Research article

Exploring $PM_{2.5}$ variations from calibrated low-cost sensor network in Greater Kampala, during COVID-19 imposed lockdown restrictions: Lessons for Policy

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Abstract

Air pollution is considered a major public health risk globally, and the global South including sub-Saharan Africa face particular health risks, but there is limited data to quantify the level of pollution for different air quality contexts. The COVID-19 lockdown measures led to reduced human activities, and provided a unique opportunity to explore the impacts of reduced activities on urban air quality. This paper utilises calibrated data from a low-cost sensor network to explore insights from the diverse ambient air quality profile for four urban locations in Greater Kampala, Uganda before and during lockdown from March 31 to May 5 2020, highlighting the uniqueness of air pollution profiles in a sub-Saran Africa context. All locations saw year to year improvements in 24-hour mean $PM_{2.5}$ between 9 and 25µg/m^3 (i.e. 17-50% reduction from the previous year) and correlated well with reduction in traffic (up to approx. 80%) and commercial activities. The greatest improvement was observed in locations close to major transport routes in densely populated residential areas between 8 pm and 5 am. This suggests that the reduction in localised pollution sources such as nocturnal polluting activities including traffic and outdoor combustion including street cooking characteristic of fast-growing cities in developing countries, coupled with meteorological effects led to amplified reductions that continued well into the night, although meteorological effects are more generalised. Blanket policy initiatives targeting peak pollution hours could be adopted across all locations, while transport sector regulation could be very effective for pollution management. Likewise, because of the clustered and diffuse nature of pollution, community driven initiatives could be feasible for long-term mitigation.

Keywords

Ambient air quality, COVID-19, Low-cost sensors, Urban air quality, sub-Saharan Africa

Introduction

Air pollution is now considered one of the major public health risk factors for global morbidity and mortality, primarily associated with increased risk of respiratory illnesses, heart diseases, and there are growing links to mental health and cognitive impairment (Seaton et al. 1995; Brunekreef and Holgate 2002; Cohen et al. 2017; Pope III and Dockery 2006; Chen and Schwartz 2009; Xue et al. 2019). According to the World Health Organisation (WHO), more than 90% of the population in monitored urban centres worldwide are exposed to air pollution above WHO Air Quality Guideline (AQG) levels (World Health Organisation 2018; 2021). Populations in low- and middle-income countries such as those in sub-Saharan Africa with some of the highest urban population growth rates are among the most at risk of pollution exposure (United Nations 2018). In Africa, the socio-economic costs of air pollution are estimated to be much higher than malnutrition and unsafe sanitation (Roy 2016). Sub-Saharan Africa is home to over 475 million people (Lall, Henderson, and Vernon 2017), and the urban-settings face unique air quality challenges including; diffuse and clustered sources from increasing combustion emissions, increased informal settlements, lack of streamlined and efficient public transport systems, limited environmental regulations and urban planning deficiencies; in part arising from rapid urbanisation. (Petkova et al. 2013; Liousse et al. 2014). In the contemporary policy environment, diffuse pollution sources that often result into localised and clustered impacts present complexities for mitigation as the resulting pollution is from a conflation of activities within an air-shed as opposed to major point source situations. Ultimately, management of diffuse pollution cannot neatly fit within the conventional regulatory framework that allows for source-monitoring and permitting, and so spatio-temporal insights on pollution sources are essential to inform mitigation actions. This is the case for most of today's urban centres especially sub-Saharan Africa where diffuse activities continue to dominate the pollution profile (Liousse et al. 2014; Karagulian et al. 2015), but continuous monitoring datasets exploring different contexts remain extremely inadequate.

In this paper, we explore the impact of major disruptions to the scale of COVID-19 lockdown restrictions on ambient air quality for diverse physical environments within the same analytical unit/airshed considered. We hypothesize that the diversity and variations in the pollution profile in Greater Kampala, a typical sub-Saharan African context can provide unique insights not usually experienced in other geographic contexts during a major disruption, thus having important policy implications. The wide measure of variations in the restrictions adopted and implemented by different countries would equally be instructive in presenting each geographic context as a potential case study.

COVID-19 lockdown and air quality

There is growing body of literature on the relationship between air pollution and the COVID-19 pandemic. Evidence from recent preliminary studies suggests that exposure to high levels of particulate matter and fossil-related air pollution increases the risk of contracting COVID-19 and eventually mortality. Firstly, by raising the susceptibility of individuals by weakening lung function and secondly by particles providing a transmission mechanism for the spread of the coronavirus (Wu et al. 2020; Setti, Passarini, De Gennaro, Baribieri, et al. 2020; Setti, Passarini, De Gennaro, Barbieri, et al. 2020; Luigi Sanita di Toppi, Lorenzo Sanita di Toppi, and Bellini 2020; Travaglio et al. 2020), etc. Although still emerging, these linkages re-emphasise air pollution as an important public health risk. Since the WHO declared the pandemic on 12 March 2020, many countries introduced restrictions on mobility, social interactions and economic activities to contain the spread of the coronavirus and reduce the burden on health systems. The containment measures will undoubtedly have significant immediate and long-term impacts on the national and global economy, some of which are already being felt (Kabir et al. 2020; Nicola et al. 2020; Atkeson 2020; Baldwin and Tomiura 2020).

In almost equal measure, the restrictive measures have also had unintended consequences on the atmospheric environment including ambient air quality. Several specific case studies utilising data from satellite observations and ground station monitors have already been presented (Dantas et al. 2020; Mahato, Pal, and Ghosh 2020; Tobías et al. 2020). These studies indicate distinctive variations but largely significant reductions in air pollution in a range of environments. Susanta et al. (2020) conducted an analysis on the impact of air pollution during the lockdown period for New Delhi, India. The study shows an improvement in air quality by about 50% Nitrogen dioxide (NO_2), 30% Carbon monoxide (CO), and 50% particulate matter ($PM_{2.5}$ and PM_{10}) compared to the days immediately before (Mahato, Pal, and Ghosh 2020). A study in Barcelona, Spain showed a reduction of 45-51% for NO_2 and Black Carbon, 28-31% for PM_{10}, and an increase of 33-57% for Ozone (O_3) during the lockdown period (Tobías et al. 2020). Venter et al. (2020) found reduction of 60% and 31% for NO_2 and $PM_{2.5}$ respectively for population weighted concentrations with a 95% Confidence Interval. There are also several other studies that explored changes in air pollution for different locations worldwide (He, Pan, and Tanaka 2020; Venter et al. 2020; Ju, Oh, and Choi 2021; Mostafa, Gamal, and Wafiq 2021). However, to the best of our knowledge, a few studies (McFarlane et al. 2021) have published research investigating the impact of the COVID-19 lockdown on air pollution in urban sub-Saharan Africa while exploring the implications for air pollution mitigation. This is partly because ground monitoring remains extremely limited in Africa (Petkova et al. 2013; Liousse et al. 2014; World Health Organisation 2016) due to the prohibitive costs of establishing and maintaining traditional air monitoring networks that lead to sparse distribution of monitoring networks in resource-strained environments.

