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Air pollution ($PM_{2.5}$) and its meteorology predictors in Kampala and Jinja cities, in Uganda†

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Air pollution disproportionately affects African countries, including Uganda, but it is inadequately studied in these settings. The emergence of low-cost sensors offers an opportunity to improve routine air quality monitoring, assess interventions, and track progress. This study aimed to assess the spatiotemporal trends of $PM_{2.5}$ in Kampala and Jinja cities in Uganda, whilst exploring the influence of meteorological parameters on $PM_{2.5}$. Calibrated $PM_{2.5}$ values and meteorological parameters for three years (2020 to 2022) were obtained from 58 local low-cost sensors and 6 weather stations. Hourly averages for $PM_{2.5}$ and meteorological data underwent necessary pre-processing, and various statistical analyses, including descriptive statistics, time series trends, spatial variation, Spearman rank correlation, and multivariate regression, were performed. The multivariate linear regression with a gamma-link function was selected as the model with the best fit. The average annual $PM_{2.5}$ levels in Kampala and Jinja were 41.1 μg m^{-3} (±18.91 μg m^{-3}) and 25.6 μg m^{-3} (±15.5 μg m^{-3}), respectively, significantly exceeding the recommended World Health Organisation annual guideline values of 5 μg m^{-3}. Meteorological parameters exhibited varying degrees of relationships with $PM_{2.5}$ in both cities; multivariate regression indicated that meteorological factors could explain about 18% of the variation of $PM_{2.5}$ in Kampala and 7% in Jinja. Both cities experienced a decrease in $PM_{2.5}$ levels during the COVID-19 pandemic lockdown with Kampala experiencing a 31% reduction (average decrease of 11.2 μg m^{-3}) and Jinja a 17% reduction (average decrease of 3.8 μg m^{-3}). This study provides insights into the air quality challenges faced by a rapidly urbanising city in sub-Saharan Africa, the promise of locally made low-cost sensors, and how meteorology influences local air pollution and lays the foundation for informed decision-making to safeguard public health and promote a sustainable environment. The findings highlight the urgent need for targeted interventions and policy initiatives to address air pollution in Uganda.

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Environmental significance

By highlighting the trends in $PM_{2.5}$ and the effect of meteorological parameters on local air quality (contributing to 18% variation in $PM_{2.5}$ in Kampala and 7% in Jinja), our study provides critical evidence for informed decision-making and developing of context-specific interventions to safeguard public health and the environment in the two cities. The dual-city investigation in our paper provides a broader understanding of the spatial distribution of air pollution ($PM_{2.5}$) across different urban environments which informs formulation of more targeted interventions to the cities. Given the current paucity of air quality data in resource-constrained settings especially African cities, this study demonstrates the opportunities available from utilising locally made low-cost sensors as a practical and cost-effective solution for air quality monitoring.

1 Introduction

Air pollution is the largest environmental risk to public health,[1] causing approximately seven million deaths globally every year.[2] In 2019, air pollution contributed to approximately 1.1 million deaths in Africa, making it the second leading cause of death after malnutrition.[3] Air pollution causes a number of non-communicable diseases (NCDs), including cardiovascular disease, stroke, chronic obstructive pulmonary disease, lung cancer and Alzheimer's,[1,4–8] and has been linked to mental health.[9–11]

Many high-income countries (HICs) have seen reduced ambient air pollution due to control measures over the recent decade.[12,13] Strict emission reduction policies from 2012 to 2020 led to a 54% drop in $PM_{2.5}$ levels in Beijing and a 23% decrease in nitrogen deposition across China.[14,15] Reduction in ambient air pollution has subsequently led to improved health impacts,

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including reduced incidence of asthma, hospital admissions, and premature mortality.[16,17] One critical factor has been the widespread implementation of air quality monitoring, which in turn has increased the evidence on air quality in indoor and outdoor spaces, increased public awareness and advocacy, and paved the way for local interventions such as Low Emission Zones in cities. In Europe and North America, most urban areas have approximately one ambient $PM_{2.5}$ monitor per 100 000–600,000 residents,[18,19] enabling the formulation of robust policies and substantial decreases in $PM_{2.5}$ levels.[20] Within sub-Saharan Africa (SSA), the ratio is just one ground-level monitor per 15.9 million people,[19] despite African cities recording some of the highest air pollution levels worldwide.[12,21]

The prohibitive cost of reference-grade monitors, coupled with significant operating and maintenance costs, has limited the implementation of a dense network of monitors within resource-limited settings, for example, in African cities. However, the recent proliferation of low-cost air quality devices[22,23] presents an opportunity to increase routine monitoring in cities, providing high spatial and temporal resolution measurements at relatively affordable costs.[12,24] Calibrating these low-cost sensors to reference traditional Air Quality Monitoring methods further enhances their accuracy.[25]

Air pollution in Uganda reflects that of many countries across the African continent. Despite experiencing over 30 000 deaths annually associated with air pollution and high outdoor air pollution in urban areas,[12,26] the country lacks the substantive capacity for air quality monitoring and assessment.[27] However, the proliferation of locally made low-cost air sensors, namely AirQo,[23] has increased air quality monitoring in various cities, thus supporting the closing of the gap of the scarcity of air pollution data through established air monitoring networks.

It is worth emphasising that the spatial and temporal concentration of pollutants in outdoor air depends on many factors, including natural, meteorological, and anthropogenic factors.[28] Additionally, meteorological conditions are highly variable across different geographical locations. Thus, monitoring local weather-related patterns is crucial for comprehending air quality spatial and temporal changes/characteristics across different seasons and geographical locations. Several studies have indicated that drastic weather changes contribute to increased exposure to air pollution, exacerbating the adverse health effects caused by polluted air.[1,29,30]

Our study aimed to assess the temporal trends and spatial distribution of $PM_{2.5}$ in Kampala (the capital city of Uganda) and Jinja (a secondary city) using locally made low-cost air quality sensors whilst exploring the influence of meteorological conditions on $PM_{2.5}$ in these settings.

