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Predictive Machine Learning Modeling of Urban Traffic Air Pollution:
A Case Study of the Entebbe–Kampala Road, Uganda

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Abstract

Air pollution in Africa is a growing yet often overlooked threat, worsened by increased industrial activity, urban development, air travel, and road traffic. This study examines the impact of traffic flow and meteorological conditions on urban air quality along the Entebbe–Kampala corridor in Uganda. Traffic monitoring was conducted on three road sections and air quality was measured using AirQo mobile sensors. Traffic surveys showed motorcycles, saloon cars, and light goods vehicles dominate, while heavy trucks contribute minimally. Pearson correlation, regression analysis and extreme gradient boost models were used in analysis with Shapley Additive Explanation quantifying marginal contributions of traffic and meteorological variables to emission levels. Air quality monitoring revealed temporal variation, with $PM_{2.5}$ peaking at night due to stable atmospheric conditions limiting dispersion. Correlations confirmed pollutant co-occurrence during evening and night, emphasizing risk of accumulation under low atmospheric mixing. Regression analyses demonstrated strong positive relationships between Average Daily Traffic and $PM_{2.5}$, CO_2, and TVOC concentrations with R^2 values ranging from 0.89 to 0.986. Wind speed explained 45 to 71% of pollutant variances, reflecting its role in pollutant dispersion and resuspension. Traffic volume emerged as a primary driver of emissions using SHAP explanations. This study considered a small sample size and limited data collection which may affect applicability and fail to reflect seasonal or long-term variations in patterns of emissions and traffic. It underscores the need for urban air quality policies in Uganda integrating pollutant-specific measures like traffic control to reduce $PM_{2.5}$, stricter speed regulation for TVOCs, and enhanced fuel efficiency for heavy vehicles to lower CO_2. The study provides validated, locally calibrated models and evidence-based insights to guide targeted traffic and emission management in rapidly urbanizing African cities.

Keywords: Entebbe-Kampala Road, machine learning, $PM_{2.5}$, traffic emissions, urban air quality, Uganda

INTRODUCTION

Air pollution from urban traffic remains one of the most pressing environmental and public health challenges globally. Road transport significantly contributes to emissions of carbon dioxide (CO_2), Total Volatile Organic Compounds (TVOCs), and $PM_{2.5}$ (Fine Particulate Matter ≤ 2.5 µm), which have an impact on the environment, the cardiovascular and respiratory systems, and thereby reduce the life expectancy of people (Gao & Zhu, 2022; World Health Organisation, 2021). The rapid urbanisation, coupled with the prioritisation of motorised transportation and increasing private vehicle ownership, exacerbates traffic congestion and deteriorates the air quality in many cities globally (Anenberg et al., 2019). Low- and middle-income countries lack adequate monitoring and mitigation measures, hindering the Sustainable Development Goal to create resilient and sustainable cities by 2030 (Maumoh & Onoja, 2024).

In Uganda, like many Sub-Saharan African countries, urban transport emissions are an emerging environmental health risk. The region continues to experience accelerated motorisation with limited advancement in emissions control technologies and integrated transport planning (Ekeh et al., 2014; Olubusoye & Musa, 2020). As

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a result, many African cities exceed World Health Organization (WHO) air quality guidelines, and several traffic corridors remain critical pollution hotspots. Despite growing concern, few studies in Uganda have applied advanced modelling to quantify traffic emissions, limiting evidence-based interventions. Addressing this research gap, this study applies machine learning methods to model and quantify traffic-related air pollution in Uganda's urban settings.

Entebbe–Kampala Road is a vital and heavily trafficked corridor linking Entebbe International Airport to Kampala, Uganda's capital. The route experiences high vehicle volumes, congestion, and a diverse mix of transport modes including motorcycles, private cars, commuter taxis, and heavy trucks. These factors create localized emission hotspots that pose risks to both community health and the environment. Despite the corridor's significance, empirical data and modelling assessments to inform policy interventions remain limited. This study aims to establish the relationship between traffic volume, composition, and air emissions; to examine the influence of meteorological conditions on pollutant concentrations; and to develop and interpret predictive models to estimate ambient air pollution levels along the Entebbe–Kampala Highway. It quantifies how traffic characteristics and meteorological factors influence pollutant concentrations and provides validated, locally calibrated models to guide urban air quality management in Uganda.

This paper is structured into seven sections. It begins with an introduction that contextualizes the urban air pollution challenge in Uganda and identifies research gaps. The literature review synthesizes existing knowledge on traffic-related air emissions and modeling approaches. The research methods section details data collection and analytical techniques used along the Entebbe–Kampala Road. Results present findings on pollutant concentrations and their relationships with traffic and meteorological variables. The discussion interprets these findings within broader urban transport planning and air quality management frameworks. Recommendations offer strategies for emission mitigation, and the conclusion summarizes key insights while suggesting directions for future research. This paper is structured into seven sections: introduction, literature review, methods, results, discussion, conclusion, and recommendations.

THEORY

Numerous studies have focused on ambient air quality in urban areas. Ghaffarpasand et al. (2024) showed a strong correlation between urban mobility and roadside $PM_{2.5}$ levels and a weaker relationship with urban $PM_{2.5}$ levels. Similarly, previous studies have highlighted that urban road transport is an important source of emissions (Assamoi & Liousse, 2010; Krief et al., 2020; Liousse et al., 2014). However, the integration of traffic with emission modelling is less explored in the country. Such approaches can provide resolved estimates of pollutant concentrations, enabling scenario testing for traffic management, infrastructure improvement, and emission reduction in urban areas.

Traffic Emission Studies

Globally, urban traffic-related air pollution (TRAP) remains a leading contributor to excess morbidity and mortality, with CO_2, TVOCs, and $PM_{2.5}$ among the dominant pollutants of concern near busy roads. The World Health Organization (WHO) guidelines on air quality highlight limiting pollution, for example, $PM_{2.5}$ annual average is limited to 25 µg/m3, while CO_2 and TVOCs are limited to 7 mg/m3 and 600 µg/m3, respectively, for 24 hours (Goshua et al., 2022). Ajayi et al. (2023) revealed that pollutant emissions increased rapidly during peak hours of the day in Lagos, Nigeria. De Barros Baltar et al. (2021) studied the impact of traffic congestion on emissions in Avenida Brazil. Findings showed that incidents contribute to a 22% increase in CO_2 emissions, with broken-down vehicles having the greatest impact due to their high frequency. Furthermore, morning and afternoon peak hours account for 82.4% of the incident-related rise in CO_2 emissions. Condurat et al. (2017) studied the environmental impact of traffic on emissions in Romania, findings showed that there are exponential increments in emissions and fuel consumption. Additionally, findings by Nsereko (2020) on traffic related exposure and its effects showed that exposure to pollutants was associated with various health impacts in Kampala. At the same time, urban-specific traffic studies identify other challenges such as traffic congestion drivers, bottlenecks, improper junctions, and motorist behaviour along the Entebbe–Kampala corridor within the Greater Kampala Metropolitan Area (GKMA).

