

Accuracy of Smartphone-Based Road Traffic Noise Measurement in Nairobi City, Kenya

Akech Elisha Ochungo^{1,2*}, Simpson Nyambane Osano², John Francis Gichaga²

¹Department of Civil, Faculty of Engineering and Technology (FoET), Multimedia University, Nairobi, Kenya

²Department of Civil and Construction Engineering, University of Nairobi, Nairobi, Kenya

Email: *elishakech1@gmail.com

How to cite this paper: Ochungo, A.E., Osano, S.N. and Gichaga, J.F. (2025) Accuracy of Smartphone-Based Road Traffic Noise Measurement in Nairobi City, Kenya. *World Journal of Engineering and Technology*, **13**, 816-834.
<https://doi.org/10.4236/wjet.2025.134051>

Received: August 11, 2025

Accepted: October 14, 2025

Published: October 17, 2025

Copyright © 2025 by author(s) and Scientific Research Publishing Inc.

This work is licensed under the Creative Commons Attribution International License (CC BY 4.0).

<http://creativecommons.org/licenses/by/4.0/>



Open Access

Abstract

Conventionally, Sound Level Meters have been used to measure Road Traffic Noise in cities to monitor the acoustic soundscape of neighborhoods. However, today, use of smartphone to record Road Traffic Noise is gaining traction. The key limitation in this shift remains the accuracy gap between the calibrated Sound Level Meter's data and the smartphone-captured data. In this study, a handheld Android Smartphone, the Samsung Galaxy A12 Model SM-A127F/DS, was used alongside the Lutron SL-4033SD, a Class 1 Sound Level Meter, to establish the accuracy of smartphone integration in the measurement of road traffic noise data in Nairobi, the capital city of Kenya. In previous works, authors have commonly used statistical methods such as; Mean Absolute Error (MAE), Standard Deviation (SD), Root Mean Square Error (RMSE), and Pearson's correlation coefficient to evaluate the accuracy of smartphone-based noise measurements against reference Sound Level Meters (SLMs) with whose reported error ranges falling typically between ± 0.5 dB(A) and ± 3.5 dB(A) depending on the device model, environment, and methodology used. The present study used the metrology of the Margin of Error (MoE) formula to give confidence in the integration of smartphones into city's noisescapes assessment. The results of the measurement indicate that the Margin of Error is ± 0.4247 dB(A). This lends credence to the possible innovative application of smartphones in noise measurement, given their widespread presence. Hence, the potency of applying the citizen science method (crowdsourcing) in real-time noise level monitoring. Its only drawback is the computation of the equivalent continuous sound level (L_{eq}) from raw audio data, where one has to use coding-based applications. However, in this era of Artificial Intelligence (AI) and Machine Learning (ML), such codes can be embedded in the web platforms for automatic transformations. This is presumed to be cheaper than the installation of a noise measurement sensor network. Nairobi city management can therefore, in the future, adopt crowdsourced noise data from smartphones to

update its real-time noise map.

Keywords

Noise, Smartphone, Sound Level Meter

1. Introduction

Sound plays an important role in human life, enabling communication, emotional expression, environmental awareness, and safety. However, this positive perception is being increasingly disturbed by excessive and undesired sound, also referred to as environmental noise pollution, in the context of urbanization. Among the various sources of noise pollution, Road Traffic Noise (RTN) is the most common source of environmental noise in urban areas [1] [2]. The World Health Organization (WHO) identifies Road Traffic Noise as the second most critical environmental risk to public health in Europe, following air pollution, a ranking that underscores the urgency of noise pollution research even in regions where regulation already exists. Road Traffic Noise is not merely a disturbance; it also poses substantial threats to public health. Long-term exposure to noisy surroundings has been linked to increased stress, accelerated heartbeats, abnormal sleep cycles, and impaired cognitive function [3] [4].

In developing cities such as Nairobi, Kenya, the issue of road traffic noise (RTN) is aggravated by rapid and often unstructured urban growth, limited noise zoning enforcement, and the increase of informal settlements near major roads. These factors are exacerbated by outdated and occasionally simplistic environmental laws as well as a lack of public knowledge concerning noise pollution. Around fifty-five percent of all urban noise pollution is caused by motor vehicle traffic, which makes up a substantial portion of the urban environment [5]-[7].

The road network for Nairobi includes: highways, feeder roads, roundabouts, and informal transport corridors. This network presents a complex acoustic environment due to variable traffic flows, frequent congestion, and a diverse traffic mix comprising Bicycles, Motorcycles, Saloon Cars, Pick-ups, SUVs, Public Service Vehicles (PSVs), Buses, Light Trucks, Medium Trucks, Heavy Trucks, and other forms such as tractors. Nairobi has a dynamic and unpredictable traffic flow pattern, leading to frequently varying noise levels throughout the day, as compared to other cities with well-regulated transportation systems.

Despite these challenges, thorough city-wide research on RTN in Nairobi is still scarce. Few empirical studies are available on the public domain, and the majority of the literature is made up of individual case studies or brief monitoring initiatives. For instance, using spot measurements made during specific hours, [8] created a Geographical Information System (GIS)-based map of Nairobi's noise pollution, providing an early visual representation of noise hotspots. A short-term environmental noise assessment in Nairobi's Central Business District by [9]

found very high noise levels, although it lacked more comprehensive coverage. Similar to this, [10] used Standard Level Meters (SLMs) to examine vehicle noise pollution in Nairobi's downtown area. A decade ago, a study by [11] also used conventional dosimetry techniques to investigate road traffic noise levels in certain zones of the city. And most recently, [12] used noise maps to compare the amounts of noise that were probable and observed; however, their validation mostly relied on modelled estimations rather than real-time data. This lack of robust and consistent data inhibits the development of targeted urban planning policies, noise zoning frameworks, and effective RTN abatement countermeasures for Nairobi city.

