CleanAtlantic

Tackling Marine Litter in the Atlantic Area

WP 5 – Monitoring and Data Management

Activity 5.2 – Monitoring the presence of marine litter in the marine environment

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1. Introduction

Over the last decades, marine litter has increasingly captured the attention and concerns of scientists, decision makers and civil society. The incessant and growing delivery of plastic trash and debris to our oceans has become one of the most significant forms of marine pollution.

The persistent nature of plastic materials and their increasing global presence in both aquatic (Andrady, 2011; Akindele et al., 2019) and terrestrial ecosystems (Al-Jaibachi et al., 2018) has resulted in the conception of a new era - “The Plasticene” (Reed, 2015). Tackling plastic pollution in the marine environment requires concerted strategies and strong actions from policy makers and stakeholders on a global scale. Indeed, several efforts are already in place at the international, regional, and national levels, with several instruments [e.g., United Nations Convention on the Law of the Sea (UNCLOS), United Nations Environment Programme (UNEP), Regional Sea Programme, and the European Union Marine Strategy Framework Directive (MSFD)] being developed in recent decades to reduce and manage marine litter (Chen, 2015).

To great extent, many of the efforts and advances in dealing with marine litter pollution are still focused in “diagnosing” the problem, including: establishing protocols to detect, monitor and characterise marine litter distribution, identify major sources and assess the multiple impacts of the various types of marine litter. Similarly to other locations across the globe, monitoring initiatives in Europe and in the Atlantic area face numerous challenges and difficulties in regularly collecting data in such an extremely dynamic, complex and three dimensional environment like the marine realm. This has likely contributed to most efforts by well-established monitoring programs and dedicated survey protocols to target Beached litter.

Efforts to monitor Floating litter and ocean surface contamination has mostly relied on opportunistic reporting of floating debris from vessels (Lusher et al., 2014; Rothäusler et al., 2019; Campana et al., 2018), the proxy use of ingested items from target species (Ivar do Sul & Costa, 2014; Anastasopoulou et al., 2018; Corinaldesi et al., 2021) and a few dedicated protocols with limited geographic extent (Herrera et al., 2020) or targeting micro-litter contamination of surface waters (Gajšt et al., 2016; Lusher et al., 2014). In coastal areas, beached litter monitoring typically follows guidelines or standardised protocols that enables comparisons between locations and over time. Following the same principles will require the development of standard protocols or guidelines that can be used to produce comparable data. Vessel-based dedicated monitoring can assure quantifying effort and comparable data, but it is time consuming, costly and with numerous difficulties associated with vessel size and type, weather, light and sea conditions. With floating debris being subject to weather and currents they are mostly non-stationery, giving an additional temporal dimension and complexity to the matter.

There are increasing efforts to use satellite based remote sensing technology and methods to monitor contamination levels and floating litter accumulation areas (El Mahrad et al., 2020; Farré, 2020; Haarr et al., 2019; Salgado-Hernanz et al., 2021), however, most of these applications face challenges due to sensor spatial resolution and poor detectability of small concentrations from space (Acuña-Ruz et al., 2018; Hu, 2021; Martínez-Vicente et al., 2019). Advances in spectral profiling and in sensor and satellite technology are expected to soon be able to detect and even monitor high concentration areas like the Pacific Garbage Patch and other gyres (Goddijn-Murphy & Williamson, 2019; Lebreton et al., 2018), but monitoring contamination levels in non-accumulation areas will definitely be more challenging (Garcia-Garin et al., 2020).

The recent development of inexpensive commercial off-the-shelf (COTS) drones and other advanced Unmanned Aerial Systems (UAS) has made high-tech aerial imagery platforms easily and widely accessible. Automated flight ability at low altitudes enables UAS to produce aerial imagery with higher resolution than that achieved by current satellites or by manned aerial platforms. UAS based remote sensing has already demonstrated a variety of applications in the marine realm, including assessment of intertidal areas, shallow coral reefs and estuarine algal cover, bathymetry, habitat and biotope mapping and detection beached litter (Gonçalves, Andriolo, Pinto, et al., 2020; Gray et al., 2018; Long et al., 2016; Monteiro et al., 2021; Nahirnick et al., 2019; Papakonstantinou et al., 2021; Ventura et al., 2018). Operation flexibility and simplicity make Unmanned Aerial Systems promising platforms to develop remote sensing protocols and monitor floating litter using systematic approaches.

Here, we report the efforts and advances made within the CleanAtlantic project towards the use of UAS-based Remote Sensing to monitor floating litter, including: i) general operational and processing constraints; ii) custom designed case study used to assess different processing options for RGB aerial imagery; iii) considerations and limitations of using UAS-based remote sensing for floating litter monitoring, and; iv) recommendations towards the implementation of UAS-based remote sensing protocols and monitoring programs.