Traffic-related pollutants consist of a complex mixture of gases and primary particulates. Beyond CO_2 Fuel type influences pollutant composition that is petrol engines emit CO, VOCs, NH_3, and trace heavy metals whereas diesel engines produce $PM_{2.5}$ and NO_x (Bebkiewicz et al., 2021; Q. Zhang et al., 2025). Despite regulatory advances that have mandated cleaner engine technologies and reduced emissions per vehicle, the steady growth in traffic volumes offsets much of the anticipated benefit (International Energy Agency., 2022). Comparisons show that older carbureted vehicles emitted roughly ten times more hydrocarbons, four times more CO, and three times more NO_x than newer multi-point ignition engines (Qu et al., 2015). Uganda is one of the countries in Sub-Saharan Africa that still has more older vehicles used on the road even though there are policies to limit their usage (Forster & Nakyambadde, 2020). Nonetheless, the expected reductions in emissions from automobiles can only be realized if emission-control systems are adequately maintained.

Air Pollution Modelling

Air pollution modeling is a comprehensive interdisciplinary method used to study, evaluate, and control air quality by simulating the processes of pollutant emission, dispersion, chemical transformation, and removal within the atmosphere (C. Zhang et al., 2018). It employs various model types, including dispersion models focused on near-source pollutant concentrations and grid-based chemical transport models like the Community Multiscale Air Quality (CMAQ) system that simulate the formation and transport of pollutants on regional to hemispheric scales. These models incorporate detailed inputs like meteorological data, emission inventories, and landscape features to generate pollution concentration estimates that vary spatially and temporally, aiding regulatory framework development, risk evaluation, and policy making (C. Zhang et al., 2018). Increasingly, hybrid modeling approaches combine the detailed local scale dispersion characteristics with regional-scale chemical transport to balance computational efficiency and accuracy. Complementary exposure modeling takes into account human activity patterns to better estimate pollutant intake beyond ambient air concentrations (Deveer & Minet, 2025). Despite significant advancements, challenges remain in improving data quality, computational capacities, and integration of complex chemical and physical processes to enhance Tdiesel he predictive reliability of air pollution models in dynamic and urban environments. This integrated modeling approach is vital for developing actionable strategies to manage air pollution and protect public health effectively.

Modelling Approaches

Modelling approaches for TRAP around the highways generally couple an emission estimation step with atmospheric dispersion, for example, widely used frameworks include MOVES, AERMOD, COPERT and HBEFA handbook factors (Liu et al., 2023). These estimate the speed and technology specific rates for regulated pollutants for diverse fleets and operating modes. Matara et al. (2024) conducted a simulation-based assessment of vehicle-related air pollution along the Nairobi Expressway using the AERMOD dispersion model. They estimated emissions by integrating data on vehicle kilometers travelled, emission factors, and traffic volumes. Their findings revealed that traffic contributed 3.5% to TVOC and 55% to CO in 24-hour average measurements, with smaller contributions for $PM_{2.5}$ (1.1%) and PM_{10} (1.6%). However, this methodology have data constrained contexts, localizing fleet age, fuel consumption and driving cycles. Machine learning models are more flexible, locally adaptable, and capable of real-time high-accuracy predictions, whereas traditional models like MOVES are rigid, region-specific, and data-intensive, limiting their use outside their original design environment (Chowdhury et al., 2023). Matara et al. (2024) employed advanced machine learning and statistical models in predicting concentrations of $PM_{2.5}$ pollutants while accounting for vehicular volume, meteorological conditions and vehicle speeds. The findings indicated that temperature humidity and wind speed were primary determinants in predicting $PM_{2.5}$ concentrations in the Nairobi expressway corridor. Ning et al. (2025) used Bayesian modeling approach combined with dispersion models to estimate traffic-related pollutant concentrations in an urban area. The model integrates high-resolution traffic data, meteorological conditions, and observed air quality measurements to make probabilistic predictions of pollutant levels while quantifying uncertainty. By combining outputs from the Research LINE-source (RLINE) dispersion model with statistical Bayesian data fusion methods, the approach improves spatial and temporal exposure estimates for pollutants like NO_x and $PM_{2.5}$. The Bayesian framework accounts for biases and uncertainties in emission inventories and measurement data, providing robust, spatially resolved pollution concentration predictions that can better inform exposure and health impact studies near roadways. This method enhances understanding of local traffic pollution dynamics and supports decision-making on mitigation strategies.

The literature identifies urban traffic as a major source of air pollutants like $PM_{2.5}$, CO_2, and TVOCs globally, with established patterns linking peak traffic volume to emission spikes. This has spurred an evolution in modeling, shifting from traditional, inflexible frameworks toward sophisticated machine learning techniques that better capture complex real-world interactions. However, a significant contradiction exists between this global knowledge and the local context of developing nations like Uganda. The theoretical benefits of advanced vehicle technologies and emissions standards are nullified by pervasive use of aging, poorly maintained vehicle fleets in Uganda. This is compounded by a critical gap in research while global studies increasingly use high-resolution, interpretable models that integrate traffic and meteorological data, local studies often lack such sophisticated approaches, failing to provide the actionable, locally-calibrated predictive tools necessary for effective policy intervention.

Knowledge Gaps

Critical gaps in Uganda's urban air quality research include existing models lack interpretability, they rarely integrate meteorological conditions with traffic variables, and fail to isolate traffic contributions to pollution. Using machine learning with high-resolution traffic and weather data, this research develops interpretable predictive models for the Entebbe–Kampala Road, quantifying pollutant levels across temporal patterns and traffic flow conditions. Inferences from this study will inform evidence-based strategies to reduce traffic-related emissions and improve public health outcomes in rapidly motorizing urban environments.

Figure 1 illustrates the logical structure underpinning the study. It explains how legal

