6-2022

Geospatial Methods for Mapping Domestic Waste Piles and Macro Plastics

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Geospatial Methods for Mapping Domestic Waste Piles and Macro Plastics

By

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A Thesis

Submitted to Graduate Faculty of

St. Cloud State University

In Partial Fulfillment of the Requirements

For the Degree of

Master of Science

In Geography (Geographical Information Science)

June, 2022

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Abstract

There are growing concerns about the threats posed by plastics to human society and natural ecosystems. There is evidence of the harm presented to economies, public health, and society. Although plastic pollution is an issue of great concern, low- and middle-income countries lack waste disposal services, and this leads to disposal of waste including plastics into the environment. Monitoring presence of waste disposed into the environment is crucial for assessment of remedial measures. Traditional approach for identifying locations with plastic and waste accumulation in the environment involves field surveys, and drone technology is an emerging technology being applied for mapping the presence of plastics and waste in the environment. In this study, I have presented basic requirements for collecting data using Unmanned Aerial Vehicles (UAV) to map plastics and accumulation of domestic waste in the environment. For example, it was observed that a Ground Sampling Distance (GSD) of 2.51 cm is too coarse for mapping plastics of size less than 10 cm. Additionally, the study has also utilized random forest as a machine learning algorithm to classify and identify plastics and waste piles from UAV-derived imagery in a densely populated area of Blantyre, Malawi. The random forest predictions show high performance compared to prior studies for both waste piles (Precision: 0.9048, Recall: 0.95, and F-score: 0.9268) and plastics detection (Precision: 0.8905, Recall: 0.9421, and F-score: 0.9156). With the reported accuracies, UAV imagery can be employed to guide environmental policy implementation by helping in monitoring the effectiveness of policies that have been set to mitigate and address problems such as open waste dumping.

Acknowledgements

I wish to express my sincere gratitude to all individuals and institutions that helped me to bring this project into life.

Firstly, great thanks to my advisor Dr. Mikhail Blinnikov, for providing me guidance in developing this project. Thanks to Dr. Michelle Stanton for providing me with mentorship support. The same also goes to the other members of my thesis committee, other faculty members at the Geography and Planning department of the School of Public Affairs at SCSU, specifically Mr. Thomas Oien for assisting me in collecting UAV data for my experiment.

I am also thankful to Rosheen Mthawanji, Chifuniro Baluwa, Moses Fuleya and Taonga Mwapasa for assisting me in collecting data to support my experiment in Malawi. I also thank Sustainable Plastics Attitudes to Benefit Communities and their Environments (SPACES) for providing funding to support data collection, and GLOBHE, a private company that rendered the service to collect UAV imagery across the entire Ndirande neighborhood.

Finally, I am very grateful to the Fulbright Program for sponsoring my Master's studies. In many ways, my experience in Minnesota has been intellectually rewarding.

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Chapter 1: Introduction

Background of the study

Plastic pollution is considered a global challenge. Plastics disposed in the environment are transported with rainwater to lakes and oceans, where they accumulate and harm natural ecosystems (Ostle et al. 2019; Zhu 2021). Direct effects of plastics on natural ecosystems include death and physical damage to aquatic fauna through entanglement and ingestion, and plastics account for over 92 percent of ingestion and entanglement cases (Gall and Thompson 2015). Plastics also break down into smaller particles called microplastics. Microplastics are of a size between 1 mm and 5 mm and they can pass through food webs causing bioaccumulation (Cole et al. 2011; Al-Jaibachi, Cuthbert, and Callaghan 2018; M. O. Rodrigues et al. 2019). Emerging studies also indicate that the presence of plastics in the environment serves as novel microhabitat for potentially pathogenic fungal species and other opportunistic human pathogens (Gkoutselis et al. 2021; A. Rodrigues et al. 2019). This is particularly concerning given that the global public health burden posed by microorganisms has risen because of antimicrobial resistance (Woolhouse et al. 2016). Given clear negative consequences of plastic pollution, robust control is required. However, a fundamental understanding of plastic sources, sinks, and transport mechanism has not been fully achieved (Vriend, Roebroek, and van Emmerik 2020). The use of Unmanned Aerial Vehicles (UAV) seems to be a promising tool for monitoring the environment, including plastic pollution in water and over land. This research aims to explore and evaluate the use of UAVs for mapping of plastics and aggregates of domestic waste in a selected region in Malawi.

This chapter provides a background overview of the problem of plastic pollution, followed by the research problem, aims and research questions. The rest of the text provides the organization of subsequent chapters of the document. Chapter Two presents a comprehensive literature review. Chapter Three presents methods that were employed to answer the research questions, and chapter Four presents key findings and discussions in the context of existing literature. The last chapter presents conclusions and recommendations.

The challenge of plastic pollution

Plastics refer to synthetic organic polymer made from petroleum with properties ideally suited for a wide variety of applications ("Marine Plastic Pollution" 2018). Unlike organic materials, synthetic polymers in plastics are extremely durable and may persist in the environment for centuries to millennia (Elias 2018). It has also been established that most of the plastics that are widely produced persist in the environment for at least hundreds of years. Great abundance of plastics such as polyethylene (PE), polypropylene (PP) and polyethylene terephthalate (PET) in marine environments have been reported (Erni-Cassola et al. 2019). Irrespective of this, the global production of plastics has increased exponentially since the 1960's (Figure *1*), and in 2015 the annual production of plastics exceeded 381 million tons (Ritchie and Roser 2018). Unfortunately, most of the plastics that are produced are not recycled and as of 2015, over 79 percent of the plastics that have been produced were either sitting in landfills or in the natural environment (Geyer, Jambeck, and Law 2017).

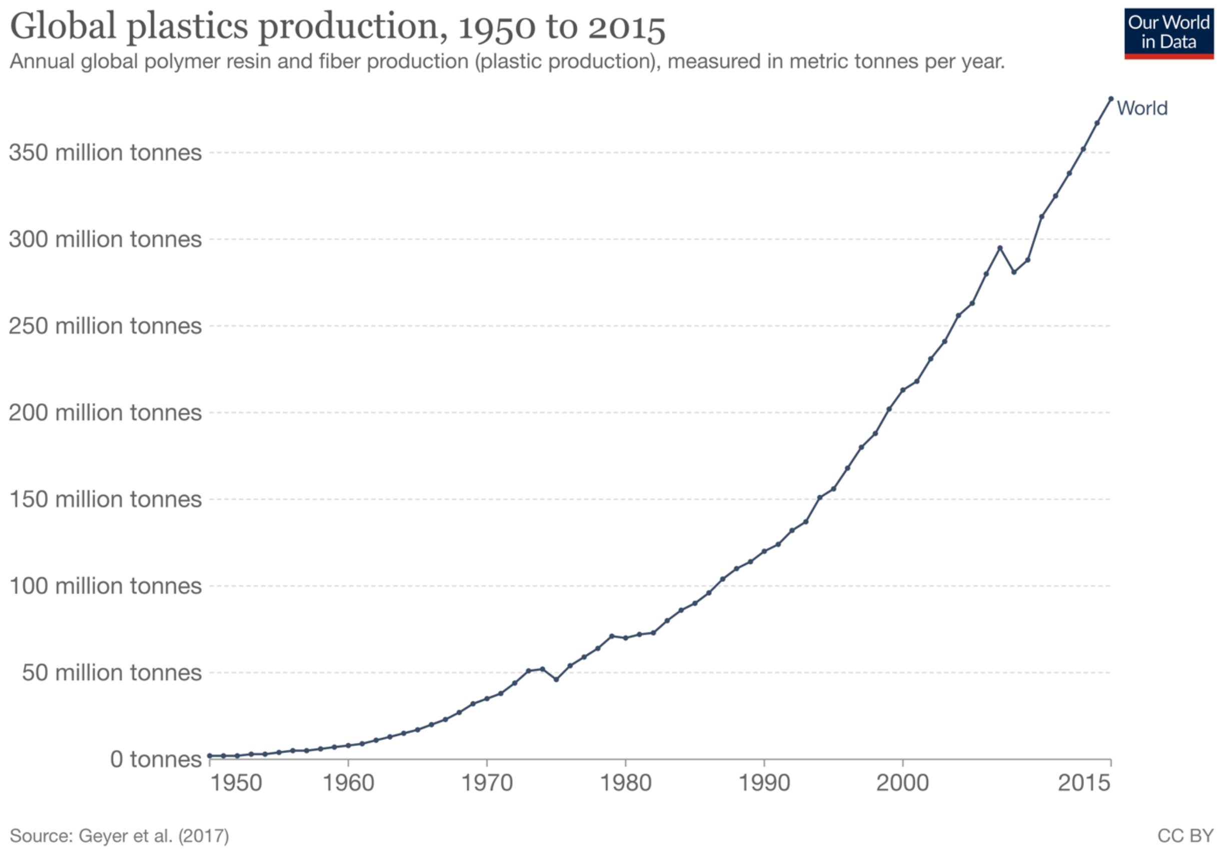

Figure 1. Global production of plastics from the 1950's. Despite evidence of damage caused by plastics, plastic production continues to be on the rise (Image source: Ritchie and Roser (2018))

Leakage of plastics into the environment is dependent on existence of waste management systems (Watt et al. 2021; Rhodes 2018). As presented in Figure 2, improper management of waste is more prevalent in in developing countries, and the practice of dumping waste in open areas, roadsides and rivers has been previously reported in many countries (Ferronato and Torretta 2019; Khatib 2011). It is estimated that between 1.15 and 2.41 million tons of plastic waste enter oceans every year from land through rivers (Lebreton et al. 2017). Sub-Saharan Africa generates about 17 million tons of plastics and yet over 70 percent of waste that is generated in the region is openly dumped (Ayeleru et al. 2020). However, unlike in the developed countries, in African cities, locations with high population density generate less quantities of waste per capita (Loukil and Rouached 2020). A recent review on plastic pollution in Africa indicates that plastic pollution is highest in southern Africa than other parts of the continent (Akindele and Alimba 2021).

Figure 2. Domestic waste disposal in a water gutter (Photo taken by the author in 2018)

Addressing plastic pollution

The need to address the problem of plastic pollution has been widely recognized. Global frameworks such as Honolulu Strategy (UNEP 2011) recognize that the problem of plastic pollution emanates from inadequate waste management systems, inappropriate human behavior, and unsustainable production and consumption (UNEP 2011). For example, consumption patterns such as usage of single use materials, single use plastics contribute about 60 to 95 percent of global marine plastic pollution (Schnurr et al. 2018). Some countries have utilized legal and economic instruments such as imposing levies on plastics or even completely banning importation and usage of some types of plastics (Schnurr et al. 2018; Nielsen, Holmberg, and Stripple 2019). However, scholars still argue that no single solution can adequately address the problem of plastic pollution (Godfrey 2019; Chen et al. 2021; da Costa et al. 2020). A multi-disciplinary and more comprehensive approach is required (Heidbreder et al. 2019; Deme et al. 2022; Abalansa et al. 2020). The Honolulu strategy highlights the need for reliable data and information for determining whether strategies are achieving expected results (UNEP 2011).

A review by Xanthos and Walker (2017) recognized a general dearth of scientific evidence on effectiveness of national policies on reduction of the presence of plastics in the environment. Much of the existing evidence cited in the review uses consumption of plastics in retail shops as a metric for assessing effectiveness of plastic mitigation policies. This approach is ineffective as there might be multiple sources of plastics other than retail shops. Monitoring abundance of plastics in the environment can be important to establish rates of accumulation of plastics and assessment of effectiveness of remediation measures (Thompson et al. 2009). Detection and quantification of plastics in the environment has the potential to build our understanding of the transportation mechanism of plastic to marine ecosystem (González-Fernández and Hanke 2017). Repeated monitoring of plastic waste disposal sites on land can help to detect new threats to the environment and check compliance to environmental standards (Ryan et al. 2020).

Approaches for monitoring plastic waste in the environment

Different approaches for monitoring plastic waste in the environment exist. These approaches depend on the size of plastics that are monitored. For example, microplastics which are small, are monitored through collection of samples of water or soil and subjecting the sample to analytical assessment (Hidalgo-Ruz et al. 2012; Renner, Schmidt, and Schram 2018). Macroplastics, which are larger and easily visible to human eyes, are monitored by visual observation of plastics and this usually involves recording abundance of plastics in transects (de Araújo, Santos, and Costa 2006; Vered and Shenkar 2021). Scholars have reported that these approaches are labor intensive, and not appropriate for monitoring large areas. Lack of consistency in methods for monitoring plastics have also been noticed (UNEP 2011). Regardless, several monitoring approaches are also emerging. One emerging approach is the use of citizen science, ‘an approach where volunteers contribute towards collection of scientific data’ (Cohn 2008). For example, tools such as ‘Openlittermap’ exist for anyone interested in contributing data on litter locations using geotagged images (Lynch 2018). Citizen science however requires compensation for data collection efforts and a robust system for data quality assessments is still needed (Silvertown 2009). Remote sensing is another emerging approach in the field of monitoring plastic pollution.

