



Senseable City Lab :::: Massachusetts Institute of Technology

This paper might be a pre-copy-editing or a post-print author-produced .pdf of an article accepted for publication. For the definitive publisher-authenticated version, please refer directly to publishing house's archive system

Research article

A Nairobi experiment in using low cost air quality monitors

Priyanka deSouza¹, Victor Nthusi², Jacqueline M. Klopp³, Bruce E. Shaw⁴, Wah On Ho⁵, John Saffell⁶, Roderic Jones⁷, Carlo Ratti⁸

¹Research Fellow, Senseable City Lab MIT, Cambridge MA 02139 desouzap@mit.edu

²Science Division, United Nations Environment Program(UNEP), UN Avenue, Nairobi, Kenya

³Center for Sustainable Urban Development, Earth Institute, Columbia University, 475 Riverside Dr. Suite 520 New York NY 10115

⁴Lamont Doherty Earth Observatory, Columbia University, Palisades, New York, USA

⁵Senior Research Scientist, Alphasense Ltd, Sensor Technology House, 300 Avenue West, Skyline 120, Great Notley, Essex CM77 7AA, UK

⁶Technical Director, Alphasense Ltd, Sensor Technology House, 300 Avenue West, Skyline 120, Great Notley, Essex CM77 7AA, UK

⁷University of Cambridge, UK

⁸Director, Senseable City Lab MIT, Cambridge MA 02139

Received: 9 February 2017 - **Reviewed:** 14 March 2017 - **Accepted:** 26 August 2017

<http://dx.doi.org/10.17159/2410-972X/2017/v27n2a6>

Abstract

Many African cities have growing air quality problems, but few have air quality monitoring systems in place. Low cost air quality sensors have the potential to bridge this data gap. This study describes the experimental deployment of six low cost air quality monitors consisting of an optical particle counter Alphasense OPC-N2 for measuring PM₁, PM_{2.5} and PM₁₀, and Alphasense A-series electrochemical (amperometric) gas sensors: NO₂-A43F, SO₂-A4, NO-A4 for measuring NO₂, NO and SO₂ in four schools, the United Nations Environment Program (UNEP) headquarters and a community center in Nairobi. The monitors were deployed on May 1 2016 and are still logging data. This paper analyses the data from May 1 2016 to Jan 11 2017. By examining the data produced by these sensors, we illustrate the strengths, as well as the technical limitations of using low cost sensors for monitoring air quality. We show that despite technical limitations, sensors can provide indicative measurements of air quality that are valuable to local communities. It was also found that such a sensor network can play an important role in engaging citizens by raising awareness about the importance of addressing poor air quality. We conclude that these sensors are clearly a potentially important complement but not a substitute for high quality and reliable air quality monitoring systems as problems of calibration, certification, quality control and reporting remain to be solved

Keywords

outdoor air quality, low cost sensors, Nairobi, citizen science, African cities

Introduction

Poor air quality is the world's single largest environmental health risk. Exposure to air pollution in 2012 was responsible for an estimated seven million premature deaths and this problem is growing (World Health Organisation 2014). Given the large public health costs of air pollution, many countries are putting in place more measures to improve air quality, including laws, regulations, monitoring systems and public awareness campaigns (<http://web.unep.org/airquality/>). As further impetus for these efforts, the new Sustainable Development Goals includes as global targets, reducing annual mean levels of urban fine particulate matter (PM₁₀ and PM_{2.5}) and the mortality rate attributed to household and ambient air pollution.

These efforts at monitoring and research are uneven across the globe. In sub-Saharan Africa, air quality data often do not exist, and regulations and laws are often not in place to curb air pollution; or if in place, are not implemented, even though

existing research shows that the annual mean fine particulate matter in these cities often exceeds World Health Organisation standards (Njee et al., 2016; Petkova et al., 2013). Few African cities operate air monitoring systems, and most cities lack any air quality monitoring capabilities (Schwela, 2012a, Njee et. al 2016). Currently, only Ghana and South Africa operate comprehensive and well organized air quality monitoring programs (Amegah and Agyei-Mensah, 2016). In addition, the air quality data that does exist is not always made public and/or communicated effectively, which limits public awareness and effective policy (Petkova et al., 2013).

Although systematic, long term monitoring is missing in most African cities, existing studies show a serious and growing problem in urban air quality due to rapid urbanization coupled with industrialization, increasing motorization and the continued use of biomass fuel as the household energy source

(UNEP, 2016; Lindén et al., 2012; Fiore et al., 2012; Schwela, 2012b). The worst urban air pollution may actually be in sub-Saharan African countries (Schwela, 2012a). There is thus an urgent need to monitor urban air quality in this region so that the health effects of pollutants can be better understood and quantified, leading to cost-effective abatement strategies and greater public awareness and pressure.

For many African cities, cost is one barrier to investing in air quality monitoring (Amegah and Agyei-Mensah, 2016; Schwela, 2012a). The cost of reference air quality monitoring systems (AQMS) is high (costing between US \$5000 and US \$200,000 for each AQM), and training and AQMS maintenance, as well as managing and analysing the data can also be expensive (Kumar et al., 2015; Mead et al., 2013). This means that even in those countries that have air quality standards and laws, there are often no monitoring systems to measure compliance.

Within this context, low-cost sensors (costing between US \$100 and US \$3000 for each node) appear to have the potential to help us move from a paradigm of high cost, highly accurate, sparsely located reference air quality monitors, to a dense, low cost, reasonably accurate air quality monitoring network that can also involve citizen science. However, currently no standards or certification criteria exist for such sensors, and there are concerns about the quality of the data (Lewis and Edwards, 2016). Further, the flood of low cost sensors onto the market makes it difficult to determine the reliability of each model. Complicating the challenge of certification, cheap sensors from the same manufacturer often have variable performance.

A US Environmental Protection Agency study of low cost sensors on the market found that either 'no lower cost sensors currently meet [the EPA's] strict requirements or have not been formally submitted to the EPA' (Williams et al., 2014). The US EPA in their study tested these sensors in a clean environment in North Carolina, but how these sensors will perform in the polluted, hot, humid environments frequently found in the developing world is unknown. This is because temperature and humidity can affect the sensitivity of some of these sensors—especially low cost electrochemical gas sensors. Therefore, more work is needed to quantify the accuracy of these sensors under different conditions. Overall, more research is needed on the performance of low cost air quality networks in the field to address the need for monitoring in many of the world's cities (Kumar et al., 2015, Lewis and Edwards 2016).

This paper presents the results and lessons learned from an experiment in using a low cost air quality monitoring network in Nairobi, Kenya. The main aim of this work is to contribute to the growing and important conversation about the role of low cost sensors in air quality monitoring efforts in cities (Kumar et al., 2015; Lewis and Edwards 2016, Kotsev et al. 2016, Piedrahita et al., 2014; Popoola 2012). We were interested in exploring the feasibility of deploying such networks in African cities as a means of gathering some basic data in a quick and efficient way that also involves citizens.

A collaboration between UNEP, the company Alphasense, the University of Cambridge, NASA-GLOBE, the Wajukuu Arts Collective and the Kibera Girls Soccer Academy, resulted in the deployment of a pilot, six node air quality network in

four schools, UNEP and one community center in the city of Nairobi, Kenya. The collaboration also aimed to share the experience of air quality monitoring with interested citizens. The sensors include an optical particle counter (Alphasense OPC-N2) that measures PM_{10} , $PM_{2.5}$ and PM_{10} , Alphasense A-series electrochemical gas sensors (NO₂-A43F, NO-A4, SO₂-A4) for measuring NO₂, NO and SO₂, temperature and humidity sensors, and a SIM card to transmit data in near real time via the GSM network.

These pollutants were chosen to be measured because particles with aerodynamic diameters less than 10 μm , when inhaled, become embedded in soft tissue and have major health effects. Particulate matter in the environment can have hundreds of different sources. NO and NO₂ are the two oxides of nitrogen that majorly affect human health. NO typically rapidly oxidizes to NO₂. However, the direct emission of NO from vehicles can result in high levels of NO close to roads. SO₂ also negatively affects health. It also reacts with other compounds in the atmosphere to form fine particulates. SO₂ is typically emitted from power plants, industrial facilities, and from the burning of diesel with high sulphur content.

This network started running on May 1, 2016 and is still in operation at the time of writing this paper. After a brief review of air pollution in Nairobi, where no continuous monitoring system yet exists, we present our methods and analyse data collected from this network. Drawing on this experimental deployment, we discuss lessons learned for the potential of low cost air quality networks to support air quality monitoring in African cities.

Background to the Nairobi Case Study

The capital of Kenya, Nairobi is a rapidly growing metropolitan area with an estimated 4 million people living or working within its city boundaries. By 2030, this population may grow to as much as 6 million (World Bank 2016). Air pollution has accompanied this urban growth. Sources include vehicles, open air burning of solid waste, industrial activity and domestic cooking using biomass (Gatari 2009, Kinney et al. 2011, Muindi et al. 2016). Despite growing air quality regulations, such as in the Environmental Management and Coordination Act (Air Quality) Regulations 2014, Nairobi, like most Africa cities, does not have an institutionalized air quality monitoring system.

Scientists at the University of Nairobi, African Population and Health Research Center and their international collaborators (Gaita et al., 2014; Gatari et al., 2009; Gatari and Boman, 2003; Kinney et al., 2011; Muindi et al., 2014; Ngo et al., 2015; Vliet and Kinney, 2007) have taken a number of measurements in Nairobi. These are, however, short-term observations at limited points around the city (background, industrial, roadways, and households in informal settlements) and limited numbers of pollutants, mostly $PM_{2.5}$. In many cases, levels of $PM_{2.5}$ appeared well above the World Health Organization (WHO) 24-h average guideline of 25 mg/m^3 and an annual average guideline of 10 $\mu g/m^3$. However, some measurements were not always comparable with these guidelines, as continuous monitoring was not taking place (Kinney et al., 2011; Ngo et al., 2015).

Methods

Air quality monitors were bought from the company: Atmospheric Sensors Ltd. in the UK (The product catalogue is found here: <http://atmosphericsensors.com/products/product-brochures/remote-air-quality-monitor/view>). The monitors comprised of an optical particle counter (Alphasense OPC-N2) and Alphasense A-series electrochemical gas sensors, temperature and humidity sensors, and a SIM card to transmit data in near real time via the GSM network. The OPC-N2 (costing USD 450 each) measures particle counts in 16 bins ranging from 0.38 μm to 17.5 μm . It does this by illuminating one particle at a time using focused light from a laser, and measuring the intensity of light scattered from aerosol particles. The amount of scattering from a particle is a function of particle size and composition, which can be calibrated using mono-disperse particles (Sousan et al., 2016). The number of particles per volume for each of these bins can be obtained by dividing the particulate counts of each bin by flow rate and sample time. Alphasense provides a partially proprietary algorithm that makes assumptions about the particle density to calculate PM_{10} , $\text{PM}_{2.5}$ and PM_{10} data from the particle count data. The OPCs in this deployment turn on and run for 20s every 60s; there is 15s of warm up then 5s of actual measurement. The sampling flow rate (SFR) is typically 3.7 mL/s, but varies with temperature. The accuracy of these monitors depends on the size distribution of particulates present, environmental factors such as humidity and the hygroscopicity of the particulates present (Sousan et al., 2016). Without this detailed information, the uncertainty in measurements of the OPC-N2 cannot be quantified.

The Alphasense A-series electrochemical (amperometric) gas sensors (NO₂-A43F, SO₂-A4, NO-A4): 4-electrode, 20 mm diameter aperture sensors (USD 50-75 each), measure NO₂, NO, SO₂. The electronics of the node used to convert the current of the electrochemical gas sensors to volts and the analogue-to-digital conversion of this voltage signal is proprietary to Atmospheric Sensors. The gas sensors log data every minute at the same time as the OPC. The monitors were coupled to a UPS in order to maintain instrument sensitivity during short power failures. Electrochemical gas sensors exhibit cross-interferences with other pollutants. For example, the NO sensor is sensitive to NO₂ (Data sheet: <http://www.alphasense.com/WEB1213/wp-content/uploads/2016/03/NO-A4.pdf>). The NO₂ sensor is extremely sensitive to O₃ (Data sheet: <http://www.alphasense.com/WEB1213/wp-content/uploads/2016/04/NO2-A43F.pdf>). The SO₂ sensor is most sensitive to H₂S and NO₂ (Data sheet: <http://www.alphasense.com/WEB1213/wp-content/uploads/2013/12/SO2A4.pdf>).

Changes in ambient temperature and humidity also affect the sensitivity and sensor gain. The sensors were pre-calibrated at the Alphasense laboratory in the UK, and calibration curves were provided for the gas sensors in order to convert the signals into gas concentrations, expressed as parts per billion by volume (ppb). Alphasense also provided the temperature correction factors for the gas sensors. Research has shown though, that although the sensor manufacturer's correction is effective for sensitivity-dependent temperature correction, it is not effective for temperature-dependent baseline change. Research has also shown that this baseline effect is more pronounced for the NO sensor than for the NO₂ sensor (Popoola et al., 2016). This shall be discussed further when the results are presented.

Data was pulled from the Alphasense server via a file transfer protocol.

One of the biggest drawbacks of our network is that co-location of the low cost monitors with a reference air quality monitor was not conducted. Thus, we have no way to test the accuracy of data from our monitors. We also did not calibrate the electrochemical gas sensors in the ambient environment. We tried to conduct a qualitative appraisal of the data we gathered by going to each site and talking to the people there about what they observed. However, we acknowledge that co-locating at least one of our monitors with a reference air quality monitor would have significantly enhanced our results. We present our analysis and data in this context.

This is the first time air quality was monitored in schools in Nairobi. We specifically engaged with three schools that were part of the NASA GLOBE community (<https://www.globe.gov/>), which is an international program that allows students the opportunity to participate in data collection. We did this to leverage the existing citizen science program in the schools. We also hoped that we could use our collaboration with NASA GLOBE to expand our deployment in other GLOBE schools in the future.

We selected our sites in a variety of locations. We deployed air quality monitors in low-income schools in the informal settlements: a) Kibera Girls Soccer Academy situated in the informal settlement: Kibera near the railway tracks and b) Viwandani community center in an informal settlement in the industrial area of Nairobi. We also deployed monitors at c) St Scholastica, situated 20 meters away from the notoriously congested Thika Highway in order to capture pollutants from vehicular emissions, d) at UNEP located in Gigiri, which is a relatively green, low density residential, and wealthy part of the city. At e) All Saints Cathedral School which is close to a major road, Mbagathi road, as well as several small shops and industries. Finally, we deployed a monitor at the elite national school, f) Alliance Girls School, located in Kikuyu, a small town to the North of Nairobi as an urban background site. By deploying our monitors in this range of sites, we hoped to capture the signature of different sources in the city as well as get a sense of the differing conditions between very poor and wealthier neighbourhoods. Figure 1 shows the geographic locations of the sites in the city.

The monitors were deployed on walls 1.5-2 meters above the ground so that they would be at close to adult breathing height, but out of reach of the casual passer-by. Note that as the monitors were mounted on walls instead of poles, the sensors only measure pollutants from air masses for a swath of 180 degrees. A plastic shield provided by Alphasense was used to protect the monitor from rain as seen on the upper right-hand side of Figure 1. As of January 11, 2017, the OPCs at all the sites, except for that at Viwandani, which experienced power outages for a few days in May and June and an extended power outage past July 2016, are logging data. The monitor at Alliance Girls School experienced a power outage for most of the month of September 2016, and the one at Kibera Girls School Academy experienced a few hours of power shortage on 19 August 2016, but otherwise have been logging data.

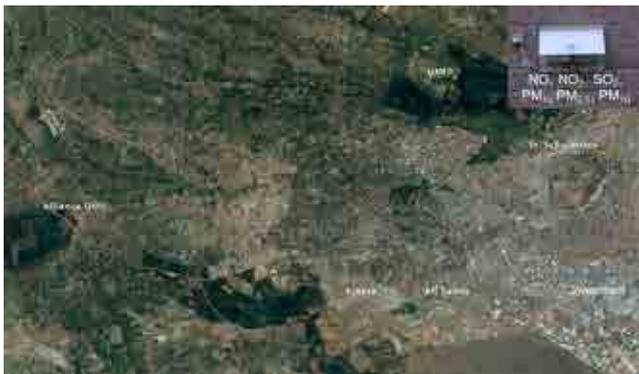


Figure 1: This shows a map of the six deployment sites with a photograph of what each site looks like. The upper right figure is a photograph of the monitor deployed at each site.

We hoped that by engaging with schools and community centers, we would be able to involve the public in air quality monitoring. Participation by residents in the monitoring is an important way to communicate the science of air pollution to citizens (Ngo et al. 2015a). Studies show that Nairobi residents from poor neighbourhoods appear to have a wide variety of often-inaccurate perceptions about air pollution, in part because they have very little information about it (Egondi et al., 2013; Muindi et al., 2014; Ngo et al., 2017, 2015). Nevertheless, a 2015 telephone survey of a representative sample of Nairobi residents, revealed that a majority of Nairobi's adult citizens perceive the air in the city as bad or very bad (69%) and among those who consider the air bad, 93% believed it had an impact on their health. This makes the idea of involving people in monitoring, especially through learning institutions, a viable and potentially important approach that we wanted to test

Finally, we presented preliminary data analysed using the 'OpenAir' package in R version 3.3.2 (Carslaw and Ropkins, 2012) to school children at each deployment site in order to raise awareness about air pollution as well as to brainstorm potential pollution management strategies for the community. We sourced large-scale wind data (that is not local, canyon-influenced wind data) averaged over a period of two minutes, half hourly for this analysis from the Wyoming Weather Website (<http://weather.uwyo.edu/surface/meteorogram/>), for the Jomo Kenyatta airport site to the south of the city at an elevation of 1624 meters.

Results

Figure 2 shows the hourly averaged PM data obtained from monitors at each of the six sites from May 5 2016 to Jan 11 2017. The monitors started running at different times on May 1 so for consistency, we ignore the data for the first 5 days of measurement. Raw minute wise PM data has been plotted in Fig 1A in the Appendix. The raw PM data showed peaks that were as high as a few 1000 $\mu\text{g}/\text{m}^3$. It is extremely unlikely for PM readings to reach such high values in a natural environment. However, without co-location with a reference instrument, it is impossible to distinguish the signal from the noise.

From Figure 2, we see that the PM readings at the informal settlements Kibera and Viwandani are routinely very high. A summary of the average minute wise PM readings for each site are provided in Table 1. We note that the difference in $\text{PM}_{2.5}$

in up-scale schools such as St Scholastica and Alliance Girls School, and the $\text{PM}_{2.5}$ recorded by the monitors at the sites in the informal settlements: Kibera and Viwandani are not very high. We also observe that particulate matter pollution recorded by our monitors at UNEP and All Saints are lower than at the other sites.

The hourly averaged periodic spikes in PM_{10} at the Alliance site are observed to reach a few 1000 $\mu\text{g}/\text{m}^3$. As mentioned previously, it is unlikely that PM_{10} reaches such high values in the natural environment. These peaks in pollution could indicate a source of pollution very close to the sensor. On going to the site, we found that the school did indeed burn wood very close to the site. This 'ground-truthing' shall be discussed further. It is interesting to note that peaks of the same magnitude as seen in the PM_{10} data were not seen in the finer particulate observations. More information on the kind of burning is required to speculate why this is the case.

