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

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49 **Abstract**

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

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

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

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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'

115 (<https://openlittermap.com/>) allow users to capture geotagged photos which later
116 enable mapping locations where waste is being dumped (Lynch 2018). However, the use
117 of handheld GPS can only limit observations to locations that are physically accessible to
118 the observer, and some dumpsites located in areas with rugged terrain or without a
119 proper access road cannot be mapped. Additionally, it is difficult to quantify the spatial
120 extent of existing waste piles. In contrast, aerial images have the potential to overcome
121 these limitations. For instance, satellite images have been used for the mapping of
122 floating marine plastics at a global scale (Topouzelis et al. 2020). Still, most open
123 satellite data have relatively coarse spatial resolution, and it is difficult to use such data
124 to map smaller waste piles, especially in urban settings (Glanville and Chang 2015). Even
125 high-resolution optically satellite images, usually provided by private companies, are
126 often affected by cloud cover (Shastry et al. 2023), and can be prohibitively expensive.
127

128 High-resolution aerial images captured by drones offer a promising alternative to
129 satellite imagery. The use of drone imagery has been employed in previous studies
130 (Pinto, Andriolo, and Gonçalves 2021; Garcia-Garin et al. 2021; Jakovljevic, Govedarica,
131 and Alvarez-Taboada 2020; Papakonstantinou et al. 2021; Wolf et al. 2020; Bao et al.
132 2018; Gonçalves et al. 2020a; 2020b; 2020c; Fallati et al. 2019; Kylili et al. 2019; Ribeiro
133 et al. 2017), which have reported different approaches for mapping waste. One
134 approach involves visual identification and manual labelling of objects considered as
135 waste (Pinto, Andriolo, and Gonçalves 2021; Garcia-Garin et al. 2021; Jakovljevic,
136 Govedarica, and Alvarez-Taboada 2020). Another approach involves manually
137 identifying and labelling a small sample of waste piles or individual objects that are
138 visible on the drone captured imagery and use these data as examples to train an image
139 classification algorithm (Papakonstantinou et al. 2021; Wolf et al. 2020). Such
140 classification algorithms that have been previously employed include a segmentation
141 threshold algorithm (Bao et al. 2018), Random Forest (RF) (Gonçalves et al. 2020a;
142 2020b; 2020c; Martin et al. 2018), Artificial Neural Networks (ANN) (Pinto, Andriolo, and
143 Gonçalves 2021) and Convolution Neural Networks (CNN) (Fallati et al., 2019; Garcia-
144 Garin et al., 2021; Gonçalves, et al. 2020; Jakovljevic et al., 2020; Kylili et al., 2019;
145 Papakonstantinou et al., 2021; Wolf et al., 2020). These algorithms were applied on
146 water surfaces and sandy beaches with a uniform background where it is relatively easy
147 to discriminate and identify waste materials. In an urban environment with a non-
148 uniform background, simple algorithms such as the segmentation threshold algorithm
149 are unlikely to work well.
150

151 This study aimed to assess the practicality of using drones to collect high-
152 resolution aerial imagery for mapping waste piles in an urban environment in Malawi.
153 We define a waste pile as a collection of waste found in the environment; these might
154 have either been disposed of by humans or dispersed by an agent such as stormwater or
155 wind. We hypothesize that on aerial images, piles of waste formed by disposing of waste

156 materials would exhibit distinct characteristics that might assist in the automatic
157 mapping of waste piles from optical aerial images. We utilized the drone imagery to
158 train classification algorithms to automate the detection of waste piles, and
159 subsequently evaluated the performance of the detection workflow. To the best of our
160 knowledge, this is the first application of low-cost drone imagery for mapping waste
161 piles along a river in Sub-Saharan Africa. It is also worth noting that this is the first time
162 to explore drone imagery for mapping waste piles in an environment other than sandy
163 beaches or coastal areas. This practical method will later be refined for use in studying
164 or interrogating how humans get exposed to pathogens that might be hosted by the
165 waste pile, thereby helping to shape public health discourse associated with open waste
166 disposal. Currently, open waste disposal is seen as more of an environmental problem
167 and less of a health problem, yet evidence of the growth of pathogenic microorganisms
168 is increasing (Yang et al. 2023; Zettler, Mincer, and Amaral-Zettler 2013; Mphasa et al.
169 2025), highlighting the public health risks tied to this issue.

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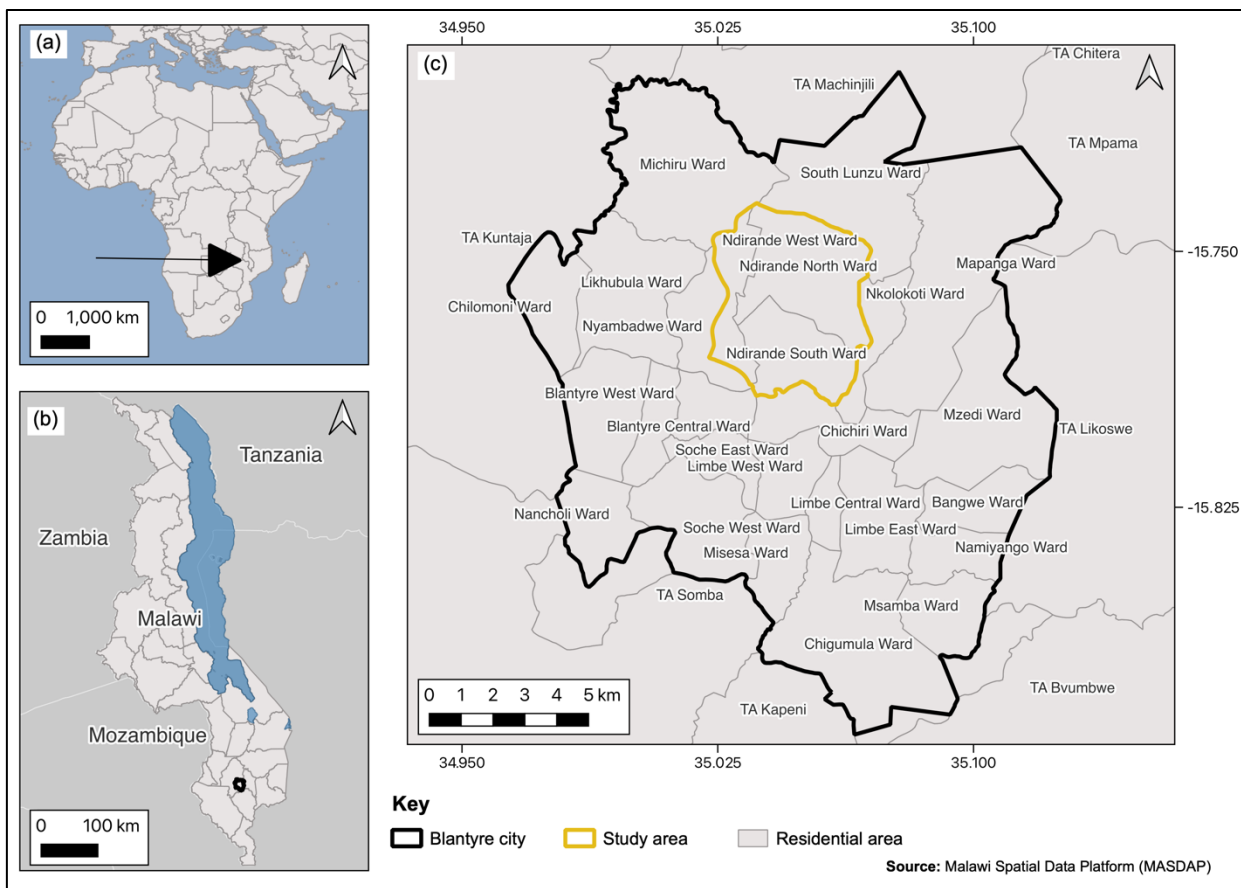
171 **2. Methods**

