Validity of Air Quality as a Measure of Human Mobility in Uganda. The COVID-19 Context.

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Research Article

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Abstract

Background

Mobility patterns are valuable in identifying transmission patterns for infectious diseases and in deriving contact matrices that are used to parametrize mathematical models. Aggregated location data from mobile phones have been the main means of measuring human mobility on a population level. However, these data come with several limitations related to individual privacy, access and restriction of the GPS location by the user that limit their use.

Methods

We explored the viability of using ground monitored air quality data as an alternative to aggregated location data from mobile phones, as a measure of human mobility in two cities in Uganda. We determined associations between air quality and human mobility; and the effect of mobility restrictions on mobility and air quality using Pearson correlation (R), multivariate regression and visualized these relationships using scatter plots.

Results

Daily mean levels for $PM_{2.5}$ in both cities were consistently higher than the WHO guideline limit, with a mean of 77.0μg/m^3 (Range = 22.0–309) for Kampala and 60.0μg/m^3 (Range = 18.2–331) for Wakiso. PM_{10} levels had a mean of 84.6μg/m^3 (Range = 25.0–318) in Kampala and 67.9μg/m^3 (Range = 21.0–340) in Wakiso. $PM_{2.5}$ was negatively correlated with the government response stringency index for Kampala ($R = -0.31$, $p < 0.001$) and Wakiso ($R = -0.21$, $p < 0.001$). In Kampala, $PM_{2.5}$ was positively associated with movement in grocery and pharmacy ($R = 0.24$, $p < 0.001$), parks ($R = 0.25$, $p < 0.001$), retail and recreation ($R = 0.24$, $p < 0.001$), transit stations ($R = 0.3$, $p < 0.001$) and work places ($R = 0.2$, $p < 0.001$); and negatively correlated with movement in residential places ($R = -0.3$, $p < 0.001$). Only associations between $PM_{2.5}$ and movement in workplaces and residential places were statistically significant in Wakiso ($R = 0.14$, $p < 0.001$ and $R = -0.19$, $p = 0.003$ respectively).

Conclusions

These findings suggest that air quality data are linked to human mobility data and could thus be used to monitor human movement patterns. This work represents a pioneer study to empirically and quantitatively assess the value of air quality data as a surrogate for human mobility in Uganda.

Background

Human mobility has previously been used as a proxy of infectious disease transmission especially of respiratory pathogens such as *Mycobacterium Tuberculosis* (1–3) and influenza (4) and other diseases such as malaria (5). More recently, the COVID–19 pandemic has emphasised the role of mobility in disease transmission (6–11). A virus that reportedly originated from Wuhan, China (12) found its way out of the city, spread throughout China and was exported to other countries with which China shares a physical border and others overseas, starting with sporadic cases in many countries and thereafter a widespread community transmission. Thus, on 11th March 2020 WHO declared COVID-19 a global pandemic. Mobility data have aided infectious disease control programmes to identify transmission hotspots and consequently informed targeted interventions. Mobility data have also been used to derive contact matrices that are used to parametrize mathematical models used in predicting COVID-19 infections that could be observed and to assess the effectiveness of interventions (13, 14).

To date, aggregated location data from mobile phones have been the main means to capture mobility patterns of individuals at population level (6). However, mobile phone location data come with various ethical challenges relating to privacy and are thus aggregated to ensure anonymity. Its other limitations include; the relative paucity of mobile phones with enabled GPS location devices in developing countries (15), the ability of users to turn off GPS location and the rather ardours and lengthy process of obtaining such data from mobile phone companies. This renders them less useful in studying infectious disease transmission. An estimated 16% and an average of 30% of people have a smart phone in Uganda and sub-Saharan Africa, respectively (15). Furthermore, air quality data provides better resolution. For example, on top of having them ground stationed, low-cost air quality sensors developed by the AirQo project (16, 17) have been mounted on boda-bodas (local motorbike transport) and commuter taxis whose ubiquity and agility facilitates more diversified and localised measurements. These two are the most used means of transport by the vast majority of people in Uganda.

Being less encumbered by the above listed limitations, ground monitored ambient air quality data could thus provide a viable alternative for understanding mobility patterns at population level. Air pollution in most cities is mainly due to vehicular movement and fumes from factories. Air quality worsens as people move from their residences to their destinations such as places of work, recreation centres, grocery shops and becomes better as movement lessens. Indeed, air quality improved during COVID-19 lockdowns in many cities around the world (18–21), indicating air quality could depict mobility patterns of individuals.

In light of the above, we explored whether air quality data could be a viable alternative to aggregated location data from mobile phones, as a measure of human mobility in two cities in Uganda i.e., Kampala and Wakiso. These two cities are found in the central region of Uganda and are part of the Kampala Metropolitan Area (KMA) which has become the country's commercial, industrial and education centre. The area has experienced significant urban growth for many decades and was one of the fastest growing urban areas in Africa pre-COVID-19. Kampala is the capital, with a population of over 1.5 million people according to the Uganda Bureau of Statistics (22). Wakiso, on the other hand partly encircles Kampala with the city headquarters lying approximately 12 miles, by road, northwest of Kampala, with a population of over 1.9 million people (22). Wakiso and Kampala are the first and second most populated districts in Uganda respectively.

We abstracted human mobility data for Kampala and Wakiso from Google Community Mobility Reports (23). It is only these two cities that had complete district-level data among Ugandan districts relating to all six kinds of places tracked by Google (grocery and pharmacy, parks, residential, retail and recreation, transit stations, and work places) since the company started tracking movement in these areas at the start of the COVID-19 pandemic. We also obtained Air Quality data for these two cities from AirQo (16, 17) an extensive air quality monitoring project that has a high resolution network of low-cost air quality sensors in the country. In addition, we collated various lockdown measures instituted by the Uganda government including the timing of these restrictions and when they were lifted. We also made use of a Government Response Stringency Index – a composite measure of the strictness of policy responses (such as mobility restrictions) over time, developed by the University of Oxford (24). We analysed mobility data as well as the air quality data, determined the association between human mobility and air quality and determined how mobility restrictions e.g. social and distancing policies impact mobility and air quality. This study represents a pioneer effort to objectively assess and calibrate the extent to which ambient air quality data can be used a measure of human mobility.

