EEET ECOLOGICAL ENGINEERING & ENVIRONMENTAL TECHNOLOGY

Ecological Engineering & Environmental Technology 2024, 25(8), 271–284
https://doi.org/10.12912/27197050/189888
ISSN 2299–8993, License CC-BY 4.0

Received: 2024.06.01
Accepted: 2024.06.17
Published: 2024.07.01

Object Detection of Macroplastic Waste Using Unmanned Aerial Vehicles in Urban Canal

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ABSTRACT

Macroplastics are a global threat to the aquatic environment and will degrade into microplastics over time. Its presence in canal causes pollution and inhibits water flow, causing flooding in urban areas; therefore, it is essential to identify and monitor its presence. Addressing knowledge gaps is critical in determining solutions for mitigation purposes. In visual object detection studies, aerial mapping is developed with advanced technology, such as unmanned aerial vehicles (UAV). This research aims to conduct aerial mapping experiments to find the right formula or technical reference for detecting macroplastic waste objects floating on the surface of the canal, including flight altitude, exposure to sunlight, and the influence of season on object detection. Aerial mapping will be done in densely populated urban canals in Southeast Asia, Indonesia, and Makassar City. The aerial mapping survey method will be used, and then the data will be processed in the digitization process and object detection with GIS. The analysis kernel in GIS tools will be used to see the distribution density of macroplastics. The research results show that autoblock occurs at heights of 5m and 10m, but this autoblock can be minimized at a flight height of 15 m. Apart from that, height also affects flight duration. The lower flying height will result in better visual accuracy and better resolution. However, at a height of 15m, macroplastic objects were still detected on a moderate scale. This research successfully distinguished various plastic waste materials, the most found being the soft polyolefin category in plastic bags. Monitoring results detected 321 items of macroplastics in the dry season and 1,163 in the rainy season, or a threefold increase with conditions spread thinly in the dry season. In the rainy season, they gather densely on one side of the canal.

Keywords: UAV, aerrial mapping, kernel density, macroplastic, canal.

INTRODUCTION

Plastic pollution has become a global issue because plastic waste has become an abundant pollutant in marine, coastal, and river environments (Conchubhair et al., 2019). Researchers reveal that 0.8–2.7 million cubic tons of plastic waste annually enters waters worldwide (Meijer et al., 2019). Rivers are a medium for plastic that enters the aquatic environment and flows into the sea. It has been suggested that rivers in Southeast Asia and Africa are considered the primary source of plastic pollution in the sea (Calcar and Emmerik, 2019). Globally, Indonesia is estimated to be the second largest marine plastic polluter after China (Jambeck et al., 2015; Lebreton et al., 2017).

In developing countries, mismanagement of land-based waste systems results in waste entering water bodies. Once in water systems, plastic pollution accumulates in hydraulic infrastructure (such as shelf structures), clogging urban drainage systems and increasing the risk of urban flooding (Honingh et al., 2020; Windsor et al., 2019). Makassar City is location of study as fastest-growing region in eastern Indonesia (Anggraini et al., 2021; Muis et al., 2024) and is a city that often experiences repeated flooding. In 2019, floods hit urban areas, inundating 1,658 houses and affecting 9,328 residents (Thoban and Hizbaron, 2020). Apart from high rainfall, one of the causes of flooding is the blockage of water channels, especially flood control infrastructure with plastic waste.

Furthermore, apart from causing floods, plastic waste is considered dangerous because it is a problem and threat to aquatic life and marine biota (Galloway et al., 2017; Wang et al., 2016). Plastic is known to be persistent and less dense than seawater and freshwater (Andrady, 2011; Zhao et al., 2018). In aquatic environments, floating plastic is carried by surface currents and wind (Van Sebille et al., 2020) and degrades into microplastics (Barnes et al., 2009). Scientists are very concerned about microplastics, even though macroplastics are no less important to study because they will later decompose into microplastics.

Plastic waste requires mitigation policies, one of which is monitoring. However, data on the presence of plastic in categories, types, distribution, and density in water bodies still needs to be studied in more depth. Visual monitoring methods generally monitor plastic waste floating in rivers (Van Emmerik et al., 2020) before it enters the sea. However, conventional visual observation still requires access on both sides of the river and is considered problematic. On the other hand, monitoring waste in waters is continuous and long-term work, so alternative monitoring methods that are effective, efficient, and reliable are needed in the future. Therefore, using unmanned aerial vehicles (UAVs) as an advanced method is considered an alternative that can overcome the limitations of manual surveys. The use of drones equipped with RGB (red, green, blue) cameras, apart from having the advantage of low cost, also enables the collection of high-resolution image data at the centimeter level (Flynn and Chapra, 2014), in a wide range, remote areas that are difficult to access, with flexible data collection times and frequencies, and in conditions where satellite use is limited (e.g., cloud cover, poor imagery, limited high resolution).

Using UAVs to detect plastic waste objects in rivers and water bodies is possible (Rahmadya et al., 2022). Many studies have used UAVs to observe trees for agricultural, animal, and building purposes. Aerial imagery has become a precise and efficient method for monitoring litter on beaches and water bodies (Escobar-Sánchez et al., 2021). Macroplastic monitoring using UAVs has been carried out previously in research conducted in sandy beach areas (Antara et al., 2024; Topouzelis et al., 2019). However, research on macroplastic waste floating on the surface of urban canals or rivers using UAVs with aerial mapping is still a challenge and has never been done before. Trials from field studies need to be carried out to gain knowledge about altitude protocols, flight times, and the influence of season on image quality so that they can be used as an object detection database. Many studies have conducted trials on sandy beaches, seas, and riverbanks and have yet to show spatial distribution and density conditions.

