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DOI:
10.1016/j.apr.2024.102057

Atmospheric Pollution Research 15 (2024) 102057

Contents lists available at ScienceDirect

Atmospheric Pollution Research

journal homepage: www.elsevier.com/locate/apr

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A R T I C L E I N F O

Keywords:
Air pollution
Urban mobility
Particulate matter
Low-cost sensors
Machine learning
East Africa

A B S T R A C T

This paper analyses the impact of urban mobility (UM) on air pollution by studying the effects of an intervention on local air quality. The study focuses on the $PM_{2.5}$ levels in Kampala, the capital of Uganda, and considers COVID-19 as an unintentional intervention. The $PM_{2.5}$ level of the city was obtained from a network of low-cost calibrated sensors, while UM is characterized by open-access Google reports. The period under consideration excludes the weeks immediately before and after the first lockdown. $PM_{2.5}$ data were deweathered using the machine learning technique of random forest (RF) to exclude the variation of meteorological factors, seasonality, and weekday-weekend effect, and then the impact of the pandemic was parametrised. The traffic pattern is discussed, and air mass clustering and pollution polar plots are used to analyse the distribution of long- and short-range sources, respectively. The percentage change from the baseline (PCfB) of the average of UM dimensions is then assessed against that of deweathered $PM_{2.5}$ level to investigate the impact of UM on the $PM_{2.5}$ level. Our analysis shows a strong correlation between urban mobility and roadside $PM_{2.5}$ levels and a weaker relationship with urban $PM_{2.5}$ levels. The profile of long-range emission sources was consistent over the study period, with more than 61% of the modelled air masses that arrived in Kampala first passing over Kenya and Tanzania. Overall, the COVID-19 pandemic reduced $PM_{2.5}$ levels in Kampala by about 10%, which is relatively small compared to many other cities that have been studied around the world.

1. Introduction

The health and environmental drawbacks of air pollution are documented in a wide body of research, see for example (Brunekreef and Holgate, 2002; Patel et al., 2021, etc.). Urban mobility in terms of road transportation is a key source of air pollutants, including fine particulate matter $PM_{2.5}$ (particulate matter with aerodynamic sizes smaller than 2.5 μm). For example, in Seoul, the capital of South Korea, it was argued that 21% of the ambient $PM_{2.5}$ concentration in 2016 came from urban road transport ((Kumar et al., 2015b)). Karagulian et al. (2015) show that traffic contributes to the level of $PM_{2.5}$ by 24%, 37%, and 16.5% in the US, India, and China, respectively. In the Chinese cities of Beijing, Shanghai, Guangzhou, and Xi'an, an average of 7% of the ambient level of $PM_{2.5}$ in January 2013 originated from traffic (Huang et al., 2014). In central Europe, in the cities of Warsaw in Poland, and Hamburg in Germany, urban transport contributes 21% and 18% to $PM_{2.5}$ exposure, respectively (Juda-Rezler et al., 2020; Ramacher et al., 2020). In Tehran, the capital of Iran, vehicle emissions contribute to 38%, 44%, 19%, and 21% of ambient $PM_{2.5}$ levels in the spring, summer, autumn, and winter of 2018, respectively (Ghaffarpasand et al., 2020a).

While research on $PM_{2.5}$ monitoring and the source apportionment to urban mobility is widespread in the Global North, many regions and cities of the world remain unmonitored, and/or most monitoring initiatives have had very limited scope. For example, the paucity of air quality (AQ) data in African cities is a challenge. Over 85% of air pollution-related deaths and damages across the globe are reported in developing countries, including those in Africa (Roy, 2016; Landrigan et al., 2018; WHO, 2018, 2021) and yet effective air quality management/improvement programmes need reliable AQ data and assessments (Agbo et al., 2021). The deployments of AQ stationary stations and corresponding networks are challenging, especially in low and middle-income countries (LMICs). The stations, as well as the required

Peer review under responsibility of Turkish National Committee for Air Pollution Research and Control.
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https://doi.org/10.1016/j.apr.2024.102057
Received 11 October 2023; Received in revised form 18 January 2024; Accepted 19 January 2024
Available online 20 January 2024

logistics, infrastructure, maintenance, and services, are expensive assets, hence they are usually not viewed as major priorities for local governments (Baldasano et al., 2003; Petkova et al., 2013; Makoni, 2020; Okure et al., 2022).

The advances in low-cost sensor technologies present affordable alternatives to conventional AQ stationary stations, especially in areas with a lack of AQ data (Kumar et al., 2015; Coker et al., 2021; Okure et al., 2022). The application, performance evaluation, calibrating techniques, trends, and challenges of low-cost sensors are studied in the review papers of Morawska et al. (2018), Kang et al. (2021), and Liang (2021). In the past few years, they have been widely used to monitor PM concentrations in urban environments, see for example Crilley et al. (2018); Pope et al. (2018); Bousiotis et al. (2021), McFarlane et al. (2021), Giordano et al. (2021), and Raheja et al. (2023).

Although low-cost sensors resolve to some extent the problem of AQ data shortage, there is still a lack of knowledge about the contribution of major emission sources to local air pollution (source apportionment) in LMICs. Typically, source apportionment is achieved using regulatory-grade equipment which is often lacking in LMICs. Many source apportionment and elemental characterisation methods are also developed to determine the contribution of major emission sources to the ambient particulate matter (PM), see for example (Osei et al., 2021; Ghaffarpasand et al., 2020b). Recently, Bousiotis et al. (2021, 2022) and Hagan et al. (2019) have evaluated low-cost PM sensors for source identification and apportionment. However, these approaches need more pollutant information than what is currently available in many African cities such as Kampala.

Without field measurements, source apportionment can be determined using numerical methods. For example, air quality models such as the ADMS-urban model, which require an extensive amount of raw information and a high capacity for processing, are proposed to model the dispersion of pollutants across urban environments and estimate the contribution of emission sources to the ambient pollution level (Dėdelė and Miškinytė, 2019; Mallet et al., 2018). However, these proprietary models are not readily accessible for LMICs in terms of the logistical implications including high acquisition costs, expert human resources, a wide variety of information and processing capacity for numerical methods, and established laboratory infrastructures for experimental practices. Hence, many regions still lack a reliable estimation of the role of urban mobility in air pollution. Systematic reviews by Karagulian et al. (2015) and Hopke et al. (2020) highlight the lack of knowledge about PM sources in the global South, especially in Africa and South Asia.

The response of the AQ levels towards interventions can provide an understanding of the role of perturbed emission sources in the ambient level of air pollution. Interventions can be planned, such as clean air zones, or unplanned, such as international/national conflicts, civil wars, natural disasters, pandemics, etc. Interventions provide unique opportunities to investigate the contribution of urban mobility/transport to local air pollution, especially in regions with less-developed AQ infrastructure.

