

# Modelling Air Pollution in Thailand: Insights from Community Mobility Data

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## ABSTRACT

This research investigates the relationship between community mobility and air pollution in Thailand, utilizing econometric and machine learning approaches to provide useful insights for policymakers to counter this issue. Data was sourced from the pollution database provided by the Ministry of Natural Resources and Environment and the community mobility database from a Google Trend search. The methodology of the research includes data extracting and pre-processing. The data analysis used an econometric model utilized Generalized Method of Moments, and a Machine Learning employed Support Vector Machines. Results of the econometric analysis reveal that residential mobility, workplace mobility, and park mobility have a significant positive relationship with changes in air pollution. The support vector machine results show that community mobility explains 58.50% of air pollution variation and has a prediction accuracy of 94.47% on the training set. The results also suggest that pollution problems should be monitored closely when air pollution changes by 20%. These findings enhance the understanding of the complex factors influencing air pollution and offer valuable insights for developing effective mitigation strategies.

## HIGHLIGHTS

- This paper employs alternative data sources, particularly the community mobility index, to investigate the association between its patterns and air pollution levels in Thailand.
- The findings suggest that changes in residential, workplace, and park-related mobility significantly influence air pollution levels.
- The research deepens our understanding of how the multifaceted drivers behind air pollution can craft sustainable and effective mitigation policies.

## 1. INTRODUCTION

Air pollution continues to pose a significant environmental and public health challenge, exerting wide-ranging effects on individual well-being, economic performance, and overall quality of life (Li et al., 2022). Exposure to clean air is consistently associated with better health outcomes, while elevated levels of pollution have been linked to respiratory illnesses, reduced outdoor activity, increased healthcare expenditures, and constraints on economic productivity (Freitas et al., 2020). To support mitigation and policy responses, many countries rely on the Air Quality Index (AQI) (Rajakumari and Priyanka, 2020), which synthesizes concentrations of key pollutants—namely sulfur dioxide (SO<sub>2</sub>), nitrogen

dioxide (NO<sub>2</sub>), particulate matter (PM<sub>10</sub> and PM<sub>2.5</sub>), ozone (O<sub>3</sub>), and carbon monoxide (CO)—to provide a standardized measure of air quality severity (Plaia and Ruggieri, 2011).

Nevertheless, the ability to estimate and forecast air quality in real time remains limited, particularly in rapidly urbanizing and economically diverse contexts such as Thailand. Traditional monitoring approaches, which primarily utilize ground-based sensors, periodic sampling, or satellite-derived observations, are often constrained by limited spatial and temporal resolution. These methods do not fully account for the dynamic nature of pollution, which is strongly influenced by human activity and mobility patterns. In this regard, emerging mobility data—tracking population

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movement across categories such as retail, recreation, transit, and residential areas—offers a potentially valuable input for enhancing the responsiveness and accuracy of air quality assessments (Kondo et al., 2014; Li et al., 2022).

The existing literature indicates a strong correlation between mobility and pollution, particularly in urban and industrialized settings (Lo et al., 2022; Zhu et al., 2020). However, in many developing countries, the integration of mobility data into real-time AQI forecasting remains underutilized. Contributing factors include inadequate digital infrastructure, limited methodological familiarity, and institutional inertia in adopting new technologies. Consequently, environmental governance in such settings often continues to rely on conventional monitoring tools that may not reflect real-time conditions, potentially resulting in delayed or suboptimal policy interventions (Das et al., 2021; Harnkijroong and Panich, 2013).

Thailand's complex economic structure—encompassing agriculture, tourism, and industrial manufacturing—produces a varied pollution landscape (Suriyawong et al., 2023). In the northern and northeastern regions, seasonal crop burning and forest fires contribute substantially to PM<sub>2.5</sub> concentrations, while in the Eastern Economic Corridor (EEC), industrial emissions are the predominant concern. In metropolitan areas such as Bangkok, traffic-related emissions are particularly severe. Despite these differences, a unified national strategy for pollution monitoring remains constrained by the absence of a granular and timely monitoring system.