Improvements in low-cost air quality sensing technologies provide opportunities to characterise and measure air quality at micro-level and at a higher resolution, difficult to achieve with expensive grade reference monitors alone (Castell et al. 2017; Morawska et al. 2018; EPA 2020b; EPA 2020a). This approach is particularly important for low- and middle-income countries where the cost of monitoring remains a major inhibitor for air quality control and management programs. This paper leverages advances in low-cost measurement technologies to explore and quantify the variations in particulate matter ($PM_{2.5}$), a common measure of ambient air quality (Pope III and Dockery 2006; R. T. Burnett et al. 2014; World Health Organisation 2016), for selected diverse urban locations in Greater Kampala, Uganda, with regard to the lockdown restrictions, while discussing implications for air quality management.

Materials and methods

COVID-19 lockdown timelines in Uganda

The first case of COVID-19 in Uganda was recorded on March 22 2020, by May 15, Uganda had registered 203 cases. On March 18, the President announced the first measures to curb the spread of COVID-19. This began with the closure of schools and universities and suspension of public gatherings.

On March 21, borders were closed and all incoming and outgoing passenger aircraft and vehicles were prohibited. This was followed by suspension of all forms of public transport on March 25. On March 30 movement for all public and private vehicles with exception of cargo delivery and authorised essential activities was prohibited. Businesses were closed and outdoor movement was restricted to 06:30 to 19:00[1]. For the purposes of this paper, we define the period beginning March 31 2020 through to the end of the second extension on May 5 2020 as the 'lockdown period'.

[1] https://www.yowerikmuseveni.com/speeches

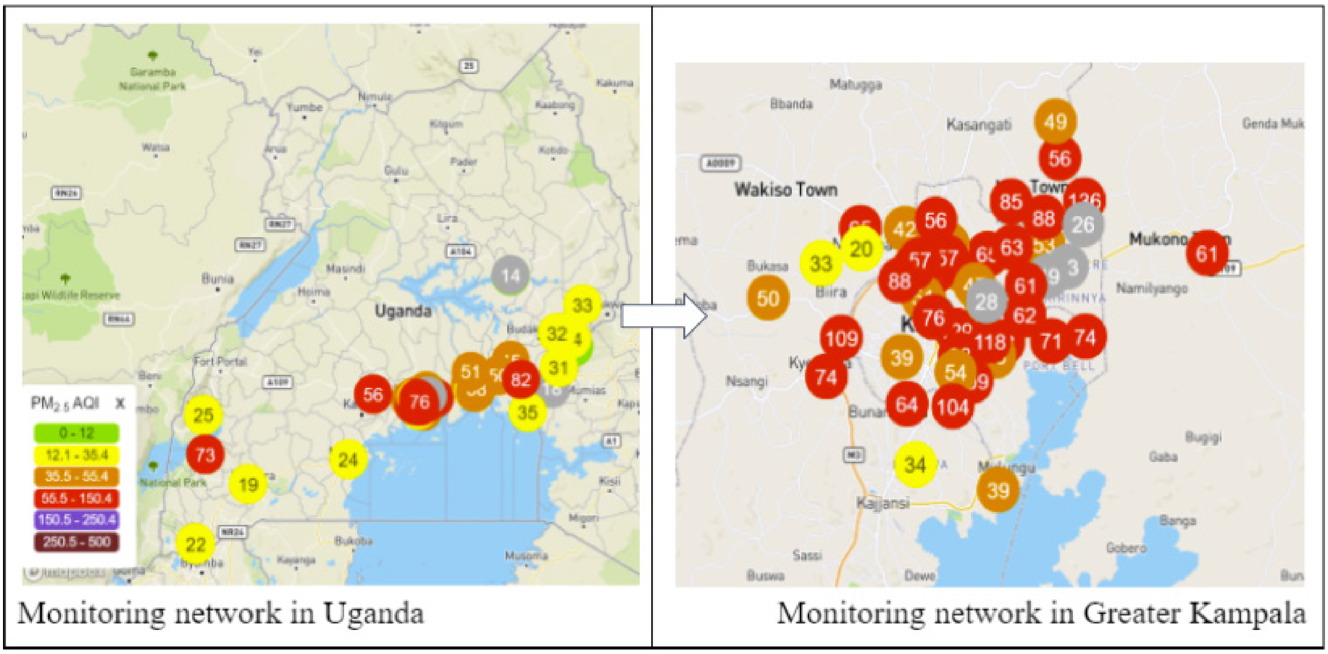


__Figure 1:__ Monitoring network in Uganda as at 01:04 EAT; 06-Oct-2021

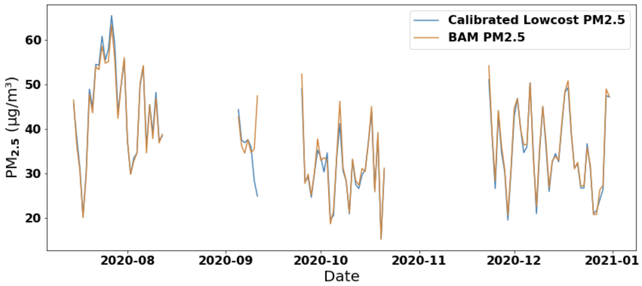


__Figure 2:__ $PM_{2.5}$ comparisons for AirQo device AQ88 vs BAM collocated at Makerere University

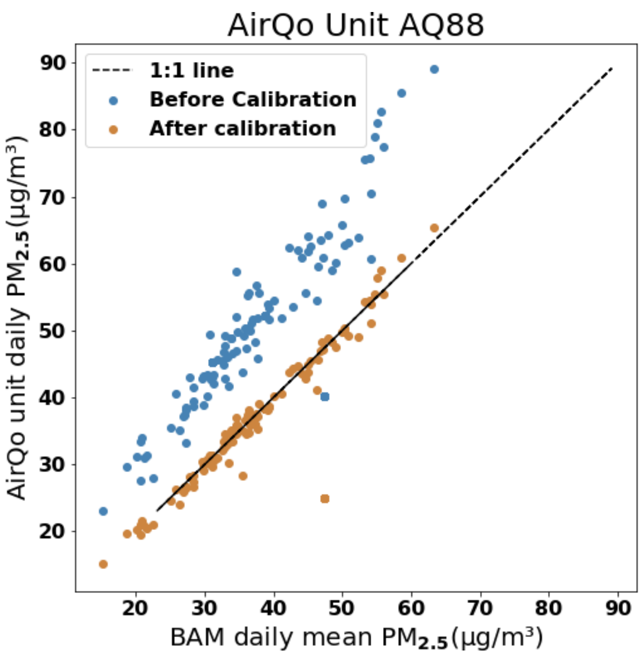


__Figure 3:__ A scatter plot showing the relationship between BAM and AirQo unit $PM_{2.5}$ before and after calibration.