A significant amount of research has been conducted on the effects of planned and unplanned interventions on air pollution. For instance, Uprety et al. (2019) analyzed the impact of the 2015 Nepal earthquake (7.8 Richter) on air pollution in Kathmandu. The results indicate an improvement in local air quality, particularly in relation to sulphur dioxide. It was attributed to the severe damage to man-made emission sources such as industries and buildings. Balasooriya et al. (2022) conducted a study on the impact of the Black Saturday bushfires (BSB) in 2009 on air pollution and public health in Australia. BSB was one of the largest bushfires in Australian history, emitting approximately four million tonnes of CO_2 into the atmosphere. The results indicate a significant impact of the increased level of air pollutants on public health. Meng et al. (2023) investigated the impact of the Russia-Ukraine war on air quality in several European cities. The results indicate that the levels of $PM_{2.5}$ and NO_2 increased by an average of around 10%. Akilan et al. (2023) investigated the impact of volcanic emissions from the Andaman-Sumatra region on air and ocean pollution in Delhi in October 2016. The study found that the toxic materials released during the volcanic eruptions significantly increased the levels of pollution in the air and sea.

The COVID-19 pandemic was one of the worst interventions human societies have faced in the last century. It significantly affected human activities across the world, some of which have been postulated as anthropogenic sources of air pollution (Agbo et al., 2021; Bray et al., 2021). Although many published studies report a reduction of 30–60% in the $PM_{2.5}$ and other air pollutant concentrations in many metropolitan urban areas such as Delhi, Los Angles, Sao Paolo, Seoul, Wuhan, and Lahore, there are considerable debates around the real impact of the response to the intervention on air quality (Rodríguez-Urrego and Rodríguez-Urrego, 2020). Ignoring the existing links between the AQ and meteorology has been recognized as the major caveat in almost all those assessments. It has been argued that meteorology could influence to some extent the relevance of the likely changes in emission sources and AQ levels (Grange et al., 2018; Grange and Carslaw, 2019; Shi et al., 2021; Yumin et al., 2021). Grange and Carslaw (2019) used a machine learning-based technique named random forest (RF) to decouple the effect of emission variations from methodology (deweathering the AQ data). In the context of COVID-19 lockdown restrictions, Shi et al. (2021) applied the same approach to discussing the impact of COVID-19 lockdowns on the AQ level of 11 metropolitan areas around the world and argued that the air quality improvements were notably more limited than some earlier published studies. Although the COVID-19 crisis has dramatically affected urban mobility around the world and could be considered a good opportunity to study the role of urban mobility, especially in under-analyzed regions, to the best of the authors' knowledge, it has not been yet used for such purposes. The lack of a precise and definitive approach to extracting the role of urban mobility by analyzing the response to the intervention is perhaps the main reason.

In this paper, we propose a new approach to analysing the impact of urban mobility on air pollution by examining the response of the ambient $PM_{2.5}$ levels to the COVID-19 pandemic. The city of Kampala presents a unique test case here because of an established network of calibrated low-cost sensors (Adong, et al.; Sserunjogi et al., 2022). We study the impact of the COVID-19 response on the local $PM_{2.5}$ level of the city to investigate the role of urban mobility upon the $PM_{2.5}$ level. We analyse the air masses that arrived at the city during the study period to determine the impacts of regional and long-range emission sources located far from the city, i.e., transboundary pollution. In addition, pollution rose analysis provides a more nuanced understanding of the likely local and short-range profiles of key emission sources and their impact on the $PM_{2.5}$ level over the study period.

In addition to the novelty of the proposed approach and the discussions provided, this study sheds light on the potential impact of urban mobility interventions on local air pollution, particularly PM levels. A large body of research has demonstrated the dramatic impact of urban mobility on PM levels in LMICs, see for example Rajé et al., (2018); Toe et al. (2021). The health effects of air pollution in LMICs, and particularly in Uganda and Kampala, have been demonstrated by many previous researchers, see for example Coker et al. (2020) and Woolley et al. (2020).

2. Material and methods

2.1. The study area

The study area is Kampala (N 0°19′ and E 32°25'), the capital of Uganda. Kampala (presented in Fig. 1) is located north of Lake Victoria and has an average altitude of 1200 m above sea level (asl). Over the past four decades, the city has undergone rapid urbanisation and has expanded to an estimated area of approximately 190 km^2. The resident

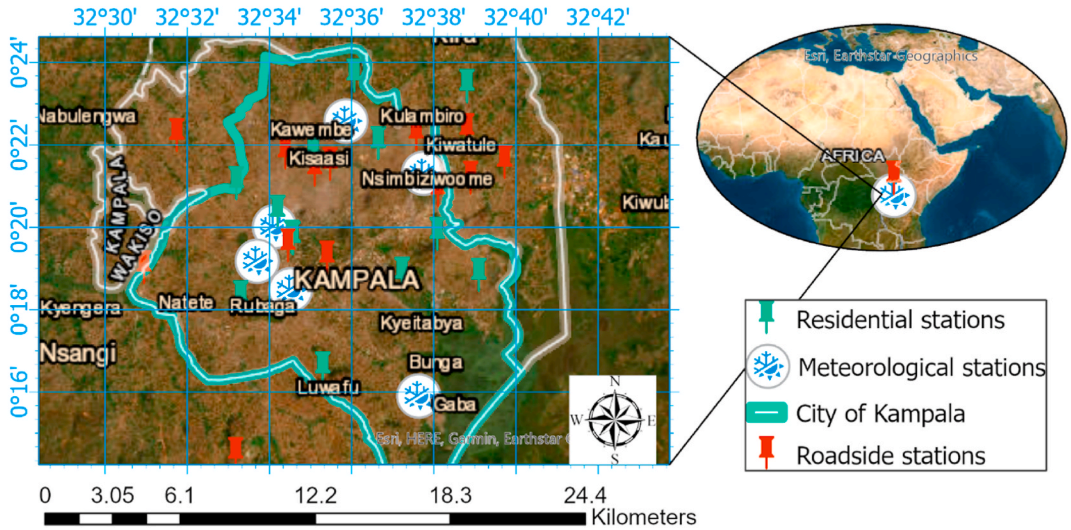

Fig. 1. Locations of residential, roadside and meteorological stations and the boundaries of the city of Kampala, the capital of Uganda.

population has increased by around 3.5 times, from about 458,503 in 1980 to 1,650,800 in 2019 (Uganda Bureau of Statistics UBOS, 2020). Kampala, the largest city in Uganda, experiences high levels of air pollution, up to 11 times the recommended health guidelines. The main driver of this issue is transport-attributed pollution, as noted by (ICF, 2009; Kirenga et al., 2015; Green et al., 2022; Singh et al., 2021).

Road transport is the most widely used and accessible mode of transportation in Uganda, accounting for over 95% of total traffic (Sheldon et al., 2022). This includes a mix of private vehicles, motorcycles (largely two-stroke), minibuses (locally known as taxis), and buses. According to the most recent statistical abstract (Uganda Bureau of Statistics UBOS, 2022), Uganda registered over 900,000 vehicles between 2017 and 2021, with 60% being motorcycles, and 15% being public vehicles over the five-year period. The fleet size has been steadily growing, however, it mainly comprises pre-owned vehicles that are often poorly maintained. According to (Uganda Bureau of Statistics UBOS, 2022), over 50% of the vehicles in operation are estimated to be in the Greater Kampala Metropolitan Area, and the national average fleet age is more than 15 years. Gasoline and diesel remain the primary transport fuels (Uganda Bureau of Statistics UBOS, 2022). Evidently, the infrastructure to support mass mobility is inadequate, resulting in longer transit times for commuters due to increased traffic flows (MoWT, 2009; JICA, 2010, Green et al., 2022; Uganda Bureau of Statistics UBOS, 2022). Meanwhile, previous studies demonstrate a consistent upward trend in traffic-related pollution levels, particularly along major roads.