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173 **2.1. Study area**

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175 This study was conducted in Ndirande, the largest informal settlement in
176 Blantyre – Republic of Malawi’s second largest city (population 800,264). According to
177 the most recent population census (conducted in 2018), Ndirande had a population of
178 97,839 people (NSO 2019). Indiscriminate disposal of waste in water drainage channels
179 is common in the community (Maoulidi 2012; Banda 2015). Ndirande neighborhood has
180 three administrative wards, namely Ndirande South, Ndirande West, and Ndirande
181 North, and the current study specifically focused on a small part of the Ndirande South
182 ward (Figure 1), chosen because the Nasolo River, a tributary of the Mudi River runs
183 through it. The Mudi River is severely polluted and it has been the subject of several
184 previous studies (Lakudzala, Tembo, and Manda 2000; Sajidu et al. 2007; Kumwenda et
185 al. 2012; Kalina et al. 2022). The community also serves as one of the primary research
186 sites for the Sustainable Attitudes to Benefit Communities and their Environments
187 (SPACES - <https://spacesproject.stir.ac.uk/>), aiming to investigate the public health
188 risks associated with plastic waste.



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

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2.2. Methodology

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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.

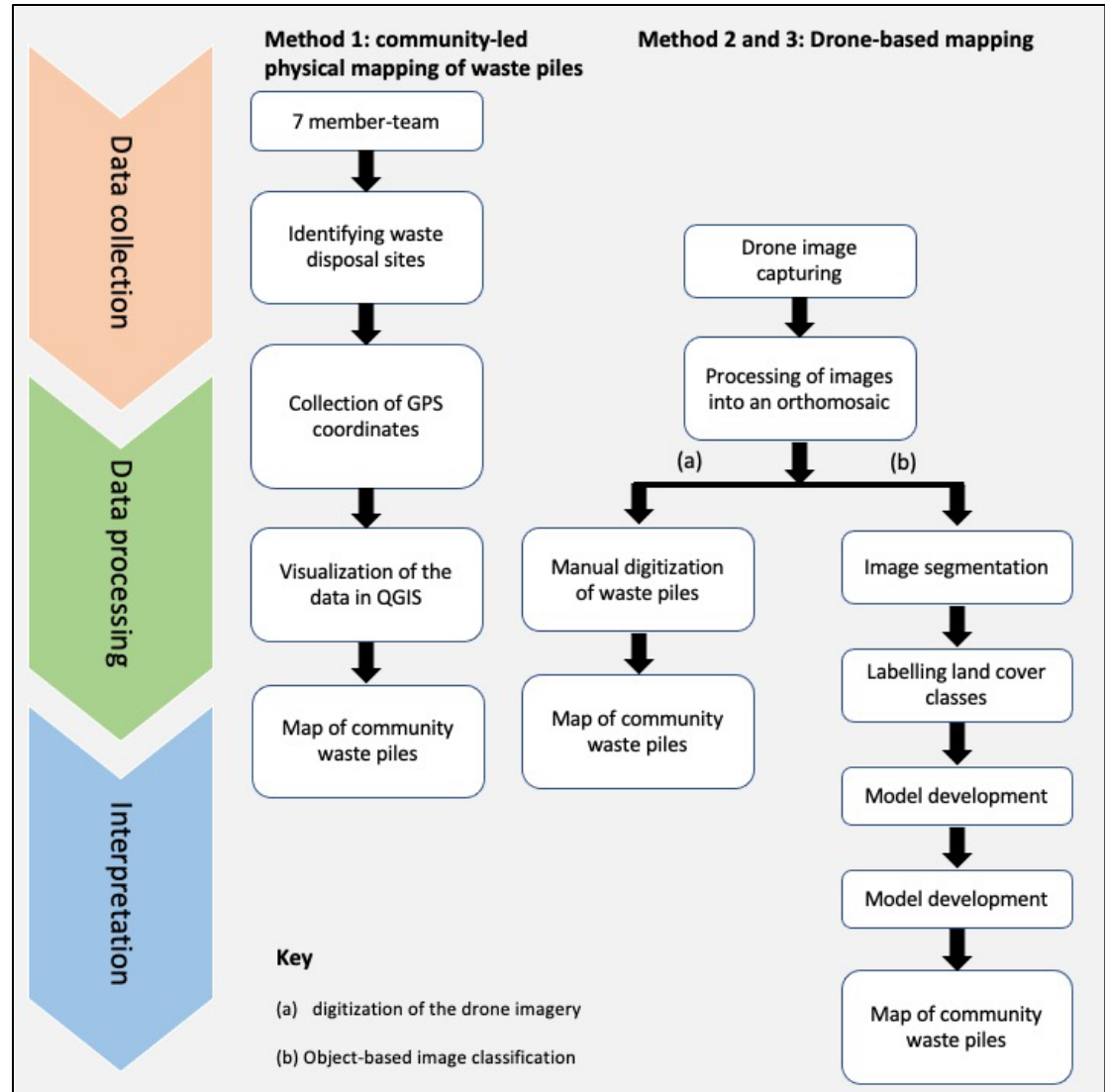


Figure 2. Graphical Workflow for all the three methods compared in the study.

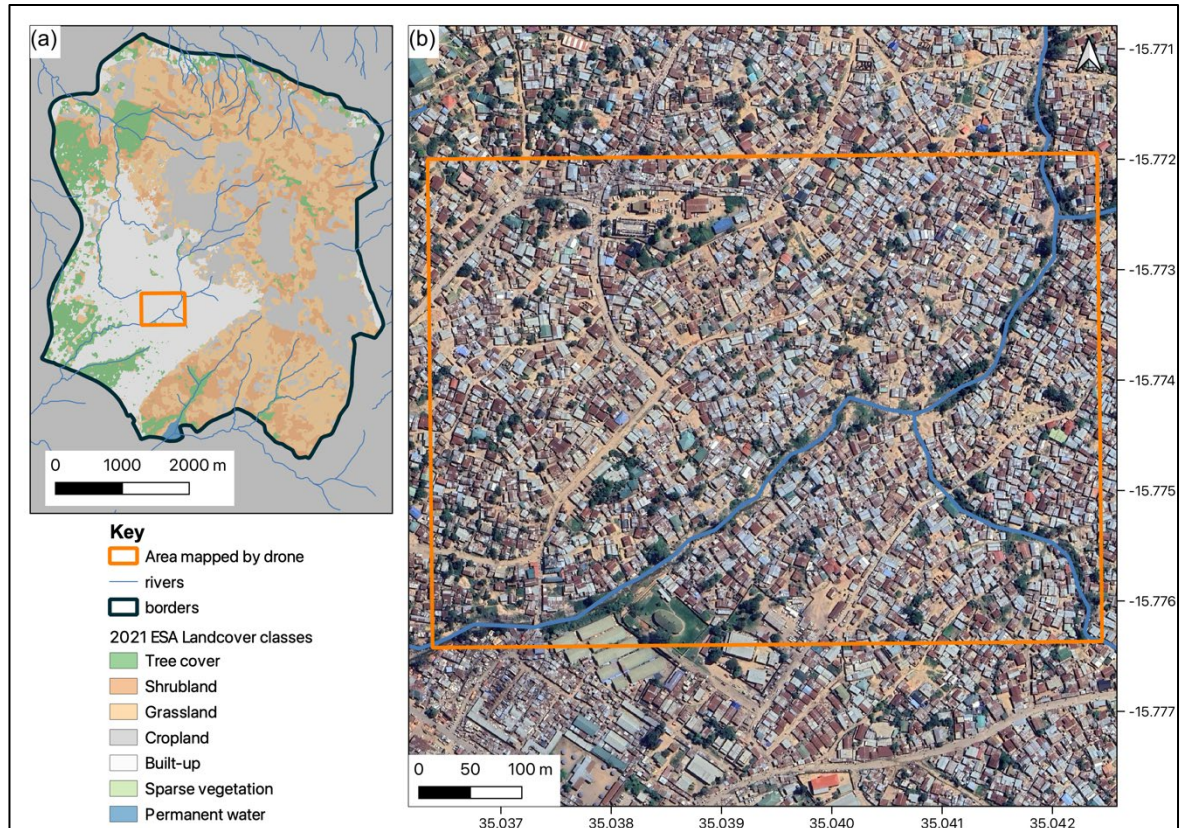
2.2.1. Mapping waste pile using community-led physical mapping of waste piles

