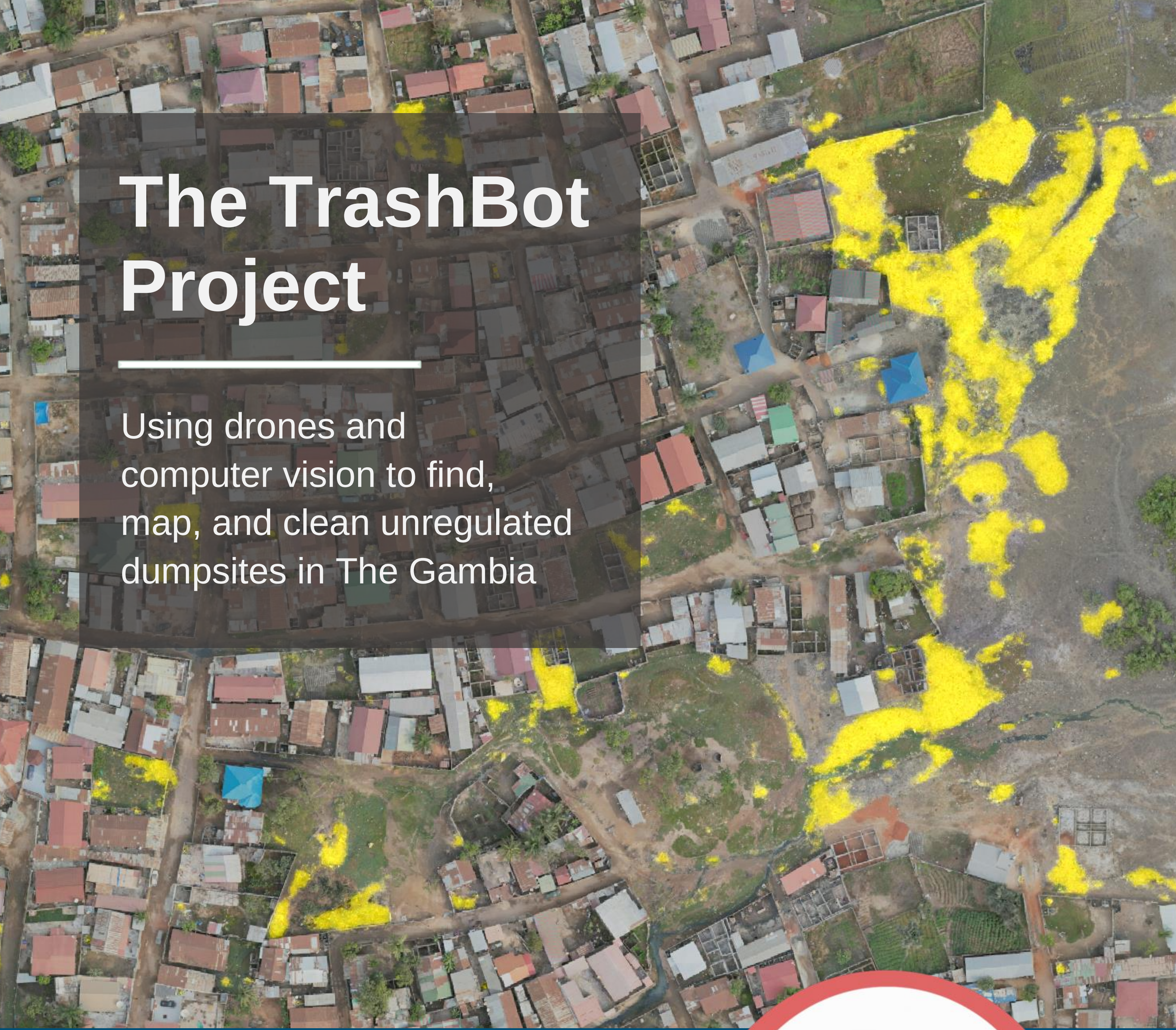

The TrashBot Project

Using drones and computer vision to find, map, and clean unregulated dumpsites in The Gambia

POLICY ANALYSIS EXERCISE

MATT ROTH

Master in Public Policy Candidate, 2023

Harvard Kennedy School of Government

Client: Kanifing Municipal Council

Faculty Advisor: Professor Akash Deep

PAE Seminar Leader: Professor Thomas Patterson

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Submitted in partial fulfillment of the requirements for the degree of Master in Public Policy

HARVARD Kennedy School
JOHN F. KENNEDY SCHOOL OF GOVERNMENT

KANIFING MUNICIPAL COUNCIL

Table of Contents

Executive Summary

Background & Motivation: Residents of Kanifing Municipality in The Gambia face a serious issue: their neighborhoods are filled with openly dumped trash. Much of the waste produced by households, businesses, and pedestrians ends up on the ground in communities instead of properly disposed of at the municipal dumpsite. This is especially true in areas with limited access to municipal waste management services. In Ebo Town and Tallinding, for example, some unregulated dumpsites have grown to cover hundreds of thousands of square feet. There is significant concern among citizens and elected officials about the consequences of these open dumps – trash left to sit in communities threatens the health and safety of residents and pollutes the environment.

Problem Statement: Under Mayor Talib Ahmed Bensouda, Kanifing Municipal Council (KMC) has made it its number one priority to clean trash from public spaces and improve waste management. This is no easy task, especially because KMC's budgetary and infrastructural constraints limit its operational capacity. Achieving better results requires getting more with less and precision-targeting interventions to areas of need. That is why this project focuses on improving KMC's operational efficiency in cleaning openly dumped trash from communities.

Project Scope: We aim to develop a scalable, repeatable, ethical, and cost-effective way to find, map, and measure unregulated dumpsites so KMC can clean public spaces with precision & economy.

Methodology: First, we conduct aerial surveys of Kanifing neighborhoods using a camera drone. Next, we train a neural network to identify trash in aerial photos and apply it to our drone images. We call this computer vision model TrashBot. Finally, we stitch together images that have been run through TrashBot to create interactive maps that highlight openly dumped trash, allowing KMC to find, map, and measure unregulated dumpsites.

Results & Deliverables: As a proof of concept, we surveyed over 600 acres in 5 Kanifing neighborhoods, where we located nearly 400,000 square feet of trash. We provide KMC with seven TrashBot maps and a suite of custom software tools so they can run the methodology independently.

Recommendations: Due to privacy implications inherent to the use of drones and machine learning, we set technical & operational standards for the ethical use of our methodology. These include image obfuscation, data security measures, purpose limitation, and democratic controls.

Finally, we develop six use cases for KMC to apply our methods to its most pressing waste management issues. These include:

1. Intervention targeting
2. Optimizing receptacle placement
3. Waste management metric tracking
4. Finding and closing unregulated dumpsites
5. Modeling health and environmental risk
6. Expanding service range strategically

Section 1:
Background & Motivation

Kanifing Municipality

Located just outside the capital city of Banjul, Kanifing Municipality is The Gambia's most populous local government area (LGA).[1] From bustling Serekunda Market to sunny Atlantic beaches and dense mangrove forests along the Gambia River, Kanifing Municipality is known for its abundance of cultural amenities, commercial centers, and natural beauty. It is no surprise, then, that people have flocked to its borders for decades, resulting in rapid population growth and economic development. In 1963, only 12,208 people, or 4% of the national population, lived in Kanifing Municipality.[2] Now, it is home to over 383,545 people, or about 20% of the national population.[3] Such rapid growth can be

[1] An administrative subdivision smaller than a region, of which there are 7, and larger than a district, of which there are 43. "Quick Facts About the Gambia | Visit the Gambia."

[2] "The Gambia: Population by Local Government Area 1963-1993."

[3] "The Gambia Bureau of Statistics."

attributed to Kanifing's particular appeal along with broader social, demographic, and economic forces that have transformed life in The Gambia in recent decades.[4]

This transformation has come with both opportunities and challenges. On the one hand, Kanifing has grown to become the country's central economic hub. The nation's tourism, trade, and finance sectors are based around Serekunda, the Gambia River, and the Atlantic coast.[5] On the other hand, there is no easy way to fit so much activity and so many people into the municipality's borders. With 4,992 people per square kilometer, Kanifing is twice as dense as the next most densely populated LGA and about 30 times as dense as the national average.[6] And due to its rapid growth and limited space, 71% of people live in informal settlements,[7] where it is difficult for the government to provide services and utilities such as waste collection, clean water, and reliable electricity to all its residents.[8] These challenges will likely continue as the population is expected to double by 2033.[9]

Kanifing Municipality's Geography

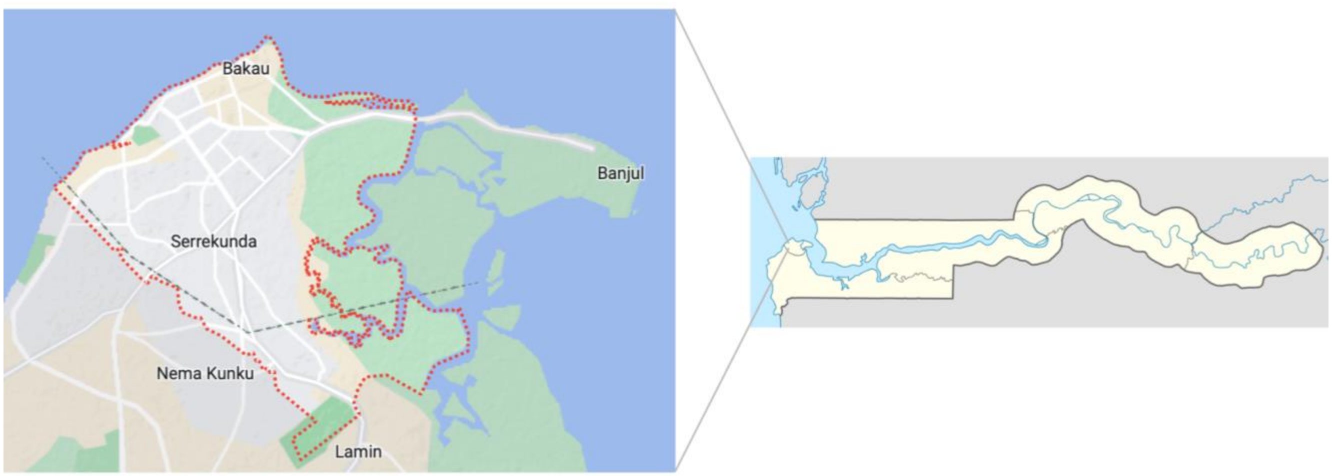

Figure 1: *Kanifing Municipality sits just outside the capital, Banjul, at the country's western tip*

Against this backdrop, Kanifing Municipal Council (KMC), led by Mayor Talib Ahmed Bensouda and the members of the General Council, is responsible for governing Kanifing's nearly half-million residents.

[4] Our World in Data, "Birth Rate."; Our World in Data, "Child Mortality."; Our World in Data, "Life Expectancy."; Our World in Data, "Share of People Living in Urban Areas."

[5] KMC, "Partial Cost Recovery."

[6] "Population Density in Census Years, 1973 - 2013 - GBoS."

[7] The Gambia Bureau of Statistics, "The 2020-2021 Gambia SDGs Monitoring Survey."

[8] UN-HABITAT, "The Gambia: Kanifing Urban Profile."

[9] "Strategic Plan for Kanifing Municipal Council (KMC) 2016- 2020."

The Municipal Solid Waste Problem

Despite Kanifing Municipality's vibrance, it is impossible to ignore the litter and large deposits of trash in markets, parks, beaches, residential neighborhoods, and other public spaces. Household trash is dumped indiscriminately in the street or burned in piles. Wrappers, bottles, and plastic packaging are routinely discarded along roadways by pedestrians and motorists. Trash piles up in vacant lots, unfinished construction sites, gutters, streams, and along the riverfront. Throughout this report, we refer to waste discarded improperly in open spaces as "openly dumped trash" and the sites where it accumulates as "unregulated dumpsites."[10] The presence of so much openly dumped trash and the municipality's challenges in dealing with it combine to form "the municipal solid waste problem."

The United Nations Human Settlements Programme defines municipal solid waste (MSW) as solid waste from households, businesses, institutions (e.g., schools and hospitals), smaller industries, street activity, and public areas.[11] The Gambia, like many developing countries, struggles with municipal solid waste management (MSW management) due to various social, demographic, and economic factors. In Kanifing Municipality, these factors have combined to form a particularly intractable problem for KMC in its efforts to ensure its residents' health and well-being and to protect the environment. Without sufficient resources to collect, remove, process, and dispose of MSW, Kanifing faces the prospect of a continually worsening crisis.

Structural Causes of the MSW Problem

Whether trash ends up on the ground or in its proper place may seem like a localized problem, but it is often influenced by broader trends. In Kanifing's case, diagnosing the issue requires looking at the societal and institutional factors contributing to it.

Economic & Demographic Forces:

Sub-Saharan Africa is the world's fastest-growing region in terms of waste generation per capita. According to the United Nations Environment Programme (UNEP), waste generation rates are expected to be three times higher in 2050 than they were in 2016. This rapid increase is due to population growth, urbanization, economic development, and changing consumption patterns as millions enter the middle class and begin using more packaged goods and single-use plastics.[12]

The Gambia is notable even within sub-Saharan Africa for its economic and demographic transformation in recent years, and Kanifing Municipality has been the center of population growth,

[10] **Note:** Not all open dumps are unregulated. We are referring only to sites where people are not supposed to dump waste

[11] Shahmoradi, "Collection of Municipal Solid Waste in Developing Countries."; UN Stats, "UN SDG Indicator Metadata."

[12] Kaza et al., *What a Waste 2.0: A Global Snapshot of Solid Waste Management to 2050*.

urbanization, and economic development in the country. As the population grows, KMC has struggled to scale waste management services and infrastructure to the nearly half-million residents who call Kanifing home. According to UNEP, urban residents generally produce more solid waste than their rural counterparts,[13] and Kanifing is no exception. Official data from the Gambia Bureau of Statistics shows that Kanifing produces the second most solid waste per capita (behind only Banjul), totaling 34% of the country's solid waste production despite accounting for only 20% of its population.[14]

Solid Waste Production by LGA

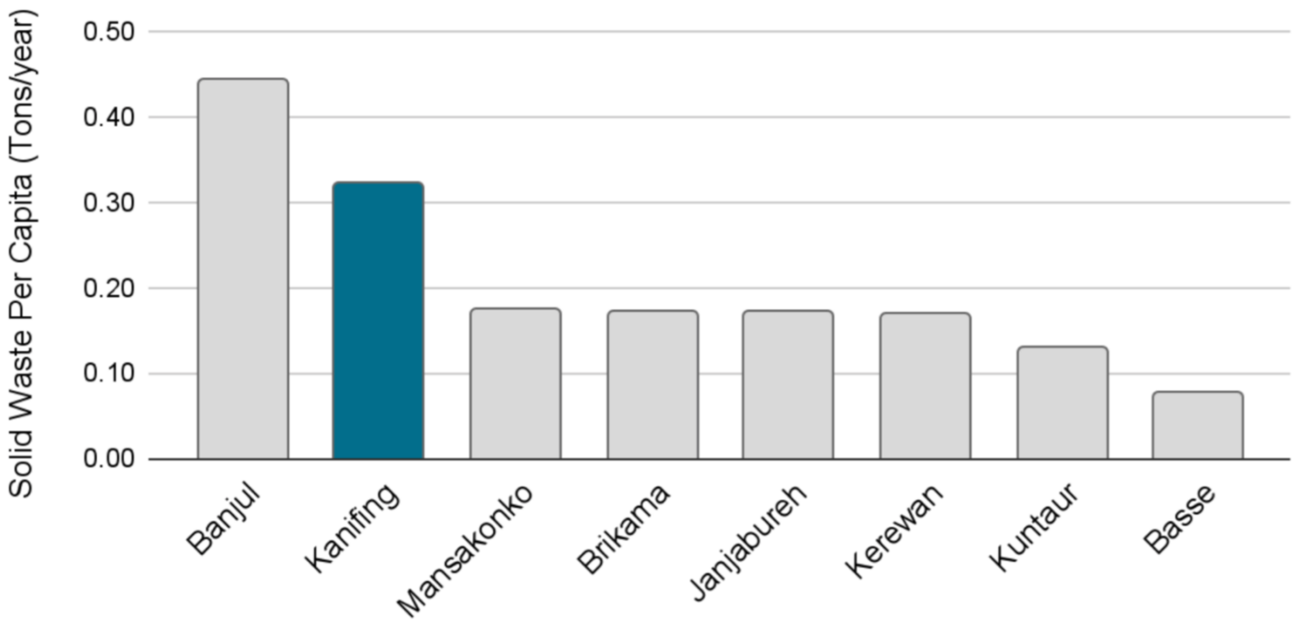

Figure 2: *Kanifing residents produce nearly twice as much solid waste per capita as other LGAs*

As Kanifing residents' wealth grows, their changing consumption habits will continue to shift the profile of their waste production away from biodegradable organics and towards packaged goods and consumer electronics. These items contain plastics, hazardous chemicals, electronic waste, and non-biodegradable materials that persist for years and leach harmful chemicals into the environment.

Limited Municipal Solid Waste Collection Capacity:

Municipal solid waste collection is logistically complex because MSW is generated in virtually all buildings and public spaces. As a city grows, it produces more waste across a broader area, making collection even more difficult.[15] Historically, KMC has lacked the capacity to offer waste collection

[13] UN Environment Programme, "Global Waste Management Outlook."

[14] "Estimated Quantity of Solid Waste Generated by Households in 2014/2015 in Tons by Type of Waste and LGA - GBoS."

[15] Sanneh et al., "Introduction of a Recycling System for Sustainable Municipal Solid Waste Management."

services to most of its residents. With its service area constrained, it prioritized markets and commercial areas, restaurants, main roads, and only a few residential neighborhoods.[16] The high proportion of residents living in informal settlements further complicates KMC's task. These areas are hard to reach because of their peripheral geographic locations and narrow, unpaved roads, which are hard to navigate in the best conditions and nearly impassable in the rainy season.