Methods

The data

Human mobility data: Human mobility data for Uganda was obtained from Google COVID–19 Community Mobility Reports (23). Since the beginning of the COVID-19 pandemic, Google has been collecting data relating to change in visits to places classified as retail and recreation (places such as restaurants, cafés, shopping centres, theme parks, museums, libraries and cinemas); supermarket and pharmacy (places such as supermarkets, food warehouses, farmers markets, specialty food shops and pharmacies); parks (places like national parks, public beaches, marinas, dog parks, plazas and public gardens); public transport (places that are public transport hubs, such as underground, bus and train stations); workplaces (places of work); and residential (places of residence). These data are available as COVID–19 Community Mobility Reports that show how visits to different places change compared to a baseline. Changes for each day are compared to a baseline value for that day of the week. The baseline is the median value, for the corresponding day of the week, during the five–week period 3rd January 2020–6th February 2020. We obtained Google Mobility data for the period 15th February 2020 to 25th August 2021.

Air Quality Data: AirQo (16, 17), has deployed a number of air quality monitors across urban areas in Uganda, Kampala and Wakiso inclusive. Hourly data for air pollutant concentrations of particulate matter ≤ 2.5 μm and ≤ 10 μm ($PM_{2.5}$ and PM_{10}, respectively) for two cities (Kampala-the capital and Wakiso her close neighbour) were obtained for the period 1st January 2020 to 6th October 2021. Across the entire available period, for each city, the 24–hour average concentration (corresponding to a given day) for each pollutant was calculated. The average for each city was obtained by averaging over all air quality monitors (sensors) in each city.

Lockdown Measures: A Government Response Stringency Index – a composite measure of the strictness of policy responses (such as mobility restrictions) over time, developed by the University of Oxford (24) was used as a measure for the strength of lockdown policies (including mobility restrictions) implemented by Uganda over time. The index on any given day is calculated as the average score of nine response (policy) indicators including school closures, workplace closures, restrictions on public gatherings, transport restrictions, stay-at-home requirements and travel bans, each rescaled to a value from 0 to 100 (100 = strictest response). We obtained stringency index data for the period 1st January 2020 to 11th November 2021.

Statistical Analysis

All data processing and analysis was done using R version 4.1.1 (25)

1. Association between air quality and human mobility

The association between air quality and human mobility was determined using Pearson correlation coefficients and visualised using scatter plots. We computed daily (24-hour) averages for air pollutants ($PM_{2.5}$ and PM_{10}) for two cities (Kampala and Wakiso) that are well covered by air quality monitors and compared those with daily changes in mobility for Kampala and Wakiso. It is these districts that had complete mobility data relating to six types of places (grocery and pharmacy, parks, residential, retail and recreation, transit stations, and work places). Multivariate analysis was performed using a linear model, adjusting for the government response stringency index.

2. Effect of mobility restrictions on human movement

To determine the effect of mobility restrictions on human movement, we computed Pearson correlation coefficients between the government response stringency index and mobility in each of the six kinds of places tracked by Google and created scatter plots for the two cities (Kampala and Wakiso).

3. Effect of mobility restrictions on air quality

To determine the effect of mobility restrictions on air quality, we computed Pearson correlation coefficients between the government response stringency index and air quality and created scatter plots for the two cities (Kampala and Wakiso).

Results

1. Mobility patterns in Kampala and Wakiso

Before 18th March 2020, mobility patterns, in both cities, within the six kinds of places tracked by Google (grocery and pharmacy, parks, residential, retail and recreation, transit stations, and work places) were close to baseline values (Fig. 1). The baseline is the median value, for the corresponding day of the week, during the five–week period 3rd January 2020–6th February 2020 (23). However, when government instituted the first set of restrictions on 18th March 2020 to prevent the anticipated widespread community transmission, the mobility patterns changed. That is, there was an increase in mobility in residential places and a decrease in mobility in non-residential places (grocery and pharmacy; parks; retail and recreation; transit stations; and work places). This is expected because the restrictions included stay at home and work-from-home orders.

When a phased lifting of restrictions begun on 4th May 2020, mobility in residential places reduced to values close to baseline values. On the other hand, mobility in non-residential places increased to close to baseline values.

During the general elections (10th November 2020 to 3rd February 2021), mobility in places of residence was slightly higher than baseline values with evident fluctuations going below the baseline values in January 2021 when the actual elections were held. On the other hand, mobility in non-residential places increased compared to pre-election period with some values going above the baseline values in December 2020 and going back to below baseline values in January 2021. Before the start of the election period, mobility patterns were similar in the two cities. However, post-election, mobility patterns were close to baseline values in Wakiso compared to Kampala.

Following the institution of a second major lockdown, mobility patterns were identical to those of the first major lockdown where mobility in residential places increased and that in the non-residential places reduced. Similarly, the lifting of the lockdown following the second wave of the epidemic led to a decrease in mobility in residential places and an increase in mobility in non-residential places.

2. Air Quality in Kampala and Wakiso

During the observation period (1st January 2020 to 6th October 2021), the 24-hour average levels for fine particulate matter ($PM_{2.5}$) in Kampala were consistently higher than the WHO recommended threshold (guideline limit) of 15μg/m^3 with a mean of 51.1μg/m^3 (Range = 15.3–150); while the 24-hour average $PM_{2.5}$ levels for Wakiso fell below the WHO guideline limit in May 2020 and April 2021 with a mean of 42.8μg/m^3 (Range = 5.6–136) (Fig. 2). On the other hand, the 24-average levels for coarse particulate matter (PM_{10}) were lower than the WHO recommended threshold of 45μg/m^3 on some days in both cities with a mean of 58.4μg/m^3 (Range = 16.9–162) for Kampala and 48.5μg/m^3 (Range = 5.95–146) for Wakiso. The difference by city in mean levels of both $PM_{2.5}$ and PM_{10} was not statistically significant ($p = 0.2396$ for $PM_{2.5}$ and $p = 0.2396$ for PM_{10}).

There was a very high positive correlation between PM_{10} and $PM_{2.5}$ at all air quality observation sites (Supplementary Fig. 1), with all Pearson correlation coefficients greater than 0.99 and all p-values < 0.001). This is expected because $PM_{2.5}$ is a subset of PM_{10}. We therefore used $PM_{2.5}$ in subsequent analyses determining the association between air quality and human mobility.