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

215 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
216 individual materials that formed the waste pile was collected. This information
217 was subsequently used to characterize the overall composition of the waste pile
218 surface.
219

220 **2.2.2. Mapping using drone imagery**

221 To understand the practicalities of using drone imagery for mapping waste piles,
222 we utilized a Mavic 2 Enterprise drone (Model: LIDE -
223 <https://www.dji.com/mavic-2-enterprise>). The drone was manufactured by DJI,
224 and it is equipped with a 12 Megapixel camera (aperture range f/2.8 – 3.8). To
225 capture the aerial images, the drone was flown at an altitude of 60 meters.
226 While method 1 focused on the entire study community (Figure 3a), we captured
227 images for a subsection of the study community selected for long-term aerial
228 monitoring by the SPACES consortium (Figure 3 b). The captured images were
229 processed using Pix4D mapper (version 4.6.4.) to produce an orthomosaic with a
230 Ground Sampling Distance (GSD) of 1.8 cm/pixel. The resulting orthomosaic was
231 saved in a projected coordinate reference system (World Geodetic System
232 1984/Universal Transverse Mercator Zone 36 S). The orthomosaic was clipped to
233 only cover 20 meters distance to the river in the study community covering an
234 area of 45,259 square meters.



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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.

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

267

268 We developed automatic classifiers for detecting waste piles using R Statistical
269 Software (version 4.1.2). Segments that represented the labeled examples were
270 divided into training and testing segments, with 80 % (406) of the labeled
271 segments used for training and the remainder (103) used for testing. The
272 extracted feature variables and labels were used to train binary and multi-class
273 classifiers. We explored four classification algorithms: (1) RF; (2) ANN; (3) naïve
274 Bayes classifier and (4) Support Vector Machine (SVM). Full description of the
275 algorithms and parameters used are presented in Table S3. Figure 4 summarizes
276 the approach employed to develop, train, and test the four classifiers. For each

277 model trained, performance was assessed using precision (Equation 1), recall
 278 (Equation 2), and F-1 score (Equation 3). Precision quantifies the proportion of
 279 correct positive predictions among all positive predictions made. Recall measures
 280 the proportion of actual positives correctly identified by the model. The F-1 score
 281 provides a harmonic mean of precision and recall, emphasizing their balance. The
 282 formulas for these metrics are presented in Table 1.

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284 Table 1: Equations for assessment of classification performance.

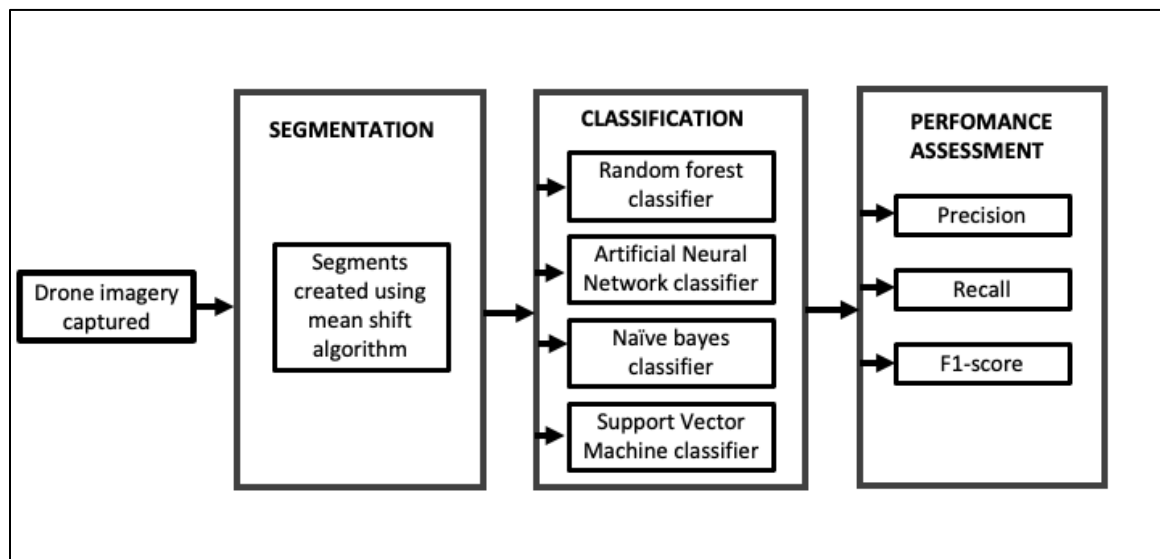
Performance measure	Formula	Equation
Precision	$\frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$	(1)
Recall	$\frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$	(2)
F-1	$\frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$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

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

293 **3. Results**

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295 **3.1. Mapping of waste piles from community-led physical mapping of waste piles**