Kampala has a tropical rainforest climate, typical of sub-Saharan African cities. The city experiences two wet seasons, from March to May (MAM) and September to November (SON), and two dry seasons, from December to February (DJF) and June to August (JJA). Supporting Information includes Fig. S1 and Fig. S2, which represent the windrose and time variation of the daily average meteorological parameters of Kampala.

2.2. COVID-19 timelines and related lockdown restrictions in Kampala

Uganda instituted the first lockdown on March 18, 2020, less than a week after the declaration of COVID as a global pandemic. The lockdown restrictions, which resulted in reduced mobility, closely mirrored those implemented in many cities around the world. There were two lockdown phases in Uganda between 18th March to August 8, 2020 and 10th May to June 22, 2021 following the outbreak of the second wave of infections. For purposes of this paper, the study period is defined as March 2019 to May 2021, covering the period before, during and after the first COVID-19 imposed lockdown restrictions. Further details of the lockdown restrictions in Kampala can be found in Green et al. (2022).

2.3. Low-cost air quality data and meteorology

PM concentrations are obtained from a network of low-cost monitors (AirQo monitors) installed over several locations within the city of Kampala. Sensors are located close to the roads and in residential areas. The locations of the roadside and residential stations and the boundaries of the city of Kampala are shown in Fig. 1. The network of low-cost devices is deployed and managed by AirQo (www.airqo.africa), and comprises custom-built devices optimised to measure $PM_{2.5}$ and PM_{10} concentrations (Coker et al., 2021; Okure et al., 2022). The devices are routinely calibrated against Federal Reference Monitors (FRM) (BAM 1020 & BAM1022) in Kampala using machine learning models with collocation datasets from permanent low-cost to reference monitor collocation sites (Green et al., 2022; Adong, et al.,). The sensor locations are collaboratively determined to incorporate the citywide air quality monitoring needs and selection is enhanced by an AI-enabled sensor optimisation tool.

Raw sensor datasets from the network are streamed via GSM (Global System for Mobile Communication) module in near-real-time to a cloud-based IoT platform where machine learning-enabled pre-processing and quality assurance take place. Corresponding meteorological data (temperature and humidity) are obtained from the nearest meteorological station through public API (Application Programming Interface) to support calibration processes (Adong, et al.,; Sserunjogi et al., 2022). A schematic picture of the data pipeline is represented in Fig. 2.

For this analysis, the hourly meteorological parameters (Met data) including ambient temperature, relative humidity, atmospheric pressure, wind speed, and wind direction, were utilised. Additional meteorological data were also obtained from the nearest meteorological observational site from the National Oceanic and Atmospheric Administration (NOAA) Integrated Surface Database (ISD) using the 'WorldMet' R package (Carslaw, 2023).

2.4. Google's Community Mobility Reports (CMR) and urban mobility variations

Urban mobility statistics are extracted from Google's global Community Mobility Reports (CMR) prepared by Google LLC and available through the Google CMR (https://www.google.com/covid19/mobility/). Google used telematics data of the users to analyse the mobility trends over different urban areas to assess the response of urban mobility toward the COVID-19 crisis over the world (Ghaffarpasand et al., 2022).

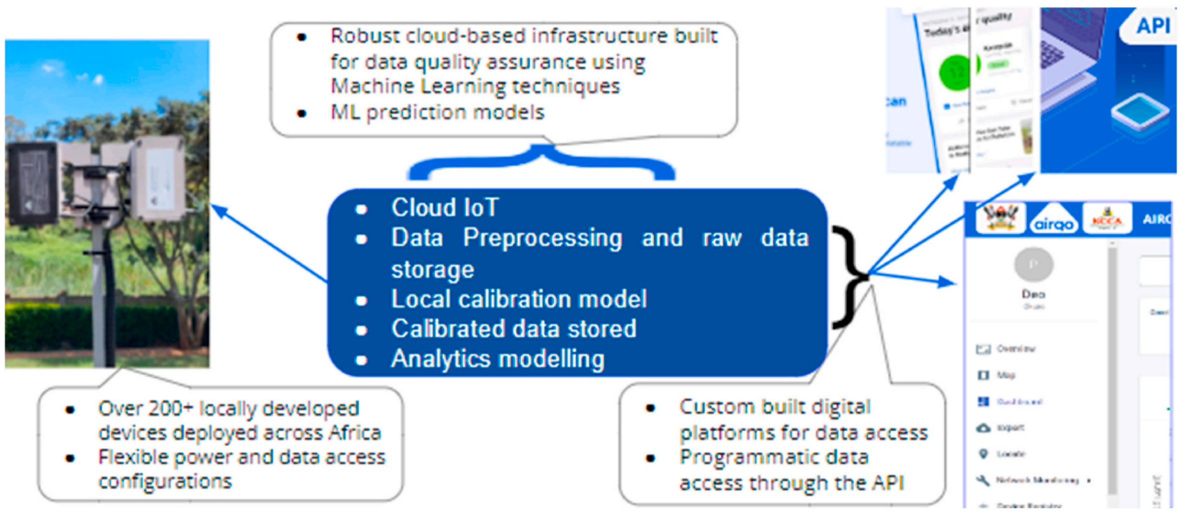

Fig. 2. Air quality data pipeline for the low-cost sensors in Uganda (From Adong, et al., and Sserunjogi et al., 2022).

