LUR) models have been particularly applied in dense urban settings [98], while ML approaches have shown superior predictive performance due to their ability to integrate multi-source predictors (see Table 1). During recent years, high resolution satellite AOD products such as MAIAC have improved PM estimation at city-scales by providing finer spatial granularity. However, urban modelling still faces distinct limitations. Bright urban surfaces can reduce AOD retrieval accuracy, while street-level pollution gradients may not be fully captured by coarse satellite resolution. Moreover, secondary aerosol formation driven by photochemistry under high temperatures complicates the direct AOD–PM relationship. Overall, urban PM estimation in SEA increasingly relies on hybrid models integrating meteorological conditions, trace gases, spatial proxies, and ensemble ML techniques.

Comparing these emission contexts reveals that PM modelling performance in SEA is strongly dependent on dominant source characteristics. Biomass-burning regions require integration of fire indicators and seasonal wind patterns, while urban areas demand high-resolution spatial proxies and anthropogenic emission indicators.

3.5 Collaboration Pattern

The chord diagram in Figure 4 illustrates the patterns of international collaboration among scientists and countries contributing to studies estimating PM concentrations in SEA region. This visualization shows strong interconnections between several Southeast Asian countries and research hubs in the United States, Europe, and Japan, indicating that collaborative efforts often extend beyond regional boundaries.

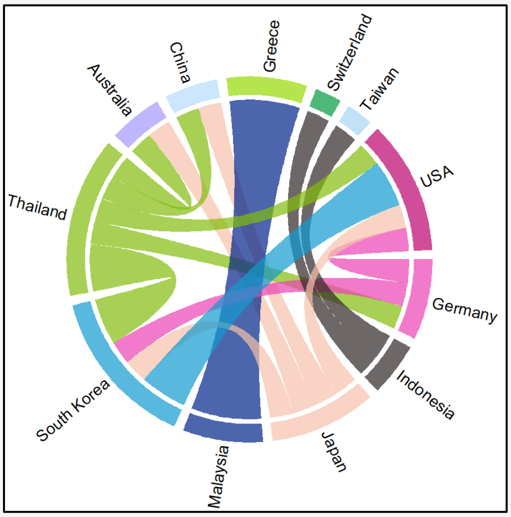

Figure 4: International collaboration network in studies on PM estimation using remote sensing in SEA region

This is particularly encouraging regarding international collaboration to optimize satellite data, techniques and models for more accurate modeling and mapping of air pollution in SEA region. Notably, Malaysia, South Korea and Thailand appear as key nodes within the region, showing multiple links to both neighboring Asian countries and Western partners such as the USA and Germany. This suggests that research output in Southeast Asia is frequently supported by technical expertise and resources from established research institutions abroad.

Collaborations with countries such as Switzerland, Greece and Australia are also evident, though less prominent, reflecting targeted partnerships or specialized methodological contributions. The dense and overlapping connections highlight the increasingly globalized nature of particulate matter research, where knowledge sharing and joint projects drive methodological advancements and improve data coverage across regions. These collaborative networks are likely to contribute to the observed growth in publication records, as international cooperation often enhances access to satellite data, computational tools and analytical expertise. This opens new horizons in SEA institutes and research teams for establishing international collaborations and new research hubs in a region that is highly sensitive to aerosol loading and climate change [42][45] and [69].

4. Conclusion

This review highlights the evolution of particulate matter (PM) estimation studies in Southeast Asia (SEA) over the past two decades. Due to growing population, industrialization and energy demand, the pollution levels in SEA region have substantially increased during the last decades and the people's concern about air pollution and related impacts on atmospheric environment, ecosystems and human health has increased. Early research, primarily relied on regression and geostatistical approaches, provided initial insights but were limited in their ability to capture the complex and dynamic atmospheric conditions over the SEA region. Subsequent studies introduced CTMs, offering physically based simulations, though their broader application in Southeast Asia remains constrained by uncertainties in emission inventories and the high computational cost. In recent years, ML has emerged as the dominant approach in PM estimations, consistently outperforming traditional methods by leveraging multi-source datasets, while DL and ensemble models are increasingly being explored for their ability to capture spatio-temporal dependencies.

Despite substantial progress in modelling techniques, spatial coverage, and predictive accuracy, several challenges remain. Frequent cloud cover and incomplete satellite retrievals limit the availability of continuous AOD data, while sparse ground monitoring networks hinder model validation. Data imbalance between haze and non-haze periods reduces the stability of model performance, and uncertainties in biomass burning and anthropogenic emission inventories challenge both statistical and physical-based modelling frameworks. Moreover, the transferability of models across diverse environments in Southeast Asia is still limited, highlighting the need for regionally adaptable strategies.

Future research should prioritize multi-sensor fusion to overcome AOD gaps and leveraging both polar-orbiting (MODIS, VIIRS) and geostationary platforms (Himawari-8, Fengyun-4A, GEMS) for higher temporal coverage. Improving the spatial and temporal resolution of PM estimates will be crucial for capturing short-lived pollution episodes, specific hotspot areas, and particularly, transboundary haze. The integration of trace gases, land-use factors, socio-economic and environmental indicators can further enhance model robustness. Beyond methodological advancements, it is equally important to recognize the uneven development of PM research across Southeast Asia in recent years. While countries such as Malaysia and Thailand have made substantial advances particularly in the application of machine learning techniques clear disparities persist within the region. Indonesia, despite being one of the largest contributors to biomass-burning emissions, still requires more comprehensive high-resolution PM modelling that extends beyond major urban areas and better integration of dynamic fire emission inventories. Vietnam has shown encouraging growth in research output; however, most efforts remain concentrated in specific cities, with limited nationwide modelling frameworks. In contrast, countries such as Cambodia, Laos, and Myanmar remain significantly underrepresented in satellite-based PM estimation studies. Strengthening observational infrastructure, enhancing regional data-sharing mechanisms, and promoting international collaboration are essential for achieving balanced scientific development and improving air quality assessment across the entire SEA region.

In summary, this research field is moving toward increasingly sophisticated data-driven frameworks that hold great promises for advancing PM monitoring in Southeast Asia. By addressing methodological limitations, improving regional equity in research capacity, and strengthening connections to health and policy applications, future studies can ensure that remote sensing–based PM monitoring contributes not only to scientific advancement but also to effective air quality management and sustainable development across SEA.

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