We analysed the temperature corrected gaseous pollutant data using the Alphasense calibration and temperature correction at each site. Figure 3 shows temperature-corrected hourly-averaged NO_2 , SO_2 and NO data at each site. Raw minute wise gaseous pollutant data for each site can be found in Figure 2A in the Appendix.

We see from Figure 3 that a significant number of gaseous pollutant observations were < 0 . Table 1 shows how much of the gaseous data recorded was < 0 . This appears to be an issue of instrument calibration and also perhaps consistency between instruments, which we will discuss in more detail in later sections.

The raw data in Figure 2A in the Appendix also shows that for each site some NO observations go to a few -100 ppb. This seems to correspond to the value of NA for the NO sensor. We have applied a filter and eliminated NO values less than -100 ppb from our analysis from here onwards.

As mentioned before, no ambient calibration was carried out for the electrochemical gas sensors and therefore the gaseous pollutant values have to be viewed with skepticism. We present them here to see if any useful signal can be gleaned from the pollutant data.

Table 1 provides a summary of the pollutant data at each site. A multi-pollutant approach of analysing air quality in Nairobi can be useful in identifying common-sources across the city, as well as in identifying possible health effects that could arise from exposure to multiple pollutants, and not just a single pollutant. (Dominici et al., 2010).

From Figure 3 we note that SO_2 is measured to be highest at Viwandani. This seems reasonable. Our site is located in the industrial area of Nairobi. Community members informed us that several factories existed in the vicinity of the site ranging from a paint factory, a factory that manufactured electrical connections and a factory that produced the raw materials for tear gas. Given this background, the high SO_2 values that we saw were not unexpected. We were, however, surprised to see the peak in SO_2 levels at St Scholastica. More work is required to verify this peak, and to identify a potential source. We posit that

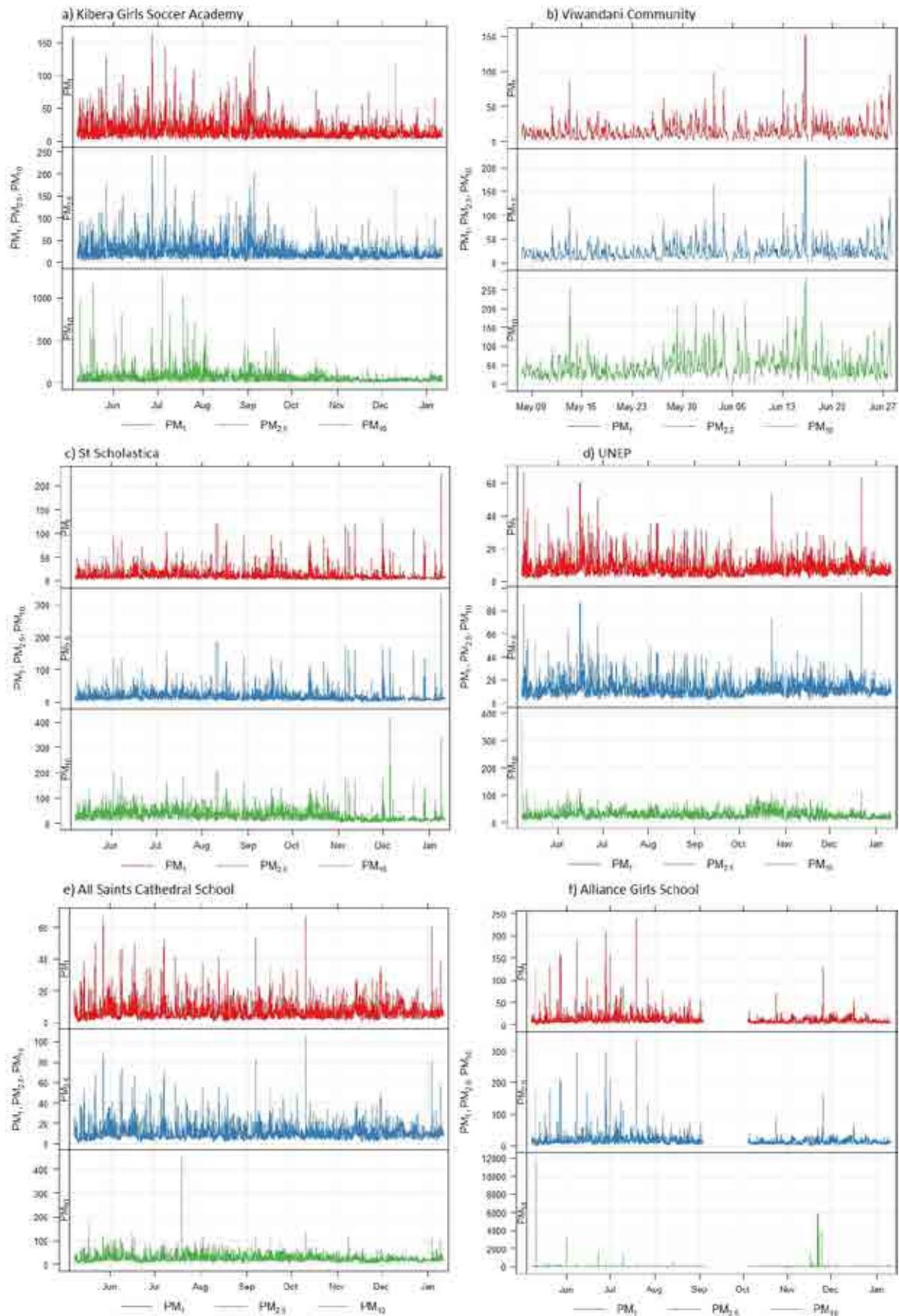


Figure 2: Hourly averaged PM_1 (red), $PM_{2.5}$ (blue) and PM_{10} (green) time series plots for each site in units of $\mu g/m^3$ a) Kibera Girls Soccer Academy, b) Viwandani Community Center, c) St Scholastica, d) UNEP, e) All Saints Cathedral School, f) Alliance Girls School from May 5 2016 to January 11 2017.

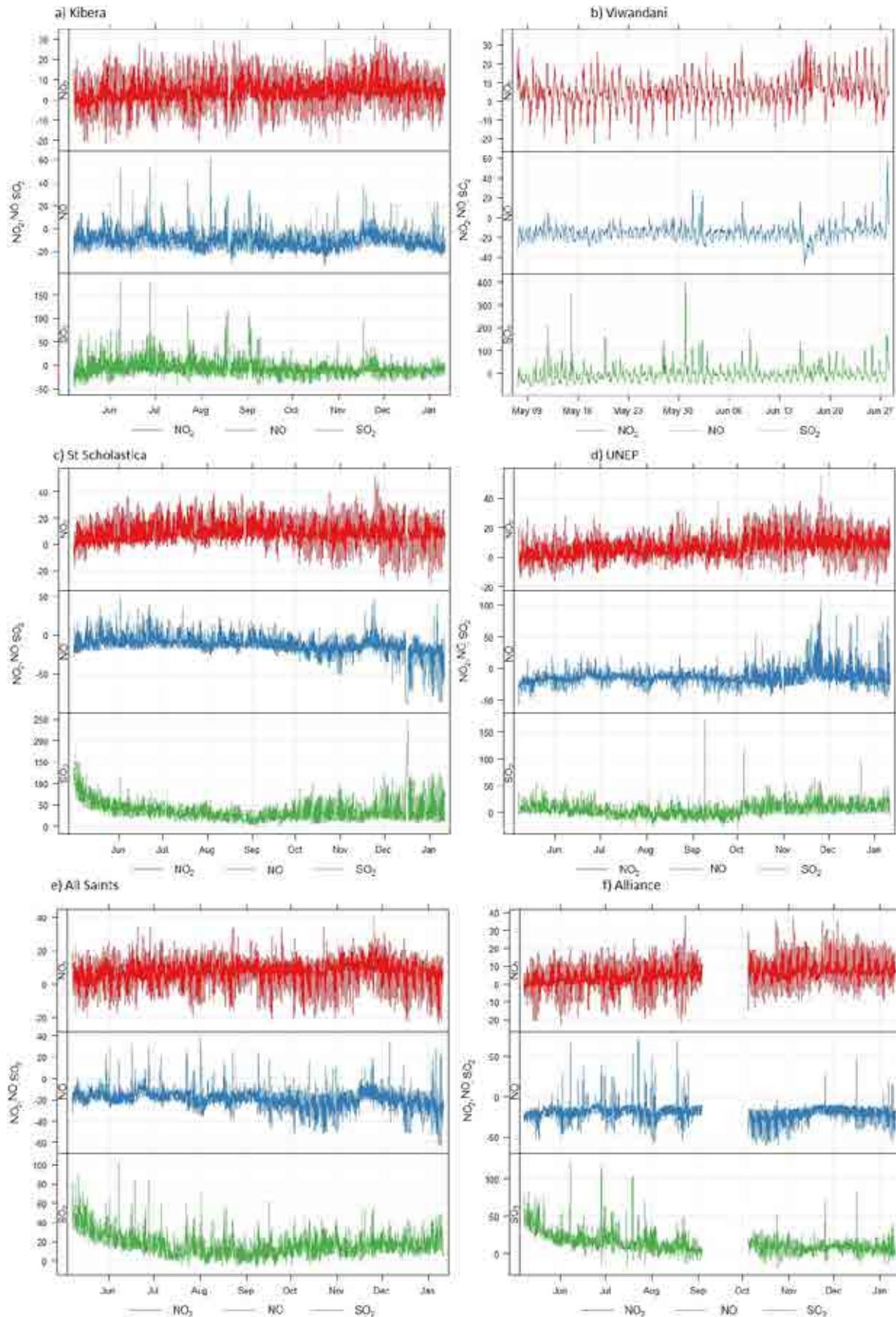


Figure 3: Hourly averaged NO₂ (red), NO (blue) SO₂ (green) time series plots for each site in units of ppb for the sites a) Kibera Girls Soccer Academy, b) Viwandani Community Center, c) St Scholastics, d) UNEP, e) All Saints Cathedral School, f) Alliance Girls School from May 5 2016 to January 11 2017.

Table 1: Summary of air quality statistics at each of the six sites. We have rounded pollutant values to the nearest whole number to avoid reporting insignificant figures. Note that for calculating correlations (R) involving the gaseous pollutants we used raw values. We only applied a filter to remove NO values that were < -100 ppb at all sites.

	Kibera	Viwandani	St Scholastica	UNEP	All Saints	Alliance
Total #	355274	72950	352926	355662	357168	312844
Mean PM ₁ µg/m ³	15	14	11	8	7	12
Mean PM _{2.5} µg/m ³	23	21	17	12	11	17
Mean PM ₁₀ µg/m ³	59	44	30	28	26	43
# NO ₂ >0	255692	54958	308370	288084	276668	248772
# SO ₂ >0	66192	21687	352638	220297	339850	283234
#NO>0	20782	1885	35812	27324	6202	5826
Mean NO ₂ in ppb for values >0	8	9	12	10	10	8
Mean SO ₂ in ppb for values >0	19	40	35	13	18	16
Mean NO in ppb for values >0	11	10	10	19	13	21
Correlation of temperature with humidity	-0.83	-0.86	-0.86	-0.89	-0.86	-0.86
Correlation of PM ₁ with temperature	-0.11	-0.2	-0.13	-0.21	-0.19	-0.18
Correlation of PM _{2.5} with temperature	-0.08	-0.18	-0.12	-0.18	-0.17	-0.17
Correlation of PM ₁₀ with temperature	0.039	-0.017	-0.054	0.12	0.05	-0.025
Correlation of NO ₂ with temperature	-0.2	-0.33	-0.11	0.059	-0.51	0.015
Correlation of SO ₂ with temperature	-0.38	-0.33	0.66	0.28	0.28	-0.0021
Correlation of NO with temperature	-0.39	-0.51	-0.69	-0.43	-0.74	-0.82
Correlation of PM ₁ with humidity	0.09	0.16	0.09	0.25	0.2	0.17
Correlation of PM _{2.5} with humidity	0.047	0.13	0.07	0.2	0.17	0.15
Correlation of PM ₁₀ with humidity	-0.06	-0.05	-0.045	-0.15	-0.12	0.05
Correlation of NO ₂ with humidity	0.09	0.26	-0.05	-0.09	0.45	-0.079
Correlation of SO ₂ with humidity	0.28	0.25	-0.5	-0.19	-0.12	0.069
Correlation of NO with humidity	0.40	0.44	0.44	0.41	0.74	0.72
Mean PM _{2.5} /PM ₁	1.6	1.6	1.53	1.53	1.63	1.45
Standard Deviation PM _{2.5} /PM ₁	0.29	0.2	0.15	0.15	0.18	0.26
Correlation between PM _{2.5} and PM ₁₀	0.43	0.71	0.87	0.64	0.62	0.12
Correlation between PM ₁ and PM _{2.5}	0.96	0.99	0.99	0.99	0.99	0.99

as St Scholastica is situated next to the notoriously congested Thika Highway, fumes from the burning of diesel with high sulphur contents could have resulted in such high values of SO₂ being observed.

NO₂ values don't vary greatly across sites. The lowest NO₂ values were observed at Viwandani and Alliance. This could be because our monitors were located far away from the main roads at both sites. The highest NO₂ values recorded were at St Scholastica, and we again posit that this could be because of the proximity of this site to Thika Highway.

We were also surprised to see the high NO values at UNEP and Alliance.

More work is required to identify how many of the values we see were signal as opposed to noise. More work is also required to identify contributing sources.

Dependence of measurements on temperature / humidity

PM

Pearson correlation coefficients (R) of the pollutants with temperature and humidity were calculated at each site. These values are also summarized in Table 1. Note that we applied a filter to the NO data and eliminated records that were < -100 ppb. Otherwise we used the raw data to calculate correlations involving gaseous pollutants- including negative observations.

Table 1 shows that except for Kibera and St Scholastica, there is a small correlation between temperature/humidity and $PM_{2.5}$ and PM_{10} . When we plotted $PM_{2.5}$ versus temperature at each site in Figure 3A, it was not clear that peaks in $PM_{2.5}$ corresponded to low temperatures. More research is required to identify how this temperature dependence affects the measurements. One possible reason for this correlation is the lower the temperature, the higher the humidity (temperature and humidity are correlated strongly). If the particles at the site are hygroscopic, the particle size increases, and the OPC detects bigger particles and thus overestimates $PM_{2.5}$. We see that the correlation between temperature/humidity and PM_{10} is negligible.

Gaseous pollutants

As stated previously, temperature and humidity greatly impact the electrochemical gas sensors performance. We thus analyse the data from our sensors in relation to these parameters in order to identify temperature and humidity ranges in which the data is more likely to be less dependent on effects of these environmental factors.

We note that NO_2 and SO_2 and NO are strongly correlated with temperature at each site as can be seen from Table 1. The correlation of each pollutant with temperature varies widely across sites. In addition we note that the sign of the correlation also is not constant across sites for NO_2 and SO_2 . We plotted the time series of NO_2 , SO_2 and NO at each site with the temperature at each site determining the colour scale in Figures 4A to 7A in order to examine this correlation in more detail.

From Figure 4A and 6A, we clearly see that high temperatures (roughly $> 20^\circ$ Celsius) correspond to negative values of NO_2 and NO being recorded. As mentioned previously, we know that the Alphasense temperature correction does not adequately account for the baseline temperature correction of electrochemical sensors, especially for NO . We also know from the chemistry of electrochemical sensors that the effect of temperature is higher at higher temperatures (Popoola et al., 2016). We thus posit that this is the reason we observe negative gaseous values. Co-location with a reference instrument is required to test this hypothesis.

We note that the sign of the correlation between NO_2 and temperature is positive for the sites UNEP and Alliance in Table 1, because although all negative values of NO_2 recorded are at high temperatures, some high temperatures also correspond to positive NO_2 values, and there are fewer negative NO_2 values for these sites. (Note that in Figure 4A, we have applied a filter and removed NO values < -100 ppb. Figure 5A in the Appendix includes these values).

From Figure 7A, we see that negative values of SO_2 correspond to high temperature readings for the sites Kibera, Viwandani and Alliance. However, for St Scholastica, UNEP and All Saints we find that very few of the temperature corrected values are < 0 (refer to Table 1) and thus we do not see the same negative correlation. We are not sure why this is the case. It could be possible that the temperature correction factor for the SO_2 sensors for the latter three sites are better than for the former, which raises the question of potential consistency across these sensors; or it could mean that cross-interference with other

pollutants are affecting the data at the sites at which they occur in significant quantities. To address questions of potential consistency between sensors, it would be helpful to test a number of these sensors at the same site.

Note, that in Table 1A, when only gaseous pollutant values > 0 were used, we see that the correlation obtained between the gaseous pollutants and temperature/humidity change dramatically, and this time, are the same sign across all sites. In addition, we find that the magnitude of correlation between the measurements that are > 0 and temperature/humidity is low indicating that the signal the sensors are picking up is more likely due to pollutants. We will thus work with these gaseous pollutant values for the rest of this analysis.

Table 1 and 1A also shows correlations between all observations of pollutants. Table 1 shows that PM_{10} and $PM_{2.5}$ are strongly correlated at each site. From Table 1A, we see a significant correlation between SO_2 and $PM_{2.5}$, NO and $PM_{2.5}$ (except at St Scholastica and UNEP), and NO_2 and $PM_{2.5}$ (except at Alliance), NO_2 and SO_2 (except at Alliance).

Intra Urban Variation of Pollution

We next examined the intra-urban variability in each pollutant across out sites. We note from the correlation between $PM_{2.5}$ for each site-pair in Table 2, that most site-pairs correlate with one other to a not-insignificant manner.

The correlation of $PM_{2.5}$ at each site-pair is not based on distance between sites. The sites at UNEP, St Scholastica, All Saints and Kibera are < 10 km away from each other. The site at Alliance Girls School is ~ 15 km away from all the sites. However, we note that correlations between Alliance, and UNEP and All Saints are relatively high, in spite of Alliance being far from these sites.

In order to understand if this correlation is due to wind, we produce continuous bivariate plots of normalized $PM_{2.5}$ for each site as a function of wind speed and wind direction using the package OpenAir as seen in Figure 3. Note by using smoothing techniques (via the polarPlot function in the openair R package) to produce the bivariate plots, we are able to identify and group similar features to help identify sources. Wind speeds are zero at the origin and increase radially in each plot. The black arrow in each plot corresponds to the direction in which the monitor at each site is facing.

We note here that for Viwandani and Alliance, for example, there appears to be a source of pollution existing in the west, so that winds from that direction result in the OPC logging high values of $PM_{2.5}$. This could partially explain the correlation in $PM_{2.5}$ we see across sites. However, we do not see any correlation between $PM_{2.5}$ at Kibera and St Scholastica even though there appear to be a source in the south-east for both sites. This could be because we are not using site-specific wind data. Local canyon effects could profoundly affect our results. In the future, we recommend using site-specific wind data for this analysis.

It must also be noted here that as our monitors were wall-mounted, their swath as mentioned before is 180 degrees instead of 360 degrees. By indicating the direction which each monitor is pointing, we can also examine if there is a directionality bias for

Table 2: Correlation (R) between PM_{10} , $PM_{2.5}$, PM_{10} , NO_2 , SO_2 , NO for each pair of sites. Gas values > 0 are considered only.