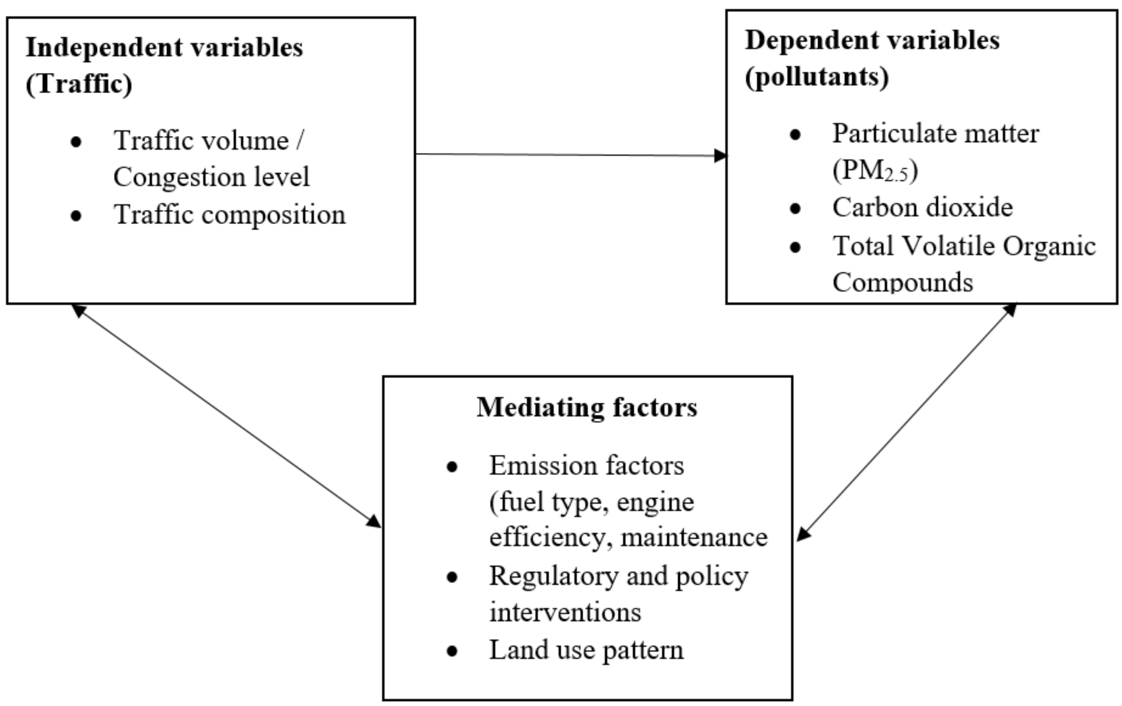

FIGURE 1
Conceptual framework showing relationships among traffic variables, meteorological factors, and pollutant concentrations
Source: Author's conceptualization based on Kenyan building laws, 2025

and institutional inputs—such as existing building regulations, professional standards, and inspection mandates—interact through inspection processes that include staged site assessments, record-keeping, and owner participation. These relationships are moderated by mediating factors such as resource availability, inter-agency coordination, and integrity controls, which collectively shape the outcomes of inspection and enforcement. The framework proposes that when these processes function effectively, outputs such as remediation, closure, or demolition decisions translate into safer buildings, greater public trust, and stronger regulatory reform. This conceptualization is adapted from contemporary regulatory enforcement and risk-governance theories (Creswell & Poth, 2018; Lipsky, 2010; Yin, 2018).

RESEARCH METHODS

Study Area

This study was conducted along the Entebbe–Kampala highway, specifically the Namasuba–Seguku section. The Entebbe–Kampala highway is a major transport corridor in Uganda's Central Region, linking Kampala to Entebbe International Airport. It traverses several urban centers including Kibuye, Namasuba, Zana, Seguku, Kajjansi, and Abayita Ababiri, covering approximately 40 km. The study was restricted to a 5 km stretch between Freedom City, Namasuba and Doctors' Hospital, Seguku. This segment was selected due to its high traffic density and proximity to residential and commercial developments, making it a good representative of urban roadside exposure conditions. The research focused on establishing the relationship between traffic activity and vehicular emissions through the collection of traffic and air quality data. The parameters collected included traffic volume, composition and ambient air quality.

Data Collection

Data collection along the Entebbe–Kampala Road (Namasuba–Seguku section) combined traffic surveys and air quality monitoring to collect data that can help in capturing the relationship between traffic activity and emissions. Qualitative triangulation was applied by comparing photographic evidence, observed defects, and official inspection records to validate field data. The data were collected between July and August 2024 during the dry season Traffic data was obtained through manual classification counts (MCCs) while air quality parameters were monitored using mobile AirQo sensors. Manual Classified Counts (MCCs) were selected for their ability to provide precise vehicle categorization and traffic composition data critical for emission source analysis. AirQo mobile sensors were chosen due to their affordability, portability, and capacity for continuous, real-time monitoring of key air pollutants ($PM_{2.5}$, TVOCs, CO_2) in urban settings lacking fixed monitoring infrastructure. These instruments together provide an effective combination for capturing the spatiotemporal variability of traffic-related air pollution in the study corridor. Traffic volume and composition were recorded using Manual Classified Counts (MCCs) at three strategically selected sites which include Namasuba, Zana at Bata Bata, and Lubowa, chosen to reflect representative travel patterns. These were done under supervision of a site supervisor to ensure collection of the right data by enumerators. Enumerators categorized vehicles using standardized sheets, while motorcycles (boda bodas) were counted separately with clickers due to their high frequency. Surveys spanned seven days with five 12-hour sessions (07:00-19:00) and two 24-hour sessions (one weekday and Saturday). Each survey site was staffed by two enumerators per direction, supervised by a site supervisor, with police officers assisting during night counts. Air quality was monitored concurrently using two AirQo mobile sensors (G5320 and G5324) equipped with dual PMS5003 laser scattering sensors to enhance data reliability and quality control and GPS, measuring $PM_{2.5}$, TVOCs, and CO_2 emissions, external temperature, external humidity and wind speed. The sensors were mounted on backpacks carried along the 5 km corridor on foot and by motorcycle, with intermittent stops at Lubowa, Zana roundabout, Bata-Bata, and Freedom City. Monitoring spanned seven days, including five 12-hour sessions (07:00–19:00) and two 16-hour sessions (07:00–22:00), with four road traverses daily. Devices used portable power banks, transmitting data to AirQo's cloud platform for machine learning based calibration under technician oversight to ensure continuous and accurate data collection.

Data Analysis

Data entry and preliminary analysis were conducted using Microsoft Excel, while advanced analyses were performed using machine learning techniques in Scikit-Learn library in python 3.7. The dataset included traffic and air quality variables such as $PM_{2.5}$, TVOCs, CO_2, wind speed, wind acceleration, traffic volume (ADT), and its composition (**Figure 2**). The study employed boxplots to find outliers and they were eliminated or replaced. Pearson correlation coefficients were computed to assess linear relationships between traffic indicators and pollutant concentrations, generated with seaborn and matplotlib for variable selection and pattern detection. Ordinary Least Squares (OLS) regression was applied to quantify and model the effects of wind speed, and ADT on emissions ($PM_{2.5}$, TVOCs, CO_2), with model fit evaluated using R^2, adjusted R^2, and p-values. To capture non-linear interactions, an Extreme Gradient Boosting (XGBoost) model was developed for predicting pollutant concentrations, Model validity was ensured through diagnostic tests for OLS assumptions normality, homoscedasticity, autocorrelation, and multicollinearity while the predictive performance of the XGBoost model was evaluated using cross-validation.

RESULTS

Traffic Volume and Composition

The average daily traffic for Namasuba was 59,812 veh/day and 21,621 veh/day including motorcycles and excluding motorcycles respectively. Motorcycles comprised 64%, saloon cars 14%, and light goods vehicles 11%, while minibuses and larger trucks registered below 7%. At Bata Bata it was 25,011 veh/day and 14,784 veh/day including motorcycles and excluding motorcycles respectively. Along the Zana (Bata-Bata) corridor, motorcycles remained the largest share (40%), trailed by saloon cars (23%) and light goods vehicles (20%), with minibuses at 11% and trucks below 5%. The average daily traffic of 12,909 veh/day and 10,166 veh/day including motorcycles and excluding motorcycles respectively. Lubowa exhibited a higher share of saloon cars (37%) and light goods vehicles (33%), while motorcycles contributed 21% and minibuses and larger vehicles collectively accounted for less than 7%. Across all sites, truck trailers and semi-trailers were negligible, underscoring the dominance of smaller and medium-sized vehicles in the traffic mix.