2. Monitoring floating litter from UAS-based Remote Sensing

2.1. Operational and Processing Considerations

The use of COTS and custom designed UAS is becoming increasingly popular for recreational, industrial, topographic surveying, monitoring and research purposes (Hardin et al., 2019; Klimkowska et al., 2016; Laliberte, 2009; Matese et al., 2015; Whitehead et al., 2014) due to their relatively low cost, operational flexibility and simplicity. Most modern UAS include automated flight capabilities, pre-planned mission controls, high resolution camera systems and geo-tagged logs that enable the construction of ortho-photomosaics and 3-d models of the surveyed area. In coastal areas these traits have been explored for monitoring beached litter (Bao et al., 2018; Garaba & Dierssen, 2018; Gonçalves, Andriolo, Gonçalves, et al., 2020; Merlino et al., 2020), however, the use of aerial photography and UAS-based remote sensing for the detection and monitoring of floating litter poses specific challenges.

In land, overlapping NADIR imagery collected drones uses unique and discrete references in the images to construct a mosaic and estimate position, slope and other topographic features along the survey area. Over open water, the lack of discrete or unique reference points, the homogeneity of images and the dynamic surface makes it difficult to reconstruct ortho-photomosaics. To assess coastal waters, one could fly at enough altitude to simultaneously include land features and ocean waters, but this is generally not a practical solution as there are safety issues and regulations that prohibit or limit the maximum altitude for UAS operations. Special authorisations can be issued for high altitude flights, but these are typically complex bureaucratic processes that hamper operational flexibility desired. One solution we explore is to use individual images, where the area covered on each image is estimated and can be used as reference for density or area proportion analysis. In this approach, multiple images can be grouped and sequentially analysed to estimate floating litter contamination along a transect, which can be repeated over time or compared to other locations.

There are additional challenges in operating UAS and using them for systematic monitoring, namely the unpredictability of weather conditions (which limits flight operations) and how varying light and sea conditions can affect imagery and, subsequently, image processing and litter detection. Flat ocean conditions are obviously better, offering a more homogeneous background where floating debris and items are more easily identified. One other important factor, that can be compounded by sea conditions, is related to lighting and light backscatter. Ideal light conditions include clear skies, during a period where the sun is at a low angle (i.e., high angles increase backscatter for NADIR imagery) and with sea conditions flat (i.e., as waves and ripples will also influence light backscatter on water surface). Overcast conditions, high sun and waves can easily decrease image quality for object detection or affecting and leading to the need of discarding a large portion of each image. The use of multispectral sensors can reduce some of the negative impacts of poor conditions, as some channels generally produce outputs that are less sensitive to light backscatter over sea surface (i.e., infra-red, near infra-red). Thermal sensors can also be adequate to detect large objects that have a large proportion that are air-exposed, however, they are typically unable to detect objects that are frequently submerged and cooled by waves and sea spray.

One other constraint to the use of UAS-based remote sensing is related to their flight range and the compromise between surveyed area and image resolution. Operational range can greatly vary depending on the UAS; however, it is reasonable to assume that UAS have a limited range from the deployment starting point and that they can be mostly used to survey a limited area. This makes UAS-based monitoring suitable for routine monitoring of coastal waters (i.e. land-based operations) or targeted open water areas (i.e. vessel-based operations). In both of these scenarios, the use of transects at predetermined altitudes can easily be used as a sampling strategy that produces comparable data. However, in order to maximise image resolution, flights need to be at low altitude (enabling the detection of small items) whereas maximising survey areas, will require flights to be at higher altitude (increasing monitored area but with lower detection capabilities).

Additional constraints for the use of UAS-based remote sensing to detect, map or monitor litter contamination, is related with the aerial imagery processing requirements. Georeferenced individual images or mosaics collected with regular RGB cameras or with additional channels, require processing and analysis to manually or autonomously detect litter or assess contamination levels. The careful visual inspection of imagery and manual annotations is the simplest solution, but more laborious, especially if dealing with large numbers of images and in long term programs. Opposingly, automated object detection can potentially reduce user interaction needs, but typically requires higher computational power and programming expertise.

In order to make UAS-based remote sensing as a feasible tool for floating litter monitoring, one needs to assess available resources and custom-design a monitoring program that is adequate to general conditions, to the available hardware and expertise level and that systematically collect and process information. To assess the trade-offs of different approaches, we aimed to compare multiple approaches using UAS-based aerial imagery to detect floating litter items. General flight operations guidelines were compiled (**Appendix I**) after an initial trial period where multiple flights were used to test flight capabilities and sensors. During this initial stage, it became evident that the low contamination of Madeira coastal waters would not provide real-life scenarios to test and optimise processing workflows or to conduct a comparative study, leading to a custom-designed case study.

