Using Low-Cost Sensors and Citizen Science: Assessing Thermal Inequality in African Slums

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Abstract

Urban heat exposure is intensifying due to climate change and urbanisation, with disproportionate impacts on vulnerable populations. Unfortunately, many urban areas, particularly informal settlements, lack sufficient data for detailed analysis to understand these impacts. Traditional air temperature measurement methods—such as meteorological stations—are sparsely distributed in African cities, typically located on city outskirts (e.g., airports), and fail to capture localized temperature variations. This study explores the use of low-cost sensors and citizen science initiatives to measure air temperature with higher spatial resolution in informal and surrounding formal settlements. A two-stage process is employed to evaluate data quality: first, statistically assessing biases in low-cost sensor (LCS) measurements, and second, employing Monte Carlo simulations to quantify uncertainties. The resulting data reveals significant temperature differences between informal settlements and surrounding formal areas, with informal settlements consistently exhibiting higher temperatures. This approach not only highlights the value of low-cost sensors and citizen science in generating high-resolution temperature data but also provides insights into thermal inequalities between different urban environments.

1. Introduction

1.1 Urban Heat Exposure Disparities

Global average temperatures have already risen by over 1°C (IPCC, 2023), resulting in an unprecedented intensification in frequency, magnitude and duration of heatwaves. A notable example is the 2003 European heatwave which claimed over 30,000 lives (United Nations Environment Programme,2003), raising serious concerns about human wellbeing in cities (World Health Organization, 2021). Specifically in Africa, these extremes are projected to have increases in magnitudes and durations twice more relative to Europe (IPCC, 2023; World Cities Report 2022, n.d.; United Nations, 2018).
Described as the ‘hotspots’ of climate change impacts by the IPCC, (2023), cities are particularly susceptible to higher temperatures as much of the impacts of heat exposure is recorded in cities (Koppe et al., 2004). Urbanization is causing an increasing proportion of impervious surfaces, which retain heat, causing higher temperatures in urban areas as compared to their surrounding semi-urban and rural areas. This phenomenon, referred to as the urban heat island, has been described by Ochola et al., (2020) as being one of the most extensive and significant signs of climate modification in the urban space.
These hazards are not experienced similarly in urban areas (Kisters et al., 2022). Prior research reveals significant temperature variabilities indicating that deprived urban areas such as informal areas, are exposed to higher temperatures. These deprived urban areas, though varied across different contexts, are often predominantly inhabited by the urban poor who are lacking the adaptive capacities to deal with the impacts of heat exposure and heat stress. For example, Rathi et al., (2017) reports higher temperatures, heat-related mortality, and health risks in informal settlements compared to surrounding formal areas in Indian cities. Egondi et al., (2012) and Scott et al., (2017) reveal similar patterns of thermal inequality and heat stress in the slums of Nairobi, Kenya. Understanding these intra-urban temperature variations in deprived urban areas is pertinent and requires high spatial and temporal resolution data (Lehnert et al., 2023; Wang et al., 2023).

1.2 Intra-Urban Temperature Measurement Techniques

Traditionally, air temperature is measured by meteorological stations usually located on the outskirts of the city or at airports. These provide highly accurate measurements with high temporal resolution but limited by sparse distribution in space resulting in coarse spatial resolution. These point scale measurements make it difficult to analyse spatial variations of temperature between and within neighbourhoods.
Current studies on intra-urban air temperature assessment propose leveraging low-cost, environmental sensors and citizen science initiatives to collect geolocated air temperature data at higher spatial and temporal resolutions, to supplement traditional measurements (Rajagopalan et al., 2020). Technological advancement has made available highly accurate portable environmental sensors at very affordable cost (widely referred to as low-cost sensors), thereby unearthing immense potential for high resolution near-surface measurement of atmospheric parameters (Gubler et al., 2021). Citizen science approaches contribute to data in research fields where traditional observations of a phenomena are sparsely located or there is reduced accessibility to information by traditional research institutions (Bouzguenda et al., 2019; Neset et al., 2021; Purtova & Pierce, 2024) Furthermore, citizen science approaches have been reported to improve relevance, rigor, and reach of scientific findings (Balazs & Morello-Frosch, 2013). Consequently, these approaches have been consistently employed together with low-cost sensors in networks to maximise the spatial resolution of point-based air temperature measurements. Table 1 presents current literature on low-cost sensors (LCS) and citizen science applications for air temperature measurement.