Correlation Analysis

The results in **Table 1** show temporal variations in air quality, given that the $PM_{2.5}$ concentrations were highest during nighttime (mean = 133.46 μg/m³) compared to daytime (56.00 μg/m³), afternoon (39.32 μg/m³), or evening (22.57 μg/m³). Nighttime also recorded historic $PM_{2.5}$

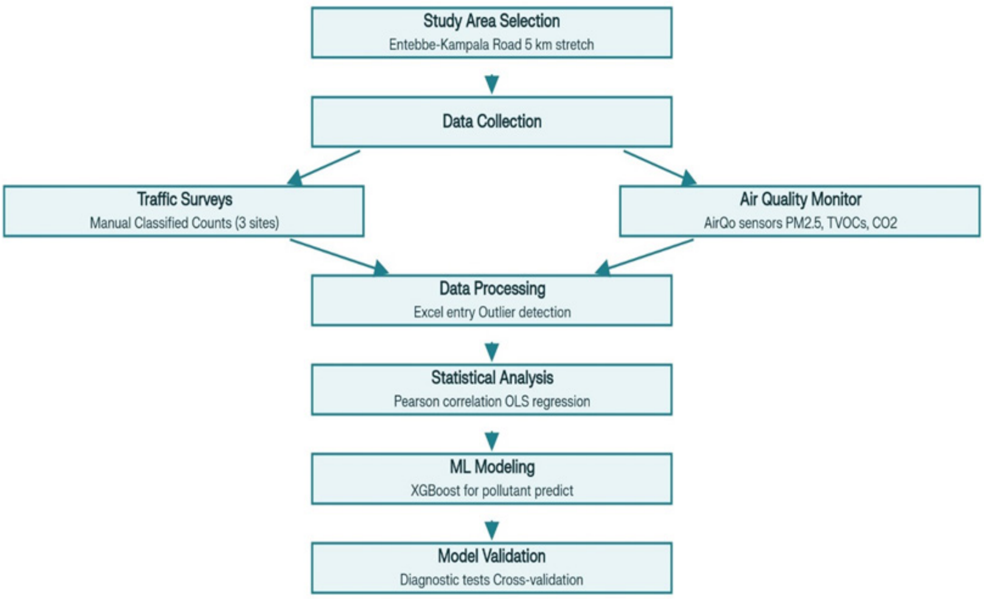

FIGURE 2
Methodology flowchart for data collection and analysis
Source: Author Analysis, 2025

TABLE 1
Concentration of emissions during different periods

Period	Statistics	$PM_{2.5}$ (µg/m³)	TVOC (ppm)	CO_2 (ppm)	Wind Speed (m/s)	Wind Acceleration (m/s²)
Day	Mean	56.00	0.06	462.28	0.17	0.00
	Minimum	47.75	0.02	403.34	0.03	0.00
	Maximum	68.73	0.11	817.82	0.48	0.01
Afternoon	Mean	39.32	0.67	406.27	0.57	0.00
	Minimum	17.11	0.20	402.70	0.03	0.00
	Maximum	59.17	1.83	425.09	8.67	0.04
Evening	Mean	22.57	0.51	404.85	0.59	0.00
	Minimum	12.66	0.11	402.45	0.00	0.00
	Maximum	77.48	1.72	412.10	4.87	0.01
Night	Mean	133.46	1.44	427.55	3.64	0.00
	Minimum	23.00	0.72	403.52	0.00	0.00
	Maximum	863.45	1.96	579.57	10.12	0.02

Source: Author's analysis (2025)

spikes (up to 863.45 µg/m³), most likely due to stable atmospheric conditions and poor dispersion, while values during the day were relatively stable. TVOCs and CO_2 were mostly low across periods, with slightly elevated TVOC values during the afternoon and night (0.67 ppm and 1.44 ppm, respectively). Night also experienced higher wind speed (mean = 3.64 m/s), but without inhibiting pollutant accumulation, suggesting close sources and limited dispersion processes. Overall, findings confirm that air pollution is strongest during night, which requires targeted mitigation activities during this period. Similar findings were observed by (Gupta & Elumalai, 2019) who revealed that traffic and meteorology play a big role in reducing or increasing emissions.

Correlation findings in **Table 2** showed daytime $PM_{2.5}$ were weak and negative correlations with TVOCs (r = –0.20) and CO2 (r = –0.28). This showed that particulate concentrations were less impacted by gaseous pollutants under more active atmospheric mixing conditions. TVOCs, CO_2, and wind speed presented high positive correlations (r = 0.62–0.84), which indicated the presence of traffic-generated combustion and evaporative emissions' influence on the interaction with weather conditions. In the afternoon, $PM_{2.5}$ correlated moderately with wind speed (r = 0.32) and wind acceleration (r = 0.26) and presented a strong positive correlation (r = 0.69) with CO_2 and TVOCs, indicating localized traffic emissions. Night and evening hours showed different patterns, and interactions among pollutants intensified strongly. Evening hours were characterized by strongly correlated $PM_{2.5}$ with TVOCs (r = 0.83), CO_2 (r = 0.59), and wind speed (r = 0.67), which suggests simultaneous accumulation of pollutants during rush hour under relatively calm weather conditions. $PM_{2.5}$ at nighttime had a very significant correlation with CO_2 (r = 0.85), reflecting common sources such as continuous traffic activity and limited atmospheric dispersion during inversion. Wind speed and CO_2 were in a negative correlation (r = –0.45), noting that higher wind speed allowed for dilution of pollutants and calm conditions favoured accumulation. Generally, the results indicate important coupling between meteorology and traffic emissions, during which nighttime and evening hours are the highest risk of pollutant co-concentration (Gupta & Elumalai, 2019).

