Research article

An assessment of ambient air quality in a densely populated urban settlement of Harare, Zimbabwe

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Abstract

Poor air quality in urban settings poses a significant global challenge with adverse environmental-health effects. In Zimbabwe, a critical knowledge gap exists regarding specific characteristics and seasonal variability of ambient air pollution in low-income, densely populated settlements, with existing studies often relying on indirect assessments. This stems from the lack of a national monitoring network, largely due to the prohibitive cost of research-grade instruments. The purpose of the was to demonstrate a viable approach to generate localized data needed to fill the national data gap through the deployment of a low-cost sensor in a representative densely populated urban settlement of Cold Comfort, Harare over a 12-month period. The deployed sensor measured particulate matter concentrations ($PM_{2.5}$ and PM_{10}) at 5-minute temporal resolution, which were then aggregated to hourly averages and analysed using open-air in R statistical packages. Results show that ambient particulate matter concentrations were elevated during winter, with annual means of 34.1 µg/m^3 for $PM_{2.5}$ and 58.1 µg/m^3 for PM_{10}. These levels significantly exceeded the WHO annual mean guidelines of 5 µg/m^3 and 25 µg/m^3 for both $PM_{2.5}$ and PM_{10}, highlighting local air quality concerns. A HYSPLIT trajectory analysis of a peak winter pollution event suggested that the high concentrations were a combination of long-range pollutant transport and enrichment from local emission sources. The low-cost sensor performance was evaluated against gravimetric measurements using Mean Absolute Error, Root Mean Square Error, and coefficient of determination. The low-cost sensor consistently under-estimated PM_{10} concentrations, showing a Mean Absolute Error of 14.2 µg/m^3, Root Mean Square Error of 19.7 µg/m^3, and an R^2 of 0.47. Despite accuracy limitations, the low-cost sensor provided a useful overview of pollution levels. As the first long-term, campaign-based study of its kind in Zimbabwe, these findings are vital for informing air quality management policy and developing targeted interventions.

Keywords

Air pollution, low-cost sensors, pollution data gap, dirty fuel

Introduction

Health and environmental issues related to air pollution remain a challenge that most countries in the global south are struggling to manage including Zimbabwe. Globally, ambient air pollution has been associated with increases in the burden of diseases that lead to wide-ranging premature deaths that are estimated at 7 million (Brauer et al., 2012; Gautam and B. Bolia, 2020; Pandey et al., 2021). The US Environmental Protection Agency (US EPA) has set up standards for six criteria pollutants that include particulate matter ($PM_{2.5}$ and PM_{10}), carbon monoxide (CO), Nitrogen dioxide (NO_2), Sulphur dioxide (SO_2), Ozone (O_3), and Lead (Pb). Exposure to high levels of these pollutants poses risks to human health and harms the environment. (Saxena, 2016). The particulate matter (PM) family of pollutants is of particular interest and is classified into fine ($PM_{2.5}$) and coarse (PM_{10}) particulates.

$PM_{2.5}$ are particulates with an aerodynamic diameter of 2.5 µm or less, while PM_{10} have an aerodynamic diameter of 10 µm or less (Matandirotya et al., 2020). $PM_{2.5}$ remains the most healthdamaging pollutant to human beings, as it can penetrate deep into the human respiratory system, thus causing respiratory infections (EPA, 2023). Additionally, exposure to high $PM_{2.5}$ levels has been associated with a high burden of cardiovascular and heart diseases (Xing et al., 2016; Bi et al., 2020; Sangkham et al., 2024).

Zimbabwe is still lagging behind in issues of air quality management and control (Abera et al., 2021) as currently no continuous air quality monitoring network exists in the country (Alvarez et al., 2020). One of the major contributors to this situation is the prohibitive cost of standard research grade monitoring instruments (Montrucchio et al., 2020) therefore ambient pollution data remains scarce. The lack of air quality data is a major drawback in tracking trends as well as making health exposure assessment difficult (Fuller and Kofi Amegah, 2022). Air pollution data gaps also hinder progress towards a coordinated approach to air quality monitoring and management (Modise, 2017; Joubert, Mantooth, and McAllister, 2020; Hodoli et al., 2025). The characterization of the state of air in Zimbabwe is critical for the development of clean air strategies that will promote a positive shift on matters concerning climate and health-related issues (Dangare et al., 2025).

Additionally, in Zimbabwe, research in the sphere of air pollution has been minimal. Few studies of air pollution and mortality epidemiology have been carried out in the country however the extent of the impact of air pollution is largely unknown. Some researchers have carried out studies to investigate the association between exposure and perceived health impacts using data gathered from questionnaires, various institutions, and demographics, without deploying any instruments to measure the actual pollution levels, which is an indirect approach (Mishra, 2003; Hystad, Duong, Brauer et al., 2019; Hystad et al., 2020). Accessing air quality data in Zimbabwe remains a major challenge, and a scarcity of air quality monitoring stations threatens sound policy development and implementation. In addition, most of the available data is accessed through remote sensing (Nyasulu, Thulu and Alexander, 2023)Estimates indicate that air quality in Zimbabwe is generally exceed the air quality guidelines prescribed by the World Health Organisation (Sithole et al., 2023; IQ Air, 2024).

Globally, various instruments have been deployed for air pollution measurements to characterise the state of air pollution in many cities around the world and hence investigate the effects of air pollution on human health and the environment. These measurements are based on detection technologies such as optical, electrochemical, gravimetric, electrical, and remote sensing. Research-grade instruments that are based on these technologies offer accurate air quality data. However, their high deployment and maintenance costs limit their availability, particularly in developing nations like Zimbabwe (Castell et al., 2017).

The use of low-cost sensors (LCSs) for measuring PM has been previously explored, yielding measurements that are informative and comparable with the standard instruments (Nguyen et al., 2021). Their accessibility and affordability, low maintenance cost, low power requirements, easy deployment, and ability to provide real-time data leveraging on Internet of Things (IoT) protocols (Morawska et al., 2018; Liu et al., 2020) allows for widespread deployment and hence, a higher density of stations. A higher density of sensors provides more detailed data, capturing variations in pollution levels across different areas and enabling a better understanding of local air quality. Additionally, low-cost sensors have been shown to facilitate community-engaged approaches to air quality monitoring, thus empowering communities to participate in air pollution research, data collection, and analysis (Ward et al., 2022).