2 Materials and methodology

This study utilised $PM_{2.5}$ and meteorological data collected in Kampala and Jinja, Uganda. The data was collected as part of a broader study applying transdisciplinary research methods to address air pollution as a risk factor for respiratory health in Kampala and Jinja cities. The $PM_{2.5}$ data were obtained from 58 calibrated low-cost sensor devices provided by AirQo between January 2020 and December 2022, while the meteorological data was obtained from 6 weather stations from the Trans-African Hydro-Meteorology Observatory (TAHMO).

2.1 Study settings

Kampala, the capital city of Uganda, is rapidly urbanising. The city was originally designed to accommodate 300 000 residents but has expanded significantly over the past 40 years and now hosts almost two million people.[31] Additionally, the city experiences a substantial influx of commuters during specific periods of the day, which drives the population up to around 4.5 million.[31] Jinja, located approximately 80 km east-northeast of Kampala, is the second largest economy in Uganda and has various industries such as fish processing, sugar manufacturing, beer processing, steel processing industries, *etc.*, established in the city.[32,33]

2.2 Ethical approval

Ethical approval for the broader study was obtained from Mulago Hospital Research Ethics Committee (MHREC) Uganda, Uganda National Council for Science and Technology (UNCST), Uganda and Psychology Research Ethics Committee, University of Cambridge, United Kingdom.

2.3 Data collection

2.3.1 Air pollution data ($PM_{2.5}$).

$PM_{2.5}$ data were collected from fifty (50) AirQo low-cost sensors[34] located across Kampala and eight (8) AirQo low-cost devices installed in Jinja. Each AirQo device uses twin Plantower (PMS 5003) light scattering sensors and transmits averaged measurements every 90 seconds (for static installations) *via* the local Global System for Mobile Communications (GSM) network to a cloud-based platform. The devices measure $PM_{2.5}$ and PM_{10} with an effective range of 0–500 $\mu g\ m^{-3}$, location data (longitude, latitude), internal and external temperature, atmospheric pressure (30–110 kPa), and humidity (0–99%). The raw $PM_{2.5}$ measurements obtained from the AirQo devices were calibrated against measurements from the Beta Attenuation monitor.

The calibrated data was obtained by applying a random forest model, which improved the Root Mean Squared Error (RMSE) and mean squared error (MAE) for $PM_{2.5}$ from 18.58 $\mu g\ m^{-3}$ to 7.22 $\mu g\ m^{-3}$ and 14.60 $\mu g\ m^{-3}$ to 4.60 $\mu g\ m^{-3}$ respectively when compared to another collocated reference monitor readings.[35] The sites where the sensors were installed were selected, taking into consideration various features, including the geographical boundaries at the parish level, population density, household density, waste management practices in a given area, vegetation cover, distance from the road, and availability of electricity, among others.[36] The sensors remained in the various locations (Fig. 1) for the entire period under consideration. It is worth noting that the sensors in Jinja were off from 05.2021 to 09.2021 due to a lack of maintenance and interdistrict travel restrictions (from Kampala to Jinja) due to the COVID-19 lockdown.

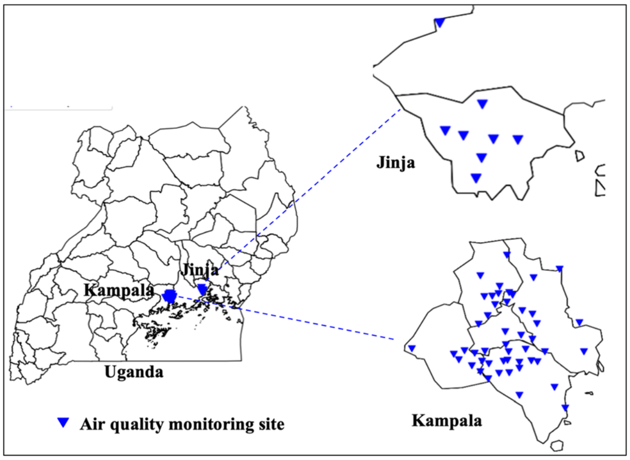

Fig. 1 AirQo low-cost sensor network measuring particulate matter in Kampala and Jinja.

2.3.2 Meteorological data. The meteorological data for the cities under study was sourced from the Trans-African Hydro-Meteorological Observatory (TAHMO).[37] Observed hourly meteorological data on precipitation, relative humidity, temperature, atmospheric pressure, wind speed, and wind gusts were obtained from the stations in Jinja and Kampala.[38,39] Each dataset contained hourly meteorological measurements of atmospheric pressure (kPa), precipitation (mm), temperature average (°C), wind gusts max (m s^{-1}), wind speed (m s^{-1}), and relative humidity. To ensure consistency with the $PM_{2.5}$ data, only data from January 2020 to December 2022 were considered, excluding 2019. Some meteorological parameters, including radiation average (W m^{-1}), temperature min (°C), temperature max (degrees Celsius), and wind direction (°), were excluded from the datasets as they were deemed unnecessary for the analysis.

2.4 Data analysis

Hourly mean $PM_{2.5}$ values were calculated from the averaged measurements from the sensors for three years, spanning from January 2020 to December 2022. Data analysis was conducted using Python version 3.10.11,[40] using various libraries for data analysis and statistical modelling. Descriptive statistics were computed to provide valuable insights into the $PM_{2.5}$ data. These statistics encompassed metrics such as the time trends, annual mean, annual median, standard deviation, standard error, and quartiles for Kampala and Jinja. We examined these measures to understand the central tendency, dispersion, and distributional characteristics of the $PM_{2.5}$ data. In addition, normality tests, including the Shapiro–Wilk test and the Kolmogorov–Smirnov test, were performed to assess the distributional assumption of the $PM_{2.5}$ data. These tests are well-established techniques to evaluate the deviation from normality,[41] ensuring the robustness of subsequent analyses. To illustrate the differences in the observations of the two geographical regions, *i.e.* interpolation, we adopted Watson and Philip's Inverse Distance Weighting (IDW).[42] We considered the IDW as appropriate, given the fact that we had a sufficient number of data samples. To explore multicollinearity among the meteorological parameters, a correlation matrix, and the variance inflation factor (VIF) were computed. The correlation matrix allowed for examining the strength and direction of the relationships between the meteorological parameters, shedding light on potential collinearities.[43] The VIF, on the other hand, served as a measure of multicollinearity, indicating the extent to which the variance of the estimated regression coefficients is inflated due to collinearity.[44] The degree of multicollinearity among the meteorological parameters was assessed by considering both measures.

