Mapping Waste Piles in an Urban Environment Using Ground Surveys, Manual Digitization of Drone Imagery, and Object Based Image Classification Approach

Patrick K. Kalonde[1,2,3], Taonga Mwapasa[4], Rosheen Mthawanji[3], Kondwani Chidziwitsano[4], Tracy Morse[5], Jeffrey S. Torguson[1], Christopher M. Jones[2], Richard S. Quilliam[6], Nicholas A. Feasey[2,7], Marc Y. R. Henrion[2,3], Michelle C. Stanton[2], Mikhail S. Blinnikov[1]

Affiliations

[1] Department of Geography and Planning, St Cloud State University, St Cloud State University, 720 4th Ave South, 56301, St Cloud, Minnesota, United States.

[2] Liverpool School of Tropical Medicine, Liverpool, United Kingdom.

[3] Malawi Liverpool Wellcome Programme, P.O. Box 30096, Chichiri, Blantyre 3, Malawi.

[4] Centre for Water, Sanitation, Health, and Appropriate Technology Development (WASHTED), Malawi University of Business and Applied Sciences, Blantyre, Malawi.

[5] Department of Civil and Environmental Engineering, University of Strathclyde, Glasgow, United Kingdom.

[6] Biological & Environmental Sciences, Faculty of Natural Sciences, University of Stirling, Stirling, FK9 4LA, United Kingdom.

[7] School of Medicine, University of St Andrews, St Andrews, United Kingdom.

Corresponding author: Patrick Ken Kalonde pkalonde@mlw.mw

Authors Email addresses:

Patrick Ken Kalonde pkalonde@mlw.mw

Taonga Mwapasa: tmwapasa@poly.ac.mw

Rosheen Mthawanji: r.s.mthawanji@liverpool.ac.uk

Kondwani Chidziwitsano: kchidziwitsano@mubas.ac.mw

Tracy Morse: tracy.thomson@strath.ac.uk

Jeffrey S. Torguson: jstorguson@stcloudstate.edu

Christopher M. Jones: chris.jones@lstmed.ac.uk

Richard S. Quilliam: richard.quilliam@stir.ac.uk

Nicholas A Feasey: nicholas.feasey@lstmed.ac.uk

Marc Y. R. Henrion: mhenrion@mlw.mw

Michelle C Stanton: michelle.stanton@lstmed.ac.uk

Mikhail S. Blinnikov: msblinnikov@stcloudstate.edu

Abstract

There is wide recognition of the threats posed by the open dumping of waste in the environment. However, tools to surveil interventions for reducing this practice are poorly developed. This study explores the use of drone imagery for environmental surveillance. Drone images of waste piles were captured in a densely populated residential neighborhood in the Republic of Malawi. Images were processed using the Structure for Motion (SfM) technique and partitioned into segments using Orfeo Toolbox mounted in QGIS software. A total of 509 segments were manually labeled to generate data for training and testing a series of classification models. Four supervised classification algorithms (Random Forest, Artificial Neural Network, Naïve Bayes, and Support Vector Machine) were trained, and their performances were assessed regarding precision, recall, and F-1 score.

Ground surveys were also conducted to map waste piles using a Global Positioning System (GPS) receiver and determine the physical composition of materials on the waste pile surface. Differences were observed between the field survey done by community-led physical mapping of waste piles and drone mapping. Drone mapping identified more waste piles than field surveys, and the spatial extent of waste piles was computed for each waste pile. The binary Support Vector Machine model predictions were the highest performing, with a precision of 0.98, recall of 0.99, and F1-score of 0.98. Drone mapping enabled the identification of waste piles in areas that cannot be accessed during ground surveys and further allowed the quantification of the total land surface area covered by waste piles. Drone imagery-based surveillance of waste piles thus has the potential to guide environmental waste policy, offer solutions for permanent monitoring, and evaluate waste reduction interventions.

Keywords: Waste Pile mapping; Object-Based Image Analysis; Orfeo Toolbox; Environmental monitoring, low-income countries, waste management

1. Introduction

Open dumping of waste poses a major global sustainability challenge, and eliminating the practice is a target on the global agenda for sustainable development (United Nations 2015) . Communities lacking systems for waste collection and disposal resort to uncontrolled dumping as the typical practice. It is estimated that three billion people worldwide lack access to controlled waste disposal facilities (Wilson et al. 2015), which presents serious consequences for natural ecosystems, human health, and economies. In Sub Saharan Africa, for example, over 70 % of the waste that is generated is openly disposed of in the environment (Ayeleru et al. 2020). On land, such disposed waste materials are generally transported by rainwater to rivers, lakes, and oceans, where they accumulate and harm natural ecosystems (Ostle et al. 2019; Zhu 2021), specifically by causing death and physical damage to aquatic fauna through entanglement and ingestion (Gall and Thompson 2015). Waste materials dumped in the environment can potentially present serious consequences for public health. Emerging studies indicate that waste materials such as plastics provide novel microhabitats for human pathogens (Gkoutselis et al. 2021; Rodrigues et al. 2019), and in 2022, a study showed for the first time the presence of microplastics in human blood (Leslie et al. 2022).

To curb the open dumping of waste into the environment, several solutions have been suggested, including the development and strict enforcement of legislation promoting household waste separation and collection, the development of adequate disposal facilities, and the implementation of waste recovery initiatives using a circular economy approach (Shi et al. 2021). Some countries have implemented a strict ban on the production and use of certain products such as plastics (Nyathi and Togo 2020; Xie and Martin 2022), discouraging the use of single-use carrier bags, promoting waste clean-up campaigns, and introducing community waste recycling programs (Dlamini and Simatele 2016). Assessing and monitoring the effectiveness of implementing these public health and environmental initiatives is essential to reducing or eliminating uncontrolled waste dumping.

Surveillance plays a crucial approach in quantifying the problems associated with waste in the environment, thereby allowing policymakers to contextualize them. Mapping existing waste disposal sites is one approach to understanding where waste is dumped and assessing the effectiveness of waste mitigation strategies. This will render the scale of this problem visible to policy makers. Waste piles can be mapped using Global Navigation Satellite System (GNSS) for example handheld Global Positioning Systems (GPS). Mobile applications such as ‘Open Litter Maps’ (https://openlittermap.com/) allow users to capture geotagged photos which later enable mapping locations where waste is being dumped (Lynch 2018). However, the use of handheld GPS can only limit observations to locations that are physically accessible to the observer, and some dumpsites located in areas with rugged terrain or without a proper access road cannot be mapped. Additionally, it is difficult to quantify the spatial extent of existing waste piles. In contrast, aerial images have the potential to overcome these limitations. For instance, satellite images have been used for the mapping of floating marine plastics at a global scale (Topouzelis et al. 2020). Still, most open satellite data have relatively coarse spatial resolution, and it is difficult to use such data to map smaller waste piles, especially in urban settings (Glanville and Chang 2015). Even high-resolution optically satellite images, usually provided by private companies, are often affected by cloud cover (Shastry et al. 2023), and can be prohibitively expensive.