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Table 1: Overview of Existing Literature

Author	Settlement	Sensors Used	Citizen science	Route/Site Selection	Implementation
(Wang et al., 2023)	Formal, City scale	LCS; Mobile	Collaboratory; Data collection	Predesigned, diverse LULC	Walking
(Romero Rodríguez et al., 2020)	Formal, City scale	LCS; Mobile & fixed	Collaboratory; Data collection	Predesigned, representative sampling of city	Bicycles
(Liu et al., 2017)	Formal, City scale	LCS: Mobile & fixed	N/A	Predesigned; city block division	Bicycles
(Rajkovich & Larsen, 2016)	Formal, City scale	Research grade Met. Station	N/A	Predesigned and randomised selection	Bicycle
(Clay et al., 2016)	Formal, City scale	LCS; Mobile	N/A	Predesigned across diverse LULC	Car
(Gubler et al., 2021)	Formal, City scale	LCS; Fixed	Collaboratory; Data collection	Predesigned across diverse LCZ	N/A
(Scott et al., 2017)	Formal, City scale	LCS; Fixed	N/A	Predesigned, diverse settlements	N/A
(Rajagopalan et al., 2020)	Formal, Regional Scale	LCS; Fixed	Collaboratory; Data collection	Predesigned, diverse locations	N/A
(Alonso, 2019)	Formal, City scale	LCS; Mobile	Participatory; Design and collection	Predesigned, diverse urban characters	Walking
(Rød & Maarse, 2021)	Formal, City scale	LCS; Fixed	Collaboratory; Data collection	N/A	N/A

Previous research typically employs these sensors in a stationary network, (Leichtle et al., 2023; Ochola et al., 2020; Scott et al., 2017) or in mobile transects (Clay et al., 2016; Rajagopalan et al., 2020; Wang et al., 2023). Whilst the former approach (stationary) may provide higher temporal resolution data of stationed points, the latter (mobile), ensures a much dense and extensive coverage thus higher spatial resolution data. Contrary to these methods that compromise between temporal and spatial resolution, few studies, (Liu et al., 2017; Romero Rodríguez et al., 2020) leveraged the advantages of both approaches, utilising both stationary and mobile network of sensors simultaneously in their surveys. These studies suggest the use of cars, bicycles or people, equipped with sensors travelling along predefined routes. These routes are traditionally predesigned before the study following detailed methodological procedures. Though different methods are prescribed based on the aims of the study, the running theme in all reviewed studies was a strict definition of the routes for surveys based on diverse spatial characters to allow a representative spatial coverage of the area. For example, Liu et al., (2017) and Rajkovich & Larsen, (2016), dictate that an effective mobile transect should pass through most of the city blocks with diverse urban patterns that exist, covering a variety of land covers, topographies, and land uses.

The limitation in previous studies is the assumption of pre-existing datasets on streets, land use etc; and open and secure entry and exit into these study areas, which is often not the case for informal settlements. None has **conducted on-the-move measurements, or mobile transects, involving slum residents in the design and implementation of *in situ* and mobile air temperature collection.** Given that informal settlements tend to lack clearly defined roads and are mainly connected by footpaths, bicycles, though more practical than cars are still not appropriate for this study environment. Equipping citizens with handheld sensors for on-foot transverses will allow access to most areas and thus ensuring a representative spatial coverage.

Another deficit is the lack of in-depth assessment of measurement errors and data quality from low-cost sensors (Gubler et al., 2021; Meier et al., 2017) as well as characterising the uncertainties of citizen science generated data (Coney et al., 2022).Understanding and addressing these potential data quality gaps ensures consistent input to remote-sensing based modelling of thermal environments, which is crucial for addressing climate-related vulnerabilities in these communities. It enhances remote sensing by providing high-resolution ground-based air temperature measurements for use in exploring LST-air temperature relationships for more nuanced predictions of urban thermal conditions.