Remote sensing involves capturing information about the earth surface from a distance. Primarily remote sensing offers a robust set of tools for large scale monitoring and frequent observation. While most environmental monitoring applications of remote sensing includes mapping impervious surfaces (Weng 2012), crop health (Moran et al. 1997), and quantifying global forest loss (Hansen, Stehman, and Potapov 2010) among others, there has been growing interest in exploring potential opportunities for monitoring plastic pollution. Studies on the use of remote sensing for mapping plastics were conducted in oceans and they have taken advantage of efficiency of clear water at absorbing near infrared (NIR) to shortwave infrared (SWIR) light (Biermann et al. 2020). In contrast, floating materials including algae and macroplastics produce a significant response in the NIR and SWIR regions of the electromagnetic spectrum and this difference has been used for detection of floating marine plastics (Topouzelis et al. 2020). However, the satellite data have limited spatial resolution for mapping domestic waste disposal sites which are often significantly smaller than industrial sites or landfills (Glanville and Chang 2015). Currently there has been a growing trend towards acquiring high-resolution data through the use of UAVs.

The UAV technology or sometimes called drone technology or Unmanned Aerial Systems refers to powered, aerial vehicles that uses aerodynamic forces to provide vehicle lift and can fly autonomously or be piloted remotely, can be expendable or recoverable, and can carry a lethal or nonlethal payload (Bhattacharya et al. 2020). It is a flexible remote sensing technology that enables low-cost acquisition of very high-resolution aerial data with resolution of less than 10 cm (Yao, Qin, and Chen 2019). The rise of UAVs for civilian applications has risen in the recent decade. UAVs have been used in environmental monitoring with applications including conducting animal counts (Wood et al. 2021), tree mapping (Zhang et al. 2016) and others. In solid waste management, the technology has been utilized for identification of illegal dumpsites, estimation of waste volume and estimation of methane emissions in landfills (Sliusar et al. 2022; Filkin et al. 2022; Mello, Salim, and Simões 2022; Kim et al. 2021). UAVs also show great potential for monitoring of the spatiotemporal distribution of riverine plastic debris (Geraeds et al. 2019).

Problem statement and justification

The need for robust tools for monitoring the environment has been widely acknowledged. Monitoring of presence of waste and plastics in the environment has been recommended in various national and international guidelines, particularly for persistent pollutants such as plastics in natural ecosystems (UNEP 2021). Research on monitoring plastic waste using remote sensing has focused much on quantifying the extent of plastic accumulation in aquatic environments ignoring terrestrial and freshwater ecosystems (Blettler et al. 2018). Conversely, tools for monitoring waste and plastics on land remain to be in infancy stage, yet it is known that 80 percent of the plastics observed in oceans originate from terrestrial sources (J. R. Jambeck et al. 2015). The use of emerging low-cost technologies such as UAVs has not been comprehensively studied to guarantee operational usage in an environmental monitoring program. In addition, there is little research from developing countries and yet these areas where a high proportion of waste is mismanaged (Bank et al. 2021; Blettler et al. 2018). Previous attempts to explore usage of low-cost tools such UAVs have been made in developed countries.

Exploring the potential of using UAVs in mapping plastics and waste piles can strengthen our understanding of the abundance of plastic and waste materials in the environment, which can subsequently improve our understanding of disposal, accumulation, and transportation mechanisms. Clearly, UAV has potential to be used to support systematic environmental monitoring and this will help in development of environmental management policies and aid tracking of mitigating efforts (Bank et al. 2021). An accurate understanding of the persistence of plastic goods in the environment is critical for many stakeholders for plastic waste management including consumers, researchers and legislators (Ward and Reddy 2020). Pattens of plastic and waste piles can serve as a baseline to identify bottlenecks, enabling setting of priorities and effective development of remedial strategies for land based plastic pollution (J. Jambeck et al. 2018). Due to the flexibility of UAVs, environmental management programs can easily generate updated data on waste presence in the environment using a UAV mapping approach. UAV technology can provide valuable information that can help policy makers and environmental authorities to investigate waste materials that are abundant in the environment. This can help to guide efforts towards implementing producer pay principle. Furthermore, the use of UAS (Unmanned Aerial Systems) equally provides an opportunity for in studies aiming at studying the impacts of plastics.

Context of the study

The current study was set to explore mapping of waste piles and plastics in the environment. Information generated from this study is key to studying the impact of waste and plastics on local communities. Consequently, part of the current study was conducted in the republic of Malawi, a country where there is an ongoing research study "Sustainable Plastic Attitudes to Benefit Communities and their Environment" (SPACES)[1]. The study is led by the University of Stirling, and it is aiming at investigating the public health risks and environmental impact of plastic pollution in developing countries. The SPACES project provided funding for acquisition of drone images in Malawi. The republic of Malawi is a country located in south-east Africa, and it shares its borders with Zambia, Mozambique, and Tanzania. The recent household population census indicates that in Malawi urban communities, waste collection by authorized

[1] Information about SPACES project: https://extremeevents.stir.ac.uk/projects/spaces/

collectors only serves around 5.1 percent of the households (NSO 2020). The Malawi State of environment report indicated that most of the domestic waste is discarded along roadside and in rivers (Government of Malawi 2010). This practice is common in many informal communities across the country (Manda 2009). Such practice has also been previously reported in most developing countries (Khatib 2011; Ferronato and Torretta 2019). Apart from previous observations of waste disposal in the environment, Malawi is an excellent country to conduct the study in as it is one of the few countries that have banned manufacturing, distribution, selling, and use of plastic bags with thickness of less than 60 microns (GoM 2015). Although there has been legal battle between government and plastic manufacturers, the recognition of the problem at the national level guarantees potential for integration of environmental monitoring tools such as UAVs in efforts to curb plastic pollution. Outputs from such monitoring efforts can be used for investigating compliance to existing regulations and quantify the impact of behavior change programs including awareness campaigns and waste cleanups on both short-term and long-term presence of plastics in the environment.

The study focus is the community of Ndirande, which is the largest informal settlement within the city of Blantyre - Malawi's commercial city - a city with a population of about 800,264 people. Ndirande has a population of about 97,839 people, approximately 12.2 percent of the population of the city of Blantyre (NSO 2019). In the community, indiscriminate disposal of waste in water drainage channels was previously reported in previous studies (Maoulidi 2012; Banda 2015). As presented in Figure *3*, Ndirande neighborhood has three administrative wards namely Ndirande South, Ndirande west and Ndirande north. A ward is the smallest administrative divisions for elected officials, and it is under a councilor. Accordingly, the current study specifically focused on a small part of Ndirande south ward. Within the community runs the Nasolo River, a tributary of the Mudi - one of the most polluted rivers in Malawi. Thus, it appeared to be a good case for study of presence and dispersal of plastics in a terrestrial ecosystem.

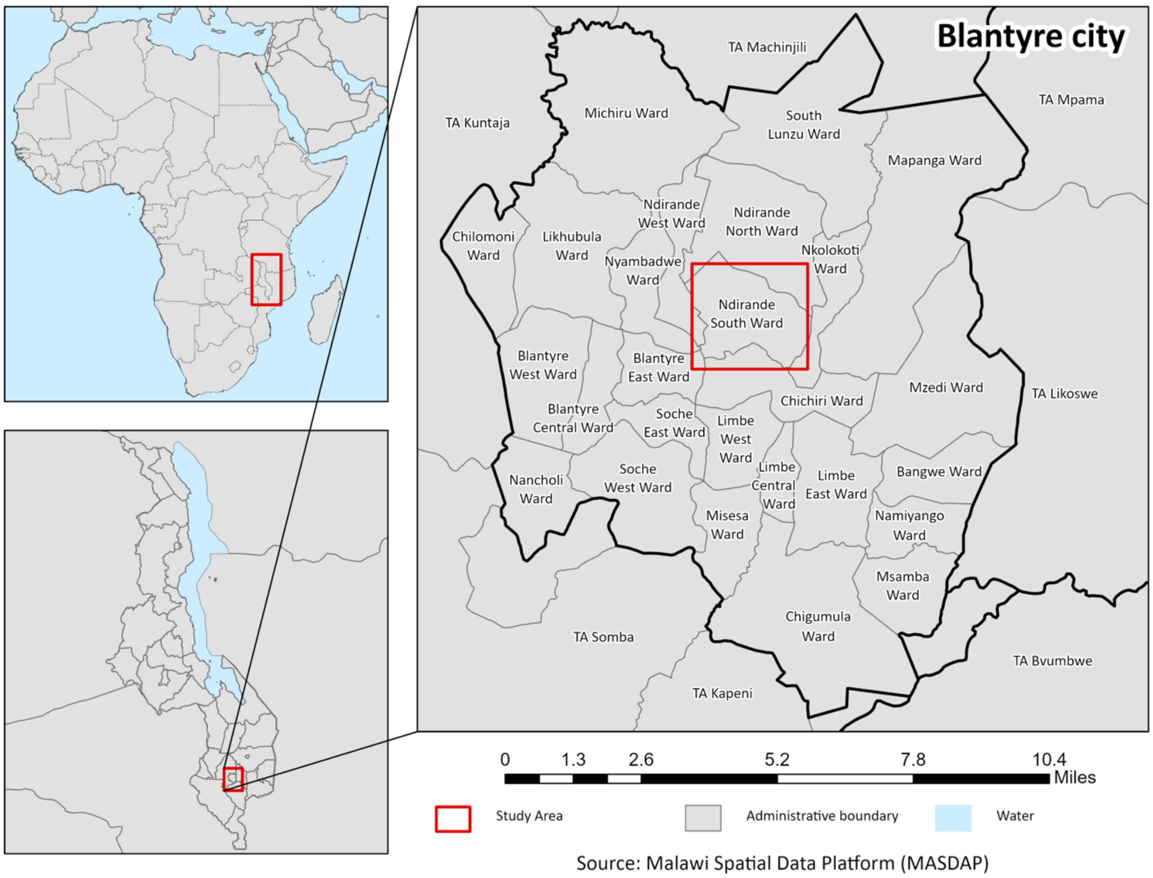

Figure 3. Map of the study location. The map was created by the author.

Research question and objectives

Key research question

The study seeks to address the question: 'How best can UAV and machine learning be utilized to map and locate plastics and waste piles in urban areas of low-income countries such as Malawi?'.

Research objectives

Specifically, the study addressed the following objectives:

1. Examine factors that affect visibility of terrestrial plastic waste from a UAV imagery.
2. Detect terrestrial waste piles from UAV imagery using machine learning approaches and present the information about detected waste piles on a web map.
3. Investigate the visibility of terrestrial plastic waste in a UAV imagery when plastics are mixed with other waste materials.

Chapter 2: Literature review

Introduction

This chapter presents a literature review of studies that explored the use of UAV imagery for mapping and detection of plastic waste. The aim of the review is to synthesize literature on mapping and detection of plastic waste using UAV imagery, identify inconsistencies and gaps left from previous studies, develop research methodology and to contribute to the scholarly discussion on integration of UAV in monitoring the environment.

Literature search

To get an impression of previous studies and the current state of research on the use of UAVs for mapping waste piles and plastics, a literature search was undertaken on Google Scholar and Academic Search Premier. The literature search was performed in October 2021 and it followed the criteria in Table 1.

Table 1. Criteria for literature review

Literature search and appraisal for the use of UAV technology for mapping plastics disposed in the environment.	
Goal of the search	To develop an understanding about how UAV technology has been used for mapping or monitoring plastics disposed in the environment.

Table 1 (continued)

Search terms	((“Plastic mapping”) OR (“Plastic monitoring”)) AND (“Drone” OR “Unmanned Aerial Vehicle” OR “UAV”)
Inclusion criteria	Articles dealing with o Plastic detection on derived orthomosaic o Implementation of algorithms for automatic detection of plastics on a derived orthomosaic
Exclusion criteria	o Detection of plastic waste on a UAV acquired video. o Detection of plastics from satellite imagery. o Studies on detection of greenhouse plastics. o Articles that did not have full texts available. o Articles not written in English.
Literature search and appraisal for the use of UAV technology for mapping waste piles	
Goal of the search	To develop an understanding about prior work and methods that have been employed to use UAV imagery for mapping and monitoring waste piles.

