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Investigating the applicability of low-cost sensors for ground-based air quality monitoring networks in developing countries: A Ghana case study

SCHOOL OF WATER, ENERGY AND ENVIRONMENT:
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ABSTRACT

While several studies have reported on the utility of low-cost sensors for air quality campaigns in advanced countries including the development of data correction and quality improvement mechanisms thereby using them to complement regulatory monitors, there is, in contrast, limited information on the use of low-cost sensors for air pollution applications in Ghana and wider parts of Sub-Saharan Africa. This PhD study presented a proof of concept approach on the feasibility of factory calibrated Alphasense OPC-N2 for two main purposes. Firstly, the suitability of low-cost sensors for high-density ground-based air pollution studies and the applicability of the high-resolution data for quantification of atmospheric emissions. Pearson's correlation analysis was applied to establish the reproducibility of the selected sensors for high-density ground-based air quality monitoring specifically for PM species due to the spatial and temporal variability and suitability of PM for developing urban air quality standards. Trend analysis, calendar plots and sectorial plots in the components of wind were experimented using the high-resolution data to quantify particulate matter (PM) and its sources. Hourly averaged data from the selected sensors have demonstrated the reproducibility of low-cost OPC-N2 for use in the selected environments for PM with correlation coefficients (Pearson's, R) between 0.97 and 0.98 for PM_1, $PM_{2.5}$ and PM_{10}. For quantification of the species monitored, PM_{10} values were 500 µg/m^3; $PM_{2.5}$ were a little below 90 µg/m^3 and PM_1 values were a little below 60 µg/m^3. These levels though preliminary, agree with PM pollution reported from these types of environments. It was also found that PM pollution was locally characterised with low wind speed (≤ 2 ms^{-1}) tied to background activities and the surrounding environment which includes traffic, wind-blown dust and roadside food cooking and vending activities. The statistical difference in mean values (*t-values* of 17.3, 11.4 and 4.2 for PM_1, $PM_{2.5}$ and PM_{10} respectively) of the reported PM species have shown that the sensors are better suited for PM_{10} monitoring. Findings from this study provide a benchmark for future (AQ) studies in Ghana, particularly in the selected exemplar urban areas. It demonstrates the feasibility of the current generation of relatively low-cost PM sensors for a high-density ground-based air quality monitoring in environments typical of large parts of West and Sub Saharan Africa.

Keywords: Air pollution; Ghana; Sub-Saharan Africa; Low-cost sensing; Air quality

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LIST OF ABBREVIATIONS

$\mu g/m^3$	Micrograms per cubic meter
AQ	Air Quality
AQM	Air Quality Monitoring
CEN	European Committee for Standardization
CO	Carbon monoxide
CO_2	Carbon dioxide
DEFRA	Department for Environment, Food and Rural Affairs
GAM	General Additive Model
GFS	Global Forecasting System
GhEPA	Ghana Environmental Protection Agency
HEI	Health Effects Institute
LCS	Low-cost sensor
NAAQS	National Air Quality Standards
NCEP	National Centres for Environment Prediction
NO	Nitric oxide
NO_2	Nitrogen dioxide
NOAA	National Oceanic and Atmospheric Administration
O_3	Ozone
OPC	Optical Particle Counter
PID	Photo Ionization Detector
PM	Particulate Matter
ppb	parts per billion
ppm	parts per million
R	Pearson's correlation coefficient
SD	Standard Deviation
SO_2	Sulphur dioxide
SSA	Sub-Saharan Africa
UCC	University of Cape Coast
UCCSM	University of Cape Coast Science Market
UNICEF	United Nations Children's Fund
USEPA	United Nations Environmental Protection Agency
VOCs	Volatile Organic Compounds
WHO	World Health Organization

1 RESEARCH CONTEXT AND NEEDS

1.1 Background

Adverse health effects associated with exposure to poor AQ have been demonstrated in several studies (e.g. Cohen et al., 2005; WHO, 2006; Bauer et al., 2019; HEI, 2019). Complex and expensive conventional monitoring approaches requiring large investment and infrastructure are used to monitor air quality (AQ) in many jurisdictions. These approaches provide accurate data on AQ species of health concern to inform air pollution monitoring and mitigation strategies. AQ species of health relevance monitored using these conventional approaches include particulate matter – PM ($PM_{2.5}$ and PM_{10}), ozone (O_3) and nitrogen dioxide (NO_2), (WHO, 2006). These types of conventional monitoring approaches are characterized by some limitations. Of particular mention are “who” collects the data, “where” the data is collected and “how” the data is accessed and reported (Snyder et al., 2013).

In most parts of Sub-Saharan Africa (SSA), air quality monitoring (AQM) is limited or non-existent and most of the countries lack monitoring capacity and AQ standards (Petkova et al., 2013). These limited AQM capabilities encountered in SSA, similar to other developing economies, are as a result of limited resources including funds, expertise, awareness of the magnitude of air pollution and its adverse effects on public health and lack of comprehensive development and implementation of guidelines including regulations (see Gulia et al., 2015; Han and Naeher, 2006). Meanwhile, several recent health and epidemiologic studies have reported that exposure to atmospheric emissions is on the rise for many countries in SSA, due to the drive for industrialization/ economic development integrated with urbanization (Ingwe et al., 2008; Droege, 2008; Ikram et al., 2012; UN, 2014; Pope et al., 2018).

These issues highlight the need for relatively low-cost appropriately sensitive AQM approaches. Addressing these highlighted issues of air pollution requires appropriate routine local/ regional AQ data. Sparsely distributed conventional monitoring approaches characterizing SSA, is insufficient and are not capable of providing a representative ground-based air quality data to influence air pollution mitigation strategies and epidemiological studies (Bell et al., 2011; Stienle et al., 2013). Additionally, the complex and varying sources of air pollution in urban settings (e.g. traffic-related pollution) cannot be fully determined with current unevenly distributed AQ networks in SSA (HEI, 2000).

The emergence of low-cost environmental sensing approaches presents an alternative to current conventional AQM approaches. Relatively low-cost cutting-edge high-resolution sensors are flexible, capable of collecting fast, reliable, real-time, in situ data (e.g. Brauer et al., 2012; Amann et al., 2013) for a range of important pollutants (e.g. SO_2, NOx, CO, O_3, PM_1, $PM_{2.5}$, PM_{10}, total VOCs and CO_2) with a single system when properly operated. Many low-cost sensors have been evaluated under ambient environmental conditions (Gao et al., 2015; Holstius et al., 2014; Wang et al., 2015) and controlled conditions (Austin et al., 2015; Wang et al., 2015). These studies have demonstrated that low-cost sensors are promising but evidence on the performance of low-cost sensors in tropical environments such as those encountered in SSA have not been fully documented (Lewis and Edwards, 2016).

There is to date limited information on the performance of low-cost sensors for monitoring different air pollutants alongside more expensive regulatory monitoring equipment in Ghana and wider SSA and how these low-cost devices can be used to bridge AQ data gaps in resource-constrained settings as those encountered in many parts of SSA including Ghana.

In the absence of evidence on the performance of low-cost sensors, the end-user cannot effectively deploy low-cost sensors for the intended purpose (Castell et al., 2017; Jovašević-Stojanović et al., 2015; Lewis and Edwards, 2016). Additionally, the challenge facing this emerging state-of-the-art approaches for AQM is partly because information regarding low-cost sensor performance is at an early stage in SSA (Mead et al., 2013; Holstius et al., 2014; de Souza et al., 2017; Amegah, 2018) and to complement data for scientific research these data need to meet an acceptable level of quality.

This study concentrated on how low-cost sensors can be used to obtain reliable ground-based observational air quality data. PM was used as a key species because of existing and growing evidence on its adverse health effects, spatial and temporal variability as well as suitability for developing urban air quality guidelines (WHO, 2006; Cohen et al., 2005; HEI, 2019). There are reports on limited ground-based data on PM species (specifically $PM_{2.5}$ and PM_{10}) in SSA (Schwela, 2012a; Petkova et al., 2013; Amega and Agyei-Mensah, 2016), information regarding PM_1 monitoring and its effect on public health is limited. Low-cost sensors are capable of reporting PM_1 data and could provide reliable data for air pollution health effect studies as well as air pollution mitigation strategies.

In this study, the term resource-constrained setting(s) is used interchangeably with low and middle-income country (ies) (LMICs) and / SSA. LMICs for this research are defined as communities with limited access to information, resources and opportunities. This case study in Ghana will serve as a benchmark for long-term deployment of a dense network of low-cost AQ monitors in Ghana and the wider SSA region.

1.2 Research questions

The two key scientific research questions which have been developed based on the context of this research are as follows:

1. How can low-cost high-resolution sensors (LCS) be used to obtain observational air quality data appropriate for air pollution studies in SSA specifically Ghana and similar environments typical of SSA?
2. How can relatively fast temporal (sub-hourly) data from LCS nodes be used to extract source features of key atmospheric pollutants in SSA and similar environments?

1.3 Aims and Objectives

This study investigated the applicability of low-cost sensors to understand the extent to which these devices can be used to obtain observational AQ data to bridge AQ data gaps in environments with limited/ no regulatory monitoring stations. This study focused on SSA using Ghana as an exemplar for wider SSA. The specific objectives are as follows:

1. To critically review the current state of AQM in Ghana and the possibilities of low-cost sensors.
2. To assess whether low-cost sensors can be used to bridge AQ data gaps in SSA by undertaking experimental performance study of selected low-cost sensors under varying urban settings in Ghana.
3. To evaluate the applicability of high-temporal data reported from LCS for source feature extraction of key atmospheric pollutants in SSA.

1.4 Study Overview

This research is structured into 6 chapters as follows:

Chapter 1 sets the research context of the PhD study;

Chapter 2 addresses objective 1 which forms an integral part of this PhD mainly identifying gaps through critical literature review and putting the research into context based on the selected study area.

Chapter 3 details the methodology and materials adopted to achieve the objectives

Chapter 4 provides the key findings for objective 2 and 3. Paper 1 [Gameli et al., (2020). Applicability of factory calibrated optical particle counters for high-density air quality monitoring networks in Ghana, Heliyon, 6 (6) e04206] addresses objective 2 and 3 of this study. Firstly on the short term performance of the selected low-cost sensors for AQM and the application of the high-resolution data for source apportionment studies. A commentary [Clean Air Journal (Gameli et al., (2018). The need for open data on air quality monitoring in logistically difficult environments, 28:25 – 26)] has been produced which addresses key areas on the application of low-cost sensors specifically in SSA taking into account the poor communication of AQ data and limited public knowledge on AQ levels and corresponding health effects. This further led to an initiative “Clean Air One Atmosphere” to demonstrate the potentials low-cost sensors offer in addressing the huge knowledge gap on air pollution in SSA. The commentary and the initiative are linked to objective 1 of this study – the current state of AQM in SSA.

Chapter 5 provides an overall discussion and critical outlook for future research by integrating the key findings from the previous chapters and

Chapter 6 is the overall conclusions and future work.

This research produced a peer-reviewed paper Gameli et al., (2020). Applicability of factory calibrated optical particle counters for high-density air quality monitoring networks in Ghana, Heliyon, 6 (6). A commentary on Gameli et al., (2018). The need for open data on air quality monitoring in logistically difficult environments, Clean Air Journal, 28 (25 – 26). This research also produced an initiative on the possibilities low-cost sensors offer regarding the usability of meaningful opensource data for public education in environments with limited knowledge on air quality/ pollution and its impacts on human health “Clean Air One Atmosphere” specifically Ghana and wider Africa.

2 LITERATURE REVIEW

2.1 Introduction

Globally, outdoor air pollution is estimated to have caused nearly 5 million premature deaths in 2017. These deaths were attributed to outdoor exposure to fine particulate matter, i.e. $PM_{2.5}$ (HEI, 2019). Half a million additional premature deaths were attributable to ozone (O_3) in the same year (HEI, 2019).

A range of adverse health effects including aggravating symptoms of asthma, respiratory and cardiovascular diseases, stroke, chronic obstructive pulmonary disease and lung cancer are linked to outdoor air pollution. An estimated 90% of air pollution-related deaths occurred in low and middle-income countries including those encountered in Africa as compared to advanced countries (WHO, 2014; HEI, 2019). A recent National Aeronautics and Space Administration (NASA) modelled study estimated that about 780,000 premature deaths annually in Africa (Table 2-1) are linked to air pollution (Bauer et al., 2019). In Ghana alone, 28,000 premature deaths per annum (WHO, 2018) are attributable to exposure to atmospheric emissions. Evidence on the adverse effects of air pollution on human health is limited in SSA (Petkova et al., 2013) including Ghana. This in part is linked to paucity of observational AQ data and consequently exposure to air pollution health effect studies from the region (Ahmed et al., 2017; Bauer et al., 2019).

In most of the cases, AQ programmes have been discontinued (Petkova et al., 2013) due to drop in funds and in some scenarios the projects are ad-hoc targeted at a particular objective within a stipulated time frame based on conditions of grants/ sponsors (Schwela, 2012a).

Table 2-1: Regional breakdown of estimated air pollution-related deaths adapted from Bauer et al., 2019

Region	Estimate
Africa	782,248
Sub-Sahara	563,218
West Africa	104,865
Central Africa	25,459
Southern Africa	17,085

Air pollution adversely impacts the wider environment specifically ecosystems including agriculture (Melamed et al., 2016). It is reported to decrease farm yields, influence temperature and rainfall patterns (Maas and Grennfelt, 2016) which poses a major threat to livelihoods in SSA including Ghana (Ramanathan and Feng, 2009).

High-income countries, such as the USA have AQ management systems which allow for development, implementation and evaluation of air pollution mitigation strategies based on reliable ground-based AQ data (e.g. National Ambient Air Quality Standards – NAAQS, provides standards for monitoring criteria species available https://www.epa.gov/criteria-air-pollutants) (Snyder et al., 2013). These systems include but are not limited to extensive compliance monitoring, source attribution of emissions integrated with emission reduction programmes.

Over time, these robust approaches have resulted in a reduction of pollutant emissions simultaneously with industrial and economic growth (USEPA, 2017). Similar systems are required in low- and middle-income countries such as Ghana and larger parts of SSA which are currently experiencing rapid economic development associated with increased atmospheric emissions mainly PM and O_3 precursors such as NOx, CH_4 and VOCs (HEI, 2019). In most cases, these robust systems are based on the use of expensive and static instrumentation. In high-income countries, these approaches have been recently complemented by the use of low-cost sensors specifically for those types of pollutants with higher spatial variability (Rai et al., 2017) (e.g. use of optical particle counters for PM and electrochemical cells for NO, NO_2 and CO) and for monitoring near-source emissions as well as personal exposure (Seinfled and Pandis, 1998; Solomon et al., 2008). Some of these supplementary monitoring approaches include infrared cells for CH_4 and CO_2 monitoring, photoionization detector (PID) sensors for total VOC sensing (Masson et al., 2015; Esposito et al., 2016; Sun et al., 2016) and electrochemical cells for O_3, H_2S and SO_2 (e.g. Baron and Saffell, 2017).

As reported by Amegah and Agyei-Mensah (2016), AQ monitoring networks are rudimentary in SSA. Though Ghana undertakes AQ monitoring, the approach is limited to sparsely distributed stations mainly in the capital Accra. AQ monitoring networks are limited in Ghana (Amegah and Agyei-Mensah, 2016). Studies on AQ and associated health effects are limited with reliance on short-term or modelled AQ data.

These types of studies do not provide an extensive and accurate understanding of air pollution and its adverse effects (Bauer et al., 2019).

Industrialisation, population growth (which has been projected to be more than 2 billion between 2010 and 2050 (UN, 2011)) in Africa coupled with increasing energy use, transportation and food production has worsened AQ and will continue to in Africa. The current Health Effects Institute report (HEI, 2019) has shown that more than 90% of the world's population lives in these areas where WHO guidelines for healthy air are exceeded (Figure 2-1). The majority of the countries in Africa represents some of the worse cases globally (Amegah, 2018; Bauer et al., 2019; Katoto et al., 2019). Ghana is characterised with industrialisation (e.g. recent oil and gas exploration activities and road and railway development projects) population growth coupled increased motorisation, increasing urbanisation, energy use and food production. Similar pattern and trend are observed in other parts of SSA (Bauer et al., 2019). There is limited capability in undertaking AQ monitoring in SSA countries because the utilisation of reference-grade monitors involves skilled human capital for operation, maintenance and calibration of instruments with standardized protocols (e.g. CEN, 2012; CEN, 2014). In contrast, most commercially available low-cost sensors can be deployed without long term human intervention or specialized/ technical skills making them suitable for addressing AQ data gaps in the Ghanaian case similar to wider SSA. The cost involved in operating reference-grade instruments does not allow for high-density deployments (i.e. a typical reference-grade instrumentation costs ~$250,000 in addition to operational costs e.g. routine maintenance and calibration; Rai et al., 2017) but local authorities need to increase the density of monitoring to understand spatial variation of atmospheric emissions in urban centres. The characteristics of low-cost sensors make them suitable for such cases (EU, 2008) because they are cheap (a unit costing ~$100, Rai et al., 2017), robust, operate on low-power, ability to report in situ data in seconds/ minutes rather than hours, minimal infrastructural requirement and user-friendly as well as the ability to report data to internet based-platforms (Mead et al., 2013; Snyder et al., 2013; Kumar et al., 2015; Rai et al., 2017; Castell et al., 2017). The operation of low-cost sensors though requires additional costs in terms of long-term data analytics with careful correction and replacement of components/ cleaning of parts, the approach is relatively cheaper as compared to operating reference-grade monitors (Snyder et al., 2013; Karagulian et al., 2019).

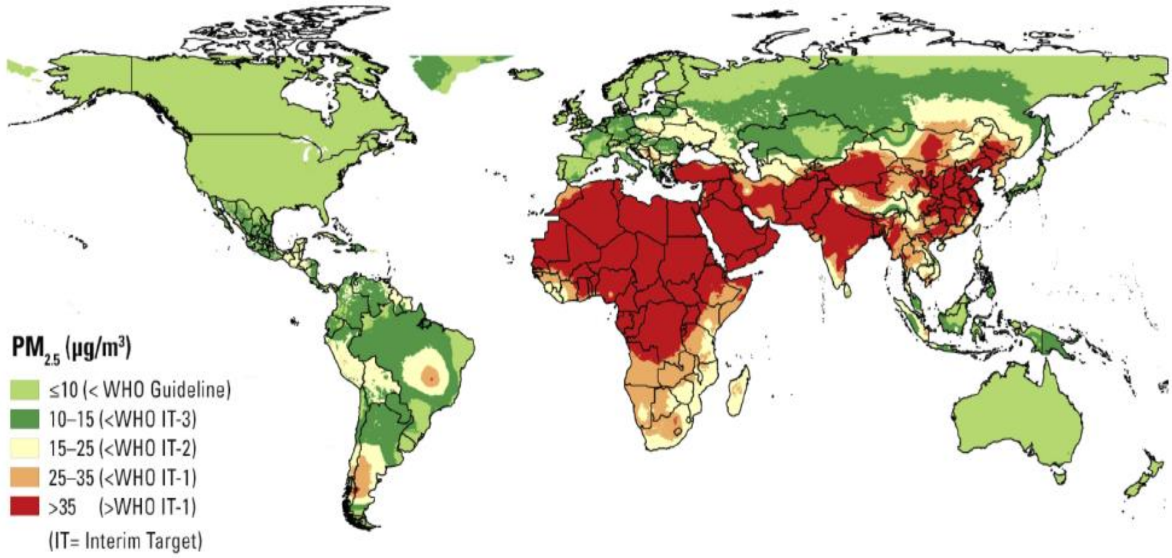

Figure 2-1: Annual average PM2.5 concentrations in 2017 relative to WHO AQ Guidelines (adapted from HEI, 2019)

This review provides critical insights into conventional monitoring techniques and the novel use of state-of-the-art low-cost sensors. It presents a case on the utility of the current state of low-cost sensors for providing reliable ground-based AQ data in environments with limited/ non-existent AQ monitoring stations specifically Ghana and wider SSA. The current challenges and opportunities in using these types of sensors for comprehensive AQ monitoring programmes in such environments are limitation of skills regarding instrument optimization, data mining, and deployment strategies of which this review provides critical areas to consider.

2.2 Conventional monitoring approaches versus low-cost sensors

Conventional AQ monitoring approaches consisting of expensive and complex instrumentation requiring large infrastructure are employed in measuring chemical species namely PM, NOx, CO, O_3 and sulphur dioxide (SO_2) in urban settings (Kumar et al., 2014; Mouzourides et al., 2015; Sharma et al., 2013). In advanced countries, cities have established AQ monitoring stations based on AQ standards/ directives. In the European Union (EU), AQ monitoring sites are determined by the EU AQ Directive 2008/50/EC (Rai et al., 2017). These directives explicitly stipulate a minimum number of static stations for a specific target key air pollutant in line with levels of air pollution, population and area (Rai et al., 2017). An official monitoring station covering about

100,000 people as against cities in developing countries (Rai et al., 2017). These approaches are defined by AQ monitoring standards/ directives. For example, there are about 300 monitoring stations in the UK (DEFRA, 2011) as compared to 600 in India (CPCB, 2017). In Ghana, there are only 16 regulatory monitoring stations sparsely distributed in the capital Accra for monitoring PM species (GhEPA, 2019). These conventional, reference-grade instrument monitoring approaches follow standardized quality assurance/ quality control (QA/QC as detailed in e.g. 2008/50/EC, Rai et al., 2017; CEN, 2012; CEN, 2014) protocols.

This approach of using expensive, fixed, complex instrumentation with large logistical demands for AQ monitoring is now changing with the emergence and utility of low-cost sensors. Low-cost sensors offer the opportunity to undertake ubiquitous AQ monitoring in a network for monitoring personal exposure (Chow et al., 2009), indoor AQ monitoring (e.g. Wan Young and Sung-Ju,2006) and hazardous leaks (Gianfranco et al., 2012).

A considerable amount of time is spent indoors hence indoor AQ is of health importance. Morawska et al., (2001) reported that indoor AQ levels are mostly influenced by location, type of dwelling and behaviour (e.g. tobacco smoking, type of energy use for cooking and heating as well as cleaning practices). The limited distribution of and costs associated with the use reference grade monitors are not capable of providing these types of information hence the need for a new approach with low-cost sensors which require data analytical skills, minimal infrastructure and handy for these types of monitoring similar to personal monitoring, identifying hotspots of air pollution and hazardous leaks (Mead et al., 2013; Moltchanov et al., 2015; Rai et al., 2017).

Similar to indoor monitoring, the large data gap encountered in Ghana and wider parts of SSA (Schwela, 2012a; Petkova et al., 2013; Bauer et al., 2019) is potentially challenging to address with conventional monitoring approaches considering the operational cost and human capital involved in running them. A cheaper, robust and high spatiotemporal resolution network could offer a feasible approach in filling these data gaps (e.g. Jovasevic-Stojanovic et al., 2015; Castell et al., 2017) though there are additional costs to time and resources required to maintaining the sensors, cleaning and analysing the reported data.

There is growing evidence on the utility of these devices for emission source feature extraction by deploying them in high density (e.g. Mead et al., 2013); road-side monitoring (e.g. Wang et al., 2009 air quality campaign for the Olympic Games) and high-way traffic monitoring and meteorological conditions as reported by Padró-Martínez et al. (2012). In Ghana and wider parts of SSA, it is challenging to supplement current conventional monitoring approaches as the majority of the AQ campaigns are discontinued coupled with poor resolution data (Petkova et al., 2013). A properly operated network of miniaturised low-cost high-resolution sensors suitable for high-density deployment presents a feasible alternative (Mead et al., 2013; Snyder et al., 2013; Kumar et al., 2015; Moltchanov et al., 2015; Rai et al., 2017). Table 2-2 illustrates conventional and new approaches to AQ sensing.