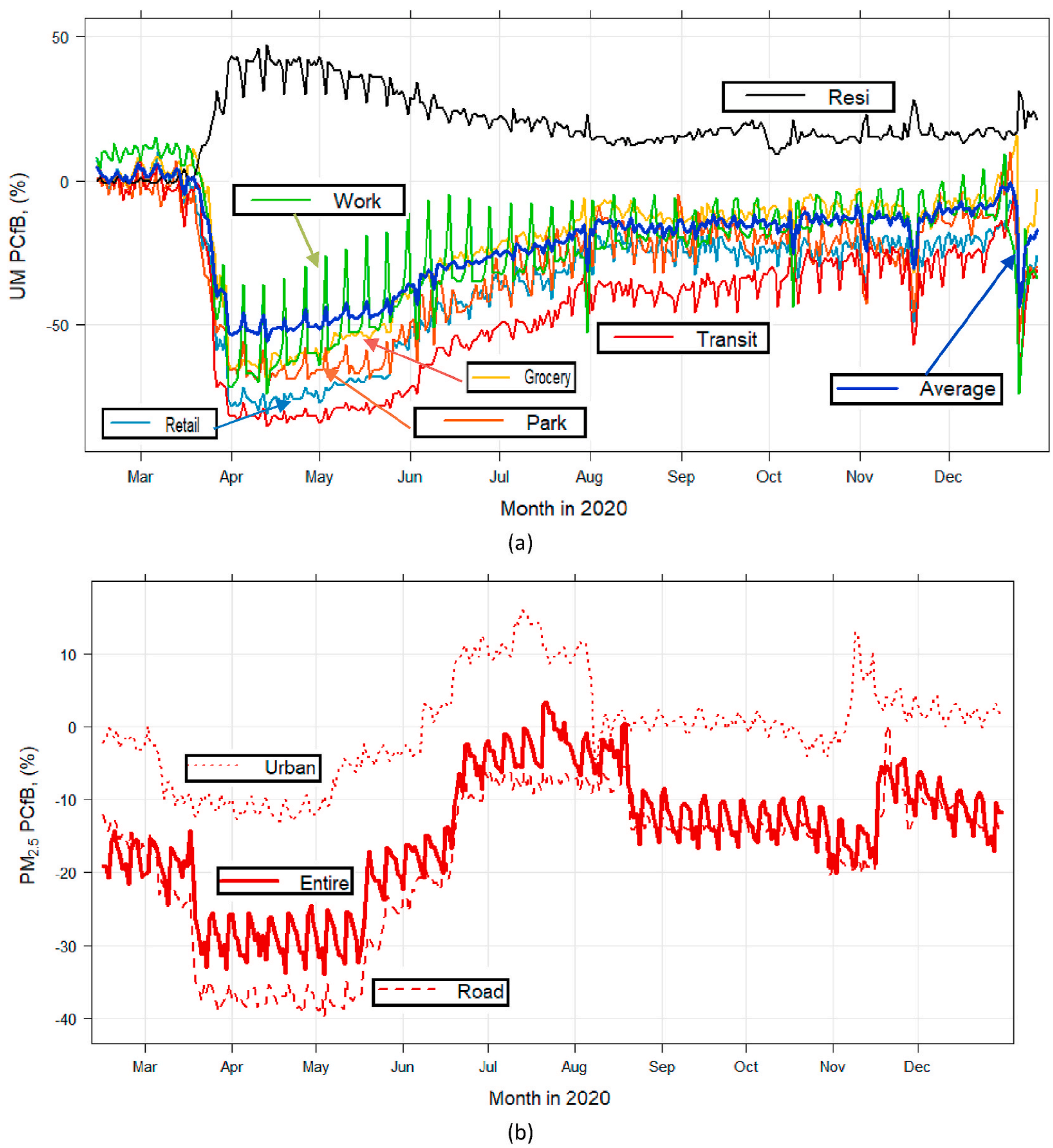

Fig. 3. The Percentage change from baseline (PCfB) for the (a) urban mobility dimensions and (b) deweathered $PM_{2.5}$ level in different areas.

Each CMR is broken down by location and displays the change in visits to places like grocery stores and parks. Google determines urban mobility by five dimensions which are.

I. *Retail and recreation*, representing the mobility trends for places such as malls, restaurants, libraries, theatres, etc.,
II. *Grocery and pharmacy*, representing the mobility trends for places such as groceries, supermarkets, food warehouses, farmers markets, food shops and pharmacies.
III. *Park*, representing the mobility trends for resort places such as national parks, beaches, parks, public gardens, country parks, etc.
IV. *Public transport*, representing mobility trends for places that are public transport hubs such as bus stations, terminals, undergrounds, trains and metro stations, Workplace, representing mobility trends for places of work
V. *Residential*, representing the mobility trends for places of residence.

It then provides a percent change from baseline (PCfB) for the period from 15th February to December 31, 2020. The relative percentage changes are estimated against the baseline days, which represent a normal value for that day of the week. The baseline day is the median value for the day-of-the-week of interest over the five weeks from 3rd January to February 6, 2020. PCfB of all urban mobility dimensions is illustrated in Fig. 3(a). All urban mobility dimensions changed to some extent due to the COVID-19 pandemic (mainly during the first lockdown) and then returned close to the baseline status.

2.5. Data analysis

2.5.1. Software package

Data analysis was conducted here using 'openair' package in R language (Carslaw and Ropkins, 2012). The pollution rose plots are created using the openair *pollutionRose* function. The 48-h backward meteorological trajectories arriving at the city of Kampala for the studied period were then calculated using the Hybrid Single-Particle Lagrangian Trajectory (HYSPLIT) model (Draxler and Rolph, 2010). The starting height was set as 500 m to ensure that the receptor was aloft but remained through the boundary layer for the considered period. We then employed TrajStat, a GIS-based software package, to perform cluster analysis. Trajsat is developed by (Wang, et al., 2009) and used by many previous investigators, such as Cui et al. (2020).

2.5.2. Deweathering and the impact of COVID-19 upon $PM_{2.5}$ level

To assess the impact(s) of external interventions upon air quality, the role of variables such as weather conditions or seasonality on the air pollution level should be excluded. We deweather the $PM_{2.5}$ concentrations using a machine-learning-based algorithm of random forest (RF) which has been proposed previously by Grange et al. (2018), and Grange and Carslaw (2019). Deweathering decouples the effects of the variation of meteorological parameters such as ambient temperature, relative humidity, atmospheric pressure, wind speed and wind direction, seasonality, rush/non-rush hour and weekday-weekend effects. During that, an RF model was developed for the $PM_{2.5}$ data considered for the analysis. 70% of the original data were then randomly selected to develop the model and then evaluated against the rest of the 30% of the dataset. These calculations were conducted using 'rmweather' R package available at https://github.com/davidcarslaw/deweather.

Model performance for each set of selected stations is presented in Fig. S3. The performance of the model is at an acceptable level, better than that of regression models. This technique was previously used by Shi et al. (2021) to assess the impact of the COVID-19 pandemic upon air quality across several cities of the world. We use the same strategy to assess the impact of the pandemic on the $PM_{2.5}$ level in the city of Kampala, whereby the average concentrations of $PM_{2.5}$ in the second and third weeks before the first lockdown for the years 2019 and 2020 are considered as the baseline values. The average concentrations of the days starting in the second week after the first lockdown are then assessed against the corresponding baseline values and the average relative differences are introduced as the impact of the COVID-19 restrictions on $PM_{2.5}$ levels. In this approach, the weeks immediately before and after the first lockdown are assumed/considered as transition weeks, for which they were excluded from the calculations.

2.5.3. The role of urban mobility in the $PM_{2.5}$ level

The role of urban mobility to the $PM_{2.5}$ levels is studied here using a stepwise approach. Firstly, the Google method (described in detail in section 2.4) was applied to estimate the percentage change from baseline (PCfB) for $PM_{2.5}$ levels after de-weathering. The period considered is the same as for the Google method, i.e., from 15th February to the end of December 2020. The percentage change from baseline in the deweathered $PM_{2.5}$ level ($PM_{2.5}$ PCfB) in different areas of the city is shown in Fig. 3(b) for the same period as in the Google report. Clear similarities between Fig. 3(a) and (b) can be observed. To understand the interaction between urban mobility and PM2.5 concentration, the percentage change from the baseline of the deweathered $PM_{2.5}$ level ($PM_{2.5}$ PCfB) was regressed against the percentage change from the baseline of urban mobility (UM PCfB) during the lockdown period where huge changes in urban mobility were observed.