To this effect, this study **seeks to provide a replicable approach to measure intra-urban air temperature in data scarce environments such as slums using low-cost sensors whilst characterising and quantifying uncertainties.**

2. Methods and Materials

2.1 Study Area

The study is conducted in six informal settlements of Nairobi, the capital city of Kenya. With a subtropical highland climate under the Köppen–Geiger classification system, it experiences its warmest months between December and March, with mean max temperatures between 25.8 °C and 26.7 °C. Recent climate reports from the city's meteorological department however suggest significant increasing temperature trends (*NCCG*, 2020). The city has a total population of 4,397,073 based on the nation's 2019 population census. Of this number, it is estimated that more than 60% reside in informal settlements that occupy less than 10% of the city's total land mass (UN-HABITAT, 2005). The Nairobi County government acknowledges the high vulnerabilities these settlements face especially in the context of climate change (*NCCG*, 2020).

There exist several citizen-initiated community activist groups such as Kibera's community mappers, that can be leveraged for collaborations on citizen science related initiatives such as this

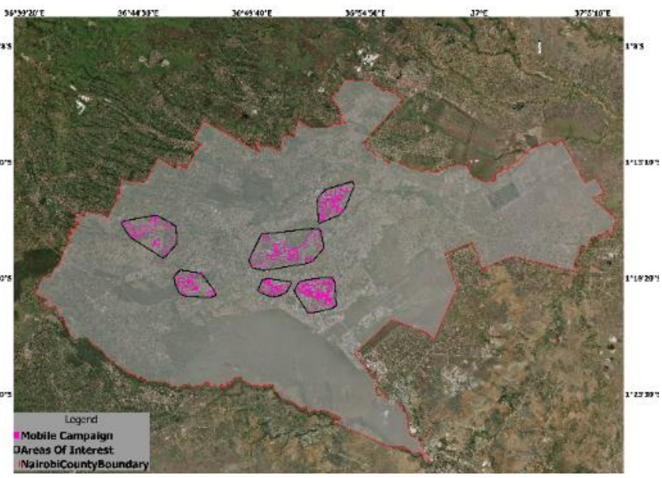

Figure 1: Study Area

study. Based on the availability of such organisations, six settlements were selected: Kibera, Mukuru, Kariobangi, Korogocho, Pumwani and Waruku,with boundaries defined by taking convex hulls of all air temperature routes (transects). These settlements form the area of interest shown in figure 1.

2.2 Workflow

The workflow of this research is structured into two main sections, as illustrated in the flowchart (Figure 2). The first outlines the methods for collecting air temperature data using low-cost sensors (LCS) and citizen science (CS) initiatives. It details out strategies for community engagement, and deployment of LCS for both mobile and stationary in-situ temperature data collection within informal settlements. The second section details the methods employed for preprocessing the collected LCS/CS data, including the quantification of associated uncertainties and biases.