While air pollution challenges in the global south countries that include Zimbabwe are evident, and the detrimental impact of pollutants on the environment and human health has been well-documented, there is still a significant knowledge gap regarding specific characteristics and seasonal variability of ambient air pollution within low-income and densely populated settlements of Zimbabwe. The few existing studies have often relied on indirect assessments, without continuous, localized monitoring data, thereby hindering the development of targeted interventions. This study, therefore, aims to address this data gap by evaluating the seasonal variations of ambient pollution using data gathered by a low-cost air quality monitor deployed in Cold Comfort settlement of Harare over a continuous 12-month period (June 2023 – May 2024). The settlement was chosen as there is a high prevalence of the use of solid fuels, and most of the roads are unpaved. This localized, data-driven approach is the first long-term community-level monitoring effort in Zimbabwe using low-cost sensors and will provide crucial insights into the air quality challenges faced by this vulnerable community. The study is also expected to contribute to a better understanding of pollution patterns and ultimately inform the development of effective and context-specific clean air strategies for Zimbabwe.

Materials and methods

Study area description

Harare is the capital city of Zimbabwe, situated in the Mashonaland region, and covers 982.3 km^2 with an estimated population of 2.487 million (ZimStat, 2024). Zimbabwe lies wholly within the tropics and experiences a sub-tropical climate that is influenced by altitude. Harare, at an altitude of about 1463 m above mean sea level, experiences two main seasons: a unimodal wet season from November to March/April of the following year and a dry season from May to October. The dry season is further divided into a cool dry period (May to August) and a warm to hot dry period (September to October) (Kamusoko, Gamba, and Murakami, 2013). It experiences seasonal temperatures varying from 14°C in the winter months (June and July) to 21°C in the summer months (December-January), about eight hours of sunshine per day, which may drop to 6 hours during the rainy season, and relatively calm wind conditions throughout the year. The prevailing winds generally

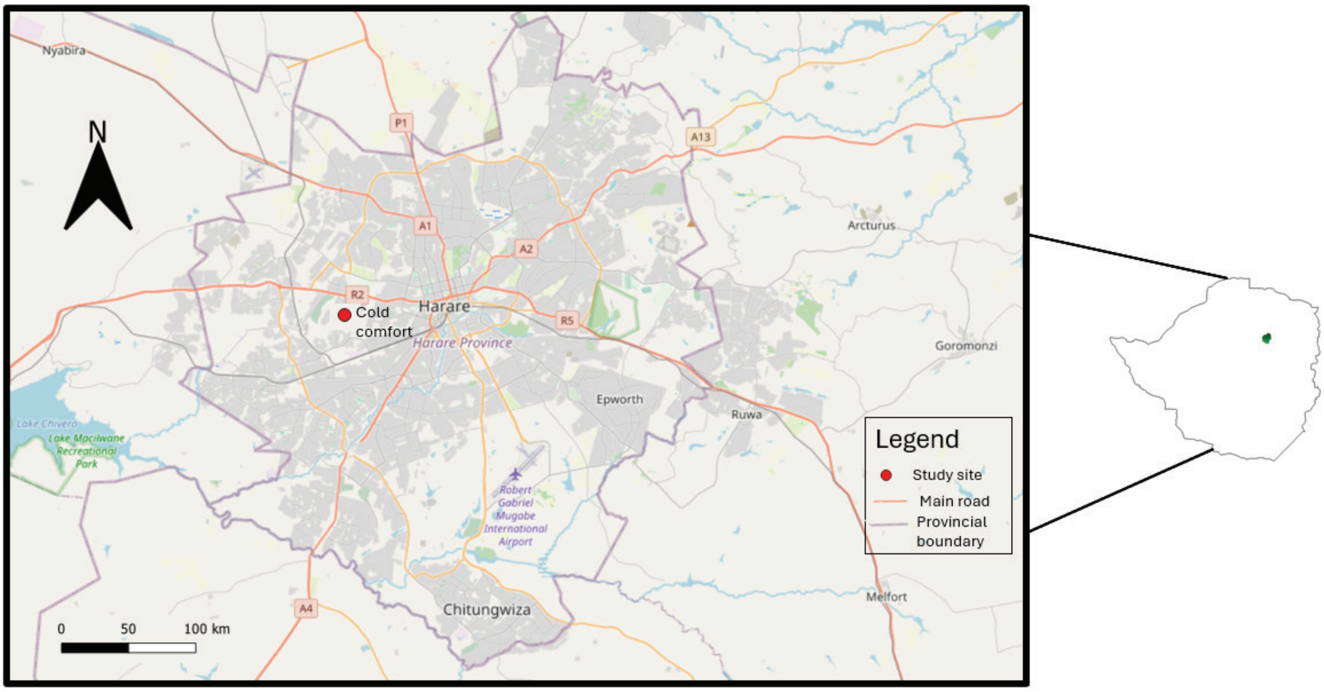

Figure 1: Study site, Cold Comfort settlement located in the city of Harare, Zimbabwe

blow from the east and northeast, with average wind speeds ranging from 3 to 5 m/s. However, occasional gusts of wind can occur during thunderstorms or weather disturbances. The air quality monitor was deployed at Cold Comfort Primary School (-17.85˚; 30.95˚ and an elevation of 1470 metres above sea level) in Cold Comfort, a densely populated urban residential area in Harare Metropolitan Province, Zimbabwe (Figure 1). Cold Comfort is located about 10 km west of the Harare Central Business District (CBD) and downwind of the main industrial sites, such as Workington (~5 km East), and Willowvale (~5 km South-East), and is likely to be an active recipient of pollution-related emissions from the city's industrial sites, vehicular exhausts, construction activities, and biomass burning. The area is also affected by traffic emissions from the nearby Bulawayo (~3km North) and High Glen Roads (~1 km West) of the study site. Neighbouring densely populated suburbs include Kuwadzana (~3.5 km West), Mufakose (~4 km South-West), and Budiriro (~7 km South) of the study site. These factors made the site ideal for the study.

