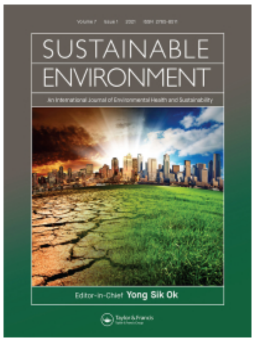

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On the potential of Google Street View for environmental waste quantification in urban Africa: An assessment of bias in spatial coverage

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ABSTRACT
Mismanaged domestic waste threatens ecosystem health, with substantial increases predicted from developing country cities if current consumption and waste service collection trends continue. Google Street View (GSV) imagery has been used to quantify urban environmental waste in high-income countries. GSV availability is increasing elsewhere, but its coverage is variable. This study aims to evaluate bias in spatiotemporal GSV coverage relative to environmental waste in two case study cities. An environmental survey measured environmental waste in Greater Accra, Ghana and Kisumu, Kenya via 95 and 81 transects, respectively. Six summary metrics of environmental waste were calculated and compared for transects with full, partial, and no GSV coverage via multi-level regression. Multi-level regression indicated no significant differences in scattered waste density for transects with versus without GSV coverage. However, both cities had significantly lower waste burning densities along transects with GSV coverage (4.3 versus 24.2 burning sites/Ha in Kisumu; 1.7 versus 13.6 sites/Ha for Greater Accra) compared to those without Street View density of large waste piles was significantly lower in Kisumu transects with Street View coverage (1.4 versus 11.5 sites/Ha). Because of partial imagery coverage, GSV imagery analysis is likely to under-estimate waste indicators such as waste burning density. Future studies using GSV to quantify waste indicators in African cities should therefore correct for coverage bias.

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KEYWORDS
Africa; mapping; neighbourhood analysis; slum; municipal waste management

1. Introduction

Widespread open dumping and burning of municipal solid waste in Low- and Middle-Income Countries (LMICs) has numerous adverse impacts. These include soil, run-off, and groundwater contamination, encouraging rodents, insects and disease vectors, and contributing to marine plastics (Ferronato et al., 2019). Sub-Saharan Africa (SSA) generated the world's lowest domestic waste per capita at an estimated 0.46 kg/capita/day in 2016. However, waste collection services covered just 43% of this region's urban households (Kaza et al., 2018). In SSA, waste service coverage lags behind urbanisation, whilst changing urban lifestyles is leading to greater domestic waste generation. If these trends continue, coastal cities such as Lagos could become major contributors to marine plastics by 2050 (Jambeck et al., 2015). An estimated 60 to 99 million metric tonnes (mmt) of mismanaged plastic waste were produced globally in 2015. Modelling suggests that this figure could triple by 2060 under a business-as-usual scenario (Lebreton & Andrady, 2019), with domestic waste a significant contributor. More precise mapping of urban areas where waste is mismanaged could support targeted waste service delivery and inform environmental modelling of plastics and other waste (Lebreton & Andrady, 2019). Map layers depicting garbage piles are thus often requested as data products by urban planners in LMICs (Georganos et al., 2021).

However, monitoring environmental waste at scale in slums remains challenging. Logistical issues such as navigating through dense, unplanned settlements and security threats to survey teams are barriers to fieldwork in such areas. Consequently, recent initiatives have sought to quantify waste in African cities remotely via satellite image processing or via Unmanned Aerial Vehicles (UAVs) (Thomson et al., 2019). UAV image processing has identified macroplastic debris against the relatively homogenous

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background of beaches (Kako et al., 2020), discriminated polyethylene terephthalate (PET) from other oceanic debris (Jakovljevic et al., 2020), and mapped waste dumps in urban Senegal (Youme et al., 2021). Recent proof-of-concept work has mapped garbage pile density from WorldView-2 imagery in Nairobi (Georganos et al., 2021). However, much work in mapping waste dump sites has taken place in developed countries (Karimi et al., 2022; Thomson et al., 2019). Furthermore, waste mapping via UAV or satellite has not yet been implemented at national scale.

Google Street View (GSV) has potential for mapping waste indicators at scale, but to date, it has only been used to map waste locally in developed countries. Since 2010, vehicles equipped with cameras have captured high-definition, panoramic street-level imagery for GSV (Keralis et al., 2020). Locational data from Global Positioning System (GPS) receivers enable accurate positioning of imagery. Overlapping images from adjacent cameras are merged to create a 360-degree product. Users can freely access images via an Application Programming Interface (API). GSV coverage is expanding in LMIC cities. Automated digital processing of GSV imagery has quantified pedestrian counts (Yin et al., 2015), building age (Li et al., 2018), number of traffic lanes (Keralis et al., 2020), and urban street tree density or greenness (Li et al., 2015; Lu, 2019; Rzotkiewicz et al., 2018). GSV image processing now enables national-scale urban charactisation. For example, computer vision was used to process 31 million GSV images and generate metrics such as street greenness for 500 US cities (Keralis et al., 2020). In the UK, observers have visually recorded garbage on streets via GSV, with high inter-observer agreement between human interpreters of GSV imagery (Odgers et al., 2012). However, in the USA, garbage identified via visual interpretation from GSV to measure neighbourhood disorder (Bader et al., 2015; Kepper et al., 2017; Less et al., 2015; Mooney et al., 2014; Rundle et al., 2011) had only moderate concordance. Other studies quantifying litter via GSV have, to date, taken place only in high-income countries such as Spain (Marco et al., 2017). However, a significant limitation of GSV is its incomplete spatial coverage because of lack of demand for imagery at some locations (Rzotkiewicz et al., 2018) Incomplete coverage also arises because GSV survey cars cannot access densely packed informal urban settlements in LMICs (Rzotkiewicz et al., 2018). Poorer quality roads in these areas may also increase GSV vehicle maintenance costs. GSV imagery may also be captured only in one season and be outdated (Rzotkiewicz et al., 2018).

Urban waste generation, collection, and the impacts of mismanaged solid waste often vary seasonally, with trends varying by city. For example, in Port Harcourt, Nigeria, consumption of sachet (water sold in plastic bags) or bottled water fell from 64% in the dry season to 24% in the wet season (Kumpel et al., 2017). However, in Johannesburg, municipal waste composition did not vary seasonally (Ayeleru et al., 2018). In Yaounde, Cameroon, municipal waste generation nearly doubled in the wet season, whilst poor road conditions inhibited waste collection in this season (Parrot et al., 2009). Transport of urban waste along streets and storm-drains increases in the wet season (Armitage, 2007). Greater clogging of storm-drains by waste has been reported in Accra, Ghana, during the wet season (Stoler, 2012). Waste collection and disposal patterns also vary within cities. Waste burning was greatest in low-income neighbourhoods of Delhi (Nagpure et al., 2015), whilst in Mombasa, Kenya, proximity to waste collection facilities and waste collection expenditure were inversely related to household income (Wekisa & Majale, 2020). Therefore, waste indicators for the season and subset of locations where GSV imagery is available may be biased. We hypothesise that they do not represent year-long, city-wide conditions.