Addressing the knowledge gap regarding macroplastic waste floating on the surface of urban canals or rivers is essential for developing mitigation strategies. This study will explore the use of UAVs to monitor floating macroplastic waste (FMW) ($\geq$ 5 cm) in urban canals (small urban rivers) for a case study in the developing country of Indonesia. This research aims to demonstrate an unprecedented aerial mapping experiment to find the right formula or technical reference for detecting macroplastic waste objects floating on the surface of the canal, with variable flight altitude, exposure to sunlight, and the influence of season in object detection. The result is recommendations for good image quality, which can be processed into a database for automatic object detection using algorithms in the future. In addition to the amount (based on material, type, and item) of macroplastic waste, data on the spatial distribution and density of FMW were obtained. This research will help researchers and stakeholders plan and conduct UAV-based floating macroplastic surveys. Macroplastic waste in urban canals, especially in developing countries, is abundant and challenging to detect continuously. It is a significant problem because it will degrade into microplastic over time.

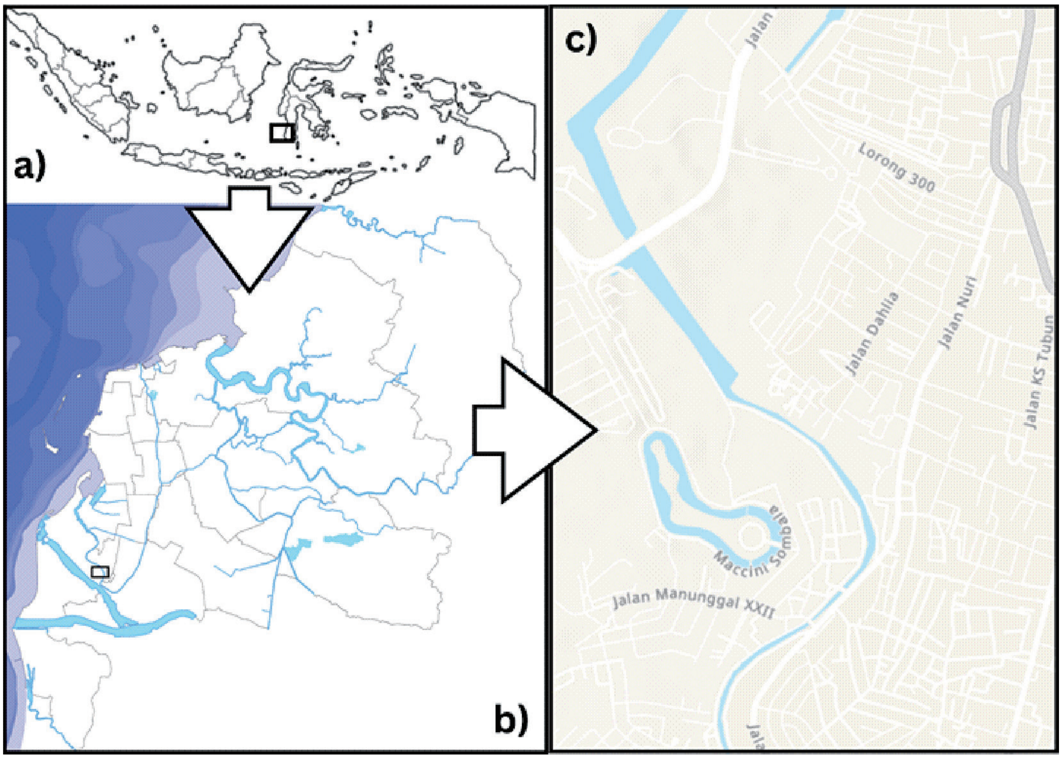

Figure 1. Location of study (a) Indonesia, (b) Makassar City, (c) The Jongaya Urban Canal

METHODOLOGY

Study location

This study was carried out in Jongaya Canal, Makassar City, east Indonesia, in 2022–2023 (Fig. 1). The Jongaya Canal is a flood system canal in Makassar City, with an area of 9.20 km² and three trash racks. This canal has a catchment area of 12.26 km, drains rainwater and domestic wastewater from the service area, and flows into the Makassar Strait. The research area is located at coordinates 5° 10' 11.5171' S, 119° 24' 16.4411' E. This canal could have potentially contributed pollutants to the estuary, leading to Makassar Strait. The downstream of the canal was chosen as the research location because waste accumulates before it heads to the broader ocean.

Additionally, the research location is after the Trashrack Point; therefore, floating litter is assumed to originate from the surrounding area. Finally, slums with poor waste management conditions surround the research location, and easy accessibility for UAV survey data collection was considered. Individual plastic object detection studies have yet to be conducted in this area; this method is considered ideal for evaluating plastic monitoring methods.

Data collection and processing

Plastic waste will be in several river compartments, some of which float on the surface, become embedded in the riverbank, and even settle on the riverbed with sediment (Emmerik and Schwarz, 2020). This research will focus on macroplastic waste that floats on the surface of canal water. This research has three main stages for visual object detection to detect the appearance of floating macroplastic waste measuring ≥5 cm. For plastic size, consistent terms and dimensions do not exist across plastic pollution studies. The most widely used terms are nanoplastics (<0.1 μm), microplastics (0.1 μm–5mm), mesoplastics (5mm–5cm), macroplastics (>5cm), and megaplastics (Frias and Nash, 2019). In this study, we focus on macroplastic debris in canals, which is possible to detect using UAVs larger than 5 cm.

The first stage is 100 m aerial mapping with UAV in the canal area at several flying altitudes, namely 5 m, 10 m, and 15 m, with flying times in the morning, afternoon, and evening. Then, the aerial mapping survey produced hundreds of images, which were made into a mosaic to detect objects from the images using the Agisoft Photoscan software. The second stage is visual object detection from FMW images to ascertain whether the resulting image has an excellent resolution for detecting floating macroplastic objects. The final stage was to analyze the influence of seasons on the amount and type of macroplastic material and the spatial distribution of floating macroplastic waste density analysis using kernel density estimation.

Aerial mapping survey

This survey was conducted using a DJI Phantom 4 UAV. As discussed in a previous study (Martin et al., 2018), the recommended protocol for monitoring beach debris, using the Phantom series UAV with a 12.4 MP camera, can be obtained with high-resolution images. A previous researcher (Geraeds et al., 2019) used the DJI Phantom 4 UAV to monitor plastic waste in Sungai Klang, Malaysia, producing good-quality plastic waste monitoring images. The UAV specifications are presented in (Table 1) (http://www.dji.com). The data acquisition for UAV surveys goes through several stages (Fig. 2).