The Spearman's rank correlation coefficient was employed to investigate the correlation between the meteorological parameters and $PM_{2.5}$. Unlike the Pearson correlation coefficient, Spearman's rank correlation captures monotonic relationships, making it suitable for analysing data that may not adhere to linear associations.[43] By utilising this non-parametric measure, a comprehensive understanding of the relationships between the meteorological parameters and $PM_{2.5}$ was attained without making unsubstantiated assumptions.

Multivariate regression models were employed to investigate the relationship between meteorological parameters and $PM_{2.5}$ levels in Kampala and Jinja. We also conducted an in-depth analysis of collinearity among the meteorological parameters to assess multicollinearity. Three different models were employed to evaluate the best fit comprehensively. The first model was a Multivariate Linear Regression (MLR), which included precipitation, relative humidity, average temperature, and wind speed as independent variables. The performance of each model was assessed using two key metrics: the coefficient of determination (R-squared) and the Akaike Information Criterion (AIC).

A modified version of the MLR model was introduced to further explore the relationship, incorporating a log transformation of the target variable ($PM_{2.5}$). This adjustment addressed potential nonlinearity in the relationship between meteorological parameters and $PM_{2.5}$ concentration. A Generalized Linear Model (GLM) with a Gamma distribution and a log link function was explored to account for potential heteroscedasticity or non-normality in the data.

3 Results

3.1 General descriptive analysis

Table 1 presents the descriptive statistics, including the mean and median $PM_{2.5}$ values for each city and the recommended WHO level. The annual average $PM_{2.5}$ concentration in Kampala for the study period was 41.1 μg m^{-3}, with a standard deviation of 18.9 μg m^{-3}. In Jinja, the annual average $PM_{2.5}$ concentration was 25.6 μg m^{-3}, with a 15.5 μg m^{-3} standard deviation. These statistics indicate that $PM_{2.5}$ levels in both cities exhibit significant variability over time.

Table 2 presents the descriptive statistics, including the mean and median values for meteorological parameters for each city. The annual averages for Atmospheric pressure, precipitation, relative humidity, temperature in Kampala and Jinja were comparable (Table 2). However, wind gusts and wind speed were dissimilar with Jinja having more wind gusts and wind speed than Kampala over the study period as shown in Table 2.

Table 1 $PM_{2.5}$ seasonal average concentrations for Kampala and Jinja from 2020 to 2022

		2020	2021	2022
City	Season	Mean $PM_{2.5}$ (±SD) μg m^{-3}	Mean $PM_{2.5}$ (±SD) μg m^{-3}	Mean $PM_{2.5}$ (±SD) μg m^{-3}
Kampala	1st dry season	46.3(±22.5)	53.7(±26.5)	48.5(±19.9)
	1st rainy season	27.3(±12.6)	37.8(±15.5)	34.6(±15.4)
	2nd dry season	43.5(±16.2)	47.4(±15.6)	41.9(±15.8)
	2nd rainy season	35.2(±15.5)	40.5(±16.7)	36.4(±13.4)
Jinja	1st dry season	30.2(±18.7)	27.1(±14.5)	31.7(±17.5)
	1st rainy season	18.7(±9.6)	23.5(±7.2)	19.8(±11.7)
	2nd dry season	28.7(±12.5)	26.8(±6.3)	26.4(±18.2)
	2nd rainy season	24.1(±8.5)	25.3(±13.3)	24.9(±14.8)

Table 2 Descriptive statistics for meteorological parameters in Jinja and Kampala[a]

Jinja (Kampala)						
	Atmospheric pressure (kPa)	Precipitation (mm)	Relative humidity	Temperature (°C)	Wind gusts (m s^{-1})	Wind speed (m s^{-1})
Mean	88.4 (87.7)	0.1 (0.1)	0.8 (0.80)	22.2 (22.0)	4.7 (2.2)	3.0 (0.6)
SD	0.2 (0.2)	1.0 (1.2)	0.1 (0.1)	3.1 (2.6)	1.8 (1.1)	1.1 (0.3)
Min	87.5 (87.1)	0.0 (0.0)	0.3 (0.3)	15.2 (15.7)	0.8 (0.2)	0.20 (0.1)
25%	88.3 (87.6)	0.0 (0.0)	0.7 (0.7)	19.6 (20.1)	3.5 (1.3)	2.3 (0.4)
Median	88.4 (87.6)	0.0 (0.0)	0.8 (0.8)	21.6 (22.1)	4.3 (2.2)	2.9 (0.6)
75%	88.5 (87.8)	0.0 (0.0)	0.8 (0.9)	24.8 (23.5)	5.6 (2.8)	3.6 (0.8)
Max	89.7 (88.3)	36.9 (61.7)	0.1 (1.0)	32.2 (31.2)	36.8 (11.1)	19.5 (2.3)

[a] SD = standard deviation; Min = minimum; Max = maximum.

3.2 Time series trends in $PM_{2.5}$ levels in Kampala and Jinja and comparison with WHO recommended level

Kampala exhibited a higher daily PM2.5 concentration compared to Jinja (Fig. 2), with the highest daily PM2.5 concentration of approximately 100 μg m^{-3} recorded in March 2021 in Kampala. The highest daily $PM_{2.5}$ concentration in Jinja was approximately 80 μg m^{-3}, observed in January 2022. The daily ambient $PM_{2.5}$ concentration in Kampala reached its lowest level during April–May 2020, which corresponds to the COVID-19 lockdown period in Uganda. However, even during this period, the $PM_{2.5}$ concentration in Kampala exceeded the WHO-recommended daily $PM_{2.5}$ concentrations of 15 μg m^{-3}.