Given the future potential of GSV for characterising mismanaged urban waste at scale, this study aims to assess differences in scattered waste density, waste burning, and dumping indicators in urban areas without GSV coverage versus those with full or partial GSV coverage. We thereby aim to evaluate bias in GSV-derived waste indicators arising from incomplete spatial coverage. Our study draws on a transect-based field survey of waste in slums in two LMIC cities, namely Kisumu in Kenya and Accra in Greater Accra Region in Ghana. These cities have contrasting population sizes and are located in countries with different policy approaches to plastic waste management. As a secondary objective to assess potential temporal bias in GSV-derived waste indicators, we also aim to assess whether GSV image acquisition is more frequent in the dry season in SSA cities, given seasonal variation in waste generation and mismanaged waste impacts. In so doing, we provide evidence on the future potential for waste quantification in LMIC cities via GSV imagery.

2. Methods

2.1. Overview of methodology

This study comprised an analysis of six waste indicators from a quantitative environmental transect survey in

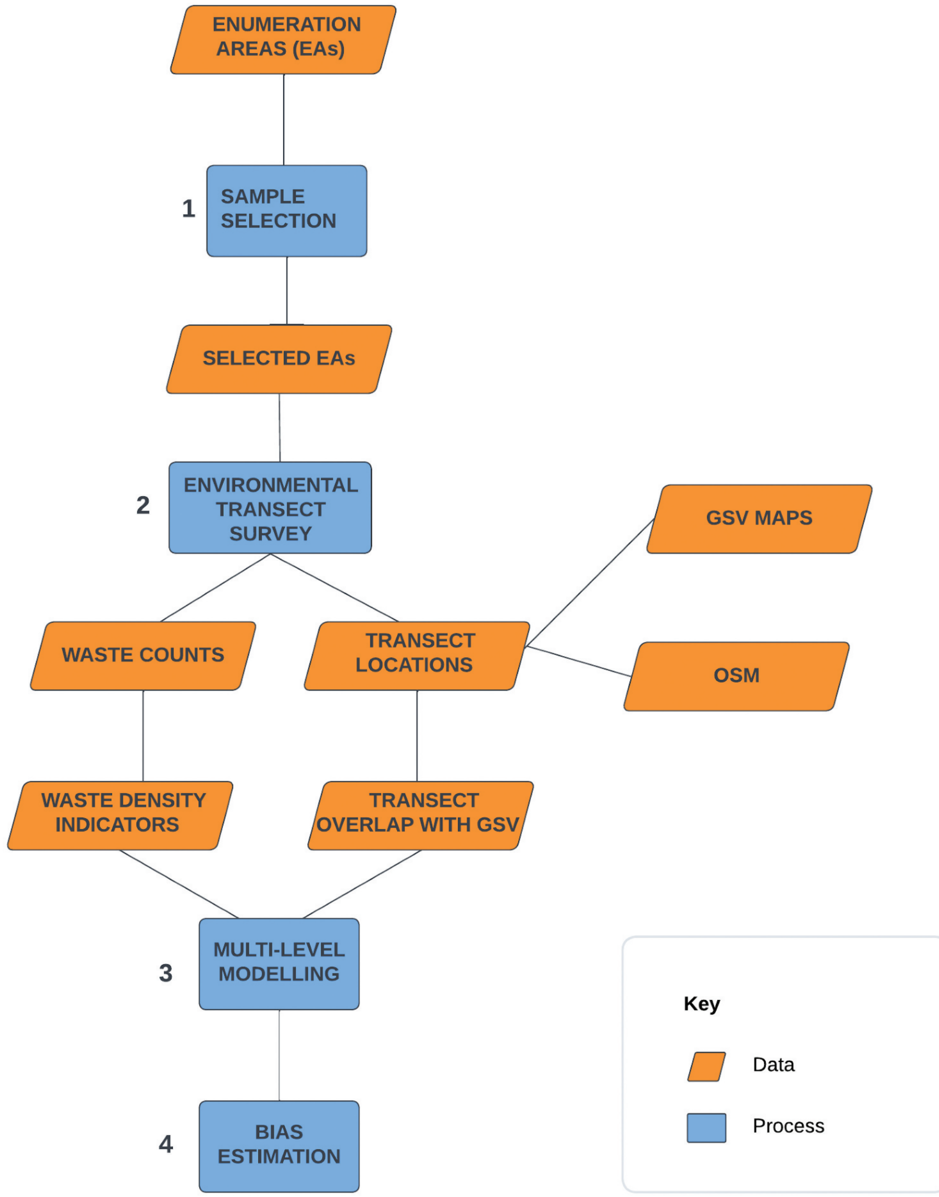

Figure 1. Summary of study design for assessing differences in waste indicators between urban areas with and without Google Street View coverage.

slum areas in Greater Accra, Ghana, and Kisumu, Kenya (Figure 1). Waste indicators were compared via multi-level regression for transects with full versus partial or no GSV coverage. In addition, in a subsidiary, complementary component, we tested for significant differences in precipitation in a sample of SSA cities with GSV for months when GSV was acquired versus months without GSV acquisition.

2.2. Study sites for assessment of spatial bias in GSV coverage

Ghana and Kenya were chosen as detailed case study countries within SSA with differing policies regulating domestic plastic waste generation. Ghana has an extensive sachet (bagged) water industry (Stoler, 2012). It raises excise duty on semi-finished and raw plastics but has not banned single-use plastics (Adam et al., 2020). In contrast, Kenya has banned single-use plastic bags since 2017 (Behuria, 2021). Kisumu is Kenya's third largest city with a population of over 500,000 and is located by Lake Victoria. Over 60% of its population live in informal settlements, typically densely populated and lacking adequate access to electricity, water, and sanitation (Sibanda et al., 2017). In 2015, its population generated an estimated 200 to 450 tonnes/day of household solid waste (approximately 0.4 to 0.9 kg/person/day), mostly comprising organic waste (Gutberlet et al., 2016). Urban Greater Accra region's population was 5.0 million in 2021 (Ghana Statistical Services, 2021). Fifty-one percent of its households having solid waste collected in 2010 (Ghana Statistical Services, 2013), the latest year with available data. Mapping identified 78 slum communities within the city in 2000, though satellite-derived classification suggests their distribution has widened subsequently (Engstrom et al., 2015). The city of Accra, within the Greater Accra region, generates an estimated 0.74 kg/person/day of solid domestic waste or 1552 tonnes/day in total (Miezah et al., 2015). Both cities have GSV coverage, particularly in more well-planned areas, as opposed to the off-grid areas, where coverage is limited.