High-resolution aerial images captured by drones offer a promising alternative to satellite imagery. The use of drone imagery has been employed in previous studies (Pinto, Andriolo, and Gonçalves 2021; Garcia-Garin et al. 2021; Jakovljevic, Govedarica, and Alvarez-Taboada 2020; Papakonstantinou et al. 2021; Wolf et al. 2020; Bao et al. 2018; Gonçalves et al. 2020a; 2020b; 2020c; Fallati et al. 2019; Kylili et al. 2019; Ribeiro et al. 2017), which have reported different approaches for mapping waste. One approach involves visual identification and manual labelling of objects considered as waste (Pinto, Andriolo, and Gonçalves 2021; Garcia-Garin et al. 2021; Jakovljevic, Govedarica, and Alvarez-Taboada 2020). Another approach involves manually identifying and labelling a small sample of waste piles or individual objects that are visible on the drone captured imagery and use these data as examples to train an image classification algorithm (Papakonstantinou et al. 2021; Wolf et al. 2020). Such classification algorithms that have been previously employed include a segmentation threshold algorithm (Bao et al. 2018), Random Forest (RF) (Gonçalves et al. 2020a; 2020b; 2020c; Martin et al. 2018), Artificial Neural Networks (ANN) (Pinto, Andriolo, and Gonçalves 2021) and Convolution Neural Networks (CNN) (Fallati et al., 2019; Garcia-Garin et al., 2021; Gonçalves, et al. 2020; Jakovljevic et al., 2020; Kylili et al., 2019; Papakonstantinou et al., 2021; Wolf et al., 2020). These algorithms were applied on water surfaces and sandy beaches with a uniform background where it is relatively easy to discriminate and identify waste materials. In an urban environment with a non-uniform background, simple algorithms such as the segmentation threshold algorithm are unlikely to work well.

This study aimed to assess the practicality of using drones to collect high-resolution aerial imagery for mapping waste piles in an urban environment in Malawi. We define a waste pile as a collection of waste found in the environment; these might have either been disposed of by humans or dispersed by an agent such as stormwater or wind. We hypothesize that on aerial images, piles of waste formed by disposing of waste materials would exhibit distinct characteristics that might assist in the automatic mapping of waste piles from optical aerial images. We utilized the drone imagery to train classification algorithms to automate the detection of waste piles, and subsequently evaluated the performance of the detection workflow. To the best of our knowledge, this is the first application of low-cost drone imagery for mapping waste piles along a river in Sub-Saharan Africa. It is also worth noting that this is the first time to explore drone imagery for mapping waste piles in an environment other than sandy beaches or coastal areas. This practical method will later be refined for use in studying or interrogating how humans get exposed to pathogens that might be hosted by the waste pile, thereby helping to shape public health discourse associated with open waste disposal. Currently, open waste disposal is seen as more of an environmental problem and less of a health problem, yet evidence of the growth of pathogenic microorganisms is increasing (Yang et al. 2023; Zettler, Mincer, and Amaral-Zettler 2013; Mphasa et al. 2025), highlighting the public health risks tied to this issue.

2. Methods

2.1. Study area

This study was conducted in Ndirande, the largest informal settlement in Blantyre – Republic of Malawi's second largest city (population 800,264). According to the most recent population census (conducted in 2018), Ndirande had a population of 97,839 people (NSO 2019). Indiscriminate disposal of waste in water drainage channels is common in the community (Maoulidi 2012; Banda 2015). Ndirande neighborhood has three administrative wards, namely Ndirande South, Ndirande West, and Ndirande North, and the current study specifically focused on a small part of the Ndirande South ward (Figure 1), chosen because the Nasolo River, a tributary of the Mudi River runs through it. The Mudi River is severely polluted and it has been the subject of several previous studies (Lakudzala, Tembo, and Manda 2000; Sajidu et al. 2007; Kumwenda et al. 2012; Kalina et al. 2022). The community also serves as one of the primary research sites for the Sustainable Attitudes to Benefit Communities and their Environments (SPACES - https://spacesproject.stir.ac.uk/), aiming to investigate the public health risks associated with plastic waste.

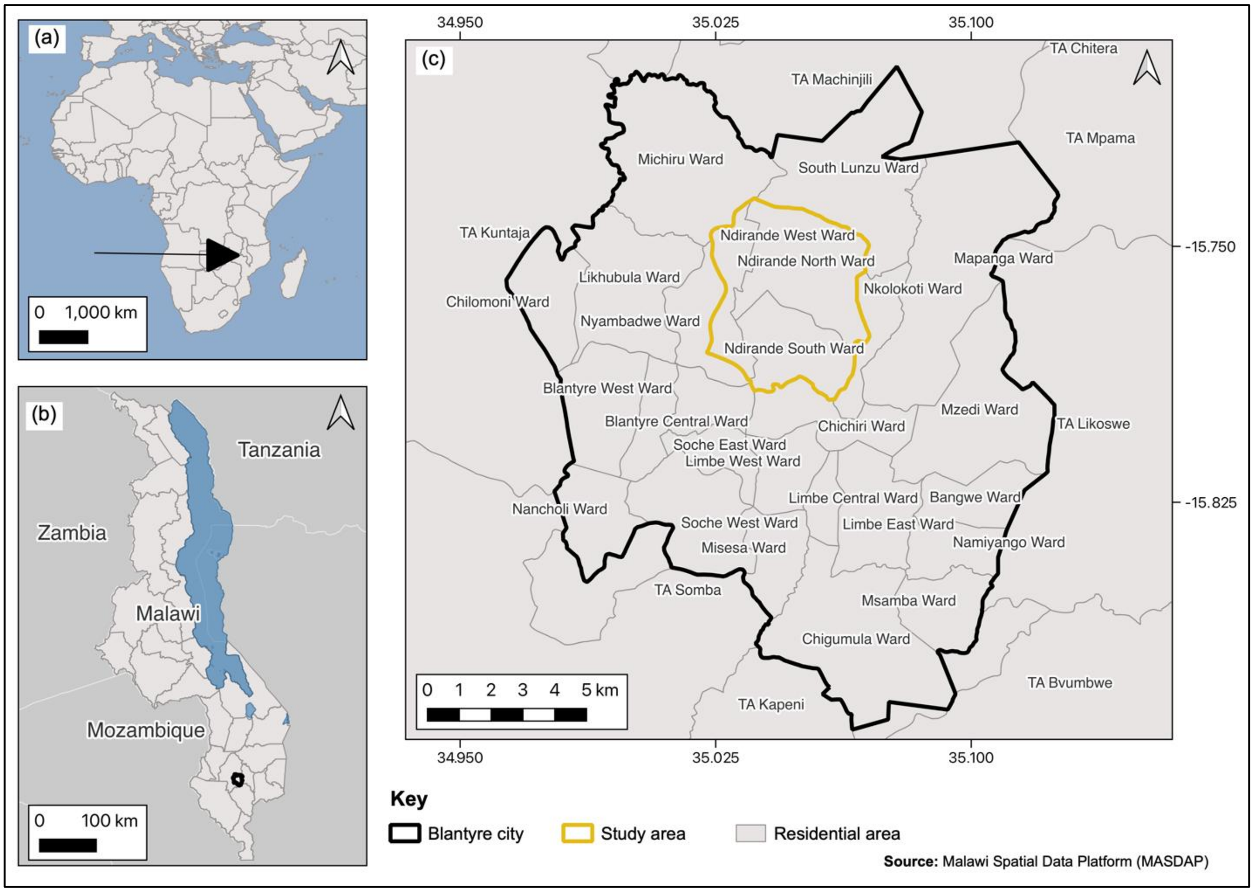

Figure 1. Map of the study location. Panel (a) shows Malawi's location on the African continent, panel (b) zooms in on Blantyre city within Malawi, and panel (c) pinpoints Ndirande within Blantyre city.