Traditionally, efforts to capture RTN measurements have relied heavily on professional instruments such as Sound Level Meters (SLMs) and Noise Dosimeters, which are capable of capturing Sound Pressure Levels with very high precision. Because of their consistent accuracy and adherence to international measurement techniques backed by standards like IEC 61672. Without a doubt, SLMs continue to be the golden tools for environmental noise evaluations worldwide. They have been generally used in several studies to monitor RTN and evaluate the impacts on public health in urban settings, for example, in cities like Paris [13], Doha [14], New Delhi [15], and Johannesburg [16]. Recent innovations have extended the use of SLMs into more mobile and creative formats, such as bicycle-mounted SLM systems in Nagpur, India [17]. This is all with an aim to offer essential insight into how noise levels change throughout the day, vary across different locations, and affect exposed populations.

However, the logistical difficulty of deploying them on a city-wide scale in resource-constrained environments has led to substantial gaps in continuous monitoring, especially in cities such as Nairobi, Kenya. Given these limitations, there is an urgent need for alternative approaches, ones that are affordable, scalable, and suited to dynamic areas. In response, researchers are increasingly exploring new affordable approaches to environmental noise monitoring. Among these, smartphones have emerged as a compelling solution.

Smartphones have increasingly been recognized as a practical and widely accepted tool for monitoring environmental noise, as highlighted by a growing number of studies globally. For instance, [18] evaluated the use of smartphone applications for accurate occupational and environmental noise assessment in the United States of America. Similarly, [19] used bicycle-mounted smartphones to gather mobile environmental noise data in Italy, and [20] leveraged crowdsourced smartphone data to develop noise exposure models in China. With over eighty percent of internet users globally now owning smartphones, these devices are becoming attractive tools for participatory environmental noise measurements. Previous studies on the integration of smartphones in noise measurements have shown that, with proper calibration, smartphone microphones combined with noise applications that have well-coded application programming interfaces (APIs) can mirror and approximate SLM measurement data [18] [21] However,

challenges still persist, including variations in smartphone hardware and software, limited microphone frequency response, lack of calibration standards, inconsistencies in application algorithms, and environmental influencing factors such as wind, temperature, and the like.

To address these challenges, this study employed a hybrid method to capture noise data in Nairobi and to validate the use of smartphones as a tool for noise measurement. A Samsung Galaxy A12, Model SM-A127F/DS, smartphone was tested alongside a calibrated Class 1 Lutron SL-4033SD SLM under real-world traffic conditions. Instead of depending only on application-displayed results, data was extracted and processed from the smartphone's audio recordings using Python, a widely used and powerful programming language known for its flexibility in scientific computing, data analysis, and signal processing. This allowed for high precision in computing the equivalent continuous sound level (L_{eq}), improving accuracy and reducing the margin of error. This approach supports the broader objective of validating smartphones as low-cost, scalable alternatives to traditional noise monitoring tools, particularly in resource-constrained urban settings.

2. Previous Related Work

Smartphones have become a “must-have” for the majority in developed nations [22]. Over the past decade, there have been improvements in smartphone microphone hardware that have been embedded in them, onboard processing, and sensor integration, making smartphones viable alternative tools for environmental noise monitoring. Over eighty percent of internet users globally own a smartphone, with the number growing every year [23]. Their popularity means that people everywhere, from low-income to high-income areas, carry a powerful device that has sensors, microphones, a Global Positioning System (GPS), and internet access. These features make smartphones not just useful as communication tools but also useful for collecting environmental data.

With increasing attention, several studies have explored the viability of smartphones in measuring environmental noise. A study by [18] conducted one of the earliest benchmark studies, comparing popular mobile applications on iOS and Android platforms against certified SLMs under controlled laboratory conditions. Their findings revealed that certain applications, especially those using uncompressed audio formats and standardized weighting, could achieve measurement accuracy within ± 2 dB(A). Worker in [24] launched the Noise Tube project, enabling citizens to crowdsource noise data using smartphones across Europe. The conclusion of this assessment was an average precision of ± 2.5 dB(A). While worker in [25] used the “2Loud?” app in Australia to monitor residential nighttime noise exposure near highways, resulting in accuracy levels of ± 3 dB(A). In Africa, [26] conducted a comparative analysis between smartphones running on the “Androidboy1” application and an Extech 407730 SLM in Abuja, Nigeria. Their findings showed a strong correlation of $r = 0.9$ between the smartphone and SLM

readings in dB(A). Recently, [27] introduced a blind calibration method within the NoiseCapture platform, algorithmically correcting device-specific biases by leveraging data from simultaneous measurements across smartphones.

Despite growing validation studies, smartphone-based approaches still face several limitations. First, many studies have been conducted in controlled laboratory settings or high-income areas, where hardware standardization and environmental stability reduce variability. Second, smartphone models vary widely in microphone quality, and most devices are not factory-calibrated for acoustic measurements. Third, there is still a scarcity of large-scale, real-world deployments of smartphone-based RTN monitoring in low-resource urban areas, particularly in Sub-Saharan Africa. Moreover, very few studies combine smartphone data collection with formal validation against certified SLMs, leaving questions around accuracy, reliability, and field applicability unanswered.