1. Planning and calibration. At this stage, the first step is determining the drone's flying location by checking the accessibility, terrain, and mapping type. Subsequently, flight parameters such as altitude, path, and overlap were determined. The gimbal on the drone camera was set at 90° to capture photographs perpendicular to the flight direction. The image resolution and speed settings were set, and the ISO (International Organization for Standardization) settings were kept constant to avoid changing the intensity levels between the images. Furthermore, the flight path was planned to allow the drone to capture a sufficient overlap between successive images for accurate splicing and processing. These steps form the basis for drone mapping and ensure the resulting data are accurate, reliable, and legal.

Table 1. The UAV specification

Type of UAV	DJI Phantom 4
Maximum speed	20 m/s (sport mode)
Maximum flight time	About 28 minutes
GPS mode	GPS
Sensor	12.4 M (effective pixels)
ISO range	100-1600 (photo)
Image size	4000 × 3000
Gimbal	Pitch -90° to +30°
Speed range	≤ 10 m/s
Altitude range	0–33 feet (0–10 m)
Battery	6000 mAh LiPo 2S

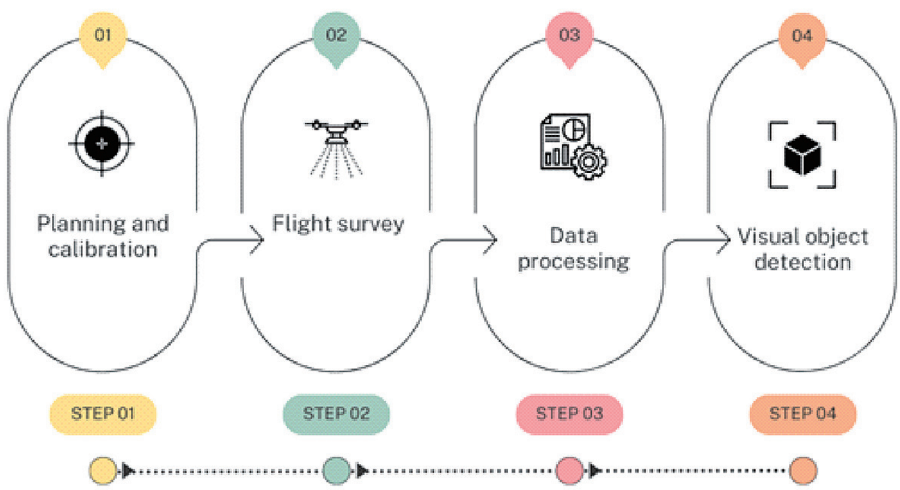

Figure 2. The stage of UAV protocol

2. Flight survey (Fig. 3): The UAV survey protocol flight in this study was aerial mapping, and the entire mission process was carried out automatically, including take-off and landing, route planning, calculating the appropriate flight altitude spatial resolution, and displaying it on the screen. The mapping and aerial photography of the patterned areas were performed during the setting process. During flight, drones collect data using various sensors, such as high-resolution cameras; the RGB camera is the most common remote sensor among UAVs (Zhang and Zhu, 2023). The data is stored in a drone. These images were processed and combined using Agisoft software (Fig. 4).
3. Data processing: Aerial mapping takes images from drone shots and assembles them into a single raster data set. A Mosaic is a combination of two or more images. This study used the Agisoft Photoscan software to process image mosaics, as previous researchers did (Taddia et al., 2021).

Visual object detection

The process of visually detecting objects in ArcMap begins by importing files from orthomosaic images with geographic information so that they are ready to be digitized through manual visual interpretation. The digitization