Institution of the first set of restrictions on 18th March 2020 led to a reduction in air pollution levels in both cities with coarse particulate matter (PM_{10}) values going below the recommended WHO threshold in May 2020 (Fig. 2). Following a phased start of lifting of restrictions on 4th May 2020, air pollution levels increased to values above the recommended WHO thresholds until August 2020 when air pollution started declining with PM_{10} values either reaching or falling below the recommend WHO threshold on some days.

There was an increase in air pollution during the election period (from 10th November 2020 when campaigns for presidential elections started to 3rd February 2021 when elections for sub county/town/municipal division chairpersons and councillors were conducted). Air pollution in Wakiso was lower than that in Kampala post-election.

3. Mobility restrictions in Uganda

The country instituted her first set of restrictions on 18th March 2020 to prevent the anticipated widespread community transmission in case the epidemic had entered the country (Fig. 1). The restrictions were tightened following the confirmation of the first case of COVID-19 in Uganda on 21st March 2020 until 4th May 2020 when a phased lifting of restrictions commenced where whole sellers, metal and wood workshops, warehouses, insurance providers and hardware shops were opened and restaurants were allowed to provide take-aways. During the election period, mobility restrictions were around 50% until a second major lockdown (increased restrictions) was instituted to contain the second wave of the epidemic. It’s worth noting that even though the country lifted restrictions on 30th July 2021 following a reduction in COVID-19 cases towards the end of the second wave of the epidemic, the stringency index remained higher than that following the lifting of restrictions following the first wave of the epidemic. In fact a report by the United Nations International Children’s Emergency Fund (UNICEF) stated that Uganda is one of the top countries that maintained closure of educational institutions the longest in the world (26, 27).

4. Association between air quality and human mobility

In Kampala, air quality as measured by the amounts of atmospheric fine particulate matter ($PM_{2.5}$) was positively associated with movement to groceries and pharmacies (Pearson correlation coefficient = 0.24, $p < 0.001$), parks (Pearson correlation coefficient = 0.25, $p < 0.001$), retail and recreation (Pearson correlation coefficient = 0.24, $p < 0.001$), transit stations (Pearson correlation coefficient = 0.3, $p < 0.001$) and work places (Pearson correlation coefficient = 0.2, $p < 0.001$); and negatively correlated with movement within residential places (Pearson correlation coefficient = -0.3, $p < 0.001$) (Fig. 3). Only associations between air quality and movement within workplaces and residential places were statistically significant in Wakiso, with Pearson correlation coefficients = 0.14, $p < 0.001$ and = -0.19, $p = 0.003$ respectively (Fig. 4).

In a multivariate analysis, air quality in Kampala was independently correlated with movement in retail and recreation (-0.55; 95% Confidence Interval = -1.009 – -0.099), parks (0.29; 95% Confidence Interval = 0.033–0.543), transit stations (0.29; 95% Confidence Interval = 0.156–0.424), workplaces (-0.25; 95% Confidence Interval = -0.43 – -0.079) and residential places in Kampala (-1.02; 95% Confidence Interval = -1.4 – -0.638) after controlling for the government response stringency index (Table 1). On the other hand, for Wakiso, only the correlation between air quality and movement in places of residence was statistically significant (-0.99; 95% Confidence Interval = -1.335 – -0.652).

Table 1
Effect of changes in mobility on fine particulate matter ($PM_{2.5}$) in Kampala district

Destination	Estimate	95% Confidence Interval	P-value
Retail and recreation	-0.55	-1.009 – -0.099	**p < 0.05**
Grocery and pharmacy	0.23	-0.111–0.566	p > 0.1
Parks	0.29	0.033–0.543	**p < 0.05**
Transit stations	0.29	0.156–0.424	**p = 0**
Workplaces	-0.25	-0.43 – -0.079	**p < 0.01**
Residential	-1.02	-1.4 – -0.638	**p = 0**

Multivariate analysis using linear regression for the linear relationship between changes in mobility within the six kinds of places tracked by Google and air quality in Kampala district controlling for lockdown restrictions i.e., the government response stringency index; with corresponding 95% Confidence Intervals (CIs) and significance codes for the p-values. Statistically significant p-values (p < 0.05) are shown in bold font.

Table 2
Effect of changes in mobility on fine particulate matter ($PM_{2.5}$) in *Wakiso district*

Destination	Estimate	95% Confidence Interval	P-value
Retail and recreation	-0.12	-0.356–0.113	p > 0.1
Grocery and pharmacy	-0.15	-0.333–0.025	p < 0.1
Parks	0.13	-0.003–0.259	p < 0.1
Transit stations	-0.04	-0.302–0.213	p > 0.1
Workplaces	0	-0.155–0.147	p > 0.1
Residential	-0.99	-1.335 – -0.652	**p = 0**

Multivariate analysis using linear regression for the linear relationship between changes in mobility within the six kinds of places tracked by Google and air quality in Wakiso adjusting for lockdown restrictions i.e., the government response stringency index; with corresponding 95% Confidence Intervals (CIs) and significance codes for the p-values. Statistically significant p-values (p < 0.05) are shown in bold font.

5. Impact of mobility restrictions on human mobility

For Kampala, the government response stringency index was negatively associated with movement in grocery and pharmacy (Pearson correlation coefficient = -0.57, $p < 0.001$), parks (Pearson correlation coefficient = -0.6, $p < 0.001$), retail and recreation (Pearson correlation coefficient = -0.65, $p < 0.001$), transit stations (Pearson correlation coefficient = -0.53, $p < 0.001$) and work places (Pearson correlation coefficient = -0.57, $p < 0.001$); and positively correlated with movement in residential places (Pearson correlation coefficient = 0.63, $p < 0.001$) (Fig. 5).

Similarly for Wakiso, the government response stringency index was negatively associated with movement in grocery and pharmacy (Pearson correlation coefficient = -0.4, $p < 0.001$), parks (Pearson correlation coefficient = -0.38, $p < 0.001$), retail and recreation (Pearson correlation coefficient = -0.49, $p < 0.001$), transit stations (Pearson correlation coefficient = -0.74, $p < 0.001$) and work places (Pearson correlation coefficient = -0.49, $p < 0.001$); and positively correlated with movement in residential places (Pearson correlation coefficient = 0.64, $p < 0.001$) (Fig. 5).