296

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

302

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

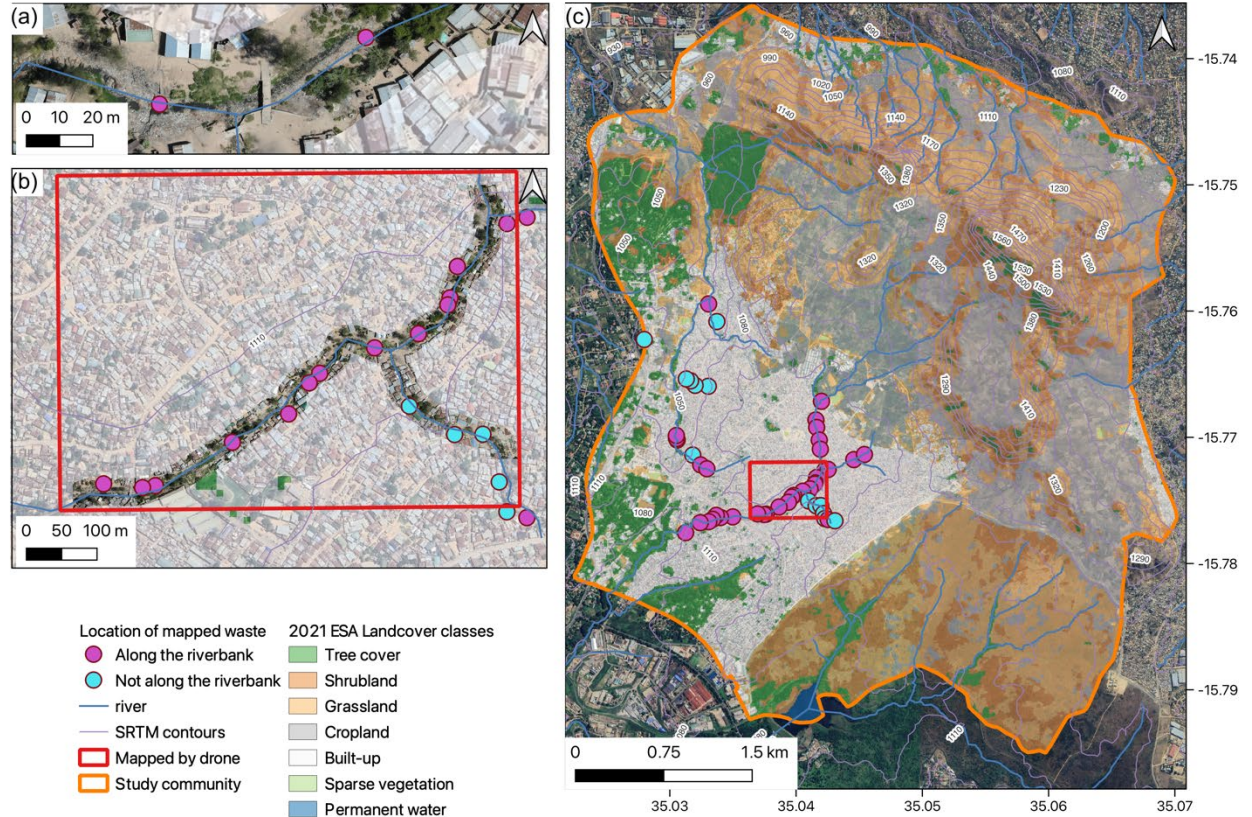
305

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

306

307 Figure 5 presents some of the waste piles mapped during the community-
 308 led physical mapping of waste piles. The mapped locations represent the center
 309 of the waste piles as identified by the research team conducting the walk. Most
 310 of the waste piles located during the community-led physical mapping of waste
 311 piles were along the banks of two local rivers, Nasolo and Chirimba, with the
 312 remaining ones not directly on the riverbank. Later observations revealed that
 313 one of the 57 waste piles had a positional accuracy of nearly 2000 meters. Of the
 314 57 waste piles, 16 were observed to be within the area that was mapped with
 315 drones.

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320 Figure 5. Detailed overview of waste piles observed during the community-led

321 physical mapping of waste piles. Subfigure (a) offers a close-up view of selected

322 waste piles, while subfigure (b) specifically emphasizes 16 waste piles mapped

323 during the community-led physical mapping of waste piles, coinciding with the

324 region covered by drone imagery. Subfigure (c) displays a comprehensive

325 overview of all 57 waste piles, showcasing their respective locations within the

326 study community.

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

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330 Figure 6 presents a map showing waste piles manually digitized from the

331 drone imagery. 50 polygons were digitized across part of the study community

332 where drone imagery was captured. Some of the digitized waste piles might

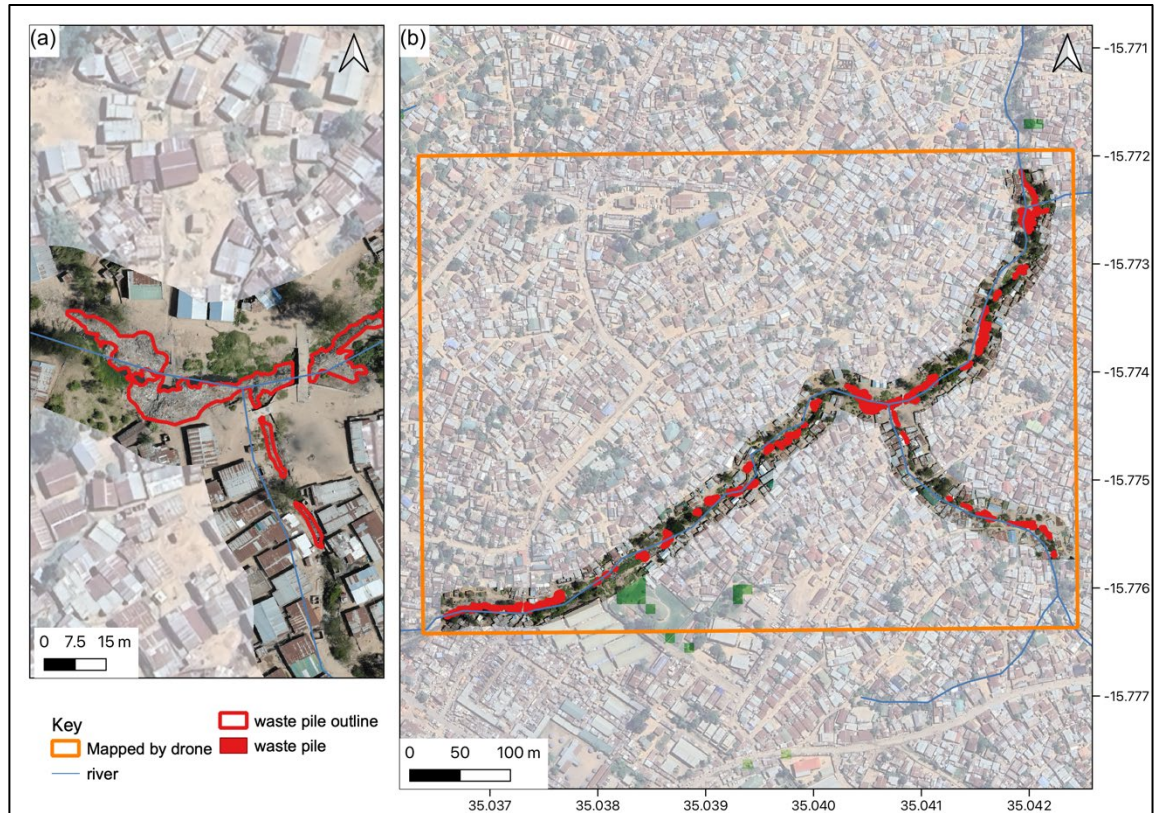
333 have been created through the dispersal of waste from some of the waste piles

334 mapped during the community-led physical mapping of waste piles. In general,

335 digitized waste piles covered 5.76 % of the area covered by the drone imagery

336 (2,609 of 45,259 square meters), with their surface area ranging from 3 to 251

337 square meters (mean = 52.15).