Low-cost sensors have the potential to drastically reduce the costs associated with conventional AQ monitoring approaches and provide meaningful ground-based location-specific high-resolution AQ dataset (Moltchanov et al., 2015) for air pollution-related studies. For example, the cost of employing a reference-grade/ regulatory equipment is about US$ 250,000 as compared to low-cost devices costing approximately US$ 100 (Rai et al., 2017). The operation of reference-grade instruments as highlighted in the introductory section inquires additional costs related to routine maintenance and calibration. Though there are associated costs on running of low-cost devices for example power, internet, security, data mining and post-processing, the utility of low-cost sensors is relatively cheaper as compared to reference-grade / conventional approaches. Low-cost sensors are suitable for obtaining high spatiotemporal data (i.e. if deployed in a high-density) that can be tied to internet-based platforms and be remotely accessed (Kanaroglou et al., 2005). This new approach provides avenues for gathering high-resolution spatiotemporal AQ data in near real-time suitable for air pollution management projects (Bossche et al., 2016; de Nazelle et al., 2013). For example, low-cost sensors can be used to (i) supplement conventional AQ monitoring; (ii) improve the link between pollutant exposure and human health; (iii) emergency response including hazardous leak detection and source compliance monitoring and (iv) improve community's engagement and awareness towards AQ issues (Rai et al., 2017).

Commercially available low-cost sensors have been examined both under ambient environmental conditions (e.g. Gao et al., 2015; Holstius et al., 2014; Wang et al.,

2015) controlled conditions (e.g. Austin et al., 2015; Wang et al., 2015) and have reported on the feasibility of the current state of low-cost sensors for AQM though with caveats. These studies, recommended approaches, for example, machine learning to improve data quality but there is limited information on feasibility studies using low-cost sensors for AQM in Ghana and wider SSA.

Table 2-2: Conventional versus low-cost monitoring approaches (Mead et al., 2013; Snyder et al., 2013; Kumar et al., 2015; Rai et al., 2017)

Item	Conventional	Low-cost
General characteristics	Large logistical demands	Handy
	Complex	Simplified
	Require human intervention	Do not require human intervention
	Routine maintenance and calibration	Do not require routine maintenance and calibration
	Usually fixed	Fixed and mobile
	Mostly sparsely distributed	Favours high-density deployment
	Expensive (single unit ~$250,000)	Low-cost (single unit ~$100)
	Require technical skills for operation	Do not require any special skills for operation
	Require considerable power to operate	Operate on low power
	Performance not affected by environmental variables	Performance is limited by environmental variables
	A unit report data on single species	A unit can report data on multiple species at the same time
	Require large infrastructure	Can be deployed easily anywhere
Data collection	Limited to local authority	Anyone
Access to data	Limited to local authority	Anyone
Objectives of data collection	Mostly compliance	Testing of new technologies and applications
Data resolution	Often hourly	Seconds to minutes

Item	Conventional	Low-cost
Data storage	Local authority	Internet-based platforms

Castell et al., 2017 recommended OPCs for particulate matter monitoring and de Souza et al., (2017) experimented the use of Alphasense OPC-N2 use in Nairobi Kenya, Eastern Africa. The results from these studies have shown that low-cost sensors can be used for establishing baseline data in these types of environments with the potential of providing reliable ground-based location-specific AQ monitoring approaches. These studies are providing promising future opportunities for LMICs including Ghana and wider SSA that will allow overcoming the long-term AQ data gaps encountered in SSA.

2.3 The need for relatively low-cost PM monitoring approaches in SSA – the Ghanaian perspective

An understanding of the magnitude of air pollution and associated health effects in Ghana and wider parts of SSA is limited due to data gaps. Nevertheless, recent estimates have shown that majority of air pollution-related premature deaths occur in Africa yearly (see Table 2-1 for regional breakdown) (Amegah and Agyei-Mensah, 2016; WHO, 2016; Bauer et al., 2019).

For example, the EU member states developed local AQ limits (EU, 2008) based on current and reliable regional and local AQ data. Current trends in Europe have shown that a reduction in long-term exposure to PM_{10} by 5 μg/m^3 prevents about 3000 to 8000 premature deaths per annum (Medina et al., 2004). In terms of health cost, DEFRA (2004) reported similar findings for $PM_{2.5}$ to be around 7 to 8 months loss of life expectancy with a corresponding health cost of £20 billion in the UK.

The fundamental challenge in SSA is the lack of reliable and up to date country-specific AQ data (Schwela, 2012a; Petkova et al., 2013). As echoed in the introduction of this study, it is challenging to make informed decisions in the absence of reliable, routine and user-friendly accessible AQ data. This is because such data is imperative for many interventions and applications such as undertaking source apportionment studies (Mead et al., 2013); accurate assessment of exposure to air pollution health studies (Amegah, 2018); inform policy direction (e.g. transportation and town planning); exposure inventories; AQ prediction and modelling (Schwela, 2012a; Petkova et al., 2013); development of efficient and location-specific air pollution mitigation strategies and tracking and evaluation of implemented air pollution mitigation strategies in the majority of SSA countries (Petkova et al., 2013) including Ghana. In contrast to LMICs including those in SSA, AQ monitoring is limited which subsequently makes the development of AQ standards challenging (Petkova et al., 2013).

The WHO database (2014) has shown that there are limited data from most of the countries in Africa including Ghana on PM (PM_{10} and $PM_{2.5}$) as a high-risk pollutant (Figure 2-2 and 2-3). As per the WHO (2014) update, ambient and indoor air pollution levels of $PM_{2.5}$ and PM_{10} are reported from 92 countries comprising of 1100 cities around the world for the years 2003 to 2010.

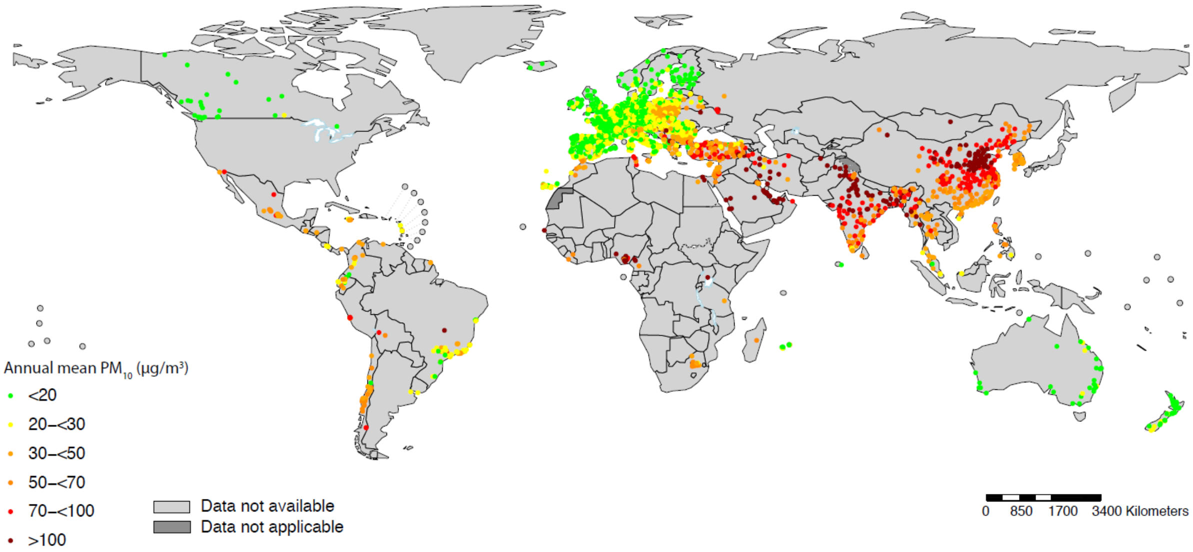

Figure 2-2: Mean ambient air pollution of particulate matter with an aerodynamic diameter of 10 µm or less [PM_{10}] in country urban areas adapted from the WHO database reported levels from 2010 to 2016 (adapted from WHO, 2014)

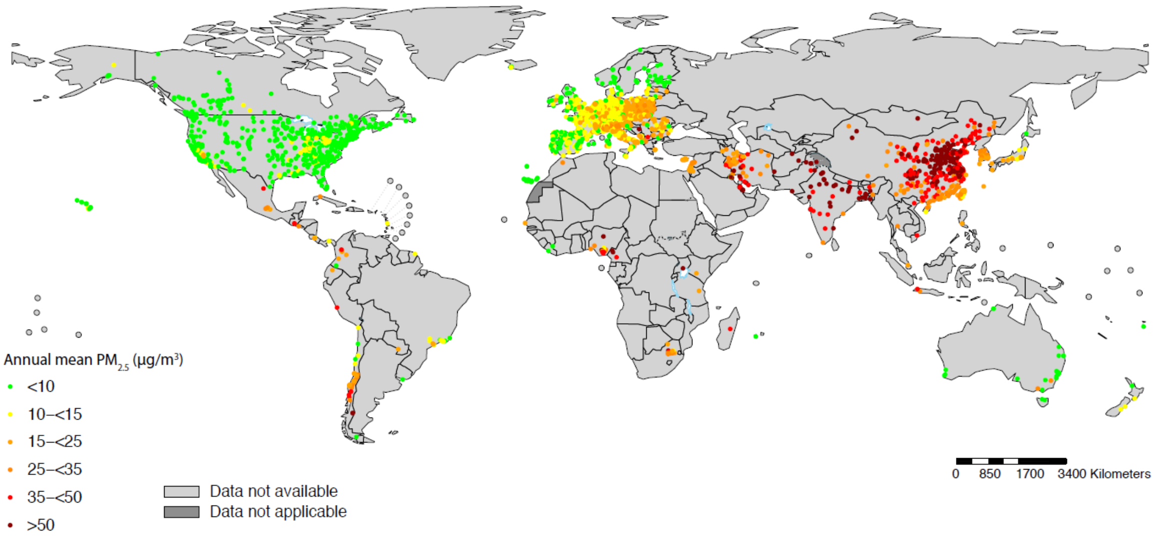

Figure 2-3: Mean ambient air pollution of particulate matter with an aerodynamic diameter of 2.5 µm or less [$PM_{2.5}$] in country urban areas adapted from the WHO database reported levels from 2010 to 2016 (adapted from WHO, 2014).

Though advanced countries have complemented sparsely distributed AQ networks with low-cost approaches, the situation in SSA including Ghana represents some of the worse globally (Amegah, 2018; Katoto et al., 2019; Bauer et al., 2019). For example, current trends have shown that ground-based AQ monitoring campaigns are fragmented and often stalled in SSA (Bauer et al., 2019).

A major propelling factor of air pollution in Africa is population growth associated with urbanization, motorization, migration as an urge for economic growth. Schwela (2012a) have shown that these driving forces exert pressure on atmospheric emissions through increasing vehicle fleet – an extensive energy consumer and source of air pollution in urban settings. Schwela (2012a) echoed the increasing daily emissions of key atmospheric species namely CO, NOx and hydrocarbons are mostly from vehicles in SSA that are often poorly managed. However, the UN (2015) report projected Africa's population to be between 1.65 – 1.71 billion by 2030 [Population 2030 Demographic challenges and opportunities for sustainable development planning] This implies that air pollution research in Africa must be integrated with air pollution mitigation strategies specifically with a focus on adopting environmentally friendly approaches for economic growth and behavioural changes including proper waste management practices.

However, current trends have shown that AQ campaigns including regulatory monitoring in Africa are few. As reported in Bauer et al (2019), a handful of studies have reported on continuous AQM field approaches. Few studies that have provided some information on atmospheric emission in the region include West Africa Atmospheric Composition Measurement in 2006 reported by Reeves et al., (2010) which provided the basis for the Sahelian Dust Transect reported by Marticorena et al., (2010). Also, Swap et al., (2002) reported on field campaign conducted in 2000 by the Southern African Regional Science Initiative. Knippertz et al., (2017) and Zuidema et al., (2016) respectively reported on aerosol-cloud interactions in West Africa and observation of aerosols above clouds and aerosols above cloud interactions in Southern Africa.

Further to this, as at 2019, Katoto et al reported on the current evidence of ambient air pollution in SSA. Evidence from this work has shown that only 60 peer-reviewed articles were published on ambient air pollution in SSA. This work further stipulated that out of this 60, only 37 described levels of ambient air pollution while the rest provided evidence on the assessment of air pollution health effects. It was also observed in these studies on ambient air pollution in SSA by Katoto et al (2019) that majority of the data used for exposure assessment were only from selected cities and temporary collaborative international projects. The results of these exposure assessment studies have also shown that as compared to the current WHO guidelines, measurements were in 10-20 fold higher (Katoto et al., 2019). Also, from the 23 studies on exposure health effects assessment, most of the countries in SSA contributed no data at all. However, 14 of these exposure assessment studies originated from South Africa indicating the huge scientific knowledge gap on the air quality monitoring and its associated health effect studies in SSA. This has reechoed the challenges of AQM in SSA as reported by for example Schwela (2012a); Petkova et al (2013); WHO, (2014) and Bauer et al (2019).

In the case of Ghana, this is due to several issues including (1) limited evidence on the use of low-cost devices for AQ campaigns in the region, (2) issues related to hardware of such devices, (3) reliable power supply, (4) reliable internet for data telemetry for devices without Secure Digital (SD) cards and global packet radio service (GPRS) and (5) tampering of instruments coupled with limited skilled human capital to operate these devices and analyse and interpret the reported data.

Environmental Quality Department of the Ghana Environmental Protection Agency (GhEPA) is responsible for AQ projects including monitoring and data processing, public awareness creation and enforcement of AQ standards. Many projects have been embarked on to protect public health; of particular importance is phasing out lead in gasoline (Schwela, 2012a) and recently a reduction of sulphur in fuels from 3,000 ppm to 50 ppm and issuance of new fuel level standards effecting from September 2017 (Appoh and Terry, 2018).

Recently, the agency in collaboration with the Ghana Standards Authority developed and implemented standards for reporting AQ data specifically to control the influx of low-cost devices for AQ monitoring and reporting of data (personal communication, GhEPA, 2019) since the performance of such devices have not been fully documented to understand the precision of and quality of data from low-cost sensors in Ghana and similar environments.

As part of the Megacity Partnership project, GhEPA recently developed an AQ management plan for Accra ("The Greater Accra AQ Management Plan" (AQMP), personal communication, GhEPA, 2019). This plan was initially developed from two samples namely the Waterberg-Bojanda Priority Area Draft AQ Management Plan and the South Coast AQ Management District AQMP (Appoh and Terry, 2018) to mitigate air pollution and ensure that AQ standards are adhered to for public health protection and environmental sustainability. This current AQMP is to serve as an exemplar for the rest urban areas in Ghana specifically regional capitals and those regions prone to urbanization due to economic reasons, for example, Takoradi (due to oil and gas exploration activities).

Currently, the agency employs filter-based approach towards data collection and uses a high-volume cascade impactor (Andersen Impactor, Tisch Environmental Inc., USA) and a mini volume sampler (MiniVol portable Air Sampler, Airmetrics, USA) for monitoring PM_{10} and $PM_{2.5}$, respectively. This monitoring approach includes chemical analysis of filter samples. This PM data can help understand source contributions to particulate matter (Appoh and Terry, 2018). This PM monitoring consists of 16 stations consisting of roadside, residential, industrial and commercial all based in Accra (Figure

2-4). AQ data is manually populated for PM_{10} and $PM_{2.5}$ from these stations at a 24-hour averaged data point every 6-days. The approach provides ~5 data points monthly (personal communication, GhEPA, 2019).

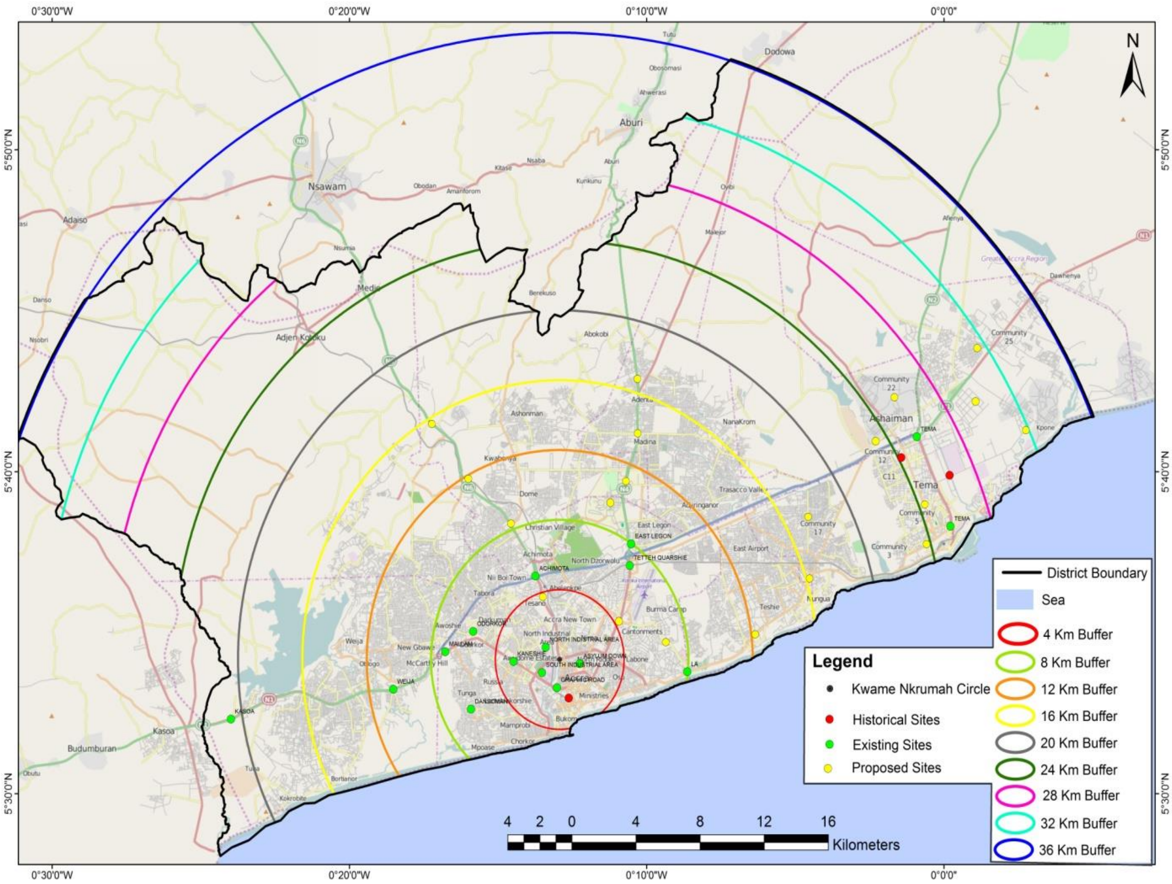

Figure 2-4: Map overview of GhEPA regulatory monitoring in Ghana showing historical (red dots), existing (green dots) and proposed stations (yellow dots) adapted from the Greater Accra AQ Management Plan (GhEPA, 2018)

2.4 Challenges with low-cost sensors for AQM

Though low-cost sensors are useful in providing high-resolution spatiotemporal AQ data, data inconsistency as compared to reference-grade instrumentation and between similar LCS from the same manufacturer, as well as different manufacturers, has been a challenge due to the effects of temperature, relative humidity as well as cross-interference (Mead et al., 2013; Kumar et al., 2015). Studies have shown that machine learning techniques (e.g. correction for hygroscopic growth for PM sensors as shown by Malings et al., 2019; correction for cross-interference for NO_2 EC cells as shown by e.g. Mead et al., 2013) can be applied to account for these issues to improve understanding of the quality of reported data from low-cost sensors; a useful approach for establishing evidence on local pollutant sources (Caslaw and Beevers, 2013; Mead et al., 2013; Kumar et al., 2015).

Ongoing and reported AQ studies with low-cost sensors have shown that end-users must consider sensor reproducibility, stability, repeatability and limits of detection to select the appropriate device for a specific monitoring objective. Brief information has been provided on the performance characteristics of low-cost PM sensors (Table 2-3), details on the EC NO_2 and O_3 cells can be found here Rai et al., (2017) as this study focused on PM though some critical information has been provided on other low-cost technologies for AQ monitoring.

Sensor reproducibility refers to the ability of the sensor to reproduce similar response under varying environmental conditions (e.g. changes in temperature and relative humidity). While some studies have documented the reproducibility of metal oxide sensors (MOS), no evidence has been established on that of electrochemical (EC) cells. (Rai et al. 2017). Moltchanov et al. (2015) and Piedrahita et al. (2014) evaluated the reproducibility of MOS by computing correlation coefficient (R^2) values of many identical sensors under similar conditions. High R^2 values were reported by Moltchanov et al (2015) i.e. R^2 = 0.85-0.98 and Piedrahita et al (2014) reported R^2 = 0.21-0.98 values.

The stability refers to the ability of the sensor to produce the same output value when measuring the same measurand over a period. Under laboratory conditions, Spinelle et al (2015a) and Spinelle et al (2016) studied the stability of four and two varying MOS and EC cells respectively for six months. Sensor drifts ranging from 0.009-0.081 ppb O_3 per day for MOS sensors and 0.016-0.142 ppb O_3 per day for EC sensors. These findings translated to -2 to 15 ppb difference for MOS sensors and 3 to 26 ppb difference for EC sensors. No notable difference between MOS and EC O_3 sensor stability characteristics but different drift values were observed for different models of the MOS and EC sensors indicating that sensor manufacturing might influence sensor stability (Rai et al. 2017).

2.5 Characteristics of low-cost PM sensors

On reproducibility, reported measurements from lo-cost PM sensors have shown poor performance when compared to referenced-grade data but post data applications such as calibration improved the reproducibility of these types of sensors (Sousan et al., 2016b). Some studies have reported on the quantification of reproducibility using the co-efficient of variation (CV) principle (see Table 2-3, Rai et al., 2017). Sousan et al., (2016a and 2016b) reported CV values of 0.9-16%. Some studies reported R^2 values to be between 0.25-1.0 (see Table 2-3, Holstius et al., 2014; Jiao et al., 2016; Kelly et al., 2017). Another principle used to define the reproducibility of low-cost PM sensors is the normalized root mean square (nRMSE). By exposing low-cost PM sensors to presumably fine particle sources (e.g. cigarette smoke as shown by Manikonda et al., 2016), there is the possibility of higher reproducibility nRMSE, 2.6-22.3% as compared to coarse particles sources (e.g. dust Manikonda et al., 2016) poor reproducibility with nRMSE of 46.1-118.2%. Additionally, the accumulation of dust over longer periods of deployment worsens sensor reproducibility. This has been confirmed with the Manikonda et al., (2016) study specifically poor reproducibility when sensors are exposed to larger particle sizes as compared to smaller particles (Rai et al., 2017).

Stability of low-cost sensors, in general, is crucial especially if these types of sensors are to be used for the long-term (Rai et al., 2017). Jiao et al., (2016) in a 2-6-month performance study of low-cost PM sensors have shown that sensor stability can be improved when “days of use” is added as a predictor in a regression model perused calibration methodology. In this study, adjusted-R^2 ($R^2{}_{adj}$) has been reported to improve from 0.45-0.56. This study (Jiao et al., 2016) has shown that sensor response changes based on the period of deployment. Further studies are required to address low-cost sensor stability.

Low-cost PM sensor repeatability proves difficult to measure. This is because low-cost PM sensors are not capable of maintaining a specific particle concentration (Rai et al., 2017). Information on the characteristics of low-cost PM sensors as reported by Wang et al., (2015) is presented in Table 2-3. In this study, Wang and co used the co-efficient of variation (CV) principle to demonstrate the repeatability of these types of PM sensors, which ranged from 2-28% (Table 2-3). Results have shown that at low PM concentrations, repeatability of the sensors worsens. All the PM sensors used in the study showed 23-26% range CV (Wang et al., 2015).