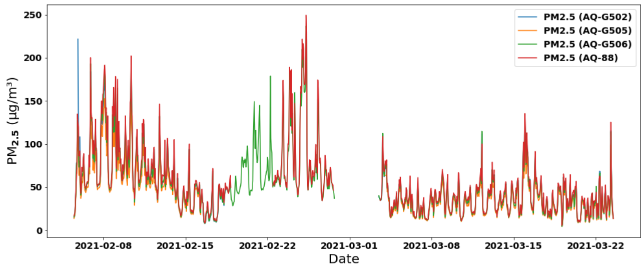


__Figure 4:__ : Comparison between hourly $PM_{2.5}$ values between AirQo devices collocated at Makerere University

Measurement of air quality

$PM_{2.5}$ measurements were obtained from a network of low-cost sensors deployed across Greater Kampala (Figure 1), operated and managed by AirQo (www.airqo.africa) (AirQo 2020; Coker et al. 2021). Each AirQo device uses twin Plantower (PMS 5003) light scattering sensors and transmit averaged measurements every 90 seconds (for static installations) via local Global System for Mobile Communications (GSM) network to a cloud-based platform. The devices have a measurement range of 0-500µg/m^3 for both $PM_{2.5}$ and PM_{10} and are optimised to run on solar energy or mains to cater for limited power availability, typical of urban settings in Sub-Saharan Africa.

As part of data quality assurance, AirQo devices are collocated with a Met One Beta Attenuation Monitor (BAM 1022) Federal Reference Monitor approved to international standards and generally correlate well against the BAM with correlation coefficient (R) of more than 0.9. The collocation data is used to develop a calibration model that translates PM concentrations from AirQo devices to BAM equivalent. In this paper, we applied random model trained with data from an AirQo to BAM collocation site at Makerere University (coordinates: 0.333534, 32.568644) from 15th July 2020 to 23rd March 2021. Employing

(a) Bugolobi area

(b) Bweyogerere area

(c) Civic Center area

(d) Entebbe Kiwafu area

Figure 5: *Study locations in and around Kampala used to describe the variations of ambient air quality before and during the lockdown period.*

the calibration model increased BAM to low-cost correlation (R) and (R^2) values from 0.9 to 0.95 and 0.49 to 0.9 respectively; and decreased RMSE and MAE from 19.11µg/m^3 to 8.2 µg/m^3 and 14.99 µg/m^3 to 5.1 µg/m^3 respectively.

Figure 2 and 3 illustrate the comparison between calibrated $PM_{2.5}$ values from AirQo devices collocated with the BAM at Makerere University between July and December 2020. It can be seen that calibrated output from the low-cost sensors follow a similar trend with the BAM with slight upward and downward shifts, with R = 0.97 for AQ88[2]. AQ88. This is relatively comparable to other Plantower sensor evaluation studies (Kelly et al. 2017; Levy Zamora et al. 2018; Mukherjee et al. 2019; Liu et al. 2020) and gives a degree of confidence in the ability of the low-cost network to provide reliable insights on the spatio-temporal variations within a given study area.

We emphasise that data from AirQo to AirQo correlate strongly with both mean correlation coefficient of R^2 = 0.98 for four AirQo units collocated at Makerere university tween 15th July 2020 to 23rd March 2021 (see Figure 4).

Implicitly, we consider calibration model trained using field collocation datasets from one AirQo monitor to be largely applicable other AirQo monitors deployed within similar physical environmental setting and context. We therefore use the calibration model developed from collocation with the reference monitor at Makerere University to correct $PM_{2.5}$ concentrations from all devises used in this study. This data correction approach is not unique to this study and has previously been adapted for low-cost datasets from different settings e.g. Barkjohn et al. (2021), and McFarlane et al. (2021).

Study location (context)

The study area includes four sites, within the Greater Kampala Metropolitan Area (GKMA), Uganda (Figures 5 and 6), furthest point about 45 km apart.

Kampala City is the economic capital and administrative centre of Uganda with a resident population of over 1.5 million and an additional daytime transient population of over 2.5 million (Uganda Bureau of Statistics 2016; World Bank 2018).

GKMA has the highest population density in the country and hosts over 32% of manufacturing businesses, contributes more than one-third of the annual GDP, and ultimately hosts the greatest concentration of pollution generating activities in Uganda (Uganda Bureau of Statistics (UBOS) 2011; Uganda Bureau of Statistics 2016; World Bank 2018). Like many sub-Saharan African cities, Kampala is urbanising fast with one of the highest urban population growth rates in the world at about 5.6% (United Nations 2018; Vermeiren et al. 2012), leading to increased demand for resources and social services, and subsequently increased alterations of the natural environment.

[2] The data gaps in figure 2 between September & October and November & December is due to prolonged outage of the sensors

Table 1: *Sensor correlation (R) matrix for the low-cost AirQo network in Greater Kampala*

Monitoring sites	Nak II	Kas.	Nan. E	Lub.	Nan. W	Luk.	Bug.	Kya.	Seg.	Kiw.	Kwt.	CvC.	Mak.
Nakaseero II (Nak. II)	1.00	0.822	0.682	0.548	0.260	0.824	0.852	0.630	0.660	0.597	0.656	0.838	0.772
Kasanga (Kas.)	0.822	1.00	0.617	0.523	0.119	0.855	0.918	0.639	0.609	0.651	0.729	0.779	0.744
Nansana east (Nan. E)	0.682	0.617	1.000	0.472	0.407	0.725	0.684	0.579	0.541	0.499	0.501	0.709	0.707
Lubaga (Lub.)	0.548	0.523	0.472	1.000	0.257	0.521	0.509	0.432	0.494	0.462	0.488	0.549	0.492
Nansana west (Nan. W)	0.260	0.119	0.407	0.257	1.000	0.266	0.192	0.233	0.275	0.088	0.042	0.337	0.408
Lukuli (Luk.)	0.824	0.855	0.725	0.521	0.266	1.00	0.891	0.658	0.626	0.633	0.640	0.842	0.896
Bugolobi (Bug.)	0.852	0.918	0.684	0.509	0.192	0.891	1.00	0.673	0.623	0.631	0.696	0.857	0.796
Kyaliwajjala (Kya.)	0.630	0.639	0.579	0.432	0.233	0.658	0.673	1.00	0.496	0.469	0.531	0.625	0.616
Seguku (Seg.)	0.660	0.609	0.541	0.494	0.275	0.626	0.623	0.496	1.00	0.549	0.522	0.643	0.587
Kiwafu (Kiw.)	0.597	0.651	0.499	0.462	0.088	0.633	0.631	0.469	0.549	1.000	0.548	0.568	0.535
Kiwatule (Kwt.)	0.656	0.729	0.501	0.488	0.042	0.640	0.696	0.531	0.522	0.548	1.00	0.614	0.539
Civic Centre (CvC.)	0.838	0.779	0.709	0.549	0.337	0.842	0.857	0.625	0.643	0.568	0.614	1.000	0.817
Makindye (Mak.)	0.772	0.744	0.707	0.492	0.408	0.896	0.796	0.616	0.587	0.535	0.539	0.817	1.00

