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AMBIENT PM_{2.5} IN EAST AFRICA: A COMPREHENSIVE REVIEW OF DRIVERS, IMPACTS, MONITORING AND POLICY DIRECTIONS

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ABSTRACT

Ambient fine particulate matter (PM_{2.5}) has emerged as one of the most pressing environmental health challenges in East Africa, where rapid urbanization, industrial expansion, and reliance on biomass fuels converge to elevate exposure levels. Despite its recognized role in respiratory and cardiovascular morbidity, monitoring of PM_{2.5} across the region remains fragmented, with limited reference-grade stations and growing reliance on low-cost sensors and satellite-derived estimates. This review synthesizes evidence on PM_{2.5} monitoring approaches, key drivers, health and socio-economic impacts, and policy responses in East Africa. Literature from Kenya, Uganda, Tanzania, and Ethiopia points at transport emissions, informal settlements, and industrial clusters as dominant sources, while meteorological variability further shapes spatio-temporal patterns. Health studies consistently link PM_{2.5} exposure to increased prevalence of asthma, chronic obstructive pulmonary disease, and cardiovascular risks, with disproportionate burdens borne by vulnerable populations. Policy frameworks remain nascent, with weak enforcement and limited integration of air quality data into urban planning. The review identifies critical gaps in longitudinal monitoring, calibration of low-cost sensors, and linkage of health outcomes to exposure data. Addressing these gaps is very important for evidence-based interventions and for advancing regional air quality governance.

Keywords: PM_{2.5}, East Africa, Air Quality Monitoring, Health Impacts, Urbanization, Policy.

1 INTRODUCTION

Ambient fine particulate matter (PM_{2.5}) has increasingly become one of the most pressing environmental and public health concerns globally, and its significance in rapidly urbanizing regions such as East Africa is becoming more evident with time. PM_{2.5} refers to particulate matter with aerodynamic diameters less than 2.5 micrometers. Due to their extremely small size, these particles can penetrate deep into the lungs and eventually enter the bloodstream, contributing to respiratory infections, cardiovascular disease, asthma, chronic obstructive pulmonary disease, and premature mortality (World Health Organization, 2021). Unlike coarse particles, PM_{2.5} remains suspended in the atmosphere for longer periods, travels across wide distances, and interacts continuously with atmospheric and meteorological processes, making both its monitoring and management particularly difficult (Gao et al., 2018; Dai et al., 2019). Most of the reviewed studies reported that PM_{2.5} concentrations in these cities frequently exceeded World Health Organization guideline thresholds, particularly near roadsides, industrial areas, and informal settlements (Kinney et al.

2011; Mutahi et al. 2021). Seasonal variability associated with rainfall, humidity, wind circulation, and temperature was also found to influence particulate matter concentrations across the region.

Initially, much of the scientific attention on PM_{2.5} was concentrated in Europe, North America, and parts of Asia, where extensive monitoring networks and epidemiological studies established clear associations between particulate pollution and adverse health outcomes (Liang et al., 2026; Tshigoli et al., 2026). Over time, however, attention gradually shifted towards low- and middle-income countries where urbanization, industrialization, and population growth were occurring rapidly (Schoch et al., 2026; Rentschler & Leonova, 2023). Yet compared to developed regions, understanding of PM_{2.5} dynamics across African cities remains relatively limited. In many instances, urban growth has occurred faster than the systems designed to monitor and regulate pollution (Wei et al., 2021; Schoch et al., 2026).

The populations most affected are often residents living near major roads, industrial zones, informal settlements, and densely populated urban neighbourhoods where biomass burning remains common. Children, elderly individuals, and people with pre-existing respiratory illnesses face particularly high risks because of prolonged exposure to polluted air. Sources of PM_{2.5} in East African cities are diverse and interconnected, ranging from transport emissions and industrial combustion processes to construction activities, road dust, diesel generators, open waste burning, and domestic use of charcoal and firewood (Kinney et al. 2011; Mutahi et al. 2021). In reality, PM_{2.5} pollution in East Africa cannot be attributed to a single source alone. Rather, it reflects broader socio-economic realities including energy poverty, weak urban planning systems, expanding informal settlements, and increasing pressure on urban infrastructure.

