Assessment of marine debris using UAV imagery in Cinta Coast, Indonesia

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Abstract. Coastal areas face a growing threat from marine debris, impacting both ecological and economic well-being. Traditional methods for studying debris distribution are often time-consuming and labor-intensive. This study explores the use of Unmanned Aerial Vehicles (UAVs) equipped with high-resolution imagery for mapping and characterizing marine debris along Cinta Coast, Indonesia. We employ two supervised classification algorithms, Maximum Likelihood Classification (MLC) and Minimum Distance Classification (MDC), to classify UAV imagery and identify the distribution of debris. Accuracy assessment of these classifications will be conducted using a confusion matrix and compared with data collected from direct transects. Our preliminary results indicate that the MLC method achieved superior overall accuracy (95.65%) compared to MDC (81.59%) in classifying debris from UAV images. This suggests UAVs offer a promising alternative for debris distribution identification, with advantages and limitations depending on field conditions. Furthermore, the MLC method appears well-suited for mapping debris distribution consistent with direct transect data. We hypothesize that oceanographic factors like tides and surface currents influence debris distribution on the Cinta Coast. Tides may transport debris closer to shore, while currents, potentially originating from rivers flowing into Jakarta Bay, might be the primary source of debris. This study's findings aim to contribute to the development of more efficient and accurate methods for marine debris monitoring, ultimately aiding in coastal conservation efforts.

Key Words: coastal area, marine debris, supervised classification algorithms, unmanned aerial vehicle.

Introduction. Coastal regions, rich in natural resources, have historically supported significant human populations and economic activities (Kibria et al 2023). The expansion of industries, services, and tourism in these areas has led to an increase in waste generation, a substantial portion of which ultimately enters the marine environment (Mejjad et al 2022). Among the countries most affected by this issue, Indonesia, with its extensive coastal population, has become a major contributor to global marine pollution (Adyasari et al 2021).

Marine debris poses a significant threat to marine ecosystems and biodiversity (Tome et al. 2024). Defined by NOAA (2013) as any persistent, manufactured, or processed solid material discarded, lost, or abandoned in the marine environment, marine debris can disrupt fragile ecosystems and have profound ecological consequences. Addressing this issue is a global priority and aligns with the United Nations Sustainable Development Goals (SDGs), particularly Goal 14, which highlights the urgent need to reduce marine pollution through effective management strategies (Assidiq et al. 2023). The environmental, economic, and public health impacts of marine debris depend on various factors, including its type, size, and distribution (Hafeez et al. 2018; Wilcox et al. 2015). The ecological consequences include habitat degradation, the entanglement of marine organisms, and the ingestion of plastic debris, all of which contribute to biodiversity loss (NOAA 2013).

Cinta Beach, located in Tanjung Pasir, Tangerang Regency in the northern part of Java Island, serves as a case study to examine the impacts of marine debris on coastal communities. The area, characterized by growing tourism and fisheries industries, is heavily affected by marine debris due to its proximity to the Cisadane River and Jakarta Bay. The accumulation of debris not only threatens local ecosystems but also disrupts economic activities such as fishing and tourism. Traditional methods for monitoring marine debris, such as beach transects, are labor-intensive and time-consuming (Rußwurm et al 2023). To address these limitations, remote sensing technologies, particularly Unmanned Aerial Vehicles (UAVs), have emerged as promising tools for rapid and efficient marine debris assessment (Guffogg et al 2021; Salgado-Hernanz et al 2021).

UAVs, or drones, offer a cost-effective and flexible platform for high-resolution aerial imaging, presenting several advantages over satellite-based monitoring (Merlino et al 2020; Takaya et al 2022). UAVs operate at lower altitudes, allowing for detailed mapping of marine debris distribution (Escobar-Sánchez et al 2022; Shen et al 2024). However, various challenges impact the accuracy and efficiency of UAV-based debris detection, including limitations in spatial resolution, weather conditions, flight duration constraints, and the complexity of data processing. For example, achieving an optimal spatial resolution (e.g., 200 pixels/meter) for mapping beach litter is difficult under changing environmental conditions (Taddia et al 2021). Adverse weather conditions such as strong winds, rain, and low visibility can further compromise image quality and obstruct UAV operations. Moreover, limited battery life constrains the area that can be surveyed in a single flight, potentially leading to incomplete data collection. Additionally, processing UAV imagery demands advanced computational techniques and robust classification algorithms, making data interpretation complex and resource-intensive (Agamuthu et al 2024).

The accuracy of UAV-based marine debris monitoring primarily relies on the image classification techniques used. Two commonly employed methods are Maximum Likelihood Classification (MLC) and Minimum Distance Classification (MDC). MLC, a statistical method that assumes a Gaussian distribution for each class, is recognized for its effectiveness in managing multi-dimensional data (Ismanto et al 2024). Research has shown that MLC can achieve high classification accuracy when applied to UAV imagery. In contrast, MDC, which classifies pixels based on the shortest distance to the mean of each class, is computationally efficient but may be less effective in complex environments where debris types share spectral characteristics (Acuña-Ruz et al 2018).

This study investigates the potential of UAV imagery for mapping marine debris at Cinta Beach and evaluates the effectiveness of different image classification techniques, specifically MLC and MDC, in identifying and quantifying marine debris. By addressing the technical challenges associated with UAV-based monitoring, this research aims to enhance the accuracy and efficiency of remote sensing applications in marine debris assessment, contributing to more effective environmental management strategies.

Material and Method

Data. This study was conducted along Cinta Beach, located in Tanjung Pasir Village, Teluk Naga District, Tangerang Regency, Indonesia. Geographically, the study area extends from 6°0'46.78" S and 106°40'45.44" E to 6°1'2.97" S and 106°41'0.92" E, as shown in Figure 1.