In contrast, the daily averages in Jinja remained significantly lower than in Kampala, and during the COVID-19 lockdown, the daily ambient $PM_{2.5}$ concentration in Jinja remained well below the WHO-recommended level. Jinja met the recommended daily WHO requirement on a few occasions ($n = 7\%$), such as in January 2020, January and May 2021, and January and May 2022. However, the period when the WHO recommended level was not met exceeded the periods when it was attained in Jinja.

The assessment of $PM_{2.5}$ levels in Kampala and Jinja unveiled distinct concentration patterns, with Kampala consistently showing higher and more prominent peaks than Jinja. Notably, both cities consistently surpassed the daily WHO-recommended $PM_{2.5}$ limit. Jinja exceeded this limit on approximately 93% of the days studied, while Kampala surpassed it every day without exception.

The 30 day moving average line revealed six distinct peaks in the time series for both cities (ESI Fig. SF4†). The first peak occurred around February 2020, followed by August 2020, February 2021, August 2021, and February and August 2022. These peaks correspond to the period of Uganda's first and second dry seasons. The peaks in Kampala were more pronounced than in Jinja. Uganda generally experiences tropical weather as a result of its equatorial position. Average temperatures throughout the year range between 20 °C and 30 °C. The country typically experiences two rainy seasons (March to May and September to November), often bringing consistent rainfall and two Dry Seasons (June to August and December to February). Kampala and Jinja experience significant rainfall during the rainy seasons due to their proximity to Lake Victoria.

3.3 Diurnal variation and weekly patterns of $PM_{2.5}$ levels in Kampala and Jinja

Both cities exhibit distinct peaks in the early morning hours (04:00–05:00) and the evening hours (17:00–18:00), indicating a bimodal pattern of $PM_{2.5}$ concentration (Fig. 3). Additionally, there is a depression observed between the hours of 07:00–14:00. Although both cities share a similar pattern with twin peaks, the $PM_{2.5}$ values in Kampala are significantly higher compared to Jinja. The peak values in Kampala reached approximately 55 μg m^{-3}, whereas the peaks in Jinja remain below 40 μg m^{-3}.

Surprisingly, no discernible differences regarding average $PM_{2.5}$ by day of the week were observed between weekdays and weekends in both cities (ESI Fig. SF6†). Despite the clear variation by hour of the day, differences between days of the week were not evident.

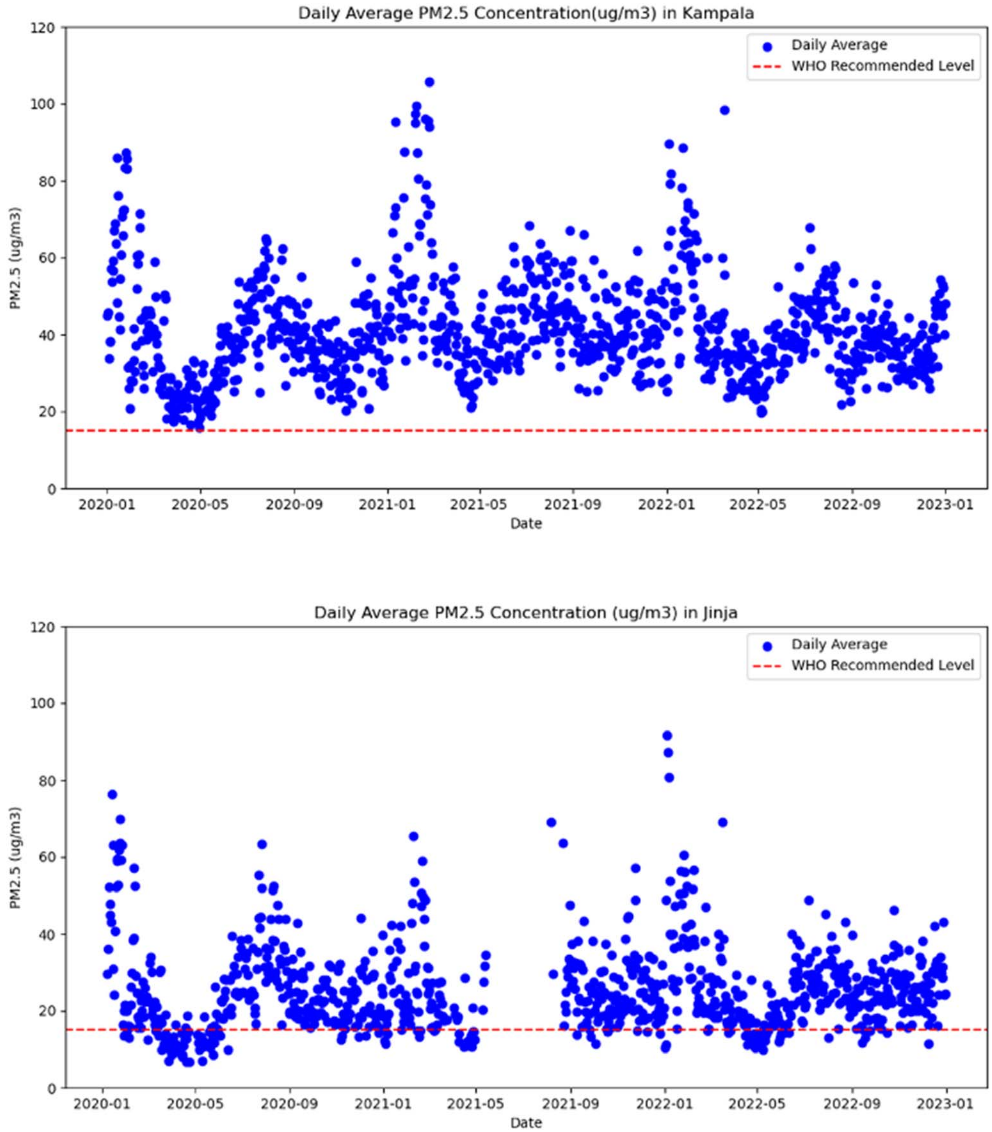

Fig. 2 Daily average $PM_{2.5}$ concentration and WHO daily recommended level in Kampala and Jinja from 2020 to 2022.