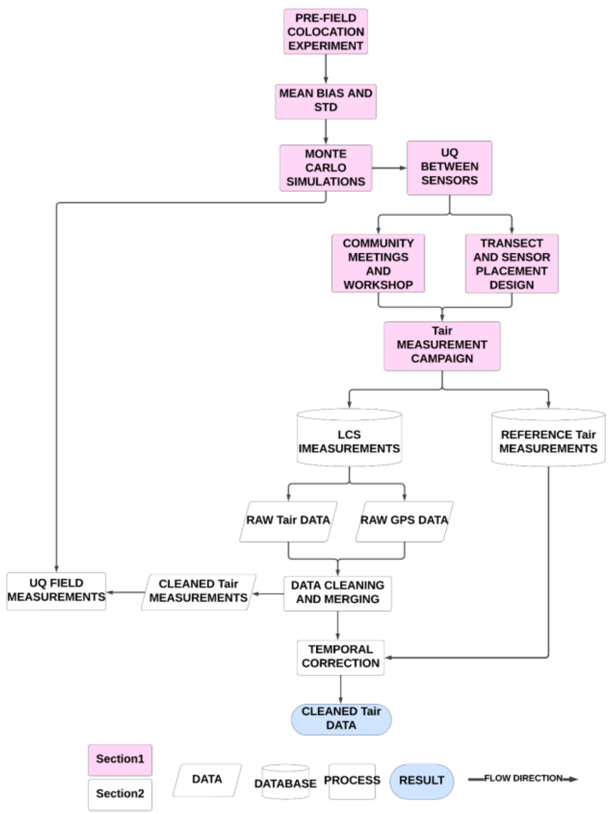

Figure 2:Flowchart

2.3 LCS and Citizen science Tair Measurements design

Instead of pre-designed transects as done in previous studies, a citizen-aided transect approach is used. This approach involves designing the transect with the community, because local knowledge is pertinent to navigate the street network. It should be noted that streets mapped in OSM may not be passable or may have changed. Considering security, citizens co-design the transect, passing through diverse urban characters such as morphology, land covers and land use based on their local knowledge of the settlements while aided by a printed high-resolution satellite image as a reference. This section details out the design and implementation of this approach.

2.3.1 All Sensors Specification

Portable, affordable and modest sensors were employed for this study to ensure ease of movement and prevent attracting crowds during the transect. Kestrel Drop D2 temperature data loggers (KestrelDrop2) were used to sense and record air temperature measurements whilst Garmin GNSS receivers (GarmineTrex10) were employed for GPS data logging. Aside these, a Kunak meteorological station (KunakLite) was used as a reference station. A total of 26 kestrel data loggers,10 Garmin GNSS receivers and 1 Kunak station were used for the entire project. In each settlement and surrounding formal areas, 10 Kestrels were employed for the mobile transect walks. The specifications of these sensors are given in Appendix 1.

Before the start of the data collection campaign, the Kestrel and Garmin sensors were labelled from 1-26 and 1-10 respectively. All Kestrels except numbered 26 are configured to log data every 10 seconds. The Garmin sensors on the other hand were set to log GPS data every 20 seconds. Plastic cable ties were used to attach each kestrel (1-10) at approximately 1metre on 1.2 metre wooden sticks. The Garmin sensor with matching label, was then attached at the top of the stick similarly. Thus, kestrel labelled 1 was matched with Garmin 1 and so forth. (See Appendix 2). At the start of every campaign, checks were carried out by clearing old logs, synchronizing the kestrels using the Kestrel-LINK application.

2.3.2 Fixed Sensor

The Kunak station was employed as a reference station to control for daily weather conditions and for temporal corrections and as such, was stationed at a fixed location throughout the transect period. Ideally, this sensor should be located at a representative location as explained by Romero Rodríguez et al., (2020). However, the reference station was placed in the most secure location within the settlement due to insecurity situations within the slums. The sensor was positioned about 2 meters above the ground and as much as possible, away from any artificial influences of temperature.

2.3.3 Mobile Sensors

Measurements for each settlement was during 2 hours of a single day in each settlement. Participants were selected from each ward (neighbourhood) in the settlement and thus ensured representative distribution of sensors. Participants were invited to engage with a printed A1 size high-resolution satellite image of their settlement in delineating the routes and locations for the data collection campaign. Starting with the meeting location as a reference, each participant was guided in outlining on the map, 4-8 kilometre (approximately 2 hours) transects within their representative wards. The routes were designed to cover diverse urban characters stated below, based on a qualitative assessment of participants local knowledge of the area;

- Land cover and land uses.
- Building densities.
- Road types (major, minor, footpaths).
- Building morphologies (high rise, low rise, size, shape etc).

Participants assigned to walk routes along the boundaries of the settlement extended their routes approximately 50-100 metres into formal areas, to allow formal and informal temperature comparisons. The walks were scheduled between 15.00 and 17.00 at which time peak temperatures are expected due to radiative heat loss. As such, at 14.30 each participant, equipped with the sensors, was transported to their starting point (homes) and instructed to start their walking routes at 15.00 simultaneously. To ensure that the sensors were approximately at least 1.23 metres above ground level to avoid ground interference, participants were instructed to keep sticks at hip level during the walk as seen in (Figure 4). They were encouraged to walk non-stop at a slow pace within this period until 17.00 at which they walked back to the meeting point. Each participant was accompanied by another citizen to serve both as security and to engage curious community members on the project. By doing this, the likelihood of stopping was reduced significantly. During the transect, two additional participants were employed to oversee the activity by calling assigned security attendants occasionally and enquiring on the progress. They were also trained and tasked with solving any technical challenges reported during the routine checks.