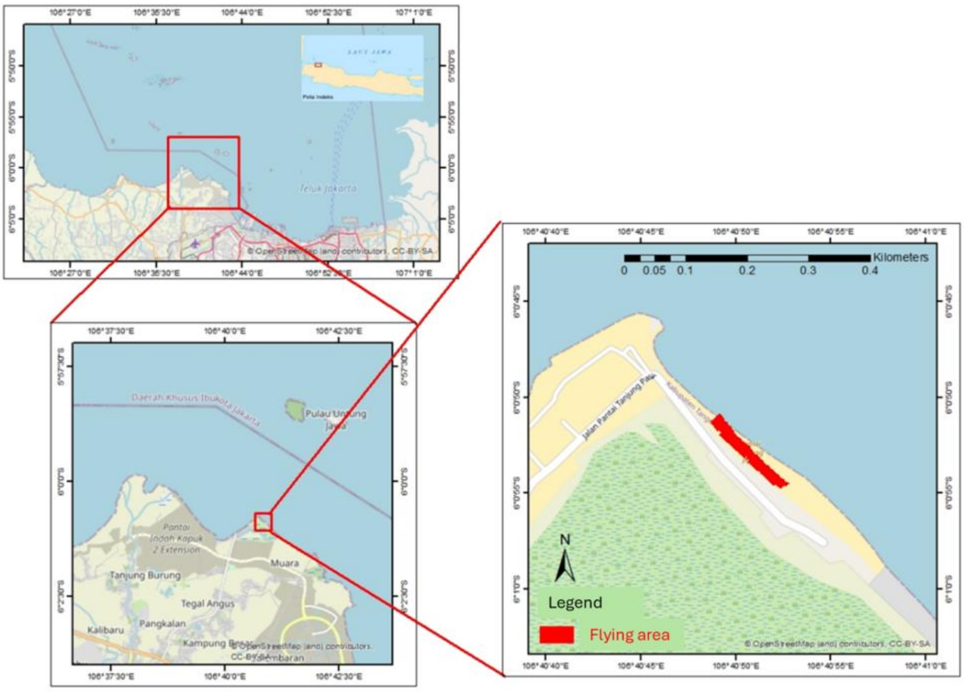


Figure 1. Research study area.

The data used in this study were collected through Unmanned Aerial Vehicle (UAV) imagery, complemented by tidal, ocean current, and wind data. High-resolution images were acquired using a DJI Phantom 3 Pro drone equipped with a 12-megapixel camera. The imagery was processed using Agisoft Photoscan to generate orthophotos. The drone flights were conducted under clear weather conditions with minimal wind (≤10 knots) at a consistent altitude of 20 meters Above Ground Level (AGL), resulting in a Ground Sampling Distance (GSD) of 1 cm/pixel. Additional flight parameters included a camera angle of 90°, 85% front overlap, 80% side overlap, a flight direction of 45°, and a mapping speed of 3 m/s.

Tidal data for June 15, 2021, were obtained from the global tidal model TMD (Tide Model Driver) and analyzed to determine high and low tide timings. Ocean current data were sourced from the Copernicus Marine Environment Monitoring Service (CMEMS) (https://resources.marine.copernicus.eu/), which provides model outputs with a spatial resolution of 0.083° × 0.083°. Wind speed data (u- and v-components in m/s) for the same date were obtained from the ECMWF Copernicus Climate Data Store. These reanalysis datasets offer hourly temporal resolution and a spatial resolution of 0.25° × 0.25°.

Drone image data processing. Imagery acquisition focused on the intertidal zone, where marine debris distribution is influenced by tidal fluctuations. The drone's flight altitude of 20 meters ensured the capture of macro-sized debris with a GSD of 1 cm/pixel. The processing workflow followed the Structure from Motion (SfM) technique, which reconstructs 3D structures from overlapping images (Westoby et al 2012; Jarahizadeh & Salehi 2024). Similar to stereoscopic photogrammetry, SfM generates a 3D model using multi-view images (Bessin et al 2023). The images were processed in Agisoft Photoscan, a photogrammetric software capable of producing high-resolution orthophotos (Barrile et al 2017), elevation points, and Digital Elevation Models (DEMs) (Gil-Docampo et al 2024). The orthophoto generation process in Agisoft Photoscan involves: 1) importing images and reconstructing flight paths; 2) image alignment; 3) inputting Ground Control Points (GCPs); 4) optimizing alignment; 5) creating dense point clouds; 6) building a 3D mesh; 7) generating a texture model; 8) creating a Digital Elevation Model (DEM); and 9) generating an orthophoto. No additional image enhancement techniques were applied, as the ortho mosaics provided sufficient contrast for distinguishing debris from sand and water.

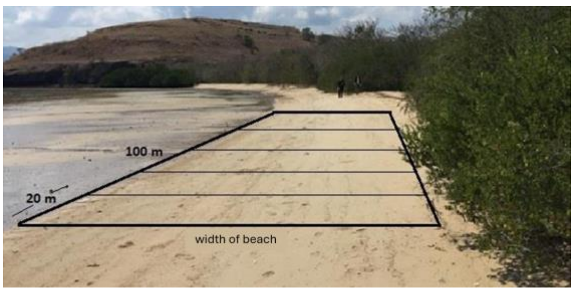
Identification of waste distribution using supervised classification method. Supervised classification requires manual input to define class boundaries using training samples, which represent the spectral characteristics of different marine debris types. Unlike unsupervised classification, where clustering is based solely on spectral similarities, supervised classification relies on predefined training areas derived from ground-truth data.

In this study, training areas were delineated using field survey data and high-resolution imagery. The MLC and MDC algorithms were employed due to their widespread use in remote sensing and ease of implementation. While more advanced classifiers such as Support Vector Machine (SVM) and Random Forest (RF) could improve accuracy, their higher computational demands and parameter tuning were beyond the scope of this study.

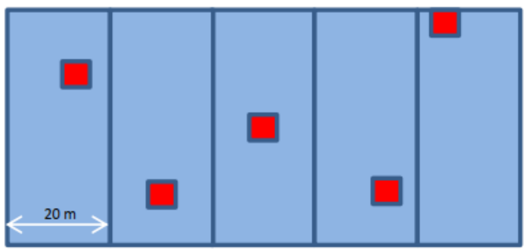
The classification process began with the selection of training areas representing different debris types, including plastic, wood, and other materials. Adequate training samples were collected to ensure statistically robust classification results. The classified image was used to map the spatial distribution of marine debris along the coast.