This study aims to address this methodological and policy gap by evaluating the extent to which community mobility data can serve as a real-time estimator of air quality in Thailand. Rather than emphasizing cross-national comparisons between developed and developing countries, the research adopts an empirical approach focused on the relationship between population movement and pollution levels within Thailand (Srikamdee and Onpans, 2019). This approach directly aligns with the study's central objective: to assess the viability of using digital mobility indicators as predictive tools for environmental outcomes.

The study further contributes to policy-relevant knowledge by proposing an applied framework for integrating mobility data into air quality management. Potential applications include urban planning, traffic regulation, and the issuance of public health alerts. By

leveraging near real-time behavioral data, policymakers may be able to implement more timely and targeted responses to pollution events, thereby supporting sustainable development goals that reconcile environmental and economic considerations (Inthisorn and Puttanapong, 2022; Nyhan et al., 2019).

In summary, this research revisits a central question by examining whether community mobility data can function as a reliable, real-time predictor of air quality. Using Thailand as a representative case of a developing country, the study aims to generate empirical evidence that is both methodologically robust and practically applicable in advancing environmental governance.

Through the bodies of issues in air pollution monitoring, and modelling were widely discussed by Bahadur et al. (2024), Bahadur et al. (2025), and Beigh et al. (2025). Accurate estimation of air quality plays a critical role in informing environmental regulation, public health policy, and emissions control. Conventional estimation techniques typically rely on fixed-site air quality monitors or satellite-based remote sensing data. While these methods provide valuable pollutant, concentration estimates and broad spatial coverage, they are often characterized by delayed reporting and low temporal resolution. In rapidly changing urban environments, this temporal limitation presents challenges for the effective implementation of policy. The growing availability of high-frequency, device-generated data provides new opportunities for timely and behaviorally informed pollution modeling. Community mobility data have emerged as a promising proxy for real-time human activity, which may exert a measurable influence on pollution dynamics.

In countries where networks of air quality monitoring systems reach maturity, such as European countries or the US, a growing body of research has demonstrated the utility of mobility data in environmental analysis. Archer et al. (2020) and Badr et al. (2020), for example, documented significant reductions in NO<sub>2</sub> levels—exceeding 65% in some U.S. cities—during COVID-19 mobility restrictions, while PM<sub>2.5</sub> levels exhibited declines, albeit on a more modest scale. Similarly, Nyhan et al. (2019) employed anonymized mobile phone data to examine individual exposure to pollutants across spatial and temporal dimensions, highlighting its relevance for both environmental and epidemiological studies. In the UK, Reis et al. (2018) utilized census-linked spatial models to demonstrate that daily shifts in population density

elevated exposure risks to NO<sub>2</sub> and PM<sub>2.5</sub>. Bahadur et al. (2023) employed machine learning in monitoring and modeling air quality. In the Singaporean context, Li and Tartarini (2020) found that pandemic-induced restrictions significantly improved air quality, reinforcing the link between mobility and emissions. Collectively, these studies illustrate the methodological maturity and policy relevance of integrating behavioral data into environmental monitoring systems.

By contrast, studies conducted in developing countries where mobility data may not be readily available frequently rely on broader satellite-based assessments or have utilized mobility-related events (e.g., lockdowns) as indirect proxies without measuring actual movement patterns. For instance, Liu et al. (2020) used a difference-in-differences approach to quantify the impact of lockdown policies on pollution in China, reporting an average reduction of 12%. In India, Srivastava et al. (2020) found that declines in vehicle use, and industrial activity led to short-term improvements in air quality during the pandemic. Othman and Latif (2021) observed significant reductions in NO<sub>2</sub> in Malaysia but did not incorporate mobility data directly into their models. Although these studies acknowledge the influence of human activity, their reliance on indirect measures underscores a persistent methodological gap.