Figure 3: Citizens Designing Transects


Figure 4: Citizens engaging in mobile measurements

2.4 In situ Air Temperature Data Quality and Preprocessing

2.4.1 Sensor Biases

The collected data was evaluated through a two-stage approach to address uncertainties and ensure reliability. First, we remove all outliers greater than the average rate of change of each data file. Subsequently, statistical measures were applied to systematically assess biases within the sensor measurements and their agreement with reference station data. This study adopted the methodology utilized by Gubler et al., (2021), for evaluating the data quality of low-cost sensors in air quality studies, where;

- **Coefficient of Variation (CV)**: Used to assess the precision of measurements between sensors.
- **R^2:** Employed to measure the temporal agreement between reference and low-cost sensor data.

Two primary types of bias were addressed:

- Internal Biases: These stem from inconsistencies inherent within the low-cost sensors. To evaluate this, a sample of Kestrel sensors was tested under controlled environmental conditions for a two-hour period. Data from the sensors was analysed using the statistical measures mentioned above to detect significant differences between measurements.
- External Biases: These biases arise from variations between different types of temperature sensors. The measurement differences between low-cost sensors and reference-grade sensors were quantified.

Monte Carlo Simulations: Monte Carlo simulations were then carried out on samples of the in-situ measurements following the sensor experiments explained above. The mean bias μ and random error σ (standard deviation) values identified in the previous steps (for both internal and external) formed the error terms that were used in monte Carlo simulation following the model below;

$$\mathbf{T_{measured}}\ (\boldsymbol{i}) = \mathbf{T_{true}}\ (\boldsymbol{i}) + \mathbf{N}\ (\boldsymbol{\mu}, \boldsymbol{\sigma}^2) \qquad (1)$$

where;

$T_{measured}$ (i) = Measured Temperature at time i
T_{true} (i) = True Temperature at time i
N (μ, σ^2) = Total measurement error term modelled as a normal distribution with mean bias μ and standard deviation σ

This method simulates $T_{measured}$ by sampling random error terms from the defined error distribution. This is replicated **10,000 times for each time point**, generating a distribution of possible true temperature values. The resulting simulated errors were statistically analysed, and a **90% confidence interval** was established to define a reliable range for true temperature estimates.

2.4.2 Temporal Decline Modelling

Temporally, due to the non-synchronous observation times for each location on the routes, there was inconsistent timing, thus making mobile measurements incomparable (Liu et al., 2017; Wang et al., 2023). Correcting the temporal influences on mobile temperature measurements ensures that spatial influences are highlighted therefore allowing the exploration of spatio-thermal relationships which is the purpose of the study. Following the single temporal correction modelling approach proposed by Fung et al., (2009) the Kunak stationary sensor was used as a reference in the temporal correction. For each settlement, the corresponding temperature measurements from the reference was used as the baseline dataset for temporal gradient modelling. Polynomial regression of varying degrees was used to model the temperature pattern over time. The model coefficients were then applied to the mobile temperature measurements thereby transposing them to the same time point (15.15) resulting in comparable temperature measurements analysis within each settlement.

2.4.3 Daily Weather Variations

A final preprocessing step was carried to ensure temperature comparability across all settlements. Temperature records from the official weather station of Nairobi (Wilson Airport) was used as the reference with the assumption that it is representative of the general weather patterns of the entire area of interest. For each day of the study period, a temperature anomaly (ΔTref) was calculated as the difference between the observed temperature at the reference station (Tref (d, t)) and the long-term average temperature for the same time (Tref,avg(t)) based on the entire study period average. This anomaly captures deviations from typical temperature conditions, accounting for daily weather variations. The measured temperature data from each settlement were then adjusted by subtracting the corresponding anomaly,

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resulting in corrected temperatures (Tadjusted) that reflects standardized conditions. This approach normalizes the data, ensuring comparisons of air temperature across the different settlements despite the non-simultaneous data collection.