Correlation analysis results in **Table 3** show that traffic flow is well correlated with air pollution concentrations, with TVOC and CO_2 being perfectly correlated (r = 1.00) and highly correlated with $PM_{2.5}$ as well, proving that these

TABLE 2
Correlation matrix of pollutants by period of day

Period	Statistics	$PM_{2.5}$ (µg/m³)	TVOC (ppm)	CO_2 (ppm)	Wind Speed (m/s)	Wind Acceleration (m/s²)
Day	PM2.5 (µg/m³)	1.00	-0.20	-0.28	-0.11	0.10
	TVOC (ppm)	-0.20	1.00	0.76	0.62	-0.14
	CO_2 (ppm)	-0.28	0.76	1.00	0.84	0.20
	Wind Speed (m/s)	-0.11	0.62	0.84	1.00	0.54
	Wind Acceleration (m/s²)	0.10	-0.14	0.20	0.54	1.00
Afternoon	PM2.5 (µg/m³)	1.00	0.09	-0.26	0.32	0.26
	TVOC (ppm)	0.09	1.00	0.69	0.27	0.16
	CO_2 (ppm)	-0.26	0.69	1.00	-0.09	-0.04
	Wind Speed (m/s)	0.32	0.27	-0.09	1.00	0.84
	Wind Acceleration (m/s²)	0.26	0.16	-0.04	0.84	1.00
Evening	PM2.5 (µg/m³)	1.00	0.83	0.59	0.67	-0.20
	TVOC (ppm)	0.83	1.00	0.64	0.62	-0.04
	CO_2 (ppm)	0.59	0.64	1.00	0.94	0.56
	Wind Speed (m/s)	0.67	0.62	0.94	1.00	0.58
	Wind Acceleration (m/s²)	-0.20	-0.04	0.56	0.58	1.00
Night	PM2.5 (µg/m³)	1.00	-0.29	0.85	-0.17	0.05
	TVOC (ppm)	-0.29	1.00	-0.24	0.20	-0.04
	CO_2 (ppm)	0.85	-0.24	1.00	-0.45	0.03
	Wind Speed (m/s)	-0.17	0.20	-0.45	1.00	0.33
	Wind Acceleration (m/s²)	0.05	-0.04	0.03	0.33	1.00

Source: Author's analysis (2025)

TABLE 3
Correlation between pollutants and Average Daily Traffic (ADT)

	$PM_{2.5}$ (µg/m³)	TVOC (ppm)	CO_2 (ppm)	ADT (veh/day)
$PM_{2.5}$ (ug/m³)	1.00	0.91	0.90	0.94
TVOC (ppm)	0.91	1.00	1.00	0.99
CO_2 (ppm)	0.90	1.00	1.00	0.99
ADT (veh/day)	0.94	0.99	0.99	1.00

Source: Author's analysis (2025)

pollutants are present under the same traffic conditions. Average Daily Traffic (ADT) also had very high correlations with all the pollutants (r = 0.99), revealing traffic density as the prime source of emissions.

Regression Analysis Results for Emissions and Wind Speed

The regression results in **Figure 3** indicate that wind speed has a statistically significant positive correlation with TVOC levels and R^2 of 0.388 indicates that 39% of the variability in TVOC is due to wind speed. The coefficient (0.129, p = 0.013) is that for each 1 m/s rise in wind speed, TVOC levels rise by about 0.129 ppm because of increased dispersion and redistribution of pollutants. Despite the low R^2, the result hints towards wind speed as an active driver of pollutant dynamics, corroborating further the importance of meteorological conditions in managing urban air quality.

The regression in **Figure 4** is highly positive between CO_2 emissions and wind speed and that

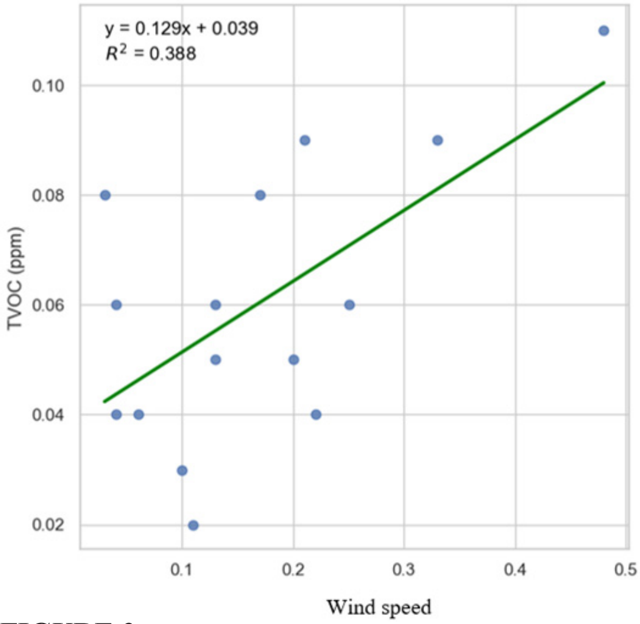

FIGURE 3
Relationship Between TVOC Concentration and Wind Speed
Source: Author Analysis, 2025

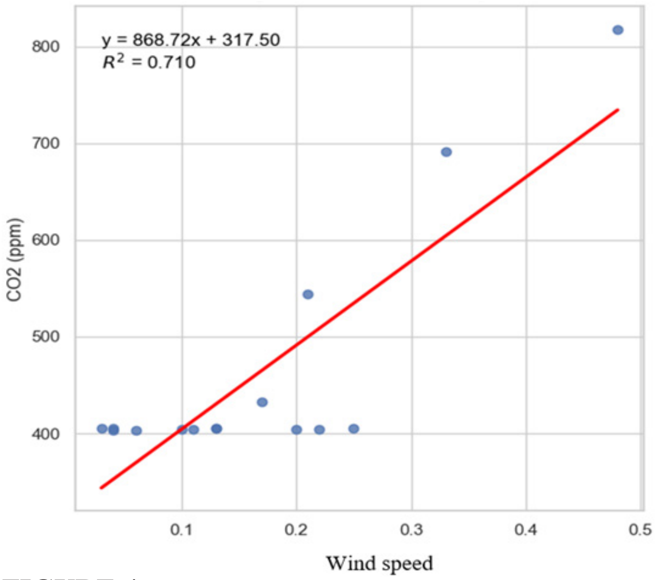

FIGURE 4
Relationship between CO_2 Concentration and Wind Speed
Source: Author Analysis, 2025

71% of variance is explained by wind speed (R^2 = 0.710). The coefficient (868.72, $p < 0.001$) signifies that when the wind speed increases by 1 m/s, CO_2 concentration rises by about 869 ppm, likely due to transport and accumulation from local sources. The intercept value (317.50 ppm) represents background CO_2 levels. The findings highlight wind speed as a significant environmental variable in the urban carbon dynamics.

The regression findings in **Figure 5** depicts that wind speed shows a significant positive relationship with the concentration of $PM_{2.5}$, where wind speed explains 45% of variance (R^2 = 0.449, $p < 0.01$). The coefficient (11.63 μg/m³, p = 0.004) indicates that with each 1 m/s rise in wind speed, concentration of $PM_{2.5}$ rises by about 11.63 μg/m³. This can be induced by wind-driven resuspension of roadside and construction dust or transport from remote areas (**Table 4**).

Regression Results for Emissions and ADT

The ADT and $PM_{2.5}$ concentration regression in **Figure 6** show a very strong positive correlation, with R^2 = 0.8925 affirming that traffic volume explains nearly 89% of the variation in particulate fine air pollution. The ADT coefficient (1.2621, $p < 0.001$) shows that one additional vehicle per day in traffic raises $PM_{2.5}$ levels by approximately 1.26 μg/m³ (**Table 5**). Even though the intercept (2421.97) is speculative, the findings provide credence to the joint contribution of motor vehicle emissions, tyre and brake wear, and road dust resuspension to urban air pollution, confirming the relevance of traffic management and emission control strategies to minimize $PM_{2.5}$ concentrations in congestion-prone corridors.