Recently, Mayor Bensouda has made it his administration's number one priority to clean trash from public spaces and improve waste management. The municipality has made great strides under his leadership by expanding collection services to more residents than ever, planning a new sanitary landfill, procuring trucks and other critical infrastructure, increasing the number of public waste bins, clearing unregulated dumpsites, and securing large grants for ambitious MSW management programs (see Appendix A for details).[17] Still, roughly half of Kanifing residents do not receive regular door-to-door collection services, and many live in areas that KMC does not, and cannot, regularly service. This places the burden of waste management on citizens, volunteers, and other private actors who do not have the resources, staffing, or incentives for such an undertaking.

Behavioral Causes of the MSW Problem

The simple fact is that people need to get rid of their waste *somehow*, and they generally have few desirable options in the absence of reliable municipal services. It is unsurprising, then, that undesirable norms around waste management have worsened the MSW problem in Kanifing.

Widespread Littering:

It is not uncommon to see Kanifing residents discard wrappers, cans, bottles, and boxes in public spaces. A recent study found that 80% of participants among a representative sample of Gambians in the Greater Banjul area littered after unwrapping and consuming a candy given to them by the researchers.[18] To explain this finding, they noted that people think it makes little difference what they do with their trash because they cannot rely on waste removal services to ensure it is properly disposed of. In this context, access to reliable municipal services is essential to behavior change because it gives citizens a better alternative to littering.

Improper MSW Disposal:

Roughly 40-45% of Kanifing residents do not receive regular door-to-door waste collection services.[19] They are left with a couple of options to dispose of their waste:

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[16] Fatty and Komma, "In-Depth Analysis of Municipal Solid Waste Management in Kanifing Municipality, The Gambia."
[17] Kumar et al., "ODI Working Paper: Waste Management in Africa."
[18] Farage, Uhl-Haedicke, and Hansen, "Problem Awareness Does Not Predict Littering."
[19] Kumar et al.

1. They can dispose of it at approved communal collection points where public or private service providers can collect and remove it.
2. They can dispose of it by incineration in backyard burn pits or public spaces, the latter of which is illegal but not uncommon.
3. They can litter or dump it indiscriminately at unregulated dumpsites.

From KMC's perspective, the use of approved communal collection points is vastly preferable to the other options. Yet, Kanifing residents usually choose otherwise. In a nationwide survey conducted in 2013 by the Gambia Bureau of Statistics, 33% of Gambians reported disposing of solid waste by incineration, 18% by dumping it in the bush or other open spaces, and only 10% reported using approved communal collection points.[20] The reasons often boil down to convenience and a lack of alternatives. In a separate survey from 2010, 42% of Kanifing residents cited poor collection as the primary reason for indiscriminate dumping, while 25% cited long distances to community bins.[21]

Several significant laws and regulations have been enacted in recent years to curb improper waste disposal without much success. For example, the Anti-Littering Regulations of 2007 made indiscriminate littering a public offense.[22] Yet, 50% of survey respondents in Kanifing believe these laws are ineffective due to a lack of awareness, and another 24% cited poor enforcement.[23]

Improper Waste Disposal in Kanifing Municipality

Figure 3: *An unregulated dumpsite in Ebo Town, a trash fire on a public street, and litter in Tallinding*

[20] The Gambia Bureau of Statistics, "The 2020-2021 Gambia SDGs Monitoring Survey."

[21] Badgie, Muda, and Manaf, "Integrated Study of Solid Waste Management System in the Kanifing Municipal Council (KMC)."

[22] Chambers, "ANTI-LITTERING REGULATIONS, 2007."

[23] Badgie, Muda, and Manaf,

Effects of the MSW Problem

It is obviously undesirable to have trash pile up in communities, but it is easy to underestimate the full range and severity of the damage it can inflict. As long as Kanifing neighborhoods are beset with open dumps, they will be at heightened risk of serious health, safety, and environmental harm.

Public Health & Safety:

Infectious Diseases: Openly dumped trash can cause harm broadly in the population by increasing the spread of infectious diseases. Plastic waste is particularly troublesome because it stays in the environment for years and collects pools of stagnant water that provide ideal breeding sites for *aedes aegypti* mosquitoes, the primary carriers of dengue, yellow fever, chikungunya, and zika; and *anopheles*, the mosquito that carries malaria. A study of the effect of openly dumped trash on mosquito-borne illnesses in Kenya concluded that plastic litter substantially increases viral disease transmission and that eliminating plastic litter would prevent “a large number of unnecessary disease cases and deaths.”[24] Stagnant water also promotes the development of pathogenic bacteria and parasites.[25] Infamously, a large cholera outbreak in Accra, Ghana, was directly linked to the cessation of waste collection in a poor neighborhood.[26]

Fires & Floods: There are two mechanisms by which poor MSW management increases fire risk. First, up to 33% of Gambians dispose of waste by incineration.[27] These fires can be dangerous and difficult to control, especially in the dry season when vegetation is primed to ignite.[28] Second, methane gasses emitted from waste decomposition can spark fires – a common occurrence around the Bakoteh Dumpsite in central Kanifing.[29] Flooding, however, has proved to be a more persistent threat than fire due to Kanifing’s topography, climate, and poor drainage system. Openly dumped trash tends to accumulate in drains and gutters, rendering them ineffective. As a result, low-lying areas become highly flood-prone. Ebo Town and Tallinding experience regular flooding in the rainy season, with the former experiencing a cholera outbreak after a 2005 flood.[30] More recently, during the 2022 rainy season, a flood killed 11 Kanifing residents and displaced over 5,000 in a disaster that experts say was exacerbated by trash-clogged drains.[31] These largely preventable disasters cause injuries, deaths, property damage, disease outbreaks, and exposure to toxic chemicals that run off from waste in neighboring regions including the Bakoteh Dumpsite.

[24] Mutuku, “Mitigating Plastic Litter Will Significantly Reduce Mosquito-Borne Disease.”

[25] Maquart, Froehlich, and Boyer, “Plastic Pollution and Infectious Diseases.”

[26] Webster, “The State of Solid Waste Management in The Gambia - A Review.”

[27] The Gambia Bureau of Statistics, “The 2020-2021 Gambia SDGs Monitoring Survey.”

[28] Wibbenmeyer et al., “Trash and Brush Burning.”

[29] Kumar et al., “ODI Working Paper: Waste Management in Africa.”

[30] UN-HABITAT, “The Gambia: Kanifing Urban Profile.”

[31] Hydara, “11 DEAD, OVER 5000 DISPLACED IN FLOODS DISASTER – The Standard Newspaper | Gambia.”

Direct Exposure: While infectious diseases, floods, and fires threaten whole populations, there are also serious risks that affect people more narrowly through direct exposure to openly dumped trash containing broken glass, sharp metal, and toxic chemicals like lead, mercury, and PFAS.[32] These hazardous materials accumulate in populated communities where people work, children play, and livestock rummage.[33] The health impacts are as ubiquitous as they are varied. One study found that 58% of children in a neighborhood lacking MSW management services reported being injured by broken glass in the streets.[34] Exposure to electronic waste, which is becoming more common as The Gambia modernizes, increases the risk of congenital disabilities, developmental disorders, respiratory illness, cancer, and cognitive impairment.[35] Organic waste attracts stray dogs, rats, and pests which may be aggressive or infected with rabies and other diseases.[36] UN-Habitat health data shows that urban areas lacking waste management services typically have double the rate of diarrhea and six times the rate of acute respiratory infections compared with better-served areas in the same cities.[37] Children in particular experience higher rates of both afflictions in households where solid waste is dumped or burned in the yard.[38]

Environmental Harm:

Air pollution: According to surveys by the Gambian Bureau of Statistics, more households dispose of solid waste by incineration than by any other method.[39] As a result, large quantities of harmful gasses and particulate matter are released into the air in residential areas. Globally, up to 29 percent of small particulate matter emissions, 10 percent of mercury emissions, and 40 percent of polycyclic aromatic hydrocarbons (PAHs) emissions come from the open burning of trash.[40] Inhalation of these substances has been shown to cause respiratory and neurological diseases.[41] And unfortunately, the costs of air pollution are disproportionately borne by residents of low-income areas and informal settlements where there are few options besides incineration to dispose of waste. It is typically women and children who breathe most of the fumes, as incineration is a household responsibility that often falls to them.[42]

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[32] Per- and polyfluoroalkyl substances

[33] "Gambia: Soaring E-Waste Affects the Health of Millions of Children!"

[34] Webster, "The State of Solid Waste Management in The Gambia - A Review."

[35] Lebbie et al., "E-Waste in Africa."

[36] Krystosik et al., "Solid Wastes Provide Breeding Sites, Burrows, and Food for Biological Disease Vectors, and Urban Zoonotic Reservoirs."

[37] UN-HABITAT, "Solid Waste Management in the World's Cities."

[38] Webster

[39] The Gambia Bureau of Statistics, "The 2020-2021 Gambia SDGs Monitoring Survey."

[40] Thompson, "For Air Pollution, Trash Is a Burning Problem."

[41] Kumar et al.

[42] van Niekerk and Weghmann, "Municipal Solid Waste Management Services in Africa."

In addition to the health-related consequences of air pollution, openly dumped trash also contributes to greenhouse gas emissions. Trash fires release carbon dioxide (CO2), and waste decomposition produces methane, which is 80 times more potent than CO2[43] and represents the solid waste sector's most significant contributor to emissions.[44]

Air Pollution from Trash Incineration

Figure 4: *Trash fires, like these in Tallinding, release smoke and toxic chemicals into the air in heavily populated areas*

Water pollution: Geographically, The Gambia consists mainly of the Gambia River, its north and south banks, and the Atlantic beachfront. As such, marine environments are central to many people's lives, and access to water provides the basis for transportation, tourism, shipping, fishing, wildlife, and agriculture. Waterfront areas, however, also tend to be popular dumpsites because they provide a buffer from populated areas. A 2014 survey by the National Environment Agency of The Gambia (NEA) noted that 70% of all existing dumpsites they visited were in wetlands, drainage channels, gullies, depressions, and waterways.[45] This is a highly concerning trend due to the sensitivity of marine ecology to pollution.

As water moves through waste, it forms a toxic liquid known as leachate, which seeps into soil and waterways, polluting the environment and causing health disorders among people and wildlife that

[43] UNEP, "Methane Emissions Are Driving Climate Change. Here's How to Reduce Them."

[44] Kaza et al., *What a Waste 2.0: A Global Snapshot of Solid Waste Management to 2050*.

[45] Kavegue and Ittner, "The Experience and Impact of Urban Floods and Pollution in Ebo Town, Greater Banjul Area, in The Gambia."

drink the contaminated water.[46] Concerningly, a 1997 study by the NEA found that the wells around the Bakoteh Dumpsite had up to 1,000 times the maximum limit of total coliform and fecal coliform.[47] When it rains, polluted water from Bakoteh flows downhill to low-lying, flood-prone neighborhoods, forming stagnant pools in some places and entering the Gambia River in others.[48]

Water Pollution from Leachate

Figure 5: *Left: Garbage clogs a waterway in Dippa Kunda. Right: A large dumpsite in Tallinding sits mere feet from a tributary of the Gambia River*

Harm to wildlife and livestock: Throughout Kanifing Municipality, it is common to see goats, donkeys, sheep, cows, and dogs rummaging around trash piles where they may eat or be exposed to harmful substances. In addition to being toxic to the animals, some of the danger is passed along to humans who eat or interact with the exposed animals.

Wildlife is also harmed by openly dumped trash, with marine animals being particularly vulnerable. One study found that most plastic waste eventually reaches oceans, resulting in biodiversity and ecosystem loss, accidental ingestion, and destruction of coastal breeding grounds.[49] Furthermore, plastic degrades into small pieces and synthetic fibers known as microplastics, which get ingested by animals up and down the food chain. Microplastics can remain in the body, damage organs, and leach

[46] Espinoza, "How Does Leachate Contaminate Our Water Supply?"

[47] The Gambian Agency for the Management of Public Works, "Preliminary and Detailed Engineering Design Study of The Bakoteh Dump Site."

[48] Kavegue and Ittner, "The Experience and Impact of Urban Floods and Pollution in Ebo Town, Greater Banjul Area, in The Gambia."

[49] Mutuku, "Mitigating Plastic Litter Will Significantly Reduce Mosquito-Borne Disease."

hazardous chemicals into the bloodstream,[50] causing neurological impairment and endocrine disruption - both of which have been observed in humans and other animals.[51]

Summary of the MSW Problem

Kanifing's solid waste production has vastly outpaced the municipality's capacity to deal with it. MSW has to go *somewhere*, though, and because it is not reliably collected, people resort to undesirable options. Communal collection points and public waste bins are underutilized because they are scarce and inconvenient. Indiscriminate dumping, littering, and incineration are therefore commonplace. Laws intended to prevent these behaviors are not widely known or well-enforced. All of this results in trash accumulating in public spaces where it pollutes the environment, causes flooding and fires, threatens public safety, and spreads diseases. For these reasons, KMC urgently needs to remove all the openly dumped trash that has piled up in communities.

[50] Thompson, "From Fish to Humans, A Microplastic Invasion May Be Taking a Toll."

[51] Campanale et al., "A Detailed Review Study on Potential Effects of Microplastics and Additives of Concern on Human Health."

Section 2:
Addressing the MSW Problem

Deconstructing a Complex Set of Issues

The fact that Mayor Bensouda's electoral success and popularity have been tied to his prioritization of the MSW problem demonstrates how widely recognized and broadly felt it is by Kanifing residents. Understandably, nobody wants their community to be filled with trash. But cleaning it up is no easy task, and as discussed earlier, the problem is caused and perpetuated by a diverse set of structural and behavioral factors. A comprehensive solution that addresses all the component issues will be slow, expensive, and logistically challenging. Perhaps that reality would be less concerning if the harms from unregulated dumpsites were not so immediate, severe, and widespread.

This tension underscores a difficult trade-off: On the one hand, KMC will only fully solve the MSW problem once it takes care of the larger, more systemic issues causing it. On the other hand, residents cannot wait years for the situation to improve - they need relief right now.

Identifying the Full Set of Problems and Possible Interventions

Over the years, Kanifing has been the subject of several detailed case studies and academic papers about MSW management.[52] Each has made recommendations to help KMC redesign its waste management system, and many of those recommendations have been implemented in policy (see Appendix A for more details). But it is clear from the literature that the problem is layered and that there is no easy solution. The studies point to 3 main problems that KMC needs to solve:

Problem 1:	Problem 2:	Problem 3:
Cleaning trash from public spaces	Preventing trash from ending up there in the first place	Processing and disposing of waste in a sustainable way

The studies also put forth a broad range of potential solutions, which are summarized and categorized in the figure below:

The Intervention Landscape: Levers to Address the MSW Problem

Figure 6: *Four intervention areas with initiatives recommended by academic papers and case studies*

[52] Sanneh et al.; Fatty and Komma; UN-HABITAT 2011; UN Environment Program 2017; KMC 2016-2020

All the interventions outlined in the figure above are necessary and important, but not all are feasible, affordable, or immediately impactful. These trade-offs were central to the scoping and design of this project as we made three fundamental choices:

1. Whether to focus on long-term reform or short-term relief
2. Which of the three problems listed above to focus on
3. Which area of the intervention landscape to target

Given the immediate and ongoing harms of the MSW problem, we chose to focus on **providing immediate relief**. That decision led us to prioritize **Problem 1: Cleaning trash from public spaces** because the other two are more long-term in nature. And among all the areas of the intervention landscape, we chose **Operational Efficiency** within the **Government Capacity Building** bucket because it has the fewest feasibility constraints.

There are several benefits to improving immediate-term operational efficiency in cleaning trash from public spaces. First, operational inefficiencies limit the scale and impact of KMC's work. Given their resource constraints, they need to find ways to get more with less. Second, it has both short and long-term benefits because it helps impactful projects to become more cost-effective, scalable, and repeatable. Third, significant improvements in operational efficiency can be made on short timescales and with small budgets. In contrast, initiatives in other areas might require millions of dollars (e.g., constructing a sanitary landfill), long timescales (e.g., paving roads), political will (e.g., regulation and law enforcement), and uncertain prospects (e.g., affecting behavioral change among half a million people).

Problem Statement:

How can KMC improve its operational efficiency in cleaning openly dumped trash from communities?

Finding, Mapping, and Measuring Openly Dumped Trash

Perhaps KMC's most significant operational inefficiency is its lack of awareness about the location and quantity of openly dumped trash. **Simply put, they cannot clean trash efficiently if they do not know where it is.** The impact that can be achieved from the municipality's scarce resources (e.g., garbage trucks, waste bins, dumpsters, sanitation workers, communal collection sites, etc.) is blunted when deployed arbitrarily or inefficiently. Therefore, developing a method to locate and measure openly dumped trash can help KMC target operational interventions with precision and economy toward the areas of most need.

Finding and measuring unregulated dumpsites also unlocks the ability to track progress and quantify the effects of interventions. This information can help KMC finetune its operations by determining what works and what does not. It can help them design, test, and iterate on new programs, evaluate the work of private and social sector partners, and identify shifting patterns in the distribution of waste as new areas of need emerge.

Currently, KMC lacks a systematic way to find and measure unregulated dumpsites. Traditional surveys are time-intensive, unreliable, expensive, and difficult to manage in the Gambian context of unpaved roads and hard-to-find dumpsites (e.g., trash dumped in unfinished construction sites, vacant lots, drains, gullies, and the bush). There is no cost-effective alternative that (1) scales to large geographic areas, (2) produces an accurate, standardized, and comprehensive accounting of trash, (3) yields geospatially meaningful data that can easily be operationalized, and (4) can be updated over time in a low-cost, low-effort way.