6. Influence of mobility restrictions on air quality

Air quality improved with stringency of restrictions in both Kampala and Wakiso districts, with Pearson correlation coefficients of -0.31 ($p < 0.001$) and − 0.21 ($p < 0.001$) respectively (Fig. 6).

Discussion

Beyond the direct counting of moving persons, several analogs could be used to represent quantification of human mobility, including road vehicular traffic volume, mobile phone tracking and fuel consumption. However collecting such data on a city or district wide scale would not only be prohibitively expensive in money and time, it would also offer low resolution and sensitivity. Mobile phone tracking comes closest but is also limited by the relative paucity of mobile phones with enabled GPS location devices in developing countries, the ability of users to turn off GPS location and the rather ardours and lengthy process of obtaining such data from mobile phone companies. Although the correspondence between human vehicular powered mobility and ambient particulate matter is in part intuitive, it has not been comprehensively tracked and studied using objective quantitative spatial-temporal metrics. This is a particularly valuable approach in the context of public health which has in recent times largely depended on mobile phone tracking to quantify human movement that could be related to disease spread. The emergence of COVID-19 and its related restrictions on movement of persons presented a rare large scale experimental control opportunity, to study and calibrate the relationship between human mobility and ambient air quality on an unprecedented scale. That opportunity coincided with the recent availability of community movement data from Google and the recent advent of extensive collection of data on atmospheric particulate matter in two cities in Uganda (16, 17).

We found that 24-hour average levels for fine particulate matter ($PM_{2.5}$) in Kampala were consistently higher than the WHO recommended threshold throughout the observation period while $PM_{2.5}$ levels for Wakiso fell below the WHO guideline limit on some days in May 2020 and April 2021 with mean values for both cities above the guideline limit. On the other hand, 24-hour average levels for coarse particulate matter (PM_{10}) were lower than the corresponding WHO guideline limit on some days in both cities but the means over the observation period were above the guideline limit. WHO reports that 91% of the world's population live in places where air pollution levels exceed WHO guideline limits (28). The findings presented here confirm that these two cities in sub-Saharan Africa are a part of that statistic.

Institution of restrictions to interrupt transmission of COVID-19 in Uganda led to a reduction in air pollution in both cities with 24-hour average values falling either to or below the recommended WHO threshold levels on some days. In fact, air quality in both cities improved with stringency of restrictions. These results are consistent with findings from other studies that showed an improvement in air quality following institution of lockdown measures in most cities around the world (18–21, 29, 30). However, these gains in air quality were short-lived and were promptyly reversed when restrictions were lifted.

We found an increase in mobility in residential places and a decrease in mobility in non-residential places tracked by Google in both cities following the institution of the first set of restrictions on 18th March 2020. This is expected because the restrictions included stay at home and work-from-home orders. Thus lockdowns are an effective policy measure for decreasing human mobility so as to reduce the spread of infectious diseases like COVID-19. Without human movement, infectious particles would be less likely to be transferred from one person/location to another. Our findings are consistent with those of previous studies that found an increase in residential mobility and a decline in mobility in non-residential places during COVID-19 lockdown periods (31–34). There was a decrease in residential mobility following the lifting of restrictions. On the other hand, mobility in the non-residential places climbed back near baseline values. Following the institution of a second major lockdown, mobility patterns were identical to those of the first major lockdown where mobility in residential places increased and that in non-residential places reduced. Similarly, the lifting of the lockdown following the second wave of the epidemic led to a decrease in mobility in residential places and an increase in mobility in non-residential places.

Before the start of the election period, mobility patterns were similar in the two cities i.e., mobility in residence places was intially above baseline values following the institution of the first major lockdown and thereafter reduced to baseline values towards the start of elections. Prior elections, non-residential mobility was below baseline values in both cities except between September and November 2021 reached baseline values except for movement to retail and recreation places and transit stations. During elections, residential mobility was above baseline values in both cities except for the months of January 2021 were the actual elections were held when it went below baseline values. On the other hand, all other forms of non-residential mobility were below baseline values except for movement to parks and workplaces where these increased and reached baseline values in January 2021. This could be because of the fear for a violent election and also because election dates for the office of the president are considered public holidays and thus most public servants and private business people were at home during these times. During the election period, mobility in places of residence was slightly higher than baseline values. This could be because of the fear for a violent election and also because election dates for the office of the president are considered public holidays and thus most public servants and some private business people were at home during these times. On the other hand, mobility in other places increased compared to pre-election period. This is because the election period was characterised by campaigns with mass gatherings of people from various parts of the country even though the country's electoral commission called for scientific (digital) campaigns with small consultative meetings. This was not the case as most campaigns were of mass gatherings. Post-election, both residential and non-residential mobility were close to baseline values in Wakiso. For Kampala on the other hand, residential mobility remained above the baseline. These results highlight the influence of elections on mobility patterns especially in Africa were mail-in voting is not yet instituted.

In Kampala, air quality declined with increase in movement to non-residential places and improved with increase in movement in residential places. Only associations between air quality and movement in workplaces and residential places were statistically significant in Wakiso. This could be because Wakiso is a more rural city compared to Kampala suggesting that air quality captures movement patterns more accurately in urban cities relative to less urban locations. This could also suggest higher compliance to movement restrictions in urban centres where enforcement is more concentrated in Uganda. This observation may also be attributed to increased domestic emissions due to people staying home more. In a multivariate analysis after adjusting for the government response stringency index, air quality in Kampala was independently correlated with movement in non-residential and residential places in Kampala. On the other hand, for Wakiso, only the correlation between air quality and movement in places of residence was statistically significant. These findings are consistent with those of a previous study in Barcelona that found a positive correlation between the mobility in places classified as retail and recreation with nitrogen dioxide and coarse particulate matter (35).

For both Kampala and Wakiso, we found that the government response stringency index was negatively correlated with movement in non-residential places; and positively correlated with movement in residential places. Thus, as movement restrictions were tightened, people stayed more at home and movement in all other places reduced significantly and leading to an improvement in air quality. This could be as a result of reduced road vehicular traffic volume. The implication of this finding is that air quality closely mirrors movement data and thus may accurately depict movement patterns at population level.

Although high levels of air pollution could indicate isolated air pollution events such as high pollution in city factories rather than depict mobility patterns at population level, here, we controlled for this by not including air quality data for sensors that showed irregular spikes at notable locations near factories in these locations.