Instrumentation and data collection

Data for the study were gathered using a low-cost sensor (IQ Air Visual Outdoor Monitor, IQAir Steinbach, Switzerland), which we deployed from 8 June 2023 to 31 May 2024.

The monitor was mounted on a metal pole at 2.5 m above the ground surface. This was done to prevent direct emissions from the ground, water splashes, as well as obstructions. The mounting height (set-up shown in Figure 2(a)) is compliant with EPA probe setting criteria (40 CFR part 58, Appendix E). The sensor location was 500 m away from nearby roads, which minimized direct emission from vehicular sources. A solar system was installed to enable a constant power supply.

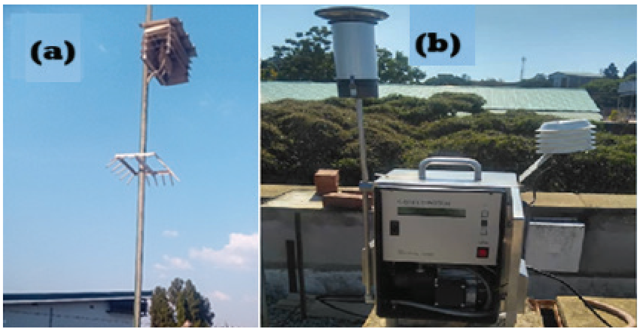

***Figure 2:** (a) IQ Air Visual outdoor monitor mounted on a metal mast and placed in a housing for protection from outdoor environmental effects; (b) Kleinfiltergerat (LVS3) reference low volume sampler for validation of the IQ Air Visual outdoor monitor.*

The deployed monitor is equipped with dual lasers that utilize optical scattering for the detection of particulates (PM_1, $PM_{2.5}$, PM_{10}) at a 5-minute temporal resolution, with a measurement range of 0-1000 μg/m^3 and stated accuracy of 10 μg/m^3. It has additional sensors available for measuring CO_2, temperature, and humidity.

Data processing and analysis

Hourly aggregated measurements of $PM_{2.5}$, PM_{10}, and meteorological data during the measurement period were downloaded and quality checked for instrument errors. The aggregation of the 5-minute raw data into hourly averages was done to account for potential noise and inherent variability in LCS data. To further mitigate instrumental errors such as transient voltage spikes, the Interquartile Range (IQR) method also known as (Tukey's Fences), was applied to detect and remove statistical outliers. The outliers were then replaced using time-based linear interpolation. This interpolation was performed using the na.approx function from the zoo package in R (version 4.5.2), which fills gaps by drawing a straight line between the two closest valid, time-ordered data points. PM outliers were also checked for temporal and circumstantial patterns. Following this cleaning process, all subsequent analysis was conducted using the openair package in R. Systematic bias was assessed by quantifying the error metrics (Root Mean Square Error (RMSE) and Mean Absolute Error (MAE)) against a gravimetric reference method. Time series plots were generated to compare pollution levels and variation patterns, while a pollution rose was generated to identify dominant source directions and characterize the influence of wind speed on pollutant transport over the study period. Since IQ Air devices do not have an option for post-deployment recalibration, we relied on the manufacturer's inherent calibration algorithms within the device.

Air mass trajectory analysis

To investigate the origin of air masses and infer possible pollutant transportation pathways during a peak pollution event, a backward trajectory analysis was performed using the Hybrid Single-Particle Lagrangian Integrated Trajectory (HYSPLIT) model (Version 5.4.2), developed by the National Oceanic and Atmospheric Administration (NOAA) of the United States of America. Three-day (72-hour) back trajectories were simulated, terminating at the study area. The model was run using archived meteorological data from the Global Data Assimilation (GDAS) dataset at simulated arrival heights of 10, 50, and 200 meters above ground level (AGL), which represents the air in the lower atmosphere where people live and breathe.

Low-cost monitor measurement validation

The low-cost IQ Air Visual Outdoor monitor was co-located with a reference low volume sampler (LVS3) from Kleinfiltergerat, Germany, fitted with a PM_{10} head (Figure 2b) at the University of Zimbabwe, Physics Department. The validation was not conducted in situ at the study site due to logistical issues regarding the LVS; also, a $PM_{2.5}$ head was not available during the validation window. The LVS3 collected eight 24-hour PM_{10} samples over eight consecutive days from 22 May 2025 to 29 May 2025, a period that falls at the beginning of the cool, dry winter season. Due to the high operational costs and limited availability of the research-grade sampler, a continuous year-long validation was not feasible.

Each sample was drawn at a flow rate of 2.3 m^3 /hr onto a 47 mm diameter Teflon filter. We then weighed these filters using a Sartorius precision electronic microbalance (Model BCE 223-1S). To account for aerosol water and humidity effects, filters were conditioned in a desiccator for 24 hours prior to both pre- and post-sampling weighing to ensure mass stability. Both the sampling and weighing processes followed the UK Health and Safety Executive (HSE) methods for determining hazardous substances (MDHS 14/3), which outlines procedures for sampling and gravimetric analysis of respirable and inhalable dust (HSE, 2000). Three statistical metrics (coefficient of determination R^2, RMSE, and MAE) were used to intercompare the mass concentrations determined by gravimetric analysis and the daily average concentrations from the low-cost sensor.

Results

Out of a total of 8,616 hours for the study duration, 1,711 had missing data, resulting in 80.14% data availability per parameter. This means nearly 20% of the data was missing (hourly time slots where no measurement was recorded or logged), which could be a result of technical issues such as intermittent power supply from the solar system, sensor malfunction, or periods of poor internet connectivity. The annual means for $PM_{2.5}$ and PM_{10} were 34 µg/m^3 and 58 µg/m^3, respectively (Table 1). These means are higher than the WHO annual air quality guidelines of 5 µg/m^3 and 25 µg/m^3 for the fine and coarse particulates.