Validation of marine debris distribution. The accuracy of the classified debris distribution was assessed using an error matrix, which compares the results from MLC and MDC classifications with ground-truth data obtained from field surveys. An error matrix (also known as a confusion matrix) evaluates classification performance using three key metrics: producer's accuracy, user's accuracy, and overall accuracy (Lillesand et al 2015). Producer's accuracy (also known as omission error) measures the probability that a given class is correctly classified. It is calculated as the number of correctly classified pixels divided by the total number of pixels in that class (Foody 2020). User's accuracy (also known as commission error) represents the likelihood that a pixel classified into a specific category truly belongs to that class. It is calculated as the number of correctly classified pixels divided by the total pixels assigned to that category (Lu et al 2017). Overall accuracy is the proportion of correctly classified pixels across all classes.

Apriyanto et al (2019) recommended kappa accuracy as a more comprehensive metric since it accounts for all matrix components. According to Khatami et al (2016), a minimum classification accuracy of 75% is required for land cover classification using satellite imagery. To validate the classification results, a direct transect survey was conducted along the coastline, dividing the study area into five subplots (Figure 2). Marine macro-debris was manually collected, categorized by type (e.g., plastic, rubber, metal, glass, fabric, wood), and weighed at each sampling point.



(a)



(b)

Figure 2. (a) Division of transect into 5 lanes (Side view) and (b) Example of sub-transect box placement in each lane (Source: KLHK 2020).

Marine debris density was calculated as the weight of debris per square meter (M) in grams per square meter (g/m²) using the following equation:

$$M = \frac{total\ weight\ of\ waste\ (g)}{transect\ box\ area\ (m^2)} \qquad (1)$$

The composition of marine debris was determined as the percentage of each debris type relative to the total debris collected within a transect box:

$$Percentage\ (\%) = \frac{x}{\sum_{i=1}^{n} x_i} x\ 100\% \qquad (2)$$

where x represents the weight of a specific debris type, $\sum_{i=1}^{n} x_i$ which is the total weight of all debris types.

Limitations and considerations. A key limitation of MLC is its assumption of normally distributed spectral data within each class, which may not always hold in real-world conditions. This can result in misclassifications, particularly for materials with similar spectral signatures. Additionally, MLC requires a sufficient number of representative training samples for each class. Although the 1 cm/pixel GSD was sufficient for detecting macro-debris, smaller debris items may have been missed. Future studies could explore advanced classification algorithms (e.g., SVM, RF) or hyperspectral imaging for improved differentiation (De Wit et al 2004; Faizal et al 2022).

The differences in accuracy between MLC and MDC stem from their underlying methodologies. MLC considers variance and covariance within each class, enabling it to handle complex spectral overlaps, whereas MDC relies on a simpler distance-based approach, making it more prone to misclassification of spectrally similar materials. For example, misclassification of sand as wood by MDC suggests spectral similarities between certain sand patches and wood debris.

Ground-truth data were obtained through direct field surveys and high-resolution imagery to delineate training areas. The classification results were validated by comparing them with manual transect surveys. While this method enhances classification accuracy, some degree of human error in debris identification and categorization remains. The spatial density of transects and subplots also influences the representativeness of the validation dataset. Georeferencing errors were minimized through UAV-based GPS data and the incorporation of GCPs, ensuring positional accuracy within acceptable limits for UAV mapping applications.

Results

Orthophoto characteristics. The UAV-captured images were processed into orthophotos. The Ground Sample Distance (GSD), or pixel resolution, was set to 0.96 cm/pixel to ensure that macro-debris (minimum size: 2.5 cm) could be detected. After image alignment, the GSD of the orthophoto increased to 1.93 cm/pixel, still sufficient for our study. The reprojection error was 1.14 pixels, indicating a good alignment. A higher error would result in more mismatched points and a poorer model. Our 80% image overlap minimized this error, which fell within the acceptable range of 1.5-2 pixels (Pham et al 2023).

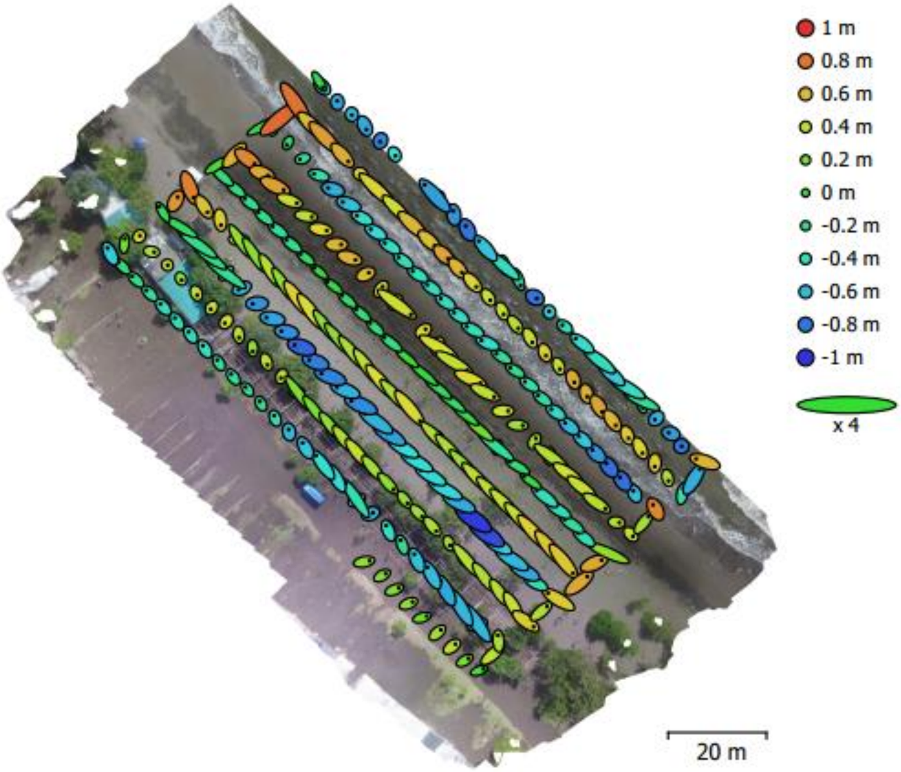
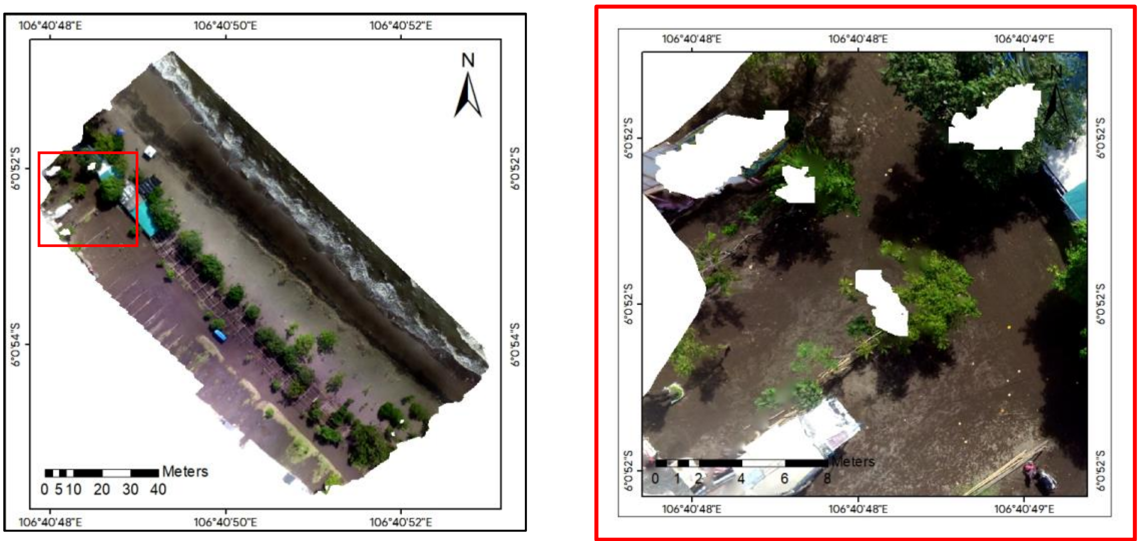