Wang et al., (2015) reported that low-cost PM sensors are generally suitable for measuring PM (i.e. $PM_{2.5}$ and PM_{10}). The limits of detection of the low-cost PM sensor is critical to consider because studies have reported that very low concentrations (<10 $\mu g/m^3$) are challenging to measure (Rai et al., 2017). These results make current low-cost PM sensors suitable for monitoring PM_{10} (Castell et al., 2017) since PM_{10} concentrations are always higher than $PM_{2.5}$ (Rai et al.,2017).

Sensor repeatability refers to the ability of the sensor to provide the same response for successive measurements when all environmental parameters and operating systems remain the same. Standard deviations (SD) of MOS and EC sensor outputs were studied under chamber conditions to ascertain the repeatability of MOS and EC sensors. Good repeatability was reported by Spinelle et al (2016) using three different MOS O_3 sensors at 100 ppb (SD = 0.2-3.3 ppb). Poor repeatability was recorded for SP-61 MOS sensor with SD value of 19.8 ppb under similar conditions. Williams et al (2014c) found varying repeatability characteristics for different MOS O_3 sensor models (SD = 2.6 - 46.2) depending on temperature, humidity and O_3 concentration. This study did not report the O_3 levels under which the studies were performed making it difficult to conclude measurement uncertainties. SD values for the EC O_3 values vary from 0.4-1.9 ppb at 100 ppb O_3. It is concluded that the MOS and EC sensors have similar repeatability, but measurement uncertainty depends on how the performance of the sensors and typically <5% at 100 ppb O_3 concentration.

The limit of detection of a sensor (LOD) is referred to as the "lowest concentration of a pollutant that can be differentiated from zero concentration". This is mathematically three-times the standard deviation (SD) of the sensor output obtained at zero concentration. Ideally, the lowest LOD value is recommended as this determines the lowest concentration level a sensor can detect. Several studies have reported the LOD values of low-cost PM and gaseous sensors in European cities (Rai et al. 2017; Wang et al. 2015).

Table 2-3: Characteristics of low-cost PM sensors adapted from Rai et al (2017); Stavroulas et al., 2020; Liu et al., 2019; Tagle et al., 2020; Badura et al., 2018.

Model	Comparison with reference measurements(R^2)	Repeatability and reproducibility	Limit of detection (μg/m³)	Effect of particle composition on sensor output	Effect of particle size on sensor output	Effect of humidity on sensor output	Effect of temperature on sensor output
Alphasense OPC-N2	R^2_{lab} = 0.94–0.99[a]	CV_{Rr} = 4.2–16%[a]	NA	δ_{PC} ≈ 30, estimated from Sousan et al.(2016a).	η_d = 0.83–1.01[a]	NA	NA
Dylos models 1100 Pro and 1700	R^2_{lab} = 0.97–0.99[b] R^2_{lab} = 0.64–0.95[c] R^2_{lab} = 0.91–0.98[d] R^2_{fld} = 0.81–0.99[b] R^2_{fld} = 0.58–0.99[e] R^2_{fld} = 0.70–0.90[f] R^2_{fld} = 0.48–0.78[g] R^2_{fld} = 0.40–0.45[h] R^2_{fld} = 0.74–0.84[i] R^2_{fld} = 0.55[j]	CV_{Rr} = 1.4–8.0%[d] R^2 = 0.67–0.98[h] nRMSE = 13.4–46.1%[c]	<1[b]	δ_{PC} ≤ 20, estimated from Sousan et al.(2016[b]). δ_{PC} ≤ 20, estimated from Northcross et al. (2013). Did not seem to affect the sensor output under ambient conditions	η_d = 0.6–1.1, estimated from Sousan et al. (2016[b]). η_d = 0.25–4.0, estimated from Han et al. (2017).	η_d = 0.5–4.8, estimated from Han et al. (2017). Slight correlation between sensor output and humidity (R^2= 0.18).[j] Seems affected by humidity.[h]	NA No correlation between sensor output and temperature (R^2= 0.03).[j] Sensor response probably not dependent on temperature.[h]
Plantower PMS 1003	R^2_{fld} = 0.82–0.93[k] R^2_{fld} = 0.69–0.99[k]	R^2= 0.99[k]	0.721–10.5[k]	NA	NA	Slight correlation between sensor output and humidity (R^2= 0.09–0.17)[k]	No correlation between sensor output and

Model	Comparison with reference measurements(R^2)	Repeatability and reproducibility	Limit of detection (μg/m3)	Effect of particle composition on sensor output	Effect of particle size on sensor output	Effect of humidity on sensor output	Effect of temperature on sensor output
							temperature (R^2 < 0.02) [k]
Plantower PMS 3003	R^2_{lab} = 0.73–0.97[k]	NA	NA	NA	NA	NA	NA
Samyoung DSM501A	R^2_{lab} = 0.88–0.90[l] R^2_{lab} ≈0.50[m] R^2_{lab} = 0.58–0.97[c] R^2_{fld} = 0.07–0.46[r]	CV_{Rt} = 2–28%[l] nRMSE = 22.3–52.7%[c]	4.28–11.4[l] 10[r]	δ_{PC} ≤ 8, estimated from Wang et al. (2015).	δ_{PS} ≤ 18, estimated from Wang et al. (2015).	δ_{RH-PM} ≤2.8, estimated from Wang et al. (2015).	δ_{T-PM} ≤1.2, estimated from Wang et al. (2015).
Sharp DN7C3CA006	R^2_{lab} = 0.98–0.99[d]	CVRr = 0.8 – 7.1%[d]	NA	δ_{PC} ≤ 2, estimated from Sousan et al. (2016)[b]	NA	NA	NA
Sharp GP2Y1010AU0F	R^2_{lab} = 0.42–0.99[c] R^2_{lab} = 0.95–0.99[d] R^2_{lab} = 0.98–0.99[l] R^2_{lab} = 0.92–0.98[m] R^2_{fld} = 0.72[n] R^2_{fld} = 0.99[o]	CV_{Rt} =5–25%[l] CV_{Rr}= 0.9–5.9%[d] nRMSE = 2.6–118.2%[c]	26.1–26.9[l]	δ_{PC} ≤ 6, estimated from Wang et al. (2015). δ_{PC} ≤ 4, estimated from Sousan et al.(2016).[b] .	δ_{PS} ≤ 2.4, estimated from Wang et al. (2015).	δ_{RH-PM} ≤ 1.5, estimated from Wang et al. (2015)	δ_{T-PM} ≤ 1.5, estimated from Wang et al. (2015). Baseline response linearly proportional to temperature. [o] Seems

Model	Comparison with reference measurements(R^2)	Repeatability and reproducibility	Limit of detection (μg/m^3)	Effect of particle composition on sensor output	Effect of particle size on sensor output	Effect of humidity on sensor output	Effect of temperature on sensor output
							unaffected by temperature.[n]
Shinyei PPD42NS	R^2_{lab} = 0.66–0.99[p] R^2_{lab} = 0.93–0.96[l] R^2_{fld} < 0.16[h] R^2_{fld} = 0.53–0.98[q] R^2_{fld} = 0.55–0.94[e] R^2_{lab} = 0.50–0.80[k]	CV_{Rt} =4–28%[l] R^2 = 0.91–0.94[e] R^2 = 0.25–0.44[h]	4.59–6.44[l] 1[p]	$\delta_{PC} \leq 18$, estimated from Wang et al. (2015).	$\delta_{PS} \leq 24$, estimated from Wang et al. (2015). $\delta_{PS} \leq 13$, estimated from Austin et al. (2015).	$\delta_{RH\text{-}PM} \leq 8.0$, estimated from Wang et al. (2015). Seems affected by humidity.[q] Slight correlation between sensor output and humidity (R^2 = 0.01–0.27).[e]	$\delta_{T\text{-}PM} \leq 1.6$, estimated from Wang et al. (2015). Seems affected by temperature.[q] No correlation between sensor output and temperature (R^2= 0.01).[e]
Shinyei PPD60PV	R^2_{fld} = 0.43[h]	R^2 = 0.98–1.0[h]	NA	NA	NA	Seems unaffected by humidity.[h]	Seems unaffected by temperature.[h]
Purple Air PA-II	R^2 = 0.87–0.98[s]	R^2 = 0.98–1[s]	NA	NA	NA	R^2 = 0.996-1[s]	R^2 = 0.989-1[s]
Nova PM sensor SDS011	R^2 = 0.55–0.71[t] R^2 = 0.63–0.87[u] R^2 = 0.79–0.86[v]	NA	NA	NA	NA	RH>80% negatively affected sensor response.[t] RH>75% overestimate PM	NA

Model	Comparison with reference measurements(R^2)	Repeatability and reproducibility	Limit of detection (μg/m^3)	Effect of particle composition on sensor output	Effect of particle size on sensor output	Effect of humidity on sensor output	Effect of temperature on sensor output
						and underestimate at RH<50%[u]	
Plantower PMS7003	R^2 = 0.83–0.89[v]	NA	NA	NA	NA	NA	NA
Winsen ZH03A	R^2 = 0.74–0.81[v]	NA	NA	NA	NA	NA	NA

R^2 and CV are the coefficients of determination and variance, respectively. The subscript is lab or fld when referring to comparison between sensor and reference measurements under laboratory or field conditions, respectively; subscript is Rt or Rr when referring to repeatability or reproducibility, respectively. nRMSE is the normalized root mean square error, which is defined as $\text{nRMSE} = \frac{(\sqrt{\frac{1}{n}\sum_{i=1}^{n}(M_{Ai}-M_{Bi})^2})}{\frac{1}{2n}\sum_{i=1}^{n} M_{Ai}+M_{Bi}}$, where MAi and MBi are the ith values measured by sensors A and B, respectively, and n is the number of measurements. δ_{PC}, δ_{PS}, $\delta_{RH\text{-}PM}$, $\delta_{T\text{-}PM}$ is the change in sensor response due to change in particle composition, particle size, relative humidity, and temperature, respectively, measured at the same mass concentration. It is defined as $\delta_x = y_{high}/y_{low}$, where the subscript x is PC, PS, RH-PM, and T-PM when refereeing to particle composition, particle size, relative humidity, or temperature, respectively. y_{high} and y_{low} are the different (high and low) sensor responses under different conditions. NA stands for not available. The alphabets refer to the following studies - a: (Sousan et al., 2016a), b: (Northcross et al., 2013), c: (Manikonda et al., 2016), d: (Sousan et al., 2016b), e: (Holstius et al., 2014), f: (Steinle et al., 2015), g: (Han et al., 2017), h: (Jiao et al., 2016), i: (Jovašević-Stojanović et al., 2015), j: (Williams et al., 2014a), k: (Kelly et al., 2017), l: (Wang et al., 2015), m: (Alvarado et al., 2015), n: (Olivares and Edwards, 2015), o: (Olivares et al., 2012), p: (Austin et al., 2015), q: (Gao et al., 2015), r: (Zikova et al., 2016), s: (Stavroulas et al., 2020), t: (Liu et al., 2019), u: (Tagle et al., 2020), v: (Badura et al., 2018)

Generally, low-cost PM sensors seem to be appropriate for measuring both $PM_{2.5}$ and PM_{10} concentrations. Since particle concentrations below 10 μg/m^3 cannot be detected and since PM_{10} values will always be bigger than $PM_{2.5}$, low-cost PM sensors are better suited for monitoring PM_{10} (Castell et al., 2017).

In addition to the above, the performance of the Alphasense OPC-N2 low-cost PM sensor has been vigorously studied under real-world conditions in advanced countries. For example studies by Sousan et al 2016a; Spinelle et al., 2017; and Crilley et al 2018 have shown that the impact of temperature and relative humidity on the quality of data reported by OPC-N2 is insignificant. In SSA, Pope et al., 2018 and de Souza et al., 2017 have demonstrated the use of the OPC-N2 for PM monitoring including traffic-related exposure. As a point of reference, Table 2-3 have shown the suitability of low-cost PM sensors for PM monitoring with emphasis on the effects of particle size and environmental variables on data quality. Of specific relevance to this PhD studies, the Alphasense OPC-N2 was selected and its functionality tested in Ghana as past studies have shown minimal sensitivity to the impacts of temperature and relative humidity on the reported data.

2.6 Addressing data quality in low-cost sensors

The aim of making low-cost sensors handy often lead to compromise in some areas. For examples sensor characteristics such as power requirement, price, selectivity, reproducibility, and sensitivity is compromised for miniaturization. This makes low-cost sensors to suffer some measurement artifacts resulting in poor data quality (Hagler et al., 2018). End-users need to seek ways to address these data quality challenge. Rai et al., (2017) reported that it is important for end-users (e.g. individuals, government agencies, academic institutions and citizen scientists) to note the performance characteristics of low-cost sensors before employing them. Ideally, the effects of temperature, relative humidity and cross-interference (for EC cells) must be accounted for when using these types of sensors.

Of specific importance in this study is the OPC for PM monitoring. Hygroscopic growth under increased relative humidity often results in PM particle under-reporting using these types of sensors (Malings et al., 2019). This has to be corrected for; for example for regulatory monitoring, PM measurements are reported under particular temperature and humidity (i.e. 20-23°C and 30-40%) respectively (US EPA, 2016b). On-going research using sensor applications is focused partly on using models (Cross et al., 2017), machine learning (Zimmerman et al., 2018) and multiple linear regression models (Jiao et al., 2016; Zimmerman et al., 2018) to improve data quality when using low-cost sensors for AQ monitoring.

One of the methodologies used in developing these types of data correction mechanisms is by collocating low-cost sensors with reference grade/ regulatory monitoring equipment in a similar environment representative of the sampling environmental conditions (Hagler et al., 2018). This period of collocation is necessary for developing data correction algorithms that are then integrated with the raw sensor data (Hagler et al., 2018) which is then applied after relocating the low-cost sensor. In homogenous environments, data correction mechanisms developed for a specific environment are applied assuming concentration at these varying locations are influenced by similar background activities over a specific time (Moltchanov et al., 2015). In some cases, commercial software has been developed to support this technique based on the homogeneity of the sampling environment (e.g., Advanced Normalization Tool for AirVision; http://agilaire.com/pdfs/ANT.pdf) (Hagler et al., 2018). Since environmental parameters introduce inconsistencies in these types of sensors (see Zheng et al., 2018; Zikova et al., 2017a, 2017b; Jayaratne et al., 2018), studies with LCS have focused on developing data correction mechanisms using these variables (i.e. relative humidity and temperature). For particle size under-reporting (Koehler and Peters, 2015; Zhou and Zheng,2016) and Liu et al., (2017) suggested using factory calibration approach by adjusting the device output to match that from the reference equipment. Malings et al., (2019) have shown that factory calibration is not enough for correcting low-cost PM sensor output inconsistencies under real-world conditions and have suggested a two-way approach to deal with it. This involves firstly accounting for aerosol hygroscopic growth employing particle composition and an absolute empirical formula using linear/ quadratic equations of environmental variables (temperature and relative humidity; see Malings et al., 2019).

2.7 Summary

The current generation of low-cost sensors has shown that these devices could complement existing sparsely distributed AQ stations and provide benchmark data for AQ studies in environments with no regulatory AQ monitoring typical of many urban areas in Ghana and wider SSA as these devices have shown promising results in advance countries. Current evidence shows that LCS offer a unique approach to governmental agencies in Ghana and wider SSA for bridging AQ data gaps specifically in identifying hotspots of air pollution and providing information for tracking and evaluation of air pollution mitigation strategies, emergency responses and engaging citizens on air pollution health exposure. Studies with low-cost sensors for AQ monitoring have shown that optical particle counters are suitable for monitoring particulate matter. The current form of EC cells can be used to obtain indicative data at the initial stage but will require post-data correction and analysis to establish data correction mechanisms. Data validation and calibration methodologies should be developed for the use of these devices if they are to complement regulatory monitoring approaches in these types of settings.

3 MATERIALS AND METHODS

Universally, there is no agreed definition of a low-cost sensor but anything with cost less than the instrumentation cost required for demonstrating compliance with AQ regulation can be referred to as low-cost. This cost should be as low as possible to achieve aims such as supplementing conventional air pollution monitoring; emergency response management, hazardous leak detection and source compliance monitoring; increasing community awareness and engagement on issues relating to AQ and improving the link between human health and pollutant exposure (Rai et al., 2017). In this research low-cost refers to a single unit (node) costing ~£4,000 capable of monitoring gaseous pollutants mainly O_3, NO, NO_2, CO; speciated particulates such as PM_1, $PM_{2.5}$ and PM_{10} and VOCs as well as environmental parameters such as relative humidity and temperature.

3.1 Instrumentation

Two AS510 multi-sensor nodes (Atmospheric Sensors, UK), were used for this study. These nodes measure: CO, NO_x, O_3, VOCs, PM and key environmental parameters relative humidity (RH) and temperature (T). Table 3-1 lists the species measured and the technologies used for these measurements. The resolution of the nodes used in this study for all measured species was 60 s for the duration of the study. This study focused on particulates and details of the Optical Particle Counter (OPC) component of the node is presented in Table 3-1. The OPC (Alphasense, UK OPC-N2) measures scattered light from particulates from the sampling beam to reconstruct particle mass levels (Hinds, 1999). The scattered light in a sampled air stream for measuring enters the OPC-N2 through a laser beam. This measurement is based on the intensity of the light scattered grouping the particles through the Mie theory calibration and particle number concentration approach developed by Alphasense. The calibration (factory) of the OPC-N2 is by using Polystyrene Spherical Latex Particles of a known diameter and RI. For particles of different density, correction factors are applied. The particle masses loaded are then calculated per the particle size spectra and concentration data. The particle species measured are PM_1 (particles with size ≤ 1 μm); $PM_{2.5}$ (particles with size ≤ 2.5 μm) and PM_{10} (particles with size ≤ 10 μm). Each of these particle sizes is classified at about 10,000 particles per second into 16 bins ranging from 0.38 to 17 μm. The resultant is a particle size histogram which is estimated per user-defined time scales. For this specific study, this time scale was set to 60 seconds. This calculation takes into account the particle density and refractive index (RI) using default settings 1.65 g/ml and RI+i0 respectively (OPC-N2 Monitor, Alphasense Ltd UK, 2015). For more on the description of the OPC design and operation see Alphasense reference note (OPC-N2 Monitor, Alphasense Ltd UK, 2015).

Table 3-1: Summary of technical characteristics of the AS510 Static Sensor Node with details of the OPC

<table>
<tr><td colspan="2">Measurands / Activity</td><td>Technology</td></tr>
<tr><td colspan="2">Particle size distribution</td><td>Optical particle counter (OPC)</td></tr>
<tr><td colspan="2">CO, NO, NO_2 and O_3</td><td>Electrochemical (ECs)</td></tr>
<tr><td colspan="2">VOCs</td><td>Photo ionization (PID)</td></tr>
<tr><td colspan="2">CO_2</td><td>Non-dispersive infra-red (NDIR)</td></tr>
<tr><td colspan="2">T and RH</td><td>Capacitive</td></tr>
<tr><td colspan="2">Timestamp and location</td><td>Global positioning system (GPS)</td></tr>
<tr><td colspan="2">Data telemetry</td><td>General packet radio service (GPRS)</td></tr>
<tr><td rowspan="4">OPC details</td><td>Particle range</td><td>0.38-17 μm</td></tr>
<tr><td>Data bins</td><td>16</td></tr>
<tr><td>Flow rate</td><td>1.2 L/min</td></tr>
<tr><td>Sample flow rate</td><td>220 mL/min</td></tr>
</table>

The unit requires a data-capable subscriber identity module (SIM) card service, which can be provided either by Atmospheric Sensors or by other providers by discussion; local storage on 16GB secured digital (SD) card of extended results from a test for later recovery and to act as a backup of results sent over the general packet radio service (GPRS) link; mains power supply, with waterproof connector and externally visible light-emitting diode (LED) to indicate unit status. The data from this node can be sampled at high rates usually averaged over 20 seconds with transmission at every 15 minutes. This can be configured to suit end-user's preference or application. The unit may be used either indoors, or outdoors if protected by a Stevenson Screen, or similar enclosure and wall mount brackets are supplied with each unit, permitting easy installation (Atmospheric Sensors UK, AS510 Manual).

3.2 Quality assurance/quality control

The framework developed and used in selecting deployment sites must follow the principles listed below with guidance from the European Union air quality directive (2008/50/EC).

i. The proposed site for deployment must be based on possibilities of high concentrations of atmospheric pollutants and likely to affect the local population.
ii. Levels obtained must be representative of the entire area.
iii. Sites must be selected to avoid measuring small micro-environments but representative of the entire vicinity (100 m for traffic-related areas and 250 m x 250 m for industrial sites).
iv. The proposed site for deployment must present complex/ varying sources of atmospheric emissions and not influenced by a single source.
v. For rural monitoring, the sites must not be closer than 5 km to industries.
vi. The proposed sites must be representative of similar settings not in their immediate surrounding.
vii. Instruments must be installed to ensure that flow around the inlet is unrestricted.

Also, consideration should be given to confounding factors namely security, access, availability of electrical power, visibility of the site (instrument), inferring sources, the safety of the entire public and operator (in this case me as the researcher), planning requirements and desirability of collocation.

In addition to the above quality assurance protocols, the measurement data reported by the low-cost sensor (in this case the OPC-N2) must meet preliminary data quality protocols echoed in existing literature. Mainly, the preliminary data on local levels will only be accepted if relative humidity reported by the sensors is ≤ ~85% including atmospheric temperature concurrently collected from the low-cost sensor is representative of the specific environment where the sensors are deployed. Additionally, a minimum of 3-week data may not be included in the data analysed due to stabilization of the sensors (see for example Sousan et al., 2016; Jiao et al., 2016; Kelly et al., 2017). For understanding the precision of low-cost sensors, the sensors must be co-located at the same height as close as possible to reference-grade/ regulatory monitors. This is similar for understanding precision between similar/ different low-cost sensors measuring the same species by co-deploying the selected low-cost sensors. Though no evidence currently exists on the distance between the selected sensors and or/ regulatory/ reference-grade monitors, a distance of ~10cm is recommended and adopted in this study. Also, refer to Table 2-3 for further details. In environments with limited/ non-existent location-specific wind component data, it concurs that NOAA data be used in such cases for source identification (see López and Schliep 2019).

Though the guidance here was used to inform the siting of the instrument, some challenges were encountered. It, therefore, makes some recommendations here an open-ended approach which is influenced by the knowledge of the investigator (in this case, me as the researcher).

- It was challenging to define whether or not the area has higher pollution levels detrimental to human health as there is no historical or current regulatory AQ data at Cape Coast (UCC site in this case). For Accra, the low-cost sensor was collocated with regulatory equipment, but the data from the regulatory equipment could not be used for understanding the precision of the low-cost Alphasense OPC-N2 and to further develop calibration protocols for the use of Alphasense OPC-N2.
- Additionally, it was difficult to understand whether the levels of PM are representative of the entire area due to lack of AQM in the region as well as the transboundary effect of air pollution and varying background activities depending on location.