The analysis of outliers reveals a stark contrast between sensor types. PM sensor was the primary source of outliers, with $PM_{2.5}$ (519) and PM_{10} (428) showing the highest numbers. The PM outliers were not evenly distributed (Figure 3), showing a higher frequency in winter (JJA) and spring (SON). In comparison, meteorological sensors were highly stable, recording almost no outliers for humidity (0) and temperature (1), and a low number for pressure (86).

Figure 4 presents the correlation matrix for all measured parameters. A near-perfect, significant positive correlation ($r = 0.99$) was observed between PM_{10} and $PM_{2.5}$. Both particulate matter metrics showed a significant moderate negative correlation with relative humidity ($r \approx -0.59$), suggesting that higher humidity may be associated with lower particle

Table 1: *Summary of measured parameters*

	$PM_{2.5}$ (ug/m^3)	PM_{10} (µg/m^3)	Humidity (%)	Pressure (Pascal)	Temperature (Celsius)
Number of valid data points	6905	6905	6905	6905	6905
Number of outliers removed	519	428	0	86	1
Mean	34.1	58.1	61.9	85982	19.6
Median	21	34	63	85956	19
Standard deviation	36.6	70.1	22.7	291	5.98
Minimum	2	1	9	85262	4
Maximum	385	795	100	86996	37

Figure 3: *Distribution of removed $PM_{2.5}$ and PM_{10} outliers over time.*

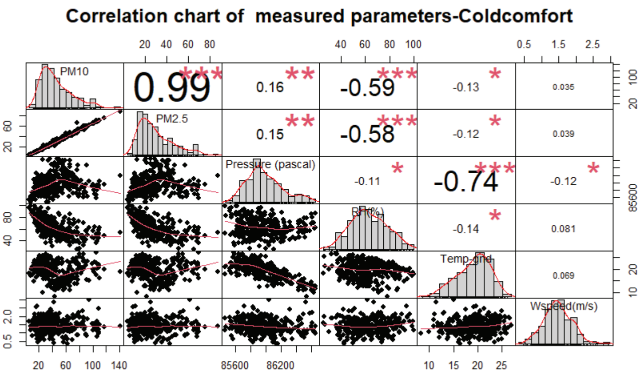

Figure 4: *Correlation matrix for particulates and meteorological parameters at Cold Comfort. The diagonal shows histograms for each variable. The lower-left panels show scatter plots with trend lines. The upper-right panels show Pearson's correlation coefficients, with asterisks (*) indicating the level of statistical significance.*

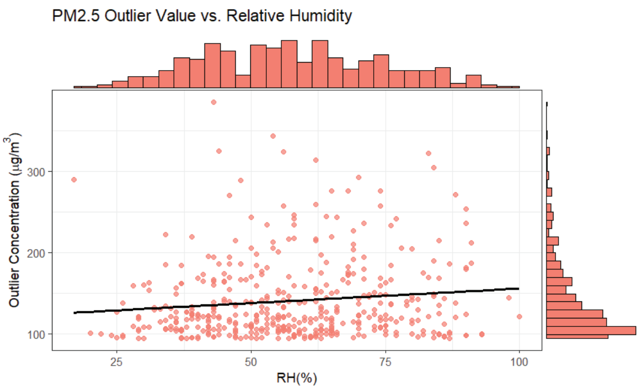

Figure 5: *Relationship between $PM_{2.5}$ outlier concentrations and relative humidity.*

concentrations. Furthermore, a strong negative correlation was found between ambient pressure and temperature (r = -0.74). Wind speed did not show a significant correlation with either PM_{10} or $PM_{2.5}$.

Figure 5 illustrates the relationship between $PM_{2.5}$ outlier events and relative humidity, showing a very weak correlation between them. The scatter plot showed a weak correlation between $PM_{2.5}$ outlier concentrations and relative humidity. The $PM_{2.5}$ outliers displayed a roughly symmetric distribution with relative humidity, which peaks centrally rather than at humidity

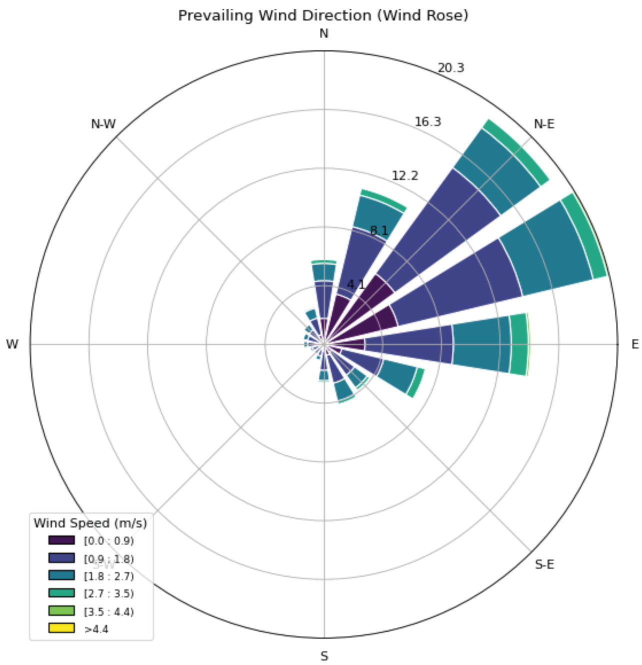

Figure 6: *Wind rose diagram showing the frequency distribution of wind direction and speed at Cold Comfort during the study period. The prevailing winds were mostly Easterly and North-Easterly.*