2.2. Methodology

Figure 2 is flowchart that illustrates the three methods that were utilized for mapping waste. The first method involved physical walking through the entire study community to map waste piles. The remaining two methods relied on drone imagery captured in a small part of the study community. All the three approaches resulted in the generation of maps highlighting community waste piles.

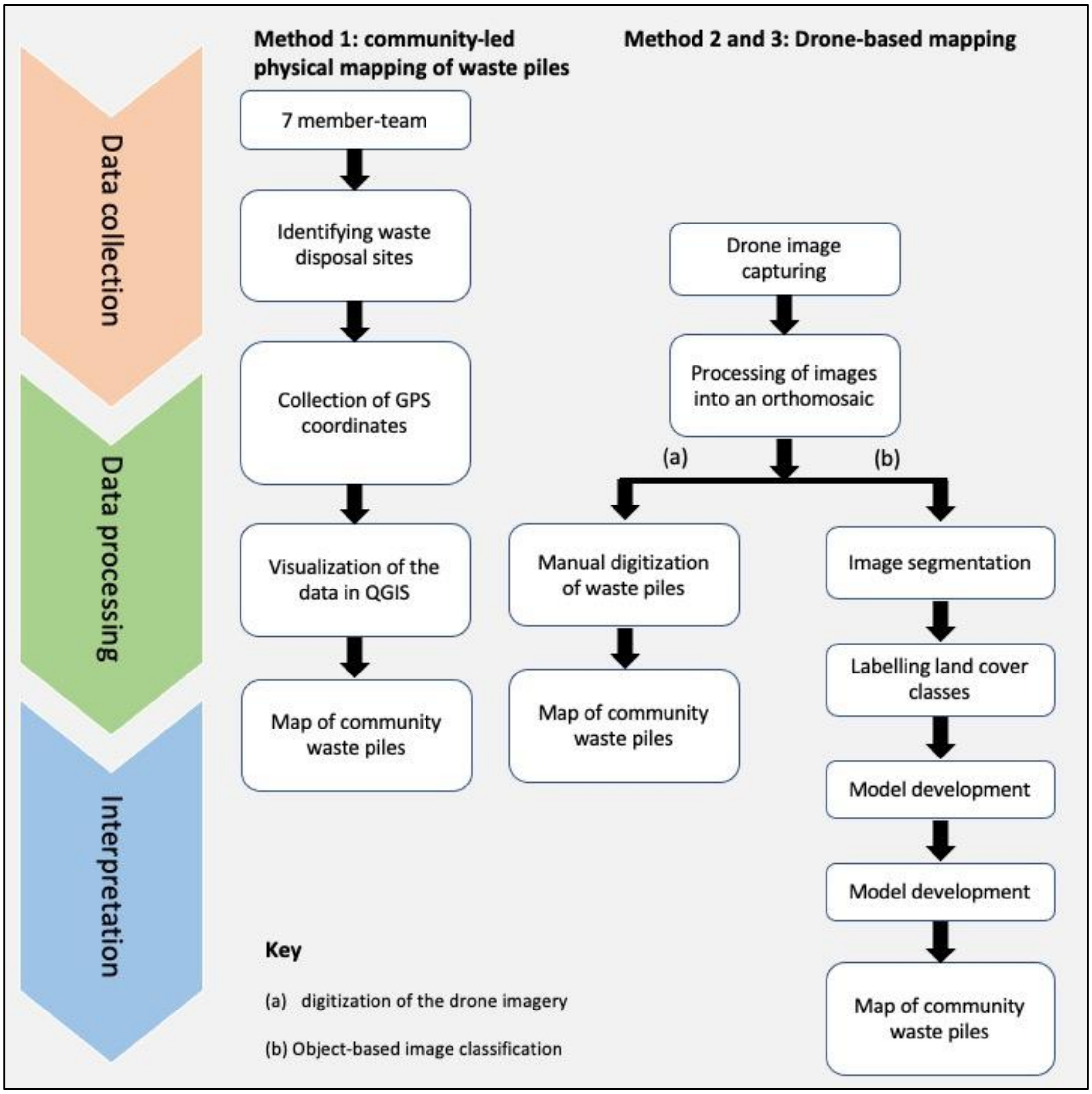

Figure 2. Graphical Workflow for all the three methods compared in the study.

2.2.1. Mapping waste pile using community-led physical mapping of waste piles

A community-led physical mapping of waste piles was conducted by a seven-member team, which comprised five researchers from the SPACES consortium and members of the local development committee. The team's task was to locate waste piles – locations where waste accumulate after direct disposal - in the study community. The community members guided the study team in locating areas with existing waste piles. Once identified, the waste piles were assigned a number, and geographical coordinates were collected using GPS from Samsung Galaxy Tab

A (https://www.samsung.com/sa_en/business/tablets/galaxy-tab-a/galaxy-tab-a-7-0-2016-t280-sm-t280nzkaksa/). Furthermore, data on specific attributes of individual materials that formed the waste pile was collected. This information was subsequently used to characterize the overall composition of the waste pile surface.

2.2.2. Mapping using drone imagery

To understand the practicalities of using drone imagery for mapping waste piles, we utilized a Mavic 2 Enterprise drone (Model: LIDE - https://www.dji.com/mavic-2-enterprise). The drone was manufactured by DJI, and it is equipped with a 12 Megapixel camera (aperture range f/2.8 – 3. 8). To capture the aerial images, the drone was flown at an altitude of 60 meters. While method 1 focused on the entire study community (Figure 3a), we captured images for a subsection of the study community selected for long-term aerial monitoring by the SPACES consortium (Figure 3 b). The captured images were processed using Pix4D mapper (version 4.6.4.) to produce an orthomosaic with a Ground Sampling Distance (GSD) of 1.8 cm/pixel. The resulting orthomosaic was saved in a projected coordinate reference system (World Geodetic System 1984/Universal Transverse Mercator Zone 36 S). The orthomosaic was clipped to only cover 20 meters distance to the river in the study community covering an area of 45,259 square meters.