Consistent with previous figures, both cities exhibit similar trends in the weekly variation of $PM_{2.5}$ levels throughout the 156 weeks of the study period, with Kampala displaying higher $PM_{2.5}$ levels than Jinja.

3.4 Correlation analysis

Spearman rank correlation analysis was performed to investigate the relationship between hourly meteorological parameters and hourly $PM_{2.5}$ levels in Kampala and Jinja as shown in Table 3. In Kampala, significant correlation included a weak negative correlation between $PM_{2.5}$ and precipitation, as well as temperature and $PM_{2.5}$. Relative humidity showed a weak positive correlation with $PM_{2.5}$. Both wind speed and wind gusts exhibited weak negative correlations with $PM_{2.5}$. However, atmospheric pressure did not show any significant correlation to $PM_{2.5}$ in Kampala.

In Jinja, the correlation analysis revealed similar trends. There was a significant weak negative correlation between $PM_{2.5}$ and precipitation, as well as temperature and $PM_{2.5}$. Like in Kampala, relative humidity showed a weak positive correlation with $PM_{2.5}$. Surprisingly, atmospheric pressure in Jinja showed a significantly weak positive relationship, contrary to its negative and insignificant correlation in Kampala. Wind speed demonstrated a weak positive correlation, while wind gusts exhibited a weak negative correlation, deviating noticeably from the close values observed in Kampala.

An in-depth analysis of collinearity among the meteorological parameters revealed a strong multicollinearity issue between wind gusts and wind speed (ESI file SF6†). Additionally, no significant correlation was found between atmospheric pressure and PM2.5 levels. Wind gusts and atmospheric pressure were, therefore, excluded from the subsequent multivariate regression analyses.

3.5 Multivariate regression models

For Kampala, the MLR model yielded an R-squared value of 0.169, indicating that the included meteorological parameters

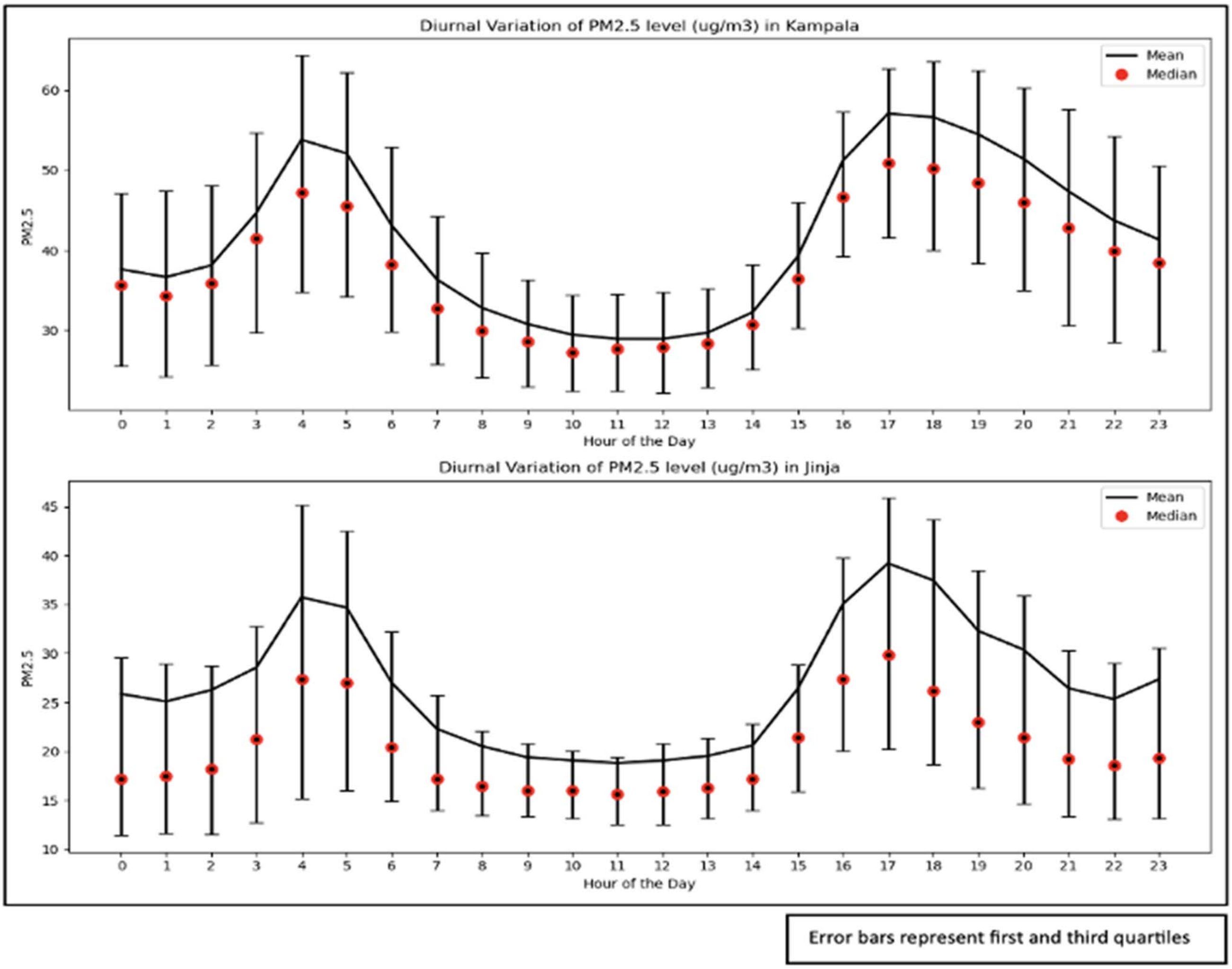

Fig. 3 Diurnal variation of $PM_{2.5}$ ($\mu g\ m^{-3}$) in Kampala and Jinja.