2.3. Transect survey of the urban waste environment

We randomly selected a sample of urban Enumeration Areas (EAs) using 2009 census data in Kisumu (Kenya National Bureau of Statistics, 2010) and 2010 census data in Greater Accra (Ghana Statistical Services, 2013). We selected 30 and 32 EAs in Greater Accra region and Kisumu County, respectively (Step 1 in Figure 1). This sample size was designed to assess inter-observer agreement in recorded waste indicators. Within Greater Accra, selected EAs also met one or more of the UN Habitat criteria for a slum (UN-Habitat, 2016) or lacked waste management services, given the project's focus on waste. Based on UN-Habitat criteria, we selected EAs where most households lived in over-crowded or non-durable housing, lacked improved sanitation or water sources, lacked secure tenure, or lacked waste services according to 2010 census data. EAs dominated by communal establishments (e.g. prisons; army barracks) were excluded. No equivalent small area census statistics were available in Kisumu, so all urban EAs were considered eligible. Following field reconnaissance, six EAs in Kisumu and 35 EAs in Greater Accra were excluded as lacking UN-Habitat slum characteristics and replacements were randomly selected. Two further EAs in Greater Accra were replaced because of concerns for field team security, particularly from organised criminal gangs, during preliminary fieldwork.

We implemented a beach litter survey methodology used by the United Nations Environment Programme (Cheshire et al., 2009) and the National Oceanographic and Atmospheric Organisation (Opfer et al., 2012), adapting this to the urban environment (Figure 1, Step 2). Uncollected waste was surveyed along two transect lines that, where feasible, bisected each EA and lay perpendicular to one another. Where possible, one transect line per EA followed a surface drainage line or storm drain. Otherwise, transect lines followed paths, tracks, or roads through the EA. Each transect line was surveyed separately by two independent surveyors. Surveys were conducted at morning, lunchtime, and evening in Kisumu, and morning and late afternoon only in Greater Accra, which necessitated more time to travel to EAs. Surveys in Greater Accra took place from 31 August to 19 October 2021 and from 10 September to 17 November 2021 in Kisumu.

Along each transect, two surveyors independently counted scattered waste items within a 2 m radius every 50 metres along the transect. They recorded waste type (e.g. PET bottles; nappies; discarded personal protective equipment (PPE)). Waste fragments in close proximity originating from the same object were counted as single items. Separately, they also recorded the locations of waste burning sites and large waste piles (greater than 1 m in diameter) 2 metres on either side of the transect. All observations were recorded onto tablets via SurveyCTO data management software (Dobility Inc., 2021), with locations surveyed via the tablets' non-differential GPS receivers.

2.4. Survey integration with Google Street View coverage and OpenStreetMap features

We recorded spatial overlap between each transect and GSV coverage via visual interpretation in December 2021 (Figure 1, Step 3). Greater Accra and Kisumu had GSV imagery acquired in March 2016 and May–June 2018, respectively. Very few transects had full GSV coverage, but some transects either partially coincided with GSV coverage. For transects with partial GSV coverage, we conducted follow-up waste surveys from transect end-points along the streets with GSV coverage, surveying a street segment randomly to the left or right of the existing transect. These follow-up surveys took place from 6 January 2022 to 19 January 2022 in Greater Accra and from 1 April 2022 to 6 April 2022 in Kisumu.

To characterise transects with and without GSV coverage, we also downloaded OpenStreetMap (OSM) features depicting roads, retail amenities, and public buildings, calculating their density within 250 m of transects. In calculating these metrics, we excluded several Greater Accra neighbourhoods that had been intensively mapped via a World Bank project (Global Facility for Disaster Reduction and Recovery, 2020).

2.5. Statistical analysis

Six example indicators were generated for each transect, characterising and quantifying waste within four environmental domains comprising: a total mismanaged waste domain (indicators: density of scattered waste items and density of large waste dumps); a mismanaged waste composition domain (indicator: density of scattered plastic waste items); a domain reflecting waste origins of policy concern (indicators: density of discarded PPE and density of discarded nappies); and a waste disposal practice domain (indicator: density of waste burning sites). Densities were calculated from waste counts and total transect areas surveyed.

Since transect observations were repeated at different times of day, we used multi-level mixed effects regression modelling to account for data clustering within transects. Multi-level models are widely used in ecology, education, and public health to handle hierarchically structured data (Snijders & Bosker, 2011). Multi-level models were tested for significant differences between waste indicators, for transects with full GSV coverage versus partial or no coverage (Figure 1, Step 4). Initially, we fitted null models without explanatory variables and models that controlled for transect-level fixed effects representing transect length and whether a transect followed a storm-drain/stream versus roads. Finally, we modelled each waste indicator at the transect-observation level in relation to transect-level random effects and fixed effects for GSV coverage. All statistical analyses were conducted in Stata (StataCorp, 2019).

2.6. Assessment of dry season bias in GSV coverage

To test for potential dry season bias in GSV image acquisition months, we sampled cities in LMICs in SSA with populations over 300,000 according to the Global Database of Metropolises 2020 (UN-Habitat, 2020) (Figure 2). We chose this database because it captures both large and medium-sized cities, since earlier work spatio-temporal GSV coverage only studied large cities (Kim & Jang, 2023). We included only LMIC cities, since waste service coverage is typically lower in LMICs (Kaza et al., 2018). GSV image acquisition months were recorded for each selected city via the GSV public interface in December 2021. Cities in 14 countries had GSV imagery, so we selected the city in each country with the most widespread GSV coverage as identified through the GSV public interface. We also purposively selected Lagos given its significance as a potential source of mismanaged waste (Jambeck et al., 2015). Monthly precipitation estimates from the Climate Hazards Infra-Red Precipitation with Stations (CHIRPS) rainfall product were calculated for each city from January 2015 to October 2021. The CHIRPS product combines infrared Cold Cloud Duration satellite imagery with a spatial resolution of 0.05° with ground-based precipitation observations via a novel interpolation algorithm (Funk et al., 2015). Since there were no CHIRPS records for December 2021, when GSV images were acquired for Kigali, it was excluded from the analysis, leaving 14 cities. Robust logistic regression, which accounted for clustering in monthly precipitation by city, was then used to test for differences in monthly precipitation anomalies (i.e. monthly precipitation minus mean annual precipitation per city) between months with and without GSV acquisition campaigns.