This divergence highlights a significant research opportunity. While real-time behavioral data are increasingly applied in developed country contexts, their integration into environmental analysis in the developing world remains limited. With the growing availability of platforms such as Google Community Mobility Reports and anonymized mobile tracking data, it is now feasible to implement such models even in countries with limited monitoring infrastructure.

Thailand is emblematic of this opportunity. To the best of our knowledge, the study of community mobility related air quality issue in Thailand remains limited despite the country's diverse pollution sources ranging from biomass burning in the north to industrial activity in the east and traffic emissions in urban centers (Othman et al., 2022). At present, most assessments rely on satellite observations or data from a relatively small number of fixed monitoring stations. Although anecdotal and seasonal patterns clearly link mobility to pollution, for example, during public holidays or COVID-19 lockdowns there remains a

paucity of research that systematically models these dynamics using contemporary analytical techniques.

The present study seeks to address this gap by testing whether mobility data from six distinct categories (e.g., retail, recreation, residential, transit) can serve as valid predictors of AQI in Thailand. By applying a combination of econometric and machine learning models, this research evaluates the predictive performance of mobility indicators in estimating air quality across different regional contexts. The findings are expected to yield methodological contributions as well as practical policy insights, particularly for enhancing adaptive environmental management in urban and semi-urban settings within developing economies. The independent variable uses in this investigation involving many categories of community movement such as retails and recreation, grocery and pharmacy, parks, transition station, workplace, and residential (Nowak and Heisler, 2010; Oudin et al., 2012; Tee Lewis et al., 2019) to explain how air pollution, which is represented by Air Quality Index, change as presented in Figure 1.

## 2. METHODOLOGY

To examine the association between community mobility and air pollution, this paper organizes the methodology into two parts: 1) Data Sources, which elaborates on the dataset used in this paper and the data preparation performed before proceeding to the next step, and 2) Analysis procedure, which provides information about the econometric and machine learning approaches used in this paper, as detailed below.

### 2.1 Data sources

This paper employed retrospective data from 2020 to 2022 from publicly accessible sources, including the pollution database, which provided average air pollution data from the Ministry of Natural Resources and Environment, and the community mobility database, which provided human movement data from random sampling by Google Co. Ltd. All retrieved data were aggregated into weekly data using the moving average approach and normalized on a scale from zero to one to reduce variation among datasets (Borkin et al., 2019). Descriptive statistics were performed using the mean and standard deviation if the data were normally distributed; otherwise, medians and interquartile ranges were used to summarize the overall characteristics of the data.

Details of the variables used in this investigation and were also present in Table 1 below.

Based on the empirical data, it was demonstrated that all the retrieved data were abnormally distributed, considering the statistical significance of the Shapiro-Wilk test, which evaluated the distribution by order statistics (sorted values) of the dataset (Royston, 1992). Therefore, medians and interquartile ranges were appropriate to present the overall characteristics of the

data. The results showed that during the study period, air pollution levels in Thailand were still low, indicating that overall air quality was still good. In contrast, the community mobility index was high for all subcategories, especially workplace mobility as well as retail and recreation mobility. This outcome implied a moderate level of air pollution when considering air quality as a nationwide indicator over time. The results are shown in Table 2.