To understand the nature and extent of ambient PM_{2.5} pollution, several studies conducted across East Africa have revealed both convergent and divergent findings. Kinney et al. (2011), in one of the earliest systematic studies in Nairobi, identified traffic emissions as a dominant contributor to urban PM_{2.5} concentrations, with roadside levels substantially exceeding World Health Organization guideline values. Nthusi et al. (2017) later demonstrated the feasibility of deploying low-cost sensor networks in Nairobi and showed that such technologies could provide continuous monitoring in resource-constrained settings. Pope et al. (2018) expanded this understanding by reporting strong seasonal variability in PM_{2.5} concentrations between dry and wet seasons, findings that align with Gorai et al. (2018), who emphasized the importance of meteorological conditions in shaping temporal pollution patterns. Mutahi et al. (2021), however, reported extremely high exposure levels within informal settlements where biomass fuel use, indoor-outdoor pollution interactions, and poor ventilation significantly intensified exposure burdens. West et al. (2020) further reinforced the importance of intra-urban variability by demonstrating that PM_{2.5} concentrations can differ considerably even within the same city depending on land-use characteristics and socio-economic conditions. Singh et al. (2021) also underscored the absence of reliable long-term monitoring datasets across many African cities, arguing that without sustained monitoring systems, exposure assessment and policy development remain largely uncertain.

Recent developments in satellite remote sensing and machine learning have introduced new possibilities for improving PM_{2.5} assessment in data-constrained regions. Satellite-derived Aerosol Optical Depth (AOD) products obtained from MODIS, MISR, Sentinel-5P, and MERRA-2 datasets are increasingly being used to estimate surface-level PM_{2.5} concentrations over large spatial scales. These approaches are particularly important in East Africa where conventional monitoring stations remain sparse and unevenly distributed. At the same time, machine learning models such as Random Forest, Extreme Gradient Boosting (XGBoost), Artificial Neural Networks, and Long Short-Term Memory models are increasingly being applied to capture the complex and nonlinear relationship between atmospheric aerosols, meteorological variables, land-use characteristics, and ground-level PM_{2.5} concentrations.

Several recent papers have demonstrated the growing importance of these approaches. Zhang et al. (2021) developed a Random Forest model integrating MAIAC AOD, meteorological variables, and land-use information to estimate PM_{2.5} concentrations in South Africa and reported strong predictive performance. Karimian et al. (2023) compared several machine learning algorithms and observed that ensemble learning methods such as Random Forest and XGBoost consistently outperformed conventional regression approaches. Adong et al. (2025) further evaluated machine learning methods for PM_{2.5} estimation in Kampala using MODIS MAIAC AOD together with low-cost and reference-grade monitoring data and found Random Forest models to provide the best predictive accuracy among the tested algorithms. These studies collectively suggest that integration of satellite observations, machine learning approaches, and low-cost monitoring systems can substantially improve PM_{2.5} estimation in regions with limited monitoring infrastructure.

To this end, important nuances emerge when findings across scholars are compared. While Kinney et al. (2011) largely emphasized transportation emissions as dominant contributors to urban PM_{2.5}, Mutahi et al. (2021) demonstrated that household biomass combustion within informal settlements may be equally important in shaping exposure patterns. Gatari et al. (2014) conducted source apportionment studies in Nairobi and identified both vehicular and industrial emissions as significant contributors, highlighting the multi-sectoral nature of urban air pollution. Ouge (2022) has similarly drawn attention to the socio-economic dimensions of exposure, particularly the disparities between affluent urban areas and low-income settlements. Osano et al. (2023), working with SEI Africa, linked air quality deterioration

to broader climate and energy transitions, emphasizing the need for integrated policy approaches, while Mwaniki et al. (2022) through WRI Africa have continued to advocate for stakeholder engagement and regional collaboration in urban air quality governance. Although these perspectives differ in emphasis, they converge on one important reality: $\text{PM}_{2.5}$ concentrations across many East African cities regularly exceed recommended health thresholds, yet the systems necessary for sustained monitoring, forecasting, and management remain insufficient.