Conclusions

In conclusion, we observed pollution levels for fine particulate matter ($PM_{2.5}$) that were above WHO guideline limits in both cities in Uganda even during COVID-19 lockdowns despite some improvement in air quality during these periods. Thus, more work needs to be done to address the problem of air pollution in this setting as well as other cities around the world. The institution of restrictions also led to an increase in residential mobility and a decrease in non-residential mobility. Thus lockdowns are an effective way of reducing human mobility to interrupt infectious disease transmission as well as improve air quality. Air quality in both cities improved with stringency of movement restrictions which was positively correlated with movement in residential places and negatively correlated with movement in non-residential places. Furthermore, in a multivariable analysis, air quality was independently positively correlated with movement in non-residential places and negatively correlated with residential mobility in Kampala. Taken together, these findings suggest that air quality data closely mirros human mobility data and could thus be used as a proxy to human movement patterns in these places.

Abbreviations

1. WHO
World Health Organisation
2. $PM_{2.5}$
Fine particulate matter
3. PM_{10}
Coarse particulate matter
4. R
Pearson correlation coefficient
5. KMA
Kampala Metropolitan Area
6. UNICEF
United Nations International Children's Emergency Fund

Declarations

Ethics approval and consent to participate

The study was approved by the Uganda National Council of Science and Technology (UNCST) under registration number SIR61ES.

Consent for publication

Not applicable

Availability of data and materials

Human mobility data is from Google Community Mobility Reports and is available from Google as a free download (https://www.google.com/covid19/mobility/). COVID-19 case data is available from the World Health Organisation (https://covid19.who.int/table). Air Quality data is available upon submitting a request at the AirQo project website (https://www.airqo.net/). The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Competing interests

The authors declare that they have no competing interests.

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Authors' contributions

R.G, D.J and E.B conceived the study. R.Gabstracted and analysed the data. R.G, D.J, E.B, F.K and D.P.K interpreted the results and were major contributors in writing the manuscript. All authors (R.G, D.J, E.B, F.K and D.P.K) read and approved the final manuscript.

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Figures

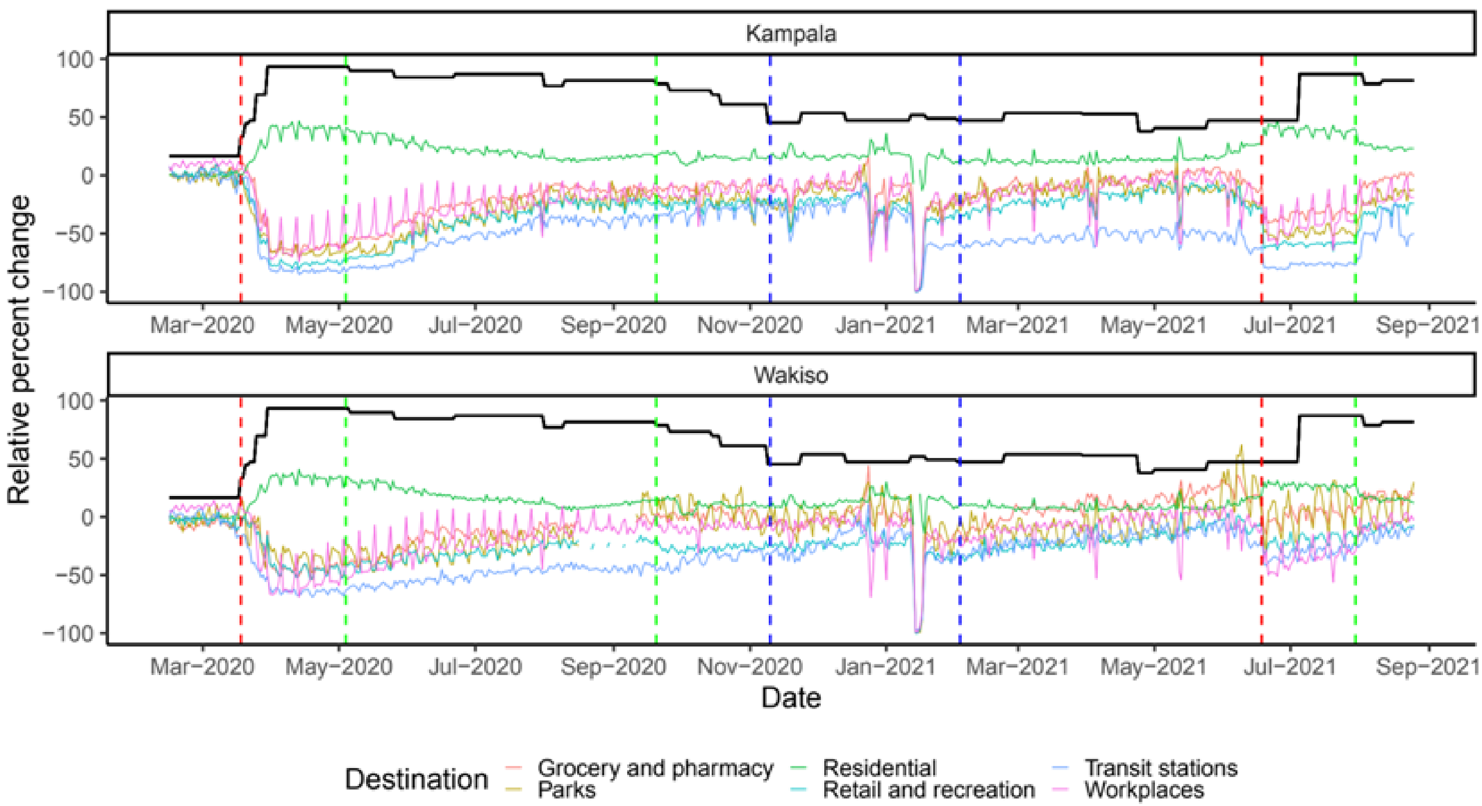

Figure 1

Change in mobility patterns in Kampala and Wakiso districts relative to the baseline.