This study aims to fill these gaps by using a smartphone-based RTN measurement approach in Nairobi, a rapidly urbanizing African city with known noise exposure challenges. This is in a bid to provide a long-term noise monitoring approach using crowdsourced data. Using an easily accessible and commonly available Android smartphone validated against a calibrated SLM, this study collected audio data from 42 locations across Nairobi in 15-minute hourly intervals for 7 days. In doing so, this research contributes to the growing evidence supporting smartphone-based noise monitoring while also addressing the underrepresentation of African cities in environmental noise literature.

3. Methodology

The methodology was designed to ensure accurate, consistent, and representative data collection and analysis. It includes the definition of the study area and site selection, instrumentation, data acquisition, data processing techniques, and analytical approaches used to interpret the findings. RTN data was collected between 6:00 AM and 6:00 PM for 7 days across 42 strategically selected sites that reflected diverse land use types, including residential zones, commercial centers, and mixed-use corridors. To capture hourly variation and traffic-related fluctuations, measurements were taken every hour for 15-minute intervals throughout the monitoring period. A Sound Level Meter and a handheld Android smartphone were used, and the collected data were subjected to both statistical and acoustic analysis.

3.1. Study Area and Site Selection

The study was conducted within the city of Nairobi, Kenya, in East Africa, covering an area of 14 km radius from the city center. Nairobi is geographically defined by a latitude of 1°09' and 1°27' South, a longitude of 35°59' and 37°57' East, covering an area of approximately 696 km². It is the political, economic, and cultural capital of Kenya and one of the most densely populated and rapidly urbanizing cities in East Africa. According to census records, Nairobi's population grew from

2.1 million in 2009 to 4.4 million by 2019 [28].

With the increase in the city's population, there has also been a significant increase in the vehicle population, with the number of registered vehicles growing from approximately 500,000 in 2012 to over 1.2 million by 2022 [29]. The vehicular mix is highly heterogeneous, ranging from bicycles, motorcycles, saloon cars, SUVs to PSVs, trucks, and buses, contributing to non-uniform and often excessive noise. Nairobi's varied land use, spanning residential, commercial, industrial, and institutional zones, further amplifies the variability of noise exposure across locations, making Nairobi a compelling case study for RTN challenges in urban cities in Africa. To ensure a representative assessment of noise exposure across Nairobi city, 42 monitoring sites were selected across the 17 sub-counties, reflecting residential, commercial, institutional, and industrial land use typologies. Preliminary site reconnaissance and traffic flow observations were used to guide the selection of locations and ensure a balanced representation of all zones. Each site was geo-located using GPS and mapped using Geographic Information Systems (GIS) to visualize spatial distribution and support subsequent analysis, see **Figure 1**. The table in Appendix 1 (**Table A1**) summarizes each site along with the rationale for its selection.

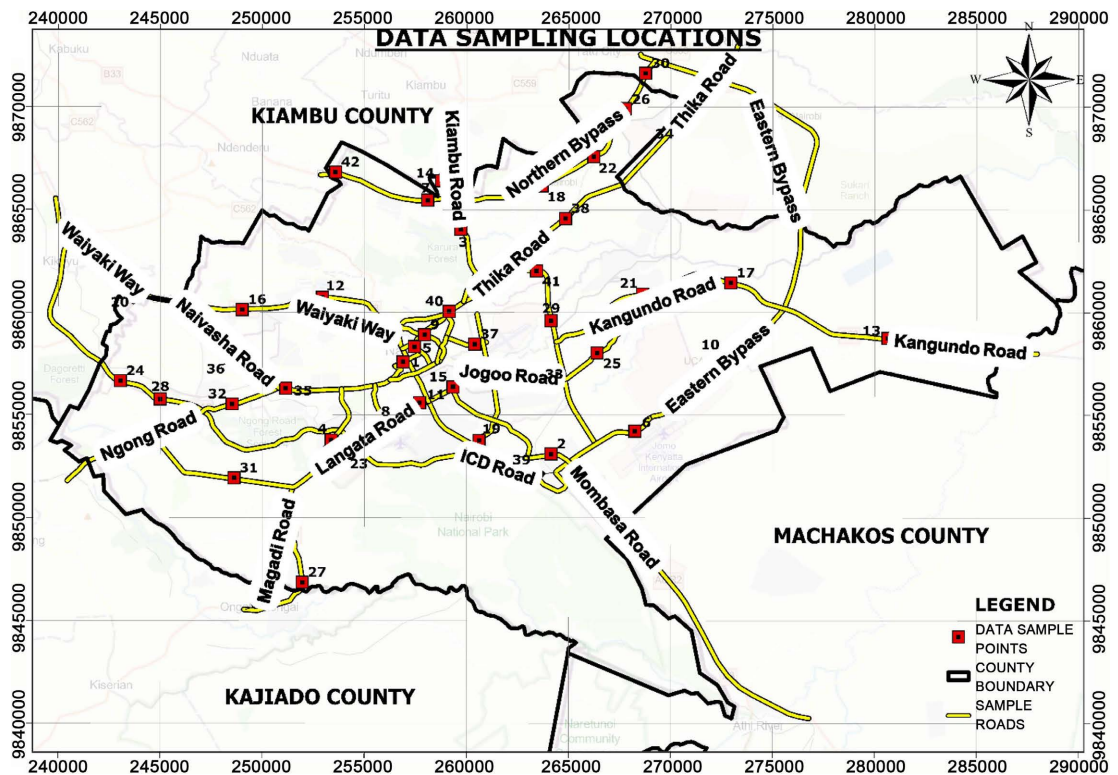


Figure 1. Map of Nairobi city with sampling points.

3.2. Instrumentation and Data Collection

A handheld Android Smartphone, Samsung Galaxy A12 Model SM-A127F/DS, was used to capture RTN through its built-in microphone, see **Figure 2**.



Figure 2. Samsung Galaxy A12 model SM-A127F/DS.