2.2. Case Study: assessing processing options

2.2.1. Description

Fluxes of litter and contamination levels in the sea vary, depending on the proximity to urban activities, coastal uses, wind and ocean currents. These factors may cause the accumulation of marine litter in oceanic convergence zones, but they often are in low densities making them harder to detect from vessel-based observers, sampling devices or from remote sensing platforms.

Floating macro-litter monitoring is mostly dependent on vessel-based observers opportunistically reporting sightings, which makes it difficult to standardise effort, methods and produced data sets. Using in situ sample collection techniques, such as manta trawl nets, allows to evaluate the litter density and contamination levels of surface waters, but it is costly and typically employed for micro and meso litter monitoring. The use of satellite remote sensing data for assessing and mapping plastic litter hotspots has been increasingly discussed in the literature (Kikaki et al., 2020; Moy et al., 2018; Themistocleous et al., 2020). The use of satellite data could potentially enable the development of cost-effective, repeatable and fast methods that estimate the marine litter amount and its distribution over large spatial scales. However, despite the efforts to develop analytical sensing methods and results are directly dependent on the spatial resolution of currently available sensors. With available resolution for RGB bands between 30 - 50 cm and multispectral bands between 1.2 - 7.5 m, current satellite remote sensing can only be used to detect: i) areas with high concentrations of litter or plastic, and/or; discrete objects that are large enough to be distinctively recognised.

There are multiple UAS platforms and methods that can be used in developing protocols and monitoring programs to detect and assess floating litter contamination levels. Initial monitoring efforts with UAV image collected in 2018 demonstrated that the low abundance of floating litter in Madeira was conditioning the ability to access and customise an imagery analysis workflow (i.e. with 10 transects of 1 km and over 700 images, only a very low number of images had floating debris and at very low abundance). Here, we report a case study designed to use low-cost commercial off-the-shelve quadcopter equipped with a high-resolution RGB camera and compare different processing workflows. The goal of this case study is to compare different imagery analysis approaches and develop guidelines for the implementation of floating litter monitoring protocols with UAS-based remote sensing.

2.2.2. Experimental trial setup

Initial testing for the experimental trials were conducted using bread as dummy floating litter objects to assess detectability from aerial imagery at different altitudes and establish thresholds in flight and camera settings. Follow up experimental trials were conducted where floating litter objects were deployed from a boat while a UAS flying between 10-30 meters was used to collect multiple pictures of the sea surface area where the items had been deployed. The UAS was initially positioned over the vessel and image capture was setup to collect individual images at each 10 seconds. Items were launched to the water and the vessel was repositioned to be outside of the image frame (**Figure 1**). Deployed objects naturally drifted at different speeds and directions, for which after some hovering time collecting imagery 5-10 mins, the UAS was recovered and all items collected. Deployment was repeated to collect additional data and compare processing of imagery with different exposure settings (i.e., normal exposure and low exposure; **Figure 2**) to collect aerial imagery for the development and streamlining the processing and analysis workflow. The collection of low exposure imagery (**Figure 2**) was included to enable a major reduction in light and colour variations of the background (i.e., sea surface) while maintaining the ability to detect floating objects. A total of 148 valid images (with objects and no vessel in frame) were collected to use on the analysis workflow development, 74 images with normal exposure (blue background) and 74 images under-exposed (dark background).

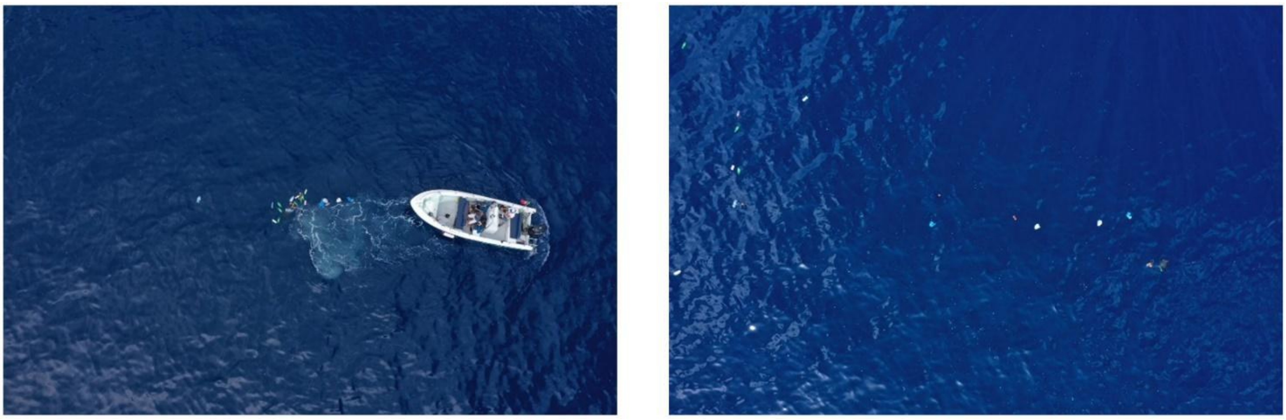

Figure 1: Example of an aerial image of the experimental trial where floating litter objects were deployed from the boat to collect aerial imagery.