3. Results

3.1. Spatial overlap between Google Street View coverage and environmental waste survey transects

In Kisumu, field surveys generated 20 transects with full GSV image coverage, 17 with partial GSV coverage, and 44 with no GSV coverage (Figure 3). In Greater Accra, the field survey generated 14 transects with full GSV coverage, 28 with partial coverage, and 53 with no GSV coverage (Figure 4). Following repeat surveys of the same transect by separate observers at different times of day, a total of 586 transect observations were recorded in Kisumu and 359 in Greater Accra.

In both cities, overlay with OSM-derived public building and retail density indicated higher retail density along transects with GSV coverage (Table 1). Transects with full GSV coverage were typically longer. A greater proportion of transects with full GSV coverage also followed major roads. 88.31% and 30.96% of transects with full GSV coverage followed major roads in Kisumu and Greater Accra, respectively, compared with 10.48% and 6.14%, respectively, of transects without full GSV coverage.

Initial visualisation of the six waste indicators indicated that mean waste burning densities in both Greater Accra and Kisumu were much greater in areas without GSV coverage than in areas with coverage (Table 1 and Figure 5a). Most other indicators, including scattered waste density (Figure 5b), were similar in areas with and without GSV. However, scattered waste density and density of scattered plastics were approximately three times greater in Kisumu than Greater Accra (Table 1 and Figure 5b).

3.2. Differences in environmental waste indicators between areas with different levels of overlap with Google Street View imagery

Preliminary multi-level models indicated no significant impact of either transect length or type (along street versus drainage line) on waste indicators in

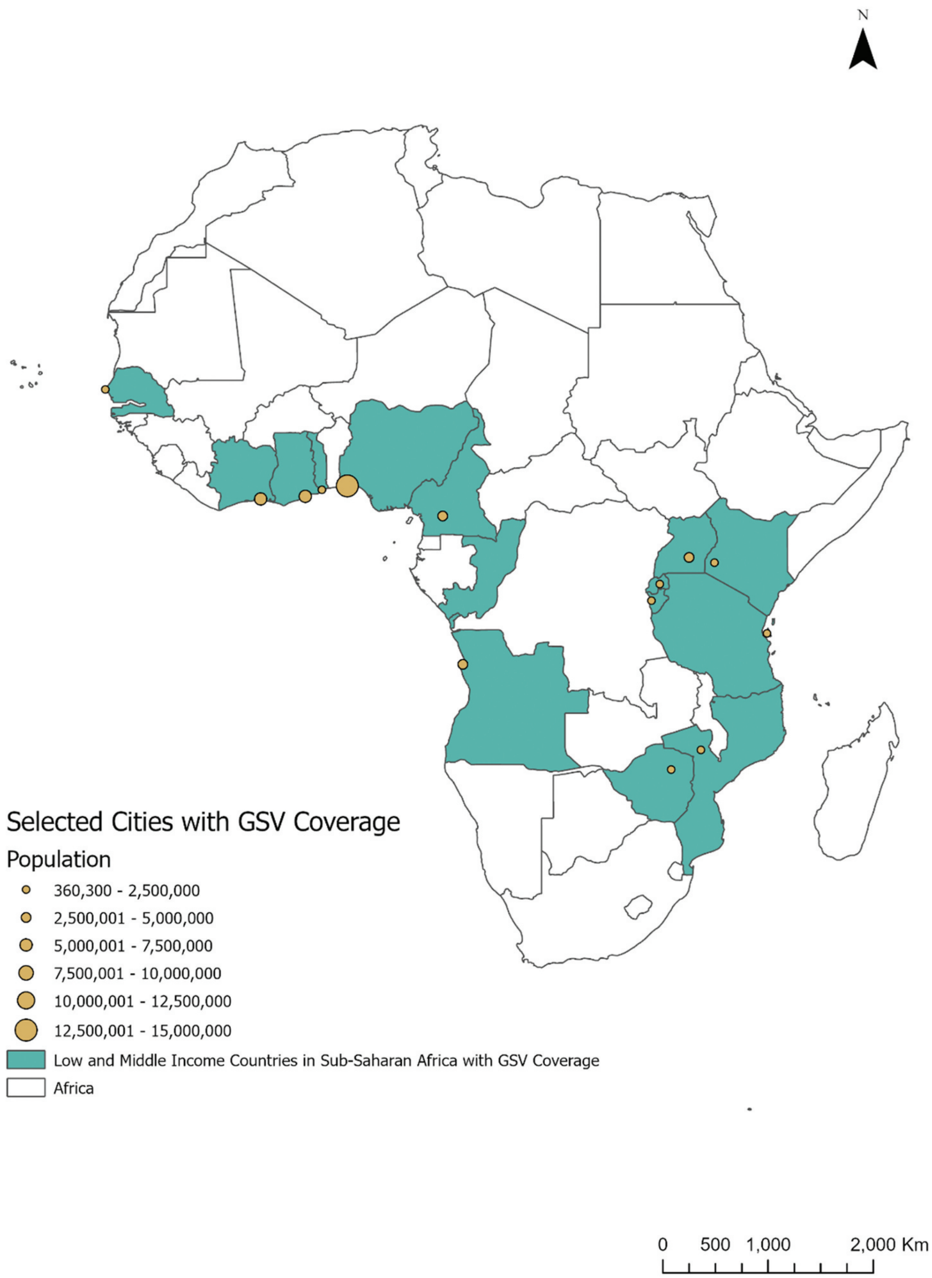

Figure 2. Metropolises with populations over 300,000 in 2020 in low- and middle-income sub-Saharan African countries where Google Street View imagery is available (sources: city populations: UN Habitat Global Database of Metropolises 2020, country boundaries: Planet; World Bank country classification, 2021; (Google, 2023)).

either city. Tables 2 and 3 show final multi-level regression model coefficients and their statistical significance. Positive coefficients indicate greater densities of waste sites or items for transects with GSV coverage, relative to those with no overlap, whilst negative coefficients indicate lower densities for transects with GSV coverage. There were thus no significant differences in total scattered waste density and scattered plastic waste density in Kisumu (Table 2). Discarded PPE density was significantly greater for transects with full GSV coverage than those with no coverage, but only marginally. Discarded nappy density was significantly lower for transects with partial GSV coverage than those with no coverage, but again only marginally. Density of large waste piles and density of waste burning sites were significantly lower for transects with full GSV coverage.