Table 1 (continued)

Search terms	(“Waste mapping” OR “Waste monitoring”) AND (“Drone” OR “Unmanned Aerial Vehicle” OR “UAV”)
Inclusion criteria	Articles dealing with o Waste mapping using an orthomosaic generated from a UAV imagery. o Utilization of automatic methods for detection of waste piles.
Exclusion criteria	o Detection of gas emissions from waste piles. o Studies focusing on use of sensors for monitoring waste accumulation in a waste bin. o Studies that are not focused on domestic waste, examples of such studies include papers studying nuclear waste or detecting heat signatures of burning waste. o Articles not written in English.

Appraisal of searched literature

The search on plastic mapping returned one article on Academic Search Premier, and forty-five articles on Google Scholar. After reading the titles and abstracts of these articles, five articles were downloaded and skimmed to assess relevancy. All five articles fell within the scope of this study and were considered. The articles were read to locate other relevant studies. At the end, 15 articles met the inclusion requirements and were considered in this review.

The search for literature on waste mapping returned 120 articles on Google Scholar, and there was 1 article on Academic Search Premier. After screening the titles and abstracts, the majority of the studies focused on automatic waste detection using IoT sensors on waste bins with few studies mentioning waste mapping within the context in which we were most interested in. A total of seven articles were downloaded and assessed for relevancy. After skimming through the seven articles, only one article appeared to be relevant and they have been considered in this study (Merlino et al. 2020). However, as the study constantly cite and draws insights from studies on plastic mapping, the literature has been reviewed together. The majority of the studies were conducted in Portugal, Greece, Spain, Hong Kong, Germany, Italy, Bosnia-Herzegovina, Cambodia, Maldives, Saudi Arabia and China.

UAV image acquisition

First, the review examined the methods that were employed for acquisition of UAV imagery. In most of the studies reviewed, UAVs were acquired from a low flight altitude and the resulting images had Ground Sampling Distance (GSD) of less than 5 mm (Martin et al. 2018; Fallati et al. 2019; Jakovljevic, Govedarica, and Alvarez-Taboada 2020; Papakonstantinou et al. 2021; Han et al. 2021; Merlino et al. 2020). Low GSD indicates a small distance between centers of adjacent pixels; this represents high spatial resolution, and more details are visible[2]. Papakonstantinou et al. (2021) remarked: ‘a Ground Sampling Distance of 5 mm is sufficient enough to capture a standard bottlecap into four pixels. However, to generate a UAV imagery with low GSD undermines remote survey time efficiency as a small area is captured and this results in more flight time and relatively high number of images captured (Martin et al. 2018). Regardless, acquiring imagery using high quality cameras can improve time efficiency, however this can come with high financial cost and still there will be high imagery load and more computational resources will be required.

A study by Lo et al. (2020) investigated how the conditions through which UAV is being operated affect the ability to detect plastics. The study involved mapping of plastic targets with known characteristics such as sizes and color from a UAV which was flown from different heights across different times of the day. The study reported that weather, time of the day and altitude have an effect on the number of false positives (Lo et al. 2020). A similar experimental work reported that color of plastics and presence of background noise affect the ability to correctly identify plastics (Hengstmann and Fischer 2020). The study reported that ‘transparent plastics tend to be easily misclassified than other colors when mapped from a high altitude’. A study by Jakovljevic et al (2020) related this problem to GSD. In their study it was observed that 2 cm squares of plastics were omitted during detection of plastics from imagery captured at 55 meters (GSD = 1.8 cm). The authors explained that it is difficult to observe small pieces of

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[2] Information on “Ground Sampling Distance (GSD) in Photogrammetry.” https://support.pix4d.com/hc/en-us/articles/202559809-Ground-sampling-distance-GSD-in-photogrammetry

plastic because there were not enough pixels for smaller plastics to be detected. GSD must be twice the size of the object for the latter to be detected (Jakovljevic et al. 2020).

In the context of acquiring UAV images for mapping plastics, the reviewed studies highlight that smaller plastics can be detected if UAV imagery is captured with low GSD (Martin et al. 2018; Fallati et al. 2019; Lo et al. 2020; Hengstmann et al 2020). However, since achieving low GSD requires UAV mapping from a low flight altitude, this approach might not be practical in mapping and detection of plastics in a residential community as in the current study. Some of the reviewed articles discussed this problem, and the use of UAVs with high quality camera has been suggested as such UAVs can safely capture UAV imagery from high flight altitude without compromising GSD. The GSD for the reviewed studies, minimum height has been presented in Table 2.

Table 2. Attributes of the identified articles

Author name, year of publication and location	**UAV Platform, minimum flight height and GSD**	**Modelling approaches employed**	**Highest reported Accuracy**
(Bao et al. 2018) China	DJI Phantom 4 Pro (20 MP - RGB) 33 – 100 m GSD (1 – 3 cm)	Threshold method/algorithm	Overall accuracy 98.6 %

Table 2 (continued)

(Martin et al. 2018) Saudi Arabia	DJI Phantom 3 (12 MP - RGB) 10 m GSD (0.5 - 0.7 cm)	Random forest	39.5 %
(Fallati et al. 2019) Maldives	DJI Phantom 4 (12.4 MP - RGB) 10 m GSD (0.44 cm)	Convolutional Neural Network (CNN)	Precision = 0.54 Recall = 0.44 F1-Score = 0.49
(Kylili et al. 2019)	Not Mentioned	CNN (VGG-16)	99 %
(Wolf et al. 2020) Cambodia	Multiple UAVs (20 MP - RGB) 3- 60 meters	CNN	Precision = 0.77 Recall = 0.77 F1-Score = 0.77
(Jakovljevic et al. 2020) Bosnia and Herzegovina	DJI Mavic Pro (20 MP - RGB) 12 meters GSD (0.4 cm)	CNN (Imagenet)	Precision = 0.82 Recall = 0.75 F-Score = 0.78

Table 2 (Continued)

(Gonçalves, Andriolo, Gonçalves, et al. 2020) Portugal	DJI Phantom 4 Pro (RGB) 20 meters GSD (0.55 cm)	Support Vector Machine KNN **Random forest**	Precision = 0.75 Recall = 0.70 F1-Score = 0.73
(Gonçalves, Andriolo, Pinto, and Bessa 2020) Portugal	DJI Phantom 4 Pro (20 MP - RGB) 20 meters GSD (0.55 cm)	Random forest	Precision = 0.73 Recall = 0.74 F1-Score = 0.75
(Hengstmann et al. 2020) Germany	DJI Phantom II Vision 14 MP (RGB)	K-means clustering	55%
	DJI Phantom 4 Pro 20 MP (RGB) 7 – 80 meters		

Table 2 (Continued)

(Lo et al. 2020) Hong Kong	DJI Mavic Pro (12 MP - RGB) 5 – 15 meters No GSD reported	Manual examination	NA
(Gonçalves, Andriolo, Pinto, and Duarte 2020) Portugal	DJI Phantom 4 (20 MP - RGB) 20 m GSD (0.55 cm)	Manual **Random forest** CNN (Densenet)	Precision = 0.7 Recall = 0.71 F1-Score = 0.7
(Merlino et al. 2020) Italy	DJI Phantom Pro v2 (20 MP - RGB) 6 m GSD (0.18 cm)	Manual	---
(Garcia-Garin et al. 2021) Spain	Multiple UAVs and a manned aircraft (RGB) 20 meters	CNN	Precision = 0.82 Recall = 0.84 F1-Score = 0.83

Table 2 (Continued)

(Pinto et al 2021) Portugal	DJI Phantom 4 RTK (RGB) 30 meters GSD (0.9 cm)	Shallow feed forward neural network	Precision = 0.56 Recall = 0.49 F1-Score = 0.49
(Andriolo et al. 2021) Portugal	DJI Matrix 210 RTK V2 12.3 MP (Multispectral Sentera AGX 710) 40 meters GSD (1.2 cm)	No Algorithm (Segmentation then label)	NA
(Papakonstantinou et al. 2021) Greece	DJI Phantom 4 (20 MP - RGB) 18 meters GSD (0.49 cm)	CNN (ImageNet)	Precision = 0.83 Recall = 0.72 F1-Score = 0.77

Key terminologies and concepts

'Waste' refers to presence of waste piles or trash in the UAV imagery

'Precision' is a metrics for performance that refers to the ratio of correctly predicted objects over the actual number of the object of interest, the object can be waste piles or individual waste materials. Mathematically precision is calculated using equation 1.

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives} \tag{1}$$

'Recall' represents a fraction of correctly labelled objects within each class. Recall is used interchangeably with the word "sensitivity", because it reflects sensitivity of the method to avoid generating false negatives (Gonçalves, Andriolo, Pinto, and Bessa 2020). Recall is calculated using equation 2.

$$Recall = \frac{True\ Positives}{False\ Positives + False\ Negatives} \tag{2}$$

'F-1 score' represents a single statistical measure of the overall quality of the methods and it combines precision and recall as in equation 3. The higher score means better quality.

$$F1 = \frac{2\ \times Precision\ \times Recall}{Precision + Recall} \tag{3}$$

Methods for detection of plastic waste from UAV imagery

The review highlighted that different author used a variety of methods for detection of the presence of plastics or waste piles in UAV imagery. Despite the general lack of uniformity in the approaches for detection of plastics from UAV imagery, two primary approaches were observed.

The first one is a manual approach that involves visual identification of plastic waste from a UAV imagery by a trained analyst (Pinto et al. 2021; Garcia-Garin et al. 2021; Jakovljevic et al. 2020). Here an observer inspects the UAV imagery to identify and manually label individual plastics. Gonçalves, Andriolo, Pinto, and Duarte (2020) indicated that this approach can be subjective because different operators can have different interpretations of object color, size and shapes. However, in Pinto et al (2021) a general consistency was observed in the labels developed by different operators and it was recommended involving multiple visual operators. Instead of allowing different people to identify litter from UAV imagery, Garcia-Garin et al. (2021) reported of safeguarding reliability of labels created manually by involving another scientist who checked doubtful items.

The other approach is by automating the process of identifying waste piles or individual objects such as plastics. This approach overcomes drawbacks of manual approach. Manual approach is time consuming and labor-intensive, and generally not practical for large scale mapping (Jakovljevic et al. 2020). Given the necessity for a faster approach, the research direction for the mapping of plastics and waste piles (litter) has leaned towards automating detection protocols (Papakonstantinou et al. 2021). In the next section more details on automating the process of identifying waste will be described.

Overview of automatic detection of plastics or waste materials

Automatic detection of plastics requires development of training labels that are used as examples by the machine learning model. One approach involves partitioning of the UAV imagery into smaller image tiles which are labelled based on whether they contain waste or plastics or not (Papakonstantinou et al. 2021; Wolf et al. 2020). The size of the resulting tile is dependent on the requirement of the algorithm to be used for classification. For example, Convolution Neural Network with the architecture of VGG-16 requires the input image to be of dimensions of 224 pixels by 224 pixels (Kylili et al. 2019).

Instead of creating image tiles, another approach involves grouping spatially and spectral homogenous objects into segments Gonçalves, Andriolo, Gonçalves, et al. (2020). This approach differs from other approaches where properties of individual pixels are considered. Regardless, using this approach segments are manually labelled to be used for model development. Both Andriolo et al. (2021) and Gonçalves, Andriolo, Gonçalves, et al. (2020) implemented this approach using commercial software eCognition.

Another critical issue that was observed in the reviewed studies is the number of classes to be used in the classification model. It came out clear that while it might be desirable to develop binary classification models that allows differentiation of plastics from non-plastics, the reviewed studies indicated that binary classification models have low classification accuracies (Gonçalves, Andriolo, Gonçalves, et al. 2020). Binary classification models are developed by grouping together all other land cover classes as 'other' and generalizing plastics of assorted colors as simply 'plastics'. It has been reported that in this way objects tend to exhibit high intra-class variability, and this has been associated with low detection performance (Bao et al. 2018; Pinto, Andriolo, and Gonçalves 2021). Yet, despite overlapping spectra characteristics, the maps that are generated have fair agreement with maps that are created through manual image screening (Pinto, Andriolo, and Gonçalves 2021). This suggests that multi-class models is a recommended for automatic detection and identification of waste and plastics from a UAV imagery.