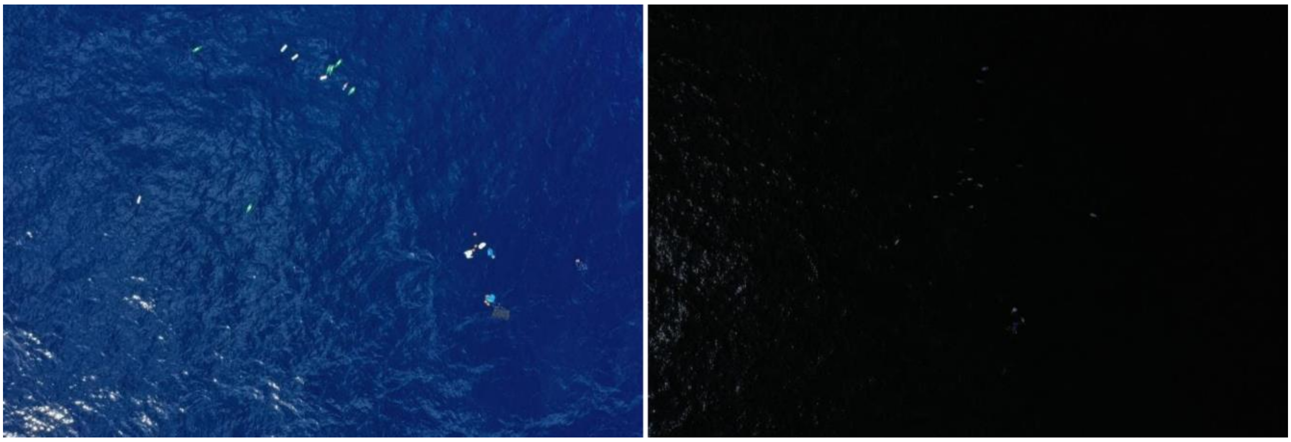

Figure 2: Example of two types of aerial images collected; left is normal exposure (Blue) and right is exposure for low EV (Dark).

2.2.3. Classification procedures

The experimental trials enabled collecting imagery with discrete floating litter items that could be used to assess and compare different strategies and analytical procedures for monitoring floating litter with UAS-based remote sensing. In this experimental trial, we selected three different strategies for analysing collected imagery and compare how they can be used in assessing contamination levels or detecting floating litter items: i) a visual inspection with manual annotation (**Figure 3**); ii) a colour and pixel-based analysis (**Figure 4**), and; iii) the use machine learning (ML) for automated object identification and classification (**Figure 5**). Additionally, individual image footprint areas were estimated using Pix4D GSD Calculator[1] and the formulas:

$$GSDh = \frac{Flight\ Height * Sensor\ Height}{Focal\ length * Image\ Height}$$

$$GSDw = \frac{Flight\ Height * Sensor\ Width}{Focal\ length * Image\ width}$$

Ground Sampling Distance height (GSDh) and width (GSDw) were than used to estimate total footprint area of each image using the formula:

$$Image\ footprint\ area = (GSDh * image\ height\ nº\ pixels) * (GSDw * image\ width\ nº\ pixels)$$

i) Visual Inspection and manual classification

Images of both dark and blue sets were compiled for visual inspection and annotation using the software DotDotGoose[2] **Figure 3**; (Felis et al., 2019). Two independent annotations were performed: one to simply identify and count floating objects, where a broad, all-inclusive category "floating Item" was used as label during image inspection and annotation, and; a second to classify floating objects within different categories (e.g., Cleaner Bottles – Containers; Drink Bottles – Green; Drink Bottles – Transparent; Drink Bottles – Large (>5L); Tetra Pak; Plastic Bags; Other Containers; Floating Fishing Gear and Other Floating Debris). For each image, inspection and annotation times were registered. Data was exported from annotation software as .CSV files and compiled into a summary table that included information on image file, image set (i.e.; blue and dark sets), number of floating items, number of items per category, object identification time and object classification time.