Figure 3. Camera position and error estimation.

Figure 3 shows the camera locations (black dots) and error ellipses. The ellipses indicate the X (longitude), Y (latitude), and Z (altitude) errors, reflecting the quality of the geotagging. These errors can be influenced by factors such as the geotagging process and the UAV's flight speed, which can affect GPS accuracy. The model yielded X, Y, and Z errors of 0.684 m, 0.631 m, and 0.481 m, respectively, with a total error of 1.048 m. Given the typical GPS accuracy of UAVs (0-30 meters), this total error is acceptable (Gregory 2009). Figure 4a presents the corrected orthophoto. The white areas in Figure 4b represent regions where image alignment failed due to mismatched points.



(a) (b)

Figure 4. Orthophoto map of the coastal area of Cinta Beach, Tangerang Regency (a) and snapshot of the perforated section on the orthophoto (b).

The orthophoto reveals that the rear of Cinta Beach is dominated by trees and semi-permanent structures. Both the beach and the terrestrial area exhibit varying levels of debris, including a mix of trash and wood. The region's moderate tourism activity likely contributes to the debris, along with marine litter.

Region of interest (ROI) and training data. This study focused on the intertidal zone of the coastline. The initial orthophoto, which included both land and coastal areas, was cropped to create a Region of Interest (ROI) (Figure 5). The ROI, representing the target study area, covers 2943.28 m² or 0.294 ha.

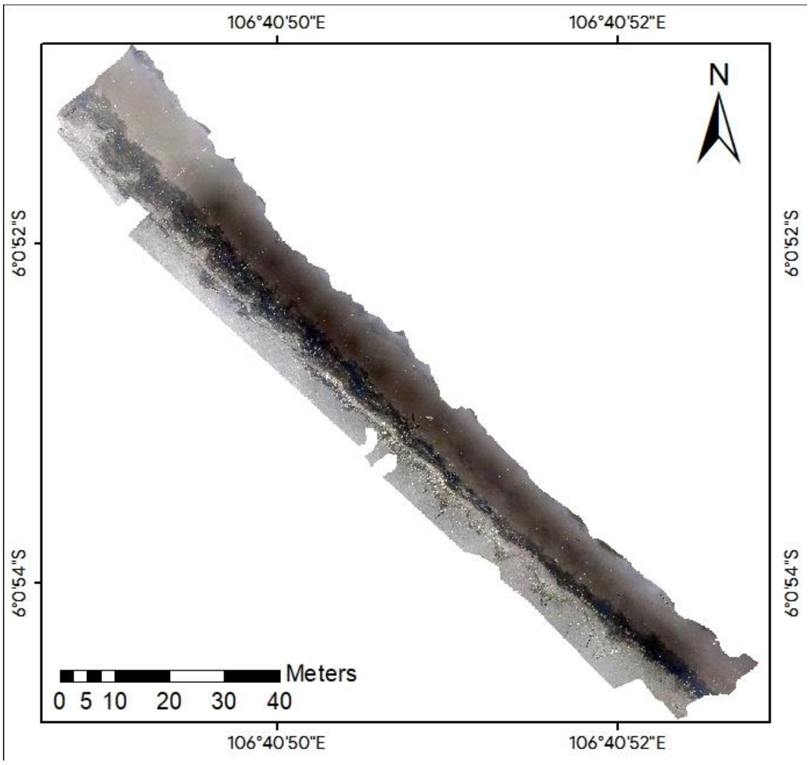


Figure 5. Region of interest.

A supervised classification approach was employed to map the distribution of marine debris within the ROI. Training samples, representing the classes of interest (plastic, wood, and sand), were defined based on ground truth data and visual interpretation of the imagery. Due to the similar spectral signatures of different plastic types in the imagery, plastic debris was classified as a single class. The classification scheme is illustrated in Figure 6.

The distinct spectral characteristics of each class were used to create training data. Two supervised classification methods, MLC and MDC, were applied to classify the marine debris in the Cinta Coast. Both methods assign pixels to predefined classes based on their spectral similarity to the training data. If the pixel value falls within the specified range of the training data, it is classified into the corresponding class.