The baseline is the median value, for the corresponding day of the week, during the five–week period 3rd January 2020 – 6th February 2020 (23). The red dashed vertical lines indicate dates for institution of major restrictions with the first one (from left to right) indicating the date (18th March 2020) for start of restrictions in Uganda when mass gatherings were suspended. The second red line indicates the date (18th June 2021) for institution of a second major lockdown following a surge in cases that led to a second wave of the epidemic in Uganda. First green dashed vertical line (from left to right) indicates the date (4th May 2020) for the start of the first phase of easing restrictions where whole sellers, metal and wood workshops, warehouses, insurance providers and hardware shops were opened and restaurants were allowed to provide take-aways. The second green dashed line is the date (20th September 2020) when the country's only International Airport and land borders were opened for tourists, Restrictions on movements on border districts were lifted, and places of worship and sports activities were opened. The third green dashed vertical line is the date (30th July 2021) when restrictions were lifted following a reduction in COVID-19 cases during the second wave of the epidemic. The space between the blue dashed lines indicates the election period from 10th November 2020 when campaigns for presidential elections started to 3rd February 2021 when elections for sub county/town/municipal division chairpersons and councillors were conducted.The black line indicates how government response stringency index varied over time during the observation period.

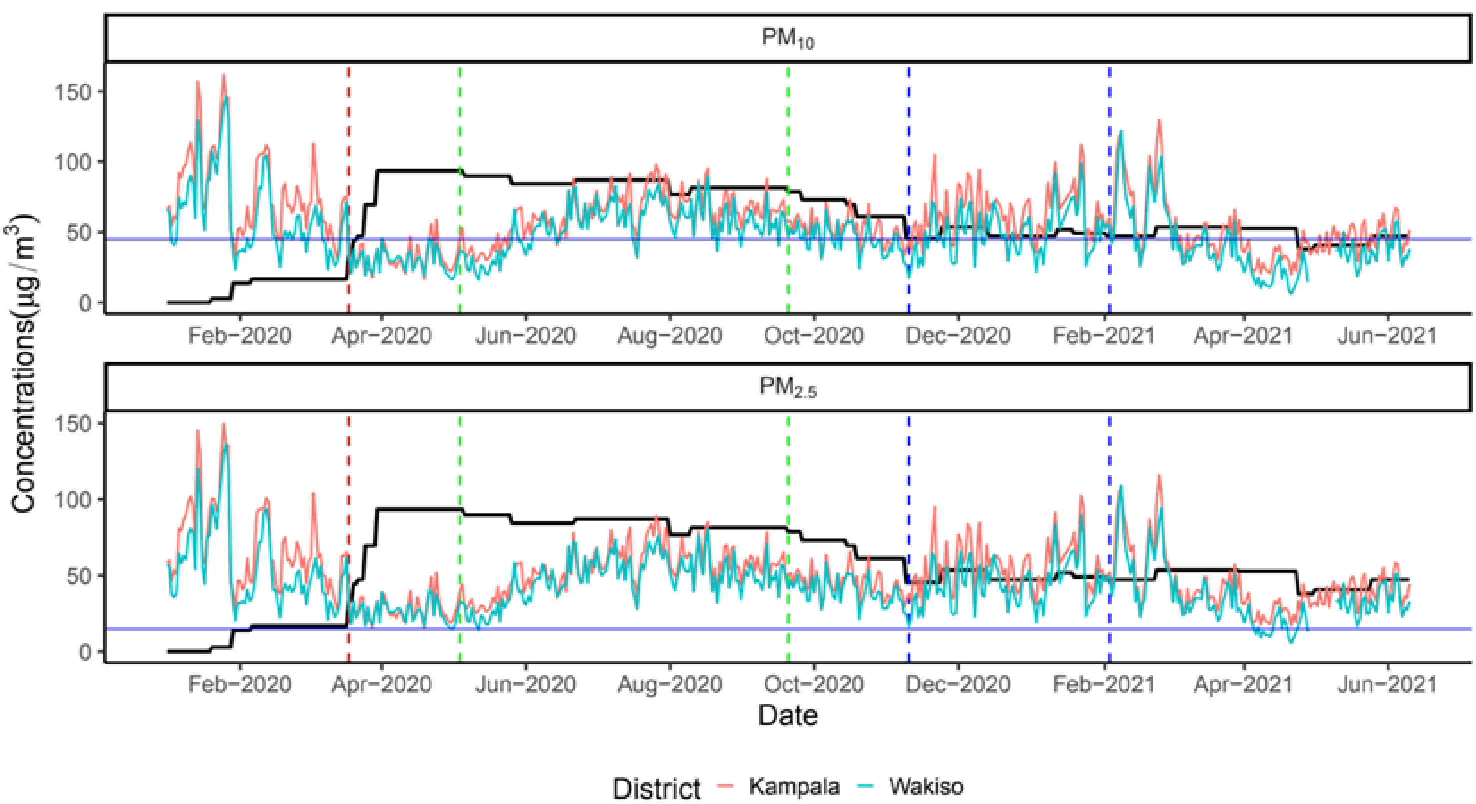

Figure 2

Overall ambient air quality temporal variation for Kampala and Wakiso districts.

The horizontal blue lines are the 24-houraverage levels recommended by WHO i.e., 15µg/m^3 for $PM_{2.5}$ and 45µg/m^3 for PM_{10}. The reddashed verticalline indicates thedate for start of restrictions in Uganda when mass gatherings were suspended i.e., 18th March 2020. The first green dashed vertical line (from left to right) indicates the date (4th May 2020) for the start of the first phase of easing restrictions where whole sellers, metal and wood workshops, warehouses, insurance providers and hardware shops were opened and restaurants were allowed to provide take-aways. The second green dashed line is the date (20th September 2020) when the country's only International Airport and land borders were opened for tourists, restrictions on movements on border districts were lifted, and places of worship and sports activities were opened.The space between the dashed blue lines indicates theelection period from 10th November 2020 when campaigns for presidential elections started to 3rd February 2021 when elections forsub county/town/municipal division chairpersons and councillors were conducted. The black line indicates how government response stringency index varied over time during the observation period.