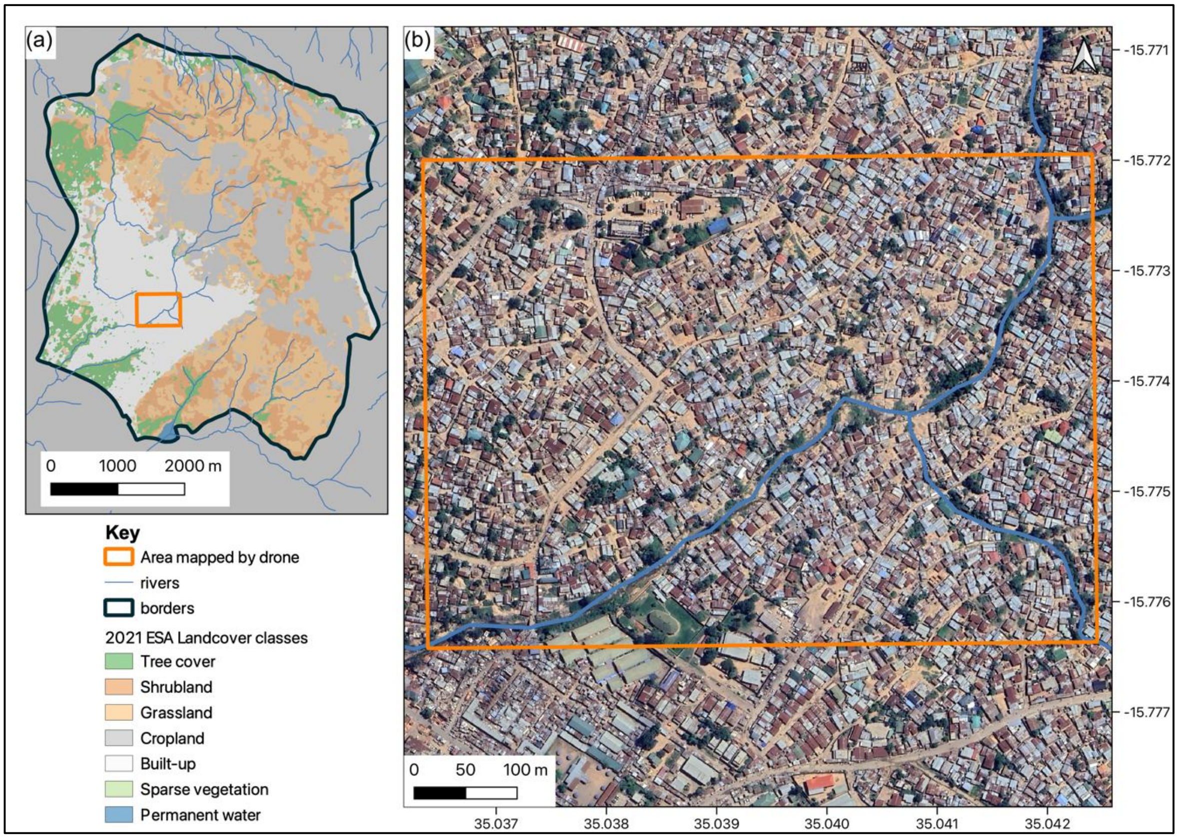

Figure 3. Overview of the study community and a highlight of the area that was targeted for aerial mapping using drone technology. Subfigure (a) presents the study community and a highlight of the area that was targeted for drone mapping. Subfigure (b) is a closeup view of the section of the entire study community that was targeted for drone mapping, displayed on a standard basemap (Google Satellite), accessed through QuickMapServices plugin in QGIS (version 3.22.10).

For method 2, the orthomosaic generated was visualized in QGIS (version 3.22.10). The orthomosaic was inspected manually to identify waste piles, which were then manually digitized as polygons. The total surface area covered by waste piles was calculated by summing the surface of all digitized polygons using the field calculator tool in QGIS software.

For method 3, waste piles were automatically identified using an Object-Based Image Analysis (OBIA) approach. OBIA involves grouping similar pixels into segments, calculating feature variables for each segment (e.g., spectral reflectance, texture), and building a segment-level classification model based on these feature variables. A mean-shift algorithm was implemented in the open-source software Orfeo Toolbox to group homogenous neighboring pixels of the orthomosaic into segments (Grizonnet et al. 2017). The mean reflectance of the optical bands was computed for each segment alongside segment Haralick textural characteristics. Haralick textural characteristics represent textural characteristics of adjacent pixels based on grey-level values (Haralick, Shanmugam, and Dinstein 1973). A total of twenty-two segment-level feature variables were extracted (Table S1). To train algorithms for automatic classification of the segments to identify waste piles, the drone imagery was examined to identify and label examples of major land cover classes, namely building rooftops, bare earth (soil), vegetation, waste piles, surface water, and shadow. A total of 509 segments were labeled, covering these land cover classes (Table S2).

We developed automatic classifiers for detecting waste piles using R Statistical Software (version 4.1.2). Segments that represented the labeled examples were divided into training and testing segments, with 80 % (406) of the labeled segments used for training and the remainder (103) used for testing. The extracted feature variables and labels were used to train binary and multi-class classifiers. We explored four classification algorithms: (1) RF; (2) ANN; (3) naïve Bayes classifier and (4) Support Vector Machine (SVM). Full description of the algorithms and parameters used are presented in Table S3. Figure 4 summarizes the approach employed to develop, train, and test the four classifiers. For each model trained, performance was assessed using precision (Equation 1), recall (Equation 2), and F-1 score (Equation 3). Precision quantifies the proportion of correct positive predictions among all positive predictions made. Recall measures the proportion of actual positives correctly identified by the model. The F-1 score provides a harmonic mean of precision and recall, emphasizing their balance. The formulas for these metrics are presented in Table 1.

Table 1: Equations for assessment of classification performance.

Performance measure	Formula	Equation
Precision	$\frac{True\ Positives}{True\ Positives + False\ Positives}$	(1)
Recall	$\frac{True\ Positives}{True\ Positives + False\ Negatives}$	(2)
F-1	$\frac{2 \times Precision \times Recall}{Precision + Recall}$	(3)