3. Results and discussions

3.1. The impact of COVID-19 lockdown restrictions on $PM_{2.5}$ levels

The variations of observed and deweathered $PM_{2.5}$ concentrations across the city of Kampala for the studied period are represented in Fig. 4 (a) and (b), respectively, for the whole studied period (March 2019 to May 2021). We split the data into two subsets before and after March 2020. March 2020 to the end of May 2021 is the period when the world was struggling with the COVID-19 pandemic, see section 2.2 for more details. Fig. 4 shows that the COVID-19 lockdown restrictions during the period considered likely reduced the average hourly level of $PM_{2.5}$. The deweathered $PM_{2.5}$ (Fig. 4(b)) suggests the reductions were approximately 5.5%. It should be noted that, while the reduction appears much lower than the results from our previous work i.e. Green et al. (2022); our current analysis did not consider the data from the weeks immediately before and after the lockdown period, and instead considered the 'transition' period in the current analytical framework.

To be able to compare the Kampala data with other global cities studied by Shi et al. (2021), see section 2.5.2, we used the same comparison periods as they did. It is noted that these periods are much shorter in timescale than that shown in Fig. 4. The percentage changes are shown in Table 1. Over the shorter comparison period of the Shi et al. (2021) method, Kampala shows relatively small reductions compared to some cities, for example Beijing and New York. It is noted that some cities, such as London showed increases in $PM_{2.5}$ during the same period.

Because traffic and road emissions are known sources of $PM_{2.5}$ pollution (Ghaffarpasand et al., 2020), the hourly variation of the $PM_{2.5}$ concentrations, especially at roadside locations, could be used as a proxy of traffic patterns. The heatmaps of the hourly observed $PM_{2.5}$ level over the roadside and urban stations of the city of Kampala are illustrated in Fig. 5. In 2019 (pre-COVID year), morning and evening rush hours are easy to discern. Typically, the $PM_{2.5}$ concentrations in the evening rush hours are higher than that in the morning rush hours. Meanwhile, a slight shift toward the late evening time is observed, especially in the evening rush hours, which could be due to the weather pattern in the second half of the year. December and January have the highest evening (rush hour) $PM_{2.5}$ concentrations, which could be attributed to the prevailing weather conditions (Okure et al., 2022). Urban monitoring sites (Fig. 5(b)) had lower $PM_{2.5}$ concentrations compared to the roadside ones (Fig. 5(a)). In Fig. 5, pronounced 'rush hours stains' in the pre-COVID period almost disappeared after the first lockdown in March

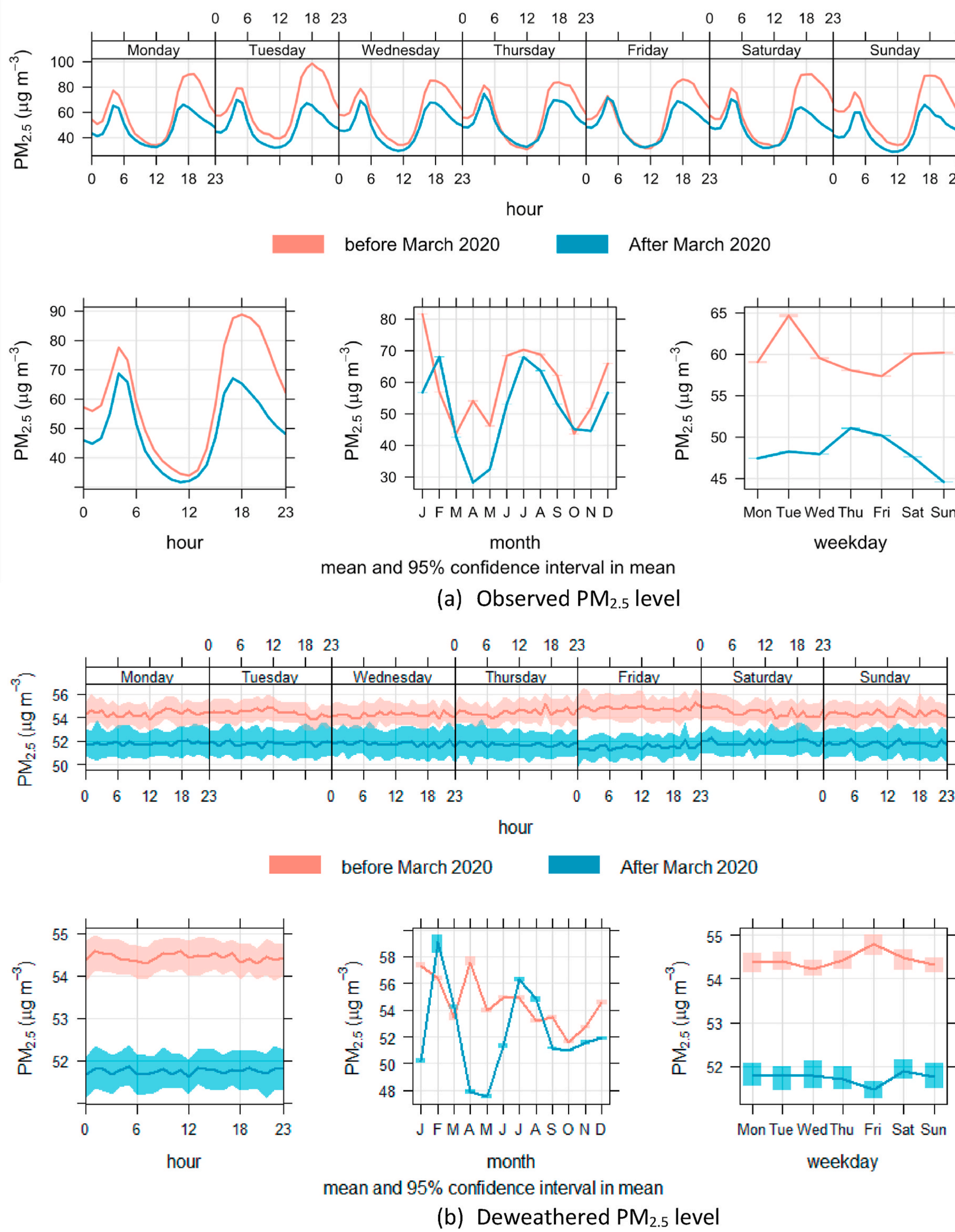

Fig. 4. Time variation of the averaged (a) observed and (b) deweathered PM$_{2.5}$ level for all measurement locations in the city of Kampala for the studied period (March 2019 to May 2021).

2020 and then started to appear in June and July when the lockdown was gradually being eased, implying that the public compliance and response to the crisis resilience policy at the time could have been a primary factor. This phenomenon was first discussed in an earlier paper that explores PM$_{2.5}$ variations for the same period in greater Kampala (Green et al., 2022). It is noted that Kampala shows seasonal behaviour in PM$_{2.5}$ due to wet and dry seasons. Two interesting aspects are observed in the post-COVID-19 heatmaps: firstly, heatmaps in the roadside and urban areas have similar patterns, and then the traffic patterns did not return to the pre-COVID-19 status even in 2021. It is worth noting that the easing of the lockdown was gradual and some sectors of the economy were only allowed to resume operations in the following year (2022); although this cannot be the sole explanation, it could have compounded the behavioural and mobility dynamics within the city.

Table 1
Percentage change (%) due to COVID-19 in deweathered $PM_{2.5}$ levels for different places around the world. The results of other places than Kampala are extracted from the study of (Shi et al., 2021).