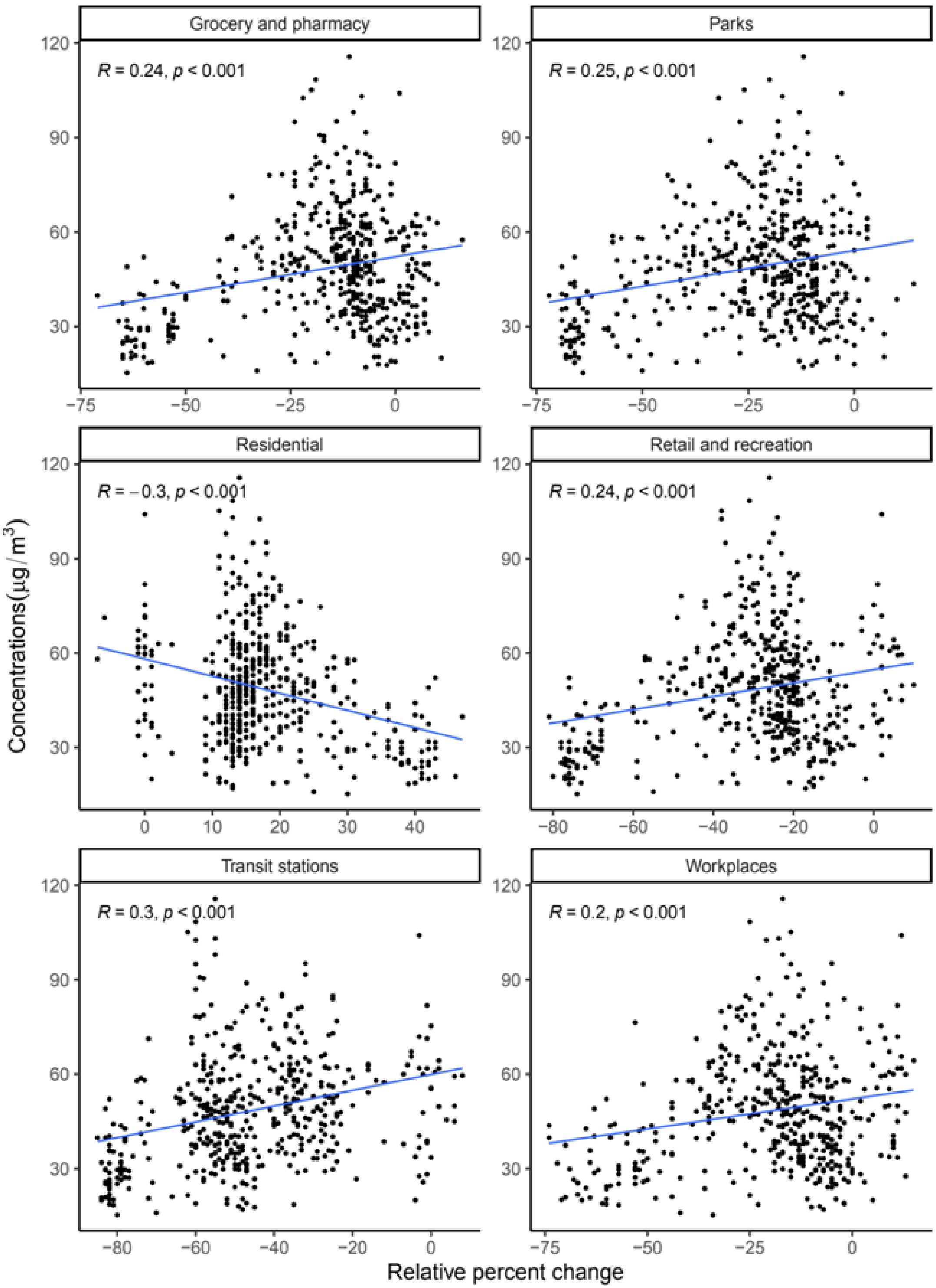

Figure 3

Correlation between changes in mobility (relative to the baseline) and fine particulate matter ($PM_{2.5}$) in Kampala district.

The baseline is the median value, for the corresponding day of the week, during the five–week period 3rdJanuary 2020 – 6thFebruary 2020. Scatter plots, associated Pearson correlation coefficients (R) and p-values (p) are shown.