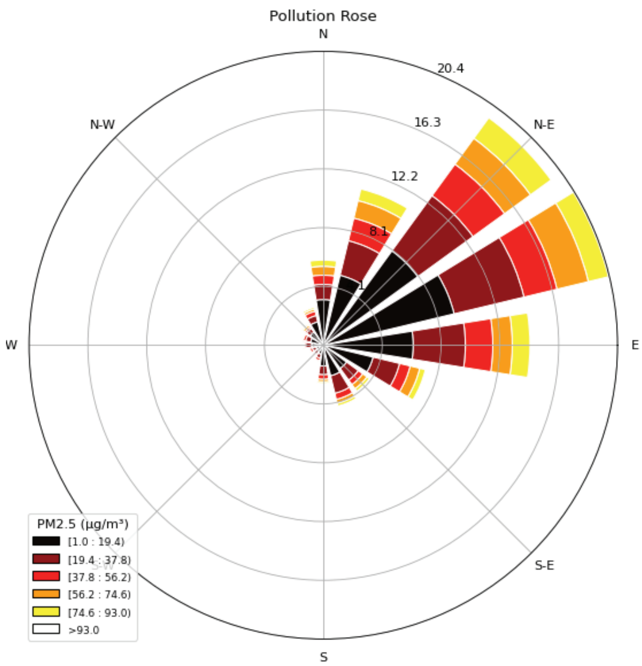

Figure 7: *Bivariate pollution rose of $PM_{2.5}$ concentrations at the Cold Comfort monitoring site. The radial axis represents wind direction probability, and the colour scale represents concentration intervals. High-concentration events are directionally dependent, aligning with the North-East and East sectors.*

extremes. The outliers did not cluster at high humidity (90-100%), ruling out condensation errors where water droplets are misread as particles, nor at low humidity (10-20%), ruling out dry wind-blown dust. The cause is likely unrelated to humidity, pointing instead to local pollution events such as smoke from cooking fires or waste burning, including sensor errors such as power spikes.

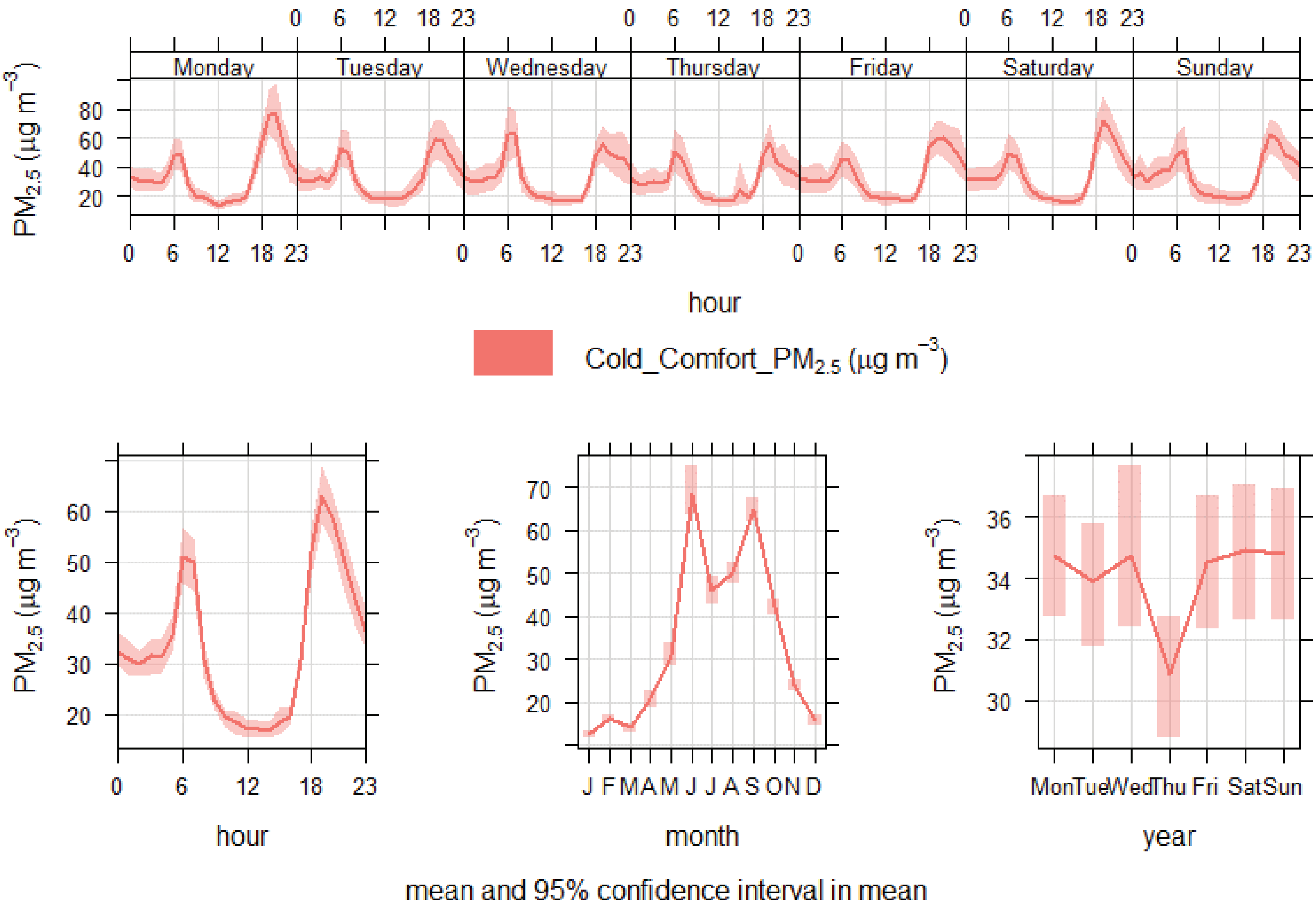

Figure 8: *Time variation plots for mean pollutant concentrations averaged by the hour of the day, day of the week, and month of the year. Emissions peaked during the months of the winter season, extending to spring, which are cool and dry in Harare.*

The wind climatology for the study period is summarized in Figure 6. The site exhibits a dominant prevailing wind flow from the North-East (NE) and East (E) sectors, which collectively account for over 40% of the observed data. In contrast, westerly flows are negligible. The wind speeds are generally low to moderate, with most observations falling below 2.7 m/s (indicated by the purple and blue bands).

The prevailing Easterly and North-Easterly winds place the Cold Comfort site directly downwind of Harare's major anthropogenic sources, including the Workington industrial zone (situated East of the site) and Bulawayo Road (situated North of the site). Consequently, the prevailing winds can transport industrial and vehicular plumes directly toward the residential settlement. However, with only one measurement site, definitively attributing a precise percentage of the pollution to each specific source remains a key challenge for this study.