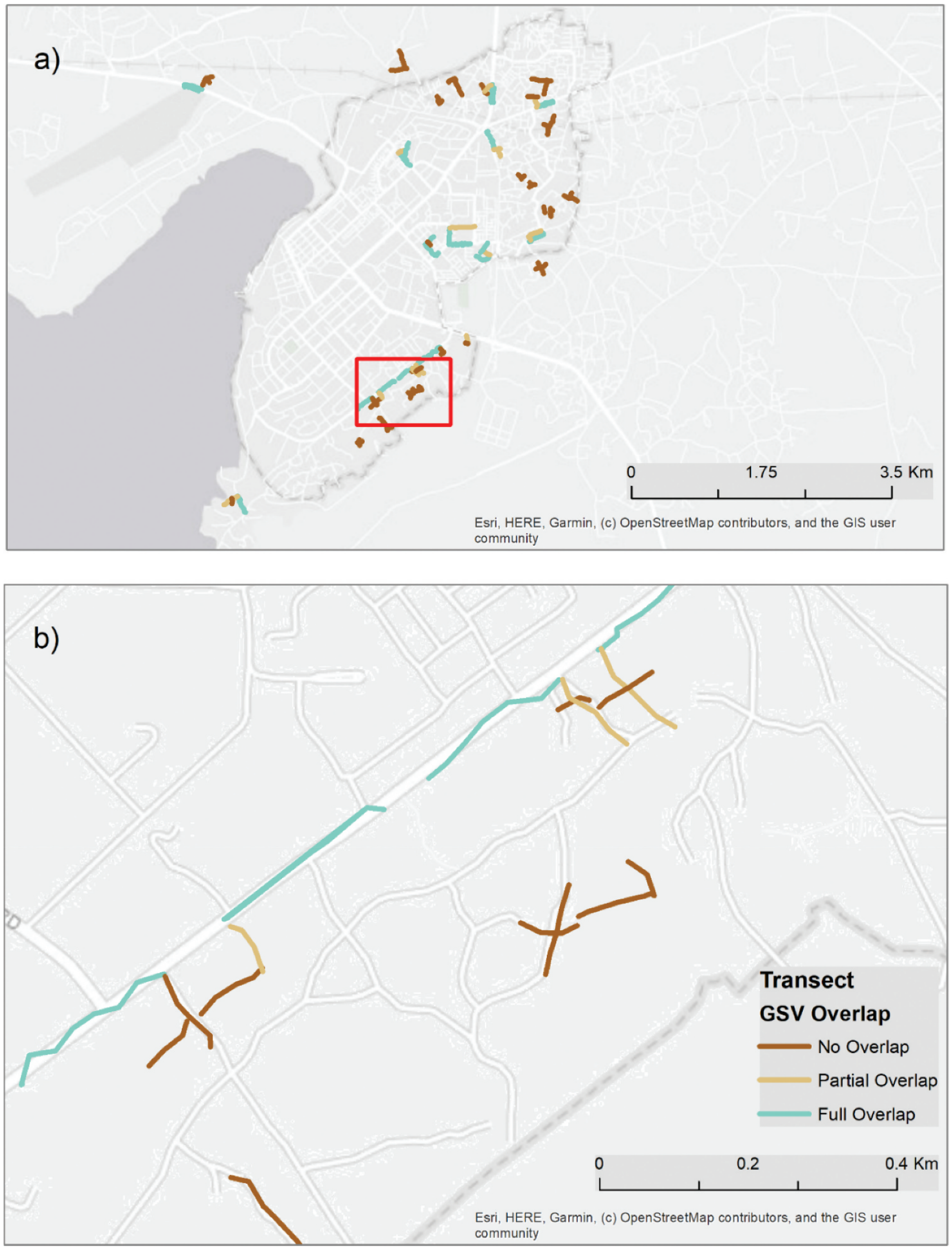

Figure 3. (a) Locations and 2022 Google Street View coverage of environmental transects in Kisumu, Kenya. (b) Inset map showing transects in three case study enumeration areas.

In Greater Accra, there were no significant differences in any of the waste density indicators between transects with and without GSV coverage except for the density of waste burning sites. Densities were significantly lower for transects with full GSV coverage compared with those with no coverage, but only marginally so (Table 3).

3.3. Dry season bias in Google Street View acquisition dates

The driest city sampled was Luanda, Angola, with long-term monthly mean precipitation of 35.6 mm, and the wettest was Enugu, Nigeria, with 144.3 mm/month. Almost all cities had GSV imagery from a single month only, with acquisition months ranging from May 2015 for Kampala, Uganda, to July 2021 for Yaoundé, Cameroon. Robust logistic regression analysis of CHIRPS rainfall data for the 14 case study cities suggested that months when GSV was acquired, were somewhat drier than those without GSV acquisition campaigns. However, these differences were not significant (odds ratio for GSV acquisition: 0.90 per 100 mm of precipitation monthly difference from long-term mean; 95% confidence intervals 0.62 to 1.32).

Figure 4. (a) Locations and 2022 Google Street View coverage of environmental transects in Greater Accra, Ghana. (b) Inset map showing transects in two case study enumeration areas

4. Discussion

4.1. Implications of GSV coverage bias for waste quantification

GSV could provide a valuable future resource for quantifying mismanaged waste in cities to inform policy, targeting resources towards hotspots of mismanaged waste and identifying specific discarded waste items of policy concern. However, a key question is whether GSV's spatio-temporal coverage is biased relatively to indicators of urban waste patterns. In both Greater Accra and Kisumu, we found significantly lower densities of waste burning sites between transects with full versus limited or no GSV coverage (Tables 2 and 3). We also found significantly lower densities of large waste piles and higher discarded PPE densities in Kisumu transects with GSV coverage (Table 2), but no significant differences in any other waste indicators. Thus, overall, we found evidence that GSV spatial coverage exhibited bias for some waste indicators, with density of waste burning sites and large waste piles lower in sites with GSV coverage. There was little bias evident in