3.3 Site selection and data acquisition

Both AS510 multi-sensor nodes (each containing electrochemical sensors for CO, O3 and NOx; photoionization detector sensor for VOCs; an infrared sensor for CO2 and OPC-N2 for PM) were co-deployed at a central site at Cape Coast, Ghana based on the quality assurance protocols in Section 3.2 above. This site was selected as being typical of expanding urban settings outside of Accra with a broadly similar composition as other urban areas of this type. Co-deployment was for 6 weeks (August 9th to September 18th, 2018; See Figure 3-1) and provided a baseline for comparison of data between the sensor nodes. Cape Coast is situated in the south of the country on the Gulf of Guinea with a population of approximately 170,000 (GSS, 2012). The region is relatively humid with mean monthly relative humidity (RH) ranging between 85% and 99% from the nearest weather station at Takoradi (~63 km from Cape Coast) as compared with a range of 77% to 85% in Accra (Climate in Cape Coast, Ghana). The predominant wind direction at Cape Coast (deployment site – see Figure 5-1 under Section 5.6 on page 72) is from the NNE which has the potential to transport pollutants from across the region to Cape Coast as well as for onshore relatively clean air masses to be transported. Nodes were mounted 10 cm apart (to understand the precision of AS510 for a high-density deployment at a height of ~4 m (to prevent vandalism and allow airflow into the inlets – see the adopted framework in Section 3.2) above the ground (Figure 3-1). Typical sources in the area (Cape Coast) include unpaved roads (re-suspended dust), road-side food preparation (biomass and gas combustion), taxi rank (vehicular) and roads used by private vehicles as well as heavy trucks and commercial vehicles.

After completion of the initial 6 weeks co-deployment measurement period, one node was relocated to central Accra (approximately 147 km north of Cape Coast) alongside the GhEPA reference high volume sampler used for monitoring PM_{10} is located (see Figure 3-2). Accra covers approximately 225.67 km^2 with a population of 2.5 million (GSS, 2012) and is the economic and industrial capital of Ghana. The node was moved there as a study investigating the potential for cross-validation of sensors or radically different operational cycles. This type of low resolution, low technical overhead PM monitoring in Ghana is more widespread than online routine PM monitoring across the region (HEI, 2019). The reference site is a residential area (associated with poor waste management practices including garbage burning at the monitoring site – though GhEPA's AQ monitoring equipment is located in this area) close to the relatively high use Dansoman Highway, a local open market (including open food preparation), a fuel station and more dispersed road-side food vendors.

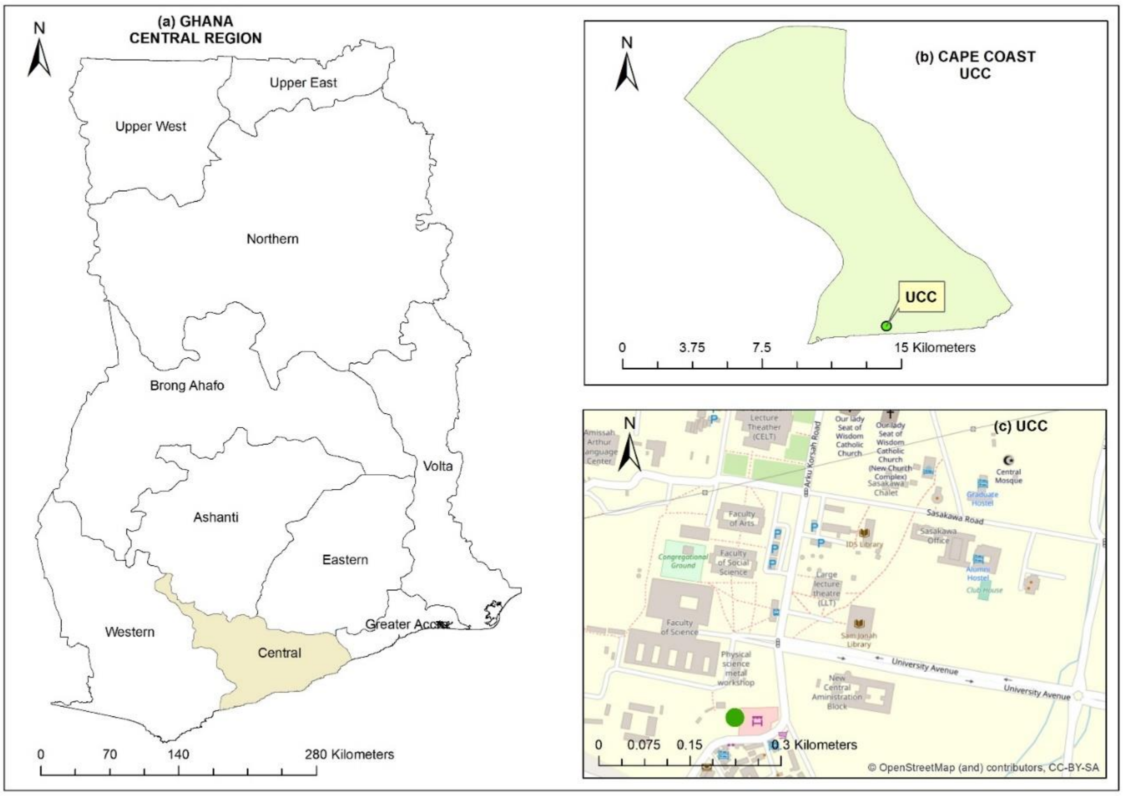

Figure 3-1: Overview of the deployment area at the University of Cape Coast (UCC) The green circle shows the location of the two co-deployed nodes ~10 cm apart (05°06′N 01°15′W)

Due to the limited availability of local meteorological data, modelled wind data from the Global Forecast System (GFS) repository was used for source apportionment in this study (NOAA, 2019; López and Schliep 2019). The GFS is a dataset from the National Oceanic and Atmospheric Administration (NOAA) and the National Centres for Environmental Prediction (NCEP) (López and Schliep

2019). Within this database, wind data since 2011 is saved at 3-hour intervals daily in velocity vector format with a resolution of 0.5 degrees and ~50 km.

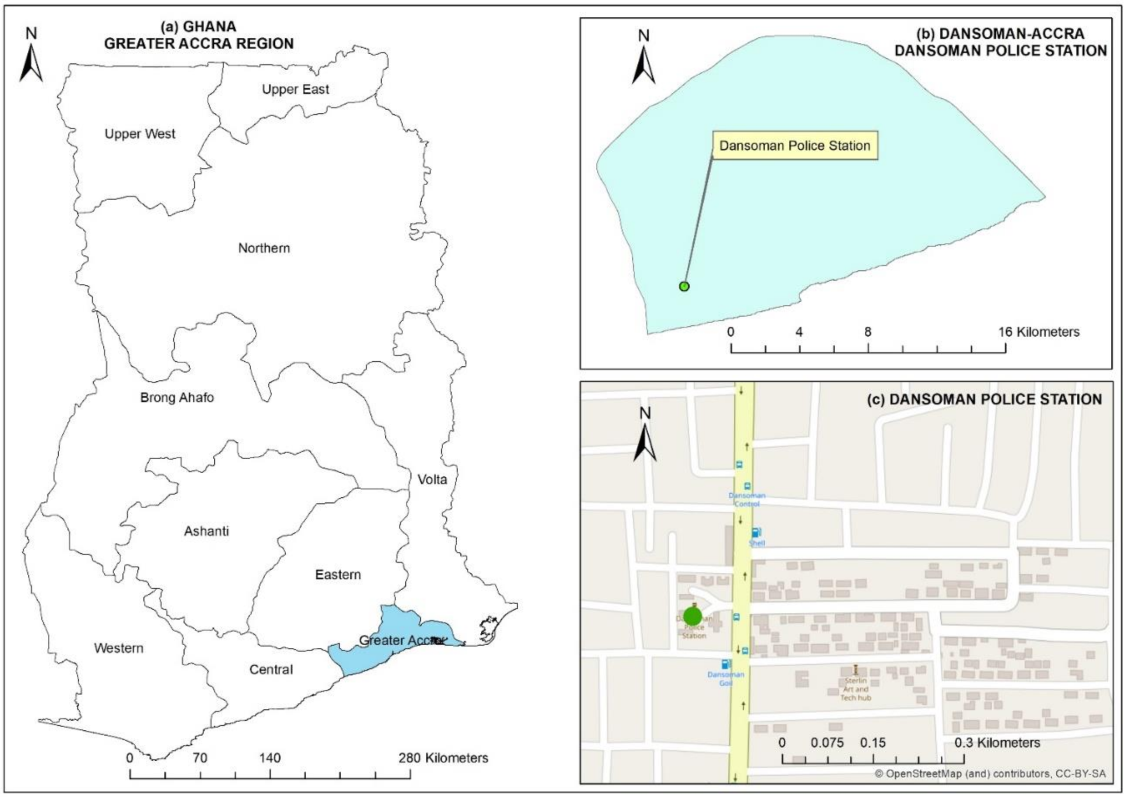

Figure 3-2: Overview of the Dansoman-Accra site deployment (Green circle: location of the node collocated ~10 cm apart with the GhEPA monitoring reference device) GhEPA (5°32′28″N 0°16′8″W)

3.4 Data processing and analysis

In Figure 3-3, a framework on the novel approach used for low-cost sensor deployment and data acquisition in this study is presented. Firstly, the selected low-cost sensors were factory calibrated and then deployed in the field in Ghana based on best practices such as site and height (see subsection 5.2 of chapter 5). The selected sensors were installed and the data transmitted via global packet radio service to a central internet-based platform. This data is then accessed using credentials provided by the manufacturer (in this case Atmospheric Sensors, UK) using a file transfer protocol system (FileZilla for this particular research) with a personal computer. A folder repository is generated for this data (two folders were created with the names node5 and node79 for this research).

This folder includes readme files specifically on the type/ format of data, for example, time resolution, key species monitored, header files and specific values to use for investigation of the data such as temperature corrected (TC) values. This data is then imported into the analytical environment (R in this case) and examined with scripts (data mining tools). This interrogation of the data takes into account dates and time as well as reported measurements of key species e.g. PM values. The reported data is cleaned by removing zeros and unwanted values.

This cleaning process involves selected specific species of interest (e.g. PM – PM_1, $PM_{2.5}$ and PM_{10}; CO, NO, NO_2, O_3, and CO_2). TC values were selected in this case as it has been shown in chapter 1 and 2 of this research that these environmental variables introduce inconsistencies in the low-cost sensor data. No data correction mechanism was applied in this case as the study focused on how sensor manufacturer's data correction algorithms, as well as factory calibrated low-cost sensors (i.e. current state of low-cost sensors), can be useful for AQM in the defined environments. This approach was adopted because during this PhD study, no further data correction mechanism was possible due to limited resources (for example reference/ regulatory-grade regional monitoring dataset with similar/ applicable resolution and poor resolution dataset from the regulatory equipment used by the GhEPA including monthly mismatching datasets from the deployed OPC-N2 and regulatory datasets). Nevertheless, these preliminary data provided evidence on the feasibility of using these types of sensors for various gases monitoring in these environments.

Preliminary plots such as summaryPlots are then generated to interrogate the data. Consequently, time series plots are developed and analysis undertaken per satisfaction based on atmospheric science standards e.g. observed levels of $PM_{2.5}$ not greater than PM_{10}. These preliminary plots are the basis for analysis such as trend analysis (using timeVariation function), bivariate polar plots (using polarPlot function) and cluster analysis (using polarclusterPlot function). Additionally, mathematical models can be integrated into these types of analysis to understand the precision/ consistency between the selected low-cost sensors, for example, Pearson's correlation analysis (inbuilt command in the "openair" package) was used to determine the consistency between the two nodes which influenced the applicability and suitability of the Alphasense OPC-N2 for AQM in the defined environments. This approach was used because it is widely accepted and used as an indication of the levels of bivariate correlation between selected the species.

All analysis in this study was based on the "openair" package for air pollution data analysis; a widely accepted tool for air pollution data analysis developed by David Carslaw (2015) using the R language and environment.

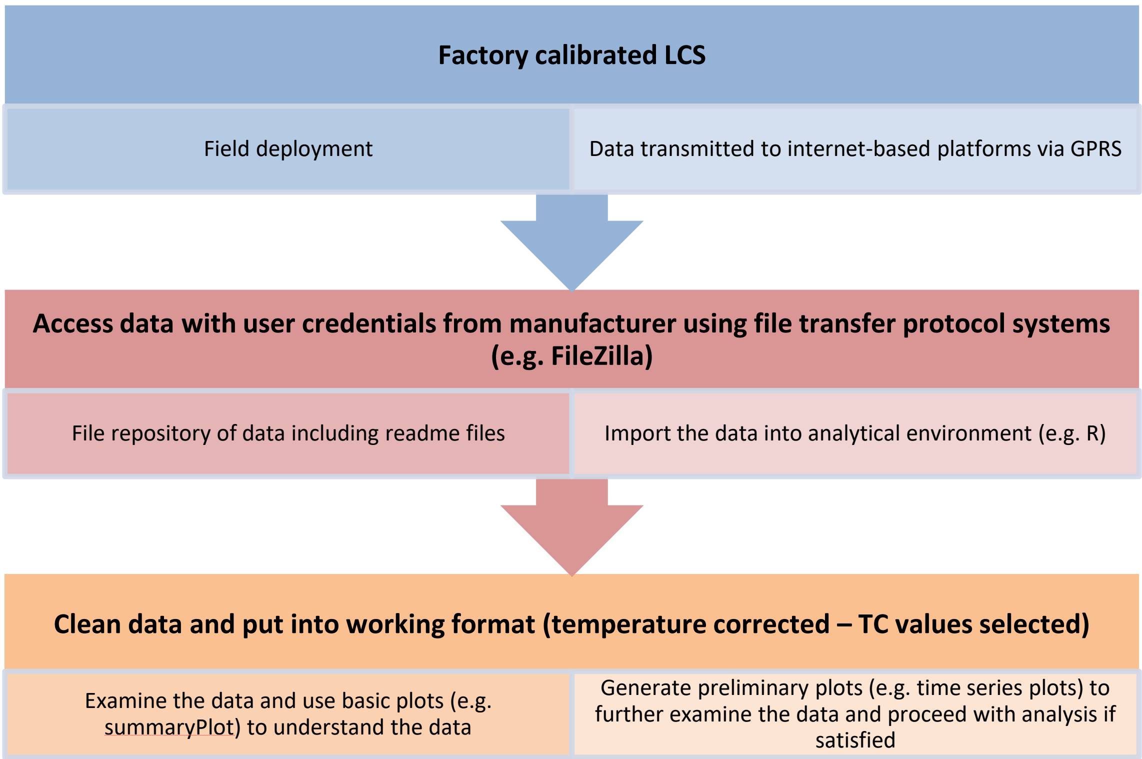

Figure 3-3: Schematic framework for LCS (low-cost sensor) deployment and usability of reported data tied to the protocols in subsection 3.2 of chapter 3.

3.4.1 Source apportionment

The bivariate polar plot approach adapted from Carslaw and Ropkins (2012) using the reported data from the low-cost sensor to plot the mixing rations of PM alongside modelled wind components. The approach of having a concentration of pollutants plotted in polar coordinates to identify sources is not new (Carslaw and Ropkins, 2012) but is suited to small sensors because these devices are capable of acquiring huge AQ data at higher resolutions and in some cases higher spatiotemporal data if they are deployed in a high-density (see e.g. Mead et al., 2013; Snyder et al., 2013; Rai et al., 2017). This approach has been demonstrated by source apportionment studies in an airport setting and in exploring characteristics of dispersion of pollutants in street canyons (Carslaw et al., 2006).

Bivariate polar plots suggest potential sources of air pollutants based on wind speed, wind direction and pollutant level. The acquired measurement data (in this case concentrations of PM) are plotted as a function of wind speed and direction. The data are grouped into bins based on wind speed and wind direction. Means are then calculated for each of these bins (Carslaw and Ropkins, 2012; Carslaw, 2015). The combination of wind speed and direction is an efficient approach in differentiating varying sources of air pollution (Carslaw and Beevers, 2013). By approximating available wind direction data to 10°, typical surface measurements are usually between 0-30 ms^{-1}. Wind speed intervals beyond 30 ms^{-1} are difficult to justify (Carslaw and Beevers, 2013) and hence not included.

This aggregation of data provides a reduction technique without a bias analysis of the plots since wind component data is variable and tend to diffuse making raw data to yield limited results (Carslaw, 2015). These types of plots have been tested on a wide variety of data and it has been suggested that wind direction intervals of 10 to 30° capture enough detail of pollutant dispersion to allow for source identification (Carslaw and Beevers, 2013). In pollution prediction the relationship between variables is non-linear but the interactions between these variables are important. To account for this, a surface fitting model, the Generalized Additive Model (GAM) (e.g. Hastie and Tibshirani, 1990; Wood, 2006) is applied to the polar plots (Carslaw and Ropkins, 2012) to provide a smoothing approach useful for pollution prediction.

3.4.2 Cluster analysis for source identification and extraction

Cluster analysis is a useful tool for identifying features and source extraction from polar plots (details can be found here Carslaw, 2015). This is an advanced technique which selects groups with similar characteristics and maps them and provides means to understand source features than the polar plots. Bivariate polar plot interpretation is limited by the ability of the investigator that may lead to bias. Since some patterns may not be plotted in the selected intervals of the wind components (Carslaw, 2015), cluster analysis using the *k*-means algorithm provides a better approach. This algorithm for clustering was introduced by Hartigan (Hartigan, 1975). This procedure allocates several observations into K clusters. The data allocation process groups the pollution data with similar diurnal patterns into one group using the *k*-means. With the *k*-means, (i.e. grouping the data by making in-group data points more similar to each other than to out-of-group data points), cluster analysis is performed in which features in bivariate polar plots are identified and categorized (Shi et al., 2014). This categorisation helps to identify records in the original time series data, enhancing post-processing for identification of potential source characteristics.

Firstly, *k* points are randomly selected from the space represented by the objects that are being clustered into *k*-groups. These group points are then represented as centroids and every object is attached to a group with the closest centroid (Carslaw, 2015). The k centroids are then recalculated after assigning all objects; recalculation and group assignment is done until the centroids no longer move, in which case the objects are grouped to minimize the algorithm's metric. The three most important variables in this analysis are wind speed, direction measure and concentration.

Furthermore, the polarCluster command used in this research is similar to other "openair" applications. There is however no specific methodology for selecting the number of clusters for these types of analysis. The process, however, involves a test running of a selected number of clusters to reveal potential sources to the satisfaction of the investigator. This basic approach, however, is to have a solution of clusters and chose the one that offers the most appropriate solution for visualization and interpretation – post-processing (Carslaw and Ropkins, 2012). In the case of this study, 4 clusters were used because removal of one cluster or class removed a significant amount of resolution in the bivariate polar plots and the populations of each cluster are reasonably comparable. The addition of a fifth class or cluster was not used as on analysis of the dataset, this fifth cluster was composed of very few data points. This knowledge influenced the number of clusters used for the analysis presented in section 4.5

In this approach, more weight is given to the concentration rather than the wind components though this tends to identify clusters with similar concentrations with varying sources (Carslaw and Ropkins, 2012). Data binned by cluster can be presented as a stacked bar chart time series (Carslaw, 2015). This approach is often used to support outputs from the cluster analysis (Carslaw and Ropkins, 2012).

4 RESULTS

This chapter presents findings from this research specifically on the pilot study and the experimental approach to identifying sources of atmospheric pollution with the use of low-cost sensors. Based on the aims and specific objectives of this research, this section is presented in two sections; firstly focused on the short-term functionality of the selected sensors to understand the extent to which these types of sensors can be used to obtain observational ground-based AQ data in resource-constrained settings as well as the consistency between the two devices considering data reproducibility. The second part focused on how high-resolution data from these types of sensors can be used for applications such as emission source identification. These aspects are of particular importance especially in environments with limited AQ monitoring capabilities as those encountered in Ghana and the majority of the countries in SSA.

4.1 Performance of selected atmospheric sensor nodes in Ghanaian urban areas for PM measurement

As reported by several studies on the utility of low-cost sensors, the effects of environmental variables specifically temperature and relative humidity (. Studies reporting on the use of the Alphasense OPC-N2 for field campaigns have shown that these types of OPCs are suitable for PM monitoring with insignificant effect from these variables. On data quality, relative humidity below 85% has been found not to significantly affect the reported OPC data (Crilley et al., 2018) . Spinelle et al., (2017) also found no impact of temperature and relative humidity on reported OPC-N2 data. The reported data from this study as shown in Figure 4-1 have shown that these preliminary requirements with relative humidity being ~85%. In addition to the above, the measurements on environmental variables is representative of the study area as reported in Chapter 3 section 3.2. Additionally, in cases where the effects of particle composition affect the reported low-cost OPC data, studies, for example, Malings et al., 2019 and Crilley et al 2020 have demonstrated applicable methodologies for data correction for OPCs in measuring PM species provided there’s a statistically sufficient amount of regulatory data concurrently collected in following the quality assurance/ control protocols stated in Section 3.2.

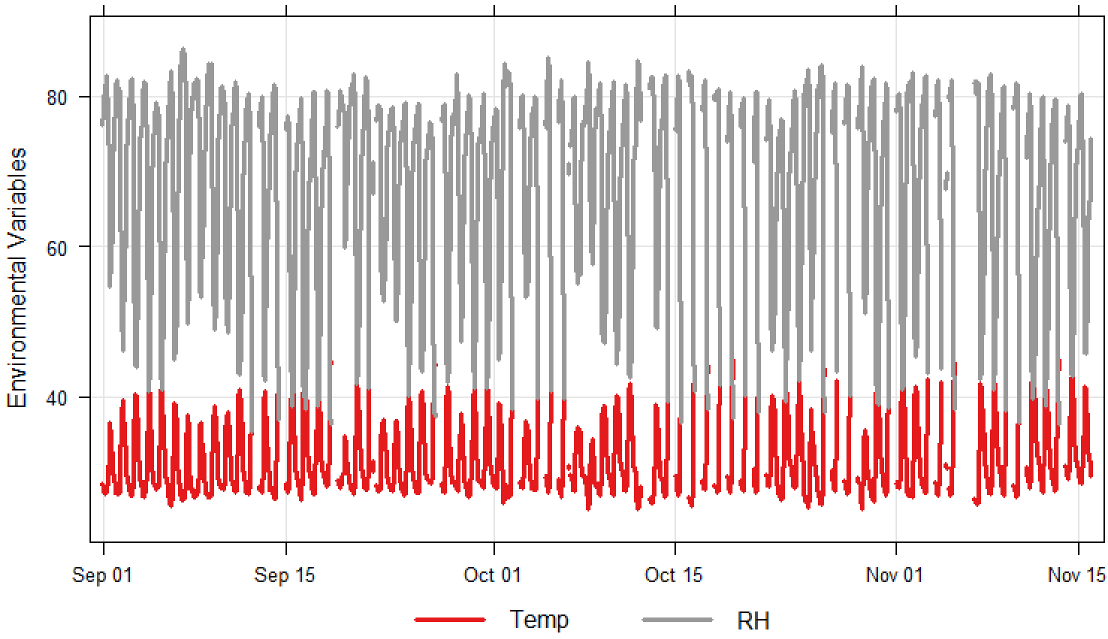

Figure 4-1: Hourly time series plot of Temperature (red) and Relative Humidity (grey) at UCC corresponding to acceptable ranges recommended for these types of sensors

Hourly averaged PM (PM_{10}, $PM_{2.5}$ and PM_1) data from the selected two nodes during the deployment at Cape Coast (i.e. UCC site) showed that the reported data from the nodes are highly reproducible as the signal acquisition of the two nodes is similar (Figure 4-1: a, b and c) with corresponding Pearson's correlation analysis (R) of 0.97 and 0.98 for PM_1, $PM_{2.5}$ and PM_{10}, respectively (Figure 4-1). The first 3 weeks of deployment have not been included in this analysis as issues with data telemetry compromised the amount of data recorded.