Section 3: Designing a Solution

A New Way to Find, Map, and Measure Trash

In partnership with representatives from KMC’s Environment & Sanitation Unit (ESU) and Environmental Transformation Programme (KETP), we designed and carried out a program to map and quantify unregulated dumpsites using drone photography, computer vision, and ortho mapping (the process of combining discrete aerial photos into a contiguous map). As a proof of concept, we selected seven parcels to create a comprehensive ground-truth dataset of the location and quantity of openly dumped trash. Parcels were chosen to represent a wide range of environments where KMC faces MSW management challenges. These included informal settlements, riverine areas, highways, markets, and areas with open drains. We used computer vision to locate trash in drone photos and ortho mapping technology to translate our results into detailed, interactive maps that KMC can easily integrate into their operations.

Seven Parcels to Test our Methodology

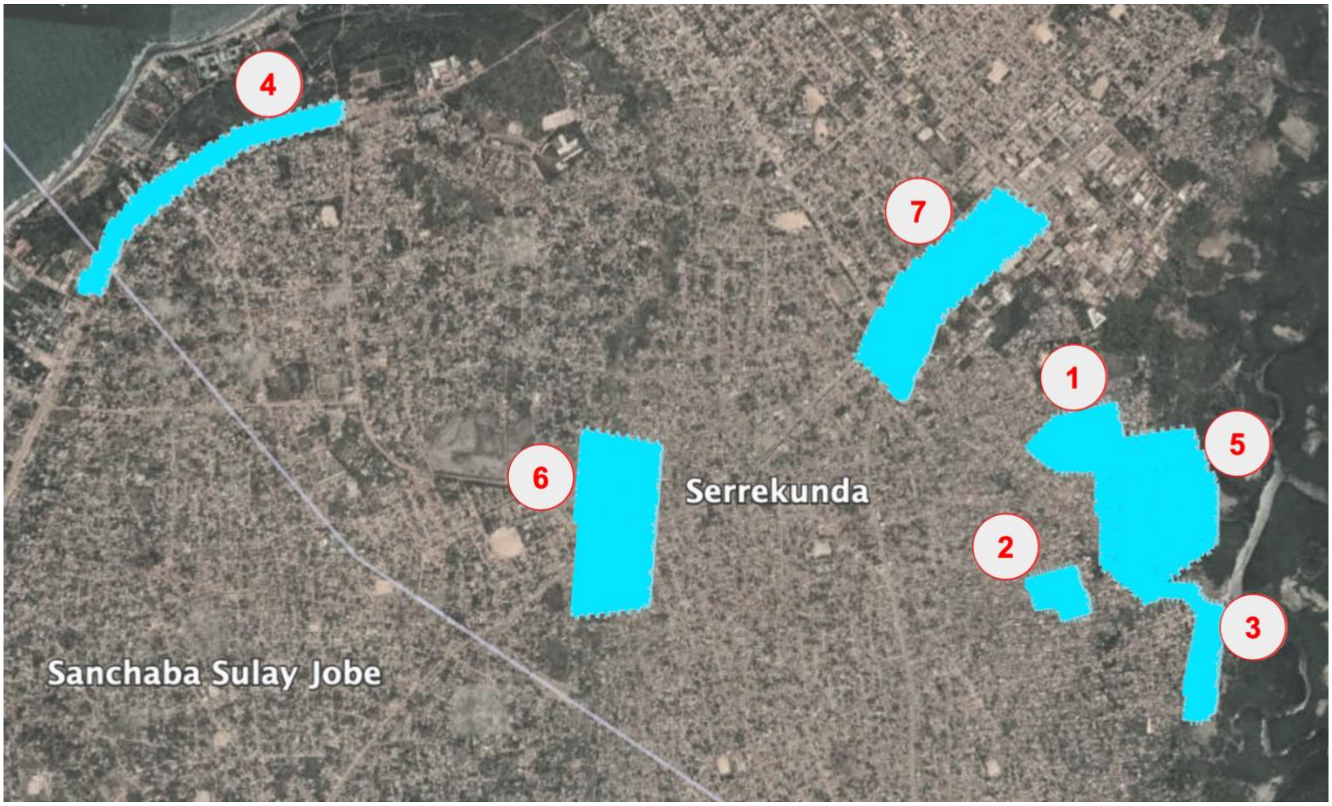

Figure 7: *Seven parcels spanning a wide range of environments were selected to conduct aerial surveys (see Aerial Survey Results for more details on each parcel)*

Success Criteria

We developed the following six criteria to guide the design and evaluation of our project:

Criterion	Why it's important
Privacy protectiveness	Privacy is a fundamental right that governments should not unduly infringe upon. However, aerial surveys have unavoidable privacy implications. We must therefore ensure that sensitive data is minimized, protected, and scrubbed whenever it is possible to do so. A detailed accounting and discussion of this issue can be found in the Methodology and Discussion sections.
Operational usefulness	There is little value in locating unregulated dumpsites if doing so does not help KMC to actually clean them. We aim to provide actionable data and operational tools that enable KMC to perform MSW management tasks better and more efficiently.
Accuracy	Our data must be trustworthy to be useful. False positives will send resources where they are not needed, while false negatives will cause KMC to miss areas of need.

Scalability	It should be trivial to scale our solution to any neighborhood where it might be impactful. At the very least, we aim for orders-of-magnitude improvements over existing ground-based surveying techniques.
Ease-of-use / self-sufficiency	The methodology should be easy enough for somebody to manage without specific credentials or expertise (i.e., no drone experience or computer programming skills necessary). KMC itself should be able to run the program without relying on outside vendors or consultants.
Cost-effectiveness	Given KMC's budget constraints, the methodology must be cheap to be feasible. We rely on cost-effective tools and free, open-source software where available to keep costs down.

Table 1: *Success criteria informing the design of our program*

Technological Choices

Each of the technologies we relied upon to find and map trash presents benefits and drawbacks. These are analyzed in the table below, with more detail provided in Appendix B.

Technology	Benefits	Drawbacks
Drone Surveying A type of remote sensing where camera drones are used to measure or observe a particular area	1. **Resolution:** Overhead drone photos easily achieve 2 cm/pixel resolution, which is 15x better than satellites. Higher-quality images make it easier to identify trash 2. **Scalability:** Each drone photo captures an area of 65,000 sq ft, and drone flight neutralizes the challenges of road travel in Kanifing 3. **Comprehensiveness:** Aerial photos cast a broad net, so if there is trash present in an area, it is likely to appear in drone photos 4. **Standardization:** Overhead photos provide a uniform perspective of the ground, making it possible to compare different parcels of land without worrying that the observer's perspective affected measurements	1. **Privacy:** Drone photos capture more than they need, making it impossible to avoid photographing people, private spaces, and private life 2. **Visual obstacles:** Drones are not able to see trash under the cover of trees, awnings, or other obstructions. Pedestrians and vehicles also may obscure a drone's line of sight to the ground 3. **Physical obstacles:** Tall buildings, trees, and restricted airspace make some areas off-limits to drone surveying

Computer Vision A broad term applied to the field of artificial intelligence that enables computers to derive meaningful information from digital images[53]	1. **Scalability:** Once a model is trained, it can be applied to an unlimited number of photos at zero marginal cost. This enables our methodology to scale cheaply 2. **Efficiency:** Manually finding and labeling trash in photos is a dull and time-consuming task. A computer vision algorithm does the job in seconds 3. **Precision:** Computer vision can identify trash at the pixel level, meaning it can be used to make precise measurements (e.g., area, volume, and geolocation)	1. **Ethical considerations:** The use of AI in government programs raises important ethical questions. We believe the risk in our use-case is low, however, because the model can only identify trash (see Privacy Considerations for more detail) 2. **Technical complexity:** Developing and training a model has a high up-front cost. Troubleshooting and maintenance require specific domain knowledge and technical skills
Ortho Mapping The process of creating a contiguous, interactive map from many discrete aerial photographs	1. **Operational usefulness:** Ortho mapping produces geocoordinates for every pixel in a photo and translates a set of images into a more useful format - an interactive map. It also creates a detailed elevation map called a DSM (digital surface model) that KMC can use to model flooding and environmental risk 2. **Interactivity & exportability:** A user can interact with an ortho map by zooming, panning, dropping pins, making annotations, and drawing polygons. Maps can be exported as KML or TIFF files for use with other mapping and navigation software (e.g., Google Earth and ArcGIS)	1. **Requires extreme precision:** Ortho mapping only works if photos are taken in precise locations with consistent altitude, bearing, image overlap, etc. This necessitates flight automation and a higher degree of pre-planning before each surveying session

Table 2: *Description of the technologies enabling our methodology*

[53] IBM, "What Is Computer Vision?"

Methodology

Our methodology follows four stages:

1. **Aerial Surveying:** Designing flight plans and flying survey missions
2. **Computer Vision:** Finding and highlighting trash in drone photos
3. **Ortho Mapping**: Translating the data to an operationally useful format
4. **Deployment:** Using the data to improve operational efficiency in cleaning trash

Each stage and its subcomponents are outlined in this section, with additional technical details provided in Appendix B.

Overview of the Methodology

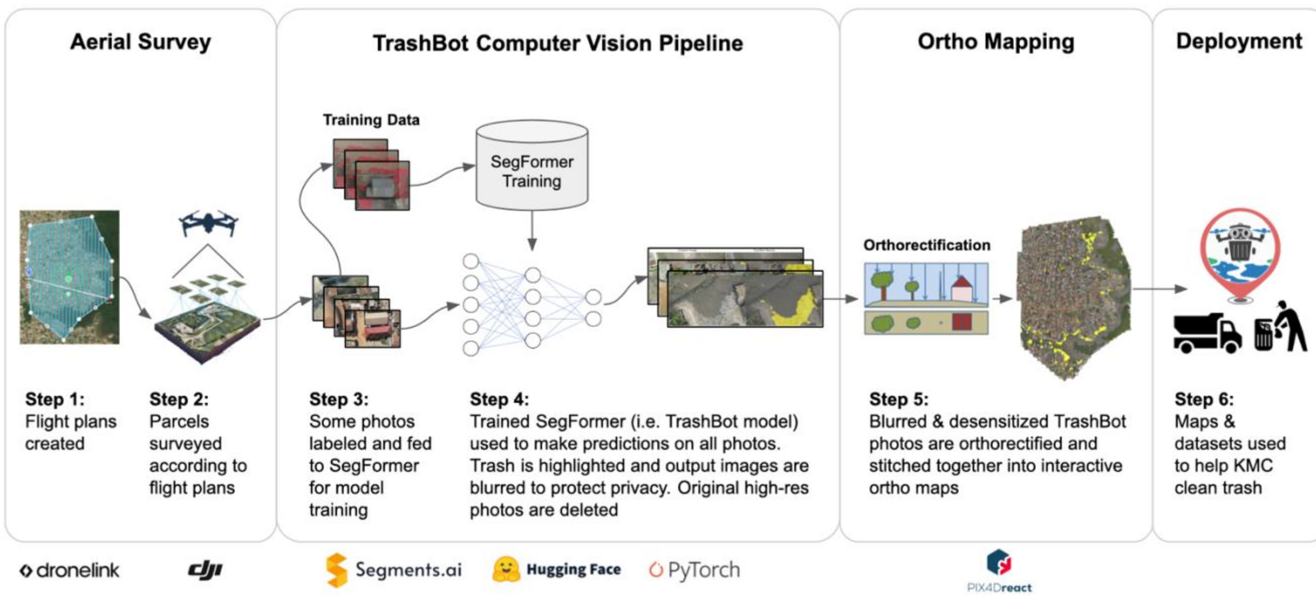

***Figure 8**: All stages of our methodology - each step is described below*

Step-by-Step Process

1. Flight plan design:

Because creating an interactive map from drone photos requires a high degree of precision, we rely on flight automation software to manage aerial surveys. Each parcel is programmed into a tool called Dronelink to create flight plans. Flight parameters, including the takeoff/landing zone, parcel shape and size, flight grid orientation, and drone speed and altitude are set based on surveying goals and technical constraints, such as battery life and radio control range. Dronelink uses all these parameters to set optimal photo waypoints along the drone's route.

Designing Flight Plans

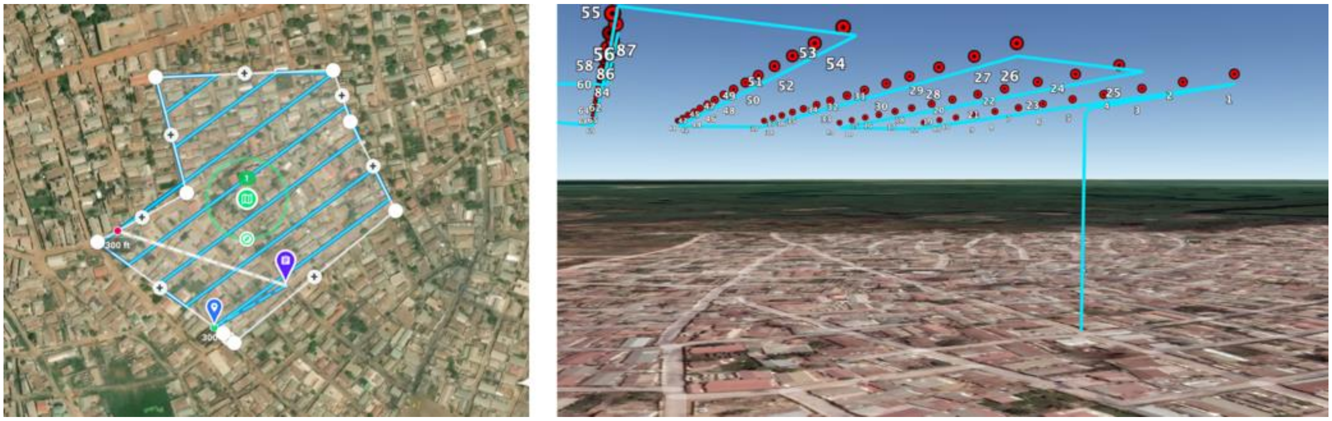

Figure 9: *A flight plan (left) with photo waypoints highlighted in a simulated rendering (right)*

2. Data collection by aerial survey:

Each surveying mission flies a pre-programmed path, taking photos at optimal waypoints. During automated flights, the drone operator's primary responsibilities are managing takeoff and landing, changing batteries, explaining the work to residents, troubleshooting issues, and being on hand to take manual control of the drone if necessary. Drone operation requires no special permit or technical skills, so anybody can do it after a short training.

Drone Photography for Aerial Surveys

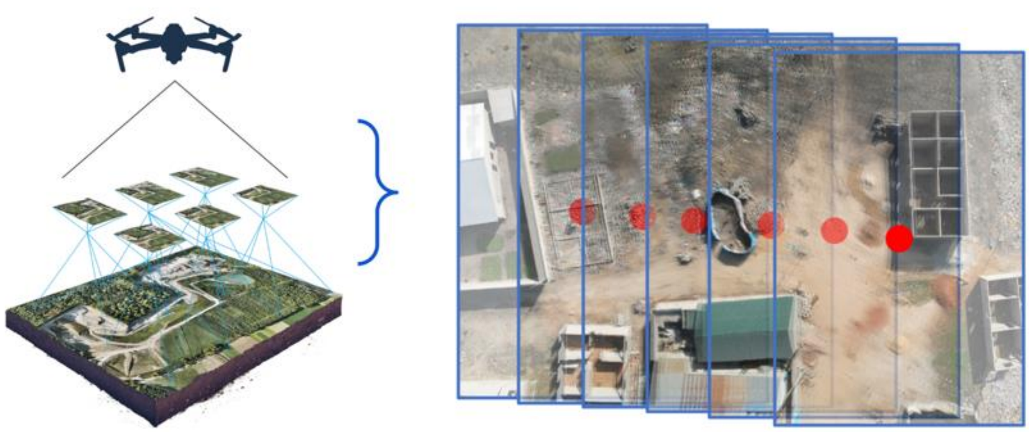

Figure 10: *The drone takes photos at precise locations to be stitched together into a contiguous map in a later step. The red circles represent the drone's location from six photos taken along a route in Tallinding. Because they overlap by a set amount, they can be composed into a single larger image*

3. Image labeling & model training:

We randomly selected 100 photos from each of the first three surveying sessions to be manually labeled as a "truth-set" to train and evaluate our computer vision model. We used Segments.ai to annotate photos, highlighting all the pixels corresponding to openly dumped trash. This step does not need to be repeated now that the model has already been trained.

Labeling Images for Model Training

Figure 11: *Trash pixels (blue) were manually labeled to create a truth-set for training the computer vision model*

The 300 photos that underwent manual labeling were used to train a type of neural network known as a SegFormer, which excels at a particular type of computer vision task called "semantic segmentation." Semantic segmentation provides the same label to all pixels belonging to a given class, allowing us to highlight trash in drone images and make precise quantitative measurements of the size and location of unregulated dumpsites. We call our trained model TrashBot.

Using TrashBot to Find Openly Dumped Trash in Drone Photos

Figure 12: *The TrashBot model identifies and highlights trash in drone photos*

TrashBot is stored on Hugging Face Hub, a free, open-source platform allowing users to share machine learning models. It can be downloaded and applied to an unlimited number of new images.

5. Applying TrashBot to the full set of drone photos:

All drone photos are fed into the TrashBot model. TrashBot highlights all the pixels it classifies as trash, creating a heat map overlaid on each image. It also counts the trash pixels and computes the confidence level of every classification, allowing us to make quantitative measurements and account for uncertainty.