The pollution source dynamics are visualized in the Pollution Rose (Figure 7), which reveals two distinct pollution regimes driven by wind conditions. The first regime is characterized by local stagnation, indicated by a dark central cluster where moderate pollution (18 – 37 µg/m^3) persists under calm conditions. This confirms that when dispersion is poor, air quality is primarily driven by local domestic emissions, such as biomass burning and waste incineration.

In contrast to this local effect, the plot exhibits a crucial directional dependency for peak pollution events, signifying regional transport. The North-East (NE) sector displays the highest frequency of severe pollution (Yellow bands, > 74 µg/m^3). Geographically, this sector corresponds to the Harare Central Business District (CBD) and major transport corridors located approximately 10 km upwind. This indicates that strong north-easterly winds transport particulates directly into the Cold Comfort settlement. Additionally, the East (E) sector shows elevated contributions linked to the Workington industrial zone, confirming that the site acts as a receptor for emissions from the city's primary anthropogenic centres.

The study further explored the $PM_{2.5}$ levels at hourly, weekly, and monthly timescales by means of a time variation plot (Figure 8). The monthly plots revealed pollutant level characteristics, where concentration levels peaked during winter. Daily cycles show that $PM_{2.5}$ exhibits two emission peaks within a 24-hour period: the morning peak, which starts around 06:00 (local time) and ends around mid-morning, followed by the evening peak, which starts around 18:00 (local time) and ends around midnight. These two peaks are typical of urban vehicular emissions due to the morning and evening rush hours (Gately et al., 2017; Gupta and Elumalai, 2019).

The analysis of the weekly cycle (Figure 8, bottom right panel) reveals a pattern distinct from typical urban commercial settings. Rather than exhibiting a sharp decrease on weekends, $PM_{2.5}$ concentrations at Cold Comfort remain elevated on Saturdays and Sundays, comparable to levels observed on Monday and Wednesday. This persistence suggests that domestic emissions may be the primary driver of local pollution, outweighing the influence of vehicular emissions. As residents spend more time within the settlement on weekends, the reliance on solid fuels for domestic energy sustains the high pollution load. A notable reduction in mean concentration is observed on Thursdays; this anomaly may be linked to specific local variations such as the electricity load-shedding schedule.

A Kruskal-Wallis non-parametric test was performed to determine whether there is a significant difference between seasonal particulate concentrations, with the data grouped by the four seasons (Spring, Summer, Autumn, and Winter). The null hypothesis stated: there is no significant difference between seasonal particulate concentrations, which was to be rejected if p<0.05.

Table 2: *Results of the Kruskal-Wallis test, with χ^2 as the test statistic.*

Pollutant	χ^2	Degrees of freedom(df)	p
$PM_{2.5}$	2555	3	2.2×10^{-6}
PM_{10}	2557	3	2.2×10^{-6}

Large values of χ^2 and very small values of p≈0 observed in Table 2 indicate highly significant differences between seasonal emissions. To identify which specific seasonal pairs were different, a Dunn's post-hoc test was performed with a null hypothesis: there is no significant difference between seasonal pairs (p=0.025). The null hypothesis was to be rejected if p≤0.025. The Dunn's test showed that all seasonal emission pairs for both $PM_{2.5}$ and PM_{10} were significantly different, except for the winter-spring pair, which had p>0.05. This might suggest similar emission patterns or meteorological effects for particulate emissions in both dry seasons.

Time series plots (Figure 9) of the particulates reveal that concentration levels peaked during winter and reduced during the rainy season (November to March) and that, greater than 75% of the period under study, both $PM_{2.5}$ and PM_{10} levels were elevated above the WHO daily standard limits (15 µg/m³ and 45 µg/m³, respectively).

These prolonged elevated levels are very concerning, considering that the study site is in a school environment where pupils below the age of 12 and with different health backgrounds are present. Exposure to elevated levels of air pollution can pose serious health risks to sensitive pupils, such as those with asthma, potentially leading to respiratory ailments that may hinder their academic performance and overall well-being.

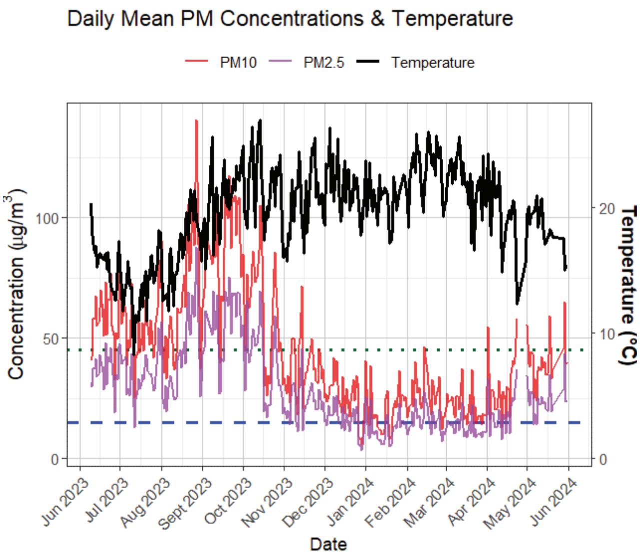

Figure 9: *Daily average variations of $PM_{2.5}$ and PM_{10} concentrations plotted against ambient temperature. The blue dashed line represents the WHO 24-hour guideline for $PM_{2.5}$ (15 µg/m³), and the dark green dotted line represents the guideline for PM_{10} (45 µg/m³). The PM concentrations show a seasonal inverse relationship with ambient temperature.*

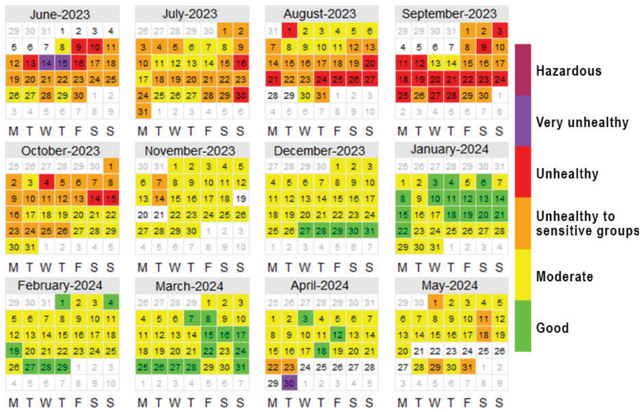

Figure 10: *Calendar plot of air quality indexed according to the US-EPA colour coding.*

The air quality index (AQI) for the study period is shown in the calendar plot (Figure 10), categorized according to the US-EPA color-coding standard. This plot visualizes the seasonal nature of pollution, with a higher frequency of "Unhealthy" days occurring during the winter (JJA) and spring (SON) months. Notably, the monitor detected a significant pollution event on June 14-15, 2023, with air quality classified as "Very Unhealthy." This specific event was selected for a source-receptor analysis to determine the origin of the air mass using the NOAA HYSPLIT model.