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340 Figure 6: Overview of the waste piles that were manually digitized in the part
341 of the study community where drone imagery was captured. Subfigure (a)
342 provides a zoomed overview of one of the manually digitized waste piles, and
343 subfigure (b) provides a broader overview of all the waste piles that were
344 mapped.
345

346 3.3 Mapping waste piles through OBIA classification approach

347
348 The use of mean-shift algorithm to segment the drone imagery produced
349 2356 segments, of which 509 of them were manually labeled to support model
350 building. Table 3 presents a summary of the characteristics of the feature
351 variables (in terms of mean and standard error) extracted from the drone
352 imagery for each of the land cover classes. It is worth noting that the mean
353 values for some feature variables such as red, green, blue, cluster shade and
354 haralick correlation show variations across the land cover classes and may be
355 useful for building of an automatic classification model. Out of the 509 segments
356 used for model development, 406 were for model training, and 106 were for
357 model testing.
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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

363 Table 4 presents the performance of four automatic classifiers - trained
364 using RF, ANN, Naïve Bayes, and SVM algorithms respectively – in mapping waste
365 piles from drone imagery using OBIA approach. Additionally, the table includes
366 the performance metrics of analogous studies conducted previously. Among the
367 four algorithms utilized, binary classifiers outperformed multi-class models
368 (Table S4-10), with the mean Kappa of 0.815 [Range: 0.64-0.90] and accuracy of
369 0.94 [Range: 0.88-0.97], compared to multi-class classifier with mean Kappa at
370 0.675 [Range: 0.26-0.85] and accuracy of 0.73 [Range: 0.40-0.87]. In terms of the
371 algorithms, ANN and SVM has the highest F-1 scores (0.98) highlighting best
372 overall performance for binary classification. However, for a multi-class classifier,
373 the RF predictor has the highest F-1 score (0.90) indicating that it outperformed
374 the other multi-class models trained. The performance of each of the trained
375 models at classifying the testing dataset has been presented in the
376 supplementary tables. It has also been observed that there are instances where
377 the automatic classifier could misclassify the segments, for example, by
378 suggesting that a segment is a waste pile while in a real sense, the segments
379 represent one of the other land cover classes considered, and vice-versa. This
380 was observed for rooftops and vegetation (Supplementary Table S6). However,
381 automatic classifiers estimated that waste piles covered more area than manual
382 mapping. For example, the trained binary SVM classifier estimated that waste
383 piles covered approximately 10,697.5 square meters, whereas the best multi-
384 class model estimated that waste piles covered approximately 5500 square
385 meters.
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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	---	---	---

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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

395 team that walked in the community for nearly half a day to scout for waste piles.
 396 In contrast, the use of drone imagery involved a team that set up a ground
 397 control station, and the drone captured aerial pictures of the area of interest
 398 using a predetermined flight route. Processing the raw drone images into an
 399 orthomosaic with Pix4D mapper (version 4.6.4) took several minutes. However,
 400 segmenting the orthomosaic, generating segment-level statistics, and manually
 401 labeling training and testing segments was time consuming, taking
 402 approximately more than 6 hours. Model fitting and results extraction took a
 403 further few minutes, but once the model was developed, it could be reused.
 404

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

407

	Community-led physical mapping of waste piles	Drone imagery (manual digitization)	Drone imagery (automatic mapping using OBIA)
Pros	<ul style="list-style-type: none"> • 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 	<ul style="list-style-type: none"> • 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 	<ul style="list-style-type: none"> • 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	<ul style="list-style-type: none"> • Only provide point information showing 	<ul style="list-style-type: none"> • Visibility of waste piles is limited by 	<ul style="list-style-type: none"> • Visibility of waste piles is limited by

- | | | |
|--|---|---|
| <p>locations where waste is being disposed in the study area.</p> <ul style="list-style-type: none"> • 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. | <p>the presence of vegetation.</p> <ul style="list-style-type: none"> • 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 | <p>the presence of vegetation.</p> <ul style="list-style-type: none"> • 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 |
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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

417 disposed of in areas not along the riverbanks might possibly be dispersed by
418 wind and rainwater; potentially, they get dispersed into the river system. Non-
419 biodegradable materials such as plastics are present in these waste piles, raising
420 concerns about their impact on the environment and human health. There is a
421 growing body of evidence reporting the presence of communities of pathogenic
422 microorganisms on plastic surfaces (Liang et al., 2023), with some studies
423 reporting the enrichment and dispersal of antimicrobial resistance genes (Rasool
424 et al., 2021; Yang et al., 2022). Furthermore, reports suggest that rivers play a
425 role in the dispersal of plastics, contributing to the spread of pathogenic
426 microorganisms (Rodrigues et al. 2019; Silva et al. 2019).

427 428 **4.2. Comparison between the three mapping approaches**

429
430 In general, the current study presented three mapping approaches: (1)
431 community-led physical mapping of waste piles; (2) manual digitization of drone
432 imagery; and (3) automatic mapping of waste piles from drone imagery using
433 OBIA. Drone imagery enabled the identification of waste piles that could not be
434 reached by ground surveys, for example, due to lack of access roads or
435 dangerous terrain (Lo et al. 2020). However, mapping waste piles using drone
436 imagery depends on the reflectance captured by the drone sensor. In our study
437 area, there are many big trees, and it could not be ascertained what was
438 beneath the branches using drone imagery. Previous studies have also reported
439 that waste materials might be hidden by shadows or vegetation, so much so that
440 they are difficult to detect, resulting in a general underestimation of waste
441 material density (Martin et al. 2018). Nonetheless, drone imagery provides
442 information such as the spatial extent of waste piles, and though not explored in
443 this study, the volume of the waste pile can also be explored.

444
445 There is a sharp distinction between mapping waste piles from drone imagery
446 manually and automating the process with OBIA. The number of waste piles and
447 total surface area detected by OBIA was greater than the corresponding figures
448 generated through manual digitization. OBIA has a possibility of misclassifying
449 other land cover classes as waste piles or vice versa, and this can falsely increase
450 or decrease the number of waste piles in the study region. OBIA
451 misclassifications may have arisen from two possible sources. One possible
452 explanation is that OBIA could not detect objects by detecting multiple objects as
453 one (under segmentation). Another possible explanation might be the
454 algorithm's shortcomings from learning patterns that differentiate waste piles
455 from other classes. Still, depending on the application, misclassified waste piles
456 can be filtered using posterior class probabilities. Nonetheless, manual
457 digitization can be slow when human resources are limited; however, this

458 approach requires limited training in image labeling. In a previous study by
459 Papakonstantinou et al. (2021), 27 volunteers underwent training in image
460 labeling. They successfully classified and labeled 30,793 objects based on
461 whether they contained waste materials or not (Papakonstantinou et al. 2021).
462 Nevertheless, waste piles generated through manual digitization might require
463 ground validation and quality assurance processes to be developed to be reliable
464 and reproducible. Crowdsourcing labeling platforms such as Humanitarian
465 OpenStreetMap Tasking Manager (<https://tasks.hotosm.org/>) or MapSwipe
466 (<https://mapswipe.org/>) offer opportunities for crowdsourcing mapping effort
467 and validation. These platforms have the potential to accelerate manual mapping
468 especially when human resources are limited. Automating the digitization of
469 waste piles using OBIA is a faster approach, and once a model has been
470 developed, it can be reused and applied on a large scale. While OBIA has
471 previously been applied to mapping marine waste (Gonçalves et al. 2020b),
472 categorizing beach macro waste items (Gonçalves and Andriolo 2022), and
473 studying the role of vegetation in trapping beach waste (Andriolo et al. 2021),
474 this study extends its application to mapping waste on land for the first time. The
475 study also breaks new ground for leveraging entirely free software, including the
476 Orfeo Toolbox (<https://www.orfeo-toolbox.org/>) and R Statistical Software (R
477 Core Team 2022), to implement the approach.

478 **4.3. Potential improvement on using OBIA for mapping waste piles**

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

499 aggregates of waste has the potential to serve as indicators for monitoring the impact of
500 waste management programs on reducing waste disposal in the environment.