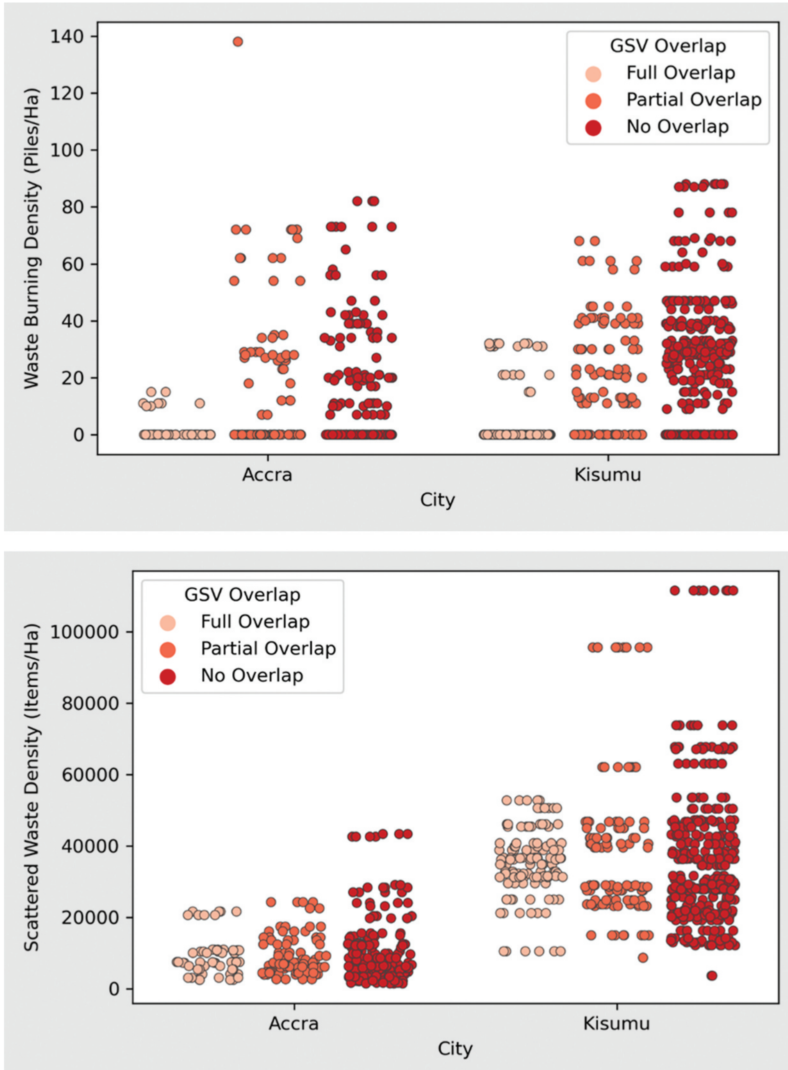

Figure 5. Distribution of (a) waste burning density and (b) scattered waste density for transects in Greater Accra and Kisumu with full, partial, or no Google Street View coverage

scattered waste indicators. Such bias was city-specific and indicator-specific.

Our finding that GSV coverage is biased for waste indicators agrees with previous studies examining GSV coverage by street and neighbourhood type. For example, a multi-level modelling analysis of GSV availability within 371 Latin American cities found significantly higher GSV availability in sub-city units with higher socio-economic condition scores (Fry et al., 2020). Similarly, a US study found fewer GSV images available on minor streets in San Diego compared with major streets (Smith et al., 2021). In Kisumu and Greater Accra, we also found greater GSV coverage on major as opposed to minor roads (Section 3.1). Studies elsewhere indicate waste generation, management and disposal vary locally in a complex pattern. For example, in an Australian study (Spennemann, 2021), PPE densities were much higher in car parks than on footpaths or in other urban spaces. Kisumu's GSV followed major roads (Section 3.1) where motorbike taxi stands are commonly found. Thus, discarded PPE items in Kisumu also appeared more concentrated in crowded public spaces as opposed to minor residential streets and walkways. Studies in high-income countries such as the USA suggest that some forms of scattered waste are concentrated near retail outlets (Marah & Novotny, 2011). However, in Greater Accra and Kisumu transects with GSV coverage had scattered waste densities no higher than elsewhere despite having greater retail outlet densities (Tables 1–3). Relationships between waste generation and urban form may thus be country- or city-specific. Our field teams observed that in both Greater Accra and Kisumu, waste service providers favoured surfaced roads to avoid damage to refuse collection

Table 1. Summary statistics describing characteristics of environmental transects with different levels of GSV overlap in Kisumu and Greater Accra (OSM: OpenStreetMap)

	Mean (standard deviation)		
Characteristic	Full overlap	Partial overlap	No overlap
Kisumu			
No. transects	20	17	44
No. repeat transect observations	126	114	346
Transect length (m)	310 (141.3)	137.3 (65.4)	114.8 (65.2)
OSM retail outlet density (outlets/Ha)	0.44 (0.35)	0.46 (0.40)	0.32 (0.32)
OSM communal building density (outlets/Ha)	0.16 (0.13)	0.13 (0.11)	0.16 (0.12)
Total Scattered Waste Density (items/Ha)	44714.96 (46956.66)	53931.19 (105034.50)	39682.94 (43801.88)
Scattered plastic waste density (items/Ha)	11999.78 (19173.4)	8753.52 (5278.57)	10133.48 (11111.11)
Discarded nappy density (items/Ha)	404.203 (1319.14)	1521.74 (7146.35)	197.79 (813 (59)
Discarded PPE density (items/Ha)	593.67 (922.20)	418.82 (619.22)	358.78 (845.71)
Waste burning site density (sites/Ha)	4.33 (10.21)	18.90 (19.40)	24.15 (22.64)
Large waste pile density (piles/Ha)	1.39 (5.76)	9.59 (15.34)	11.46 (17.89)
Greater Accra			
no. transects	14	28	53
No. repeat transect observations	56	103	200
Transect length (m)	189.0 (119.1)	129.3 (96.9)	131.5 (106.9)
OSM retail outlet density (outlets/Ha)	0.23 (0.93)	0.09 (0.49)	0.03 (0.06)
OSM communal building density (outlets/Ha)	0.03 (0.04)	0.02 (0.03)	0.01 (0.02)
Total Scattered Waste Density (items/Ha)	9093.69 (7852.96)	8814.53 (7677.62)	10124.84 (12459.95)
Scattered plastic waste density (items/Ha)	3767.95 (3910.58)	3589 (3748.21)	3457.17 (4663.44)
Discarded nappy density (items/Ha)	4.73 (35.44)	1.71 (12.26)	4.00 (32.51)
Discarded PPE density (items/Ha)	58.28 (186.78)	24.12 (81.63)	34.07 (149.41)
Waste burning site density (sites/Ha)	1.67 (4.20)	17.55 (26.49)	13.63 (20.92)
Large waste pile density (piles/Ha)	2.74 (8.55)	9.38 (20.43)	4.57 (11.73)

Table 2. Coefficients for transects with full and partial Google Street View, derived from a multi-level model predicting six environmental waste indicators in Kisumu, Kenya (based on 126 observations of transects with full GSV coverage, 114 observations of transects with partial GSV coverage, and 346 observations of transects with no GSV coverage; reference category: no GSV coverage)