Area	Kampala, Roadside	Kampala, Residential	Kampala, Entire	Beijing
Change, (%)	−14.2 ± 2.2	−8.3 ± 0.7	−10.4 ± 1.1	−19.3 ± 9.6
Area	Paris	London	New York	Los Angeles
Change, (%)	+16.5 ± 10.7	+8.6 ± 8.3	−21.5 ± 2.6	−18 ± 5.4

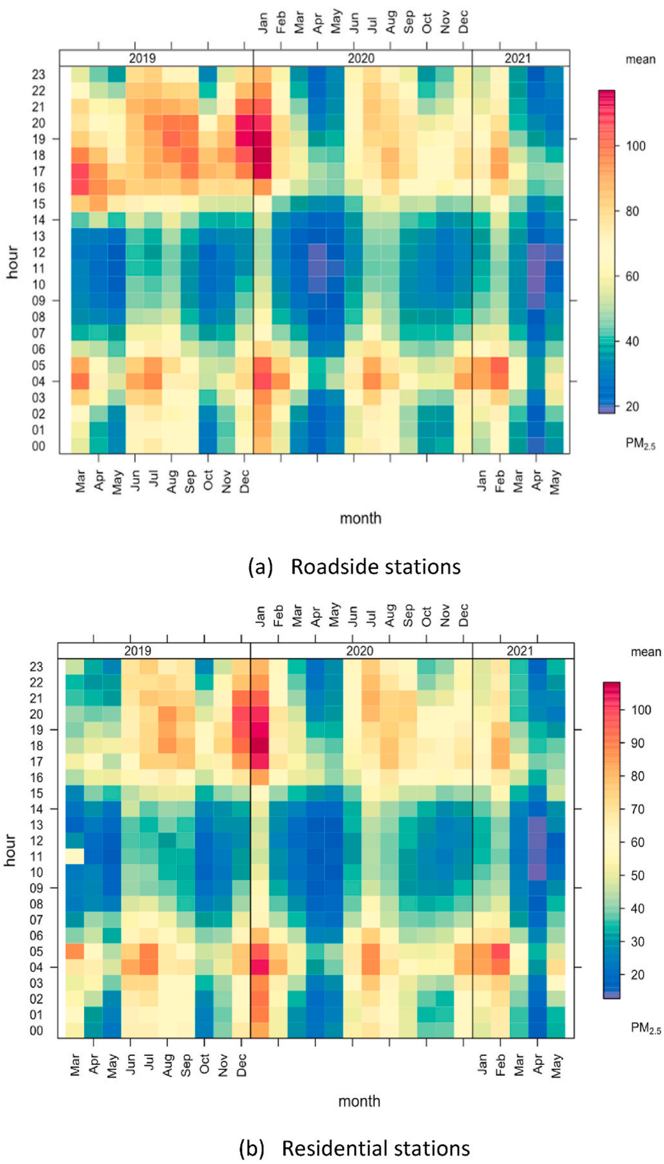

Fig. 5. Heat maps of the hourly averaged observed $PM_{2.5}$ level over (a) roadside and (b) residential stations.

3.2. *The likely impacts of long- and short-range sources*

We now investigate the contribution of likely long-range sources to Kampala's air quality. For the studied years before and after the COVID-19 crisis, the air masses arriving at the city of Kampala are classified into six clusters which are represented in Fig. 6(a) and (b), respectively, see section 2.5.1. The distribution of the air masses arriving in Kampala did not change significantly between the years. In the periods before and after the pandemic, the air masses with longer transport distances arrive from the southeast and contributed to over 61% of the total air masses arriving in Kampala. They passed over Kenya (including the capital Nairobi), and Tanzania. Clusters passing over Lake Victoria and arriving at the city from the west and southwest made up for 13.4% and 17.7% of air masses in the years before and after the COVID-19 crisis, respectively. The rest of the air masses, in both time periods, pass over Uganda and arrive at the city from the northeast.

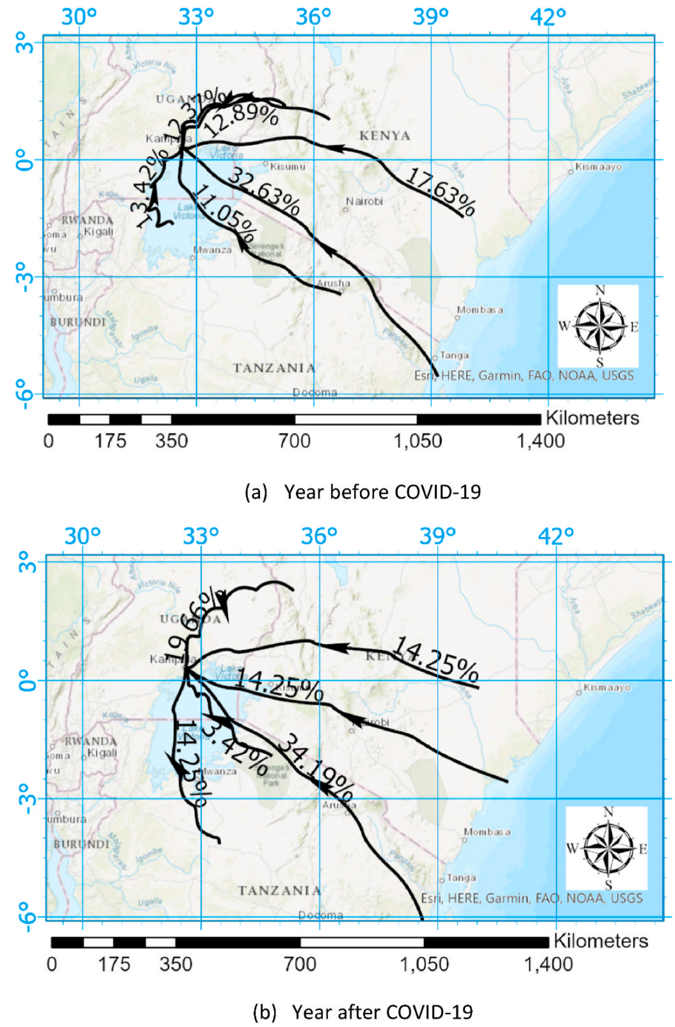

Fig. 6. Cluster analysis of the averaged 48-h air mass back-trajectories arriving at the city of Kampala for a year (a) before (2019) and (b) after (2020) the COVID-19 pandemic.

Polar plots of the mean $PM_{2.5}$ (observed) concentration can provide useful information on local (short-range) sources. (Grange et al., 2016) used polar plots of the mean $PM_{2.5}$ concentration to discuss the local source apportionment around one of the London AQ stations. Polar plots of the mean $PM_{2.5}$ concentration for the three periods of pre-lockdown, lockdown, and post-lockdown for the two groups of the studied stations, i.e., roadside and residential stations, are represented in Fig. 7. The dominant winds in the studied period are low-speed winds. The elevated $PM_{2.5}$ concentration at low-speed winds also suggests the presence of locally-sourced PM in the city of Kampala. Low wind speed values and the dominant contribution of short-range emission sources to the polar plot of Kampala $PM_{2.5}$ level were also previously observed by Singh et al. (2020).