3. Results

3.1 LCS Data Quality Assessment

3.1.1 LCS Internal Bias and Reliability

The results from the co-location experiments involving 10 Kestrel low-cost sensors (LCS) demonstrate a high level of consistency in temperature readings. With an average coefficient of variance (CV) of 0.5% and a standard deviation (std) of 0.1°C, the variability between sensor readings is minimal, indicating strong precision across the Kestrel sensors. Figure 5 below plots the temperature measurements from the 10 sampled Kestrel sensors over three days. The graph shows that the readings from all sensors are closely aligned throughout the period, with only minor deviations (< 0.10°C) that tend to converge during peak temperature periods. This high level of consistency suggests that, under controlled conditions, environmental factors influence the sensors uniformly. Therefore, it can be inferred that temperature variations recorded during field measurements are primarily driven by environmental factors rather than inherent biases or inconsistencies within the Kestrel sensors themselves.

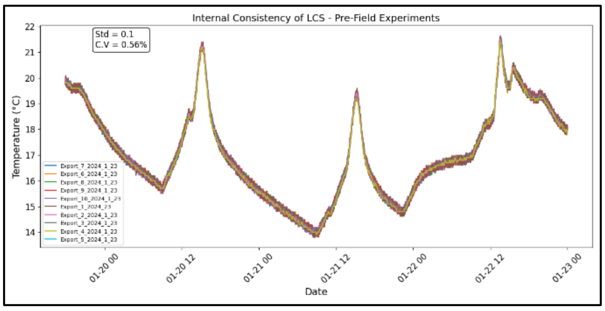

Figure 5: Internal Consistency of LCS

3.1.2 LCS Bias and Reliability: Comparison with Reference

Colocation experiments between the LCS (Kestrel) and the reference sensor (Kunak station) reveals that the kestrel sensors are generally able to follow the temperature trends captured by the reference (see figure 6), indicating that the LCS sensors have good temporal consistency and can reliably track changes in air temperature over time. There are, however, some notable deviations in magnitude of the temperature readings themselves. On average, the Kestrel sensors measure approximately 0.6°C below the reference reference with a standard deviation of 0.39°C, indicating moderate variability in the differences between the two sensors. This relatively low variability suggests that the Kestrel sensors are reasonably consistent in their deviations from the reference, though a systematic negative bias is evident.

However, in instances of rising temperatures, the Kestrel sensors appear to overestimate by up to 0.3°C compared to the reference station. Changes in environmental factors thus, affect the sensors differently, a discrepancy likely due to differences in protective shielding. The reference station, equipped with a protective casing, is shielded from direct sunlight and radiation, resulting in more stable readings. In contrast, the Kestrel sensors, lacking protective casings, are more susceptible to heat absorption due to external influences such as direct sunlight and radiation resulting in an overestimation during rising temperatures.

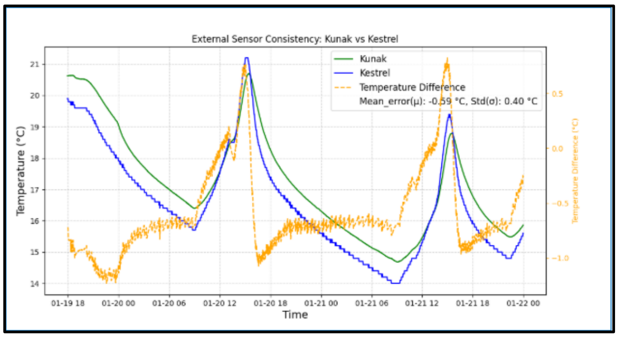

Figure 6: External Sensor Consistency

3.1.3 Uncertainty Quantification using Monte Carlo Simulation

Using an average temperature difference of -0.59°C and standard deviation of 0.39°C, (calculated between the Kestrel and reference station colocation experiment from the previous steps.) the Monte Carlo simulation generated 100,000 iterations to model the potential range of true temperatures based on these observed errors. The simulations were conducted using a log-normal distribution to account for the slight right skew seen in the error distribution. The results reveal low variability and high precision in the LCS measurements with a mean bias of -0.40°C, standard deviation of 0.24°C and 95% confidence interval. Simulated temperatures fall within the confidence interval range even during the peaks that recorded the highest deviation. This thus demonstrates the precision and reliability of the LCS in capturing not only the trends but true measurements. (see figure 7)