Approaches for automatic detection of plastic waste

The reviewed articles reported different approaches for automatic detection of plastics. These include Threshold Algorithm (Bao et al. 2018), Random Forest (Gonçalves, Andriolo, Pinto, and Bessa 2020; Gonçalves, Andriolo, Pinto, and Duarte 2020; Martin et al. 2018), Artificial Neural Networks (Pinto et al. 2021), and Convolution Neural Networks (Fallati et al. 2019; Garcia-Garin et al. 2021; Gonçalves, Andriolo, Pinto, and Duarte 2020; Jakovljevic, Govedarica, and Alvarez-Taboada 2020; Kylili et al. 2019; Papakonstantinou et al. 2021; Wolf et al. 2020). Merlino et al. (2020) reported using in-house software. The implementation of these approaches and the observed performance in the context of mapping plastics has been described below.

Use of Threshold Algorithm

Bao et al. (2018) reported on detecting plastics and litter on sandy beaches in China. The study utilized ENVI 5.3 software to select an adequate threshold of gray for extracting objects from their background (Otsu 1979). The study involved drawing polygons around each of the litter items and spectral properties were extracted and plotted on a scatter plot. Waste materials were distinguished and extracted using mean value of the spectral reflectance of litter items plus or minus 3 times the variance as a threshold. The approach performed well; however, the approach is inadequate for universal application especially in complex environments (Gonçalves, Andriolo, Gonçalves, et al. 2020).

Plastic detection using Artificial Neural Networks

Pinto et al., (2021) reported the development of Artificial Neural Networks (ANN) to detect different classes of litter. The litter items included plastic bottles, fishing ropes, octopus pots and fragments. Just like Gonçalves, Andriolo, Pinto, & Bessa, (2020), the UAV imagery was converted to other color spaces. This provided 12 color channels and they were used as nodes in shallow Feed-Forward neural network. Shallow Feed-forward neural networks refer to implementation of ANN that have few hidden layers, where the nodes of a hidden layer only have connections to the subsequent hidden layer (hence, Feed-Forward) and do not have any feedback connections to the previous layer (Langenbucher et al. 2021). The study reported a low overall accuracy (F-score = 0.49), and performance was higher (F-score = 0.73) when binary detection of litter was considered compared to the detection of multiple classes.

Plastic detection using CNN

Convolutional Neural Networks (CNN) are multi-layer artificial neural networks specially designed to handle two-dimensional input data (Al-Saffar, Tao, and Talab 2017). CNN allows solving complex problems such as speech recognition and object detection (Liu et al. 2020). Convolution Neural Networks (CNN) have been used for detection of plastics (Fallati et al. 2019; Garcia-Garin et al. 2021; Gonçalves, Andriolo, Pinto, and Duarte 2020; Jakovljevic, Govedarica, and Alvarez-Taboada 2020; Kylili et al. 2019; Papakonstantinou et al. 2021; Wolf et al. 2020; Han et al. 2021).

Kylili et al. (2019) first reported the use of CNN to detect plastics on a UAV imagery. The study used ImageNet, a large dataset that serves as a resource for computer vision research (Deng et al. 2009). The study reported detecting floating litter with an accuracy of approximately 86 percent (Kylili et al. 2019). The use of ImageNet for plastic detection was also seen in some of the subsequent studies (Jakovljevic, Govedarica, and Alvarez-Taboada 2020; Papakonstantinou et al. 2021). Jakovljevic et al (2020) pretrained four different architectures on ImageNet dataset and assessed the detection of plastic targets on a water body. The study reported that among the tested pretrained models, ResUNet-50 has high accuracy in detection plastics even when data of different spatial resolution is provided (Jakovljevic, Govedarica, and Alvarez-Taboada 2020). The reviewed literature also reported manual labelling of training datasets from the acquired UAV imagery. This approach is used as an alternative approach to the use of pretrained datasets such as ImageNet (Garcia-Garin et al. 2021; Wolf et al. 2020).

The seven papers that used CNN employed different CNN architectures. The architectures used include Visual Geometry Group (VGG) (Kylili et al. 2019), U-Net (Jakovljevic et al. 2020), and DenseNet (Gonçalves, Andriolo, Pinto, and Duarte 2020). Papakonstantinou et al., (2021) compared the performance of DenseNet and VGG on detection of litter. The study found that VGG architectures performed better than DenseNet, with F-score between 0.68 to 0.77 for VGG while the F-score for DenseNet was in the range of 0.26 to 0.29.

In terms of the implementation of the algorithm, the studies reported utilization of different platforms. The platforms included the use of commercial software programs (Fallati et al. 2019), user developed scripts using Python language (Jakovljevic, Govedarica, and Alvarez-Taboada 2020), or R Statistical software (Garcia-Garin et al. 2021).

Plastic detection using Random Forest

Random Forest (RF) algorithm has been also used for identification of plastics or litter in the environment (Gonçalves, Andriolo, Pinto, and Bessa 2020; Gonçalves, Andriolo, Pinto, and Duarte 2020; Martin et al. 2018). RF is an algorithm consisting of a collection of tree-structured classifiers that produces multiple decision trees using randomly selected subsets of training samples and variables (Belgiu and Drăguţ 2016; Breiman 2001).

Of the reviewed studies, the first utilization of RF for detection of waste was conducted by Martin et al. (2018) in Saudi Arabia. The study involved calculating Histogram Oriented Gradient (HoG) descriptors from RGB UAV imagery and used them to develop an RF model. It is known that HoG extracts distinctive features that are invariant to image scale and rotation, thereby providing robust identification of objects among clutter and occlusions (Lowe 2004). Unfortunately, Martin et al. (2018) reported a general low performance of this approach with a correct detection rate of merely 44 percent.

In a subsequent study Gonçalves, Andriolo, Pinto, and Bessa (2020) developed an RF model using a pixel-level classification scheme and color intensity feature descriptors. The study argued that the use of other color intensity feature descriptors was to overcome the drawback of RGB, particularly its sensitivity to illumination intensity, high correlation between the bands and being not perceptually uniform (Gonçalves, Andriolo, Pinto, and Bessa 2020). So instead of relying on RGB color space only, the study incorporated other color spaces including the following: (a) Hue, Saturation, Value (HSV); (b) CIE-Lab and; (c) YCbCr. It is known that HSV is among Hue Based Color space, CIE lab is a perceptually unform color space and YCbCr is a Luminance based color space (Shaik et al. 2015). With this approach an F-score of 0.75 was observed. Though the reported accuracy is lower than the accuracies reported by in Kylili et al. (2019), Kylili et al. (2019) only reported the results as percentages. However, for multiclass models, computing precision, recall and F-1 score provides insights about model misclassifications of the classes.

In a different study, RF developed using other color spaces showed superior performance when compared with KNN and SVM (Gonçalves, Andriolo, Gonçalves, et al. 2020). Apart from outperforming SVM at identifying litter, implementation of RF was observed to be faster than implementation of CNN (Wolf et al. 2020). Equally, using the same training and testing samples RF outperformed CNN at predicting marine litter (Gonçalves, Andriolo, Pinto, and Duarte 2020).

Presentation of the results

Some of the reviewed articles presented the results of models' predictions. The approaches for presenting include the use of density maps (Gonçalves, Andriolo, Gonçalves, et al. 2020; Gonçalves, Andriolo, Pinto, and Bessa 2020; Gonçalves, Andriolo, Pinto, and Duarte 2020; Martin et al. 2018; Papakonstantinou et al. 2021), the use of a web app (Garcia-Garin et al. 2021), and bounding box and pixel-wise heat map (Fallati et al. 2019). The use of density maps is quite common. Papakonstantinou et al., (2021) presented the density maps in a 10 meter by 10 meter tile and Gonçalves, Andriolo, Pinto, and Duarte (2020) presented the density map in hexagons.

Gap in knowledge and implication for the current study

The review highlights the general framework and approaches that are employed to map or detect plastic waste from a UAV imagery. Beginning with image acquisition, the studies highlighted the need to acquire images with low GSD to enable categorization of individual objects. Equally, of the different approaches for automatic detection of plastics, RF seems to have demonstrated the best performance so far. Irrespective of the knowledge generated up to this point, none of the studies explored the use of UAV technology detection of actual waste piles or locating individual plastics in a complex environment on land such as a built-up urban community. Yet as established in chapter one, 80 percent of plastic waste is transported from land-based sources (Leous and Parry 2005), and it is not clear on whether such monitoring tools can be used for monitoring plastic and other waste materials in such an environment. The current study aims to extend the utilization of UAV technology for mapping plastics and litter in terrestrial contexts. This is to provide an additional toolset for monitoring accumulation of plastics and waste on land which can help the development of effective strategies for limiting emission of plastic waste (Hurley et al. 2020).

Chapter 3: Methods

Introduction

This chapter presents the methods that have been employed to meet the research objectives. The chapter begins by describing the design of an experiment for mapping plastic targets of known characteristics, followed by the methods that were employed to enable automatic mapping of waste piles from UAV imagery. The chapter ends by comparing two machine learning algorithms for automatic detection of plastics in waste piles. All the methods are drawn from the techniques that were reported in the reviewed studies and author's own judgement.

Methodology for developing understanding of the science for mapping plastics

An experimental mapping of plastic targets was conducted at St Cloud State University. The primary aim of the experiment was to understand factors that are associated with visibility of plastics on UAV imagery. It was hypothesized that flight altitude, GSD, color, background, and size of the plastic object affects visibility of plastics on a UAV imagery.

Experimental setup

The plastic target materials considered in the study include plastics of the following colors: (1) white; (2) brown; (3) green and (4) red. The plastics were carefully cut into pieces of the following dimensions: (1) 2.5 cm by 2.5 cm; (2) 5 cm by 5 cm; (3) 10 cm by 10 cm and (4) 20 cm by 20 cm. All plastics were laid out on a black background, and to account for the effect of the background, plastics of size 10 cm by 10 cm were replicated and laid out on a grass which gave a green background. Overall, without considering the objects that were laid out on the green grass, the experiment had 16 plastic pieces (Table 3). Please note that one target plastic of 2.5 cm by 2.5 cm was integrated in the experimental setup by mistake, but it has been incorporated into the statistical analyses.

Table 3. Summary for counts of target plastic materials considered in the experimental mapping.

	White	**Brown**	**Yellow**	**Green**	**Red**
25 mm by 25 mm	1	2	1	0	0
50 mm by 50 mm	1	1	1	0	0
100 mm by 100 mm*	3	2	2	2	2
250 mm by 250 mm	1	1	1	0	0

Mapping was conducted using a DJI Matrice 210 V2 mounted with Sentera AGX710 sensor. All the flight missions were planned to use Pix4D capture, and the images were acquired at Nadir (90 degrees angle to the ground). The first mission involved capturing of images from a flight altitude of 50 feet (~15m), and subsequent flights were increased to 75 feet (~23m), 100 feet (~30m) and 300 feet (~91m) respectively. Images were captured with both front and side overlap of 75 percent. However, as the flight altitude was increased to 300 feet, there were not enough images to support proper development of an orthomosaic using photogrammetry techniques, so the flight overlap was increased to 90 percent. The flight heights considered generated GSD ranging from 0.1 cm to 1.7 cm.

Data processing and analysis

The acquired data was processed in Pix4D mapper (version 4.6.4.) and default parameters were used to generate an orthomosaic, each for the specified flight altitudes (

Figure 4). The resulting orthomosaic had a projected Coordinate Reference System with UTM Zone 15 N. All the imagery was imported to QGIS and by means of photo examining the imagery, visibility of target plastics at different flight altitude was determined and recorded. Of the studied variables, flight height and GSD were observed to be highly correlated ($r = 0.98$); so, in the current analysis GSD was used and flight altitude was excluded. Considering visibility with each of the variables, a binomial regression model was fit to the data with explanatory variables including size of the plastics, GSD, color of the plastics and background color. Additionally, the characteristics of the target materials with respect to increase in flight altitude was observed and described to support explaining how mapped objects vary when mapped from different flight altitudes.