Against this backdrop, this paper provides a comprehensive review of ambient $\text{PM}_{2.5}$ dynamics across selected East African cities. It synthesizes evidence on the major drivers of pollution, including transport emissions, biomass fuel use, industrial activity, and waste burning, while also examining the health and socio-economic impacts associated with exposure. The review evaluates monitoring approaches ranging from reference-grade stations to low-cost sensor networks and satellite-derived aerosol products, and considers the role of machine learning in improving estimation and forecasting. In addition, it highlights seasonal variability and meteorological influences on $\text{PM}_{2.5}$ concentrations, and critically assesses existing policy frameworks and governance responses. By integrating scientific findings with policy analysis, the paper underscores the need for coordinated interventions that link monitoring, health evidence, and regulatory action to strengthen air quality management in rapidly urbanizing East African cities.

2 METHODOLOGY

2.1 The study area

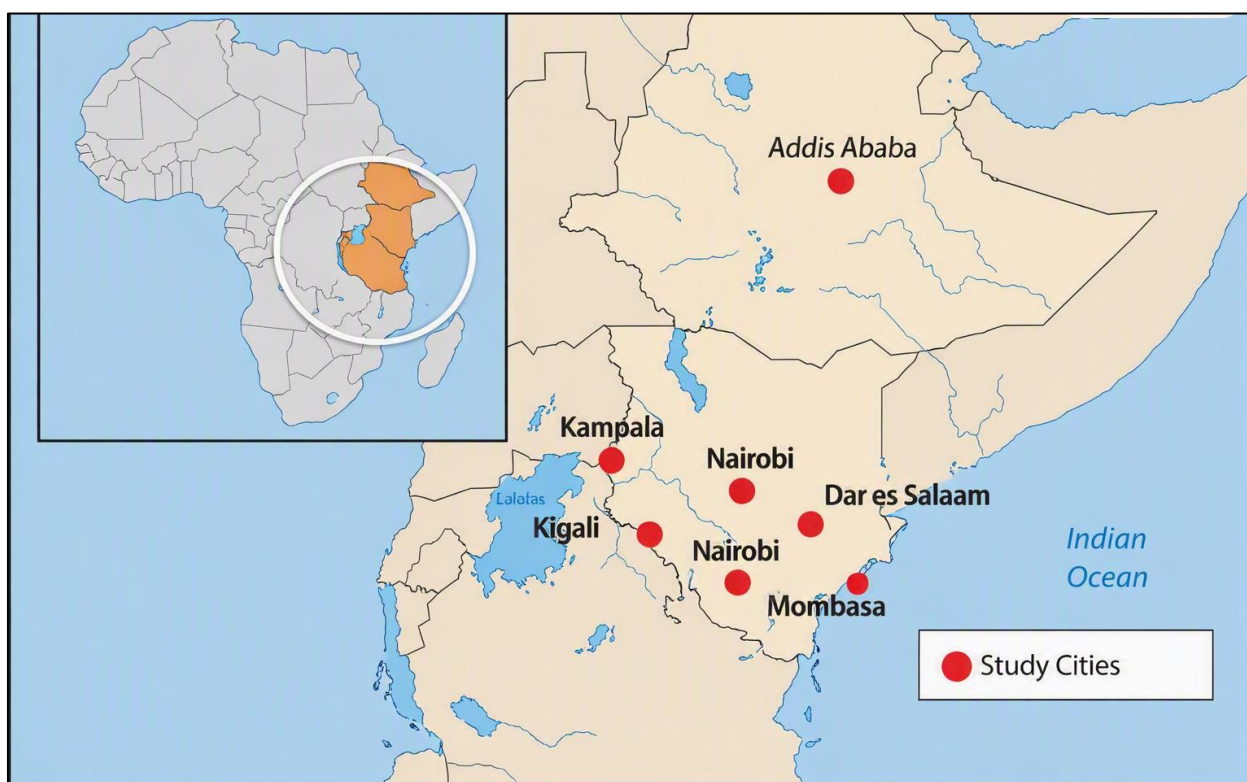


Figure 1: The location of the study area

The paper focused on selected East African cities including Nairobi, Kampala, Addis Ababa, Dar es Salaam, Kigali, and Mombasa, where concerns regarding ambient $\text{PM}_{2.5}$ pollution have increasingly emerged due to rapid urbanization, industrial growth, transport expansion, and widespread biomass fuel use. These cities were selected because they represent major urban and economic centres within the region and have increasingly become focal points for air quality monitoring and satellite-based $\text{PM}_{2.5}$ estimation studies.