PM₁₀	Kibera	Viwandani	Scholastica	UNEP	All Saints	Alliance
Kibera	1	0.13	0.09	0.18	0.19	0.15
Viwandani		1	0.11	0.25	0.29	0.14
Scholastica			1	0.18	0.09	0.11
UNEP				1	0.30	0.26
All Saints					1	0.22
Alliance						1
PM_{2.5}	Kibera	Viwandani	Scholastica	UNEP	All Saints	Alliance
Kibera	1	0.13	0.08	0.16	0.18	0.13
Viwandani		1	0.10	0.24	0.28	0.14
Scholastica			1	0.16	0.09	0.10
UNEP				1	0.28	0.23
All Saints					1	0.21
Alliance						1
PM₁₀	Kibera	Viwandani	Scholastica	UNEP	All Saints	Alliance
Kibera	1	0.04	0.07	0.06	0.08	0
Viwandani		1	0.15	0.15	0.28	0.01
Scholastica			1	0.24	0.2	0
UNEP				1	0.25	0.02
All Saints					1	0.01
Alliance						1
NO₂	Kibera	Viwandani	Scholastica	UNEP	All Saints	Alliance
Kibera	1	0.53	0.49	0.53	0.67	0.51
Viwandani		1	0.32	0.46	0.62	0.38
Scholastica			1	0.53	0.32	0.45
UNEP				1	0.41	0.58
All Saints					1	0.35
Alliance						1
SO₂	Kibera	Viwandani	Scholastica	UNEP	All Saints	Alliance
Kibera	1	0.29	0.11	0.12	0.18	0.22
Viwandani		1	0.044	0.09	0.17	0.12
Scholastica			1	0.17	0.56	0.14
UNEP				1	0.15	0.018
All Saints					1	0.21
Alliance						1
NO	Kibera	Viwandani	Scholastica	UNEP	All Saints	Alliance
Kibera	1	0.23	0.03	0	0.17	0.32
Viwandani		1	0.18	0.18	0.11	0.33
Scholastica			1	0.099	0	-0.06
UNEP				1	0.09	-0.13
All Saints					1	0.10
Alliance						1

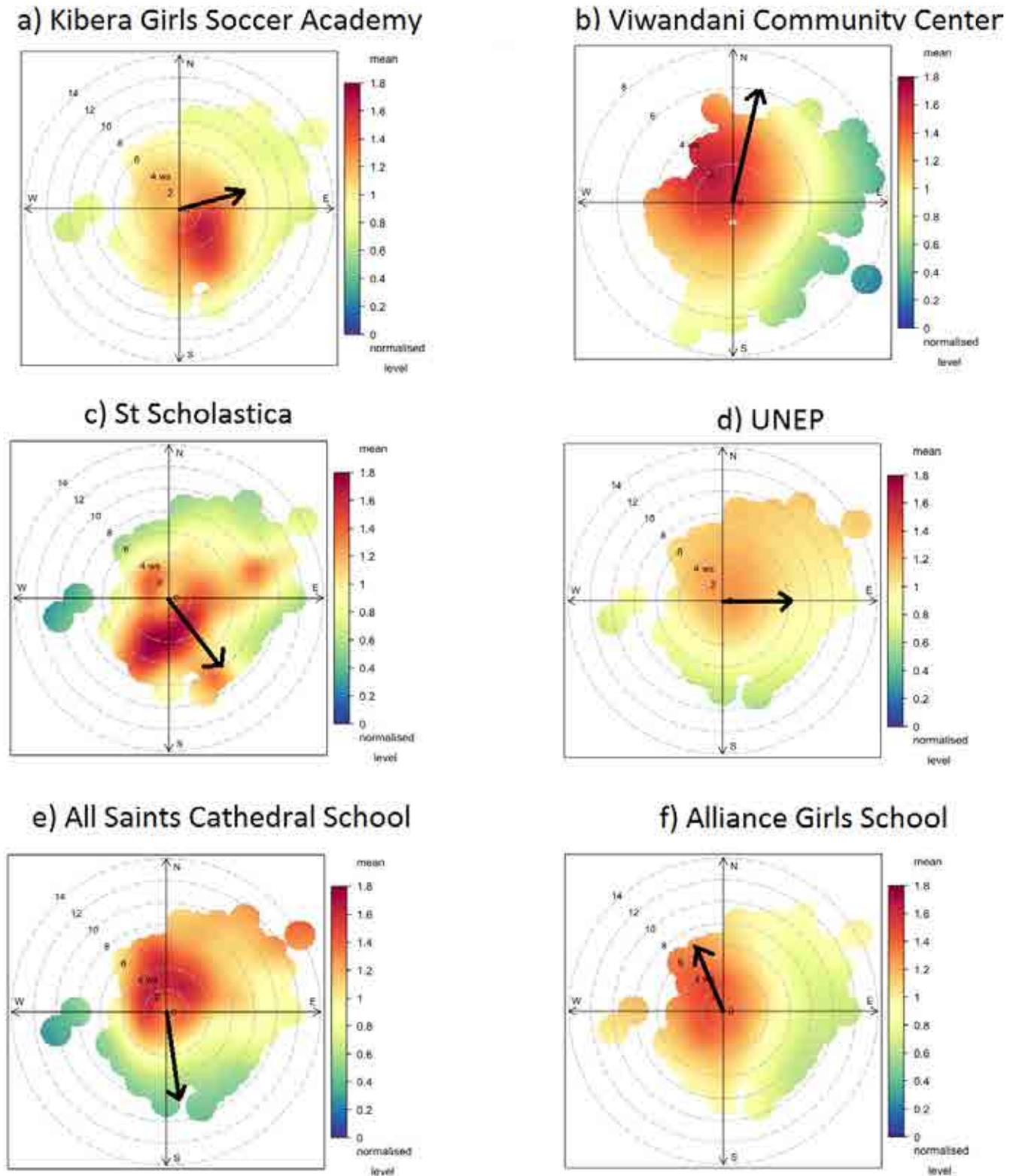


Figure 4: Bivariate plot of $PM_{2.5}$ normalised by dividing by their mean value from 5 May 2016 to 11 January 2017 plotted against wind speed and wind direction for the sites a) Kibera Girls Soccer Academy, b) Viwandani Community Center, c) St Scholastica, d) UNEP, e) All Saints Cathedral School, f) Alliance Girls School. Wind speed is zero at the origin and increases radially. The color scale indicates the $PM_{2.5}$ concentration. The black arrow in each plot points in the direction each monitor is facing.

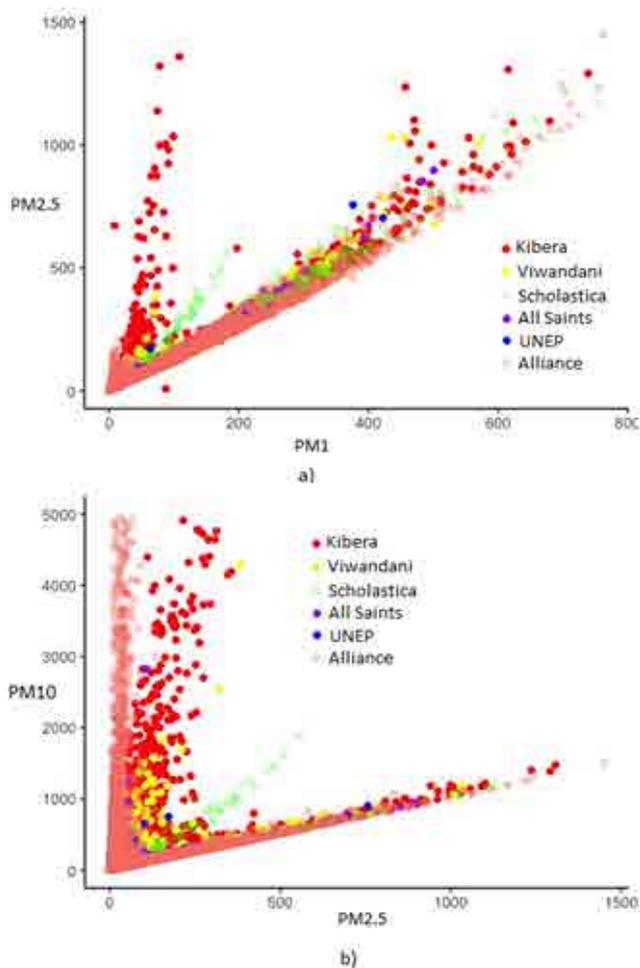


Figure 5: Scatter plots of $PM_{2.5}$ versus PM_1 and PM_{10} for each site. Units are in $\mu\text{g}/\text{m}^3$

each monitor. It appears that the monitors record pollution in the direction in which they are facing, indicating that the limited swath of our monitors could also affect our results.

Analyzing the chemical composition of $PM_{2.5}$ at each site to conduct a source apportionment could also provide further insights into the correlation of $PM_{2.5}$ between sites.

Figure 4 provides us with further insights in itself. We see that for our sites in Kibera and Viwandani, fine particulates impinge on the monitor from many directions, even at low wind speeds, with the greatest pollution coming from the south-east for the former and north-west for the latter.

From Figure 4 we also note that for St Scholastica, there is a major source of pollution to the south of the site for fairly high wind speeds. Thika Super Highway is to the south-east of the monitor, and it is possible that most of the fine particulates that the monitor has registered are from vehicular emissions coming from the highway.

We note from Table 2 that the correlation for NO_2 across all sites is high. The correlation for NO across all sites is low on the other hand. NO is a chemical that persists in the atmosphere for a very short time before being oxidized to NO_2 . This could explain the low correlation between NO across all sites. However, NO_2

persists longer and is mainly emitted from vehicles. Traffic patterns in Nairobi are roughly the same across the city at all sites and this could explain the high correlation in NO_2 across all sites.

We next look at the minute-wise $PM_{2.5}/PM_1$ and $PM_{10}/PM_{2.5}$ at each site as shown in Figure 5. These values are summarized in Table 1. We see that PM_1 and $PM_{2.5}$ correlate strongly. Figure 5 shows that observations from all sites can be viewed in 2 clusters. The bulk of the observations have a $PM_{2.5}/PM_1$ ratio between 1.4 and 1.7. A small cluster of observations have a much higher $PM_{2.5}/PM_1$ ratio ~ 5 . St Scholastica, is unique in that the monitor at this site records some observations that have a $PM_{2.5}/PM_1$ of ~ 2.5 .

This could indicate a unique source at this site. A visit to each site is required to test this hypothesis. Table 1 is a summary table that provides the mean $PM_{2.5}/PM_1$ at each site and the standard deviation of each ratio. We also note the clusters of data seen in the plot of $PM_{10}/PM_{2.5}$.

In order to understand the latter more closely we look at the variation in the ratio of $PM_{10}/PM_{2.5}$ with respect to wind speed and wind direction. This will allow us to look at the signature of different sources of pollution, located in different directions and different distances from each site.

We thus plotted PM_{10} versus $PM_{2.5}$ for each site versus wind speed and wind direction as seen in Figure 6. We see that the ratio of $PM_{10}/PM_{2.5}$ is somewhat dependent on wind speed and wind direction.

We repeat the same analysis for the gaseous pollutants and have plotted observations of NO_2 , NO and SO_2 that are > 0 versus $PM_{2.5}$ for each site as seen in Figure 7. We see that the SO_2 - $PM_{2.5}$ ratio is correlated more strongly than any of the other pollutant combinations in Figure 7.

We will now examine the pollutants at each site in detail.

Site Analysis

Kibera Girls Soccer Academy

Figure 8 shows the raw PM concentration variations averaged over a week and over a single day, for the measurement timeframe: May 5, 2016 to January 11, 2017 at the Kibera Girls Soccer Academy site in the informal settlement of Kibera. We see pollution peaks in the morning shortly before 6 am and in the afternoon on weekdays. However, on Saturday, we see another sharp peak at noon. Pollution appears to reduce on Sundays.

The pollution at this school is far worse than at the other sites. PM_{10} goes up to $100 \mu\text{g}/\text{m}^3$ frequently and exceeds this value during peak hours. Kibera was the only site where on certain days, the 24-hour limit value for PM_{10} ($100 \mu\text{g}/\text{m}^3$) set out in Kenya's EMCA (Air Quality) Regulations (2014) was exceeded. This limit was exceeded for 17 days for the time-period of measurement.

The high concentration of particulates could indicate the presence of a significant local source of pollutants. The practise

of burning waste due to inadequate waste collection is common here and could be the cause of the high values of pollutants recorded. $PM_{2.5}$ is above the WHO standard, an average of $20 \mu\text{g}/\text{m}^3$ over the course of a day. These results are similar to the high $PM_{2.5}$ levels measured in the poor neighbourhood of Mathare (Ngo et. al 2015a).

PM counts decrease at night, indicating that most of the PM pollution is due to daytime human activity.

In order to examine the various sources for this site in more detail, we again used bivariate plots using the OpenAir package (Carslaw and Beevers, 2013), and mapped all the pollutants with respect to wind speed and wind direction to identify common sources. Figure 9 shows continuous bivariate plots produced of each pollutant recorded with respect to wind speed and wind direction at the site. Although we are aware that the gas pollutant data in particular is suspect, we believe that by plotting bivariate plots of each pollutants and common sources are identified, that could give us some indication if we are observing any signal in the gaseous pollutant data and thus allow us to vet this data crudely. It is with this perspective that we examined the data. As mentioned earlier, smoothing techniques is used in producing these plots to identify similar groups of pollutants. We used a smoothing parameter of 100 (low smoothing) for producing plots for particulate matter and NO_2 , while we used a smoothing parameter of < 50 (high smoothing) for NO and SO_2 as we did not have enough data to produce smooth continuous surfaces for higher cluster sizes.

It can be seen from Figure 9 that there appears to be a major source of particulate matter, some NO and some NO_2 in the south-east. When we visited the site, we learnt that a significant amount of burning was happening to the south of our site near the railway track and this could be a potential source of the particulates. There is a source of SO_2 and NO_2 pollution from the north-west for high wind speeds. The main road is to the west of the site, and this could be a source of these pollutants.

It is not clear if, given that the monitor faces the north-east, there is a bias in the directionality of particulates the monitor registers. Further studies will be needed to determine this.

Wiwandani Community Center

Unfortunately, the OPC at this site stopped recording values in early July. However, for the months of May and June, we repeated the above analysis and obtained Figure 10.

We see that here, as at Kibera, PM_{10} levels are higher than at other sites. The monitor here is situated in an informal settlement in the industrial area of Nairobi that is highly polluted, which explains the high values of pollutants recorded. We see that particulate pollution peaks in the morning before 6 am, and in the evening around 6 pm. Pollution reduces on average on Sundays but peaks on Saturdays. Given that the pollution here too reduces in the night, we can conclude that pollution is driven by human activities. Thus, the time variation of the pollution provides us an idea of the time at which activities (cars on the street, burning of waste) take place at this site.

We also see that here, unlike in Kibera, $PM_{2.5}$ and PM_1 track PM_{10} more closely (the correlation between $PM_{2.5}$ and PM_{10} as shown

in Table 2 is 0.71 as opposed to 0.43 for Kibera). An examination of the different sources in this area needs to be conducted to determine why this is the case.

Here too we plot bivariate plots for each pollutant at the site to identify common sources in Figure 11. We see that there appears to be a common source of fine and coarse particles as well as SO_2 , NO_2 from the north of the site. We note that there appear to be multiple clusters of pollutants indicating the presence of multiple sources of pollution close to the site. Here, as in Kibera, we used a smoothing parameter of < 50 for SO_2 (note we did not have enough data to plot NO), while for the other pollutants we used a smoothing parameter of 100.

St Scholastica School

The time variation of PM_1 , $PM_{2.5}$ and PM_{10} at St Scholastica School as shown in Figure 12. Here we see that PM peaks in the morning and in the evening. These peaks corresponds to the flow of traffic of people coming to work in the morning, and leaving in the evening, implying that emissions from vehicles is a major source of pollution at this site. The peaks in particulates are far more pronounced than at UNEP (Figure 14) which is also next to a road. Indeed, $PM_{2.5}$ during the day is as much as $15 \mu\text{g}/\text{m}^3$ higher than during the night. This could be because Thika Highway, a major highway closer to the school, accommodates far more traffic than UN Avenue where UNEP is located. Pollutant concentrations decrease on average on both Saturday and Sunday, and not just on Sunday as seen at UNEP. PM peaks in June as at UNEP.

Figure 13 shows bivariate plots of all pollutants. It can be seen that there is a source of particulate matter in the south. We see there appear to be multiple sources of SO_2 from different directions. There also appears to be a source of NO_2 and NO in the west for high wind speeds. Thika Highway running from the south-west to the north-east of the monitor could be a major source of pollutants.

UNEP

Figure 14 shows the variation of minute-wise particulate matter concentrations over a typical week and a typical day for our other urban background site at UNEP.

Note that typical $PM_{2.5}$ concentrations vary between $10\text{--}15 \mu\text{g}/\text{m}^3$ for this site in keeping with the studies done earlier by (Gaita et al., 2014). Here, as at St Scholastica, particulate matter concentrations tend to peak in the morning and evening from Monday to Saturday, corresponding to the flow of traffic of people coming to work in the morning, and leaving in the evening, implying that emissions from vehicles is a major source of pollution at this site. The peak registered on Saturday evenings is surprisingly high, and we still have to account for its cause. We speculate that it is due to people visiting the nearby mall Village Market. Note that on Sunday, pollutant levels are low. We can also see that PM levels are also highest in June.