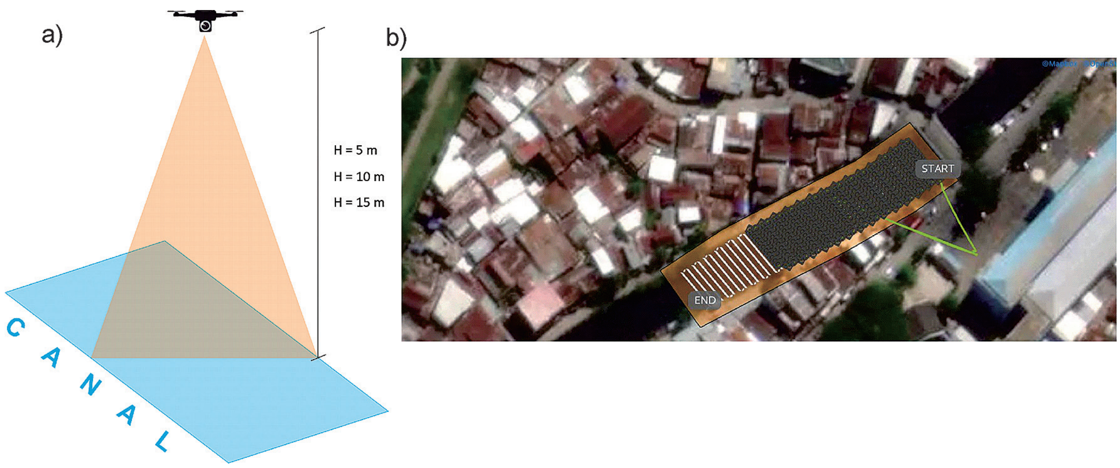

Figure 3. a) Drone height scheme when flying, b) Drone transects aerial mapping

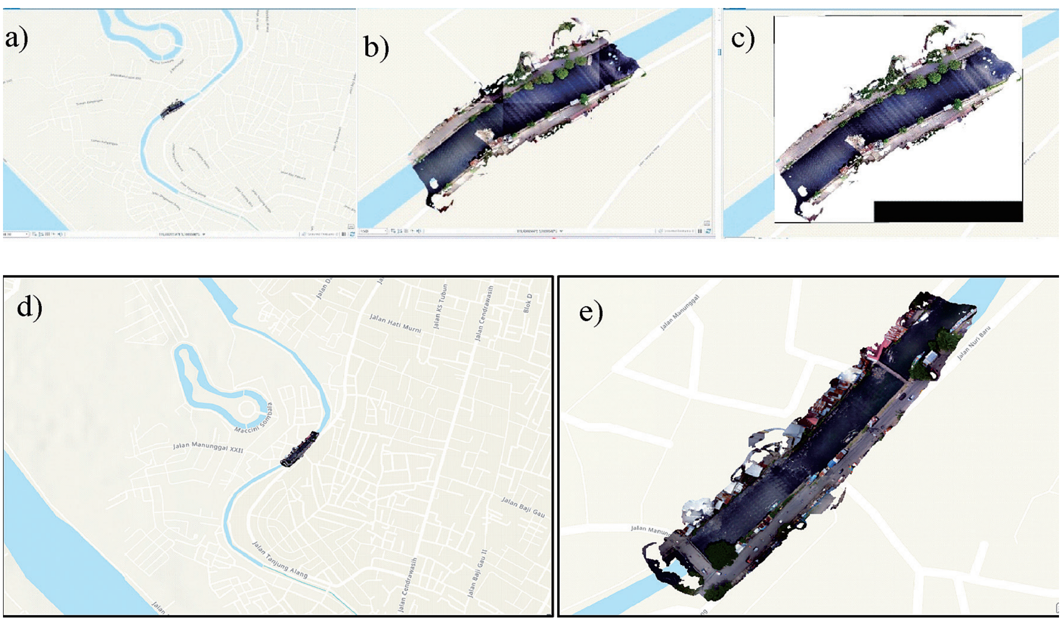

Figure 4. a) Survey location 10m altitude, b) Mosaic data from 561 images into seven raster data, c) Mosaic seven images into 1 raster data, d) Survey location 15 altitude, e) Mosaic data from 351 images into one raster data

Figure 5. Plastic categories based on adaptation of Tasseron et al. (2020)

process is grouping objects based on each object's material, type, and name. This process will produce data on the amount of litter distributed on the canal water's surface. Litter density will be analyzed using kernel density estimation. The category of solid waste to be calculated is macroplastic (≥5 cm) in seven categories based on the polymer configuration as follows: PET (polyethylene terephthalate), PS (polystyrene), EPS (expanded polystyrene), POhard (polyolefin), POsoft (polyolefin), multilayer (multilayer plastics), and others (Fig. 5).

Kernel density analysis

Determination of macroplastic density in this research using the Kernel Density (Spatial Analyst) tool on ArchGIS. The predicted density at a new (x, y) location is determined by the following formula:

$$Density = \frac{1}{(radius)^2}\sum_{i=1}^{n}\left[\frac{3}{\pi}\cdot pop_i\left(1-\left(\frac{dist_i}{radius}\right)^2\right)^2\right] \quad (1)$$
$$\text{For } dist_i < radius$$

where: i = 1,…,n are the input points. Only include points in the sum if they are within the radius distance of the (x, y) location. pop_i is the population field value of point I, which is an optional parameter. $dist_i$ is the distance between point i and the (x, y) location.

The calculated density is then multiplied by the number of points, or the sum of the population field if one was provided.

RESULT AND DISCUSSION

UAV survey result

The UAV survey was carried out on 13 September 2022 and 5 March 2023 in the Jongaya Canal, Makassar City, Indonesia, for a length of 100 m with test flight heights of 5 m, 10 m, and 15 m (Table 2). A UAV flight height of 5 m is recommended by Martin et al. (2018) as the best image resolution in coastal trials; however, carrying out automated aerial mapping missions in densely populated areas such as the study area is a challenge. There are some obstacles in applying 5 m and 10 m drone flight altitudes at this research location. Therefore, including it in aerial mapping surveys in urban canals or river areas with medium to narrow dimensions and congested conditions is inadvisable. During the aerial mapping survey, the automatic flight process was stopped when obstacles such as trees, electricity poles, or buildings were encountered at 5 m and 10 m altitudes. A 10 m altitude suits sea areas, beaches without flight obstructions, and main river flights. Height planning in automatic flight is essential to consider obstacles in the flight path, such as buildings or trees; however, autoblock can be minimized at flight heights of 15 m. A flying height of 5 m requires a slow flying speed, so the flying duration is longer than the flying height of 10m and 15 m. However, the higher photo-taking heights of 10 m and 15 m can cover a wider area, so the flying duration is slightly faster. The number of images will increase in the low-flying position, where the results of aerial mapping at a flying height of 10m produce 561 images that will be mosaicked. In comparison, at a flying height of 15 m, only 351 images were collected (Fig. 3). All data collected will be compiled into a georeferenced orthophoto map. From visual accuracy and orthophoto resolution, the 5 m flight scheme is considered the best compared to other flight schemes. However, the 10m flight scheme is still good, and the 15m flight scheme is on a moderate scale for detecting images of macroplastic waste measuring ≥ 5 cm.

Here, we conduct several time-based image retrieval experiments. The research location is almost in central Indonesia, with tropical climate conditions crossed by the equator where the sun is perpendicularly overhead during the day, influencing the shadows of objects when taking pictures. The disadvantage of this method is that weather conditions highly influence it; drones show poor performance in bad weather conditions, such as cloudy rain, thunderstorms, lightning (Rahmadya et al., 2022), and wind Furthermore, floating waste surveys should be carried out when the sky cover is uniform, whether apparent or cloudy. Cloud reflections scattered on water surfaces, such as the sea, can also influence the detection of floating waste (Colefax et al., 2018; Garcia-Garin et al., 2020). Based on sun exposure (Table 3), the best category for the survey is carried out on a sunny day at 08.00–10.00 AM and 3.00–5.00 PM with minimal reflection of sunlight on objects (suitable), but at 11.00–2.00 PM, then the sun is in the middle so that the sun's reflection occurs, making objects reflect and become biased (bad).