All Photos are Fed into the TrashBot Model

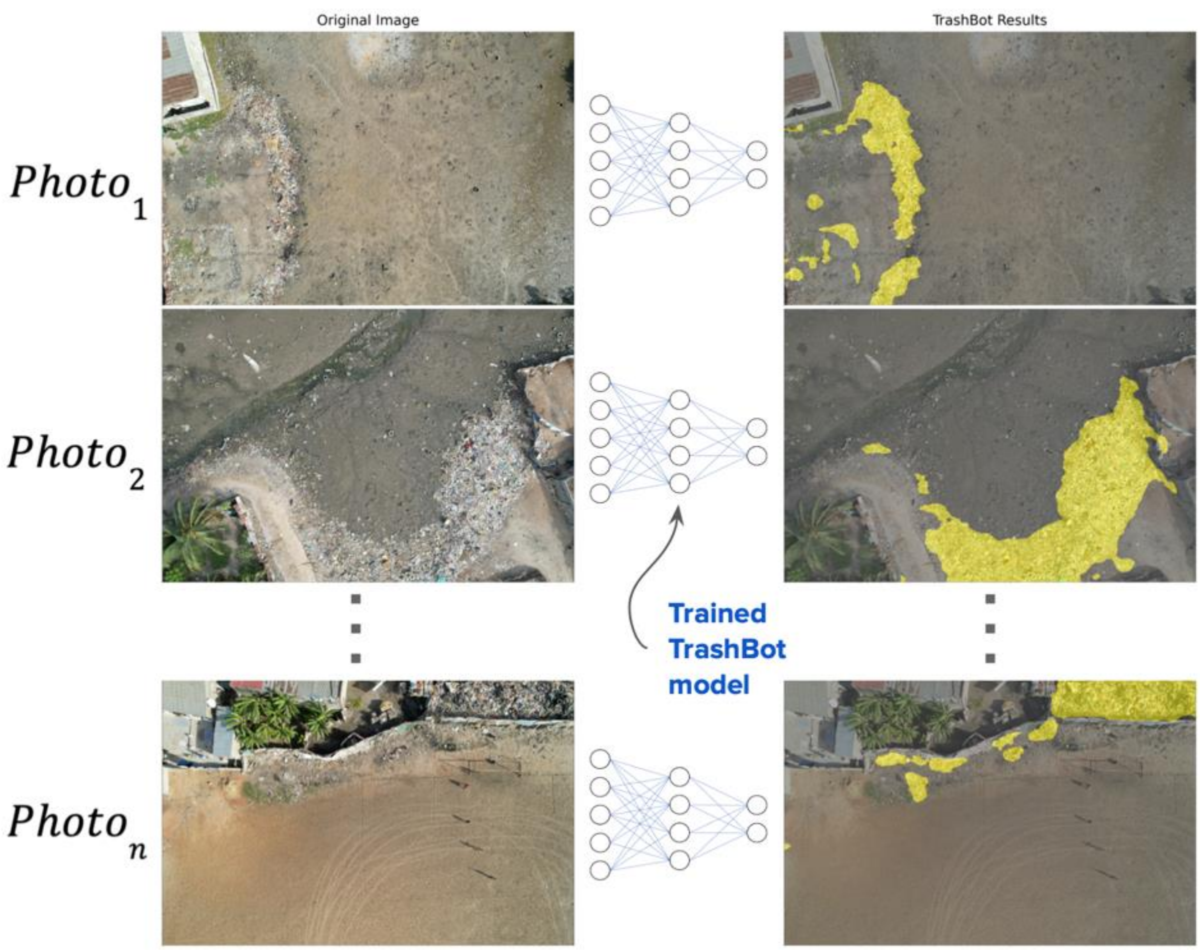

Figure 13: *All photos are fed through the trained TrashBot model, which highlights trash pixels*

6. Blurring, desensitization, and post-processing:

Photos are blurred as soon as they pass through TrashBot to minimize privacy risks. This is the earliest point in the process that images can be desensitized because the model requires high-resolution photos to identify trash accurately. Blurring TrashBot's output ensures three key privacy criteria are met (see Privacy Considerations for more details):

1. A viewer should not be able to identify individuals
2. A viewer should not be able to confidently identify objects smaller than a car
3. The maps should not be useful for anything other than locating trash

After blurring, the original high-resolution images can be deleted.

Blurring out Potentially Sensitive Details

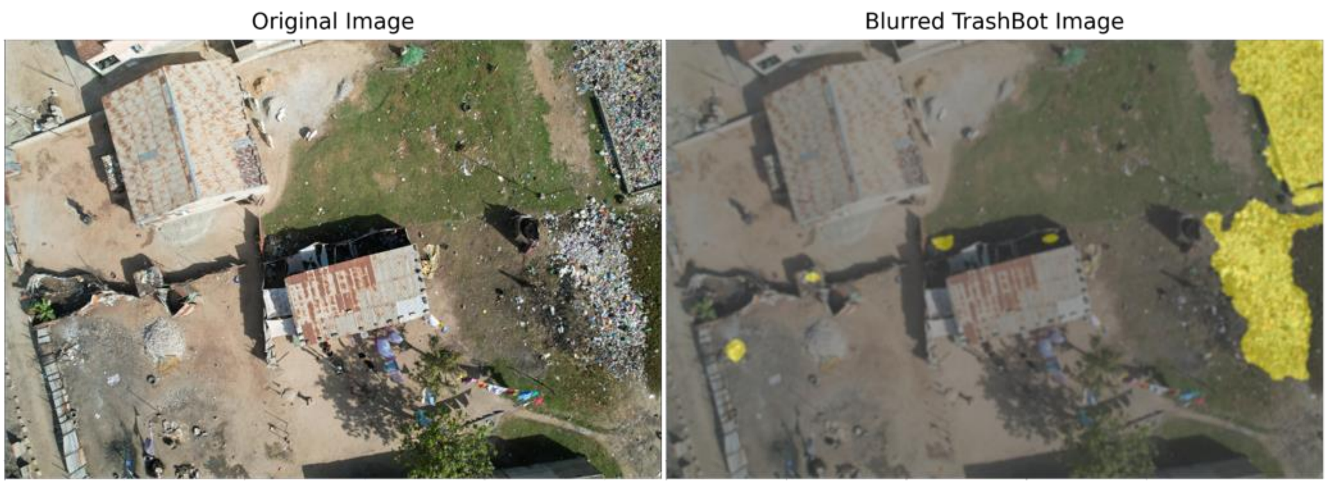

Figure 14: *We blur photos after they are fed through TrashBot to minimize privacy risks*

7. Ortho mapping:

After TrashBot runs on all photos from a parcel, the highlighted output images are combined into a contiguous, interactive map. First, we use a program called PIX4Dreact to remove geometric distortion in the drone photos to ensure pixels can be mapped to their true geographic locations.

Orthorectification: Removing Geometric Distortion from Drone Photos

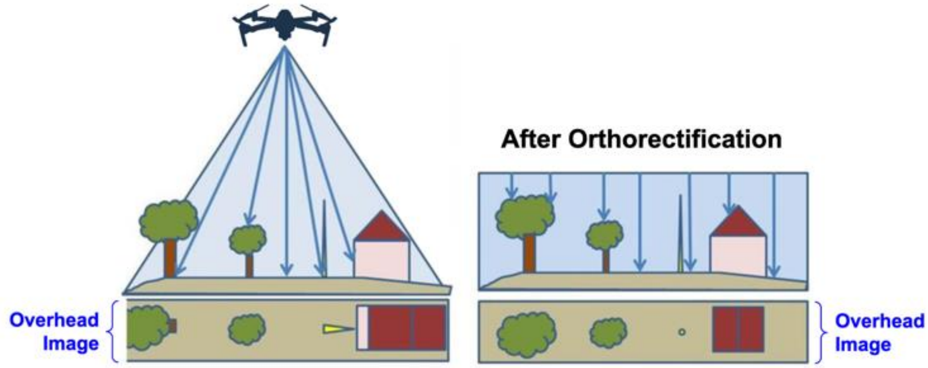

Figure 15: *Anything not directly under the drone's camera is captured at an angle, distorting the overhead image (left). Orthorectification corrects that distortion, allowing for ortho mapping (right)*[54]

Next, PIX4Dreact stitches orthorectified photos together into an interactive map by edge-matching objects in overlapping portions of the images and aligning pixels by their geocoordinates. The result is then exported in filetypes that KMC can access and use in programs like Google Earth and ArcGIS.

Creating an Ortho Map from Discrete Images

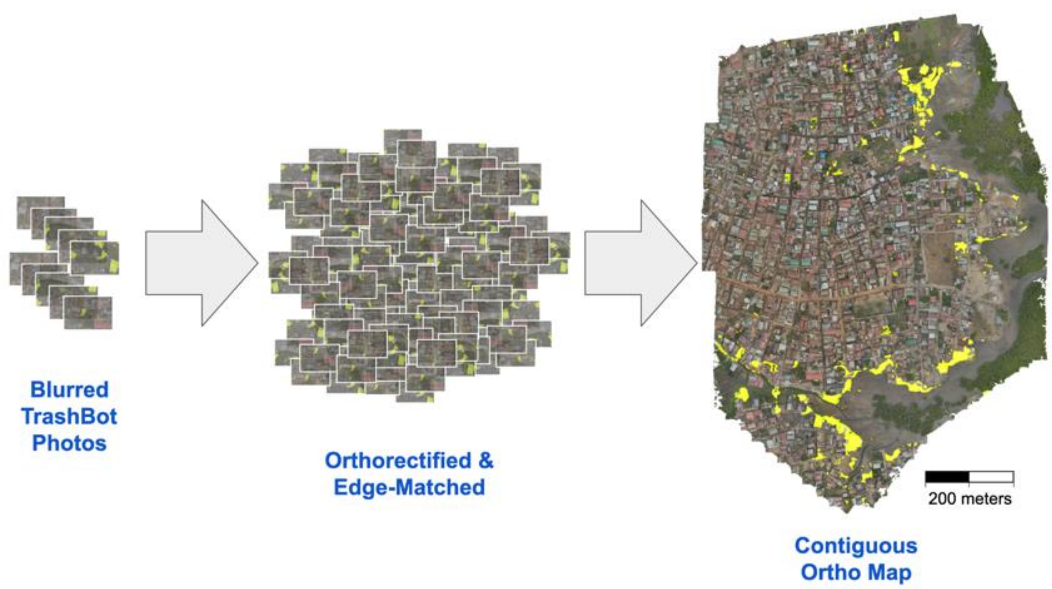

Figure 16: *Stitching the blurred and highlighted TrashBot photos into a contiguous ortho map shows exactly where openly dumped trash is located. The maps can be seamlessly integrated into interactive mapping and navigation tools like Google Earth and ArcGIS*

[54] Geavis, "How Are True Orthophoto Mosaics Made?"

8. Using TrashBot maps to clean unregulated dumpsites:

The interactive ortho maps provide KMC with situational awareness and actionable tools to clean unregulated dumpsites more efficiently. We identified six ways to apply our methods to some of KMC's most pressing MSW management issues (see Use Cases & Operationalization for more detail):

1. Precision-targeting interventions
2. Optimizing receptacle placement (e.g., bins, dumpsters, and communal collection sites)
3. Tracking MSW metrics over time
4. Finding and closing unregulated dumpsites
5. Modeling health and environmental risk
6. Prioritizing areas of need for service area expansion

Section 4:
Results & Analysis

Aerial Survey Results

Over the course of nine days, we mapped seven parcels in five neighborhoods, totaling 607 acres. Using the number of trash pixels identified by our computer vision model, we were able to compute the precise land area of unregulated dumpsites. We located over 380,000 square feet of openly dumped trash, most of which was in large concentrations along the riverfront. The relative land area covered by open dumps in each parcel ranged from 0.02% along Bertil Harding Highway to 5.12% in the riverine area of Tallinding. In terms of absolute land area, riverine Ebo Town had the most trash, with 250,761 square feet.

Summary of Aerial Surveys

Parcel Location (map links in Appendix G)	Flight Altitude	Flight Time	Survey Area	Total Photos	Training Photos	Total Trash Area	Percent Trash
Ebo Town Market 	100 ft	35 mins	17 acres	432	100	0.05 acres 2,031.01 sq.ft	0.27%
Tallinding 	100 ft	35 mins	19 acres	876	100	0.05 acres 2,120.90 sq.ft	0.26%
Riverine Tallinding 	100 ft	55 mins	46 acres	1030	100	2.35 acres 102,500.13 sq.ft	5.12%

Bertil Harding Hwy 	200 ft	38 mins	105 acres	934	0	0.02 acres 855.65 sq.ft	0.02%
Riverine Ebo Town 	200 ft	55 mins	162 acres	1119	0	5.76 acres 250,760.72 sq.ft	3.55%
Dippa Kunda 	200 ft	41 mins	139 acres	925	0	0.47 acres 20,556.33 sq.ft	0.34%
Westfield 	200 ft	40 mins	119 acres	690	0	0.06 acres 2,736.55 sq.ft	0.05%
	Totals:	**299 mins**	**607 acres**	**6006 photos**	**300 photos**	**8.76 acres 381,561.28 sq.ft**	**1.44%**

Table 3: *Summary statistics of our aerial surveys – links to interactive ortho maps are in Appendix G*

Insights from Aerial Surveys

By observing a broad and varied swath of Kanifing, we can use our aerial survey data to draw inferences about how openly dumped trash is distributed across the municipality. The data provide evidence that trash is usually dumped in riverine areas, vacant lots, grassy spaces, small waterways, and abandoned construction sites. Informal settlements like Ebo Town have significantly more trash than established areas like Westfield.

The following examples (Figures 17-20) illustrate general patterns we observed in the types of areas where trash is most commonly dumped:

1. Informal settlements: These neighborhoods are often poor, hard to reach, and underserved. In the absence of reliable public waste collection services, openly dumped trash piles up wherever there is space for it.

Unregulated Dumpsites in Informal Settlements

Figure 17: *This portion of Ebo Town demonstrates typical patterns in the distribution of trash. Large concentrations pile up along the riverfront (right) and in open grassy spaces (lower-middle). This image alone shows over 79,000 square feet of trash along the riverfront. Further inland (left), people dump waste in vacant lots, alleys, and construction sites every few blocks.*

2. Riverine areas: The largest dumpsites are along the shores of the Gambia River. Some stretch for up to a quarter mile and cover over 100,000 square feet. Their proximity to mangrove forests and sensitive marine ecosystems presents serious environmental risks.

Trash Dumped in Riverine Areas

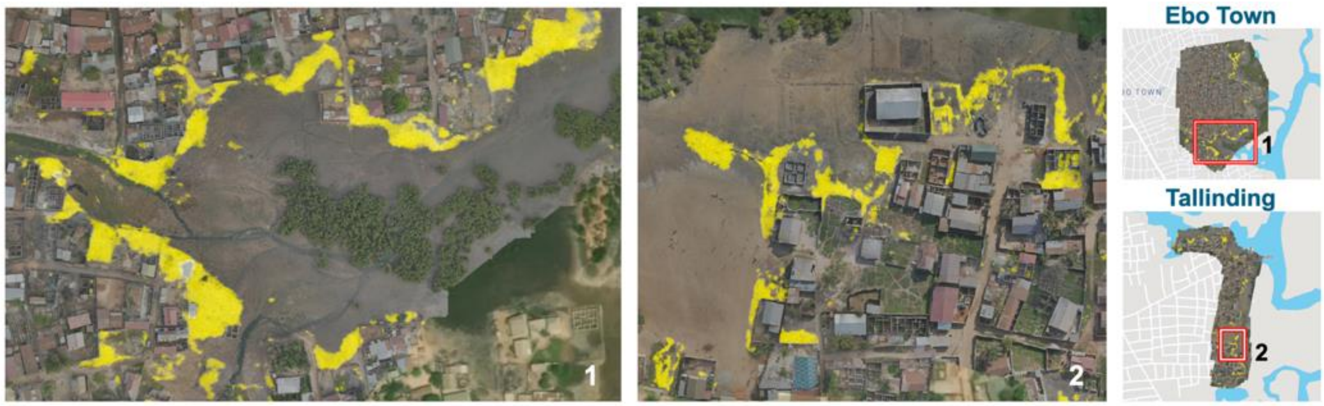

Figure 18: *The riverfront in Ebo Town (left) and Tallinding (right) has some of the largest dumpsites we found*

3. Abandoned construction sites: Many unregulated dumps are located in and around abandoned construction sites, where partially built structures conceal trash out of sight. Aerial surveying is particularly effective at finding these sites since the structures rarely have roofs.

Trash Dumped at Construction Sites

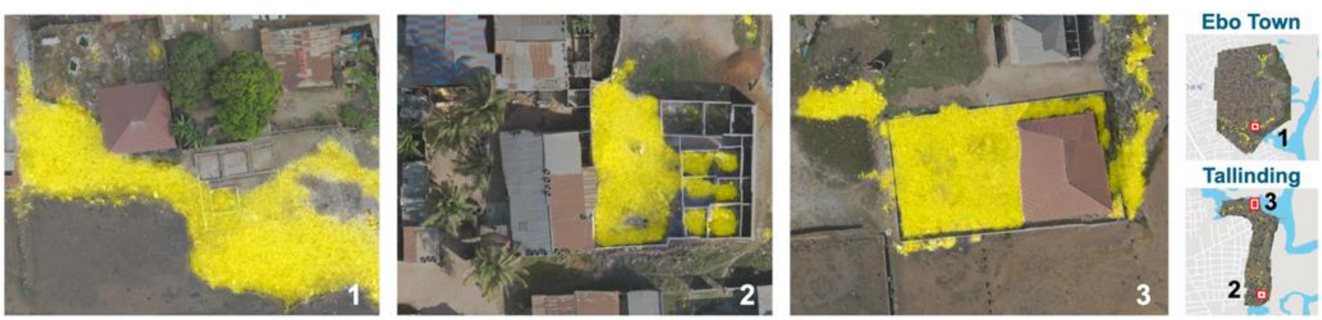

Figure 19: *Trash is dumped in and around unfinished construction sites in Ebo Town (left) and Tallinding (center & right)*

4. Streams and canals: Large amounts of trash are dumped in small waterways that cut through residential neighborhoods. Waste generally piles up along the embankments but is sometimes dumped directly into the water.

Trash Dumped in Streams & Canals

Figure 20: *A small creek in Ebo Town is bordered by trash (left). Trash is dumped directly into a waterway in Dippa Kunda (right)*

Incorporating Elevation Data

In addition to ortho maps, our surveying technique allows us to produce detailed elevation maps of each parcel. Because the photo waypoints along the drone's surveying route overlap by a prespecified amount, the images create a stereoscopic view of the ground called a digital surface model (DSM). The DSM is a byproduct of ortho mapping (it is used to determine the precise geographic location of each pixel), but it also provides its own unique value to KMC when overlaid on ortho maps. The DSM can be used to model flooding risk and to identify low-lying areas that may be affected by runoff or clogged drains in uphill regions. It can also be used to calculate the volume of trash at dumpsites to help KMC determine how many workers or trucks might be needed to clean them (without elevation data, we could only calculate 2D area, not 3D volume).