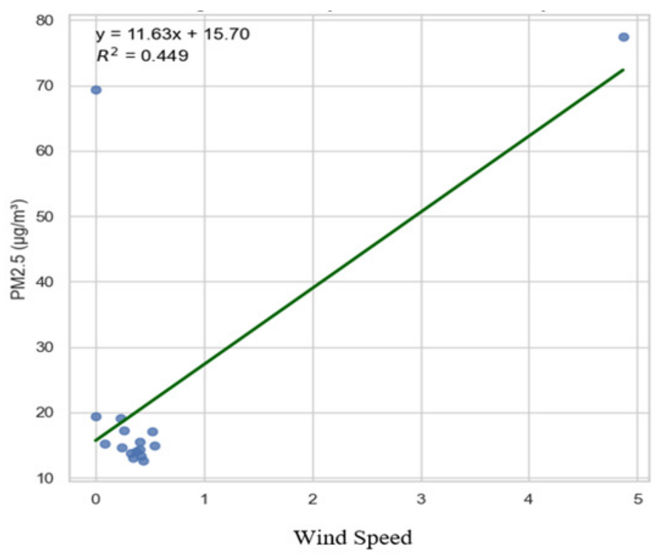

FIGURE 5
Relationship between $PM_{2.5}$ Concentration and Wind Speed
Source: Author Analysis, 2025

TABLE 4
Regression Results of $PM_{2.5}$ Concentration and Average Daily Traffic (ADT)

	Coefficient	Std. Error	t-Statistic	P-Value	95% CI Lower	95% CI Upper
Intercept	2421.9670	703.518	3.443	0.006	854.432	3989.502
ADT	**1.2621**	**0.139**	**9.110**	**0.000**	**0.953**	**1.571**

Source: Author's analysis (2025)

R-squared = 0.8925, Adjusted R-squared = 0.882, Model = OLS (Ordinary Least Squares), F-statistic = 83.00, Prob (F-statistic) = 3.71e-06, Durbin-Watson = 0.379, Kurtosis = 2.131, Skew = -0.384, Jarque-Bera (JB) = 0.673, Prob (JB) = 0.714, Prob (Omnibus) = 0.704

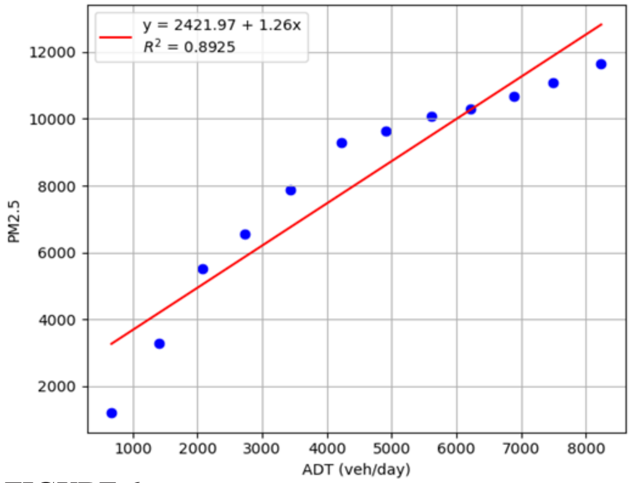

FIGURE 6
Predictive Relationship Between Average Daily Traffic (ADT) and $PM_{2.5}$ Concentration
Source: Author Analysis, 2025

TABLE 5
Regression Results of Total Volatile Organic Compounds (TVOC) and Average Daily Traffic (ADT)

Predictor	Coefficient	Std. Error	t-Statistic	P-Value	95% CI Lower	95% CI Upper
Intercept	-7.3668	2.578	-2.858	0.017	-13.111	-1.623
ADT	0.0135	0.001	26.646	0.000	0.012	0.015

Source: Author's analysis (2025)

R-squared = 0.986, Model = OLS (Ordinary Least Squares), F-statistic = 710.0, Adjusted R-squared = 0.985, Prob (F-statistic) = 1.28e-10, Durbin-Watson = 0.570, Kurtosis = 1.679, Skew = -0.409, Jarque-Bera test (p = 0.547), Prob (Omnibus) = 0.278, Jarque-Bera (JB) = 1.207.

Regression between Average Daily Traffic (ADT) and Total Volatile Organic Compounds (TVOC) in **Figure 7** shows a very strong positive linear relationship with $R^2 = 0.986$, which means traffic volume accounts for 98.6% of the TVOC variation. ADT coefficient (0.0135, $p < 0.001$) indicates that an additional vehicle contributes 0.0135 ppm to TVOC concentration, confirming traffic as

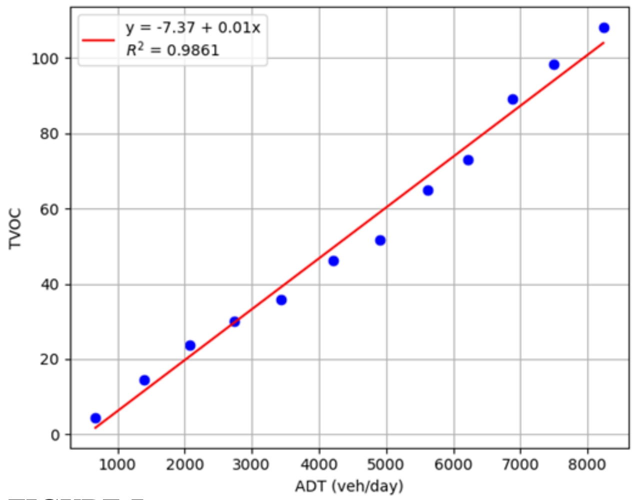

FIGURE 7
Predictive Relationship Between Average Daily Traffic (ADT) and TVOC Concentration
Source: Author Analysis, 2025

a major source of VOC emissions. The model is statistically significant, with ($p < 0.0001$) and very high t-statistic for ADT (26.646). As shown in **Table 6** such outcomes underscore the inherent role of traffic-generated vehicular traffic in VOC pollution as well as the importance of factoring traffic emissions in urban air quality management (Yang et al., 2023).

The ADT regression on CO_2 concentration in **Figure 8** is extremely positive with an R^2 of 0.9825, as approximately 98.25% of variability in CO_2 is explained by traffic volume. The ADT coefficient (11.1294, $p < 0.001$) reveals that an addition of one vehicle increases CO_2 concentration by approximately 11.13 ppm. Although the p-value (0.865) is not statistically significant, it suggests potential effects from unmeasured confounding variables. The results highlight traffic flow as among the most influential factors behind CO_2 emissions, revealing its central role in controlling urban air quality (Adamidis et al., 2020).

SHAP Analysis

In **Figure 9** SHAP analysis for $PM_{2.5}$, Average Daily Traffic (ADT) has the largest positive impact on emissions, meaning increased traffic volume leads to higher $PM_{2.5}$ levels. Wind speed and acceleration also importantly affect pollutant dispersion. Different vehicle types emit $PM_{2.5}$ at varying rates depending on their speeds, with heavy vehicles notably contributing more.