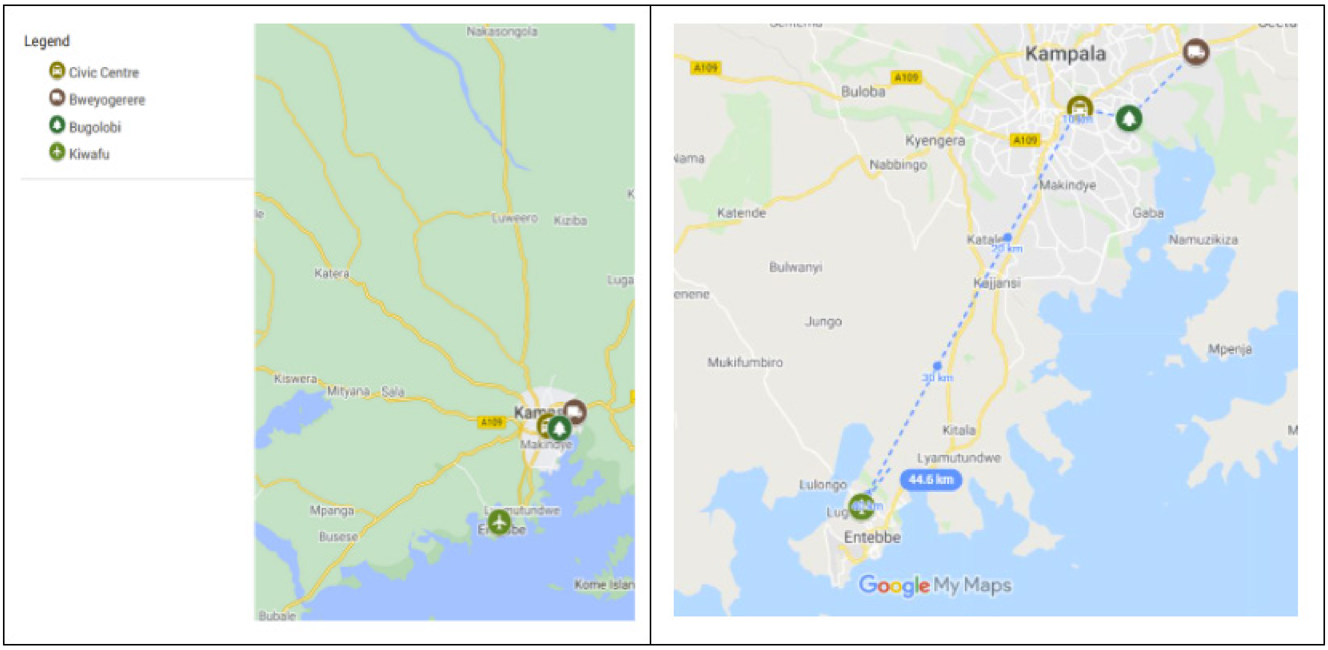


Figure 6: *Furthest distance between the monitoring locations*

Consequently, a large proportion of the population within GKMA live and work near pollution sources. The prevailing urban planning shortfalls have precipitated the growth of saturated informal settlement clusters (Richmond, Myers, and Namuli 2018) often intertwined with formal settlements and local pollution generating activities. In essence, local pollution levels tend to be largely influenced by the usually diverse and diffuse surrounding pollution generating activities coupled with the nature of settlements resulting into largely localised impacts (Okure et al. 2022). However, the unique variations in the air pollution profile is typical for many fast-growing urban areas in sub-Saharan Africa where pollution is dominated by multiple diffused sources (Marais and Wiedinmyer 2016; Pfotenhauer et al. 2019).

Table 1 shows the Greater Kampala pollution variations (clustered airsheds) using the sensor correlation matrix for 13 monitoring locations over a 6-month period, with an average correlation of 0.581, a function of the distance between the sensors and actual pollution levels in the monitoring locations/ intensity of immediate local sources. This socio-economic context suggests that the consequences of the disrupted socio-economic interactions with the ambient environment due to the lockdown restrictions will be more significant in this region, also consistent with novel findings on pollution progression and urbanisation (Mage et al. 1996). While in-depth investigation of the sensor variations highlighted in Table 1 is beyond the scope of this paper, we find that it reinforces the need for exploring air quality dynamics in a metropolitan city. Air quality insights from

Table 2: *Profiles of the study locations (Uganda Bureau of Statistics 2016)*

	Area km²	Population	Popn Density	Households per km²	Firewood/ Charcoal cooking households per km²	Domestic waste burning households per km²
Bugolobi	3.88	5023	1,295	327	103	23
Bweyogerere	11.27	58,679	5,207	1,363	1,153	575
Civic Centre	~1	375	375	130	24	1
Kiwafu Ward	5.30	22,243	4,194	1,081	238	242