Table 3 Spearman rank correlation between meteorological parameters and $PM_{2.5}$ levels in Kampala and Jinja[a]

	Meteorological parameters correlation with $PM_{2.5}$ by city					
City	Precipitation	RH	Temp	Atm pressure	Wind speed	Wind gusts
Kampala	−0.027*	0.071*	−0.208*	−0.005	−0.336*	−0.388*
Jinja	−0.021*	0.096*	−0.176*	0.026*	0.060*	−0.110*

[a] *$P < 0.05$; RH = relative humidity; Temp = temperature; Atm = atmospheric.

could explain approximately 16.9% of the variance in $PM_{2.5}$ levels. The corresponding AIC was 2.244×10^5, suggesting a moderate fit for the model. In Jinja, the MLR model resulted in an R-squared value of 0.064, indicating that around 6.4% of the variance in $PM_{2.5}$ levels could be explained by the considered meteorological factors. The AIC for the Jinja model was 2.111×10^5, suggesting a similar fit to the Kampala model.

In Kampala, the MLR model with the log-transformed target variable exhibited an improved R-squared value of 0.177, indicating that the included meteorological factors could explain approximately 17.7% of the variance in the log-transformed $PM_{2.5}$ levels. The corresponding AIC was 2.654×10^4, suggesting a better fit compared to the original MLR model. Similarly, in Jinja, the MLR model with the log-transformed target variable demonstrated an enhanced R-squared value of 0.072, suggesting that around 7.2% of the variance in the log-transformed $PM_{2.5}$ levels could be explained. The AIC for this model was 3.331×10^4, indicating a better fit compared to the MLR model without the log transformation.

The GLM results for Kampala exhibited a pseudo-R-squared value of 0.183, indicating that the included meteorological factors could explain approximately 18.3% of the variance in

$PM_{2.5}$ levels. The corresponding AIC was calculated as 2.175×10^5, suggesting that the MLR model with the log-transformed target variable provided a better fit. For Jinja, the pseudo-R-squared value was 0.069, suggesting that the model could explain only approximately 7% of the variance in $PM_{2.5}$ levels. However, the unexpected negative AIC for Jinja's GLM model indicated potential issues with the model estimation.

The MLR model with the log-transformed target variable exhibited the best fit in both cities, explaining the highest proportion of variance. The full result of the Regression models is included in the ESI files.†

4 Discussion

4.1 Spatiotemporal variation in $PM_{2.5}$ across Jinja and Kampala

Study findings reveal significant temporal and spatial variations in $PM_{2.5}$ levels between Kampala and Jinja. As observed, Kampala, a more urban and densely populated city, experiences higher $PM_{2.5}$ levels than Jinja. These results align with previous research conducted in Africa[45–47] and emphasise the disparities in air pollution burdens between capital cities and secondary cities. The spatial distribution analysis confirmed that Kampala had elevated $PM_{2.5}$ concentrations. This is likely due to Kampala having more areas with higher population density, such as the central business district and major traffic intersections. These areas are usually characterised by increased vehicular emissions and industrial activities, contributing to the pollution burden. Certain hotspots near industrial zones or specific pollution sources may also have higher concentrations. In contrast, Jinja demonstrates relatively lower $PM_{2.5}$ levels. This can be attributed to factors such as lower population density and fewer industrial activities.

The annual $PM_{2.5}$ levels in Kampala and Jinja far exceed the WHO recommended annual level of 5 $\mu g\ m^{-3}$.[48] Jinja's annual ambient $PM_{2.5}$ levels were approximately five times higher than the recommended level, while Kampala's were about eight times higher. Furthermore, the 24 hour averages for both cities consistently surpass the recommended daily level of 15 $\mu g\ m^{-3}$ (ref. 48) throughout the three-year study period. $PM_{2.5}$ levels in Kampala were particularly consistently high, with only a brief period during the COVID-19 lockdown where it met the daily recommended level. On the other hand, Jinja remained below the recommended level during the March to May 2020 period but mostly remained above it throughout the study duration. In addition to the recommended $PM_{2.5}$ level, WHO sets interim annual and daily targets to support incremental milestones for regions and countries struggling with high air pollution.[48,49] The annual targets include levels of 35 $\mu g\ m^{-3}$, 25 $\mu g\ m^{-3}$, 15 $\mu g\ m^{-3}$, and 10 $\mu g\ m^{-3}$ and daily interim targets of 75 $\mu g\ m^{-3}$, 50 $\mu g\ m^{-3}$, 37.5 $\mu g\ m^{-3}$ and 25 $\mu g\ m^{-3}$.[48] Based on the study results, both cities have a long way to go in achieving these targets and ultimately reaching the recommended annual and daily $PM_{2.5}$ levels. It is crucial to recognize that there is no safe level of $PM_{2.5}$,[50] and exposure to high levels of this pollutant has dire implications for health.

The diurnal variation analysis reveals a similar pattern in the 24 hour average of $PM_{2.5}$ in both cities, characterized by twin peaks in the early morning and evening hours. This bimodal pattern corresponds to the morning and evening "rush hours" associated with increased human activities, including domestic, commercial, and transportation-related activities.[45] Similar diurnal variations in pollutant concentrations have been reported in other studies.[24,45,47,51,52] Notably, $PM_{2.5}$ levels are generally higher at night and early morning than in the afternoon, which can be attributed to the rising and falling air temperature and changes in the planetary boundary layer (PBL).[53] The PBL, the lowest layer of the troposphere significantly affected by the earth's surface, plays a role in dispersing $PM_{2.5}$. As the PBL height rises, $PM_{2.5}$ is dispersed at a potentially higher volume, whereas a decrease in the PBL height compresses $PM_{2.5}$ into a smaller volume.[53] It is worth mentioning that the observed diurnal variation is more evident in LMICs compared to HICs.[51]

Contrary to diurnal variation, no significant variation is observed between weekdays and weekends in both cities, consistent with findings from other studies in sub-Saharan Africa.[46,47,54] This suggests that the factors influencing $PM_{2.5}$ levels are not strongly associated with the day of the week but are more closely tied to daily human activities and environmental conditions.