The audio recordings captured by the smartphone's default audio recording application (Voice Recorder) were saved in the MPEG-4 Audio format (M4A). M4A is a high-quality audio format that uses Advanced Audio Coding (AAC) to compress the audio, hence reducing its file size while still maintaining much of the original sound quality. It is commonly used in modern smartphones because it offers better sound fidelity than older formats like MPEG-1 Audio Layer 3 (MP3), especially at the same file size. Unlike MP3, which may discard important audio details, M4A offers a better balance between file size and quality, making it suitable for environmental noise measurements where accuracy is important. To ensure that the noise data captured was accurate and detailed, the smartphone recorded at a sampling rate of 48 kHz and 16-bit depth.

The sampling rate means that the audio was captured 48,000 times per second. This rate is widely used in audio applications and is high enough to capture all sounds within the range of human hearing, which is up to about 20 kHz. The bit depth of 16-bit defines how detailed each of those measurements is. A higher bit depth captures more detail, allowing for a wide dynamic range, thus both soft and loud traffic sounds were recorded with good accuracy. The noise data was also captured at a bit rate of 256 kbps, meaning 256,000 bits of audio data were stored every second. This is considered high-quality audio, almost indistinguishable from lossless formats in many cases, and is well above the threshold needed to detect subtle sound differences, especially in noisy environments.

In parallel, a calibrated portable Class 1 Sound Level Meter (Lutron SD4033), conforming to IEC 61672-1 standards, see **Figure 3**, was used to record noise levels. The SLM was set in fast response mode, which is ideal for recording the quickly varying nature of RTN. To account for the human ear's response to sound, an A-weighting filter setting was used. High resolution was ensured by logging data at 2-second intervals during each 15-minute sampling session, enabling the computation of key acoustic metrics such as the L_{eq} .



Figure 3. SLM.

At each of the 42 selected sites, noise data was recorded for 15-minute intervals every hour, starting from 6:00 A.M. to 6:00 P.M., resulting in 13 recordings per site, per day. For each day, the equivalent continuous sound levels (L_{eq}) collected were averaged to obtain a daily average L_{eq} . This process was repeated for 7 days, after which the final L_{eq} for each location was computed as the average of the 7 daily L_{eq} values. During data collection, both the SLM and the smartphone were handheld and positioned at an approximate height of 1.2 meters, maintaining a horizontal distance of about 1.5 meters from the road edge to minimize reflections and direct influence from passing vehicles. They were oriented towards the traffic flow to ensure direct exposure to incident sound waves, see **Figure 4** and **Figure 5**.

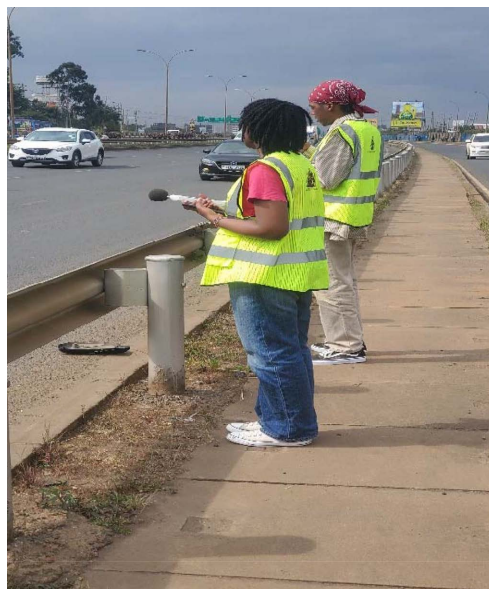


Figure 4. Data collection.

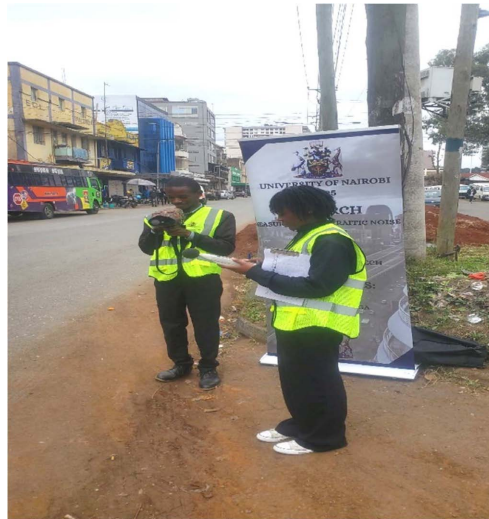


Figure 5. Data collection.

3.3. Data Processing

3.3.1. Noise Data Acquisition

Once the audio recordings were collected using the smartphone, the audio M4A files were transferred to a computer for analysis. Rather than relying on application-displayed sound levels, the actual audio data was analyzed directly using Python, a powerful programming language. Python provided flexibility and control through libraries such as librosa and scipy.io for reading and analyzing the audio files, numpy for mathematical operations, and pandas for organizing and processing large volumes of data across multiple sites and times.