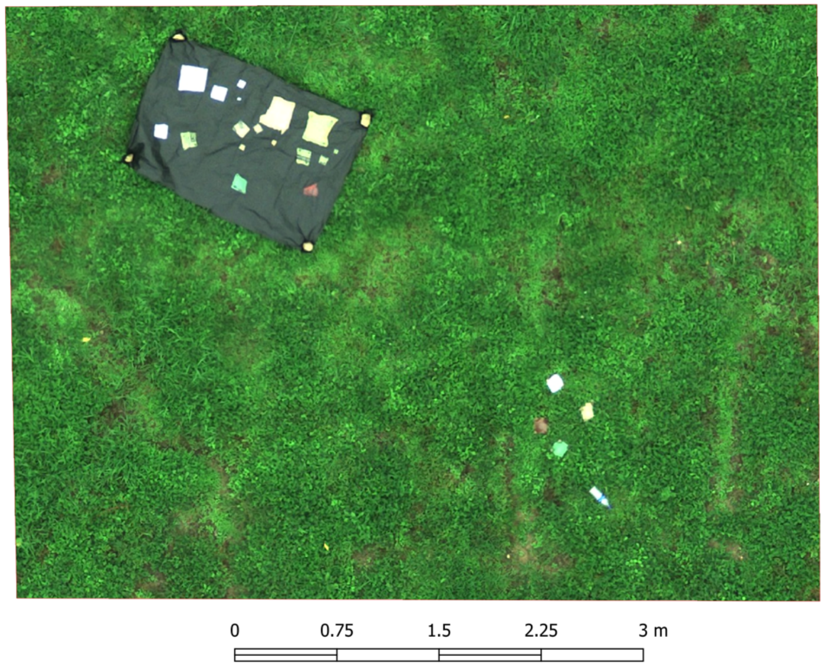


Figure 4. Processed imagery of the target plastics considered in the experiment. On the black sheet are objects that have been considered in the experiment and on green grass are objects that have been incorporated to study the effect of the background surrounding the plastics.

Mapping Waste piles in the study community

UAV Image acquisition

A transect walk was undertaken to map waste piles in part of Ndirande South (the study area). Following the transect walk a total of 17 waste piles were identified by the field team within a 800m by 300m area of Ndirande, primarily situated along the river channel. All subsequent activities have focused on this area (Figure *5*). In December 2021, a UAV imagery of the area was captured by a Mavic Enterprise drone at an altitude of 60 meters and processed into an orthomosaic, resulting in an image with a GSD of 1.8 cm/pixel. Understandably, waste piles observed through ground surveys are expected to underestimate the abundance of waste piles in the study community because they only target accessible sites, leaving difficult to access locations unmonitored (Martin et al. 2018).

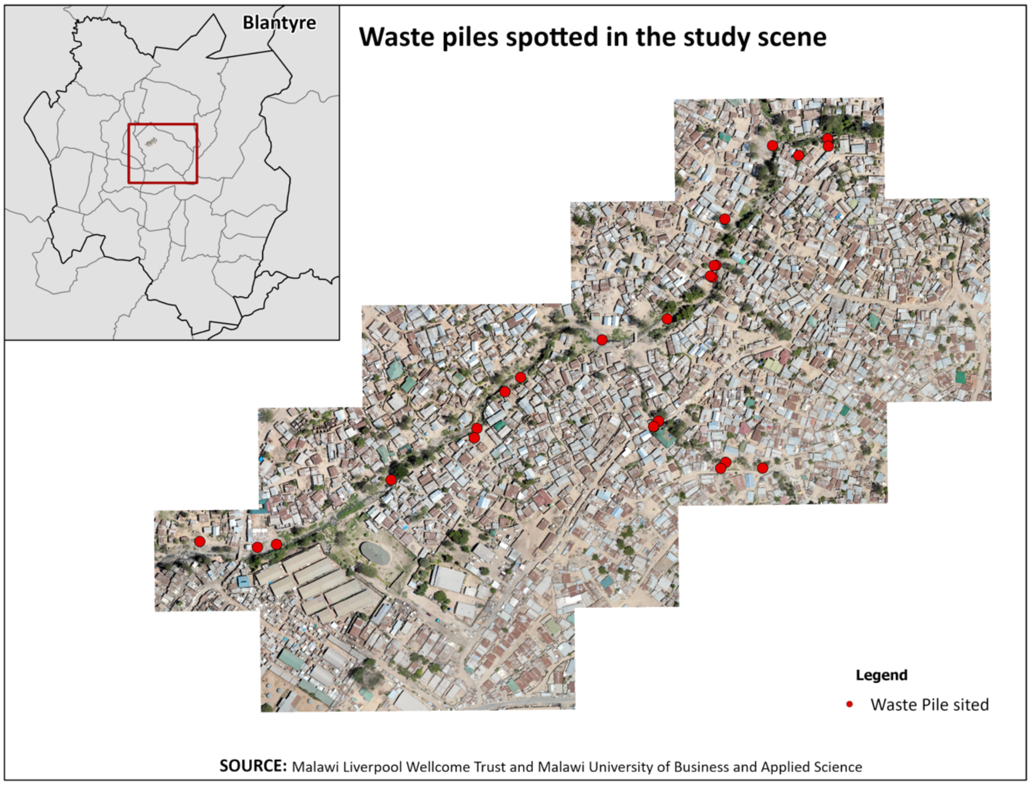


Figure 5. Waste piles sited in the study scene

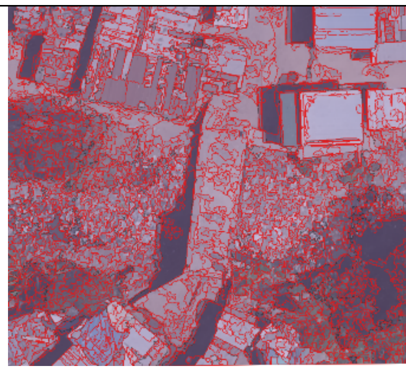
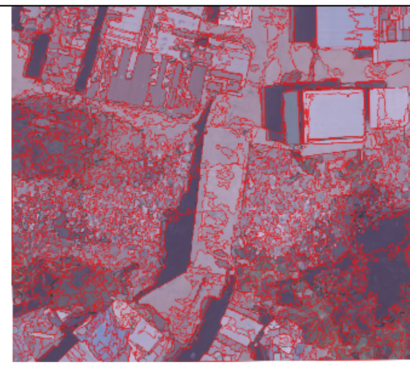
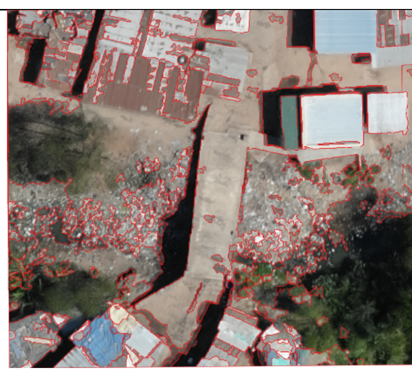
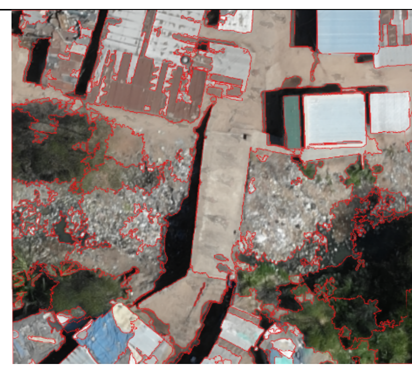
The UAV imagery was processed using Pix4D mapper (version 4.6.4.) and the resulting orthomosaic was saved in projected coordinate reference system (WGS 84/UTM Zone 36 S) After examining the UAV imagery for the study scene, waste piles were observed to exhibit unique characteristics that make them to be easily distinguished (visually) from other land cover classes (Figure 6). Given that UAV surveys are faster than traditional approaches of monitoring waste piles through walking (Martin et al. 2018), it was hypothesized that such unique characteristics of waste piles can be utilized to automate waste pile mapping from UAV imagery.

Figure 6. Waste pile seen in the Clipped UAV imagery captured with a GSD of 3.79 cm.

Mapping of waste piles from UAV Imagery

To reduce the computational requirements when locating waste piles along the river in the study community, a section of the river was digitized from the UAV imagery that was captured. A buffer of 20 meters was created and this area was clipped for subsequent analysis. Afterwards, an Object Based Image Analysis Approach (OBIA) was used for detection of waste piles. OBIA involves grouping together homogenous neighboring pixels into segments, and the segments are use used in image classification instead of individual pixels. This segmentation was performed using an Open source software 'Orfeo toolbox' (Grizonnet et al. 2017). Within Orfeo toolbox, the study employed a mean-shift algorithm to specify the rules for grouping together similar pixels. The sensitivity of the algorithm is specified through the spatial and range radius parameters, and minimum size is employed to remove small regions whose size is less than the given minimum size parameter (LargeScaleMeanShift. n.d.). Although many previous studies that utilized Orfeo toolbox reported either utilizing default parameters or using a trial-and-error approach, in this study a grid of combination of values for randomly selected spatial radius (5, 25 and 50) and range radius values (5, 15, 30, 45, 60) were set and tested on a small location until satisfactory segments were created. In the context of this study, satisfactory segments refer to segments which are visually not exhibiting either over-segmentation or under segmentation (An example of this has been presented in Table *4*).

Table 4. Combination of few selected spatial Radius and Range Radius considered in the optimization.

	Spatial radius		
		5	50
Range radius	5		
	30		
	60		

Even though a combination of spatial radius of 50 and range radius of 30 presented visually satisfying segments, when the parameters were applied to the whole imagery under-segmentation was observed in in relation to objects of some classes. To solve the problem, a small portion of the imagery where under-segmentation was observed was examined more closely. The process of optimizing was repeated on this smaller area, varying the value of the range radius only until the required segmentation was achieved (Figure *7*). This resulted in the optimal parameters being: (1) Range radius of 25; (2) Spectral radius of 50 and (3) minimum segment size of 2500 pixels.

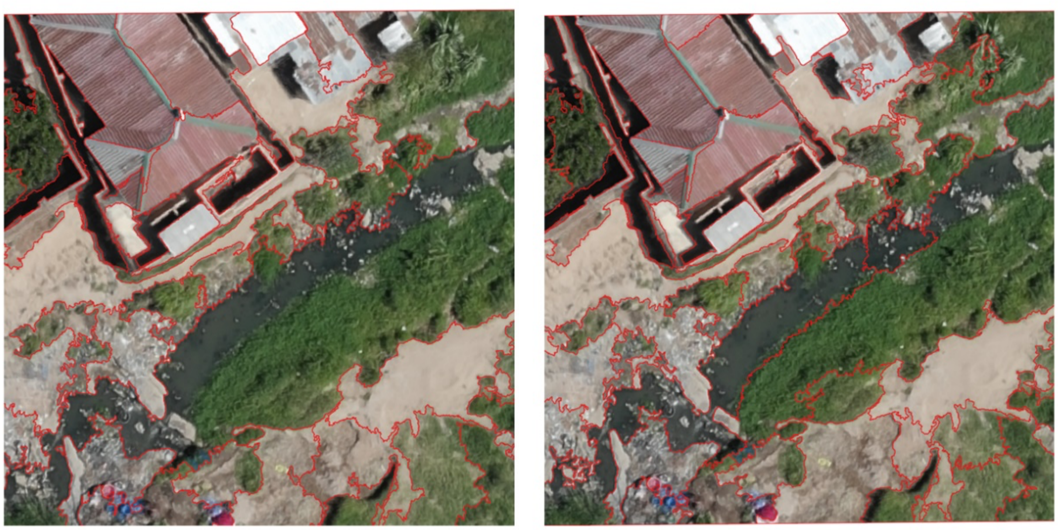


Figure 7. Comparison of segments with spectral radius of 50 radiometry units, the image to the left was developed using a range radius of 30 radiometry units while the image on the right was created using range radius of 25 radiometry units.

Development of training labels

The UAV imagery was examined to identify major land cover classes. Six land cover classes were identified in the study scene. Examples of each land cover class were manually labelled and except for surface water, a total of 100 training labels were created for each land cover class. The land cover classes that were considered, and their counts have been presented in Table 5.

Table 5. Major land cover classes over the study scene

Macro class	**Counts**
Building rooftop	100
Bare earth	100
Vegetation	100
Waste piles	100
Surface Water	52
Shadow	100

Selection of predictor variables

Within QGIS several image statistics can be extracted for the segments. These include reflectance of optical bands and segment textural characteristics computed using grey tone spatial dependencies (Haralick, Shanmugam, and Dinstein 1973). Textural characteristics computed using Haralick method will be referred to as Haralick texture descriptors in this document. All the predictor variables considered in the current study have been presented in Table *6*.

Table 6. Parameters considered in the study.

Set of descriptors	Specific parameters
Optical bands	Red, Green and Blue
Simple Haralick features	Energy, Entropy, Correlation, Inverse Difference Moment, Inertia, Cluster Shade, Cluster Prominence, Haralick Correlation.

Model fitting

This study employs Random Forest algorithm for automation of the process of classifying segments to detect waste piles. This approach was reported in prior studies of having high detection rate (Gonçalves, Andriolo, Pinto, and Duarte 2020). However, with random forest, the presence of correlated predictors impacts the ability to identify strong predictors (Gregorutti, Michel, and Saint-Pierre 2017). Recursive feature elimination is an approach that is used to eliminate correlated features (Gregorutti, Michel, and Saint-Pierre 2017). However, a model developed with both mean and median reflectance values was implemented because it showed high performance compared to other calculated statistics for the segments.