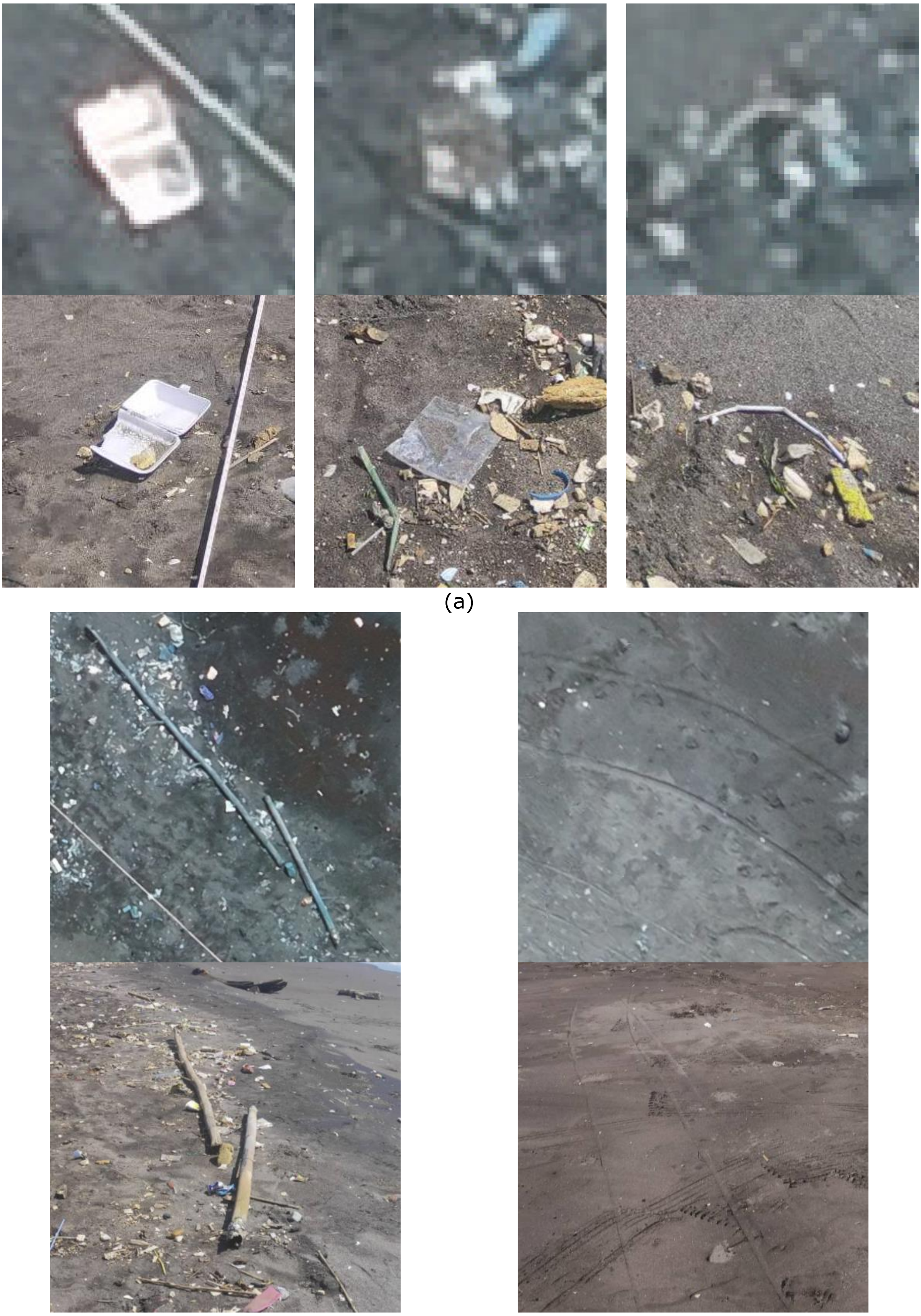
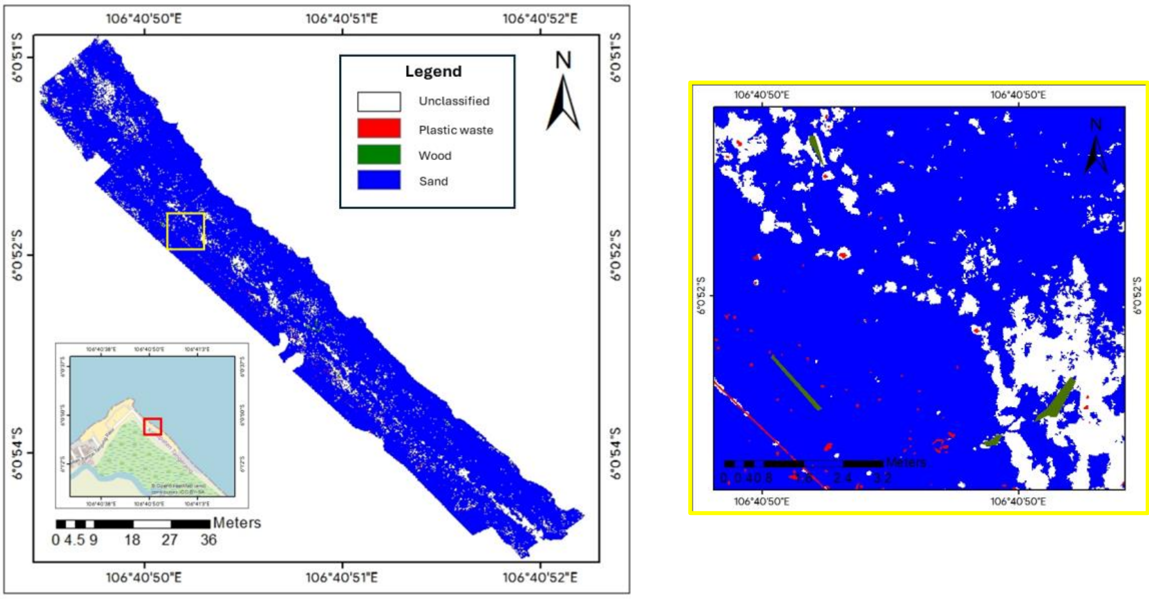
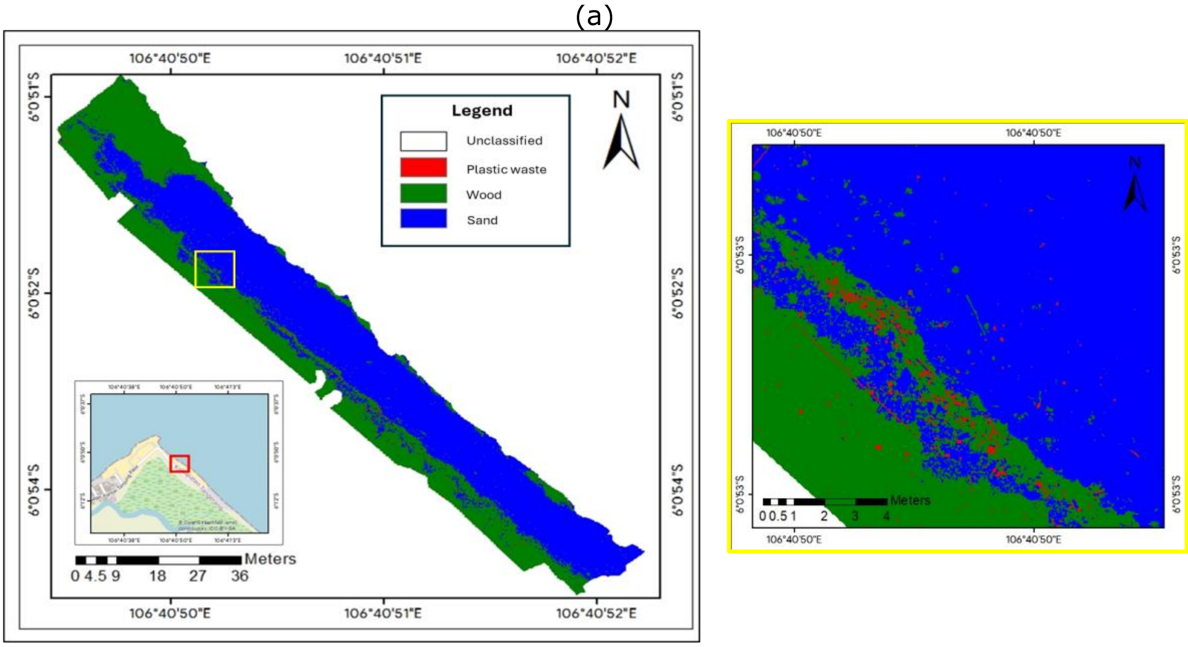