In **Figure 10** SHAP analysis of TVOCs prediction model, ADT remains the primary factor, but wind speed and acceleration have relatively more influence compared to $PM_{2.5}$, since gaseous pollutants diffuse more easily. Small buses (matatus), light goods vehicles, and motorcycles are significant contributors to TVOC, while heavy trucks have a minor role.

TABLE 6

Regression Results of Carbon Dioxide (CO_2) Concentration and Average Daily Traffic (ADT)

	Coefficient	Std. Error	t-Statistic	P-Value	95% CI Lower	95% CI Upper
Intercept	-414.9674	2385.685	-0.174	0.865	-5730.605	4900.671
ADT	11.1294	0.470	23.690	0.000	10.083	12.176

Source: Author's analysis (2025)

R-squared = 0.9825, Model = OLS (Ordinary Least Squares), F-statistic = 561.2, Adjusted R-squared = 0.981, Prob (F-statistic) = 4.08e-10, Durbin-Watson = 0.449, Kurtosis = 1.499, Skew = -0.108, Jarque-Bera test (p = 0.563), Prob (Omnibus) = 0.156, Jarque-Bera (JB) = 1.150

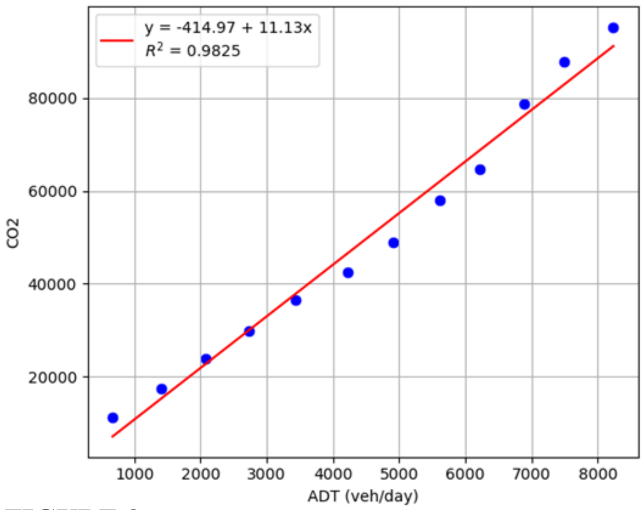

FIGURE 8

Predictive Relationship Between Average Daily Traffic (ADT) and CO_2 Concentration

Source: Author Analysis, 2025

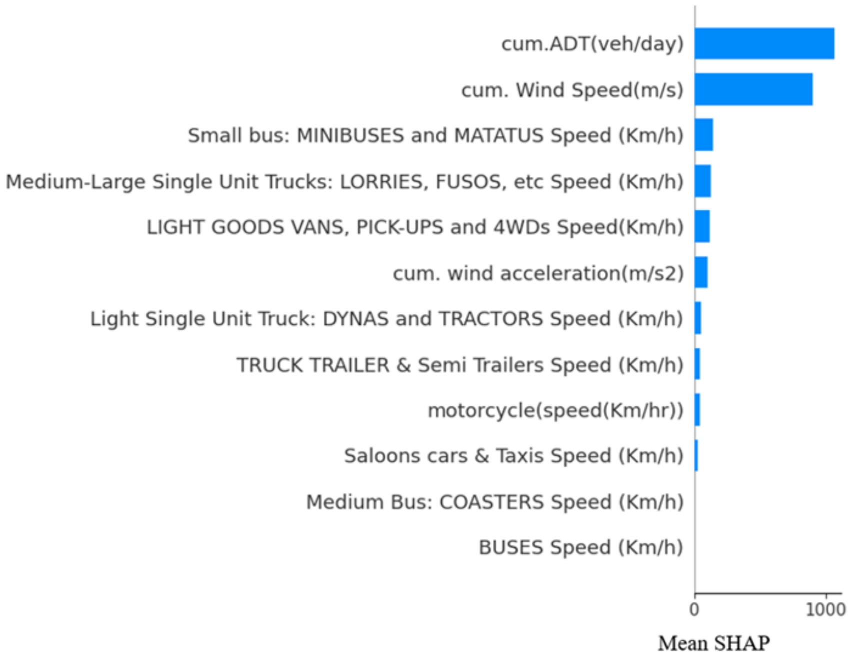

FIGURE 9
SHAP Analysis for $PM_{2.5}$ Prediction Model
Source: Author Analysis, 2025

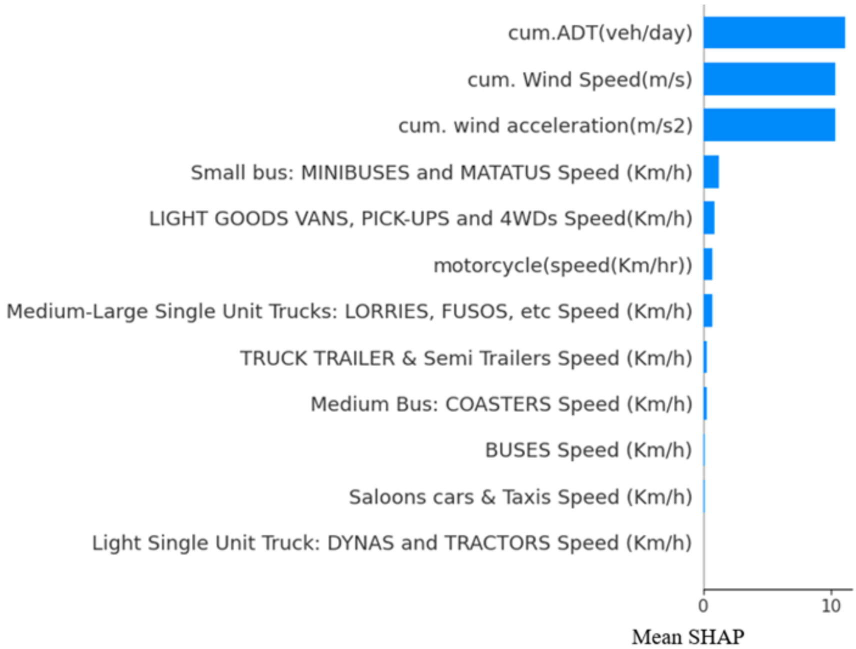

FIGURE 10
SHAP Analysis for TVOC Prediction Model
Source: Author Analysis, 2025

In **Figure 11** SHAP analysis of CO_2 prediction model, while ADT is important, wind factors (speed and acceleration) dominate, reflecting CO_2's nature as a globally mixed greenhouse gas sensitive to dispersion. Heavy vehicles contribute most to CO_2 emissions due to their high fuel consumption, whereas motorcycles, significant for TVOC, contribute less to CO_2.

DISCUSSION

The most significant emissions occurred at points with the highest traffic, like Namasuba, where motorcycles had biggest percentage

FIGURE 11
SHAP Analysis for CO_2 Prediction Model
Source: Author Analysis, 2025

of the traffic composition. Since motorcycles usually use inefficient two-stroke engines, their preponderance in Kampala's transport exacerbates air pollution. This must be in line with previous research in African cities, where old and poorly maintained vehicles are the primary sources of emissions(Carreón-Sierra & Salcido, 2022). Heavy trucks and buses were higher contributors to CO_2 levels because they use more fuel, further bolstering the need for more stringent emissions standards for commercial vehicles.