Due to the low values of wind speeds in the polar plots, it can be

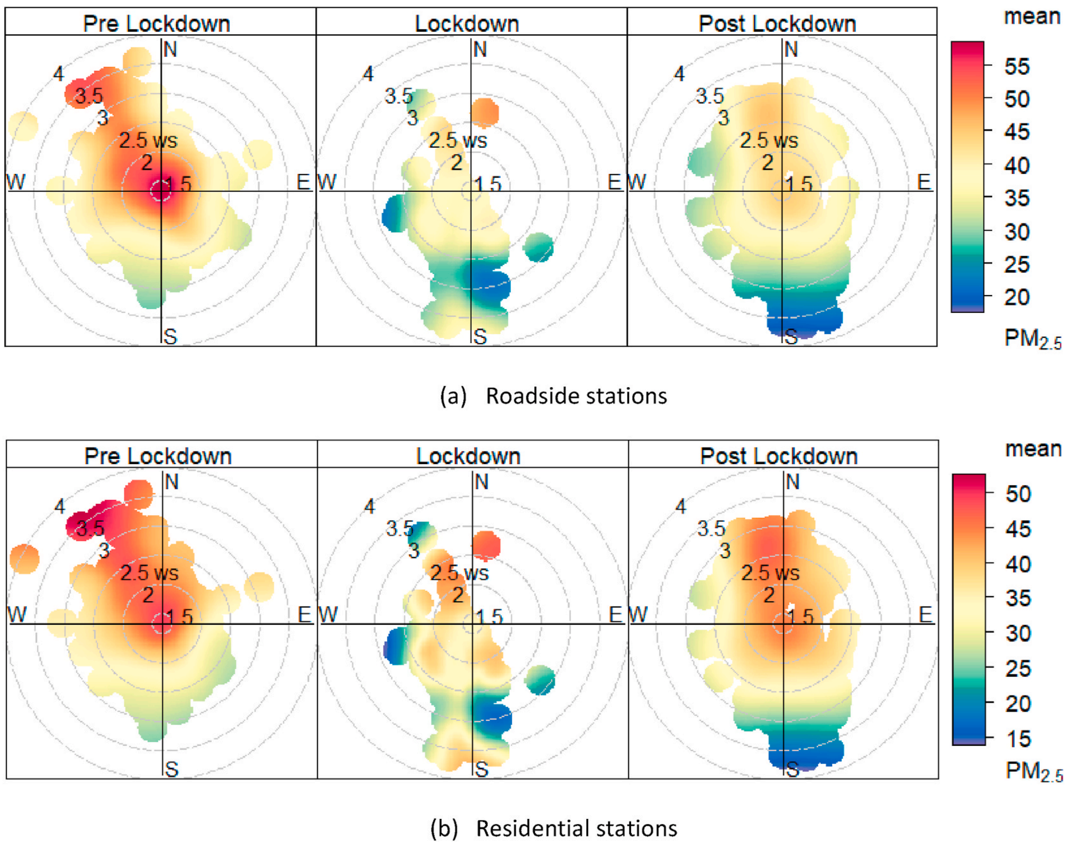

Fig. 7. Polar plots of the mean concentration of $PM_{2.5}$ for the studied periods at (a) roadside and (b) residential stations.

deduced that local sources such as urban mobility/transport are the predominant emission sources. Other characteristic local emission sources in the region such as domestic combustion, dust, etc. often with localised effects have been discussed in earlier studies including Gaita et al. (2014), Kirenga et al. (2015), Pope et al. (2018); Singh et al. (2020), Okure et al. (2022), Green et al. (2022), and others. Futhermore, in the current study, we deliberately omitted data from the 'transition window' (the first two weeks of the lockdown) which should account for the difference in the percentage PM2.5 reduction compared to our previous analysis (Green et al., 2022). This difference advances the evidence and findings from previous works on localised pollution dynamics in the region. The highest $PM_{2.5}$ concentrations were experienced with north-westerly low-speed winds both during and after the COVID-19 crisis. The activity of the short-range sources dramatically deteriorated after the pandemic and during the lockdown period. Fig. 7 also suggests higher impacts of the COVID-19 crisis upon the emission of local emission sources in the roadside stations compared with residential ones. It should be noted that polar plots were not produced for the deweathered AQ data, whereby the likely role of seasonality on the observed reduction in PM concentration level should not be ignored.

The scatter plot of observed $PM_{2.5}$ and PM_{10} for the studied period (Fig. 8) shows a high level of correlation between the two particle size fractions. In essence, there is no obvious indication that different source types contribute to the overall scatter of points. Meanwhile, there is no significant variation in the mean ratio between $PM_{2.5}$ and PM_{10} for all the studied cases here; the mean ratio between $PM_{2.5}$ and PM_{10} was around 0.74, as determined by the ordinary least-squares linear regression model and it explained over 93% of the variation.

3.3. Urban mobility impact on the $PM_{2.5}$ level

Google's Community Mobility Reports (CMR) provides a percentage change from baseline (PCfB) for each urban mobility (UM) dimension, see section 2.4. A similar approach is used here to estimate the PCfB of deweathered $PM_{2.5}$ concentrations. As was observed in Fig. 3, the PCfB profiles of the deweathered $PM_{2.5}$ concentrations correlate with the urban mobility dimensions. The Pearson correlation coefficients between the PCfB profiles of UM dimensions and $PM_{2.5}$ levels in the different studied areas are reported in Table 2. PCfB profiles of $PM_{2.5}$ levels at roadside stations have the highest correlations with the UM dimensions. Among the PCfB profiles of the UB dimensions, grocery & pharmacy, park, retail & recreation have the highest correlation coefficients with that of $PM_{2.5}$ level. The PCfB profile of 'residential' is negatively correlated with that of $PM_{2.5}$ level, whereby with increasing residential activity decreasing $PM_{2.5}$ levels in all study areas.

It should be remembered that the CMR results were developed using the location data collected from GPS-based devices and may not fully represent the entire dynamics by the population in the study areas. The increase in residential activity for the COVID period (seen earlier in Fig. 3(a)) is mainly attributed to the quarantines and related restrictions, people stayed in their homes and commuted nearby. However, residential activity levels did not return to normal before the pandemic (Fig. 3(a)). This may be attributed to changes in lifestyle, e.g. working from home, which was also observed in the $PM_{2.5}$ hourly level pattern in Fig. 6.

4. Conclusions, limitations and future research directions

This study presents a novel method for examining the impact of urban mobility (UM) on air pollution. The city of Kampala is used as a case study, and the COVID-19 pandemic is employed as a practical experiment due to its significant effects on UM. The study period was from March 2019 to May 2021, and $PM_{2.5}$ is used as an indicator of air pollution.