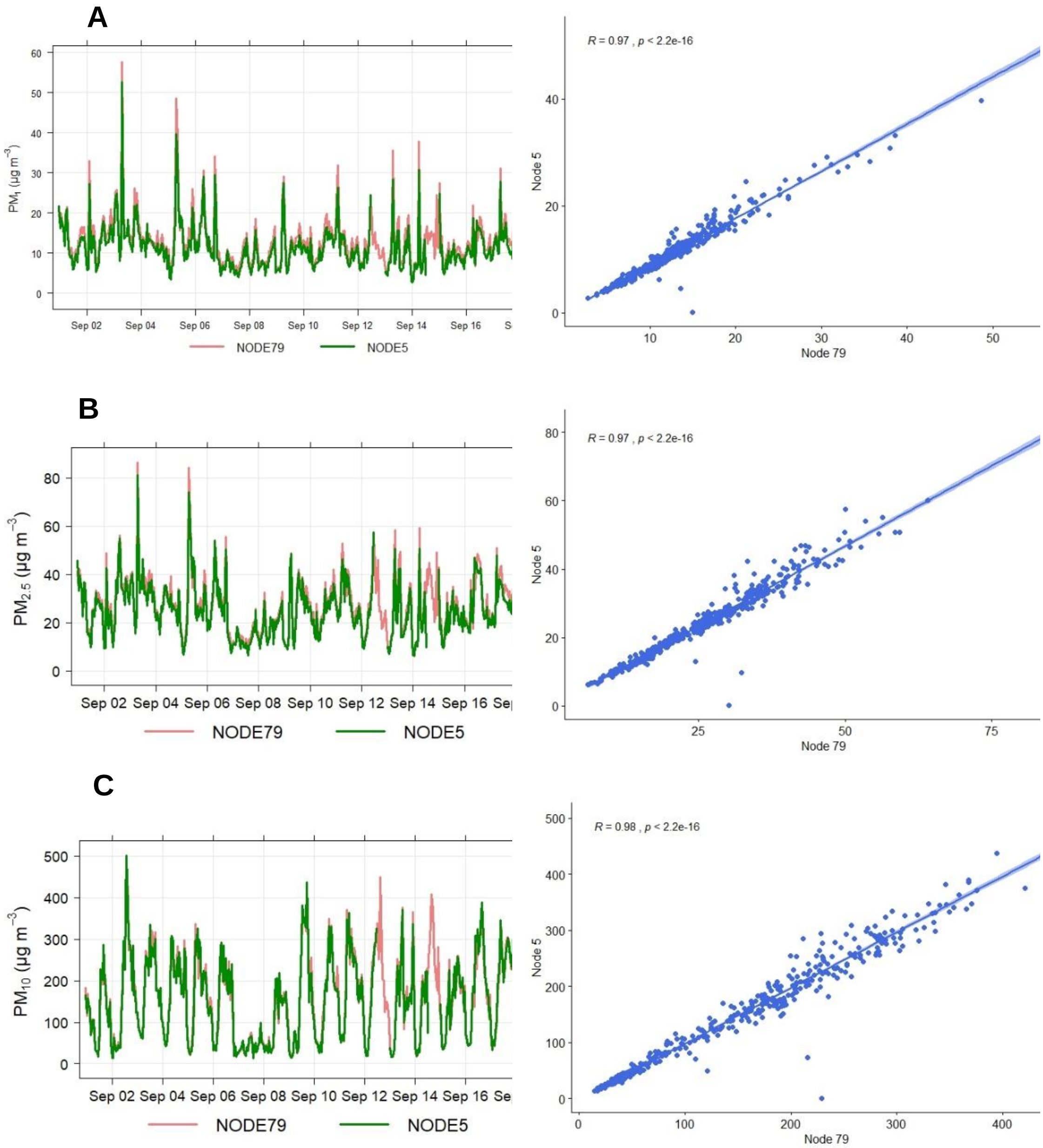

Figure 4-2: Hourly time series and corresponding Pearson correlation plot of data from Node 79 versus Node 5 at UCC: (a) PM_1, (b) $PM_{2.5}$, and (c) and PM_{10} with reported data from the selected LCS

The mean PM values of the two nodes have shown the inconsistency between the two nodes. Comparing the mean values of each of the PM categories from the two devices and the corresponding *t-values* it can be seen that there is a statistical difference (see Table 4-1) which reduces for PM categories in the order of PM_1, $PM_{2.5}$ and PM_{10}.

Though a similar response of PM measurement data is demonstrated by the time series plots from the two nodes (Figure 4-1) this statistical difference in mean values for each of the nodes in shows that the selected nodes are suitable for PM_{10} measurements in most polluted and resource-constrained settings (Castell et al., 2017).

Table 4-1: Mean and standard deviation of PM in µg/m3 with t and p-values showing the statistical difference between the two nodes at UCC.

Species	Node 5		Node 79		Statistical difference	
	Mean	SD	Mean	SD	*t*	*p-value*
PM_1	11.4	8.9	12.9	10.1	17.3	<2.2e-16
$PM_{2.5}$	24.7	19.7	26.8	21.3	11.4	<2.2e-16
PM_{10}	149	175.1	156.6	179.2	4.2	1.9e-5

These findings are in agreement with the assertion that current OPCs require optimisation (e.g. application of machine learning/ post data correction with sophisticated mathematical models) for measuring fine particles since they measure particles lager than 0.3 µm. The statistical difference between the two nodes from the same manufacturer with p-value <0.05 echoed the challenges on the use of low-cost sensors, for example, depending on inbuilt correction algorithms which is mainly influenced by time and resources invested by the manufacturer (Baron and Saffell, 2017). These differences show the need for post data correction/ validation (Mead et al., 2013; Baron and Saffell, 2017) as inbuilt data correction mechanisms.

PM_{10} concentrations peak at 500 µg/m^3. This is in agreement with levels recorded in other polluted environments (Wang et al., 2015) and SSA (Brauer et al., 2012; HEI, 2019). Though these pilot findings are in agreement with levels of PM pollution recorded in such environments specifically Ghana, limited studies are using these types of low-cost sensors for comparison and justification. Studies with emerging low-cost sensors have shown that low-cost sensor technologies suffer environmental artefacts namely relative humidity and temperature thereby affecting the measured data and do not agree well with measurements from instruments using different measurement technologies/ principles (Watson et al., 1998; Wilson et al., 2002; Chow et al., 2008). For example, Zheng et al., (2018) found that low-cost $PM_{2.5}$ sensor Plantower model PMS3003 corresponds very well with a scattered light spectrometer (r of 0.8) versus low correlation with a beta attenuation monitoring (r of 0.5). These findings provide a benchmark for future studies with these types of low-cost sensors especially in developing data correction/ validation and calibration procedures for the use of low-cost sensors for AQ monitoring in Ghana and similar environments.

Calendar plots were used to identify the days where the recommended WHO AQ guideline values of 25 and 50 µg/m³ for $PM_{2.5}$ and PM_{10}, respectively were exceeded (Figure 4-2). This type of analysis is currently unachievable with the GhEPA monitoring settings as only 24-hour averaged data can be collected roughly 5 times a month. Even though the reported data from the AS510 nodes used in this study is not validated with data from site-specific reference equipment, the PM levels reported are in agreement with levels recorded previously in SSA (Amegah, 2018; HEI, 2019). This finding shows that the selected nodes can be used for real-time daily monitoring of PM in highly polluted regions as shown by Castell et al (2017).

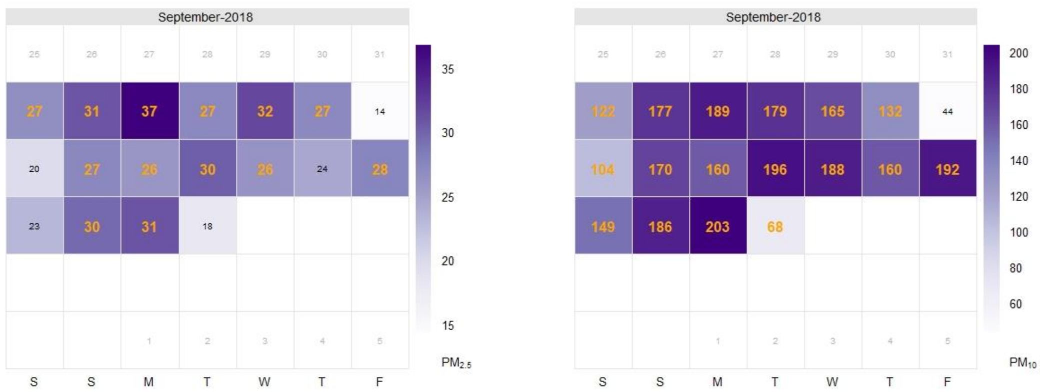

Figure 4-3: Calendar plot of PM at UCC for September 2018 showing potentials of comparing reported data to location-specific regulatory standards e.g. WHO daily mean values (25 µg/m³ for $PM_{2.5}$ and 50 µg/m³ for PM_{10}) if validated. Dark orange values represent days where the daily guidelines were exceeded

4.2 PM trends

Trends of PM species showed peak levels in the mornings which are attributable to typical sources such as unpaved roads (re-suspended dust), road-side food vendors (biomass and hydrocarbon combustion), taxi ranks (tailpipe) and roads used by heavy trucks and commercial vehicles (Figure 4-3). Urbanisation coupled with increasing motorization is indeed a major source of air pollution in SSA (Petkova et al., (2013) Schwela, 2012a; Amegah and Agyei-Mensah, 2016).

A drop in PM level was observed on Friday which is attributable to reduced human activities and peaks again on Sundays due to increased anthropogenic activities. These findings are unachievable with conventional and sparsely distributed AQM stations (e.g. in Ghana, data is averaged 24 hr and collected every 6 days).

Understanding the complexity of emission sources in urban areas requires monitoring at fine scales (Jerrett et al., 2005; Karner et al., 2010; Eeftens et al., 2012) and ability to potentially establish a dense network without large infrastructure. Low-cost sensors offer these opportunities and can be used in resource-constrained settings (Snyder et al., 2013, Mead et al., 2013, Castell et al., 2017).

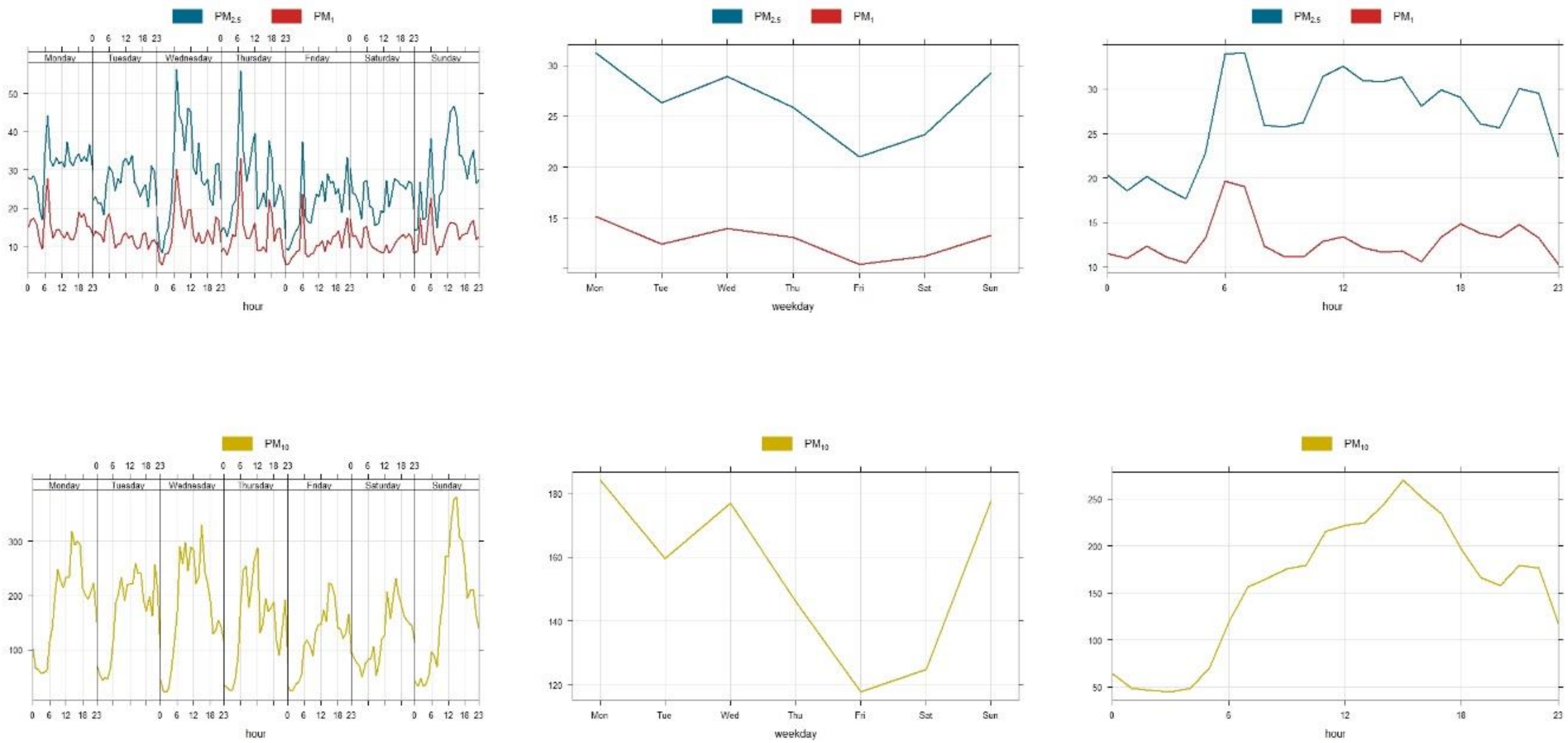

Figure 4-4: Trends of PM_1 and $PM_{2.5}$ (top) and PM_{10} (bottom) by hour and day of the week (left), by weekday (centre) and by hour of the day (right) at the UCC sampling site

4.3 Local PM sources

Polar plots were used to identify the sources of monitored species based on the high-resolution data from the low-cost devices (Figure 4-4) for this period. The trend between PM_1 and PM_{10} suggests that an important source of particulate matter is located towards the NNE.

This source is either biased towards lighter particles or that larger particles are removed before arriving at the monitoring site. The reported data potentially points towards a more local source of lighter particulates nearer to the monitoring site which has an important role in composition at lower wind speeds. Under still conditions, it seems there is no major local source.

Overall PM levels were relatively high (20 µg/m^3 for PM_1, 35 µg/m^3 for $PM_{2.5}$ and 220 µg/m^3 for PM_{10} as compared to the recommended 25 µg/m^3 and 50 µg/m^3 limits of the WHO for $PM_{2.5}$ and PM_{10}, respectively). Locally PM_1 and $PM_{2.5}$ concentrations were high while high PM_{10} concentrations were experienced at higher wind speed.

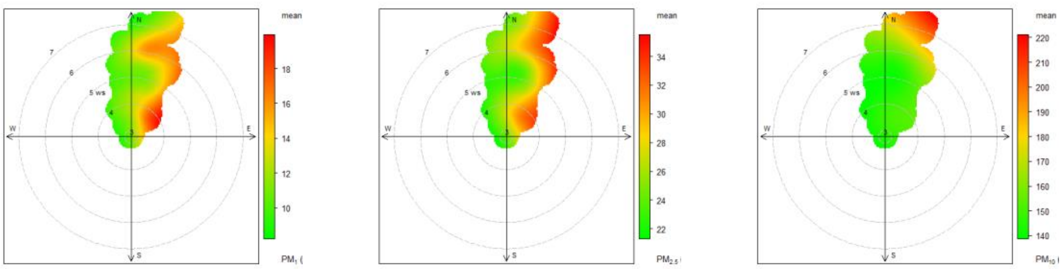

Figure 4-5: Hourly bivariate polar plot of PM_1, $PM_{2.5}$ and PM_{10} at the UCC site

These results reflect that both nodes were installed (at the UCC site) in a traffic dominated area. The region to the NNE is mostly unpaved flat area close to the Gulf of Guinea. The nature of the deployment site (unpaved roads with associated re-suspended wind-blown dust) coupled with the topography of the area (a relatively flat field) would be expected to have contributed to higher PM_{10} levels with increased wind speed. Especially considering that the area to the NNE is dominated by unpaved road, win-blown dust and sea salt from the nearby coast. As it has been shown that coarse PM dispersion is linked to higher wind speed

(Carslaw and Ropkins, 2012) we would expect a reduction in the PM_{10} signal at lower wind speeds (2-5 ms^{-1}) and higher levels were observed at higher wind speed (6-8 ms^{-1}).

4.4 PM trends between two different socio-economic settings

In Accra, peak values of PM_1 were observed on Monday which then drastically reduced to a concentration below 50 µg/m^3 (Figure 4-5). This preliminary finding could be linked to emissions from background activities such as garbage burning, vehicular emissions or linked to the functionality of the deployed device. In a study to understand the patterns of air pollution in the neighbourhoods of Accra, it was observed that poorer households are highly exposed to air pollution. This in part is due to the use of biomass and/ or solid fuel as a source of energy for heating and cooking (Dionisio et al., 2010).

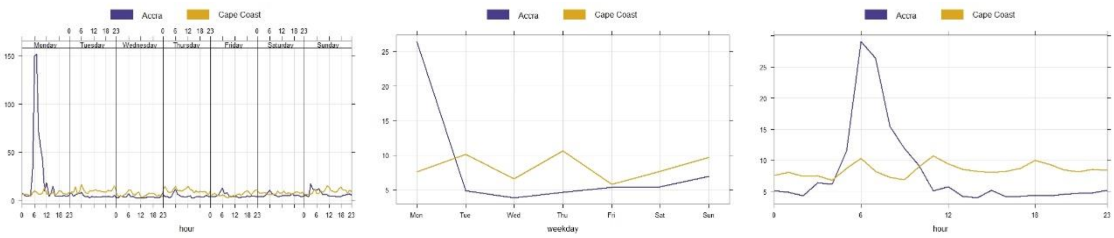

Figure 4-6: Trend plots for PM_1 at Dansoman-Accra and UCC-Cape Coast showing (left panel) day of week, (middle panel) hour of day by week and (right panel) integrated hour of day

Apart from Monday and Friday, PM_1 concentrations remain relatively high at Cape Coast (Figure 4-5), a relatively poor socio-economic setting is potentially linked to this assertion; energy source (use of biomass and/ or solid fuel as a source of energy for heating and cooking) as compared to the site in Accra. Though higher PM level is expected because of the nature of the deployment site; near the Dansoman Highway and a residential area and mini refuse damp (e.g. garbage is sometimes burnt during cleaning activities including car tyres), future research is required to provide a better understanding of this finding since the peak occurs on a single day (Monday). This will help establish whether the spike is attributable to sensor response or refuse burning activities.

Monday morning peaks (rush hour) were not observed at Cape Coast as compared to Accra, the concentrations remained moderately higher for the rest of the period except for Friday.

4.5 Source characterisation of PM species

At low wind speed (i.e. ≤ 2 ms^{-1}), elevated levels of PM were observed, implying that local sources contributed most heavily to PM concentrations (Figures 4-6a, 4-8a and 4-10a). For PM_1 and $PM_{2.5}$ higher concentrations were experienced at westerly and north-westerly winds whereas the lowest concentrations were experienced at north-easterly winds (Figures 4-6a and 4-8a). For PM_{10}, higher concentrations were observed at northerly and north-easterly winds (Figure 4-10a). Using the cluster analysis to extract source feature, cluster 4 (associated with northerly winds with speeds from 4-7 ms^{-1}) contributed to PM levels as high as 11 µg/m^3 for PM_1; 24 µg/m^3 for $PM_{2.5}$ and 125 µg/m^3 for PM_{10}.

The analysis has shown that higher wind speeds (7-8 ms^{-1}) from the north contributed to the elevated PM. Regardless of the wind speed, PM_1 is highest when winds are from the NNW direction (Figure 4-6a). For $PM_{2.5}$, higher levels were experienced at low wind speeds and from NNW (Figure 4-8a). PM_{10}, on the other hand, is highest with both low wind speed from the north (associated with cluster 1) and high wind speed from the northeast (associated with cluster 4) (Figure 4-10b). This indicates a likely source to NNW for finer particles but more distant sources of coarse particles to NNE.

An examination of the background environment has shown that this type of result is expected as N is mainly an unpaved flat area (lorry/ taxi park) adjacent the main road which is usually dusty though paved; E is the main road which is often used by taxis, commercial vehicles and heavy-duty cars (diesel engines); NE is the mini-market with roadside food vendors including cooking; S is mainly office complexes with the coast about 3 km away; W is the main road but mostly unpaved about 100 m away from the deployment and NW is similar to NE except for high levels of wind-blown dust from the unpaved road.

To demonstrate this, a time-domain analysis was carried out using the clusters identified. The categorical bar chart obtained with this analysis (Figures 4-7, 4-9 and 4-11) have shown that the peaks of PM are associated with cluster 4 (Figures 4-7 4-9 and 4-11). At relatively higher wind speed (4-8 ms^{-1} associated with cluster 4), the effects of meteorology on atmospheric pollution changes are reduced (Carslaw and Beevers, 2013) which accounted for the agreement in the sources of PM as linked to the temporal variation plot. It is important to note that this cluster analysis consistently grouped pollution levels from potentially the same source/ wind direction which was not shown in the bivariate polar plots. The downward trend shown in the PM species with high local levels (Figures 4-6a, 4-8a and 4-10a) and the contribution of the clusters from NNE winds as shown in the temporal variation plots (Figures 4-7, 4-9 and 4-11) is basically because they are influenced by road traffic emissions as previous studies have reported similar scenarios (e.g. Kim et al., 2014).

Cluster 4 associated with N winds dominated in contributing to PM concentration, the temporal variation plots for each of the species by the contribution of each of the clusters have shown that daily averages are influenced not only by cluster 4. There are instances where non-dominating clusters contributed to higher PM levels. For example, for PM_1, from August 30th to October 1st, cluster 3 and 4 dominates with minor contributions from cluster 2 and the least being cluster 1. On daily averages, though the temporal patterns have shown that cluster 3 contributed to levels beyond 20 $\mu g/m^3$. Additionally, there are instances where more than one cluster contributed to the levels recorded with some clusters mainly associated with low concentrations and the vice versa. Between September 1st and September 19th, all clusters contributed to PM_1 levels but cluster 1 contributed to the lowest levels recorded on September 16th with a daily average of a little below 5 $\mu g/m^3$. Cluster 3 though not dominant, contributed to higher daily average (i.e. beyond 20 $\mu g/m^3$) followed by cluster 4 which dominates with daily averages of a little below 15 $\mu g/m^3$. A similar trend was observed from October 2nd to 16th.

Similar to the cluster contribution to PM_1, daily averages of $PM_{2.5}$ have shown that from August 30th to September 18th, all 4 clusters contributed to $PM_{2.5}$ levels. The lowest daily average contribution is associated with cluster 1 of concentrations below 10 µg/m^3. The dominating cluster contributing to $PM_{2.5}$ is 4 but with concentrations not more than 38 µg/m^3 whereas cluster 3 though not dominating, is associated with the highest daily average of 48 µg/m^3.

With PM_{10}, though there are some areas of cluster 3 associated with higher levels, high daily averages are associated with cluster 4. These daily levels were as high as 200 µg/m^3. The least contributing cluster to daily levels is cluster 1 with concentrations 10 µg/m^3. Associating the clusters with the specific wind components have shown that concentrations of PM within urban areas are influenced by outstanding environmental and meteorological conditions tied to anthropogenic activities. These findings are in agreement with similar findings by Zikova et al., (2017) using these types of sensors for PM estimation across urban centres. These findings do not only reflect possible multiple sources of PM with some specks attributed to higher wind speed specifically for PM_{10} but contributed to established evidence on the operation of low-cost sensors within established atmospheric sensing standards to obtain appropriate data for source identification (e.g. Mead et al., 2013; Zikova et al., 2017). From the viewpoint of established atmospheric chemistry, winds are responsible for the transportation and mixing of chemical constituents which has been re-echoed in this study with the utility of low-cost high-resolution sensors for source apportionment studies using Ghana as an exemplar for wider SSA.