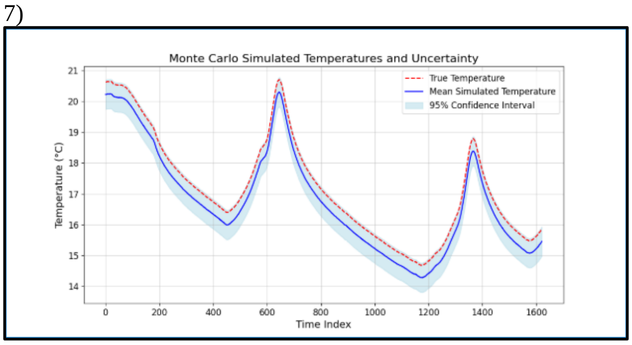

Figure 7: Simulated Errors and Uncertainty

The CDF curve (figure 8) supports this, as seen in the steep rise of the curve at (mean error) 0.4 indicating most errors are concentrated around this range. Overall, 60% of the errors fall within ±0.5°C of the reference measurements, with decreasing probability of large errors occurring, (100% probability that errors will be ≤ 0.5°C). This is lower than the 95% expected for a normal distribution due to the right skew and heavier tails of the log-normal distribution as seen in the histogram of error distribution which shows an almost normal distribution with a slight right skew suggesting that though there is a systematic underestimation, LCS occasionally record larger positive errors (overestimations) compared to negative errors (underestimations).

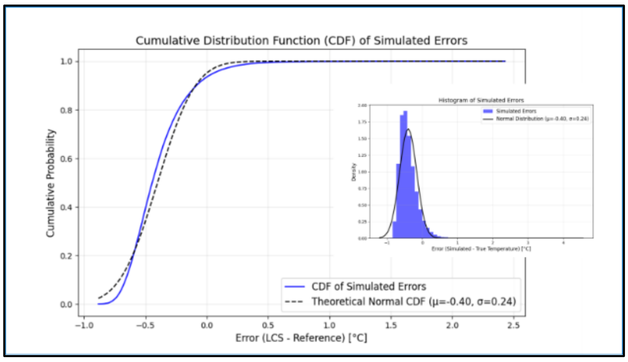

Figure 8: CDF of Simulated Errors

3.2 Intra-Settlement Temperature Patterns

The resulting dataset following the data quality assessments and preprocessing, we calculated mean and maximum temperatures in all settlements compared to the official weather station in Nairobi (Nairobi Wilson Airport weather station Nairobi_Met_Station). We find that the slum settlements consistently have both higher mean and maximum temperatures compared to the nearest meteorological station measurement at the same time. The highest mean temperatures were recorded in Mukuru and Korogocho, both of which have very compact, dense buildings and least vegetative cover compared to the other settlements. Waruku, located on a significantly higher elevation, recorded the lowest mean and maximum temperatures, though still higher than the meteorological station measurements.

Table 2: Measured Temperatures

Settlement	Km Covered	Min	Max	Mean	Met Station
Kibera	368.5	25.3	33.5	28.3	26
Mukuru	1308.4	28.1	36	30.9	26.2
Koriogocho/ Kariobangi	459	25.8	34.5	30.7	26.1
Pumwani	587.9	25.5	36.1	29.9	27
Waruku	646.8	25.5	31.5	27.3	26.6

As mentioned previously (3.2) mobile measurements were taken about 50-100 metres outside the boundaries of the informal settlements. Air temperature data was thus compared within and outside the settlements as shown in the boxplots below (figure 9). Across all settlements, we find temperature differences between settlement types, with formal settlements experiencing approximately 1°C lower in both median and minimum temperature values compared to informal areas. With a p-value of 1.14×10^{-98} from the non-parametric Mann-Whitney U statistic, we assume a significant temperature difference between these two groups.
Comparing these differences per settlement, informal areas consistently had higher mean and median temperatures than surrounding formal areas, despite being only 50-100 metres away. This presupposes potential lower temperatures in core formal settlements or further away from informal settlements.