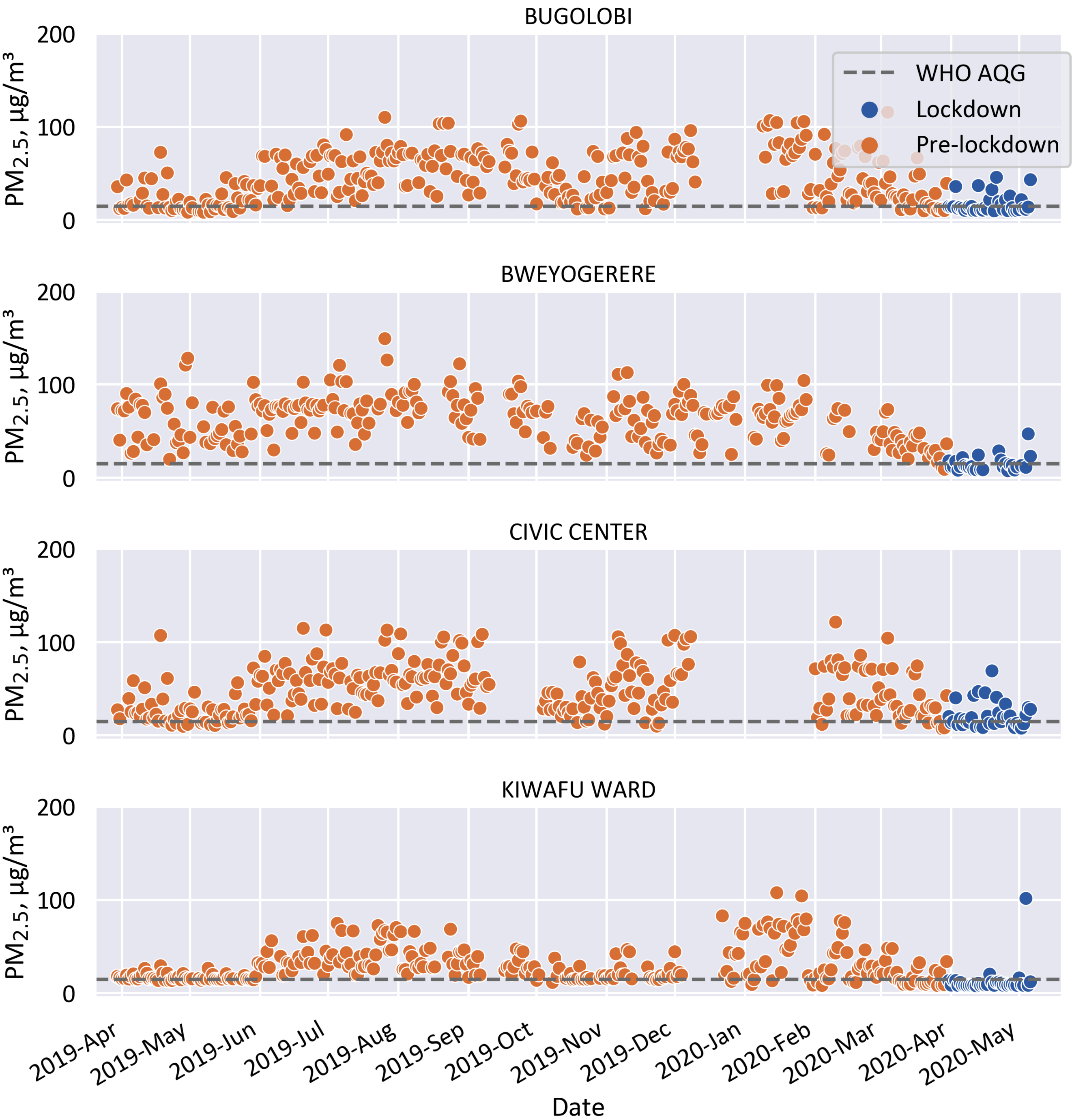


Figure 7: *Daily mean $PM_{2.5}$ concentrations, by location March 31 2019 - May 5 2020*

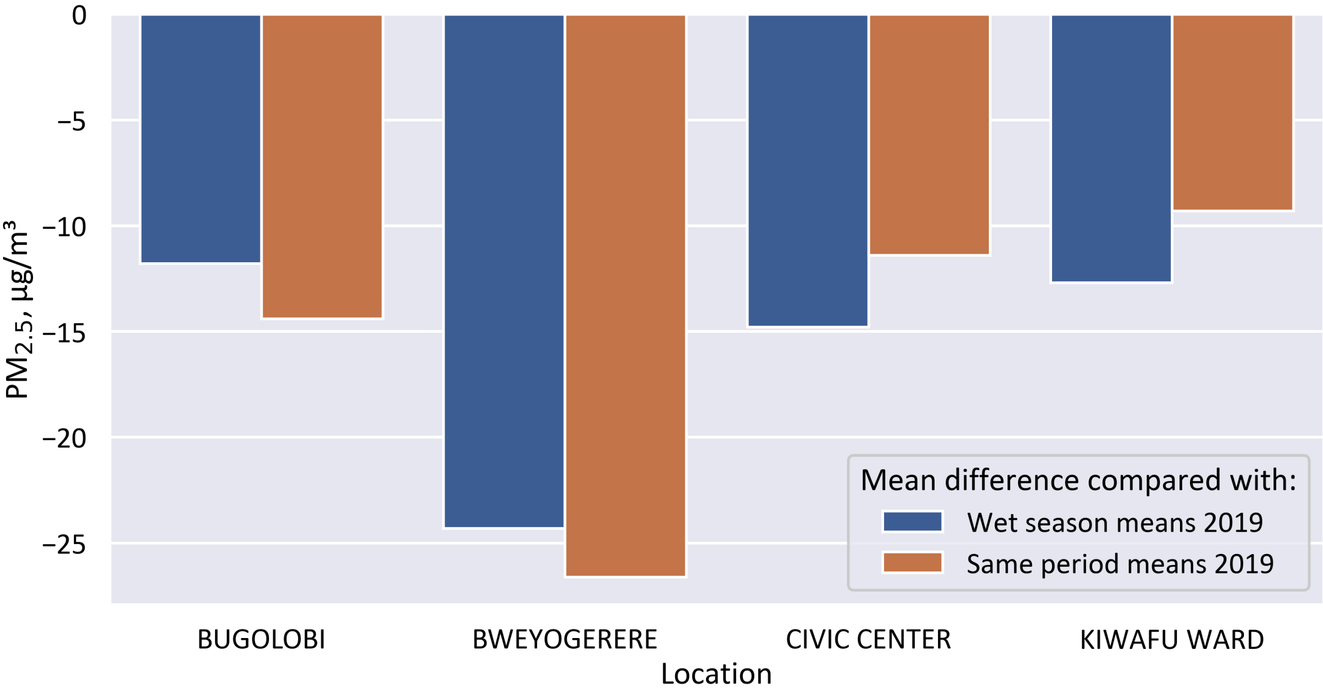


Figure 8: *Mean reduction $PM_{2.5}$ values for lockdown compared to typical wet season 2019 and equivalent lockdown period prior year*

Greater Kampala during such an unprecedented circumstance would provide a rare opportunity for exploring mitigation policy insights for a sub-Saharan African setting.

In order to capture a cross section of the GKMA urban environment, we used parish level population distribution, observed satellite imagery from Google earth, knowledge of local context and availability of data for the 211 period of interest to identify four monitoring locations based on land use clusters i.e., residential/urban background and urban/traffic typically characteristic of land uses within the greater Kampala. This is also informed by the known pollution dynamics for various land uses (Harrison and Deacon 1998; Spangl et al. 2007; Alsahli and Al-Harbi 2018).

Inherently, diverse pollution profile would make it difficult to identify homogeneous land use clusters, which in theory, could introduce an analytical uncertainty. However, we attempted to obtain a fair spatial representation of the idealised location clustering which should provide spatially representative reference insights for the respective land uses taking into consideration that particulate matter is not always entirely constrained to immediate local sources like gaseous pollutants e.g. NO_2, and CO (Khuzestani et al. 2017), this does not present any significant limitations.

The locations represent a balance between densely and less populated areas with a wide measure of variations in pollution levels. The respective physical and demographic profiles for attributes with direct impact on local air pollution are presented in Table 2.

Results and discussion

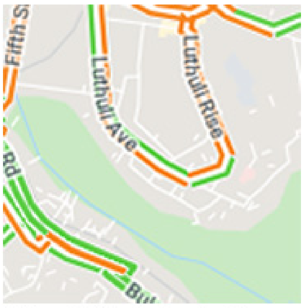
Daily $PM_{2.5}$ levels

Figure 7 shows that for all locations there is substantial variation in daily mean $PM_{2.5}$ across the year. The blue section of the chart captures the lockdown period which records some of the lowest readings of the year for all locations. The cycles observed above vary in line with seasons with the two wet seasons (March-May/September-November) experiencing the lowest $PM_{2.5}$ levels. This corresponds to the influence of precipitation and unstable weather conditions on particulate suppression and decay (Chow et al. 1999; Yan et al. 2016).