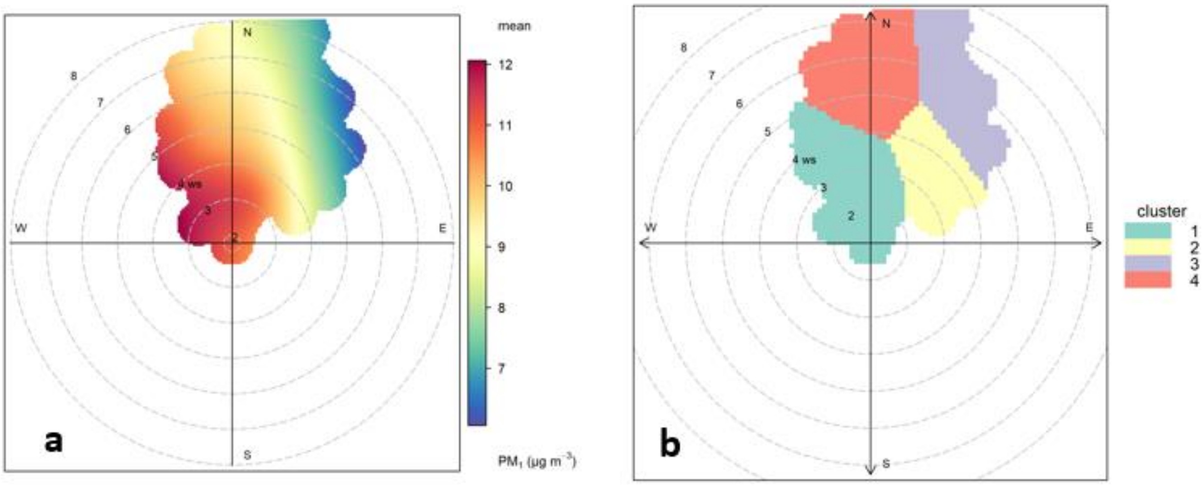

Figure 4-7: (a) Hourly bivariate polar plot and (b) 4 cluster plot of PM_1 at UCC

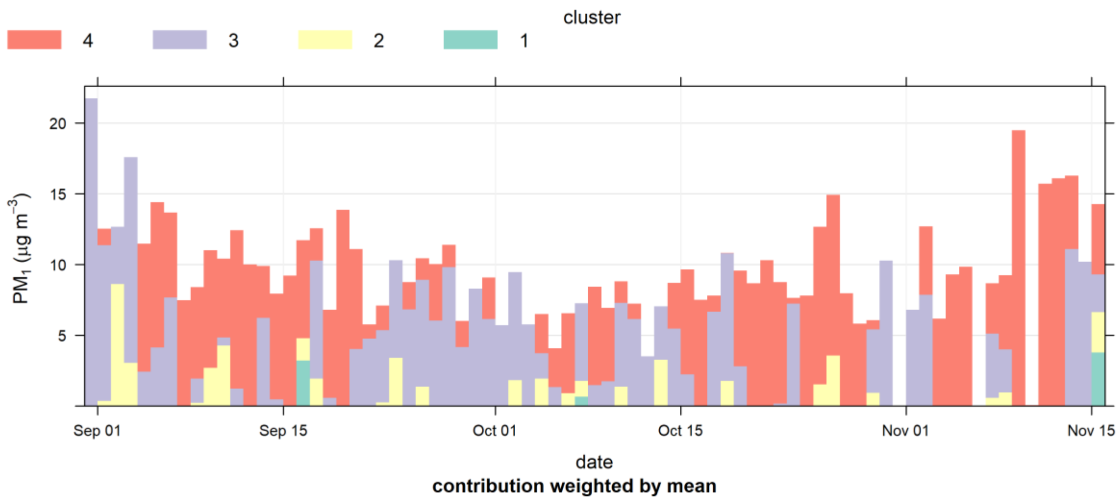

Figure 4-8: Temporal variation in daily PM_1 concentration at UCC by the contribution of each cluster for the entire period of deployment

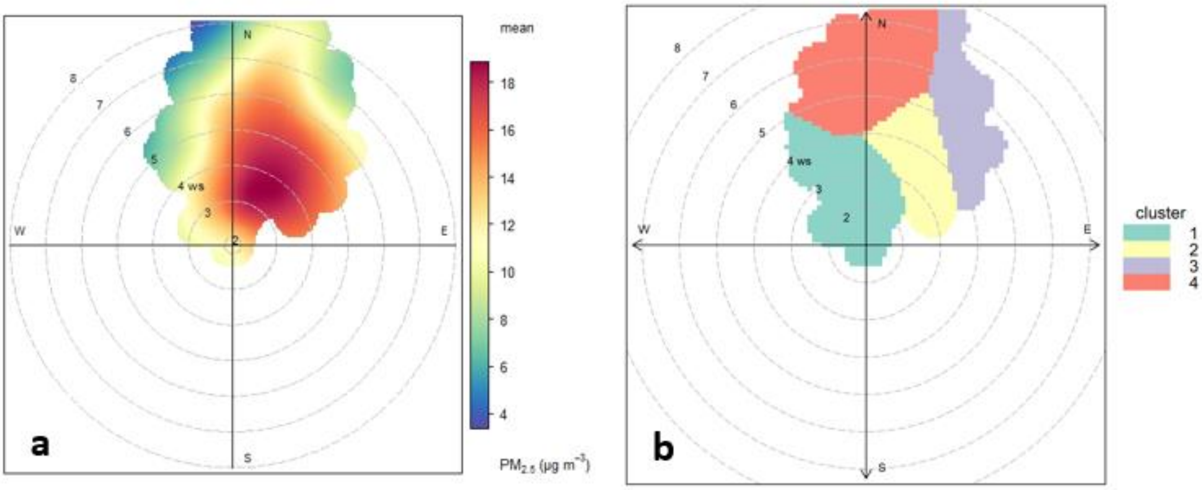

Figure 4-9: (a) Hourly bivariate polar plot and (b) 4 cluster plot of $PM_{2.5}$ at UCC

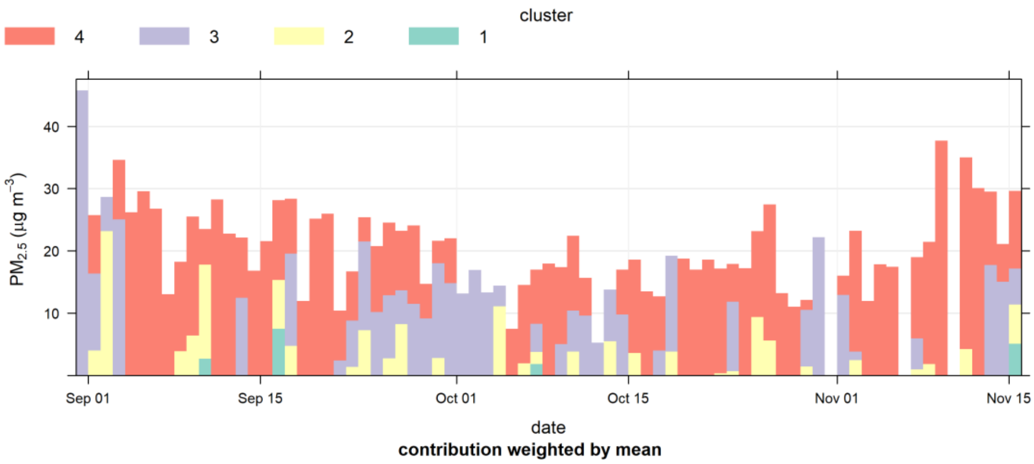

Figure 4-10: Temporal variation in daily $PM_{2.5}$ concentration at UCC by the contribution of each cluster for the entire period of deployment

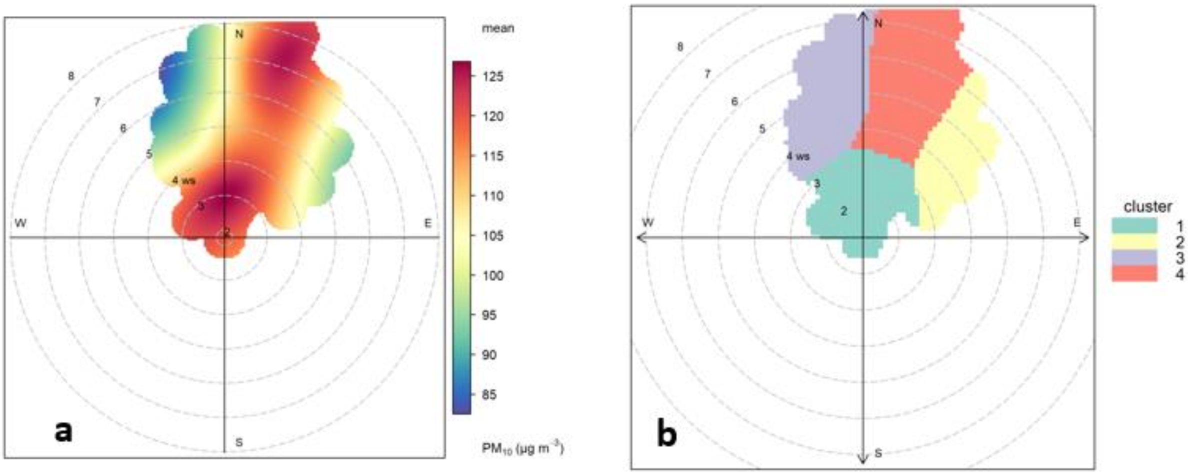

Figure 4-11: (a) Hourly bivariate polar plot and (b) 4 cluster plot of PM_{10} at UCC

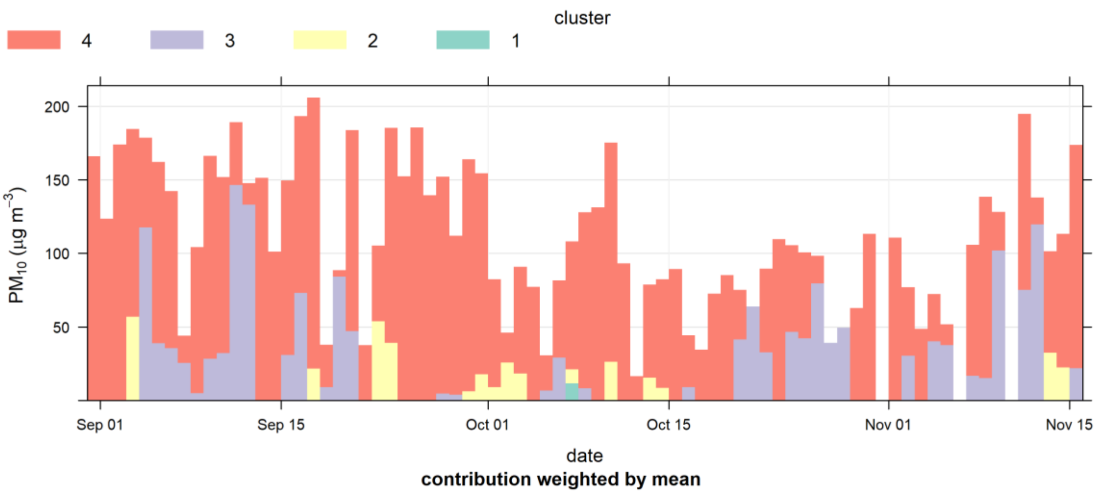

Figure 4-12: Temporal variation in daily PM_{10} concentration at UCC by the contribution of each cluster for the entire period of deployment

4.6 Indicative measurement of gaseous species

In this section, a synopsis is presented on the initial data reported from the deployed nodes on gaseous species. Exemplar species CO, NO_2, CO_2 and O_3 are presented. Though data correction mechanisms are required based on regional values, the utility of the nodes for understanding the presence of atmospheric pollutants specifically for CO, NO_2, CO_2 and O_3 is provided.

i. **Hourly time series plot of CO, NO_2, and O_3**

Using data from one (as an exemplar) of the nodes deployed at Cape Coast, an initial visualization of the reported data is presented for the gases CO, NO_2 and O_3. For all the species reported here (i.e. CO, NO_2 and O_3) some readings are in the negative. For the NO_2 species, all the data reported are in the negative but the opposite is reported for O_3 and a combination of positive and negative values reported for the CO. Nonetheless, CO was 2500 ppb, O_3 was a little above 200 ppb and NO_2 was ~100 ppb. Also, an inverse relationship is observed between the NO_2 and O_3 data echoing the cross-interference of the NO_2 and O_3 electrochemical sensors.

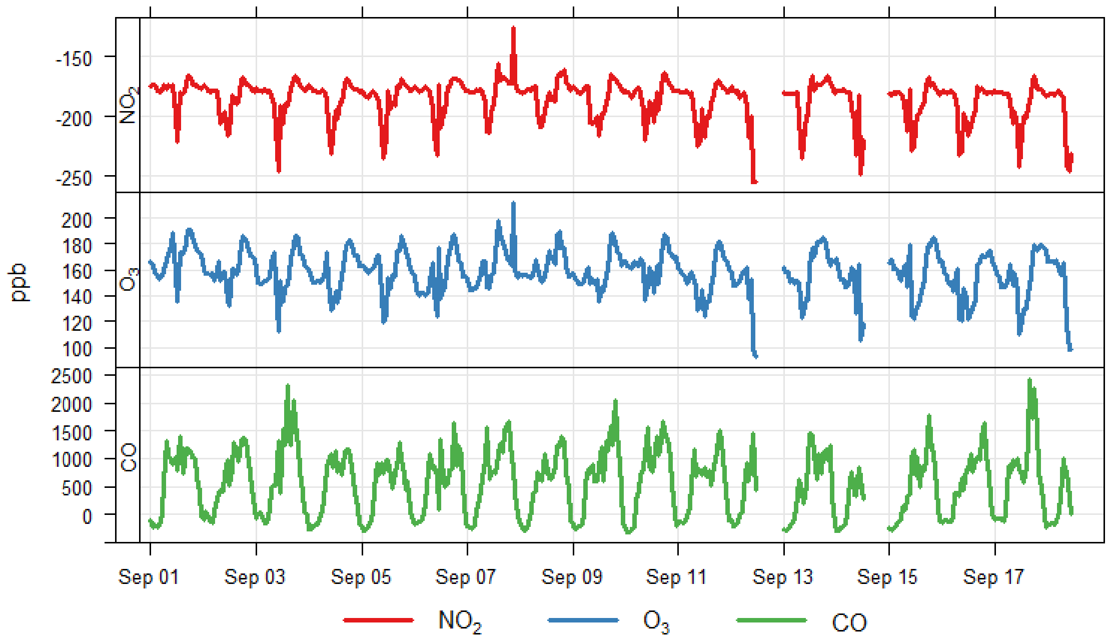

Figure 4-13: Indicative hourly time series plot of CO, NO_2 and O_3 at UCC

ii. **Hourly time series plot of CO_2**

Initial hourly time series plot of CO_2 have shown that peak levels could reach as high as 700ppm. A significant amount of the data reported have shown that hourly averages are between 625 – 655ppm. This is illustrated in Figure 4-14.

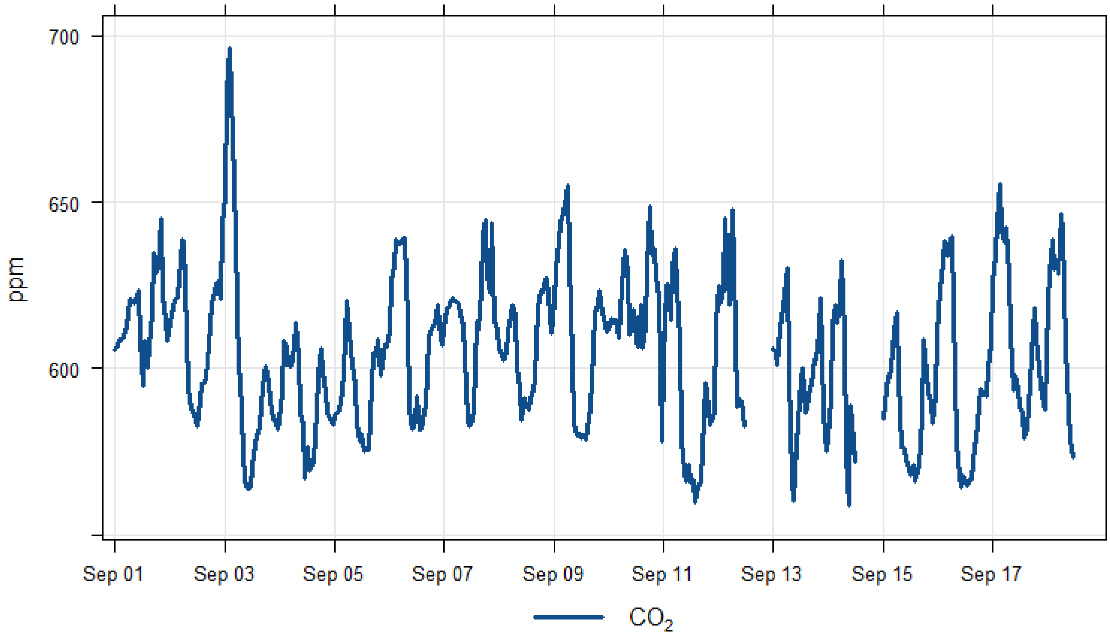

Figure 4-14: Indicative hourly time series plot of CO_2 at UCC

iii. **Indicative trend analysis of CO_2**

Figure 4-15 shows an indicative trend analysis of CO_2. The top panel shows day of the week, left bottom panel shows hour of the day, the middle bottom panel shows monthly and the bottom right panel shows daily. Levels of CO_2 peaks at 0600hrs and 1800hrs and drops at 1200hrs each day. Peak values for CO_2 is 650ppm which occurred on Monday around 0500hrs and drops to 580ppm around 1200hrs. A similar trend was though the peak levels were not the same for all the days. Hourly average CO_2 observed is 628ppm. The least average of CO_2 was recorded on Tuesday.

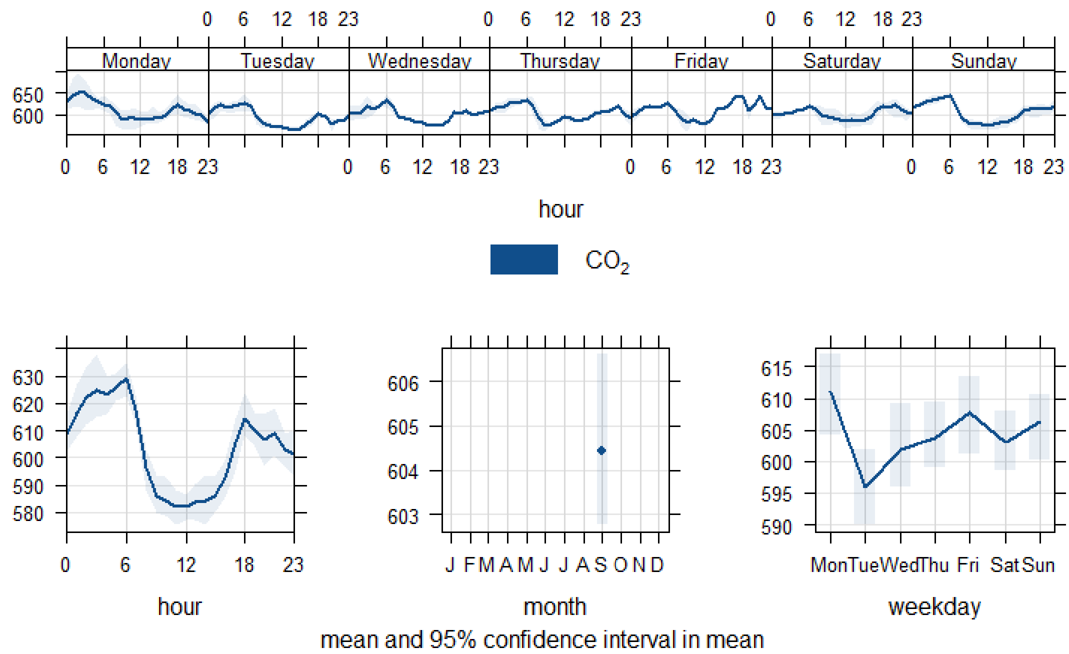

Figure 4-15: Indicative trend analysis of CO_2 at UCC

4.7 Summary

Low-cost sensors allow for in near real-time, autonomous in-situ AQ data measurement in environments previously unachievable as well as providing high-resolution data for an understanding of air pollution in urban settings. The use of low-cost sensors is swiftly increasing and offer the potential to propel regulatory action in environments with limited monitoring capabilities. The findings presented here have contributed to firstly bridging the scientific knowledge gap that exists in Ghana and wider SSA on the use of low-cost sensors and offers a new approach to undertaking AQM in quantifying and identifying air pollution sources.

The optical particle counters (Alphasense OPC-N2 in this case) have shown to be suitable for characterizing PM species and can be used to track and evaluate exposure levels, understand emission trends, define pollution level at varying locations with different background activities and suitable for reporting reliable high-resolution data useful for source identification. In the Cape Coast (study area) scenario, increased wind speed resulted in high PM_{10} levels. The nature of the deployment site at Cape Coast and background activities accounted for this; closeness to a traffic dominating area coupled with unpaved roads and the Gulf of Guinea.

For gas-phase pollutants, indicative levels are reported for the species CO, NO_2, O_3 and CO_2. Concerning NO_2 and O_3 the initial results presented highlight the need for post data correction based on the availability of regional values of the monitored species. Calibration and data validation (e.g. Mead et al., 2013; Kumar et al., 2015; Lewis et al., 2016) is integral for the use of this devices but in many cases not undertaken (Mijling et al., 2018).

Future studies need additional focus on data correction/validation when using these types of sensors in these types of environments (specifically Ghana and wider SSA). The statistical difference in mean values with reported data from the two nodes highlighted the limitation of relying on inbuilt data correction mechanisms by low-cost sensor manufacturers for effects of temperature and relative humidity on the performance of low-cost sensors (Becker et al., 2000; Lee, 2001; Baron and Saffell, 2017).

In resource-constrained settings such as those found in Ghana and the wider SSA, the utility of low-cost sensors for AQ studies to inform decision making is challenging because guidelines on the use of such devices are not fully defined (Williams et al., 2014b) and information regarding the use of low-cost sensors is at a fundamental stage. These findings provide initial results indicative of the measured species of which future AQ projects can be built on to develop correction mechanisms to obtain representative data.

This study of air pollution data was undertaken as a source apportionment exercise. In this section, the possibility of identifying potential sources of PM (i.e. air pollutants of interest) is demonstrated using bivariate polar plots and cluster analysis on acquired high-temporal resolution PM data from the low-cost sensor systems.

Source feature identification was maximized by applying post-processing techniques to characterize sources with a similar contribution to PM levels as observed at the University of Cape Coast Science Market (Cape Coast Municipality of the Central Region of Ghana). The methodology as presented in this study can be applied to other pollutant species provided an appropriate amount of data is gathered of an appropriate quality with local wind data.

Accurate local wind data is required as modelled data only provides information indicative of the wind components influencing the sources identified. This analysis highlights the possibilities of using low-cost sensors and integrating data from these devices with meteorological data to identify sources of PM (or other pollutants of interest) especially in highly polluted environments with complex sources of air pollutants but limited AQM capacities. This will help in developing, implementing and tracking specific mitigation measures. This methodology has the potential to improve our understanding of air pollution sources using data from multiple PM sensors (or other AQ species of interest) to identify multiple sources in urban areas.