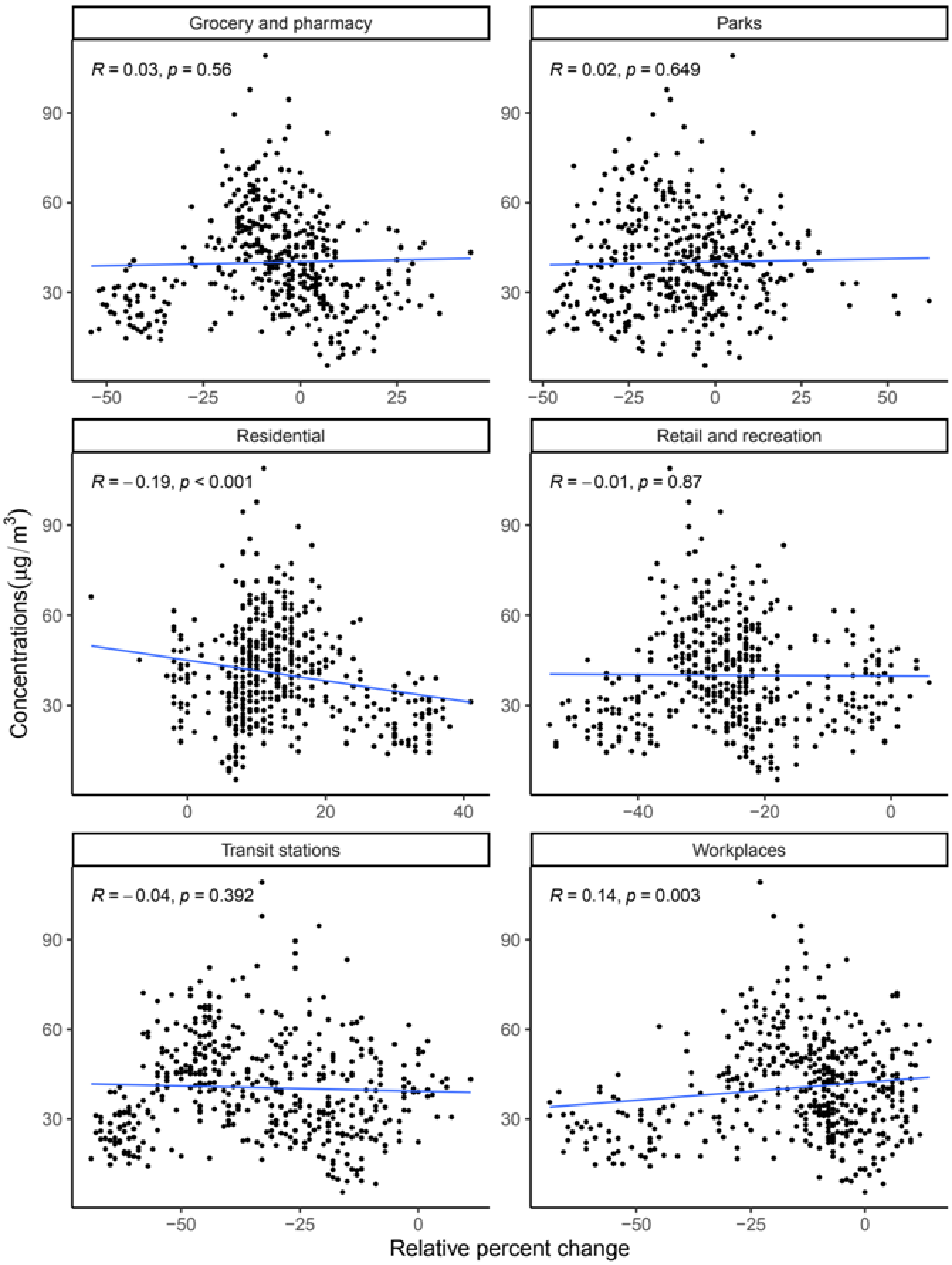

Figure 4

Correlation between changes in mobility (relative to the baseline) and fine particulate matter ($PM_{2.5}$) in Wakiso district.

The baseline is the median value, for the corresponding day of the week, during the five–week period 3rd January 2020 – 6th February 2020. Scatter plots, associated Pearson correlation coefficients (R) and p-values (p) are shown.

Figure 5

Correlation between changes in mobility (relative to the baseline) in Kampala and Wakiso districts and government response stringency index.

The baseline is the median value, for the corresponding day of the week, during the five–week period 3rd January 2020 – 6th February 2020. Associated Pearson correlation coefficients (R) and a significance code for the p-value (p) are shown.

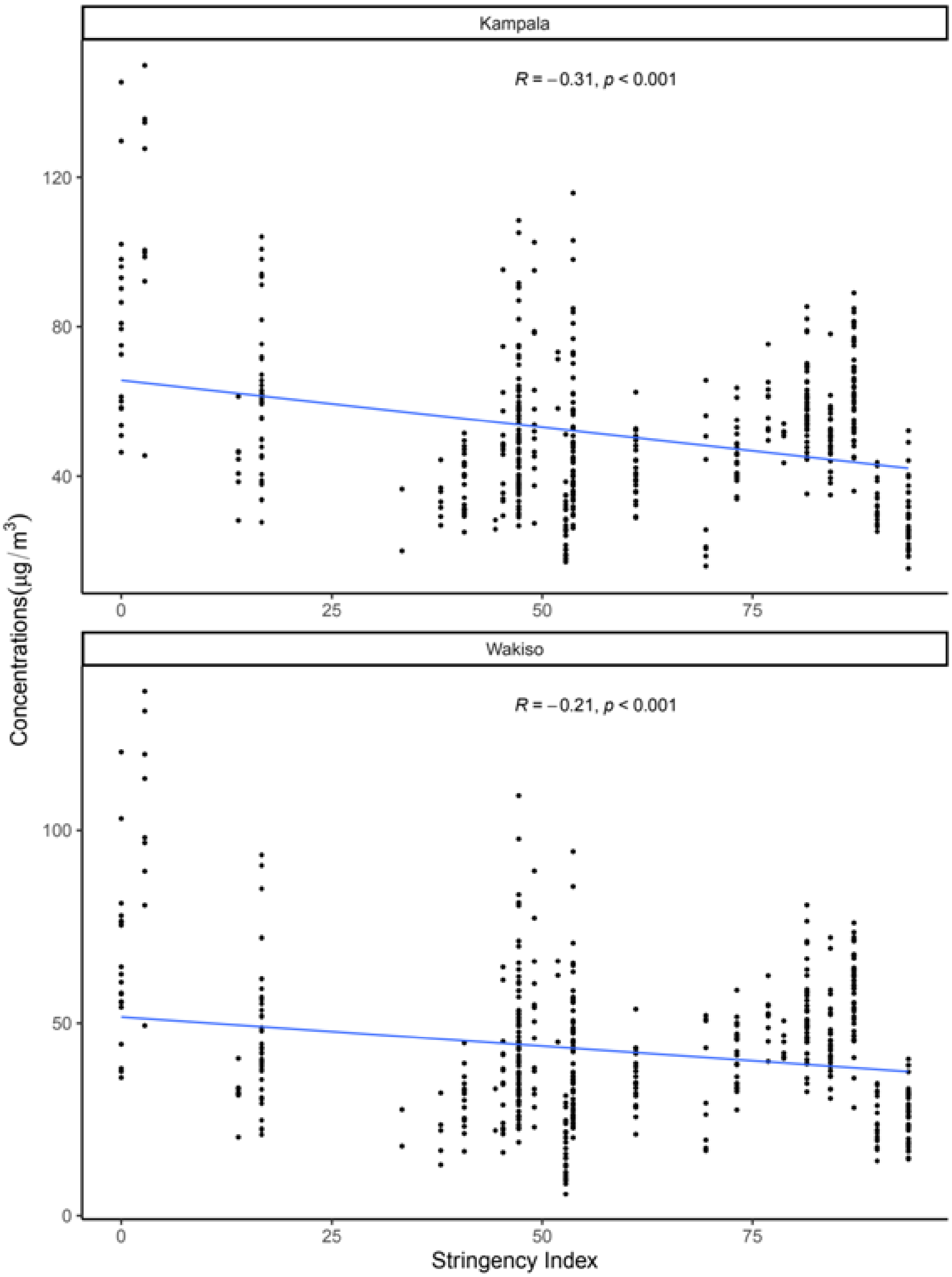

Figure 6

Correlation between fine particulate matter ($PM_{2.5}$) in Kampala and Wakiso and government response stringency index.

Associated Pearson correlation coefficients(R) and a significance code for the p-value (p) are shown.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- SupplementaryMaterialsFinal.docx