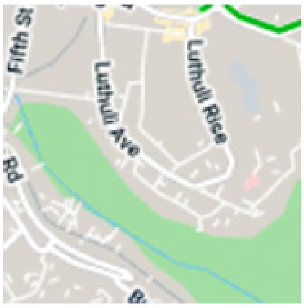
Overall, Bweyogerere area which has greater population density, proximity to industries, with a major road network, and multiple diffuse sources, observes typically higher $PM_{2.5}$. Unsurprisingly, Kiwafu Ward in the smaller town of Entebbe with no major through-roads, less households using charcoal/firewood coupled with limited industrial and commercial activities experiences much lower levels. This suggests that both location-specific and meteorological factors impact on observed air quality during lockdown, with meteorological being more generalised (Cole and Neumayer 2004).

To establish the extent to which improvements in air quality coincide with lockdown measures, levels during lockdown are compared with wet season means for 2019, and the mean for the lockdown equivalent period in the previous year.

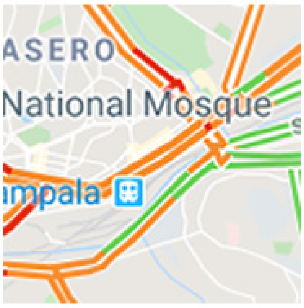
The results are as shown in Figure 8 with the bars representing the estimated differences in $PM_{2.5}$ between the two periods. Bweyogerere shows the greatest observed reduction in $PM_{2.5}$ at approximately 25µg/m³ or 50% lower than seasonal and



(a) Bugolobi: Typical pre-lockdown



(b) Bugolobi: Lockdown



(c) Civic Center: Typical pre-lockdown

(d) Civic Center: Lockdown

Figure 9: *Sample traffic activity images from Monday 8pm typical pre-lockdown and during lockdown*

the previous year means. Other locations saw reductions of around 9-15µg/m³. This is an indication that meteorology is not sufficient to explain the lower $PM_{2.5}$ levels during the lockdown period, but at the same time highlights the clustered nature of the pollution reduction. Modelling the meteorological impact on daily levels could provide precise estimates on the meteorological influence.

To further explore the extent of the impact of lockdown restrictions on the different physical environments, we used a working assumption that the impact of socio-economic factors i.e. population density, household energy use, will remain relatively constant during the lockdown period and possibly increase as people spend more time, cook and eat more at home than would normally be the case. We utilised data from the most recent census (Uganda Bureau of Statistics 2016) to obtain context for each of the land use areas. Bweyogerere, the most densely populated and probably the largest domestic emitter again experienced the greatest reduction in $PM_{2.5}$. Other parishes, from the densely populated Kiwafu Ward to the largely resident free Civic Centre experience comparable reductions. These insights provide little indication to suggest that the probable changes have led to a decrease in $PM_{2.5}$ that outweighs any benefits from other lockdown measures.

Localised influence of traffic activity

Because of the prohibitive logistical implications of conducting traffic counts; we employed Google Maps Traffic App that utilises smartphone data with activated location features, and recorded in motion to capture proxy data. 'Typical' traffic data was captured for day of the week between 6 am and 10 pm (the times available from Google Maps) for each location prior to lockdown. Hourly data from coloured pixels was collected throughout the lockdown period. Figure 9 demonstrates an example of the difference in activity after curfew, before and during lockdown. Figure 10 shows the level of traffic activity for each location at lock down levels compared to typical. Kiwafu Ward shows the greatest reduction in traffic activity with levels below 20% (about 80% reduction) of typical.

Access to the international airport and recreation are the main reasons for visiting the town and these options were no longer possible. Other locations show much higher activity, in the range of 20 to 40% of normal in the first two weeks of lockdown but rising to between 40 and 60% of normal in the second two weeks with Civic Centre as the most active.

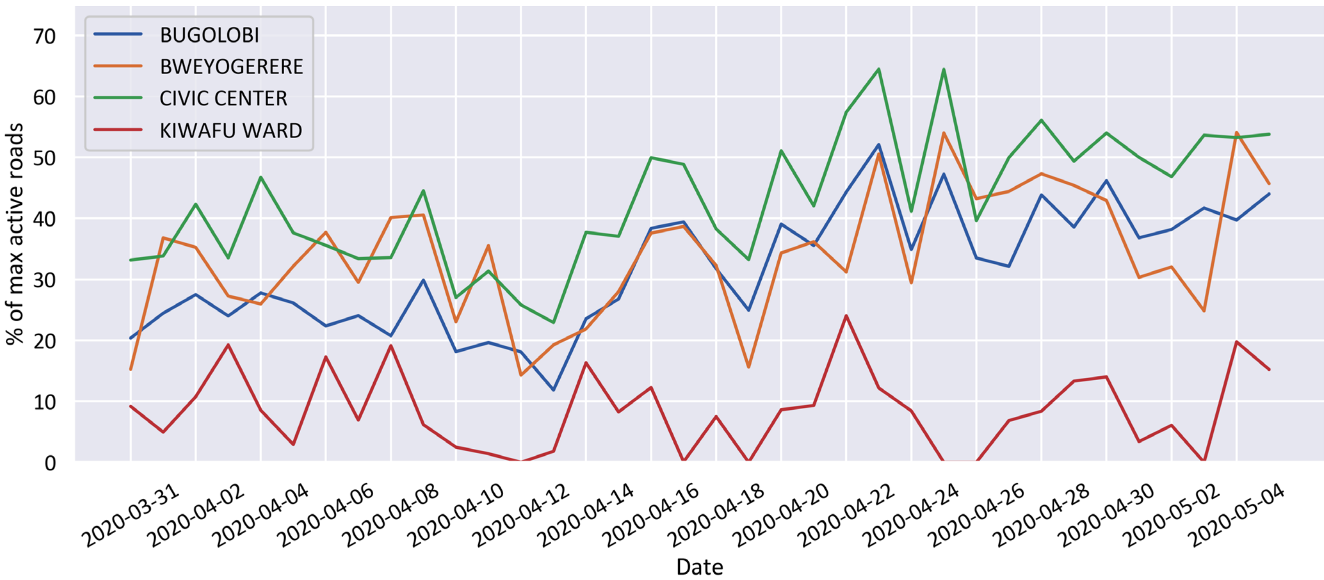


Figure 10: *Daily traffic activity during lockdown as a percentage of maximum typical levels*