5 GENERAL DISCUSSION

5.1 Introduction

Large areas of developing countries are poorly monitored including large portions in rural environments in the developed countries (Schwela, 2012a; Petkova et al., 2013; Amegah and Agyei-Mensah, 2016; Martin et al., 2019; HEI, 2019). Air quality monitors tend to be deployed in cities around the world but worse in developing countries specifically SSA. Exploring the feasibility and applicability of low-cost sensors for AQM in such environments to bridge data gaps is expanding rapidly.

This study presents scientific evidence on a proof of concept of the feasibility of low-cost sensors for AQM under real-world conditions in developing countries (i.e. Ghana in this case) to understand the reproducibility of low-cost sensors to provide information for characterising key air pollutants or similar (**Chapter 4, Sections 4.1; 4.2 and 4.4**) and the extent to which high-resolution data from low-cost sensors can be used for emission source identification (**Chapter 4, Sections 4.3 and 4.5**) in these environments with fragmented air quality monitoring approaches. With limited scientific knowledge on the use of low-cost sensors for quantifying air pollution and identifying emission sources, this study presented vital information on the utility of low-cost sensors specifically deployment, data acquisition, management, and analysis to address air pollution health crises.

Scientific knowledge on the suitability of low-cost sensors for AQM in SSA is at an early stage. For example, de Souza et al (2017) have shown that low-cost sensors are capable of providing a high-spatiotemporal data if deployed in a high-density in these environments though the authors recommend future studies to develop calibration toolbox for improved data quality. This was tested in Ghana by deploying selected low-cost sensors under varying urban settings to investigate the suitability low-cost sensors for obtaining a high-spatiotemporal data (i.e. by co-deploying the two nodes) to quantify key air quality species (PM – PM_1, $PM_{2.5}$ and PM_{10}; CO, NO, NO_2, CO_2 and O_3). It is deduced from the results of this research that indeed, low-cost sensors are capable of providing high-spatiotemporal data by how low-cost sensors characterise atmospheric pollutants if deployed in a high density.

Of particular mention is the reproducibility and consistency between the two PM sensors (Alphasense OPC-N2) in quantifying PM species justifying the functionality and feasibility of low-cost sensors for AQM in such environments. The gaseous species, reported indicative measurements highlighting the need for post-data correction based on regional values. Nonetheless, this study is the first of its kind using these types of sensors and have contributed to bridging the scientific knowledge deficit in using these types of sensors for AQM in Ghana and wider SSA.

In this research, the results from the pilot study at Cape Coast and Accra (study areas) in Ghana have shown that these sensors are capable of providing baseline data to influence decisions by quantifying and establishing sources of atmospheric pollutants. For example, location-specific air pollution mitigation strategies and actionable regulatory measures. Firstly, observational levels of the monitored species (PM in this case) have been presented and the measurements compared to established WHO requirements as well as studies reporting PM levels from this types of environments (e.g. HEI, 2019; Dionisio et al., 2010).

5.2 Deployment of low-cost sensors for AQ studies

Currently, the challenge remains on the exact protocols to follow regarding how end-users can deploy low-cost sensors to obtain baseline data (Williams et al., 2013). The scenario is worse in developing countries including those encountered in wider SSA. This in part is due to the limited number of studies emanating from the region on the use of low-cost sensors. Site selection and installation (e.g. at what height and type of urban setting) of low-cost sensors to provide baseline data is still a challenge.

Another key consideration is limited knowledge on the number of sensors to deploy to obtain representative data in a specific urban setting. To the best of our knowledge, this PhD research has provided the needed fundamental protocols (site selection, sensor installation, data acquisition, management and analysis) to adopt in the use of these types of sensors in these environments (**Chapter 3**, **Sections 3.2 and 3.3**).

At Cape Coast (pilot study area), the selected sensors were co-deployed approximately 10 cm apart and 4 m (above the ground adjacent in traffic dominated setting coupled with varying background activities. The two nodes were co-deployed about 10 cm apart in the same environment to investigate the feasibility of AS510 nodes for high-density deployment taking into account data reproducibility and precision. The ~4 m height was selected to avoid public vandalism though breathing zone is about 1.5 m. The protocols experimented for this study is adopted from the EU directive (2008/50/EC) (**Chapter 3, Section 3.2**).

No regulatory air quality monitoring exists in Cape Coast as at the time of this study. The area is representative of other emerging urban environments in wider SSA because no regulatory monitoring is established in the area coupled with varying and complex emission sources (refer to Chapter 3). The main goal was to test the appropriateness of these sensors for obtaining reliable ground based-data for quantifying key air quality species and suitability of the high-resolution data for emission source apportionment studies.

Though the selected sensors were used to monitor PM, CO, NO, NO_2, CO_2 and O_3, this study focused on PM but highlighted the need for skills and calibration requirement to obtain a representative data for the gaseous species. This is in agreement with current evidence on the suitability of current state of low-cost sensors for AQM in developing countries (see Kumar et al., 2015; Castel et al., 2017; Snyder et al., 2013) though studies are required to establish this.

The findings on quantification and source identification of PM as documented have shown that indeed, these types of sensors can be used for traffic-related monitoring, for example, NO, NO_2, CO, CO_2 and O_3 (though not included), fine particles (in this case PM_1 and $PM_{2.5}$) as well as coarse particles (PM_{10}) and able to function in a highly polluted environment such as Cape Coast and Accra typical of wider emerging urban settings and megacities respectively in SSA. Secondly, the reproducibility of the selected sensors was determined to provide evidence on establishing a high-density network to provide high spatiotemporal data for understanding urban air quality. This information is paramount to developing location-specific mitigation measures and routine AQM for tracking of such interventions. Studies have reported on spatial variation in air pollution at about 1-10 km (e.g. Lefler et al., 2019) but the associated cost with conventional monitoring and logistical requirements make the use of conventional monitoring challenging thereby limiting distribution for these types of work, for example, a single unit is about $250, 000 aside operational and maintenance cost whereas a single unit of the low-cost sensor is about $100 (Rai et al., 2017).

The approach documented in this research with low-cost sensors presents a unique opportunity for addressing AQM data gaps in SSA by employing relatively cheaper methodologies (refer to Table 2-2 in chapter 2 on characteristics).

5.3 Sensor intercomparison

Hourly averaged PM (PM_{10}, $PM_{2.5}$ and PM_1) data from the selected two nodes during the deployment at Cape Coast (i.e. UCC site) showed that the reported data from the nodes are highly reproducible as the signal acquisition of the two nodes is similar (Figure 4-2: a, b and c) with corresponding Pearson's correlation analysis (R) of 0.97, 0.97 and 0.98 for PM_1, $PM_{2.5}$ and PM_{10}, respectively (Figure 4-22: a, b and c). The first 3 weeks of deployment have not been included in this analysis as issues with data telemetry led to limited data for the study. Several studies have reported on the precision between the same low-cost sensors from a specific manufacturer and different manufacturers (see for example Rai et al., 2017) as well as low-cost sensor and regulatory/ reference-grade monitors (see for example Malings et al., 2019; Baron and Saffell, 2017; Mead et al., 2013) using regression models. In this PhD research, such an approach was developed and experimented using Pearson's correlation analysis as reported above. These types of approaches are relevant for establishing the precision between similar/different low-cost sensors and reference-grade monitoring equipment for high-density deployment. In the case of Ghana as documented here, the approach was used to provide evidence on the reproducibility of the selected sensors.

Further to the above, the mean PM values of the two nodes are significantly different. Comparing the mean values of each of the PM categories from the two devices and the corresponding *t-values* it can be seen that this statistical difference (see Table 4-1) reduces for PM categories in the order of PM_1, $PM_{2.5}$ and PM_{10}. Additionally, since PM_{10} values > $PM_{2.5}$ values > PM_1 values as demonstrated in the statistical difference between the PM species indicates that low-cost PM sensors are suitable for coarse particle monitoring in these types of environments as compared to fine particles but further studies are required to support this preliminary claim. This finding, however, is in agreement with previous reports using these types of sensors, for example, Castell et al., 2017. Studies on the use of low-cost sensors for AQM seek to know whether low-cost sensors have passed "fitness for purpose" stage to support air pollution applications (e.g. routine air quality monitoring, emission source monitoring and tracking air pollution). For example, Malings et al., (2019); Baron and Saffell, (2017) and Mead et al., (2013) have reported on data quality and specific calibration mechanisms (e.g. use of regression models) that can be employed to improve data quality. As shown in Table 2-3 of this research, apart from Alphasense OPC-N2 (used in this study), Dylos models 1100 Pro and 1700 and Sharp DN7C3CA006, the effects of temperature and relative humidity have a significant effect on the performance of low-cost PM sensors. This echoes similar reports from for example Hagler et al., (2018); Zikova et al., (2017a), (2017b) and Jayaratne et al., (2018). The preliminary findings presented in this research however have shown that the effects of these environmental variables are insignificant specifically for the Alphasense OPC-N2. This is in agreement with similar findings in advanced countries on the use of Alphasense OPC-N2 (see Rai et al., 2017). Additionally, the temperature and relative humidity measurements reported from the selected sensors are in agreement with average readings from the locations (study areas).

The evidence documented in this study demonstrating the suitability of low-cost PM sensors for obtaining location-specific reliable data for AQM has shown that these types of sensors are useful for bridging the air quality data gap in SSA.

The challenge, however, remains partly on limited technical know-how, funding and little information on the usability, visualization, analysis and interpretation of low-cost sensor data. To some degree, the use of the current state of low-cost sensors to support local policies based on the reported data is limited. This piece of work contributes greatly to bridge these scientific knowledge gaps making the approaches documented in this research vital information for future air quality research using low-cost sensors.

In light of this, the application of a widely accepted open-source tool, “openair” package for air pollution data analysis was experimented using the high-resolution data acquired from the selected low-cost sensors. This study has shown that if appropriate data mining tools are developed, for example, a toolbox for trend analysis, source identification and daily averages, low-cost sensor data can provide a reliable source of information on local air quality. These are based on understanding daily levels of atmospheric levels, trends, emission source feature extraction and comparison of air quality levels within varying urban settings.

The data mining tools developed for these types of analysis were based on the packages in the “openair” manual and are reproducible provided an appropriate data is acquired from low-cost sensors. The challenges encountered in performing these visualization and analysis are tied to the changing format of data reported from the same manufacturer of the selected sensors used in this research for example date and time formats and header files which consistently influenced and delayed the development and application data mining tools.

Low-cost data is presented in many formats and most difficult for end-users to understand, visualize or analyse. In some cases (as experienced in this research), these challenges were experienced though the selected sensors were from the same manufacturer. Data storage, gaps in reporting (due to low-latency per the manufacturer's feedback) and access (solely internet-based) have been a challenge nevertheless this research has proven that the application of reliable open-source data analysis protocols can be employed to understand air quality in environments with limited monitoring approaches using reported data low-cost sensors. The tools used from the “openair” package has been documented and interpretation provided.

5.4 Wider comparisons (PM)

These findings are in agreement with the assertion that current OPCs require optimisation (e.g. application of machine learning/ post data correction with sophisticated mathematical models) for measuring fine particles since they measure particles lager than 0.3 µm. Also, the statistical difference between the two nodes from the same manufacturer with p-value <0.05 echoed the challenges on the use of low-cost sensors, for example, depending on inbuilt correction algorithms which is mainly influenced by time and resources invested by the manufacturer (Baron and Saffell, 2017).

PM_{10} concentrations peak at 500 µg/m^3. This is in agreement with levels recorded in other polluted environments (Wang et al., 2015) and SSA (Brauer et al., 2012; HEI, 2019). Though these pilot findings are in agreement with levels of PM pollution recorded in such environments specifically Ghana, limited studies are using these types of low-cost sensors for comparison and justification. Studies with emerging low-cost sensors have shown that low-cost sensor technologies suffer environmental artifacts namely relative humidity and temperature thereby affecting the measured data and do not agree well with measurements from instruments using different measurement technologies/ principles (Watson et al., 1998; Wilson et al., 2002; Chow et al., 2008). For example, Zheng et al., (2018) found that low-cost $PM_{2.5}$ sensor Plantower model PMS3003 corresponds very well with a scattered light spectrometer (r of 0.8) versus low correlation with a beta attenuation monitoring (r of 0.5). These findings, however, provide a benchmark for future studies with these types of low-cost sensors especially in developing data correction/ validation and calibration procedures for the use of low-cost sensors for AQ monitoring in Ghana and similar environments.

Additionally, the reported data plotted in this calendar format (Figure 4-3) demonstrate the potentials LCS offer in reporting high-resolution routine and site-specific data suitable for tracking air pollution regulations. Comparisons can be drawn using data from these types of sensors if the reported data is improved/

validated. Rai et al., 2017 has reported that LCS does offer the opportunity to increase a community's awareness of air pollution and help track exposure to human health as well as support emergency responses. The capability of LCS to obtain routine site-specific data which can be quantified with data mining approaches as demonstrated in this calendar plot is useful for air pollution control specifically in environments with limited knowledge on air pollution and its adverse health impacts such as Ghana and wider SSA.

Here, the approach was experimented by comparing the reported data to current WHO AQ guideline values of 25 and 50 µg/m³ for $PM_{2.5}$ and PM_{10} respectively for September 2018. These thresholds were exceeded. Even though the reported data from the AS510 nodes used in this study is not validated with data from site-specific reference equipment, the PM levels reported are in agreement with levels expected and recorded previously in SSA (Amegah, 2018; Bauer et al., 2018; HEI, 2019) and have shown that high-temporal data from low-cost PM sensors are suitable for tracking air quality guidelines and inform decisions. Further to this, this type of analysis is currently unachievable with the GhEPA monitoring regime as only 24-hour averaged data can be collected roughly 5 times a month.

Low-cost sensors have changed the paradigm of air quality monitoring in the past decade. They present a revolutionary advancement to increase spatial air quality monitoring in urban settings (Morawska et al., 2018) due to the handy characteristics and minimal infrastructural requirements of low-cost sensors. In the light of this, most governments, research institutions, civil societies have developed an interest in the utility of low-cost sensors to increase the temporal and spatial resolution of air quality monitoring (Morawska et al., 2018).

Most of the studies using low-cost sensors report varying degrees of success coupled with a focus on recommendations for studies. Until now, no specific procedures have been developed on the use of low-cost sensors for observational air quality monitoring specifically in developing countries. These countries are experiencing poor air quality and lack monitoring capabilities and limited evidence on the functionality of low-cost sensors in these environments. For example, White et al., (2012) and Snyder et al., (2013) reported on the use of low-cost sensors by the US EPA in the USA. In Europe, Borrego et al., (2015) recommended regulating the use of low-cost sensors and to include in the European Air Quality Directive. The US and Europe have provided grants for projects focused on the performance evaluation of low-cost sensors (see for example CITI-SENSE, 2016; USEPA, 2016). This research presents a case on the use of the current state of low-cost sensors for understanding urban air quality specifically in these types of environments.

Here, the study focused on the performance of the selected low-cost sensors and how they can function in SSA using varying urban settings in Ghana as examples. On the performance of the selected sensors under varying urban settings in Ghana, it has been shown that these types of sensors can obtain appropriate data to understand trend levels, daily air quality levels and offer a reliable data for air quality studies and complement regulatory monitors. This is important for understanding the behaviour of air quality species and the opportunities these sensors offer in undertaking these studies.

Diurnal patterns of PM (as the focused species in this study) were defined. The levels of PM per this study are consistent with reported PM levels in these types of environments emphasising the capability of these types of sensors for supplementing AQM in these environments. At each location (Cape Coast and Accra), the feasibility of these sensors to obtain observational data in understanding air quality levels with varying background activities were explored.

As expected, high levels of PM were observed especially in poor socio-economic settings considering land use and unpaved roads. For example, the current HEI report (HEI, 2019) have shown that poorer about 92% of the world's population lives in areas experiencing poor air quality specifically those from poorer socio-economic settings. Comparing the reported data from Accra (an affluent setting) to Cape Coast (an emerging and poor socioeconomic setting), air quality levels were poor at Cape Coast. These findings have demonstrated the capability of low-cost sensors built on proven atmospheric approaches for these types of monitoring.

5.5 PM trends

Trends of PM species showed peak levels in the mornings which are attributable to typical sources such as unpaved roads (resuspended dust), road-side food vendors (biomass and hydrocarbon combustion), taxi ranks (tailpipe) and roads used by heavy trucks and commercial vehicles (Figure 4-4). Urbanisation coupled with increasing motorization is indeed a major source of air pollution in SSA (Petkova et al., (2013) Schwela, 2012a; Amegah and Agyei-Mensah, 2016). A drop in PM level was observed on Friday which is attributable to reduced human activities and peaks again on Sundays (Figure 4-4) due to increased anthropogenic activities. Though this is not documented, Ghanaians are identified as highly religious people hence the high specks of PM levels on Sundays is attributable to motorization for religious activities specifically church activities. This does require further studies as meteorological parameters are influential in atmospheric emissions. These findings are unachievable with conventional and sparsely distributed AQ monitoring stations (e.g. in Ghana, data is averaged 24 hr and collected every 6 days). Also, understanding the complexity of emission sources in urban areas requires monitoring at fine scales (Jerrett et al., 2005; Karner et al., 2010; Eeftens et al., 2012) and ability to potentially establish a dense network without huge infrastructure. Low-cost sensors offer these opportunities and can be used in resource-constrained settings (Snyder et al., 2013, Mead et al., 2013, Castell et al., 2017).

In Accra, peak values of PM_1 were observed on Monday which then drastically reduced to a concentration below 50 $\mu g/m^3$ (Figure 4-6). This preliminary finding could be linked to emissions from background activities such as garbage burning, vehicular emissions or linked to the functionality of the deployed device. In a study to understand the patterns of air pollution in the neighbourhoods of Accra, it was observed that poorer households are highly exposed to air pollution. This in part is due to the use of biomass and/ or solid fuel as a source of energy for heating and cooking (Dionisio et al., 2010).

Apart from Monday and Friday, PM_1 concentrations remain relatively high at Cape Coast (Figure 4-6), a relatively poor socio-economic setting is potentially linked to this assertion; energy source (use of biomass and/ or solid fuel as a source of energy for heating and cooking) as compared to Accra. Though higher PM level is expected because of the nature of the deployment site; near the Dansoman Highway and a residential area and mini refuse damp (e.g. garbage is sometimes burnt during cleaning activities including car tyres), further research is required to provide a better understanding of this finding since the peak occurs on a single day (Monday). Monday morning peaks (rush hour) were not observed at Cape Coast as compared to Accra, the concentrations remained moderately higher for the rest of the period except for Friday.

Further to this, the co-location of the low-cost sensor used with the GhEPA regulatory grade equipment in this study was aimed at determining the precision of the OPC-N2 for PM monitoring. However, due to lack of statistically sufficient data from the regulatory equipment (~5 data points in a month as compared to 60 s data routinely) made this comparison unattainable. Additionally, low power latency resulting in data gaps from the low-cost sensor does not support this comparison as there have been variations in monthly data. Specifically, the data from the low-cost and regulatory data vary in terms of months (i.e. variability in monthly data from the low-cost sensor and the regulatory equipment). The results as presented here on the PM species however is representative of PM pollution in these types of environments but long-term monitoring and application of reference-grade monitors with similar temporal approaches are required for determining the precision of the low-cost sensors.

5.6 Applicability of high-resolution data from low-cost sensors for emission source identification

To establish the applicability of the high-resolution data for emission source identification, windRose command in the R environment was used to generate wind variation during the period of deployment. Reported data from Node 5 (as an exemplar) with meteorological data following protocols defined in section 3.2 was used to show the frequency of wind contribution in percentage (represented as counts) by wind direction. Intervals of 10% were used to establish wind conditions and highlight the sources of atmospheric emissions reported in section

4.3 and 4.5. This is shown in Figure 5-1. This, therefore, shows that NNE winds are the main source of atmospheric emissions at Cape Coast (the study area). These were shown in the polar plots where the polarPlot command pointed to local sources as shown in the Figures 4-7a, 4-9a and 4-11a used to identify the sources of monitored species based on the high-resolution data from the low-cost devices (Figures 4-5; 4-7a; 4-9a; and 4-11a) for this period. The trend between PM_1 and PM_{10} suggests that an important source of particulate matter is located towards the NNE. This source is either biased towards lighter particles or that larger particles are removed before arriving at the monitoring site. The data also potentially points towards a more local source of lighter particulates nearer to the monitoring site which has an important role in composition at lower wind speeds. Under still conditions, it seems there is no significant local source. Overall PM levels were relatively high (20 μg/m^3 for PM_1, 35 μg/m^3 for $PM_{2.5}$ and 220 μg/m^3 for PM_{10} as compared to the recommended 25 μg/m^3 and 50 μg/m^3 limits of the WHO for $PM_{2.5}$ and PM_{10} respectively). Locally PM_1 and $PM_{2.5}$ concentrations were high while high PM_{10} concentrations were experienced at higher wind speed.

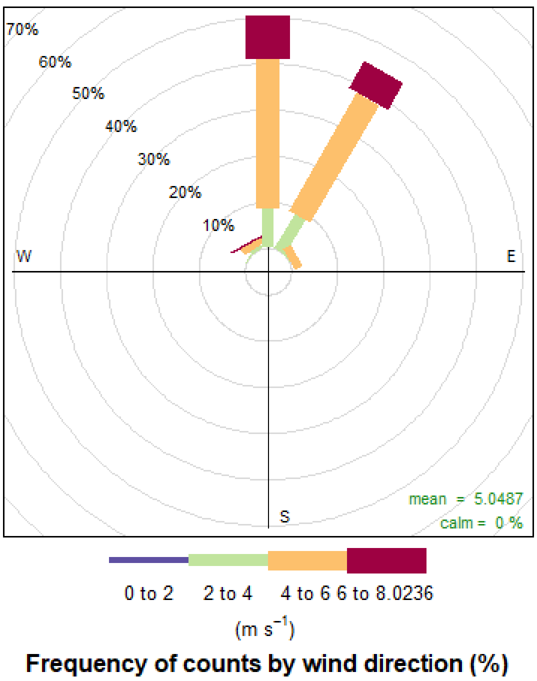

Figure 5-1: windRose of meteorological data at UCC during the period of deployment

These results reflect that both nodes were installed (at the UCC site) a few meters away from the main road and in a traffic dominated area. The region to the NNE is a mostly unpaved flat area close to the Gulf of Guinea. The nature of the deployment site (unpaved roads with associated resuspended wind-blown dust) coupled with the topography of the area (a relatively flat field) would be expected to have contributed to higher PM_{10} levels with increased wind speed. Especially considering that the area to the NNE is dominated by unpaved road, wind-blown dust and sea salt from the nearby coast. As it has been shown that coarse PM dispersion is linked to higher wind speed (Carslaw and Ropkins, 2012) we would expect a reduction in the PM_{10} signal at lower wind speeds (2-5 ms^{-1}) and higher levels were observed at higher wind speed (6-8 ms^{-1}).

At low wind speed (i.e. ≤ 2 ms^{-1}), elevated levels of PM were observed, implying that local sources contributed most heavily to PM concentrations (Figures 4-5; 4-7 a, b; 4-9 a, b; 4-11 a and b). For PM_1 and $PM_{2.5}$ higher concentrations were experienced at westerly and northwesterly winds whereas the lowest concentrations were experienced at northeasterly winds (Figure 4-5). For PM_{10}, higher concentrations were observed at northerly and northeasterly winds (Figure 4-5). Using the cluster analysis to extract source feature, cluster 4 (associated with northerly winds with speeds from 4-7 ms^{-1} in Figures 4-7b; 4-9b and 4-11b) contributed to PM levels as high as 11 $\mu g/m^3$ for PM_1; 24 $\mu g/m^3$ for $PM_{2.5}$ and 125 $\mu g/m^3$ for PM_{10}.