Figure 15 shows the bivariate plots of each pollutant with respect to wind speed and wind direction. Note to produce the plots we used a smoothing parameter of 100 for all pollutants except for NO, where we used a smoothing parameter of < 50 . We see that there is a source of fine particulates close to the monitor. We see there is a major source of coarse particulates

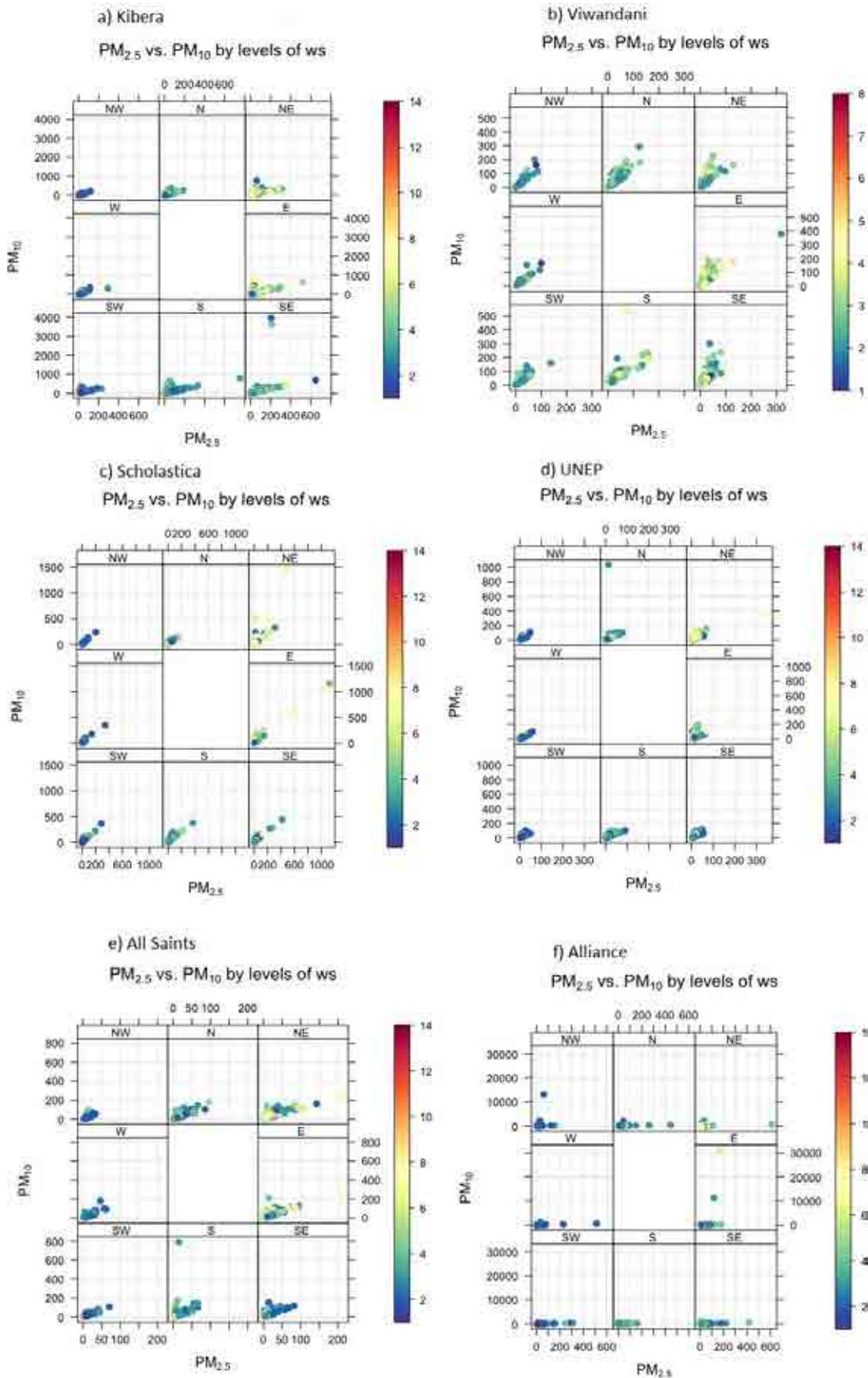


Figure 6: Scatter plots of $PM_{2.5}$ versus PM_1 and PM_{10} for each site with the color scale indicating wind speed, broken up by wind direction. Units are in $\mu\text{g}/\text{m}^3$.

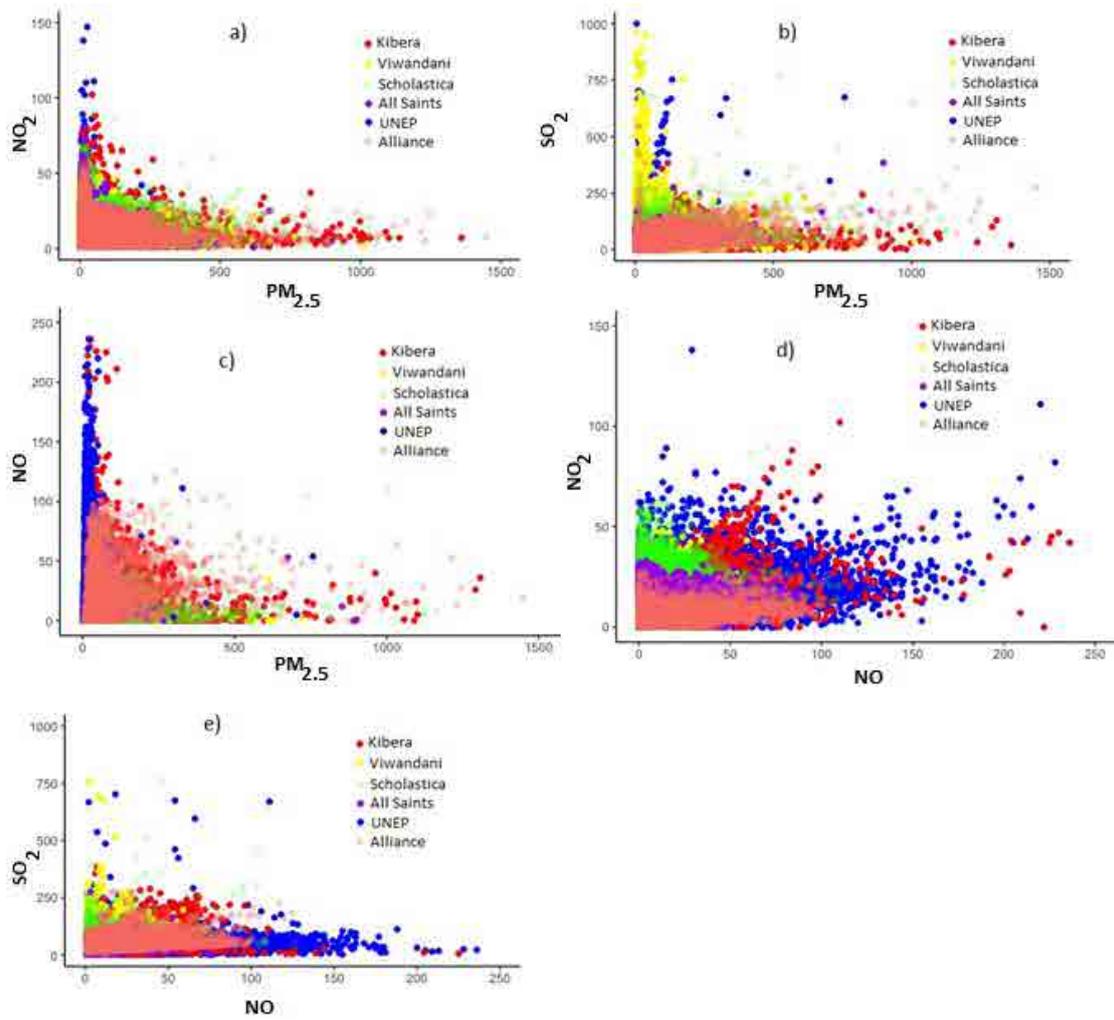


Figure 7: Scatter plots of a) NO_2 , b) SO_2 and c) NO (units in ppb) versus $\text{PM}_{2.5}$ (units are in $\mu\text{g}/\text{m}^3$) for each site, d) NO_2 versus NO at each site, e) SO_2 versus NO at each site (all gases are reported in ppb).

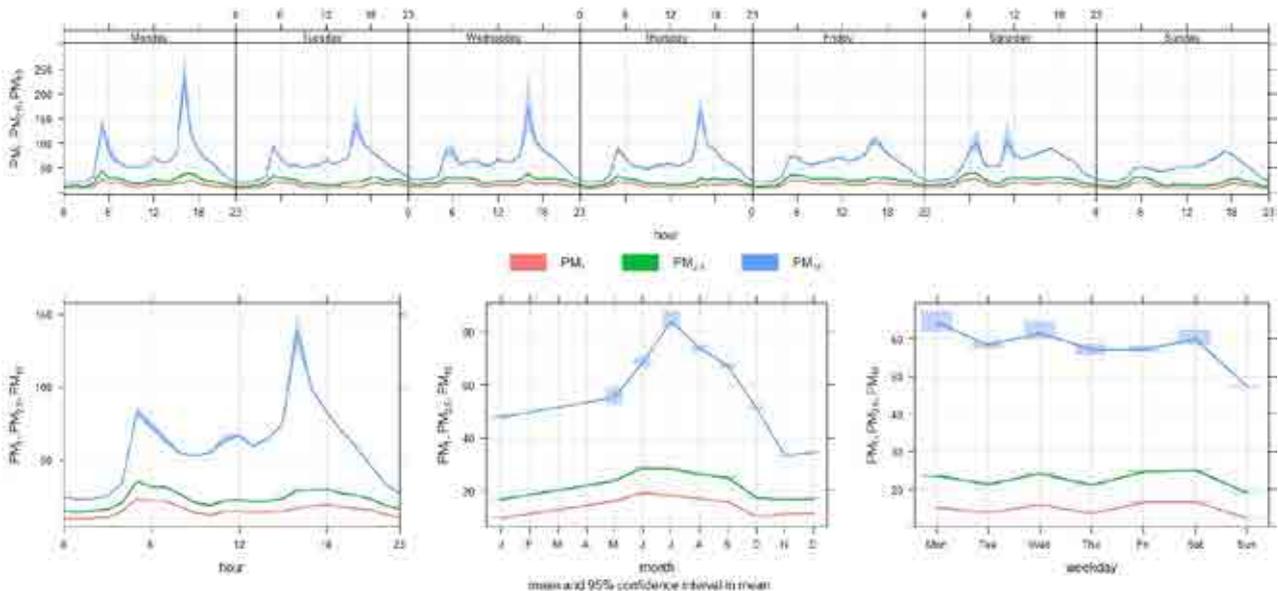


Figure 8: Kibera Girls Soccer Academy. The top panel shows the variation of PM_{10} , $\text{PM}_{2.5}$ and PM_{10} over the course of an average week in units of $\mu\text{g}/\text{m}^3$. The panel on the bottom left shows these concentrations varying over the course of an average day. The bottom middle figure shows the variation of PM_{10} over 8 months (May 5, 2016 to Jan11, 2017). The bottom right figure shows concentrations during an average week. The shadings in the plot indicate 95% confidence intervals.

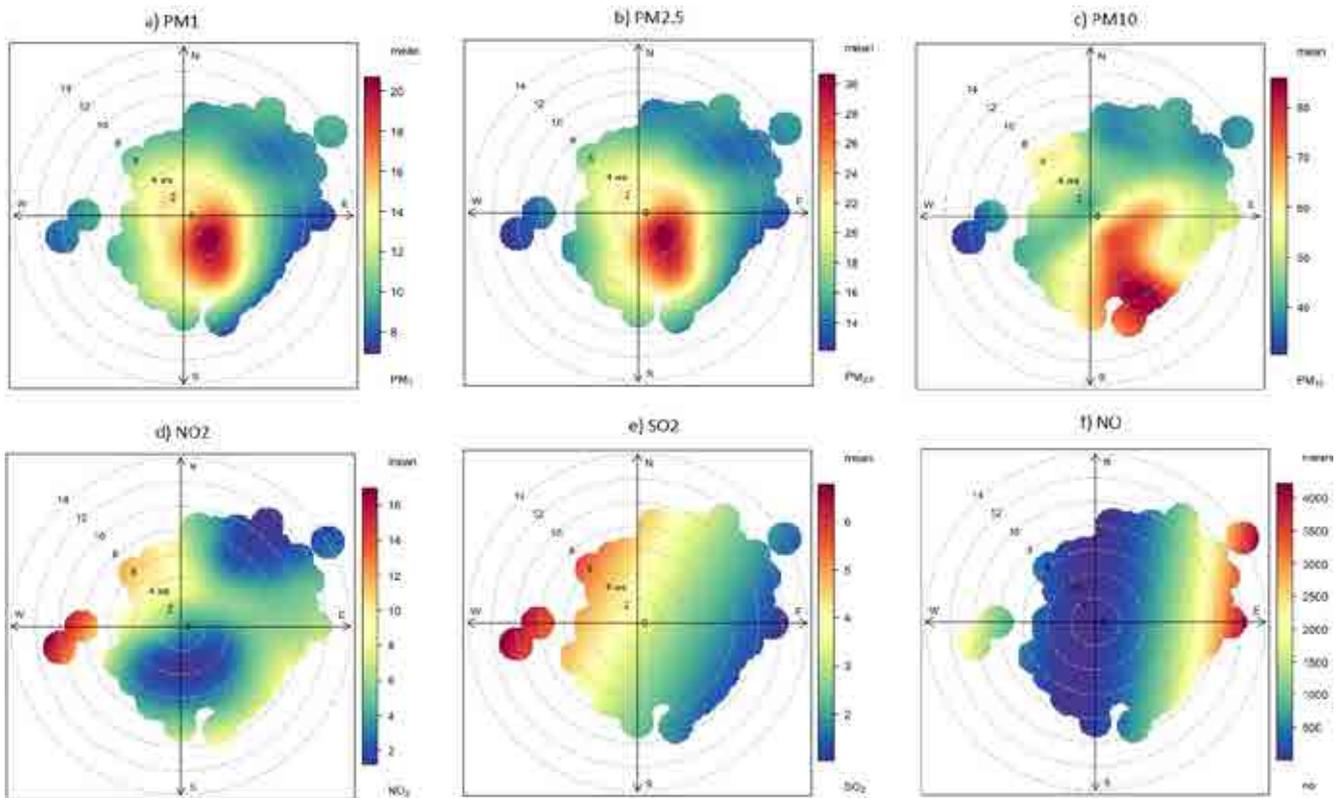


Figure 9: Kibera Girls Soccer Academy. Bivariate plots of each pollutant (note even negative values of the gas pollutants were considered) with respect to wind speed and wind direction from May 5, 2016 to Jan11, 2017. The image at the bottom shows the site and the black arrow indicates the direction that the monitor.

in the south east and north east for high wind speeds. There is a common source of SO_2 in the southeast. There are sources of NO in the north-north west and south-south-west of our site. There is a source of NO_2 and NO from the west. UN Avenue is located to the west of the monitor and is a potential source of vehicular pollution.

All Saint’s Cathedral School

The particulate matter pollution at All Saint’s Cathedral School is shown in Figure 16. Here as for the previous two sites, we see peaks of pollutants in the morning and in the evening corresponding to traffic patterns. Note that the values of PM registered at this site are in the same range as at UNEP. Here too, PM levels dip on Sunday but not on Saturday. This indicates that people come into the city on Saturdays but not Sunday .

From Figure 17, we see there is a common source of fine

particulates in the north west for low wind speeds. We see that there is also a source of SO_2 in the north west. There is a common source of SO_2 and coarse particulates in the east. Note there are several small industries and shops in this area which are potential sources of pollution. We did not have enough data to produce a similar plot of NO .

Alliance Girls School

We examined the data further to see why pollution was so high at Alliance Girls School. Figure 18 indicates that on some mornings, between midnight and 6 am, there is an immense spike in PM_{10} registered by the OPCs. When we examine the total PM time series plot in Figure 2, we see periodic spikes in PM_{10} as well. On speaking to the schoolchildren, we were told that boilers were lit using firewood at a site located very close to the deployed air quality monitor. Our monitors were thus able to highlight an important finding.

Figure 19 indicates NO_2 comes mainly from the south and west of the site at rather high wind-speeds. The Southern Bypass a major highway is in this direction, and it is possible that vehicular fumes from this road are a major source of NO_2 . Figure 18 also indicates that there is a major common source of PM_{10} , $\text{PM}_{2.5}$ and SO_2 from the west as well which could also be due to traffic on the Southern Bypass. Trucks typically use the Southern Bypass. They burn diesel with high levels of sulphur, which could be the source of the SO_2 seen. However, there is a major source of PM_{10} from the north-east as well. The burning of firewood takes place at the north of our site and thus it is highly likely that it is this that is the major source of the coarse particulates picked up by the monitor. Note we do not have enough data to plot NO for this site.

Discussion and Policy Implications

Even with technical limitations in both the study and the sensors, we were nevertheless able to glean a number of insights from the data. At a local level, the data we gathered led to new discussions about air pollution within the schools, which up to this point have not been sites for air quality measurements. The exception is the monitoring station at the University of Nairobi, which is primarily used for teaching and research on campus. This suggests that further experimenting with sensors through citizen science efforts can be a valuable way of spreading awareness and having public discussions, as long as the potential uncertainties in the data are also part of the conversation (Impressing on the communities the working of the optical particle counter that we used to measure particulate matter allowed them to understand the limitations of the instrument).

For example, identifying the peak in PM_{10} at Alliance Girls School on Wednesday mornings was an important discovery- especially as the monitor was deployed on the wall of a dormitory. Conversations with the school led us to discover the burning of firewood to heat water as a source of this pollution. This allowed us to engage with the school and discuss with students and staff the hazards of air pollution, as well as ways to mitigate their particular source by using cleaner fuels or burning firewood in a different location far away from the students. Identifying that the school was in control of this burning allowed us to work with them to think through various possible pollution management plans. Continued monitoring will reveal if the measures the schools adopts are effective.

Conversations with students at the Kibera Girls Soccer Academy were more complex because the school is located in a large slum and faces a multi-faceted air pollution source problem. Thus, mitigation became part of the conversation – for example, whether planting trees might block the influx of particulates into the school premises from the south-east. This type of conversation around air pollution mitigation also came up in the conversations in Mathare slum (Ngo et al 2015b). More accurate measurements of local, canyon-influenced wind speed and wind direction over different seasons will be crucial to improving the efficacy of any interventions aimed at addressing sources. Given the poor services in these slum areas, waste burning is likely to be one source that needs addressing. However, without alternatives such as better solid waste disposal, mitigation techniques like tree planting or finding ways to avoiding the

worst sources where possible becomes important (Ngo et al. 2015b). Finally, our discussion with the community at the Viwandani Community Center led to the community leaders resolving to bring this issue up with the Nairobi City County, which is responsible for solid waste disposal, and also air quality along with the National Environmental Management Authority (NEMA).

It is important to note that the monitors were not stolen as many people had feared. Our discussions with the community led to them to appreciate the importance of our monitoring instruments. The Kibera Girls Soccer Academy even built a small gate to the alley on which our instrument was located, at their own cost to protect the instrument. However, the OPC at the Viwandani community center and at Alliance Girls School did lose power. Better understanding of the electric power situation and how it can be addressed at each location will be necessary for future deployments. This suggests overall, that more experiments with air quality sensors in collaboration with citizens are possible and provide a fruitful way to get some data and discussion on air quality in the absence of systematic air quality monitoring going on in the city. It is also a way to help citizens and entities like schools understand how they can play a role in improving air quality and ask more of their government.

Some broader conclusions can be drawn regarding air quality in the city of Nairobi. The pattern of peaks in data at most of our school sites indicates that vehicular emissions are a major source of pollution. Therefore, this implies that the city should prioritize a shift toward non-motorized transport, better fuel standards, and adopting cleaner vehicular technologies, as opposed to widening existing roads and building super highways. Another point of interest is that PM seems to peak in June over the roughly 8 months that the deployment took place. This needs to be examined in more detail. However, the policy implications could be that the Nairobi city council should focus especially on reducing vehicular traffic during this month. Another interesting observation is that the morning pollution peaks in the informal settlements occur earlier in the day than at the UNEP, St Scholastica and All Saints Cathedral sites. This is important to note, as it speaks to the way different groups of people use the city. Do people have to set off to work earlier in the informal settlements, as their workplaces are further, and transportation less convenient? This raises important questions around “spatial mismatch” in the city.

This study had many technical limitations. With sparse resources, we were not able to calibrate the gas sensors in the ambient conditions of Nairobi, which we know to be very important (Piedrahita et al. 2014). We therefore do not know how environmental factors and interference from other pollutants affected the gas sensors in the field. The interference from other pollutants could be large (Hasenfratz et al., 2012.; Popoola et al., 2012) . We also did not analyse the particle size distribution or the chemical composition of the particles sampled by the OPC, which could help determine the density of the particles sampled. In addition, the analysed data we obtained were noisy, and we were unable to determine which filter to apply to separate the signal from the noise without having access to any air quality measurements from a reference instrument.