The M4A format, while efficient and storage-friendly, is not ideal for detailed acoustic analysis, as compression can lead to minor losses in signal accuracy. Therefore, for precise signal processing, the audio was converted to Waveform Audio File Format (WAV), an uncompressed, high-fidelity format commonly used in professional sound engineering and scientific research. WAV files preserve the quality and frequency content of the original signal, making them ideal for sound pressure level (SPL) computation. Each 15-minute recording was split into frames of 6-second duration to allow for frame-by-frame analysis of the sound pressure level (SPL). An A-weighting filter was first applied to mimic how the human ear responds to sound. Frequencies below 20 Hz or above 20 kHz are attenuated, and mid-frequency sounds between 1 kHz to 6 kHz are emphasized, aligning results with standard environmental noise assessments in dB(A). For each frame, the Root Mean Square (RMS) of the audio data was calculated using the formula:

$$\text{RMS} = \sqrt{\frac{1}{N} \sum_{i=1}^N (x_i)^2} \quad (1)$$

where: x_i is the amplitude of the i^{th} audio sample in the frame, N is the total number of samples in that frame, and RMS is the measure of the effective (average power) amplitude of the signal. To prevent computational issues caused by ex-

tremely small RMS values, which would result in negative infinity ($-\infty$) as the result, a minimum threshold was applied to the RMS values using a constant (epsilon). After applying the threshold, the RMS values were converted into sound pressure level values in dB(A) using the standard logarithmic formula:

$$L_i = 20 \times \log_{10} \left(\frac{\text{RMS}(t)}{p_0} \right) \quad (2)$$

where: $\text{RMS}(t)$ is the Root Mean Square amplitude of the audio signal at time t , $p_0 = 20 \mu\text{Pa}$ is the reference sound pressure in air and L_i represents each instantaneous Sound Pressure Level value.

The Equivalent Continuous Sound Level (L_{eq}) for each 15-minute sampling session was then calculated as the energy-averaged SPL over all frames using the formula:

$$L_{eq} = 10 \log_{10} \left(\frac{1}{N} \sum_{i=1}^N 10^{\frac{L_i}{10}} \right) \quad (3)$$

where L_i represents each instantaneous SPL reading, and N is the number of 6-second frames in the 15-minute sample.

The SLM was on the other hand, was configured to log 2-second SPL values directly into an Excel spreadsheet throughout each 15-minute interval. The L_{eq} was computed on Excel using the logarithmic energy averaging formula as shown in Equation (3).

For both devices, the SLM and the smartphone, the hourly L_{eq} values were computed for each location. For each day, the equivalent continuous sound levels (L_{eq}) collected were averaged to obtain a daily average L_{eq} per location. This process was repeated for all the data, and finally, the L_{eq} for each location was computed as the average of the 7 daily L_{eq} values.

3.3.2. Margin of Error

Previous studies have used various statistical methods to assess the accuracy and reliability of smartphone-based noise measurements when compared to standard Sound Level Meters. Kardous and Shaw (2014) evaluated several noise applications by computing the Mean Error between the smartphone-recorded levels and a calibrated Type 1 SLM using the formula:

$$\text{Mean Error} = \frac{1}{N} \sum_{i=1}^N (L_{\text{smartphone}} - L_{\text{SPL}}) \quad (4)$$

where N is the number of paired measurements. Their findings showed that certain apps revealed a Mean Error of ± 2 dB under controlled indoor conditions.

D'Hondt *et al.* (2013) applied linear regression to quantify the relationship between smartphone and SLM readings, using the formula:

$$\text{SPL}_{\text{SLM}} = a \times \text{SPL}_{\text{smartphone}} + b \quad (5)$$

where a and b are regression coefficients, and the strength of the relationship was assessed using the coefficient of determination (R^2). R^2 values above 0.9 were reported for well-conditioned recordings.

Murphy and King, (2016) on their part used the Root Mean Square Error (RMSE) to evaluate accuracy, given by:

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N (L_{\text{smartphone}} - L_i)^2} \quad (6)$$

and they also constructed Bland-Altman plots to visualize the bias and limits of agreement.

In this study, the Margin of Error was computed to quantify the level of uncertainty and assess the accuracy and viability of smartphones as tools for noise measurements compared to that of the reference SLM. By calculating the Margin of Error, the study established the confidence level using average smartphone readings across different locations, ensuring the scientific integrity of results derived from non-calibrated consumer-grade devices, and validating the use of smartphones as a potential and alternative tool for RTN measurement.

The Mean Absolute Error (MAE) was calculated using the formula:

$$\text{Mean Absolute Error} = \frac{1}{N} \sum_{i=1}^N |(L_{\text{smartphone}} - L_{\text{SPL}})| \quad (7)$$

And the standard deviation is calculated from the formula:

$$\sigma = \sqrt{\frac{1}{N} \sum_{i=1}^N (x_i - \bar{x})^2} \quad (8)$$

where x_i is the error at each site i , \bar{x} is the mean error and N is the number of measurement sites. From these, the Margin of Error (MoE) at a 99% confidence level was computed using:

$$\text{MoE} = z \times \frac{\sigma}{\sqrt{N}} \quad (9)$$

where $z = 2.58$ for 99% confidence and σ is the standard deviation computed from Equation (9).

Given observed discrepancies between L_{eq} values measured by smartphones and those recorded using reference-grade SLMs, a linear regression model was developed, establishing the best line of fit hence calibrating the smartphone readings. This model allowed for adjustment of systemic deviations and assessment of whether smartphones could reliably be used as tools of RTN measurement by approximating SLM values. The regression analysis was conducted using Python, and the model aimed to express the SLM-measured L_{eq} as a function of smartphone-measured L_{eq} using the form:

$$L_{eq(\text{SLM})} = \beta_0 + \beta_1 \cdot L_{eq(\text{smartphone})} + \varepsilon \quad (10)$$

where β_0 and β_1 are regression coefficients and ε is a random error term.

4. Results

Table A2, presented as Appendix 2, is the result obtained from parallel noise measurements at 42 locations using a smartphone (Samsung Galaxy A12, Model SM-A127F/DS) and a reference Sound Level Meter (Class 1 Lutron SL-4033SD).