Furthermore, these results were continued on visual accuracy and orthophoto resolution, which gave poor results in the UAV survey at 11.00 AM-2.00 PM because the sun's reflection influenced the results of poor data mosaics and objects that became difficult to recognize. Cloudy and rainy conditions are not recommended. Daylight photography is not recommended for this study. This result differs from a case study on the Maldives coast (Fallati et al., 2019), where researchers carried out drone photography at 12.00 PM, producing data with reasonable accuracy. This may be because the research location is not on the water surface but on a sandy beach, resulting in different conclusions.

Indonesia has a tropical climate at the equator, with only two seasons, rainy and dry. In several regions in Indonesia, the rainy season usually occurs around October – March, while the dry season ranges from April to September. Apart from the influence of UAV flying height and survey time, this research also wanted to look at the influence of season, so the survey was carried out in two different seasons, namely the dry season (13 September 2022) and the rainy season (5 March 2023) (Table 4). The result from the visualization aspect of accuracy is that surveys in the dry season are better

Table 2. Results of UAV survey based on altitude

Flight altitude	5 m	10 m	15 m
Autoblock	High potential autoblock	High potential autoblock	Autoblock minimize
Number of collection picture	Very high	High	Slightly high
Visual accuracy	Very accurate	Accurate	Moderate
Orthophoto-resolution	Very good	Good	Moderate
Flight duration	Very long	Long	Moderate

Table 3. Results of UAV survey based on time of survey

Time of survey	08.00 – 10.00 (AM)	11.00 (AM) - 2.00 (PM)	15.00 – 5.00 (PM)
Sun exposure	Minimal reflection of the sun on objects (good)	The reflection of the sun makes objects reflect (bad)	Minimal reflection of the sun on objects (good)
Visually accurate	Accurate	Not accurate	accurate
Orthophoto-resolution	Good	Not Good	Good

Table 4. Results of UAV survey based on season

Season	Dry	Rainy
Visually accurate	Good (floating litter spreads out, easy to detect)	Moderate (too many piles of floating litter)
Orthophoto-resolution	Good	Moderate (water moves although at a slow speed)
Density of object	Floating litter spread over the surface of the channel	Floating litter is collected on one side of the canal

because the floating macroplastic is spread out and easily detected. In contrast, in the rainy season, the results are moderate because too many piles of floating waste make it difficult to identify objects visually.

Furthermore, the orthophoto-resolution aspect provides good results in the dry season, where the canal conditions are stable with prolonged water flow. In contrast, in the rainy season, the results are moderate because the water moves even at a slow speed. Lastly is object density; in the dry season, floating waste spreads across the canal's surface, while in the rainy season, floating waste collects on one side of the channel.

Visual object detection result

The UAV survey will produce many images, mosaicking into one data raster. The process of visually detecting objects in ArcMap begins by importing files from orthomosaic images with geographic information so that they are ready to be digitized through manual visual interpretation. The results showed excellent image quality for detecting plastic waste floating on the water surface, macroplastics $\geq$ 5 cm in size were visible and could be recognized according to the material and type of item at a height of 10 m. Plastic items, such as plastic bags of various colors and transparencies, float on water's surface. The photographic results show

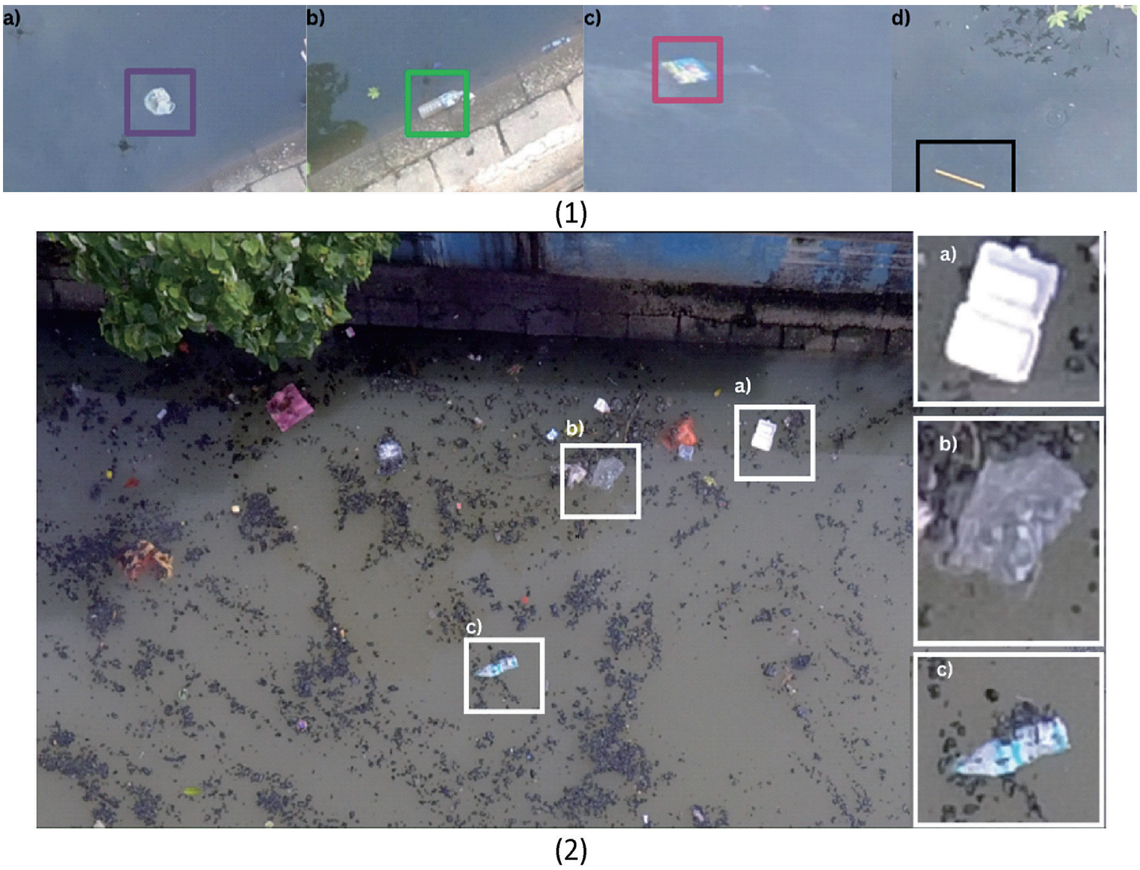

Figure 6. 1. Floating macroplastic object detection result from 10m altitudes a) plastic bag (POsoft), b) plastic bottle (PET), c) plastic (crips) (multilayer), d) straw (PS). 2. Floating macroplastic object detection result from 15m altitudes a) styrofoam food box (EPS), b) plastic bag (POsoft), c) plastic bottle (PET)