501
502 In terms of the algorithms that were trained to build the models, the current
503 study observed that the model developed using an SVM algorithm slightly outperformed
504 the other binary models, achieving the highest precision, recall, F1-score, overall
505 accuracy, and Kappa. Similarly, the trained RF model slightly outperformed other multi-
506 class models, also demonstrating the best performance across these metrics.
507 Nevertheless, studies that explored automating the mapping of waste materials have
508 reported the use of diverse descriptor variables and model-building practices. For
509 example, Martin (Martin et al. 2018) used histogram oriented gradients (HOG) as
510 descriptor variables to train a SVM classifier. Conversely, numerous other published
511 works transformed RGB bands into alternative color spaces, including Hue Saturation
512 Value (HSV), CIE-Lab, and YCbCr for modelling purposes(Gonçalves et al. 2020b; 2020c;
513 2020a). This underscores the need for standard approaches in developing and
514 implementing classifiers for mapping waste materials in various environments.

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517 **4.4. Study strengths and limitations**

518

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

537

538

539 5. Conclusions and outlook for further work

540
541 The current study illustrates the practicalities associated with using images
542 collected by drones for mapping waste piles on land in an urban environment in Malawi.
543 Drone imagery enables the mapping of inaccessible waste piles and the characterization
544 of their sizes, surpassing the capabilities of field walks. To our knowledge, this is the first
545 successful application of drone-based remote sensing for mapping waste in an
546 environment other than beaches or coastal areas, particularly on land and in an urban
547 environment. Implementation of OBIA for automating waste pile detection reported
548 higher accuracy than previous studies. Considering these observations, drone imagery
549 can be used for mapping waste piles. Thus, future work should focus on three areas: (1)
550 establishing mapping requirements for mapping materials and individual objects on the
551 surface of waste piles; (2) exploring the operational performance of different image
552 classification approaches for automating the process of mapping waste piles; and (3)
553 translating generated information on waste piles into practical policy actions.

554
555 Currently, we are focused on mapping the distribution of plastic waste within
556 waste piles and quantifying its dispersal patterns. Future work on automating waste pile
557 mapping can focus on improving image capturing, object detection, and classification.
558 For image capturing, we recommend exploring optimal spatial resolution for mapping
559 individual waste materials (such as plastics). Furthermore, investigating the potential
560 contribution of different camera choices (optical sensor, infrared, thermal, etc.) on the
561 performance of the waste pile mapping models is recommended. Besides, exploring
562 emerging object detection and classification approaches, especially those with capability
563 to learn patterns associated with waste materials without needing to know the actual
564 variables needed for model training - only requiring imagery spectral bands will simplify
565 the model development process.
566

567 **Declarations**

568 **Authors contributions**

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

578 **Ethical statement**

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

580 **Ethical Responsibilities of Authors**

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

583 **Competing interests**

584 The authors declare no competing interests.

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593 mapping of waste piles, and GLOBHE, the private company that was hired to collect some of the
594 aerial imagery. St Cloud State University provided access to needed hardware and software.

595 **Data availability**

596 The drone imagery used in this paper is available on OpenAerialMap:

597 <https://map.openaerialmap.org/#/35.03883361816406,->

598 [15.773752343761437,10/user/6149611b8c56070006259d24/644f84655874aa0006657733? k=](https://map.openaerialmap.org/#/35.03883361816406,-15.773752343761437,10/user/6149611b8c56070006259d24/644f84655874aa0006657733?k=)

599 [Orpqn4](#)

600 **Code availability**

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

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References

- 604
605
- 606 Andriolo, Umberto, Gil Gonçalves, Paula Sobral, and Filipa Bessa. 2021. "Spatial and Size
607 Distribution of Macro-Litter on Coastal Dunes from Drone Images: A Case Study on the
608 Atlantic Coast." *Marine Pollution Bulletin* 169 (August):112490.
609 <https://doi.org/10.1016/j.marpolbul.2021.112490>.
- 610 Andriolo, Umberto, Konstantinos Topouzelis, Tim H. M. van Emmerik, Apostolos
611 Papakonstantinou, João Gama Monteiro, Atsuhiko Isoke, Mitsuko Hidaka, Shin'ichiro
612 Kako, Tomoya Kataoka, and Gil Gonçalves. 2023. "Drones for Litter Monitoring on Coasts
613 and Rivers: Suitable Flight Altitude and Image Resolution." *Marine Pollution Bulletin* 195
614 (October):115521. <https://doi.org/10.1016/j.marpolbul.2023.115521>.
- 615 Ayeleru, Olusola Olaitan, Sisanda Dlova, Ojo Jeremiah Akinribide, Freeman Ntuli, Williams
616 Kehinde Kupolati, Paula Facal Marina, Anton Blencowe, and Peter Apata Olubambi.
617 2020. "Challenges of Plastic Waste Generation and Management in Sub-Saharan Africa:
618 A Review." *Waste Management (New York, N.Y.)* 110 (June):24–42.
619 <https://doi.org/10.1016/j.wasman.2020.04.017>.
- 620 Banda, Felemont Kayulayula Zilale. 2015. "The Role of Contextual Factors in Flood Impact
621 Vulnerability in the Context of Climate Change: Case Study of Ndirande and South Lunzu,
622 Blantyre City."
- 623 Bao, Zhongcong, Jinming Sha, Xiaomei Li, Terefe Hanchiso, and Eshetu Shifaw. 2018.
624 "Monitoring of Beach Litter by Automatic Interpretation of Unmanned Aerial Vehicle
625 Images Using the Segmentation Threshold Method." *Marine Pollution Bulletin* 137
626 (December):388–98. <https://doi.org/10.1016/j.marpolbul.2018.08.009>.
- 627 Dlamini, SQ, and D Simatele. 2016. "Unrecognized Informal Solid Waste Recycling in an
628 Emerging African Megacity: A Study of Johannesburg, South Africa." *WIT Transactions
629 on Ecology and the Environment: Johannesburg, South Africa* 202:13–25.
- 630 Fallati, L., A. Polidori, C. Salvatore, L. Saponari, A. Savini, and P. Galli. 2019. "Anthropogenic
631 Marine Debris Assessment with Unmanned Aerial Vehicle Imagery and Deep Learning: A
632 Case Study along the Beaches of the Republic of Maldives." *Science of The Total
633 Environment* 693 (November):133581. <https://doi.org/10.1016/j.scitotenv.2019.133581>.
- 634 Gall, S. C., and R. C. Thompson. 2015. "The Impact of Debris on Marine Life." *Marine Pollution
635 Bulletin* 92 (1): 170–79. <https://doi.org/10.1016/j.marpolbul.2014.12.041>.
- 636 Garcia-Garin, Odei, Toni Monleón-Getino, Pere López-Brosa, Asunción Borrell, Alex Aguilar,
637 Ricardo Borja-Robalino, Luis Cardona, and Morgana Vighi. 2021. "Automatic Detection
638 and Quantification of Floating Marine Macro-Litter in Aerial Images: Introducing a Novel
639 Deep Learning Approach Connected to a Web Application in R." *Environmental Pollution*
640 273 (March):116490. <https://doi.org/10.1016/j.envpol.2021.116490>.
- 641 Gkoutselis, Gerasimos, Stephan Rohrbach, Janno Harjes, Martin Obst, Andreas Brachmann,
642 Marcus A. Horn, and Gerhard Rambold. 2021. "Microplastics Accumulate Fungal
643 Pathogens in Terrestrial Ecosystems." *Scientific Reports* 11 (1): 13214.
644 <https://doi.org/10.1038/s41598-021-92405-7>.