Waste Domain: indicator	Regression coefficient: full GSV overlap (95% confidence intervals)	p value	Regression coefficient: partial overlap (95% confidence intervals)	p value	Constant (95% confidence intervals)
Total mismanaged waste: scattered waste density (items/Ha)	5,661 (−11,459 to 22,781)	0.517	−12,271 (−30,830 to 6,287)	0.195	51,791 (35,710 to 67,871)
Total mismanaged waste: density of large waste piles (piles/Ha)	−9.822 (−16.377 to -3.306)	0.003	0.619 (−6.577 to 7.816)	0.866	10.644 (4.422 to 16.866)
Mismanaged waste composition: scattered plastic waste density (items/Ha)	2,004 (−3,000 to 7,007)	0.433	1,455 (−4,066 to 6,977)	0.605	8,619 (3,843 to 13,395)
Waste origins of policy concern: discarded nappy density (items/Ha)	206 (−933 to 1,344)	0.723	−1,288 (−2,539 to −36)	0.044	1,484 (400 to 2,567)
Waste origins of policy concern: discarded PPE density (items/Ha)	240 (10 to 470)	0.041	−58 (−307 to 191)	0.648	415 (199 to 631)
Waste disposal practices: density of waste burning sites (sites/Ha)	−21.000 (−30.368 to −11.632)	0.000	−6.480 (16.851 to 3.890)	0.221	24.786 (19.567 to 30.006)

vehicles and tricycles. Lack of penetration of waste collection services along minor roads and walkways with lower GSV coverage could therefore explain greater waste burning in such areas as an alternative means of waste disposal.

Based on our assessment of 14 SSA cities, we found no evidence that GSV acquisition periods were concentrated in drier months. This suggests that dry season bias in image acquisition months would not affect overall waste metrics derived from international studies of multiple cities. However, GSV-derived waste indicators in a particular city may be affected by seasonal variation depending on imagery acquisition month. Our analysis of seasonal patterns of GSV image acquisition dates extends previous studies, which found variation in the age of the most recent GSV image or the number of images available at a given site (Kim & Jang, 2023; Smith et al., 2021).

Given that GSV spatial coverage leads to bias in some waste indicators, we recommend that any future GSV-based studies generating city-level waste indicators for LMIC cities assess and, if necessary, adjust for such bias. Although GSV cars struggle to operate in densely packed informal settlements, there are both

Table 3. Coefficients for transects with full and partial Google Street View, derived from a multi-level model predicting six environmental waste indicators in Greater Accra, Ghana (based on 56 observations of transects with full GSV coverage, 103 observations of transects with partial GSV coverage, and 200 observations of transects with no GSV coverage; reference category: no GSV coverage)

Waste Domain: indicator	Regression coefficient: full GSV overlap (95% confidence intervals)	p value	Regression coefficient: partial overlap (95% confidence intervals)	p value	Constant (95% confidence intervals)
Total mismanaged waste: scattered waste density (items/Ha)	−1201 (−5,944 to 3542)	0.428	1509 (-,2,222 to 5,241)	0.428	8,785 (5,762 to 11,809)
Total mismanaged waste: density of large waste piles (piles/Ha)	−1.834 (−9.757 to 6.087)	0.650	−4.273 (−10.517 to 1.971)	0.180	8.805 (3.721 to 13.888)
Mismanaged waste composition: scattered plastic waste density (items/Ha)	263 (−1,752 to 2,279)	0.797	−189 (−1,771 to 1,393)	0.815	3,693 (2,411 to 4,975)
Waste origins of policy concern: discarded nappy density (items/Ha)	0.394 (−9 to 10)	0.937	−2.654 (−5 to 10)	0.505	1.687 (−4 to 8)
Waste origins of policy concern: discarded PPE density (items/Ha)	19 (−45 to 83)	0.557	16 (−34 to 66)	0.535	22 (−18 to 63)
Waste disposal practices: density of waste burning sites (sites/Ha)	−11.523 (−22.961 to −0.085)	0.048	−4.280 (−13.301 to 4.740)	0.352	17.483 (10.142 to 24.824)

motorbikes (Street View Three-Wheeler) and backpacks (Street View Trekker) that have captured GSV imagery in these environments, such as urban Indonesia (Google, 2022). Future targeted use of these technologies to sample off-grid urban communities could help address spatial bias in GSV coverage. Alternatively, waste metrics derived from GSV via image interpretation or processing could be combined with UAV-based sample surveys covering areas with and without GSV imagery (Jakovljevic et al., 2020; Youme et al., 2021) to adjust for coverage bias in GSV. There is inevitably an elapsed time lag between GSV image acquisition and subsequent field survey or use of any derived indicators to inform urban planning (Mooney et al., 2014). Given this time lag, GSV-based mismanaged waste characterisation may be better suited to those neighbourhoods that have not experienced rapid development or transitions, which could be identified by expert knowledge or via multi-temporal earth observation data.

As image availability spreads, provided steps were taken to address coverage bias, GSV could be used in future to quantify mismanaged urban waste at international scale. Studies have already used visual GSV interpretation to quantify street litter at city scale (Mooney et al., 2014; Odgers et al., 2012). Meanwhile, automated GSV analysis has recently quantified street greenness, pedestrian crossings, traffic lanes, and single occupancy homes at continental scale across 500 US cities (Keralis et al., 2020). In future, subject to computer vision algorithm development, automated GSV analysis could be used to monitor urban waste at scale in a similar way. Waste estimates derived from GSV using a consistent methodology could be especially valuable, given international monitoring of urban waste systems often relies on existing study findings (Kaza et al., 2018), which may vary in their methodologies. In cities with widespread GSV coverage, there may be potential to target mismanaged waste hotspots via such an approach. GSV could also be used to identify specific waste items of policy concern, such as single-use disposable nappies (Reese et al., 2015), pandemic-related PPE (Ammendolia et al., 2021), or discarded water bottles and sachets (Stoler, 2012; Wardrop et al., 2017).

In our analysis, we have evaluated potential spatio-temporal bias in GSV coverage for solid waste indicator generation, based on field survey data concerning mismanaged waste in two cities. Future studies could develop visual interpretation or digital image processing methods to generate waste indicators from GSV imagery, assessing their accuracy, for example, by comparing waste item counts in GSV imagery with those from field surveys.