that the transparent types can also be detected visually (Fig. 6). This result is in line with research conducted along the coast of the Republic of Maldives with drone testing for anthropogenic marine debris detection, which found that a height of 10 m is the ideal height to obtain results with good image quality (Fallati et al., 2019).

Although the study in the Republic of Maldives was carried out on a sandy beach, our study was carried out in an urban canal, which makes it more challenging to produce good image quality for object detection. Another study in the Po River Delta (Italy) conducted a plastic waste detection test at a height of 10 m with excellent results. Furthermore, previous research on the Baltic Coast on the efficiency of aerial drones for monitoring macro-litter also focused on drone flights at 10 m above ground level (Escobar-Sánchez et al., 2021). The study performed visual playback of drone images in a recovery experiment (50 m² area), revealing an accuracy of 99%. The result of drone flight at a height of 15m showed that the image of the plastic waste was still visible on a moderate scale. A flight altitude of 15m was recommended for surveying dense urban canals and rivers. The obstacles to automatic aerial mapping flights can be minimized at a height of 15 m. Various macroplastic objects with sizes ≥5 cm could be identified visually and categorized according to the material and type (Fig. 5). The amount of organic waste on the surface of the water is also a nuisance during the visual detection process but does not cause any significant problems. Through observations in this study, macroplastics with a size of <5 cm were still visible in flakes but were not included in calculating the number of items category.

Seasonal influences result

Based on the visual object detection results, floating litter items were successfully detected in the dry season with 321 items (Table 5). In contrast, in the rainy season, it tripled to 1,163 items (Fig. 7). Plastics were the most common items (90% and 77% in dry

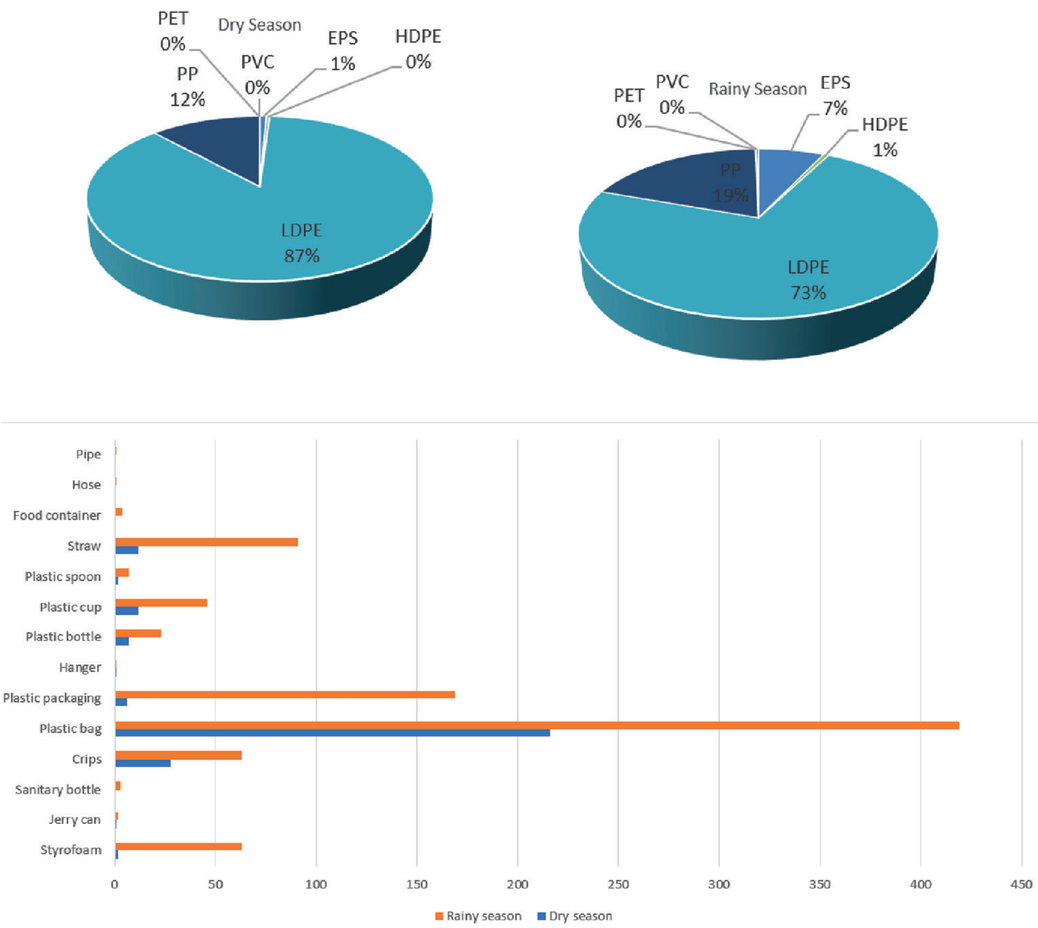

Figure 7. a) Floating macroplastic material percentation based on season (Mission 1 for dry season and Mission 2 for rainy season), b) Floating macroplastic type of item based on season