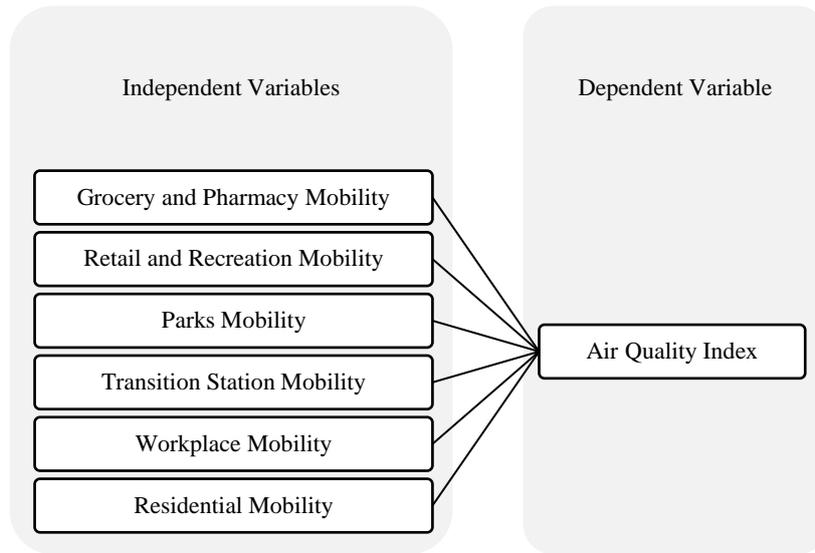


Figure 1. Conceptual framework

Table 1. Variable description

Variables	Unit
Air quality index (AQI)	Integer ranges from 0 to 500
Retail and recreation mobility (CM1)	Percent change from baseline
Grocery and pharmacy mobility (CM2)	Percent change from baseline
Parks mobility (CM3)	Percent change from baseline
Transition station mobility (CM4)	Percent change from baseline
Workplace mobility (CM5)	Percent change from baseline
Residential mobility (CM6)	Percent change from baseline

Remark: Baseline was the median value from the 5-week period Jan 3-Feb 6, 2020

Table 2. Descriptive statistics of the data

	Normality	Mean	Std. Dev.	Median	IQR
Air quality index (AQI)	6.925***	0.186	0.192	0.118	0.189
Retail and recreation mobility (CM1)	4.233***	0.588	0.204	0.642	0.219
Grocery and pharmacy mobility (CM2)	2.398***	0.510	0.206	0.473	0.318
Parks mobility (CM3)	2.876***	0.353	0.190	0.382	0.304
Transition station mobility (CM4)	4.090***	0.463	0.224	0.535	0.363
Workplace mobility (CM5)	2.059***	0.658	0.195	0.686	0.265
Residential mobility (CM6)	2.231***	0.391	0.224	0.366	0.340

\*\*\*denote the statistically significant at 0.01

Remark: The data analyzed through STATA version 18 license from Thammasat University

## 2.2 The model

This section aims to elaborate on the details of the investigation model used in this paper, which consists of two parts: the econometric model—a conventional tool for estimation and prediction—and the machine learning model—an advanced tool for prediction. These two models have distinct advantages. For example, the econometric model can estimate the marginal rate of change through its parameters, which is beneficial for a deeper understanding of the impact of factors. However, its parameterization must be strictly aligned with the data distribution, leading to poor predictions when the data is not normally distributed (Inthisorn and Puttanapong, 2022). On the other hand, the machine learning model provides better predictions since it relies on finding the best solution based on data distribution, though it lacks detailed insights (Hua et al., 2024).

### 2.2.1 Econometric model

To investigate the relationship between community mobility (CM) and air pollution index (AQI), a generalized method of moments (GMM) is employed for parameter estimation. This method allows for obtaining unbiased coefficients even when the data exhibits a non-linear relationship and a non-normal distribution (Gujarati and Porter, 2008), as evidenced in Table 2. Additionally, this paper incorporates a time variable to capture the unobserved effects of time growth to the estimated model, which can be algebraically displayed as shown in Equation 1.

$$AQI_t = \alpha_0 + \pi_i \sum_{i=1}^N CM_{it} + \text{time} + v_t \quad (1)$$

Where:  $AQI_t$  = the normalized index of air quality reported at time  $t$ ;  $CM_{it}$  = the normalized volume vector of sub-categories for mobility types at time  $t$  (where:  $i = 1$  is retails and recreation mobility,  $i = 2$  is grocery and pharmacy mobility,  $i = 3$  is parks mobility,  $i = 4$  is transition station mobility,  $i = 5$  is workplace mobility,  $i = 6$  is residential mobility); time is time variable;  $\alpha_0$  is constant terms;  $v_t$  is disturbance terms;  $\pi_i$  is the vector of estimated parameters.