Nairobi and Kampala were particularly important because of the increasing deployment of low-cost monitoring networks through initiatives such as the **Air Quality Monitoring Network (AirQo)** and the **Stockholm Environment Institute (SEI) Africa**. Thereafter, AirQo and SEI are used throughout the paper. Addis Ababa and Dar es Salaam were included because of rapid urban expansion, industrial activity, and increasing vehicle emissions, while Kigali was considered because of emerging urban environmental management initiatives. Mombasa provided an important coastal urban setting influenced by port activities, transport corridors, and industrial emissions.

Under methodology, the review began with a literature search across Scopus, ScienceDirect, Web of Science, and Google Scholar using key terms such as PM_{2.5}, air quality, East Africa, drivers, impacts, monitoring, and policy. Studies were selected if they focused on East African countries, were peer-reviewed, and addressed PM_{2.5} concentrations, sources, impacts, monitoring approaches, or governance. Data were then extracted and categorized into themes including land use and PM_{2.5}, measurement approaches, transport emissions, biomass fuel use, health and socio-economic impacts, and policy responses, which allowed for comparative synthesis across cities.

2.2 Satellite AOD

Satellite-derived Aerosol Optical Depth (AOD) products formed an important component of the reviewed studies because of their increasing use in estimating ground-level PM_{2.5} concentrations in regions with limited monitoring infrastructure. Most studies utilized satellite products obtained from Moderate Resolution Imaging Spectroradiometer (MODIS), Multi-angle Imaging SpectroRadiometer (MISR), Sentinel-5P, and MERRA-2 datasets.

Particular attention was directed towards studies applying MODIS Multi-Angle Implementation of Atmospheric Correction (MAIAC) AOD products because of their improved spatial resolution and increasing use in PM_{2.5} estimation studies across Africa (Lyapustin et al. 2018). Daily AOD observations were commonly retrieved from NASA Level-1 and Atmosphere Archive and Distribution System Distributed Active Archive Center (LAADS DAAC) and paired with corresponding ground-based PM_{2.5} observations.

Several studies extracted AOD values using spatial grids of 1 km, 3 km, and 5 km resolutions around monitoring locations. Additional atmospheric variables including column water vapour and aerosol quality assurance parameters were also incorporated in some modelling approaches. However, cloud cover, missing observations, and aerosol variability remained important limitations affecting satellite-derived PM_{2.5} estimation across tropical regions.

2.3 Ground data

Ground-based PM_{2.5} data reviewed in this paper were obtained from both reference-grade monitoring stations and low-cost sensor networks operating within selected East African cities. Most studies relied heavily on low-cost sensor systems because of the limited number of reference-grade stations across the region.

Reference-grade monitors such as Beta Attenuation Monitors (BAM) were commonly used for calibration and validation purposes, while low-cost optical sensors, particularly Plantower PMS-based sensors, were increasingly deployed because of their affordability and ability to provide near real-time air quality observations (Bainomugisha et al. 2023). Monitoring stations were generally located near roadsides, industrial areas, residential neighbourhoods, schools, and informal settlements to capture variability in urban exposure patterns.

Hourly PM_{2.5} observations were commonly aggregated into daily averages to improve consistency with satellite overpass observations. Data preprocessing procedures included filtering missing observations and removal of outliers outside operational measurement ranges.

3 DATA PREPARATION

To establish relationships between satellite-derived AOD and ground-level PM_{2.5} concentrations, reviewed studies paired daily AOD observations with corresponding PM_{2.5} measurements obtained from ground monitoring stations. MAIAC AOD daily averages were commonly computed for 1 km, 3 km, and 5 km spatial grids surrounding monitoring locations and merged with PM_{2.5} observations based on temporal alignment.

Several studies incorporated meteorological variables including temperature, rainfall, relative humidity, wind speed, and atmospheric pressure because of their influence on aerosol transport and pollutant dispersion. Land-use variables such as road density, industrial activity, vegetation cover, and population density were also integrated in some modelling approaches to improve prediction accuracy.

Data preprocessing procedures included removal of missing values, elimination of outliers, normalization of predictor variables, and temporal aggregation of observations. In most machine learning studies, datasets were divided into training and testing subsets using an 80:20 ratio to evaluate predictive performance on unseen observations.