Elevated wind speeds correlated with high concentrations of $PM_{2.5}$ and TVOC, which may be due to road dust resuspension and pollutant redistribution affecting pollutant redistribution (Atuyambe et al., 2024). In contrast, levels of CO_2 were extremely wind pattern-sensitive, reflecting that atmospheric conditions also play significant roles in controlling the dispersion of greenhouse gases. This concurs with other tropical city studies, where patterns of wind affect hotspots of pollution significantly (WHO, 2006).

Pollution levels also had temporal variations. Maximum emissions happened during morning and evening peak hours with additional traffic jams, while nocturnal pollution was still very high most likely due to temperature inversions trapping pollutants near the surface. This trend is corroborated by findings in other rapidly expanding cities where nighttime generator, biomass, burning, and industrial emissions contribute to vehicular emissions (Atuyambe et al., 2024). Comparable diurnal and nocturnal emission trends have been observed in Nairobi and Kampala (Ghaffarpasand et al., 2024).

The findings of the OLS predictive model considering wind speed scored the highest R^2 value for CO_2 compared to $PM_{2.5}$ and TVOC whereas the predictive model considering ADT scored the highest R2 value for TVOC compared to CO_2 and $PM_{2.5}$. The predictive model considering vehicle speeds produced the highest R^2 value for CO_2 compared to $PM_{2.5}$ and TVOC. These models highlighted a high calibre of performance. Relationships between emissions and traffic, with high R^2 values demonstrated that the model effectively captures how emissions vary with traffic flow. However, comparatively lower R^2 values for wind speed suggested that meteorological factors may introduce variability that could influence model transferability. Therefore, the model may be adopted for applicability in different road sections due to its robustness.

SHAP analysis provided additional insight into the importance of features, confirming that ADT was most critical in the case of $PM_{2.5}$ and TVOC. At the same time, wind conditions were more critical in the case of CO_2. The analysis also found that different types of vehicles account for pollution differently, and, therefore, identifying such targeted policies as phasing out highly emitting motorcycles or improving fuel quality would yield maximum air quality gain.

Overall, the findings confirm that meteorological and traffic variables jointly determine emission intensity, reinforcing the potential of machine learning to support localized mitigation strategies

Study limitations: Data collection was limited to only three survey sites and short monitoring periods which may not capture the spatial and temporal variability of air pollution across the broader urban area. The study focused mainly on traffic emissions and did not consider other pollution sources that might contribute to ambient air quality. Limited data on vehicle fleet details such as age, maintenance and fuel type constrained precise emission factor estimations. The relationship between air quality data and health outcomes were not established which limits policy implications based on direct health impacts for more comprehensive urban air quality management.

CONCLUSION

The aim of this study was to model urban air related traffic emission taking Entebbe-Kampala Road as a case study. It makes significant contribution to the literature by providing empirical data and advanced modeling of traffic-related air pollution in Uganda, an under-researched area. It integrates traffic volume, composition, meteorological conditions, and pollutant measurements using low-cost mobile sensors and machine learning techniques to unravel complex relationships and offer enhanced prediction capabilities. By addressing knowledge gaps in urban air quality monitoring in Sub-Saharan Africa, the rigorous validation and diagnostic tests of statistical models advance understanding and practical management of urban air pollution challenges in developing cities, emphasizing the need for integrated traffic and environmental management strategies. The following conclusions were made in relation to the three objectives respectively;

i. Traffic volume is strongly correlated with increased air pollutant concentrations of $PM_{2.5}$, TVOCs, CO_2, with motorcycles and light vehicles being major contributors along the corridor.
ii. Wind speed significantly influences pollutant dynamics by affecting dispersion and resuspension which explains the pollutant variability. Nighttime pollutant concentrations, especially for $PM_{2.5}$, were considerably higher due to atmospheric stability and reduced dispersion.
iii. SHAP analysis highlights the need for pollutant-specific policies, such as managing traffic volume to reduce $PM_{2.5}$, targeting motorcycle emissions to control TVOCs, enforcing strict fuel efficiency for CO_2, and integrating weather data into urban air quality strategies. These insights confirm the importance of tailored traffic management, specific vehicle emission controls, and consideration of meteorological factors to effectively reduce urban air pollution and protect public health.
iv. The XGBoost model demonstrated superior predictive accuracy, validating its suitability for localized air pollution modeling in data-limited contexts."

RECOMMENDATIONS

To mitigate urban traffic-induced air pollution on the roads in Uganda, several strategic measures can be considered;

Traffic Management and Control

i. The study concluded that increased car speeds were the primary drivers of elevated CO_2 and $PM_{2.5}$ levels. To monitor this, local traffic authorities should impose accurate speed limits, install speed-reducing infrastructures such as speed bumps and rumble strips, and re-engineer the roads to discourage over speeding. Radiant traffic lights and speed cameras would also help maintain constant driving speeds, hence reduce uneven acceleration and emissions peaks.
ii. Governments should invest in intelligent traffic management systems that can maximize the flow of vehicles and mitigate congestion. These involve synchronizing traffic lights that direct vehicles based on current traffic patterns and provide priority

to public transport corridors. Long-term urban transport planning should also be a high priority, with modal shift strategies promoting Non-Motorized Transportation (NMT) modes such as walking, cycling, and public transportation use, thereby reducing dependence on private car travel.

Driver Education

i. Implement public campaigns to educate drivers on eco-driving practices to hard acceleration, idling, and speeding. Fleet managers should be particularly encouraged to install real-time vehicle monitoring systems that display fuel economy and driving behavior. This will enhance and encourage more responsible driving, hence yielding a significant reduction in pollutants.

Policy

i. There must be enforcement of specific nighttime emission control policies. Policies that limit the use of high-emitting cars at night or require them to adhere to stricter emissions regulations would be beneficial.
ii. Encouraging the use of cleaner vehicle options, s*u*ch as Electric Vehicles (EVs), and enabling overnight freight consolidation can also greatly help reduce these emissions.

Air quality monitoring

i. Establishment of permanent roadside monitoring stations will enable authorities to continuously monitor the rate of pollution and assess the effectiveness of mitigation measures applied. Data transparency and public access to emissions reports can facilitate public involvement and enhancement of environmental management in the country.

Research

i. Expand monitoring to more sites and extend the duration to capture both spatial and seasonal variations in pollutant levels.
ii. Integrate other major emission sources, such as industrial activities and domestic fuel use, to better isolate traffic-related contributions.
iii. Long-term studies linking air quality data with health outcomes would provide stronger evidence for targeted policy interventions.

To effectively combat urban traffic induced air pollution along Entebbe-Kampala corridor and similar settings, immediate action on the above-mentioned recommendations will provide measurable improvement in air quality and safeguard vulnerable populations from the harmful effects of traffic-related pollution.

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