Elevation Data from the Digital Surface Model (DSM)

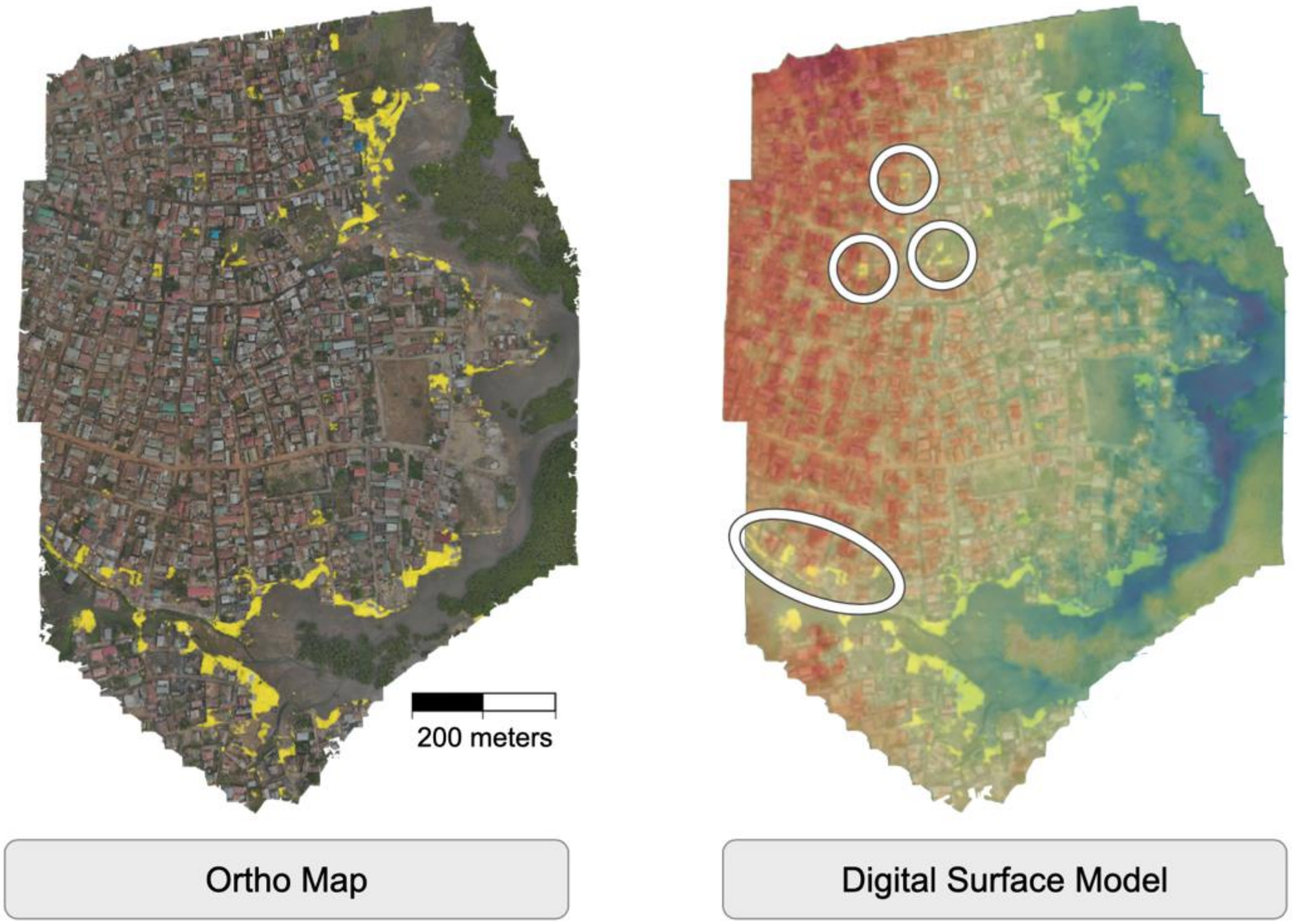

Figure 21: *Using the DSM, KMC can model flooding risk in relation to openly dumped trash. The circled areas highlight trash at higher elevations (red) in Ebo Town that may cause problems for downhill regions (blue).*

Model Performance

We evaluated model performance by measuring the “intersection over union” (IoU) of pixels belonging to the “trash” class. IoU is calculated by comparing truth-set labels from the training data with TrashBot labels on the same images. Formally, it is the number of pixel labels shared between them as a proportion of all the “trash” pixels across both sets:

$$\boldsymbol{IoU} = \frac{\boldsymbol{TrashBot_{Trash}} \cap \boldsymbol{TruthSet_{Trash}}}{\boldsymbol{TrashBot_{Trash}} \cup \boldsymbol{TruthSet_{Trash}}} \text{ or alternatively } \frac{\boldsymbol{True\ Positives}}{\boldsymbol{True\ Positives + False\ Positives + False\ Negatives}}$$

Also known as the Jaccard index, this metric is well-suited to semantic segmentation tasks because it rewards accurate classifications and penalizes models that are both too loose *and* too strict in assigning pixels to the class of interest.

The TrashBot model achieved an IoU of 0.81 out of 1.0 on the "trash" class, making it capable of accurately identifying trash in drone photos. False positives are notably rare. Two exceptions are mosaic driveways, which appear very similar to trash when seen from overhead, and construction rubble. False negatives are more common and generally occur when lighting conditions are poor.

Intersection Over Union (IOU)

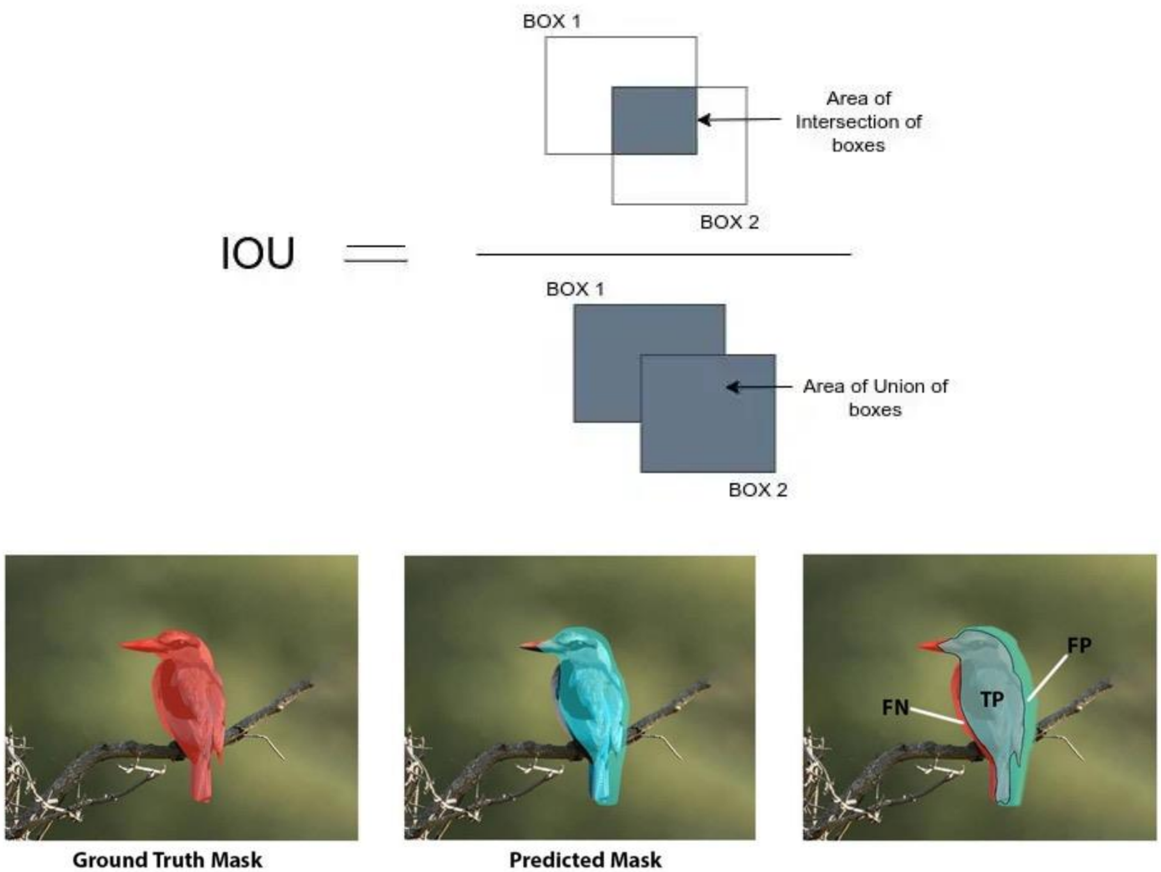

Figure 22: *Top: An illustration of Intersection over Union (IoU) metric.*[55] *Bottom: An example of IoU applied to a semantic segmentation task*[56]

[55] Subramanyam, "IOU (Intersection over Union)."

[56] Kukil, "Intersection Over Union IoU in Object Detection Segmentation."

Two significant factors limit our model's performance. First, there is a high degree of uncertainty baked into the classification task itself because trash piles have poorly defined boundaries that cannot be labeled precisely or objectively in a truth-set. Second, the model was only trained and evaluated on photos taken at an altitude of 100 feet. We originally planned on conducting all surveys at 100 feet but decided after the third session to increase to 200 feet because it significantly reduced privacy concerns while only marginally reducing image quality. We do not have performance metrics on photos from 200 feet because of the prohibitive time investment required to label a new truth-set for training and evaluation. To the eye, however, there does not appear to be much drop-off in performance when the model is applied to images from the higher of the two altitudes. Both limitations are discussed in more detail in the Limitations section.

Section 5: Implementation

Using TrashBot Data to Clean the Municipality

The key to unlocking value from TrashBot data is in applying it towards improving the efficiency with which KMC can clean unregulated dumpsites. Historically, they have not known exactly where their services were needed. With TrashBot, that is no longer a limitation. Knowing the exact location and quantity of openly dumped trash enables them to precision-target areas of need so that their limited resources can achieve maximal reach and impact. If deployed strategically, KMC can use TrashBot data to meaningfully reduce the amount of trash on the ground in public spaces. That means less leachate seeping into the river, fewer floods and fires, lower risk of malaria and bacterial outbreaks, and neighborhoods free of open dumps.

Training & Rollout

A small group of KMC employees could be trained in less than one week to conduct future surveys independently. We designed the methodology to be repeatable without the need for specific technical skills or domain knowledge. The software is intended to be user-friendly, and the drone piloting portions are mostly automated. A single person could carry out the whole program if necessary. Otherwise, responsibilities can be divided among a small team.

Use-Cases & Operationalization

We identified six ways the TrashBot model and methodology can help KMC deal with MSW management challenges more efficiently. Each is described below with a basic implementation roadmap:

Using TrashBot to Improve Operational Efficiency in MSW Management

Intervention Targeting

Description

If KMC knows the location of openly dumped trash, they know where to direct their resources & attention

Value Proposition:

KMC can get more impact from its existing resources by precision-targeting interventions. They can send sanitation workers, trucks, and tricycles directly to dumpsites or clogged drains, and they can direct community cleanups and private-sector partners to areas of need

Implementation:

No new processes need to be introduced, but TrashBot data must be integrated into existing processes. This can be done simply by having decision-makers look at maps to make more informed choices, or by involving the GIS team to generate geospatial insights and pass that data to operational teams

Optimizing Receptacle Placement

Description:

KMC can use the distribution of openly dumped trash to infer where waste receptacles & communal sites ought to be

Value Proposition:

Bins and dumpsters keep trash off the ground. The more optimally they are placed, the greater their impact – especially given that a leading factor in indiscriminate dumping is long distances to the nearest approved disposal site

Implementation:

This strategy can be deployed independently or as part of the Kanifing Environmental Transformation Programme (KETP) "zero-waste municipality" initiative, which involves distributing 35,000+ trash cans. It can also inform KMC's plans to deploy more dumpsters. Areas with high concentrations of trash and wide access roads might be ideal. A technical approach could use clustering algorithms to find optimal locations for any number of bins or dumpsters

Finding & Closing Dumpsites

Description:
TrashBot data can help KMC find unregulated dumpsites and detect when previously closed sites re-establish themselves

Value Proposition:

KMC has closed dozens of illegal dumpsites in recent years, but many remain. And many more may exist outside of KMC's awareness. TrashBot data makes it easy to find these sites & detect when previously closed sites reopen

Implementation:
KMC would need to develop a database of known dumpsites with their status (i.e. whether they have already been shut down). Then they could compare TrashBot data to the set of known dumpsites to (1) add newly found sites to the repository, (2) schedule newly found sites for inspection / closure, and (3) detect when previously closed sites have reopened

Tracking MSW Over Time

Description:
Parcels can be surveyed repeatedly at regular intervals. Each time, the quantity of trash detected by TrashBot can be compared with prior surveys of the same area

Value Proposition:

KMC can use longitudinal TrashBot data to track operational metrics and evaluate sanitation programs (e.g. community cleanups and tricycle deployment to hard-to-reach areas)

Implementation:
KMC should consider which operational metrics could come from TrashBot data (e.g. trash ground area & volume, number of dumpsites). Parcels would need to be scheduled for repeat visits. These might be timed up with monthly community cleanups, done on arbitrary periods (quarterly, yearly, etc.), or simply before & after specific interventions

Modeling Health & Environmental Risk

Description:
Geospatial insights from TrashBot can be used to focus attention on high-risk areas

Value Proposition:

The level of risk presented by unregulated dumpsites is partially determined by their location. TrashBot data can help KMC identify the trash concentrations (and ideally also burn pits and clogged drains) that are the most likely to cause harm to people or the environment

Implementation:
This use-case would likely need to incorporate knowledge and data from public health and environmental authorities, who could relate geospatial insights from TrashBot to domain-specific risks (e.g. flooding, groundwater contamination, air pollution, epidemiology). KMC could make use of the TrashBot elevation maps as a new data source for modeling flooding & water pollution risk

Prioritizing Needy Areas for Service Expansion	**Description:** Areas outside KMC's current service range can be evaluated to see how urgently they need waste management services **Value Proposition:** As KMC expands its waste collection service range, information about the distribution and quantity of openly dumped trash can help ensure that services are expanded first to areas where they are most urgently needed	**Implementation:** KMC would need to survey comprehensively in areas outside their current service range. A narrower approach might target areas that will become reachable when KMC expands its fleet of tricycles to access hard-to-reach areas. Tricycle routes can be created to target the neediest of the newly reachable neighborhoods

Table 4: *Six ways KMC can use our methodology to increase operational efficiency in dealing with the MSW problem*

Costs and Scalability

Costs: The costs of this program are relatively modest compared with other line items in KMC's waste management budget.[57] The main up-front cost is for hardware. The DJI Air 2S drone we used cost $1,134. We purchased a bundle with two extra batteries (highly recommended because each battery adds 20-25 minutes of flight time) and other useful accessories. Ongoing program costs include labor and about $100/month for software ($70/month for PIX4Dreact and $30/month for Dronelink).

Scalability: We surveyed 0.95 square miles (607 acres) in 5 hours of flight time, but our first three flights were flown at low altitudes and therefore covered less ground. After adjusting to 200 feet and working out some operational inefficiencies, we averaged about 3 acres per minute, or about 3.5 hours per square mile. At that rate, one person with one drone could map every square inch of Kanifing Municipality in about 100 hours. Using multiple drones would increase efficiency by multiples. One person could theoretically operate more than one drone on adjacent routes since they are flown autonomously. In practice, managing more than two drones simultaneously would probably be difficult.

[57] Kumar et al., "ODI Working Paper: Waste Management in Africa."

Total operating costs can be modeled with the following formula:

$$operatingCost = (1134 * nDrones) + \left(nSurveyors * wage * \left(sq.mi * \frac{3.55}{nDrones}\right)\right)$$

Where *nDrones* is the number of drones in operation, *nSurveyors* is the number of workers, *wage* is the average hourly wage of the surveyors, and *sq.mi* is the number of square miles surveyed.

Operating Costs as a Function of Survey Area

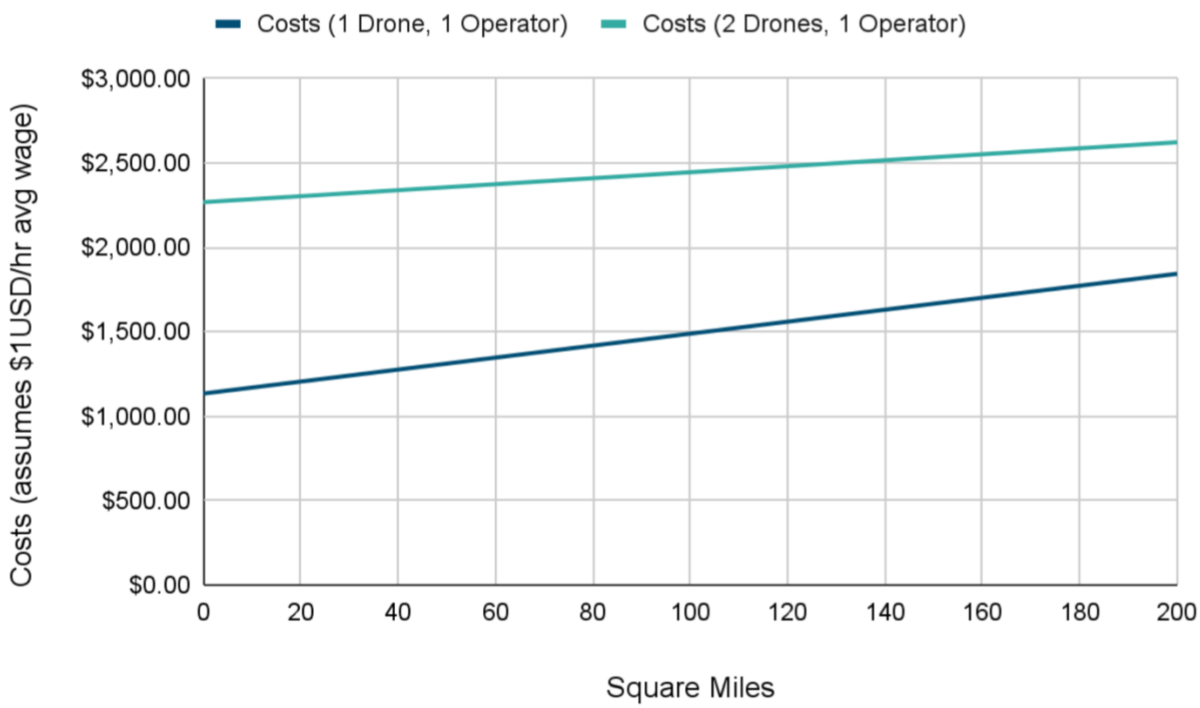

Figure 23: *KMC can survey the entire municipality for about $1,200 USD plus software costs. Note that at a certain point, the extra up-front costs of a second drone are more than paid for by efficiency gains. Due to low labor costs in The Gambia, that point is quite high (about 640 square miles)*

Key Operational Learnings

Although our methodology relies heavily on automation, there are important lessons we learned by working through issues in the field. Appendix C details key operational learnings, including timing and seasonality, obstacles and restricted flight zones, route design best practices, and privacy considerations.