- 645 Glanville, Katharine, and Hsing-Chung Chang. 2015. "Remote Sensing Analysis Techniques and
646 Sensor Requirements to Support the Mapping of Illegal Domestic Waste Disposal Sites in
647 Queensland, Australia." *Remote Sensing* 7 (10): 13053–69.
648 <https://doi.org/10.3390/rs71013053>.
- 649 Gonçalves, Gil, and Umberto Andriolo. 2022. "Operational Use of Multispectral Images for
650 Macro-Litter Mapping and Categorization by Unmanned Aerial Vehicle." *Marine
651 Pollution Bulletin* 176 (March):113431.
652 <https://doi.org/10.1016/j.marpolbul.2022.113431>.
- 653 Gonçalves, Gil, Umberto Andriolo, Luísa Gonçalves, Paula Sobral, and Filipa Bessa. 2020a.
654 "Quantifying Marine Macro Litter Abundance on a Sandy Beach Using Unmanned Aerial
655 Systems and Object-Oriented Machine Learning Methods." *Remote Sensing* 12 (16):
656 2599. <https://doi.org/10.3390/rs12162599>.
- 657 Gonçalves, Gil, Umberto Andriolo, Luís Pinto, and Filipa Bessa. 2020b. "Mapping Marine Litter
658 Using UAS on a Beach-Dune System: A Multidisciplinary Approach." *Science of The Total
659 Environment* 706 (March):135742. <https://doi.org/10.1016/j.scitotenv.2019.135742>.
- 660 Gonçalves, Gil, Umberto Andriolo, Luís Pinto, and Diogo Duarte. 2020c. "Mapping Marine Litter
661 with Unmanned Aerial Systems: A Showcase Comparison among Manual Image
662 Screening and Machine Learning Techniques." *Marine Pollution Bulletin* 155
663 (June):111158. <https://doi.org/10.1016/j.marpolbul.2020.111158>.
- 664 Grizonnet, Manuel, Julien Michel, Victor Poughon, Jordi Inglada, Mickaël Savinaud, and Rémi
665 Cresson. 2017. "Orfeo ToolBox: Open Source Processing of Remote Sensing Images."
666 *Open Geospatial Data, Software and Standards* 2 (1): 15.
667 <https://doi.org/10.1186/s40965-017-0031-6>.
- 668 Haralick, Robert M, Karthikeyan Shanmugam, and Its' Hak Dinstein. 1973. "Textural Features for
669 Image Classification." *IEEE Transactions on Systems, Man, and Cybernetics*, no. 6, 610–
670 21.
- 671 Jakovljevic, Gordana, Miro Govedarica, and Flor Alvarez-Taboada. 2020. "A Deep Learning
672 Model for Automatic Plastic Mapping Using Unmanned Aerial Vehicle (UAV) Data."
673 *Remote Sensing* 12 (9): 1515. <https://doi.org/10.3390/rs12091515>.
- 674 Kalina, Marc, Jonathan Kwangulero, Fathima Ali, Yared Getachew Abera, and Elizabeth Tilley.
675 2022. "'Where Does It Go?': Perceptions and Problems of Riverine and Marine Litter
676 amongst South Africa and Malawi's Urban Poor." *PLOS Water* 1 (3): e0000013.
677 <https://doi.org/10.1371/journal.pwat.0000013>.
- 678 Kumwenda, Save, Madalitso Katsama, Khumbo Kalulu, and Christabel Kambala. 2012.
679 "Determination of Biological, Physical and Chemical Pollutants in Mudi River, Blantyre,
680 Malawi." *Journal of Basic and Applied Scientific Research*.
- 681 Kylili, Kyriaki, Ioannis Kyriakides, Alessandro Artusi, and Constantinos Hadjistassou. 2019.
682 "Identifying Floating Plastic Marine Debris Using a Deep Learning Approach."
683 *Environmental Science and Pollution Research* 26 (17): 17091–99.
- 684 Lakudzala, DD, KC Tembo, and IK Manda. 2000. "An Investigation of Chemical Pollutants in
685 Lower Shire River, Malawi." *Malawi Journal of Science and Technology* 5.
- 686 Leslie, Heather A., Martin J. M. van Velzen, Sicco H. Brandsma, A. Dick Vethaak, Juan J. Garcia-
687 Vallejo, and Marja H. Lamoree. 2022. "Discovery and Quantification of Plastic Particle

- 688 Pollution in Human Blood.” *Environment International* 163 (May):107199.
 689 <https://doi.org/10.1016/j.envint.2022.107199>.
- 690 Lo, Hoi-Shing, Leung-Chun Wong, Shu-Hin Kwok, Yan-Kin Lee, Beverly Hoi-Ki Po, Chun-Yuen
 691 Wong, Nora Fung-Yee Tam, and Siu-Gin Cheung. 2020. “Field Test of Beach Litter
 692 Assessment by Commercial Aerial Drone.” *Marine Pollution Bulletin* 151
 693 (February):110823. <https://doi.org/10.1016/j.marpolbul.2019.110823>.
- 694 Lynch, Seán. 2018. “OpenLitterMap.Com – Open Data on Plastic Pollution with Blockchain
 695 Rewards (Littercoin).” *Open Geospatial Data, Software and Standards* 3 (1): 6.
 696 <https://doi.org/10.1186/s40965-018-0050-y>.
- 697 Maoulidi, Moumié. 2012. “Water and Sanitation Needs Assessment for Blantyre City, Malawi.”
- 698 Martin, Cecilia, Stephen Parkes, Qiannan Zhang, Xiangliang Zhang, Matthew F. McCabe, and
 699 Carlos M. Duarte. 2018. “Use of Unmanned Aerial Vehicles for Efficient Beach Litter
 700 Monitoring.” *Marine Pollution Bulletin* 131 (June):662–73.
 701 <https://doi.org/10.1016/j.marpolbul.2018.04.045>.
- 702 Mphasa, Madalitso, Michael J. Ormsby, Taonga Mwapasa, Peter Nambala, Kondwani
 703 Chidziwisano, Tracy Morse, Nicholas Feasey, and Richard S. Quilliam. 2025. “Urban
 704 Waste Piles Are Reservoirs for Human Pathogenic Bacteria with High Levels of Multidrug
 705 Resistance against Last Resort Antibiotics: A Comprehensive Temporal and Geographic
 706 Field Analysis.” *Journal of Hazardous Materials* 484 (February):136639.
 707 <https://doi.org/10.1016/j.jhazmat.2024.136639>.
- 708 NSO. 2019. “2018 Malawi Population and Housing Census: Main Report.” Malawi National
 709 Statistical Office.
 710 http://www.nsomalawi.mw/images/stories/data_on_line/demography/census_2018/2018%20Malawi%20Population%20and%20Housing%20Census%20Main%20Report.pdf.
- 711 Nyathi, Brian, and Chamunorwa Aloius Togo. 2020. “Overview of Legal and Policy Framework
 712 Approaches for Plastic Bag Waste Management in African Countries.” *Journal of
 713 Environmental and Public Health* 2020 (October):e8892773.
 714 <https://doi.org/10.1155/2020/8892773>.
- 715 Ostle, Clare, Richard C. Thompson, Derek Broughton, Lance Gregory, Marianne Wootton, and
 716 David G. Johns. 2019. “The Rise in Ocean Plastics Evidenced from a 60-Year Time Series.”
 717 *Nature Communications* 10 (1): 1622. <https://doi.org/10.1038/s41467-019-09506-1>.
- 718 Papakonstantinou, Apostolos, Marios Batsaris, Spyros Spondylidis, and Konstantinos
 719 Topouzelis. 2021. “A Citizen Science Unmanned Aerial System Data Acquisition Protocol
 720 and Deep Learning Techniques for the Automatic Detection and Mapping of Marine
 721 Litter Concentrations in the Coastal Zone.” *Drones* 5 (1): 6.
 722 <https://doi.org/10.3390/drones5010006>.
- 723 Pinto, Luis, Umberto Andriolo, and Gil Gonçalves. 2021. “Detecting Stranded Macro-Litter
 724 Categories on Drone Orthophoto by a Multi-Class Neural Network.” *Marine Pollution
 725 Bulletin* 169 (August):112594. <https://doi.org/10.1016/j.marpolbul.2021.112594>.
- 726 R Core Team. 2022. *R: A Language and Environment for Statistical Computing*. Vienna, Austria:
 727 R Foundation for Statistical Computing. <https://www.R-project.org/>.
- 728 Rasool, Farah N., Mariana A. Saavedra, Siajali Pamba, Vonica Perold, Aviti J. Mmochi,
 729 Mohammed Maalim, Lone Simonsen, et al. 2021. “Isolation and Characterization of
 730 Human Pathogenic Multidrug Resistant Bacteria Associated with Plastic Litter Collected
 731