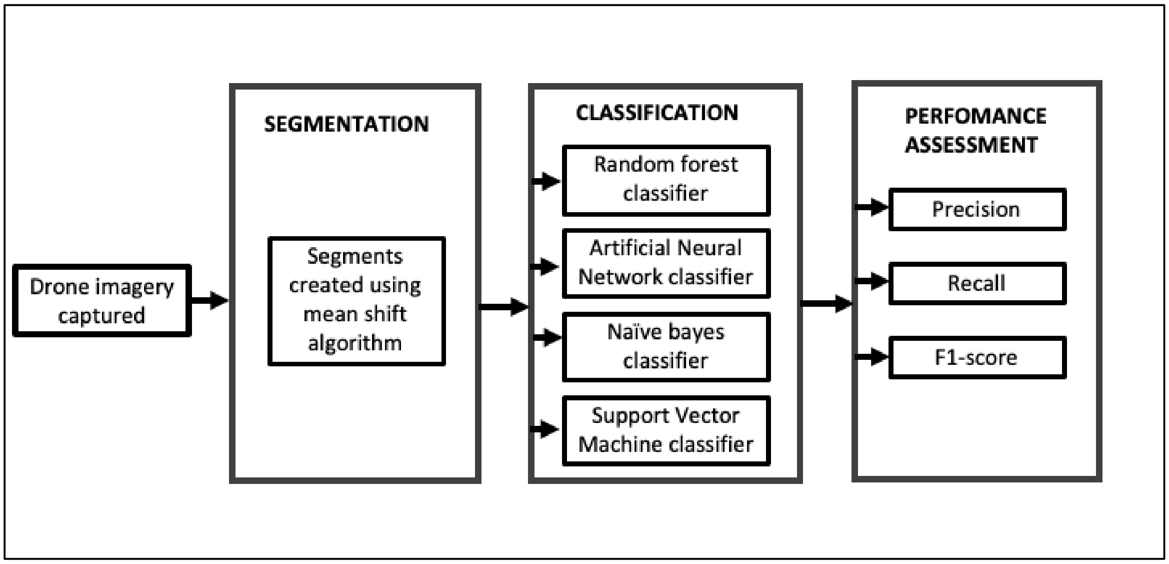

Figure 4: Flowchart used to implement the OBIA process for automating mapping of waste piles.

3. Results

3.1. Mapping of waste piles from community-led physical mapping of waste piles

Table 2 summarizes the observations from the community-led physical mapping of waste piles conducted across the entire study community. The materials observed to be disposed of in the environment were almost uniform, encompassing common items such as plastics, textiles, cardboard, soil, glass, metal, and organic waste, including food waste, among others.

Table 2. Summary of the characteristics of the waste piles observed during the community-led physical mapping of waste piles.

Waste pile located along the riverbank	Total number of piles and percentage
Yes	51 (89.5%)
No	6 (10.5%)

Figure 5 presents some of the waste piles mapped during the community-led physical mapping of waste piles. The mapped locations represent the center of the waste piles as identified by the research team conducting the walk. Most of the waste piles located during the community-led physical mapping of waste piles were along the banks of two local rivers, Nasolo and Chirimba, with the remaining ones not directly on the riverbank. Later observations revealed that one of the 57 waste piles had a positional accuracy of nearly 2000 meters. Of the 57 waste piles, 16 were observed to be within the area that was mapped with drones.

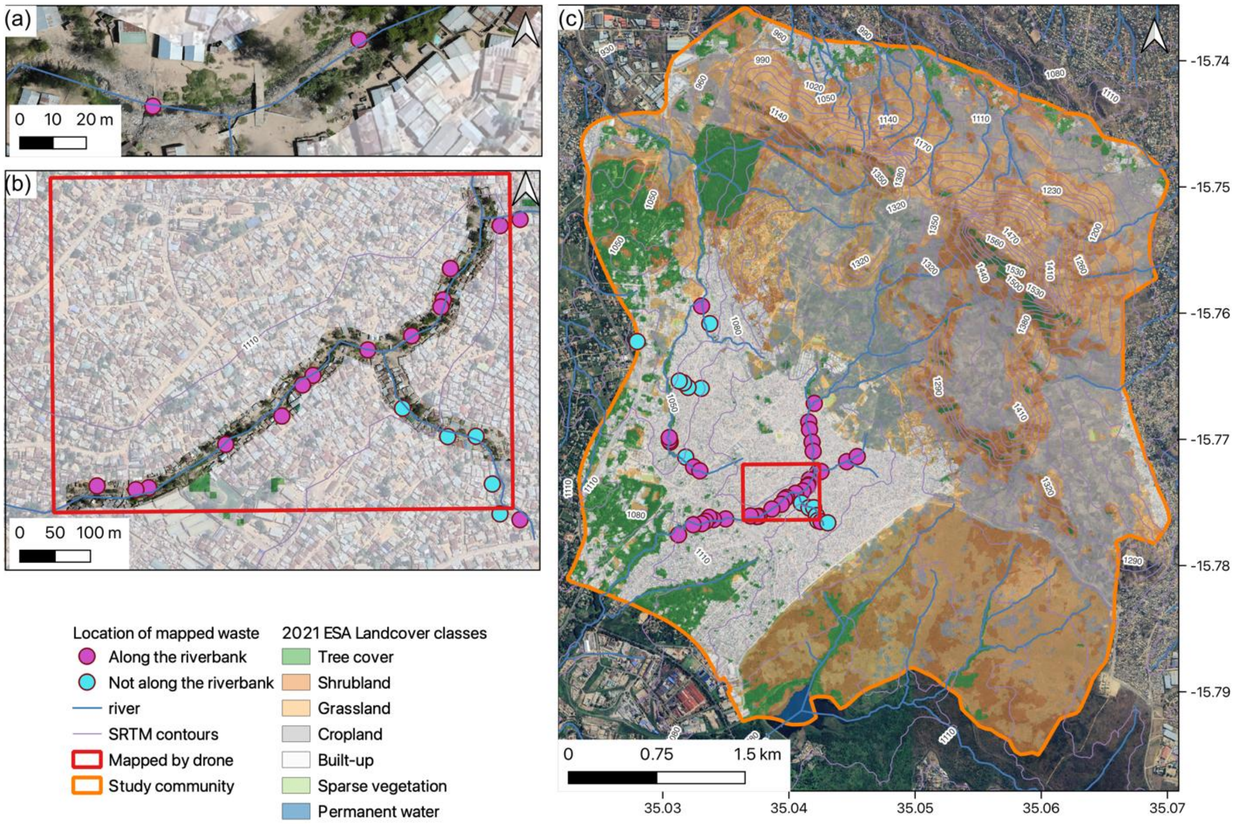

Figure 5. Detailed overview of waste piles observed during the community-led physical mapping of waste piles. Subfigure (a) offers a close-up view of selected waste piles, while subfigure (b) specifically emphasizes 16 waste piles mapped during the community-led physical mapping of waste piles, coinciding with the region covered by drone imagery. Subfigure (c) displays a comprehensive overview of all 57 waste piles, showcasing their respective locations within the study community.

3.2. Mapping of waste piles by manual digitization of the drone imagery

Figure 6 presents a map showing waste piles manually digitized from the drone imagery. 50 polygons were digitized across part of the study community where drone imagery was captured. Some of the digitized waste piles might have been created through the dispersal of waste from some of the waste piles mapped during the community-led physical mapping of waste piles. In general, digitized waste piles covered 5.76 % of the area covered by the drone imagery (2,609 of 45,259 square meters), with their surface area ranging from 3 to 251 square meters (mean = 52.15).