and rainy seasons) compared to non-plastic items; some objects could not be detected visually. Undetected items are opaque and cannot be visually recognized when the data is collected. These items were often found in the rainy season (14%) and in the dry season (3%) because the amount of litter was denser in the rainy season, and the flying altitude of 15m was higher than that of the dry season. The season's influence was also evident, with increased litter in the rainy season. Generally, a large amount of plastic waste accumulates in aquatic environments and survives on the surface because of the durability of plastic and its lower density than that of water (Fazey and Ryan, 2016; Thompson et al., 2009). Additionally, plastic is the most dominant item because of its wide use, long durability, and buoyancy, making it easily carried away by currents and not easily degraded in the environment (Moore, 2008). LDPE, HDPE, and PP plastics have lower densities than fresh water (density ~ 1,000 kg/m³) (Zhao et al., 2018) creating an ample buoyancy that limits surface water. When managed, most solid waste is transported to landfills (Horton et al., 2017). In contrast, in urban areas, waste mismanagement results in plastic waste entering river/flood channels from the domestic sector, which is disposed of directly from terrestrial to aquatic environments. The abundance of plastic waste on the canal surface remains a challenge for the implementation of local government programs to limit the use of plastic bags (Makassar et al. Number 7 of 2019 concerning controlling the use of plastic bags) and recycling through waste banks (Makassar et al. Number 36 of 2018). The Government of Indonesia has committed to banning single-use plastics (Regulation of the Ministry of Environment, No. 75 of 2019). The prohibited use

Table 5. Results of visual detection of orthomosaic canals: quantity of litter items (n items), density of litter items (items· m^2) and relative percentage (%) of floating litter categories

Category	Plastic material	Type of item	Dry season			Rainy season		
			Quantity (n items)	Density (Item m^2)	Percentage (%)	Quantity (n items)	Density (Item m^2)	Percentage (%)
Macroplastic	PET	Plastic bottle	7	0.07	2.20	23	0.23	1.98
		Food container	0	0	0.00	4	0.04	0.34
	PS	Plastic cup	12	0.12	3.77	46	0.46	3.96
		Plastic spoon	2	0.02	0.63	7	0.07	0.60
		Straw	12	0.12	3.77	91	0.91	7.82
		Hanger	1	0.01	0.31	1	0.01	0.09
	EPS	Styrofoam	2	0.02	0.63	63	0.63	5.42
	PO-hard	Sanitary bottle	0	0	0.00	3	0.03	0.26
		Jerry can	1	0.01	0.31	2	0.02	0.17
		Hose	0	0	0.00	1	0.01	0.09
		Pipe	0	0	0.00	1	0.01	0.09
	PO-soft	Plastic bag	216	2.16	67.92	419	4.19	36.03
	Multilayer	Chips bag	28	0.28	8.81	63	0.63	5.42
		Multi-layer packaging	6	0.06	1.89	171	1.71	14.70
	Others	Gallon bottle	0	0	0.00	1	0.01	0.09
	Total		287			896		
Non-plastic	Cardboard	Tetrapack	1	0.01	0.31	12	0.12	1.03
		Egg rack	1	0.01	0.31		0	0.00
	Leather	Shoes	0	0	0.00	1	0.01	0.09
	Plant residue	Leaf	18	0.18	5.66	67	0.67	5.76
		Twigs	2	0.02	0.63	0	0	0.00
		Wood	1	0.01	0.31	5	0.05	0.43
	Rubber	Slippers	0	0	0.00	14	0.14	1.20
	Total		23			99		
Not detected item			8			168		
Grand total			318			1163		

of single-use plastics includes plastic packaging, straws, plastic bags, and containers. The existence of waste floating in the canals of the flood control system requires serious mitigation.

Based on category, POsoft was the dominant plastic waste, with most items in plastic bags (75% and 43.7%). The same finding was shown in a study in the Riverbank Rhine-Meuse Delta, Netherlands; plastic was the most frequently found category (55.8%) (Van Emmerik et al., 2020), and the most items found were POsoft (33.4%) and EPS. Another study conducted in Jakarta Bay, Indonesia, found that plastic is the dominant waste in rivers and canals and is dominated by multilayers and POsoft (bags, films, and foils) (Van Emmerik et al., 2019). Furthermore, 14 types of plastic items were detected visually through manual interpretation. Plastic bags, packaging, straws, and styrofoam food boxes were the most found plastic items. The trend shows increased numbers from the dry to rainy season (Fig.6).

The images collected by drones (UAVs) are efficient for mapping and monitoring floating objects, such as floating litter, which allow remote sensing techniques to replace traditional methods for monitoring litter (Andriolo et al., 2022), further enhancing the knowledge of water litter dynamics. The distribution and density of macroplastic waste can be determined using aerial mapping. These data can be used as a database to monitor the presence of macroplastics