Section 6: Discussion

Privacy & Impact Statement

When assessing our methodology's potential impact, we should not presume that it is always justifiable for governments to conduct drone surveys or use AI to solve public problems. There are few well-established rules or norms around either technology, and people in different social, legal, and cultural contexts may have different views. There is, however, some precedent for governments using remote sensing to improve their operations in other parts of the world. For instance, French[58] and Greek[59] authorities have used satellite imagery to spot unregistered swimming pools and collect unpaid property taxes from the owners.

But there is also precedent for public opposition to the practice.[60] Aerial imagery is particularly controversial in the context of law enforcement. The American Civil Liberties Union (ACLU) has

[58] Kumar et al., "ODI Working Paper: Waste Management in Africa."
[59] Steinvorth, "Finding Swimming Pools with Google Earth."
[60] Nichols, "Is Google Earth Eyeing Your Pool?"

published reports outlining risks[61] and documenting specific instances of government drone usage[62] to highlight how the practice can threaten civil liberties. They cite mission creep (i.e., when innocuous drone programs morph into more harmful ones as governments start experimenting with new ideas), voyeurism, the threat of institutional abuse, and other potential harms before recommending measures to mitigate privacy concerns. These include usage restrictions (e.g., “to only non-law enforcement purposes…where privacy will not be substantially affected”), image retention restrictions, public notice requirements, democratic control, and auditing practices. We consider these mitigation techniques essential to this project's viability. If our methodology cannot be carried out in an ethical and privacy-protective way, it should not be implemented at all.

Throughout this project's design and research phases, we took every precaution to decrease privacy risks and minimize the chance of harming or wronging Kanifing residents. Our efforts included increasing flight altitude from 100 to 200 feet after the first few surveys, blurring photos, storing files in encrypted and password-protected folders, and deleting images when processing was finished. Still, it is important to evaluate the privacy implications of our methodology in detail to determine whether and how KMC ought to proceed.

Privacy Considerations

Because we designed a novel technological approach to address KMC’s MSW problem, there is no direct comparison between the privacy considerations of our methodology and established surveying techniques. The closest comparison is the use of satellite photos in aerial surveys. Virtually every inch of land has been photographed extensively by satellite cameras and assembled into detailed maps like our own. For instance, Google Maps gives anybody free access to imagery ranging from 15 cm/pixel to 15 m/pixel.[63] And in many areas, Google Maps augments satellite imagery with higher-resolution images taken from planes. Like our methodology, satellite surveys cast a broad net and cannot avoid photographing private spaces like backyards. Yet, most people would not consider Google Maps to be intrusive.

But our maps differ from satellite maps in two crucial ways. First is image resolution. Drone-based surveys can achieve pixel resolutions up to 100x better than satellites, and it is reasonable to conclude that high-resolution imagery is more intrusive than low-resolution imagery. Second is the fact that people on the ground are aware that a camera is overhead taking pictures. A drone is visible and can be quite noticeable, whereas a satellite is not.

[61] Stanley and Crump, “Protecting Privacy From Aerial Surveillance: Recommendations for Government Use of Drone Aircraft.”

[62] ACLU of New York, “Prying Eyes.”

[63] For comparison, our drone captured 1,85 cm/pixel resolution at 200 feet and 0.93 cm/pixel at 100 feet

Comparing and contrasting the ethics of drone and satellite surveys may help reveal (1) lines that should not be crossed in the design and deployment of our methodology, and (2) specific steps that should be taken to reduce privacy risks.

If we consider image resolution to be an important factor in the acceptability of aerial surveys, it stands to reason that there is some threshold where on one side, an aerial image is not a privacy risk, and on the other side, it is. For instance, Google Maps is widely considered to be permissible, while drone photos are more controversial. To ensure our maps fall on the right side of the threshold, we built a tunable parameter into our image processing pipeline to add a specified amount of blur to all photos before they are stitched into ortho maps. This ensures that image resolution can be reduced to an acceptable level before anybody uses the maps. We developed the following criteria to assess whether our maps were low-resolution enough for use:

1. **A viewer should not be able to identify individuals in photos or maps.** Where people are present, they should look like pixelated smudges if they are distinguishable at all.
2. **A viewer should not be able to confidently identify objects smaller than a car.** This is intended to prevent prying into people's private spaces. For instance, our maps will not enable a viewer to see what somebody has in their backyard.
3. **The map should only be useful for locating trash.** This criterion is intended to prevent mission creep. Our maps should not facilitate any unintended use cases that may have more sensitive privacy implications.

With these criteria in place, it is unlikely that our maps will pose a risk to any individual or be misused in any way. But even if risk and harm are completely mitigated, we must address the possibility that some residents might be uncomfortable with drone surveys. The fact that drones are visible as they take photos, whereas satellites are not, creates the possibility of people feeling discomfort or distress due to seeing a drone as it surveys their area. This is especially likely if they do not know what the drone is being used for. A recent study interviewed 20 U.S. participants about their perception of drones and found that 55% felt as if they were being watched when they were around one. Some participants said that drone photography of private spaces was intrusive and that the detachment and anonymity of the drone operator exacerbated their unease. 80% of participants were concerned about the potential of being recorded in public or their own homes without knowledge or consent.[64]

These concerns are valid and important to consider for our project's viability. Critically, they point to the importance of public disclosure and democratic control. Residents should be consulted with and made aware of any government program conducting drone surveys in their neighborhood. They should also have an opportunity to voice their concerns and potentially to veto the proposal. Elected

[64] Chang, Chundury, and Chetty, "Spiders in the Sky."

representatives (e.g., KMC councilors) and community leaders can communicate the program's risks and benefits to residents and represent their interests when deciding whether and where aerial surveys should be conducted.

The Risks of Using AI & Computer Vision in Government Programs

Another potential area of concern is the use of AI and computer vision in government programs. Although there may be risks associated with these technologies in some use cases, we do not believe our program presents any significant issues. The TrashBot model can only do one task - identify trash. It cannot detect people, cars, houses, or anything potentially sensitive. Everything is either "trash" or "not trash." Misclassifications and errors are unlikely to result in harm, and the model simply ignores all potentially sensitive data.

Recommendations

The benefits of our methodology are significant, but the potential for harm cannot be completely eliminated. Ultimately, communities should have some say in whether their government uses drones and computer vision for MSW management. Community leaders and democratic bodies (e.g., KMC council members representing their respective wards) should be consulted before any program like ours is implemented on a large scale. People should have a forum to give their input about whether they think the pros outweigh the cons and what privacy criteria must be in place for the program to be acceptable.

Limitations & Future Directions

Limitations

There are three significant limitations of our model's performance and applicability. First, it failed at identifying litter and burn pits - both of which KMC expressed interest in. Second, classification accuracy is somewhat affected by the fact that our training data is composed of images taken at 100 feet, even though we increased flight altitude to 200 feet for privacy reasons after the third survey. Third, the task of labeling trash is inherently subjective and imprecise (i.e., because trash piles usually do not have distinct boundaries), so there is a limit to model performance based on this baked-in uncertainty. Appendix D describes these limitations in more detail and provides strategies for overcoming them.

Future Directions

Other Applications:

This project proves that combining drone photography, computer vision, and ortho mapping is viable for detecting trash in urban settings in The Gambia. The same methodology may work in other environments or geographies. Within Kanifing Municipality, we could try detecting trash in parks, waterways, beaches, and drains & gutters. KMC has expressed interest in each of these possibilities - especially the latter. There is some precedent for using drones and computer vision to find trash on beaches[65] and in open waters,[66] and there are cases where our model successfully detected trash in waterways and parks. Drains & gutters may be more difficult but more impactful. If KMC could map clogged drains right before the rainy season starts, they could clear the most concerning blockages and significantly reduce flooding risk.

We could also adapt our methodology for other government use cases, such as measuring reforestation efforts in mangrove forests. KMC has invested considerable resources in environmental management and has expressed interest in such a program.

Improving Model Performance:
While model performance was good enough to make TrashBot immediately viable, we could improve performance by retraining the model on observations taken from 200 feet. To maximize the performance of a computer vision model, it is generally advisable to ensure the training data looks as much as possible like unseen observations. Creating a new training set would take about 20-30 hours, although the process could be sped up considerably by outsourcing the work or leveraging TrashBot to help label a new training set.[67]

Another approach to improving model performance would be creating separate models for each parcel. Ebo Town Market, Dippa Kunda Creek, and Riverine Tallinding all look fundamentally different. The first is crowded and urban, the second is bisected by a waterway with grassy banks, and the third is sandy and expansive. Even though TrashBot generalized well across environments, we would probably achieve better performance by creating a separate model for each area. The up-front time investment in labeling that many training sets and building that many models might pay off in the long run if parcels are visited repeatedly as part of a broader implementation.

Using Other Remote Sensing Technologies:
High-end drones can be outfitted with multispectral cameras that are sensitive to polarization and multiple bands of wavelengths. We used a much simpler camera due to budget constraints. However, multispectral cameras might perform better, especially in unideal lighting conditions where our model struggled to identify trash.

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[65] Coxworth, "AI-Enabled Drones Will Tell Human Teams Where to Find Marine Debris."

[66] Garcia-Garin et al., "Automatic Detection and Quantification of Floating Marine Macro-Litter in Aerial Images."

[67] A practice called "model assisted labeling"

But what if we didn't have to use drones at all? The relative merits and drawbacks of satellites and drones are discussed in Appendix B, but in short, satellites cover much more territory at a much lower resolution than drones. Although satellite imagery is more scalable by orders of magnitude, the viability of computer vision models on small, fine-grained objects like trash requires sharper images than satellites can provide. This may change soon, though. The next generation of satellites launching in 2024 will achieve 10 cm/pixel resolution. [68] For comparison, the current state-of-the-art for satellite imagery is 30 cm/pixel, and our drone captured images at 1.85 cm/pixel. 10 cm/pixel resolution may be sharp enough for a computer vision model like TrashBot to work. Whether the feasibility threshold is 10 cm or something smaller, it seems plausible that trash detection by satellite will eventually become a reality as the technology continues to improve. It would benefit governments to start thinking about how they can leverage remote sensing data now, knowing that it will be available at increasingly larger scales and higher resolutions in the near future. And importantly, citizens benefit if their governments have experience grappling with the ethical questions raised by deploying these new technologies for public impact.

[68] Satellite Imaging Corp, "Albedo Satellite Constellation (10cm)."

Section 7: Conclusion

This project established the viability of using drones, computer vision, and ortho mapping as tools for KMC to find, map, and measure unregulated dumpsites. We fulfilled all our success criteria: (1) we developed and implemented ethical standards to protect residents' privacy, (2) we identified six practical use cases for operational impact, (3) we built a model that can accurately detect trash, (4) we designed a process that can scale to the whole municipality, (5) we built software for KMC to run the methodology on its own, and (6) we kept costs low enough to ensure feasibility.

But just because the methodology is viable, it does not mean it should be implemented without careful consideration. KMC should engage with residents and community leaders to ensure that the benefits outweigh the risks and that people are comfortable with the government using drones and AI to locate trash.

If that hurdle is cleared, KMC has a new tool to improve the efficiency with which it cleans trash from public spaces. By finding, mapping, and measuring openly dumped trash, KMC can work towards providing immediate and ongoing relief to communities struggling with openly dumped trash.

Appendices

Appendix A: Waste Management in Kanifing

In 2002, the Local Government Act established the current system of local governance and delineated the responsibilities of each LGA. Waste management was one of the duties given to local authorities, meaning that each LGA became responsible for planning, financing, and operating its own waste management system. There are national policies that guide their implementations, however, including the National Environmental Management Act (1994), the National Solid Waste Management Strategy (1997), the Environmental Quality Standards Regulations (1999), the National Waste Management Bill (2007), and the Anti-Littering Regulations (2008).[69]

Within KMC, the Environment and Sanitation Unit (ESU) in the Department of Services is responsible for municipal solid waste management and environmental issues. The ESU's responsibilities include cleaning streets, markets, schools, hospitals, and other public spaces, and clearing unregulated

[69] Kumar et al., "ODI Working Paper: Waste Management in Africa."

dumpsites. They employ 173 laborers, 17 drivers, 16 drainage maintenance workers, 12 mechanics, and nine tricycle drivers.[70]

In 2019, KMC established "The Mbalit Project" to expand upon the ESU's work by implementing the nation's first household waste collection service. The municipality procured 23 state-of-the-art compactor trucks for the job. One truck is allocated to each ward for daily service, and the remainder are used for overflow capacity and catching up on missed routes. The trucks also attend to large dumpsters at communal collection sites. Notably, the Mbalit Project provides service everywhere that they can access, but many areas - especially in informal settlements - cannot be reached by truck due to the narrow throughways and the state of the largely unpaved roads. The trucks' service range is further limited in the rainy season when flooded, muddy streets make much of the municipality unreachable. Currently, KMC is investing in a fleet of motorized tricycles that will expand services to the harder-to-reach areas of the municipality.

Because Kanifing only has one landfill and no transfer stations or facilities for separation and recycling, all collected waste is brought to the Bakoteh Dumpsite. Covering nearly 44 acres, the sprawling landfill has been in operation since the early 1980s despite its substandard conditions.[71] Its central location near densely populated areas makes it an unideal destination for the municipality's waste. KMC is currently planning construction of a new sanitary landfill to replace Bakoteh.

In addition to public sector resources, waste management in Kanifing depends on a patchwork of private actors who are paid by residents at the point of collection, and by the municipality upon depositing waste at Bakoteh. Known as Donkey Men, they often use donkey-drawn carts or other small vehicles to access areas that KMC struggles to reach. Too frequently, though, private collectors lack the financial incentive to bring waste all the way to Bakoteh, choosing instead to dump it locally at unregulated sites. KMC has begun offering payment to Donkey Men to empty their carts directly into garbage trucks to prevent them from contributing to the growth of open dumps.

Citizens have also been tapped to contribute to the waste management effort. Three programs known as Operation Clean the Nation, Operation Clear Illegal Dumps, and Operation Clean the Drains rely on residents to take direct action in their communities. Established in 2004, Operation Clean the Nation, known locally as Set-Settal, has lost much of its popularity in recent years, reducing its impact in most of the country. The NEA is working on reestablishing the program, and the first event was held on January 28, 2023.[72]

[70] Kumar et al.

[71] Jallow, "National Technical Workshop on Environment Statistics in The Gambia."

[72] Tamba, "Gov't To Bring Back Monthly 'Set-Settal.'"

Despite its constraints, KMC has made noticeable improvements to the state of waste management in the municipality due to Mayor Bensouda's decision to make it his number one priority. Recent initiatives include the Mbalit Project, renovation of Bakoteh access roads, procurement of trucks and motorized tricycles, programs to separate compostable waste in markets, plans to build transfer stations and a new landfill, investment in recycling and waste-to-energy capabilities, and establishment of a call center to field complaints and questions relating to waste management.[73]

[73] Kumar et al.

Appendix B: Technological Details & Methodological Notes

Aerial Surveying

We decided an aerial survey would have the greatest chance of successfully creating a ground-truth dataset of the location and quantity of openly dumped trash. Compared with ground-based surveying methods, aerial surveys offer three key advantages:

First, more territory can be covered by making observations from above. A single photograph from 200 feet altitude captures an area of 312 by 208 feet - a total of 64,896 square feet. It might take a person on the ground dozens of photos and a substantial amount of time to document the same area. This particular advantage is magnified by the poor road conditions in much of Kanifing Municipality. Driving through windy, narrow, unpaved roads makes for slow-going, whereas flying overhead is comparatively easier.

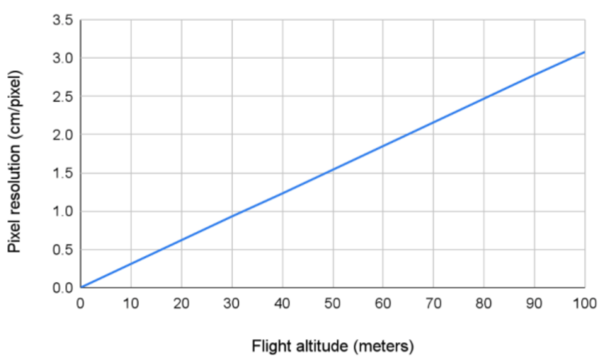
Second, aerial surveying is more comprehensive than ground-based surveying. An aerial survey can observe everything on the ground, making it less likely that key details are missed. A ground-based survey is more likely to result in incomplete data because observations are dependent on the surveyor's ability to find and document all key details. In other words, an aerial survey casts a broad net, so if a given area does in fact have openly dumped trash, it is very likely to be present in aerial photos. Because ground-based surveys are more reliant on the observer's attention, we might reasonably doubt whether an area recorded as having no trash actually has none or if the surveyor simply failed to document it.