At the weekly level, both cities exhibit similar trends in $PM_{2.5}$ variations throughout the study period, indicating a discernible pattern. These consistent patterns suggest the presence of underlying factors contributing to $PM_{2.5}$ levels in both cities. Investigating these factors and their implications for air quality management is essential for developing effective strategies to reduce pollution and protect public health.

Moreover, seasonal variations are observed in $PM_{2.5}$ levels in both cities, with lower levels during the rainy seasons of March–May and September–November compared to the dry seasons of December–February and June–August. The higher $PM_{2.5}$ levels during the dry seasons may be attributed to the absence of rain and the prevalence of higher wind speeds and gusty winds, which can transport $PM_{2.5}$ particles. This phenomenon has also been reported in other studies conducted in sub-Saharan Africa.[45–47] The dry seasons with higher $PM_{2.5}$ concentrations can be influenced by factors such as dust particles from the Saharan desert and local anthropogenic emissions.[55] In contrast, the rainy seasons exhibit lower $PM_{2.5}$ levels due to the direct effect of rain in washing out pollutants from the atmosphere.[56,57] These seasonal variations highlight the dynamic nature of air pollution and the need for targeted interventions that consider specific seasonal factors.

4.1.1 Influence of meteorological factors on air pollution. The influence of meteorological factors on air pollution is crucial to understanding spatiotemporal variations in air quality, including $PM_{2.5}$. These parameters influence the conglomeration and diffusion of air pollutants.[58] This study examined various meteorological factors for their correlations with $PM_{2.5}$ concentrations, shedding light on their significant role in air quality management.

Temperature exhibited a negative correlation with $PM_{2.5}$ in Kampala, indicating that higher temperatures were associated with lower $PM_{2.5}$ levels. This observation aligns with the diurnal trends previously discussed, where $PM_{2.5}$ levels were generally higher during the night and early morning when temperatures were lower. Precipitation also demonstrated a negative correlation, suggesting that rainfall contributed to reduced $PM_{2.5}$ concentrations, potentially due to the removal of pollutants from the atmosphere. Conversely, relative humidity exhibited a positive correlation, implying that higher humidity levels were associated with higher $PM_{2.5}$ levels. This relationship may be attributed to the ability of water vapour to absorb certain pollutants and facilitate their dispersion. These findings corroborate with studies conducted in other locations, such as Japan,[59] Ghana,[60] and India,[61] where temperature, precipitation and relative humidity were found to have significant impacts on $PM_{2.5}$ concentrations.

However, the improved air quality during rainy seasons does not necessarily indicate a resolution of the pollution sources. Rainfall can dissolve gaseous pollutants, like sulphur dioxide, resulting in the formation of acid rain, which can damage materials and vegetation.[1,62]

The study further explored the impact of wind speed and wind gusts on $PM_{2.5}$ concentrations. In Kampala, wind speed showed a positive correlation, indicating that higher wind speeds were associated with elevated $PM_{2.5}$ levels. This finding suggests that stronger winds may disperse pollutants less effectively, leading to their accumulation in the atmosphere. In contrast, Jinja exhibited a negative correlation between $PM_{2.5}$ concentrations and wind gusts, suggesting that stronger gusts were associated with lower $PM_{2.5}$ levels. This phenomenon could be attributed to the enhanced dispersion of pollutants under stronger gusty winds. These findings highlight the complex relationship between meteorological factors and $PM_{2.5}$ concentrations, varying depending on the location and prevailing atmospheric conditions. Yang *et al.*, in their study on the relationship between $PM_{2.5}$ and meteorological parameters in China, also noted that the correlations of $PM_{2.5}$ with meteorological conditions vary within cities and regions even in the same country.[63]

Studies in other regions have also explored the association between meteorological parameters and PM concentrations. For example, research conducted in Auckland, New Zealand, found a negative correlation between temperature and PM_{10} concentrations over a diurnal period, while relative humidity showed a positive correlation with PM_{10} concentrations up to a certain threshold.[64] Similarly, in İzmir, Türkiye, relative humidity was identified as the most influential factor affecting PM_{10} concentrations in urban and rural environments.[65]

However, it is essential to recognise that meteorological factors alone cannot fully explain the variations in $PM_{2.5}$ concentrations. In the multivariate regression analysis conducted in this study, meteorological factors accounted for approximately 18% of the variation in $PM_{2.5}$ in Kampala and about 7% in Jinja. A study by Tai *et al.* documented that meteorological parameters could explain up to 50% variation in $PM_{2.5}$.[58] A similar study in Bangladesh highlighted that meteorological factors could be responsible for up to 39% of the variability observed in $PM_{2.5}$, especially on high pollution days.[66] This indicates that other factors, such as emissions from different sources (*e.g.*, industrial activities, vehicular emissions, biomass burning), local pollution sources, and human activities, also play significant roles in determining $PM_{2.5}$ levels.

4.1.2 Impact of COVID-19 lockdown on air pollution. The outbreak of the COVID-19 pandemic led to unprecedented global lockdown measures, profoundly affecting various aspects of human life. One of the notable consequences was the impact on air pollution levels, including the concentration of fine particulate matter ($PM_{2.5}$). The present study revealed that $PM_{2.5}$ levels decreased during the COVID-19 lockdown period compared to pre-lockdown levels. However, even during the lockdown, $PM_{2.5}$ concentrations remained above the recommended WHO level in Kampala and just below it in Jinja. These findings are consistent with similar studies conducted in Uganda and other parts of the world. For instance, Galiwango *et al.* conducted a study on air pollution and mobility patterns in Kampala and Wakiso cities in Uganda, revealing a notable decrease of 40–50% in the mean concentration of $PM_{2.5}$ in both cities during the lockdown.[67] Furthermore, a study on 16 Indian cities showed a 30–50% reduction in air pollutants during the lockdown period.[68] Similar outcomes were observed in China,[69] Europe and North America.[70]

However, it is important to recognize that this improvement in air quality was temporary, as the pollution levels swiftly returned to their usual levels once the lockdown restrictions were lifted, as observed in this study and others.[70–72] This underscores the dominant role of human activities, particularly transportation, in influencing air pollution levels.