Figure 6. Clustering by Appearance in UAV Imagery and Field for (a) Plastic, (b) Wood, and (c) Sand.

Comparison of image classification results using MLC and MDC methods. This supervised classification involved intensive analysis of the training area, which consisted of three classes: plastic waste, wood, and sand. The resulting maps of marine debris distribution, classified using MLC and MDC, are presented in Figure 7.



(a)



(b)

Figure 7. Results of marine debris distribution by methods (a) MLC and (b) MDC at Cinta Beach, Tangerang Regency.

The MLC produced three classes: plastic waste (red), wood (green), and sand (blue) (Figure 7a). The largest area was classified as sand, covering 10,776.4 m² (Table 1). White areas indicate pixels that did not belong to any defined class due to their spectral characteristics. The MDC used the same training samples as the MLC. Figure 7b shows the resulting marine debris distribution map. Similar to the MLC, three classes were identified: plastic waste (red), wood (green), and sand (blue). The area of each class is presented in Table 1. The largest area classified by MDC was sand, covering 6,919.65 m².

Table 1

Area calculation of classification results of (a) MLC and (b) MDC methods

Class	MLC method		MDLC method	
	Count (pixels)	*Area (m^2)*	*Count (pixels)*	*Area (m^2)*
Plastic waste	175860	65.5	175297	65.3
Wood	13451	5.01	13031509	4854.11
Sand	28930709	10776.4	18576752	6919.65

The accuracy of the classification results was assessed using a confusion matrix, comparing the classified image to ground truth data collected in the field. Both MLC and MDC results were evaluated. Table 2 shows that for both MLC and MDC, most plastic waste and wood pixels were correctly classified. However, some misclassifications occurred, especially for pixels with spectral characteristics similar to other classes.

Table 2

Error matrix of methods (a) MDC and (b) MLC

		MLC method				MDC method			
		Plastic waste	*Wood*	*Sand*	*Total*	*Plastic waste*	*Wood*	*Sand*	*Total*
Field Data	Plastic waste	94	1	0	95	96	1	0	97
	Wood	0	6	0	6	2	0	30	32
	Sand	0	8	98	106	0	4	68	72
	Total	94	15	98	207	98	5	98	201

The confusion matrix provides essential information for evaluating classification accuracy, including overall accuracy, producer's accuracy, user's accuracy, and kappa coefficient. Overall accuracy, which measures the proportion of correctly classified pixels, is commonly used to compare different classification methods. A minimum threshold of 75% is generally considered acceptable (LAPAN 2015). The confusion matrix for MLC is presented in Table 3.

Table 3

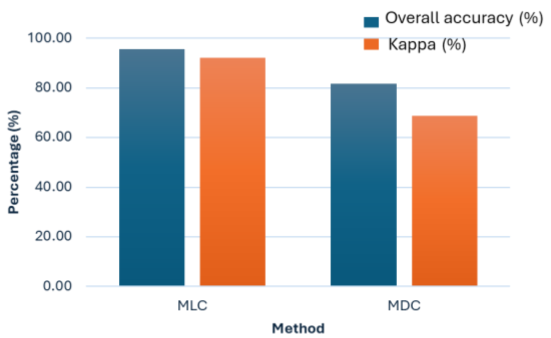
Calculation of producer and user accuracy based on MDC method error matrix

		Producer accuracy (%)		*User accuracy (%)*		*Total accuracy (%)*	*Kappa (%)*
		Accuracy	*Commission error*	*Accuracy*	*Commission error*		
MLC Method	Plastic waste	100	0	98.95	1.05	95.65	92.05
	Wood	40	60	100	0		
	Sand	100	0	92.45	7.55		
MDC Method	Plastic waste	97.96	2.04	98.97	1.03	81.59	68.59
	Wood	0	100	0	100		
	Sand	69.39	30.61	94.44	5.56		