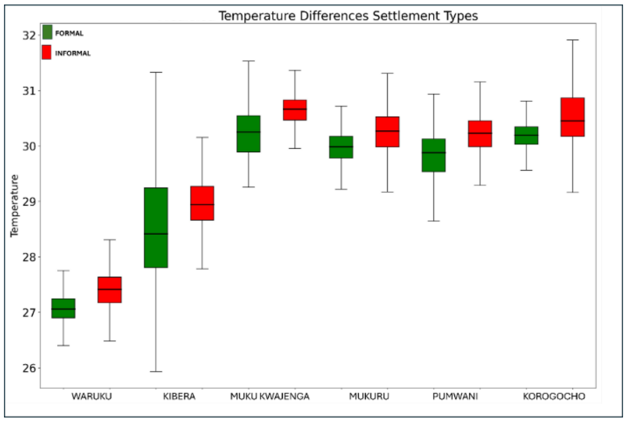

Figure 9: Temperature Differences Across Settlement Type

4. Discussion And Conclusion

This study advances intra-urban temperature measurement in informal settlements by integrating low-cost sensors (LCS) with a novel citizen science (CS) framework whilst addressing critical data gaps and uncertainty concerns. This section contextualises the findings within existing literature and concludes the study.
The CS framework diverged fundamentally from prior approaches, as all reviewed literature relied on top-down methods predefined by researchers. This study on the other utilised a participatory co-design process which is better suited for data scarce environments providing evidence that integrating local knowledge can compensate for missing and outdated geospatial data. Again, this study embedded security protocols to mitigate insecurity risks and inaccessibility noted by Scott et al., (2017) — a solution absent in most citizen science studies and a novel adaptation not documented in prior literature.
The study demonstrated that while LCS exhibit systematic biases (-0.6°C underestimation compared to reference sensors), they reliably capture temporal trends ($R^2 > 0.9$).
However, the narrow confidence interval derived from Monte Carlo simulations demonstrates that, even with these limitations, LCS can reliably provide valuable information when error margins are defined such that temperature variabilities can be contextualised within confidence intervals ensuring robust analysis despite sensor limitations. This ultimately provides a practical alternative for generating high-resolution thermal datasets in informal settlements.

The study identified statistically significant temperature disparities (Mann-Whitney U statistic p-value of 1.14×10^{-98}): informal settlements averaged 1°C warmer than adjacent formal areas, with peaks exceeding 36°C in high-density zones like Mukuru. These findings echoes Rathi et al., (2017) observations in Mumbai's slums and align with Scott et al., (2017) study that documented similar thermal inequities in Nairobi's informal settlements, although using different methodologies.
While this study advances low-cost sensor (LCS) and citizen science applications, limitations persist. The lack of sensor shielding remains the most critical hindrance, as unshielded devices are prone to microenvironmental interference (e.g., direct sunlight or wind gusts). Additionally, the reference sensor's placement in secure but potentially unrepresentative locations could introduce spatial biases. In this study, while insecurity concerns necessitated securing the reference station in a safe area, experiments confirmed the reference station still captured general temperature trends. However, this assumption may not hold universally; future works must prioritize representative sensor

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placement where feasible. Furthermore, uncertainties derived from colocation experiments were applied to field measurements, though unaccounted variables—such as citizen scientists' influences could introduce additional biases. These gaps reveal the need for studies quantifying uncertainties inherent to citizen science methodologies.
This study contributes to intra-urban heat island assessments in informal settlements by merging LCS affordability with citizen science adaptability to overcome data scarcity and methodological rigidity. By validating the reliability of LCS and citizen-generated data, we demonstrate that participatory, low-cost methods can serve as pragmatic alternatives for intra-urban thermal assessments, particularly in data-scarce environments.

While satellite-derived land surface temperature (LST) is widely used to study urban heat, its relationship to near-surface air temperature (which directly impacts human health) remains complex particularly in heterogeneous informal settlements. By providing methods for high resolution air temperature measurements, this work could enable robust calibration of LST-air temperature models, improving their predictive accuracy in underserved urban areas. For instance, integrating these datasets with RS covariates can enhance machine learning models that predict microclimatic variations.

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Appendices

Appendix 1

Table 3:Sensor Specifications

Sensor	Resolution	Accuracy	Setting	Purpose
Kestrel	0.1 °C	± 0.5 °C	10 secs	Temperature logger
Garmin	3 metres	3metres	20 secs	Location logger
Kunak Station	0.01 ºC	± 0.9 ºC	10 secs	Reference Station

Appendix 2

Figure 10: Sensors Used

Appendix 3

Figure 10: Sensor Preparation