We strongly recommend the calibration of low cost gas sensors

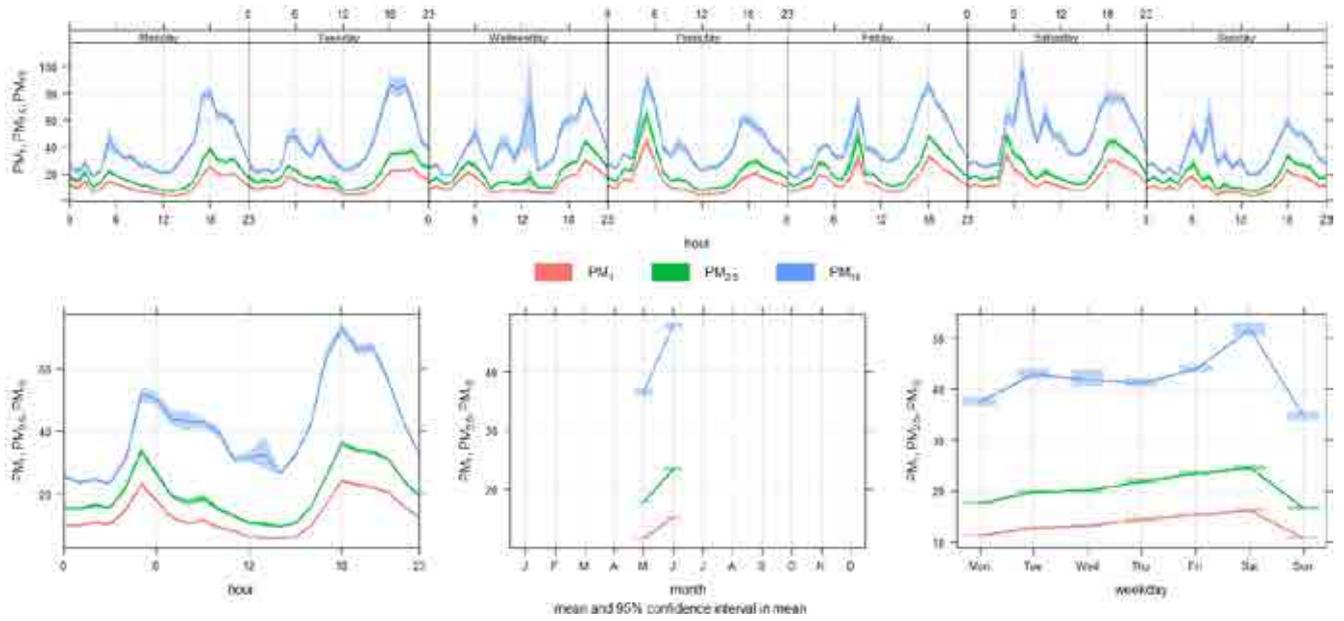


Figure 10: Same as Figure 8 but for the Viwandani Community Center site for the period May 5, 2016-June 27, 2016.

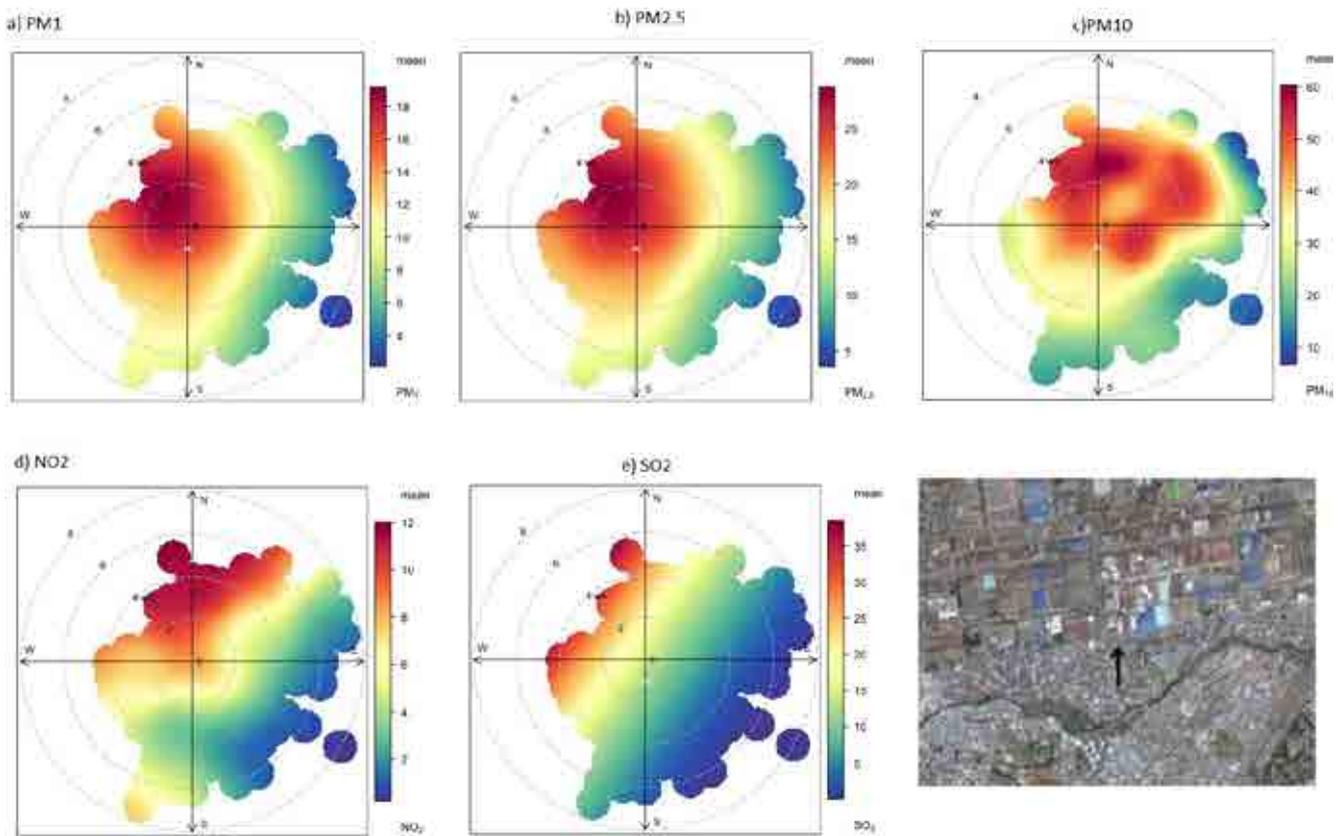


Figure 11: Same as Figure 9 but for the Viwandani Community Center site for the period May 5, 2016-June 27, 2016. The image at the bottom shows the site and the black arrow indicates the direction that the monitor faces. The image has been taken such that the direction north in the image is towards the top of the page.

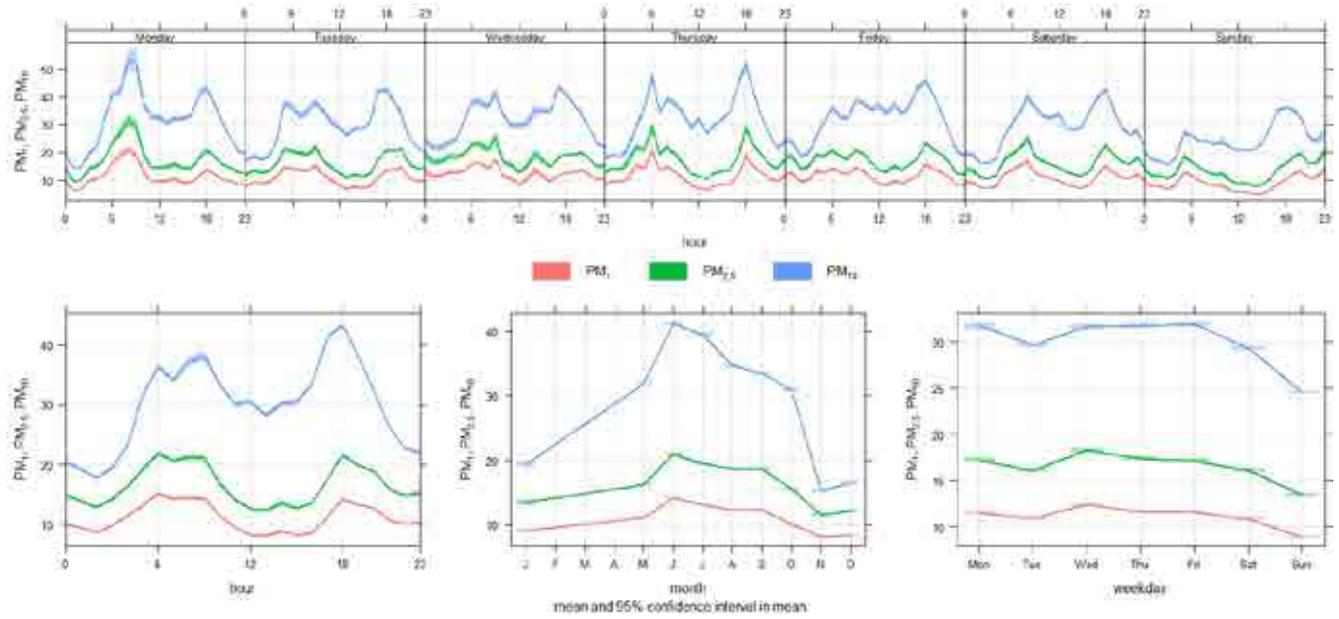


Figure 12: Same as Figure 8, but for the St Scholastica site.

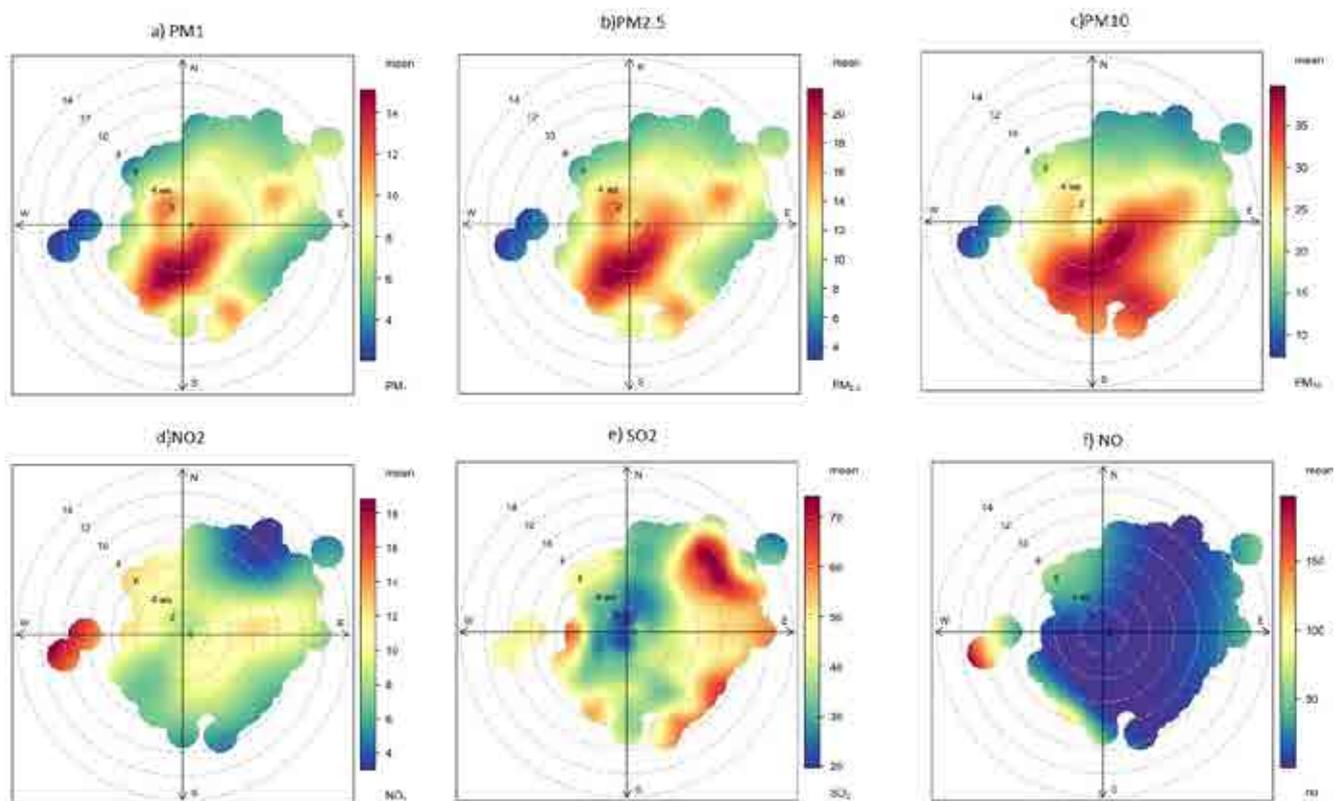


Figure 13: Same as Figure 9 but for the St Scholastica site. The image at the bottom shows the site and the black arrow indicates the direction that the monitor faces. The image has been taken such that the direction north in the image is towards the top of the page.

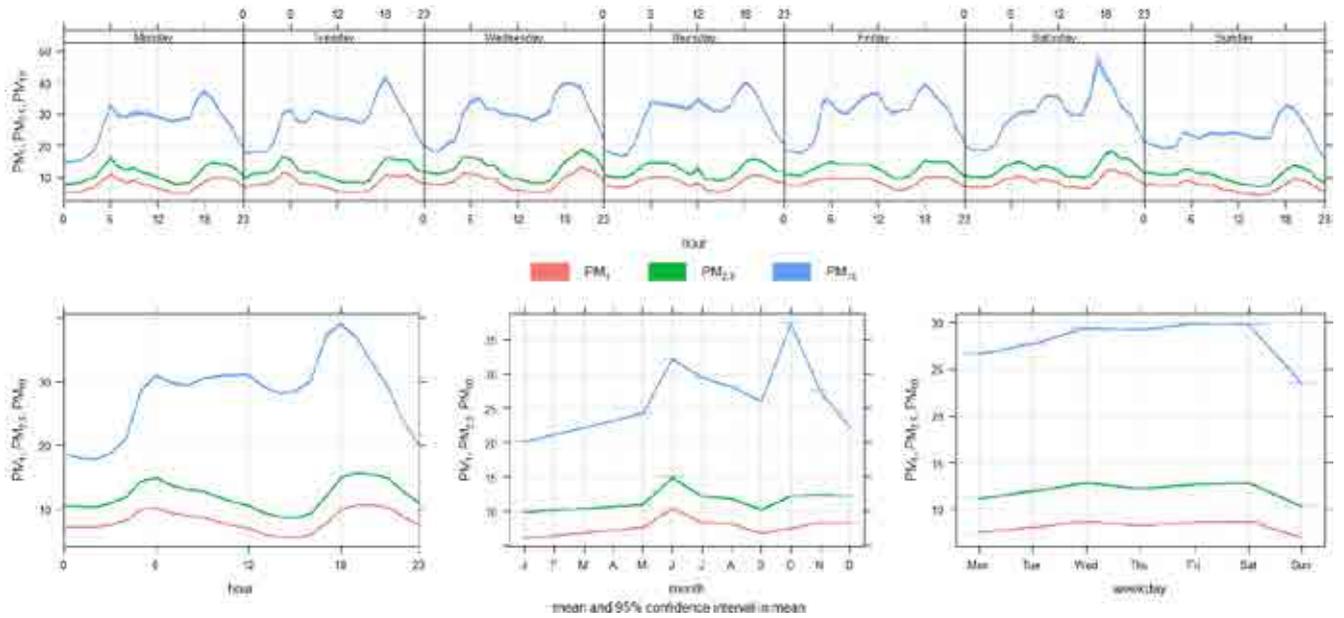


Figure 14: Same as Figure 8, but for the UNEP site.

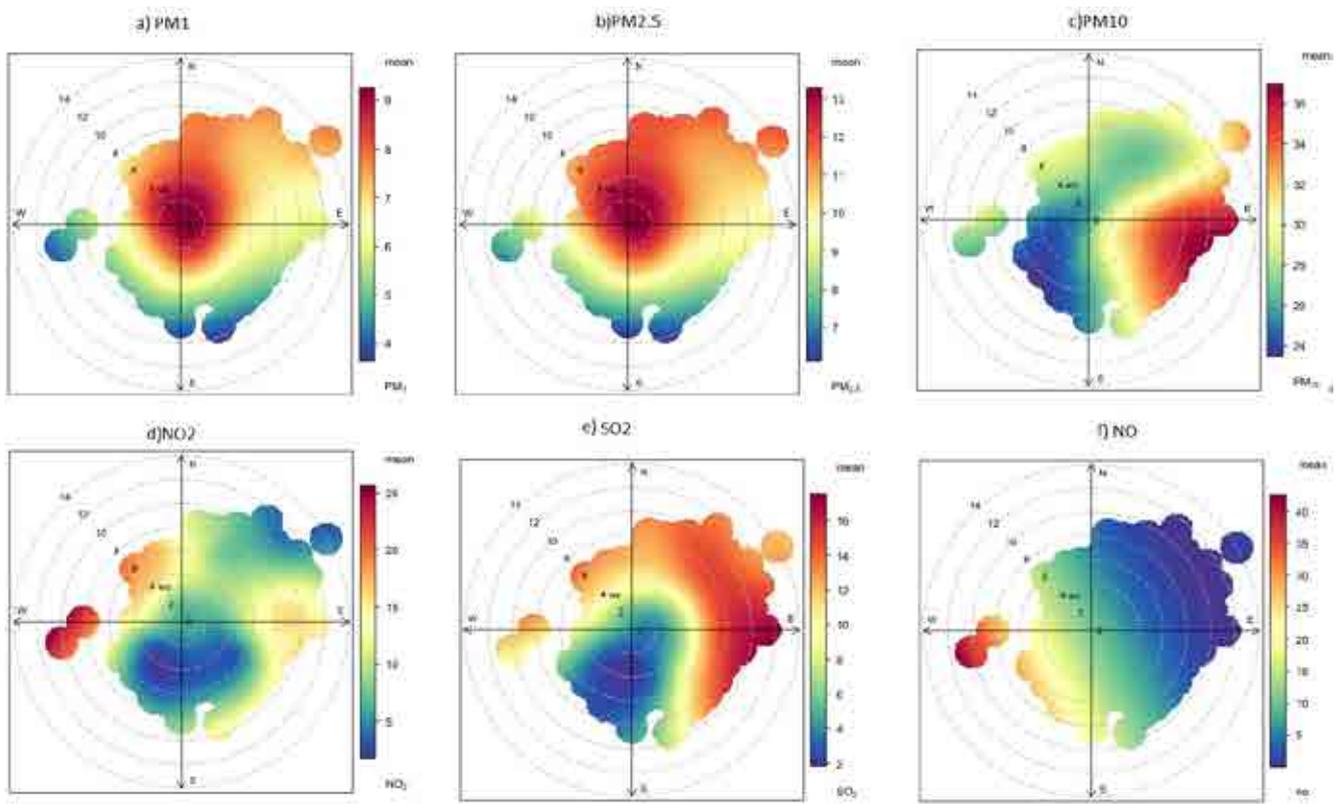


Figure 15: Same as Figure 9 for the UNEP site. The image at the bottom shows the site and the black arrow indicates the direction that the monitor faces. The image has been taken such that the direction north in the image is towards the top of the page.