Model development was performed in R statistical software (version 4.1.2.) using the caret package. Within R environment there are also advantages to optimize model performance by tuning hyperparameters of the developed models. For random forest, these hyperparameters include the number of tree ensembles (Ntree), depth of the trees (MaxDepth) and the number of randomly selected variables at each split (mtry). To find the best combination of parameters, a cartesian grid search was employed and the possible combination of parameters with highest accuracy was utilized for the modelling. Stratified by land cover classes, the segments were split into training segments comprising of 80 percent of the labelled segments and testing dataset with the remaining segments. A random 5-fold cross-validation repeated 5 times model fitting process was implemented to identify the optimal values of the hyperparameters. Using caret package in R, the performance of different possible combinations of model settings was tested. Having identified optimal model parameters, the model was then applied to the withheld testing data and the performance of the developed model was computed and recorded in terms of precision, recall and accuracy.

The detected waste piles were visualized on an online web map developed using ArcGIS online framework. Development of the web map involved the use of Hypertext Markup Language (HTML), cascading style sheets (CSS) and JavaScript. The full workflow for the development of the web map has been described in Figure *8*.

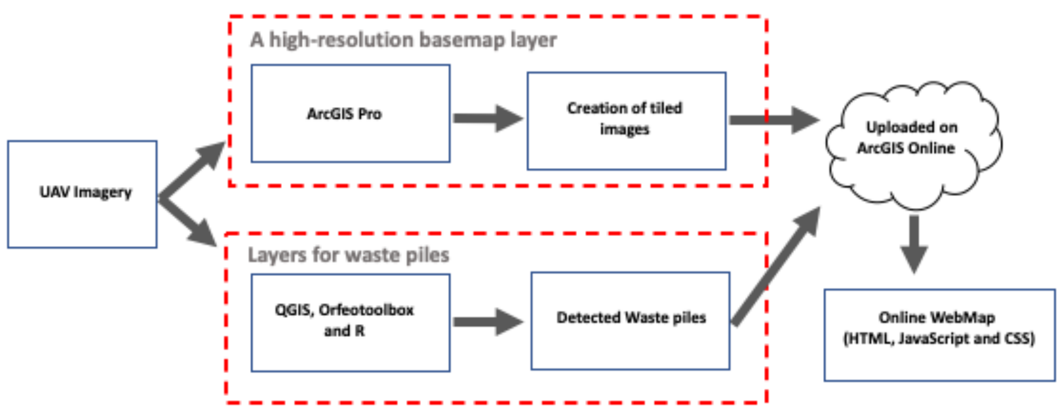


Figure 8. The workflow for development of the web application for waste pile locations.

Mapping plastics in waste piles

An experimental mapping was conducted to investigate the identification of plastics in waste piles. This experiment involved examining different approaches for distinguishing plastics from non-plastics in a single waste pile within the study area from a UAV imagery captured with optimal GSD. Secondary to identification of plastics, the experimental mapping also explores visibility of plastics present in waste piles from UAV imagery captured with different GSDs.

Selection of target waste pile

To select the waste pile to be considered for this exercise, a ground team surveyed waste piles in the study scene and identified a waste pile that was not near buildings, power lines, trees, and other obstacles to UAV flights. This was to necessitate image capturing at an extremely low flight altitude (10 meters). Figure *9* presents a waste pile that was selected for UAV image capturing.

Figure 9. Image of waste piles selected for mapping plastics (Photo captured by Taonga Mwapasa)

UAV Image capturing

The ground-based study team captured UAV imagery from varying altitudes. This enabled generation of UAV imagery with given different GSDs and henceforth exploration of the minimum GSD that can be targeted for mapping plastics. All the flight missions were planned to use Pix4D Capture app and a snapshot of the study area in the application has been presented in Figure *10*. All images were captured with both front and side overlap of 90 percent. Mapping started with a base height of 10 meters and the subsequent flights followed a height increment of 10 meters till a maximum height of 70 meters was reached. This resulted in a total of 7 different mapping missions and the expected GSD was of the range between 0.27 cm to 1.91

cm. The imagery was later processed in Pix4D mapper (version 4.6.4.) and it was saved in Projected Coordinate Reference System (WGS 84/UTM Zone 36 S)

Figure 10. Snapshot of Pix4D Capture application.

Development of training labels

A transect of 6 meters by 6 meters was clipped from the UAV imagery of the identified waste pile. Figure *11* presents the area that was targeted for acquisition of the UAV images.

Figure 11. Selected portion of the waste pile utilized for model building.

The plastics observed in the UAV imagery can be manually located and quantified. This process has been reported previously to be labor intensive. The current study utilized the imagery of highest resolution to explore the use of automatic approaches for detection of plastics. The study employs an Object-Based Image Analysis (OBIA) approach. Using the clipped imagery, major categories of surface waste were located through visual examination of the UAV imagery. Table *7* presents the major classes of objects that were identified in the clipped area.

Table 7. Classes of objects observed in the study scene.

Macro class and ID	Micro classes	Counts
Plastics [1]	Blue plastics	616
	Transparent plastics	119
	Black plastics	33
	Plastic bottle	8
	Yellow bag	25
	Milk packet (plastic)	4
	Snacks packet	7
	Red plastic bag	163
Vegetation [2]	Grass	450
	Blue gum tree leaves (eucalyptus)	204
	Tree leaves	29
Soil [3]	Normal soil	84

Table 7 (continued)

Cardboard [4]	Ordinary cardboard	4
	Local beer packet (Chibuku)	5
Organics [5]	Maize cobs	168
	Partly composted materials	56
	Dry leaves	3

Model fitting

Stratified by the identified macro classes, 80 percent of the labelled segments were allocated as training segments and 20 percent were used for testing. The same predictor variables and procedure that were used for detecting waste piles have been used for mapping objects in the waste piles. For detection of plastics, Random Forest was employed as previously described and accuracy was also reported in terms of F-score, precision, and recall.

Associations between Ground Sampling Distance (GSD) and visibility of the plastics

UAV images that were captured from different flight altitudes enable exploring the relationships between GSD and visibility of individual plastics. All the orthomosaics that were generated were carefully examined by one person. From a manual inspection of the orthomosaic, the minimum GSD for mapping plastics was identified.

Chapter 4: Results

Introduction

This chapter presents the analysis of the data captured from an aerial survey at St Cloud State University and in Ndirande neighborhood in Malawi. The chapter is organized in three sections structured based on the study objectives. The first section presents the visibility of plastic targets mapped from varied flight altitudes. The second section presents mapping waste piles from UAV imagery, and it ends by presenting a web map that has been developed to present information about waste piles. The last section demonstrates the practical use of UAV imagery with low GSD for mapping plastics in a waste pile.

Experimentation to map plastic targets using UAV Imagery

Visibility of plastics

presents the percentage of plastics targets that are visible from different flight altitudes. All the target items are visible at the lowest altitude, and the visibility of smallest target items is observed to start decreasing when the images are captured from a flight altitude of about 100 feet (30.48 meters). At 300 feet, all smaller target items, both 25 mm by 25 mm and 50 mm by 50 mm are not visible.

Table 8. Percentage of visibility of target plastics from different flight altitudes.

	25 mm by 25 mm	**50 mm by 50 mm**	**100 mm by 100 mm**	**250 mm by 250 mm**
50 feet (GSD = 0.4 cm)	100 % (4/4)	100 % (3/3)	100 % (11/11)	100 % (3/3)
75 feet (GSD = 0.86 cm)	100 % (4/4)	100 % (3/3)	100 % (11/11)	100 % (3/3)
100 feet (GSD = 1.09 cm)	50 % (2/4)	100 % (3/3)	100 % (11/11)	100 % (3/3)
300 feet (GSD = 2.51 cm)	0 % (0/4)	0 % (0/3)	81.8 % (9/11)	100 % (3/3)

Table 9 indicates the associations between the studied variables and visibility of plastics. It has been observed that regardless of color visibility is positively associated with size of plastics (Estimate = 0.0268 ± 0.009, P = 0.00428). Equally, visibility is negatively associated with GSD (Estimate = 1.9861 ± 0.5438, P = 0.00026). No significant associations were observed for other variables considered.

Table 9. Associations between visibility and the variables considered in the study.

Variable	Estimate	Standard Error	P-Value	AIC
Size	0.026883	0.009411	0.00428**	54.949
GSD	-1.9861	0.5438	0.00026***	48.585
Color green	1.662e + 00	2.306e + 03	0.99425	72.076
Color red	-8.473e-01	1.024e+00	0.40777	72.076
Color white	-4.837e-16	8.729e-01	1	72.076
Color yellow	-2.113e-01	8.793e-01	0.81008	72.076
Background	-0.9502	1.0881	0.38251	68.271

Significance codes: 0 '***' 0.001 '**'

***Appearance of plastics with increase in flight* altitude**

Figure 12 presents the appearance of plastics as they are mapped from varied flight altitudes. With increase in flight altitude, edges of objects begin to lose clarity and it becomes challenging to appreciate the shape and size of the object.

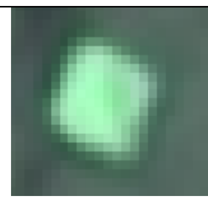
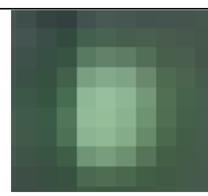
Flight altitude	Picture of green plastic object
50 ft (GSD = 0.4 cm)	
75 ft (GSD = 0.86 cm)	
100 ft (GSD = 1.09 cm)	
300 ft (GSD = 2.51 cm)	

Figure 12. Appearance of a plastic object when mapped from different flight altitudes.

Mapping of waste piles from UAV imagery

Observations from model building

Figure 13 presents relative importance of the descriptors that were utilized for development of the classification model. From the descriptors considered, it was observed that average values of the optical bands play an important role in classifying the segments as compared to average values of Haralick texture descriptors. As previously mentioned Haralick texture descriptors represent textural characteristics of adjacent pixels based on grey level values.

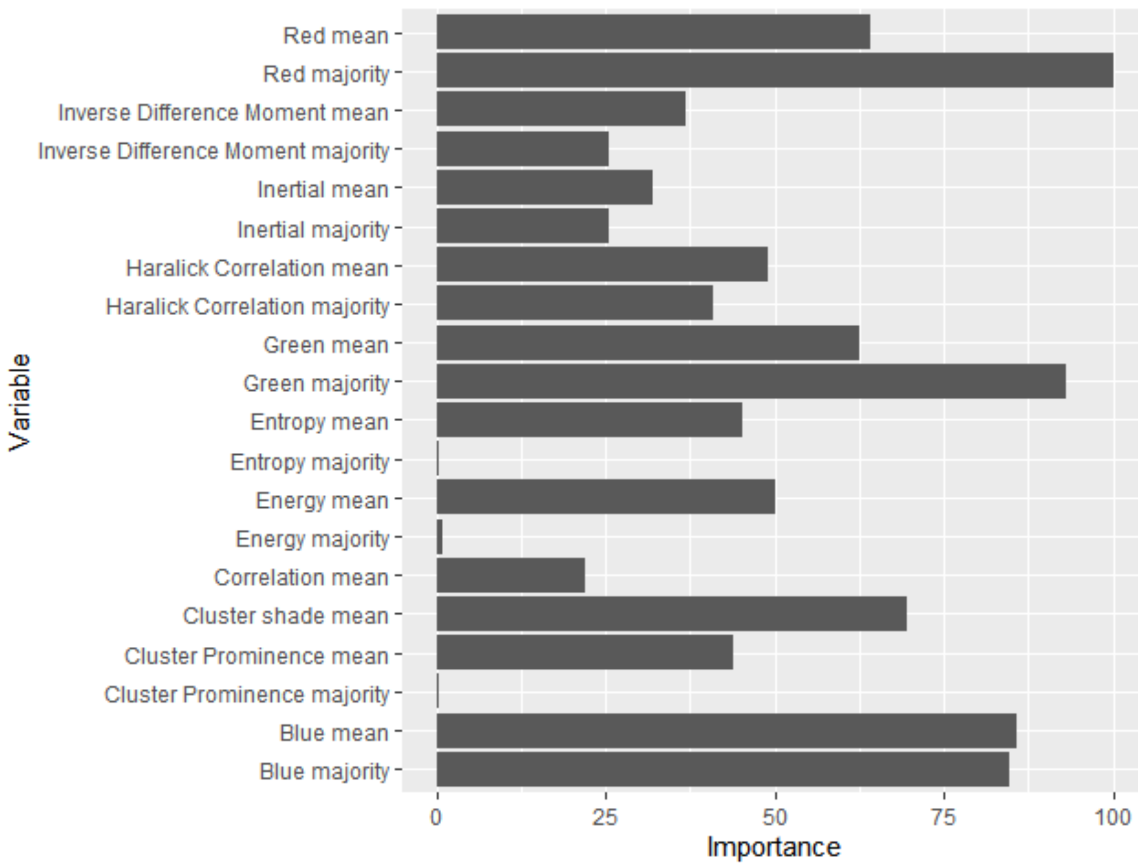


Figure 13. Overall importance of model predictor variables.