Third, aerial photography can be standardized more effectively than ground-based observations. Overhead photos provide a uniform perspective of the ground as long as details like altitude and zoom are controlled for. This consistency makes it possible to compare different parcels of land, apples-to-apples, without worrying that the observer's perspective will affect observations and measurements. In contrast, a ground-based surveyor's observations may have an extreme amount of variance based on how close they stand to the trash, the angle and zoom of the photo, how the trash is positioned in the frame, or how much of it they can capture in a single photo. Such observations may work for simply locating openly dumped trash, but it would be hard to accurately measure and compare quantities across multiple observations.

Despite its advantages, aerial surveying has some notable drawbacks. First, aerial photos cannot document trash that is located beneath overhead cover such as trees, sheds, or awnings. Additionally, visual evidence of trash might be obscured in heavily trafficked areas including outdoor markets and commercial centers, where pedestrians, cars, and street vendors clutter the frame and make it hard to see through to the ground. Second, there may be areas where aerial photography is impossible due to tall buildings, restricted airspace, or other obstacles. Third, aerial surveys present more privacy concerns since they capture more information than they need including private property.

Why Use Drones?

High-resolution images are needed to detect trash from above. This requirement rules out satellite imagery, which does not achieve high enough resolution for the task. Best-in-class commercial satellites generally achieve 30 cm ground sampling distance (GSD), meaning each pixel captures a 30x30 cm area.[74] We received sample images from Airbus Intelligence's Pléiades Neo satellite to assess the viability of 30 cm GSD imagery for our use-case. The best proxy for Kanifing Municipality that Airbus had available was Dakar, Senegal. From these photos, we determined that 30 cm GSD images would not be sharp enough for our purposes. Some providers offer satellite imagery that is upscaled to 15 cm resolution, but because the fine-grained details necessary for identifying trash are not present in 30 cm GSD images, they cannot be sharpened by the upscaling process. Drones, in comparison offer a much higher pixel resolution. For example, a DJI Air 2S flying at an altitude of 100 feet achieves a pixel resolution of 0.93 cm - roughly 32 times better than most state-of-the-art satellites.



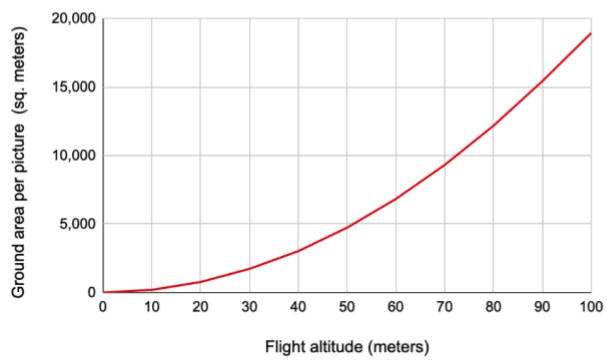


Figure 24: *Pixel resolution (left) and ground coverage (right) at various flight altitudes for a DJI Air 2S drone. Note that resolution scales linearly and ground area scales quadratically. This is important when optimizing the resolution / scalability trade-off*

To date, the use of drones in MSW management has primarily been applied to monitoring landfills[75] and marine environments.[76] Using technologies like multispectral imagery, environmental sensors, and 2D/3D mapping, drones have proven to be effective tools in assessing the size, location, contents, and environmental effects of trash in these settings. There is less precedent, however, for drones being used in urban settings for similar purposes.

[74] "Image Specs | European Space Imaging."

[75] Sliusar et al., "Drone Technology in Municipal Solid Waste Management and Landfilling."

[76] Gonçalves et al., "Beach Litter Survey by Drones."

Drone Ortho Mapping

The most significant limitation of using drones instead of satellites is that drones capture a much smaller ground area with each picture. For this reason, we rely on a process known as ortho mapping to stitch together thousands of images into a contiguous map covering a large area.

Ortho mapping requires a high degree of precision to work. The drone's flight path must be programmed in advance and flown autonomously. The locations where the drone captures images are set depending on the size and shape of the surveying area. These waypoints are determined so that the full ground area is covered, and the images have enough overlap to be seamlessly stitched together. Each photo is taken directly overhead with the camera facing straight down. The resulting set of images covers the desired area but needs to be corrected for distortion so that the individual photos combine to a geographically accurate map.

First, the actual ground position of each pixel is determined by combining camera calibration information (e.g. pixel size and focal length), with geographic data (e.g. the drone's latitude, longitude, bearing, and elevation). Pixel locations are further refined by creating a digital surface model (DSM) that calculates ground and structure elevation by comparing images of the same region from multiple points of view. The geographic overlap between photos creates stereoscopic imagery, which the DSM can use to compute ground contours and structure height.

Next, the images are scaled, color balanced, and resampled so that all pixels accurately represent their true geographic positions. This process, known as orthorectification, removes geometric distortion from the images so that the resulting photos appear as if they were taken directly overhead.[77] Without orthorectification, measurements relying on the position of pixels, such as an object's size, area, and exact location, would be inaccurate.

The set of orthorectified images, known as an orthomosaic, is then merged into a contiguous whole by a process called edge matching. Edge-matched photos are aligned using geographic and visual information in overlapping portions of orthoimages to create an accurate map. Finally, the ortho map can be exported in standard formats (e.g. GeoTIFF (.tif) and Keyhole Markup Language (.kml)) to be used interactively with mapping software such as ArcGIS and Google Earth.

Computer Vision

To maximize the scale and efficiency with which KMC can survey areas for unregulated dumpsites, we use computer vision to automate the process of detecting and quantifying trash in our overhead

[77] ArcGIS, "What Is Photogrammetry?"

photos. This process allows for order-of-magnitude efficiency gains over manually tagging trash in photos, which itself is considerably more efficient than ground-based surveying.

Computer vision is a broad term applied to the field of artificial intelligence (AI) that "enables computers and systems to derive meaningful information from digital images, videos and other visual inputs."[78] Generally, the process involves training a model on labeled digital images so that it can learn patterns that are useful for making predictions on unseen samples. In our case, we want a computer vision model to be able accurately identify trash in drone photos so we can automatically measure the presence, quantity, and location of openly dumped trash in any area that we survey.

There are several computer vision methods that could be applied to our use-case, each with its own benefits and drawbacks. We considered how all of them might be used to solve our problem before deciding on semantic segmentation. Each method is briefly described below to provide context on our decision:

Image Classification: An image classification model takes an image as input and yields labels of the image's contents as output. For example, an image classification model trained to identify litter and burn pits (i.e. sites where trash is incinerated) might output "litter" if an image only contains litter, "burn pit" if the image only contains burn pits, "litter, burn pit" if it contains both, or nothing if it contains none. An image classification model requires very little preprocessing compared with other methods - it simply needs to know which classes are present in each training photo. A major limitation, though, is that it yields results at the image-level, so it will not provide information about the quantity, size, or location of instances of each class.[79]

Object Detection: An object detection model provides information about the size and location of objects in addition to just the class label. Generally, an object detection model will draw a bounding box around each instance of an object belonging to a class. Returning to the previous example, an image with litter and burn pits will have boxes drawn around every piece of litter and every burn pit that the model detects. Object detection models require more preprocessing than image classification models because annotated images in the training set need to include boxes drawn around each instance of each class.[80]

Segmentation: A segmentation model provides information about the presence, size, shape, and location of objects. It works by labeling pixels, grouping them together, and making classifications on pixel groupings. The resulting predictions show the outline and area of each object rather than

[78] IBM

[79] Bandyopadhyay, "Image Classification in Machine Learning."

[80] Patel, "What Is Object Detection?"

a rough bounding box, as is the case with object detection models. Using the same example from before, our model's output would shade in each piece of litter and each burn pit. Segmentation requires a much higher degree of preprocessing. Images in the training set must have precisely labeled classes that hew closely to each object's borders.

A segmentation method known as semantic segmentation is best suited for our use-case. Semantic segmentation provides the same label to all pixels belonging to a given class. For example, if there were two burn pits in an image, both would be labeled as "burn pit" rather than as separate instances, "burn pit 1 and burn pit 2." Using semantic segmentation, we can visualize the location of trash and other items of interest and make quantitative measurements of their size and location. The up-front preprocessing costs in labeling a truth-set, pixel-by-pixel, pay off in the detail provided by the model's output.

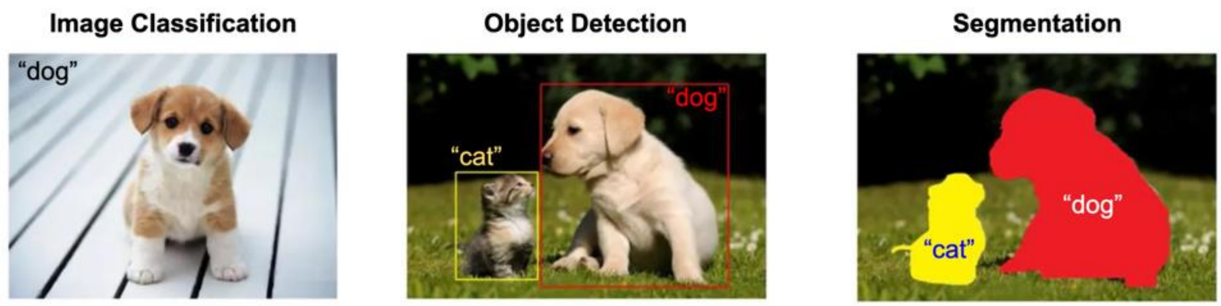


Figure 29: *An illustration of the differences between various computer vision methods*[81]

Model Selection: We used SegFormer-B5, a state-of-the-art semantic segmentation model. The SegFormer model was developed by researchers at Caltech, The University of Hong Kong, Nanjing University, and NVIDIA. Its neural architecture and large training dataset make it the highest performing semantic segmentation model available. We use a method called "transfer learning," by which existing models can be applied to new data or new problems, to leverage the properties of SegFormer that make it generally well-suited for computer vision tasks. We simply fine tune it with our labeled training data and it learns to recognize trash.

SegFormer is made available publicly and for free through Hugging Face, an open-source platform that allows users to share machine learning models and datasets. By uploading our labeled training data to a private repository on Hugging Face Hub, we could use Hugging Face's Transformers Library, a Python package that has open-source implementations of pretrained models, to instantiate and finetune a SegFormer. Afterwards, our model, which we call TrashBot, was saved and pushed to our project repository where it can be downloaded and applied to new images.

[81] "New Deep Learning Model Brings Image Segmentation to Edge Devices."

Equipment and Software

Due to the technical requirements of our research, equipment and software selection played a large role in shaping our methodology. We used a camera drone for the aerial survey; commercial software for automated flight planning, ortho mapping, and image segmentation; and open-source software for computer vision. Our selections are described below.

Equipment: Our choice of drone was based on several key requirements: image resolution, low-light performance, automated flightpath capability, portability, and price. We opted to use a DJI Air 2S. Smaller, cheaper models, such as the DJI Mini, might have allowed us to cover more territory by purchasing and operating two drones rather than one, but we were concerned the reduced image resolution and low-light performance might limit the effectiveness of our computer vision model. Newer drone models, such as the DJI Mavic 3, are not yet supported by flight automation software, though that will likely change by mid-2023.

Software: We used Dronelink for flight planning and automation, PIX4Dreact for ortho mapping, and Segments.ai for image segmentation. All three are commercially available for a monthly fee, and Segments.ai offers free licenses for academic institutions. Our computer vision model accessed SegFormer-B5 through Hugging Face Hub, which is a free, open-source project.

Appendix C: Key Operational Learnings

Timing & Seasonality

In a perfect world, surveys would be conducted at a time when nobody is outside and lighting conditions are perfect. In these hypothetical conditions, there would be minimal privacy risk, few pedestrians and vehicles obstructing the line of sight to ground-level, and brightly lit photos without shadows. Lighting conditions are generally best in the middle of the day when the sun is directly overhead. At this high angle, shadows are very small, and objects are brightly lit. In the mornings and evenings, the angle of the sun is lower, so shadows tend to be longer and more obstructive. Unfortunately, however, the middle of the day tends to be the busiest time for pedestrians and vehicles. We chose to schedule our surveys early in the morning shortly after dawn to prioritize privacy considerations. Future surveys might incorporate local knowledge to schedule high-traffic areas in the early morning and low-traffic around midday. Alternatively, drones with low-light or multispectral cameras could be used so that missions could flown before the sun rises above the horizon, when lighting is faint but uniform.

In terms of seasonality, we conducted our surveys in January, which is in the middle of the dry season. Heavy rains from June to October might make it difficult to fly missions. Extreme heat above 100º F, which occurs most often between February and June may also make drone operation impossible.

Obstacles & Restricted Flight Zones

While most drones have on-board obstacle avoidance systems, they cannot be relied upon in all cases. Obstacles that cast a small profile, such as power lines, may not be detected reliably. This is especially problematic when the drone is flying beyond the operator's line of sight. It is advisable to figure out the tallest obstacles the drone is likely to encounter in any given area. Buildings, mosque minarets, radio towers, trees, and power lines are safely below our recommended flight altitude of 200 feet almost everywhere in The Gambia. The operator should make sure the take-off and landing areas have no obstacles overhead and that the automated flight path is programmed to reach a safe altitude before moving laterally beyond the take-off zone.

Stationary obstacles are relatively easy to avoid - birds are another story. To our surprise, some flocks of birds acted territorially when they became aware of our drone. They would follow it over great distances and sometimes make aggressive dives in its direction. Pied Crows, Black Kites, and Egrets were the most common offenders. No bird ever actually interfered with the drone, but there were dozens of close calls. In fact, we cut our first day's survey short after a flock of Pied Crows made enough threatening swoops at our drone for us to fear losing it on its maiden voyage. A few days in, we became more confident that birds would not actually take the drone out of the air. Still, it is important to (1) consider whether any aggressive birds might be present in an area before surveying it, and (2) make sure the drone will not harm any birds inadvertently.

Finally, it is important to note that there are flight and/or altitude restrictions around sensitive areas including airports, embassies, government buildings, and military bases. Surveyors should plan around these restricted areas carefully.

Route Design

The most important considerations in designing routes are take-off and landing locations and operator positioning. As mentioned earlier, the drone should take off and land in an area with open skies above and few pedestrians around. Positioning is important because the remote control signal has a limited range. When the drone loses signal, it automatically rises to a safe altitude and returns to its take-off location. To prevent this from happening, the operator should be positioned near the middle of the route to minimize the average distance between the operator and the drone. We found that the drone could stay connected up to a distance of 0.5 – 1 mile. Areas with more interference from radio towers, cars, and commercial activity had smaller operating ranges. We wasted a significant amount of our limited battery life on nearly every route trying to reestablish connection with our drone – smarter route planning might have enabled us to have more flight time and cover more territory. It is also worth noting that controllers with stronger radio signals can be purchased for a few hundred dollars.

Privacy

We initially chose a flight altitude by testing heights between 50 and 300 feet and deciding 100 feet was the sweet spot where it was low enough to get sharp photos but high enough to avoid obstacles and intrusions into people’s lives at ground level. After three surveys, however, we changed our mind. The drone was noticeable enough on the ground to cause some commotion. In Tallinding, groups of children chased it up and down the riverfront as it passed by. In Ebo Town, it stalled above a busy intersection after momentarily losing signal, attracting a group of onlookers. More concerningly, a man in Tallinding told us that some people have semi-outdoor bathrooms, and they might be concerned with a drone flying overhead. We decided that the photos taken at 100 feet were far sharper than what we needed for computer vision to work, and that the privacy concerns at that altitude necessitated a change. As a result, we doubled the altitude for all remaining flights. At 200 feet, the drone is barely visible or audible, and the pictures are not sharp enough to be intrusive or compromising. We further blur photos during image processing to ensure privacy is respected. With more time, we might have tested altitudes up to 400 feet to see if computer vision could still work above 200 feet - we suspect it can for larger dumpsites.

Appendix D: Limitations

Failure on Litter & Burn Pit Classes

We originally intended on using computer vision to detect large trash deposits, litter, and burn pits (i.e. sites where people have burned trash). The TrashBot model proved to be ineffective in the latter two cases. Identifying litter is intractable due to the extreme time commitment needed to create a truth-set with all the litter labeled. There is simply too much for one person to label. And without a comprehensively labeled truth-set, the model cannot learn to properly identify litter.

There are two potential solutions. First, more people can be brought into the labeling process. A small team might be able to annotate a few hundred photos in a tolerable amount of time. Second, we could leverage model-assisted labeling, which is a process by which a small truth-set is used to train a model that makes predictions on a larger set of images to be used as the training set for the final computer vision model. After the intermediate model makes its predictions, a human can review and correct annotations to finalize the full-sized truth-set. This requires much less time than labeling everything by hand, and can allow one person's work to scale to a sufficiently large training set. This is a logical next step if the work in this project is to continue. Model-assisted labeling might lead to a model that can identify litter, and it could also improve performance across all classes by expanding the size of the training set. It is worth noting, however, that even if a model is technically capable of identifying litter, it may not be useful to do so. There is so much litter spread so widely throughout the municipality that insights from a litter-detecting model might not be operationally useful.

Using Training Data Only from 100-Foot Surveys

All 300 photos in our training set were from surveys conducted at 100 feet altitude. Generally, it is advisable to have training data that looks similar to new data you feed into the model for predictions. In our case, however, we changed our methodology after the 3rd survey to fly at 200 feet for privacy considerations. This means photos from 4 of our 7 surveys were taken under fundamentally different conditions than our training images. Ideally, we would have created a new training set from 200-foot photos, but the process of manually labeling a new truth set was prohibitively time-intensive. It took about 25 hours to label our original truth set, so we decided to proceed with it and only create a new training set if the model did not appear to generalize well to 200-foot photos. Luckily, the model's performance did not suffer much. If KMC implements this program, it would probably be worthwhile to invest the time in creating a new training set from 200-foot photos to maximize model performance.