From the results, a linear regression was carried out, and the best line of fit was established between the SLM readings and the smartphone readings, see **Figure 6**, yielding the following equation based on Equation (10).

$$L_{eq(\text{corrected})} = 0.2161 \cdot (L_{eq(\text{smartphone})}) + 54.331$$

With R^2 being equal to 0.3021. This indicates a moderate relationship between the two readings.

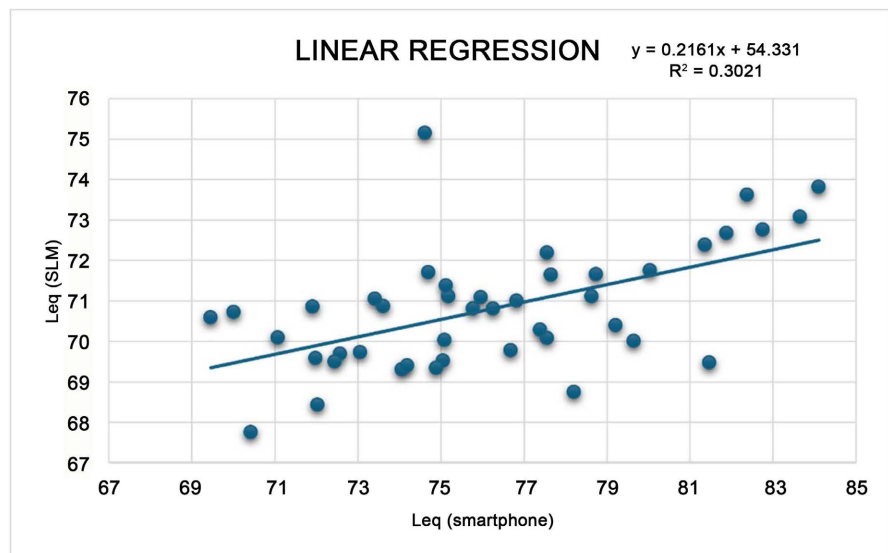


Figure 6. Linear regression.

The new $L_{eq(\text{corrected})}$ values were computed as shown in **Table A2**. For accuracy validation between the smartphone and the corrected readings, the Mean Absolute Error, the standard deviation, and the Margin of Error were calculated using Equations (7), (8), and (9) from the Methodology section. The average difference (MAE) across sites was found to be ± 1.288 dB(A), which agrees with the commonly accepted tolerance of ± 2 dB(A) for environmental noise measurement comparisons (Murphy and King, 2014). A standard deviation of ± 1.066 dB(A) and a Margin of Error of ± 0.4247 dB(A) brought about a general agreement in long-term averages. These findings support the claim that when carefully processed, smartphones can reliably approximate L_{eq} measurements from professional SLMs, offering a low-cost alternative for real-time noise monitoring using crowdsourced data.

5. Discussion

The findings of this study provide meaningful insight into the potential of smartphones as practical tools for environmental noise measurement in urban areas. While professional tools such as the Sound Level Meters (SLMs) remain the standard for such measurements, the increasing sophistication of smartphone hardware and the wide accessibility of audio processing software present a prom-

ising alternative for large-scale noise measurement or crowdsourced data.

From the comparative statistical analysis between smartphone measurements and SLM, three indicators were derived: the Mean Absolute Error (MAE) of ± 1.288 dB(A), the standard deviation of ± 1.066 dB(A), and a Margin of Error of ± 0.4247 dB(A) at a 99% confidence level. The relatively low margin of error indicates a high level of statistical confidence in the average performance of smartphone readings. The statistical spread observed, that is the standard deviation, remains within an acceptable range for non-regulatory but informative noise measuring purposes, such as noise mapping, policy making, public health awareness campaigns, and noise abatement strategies. Environments with higher background noise levels generally exhibited smaller deviations, while quieter or more acoustically complex settings tended to produce larger errors. These deviations could stem from several factors, such as wind or the absence of real-time calibration for smartphone microphones. This aligns with similar challenges reported by Murphy and King (2016) and Maisonneuve *et al.* (2010), who highlighted that uncalibrated smartphone microphones tend to underestimate or overestimate SPL, especially in fluctuating or low-noise conditions. Despite these limitations, the results affirm that smartphones can serve as credible tools for RTN measurement, especially when consistent sampling intervals and processing algorithms are used.

6. Conclusions and Recommendations

In conclusion, while smartphones are not poised to replace SLMs in compliance-grade assessments, they represent an accessible, scalable, and low-cost alternative for RTN measurement studies, especially in resource-constrained areas like cities in developing nations. Their accuracy, when averaged across many sites, and the narrow margin of error observed, offer confidence for their usage in wider environmental monitoring applications. Future studies may focus on integrating smartphones with external microphones, refining smartphone calibration techniques, and improving data processing algorithms to minimize deviations further and expand the operational reliability of smartphones in noise pollution studies.

Given the demonstrated reliability of smartphones in capturing acoustic data comparable to that of standard SLMs, it is recommended that smartphones be integrated into environmental noise monitoring. Their widespread availability and affordability make them ideal tools for real-time community-driven noise surveillance. With data processing algorithms being widely found on the internet, urban authorities can leverage the use of smartphones to build noise mapping systems from crowdsourced data from anywhere in the city, thus democratizing noise monitoring, reducing infrastructure costs, and enabling inclusive public participation in decision-making.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