In light of these findings, it becomes evident that implementing effective long-term environmental policies can lead to significant air quality improvements at relatively lower long-term economic and social costs. To achieve this, there is a need for a strategic focus on designing cities better, regulating motorised transport, and promoting walking and other sustainable transportation alternatives.

This need for action is particularly critical in Uganda and other African countries, where megacities are projected to reach thirteen by 2100.[3] Embracing this opportunity to incorporate these measures into the development of these cities can pave the way for cleaner, healthier, and more sustainable urban living.

4.2 Role of low-cost sensors in closing air quality data gap

Low-cost sensors have emerged as pivotal components[12] and are vital in closing the air quality data gap in several African countries, including Uganda. This will subsequently play a crucial role in providing comprehensive data on exposure levels and related health impacts. The affordability and accessibility of low-cost sensors render them particularly suitable for resource-constrained regions like Africa, where establishing comprehensive air quality monitoring networks can be financially challenging. The availability of localised air pollution data will provide evidence for informed decision-making and targeted interventions to mitigate the adverse health impacts of air pollution. This will establish the foundation for long-term air quality monitoring and management strategies, promoting sustainable environmental practices.[73] Besides their technical advantages, deploying low-cost sensors will likely initiate broader public discourse on air pollution.

4.3 Strengths and limitations

4.3.1 Strengths. In response to the paucity of air quality data in resource-constrained settings, this study demonstrates the opportunities available from utilising affordable and accessible low-cost sensors as a practical and cost-effective solution for air quality monitoring in resource-constrained settings. This approach highlights the potential for wider implementation of low-cost sensors to enhance air pollution data availability and inform targeted interventions in LMICs, where financial constraints may hinder the establishment of comprehensive air quality monitoring networks.

Another significant strength of this study lies in its analysis of data from two distinct locations, namely Kampala and Jinja. This dual-city investigation provided a broader understanding of the spatial distribution of $PM_{2.5}$ concentrations and how they vary across different urban environments. Consequently, the findings shed light on potential local factors contributing to air pollution levels, enabling more targeted interventions and policy recommendations tailored to specific cities.

Furthermore, utilising hourly data instead of daily averages achieved a more in-depth analysis of the association between air pollution and meteorological conditions. The finer temporal resolution offered by hourly data allowed for examining short-term fluctuations in $PM_{2.5}$ concentrations, enhancing the precision of the study's findings and contributing to a deeper understanding of air pollution dynamics.

By utilising ground-level air quality sensors the study achieved a more accurate estimation of hourly $PM_{2.5}$ concentrations, avoiding biases introduced by cloud cover that often compromise the utilisation of satellite-generated estimates.[74]

The study's use of three different models to understand the relationship between $PM_{2.5}$ and meteorological factors is a significant methodological strength. By employing multiple models and selecting the one that best fits the data, the research ensures robustness in the analysis and enhances the reliability of the conclusions drawn.

By highlighting the trends in $PM_{2.5}$ and the effect of meteorological parameters in Uganda, this research lays the groundwork for informed decision-making and targeted interventions to safeguard public health and the environment.

4.3.2 Limitations. Missing data, particularly in Jinja, could have introduced biases and compromised the overall accuracy of the findings for this specific location. While MICE is a robust way of filling in missing data, the absence of neighbouring data in some parts of the data could have led MICE to resort to filling with the mean of the dataset, which may not accurately represent the true values of the missing data.

Low-cost air quality sensors also pose a number of challenges and there is generally a trade-off between price, size, and power consumption and accuracy and precision of measurements.[75,76] Previous research on low-cost PM sensors has demonstrated that these devices may underestimate or overestimate $PM_{2.5}$ concentrations.[77,78] However, calibrating the raw data against a reference monitor, the calibration process aims to minimise the inherent errors and biases associated with the low-cost sensors.

Finally, the study recognized seasonal variations in $PM_{2.5}$ levels, but it did not explore the impact of seasonal variation on the relationship between PM2.5 and meteorological parameters. Investigating how meteorological parameters influence pollutant concentrations across different seasons could provide valuable insights for designing targeted interventions and policies.

5 Conclusion

Our study sheds light on the significant public health challenge of air pollution in rapidly urbanising cities in Africa, with a particular focus on Kampala and Jinja, Uganda. Calibrated low-cost air quality sensors provided valuable insights into the spatiotemporal variation in $PM_{2.5}$ concentration in the two cities over three years. The findings revealed alarmingly high $PM_{2.5}$ in both cities, far exceeding the recommended levels set by the WHO, accentuating the urgent need for immediate attention and action.

The diurnal variation analysis highlighted the influence of human activities on air pollution, with distinct patterns of twin peaks observed during morning and evening hours. Meteorological factors were found to play a role in $PM_{2.5}$ variation, but it was evident that other contributing factors require consideration for a comprehensive understanding. The COVID-19 lockdown temporarily reduced $PM_{2.5}$ levels in both cities, emphasising the influence of human activities on air pollution dynamics. However, this improvement was short-lived highlighting the need for long-term, sustainable strategies to combat air pollution.

This research exposed not only the pressing environmental and public health challenges posed by air pollution in Uganda but also the opportunities afforded by utilising low-cost sensors to bridge the gap in air quality measurement in LMICs to enable evidence-based decision-making.

Addressing air pollution effectively demands a multi-faceted approach that prioritizes citizen engagement, and sustainable urban planning. Implementing cleaner transport options, renewable energy sources, and stricter emission regulations are crucial steps in mitigating air pollution.

Overall, this study contributes essential insights into the air quality challenges faced by two rapidly urbanising cities in Uganda and lays the groundwork for informed decision-making to protect public health and promote a sustainable environment for all citizens. By adopting a comprehensive approach encompassing sustainable planning, citizen participation, and robust data-driven strategies, Uganda and other resource-constrained settings can work toward a cleaner and healthier future. The urgency of this matter cannot be overstated, and collective efforts are required to safeguard the health and well-being of present and future generations.

Data availability

The data that support the findings of this study are available on request from the corresponding author, GO.

Conflicts of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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