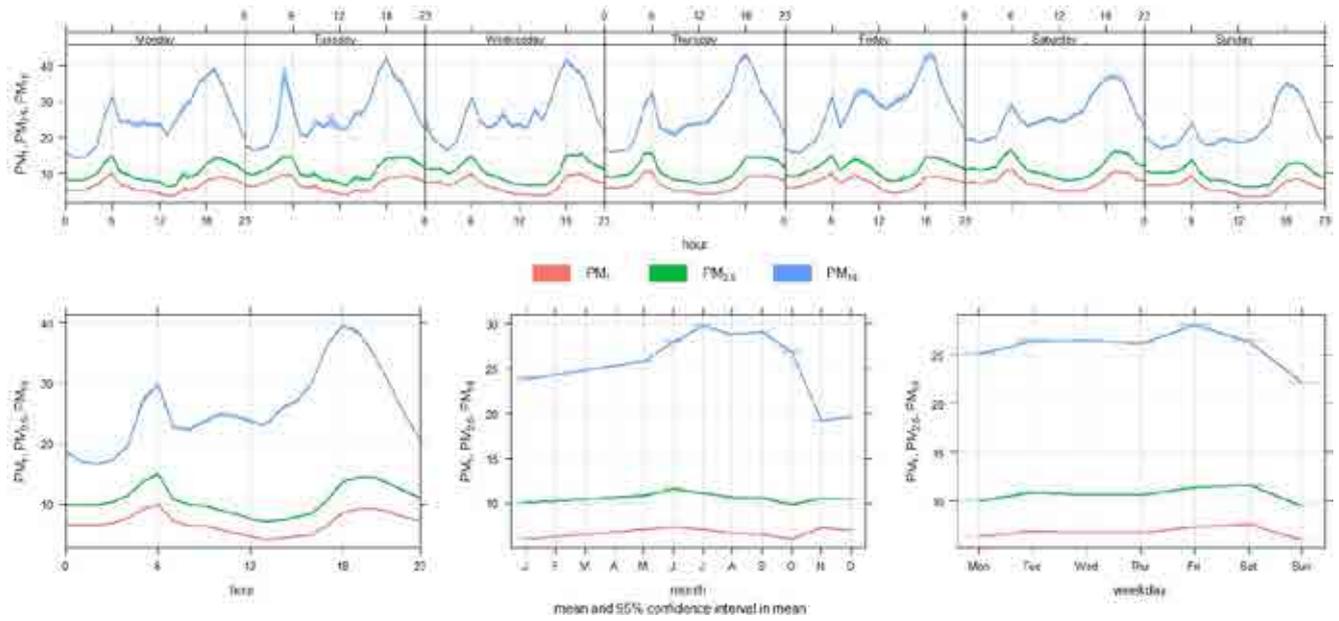


Figure 16: Same as Figure 8 but for the All Saints.

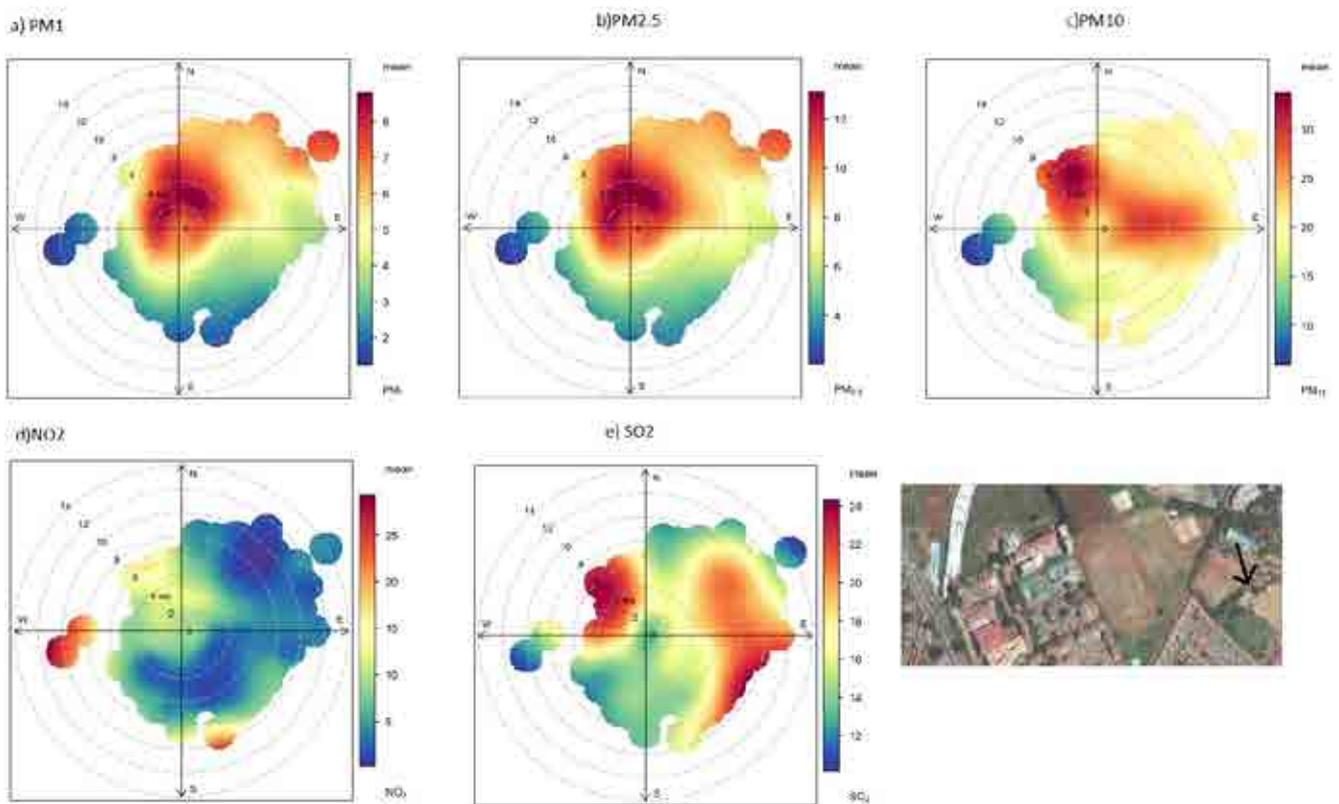


Figure 17: Same as Figure 9 but for the All Saints Cathedral site. The image at the bottom shows the site and the black arrow indicates the direction that the monitor faces. The image has been taken such that the direction north in the image is towards the top of the page.

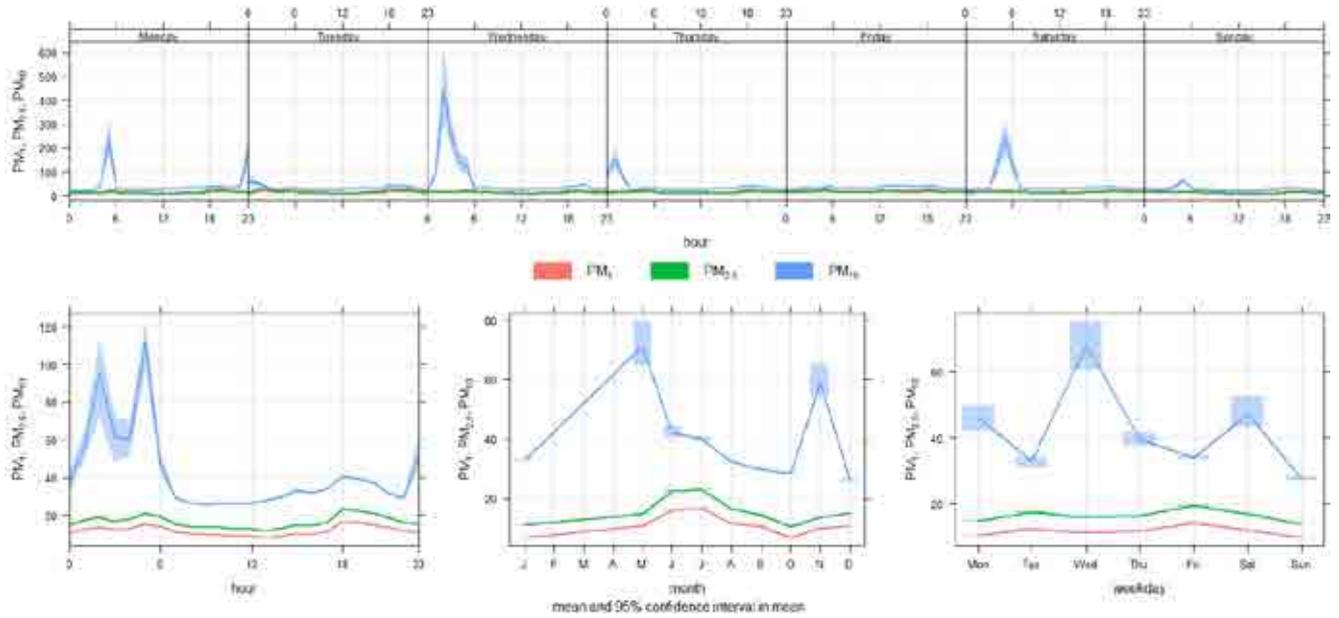


Figure 18: Same as Figure 8 but for the Alliance Girls School site.

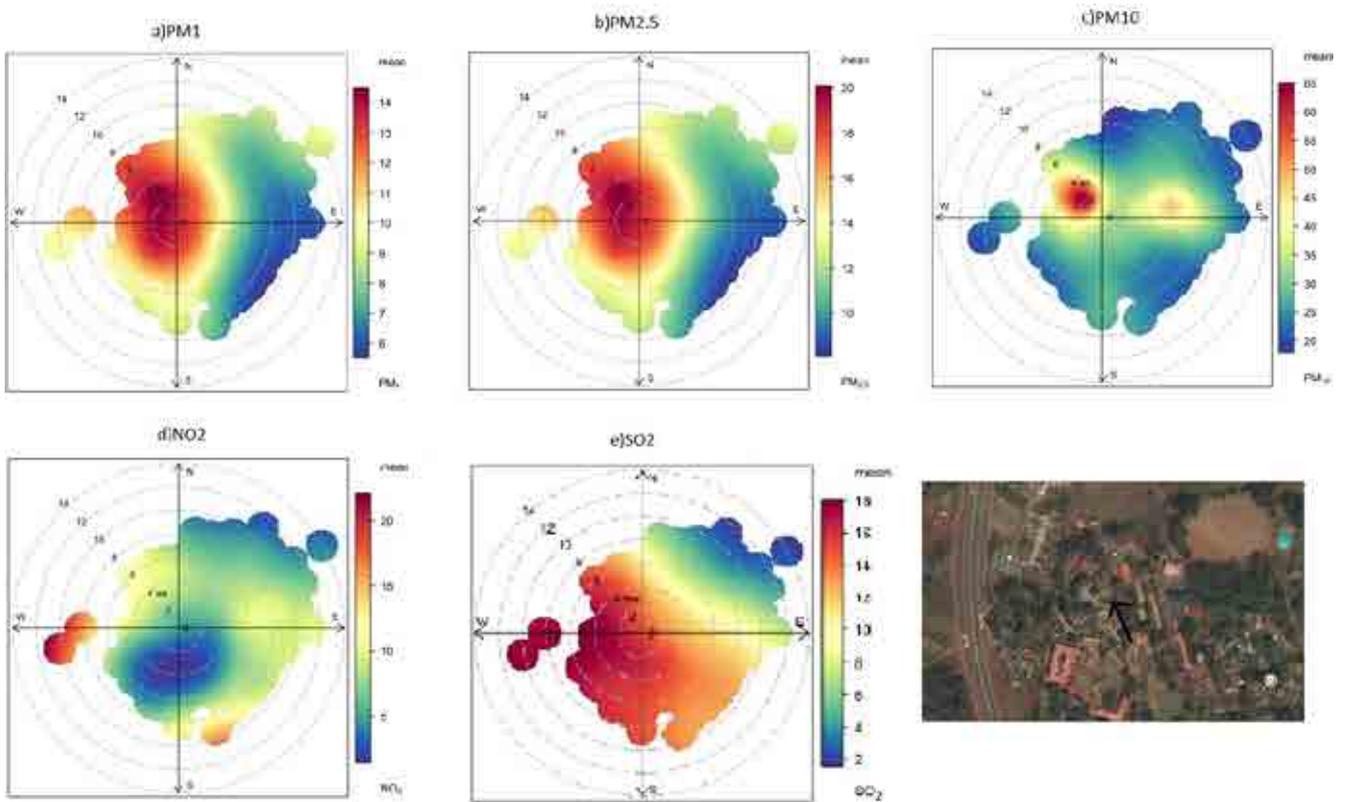


Figure 19: Same as Figure 9 but for the Alliance Girls School site. The image at the bottom shows the site and the black arrow indicates the direction that the monitor faces. The image has been taken such that the direction north in the image is towards the top of the page.

with reference air quality monitoring instruments in ambient conditions in order to determine the error in sensor readings due to interference effects of other pollutants and the effect of environmental conditions: specifically temperature and humidity. In addition, the rate of sensor drift depends on the season of the year so it is important to validate the network by regular calibrations of the sensors in each season. Work is underway on using machine learning algorithms to increase the accuracy of low cost sensors (Esposito et al., 2016), and we see this work as being very important for reducing calibration costs and improving data reliability.

We also strongly recommend obtaining a better understanding of the size distribution of particles collected by the OPC at each site over time. This is because the OPC does not function very well for counting particles of sizes < 380 nm. Thus, depending on the size distribution of particles (which varies over time), our measurements could have large errors, and understanding the extent of these errors is important for drawing inferences from the sources and type of particulate pollution. In addition, analysing the chemical composition of particulates at each site can help us develop a better understanding of sources of pollution, as well as help us in identifying correct value of density to use to convert the particle counts collected by the OPC to obtain particulate mass. This could also help us reduce the error in measurement.

Another limitation stemming from the proprietary nature of the technology is that we cannot report in detail on the performance of the electronics or the configuration of the device. These factors can affect results as well, and more research is required to identify standard configurations to facilitate comparisons of experiments. We believe that it is important to set a precedent for the reporting of the type of sensor used because, for example, it is unclear how the Alphasense A series gas sensors compare with the B series. No reports have been published examining this comparison. This makes comparing data from different low cost air quality sensor experiments difficult. In addition, components such as the analogue to digital converter (ADC) could add noise to the data, and thus reporting the kind of converter used could allow for a greater degree of comparison across networks. Over all, better reporting on the mechanics of low cost monitoring projects is needed moving forward.

Conclusions

Low cost sensors and apps that draw on their data to inform citizens about air pollution are becoming more and more prevalent. Given the magnitude of the data gaps in African cities, the growing availability of low cost sensors presents an important opportunity. This is especially the case as plans move forward to measure air pollutants for the Sustainable Development Goals and fight against climate change. However, much more research is needed on how well these new devices work under widely varied conditions, and whether the less accurate data these sensors generate is helpful or even harmful (Lewis and Edwards 2016, Kumar et al. 2015).

Our experiment using less expensive, lower-quality sensors in Nairobi schools contributes to this critical discussion. We did find significant technical limitations that need further work. However, we found that less accurate but carefully interpreted

data created by sensors within a citizen science initiative was clearly better than no data. Both the process of getting the data and the data itself, once carefully interpreted, helped to generate broader public understanding and interest in monitoring air quality and addressing likely sources of ambient outdoor air pollution. We also gained some idea of the air pollution problems affecting schoolchildren across class divides with more challenges clearly facing low income children in the slums.

The deployment and analysis of our network also showed that the cost of the sensors is only a small fraction of the total cost of network deployment. This is because maintenance of the network, calibration of the sensors and the analysis of the data is time consuming and therefore expensive. It is also abundantly clear that “low cost” sensors cannot obviate the need for stronger investment in high quality monitoring and related local scientific research around air quality in African cities. While low cost sensors can allow for more measurements and more civic engagement, this is ideally conducted in collaboration with local scientists who are well-equipped to ensure data are collected and interpreted accurately for the public. Lewis and Edwards (2016) suggest “well designed sensor experiments, that acknowledge the limitations of the technologies as well as the strengths, have the potential to simultaneously advance basic science, monitor air pollution — and bring the public along”. We believe we have shown this to be the case for African cities like Nairobi that currently do not have an air quality monitoring system but do have a substantial air quality problem.

Acknowledgements

The authors would like to thank Dr. Jacqueline McGlade, United Nations Environment Program (UNEP), Sami Dimassi, United Nations Environment Program (UNEP), Valentin Foltescu, United Nations Environment Program (UNEP), the company Alphasense, the company Atmospheric Instruments, Charles Mwangi from the NASA GLOBE program, the Wajukuu Arts Collective and the Kibera Girls Soccer Academy, Alliance Girls School, St Scholastica, All Saint’s Cathedral School and Viwandi Community Center. We also thank Dr Ralph Kahn for his valuable comments.

References

- Amegah, A.K., Agyei-Mensah, S., n.d. Urban air pollution in Sub-Saharan Africa: Time for action. *Environ. Pollut.* doi:10.1016/j.envpol.2016.09.042.
- AQ_GlobalReport_Summary.pdf, n.d.
- Carslaw, D.C., Beevers, S.D., 2013. Characterising and understanding emission sources using bivariate polar plots and k-means clustering. *Environ. Model. Softw.* 40, 325–329. doi:10.1016/j.envsoft.2012.09.005.
- Carslaw, D.C., Ropkins, K., 2012. openair — An R package for air quality data analysis. *Environ. Model. Softw.* 27–28, 52–61. doi:10.1016/j.envsoft.2011.09.008.
- Development, O. of R.&, n.d. Sensor Evaluation Report [WWW Document]. URL https://cfpub.epa.gov/si/si_public_record_report.cfm?dirEntryId=277270 (accessed 10.17.16).