4.2. Implications of environmental transect survey for waste management

Our transect survey shows that Kisumu has greater scattered waste densities than Greater Accra (Figure 5b). Beach surveys following the same transect methodology use a clean coast index to measure plastic waste in the environment. Plastic waste densities greater than 0.5 items/m^2 are considered dirty and greater than 1 part/m^2 extremely dirty (Alkalay et al., 2007). According to the clean coast index, 33.1% of Kisumu transects were extremely dirty, compared to 6.7% of Greater Accra transects. Median total scattered waste densities were nearly three times higher in Kisumu than Greater Accra. Our survey highlights the consequences of only 10% of Kisumu's households having waste collected in

2019 (Kenya National Bureau of Statistics, 2019). Our transect survey also highlights specific products generating mismanaged scattered waste (Table 1). Corroborating studies in coastal Kenya and urban South Africa that also found increased hygiene-related waste during the COVID-19 pandemic (Okuku et al., 2021; Ryan et al., 2020), we find locally high densities of discarded PPE in both Kisumu and Greater Accra. We also found locally high densities of discarded disposable nappies in Kisumu, reflecting reported mismanaged disposable diaper waste in other LMICs such as Zimbabwe (Mbiba, 2014) and Indonesia (Agestika et al., 2021). Finally, discarded packaging from water sachets represented a greater proportion of scattered waste in Greater Accra, reflecting extensive consumption of packaged water sold in bags in urban Ghana (Wardrop et al., 2017).

4.3. *Study limitations*

Our findings are subject to several uncertainties and limitations. This includes measurement uncertainty arising from inter-observer variation in observed waste distribution. Since fieldwork took place in the pandemic, to protect survey teams from infection risk, teams observed waste counts but did not pick up and weigh waste items. This prevented waste analysis by weight or volume. Small discrepancies in surveyor location resulting from the use of non-differential GPS receivers, miscounting or misclassification of waste items, and transcription errors recording waste counts on transects will all contribute to transect survey errors. Communities may also have reacted to the presence of survey teams by tidying mismanaged waste. However, community entry procedures were designed to minimise this risk. Furthermore, mismanaged waste metrics generated via fieldwork are inherently different from those generated via visual interpretation of GSV imagery. This is an inherent limitation of any comparison of field observations of mismanaged waste versus GSV imagery. Since only image acquisition month and not acquisition hour or day is documented for GSV, the extent of weekly or diurnal coverage bias remains uncertain. In Delhi in India, transect-based observations of burning of municipal solid waste revealed significant diurnal variation in burning, with higher burning taking place in mornings than in evenings (Nagpure et al., 2015). Since waste generation, collection, and disposal may operate to diurnal, weekly patterns, there may be more granular temporal bias in GSV coverage that we were unable to evaluate. Spatial bias in waste indicators may also vary over time, so our estimates of spatial bias may differ from those at the time when GSV imagery was acquired. Finally, our transect sample size was not statistically powered to compare waste indicators for transects with differing GSV coverage. The relatively small number of transects surveyed will have limited our ability to detect bias of smaller magnitude in waste indicators.

5. Conclusions

As its coverage expands in LMICs, GSV image analysis has potential for the characterisation of the urban solid waste environment at scale in developing country cities where waste collection service coverage remains low. To evaluate potential bias in spatio-temporal coverage of GSV in relation to the urban solid waste environment, we used multilevel modelling to test for significant differences in waste indicators between field survey transects with no, partial, or full GSV coverage. Our study reveals significant difference in some but not all waste indicators between areas with full versus partial or no GSV coverage. In both Greater Accra and Kisumu, density of waste burning sites was significantly lower in areas with full GSV coverage. In Kisumu, density of large waste piles was significantly lower and density of discarded PPE higher in areas with full GSV coverage. Otherwise, there were no significant differences in other indicators derived from scattered waste observations. We further find in a sample of SSA cities that there is no evidence of GSV image acquisition campaigns being concentrated in dry season months. Thus, whilst GSV has potential for generating indicators to inform waste policy and management in LMICs, we recommend that future studies should assess and adjust GSV-derived waste indicators to account for bias arising from GSV's incomplete spatial coverage in such cities. Similarly, expanded GSV coverage that captures low-income neighbourhoods in SSA cities could have societal benefits in monitoring and reduced mismanaged solid waste.

List of Abbreviations and Acronyms

API	Application Programming Interface
CHIRPS	Climate Hazard Group InfraRed with Station
CI	Confidence Interval
EA	Enumeration Area
GPS	Global Positioning System
GSV	Google Street View
LMIC	Low- and Middle-Income Country
PET	Polyethylene Terephthalate
PPE	Personal Protective Equipment
SSA	Sub-Saharan Africa
UN	United Nations
UAV	Unmanned Aerial Vehicle

Highlights

- We evaluated bias in spatial-temporal coverage of Google Street View (GSV)
- A transect survey recorded solid waste indicators in two African cities
- Multi-level models showed much lower waste burning for transects with GSV imagery
- GSV may under-estimate waste densities in some cities because of partial coverage
- Studies should assess and adjust waste metrics from GSV for spatial coverage bias

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Public Interest Statement

When mismanaged waste enters the environment, it threatens ecosystems and public health. This issue could soon escalate in developing country cities, given current trends. In future, Google Street View (GSV) imagery could help monitor mismanaged waste, as US researchers have already successfully counted street litter visible on GSV. However, GSV in sub-Saharan Africa mostly covers main roads, with little coverage of minor roads and slums. These minor roads are often inaccessible for waste collection vehicles or home to communities who cannot afford waste services. By missing such areas, GSV could potentially underestimate mismanaged waste. To investigate this, our paper compares indicators such as waste burning and street litter between areas with and without GSV. Via a field survey in Greater Accra (Ghana) and Kisumu (Kenya), we found more waste burning in areas without GSV. This highlights the need to correct any future waste estimates from GSV for bias.

Data availability statement

For the Greater Accra and Kisumu analysis, the environmental transect data are openly available as:

Umar, F., Amponsah, M., Damkjaer, S. Dzodzomenyo, M., Okotto, L.G., Okotto-Okotto, J., Oigo, J., Shaw, P., Wright, J, and Väisänen, H., Wanza, P. (2023). Environmental Transects Surveys of Mismanaged Waste in Off-Grid Neighbourhoods of Kisumu, Kenya, and Greater Accra, Ghana, 2021 [Data Collection]. Colchester, Essex: UK Data Service. https://dx.doi.org/10.5255/UKDA-SN-856145.

OpenStreetMap data are openly available from multiple sources, including Planet: https://planet.openstreetmap.org/.

For the analysis of dry season bias, the UN Habitat Global State of Metropoles Database 2020 is openly available via https://urbanpolicyplatform.org/global-state-of-metropolis/. The World Bank country classification is openly available here: https://datatopics.worldbank.org/world-development-indicators/the-world-by-income-and-region.html. CHIRPS rainfall data are openly available here: https://www.chc.ucsb.edu/data/chirps. Country boundaries are openly available from: https://www.naturalearthdata.com/about/terms-of-use/.

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