- 732 in Zanzibar." *Journal of Hazardous Materials* 405 (March):124591.
 733 <https://doi.org/10.1016/j.jhazmat.2020.124591>.
- 734 Ribeiro, Joana, Duarte Viveiros, João Ferreira, Alexia Lopez-Gil, Alejandro Dominguez-Lopez,
 735 Hugo F. Martins, Rosa Perez-Herrera, et al. 2017. "ECOAL Project—Delivering Solutions
 736 for Integrated Monitoring of Coal-Related Fires Supported on Optical Fiber Sensing
 737 Technology." *Applied Sciences* 7 (9): 956. <https://doi.org/10.3390/app7090956>.
- 738 Rodrigues, Alyssa, David M. Oliver, Amy McCarron, and Richard S. Quilliam. 2019. "Colonisation
 739 of Plastic Pellets (Nurdles) by E. Coli at Public Bathing Beaches." *Marine Pollution*
 740 *Bulletin* 139 (February):376–80. <https://doi.org/10.1016/j.marpolbul.2019.01.011>.
- 741 Sajidu, S. M. I., W. R. L. Masamba, E. M. T. Henry, and S. M. Kuyeli. 2007. "Water Quality
 742 Assessment in Streams and Wastewater Treatment Plants of Blantyre, Malawi." *Physics*
 743 *and Chemistry of the Earth, Parts A/B/C* 32 (15–18): 1391–98.
- 744 Shastry, Apoorva, Elizabeth Carter, Brian Coltin, Rachel Sleeter, Scott McMichael, and Jack
 745 Eggleston. 2023. "Mapping Floods from Remote Sensing Data and Quantifying the
 746 Effects of Surface Obstruction by Clouds and Vegetation." *Remote Sensing of*
 747 *Environment* 291 (June):113556. <https://doi.org/10.1016/j.rse.2023.113556>.
- 748 Shi, Yu, Yao Wang, Yang Yue, Jun Zhao, Tek Maraseni, and Guangren Qian. 2021. "Unbalanced
 749 Status and Multidimensional Influences of Municipal Solid Waste Management in
 750 Africa." *Chemosphere* 281 (October):130884.
 751 <https://doi.org/10.1016/j.chemosphere.2021.130884>.
- 752 Silva, Mariana Muniz, Gustavo Carvalho Maldonado, Rebeca Oliveira Castro, João de Sá
 753 Felizardo, Renan Pereira Cardoso, Roberto Meigikos Dos Anjos, and Fábio Vieira de
 754 Araújo. 2019. "Dispersal of Potentially Pathogenic Bacteria by Plastic Debris in
 755 Guanabara Bay, RJ, Brazil." *Marine Pollution Bulletin* 141:561–68.
- 756 Topouzelis, Konstantinos, Dimitris Papageorgiou, Alexandros Karagaitanakis, Apostolos
 757 Papakonstantinou, and Manuel Arias Ballesteros. 2020. "Remote Sensing of Sea Surface
 758 Artificial Floating Plastic Targets with Sentinel-2 and Unmanned Aerial Systems (Plastic
 759 Litter Project 2019)." *Remote Sensing* 12 (12): 2013.
 760 <https://doi.org/10.3390/rs12122013>.
- 761 United Nations. 2015. "Transforming Our World: The 2030 Agenda for Sustainable
 762 Development." In . Vol. RES/70/1.
 763 [https://www.un.org/en/development/desa/population/migration/generalassembly/doc](https://www.un.org/en/development/desa/population/migration/generalassembly/docs/globalcompact/A_RES_70_1_E.pdf)
 764 [s/globalcompact/A_RES_70_1_E.pdf](https://www.un.org/en/development/desa/population/migration/generalassembly/docs/globalcompact/A_RES_70_1_E.pdf).
- 765 Wilson, D. C., L. Rodic, P. Modak, R. Soos, A. Carpintero, K. Velis, M. Iyer, and O. Simonett. 2015.
 766 "Global Waste Management Outlook." Monograph. UNEP. September 8, 2015.
 767 [http://web.unep.org/ourplanet/september-2015/unep-publications/global-waste-](http://web.unep.org/ourplanet/september-2015/unep-publications/global-waste-management-outlook)
 768 [management-outlook](http://web.unep.org/ourplanet/september-2015/unep-publications/global-waste-management-outlook).
- 769 Wolf, Mattis, Katelijan van den Berg, Shungudzemwoyo P. Garaba, Nina Gnann, Klaus Sattler,
 770 Frederic Stahl, and Oliver Zielinski. 2020. "Machine Learning for Aquatic Plastic Litter
 771 Detection, Classification and Quantification (APLASTIC-Q)." *Environmental Research*
 772 *Letters* 15 (11): 114042. <https://doi.org/10.1088/1748-9326/abbd01>.
- 773 Xie, Jian, and J Martin. 2022. "Plastic Management in Rwanda." Washington DC: World Bank.
 774 <https://openknowledge.worldbank.org/handle/10986/37607>.

- 775 Yang, Le-Yang, Xin-Rong Huang, Roy Neilson, Zhao-Lei Li, Xiao-Ru Yang, and Xiao-Xuan Su. 2023.
776 "Characterization of Microbial Community, Ecological Functions and Antibiotic
777 Resistance in Estuarine Plastisphere." *Science of The Total Environment*, 161322.
- 778 Yang, Yang, Teng Li, Peng Liu, Huixin Li, and Feng Hu. 2022. "The Formation of Specific Bacterial
779 Communities Contributes to the Enrichment of Antibiotic Resistance Genes in the Soil
780 Plastisphere." *Journal of Hazardous Materials* 436:129247.
- 781 Zettler, Erik R., Tracy J. Mincer, and Linda A. Amaral-Zettler. 2013. "Life in the 'Plastisphere':
782 Microbial Communities on Plastic Marine Debris." *Environmental Science & Technology*
783 47 (13): 7137–46. <https://doi.org/10.1021/es401288x>.
- 784 Zhu, Xia. 2021. "The Plastic Cycle – An Unknown Branch of the Carbon Cycle." *Frontiers in*
785 *Marine Science* 7:1227. <https://doi.org/10.3389/fmars.2020.609243>.
786