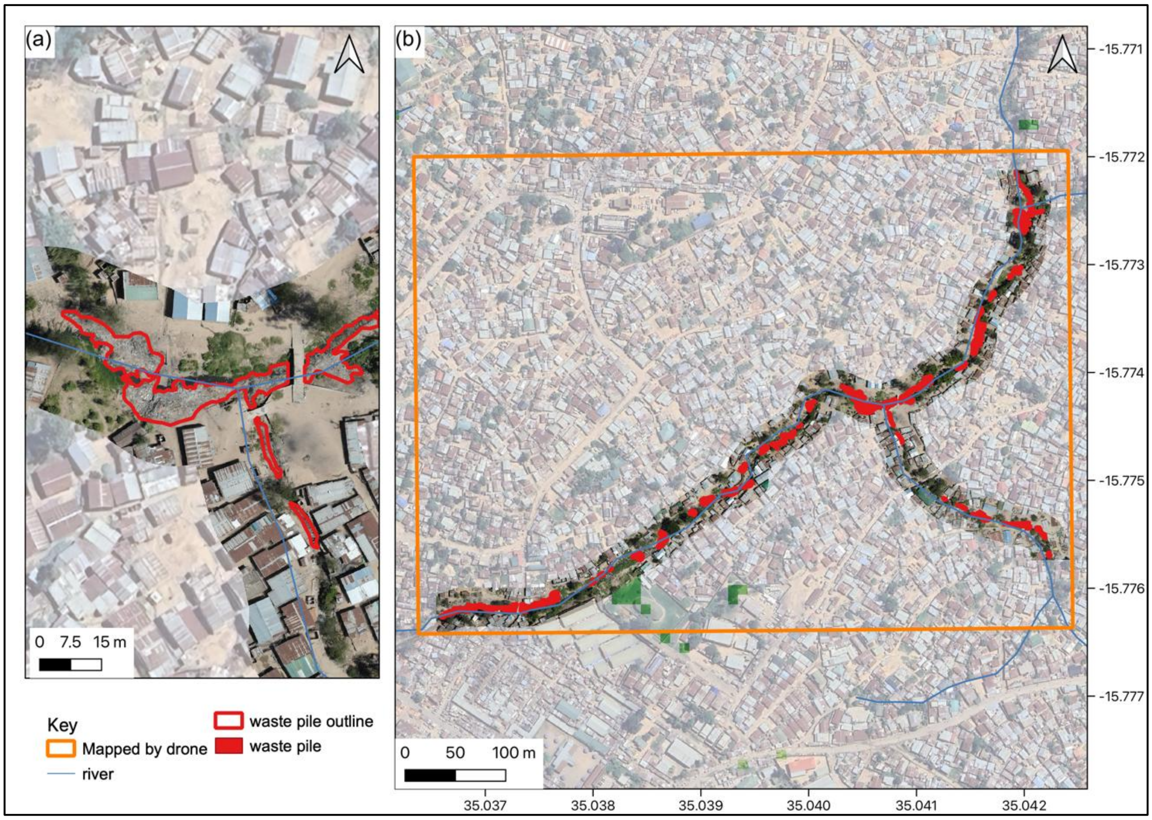

Figure 6: Overview of the waste piles that were manually digitized in the part of the study community where drone imagery was captured. Subfigure (a) provides a zoomed overview of one of the manually digitized waste piles, and subfigure (b) provides a broader overview of all the waste piles that were mapped.

3.3 Mapping waste piles through OBIA classification approach

The use of mean-shift algorithm to segment the drone imagery produced 2356 segments, of which 509 of them were manually labeled to support model building. Table 3 presents a summary of the characteristics of the feature variables (in terms of mean and standard error) extracted from the drone imagery for each of the land cover classes. It is worth noting that the mean values for some feature variables such as red, green, blue, cluster shade and haralick correlation show variations across the land cover classes and may be useful for building of an automatic classification model. Out of the 509 segments used for model development, 406 were for model training, and 106 were for model testing.

Table 3. Summary of feature variable values derived from the segments by land cover class.

	Rooftops		Bare earth (Soil)		Vegetation		Waste piles		Surface water		Shadow	
	Mean	SE	Mean	SE	Mean	SE	Mean	SE	Mean	SE	Mean	SE
Red	149	3.9	173	3.1	74	1.9	132	2.6	67	2.5	43	2.7
Mode (red)	152	4.4	185	3.2	71	2.2	132	3.7	58	3.3	32	3.4
Mean(green)	149	4.1	161	2.9	80	1.9	129	2.4	71	2.4	42	2.5
Mode (green)	151	4.7	171	2.9	80	2.3	128	3.2	63	3.2	32	3.4
Mean(blue)	144	4.3	145	2.7	57	1.6	120	2.4	64	2.2	40	2.3
Mode (blue)	147	5	153	2.8	52	1.9	118	3.3	56	2.7	32	3.1
Mean(energy)	0.6	0.01	0.7	.01	0.5	.01	0.4	.01	0.6	.01	0.6	.01
Mode (energy)	0.9	.00	1	.00	0.9	.01	0.9	.02	1	.00	1	.00
Mean(entropy)	1.2	.04	0.9	.02	1.4	.03	1.9	.03	1.4	.06	1.2	.04
Mode (entropy)	0	.00	0	.00	0.03	.01	.05	.02	0	.00	0	.00
Mean(correlation)	0.9	.04	0.8	.02	0.9	.02	0.9	.01	0.8	.03	0.7	.05
Mode (correlation)	-.01	.01	0	.00	.01	.01	.02	.02	0	.00	0	.00
Mean (inverse difference moment)	0.9	.00	0.9	.00	0.9	.00	0.8	.00	0.9	.00	0.9	.00
Mode (inverse difference moment)	0.9	.00	1	.00	0.9	.01	0.9	.01	1	.00	1	.00
Mean(inertia)	0.3	.01	0.2	.01	0.3	.01	0.4	.01	0.3	.02	0.3	.02
Mode (inertia)	.02	.01	0	.00	0.2	.01	0.2	.01	.01	.01	.03	.01
Mean (cluster shade)	-0.2	.04	-.1	.01	0.1	.02	0.2	.02	0.6	.04	1.2	.09
Mode (cluster shade)	0	.00	0	.00	0	.00	0	.00	0	.00	0	.00
Mean (cluster prominence)	5.1	.4	2.5	.2	2.4	.2	4.8	.3	5.2	.4	15.3	1
Mode (cluster prominence)	0	.00	0	.00	0	.00	0	.00	0	.00	0	.00
Mean (haralick correlation)	321	13	352	6	83	5	316	9	95	8	81	7
Mode (haralick correlation)	180	10	261	7	32	3	140	8	21	6	15	5

Table 4 presents the performance of four automatic classifiers - trained using RF, ANN, Naïve Bayes, and SVM algorithms respectively – in mapping waste piles from drone imagery using OBIA approach. Additionally, the table includes the performance metrics of analogous studies conducted previously. Among the four algorithms utilized, binary classifiers outperformed multi-class models (Table S4-10), with the mean Kappa of 0.815 [Range: 0.64-0.90] and accuracy of 0.94 [Range: 0.88-0.97], compared to multi-class classifier with mean Kappa at 0.675 [Range: 0.26-0.85] and accuracy of 0.73 [Range: 0.40-0.87]. In terms of the algorithms, ANN and SVM has the highest F-1 scores (0.98) highlighting best overall performance for binary classification. However, for a multi-class classifier, the RF predictor has the highest F-1 score (0.90) indicating that it outperformed the other multi-class models trained. The performance of each of the trained models at classifying the testing dataset has been presented in the supplementary tables. It has also been observed that there are instances where the automatic classifier could misclassify the segments, for example, by suggesting that a segment is a waste pile while in a real sense, the segments represent one of the other land cover classes considered, and vice-versa. This was observed for rooftops and vegetation (Supplementary Table S6). However, automatic classifiers estimated that waste piles covered more area than manual mapping. For example, the trained binary SVM classifier estimated that waste piles covered approximately 10,697.5 square meters, whereas the best multi-class model estimated that waste piles covered approximately 5500 square meters.