- [1] Behzad, M., Ghadiri, H. and Hashemi, H. (2007) Traffic Noise in Urban Environments: A Study of Source Contribution and Health Impact. *Iranian Journal of Public Health*, **36**, 1-7.
- [2] Skånberg, A. and Öhrström, E. (2002) Adverse Health Effects in Relation to Urban Road Traffic Noise and the Influence of Attitudes towards Noise. *Environment International*, **28**, 659-669.
- [3] Savale, P.A. (2014) A Review on Noise Pollution and Its Impact on Human Health. *International Journal of Advanced Research in Engineering and Applied Sciences*, **3**, 1-15.
- [4] Fiedler, P.E.K. and Zannin, P.H.T. (2015) Evaluation of Noise Pollution in Urban Traffic Hubs-Case Study: Curitiba, Brazil. *Journal of Urban and Environmental Engineering*, **9**, 66-73.
- [5] Pandya, A.B. and Dharmadhikari, D.M. (2002) Traffic Noise Pollution and Control in Indian Cities. *Indian Journal of Environmental Protection*, **22**, 432-439.
- [6] Sinha, A. and Sridharan, S. (1999) Noise Pollution in Urban Environments. *Environmental Engineering and Management Journal*, **7**, 343-350.
- [7] Vijay, R., Tripathi, M. and Sharma, M. (2014) Noise Pollution Levels in Indian Cities: A Review. *Journal of Environmental Health Science & Engineering*, **12**, 36.
- [8] Wawa, E.A. and Mulaku, G.C. (2015) Noise Pollution Mapping Using GIS in Nairobi, Kenya. *Journal of Geographic Information System*, **7**, 486-493.
<https://doi.org/10.4236/jgis.2015.75039>
- [9] Gongi, J.N., Kaluli, J.W. and Kanali, C.L. (2016) Assessment of Noise Pollution in Nairobi Central Business District, Kenya. *International Journal of Environmental Monitoring and Analysis*, **4**, 154-161.
- [10] Mwangi, C.M. (2011) Assessment of Environmental Noise Pollution in Nairobi City, Kenya. Master's Thesis, University of Nairobi.
- [11] Chauhan, S. (2015) Road Traffic Noise Levels in Selected Areas of Nairobi City, Kenya: An Evaluation Using Dosimetry. *Journal of Environmental Protection*, **6**, 1260-1270.
- [12] Nyaranga, M., Mutua, B.M. and Wambua, G.M. (2024) Noise Pollution Mapping Using GIS-Based Spatial Analysis in Nairobi, Kenya. *Environmental Research and Public Health*, **21**, 1021.
- [13] Can, A., Aumond, P., Michel, S. and De Coensel, B. (2015) Intra-Urban Variations of Environmental Noise: New Insights from Mobile Monitoring. *Applied Acoustics*, **99**, 44-53.
- [14] Al-Hemoud, A., Al-Khayat, A., Al-Mutairi, N. and Al-Dousari, A. (2021) Assessment of Noise Pollution in Doha, Qatar: Sources, Levels, and Effects. *Environmental Monitoring and Assessment*, **193**, 321.
- [15] Jain, R. and Srivastava, S. (2021) Assessment of Traffic Noise in Urban Environments Using SLMs: A Case Study in New Delhi, India. *Transportation Research Part D: Transport and Environment*, **94**, Article ID: 102800.
- [16] Akintan, O.L. and Agboola, O.M. (2022) Assessment of Environmental Noise Pollution in Johannesburg Metropolitan Municipality. *Journal of Environmental Studies and Sciences*, **12**, 45-58.
- [17] Chandigarh, M., Singh, R. and Patel, P. (2019) Bicycle-Based Sound Monitoring: A Smart Mobility-Integrated Approach in India. *Transportation Research Part D*.

Transport and Environment, **68**, 278-289.

- [18] Kardous, C.A. and Shaw, P.B. (2014) Evaluation of Smartphone Sound Measurement Applications. *The Journal of the Acoustical Society of America*, **135**, EL186-EL192. <https://doi.org/10.1121/1.4865269>
- [19] Gagliardi, A., Rossi, L. and Attanasio, G. (2022) Crowdsourcing Environmental Noise Data Using Smartphone Sensors Mounted on Bicycles. *Environmental Monitoring and Assessment*, **194**, 391.
- [20] Wang, J., Yang, X. and Liu, W. (2023) Using Smartphone-Collected Noise Data to Model Real-Time Noise Exposure. *Environmental Modelling & Software*, **165**, Article ID: 105675.
- [21] D'Hondt, E., Stevens, M. and Jacobs, A. (2013) Participatory Noise Mapping Works! An Evaluation of Participatory Sensing as an Alternative to Standard Techniques for Environmental Monitoring. *Pervasive and Mobile Computing*, **9**, 681-694. <https://doi.org/10.1016/j.pmcj.2012.09.002>
- [22] Murphy, E. and King, E.A. (2016) Environmental Noise Pollution: Noise Mapping, Public Health, and Policy. Elsevier.
- [23] Statista (2023) Smartphone User Penetration Worldwide from 2016 to 2023. <https://www.statista.com/statistics/203734/global-smartphone-penetration-per-capita-since-2005/>
- [24] Maisonneuve, N., Stevens, M., Niessen, M.E., Hanappe, P. and Steels, L. (2010) Citizen Noise Pollution Monitoring. *Proceedings of the 10th Annual International Conference on Digital Government Research*, Puebla, 17-20 May 2009, 96-103.
- [25] Leao, S., Ong, K. and Krezel, A. (2014) 2Loud? Community Mapping of Exposure to Traffic Noise with Mobile Phones. *Environmental Monitoring and Assessment*, **186**, 6193-6206. <https://doi.org/10.1007/s10661-014-3848-9>
- [26] Ibekwe, L.U. and Folorunsho, M.S. (2016) Assessment of Environmental Noise Pollution Using Android-Based Smartphone Apps: A Case of Abuja, Nigeria. *Journal of Engineering Research and Reports*, **1**, 1-10.
- [27] Boumchich, A., Goudarzi, R. and Lambert, J. (2024) Noise Capture: Blind Calibration Approach for Smartphone-Based Environmental Noise Monitoring. *Applied Acoustics*, **207**, Article ID: 108702.
- [28] Kenya National Bureau of Statistics (KNBS) (2019) 2019 Kenya Population and Housing Census Reports. Government of Kenya. <https://www.knbs.or.ke>
- [29] NTSA (National Transport and Safety Authority) (2022). Annual Motor Vehicle Registration Statistics Report. <https://www.ntsa.go.ke>

Appendix 1

Table A1. Table showing rationale for site selection for RTN measurement.