[1] Pix4D GSD Calculator: https://support.pix4d.com/hc/en-us/articles/202560249-TOOLS-GSD-calculator

[2] American Museum of Natural History, creator of DotDotGoose. Open-source software who assist with manually counting objects in images. https://biodiversityinformatics.amnh.org/open_source/dotdotgoose/

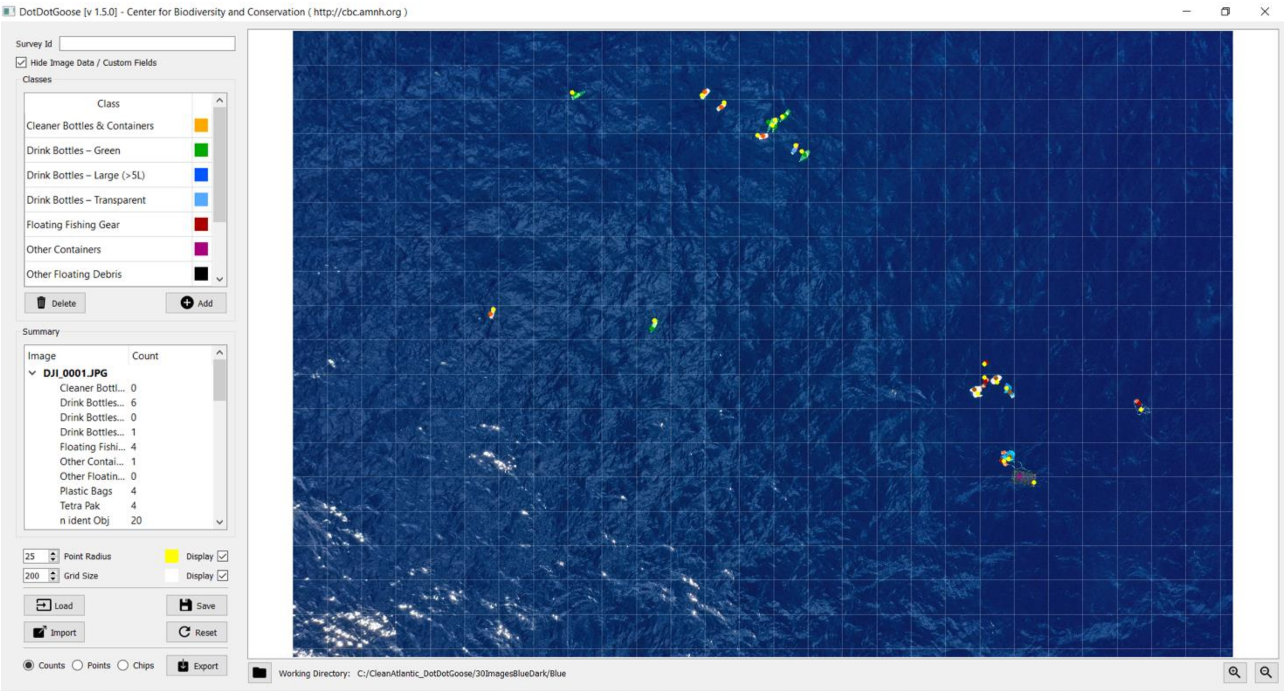

Figure 3: Example of DotDotGoose interface. Used to perform Manual Count.

ii) Colour and pixel-based analysis

Images of both dark and blue sets were compiled for analysis using pixel colour differences to estimate floating debris contamination (Kataoka & Nihei, 2020). Individual images were smoothed using a uniform box filter (5×5 px) to remove noise. For smoothing, the median filter is applied to the original frame image, and the window size of the filter is 200×200 px. To quantify the difference in colour between the original and smoothed images, the RGB colour space of both images is converted into the CIELuv colour space. The CIELuv colour space attempts to obtain a perceptual uniformity of the colour difference in the three-dimensional space (i.e., L*, u*, and v*) (Fairchild, 2013). The colour difference (ΔE) is expressed by the Euclidean distance between two points in the CIELuv colour space (Kataoka & Nihei, 2020). Pixels of macro-debris were extracted by determining the appropriate constant threshold value in the difference image (**Figure 4**). For each image, estimation of floating debris contamination used the percentage of total image pixels that were identified as marine debris.