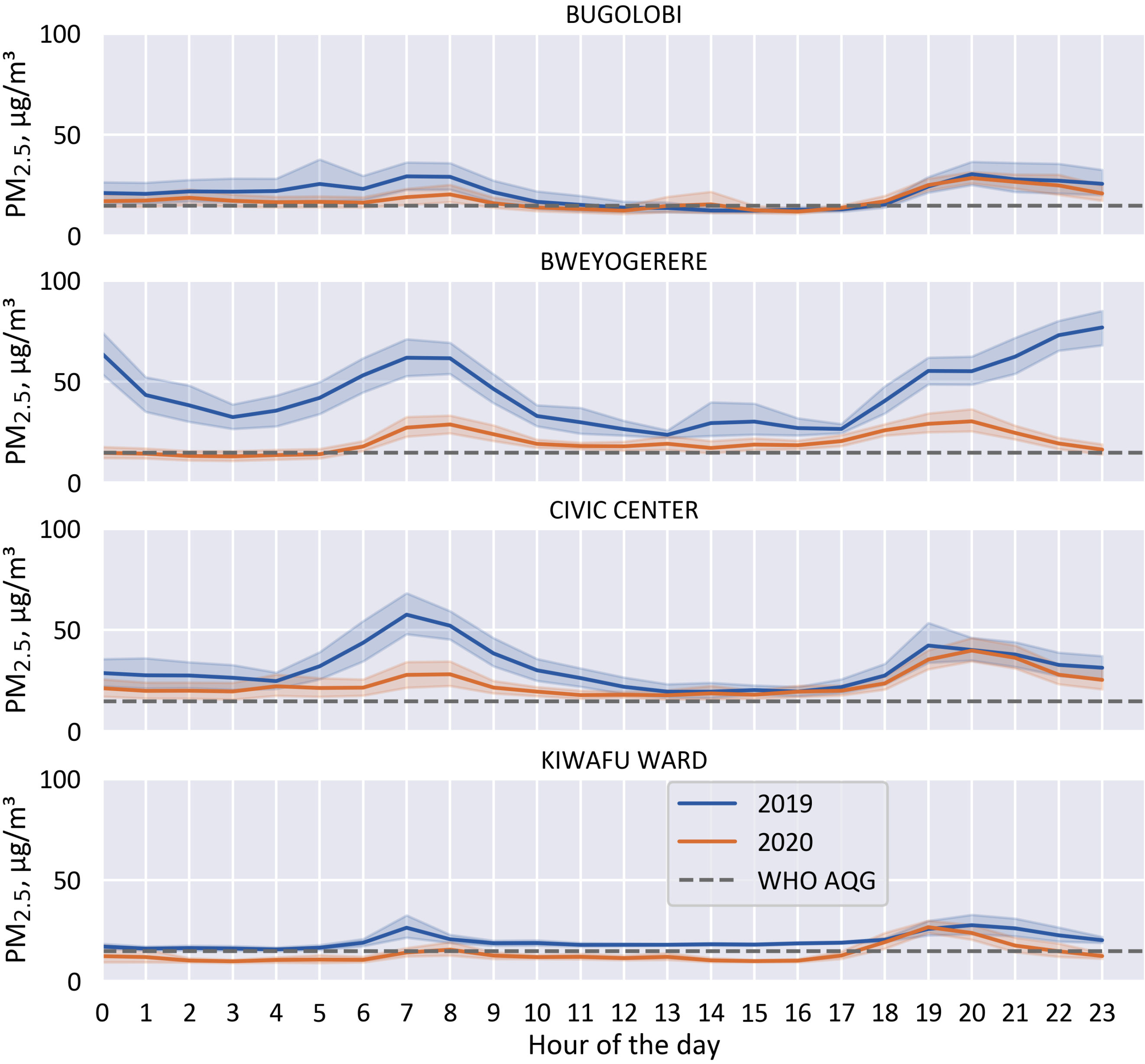


Figure 11: *Diurnal variations for lockdown period 2019 and 2020*

These locations, while varying in population density, remain on or close to major commercial through-routes across the city and so see higher sustained traffic volumes.

While Bugolobi has low population density and is beside wetland, it lies downwind from an informal settlement, an industrial area and a congested road which may explain higher activity rates.

Explanations for the increase over time may include; businesses adapting to the changing environment by investing in permissible transport such as motorcycles, home delivery services or increased mobility for essential workers and emergencies. This upward trend is not observed in daily $PM_{2.5}$ changes which are influenced more by daily weather variations. In summary, while the season of the year explains some of the improvement in daily air quality during the lockdown period, influence of lockdown restrictions appear to have been very significant. More detailed modelling of weather and pollution transport be required to identify the relationship between these features more precisely, while considering other emission parameters such as NO_2 (Mage et al. 1996; Watson and Chow 2002).

Diurnal variation

In Figure 11 we explore the difference between diurnal $PM_{2.5}$ levels during the lockdown period and the equivalent period in 2019. We observe that all locations carry the characteristic sinusoidal profile. A characteristic feature for pollution dispersion is the Boundary Layer Effect (BLE) (Ding et al. 2005) which creates the U-shape curve observed during daylight hours. As the sun rises around 7am, the ground warms due to radiation. This warms the air which rises lifting particulate matter with it creating

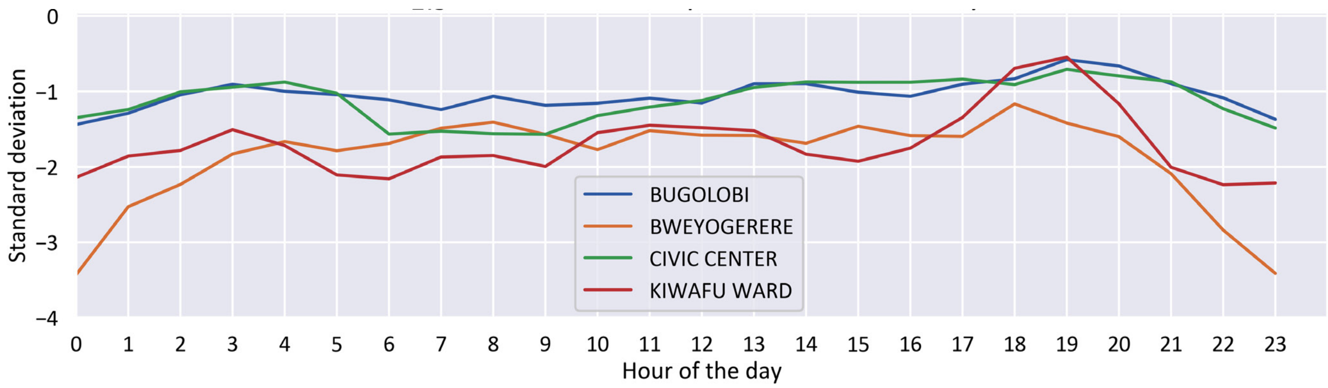


Figure 12: *Normalised $PM_{2.5}$ variation for the period March 31-May 5, 2019 to 2020*