LOCATION	REASON FOR SELECTION
1	Near the Central Business District, where there is high pedestrian and traffic interaction.
2	Busy commercial area along Mombasa Road, near junctions and high vehicle turnover.
3	Major arterial road with heavy commuter traffic, linking suburbs to the Central Business District.
4	Connector road with moderate traffic; residential and school zones nearby.
5	Within the Central Business District; high urban noise levels.
6	Located in a busy industrial and residential zone.
7	Upmarket residential area; contrast with higher noise regions for baseline analysis.
8	Key thoroughway with moderate congestion; mixed land use nearby.
9	High Density residential and commercial are near the Central Business District.
10	Fast developing residential zone near a major bypass; captures emerging urban traffic.
11	Fast growing satellite town; traffic congestion from Kiambu and Limuru roads.
12	Mixed-use area along Langata Road; constant traffic.
13	Located along a major highway; captures high speed and vehicle commercial noise.
14	Populated residential and commercial area on Kangundo Road.
15	Duplicate site for comparative data collection on same corridor under different conditions.
16	Industrial and logistics zone; exposure to heavy goods vehicle traffic.
17	Dense urban settlement along Waiyaki Way; congestion and informal transport hubs.
18	Industrial facility zone
19	Suburban residential are off Thika Road; moderate noise for baseline comparison.
20	Religious facility near high traffic road; event related traffic surges.
21	Residential estate with frequent matatu activity.
22	Represents peri-urban corridor.
23	Major traffic artery bypassing the Central Business District.
24	Monitor noise exposure near healthcare facilities.
25	Major bypass road, suitable for studying noise from high-speed long-distance traffic.
26	Commercial center; medium level traffic exposure in residential setting.
27	Sensitive area near educational and medical institutions.
28	University environment near busy roads; monitors academic exposure to RTN.
29	Duplicate site along a major bypass road for comparative data.
30	Along Outer ring Road; majorly experiences truck and Psvs congestion.
31	Duplicate site along a major bypass for comparative study.
32	Near an educational institution.
33	Heavily used arterial road with commercial and institutional land use.
34	Densely populated, noisy corridor serving Eastlands commuters.
35	Major superhighway with consistent heavy traffic; high noise source.

Continued

- | | |
|----|--|
| 36 | Major retail center along Ngong road. |
| 37 | Informal settlement with high human and vehicle activity. |
| 38 | Busy commercial hub with vibrant informal trade and traffic congestion. |
| 39 | Duplicate location along a major superhighway for comparative studies. |
| 40 | Industrial Cargo Depot Road with high truck volume and logistics-based traffic. |
| 41 | Near congested Pangani interchange; high traffic noise. |
| 42 | Industrial area with continuous truck movement; captures occupational and ambient noise. |
-

Appendix 2

Table A2. Results showing the L_{eq} in dB(A) obtained from the Smartphone and SLM and the L_{eq} (corrected) computed after linear regression.

LOCATION	L_{eq} dB(A) from Smartphone	L_{eq} dB(A) from SLM	L_{eq} (corrected) dB(A) after linear regression
1	69.6893924	72.57	69.3908777
2	72.66752692	81.88167	70.03445257
3	70.02563216	75.08167	69.46353911
4	68.43016686	72.03333	69.11875906
5	70.80621494	75.775	69.63222305
6	72.75063854	82.745	70.05241299
7	70.39572739	79.21833	69.54351669
8	71.10636003	78.63333	69.6970844
9	69.29500422	74.045	69.30565041
10	71.64136581	77.64833	69.81269915
11	69.77025554	76.685	69.40835222
12	70.00759216	79.64833	69.45964066
13	71.7440467	80.02833	69.83488849
14	69.52143366	75.05833	69.35458181
15	69.39468559	74.19167	69.32719156
16	71.70114247	74.69	69.82561689
17	70.85082799	71.90667	69.64186393
18	69.33546364	74.89	69.31439369
19	69.49419385	72.44667	69.34869529
20	70.58772155	69.45167	69.58500663
21	70.7181814	70.00167	69.613199
22	69.72582066	73.055	69.39874985
23	69.4688107	81.46	69.34320999
24	70.86468167	73.61667	69.64485771
25	71.10874198	75.17917	69.69759914
26	70.08844778	71.06167	69.47711357
27	71.0393983	73.4	69.68261397
28	69.58140526	71.97667	69.36754168
29	70.06977169	77.54833	69.47307766
30	71.37352361	75.12	69.75481845
31	71.08148872	75.965	69.69170971
32	67.74234451	70.41333	68.97012065
33	72.38034657	81.36417	69.97239289

Continued

34	75.1467582	74.6125	70.57021445
35	73.07122396	83.64667	70.1216915
36	70.9911466	76.83167	69.67218678
37	70.28288078	77.38833	69.51913054
38	73.61540483	82.365	70.23928898
39	73.81208793	84.1	70.2817922
40	68.73831338	78.19167	69.18534952
41	71.6534878	78.735	69.81531871
42	72.1887091	77.545	69.93098004