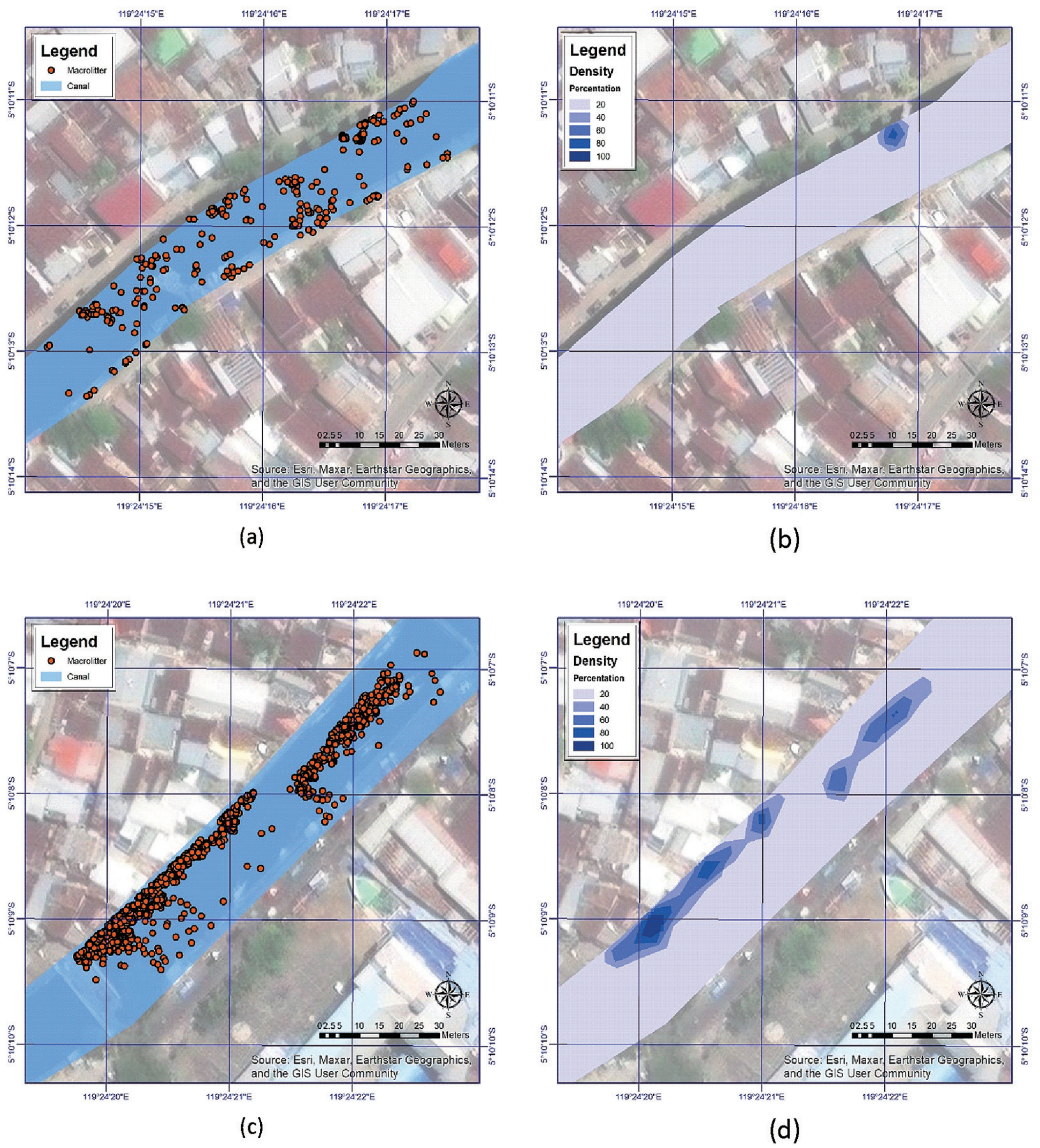

Figure 8. Spatial distribution and density map (in percentage) of floating litter in the urban canal a) Spatial distribution map in dry season, b) Density map in dry season, c) Spatial distribution map in rainy season, d) Density map in rainy season

and their relationship with the surrounding environment. During the rainy season, the accumulation of floating waste occurred on one side of the canal directly adjacent to the lower middle-class slums. In contrast, the canal was directly adjacent to the collector road. The water discharge outlet from the service area drains into the canal and carries large amounts of litter. The plastic litter density decreases in the middle. The rainy conditions cause the water to flow faster and wash away floating waste. Different things are shown from the litter concentration in the dry season; the survey was conducted during the dry season, and the distribution pattern of plastic litter was spread throughout the canal area (shown in Fig. 8).

Monitoring with UAVs has the potential to be developed spatially with a broader coverage area, particularly in hard-to-reach areas, and provides abundant waste monitoring, particularly in hotspots. Waste in water bodies has become a global problem that requires mitigation and management strategies. Monitoring floating macroplastics is a sustainable and long-term process; therefore, this activity must save time and cost, and monitoring with UAVs is an attractive alternative. Currently, visual screening is performed manually; however, in the future, this data can be used as a database for automatic object detection processes using machine and deep learning.

CONCLUSSIONS

This research conducted visual object detection through aerial mapping using DJI Phantom 4 UAV in a densely populated urban canal in Makassar City, Indonesia, with slow water flow to detect macroplastics (≥5cm). Several test parameters have been carried out, starting from differences in UAV altitude, flight time, and seasonal differences. The research results show that a height of 15m is recommended for minimizing autoblock in automatic flights and has image quality that still allows for object detection, although not as good as the image quality at a height of 10m or 5m. The best time suggested is 08.00–10.00 and evening 15.00–17.00 on sunny days. Several macroplastics successfully detected were PET, PS, EPS, PO-Hard, PO-Soft, Multilayer, and Others. The most common finding is PS-type plastic material in plastic bags (as much as 75% in dry and 43% in rainy seasons). However, other categories of floating waste detected are non-plastic (9% in rainy and 7% in dry season) waste such as cardboard, leather, plant residues, and rubber. Nevertheless, 14% in the rainy season and 3% in the dry season of material could not be detected in this study because of blurred images. Based on seasonal parameters, it was found that there were more floating macroplastics in the rainy season than in the dry season because the drainage system was open, which channeled rainwater and floating waste into the channels. The results of the Kernel analysis show a map of floating waste density with a different appearance in each season; in the dry season, the floating waste appears to spread across the canal's surface, while in the rainy season, the waste is denser on one side of the canal. This study can be a basis for monitoring plastic waste in urban rivers or canals using UAVs. However, visual detection is time-consuming because the detection process is performed manually. The need for automatic data processing using deep learning increases the data processing time and can reach a wider area of canals or rivers. Our research database can be the base for creating a database for automatically detecting macroplastic waste in water. Automatic detection of macroplastics remains a technological challenge, and further research is required to increase the effectiveness of existing automation algorithms. Experiments need to be conducted on other types of UAVs to increase our knowledge of macroplastic dynamics in densely populated urban rivers and canals.

Acknowledgements

We thank the Matsumoto Laboratory, Graduate Programs in Environmental Systems, Graduate School of Environmental Engineering, and the University of Kitakyushu, Japan, for support so that this research can be carried out. Remember to thank all those who have supported the implementation of this research.

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