Performance of machine learning model at detecting waste piles from UAV imagery

Table 10 presents a confusion matrix presenting model predictions together with actual classes of the test datasets. Of the 20 waste piles included in the test dataset, the model was able to predict 19 correctly as waste piles. Additionally, it has been observed that the model misclassified some segments which were supposed to be assigned as rooftop (1/19) and vegetation (1/19) to be a waste pile.

Table 10. Confusion matrix for prediction of land cover classes

		Reference					
		Rooftop	**Bare earth**	**Vegetation**	**Waste pile**	**Water**	**Shadow**
Predictions	**Rooftop**	17	1	2	0	0	3
	Bare earth	1	18	0	0	0	0
	Vegetation	0	0	14	1	0	0
	Waste pile	1	0	1	19	0	0
	Water	0	0	1	0	7	0
	Shadow	0	0	1	0	1	15

Overall, the model predictions have a Kappa Value of 0.8467 and an accuracy of 0.8738 [95% CI: 0.7938 - 0.9311]. The performance of the model at predicting specific classes have been presented in Table 11. The predictions for waste pile indicate a general high performance with a high recall relative to precision.

Table 11. Accuracy table for classification of major land cover classes.

Land cover class	Precision	Recall	F1
Rooftop	0.7391	0.8947	0.8095
Bare earth	0.9474	0.9474	0.9474
Vegetation	0.9333	0.7368	0.8235
Waste pile	0.9048	0.95	0.9268
Water	0.875	0.875	0.875
Shadow	0.8824	0.8333	0.8571

Figure 14 presents a map of the study community showing the waste piles detected in the study after applying the developed model. Regardless of a few misclassifications, it is clear that along the river in the study community, there are more waste piles that previously identified. UAV imagery has enabled mapping of waste piles in parts of the river that are not easily accessible. In addition to this, the spatial extent of the waste pile is noticeable. By examining the predictions made on unlabeled segments, it has been observed that in locations where there are trees, waste piles are not visible from UAV imagery. Also, misclassifications are observed in locations where two or more classes are present in the same segment (under-segmentation). Such segments, if present in the training sample, can affect model development.

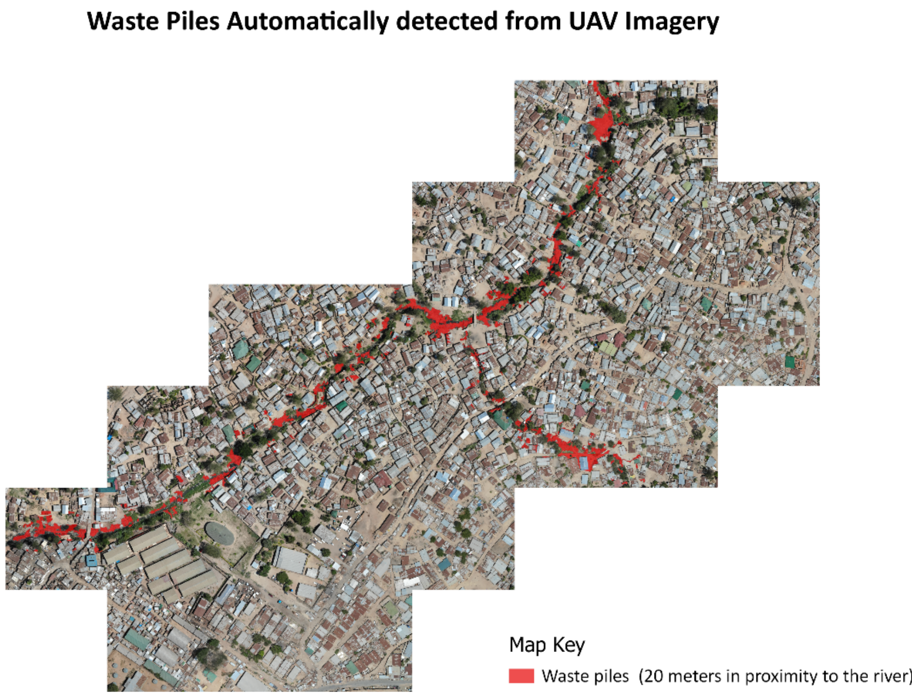


Figure 14. Waste piles along Nasolo river detected from UAV imagery

The predictions have also been presented on an online web map created using ArcGIS online JavaScript API and has been shared publicly as a GitHub page (the page can be found here: https://kalondepatrick.github.io/wastemapping/). Unlike Figure *14* such online maps are interactive and can be easily updated if there is repeated acquisition of UAV imagery in the study community.

Automatic detection of plastics in waste piles

Automatic detection of plastics

Figure 15 presents boxplots for selected variables that were included in the model fitting. Each of the boxplots represents a class and class 1 is for plastics. For most of the classes there is an overlap in the values for the classes. However red mean, blue mean and blue majority, the values for plastics are quite distinct with minimum overlap.

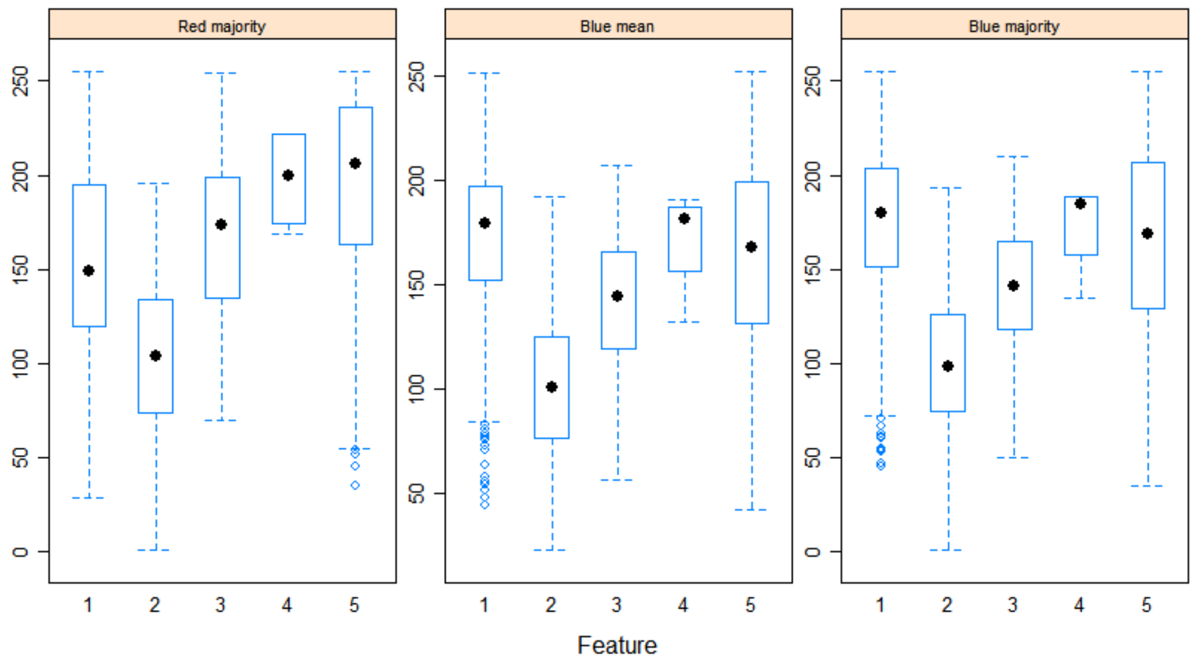


Figure 15. Box plots representing three study variables as an example to illustrate differences in average segment values for the land cover classes considered in the study. The x axis represents classes 1, 2, 3, 4 and 5, these classes represent plastics, vegetation, soil, cardboard and organics respectively.

Table 12 presents a confusion matrix of predictions made by random forest on testing segments against known object labels for the same segments. The matrix indicates that a good deal of plastics is correctly classified as plastics by the prediction model. Equally, there are few segments belonging to other classes that ended up being misclassified as plastics.

Table 12. Confusion matrix of the classes of testing segments predicted by RF against actual classes

		Reference				
		Plastics	Vegetation	Soil	Cardboard	Organics
Predictions	Plastics	179	7	2	4	9
	Vegetation	1	121	1	0	3
	Soil	1	0	3	0	2
	Cardboard	0	0	0	0	0
	Organics	9	2	3	1	41

Table 13 presents the performance of the random forest model at predicting objects in the waste pile. The developed model has a Kappa coefficient of 0.813. To put in perspective, the recall of 0.9421 indicate that the model is able to correctly identify 9,308 plastics out of 10,000 known plastics. Additionally, the precision value of 0.8905 is similar to a situation where out of 10,000 objects that are classified as plastics, 8,905 are indeed plastics.

Table 13. Performance of a model predicting micro classes of objects in the studied waste pile.

Land cover class	Precision	Recall	F1
Plastics	0.8905	0.9421	0.9156
Vegetation	0.9603	0.9308	0.9453
Soil	0.5	0.33	0.4
Cardboard	---	0	---
Organics	0.7321	0.7455	0.7387

Figure 16 presents different categories of objects in the waste pile based on model prediction. The classified map looks congruent to the unprocessed imagery when compared visually.

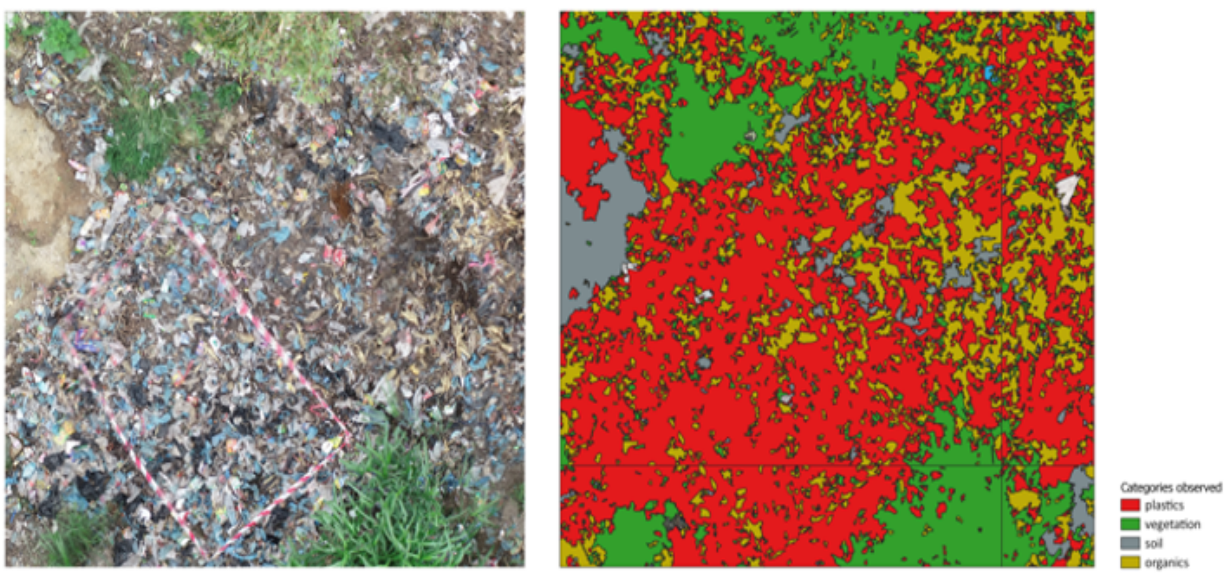


Figure 16. Comparison of the drone imagery and predictions of major categories of surface waste in the studied waste pile.

Table 14 indicate the percentages of the surface area of the waste piles that is covered by different categories of waste. The results indicate that plastics represent the most abundant class on the surface of the waste pile. It is also important to note that 20% of the studied area was covered by vegetation and it was difficult to visually locate the plastics underneath.

Table 14. Area covered by different objects observed on the surface of the waste Piles.