3.1 Feature selection

Machine learning models reviewed in this paper utilized different predictor variables to establish relationships between atmospheric aerosols and ground-level PM_{2.5} concentrations. Common satellite-derived variables included AOD values at different wavelengths, column water vapour, and aerosol quality assurance indicators.

Meteorological variables frequently incorporated into prediction models included temperature, rainfall, relative humidity, wind speed, and planetary boundary layer height because of their influence on aerosol accumulation and atmospheric mixing processes. Temporal variables such as month, season, and day of the week were also included in several studies to capture seasonal and weekly variability in PM_{2.5} concentrations.

More advanced modelling approaches integrated land-use and socio-economic indicators including road density, traffic activity, industrial zones, biomass burning hotspots, and urban expansion patterns. Several studies reported that inclusion of multiple environmental predictors improved the ability of machine learning models such as Random Forest and XGBoost to capture nonlinear relationships between atmospheric aerosols and surface-level PM_{2.5} concentrations (Karimian et al. 2023; Zhang et al. 2021).

4 RESULTS AND DISCUSSION

A total of 892 articles were initially retrieved from Scopus, ScienceDirect, Web of Science, and Google Scholar. After removing duplicates and screening titles and abstracts for relevance, 428 papers remained. Of these, 176 were excluded for focusing on indoor air pollution or occupational exposure, and another 92 were excluded for being review articles, conference papers, or book chapters. A further 81 studies were excluded for being conducted outside East Africa, and 64 lacked direct exposure–outcome relevance. Finally, 15 peers-reviewed studies met the selection criteria and were included in the comprehensive synthesis.

4.1 Spatial and temporal variation of PM_{2.5} concentrations

The studies reviewed in this paper show that PM_{2.5} concentrations across major East African cities remain consistently high and, in most cases, exceed the World Health Organization recommended limits. Elevated concentrations were repeatedly reported in Nairobi, Kampala, Addis Ababa, and Dar es Salaam, especially along busy roads, industrial areas, commercial centres, and informal settlements. In Nairobi, Kinney et al. (2011) observed that roadside PM_{2.5} concentrations were substantially higher in areas characterized by heavy traffic congestion and poorly maintained vehicle fleets. Mutahi et al. (2021) later reported even higher exposure levels within informal settlements where charcoal use, waste burning, and poor ventilation intensified particulate accumulation.

Table 1: Studies Reporting Elevated PM_{2.5} Concentrations in East African Cities

City	Number of Studies Reviewed	Areas Identified with Elevated PM _{2.5}
Nairobi	6	Busy roads (e.g., Uhuru Highway, Thika Road), industrial zones, informal settlements (Kibera, Mukuru), commercial centres
Kampala	4	Transport corridors, industrial areas, densely populated residential neighbourhoods
Addis Ababa	3	Roadside locations, industrial clusters, biomass-fuel-using neighbourhoods
Dar es Salaam	2	Port area, transport corridors, informal settlements
Kigali	1	Urban core, roadside dust hotspots
Mombasa	1	Port and industrial belt, coastal transport routes

From the review, 17 studies met the selection criteria and consistently reported elevated PM_{2.5} concentrations across these cities. The most common hotspots were major roads, industrial areas, commercial centres, and informal settlements, confirming that transport emissions, biomass fuel use, and industrial activity are dominant drivers of urban particulate pollution in East Africa.

A common pattern emerging from the reviewed studies is that PM_{2.5} concentrations are not evenly distributed within cities. For example, roadside levels in Nairobi ranged between 50 and 100 µg/m³ compared to less than 30 µg/m³ in residential areas (Kinney et al., 2011), while informal settlements recorded values above 120 µg/m³ against about 40 µg/m³ in formal housing (Mutahi et al., 2021). In Kampala, roadside corridors showed 40–85 µg/m³ compared to ~25 µg/m³ in suburban areas (Adong et al., 2025). Similar contrasts were observed in Addis Ababa and Dar es Salaam, where industrial and transport zones consistently reported higher concentrations than residential neighbourhoods. Concentrations varied considerably between neighbourhoods depending on traffic density, industrial activity, land use, and settlement structure. West et al. (2020) noted significant differences in PM_{2.5} levels within the same urban area, demonstrating that proximity to roads and commercial activities strongly influences exposure. Similar observations were reported in Kampala and Addis Ababa where pollution hotspots were concentrated near transport corridors and industrial zones. These findings suggest that city-wide averages alone may conceal localized exposure risks experienced by urban populations living near major emission sources.