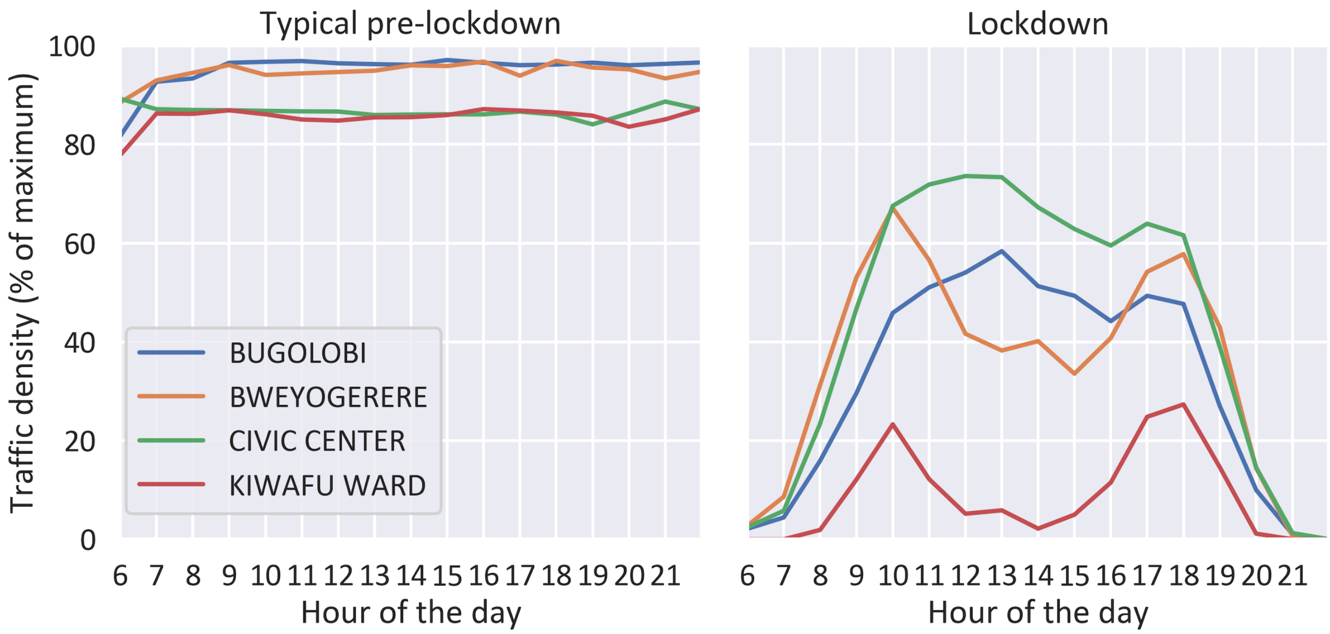


Figure 13: *Diurnal variation in traffic activity within 2.2km X 2.2km bounding box of the monitoring device for the pre-and during lockdown period*

turbulent ambient conditions. Pollution is now dispersed over a much greater vertical height and exposure levels reduce, being at their lowest mid-afternoon. During the evening conditions, cooler air is compressed into a smaller vertical space leading to higher concentrations during the night. These diurnal patterns are not unique to this study and have been replicated in other geographic settings (Chow et al. 1999; DeGaetano and Doherty 2004; Chen, Tang, and Zhao 2015), with levels dependent on location-specific activity patterns.

During the 2020 lockdown, mean $PM_{2.5}$ levels are consistently below the 2019 equivalent period. The morning and evening peaks are levelled out by reduced activity. We can see that while pre-lockdown levels (averagely) are always at or above new WHO daily AQG levels of 15µg/m^3 (World Health Organisation 2021), lockdown levels only exceed the threshold if only peak times are considered.

Investigating the difference further, Figure 12 shows the variation in mean hourly PM25 values during the lockdown period compared with the normalised values for the equivalent dates in 2019. All locations show a variation of greater than or equal to one standard deviation below equivalent period in the prior year. Similarly, all locations show a modest peak around 7 pm when levels are closest to prior year mean. Greater reductions are seen after 7 pm and continuing through until 3-5 am. This is in line with a substantial decrease in activity during the hours of curfew (7 pm-6:30 am). There is also variation between Civic Centre and Bugolobi, and Bweyogerere and Kiwafu with the latter pair seeing much greater reductions during the day and especially during night time. This difference can be explained by reduction in evening activity to be explored below, but also reinforced by the BLE which usually traps evening particulate matter close to the ground level, where it remains, reducing only slowly throughout the night. This is especially harmful for those living in open homes and in cities such as Kampala where polluting activity continues into the night.

As mentioned above we are assuming that cooking and waste burning activities remain the same or increase during the lockdown. Air quality improved at every stage of the day during lockdown and follows a similar pattern for all locations especially in the evening after curfew. It appears changes in domestic emissions are not a significant factor in explaining these observed patterns.

On traffic activity, the contrast between the typical and lockdown periods in figure 13 is striking. Typical levels show traffic activity at well above 80 percent of full activity at all times between 6 am and 10 pm. Under lockdown however there is very clear evidence that the curfew is being observed for all locations. All locations only begin to increase activity from 7 am. Civic Centre and Bugolobi locations continue to increase before falling steadily until 7 pm and then dropping sharply. For Bweyogerere and Kiwafu however, traffic activity drops away sharply at 10 am, remaining low through the day, before rising to a second peak at 6 pm and dropping away more sharply than others before curfew. This pattern of lower activity in Bweyogerere and Kiwafu is consistent with the lower $PM_{2.5}$ levels seen in Figure 12.

One possible explanation for why Kiwafu and Bweyogerere experience a greater drop after curfew is that being densely populated, lower income residential areas close to major roads they experience high levels of night-time combustion activities, typically charcoal and waste. Under lockdown scenario, traffic is reduced, but also polluting activities moves away from the main roads (and away from our sensors) possibly into homes. In the more affluent Bugolobi and the non-residential Civic Centre, only the traffic reduction which is already typically lighter in the evening is seen and limited outdoor combustion and reliance on street food much lower.

In summary, diurnal variation is largely explained by meteorological factors. Adjusting for this we observe that reduced traffic activity during the day leads to general reduction of 1 standard deviation across all regions, the greatest improvement comes at night for locations on major roads close to dense residential areas with heavy traffic and where outdoor combustion and street cooking is known to be prevalent. These findings indicate that policy initiatives that regulate transport activities would lead to immediate improvement on ambient air quality.

Conclusion and policy recommendations

This study explored the impact of COVID-19 lockdown restrictions on diverse air quality profiles for four distinctive locations in the Greater Kampala region of Uganda. We identify a reduction in $PM_{2.5}$ of between 17 and 50% compared with the same period in 2019 with the greatest increase coming in densely populated areas close to major roads. Investigation into diurnal variation reveals a broadly consistent improvement for all locations at all times. The greatest reductions occurred after the 7pm curfew and again, mostly in densely populated areas close to major roads. Implicitly, blanket policy interventions that target peak pollution periods could be proportionately adopted across the study area. Assuming that domestic fuel use is unlikely to have decreased, we identify traffic density, and street cooking and outdoor combustion as likely sources of the reduction. Policy initiatives in the transport sector such as vehicle emissions controls, traffic management, mass transit systems and pedestrianisation, in addition to regulation of outdoor open burning should be adopted to reduce the impact on air quality. Similarly, exploring the prospects of community driven initiatives could be essential to tackling diffuse and clustered pollution sources.

CRediT authorship contribution statement

Engineer Bainomugisha: supervision, conceptualization, review and editing. Paul Green: project administration, formal analysis, writing–original draft. Deo Okure: methodology, writing-original draft, writing-review and editing. Priscilla Adong: data curation, calibration, visualisation. Richard Sserunjogi: software, calibration, visualisation.

Declaration of competing interest

Authors declare no known competing financial and/or personal interests that could influence the findings of the paper.

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