To identify the best-fitting model, parameter estimation is carried out in three steps: 1) estimation of the restricted model by expressing the dependent variable in terms of a time trend, 2) estimation of the unrestricted model by including all independent

variables in the specification, and 3) determination of the final fitted model by removing variables that are not significant based on the Wald test criteria.

The robustness of the model is tested using the bootstrapping method after parameter estimation. To verify the validity and reliability of the estimated model, bootstrapping involves randomly selecting new values and re-estimating the model 1,000 times, assuming that the disturbance term is independent and identically distributed. If the results consistently show the same sign, magnitude, and statistical significance, this indicates that the model is robust (Escanciano and Lobato, 2009; Gujarati and Porter, 2008).

### 2.2.2 Machine learning model

Given the limitations of the specified methodology which only indicated the relationship between community mobility (CM) and air pollution index (AQI), therefore, a machine learning technique will be used to identify the prediction accuracy of the independent variable set on the air quality index utilizing support vector machines. This approach aims to find a function that best approximates the relationship between input features and continuous target variables. It is capable of handling complex and nonlinear problems, including noise, outliers, and high-dimensional feature spaces (Emsia and Coskuner, 2016). Kernel functions are employed to estimate these nonlinear relationships, as given in Equation 2.

$$AQI = f[\sum_{i=1}^n CM_i] \quad (2)$$

Then, non-linear relationships will be transformed into high-dimensional feature spaces to enable linear separation using kernel functions, as shown in Equation 3.

$$AQI = \sum_{i=1}^n (\theta_i - \theta_i^*) \cdot K(CM_i, CM^*) + \eta \quad (3)$$

Each dimension is a symmetric matrix with non-negative eigenvalues, according to the underlying probability density function as presented in Equation 4.

$$k(CM_i, CM_j) = (CM_i, CM_j)^d \quad (4)$$

Since this paper considers all subcategories of community mobility simultaneously, the hyperplane that maximizes the margin for each dimension can be expressed as shown in Equation 5.

$$AQI = \sum_{i=1}^n (\theta_i - \theta_i^*) (CM_i, CM_j)^d + \eta \quad (5)$$

The 70/30 data ratio was used for model training and model validation respectively. During the parameterization process. The goodness-of-fit for both technique are measured using R-squared and RMSE,

by comparing the training and testing sets (Molinaro et al., 2005). The entire process is illustrated as shown in Figure 2 below.

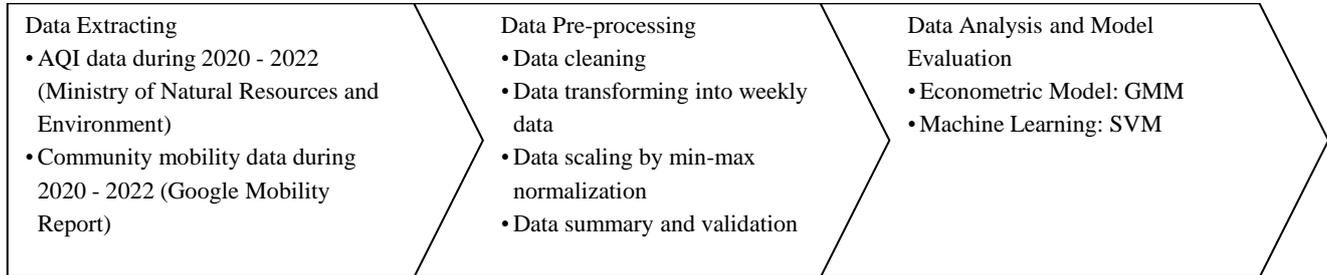


Figure 2. The research flowchart

### 3. RESULTS AND DISCUSSION

According to the previously discussed methodology, the results from the generalized method of moments estimation will be presented first, followed by the results from the support vector machine analysis. The details are as follows.