- Dominici, F., Peng, R.D., Barr, C.D., Bell, M.L., 2010. Protecting Human Health from Air Pollution: Shifting from a Single-Pollutant to a Multi-pollutant Approach. *Epidemiol. Camb. Mass* 21, 187–194. doi:10.1097/EDE.0b013e3181cc86e8.
- Egondi, T., Kyobutungi, C., Ng, N., Muindi, K., Oti, S., Vijver, S. van de, Ettarh, R., Rocklöv, J., 2013. Community Perceptions of Air Pollution and Related Health Risks in Nairobi Slums. *Int. J. Environ. Res. Public Health* 10, 4851–4868. doi:10.3390/ijerph10104851.
- Esposito, E., De Vito, S., Salvato, M., Bright, V., Jones, R.L., Popoola, O., 2016. Dynamic neural network architectures for on field stochastic calibration of indicative low cost air quality sensing systems. *Sens. Actuators B Chem.* 231, 701–713. doi:10.1016/j.snb.2016.03.038.
- Gaita, S.M., Boman, J., Gatari, M.J., Pettersson, J.B.C., Janhäll, S., 2014. Source apportionment and seasonal variation of PM_{2.5} in a Sub-Saharan African city: Nairobi, Kenya. *Atmos Chem Phys* 14, 9977–9991. doi:10.5194/acp-14-9977-2014.
- Gatari, M.J., Boman, J., 2003. Black carbon and total carbon measurements at urban and rural sites in Kenya, East Africa. *Atmos. Environ.* 37, 1149–1154. doi:10.1016/S1352-2310(02)01001-4.
- Gatari, M.J., Boman, J., Wagner, A., 2009. Characterization of aerosol particles at an industrial background site in Nairobi, Kenya. *X-Ray Spectrom.* 38, 37–44. doi:10.1002/xrs.1097.
- Hasenfratz, D., Saukh, O., Thiele, L., 2012. On-the-Fly Calibration of Low-Cost Gas Sensors, in: SpringerLink. Springer Berlin Heidelberg, pp. 228–244. doi:10.1007/978-3-642-28169-3_15.
- Kinney, P.L., Gichuru, M.G., Volavka-Close, N., Ngo, N., Ndiba, P.K., Law, A., Gachanja, A., Gaita, S.M., Chillrud, S.N., Sclar, E., 2011. Traffic Impacts on PM_{2.5} Air Quality in Nairobi, Kenya. *Environ. Sci. Policy* 14, 369–378. doi:10.1016/j.envsci.2011.02.005.
- Kumar, P., Morawska, L., Martani, C., Biskos, G., Neophytou, M., Di Sabatino, S., Bell, M., Norford, L., Britter, R., 2015. The rise of low-cost sensing for managing air pollution in cities. *Environ. Int.* 75, 199–205. doi:10.1016/j.envint.2014.11.019.
- Lewis, A., Edwards, P., 2016. Validate personal air-pollution sensors. *Nat. News* 535, 29. doi:10.1038/535029a.
- Lindén, J., Boman, J., Holmer, B., Thorsson, S., Eliasson, I., 2012. Intra-urban air pollution in a rapidly growing Sahelian city. *Environ. Int.* 40, 51–62. doi:10.1016/j.envint.2011.11.005.
- Mead, M.I., Popoola, O.A.M., Stewart, G.B., Landshoff, P., Calleja, M., Hayes, M., Baldovi, J.J., McLeod, M.W., Hodgson, T.F., Dicks, J., Lewis, A., Cohen, J., Baron, R., Saffell, J.R., Jones, R.L., 2013. The use of electrochemical sensors for monitoring urban air quality in low-cost, high-density networks. *Atmos. Environ.* 70, 186–203. doi:10.1016/j.atmosenv.2012.11.060.
- M. Fiore, A., Naik, V., V. Spracklen, D., Steiner, A., Unger, N., Prather, M., Bergmann, D., J. Cameron-Smith, P., Cionni, I., J. Collins, W., Dalsøren, S., Eyring, V., A. Folberth, G., Ginoux, P., W. Horowitz, L., Josse, B., Lamarque, J.-F., A. MacKenzie, I., Nagashima, T., M. O'Connor, F., Righi, M., T. Rumbold, S., T. Shindell, D., B. Skeie, R., Sudo, K., Szopa, S., Takemura, T., Zeng, G., 2012. Global air quality and climate. *Chem. Soc. Rev.* 41, 6663–6683. doi:10.1039/C2CS35095E.
- Muindi, K., Egondi, T., Kimani-Murage, E., Rocklov, J., Ng, N., 2014. “We are used to this”: a qualitative assessment of the perceptions of and attitudes towards air pollution amongst slum residents in Nairobi. *BMC Public Health* 14, 226. doi:10.1186/1471-2458-14-226.
- Ngo, N.S., Gatari, M., Yan, B., Chillrud, S.N., Bouhamam, K., Kinney, P.L., 2015. Occupational exposure to roadway emissions and inside informal settlements in sub-Saharan Africa: A pilot study in Nairobi, Kenya. *Atmos. Environ.* 111, 179–184. doi:10.1016/j.atmosenv.2015.04.008.
- Ngo, N.S., Kokoyo, S., Klopp, J., 2017. Why participation matters for air quality studies: risk perceptions, understandings of air pollution and mobilization in a poor neighborhood in Nairobi, Kenya. *Public Health* 142, 177–185. doi:10.1016/j.puhe.2015.07.014.
- Njee, R.M., Meliefste, K., Malebo, H.M., Hoek, G., 2016. Spatial Variability of Ambient Air Pollution Concentration in Dar es Salaam. *J. Environ. Pollut. Hum. Health J. Environ. Pollut. Hum. Health* 4, 83–90. doi:10.12691/jephh-4-4-2.
- Petkova, E.P., Jack, D.W., Volavka-Close, N.H., Kinney, P.L., 2013. Particulate matter pollution in African cities. *Air Qual. Atmosphere Health* 6, 603–614. doi:10.1007/s11869-013-0199-6
- Piedrahita, R., Xiang, Y., Masson, N., Ortega, J., Collier, A., Jiang, Y., Li, K., Dick, R.P., Lv, Q., Hannigan, M., Shang, L., 2014. The next generation of low-cost personal air quality sensors for quantitative exposure monitoring. *Atmos Meas Tech* 7, 3325–3336. doi:10.5194/amt-7-3325-2014.
- Popoola, O., Stewart, G., Jones, R.L., Mead, I., Saffell, J., 2012. 7.4.4 Electrochemical Sensors for Environmental Monitoring in Cities. *Proc. IMCS 2012* 640–640. doi:http://dx.doi.org/10.5162/IMCS2012/7.4.4.
- Schwela, D., 2012a. Review of urban air quality in Sub-Saharan Africa region - air quality profile of SSA countries (No. 67794). The World Bank.
- Schwela, D., 2012b. Review of urban air quality in Sub-Saharan Africa region - air quality profile of SSA countries (No. 67794). The World Bank.
- Sousan, S., Koehler, K., Hallett, L., Peters, T.M., 2016. Evaluation of the Alphasense optical particle counter (OPC-N2) and the Grimm portable aerosol spectrometer (PAS-1.108). *Aerosol Sci. Technol.* 50, 1352–1365. doi:10.1080/02786826.2016.1232859.
- Vliet, E.D.S. van, Kinney, P.L., 2007. Impacts of roadway emissions on urban particulate matter concentrations in sub-Saharan Africa: new evidence from Nairobi, Kenya. *Environ. Res. Lett.* 2, 045028. doi:10.1088/1748-9326/2/4/045028.
- World Health Organization (WHO) Burden of Disease from Ambient Air Pollution for 2012, WHO, Geneva (2014). Available: http://www.who.int/phe/health_topics/outdoorair/databases/AAP_BoD_results_March2014.pdf

Appendix

Figures 1A and 2A show the raw 1-minute data recorded of particulate pollutants and the gaseous pollutants, respectively.

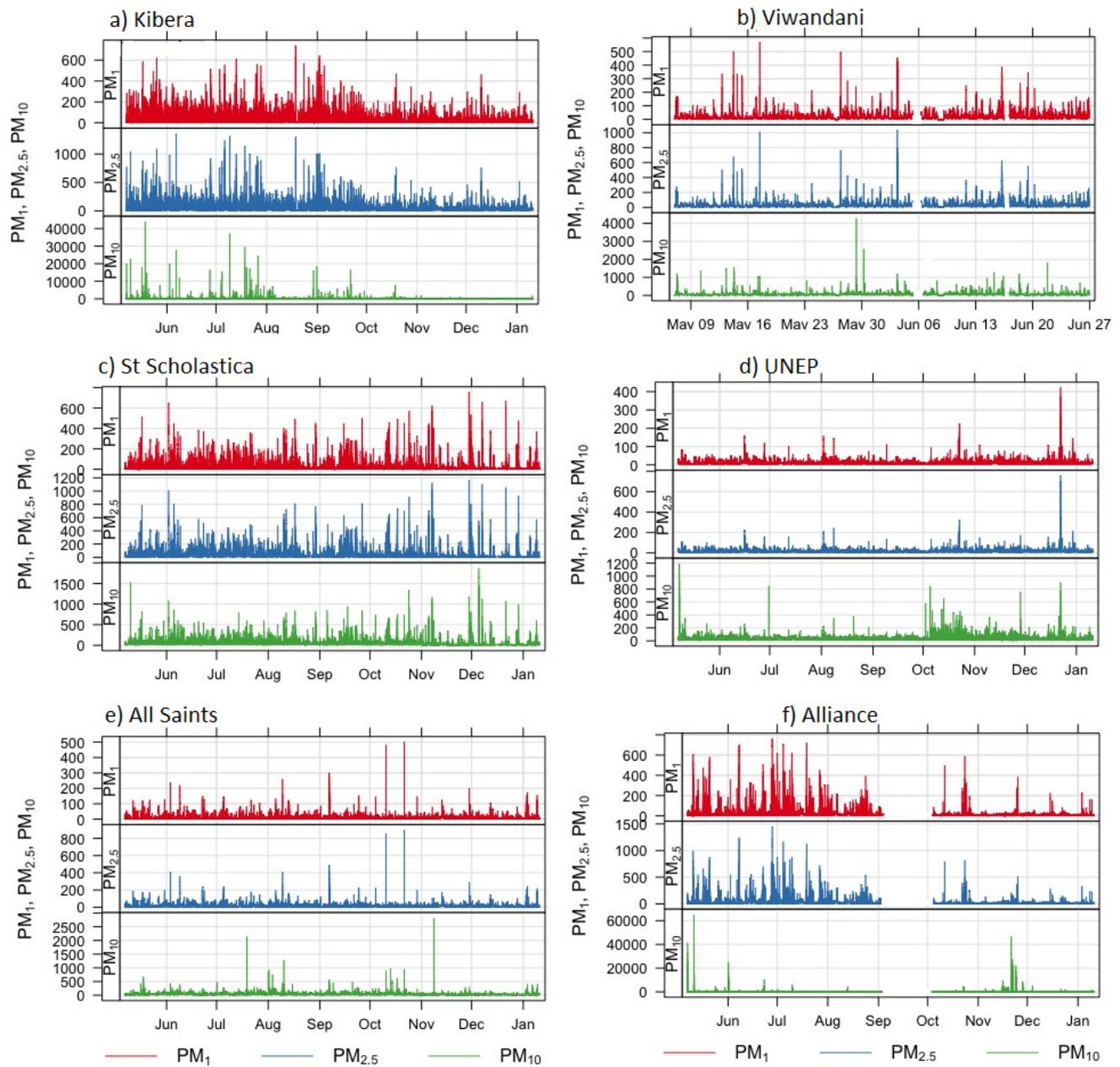


Figure 1A: 1-minute PM_1 (red), $PM_{2.5}$ (blue) and PM_{10} (green) mass concentration ($\mu\text{g}/\text{m}^3$) time series plots for each site; a) Kibera Girls Soccer Academy, b) Viwandani Community Center (note that due to an extended power outage this monitor stopped logging data after June 27, 2016), c) St Scholastics, d) UNEP, e) All Saints Cathedral School, f) Alliance Girls School from May 1, 2016 to January 11, 2017.

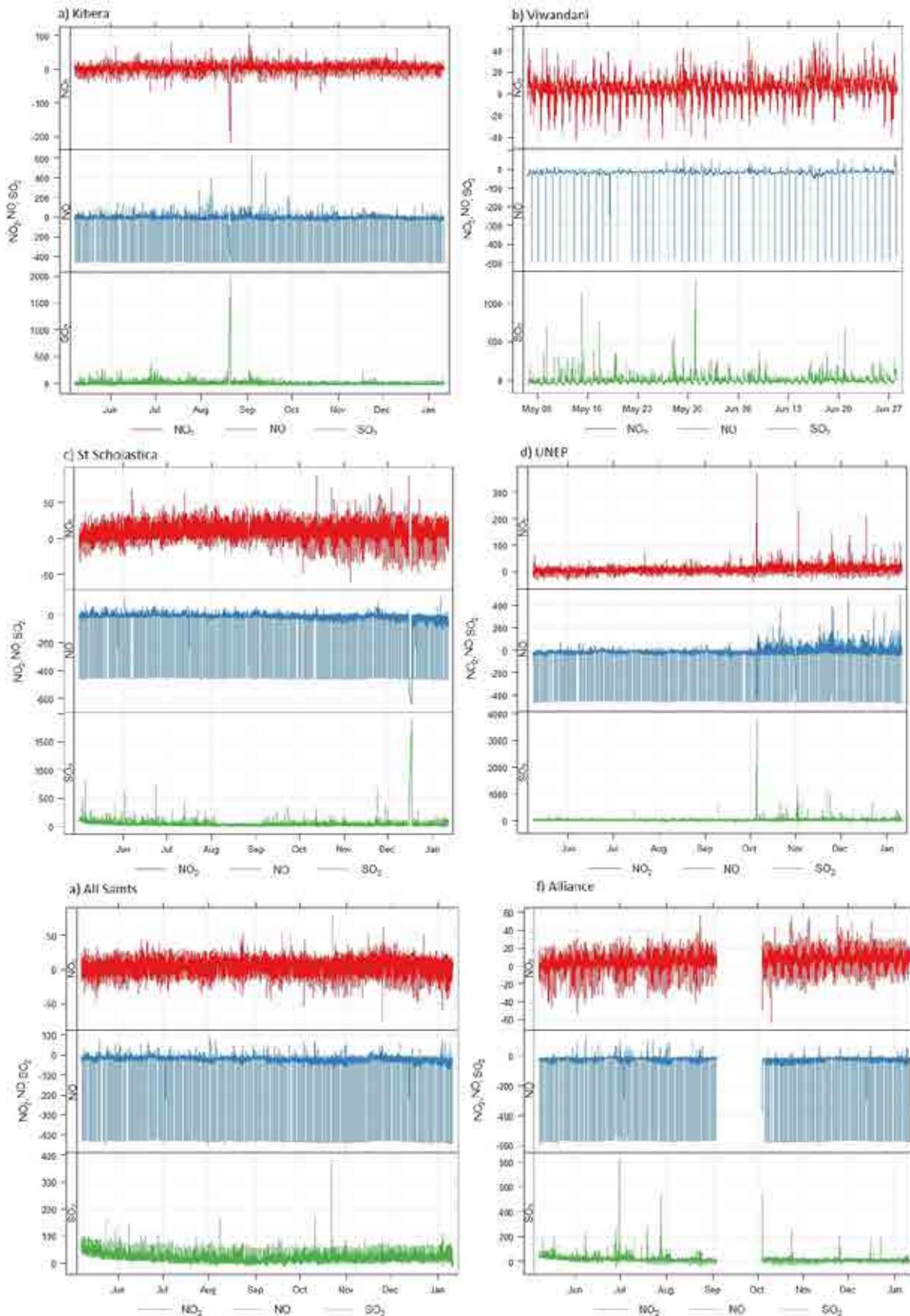


Figure 2A: : 1-minute NO_2 (red), NO (blue) and SO_2 (green) concentration (ppb) time series plots for each site a) Kibera Girls Soccer Academy, b) Viwandani Community Center (note that due to an extended power outage this monitor stopped logging data after June 27, 2016), c) St Scholastics, d) UNEP, e) All Saints Cathedral School, f) Alliance Girls School from May 1, 2016 to January 11, 2017.

Table 1A shows the correlation between gaseous pollutant values > 0 and temperature/humidity and the other pollutants measured at each site. This table shows that for gaseous pollutants with values > 0, the correlation between temperature and humidity is low, and has the same sign across sites. This indicates that the signal registered is more likely to only be due to the pollutants and is not affected by environmental factors.

Table 1A: Summary of the Pearson correlation coefficient (R) at each of the six sites for all gaseous pollutant observations greater than zero.

	Kibera	Viwandani	St Scholastica	UNEP	All Saints	Alliance
Correlation of NO ₂ with temperature	0.13	0.02	0.17	0.32	-0.045	0.38
Correlation of SO ₂ with temperature	0.027	0.01	0.18	0.18	0.25	0.04
Correlation of NO with temperature	0.028	-0.12	-0.17	-0.04	-0.28	-0.12
Correlation of NO ₂ with humidity	-0.13	-0.032	-0.27	-0.31	0.099	-0.39
Correlation of SO ₂ with humidity	-0.056	-0.018	-0.16	-0.16	-0.11	0.013
Correlation of NO with humidity	-0.15	-0.09	0.26	0.06	0.058	-0.06
Correlation of NO with NO ₂	0.32	0.11	0.098	0.26	-0.097	0.27
Correlation of NO with SO ₂	0.55	0.24	0.31	0.33	0.47	0.36
Correlation of NO with PM ₁₀	0.13	0.16	0.12	0.12	0.37	0.19
Correlation of NO with PM _{2.5}	0.16	0.13	0.09	0.06	0.27	0.16
Correlation of NO with PM ₁	0.16	0.12	0.09	0.03	0.27	0.17
Correlation of NO ₂ with SO ₂	0.16	0.14	0.21	0.28	0.18	0.066
Correlation of NO ₂ with PM _{2.5}	0.13	0.29	0.1	0.16	0.28	0.02
Correlation of NO ₂ with PM ₁₀	0.058	0.32	0.24	0.31	0.26	0
Correlation of NO ₂ with PM ₁	0.12	0.3	0.089	0.12	0.27	0.014
Correlation of SO ₂ with PM _{2.5}	0.25	0.13	0.12	0.18	0.25	0.12
Correlation of SO ₂ with PM ₁₀	0.086	0.12	0.19	0.22	0.25	0.01
Correlation of SO ₂ with PM ₁	0.26	0.13	0.12	0.16	0.23	0.12

Figures 3A to 7A clearly show the variation of the gaseous pollutants with temperature. It is clear from these figures that for high temperatures (roughly > 200 C), negative values of pollutants are registered. Co-location with a reference monitor is required in order to truly identify the ranges in which the values are correct. However, plotting these graphs is a rough way to identify temperature ranges in which the sensors clearly make incorrect measurements.