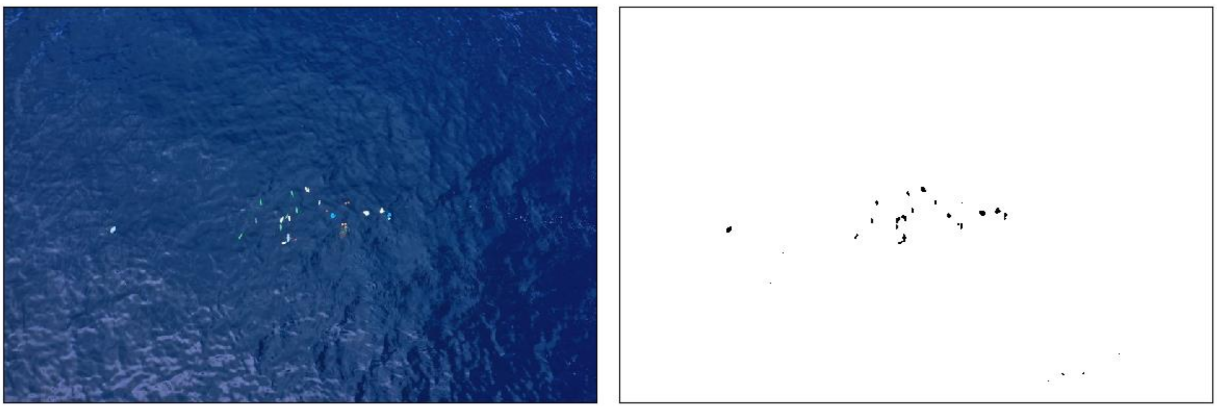

Figure 4: Pixel base detection of floating debris using colour difference to generate binary image (right) and estimate the proportion of floating debris pixels (%).

iii) Machine learning for automated object detection and classification

Images of both dark and blue sets were compiled for analysis and automated object detection and classification using Convolutional Neural Network (CNN) models. As a base model architecture, combined MobileNetV2 (Sandler et al., 2018) with Single-Shot Detection (SSD) algorithm (Liu et al., 2016) was used. Individual images from each of the image sets were visually inspected and annotated using Supervisely[3] (Temitope Yekeen et al., 2020) an Artificial Intelligence Platform, with an online image annotation tool, that leverages state-of-the-art object detection algorithms (**Figure 5**). Similarly, to the manual annotation, for each of the image sets, two different strategies and trials were performed: one to identify any floating object, by using a general label of "floating debris" and, a second one, to classify floating objects by using different categories (e.g., Cleaner Bottles – Containers; Drink Bottles – Green; Drink Bottles – Transparent; Drink Bottles – Large (>5L). For each of the image sets (i.e.; normally exposed "blue" and underexposed "dark'') a total of 74 images were used for model training and 4 images for validation (with model inference during the training repeated each 100 iterations). The procedures involved single and multi-class identification using object detection, based on ground truth annotation and bounding box. The model was trained using NVIDIA Tesla P100 PCI-E 16GB GPU on Google Collab, using TensorFlow 1.15.2. Model was trained using 200k iterations and with batch size 12, with 6 hidden layers, with input imagery down sampled to be 300x300 px, using ReLU6 activation function and initial learning rate 0.004. Data inquiry for training and validation included mean average precision, mean average precision at 50% Intersection of Union (IoU), mean recall and loss score function. For each image, information from both models (i.e.; detection of floating items and categorisation of different floating items) was compiled for comparison and analysis. Overall model performance was assessed by computing model precision, sensitivity and F1 score (J. B. Brown, 2018). An example of the results obtained after the automated classification and object recognition can be seen on **Figure 6**.