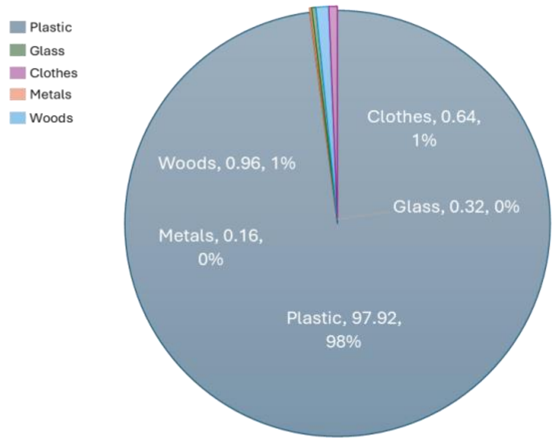
The confusion matrix provides important metrics for assessing classification accuracy, such as producer's accuracy, user's accuracy, and overall accuracy. Overall accuracy is used to compare different classification methods. According to LAPAN (2015), an overall accuracy of at least 75% is considered acceptable. For MLC, the producer's accuracy was highest for plastic waste and sand (100%), indicating that most pixels classified as these classes were correct. However, only 40% of pixels classified as wood were correct. User's accuracy was highest for wood (100%) but lowest for sand (92.45%). The overall accuracy for MLC was

95.65%, exceeding the 75% threshold. The kappa coefficient was 92.05%. For MLC, the producer's accuracy was highest for plastic waste and sand (100%), indicating that most pixels classified as these classes were correct. However, only 40% of pixels classified as wood were correct. User's accuracy was highest for wood (100%) but lowest for sand (92.45%). The overall accuracy for MLC was 95.65%, exceeding the 75% threshold. The kappa coefficient was 92.05%.

Distribution of macro debris at Cinta coast during the east season. Both the MLC and MDC methods successfully classified marine debris distribution at Cinta Coast (Figure 8a), achieving accuracies exceeding the 75% minimum threshold. However, the MLC-generated distribution map (Figure 7) exhibited greater detail compared to the MDC map. Specifically, MLC accurately classified plastic waste and sand, whereas MDC misclassified some sandy areas as woody debris. Table 3 further supports MLC's superior performance.



(a)



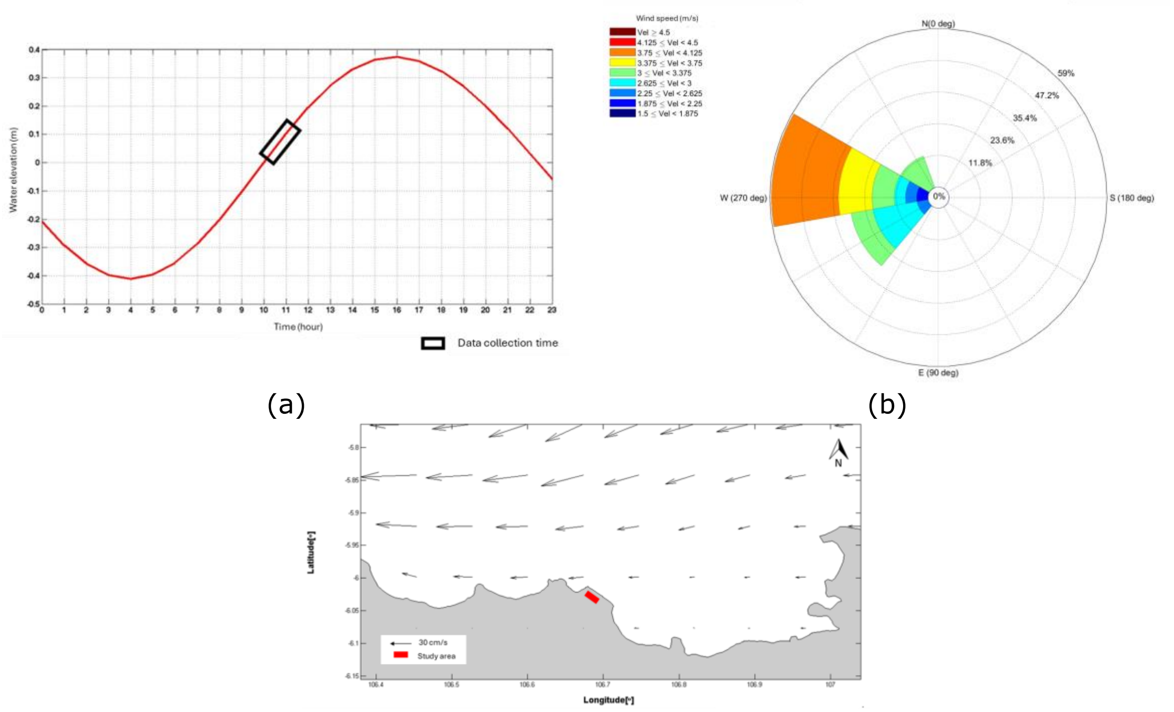
(b)

Figure 8. (a) Comparison of Accuracy Test of MLC and MDC Methods. (b) Percentage of marine debris composition from direct transect results at Cinta Beach, Tanjungsari.

A comparative analysis of classification accuracies revealed that MLC achieved a higher overall accuracy of 95.65% and a kappa coefficient of 92.05%, surpassing MDC's overall accuracy of 81.59% and kappa coefficient of 68.59%. While both methods met the minimum acceptable threshold, MLC's higher accuracies demonstrate its superiority. As noted by Septiani et al (2019), MLC's strength lies in its quantitative evaluation of spectral response variance and correlation during the classification of unknown pixels, maximizing probability based on training areas. In contrast, MDC, a simpler supervised classification method, relies on mean vectors for class assignment. MDC's lower accuracy can be attributed to its lack of parameter consideration during classification and its assumption of normal data distribution. This study's results confirm that MLC's ability to account for class variance and parameterization led to fewer misclassifications of woody debris as sand compared to MDC.

Complementing the UAV data, ground-truthing data was collected using transects. As shown in Figure 8b, plastic waste constituted the most abundant debris category (97.92%), followed by wood (0.96%), textiles (0.64%), glass (0.32%), and metal (0.16%). Comparing the classification results of MDC and MLC with the ground-truthing data (Table 3), MLC exhibited closer agreement. Both methods accurately identified plastic waste as the dominant debris type. MDC, however, showed significant discrepancies due to misclassifications. Consequently, MLC is the preferred method for mapping marine debris distribution. UAVs offer a time-efficient and cost-effective alternative for monitoring marine debris, especially for large-scale debris. However, the spatial resolution limitations of UAV imagery (1 cm/pixel in this study) can hinder the identification of smaller debris items (e.g., microplastics) compared to ground-truthing methods, which can identify items down to 2.5 cm. The limited flight time of the UAV used in this study also constrained the total area that could be surveyed. Future studies could consider using UAVs with longer flight times or employing multiple flights to cover larger regions.