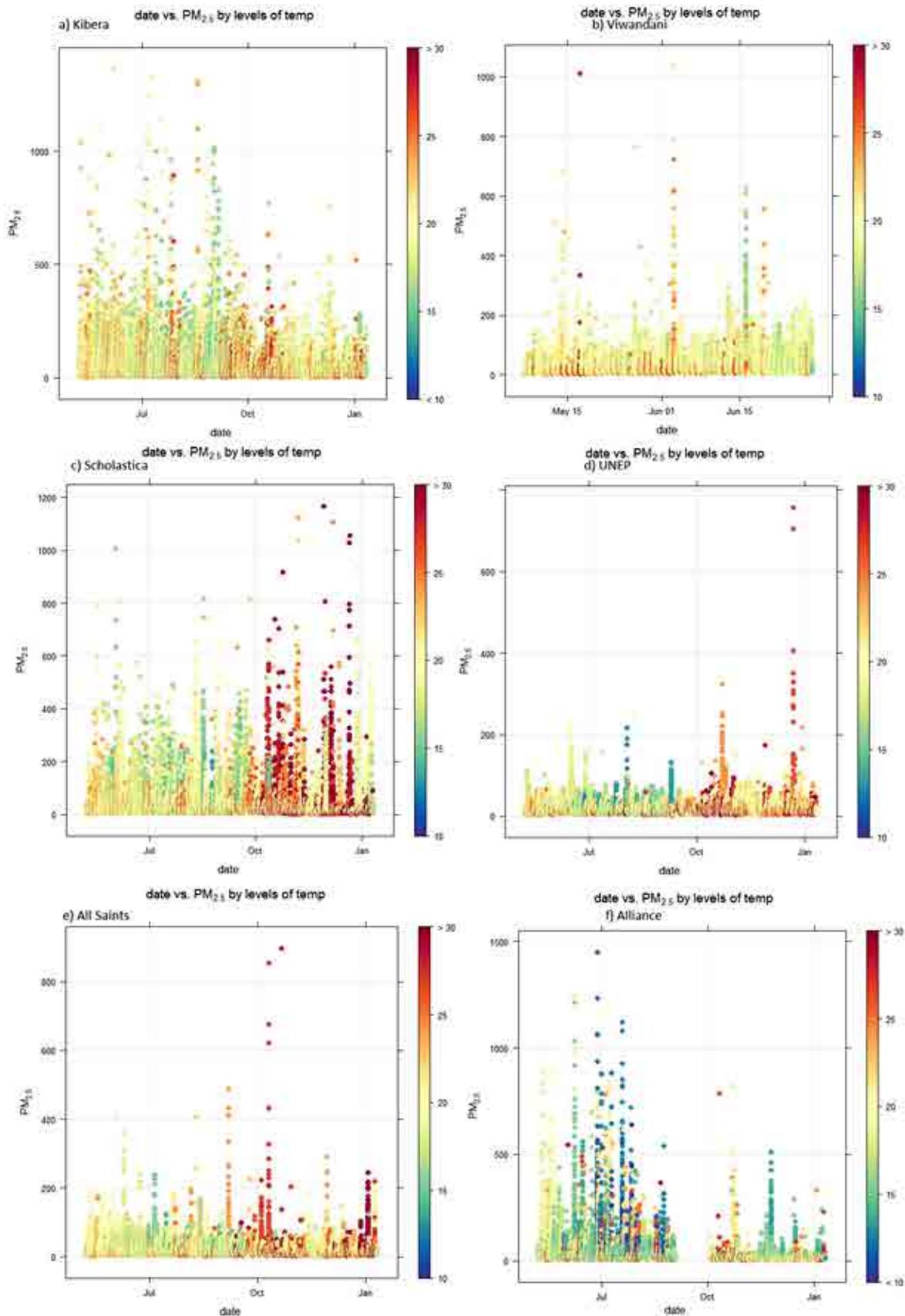


Figure 3A: Time series of $PM_{2.5}$ in units of $\mu g/m^3$ with the color scale corresponding to temperature for the sites: a) Kibera Girls Soccer Academy, b) Viwandani Community Center (note that due to an extended power outage this monitor stopped logging data after June 27, 2016), c) St Scholastics, d) UNEP, e) All Saints Cathedral School, f) Alliance Girls School from May 5, 2016 to January 11, 2017.

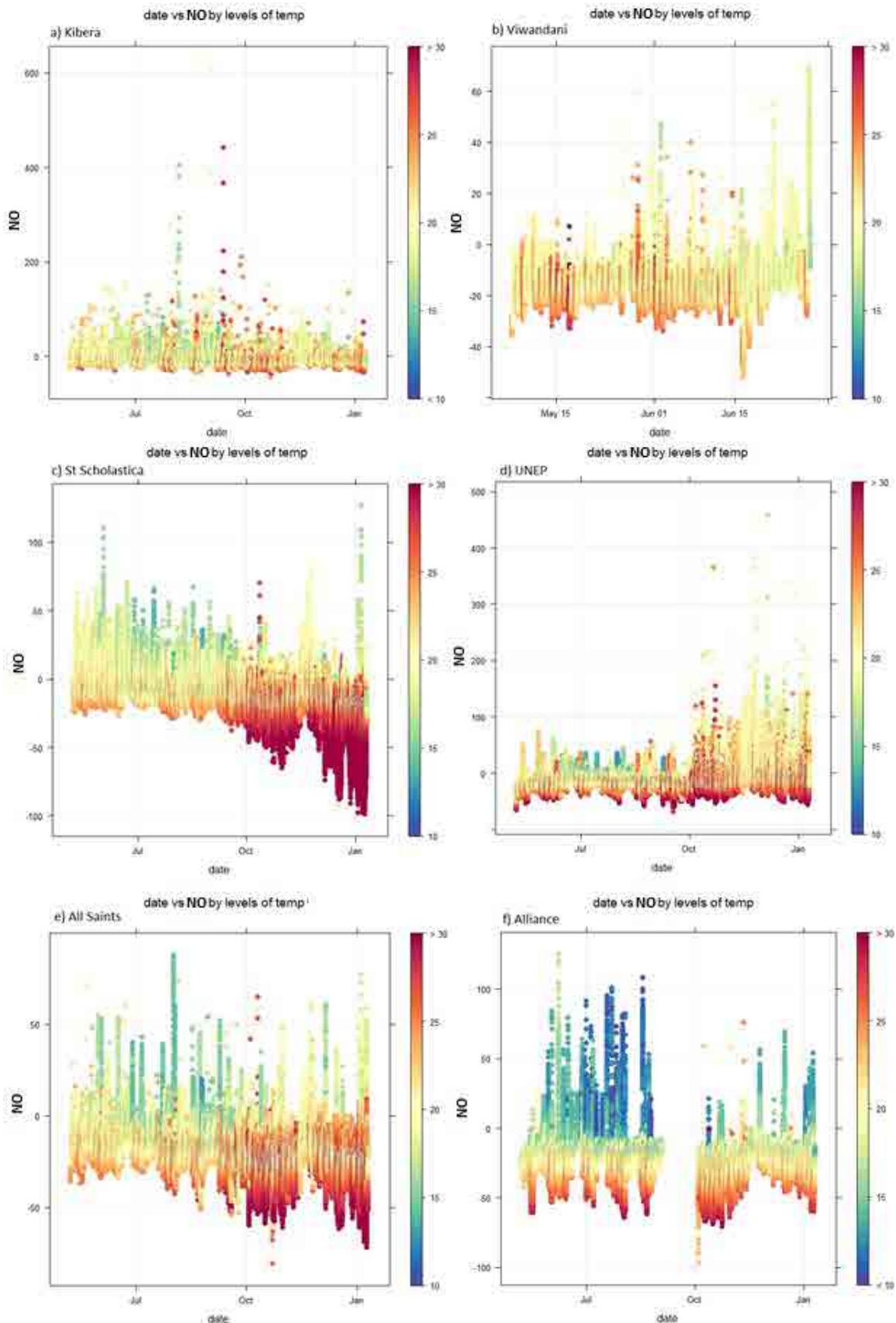


Figure 4A: Time series of NO for recordings >100ppb in units of ppb with the color scale corresponding to temperature for the sites: a) Kibera Girls Soccer Academy, b) Viwandani Community Center (note that due to an extended power outage this monitor stopped logging data after June 27, 2016), c) St Scholastics, d) UNEP, e) All Saints Cathedral School, f) Alliance Girls School from May 5, 2016 to January 11, 2017.

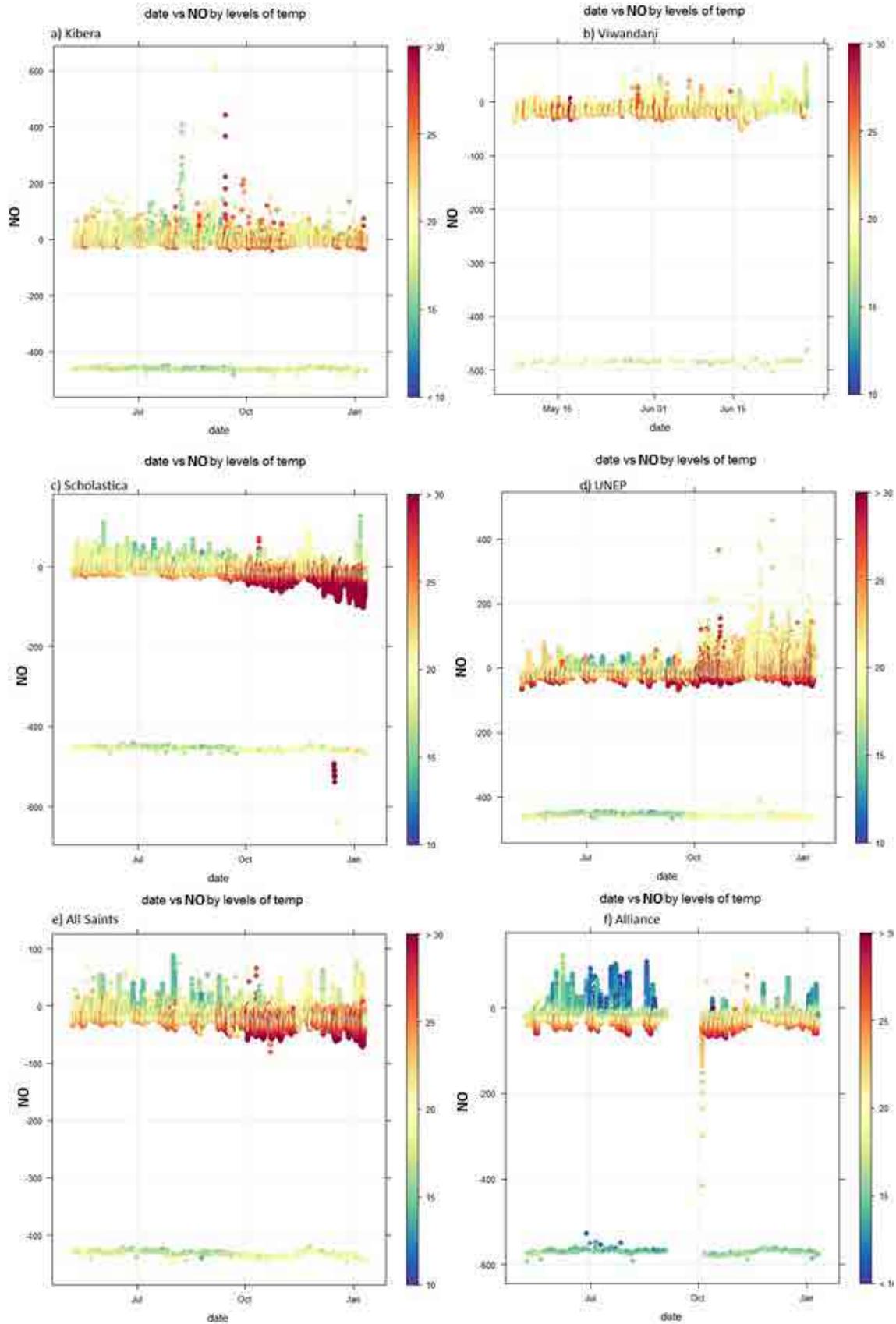


Figure 5A: Time series of NO in units of ppb with the color scale corresponding to temperature for the sites. No filter was applied to the NO data: a) Kibera Girls Soccer Academy, b) Viwandani Community Center (note that due to an extended power outage this monitor stopped logging data after June 27, 2016), c) St Scholastics, d) UNEP, e) All Saints Cathedral School, f) Alliance Girls School from May 5, 2016 to January 11, 2017.

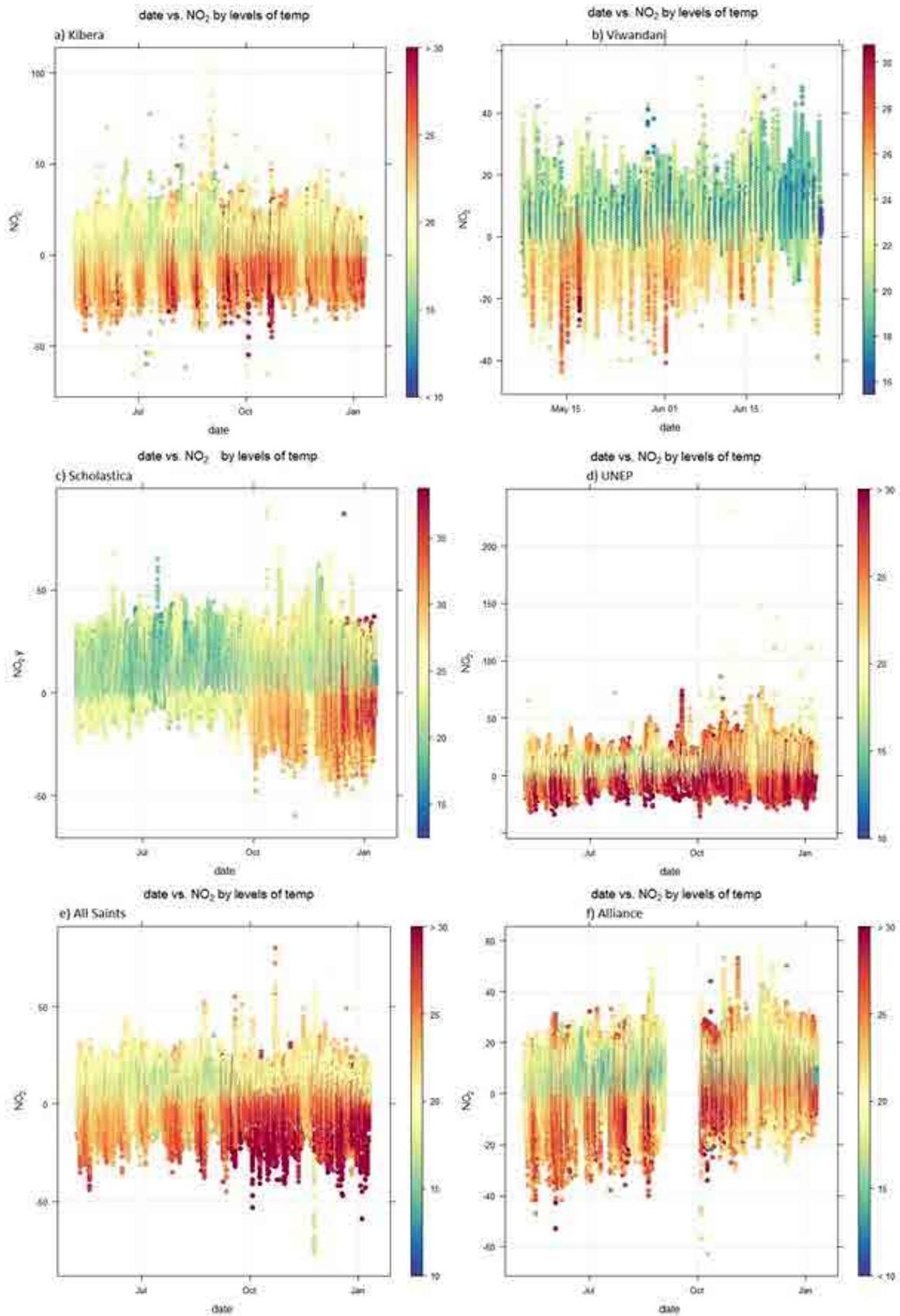


Figure 6A: Time series of NO₂ in units of ppb with the color scale corresponding to temperature for the sites: a) Kibera Girls Soccer Academy, b) Viwandani Community Center (note that due to an extended power outage this monitor stopped logging data after June 27, 2016), c) St Scholastics, d) UNEP, e) All Saints Cathedral School, f) Alliance Girls School from May 5, 2016 to January 11, 2017.

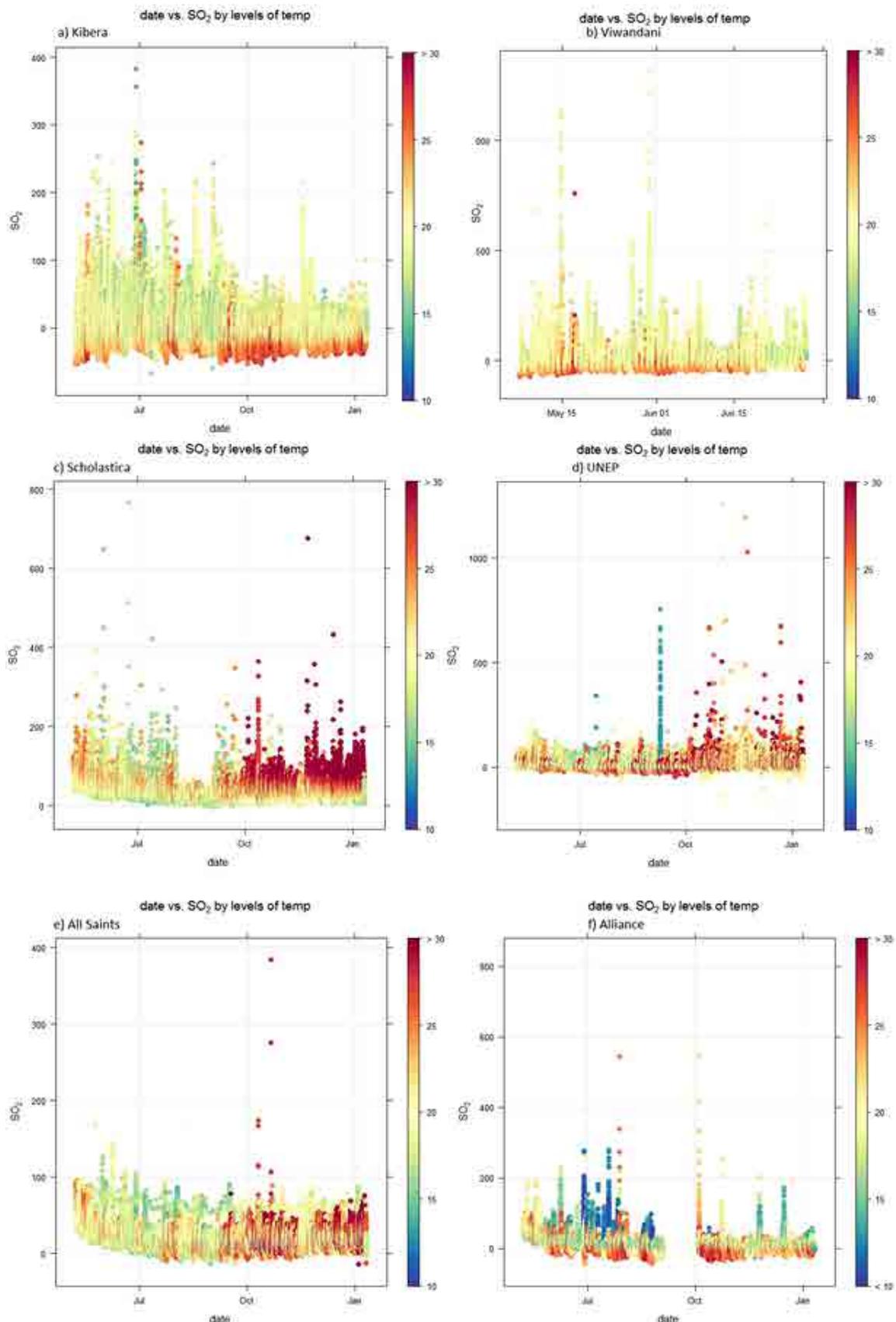


Figure 7A: Time series of SO_2 in units of ppb with the color scale corresponding to temperature for the sites: a) Kibera Girls Soccer Academy, b) Viwandani Community Center (note that due to an extended power outage this monitor stopped logging data after June 27, 2016), c) St Scholastics, d) UNEP, e) All Saints Cathedral School, f) Alliance Girls School from May 5, 2016 to January 11, 2017.