#### 3.1 The econometric results

When employing an econometric model for parameterization, the primary concerns are model specification and its potential consequences, such as specification error, multicollinearity, and heteroskedasticity. Fortunately, the generalized method of moments (GMM) can address heteroskedasticity issues more effectively than the ordinary least squares (OLS) approach. However, including all variables simultaneously may lead to multicollinearity, which can increase the standard error of the estimates. To diagnose this issue, correlation analysis will be conducted as a preliminary step. The results indicated that retail and recreation mobility (CM1), grocery and

pharmacy mobility (CM2), and park mobility (CM3) exhibited relatively high correlations among the variables, which could result in multicollinearity problems (Chen, 2012), excepted for transition station mobility (CM4), workplace mobility (CM5), residential mobility (CM6), as shown in Table 3.

To avoid these issues, the estimation process will be approached from three perspectives: First, the restricted model, which serves as the baseline for comparing the explanatory power of the model when additional variables are included. Second, the unrestricted model, which incorporates all variables. Lastly, the fitted model, which excludes retail and recreation mobility (CM1), grocery and pharmacy mobility (CM2), and transition station mobility (CM4) variables based on the Chow’s test as a criterion for model selection. The fitted model demonstrated a higher adjusted R-squared while maintaining the same level of prediction error. This result suggests that the model is more robust after the removal of irrelevant variables.

Table 3. Correlation testing for multicollinearity diagnosis

	CM 1		CM 2		CM 3		CM 4		CM 5		CM 6
CM 1	1.000										
CM 2	0.783	***	1.000								
CM 3	0.741	***	0.445	***	1.000						
CM 4	0.700	***	0.252	***	0.832	***	1.000				
CM 5	0.615	***	0.380	***	0.386	***	0.667	***	1.000		
CM 6	-0.790	***	-0.436	***	-0.401	***	-0.574	***	-0.575	***	1.000

\*\*\*denote the statistically significant at 0.01

The investigation (Table 4) reveals that residential, workplace, and park mobility all have positive effects on air pollution, consistent with

previous findings by Nowak and Heisler (2010), Oudin et al. (2012), and Tee Lewis et al. (2019). Specifically, a 1-percentage-point increase in

residential and workplace mobility is associated with increases in air pollution levels by approximately 24.2% and 36.2%, respectively. These results suggest that traffic congestion remains a primary contributor to air pollution in Thailand. In addition, park mobility

is associated with a 24.3% increase in pollution; however, this may be linked to leisure-related travel patterns, which differ from commuting behavior and warrant separate policy consideration.

**Table 4.** Econometric estimation by using GMM method for investigating relationship between community mobility index and air pollution

	Restricted model			Unrestricted model		Fitted model		
	Coeff.	Std. Err.		Coeff.	Std. Err.	Coeff.	Std. Err.	
Retails and recreation mobility				-0.404	0.449			
Grocery and pharmacy mobility				0.087	0.235			
Transition station mobility				0.050	0.268			
Parks mobility				0.368	0.283	0.243	**	0.109
Workplace mobility				0.240	**	0.171	**	0.118
Residential mobility				0.182	0.210	0.362	***	0.095
Time	-0.001	**	0.000	-0.001	0.001	-0.002	**	0.001
Constant	0.254	***	0.034	0.066	0.200	-0.103		0.073
Observations	125			125		125		
Wald's Chi-squared	2.850	*		21.250	***	19.740	***	
R-squared	0.041			0.181		0.175		
Adjusted R-squared	0.033			0.132		0.147		
RMSE	0.187			0.173		0.173		
Robustness check	Yes			Yes		Yes		

\*\*\*, \*\*, \* denoted the statistically significant at 0.01, 0.05, 0.10 respectively, Chow test was performed to fit the variables and standard error of estimate was robust. The fitted model was cleaned from endogeneity effect once compared to the IV-GMM approach, indicating that the estimated coefficient was unbiased.