Figure 11 presents the 72-hour HYSPLIT backward trajectories that terminated at Cold Comfort on 15 June 2023. The analysis points to a long-range transport event, with regional trajectories showing the air mass originating predominantly from Namibia and Botswana. The air mass was likely pre-loaded with desert dust before arriving in Harare. Crucially, the trajectories passed

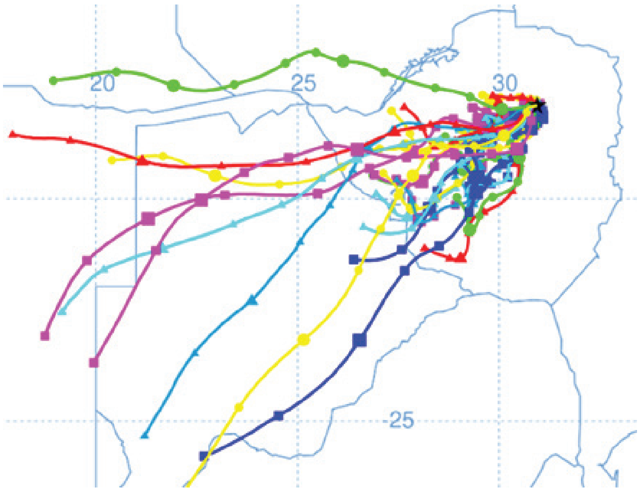

Figure 11: *Backward trajectories arriving at Cold Comfort, Harare, on June 15, 2023. The figure displays 72-hour long-range paths, where colours distinguish arrival heights of 10, 50, and 200 m AGL.*

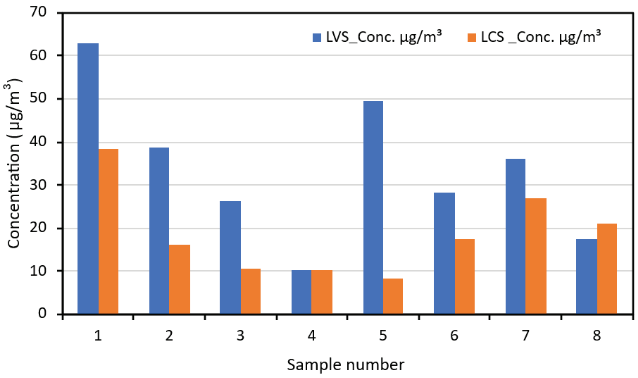

Figure 12: *Intercomparison of PM_{10} mass concentrations determined by gravimetric analysis of eight low-volume sampler filters with concurrent daily averages from a co-located low-cost sensor.*

directly over a dense corridor of Harare's most significant ground-level emission sources. As the air mass traversed the city, it likely accumulated vehicular exhaust emissions, alongside significant domestic smoke from biomass and waste burning common in winter. This strongly suggests that a combination of long-range transport and cumulative local emissions drove the pollution spike.

A comparison of the low-cost sensor PM_{10} measurements with gravimetrically determined concentrations showed that the low-cost sensor measurements showed a weak linear relationship (R^2=0.47). Notably, as shown in Figure 12, the low-cost sensor consistently underestimated PM_{10} concentrations compared to gravimetric measurements, with a Mean Absolute Error (MAE) of 14.2 µg/m^3 and a Root Mean Square Error (RMSE) of 19.7 µg/m^3. This underestimation suggests that the actual air quality could be worse than what the low-cost monitors indicate.

Discussion

This study presents the first long-term assessment of ambient particulate matter in a densely populated, low-income settlement in Harare, Zimbabwe. The findings provide crucial, localized data in a nation with a significant data gap in air quality monitoring and management. The study established that both $PM_{2.5}$ and PM_{10} ambient concentrations peaked in winter (JJA) and remained high through the spring (SON). The observed seasonal patterns are consistent with similar studies conducted in southern Africa region for example Matandirotya et al (2022), Jury and Buthelezi (2022), Matandirotya and Burger (2023), Matandirotya and Burger (2021), Kalisa et al (2023), Matandirotya et al (2023), Dangare et al (2025) highlighting a critical role played by meteorological factors and anthropogenic activities (Utsale et al., 2024). The annual mean $PM_{2.5}$ concentration of 34.1 µg/m^3 was nearly seven times the WHO yearly guideline of 5 µg/m^3.

Meteorologically, winter in the city of Harare is characterized by cool, dry conditions and the prevalence of stable atmospheric temperature inversions. These inversions trap pollutants in the lower atmosphere and inhibit dispersion (Gramsch et al., 2014; Meng et al., 2020). This effect is compounded by the lack of precipitation, which allows pollutants to accumulate. The meteorological trapping coincides with a seasonal spike in local emissions. On the other hand, although domestic cooking is a perennial activity, emission loads intensify during winter due to the added demand for space heating. The drop in temperature forces residents to prolong biomass burning events to keep homes warm. This behavioural shift is statistically confirmed by the time series analysis in Figure 9, which demonstrates an inverse seasonal relationship between temperature and PM concentrations. Simultaneously, the national electricity grid faces peak demand driven by winter wheat irrigation. This agricultural strain exacerbates load shedding, forcing households to switch from clean electricity to 'dirty' biomass fuels (firewood, charcoal) to satisfy essential energy requirements.