Object observed	**Percentage of area covered**
Plastics	50.9
Vegetation	20
Soil	5.93
Cardboard	0.0489
Organics	23.2

Recommended GSD for mapping plastics in waste piles

Figure 17 presents UAV imageries of a waste pile with plastics acquired with different GSDs. It has been observed that in all the flight heights where UAV images were captured the signature for blue plastic is visible. However, individual pieces of plastic are only visible in images that were captured from not more than 20 meters above ground (a GSD of 0.51 cm).

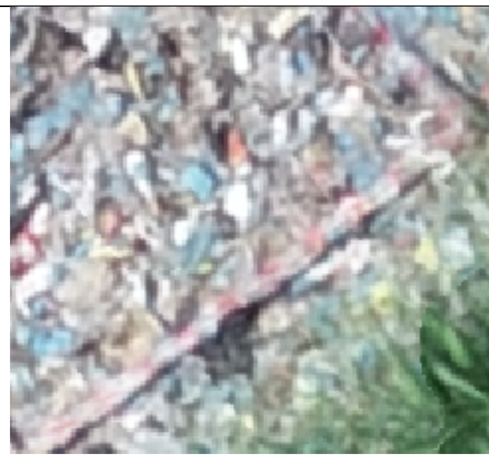
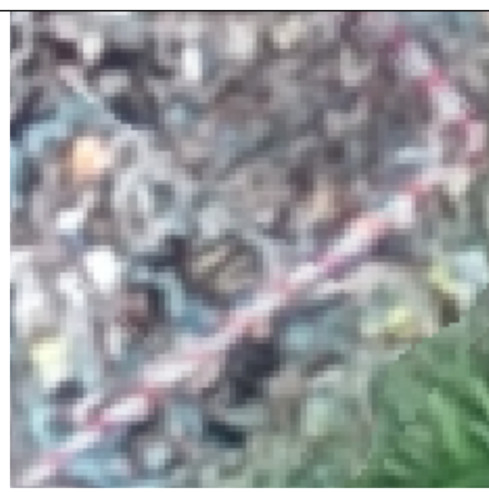
Height and GSD	Visibility of plastics
10 meters, and 0.25 cm/pixel	
40 meters, and 1.06 cm/pixel	
70 meters, and 1.86 cm/pixel	

Figure 17. Summary on the level of details observed at different GSD’s in dumpsites.

Chapter 5: Discussions and Conclusion

The study was set to explore operational usage of UAV imagery and machine learning for mapping plastics and waste piles in a developing country and in urban context. This chapter presents the study findings in relation to prior scholarly work. The structure of the text follows the set objectives. The rest of the text includes the strength of the study, its limitations, a few key conclusions, and some recommendations.

Appropriate scale for mapping plastics

First, the study explored visibility of plastics when mapped from different flight altitudes. As it was observed that the visibility of plastics is positively associated with size of the mapped plastics, and negatively associated with Ground Sampling Distance (GSD), we highlight an important consideration for mapping plastics in the real world. While it might be thought that in the real world, smaller plastics (less than 10 cm) are less likely to be found, but previous studies have reported that small portion of plastics disposed of in the environment are exposed for mapping as plastics are often partially semi-buried or partially covered by vegetation (Gonçalves et al. 2020; Andriolo et al. 2021). With such a smaller size, smaller plastics in waste piles are even difficult to detect using machine learning approaches (Martin et al. 2018).

Regarding the choice of GSD to be targeted for mapping plastics, the current study observed that a GSD of 2.51 cm has lower visibility for plastics of size less than 10 cm. This observation is similar to Lo et al. (2020) who indicate that a GSD of 2.5 cm is not recommended for mapping plastics that are smaller than 10 cm. Small plastics are not visible in images with high GSD because there are not enough pixels (Jakovljevic et al. 2020). It is worth noting that images with high GSD were observed to have diffuse edges, this makes objects to appear ambiguous and difficult to generate training samples from (Martin et al. 2018).

Mapping of Waste Piles

Another issue that was investigated in this thesis was the possibility of mapping waste piles from UAV imagery. It is worth noting that unlike ground-based surveys, UAV imagery has enabled locating waste piles in locations that were not easily accessed during the field surveys. The results have shown additional waste piles – within the river channel – presenting opportunities to understand spatial extent of waste piles, ongoing waste disposal practices and associated transportation mechanisms. These advantages of UAV technology was previously reported by Martin et al. (2018). However, mapping of waste piles does not require very high-resolution imagery. If interest is to map waste piles rather than mapping the content of the waste pile, UAV imagery with lower GSD may be of advantage. Capturing and processing such images will take less time.

In addition to the advantages of low GSD, images with high GSD have extra details that make detection of waste piles to be challenging. For example, in the current study it was observed that some rooftops have objects that were observed to cause misclassifications. Recognizing that such a level of details is not necessary for locating waste piles, all small segments were merged to nearby larger segments. Such generalization is suggestive that it is reasonable to acquire low detailed UAV to map waste piles. Such images can be acquired by flying UAV from high flight altitude. This approach can provide more advantages including decreased flight time and increase safety as most ground-based obstacles will be avoided. Equally, prioritizing mapping areas that are known to be primary waste disposal locations can be of fundamental value. For example, in the current study, collecting UAV imagery of the river only can be efficient.

Equally examining image statistics finding best combination of parameters for detection of waste piles appear to be laborious and time consuming. Especially when it was noted that Haralick features play a less significant role in predicting waste piles, options for further exploration of other possible statistics were limited. Such observation raises an important question regarding suitable descriptors for mapping of waste piles. The integration of multispectral data such as Near-Infrared and Red-edge can potentially increase the set of predictors. Furthermore, Integrating emerging object detection approaches using deep learning can enable learning of the pattern associated with an object of interest with minimal human supervision (Yang et al. 2019). CNN in particular enables identification of complex hidden patterns in images (Garcia-Garin et al. 2021). This approach automatically abstracts different patterns in a given dataset and has been widely utilized to solve complex problems such as speech recognition, mapping brain circuits without the need to know the actual parameters (LeCun et al. 2015). As promising as it is, more detailed studies focusing on the use of techniques such as CNN might be needed to simplify the model development process.

The maps produced have been shared on a web map and they can be accessed by key stakeholders interested in the problem. Furthermore, and considering the discussions raised in this article, such maps can provide changes in the presence of waste piles across time, enabling understanding of impacts and transportation mechanisms of waste piles. Future studies should consider exploring the experience of potential users of such maps so that they can generate the maximum impact possible.

Nevertheless, if all segment labels were developed manually through photo interpretation of a UAV orthomosaic, previous studies have reported that some waste materials are too small to be recognized or hidden by shadows or vegetation, so much that they are difficult to be detected resulting into general underestimation of the density of waste materials (Martin et al. 2018). As such, conducting field surveys to delineate the actual areas covered by waste can help to develop reliable correctional factors to compensate for the underestimation. Lo et al. (2020) recognized that various operating conditions such as height and lighting might affect the accuracy of assessment of the quantity of waste and with that instead of computing a single correctional factor, empirical factors for specific conditions should be computed. Future research direction should consider the practicality of integrating the two approaches in monitoring waste in the environment.

Lastly, the study has demonstrated the practical utilization of high-resolution imagery in mapping piles of domestic waste. To the best of my current understanding, there is no prior study that has reported using such imagery for mapping piles of domestic waste. The approach presented in this study can be used for tracking the effectiveness of policies that are made to improve waste management by controlling waste disposal in the environment. The web map created can be used in environmental education programs as a tool for raising awareness about waste accumulation in the environment. Furthermore, planning of environmental waste clean-up campaigns can leverage on such maps to know locations to target. Currently waste clean-up campaigns are ongoing downstream of the river at the study location.

Mapping of plastics in waste piles

The results from the mapping of plastics in waste piles indicate plastics are the most abundant surface waste in the studied waste pile. However, mapping of plastics is only possible when a UAV imagery is captured with low GSD. UAV images with a GSD of more than 0.51 cm have low level of details to visually identify individual plastics and this can allow development of models for automatic detection of plastics. However, acquiring such GSD is achieved by flying at a low flight altitude; and with the camera that was used in the current study this was limited to the imagery captured from a height of 20 meters. Acquiring UAV imagery from a very low flight altitude is challenging in an environment such as the one studied in this work, there are powerlines and buildings which are hazards that must be avoided for safe UAV operations.

In terms of automatic detection of plastics, the current study has reported superior performance of the random forest model compared to previously published works. From Table *15*, the observed high performance might result from differences in the approach that was used for model development. For instance, unlike the current study, (Gonçalves, Andriolo, Gonçalves, et al. 2020) converted the RGB imagery into other color models to create additional descriptors for model development. The current study relied on RGB values and Haralick features. Another possible explanation is the variability of values within a single class. Our class for plastics had different colors including blue, black, yellow, transparent and red. Intra-class color variability has been reported to be associated with a lower model performance and especially high percentage in overlap of spectra for the studied classes negatively affected model training because classes share some of the same colors (Pinto et al. 2021; Bao et al. 2018; Martin et al. 2018).

Table 15. Performance of model developed in current study compared to selected prior work (only those with a similar performance metrics as the current study)

Study	Method	Precision	Recall	F-1 Score
Fallati et al (2019)	CNN	0.54	0.44	0.49
Wolf et al (2020)	CNN	0.77	0.77	0.77
Jakovljevic et al (2020)	CNN	0.82	0.75	0.78
(Gonçalves, Andriolo, Pinto, and Duarte 2020)	RF	0.7	0.71	0.7
(Gonçalves, Andriolo, Pinto, and Bessa 2020)	RF	0.73	0.74	0.75
(Gonçalves, Andriolo, Gonçalves, et al. 2020)	RF	0.75	0.7	0.73
Garin-Garin et al (2021)	CNN	0.82	0.84	0.83
(Papakonstantinou et al. 2021)	CNN	0.83	0.72	0.77
My study	**RF (plastics)**	**0.8905**	**0.9421**	**0.9156**
	RF (waste piles)	**0.9048**	**0.95**	**0.9268**

On a final note, the current study identified plastics using QGIS and Orfeo toolbox, these are free and open-source products that can be easily integrated in an environmental monitoring program especially when financial resources to support purchasing software are lacking. Regardless, automatic detection of features from a remotely sensed image is believed to be less labor and computationally intensive, as compared to the manual screening of the imagery to develop labels for model development. Considering that other areas are similar to the studied region, the developed model can be used to detect waste piles other areas. As the performance of the model to a region outside the study area is not known, future studies should consider applying the model in a different area. Furthermore, in this study only a small number of training labels were created for the studied region, however for this approach to be employed in an operational program for example at municipal level, a wide variety of land cover classes and their characteristic has to be incorporated in the model. Development of training labels can be labor intensive. Crowdsourcing development of image labels using annotation tools can be a suitable solution for this. A successful example was demonstrated by Papakonstantinou et al. (2021). Their study reported training 27 volunteers who successfully classified and labelled 30,793 objects on whether they have waste or not (Papakonstantinou et al. 2021).

Study strengths and limitations

The study is the first practical application of UAV imagery for mapping plastics in sub-Saharan Africa. This is a region where 70 percent of the waste that is generated is openly dumped in the natural environment (Ayeleru et al. 2020). Development of a web app presents an opportunity for dissemination of geographical information of waste piles to key stakeholders. However, the experimentation on plastics visibility only mapped plastics from few flight altitudes and the target materials lacked replicates. It is difficult to estimate experimental error in experiments that lack replicates (Wester 1992). Waste mapping also utilized a region 20 meters to both sides of the river in the study community. Performance of the developed model to the region beyond the river remain to be an area that need further investigation. Furthermore, there were no ground control points that were collected and matching feature points were selected from a Maxar Satellite imagery provided through Google Maps. Georeferencing by matching images of different resolution is negatively affected by differences in viewpoints and temporal changes in the landscape (Zhuo et al. 2017). But the approach is reasonable given that enough landscape features were visible in the study scene to allow georeferencing. Additionally, the positional errors that associated with georeferenced imagery were insignificant considering the problem being studied.

Conclusions and recommendations

Considering the observations reported in this study, the effective mapping of individual plastics is dependent on the size of the plastics to be mapped and achieved GSD. Waste pile mapping using OBIA performs better especially when segmentation has been performed systematically. The same performance is maintained when using OBIA for mapping individual plastics in waste piles. Operational usage of UAV in an environmental monitoring program will require setting of clear mapping goals and specific scale relevant for addressing the problem. For example, on whether mapping should target individual waste materials or aggregates of waste (waste piles). In terms of methods, future studies should explore utilization of convolution neural networks in mapping waste piles. From an environmental management standpoint, future work should solicit feedback from stakeholders in the waste management arena to explore opportunities for integrating such maps to improve their operations.

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