Table 4: Performance of different algorithms and approaches for mapping waste piles

	Method	Binary approach			Multi-class approach		
		Precision	Recall	F1-score	Precision	Recall	F1-score
This study	RF	0.94	1	0.97	0.86	0.95	0.90
	ANN	0.97	1	0.98	0.72	0.65	0.68
	Naïve Bayes	0.95	0.90	0.93	0.73	0.96	0.83
	SVM	0.98	0.99	0.98	0.83	0.95	0.88
(Papakonstantinou et al. 2021)	CNN	0.83	0.72	0.77	---	---	---
(Garcia-Garin et al. 2021)	CNN	0.79	0.94	0.86	---	---	---
(Pinto, Andriolo, and Gonçalves 2021)	ANN	80	67	73	56	49	49
(Gonçalves et al. 2020b)	RF	0.73	0.74	0.75	---	---	---
(Gonçalves et al. 2020c)	RF	0.70	0.71	0.70	---	---	---
(Jakovljevic, Govedarica, and Alvarez-Taboada 2020)	CNN	---	---	---	0.82	0.75	0.78
(Wolf et al. 2020)	CNN	---	---	---	0.77	0.77	0.77
(Fallati et al. 2019)	CNN	0.54	0.44	0.49	---	---	---

3.4 Comparison of observations on the utilization of the three approaches

Table 5 presents some observations of the three methods for mapping waste piles. Generally, the community-led physical mapping of waste piles involved a team that walked in the community for nearly half a day to scout for waste piles. In contrast, the use of drone imagery involved a team that set up a ground control station, and the drone captured aerial pictures of the area of interest using a predetermined flight route. Processing the raw drone images into an orthomosaic with Pix4D mapper (version 4.6.4) took several minutes. However, segmenting the orthomosaic, generating segment-level statistics, and manually labeling training and testing segments was time consuming, taking approximately more than 6 hours. Model fitting and results extraction took a further few minutes, but once the model was developed, it could be reused.

Table 5: qualitative pros and cons of three possible approaches for mapping waste piles.

	Community-led physical mapping of waste piles	**Drone imagery (manual digitization)**	**Drone imagery (automatic mapping using OBIA)**
Pros	• Does not require expensive equipment • Convenient, it can be practical to employ teams with no or limited training. • Enables generation of data about the composition of the waste pile	• Enable mapping of inaccessible waste piles. • Allows estimation of the area covered by waste piles. • Produces mapping data for further automated or semi-automated classification processes • Once drone imagery is collected, it can serve as a mapping basis for other survey topics, too	• Waste piles are automatically generated from drone imagery. • Enable mapping of inaccessible waste piles • Allows estimation of area covered by waste piles. • Once a model has been developed, it is generally fast. • It can be tested for reuse in other areas, too
Cons	• Only provide point information showing	• Visibility of waste piles is limited by	• Visibility of waste piles is limited by

	locations where waste is being disposed in the study area. • Underestimate number of waste piles as it only records information about waste piles that are accessible. • Prone to positional errors especially when GPS receiver accuracy values are not checked in the field.	the presence of vegetation. • Time consuming • Require more expensive equipment • Requires technical experience of the pilot and drone team. • Require time-consuming ground truthing since it is a remote sensing method	the presence of vegetation. • Model development and application requires specialized training. • Labelled examples for building a classification model are not always sufficient (waste examples were limited). • Prone to misclassifications. • Require more expensive equipment • Requires technical experience of the pilot and drone team. • Require time-consuming ground truthing since it is a remote sensing method

4. Discussions

4.1. Waste disposal patterns and environmental impacts

It is worth noting that waste disposal into the environment is widespread in the study community, with 89.5 % of the waste piles located along the riverbanks, reflecting a reliance on the river as a waste management system that sweeps waste away from communities (Kalina et al. 2022). Despite this, waste materials disposed of in areas not along the riverbanks might possibly be dispersed by wind and rainwater; potentially, they get dispersed into the river system. Non-biodegradable materials such as plastics are present in these waste piles, raising concerns about their impact on the environment and human health. There is a growing body of evidence reporting the presence of communities of pathogenic microorganisms on plastic surfaces (Liang et al., 2023), with some studies reporting the enrichment and dispersal of antimicrobial resistance genes (Rasool et al., 2021; Yang et al., 2022). Furthermore, reports suggest that rivers play a role in the dispersal of plastics, contributing to the spread of pathogenic microorganisms (Rodrigues et al. 2019; Silva et al. 2019).

4.2. Comparison between the three mapping approaches

In general, the current study presented three mapping approaches: (1) community-led physical mapping of waste piles; (2) manual digitization of drone imagery; and (3) automatic mapping of waste piles from drone imagery using OBIA. Drone imagery enabled the identification of waste piles that could not be reached by ground surveys, for example, due to lack of access roads or dangerous terrain (Lo et al. 2020). However, mapping waste piles using drone imagery depends on the reflectance captured by the drone sensor. In our study area, there are many big trees, and it could not be ascertained what was beneath the branches using drone imagery. Previous studies have also reported that waste materials might be hidden by shadows or vegetation, so much so that they are difficult to detect, resulting in a general underestimation of waste material density (Martin et al. 2018). Nonetheless, drone imagery provides information such as the spatial extent of waste piles, and though not explored in this study, the volume of the waste pile can also be explored.

There is a sharp distinction between mapping waste piles from drone imagery manually and automating the process with OBIA. The number of waste piles and total surface area detected by OBIA was greater than the corresponding figures generated through manual digitization. OBIA has a possibility of misclassifying other land cover classes as waste piles or vice versa, and this can falsely increase or decrease the number of waste piles in the study region. OBIA misclassifications may have arisen from two possible sources. One possible explanation is that OBIA could not detect objects by detecting multiple objects as one (under segmentation). Another possible explanation might be the algorithm's shortcomings from learning patterns that differentiate waste piles from other classes. Still, depending on the application, misclassified waste piles can be filtered using posterior class probabilities. Nonetheless, manual digitization can be slow when human resources are limited; however, this approach requires limited training in image labeling. In a previous study by Papakonstantinou et al. (2021), 27 volunteers underwent training in image labeling. They successfully classified and labeled 30,793 objects based on whether they contained waste materials or not (Papakonstantinou et al. 2021). Nevertheless, waste piles generated through manual digitization might require ground validation and quality assurance processes to be developed to be reliable and reproducible. Crowdsourcing labeling platforms such as Humanitarian OpenStreetMap Tasking Manager (https://tasks.hotosm.org/) or MapSwipe (https://mapswipe.org/) offer opportunities for crowdsourcing mapping effort and validation. These platforms have the potential to accelerate manual mapping especially when human resources are limited. Automating the digitization of waste piles using OBIA is a faster approach, and once a model has been developed, it can be reused and applied on a large scale. While OBIA has previously been applied to mapping marine waste (Gonçalves et al. 2020b), categorizing beach macro waste items (Gonçalves and Andriolo 2022), and studying the role of vegetation in trapping beach waste (Andriolo et al. 2021), this study extends its application to mapping waste on land for the first time. The study also breaks new ground for leveraging entirely free software, including the Orfeo Toolbox (https://www.orfeo-toolbox.org/) and R Statistical Software (R Core Team 2022), to implement the approach.