These results align with existing literature that identifies workplace and residential mobility as key contributors to urban air pollution, primarily through traffic congestion and industrial emissions. Barua and Nath (2021) found that a 1% increase in transit-related mobility in the East Asia region can raise emissions by 1.6%. Similarly, Cui et al. (2019) highlights the long-term consequences of persistent pollution, including talent outmigration from cities with poor air quality. These findings underscore the importance of mobility control policies. As noted by Dang et al. (2020) and Das et al. (2021), implementing stricter regulations on traffic and commuting activities could significantly improve urban air quality.

Besides, the positive relationship between parks mobility and air pollution is likely driven by the transportation required to reach park areas. This is supported by findings from Shafeeque et al. (2021), who observed that reductions in overall mobility—including visits to parks—were significantly associated with decreased emission levels across South Asia.

Upon considering the prediction accuracy of the GMM by mapping the actual AQI values against the predicted AQI values, it is evident that the GMM

yields relatively low prediction accuracy. This is reflected by the shaded area, which indicates that the 95% confidence interval is becoming wider. Furthermore, the result also confirms the model's low predictive power, as shown by the red dashed line, which does not intersect with the dots, indicating a weak trend prediction, as seen in Figure 3.

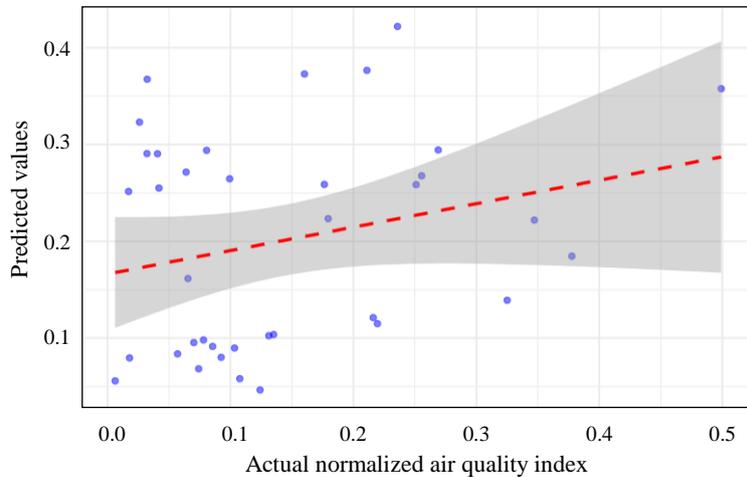
### 3.2 The support vector machine results

This section presents the results of the Support Vector Machine (SVM) analysis, based on a 70/30 split of the dataset—70% for training and 30% for testing. Besides, the SVM smooth curve is performed to evaluate the model's predictive performance, ensuring that the resulting curve reflects generalizable patterns rather than overfitting.

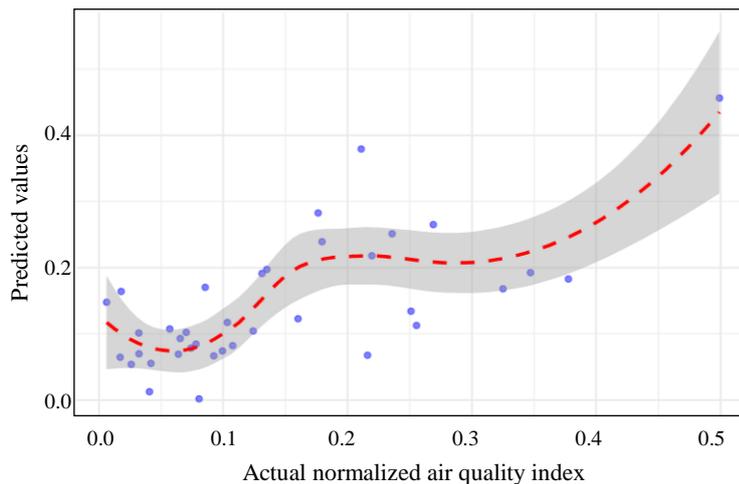
The model produced two key findings: 1) community mobility variables explained approximately 58.5% of the variance in air pollution levels, with a prediction accuracy of 94.47% on the training data. Although the accuracy on the testing set was slightly lower, it remained within an acceptable range (Hua et al., 2024), 2) The SVM model yielded relatively higher prediction accuracy, as reflected in