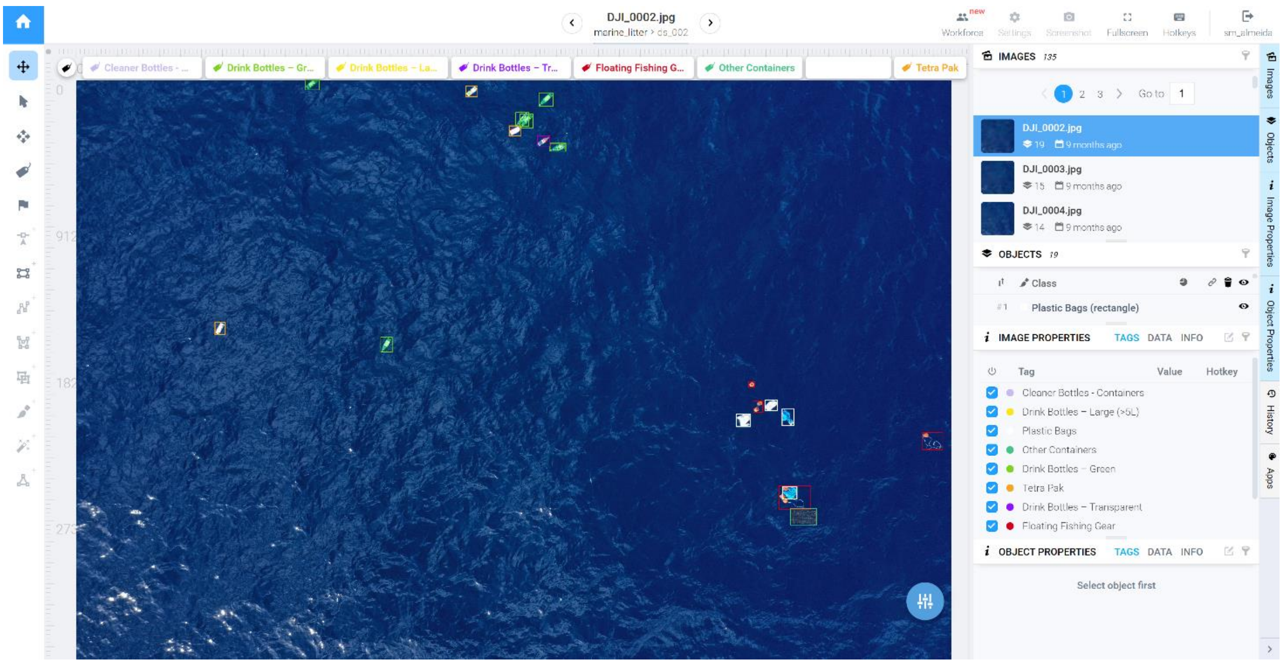

Figure 5: Example of Supervise.ly interface. Used to create the initial annotation automated detection and classification using deep learning.

[3] Supervisely a labelling platform dedicate to computer vision. https://supervise.ly/

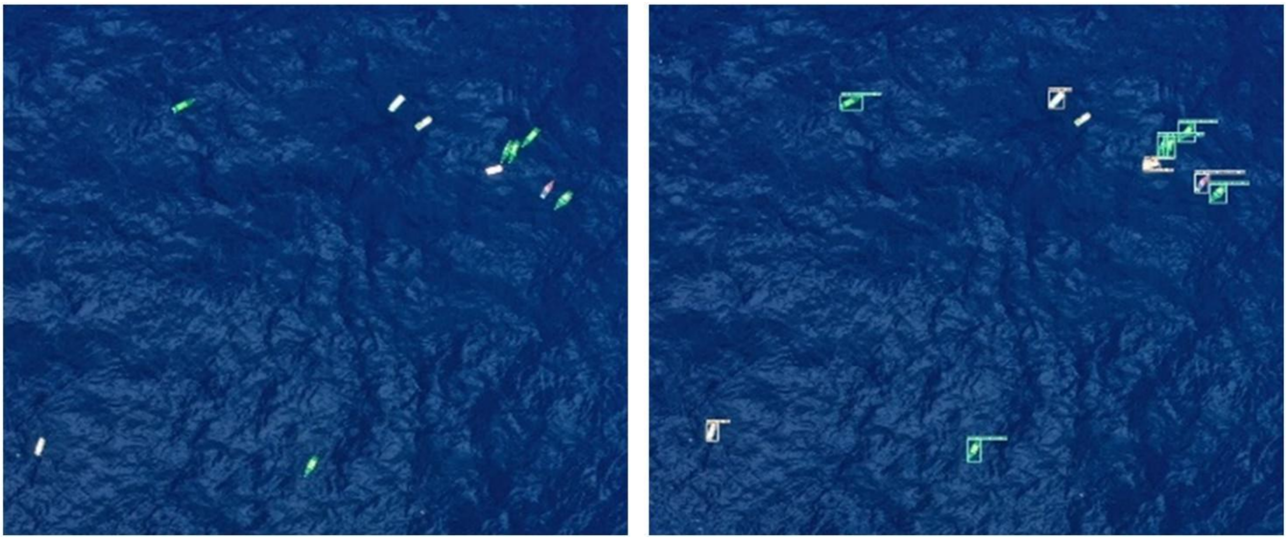

Figure 6: Examples of automated classification and object recognition using deep learning.

2.2.4. Comparing analytical approaches

For the purposes of this case study, three major aspects were considered in comparing methods: i) average time required to inspect and process each image; ii) ability to adequately assess floating litter contamination, and; iii) skills and logistical requirements for implementing a monitoring program using each method. The concept for this comparison rationale is to assess overall advantages and disadvantages of different analytical and classification approaches in order to design adequate floating litter monitoring programs with UAS-based remote sensing that can fit different conditions, training and available resources.

Average time required for each image processing was considered an essential indicator for determining most adequate methods and analytical approaches, as some require a user to inspect and make annotations on each single image, whereas automated methods may process a large number of images automatically. Despite this general advantage for automated image annotation processes, these generally have errors associated to the critical discrimination of objects, leading to the need of evaluating how good the approach is in assessing floating debris contamination or in classifying floating objects. As the approaches differ on the output, simple descriptive statistics were applied to compare outputs whereas standard metrics were used to assess deep learning classification models. Finally, an evaluation of requisites such as computational infrastructures and skills for each analytical approach must be considered, as to determine feasibility of a monitoring program that relies on imagery analysis.