4.3. Potential improvement on using OBIA for mapping waste piles

Despite a few misclassifications, it is worth noting that, binary classifiers outperformed the corresponding multi-class models for all algorithms used. This observation aligns with earlier observations in Portugal, where a binary classifier for differentiating marine litter items from non-litter items was reported to have higher accuracy than a multi-class approach (Pinto, Andriolo, and Gonçalves 2021). One possible explanation for the misclassification is that a binary classifier is trained to maximize differentiation between segments of waste and non-waste. Conversely, the multi-class classifier is optimized to differentiate multiple classes. However though, previous studies (Gonçalves et al. 2020a; 2020b; 2020c; Martin et al. 2018) focused on mapping individual waste objects disposed of in the environment, while the current study maps waste piles with aggregates of different waste types. Mapping individual objects such as plastics has the potential to aid in quantifying the abundance of pollutants or other discarded materials in the environment. However, it is equally imperative to note that drone data of GSD between 0.5 and 1.25 cm/pixel is suitable for mapping individual waste materials (Andriolo et al. 2023). Most common drone sensors can only achieve this GSD by flying low altitudes. Such flight altitude is impractical in settings with tall buildings, trees, and powerlines. As demonstrated in this study, drone data with relatively high GSD can map waste aggregates (waste piles). Thus, mapping aggregates of waste has the potential to serve as indicators for monitoring the impact of waste management programs on reducing waste disposal in the environment.

In terms of the algorithms that were trained to build the models, the current study observed that the model developed using an SVM algorithm slightly outperformed the other binary models, achieving the highest precision, recall, F1-score, overall accuracy, and Kappa. Similarly, the trained RF model slightly outperformed other multi-class models, also demonstrating the best performance across these metrics. Nevertheless, studies that explored automating the mapping of waste materials have reported the use of diverse descriptor variables and model-building practices. For example, Martin (Martin et al. 2018) used histogram oriented gradients (HOG) as descriptor variables to train a SVM classifier. Conversely, numerous other published works transformed RGB bands into alternative color spaces, including Hue Saturation Value (HSV), CIE-Lab, and YCbCr for modelling purposes(Gonçalves et al. 2020b; 2020c; 2020a). This underscores the need for standard approaches in developing and implementing classifiers for mapping waste materials in various environments.

4.4. Study strengths and limitations

The study is the first practical application of drone imagery for mapping disposed of waste in Sub-Saharan Africa. One of the key strengths of this study is the use of QGIS and Orfeo Toolbox, free and open-source software for geospatial (FOSS4G), and are ideal for environmental monitoring program, especially when financial resources to support purchasing software are lacking. Nevertheless, due to limited GSD, individual materials within waste piles are not visible in the drone imagery. Visibility of materials in aerial imagery depends on spatial resolution. Additionally, the current waste mapping only focused on mapping waste piles located within 20 meters of the river in the study community. Further investigation is needed to assess the generalizability of the developed OBIA model to the region beyond the river or images captured at different time points. We also acknowledge that we did not formally test for class separability before training the classification model, and we used all the 21 extracted feature variables without regard to their importance on class separability. Some of the extracted feature variables might not effectively contribute to class separability and could introduce noise, complicating the classification process. Future studies should investigate class separability and apply dimension reduction techniques to remove irrelevant or redundant features. This could improve model performance by focusing on the most informative feature variables and simplifying the classification process.

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5. Conclusions and outlook for further work

The current study illustrates the practicalities associated with using images collected by drones for mapping waste piles on land in an urban environment in Malawi. Drone imagery enables the mapping of inaccessible waste piles and the characterization of their sizes, surpassing the capabilities of field walks. To our knowledge, this is the first successful application of drone-based remote sensing for mapping waste in an environment other than beaches or coastal areas, particularly on land and in an urban environment. Implementation of OBIA for automating waste pile detection reported higher accuracy than previous studies. Considering these observations, drone imagery can be used for mapping waste piles. Thus, future work should focus on three areas: (1) establishing mapping requirements for mapping materials and individual objects on the surface of waste piles; (2) exploring the operational performance of different image classification approaches for automating the process of mapping waste piles; and (3) translating generated information on waste piles into practical policy actions.

Currently, we are focused on mapping the distribution of plastic waste within waste piles and quantifying its dispersal patterns. Future work on automating waste pile mapping can focus on improving image capturing, object detection, and classification. For image capturing, we recommend exploring optimal spatial resolution for mapping individual waste materials (such as plastics). Furthermore, investigating the potential contribution of different camera choices (optical sensor, infrared, thermal, etc.) on the performance of the waste pile mapping models is recommended. Besides, exploring emerging object detection and classification approaches, especially those with capability to learn patterns associated with waste materials without needing to know the actual variables needed for model training - only requiring imagery spectral bands will simplify the model development process.

Declarations

Authors contributions

Patrick Ken Kalonde and Michelle C. Stanton conceived and designed the study. Tracy Morse, Christopher M. Jones, Richard S. Quilliam and Nicholas A Feasey contributed towards conception of the study. Taonga Mwapasa, Kondwani Chidziwitsano and Rosheen Mthawanji conducted the community-led physical mapping of waste piles. Patrick Ken Kalonde and Marc Henrion performed statistical analyses and interpreted the findings. Jeffrey S. Torguson contributed towards development of the cartographic products in the manuscript. Patrick Ken Kalonde prepared the manuscript for publication. Mikhail S. Blinnikov and Michelle C. Stanton provided guidance during the planning, research, and final distribution of the results of the project. All authors revised the draft manuscript and are accountable for the work.

Ethical statement

No human or animal data were used in this study and no ethics approval were required.

Ethical Responsibilities of Authors

All authors have read, understood, and have complied as applicable with the statement on "Ethical responsibilities of Authors" as found in the Instructions for Authors.

Competing interests

The authors declare no competing interests.

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Data availability

The drone imagery used in this paper is available on OpenAerialMap: https://map.openaerialmap.org/#/35.03883361816406,-15.773752343761437,10/user/6149611b8c56070006259d24/644f84655874aa0006657733?_k=0rpqn4

Code availability

The code that was used for the classification of segments to enable automatic identification of waste piles is publicly available on GitHub: https://github.com/Kalondepatrick/Mapping-Waste

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