Inherent Uncertainty in Trash Labeling

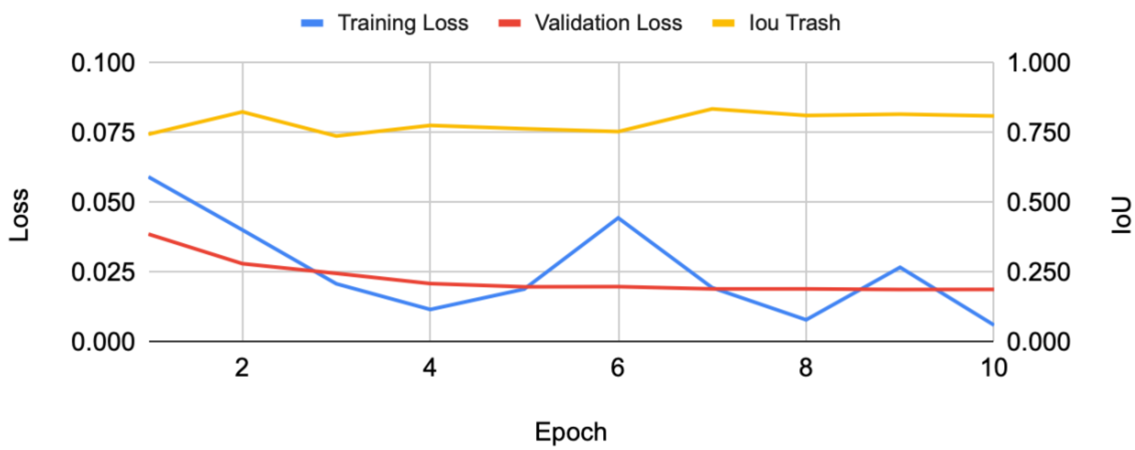
Our model's performance is limited by the impossibility of creating an objective truth set for model training. Piles of trash generally have poorly defined boundaries that cannot be accurately labeled. Two people trying to label the same photo will almost certainly disagree about where the trash ends and the surrounding dirt, sand, rocks, brush, or construction rubble begin. It is similarly impossible to align on whether a single piece of trash near a larger pile should be considered as part of the pile or distinct from it. As such, there is a high degree of uncertainty baked into our classification task itself. In many cases when the model's predictions and the truth-set disagree, the decision to label a pixel as "trash" or "not trash" may be equally defensible. This puts an unknown ceiling on the IoU we can expect to achieve.

Figure 30: *It is not feasible to label a perfect "truth set" for model training and evaluation due to the imprecise boundaries of trash deposits. Given the drone photo on the left, different people (and the TrashBot model) might label different areas as trash. The blue shading represents one manual attempt.*

Appendix E: Source Code & SegFormer Training

GitHub Repository: https://github.com/mraotttth/TrashBot
TrashBot Model on Hugging Face Hub: https://huggingface.co/mraotttth/trashbot

Model Training: We fine-tuned a SegFormer-B5 using mostly the same hyperparameters and preprocessing steps outlined in the original paper.[82] The full set of specifications can be found at the model's Hugging Face page. By default, SegFormer performs normalization, rescaling, and resizing as image preprocessing steps. We chose not to add further preprocessing methods or to tinker with the model architecture. We experimented with different batch sizes, learning rates, and epoch counts, ultimately finding the best performance at 3, 0.00006, and 10 respectively.



Epoch	Training Loss	Validation Loss	Iou Trash
1	0.059	0.039	0.745
2	0.040	0.028	0.825
3	0.021	0.025	0.738
4	0.012	0.021	0.776
5	0.019	0.020	0.764
6	0.045	0.020	0.754
7	0.020	0.019	0.835
8	0.008	0.019	0.812
9	0.027	0.019	0.817
10	0.006	0.019	0.810

Figure 31: *Model training results*

[82] Xie et al.

APPENDIX F: Project Expenses

Item	Cost	Recurrence	Category	Alternatives
DJI Air 2s Drone	$1134	One-time	Hardware	Any other drones that are compatible with flight automation software
Dronelink	$30	Monthly	Software (Flight automation)	- DroneDeploy - ArcGIS Site Scan
PIX4DReact	$70	Monthly	Software (Ortho mapping)	- Other PIX4D products - ArcGIS Pro - DroneDeploy - DJI Terra - GlobalMapper

Table 5: *Project expenses and alternative options*

Appendix G: Ortho Map Screenshots

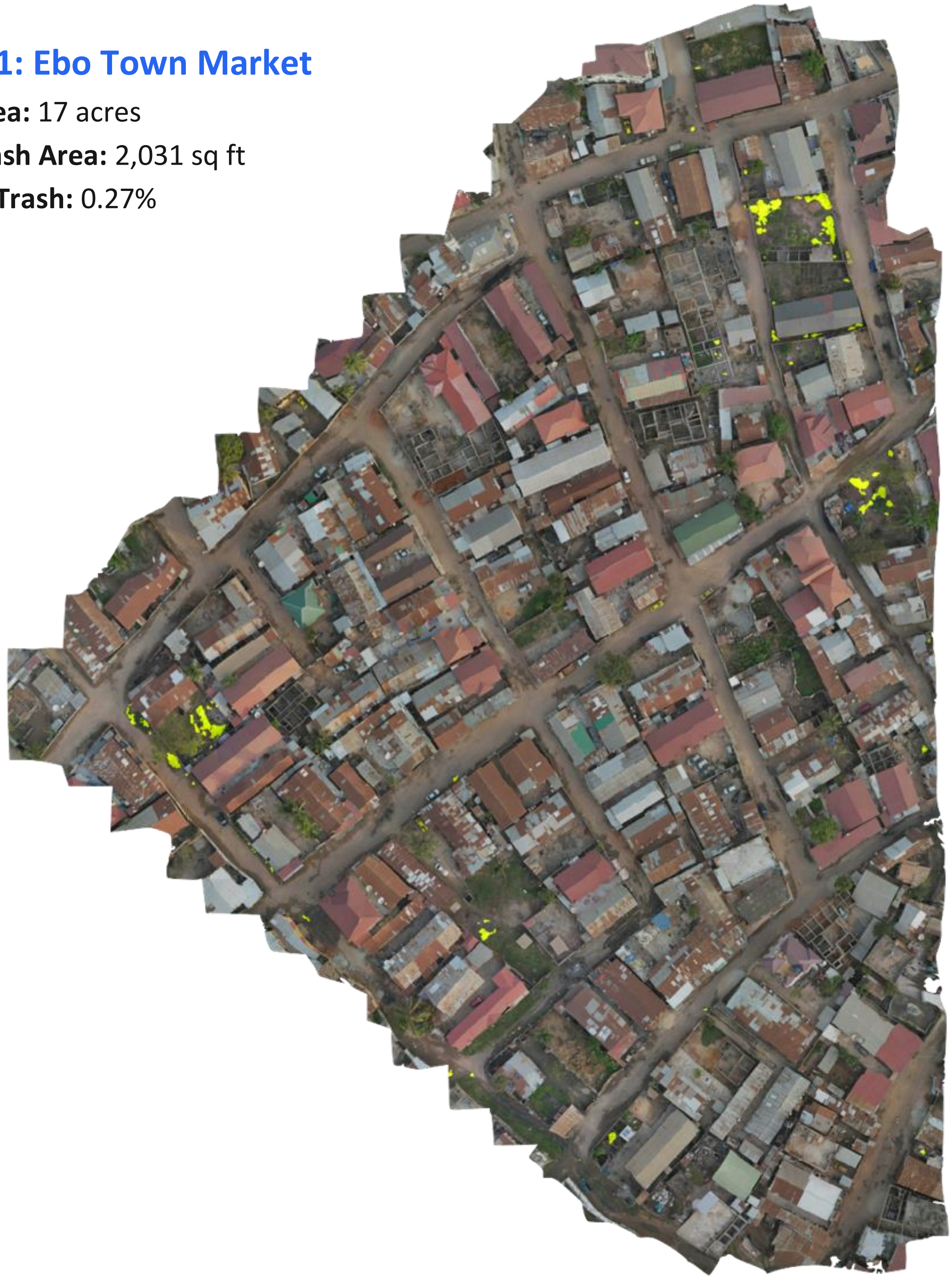
Note: if links to interactive ortho maps do not work, they are no longer being hosted on PIX4D Cloud

Parcel 1: Ebo Town Market

Total Area: 17 acres

Total Trash Area: 2,031 sq ft

Percent Trash: 0.27%



Ortho Map Link:

https://cloud.pix4d.com/dataset/1422341/map?shareToken=7f7ddc93-c87e-4e6e-b8fd-4feeb0283a32

Parcel 2: Tallinding

Total Area: 19 acres

Total Trash Area: 2,120 sq ft

Percent Trash: 0.26%

Ortho Map Link:

https://cloud.pix4d.com/dataset/1423669/map?shareToken=375e0ed
a-ddc2-418a-b959-61af0cc6cacf

Parcel 3: Riverine Tallinding

Total Area: 46 acres

Total Trash Area: 102,500 sq ft

Percent Trash: 5.12 %

Ortho Map Link:

https://cloud.pix4d.com/dataset/1423188/map?shareToken=61cd8f5c-2158-4545-8d20-03b1bbdc6233

Parcel 4: Bertil Harding Highway

Total Area: 105 acres

Total Trash Area: 856 sq ft

Percent Trash: 0.02 %

Ortho Map Link:

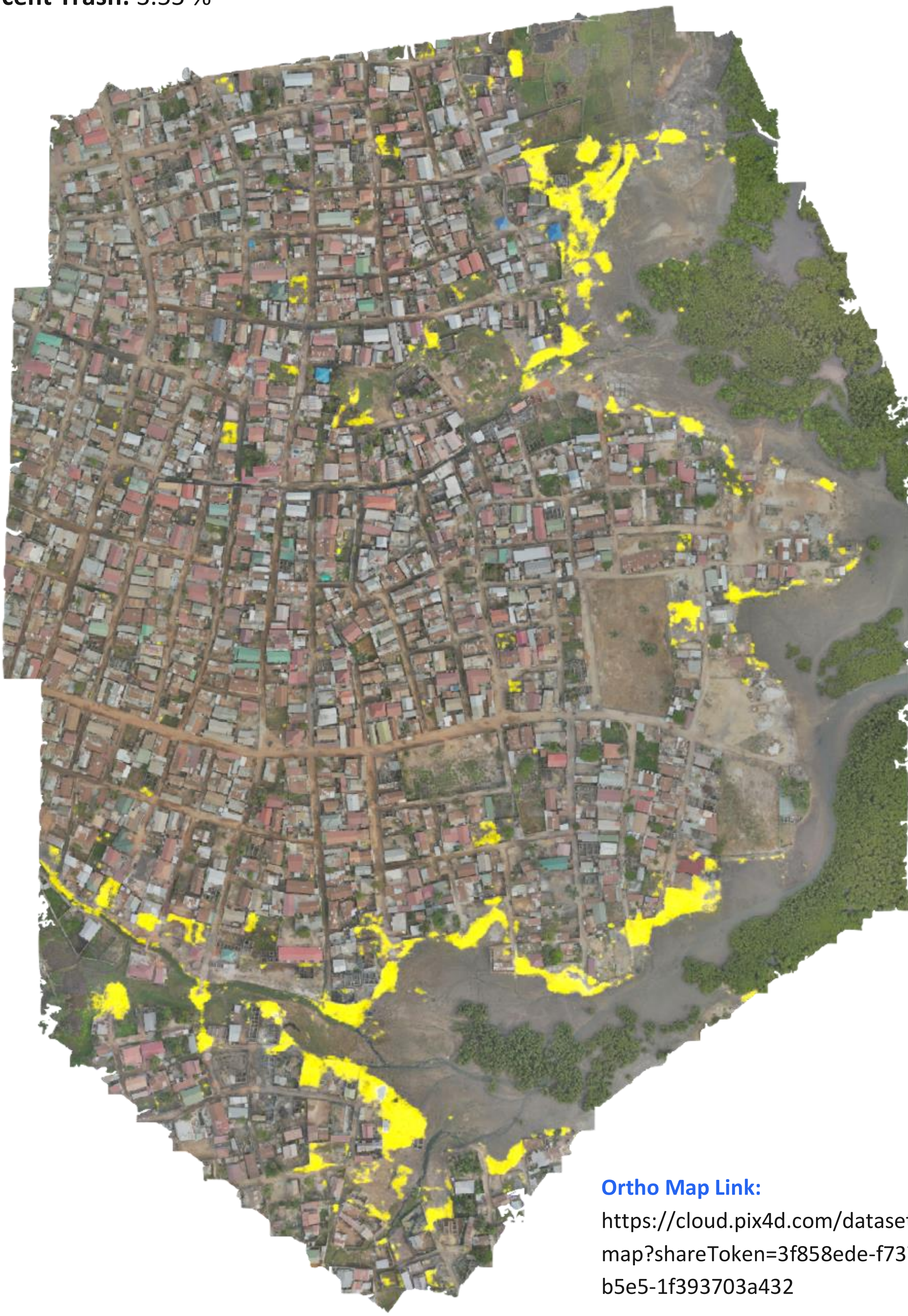
https://cloud.pix4d.com/dataset/1423822/map?shareToken=3765a88
8-1c49-4568-90d2-e3e21074a58d

Parcel 5: Riverine Ebo Town

Total Area: 162 acres

Total Trash Area: 250,761 sq ft

Percent Trash: 3.55 %



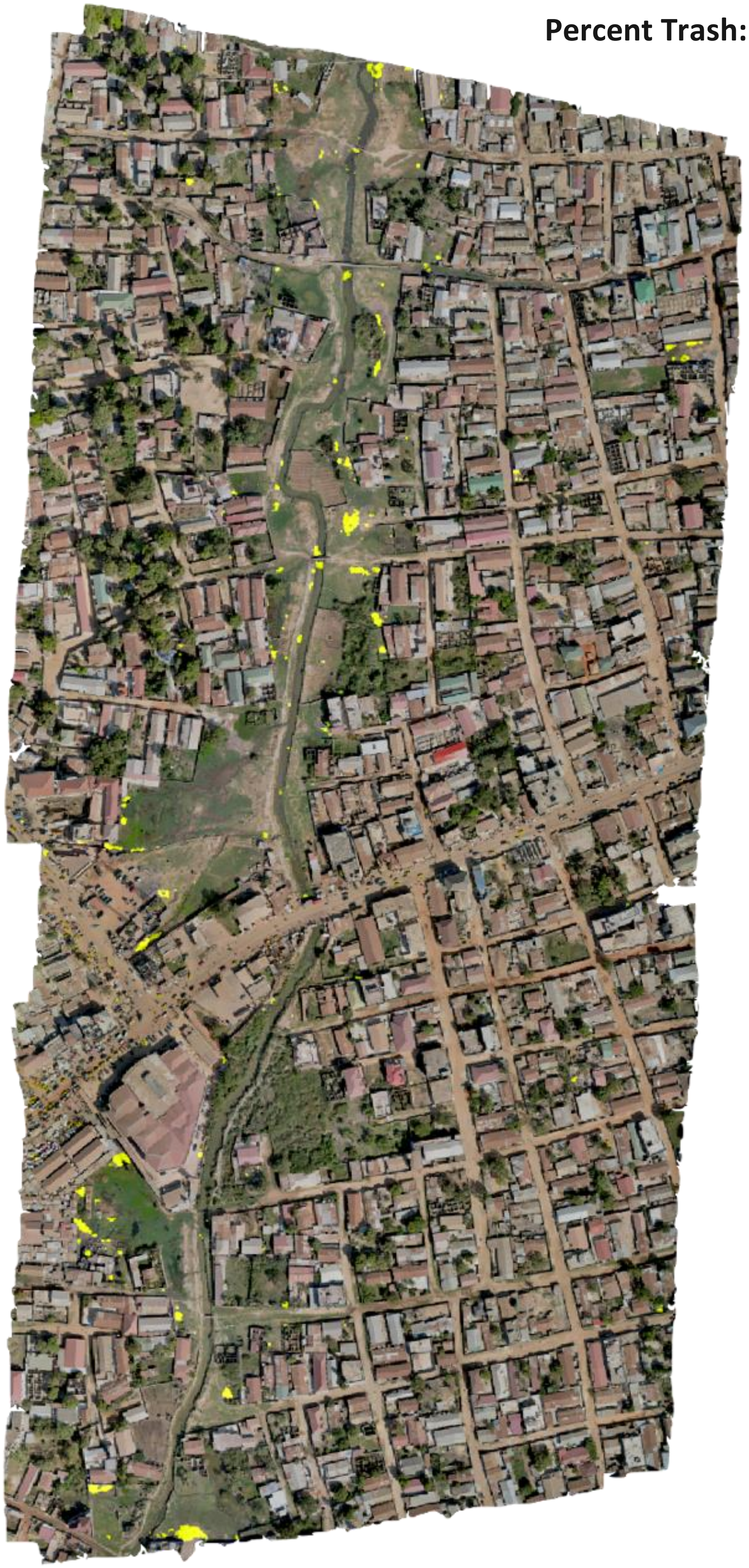
Ortho Map Link:
https://cloud.pix4d.com/dataset/1452956/map?shareToken=3f858ede-f737-42a9-b5e5-1f393703a432

Parcel 6: Dippa Kunda

Total Area: 139 acres

Total Trash Area: 20,556 sq ft

Percent Trash: 0.34 %



Ortho Map Link:

https://cloud.pix4d.com/dataset/1423464/map?shareToken=b52c4e01-fff2-4ed7-b241-3613e52bf636

Parcel 7: Westfield

Total Area: 119 acres

Total Trash Area: 2,737 sq ft

Percent Trash: 0.05%

Ortho Map Link:

https://cloud.pix4d.com/dataset/1423577/map?shareToken=30add728-c09d-4a22-b1d8-33c87424ce93

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