the shaded area of the 95% confidence interval, which becomes narrower, in addition, the model identified that a change of around 20% -as observed in the turning point of graph at 0.2 in the air quality index

signal the onset of severe pollution events, as indicated by the red dashed line representing the smoothed SVM as illustrated in Figure 4.



**Figure 3.** Assessment of GMM prediction accuracy for air quality index (Note: Author’s calculation)



**Figure 4.** Assessment of SVM prediction accuracy for air quality index (Note: Author’s calculation)

These instances fall outside the model’s optimal margin of classification, suggesting high uncertainty and aligning with the 95% confidence threshold. Overall, these results demonstrate that community mobility can be a reliable predictor of air pollution

using machine learning methods. Moreover, SVMs can be used for threshold-based classification, enabling early warnings for high pollution levels as present in Table 5.

**Table 5.** Support vector machine estimation

	Accuracy	R-squared	RMSE
Training set	94.47%	58.50%	0.0553
Testing set	91.48%	46.51%	0.0852

According to the empirical result consistent with these findings, Hua et al. (2024) report that mobility-based models, when implemented under

appropriate methodological conditions, can predict air pollution levels with an accuracy ranging from 78% to 98%. However, prediction accuracy may vary

depending on local characteristics such as urban development, transportation infrastructure, and economic activity (Davis and Weinstein, 1999; Yasumoto et al., 2019; Wu et al., 2019). These unobservable factors introduce potential model discrepancies.

Taken together, the findings highlight the importance of integrating machine learning insights into environmental policymaking. Policymakers should consider collaborative efforts with relevant agencies to implement targeted interventions. For example, promote smart urban planning and support green commuting for integrating air pollution (Murad et al., 2025; Paoin et al., 2021).

#### 4. CONCLUSION

This study examined the relationship between community mobility and model air pollution in Thailand by applying both econometric and machine learning approaches. The findings from econometric model suggest that changes in residential, workplace, and park-related mobility significantly influence air pollution levels, with residential movement emerging as the most impactful factor. Additionally, the machine learning model identified a critical threshold: A change of more than twenty percent in the air quality index may serve as an early warning signal for severe pollution events.

These results offer important policy implications. Strategies to manage community mobility—such as promoting green commuting, supporting remote or hybrid work arrangements, and implementing smart urban planning with expanded green spaces—could contribute to pollution reduction. However, as noted by Murad et al. (2025) and Sharma et al. (2003), the success of such interventions depends on contextual factors, including the level of public awareness regarding pollution, which may differ across regions and countries.

Despite its contributions, the study has several limitations. First, the national-level data may not capture local variations in mobility and pollution; future research should consider spatially disaggregated data and additional factors like seasonality and industrial activity. Second, the community mobility index may not fully reflect actual movement patterns. Developing a more comprehensive composite index, as suggested by Inthisorn and Puttanapong (2022), could improve measurement accuracy. Third, the use of a static model may obscure complex relationships; techniques such

as quantile regression, ridge, or lasso regression could enhance robustness and prediction. Integrating satellite data may also improve the analysis, especially at a finer geographic scale.

In conclusion, the insights from this study can inform the design of urban environmental and public health policies in developing countries, helping to optimize resource allocation while addressing critical pollution challenges.

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