The hourly measurements of $PM_{2.5}$ provide a detailed view of the role of the pandemic on the traffic pattern in different areas of the city. A

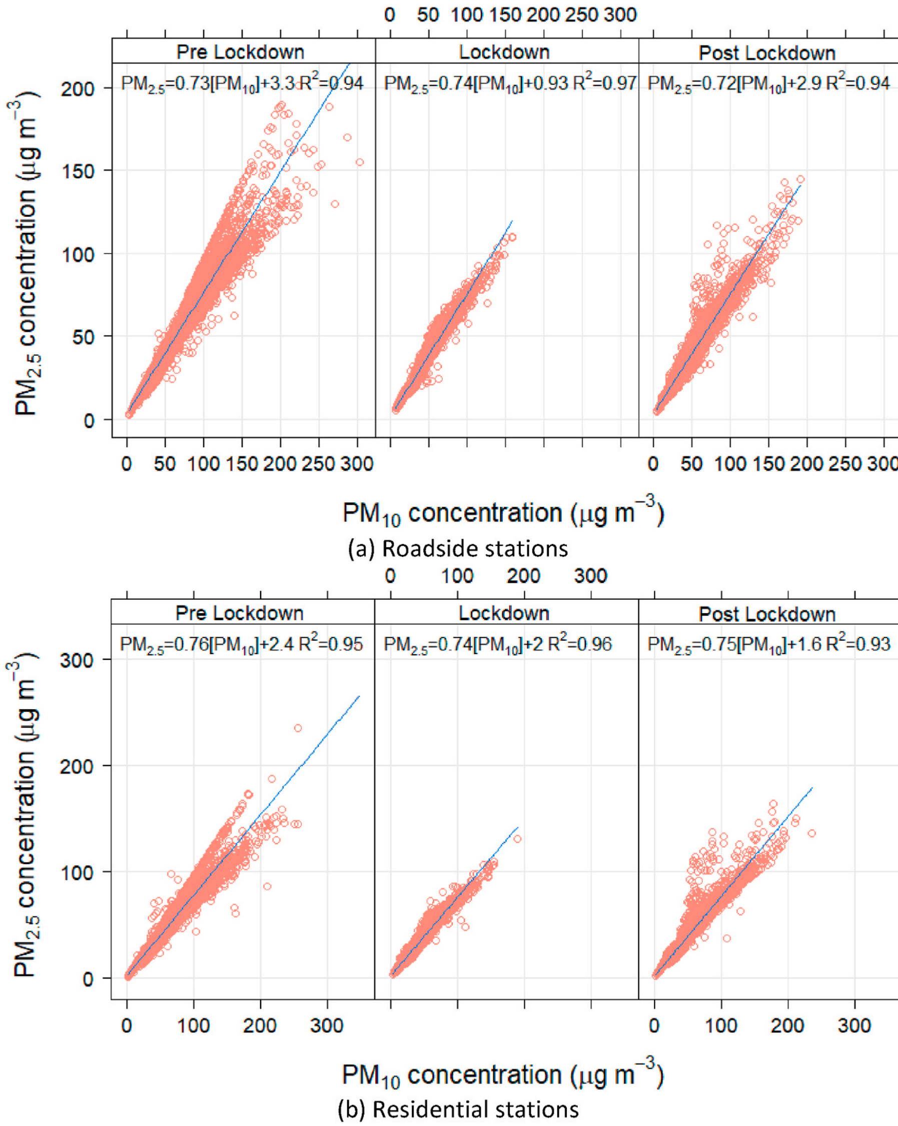

Fig. 8. Scatter plot of observed $PM_{2.5}$ and PM_{10} for the studied period at (a) roadside and (b) residential stations.

Table 2
Pearson correlation coefficients between the PCfB profiles of the urban mobility dimensions and deweathered $PM_{2.5}$ levels over the different sets of stations for the studied period (from 15th February to December 31, 2020).

		Area		
		Roadside	Urban	Entire
Urban Mobility Dimension	**Retail & Recreation**	0.67	0.35	0.49
	Grocery & Pharmacy	0.69	0.41	0.55
	Parks	0.68	0.38	0.53
	Public transport	0.55	0.25	0.41
	Workplaces	0.53	0.27	0.36
	Residential	−0.58	−0.3	−0.43
	Average	0.64	0.35	0.48

mahine learning algorithm (random forest) is used to exclude the role of the meteorological parameter variations from the $PM_{2.5}$ level and the impact of the crisis is then determined by the method proposed by (Shi et al., 2021). Clustering analysis of the air masses arriving at the city and pollution roses for the studied period are used to analyse the role of likely long- and short-range emission sources. Further, the PCfB value of the average of UM dimensions and deweathered $PM_{2.5}$ level is calculated by the method proposed by the Community Mobility Reports (CMR) prepared by Google LLC. The variations of PCfB value of the average of UM dimensions assess against that of the deweathered $PM_{2.5}$ level to estimate the contribution of UM to the $PM_{2.5}$ level. The following conclusions can be outlined from the combination of the multiple methodologies used in this study.

1. The COVID-19 crisis improved air quality in Kampala by reducing mobility and hence $PM_{2.5}$ mass concentrations.
2. The COVID-19 crisis significantly affected the traffic pattern across the city, with a return to business as usual not occurring until May 2021.
3. The profiles of the air masses arriving at the city were not changed for the studied years; over 61% of the arrived air masses originated from long distance areas and passed over Tanzania and Kenya.
4. The $PM_{2.5}$ concentrations in roadside areas were more affected by the COVID-19 crisis response than in residential areas.
5. The analyses of the $PM_{2.5}$ polar plots shows that the activity of short-range emission sources located in the northeast of the city was significantly attenuated by the COVID-19 crisis.

6. Positive correlations are observed between the UM dimensions of retail & recreation, grocery & pharmacy, and park, and $PM_{2.5}$ level, especially at the roadside areas.
7. This paper also underscores the role of meteorological parameters in assessing city-level air pollution.

The paper advances the evidence on the contribution of local emission sources in Kampala and the East African region as highlighted by previous studies including Gaita et al. (2014), Singh et al. (2020), Okure et al. (2022), and

Green et al. (2022).

The unplanned interventions such as global health risks can be used to deepen the existing understanding of the role of major emission sources in urban air pollution. The trends and behaviours in response to such a catastrophic event should be used to train intelligent algorithms to move resilient human societies to reduce the damage of similar future events. Therefore, using such trends to train learning algorithms is the certain future research direction of this study.

The work is not without limitations, it is acknowledged that the work is limited to the months associated with the COVID-19 lockdown and associated mobility disruptions. Therefore to understand all time periods, further investigation is required in a non-pandemic scenario. Additionally, the low-cost sensors used in this study were only able to monitor $PM_{2.5}$ and PM_{10} levels, providing information only on short-range (local) emission sources. However, recent studies by Bousiotis et al. (2021, 2022), and Hagan et al. (2019) have developed source apportionment techniques to estimate particulate matter sources. Therefore, future work should include extended measurements and analysis to investigate the effects of long-range transboundary pollution across different seasons, including other anthropogenic drivers such as wildfires.

CRediT authorship contribution statement

Omid Ghaffarpasand: Conceptualization, Methodology, Data curation, Formal analysis, Visualization, Writing – original draft. **Deo Okure:** Data curation, Validation, Writing – review & editing. **Paul Green:** Data curation, Validation. **Saba Sayyahi:** Methodology, Visualization, Software. **Priscilla Adong:** Data curation, Software, Validation. **Richard Sserunjogi:** Data curation, Software, Validation. **Engineer Bainomugisha:** Data curation, Project administration, Supervision. **Francis D. Pope:** Conceptualization, Methodology, Supervision, Project administration, Writing – review & editing.

Declaration of competing 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.

Acknowledgement

We gratefully acknowledge the support and funding from the EPSRC (EP/T030100/1). We also thank Google.org, Enabel-WEHUBIT and the US Embassy in Uganda for providing access to a reference monitoring dataset.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apr.2024.102057.

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