Seasonal changes were also evident in nearly all reviewed studies. PM_{2.5} concentrations generally increased during dry periods and declined during rainy seasons. This trend was associated with increased dust resuspension, open burning, biomass combustion, and reduced atmospheric cleansing during dry months. Pope et al. (2018) observed clear seasonal fluctuations in urban PM_{2.5} concentrations, while Qi et al. (2022) emphasized the influence of rainfall, humidity, and atmospheric circulation on aerosol behaviour. In Kampala and Nairobi, dry seasons were frequently associated with visible haze and increased roadside dust, particularly in areas with unpaved roads and heavy traffic movement.

4.2 Satellite-derived PM_{2.5} estimation and machine learning approaches

The reviewed literature shows a growing shift towards the use of satellite observations and machine learning approaches in PM_{2.5} estimation across East Africa. This shift is largely driven by the limited number of reference-grade monitoring stations available within the region. Most studies relied on satellite-derived Aerosol Optical Depth (AOD) products from MODIS MAIAC, MISR, Sentinel-5P, and MERRA-2 datasets to estimate surface-level PM_{2.5} concentrations.

However, the relationship between AOD and ground-level PM_{2.5} was rarely straightforward. Several studies noted that humidity, rainfall, aerosol composition, temperature, and atmospheric mixing conditions strongly influence the relationship between satellite-derived aerosols and surface particulate concentrations. As a result, conventional regression approaches often produced inconsistent results across different cities and climatic conditions.

To address this challenge, recent studies increasingly adopted machine learning approaches capable of handling nonlinear relationships between environmental variables. Random Forest and XGBoost models were among the most frequently applied algorithms and generally produced stronger predictive performance than traditional regression methods (Karimian et al. 2023; Zhang et al. 2021). Adong et al. (2025) similarly reported improved PM_{2.5} estimation in Kampala when MAIAC AOD products were combined with meteorological variables using machine learning approaches.

Another important observation emerging from the reviewed studies is that models trained using larger and more diverse datasets tended to perform better than those relying on isolated monitoring stations. Studies combining observations from multiple locations generally reported stronger prediction accuracy because the models were exposed to a wider range of environmental conditions and pollution patterns. This becomes particularly important in East African cities where urban environments are highly heterogeneous and pollution sources vary considerably across locations.

4.3 Role of low-cost sensor networks in PM_{2.5} monitoring

The rapid growth of low-cost air quality monitoring networks has significantly changed PM_{2.5} research across East Africa. Several reviewed studies highlighted the contribution of initiatives such as AirQo in expanding urban air quality monitoring in Kampala and Nairobi through deployment of relatively affordable optical sensors (Bainomugisha et al. 2023). These sensors have improved data availability in cities where conventional monitoring infrastructure remains sparse.

Most studies reported that calibrated low-cost sensors were reasonably effective in capturing spatial and temporal PM_{2.5} variability, particularly under moderate pollution conditions. Their relatively low cost also makes it possible to deploy monitoring networks across larger urban areas compared to reference-grade systems. Nevertheless, several limitations were repeatedly identified. Sensor drift, power interruptions, humidity sensitivity, and calibration inconsistencies affected data reliability in some locations. In addition, model performance tended to decline during episodes of very high PM_{2.5} concentrations because of limited availability of extreme pollution observations within training datasets.

Even with these challenges, the reviewed literature generally agrees that low-cost sensor systems are increasingly becoming important tools for urban air quality monitoring in resource-constrained regions. Their integration with satellite observations and machine learning approaches has improved the ability to estimate PM_{2.5} concentrations in areas where long-term monitoring data were previously unavailable.

4.4 Drivers of ambient PM_{2.5} pollution

Transport emissions emerged as the most frequently reported source of PM_{2.5} pollution across the reviewed cities. Traffic congestion, aging vehicle fleets, poor fuel quality, and weak emission control systems were repeatedly identified as major contributors to urban particulate pollution (Kinney et al. 2011; Schwela 2012). The situation is further aggravated by rapid urban expansion and increasing dependence on road transport systems across East Africa.