This interplay between emissions and meteorology is also evident in the diurnal cycle (Figure 8). The analysis shows two distinct concentration peaks, one in the morning (around 06:00) and one in the evening (around 18:00). These peaks align perfectly with periods of high human activity, such as the morning and evening rush-hour traffic, and more significantly, the preparation of morning and evening meals using solid fuels. Also, the daily cycle of the atmospheric boundary layer, which is at its shallowest (lowest) during these cooler times, can amplify the emission peaks by further concentrating pollutants near the ground.

While seasonal and diurnal patterns point to broad causes, the study area is impacted by a complex mix of specific local sources. Regarding $PM_{2.5}$, unpaved roads and the widespread use of solid fuels such as charcoal and wood are major contributors. The residential combustion of solid fuels impacts indoor air quality and degrades outdoor air quality, particularly in areas where this practice is common (Hystad et al., 2019). The reliance on solid fuels is not unique to Zimbabwe; in Sub-Saharan Africa, its prevalence is estimated at over 80% (Azanaw and Endalew, 2025).

The HYSPLIT analysis of the June 15 event (Figure 11) provided direct evidence linking long-range transport to the observed pollution peak. The trajectory shows the air mass passing directly over significant ground-level emission sources, including the Willowvale and Lytton industrial sites and the Zimbabwe Fertilizer Company, immediately before reaching the monitor. This raises concerns regarding indoor exposure, as studies indicate that indoor environments can be twice as polluted as the outdoors due to infiltration (Ayodele and Dayo, 2017). This is particularly relevant for dwellings located near industrial areas and heavy traffic. It is therefore evident that Cold Comfort's indoor air quality is likely compromised, and dedicated studies are urgently needed to quantify this burden.

To contextualize the magnitude of pollution at Cold Comfort, the observed particulate levels are consistent with measurements from similar residential environments in the region. The annual mean $PM_{2.5}$ concentration of 34.1 µg/m^3 is comparable in magnitude to pollution loads reported in the South African Highveld, where low-income townships heavily reliant on solid fuels for heating often exceed 40 µg/m^3 annually (Matandirotya et al., 2022b, 2023).

Furthermore, regarding the instrumentation, our results are comparable to those obtained by Huda et al. (2024) in Jodhpur, India. Using the identical IQAir Visual outdoor monitor, they reported substantial seasonal elevations driven by anthropogenic activities, validating the sensor's utility in detecting high-pollution events in resource-constrained settings (Huda et al., 2024). This comparison suggests that the situation in Cold Comfort is not an isolated anomaly but part of a broader pattern affecting densely populated, energy-poor settlements across the Global South.

The limitations of the study included a lack of long-term deployment, which means we could not capture long-term pollution trends beyond the sampled year. Also, the monitor validation was of a short-term nature thus failed to capture seasonal variations or consider $PM_{2.5}$ particle sizes though it serves as a strong indicator for other similar high-density settlements in Harare. The monitor proved effective at its primary objective of capturing the spatial-temporal pollutant in Cold Comfort thus laying a strong baseline for future studies. Future work will prioritize in situ, long-term co-location with a $PM_{2.5}$ reference monitor that will enable the development of correction model.

Policy implications

The finding that $PM_{2.5}$ and PM_{10} levels exceeded WHO daily limits for over 75% of the study period (Figure 9) in a school environment is a serious public health concern, posing risks to a vulnerable population of children. Research has indicated a strong link between air pollution and poor cognitive development in children (Miller and Vela, 2013; Hofflinger et al., 2025). This is a worrisome scenario pertaining to issues of pollutant exposure to residents. The situation is further compounded by limited public awareness of air pollution hazards, together with an old and outdated legislation framework for pollution management.

This study provides evidence base needed to move beyond indirect assessments of air pollution. For immediate public health, this data can be used to issue targeted advisories during high-pollution events, recommending that residents minimize exposure by staying indoors or wearing masks, and for long-term solutions, the results can be used to justify the development of strategies to reduce reliance on solid fuels, such as subsidizing clean energy alternatives. This work also makes a strong case to the government and other stakeholders that LCSs can be a cost-effective and essential tool for national air quality management.

Conclusion

The study assessed the quality of ambient air for a period of one year in a densely populated urban settlement of Cold Comfort in the city of Harare, Zimbabwe. Findings were like other studies conducted in Africa and other developing countries. Measurements established that high ambient pollutant concentrations were significantly higher during dry seasons (winter and spring) compared to wet seasons (summer and autumn). Coincidentally, months of winter (JJA) are the same months of peak biomass burning and highly intensive utilisation of domestic solid fuel usage mostly for indoor heating purposes. The annual means of $PM_{2.5}$ and PM_{10} were 34.1µg/m^3 and 58.1µg/m^3, respectively, which were higher than the WHO annual mean (5 µg/m^3 for both $PM_{2.5}$ and PM_{10}), indicating a significant concern for public health. The low-cost sensor consistently under-estimated PM_{10} concentrations compared to gravimetric measurements, but despite limitations in accuracy, the sensor successfully identified the strong seasonal cycle (winter peak), the clear diurnal patterns (morning/evening peaks), and specific pollution events, thus providing a useful qualitative overview of pollution patterns.

To improve air quality, we recommend boosting community awareness to reduce domestic solid fuel use and open waste burning. Additionally, authorities should implement continuous ambient air quality monitoring, especially in industrial areas, to curb industrial emissions. Future work will involve the deployment of a dense network of these low-cost sensors and rigorous calibration and validation that will provide a sustainable data infrastructure and base-level of data to influence policy and galvanize residents for clean air action.

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Ethical considerations

Ethical issues (including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, redundancy, etc.) have been completely observed by the authors.

Consent to publish

All authors read and approved the final version of the manuscript to be published.

Declaration of competing interest

The authors declare that they have no known competing interest or personal association or relationship that could have influenced the direction of the study.

Credit authorship contribution statement

Tonderai Dangare: Conceptualization, data curation, methodology, software, formal analysis, validation, visualisation, writing-original draft, writing-review and editing.
Newton R. Matandirotya: Data curation, methodology, formal analysis, validation, visualisation, writing-original draft, writing-review and editing.
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