The analysis has shown that higher wind speeds (7-8 ms^{-1}) from the north contributed to the elevated PM. Regardless of the wind speed, PM_1 is highest when winds are from the NNW direction (Figure 4-7a). For $PM_{2.5}$, higher levels were experienced at low wind speeds and also from NNW (Figure 4-9a). However, in the case of PM_{10}, is highest with both low wind speed from the north (associated with cluster 1; Figure 4-11a) and high wind speed from the northeast (associated with cluster 4) (Figure 4-11a). This indicates a likely source to NNW for finer particles but more distant sources of coarse particles to NNE. An examination of the background environment has shown that this type of result is expected as N is mainly an unpaved flat land (lorry/ taxi park) adjacent the main road which is usually dusty though paved; E is the main road which is often used by taxis, commercial vehicles and heavy-duty cars (diesel engines); NE is the mini-market with roadside food vendors including cooking; S is mainly office complexes with the coast about 3 km away; W is the main road but mostly unpaved about 100 m away from the deployment and NW is similar to NE except for high levels of wind-blown dust from the unpaved road. To demonstrate this, a time-domain analysis was carried out using the clusters identified. The categorical bar chart obtained with this analysis (Figures 4-8; 4-10 and 4-12) has shown that the peaks of PM are associated with cluster 4 (Figures 4-7b; 4-9b and 4-11b). At relatively higher wind speed (4-8 ms^{-1} associated with cluster 4), the effects of meteorology on atmospheric pollution changes are reduced (Carslaw and Beevers, 2013) which accounted for the agreement in the sources of PM as linked to the temporal variation plot. It is also important to note that this cluster analysis consistently grouped pollution levels from potentially the same source/ wind direction which was not shown in the bivariate polar plots. The downward trend is shown in the PM species with high local levels (Figures 4-5; 4-7a, b; 4-9a, b; 4-11a and b) and the contribution of the clusters from NNE winds as shown in the temporal variation plots (Figures 4-8; 4-10 and 4-12) is basically because they are influenced by road traffic emissions as previous studies have reported similar scenarios (e.g. Kim et al., 2014).

In this study, this *k* – means cluster analysis is used to explore the effects of wind components on the measured concentrations of PM at Cape Coast over time (Figures 4-7a; 4-9a and 4-11a).

Further to this, cluster 4 associated with N winds dominated in contributing to PM concentration, the temporal variation plots for each of the species by the contribution of each of the clusters have shown that daily averages are influenced not only by cluster 4. Also, there are instances where non-dominating clusters contributed to higher PM levels. For example for PM_1, from August 30th to October

1st, cluster 3 and 4 dominates with minor contributions from cluster 2 and the least being cluster 1 (Figure 4-8). This was observed on daily averages, though the temporal patterns have shown that cluster 3 contributed to levels beyond 20 µg/m^3. Additionally, there are instances where more than one cluster contributed to the levels recorded with some clusters mainly associated with low concentrations and the vice versa. For example from September 1st to September 19th, all clusters contributed to PM_1 levels but cluster 1 contributed to the lowest levels recorded on September 16th with a daily average of a little below 5 µgm^{-3} (Figure 4-8). Cluster 3 though not dominant, contributed to higher daily average (i.e. beyond 20 µg/m^3) followed by cluster 4 which dominates with daily averages of a little below 15 µg/m^3. A similar trend was observed from October 2nd to 16th (Figure 4-8).

Similar to the cluster contribution to PM_1, daily averages of $PM_{2.5}$ have shown that from August 30th to September 18th, all 4 clusters contributed to $PM_{2.5}$ levels (Figure 4-10). Also, the lowest daily average contribution is associated with cluster 1 of concentrations below 10 µg/m^3. The dominating cluster contributing to $PM_{2.5}$ is 4 but with concentrations not more than 38 µg/m^3 whereas cluster 3 though not dominating, is associated with the highest daily average of 48 µg/m^3 (Figure 4-10).

With PM_{10}, though there are some areas of cluster 3 associated with higher levels, high daily averages are associated with cluster 4. These daily levels were as high as 200 µg/m^3 (Figure 4-12). The least contributing cluster to daily levels is cluster 1 with concentrations 10 µg/m^3. Associating the clusters with the specific wind components have shown that concentrations of PM within urban areas are influenced by outstanding environmental and meteorological conditions tied to anthropogenic activities. These findings are in agreement with similar findings by Zikova et al., (2017) using these types of sensors for PM estimation across urban centres. Past studies on PM pollution in urban settings in SSA have pointed out that biomass burning, traffic, industry/ energy and Saharan dust contribute to elevated PM levels (see for example Aboh et al., 2009; Ahiamadjie, 2017; Naidja et al., 2018; Ofosu et al., 2012; WHO, 2006). The findings presented in this research using the reported data from low-cost sensors tied to background activities are in agreement with this evidence. Anthropogenic activities and wind-blown dust from the surrounding environment as established in section 3.3 have buttressed this observation.

These findings do not only reflect possible multiple sources of PM with some specks attributed to higher wind speed specifically for PM_{10} but contributed to established evidence on the operation of low-cost sensors within established atmospheric sensing standards to obtain appropriate data for source identification (e.g. Mead et al., 2013; Zikova et al., 2017). From the viewpoint of established atmospheric chemistry, winds are responsible for the transportation and mixing of chemical constituents which has been reechoed in this study with the utility of low-cost high-resolution sensors for source apportionment studies using Ghana as an exemplar for wider SSA.

In addition to the above on PM sources, clear patterns have been observed in the variation of PM species. Outstanding meteorological conditions play a major role in the behaviour of PM species (Pu et al., 2011; Gu et al., 2015) as observed at Cape Coast. PM distribution is therefore influenced by the two main seasons in Ghana and depending on the region. The major wet season ranges between April to July, followed by lean wet from August to October/ November and a dry season from December to March (personal communication, GhEPA, 2019). The relatively stable pollution source (i.e. NNE winds) at Cape Coast indicated the leading role of meteorological conditions on PM pollution. As observed in Figure 4-7a, PM_1 is local at low wind speeds at the western sector of the polar plot. A similar observation is reported for $PM_{2.5}$ except that this was at the eastern sector of the polar plot in Figure 4-9a. For PM_{10} (Figure 4-11a), this observation spanned from the eastern sector to the NNE of the polar plot. This has shown the variability of PM species in urban settings and the need for these types of low-cost monitoring approaches to understanding PM pollution. The wind removal capability which is mainly influenced by climatic conditions, topography and geographical location (Pu et al., 2011; Gu et al., 2015) was observed for PM species considering the levels of PM_1 and $PM_{2.5}$ (higher levels at lower wind speeds only) and PM_{10} (higher levels at both low and relatively higher wind speeds). This also indicates the contribution of traffic to fine particle pollution at The air pollution scenario represented in this study at Cape Coast as highlighted the findings of a similar study using these types of sensors in a similar setting in Eastern Africa by Pope et al., 2018. Also, ground-level $PM_{2.5}$ pollution is influenced by vertical wind shear as observed by Wang et al., 2020. The high levels of $PM_{2.5}$ (and potentially PM_1) are attributable to this vertical wind shear phenomenon though further studies are required to confirm these preliminary findings. The observations as reported in this piece of work on PM pollution at Cape Coast however have shown the robustness of the OPC-N2 low-cost sensor in obtaining the needed data for these types of analysis.

This study provided explicit documentation on the application of high-resolution data reported from the selected low-cost sensors to understand emission sources using PM as an exemplar species (**Chapter 4, Sections 4.3 and 4.5**). On source identification, this research has shown that low-cost sensors can be used to obtain appropriate data useful for emission source apportionment studies.

Based on proven and widely accepted standards, the bivariate polar and cluster analysis were used to identify sources of PM. The results presented have shown that low-cost sensors are capable of providing the needed data on key atmospheric species that can be used to identify sources of emissions. These sensors are useful for air quality applications such as emission source monitoring and provide in these types of environments. The utility of low-cost sensors will provide vital information for developing, implementing, and tracking air pollution mitigation approaches.

5.7 Indicative measurement of gaseous species

This research has re-echoed findings early researches on the utility of low-cost sensors specifically gas-phase low-cost monitors (i.e. electrochemical sensors for CO, NO_2 and O_3 and non-dispersive infrared detector sensors for CO_2) have documented in advanced countries. As shown in for example Barron and Saffell (2017), Malings et al., (2019), Hagler et al., 2018 and Mead et al., 2013, the need for post-data correction mechanisms is highly recommended. The results, however, presented a first-hand knowledge on the presence of health-damaging atmospheric pollutants specifically CO, NO_2 and O_3. The CO_2, a key component of climate change has also been documented. By observing the trend analysis of the CO_2 for example, a major contributory factor is anthropogenic activities tied to the background activities. The trends have pointed to vehicular emissions and use of solid fuels; a widely established source of atmospheric emission in major parts of Africa as reported in current trends (for example Bauer et al., 2019; HEI, 2019; Amegah and Agyei-Mensah, 2016; Schwela, 2012a). Additionally, the varying shaded area of the CO_2 trend analysis in sub-section iii of section 4.6 has shown the variability of the data over the course of the deployment. Though this variability is observed, it has also pointed out the robustness of low-cost sensors to measure atmospheric emissions at varying degrees and or levels. This is however not to indicate that low-cost sensor data is not without issues and therefore must be corrected against regulatory/ reference grade monitors. This type of studies have been carried out in advance countries, for example, Barron and Saffell (2017), Malings et al., (2019), Hagler et al., 2018 and Mead et al., (2013). However, in environments such as Ghana and wider parts of Africa with limited logistics for undertaking these types of studies, the current generation of low-cost sensors do offer basic information on air quality monitoring. This piece of work therefore has provided benchmark data for future works.

5.8 Summary

The reported data for the PM species is in agreement with the levels reported in such environments highlighting the usefulness of low-cost sensors for establishing ground-based AQM stations to obtain reliable data that will spur regulatory actions. Additionally, Castell et al., (2017) reported that low-cost sensors are suitable for PM monitoring and feasible for air pollution studies in developing countries. Analysis of the acquired data has shown that indeed low-cost sensors can be deployed in environments with no regulatory/ reference-grade monitors to understand air quality levels and sources of atmospheric emission. This proof of concept study in Ghana presented here has reaffirmed this conception and contribute significantly to the scientific knowledge base on the use of low-cost sensors for air quality monitoring to obtain reliable data for air pollution control strategies.

In summary, this study has shown how low-cost sensors can be deployed to initially obtain observational air quality data in environments with non-existent or limited air quality monitors as well as obtaining the required data to track sources of atmospheric emissions. The study has demonstrated to what degree low-cost sensors can be deployed for understanding urban air quality and provides the basis for future works using these types of sensors. These types of approaches are suitable for developing cost-effective location-specific air pollution mitigation measures.

6 CONCLUSIONS AND FUTURE WORK

6.1 Introduction

This research identified the potentials low-cost sensors offer in providing reliable ground-based AQ data in environments with limited/ no regulatory AQ monitoring stations; specifically, in LMICs using urban environments of Ghana typical of wider SSA as an exemplar. Its aim centred on investigating the applicability and feasibility of low-cost sensors to understand the extent to which these devices can be used to obtain meaningful AQ data to support applications such as:

i. emission source monitoring
ii. source identification with high-resolution data reported from these types of devices
iii. tracking and evaluation of air pollution mitigation policies
iv. increasing the community's awareness on air pollution and its health effects in these types of environments with limited public knowledge on the subject
v. supplement conventional monitoring approaches, and
vi. establishing a dense network to obtain high-spatiotemporal data at fine scales for emission source identification in urban areas in these types of environments

To achieve these aims:

(i) studies were carried out to understand the state of AQ monitoring in low- and middle-income countries with a focus on Ghana as an exemplar for wider SSA and the possibilities low-cost sensors offer to bridge the identified data gaps – **Objective 1**;

(ii) a pilot study was undertaken in Ghana with two selected low-cost multi-sensor nodes manufactured by Atmospheric Sensors UK Ltd at Cape Coast and Accra to determine the functionality of the devices in such environments with high levels of atmospheric emissions and whether the acquired data could be useful for AQ studies – **Objective 2** and

(iii) an experimental approach to defining emission sources with the high-resolution data obtained with the selected low-cost sensors to determine whether such sensors could be deployed in a high-density for source apportionment studies in urban areas of Ghana and wider SSA – **Objective 3**.

This chapter provides a résumé of the key findings; an overview of how each of the objectives contributed to achieving the aims of this PhD research.

Overall, this research provided a valuable knowledge regarding critical insights on conventional versus low-cost monitoring approaches and how the latter could be used to bridge AQ data gaps in environments with limited/ no regulatory AQ monitoring stations specifically Ghana as an exemplar for wider parts of SSA (**Chapter 2**).

Following on Chapter 2, a proof of concept study was undertaken in Ghana under varying urban settings. The selected nodes have shown that

(i) current OPCs (Alphasense OPC-N2) are suitable for monitoring particulates (PM_{10}, $PM_{2.5}$ including PM_1 as an air quality priority) and

(ii) (ii) EC cells are suitable for providing indicative data on gas-phase species (CO, NO, NO_2 and O_3) but

(iii) (iii) further study is required to develop data validation and calibration methodologies for the use of these types of sensors if they are to complement regulatory monitoring in these types of environments.

A collocation study with regulatory grade equipment was undertaken at Dansoman, Accra site run by the Ghana Environmental Protection Agency (GhEPA) with an initial plan of developing calibration and data validation procedures for the use of the OPCs for PM monitoring. This collocation was tied to obtaining statistically sufficient data for developing calibration and validation procedures.

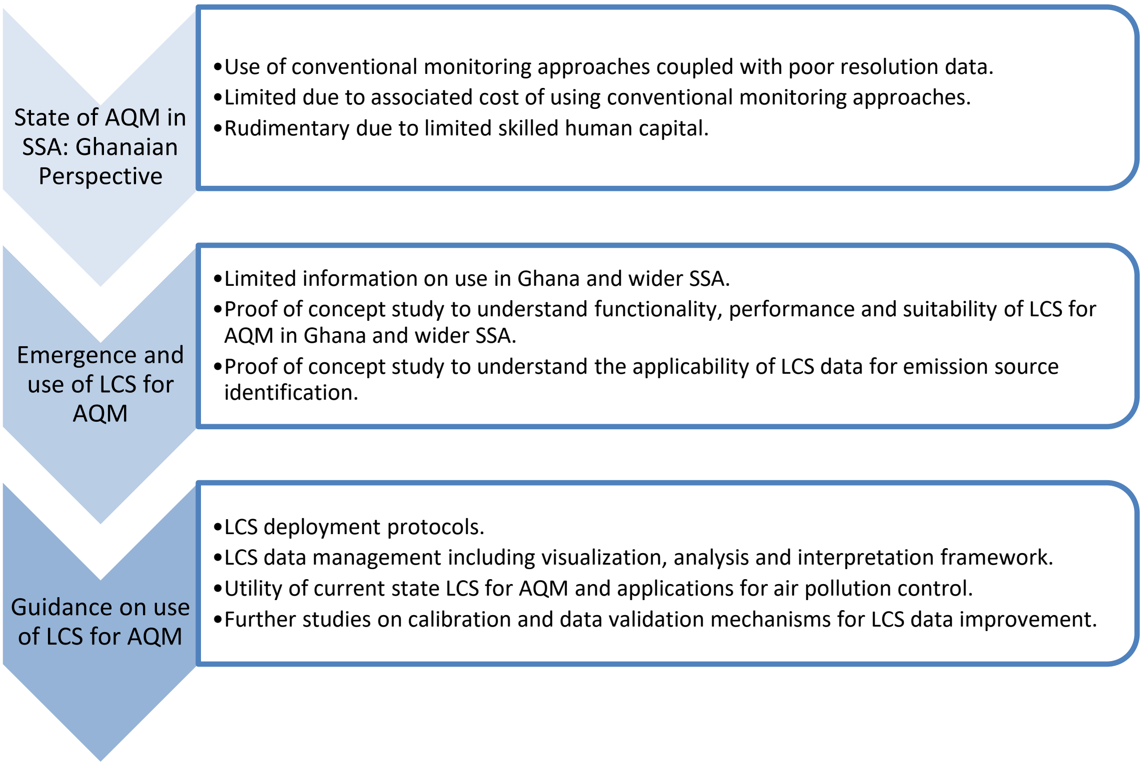

Figure 6-1: Schematic overview of the relationship between the specific objectives of this PhD research showing the novel contribution of this research to current scientific knowledge on the utility of low-cost sensors to bridge air quality data gaps in these environments. AQM (air quality monitoring), LCS (low-cost sensor) and SSA (Sub-Saharan Africa).

6.2 Key findings, implications and contribution to knowledge

The World Health Organization (WHO) has developed and implemented AQ guidelines to protect human health globally. In many of the jurisdictions globally, country-specific AQ management systems have been developed. The European Union, for example, has set measures to curb air pollution (EU AQ Directive 2008/50/EC, Rai et al., 2017).

In Ghana, specifically many parts of SSA, country-specific standards are limited/ non-existent though most of these countries aspire to adhere to the WHO AQ guidelines. This is challenging due to lack of monitoring capabilities specifically concerning the cost and human skill requirement associated with employing current conventional AQ monitoring approaches (Schwela, 2012a; Petkova et al., 2013; Bauer et al., 2019).

Overall, **Chapter 1** is presented as a contextual framework of this research emphasising on the rationale and general background of the study. It provided a critical understanding and perspective of the study where aims and specific objectives were unequivocally stated. It served as a road map for the subsequent chapters of this research.

Based on the critical review, **Chapter 2** showed that low-cost sensing technologies offer a unique way of extending the existing conventional monitoring approaches and can provide high density and coverage of empirical measurements to improve our understanding of exposure science and control. This chapter showed how low-cost sensors are useful for providing reliable ground-based AQ data in LMICs specifically Ghana and wider SSA. It compares the critical issues related to the use of conventional versus low-cost monitoring approaches, limitations and opportunities.

On the utility of low-cost sensors for bridging AQ data gaps, this chapter highlighted approaches to adopt to improve data quality specifically for the use of OPCs in monitoring particulate matter (e.g. DEFRA, 2017; Liu et al., 2017; Malings et al., 2019). Most importantly, Chapter 2 provided critical insights into the utility of low-cost sensors for real-time AQ monitoring, acquisition of high spatiotemporal resolution data for emission source identification, emergency and hazardous leak monitoring, emission source monitoring, increasing community's awareness on AQ and supplementing regulatory AQ monitoring approaches (Mead et al., 2013; Kumar et al., 2015; Rai et al., 2017; Castell et al., 2017).

In **Chapter 3**, the novel application of low-cost sensors under varying environmental settings in Ghana and the acquisition of observational air quality data adopted in this research to produce these benchmark findings have been documented. This chapter demonstrated that low-cost sensors are capable of providing reliable data though studies are required to understand the precision of low-cost sensors as against regulatory monitors. The preliminary deployment strategies presented in this chapter have shown that in the absence of regulatory air quality monitors, low-cost sensors can be employed to provide firsthand knowledge on local air quality to inform decisions as well as complementing existing sparsely distributed air quality stations.

In the pilot study, we employed Pearson's correlation analysis to specifically explore the reproducibility in characterizing PM species. For the gaseous species (CO, NO, NO_2, O_3 and CO_2) monitored, indicative measurements were determined with standardized scientific methods though not provided in the main thesis except for CO. To the best of our knowledge, this type of work is the first of its kind in Ghana and wider SSA though similar, a handful of these studies were undertaken in Eastern Africa.

These types of approaches are benchmarks for future AQ studies with these types of sensors specific to these environments; in the case of the gaseous species, post data correction methodologies can be developed based on the availability of regional values.

This work has provided the needed information required for studies using these sensors for example development of data validation and calibration methodologies as reported in similar works in advanced countries (see e.g. Mead et al., 2013; Popoola et al., 2016; Malings et al., 2019).

Chapter 4 showed that these types of sensors are useful for acquiring high-resolution data in these environments useful for understanding patterns and trends of air pollution.

Trend analysis of the reported data has shown that poorer socio-economic settings (in this case Cape Coast, an emerging urban setting) are associated with higher levels of atmospheric pollution as compared to affluent settings (in this case Accra). Similar findings have been reported by Dionisio et al., (2010) associating poor AQ to poorer socio-economic settings. Studies are required to understand the precision of these sensors if they are to supplement conventional monitoring approaches currently used in these environments.

The results with the approaches adopted using the selected LCS have been presented in two sections to the methodologies in chapter 3. The first part presented is on the performance of the two selected identical sensors (addressed **Objective 2**).

In this short-term study, analysis of the reported data has shown that indeed low-cost sensors can provide the needed information on local air quality to understand exposure levels as compared to recommended thresholds. PM levels reported using these sensors are beyond the recommended World Health Organization guidelines similar to current findings in these types of environments using modelled data (e.g. Bauer et al., 2019; HEI, 2019). This information is lacking in many parts of SSA considering limited monitoring capabilities (e.g. Petkova et al., 2013; Schwela, 2012a).

The results have shown higher reproducibility in characterizing PM species. The findings suggest that the current generation of low-cost PM sensors (OPCs) are suitable for monitoring PM (e.g. Castell et al (2017) reported on the use of these types of sensors for AQ campaign in highly polluted environments specifically developing countries) but studies are required to confirm this. The approach used in this study nevertheless is novel and can be used in bridging AQ data gaps (Schwela, 2012a; Petkova et al., 2013; Bauer et al., 2019; HEI, 2019) encountered in these types of environments.

The second part focused on the utility of the reported data from the selected low-cost sensors (PM sensor Alphasense OPC-N2 in this case) to extract source features of the sampled species (PM_{10}, $PM_{2.5}$ including PM_1 in this scenario) in low- and middle-income countries specifically Ghana as an exemplar for similar environments e.g. wider SSA (**Objective 3**).

The results have shown that the reported data from these types of devices are suitable for source identification and if deployed an in high-density, will provide vivid information for source apportionment studies in these types of environments (see e.g. Mead et al., 2013). In our experiment, PM sources were defined using bivariate polar plots and cluster analysis integrated with trend analysis (see Carslaw, 2015).

The results have echoed similar findings in environments typical of the deployment site. High PM levels were associated with low wind speed demonstrating local sources mainly traffic and wind-blown dust. The study has shown that in environments typical of the deployment site, elevated PM sources are expected locally regardless of the influence of wind components. The findings are associated with the background environment indicating that these types of sensors are useful for firstly providing meaningful AQ data and secondly, high-resolution data appropriate for source apportionment studies.

The novelty of this study is that low-cost sensors can provide high-spatiotemporal data (if deployed in a high-density) at fine-scale to support source identification of monitored key pollutants (or any species of interest). In Ghana, for example, the current monitoring approach provides only ~5 data points per month coupled with sparsely distributed AQ monitoring stations limiting these types of analysis though sampled filters can be examined for chemical speciation.

6.3 Limitations of this research

- Limited high-resolution data and lack of resources to obtain a reference-grade equipment limit our understanding of the performance of the selected low-cost devices considering precision and accuracy;

- Poor resolution data characterized by the monitoring approaches in Ghana inhibits our ability to develop calibration and data validation methodologies for the use of selected low-cost devices;

- The inability of the deployed sensors to rely on the secondary power source (e.g. solar energy) to operate resulted in data gaps for example during power fluctuations and a fire incident destroying one of the batteries (i.e. node 79 at Dansoma-Accra, reference site) hence relatively small data points were used throughout the study which may influence the models on source identification.

- Lack of in-country site-specific data on wind components may have influenced the results of the source apportionment studies since the experiment relied on modelled wind data from NOAA.

6.4 Recommendations

- This study demonstrate the need for research firstly on collocating reference-grade monitors with the deployed nodes considering a high resolution (e.g. minute/hourly resolution) to provide sufficient and appropriate data for validation and calibration.

- We recommend studies to provide a convincing report on the use of these types of sensors to supplement and bridge AQ data gaps encountered in SSA.

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