The distribution of marine debris at Cinta Coast is significantly influenced by tidal cycles. During high tide, debris is transported from the sea towards the shore, while the reverse occurs during low tide. As illustrated in Figure 9a, the tide was rising during the data collection on June 15, 2021. This rising tide caused seawater to inundate a larger portion of the coastline, concentrating debris at Cinta Coast. The UAV imagery clearly shows debris accumulating from the highest tidal point towards the shoreline, indicating a dominant seaward source of debris.



(a) (b)

(c)

Figure 9. Tidal (a), Windrose (b), and Current pattern (c) in the waters of Cinta Coast on June 15, 2021.

The prevailing wind direction at Cinta Coast on June 15, 2021, was from the west, as shown in the wind rose plot (Figure 9b). Approximately 58.3% of the wind originated from 270-300 degrees, influencing surface currents in the northern Java Sea. These westward winds drive surface currents in the same direction, a common phenomenon in Indonesian waters.

Figure 9c presents the modeled current patterns in the Java Sea, covering the northern part of Jakarta Bay to the northern coast of Tangerang Regency. The current direction at the time of data collection (10:30 AM, June 16, 2021) was predominantly westward. The average current speed was 29.2 cm/s, with higher speeds of 40-45 cm/s observed in the open sea and lower speeds of 5-10 cm/s near Jakarta Bay and Cinta Coast. This westward current is likely a contributing factor to the distribution of marine debris at Cinta Coast. While the available current data provides a general indication of westward flow, higher resolution models would be needed to accurately simulate debris transport patterns in the nearshore environment.

Situated at the mouth of Jakarta Bay, Cinta Coast is nearly perpendicular to the incoming currents from the bay. The dominance of plastic debris at Cinta Coast suggests that it originates from Jakarta Bay and rivers flowing into the bay, transported by these currents. This hypothesis aligns with Jasmin et al (2019) findings, which showed that simulated particle trajectories of macro-debris from 13 river mouths in Jakarta Bay moved westward, following surface currents, during a similar period (July 2019). The westward currents, combined with the rising tide during data collection, likely contributed to the observed accumulation of debris on the shore.

Discussion. This study demonstrated the effectiveness of UAV imagery and the Maximum Likelihood Classification (MLC) method for assessing marine debris distribution at Cinta Coast, Indonesia. MLC's superior performance compared to MDC highlights the importance of considering spectral variance and correlation in complex coastal environments (Yohanlis & Putri 2021). The dominance of plastic debris, consistent with other studies in the region, underscores the urgent need for effective waste management strategies (Taddia et al 2021).

The study also revealed the influence of oceanographic factors, particularly tides and currents, on debris accumulation (Blickley et al 2016; Krelling & Turra 2019; Steele & Miller 2022). The rising tide on the day of data collection concentrated debris along the shoreline, making it readily detectable by the UAV (Wahid & Mutaqin 2024). The westward currents in the Java Sea, driven by prevailing westerly winds, suggest a likely source of debris from Jakarta Bay and its tributary rivers (Kisnarti et al 2024). While the available current data provides a general indication of westward flow, higher resolution models would be needed to accurately simulate debris transport patterns in the nearshore environment (Burgess et al 2024; Sun et al 2024; Hernandez et al 2024).

This study contributes to the growing body of knowledge on marine debris monitoring using UAVs. Compared to satellite imagery, which offers broader spatial coverage but lower resolution, UAVs provide a more suitable tool for detailed assessments in smaller, targeted areas (Petropoulos et al 2022). Manual beach surveys, while providing high accuracy, are labor-intensive and time-consuming, making UAVs a more efficient option for repeated monitoring (Murphy et al 2020; Freitas et al 2022). The relatively low cost and ease of use of UAVs make them a promising tool for community-based monitoring programs, empowering local stakeholders to collect valuable data on marine debris accumulation and inform management strategies (Merlino et al 2020; Takaya et al 2022). Future research could explore the integration of UAV data with hydrodynamic models to predict debris transport pathways and inform targeted interventions (Maximenko et al 2021). Furthermore, incorporating hyperspectral imaging could improve the classification accuracy of different debris types, allowing for more detailed assessments of marine debris composition (Gomez et al 2024). The limitations of UAVs, including flight time constraints and susceptibility to environmental factors like strong winds or rain, should also be considered when designing monitoring programs. Future studies could consider using UAVs with longer flight times or employing multiple flights to cover larger regions (Açıl et al 2023). While the 1 cm/pixel GSD was sufficient to identify macro-debris, the identification of microplastics would require higher resolution imagery (Olyaei et al 2024). Despite these limitations, UAV-based monitoring offers a valuable tool for understanding and managing marine debris pollution, particularly in dynamic coastal environments like Cinta Coast. The data collected can be used to inform policy decisions related to marine debris management, such as targeted cleanup efforts and the implementation of waste reduction strategies (Jiang et al 2020).

Conclusions. This study aimed to identify and monitor marine debris on Cinta Coast, Tanjung Pasir, and Tangerang Regency using a UAV approach. The results showed that the guided classification method with the MLC method obtained the largest area of sand, which was 10776.4 m^2, followed by debris with an area of 65.5 m^2, and wood with an area of 5.1 m^2. Meanwhile, the MDC method produced an area of sand of 6919.65 m^2, wood with an area of 4854.11 m^2, and debris with an area of 65.3 m^2. The classification results using the MLC method appeared more detailed than those using the MDC method. The debris and sand classes in the MLC method could be classified well. In the MDC method, there was an error in interpretation, where the area that should have been classified as sand was classified as wood. The overall accuracy of the guided classification results on the UAV image with the MLC method was superior, with a value of 95.65%, while the MDC method only had an accuracy of 81.59%. The use of UAVs/drones can be used as an alternative method to identify the distribution of debris according to field conditions, with several advantages and disadvantages. The MLC method is the best method for mapping the distribution of marine debris that is consistent with direct transect results. The distribution of marine debris on Cinta Coast is influenced by oceanographic factors such as tides that move debris further towards the coast and surface currents generated by wind, which are suspected to be the source of debris on Cinta Coast, namely the movement of debris from several rivers that flow into Jakarta Bay.

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