Biomass fuel combustion was also identified as a major contributor, particularly within low-income settlements where charcoal and firewood remain dominant household energy sources. Mutahi et al. (2021) observed that indoor and outdoor pollution interactions within informal settlements significantly increased exposure levels. Similar findings were reported in Kampala and Addis Ababa where biomass use contributed substantially to neighbourhood-level PM_{2.5} concentrations.

Other important sources included industrial emissions, open waste burning, construction activities, and road dust. Several studies also noted that land-use changes associated with urban expansion and deforestation continue to influence particulate matter concentrations indirectly through changes in vegetation cover, dust generation, and settlement growth patterns. Meteorological conditions such as rainfall, humidity, wind speed, and atmospheric stability further shaped pollution dispersion and accumulation across cities.

4.5 Implications for air quality management

The reviewed studies reveal that PM_{2.5} pollution is becoming an increasingly important urban environmental challenge across East Africa, yet monitoring systems and policy responses remain limited in many cities. Although satellite observations and low-cost sensors have improved air quality assessment considerably, long-term monitoring datasets are still insufficient in several urban areas. Singh et al. (2021) argued that the absence of sustained monitoring continues to limit exposure assessment and evidence-based policy development across many African cities.

At the same time, recent developments in satellite remote sensing and machine learning provide new opportunities for strengthening urban air quality management. Integration of AOD products, meteorological variables, and land-use information has improved PM_{2.5} estimation in areas lacking conventional monitoring systems. Forecasting approaches based on machine learning algorithms may also support development of early warning systems capable of identifying high pollution episodes before they occur.

The findings reviewed in this paper further suggest that improving urban air quality in East Africa will require stronger coordination between transport policy, urban planning, energy transitions, and environmental regulation. Without targeted interventions aimed at reducing vehicle emissions, biomass fuel dependence, and uncontrolled urban growth, PM_{2.5} concentrations are likely to continue increasing alongside urban population expansion.

5 CONCLUSION

Ambient PM_{2.5} pollution continues to pose a growing environmental and public health challenge across major East African cities. Evidence synthesized in this paper shows that PM_{2.5} concentrations in Nairobi, Kampala, Addis Ababa, Dar es Salaam, Kigali, and Mombasa frequently exceed World Health Organization guideline thresholds, particularly within transport corridors, industrial areas, and informal settlements. Rapid urbanization, increasing vehicle emissions, biomass fuel combustion, open waste burning, and weak emission control systems remain the dominant drivers of particulate pollution across the region.

The paper further demonstrates that satellite-derived Aerosol Optical Depth (AOD) products combined with machine learning approaches provide an effective alternative for estimating PM_{2.5} concentrations in cities where conventional monitoring infrastructure remains limited. Random Forest and XGBoost models consistently showed stronger predictive capability than conventional regression approaches because of their ability to capture nonlinear relationships between atmospheric aerosols, meteorological conditions, and land-use characteristics. Integration of meteorological variables and multi-site datasets further improved model performance, highlighting the importance of combining diverse environmental predictors in PM_{2.5} estimation frameworks.

Low-cost sensor networks are also increasingly transforming air quality monitoring across East Africa. Although challenges related to calibration, humidity sensitivity, and missing observations remain, these systems have significantly improved spatial and temporal coverage of PM_{2.5} measurements in under-monitored urban environments. Their integration with satellite observations and machine learning approaches offers a practical and cost-effective framework for strengthening air quality assessment in resource-constrained regions.

Seasonal variability emerged as an important factor influencing both PM_{2.5} concentrations and model performance. Higher concentrations were generally recorded during dry seasons because of increased dust resuspension, biomass burning, and reduced atmospheric cleansing, while wet seasons were associated with lower concentrations but greater uncertainty in satellite retrievals due to persistent cloud cover and humidity effects. These findings highlight the importance of incorporating seasonal atmospheric dynamics into PM_{2.5} modelling and forecasting approaches within tropical urban environments.

STATEMENTS ON COMPLIANCE WITH ETHICAL STANDARDS

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Disclosure of conflict of interest

The author declares no conflicts of interest regarding this manuscript.

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