2.3. Results

2.3.1. *Comparing Processing Times*

Visual inspection and annotation are laborious tasks that can hamper efforts of using aerial imagery to assess floating litter contamination, especially if within a program that systematically collects large amounts of imagery. Unsurprisingly, when comparing the time required for a user to visually inspect an image and label floating items to the time required in automated processes, the human labelling performs within comparable ranges to those of colour-based selection of debris pixels and considerably better than those of automated floating object detection (**Figure 7**). Colour based pixel detection process is more consistent in terms of the time required (i.e. lower variance) and performs slightly better than human classification of objects, even though differences were not significant. Despite not requiring human interaction, automated classification of floating objects in this study took significantly more time per image than any other analytical approach. Despite some differences in variance, processing times did not differ much when using the normally exposed Blue image set or the underexposed Dark image set, except for Machine Learning automated classification, which had lower processing times with underexposed images.

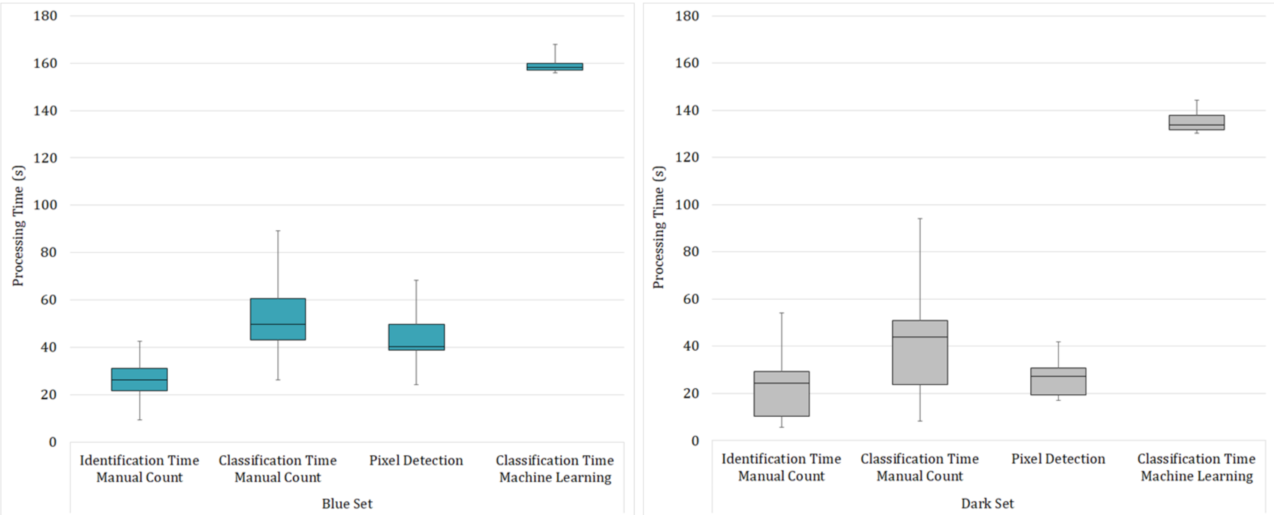

Figure 7: Timing comparison between identification and classification over the tree methods tested.

2.3.2. *Comparing performance in assessing overall debris contamination*

For the purposes of this case study, data from visual inspections and classification was considered as ground truth data for assessing how automated approaches performed. Linear regressions (**Figure 8**) were used to assess if both colour-based pixel detection and ML automated floating items detection were adequately assessing contamination. The use of linear regressions is a simplistic method to assess performance under the assumption that the number of floating items visually detected is proportional to the proportion of pixels detected using colour difference and proportional to the number of floating items detected with ML. A comparison of both methods illustrates that: i) ML object detection matches better with human visual detection, especially with normally exposed imagery; ii) colour difference selection of pixels from normally exposed imagery is inadequate for floating litter contamination assessments, and; iii) colour difference selection of pixels from underexposed imagery performs better than with underexposed imagery, but still lacks strong linear relation with number of floating items.

Overall, the lack of strong collinearity with the number of floating items renders the colour-difference detection of debris pixels from RGB imagery as a less reliable method for estimating contamination by floating debris. Despite this limitation in reliability, colour difference can be used to estimate debris contamination in underexposed imagery, if imagery is systematically collected with similar light, weather and sea conditions. One other option is to use Near-Infrared and Infrared sensors to detect floating objects and debris, as these spectra are quickly absorbed by water.

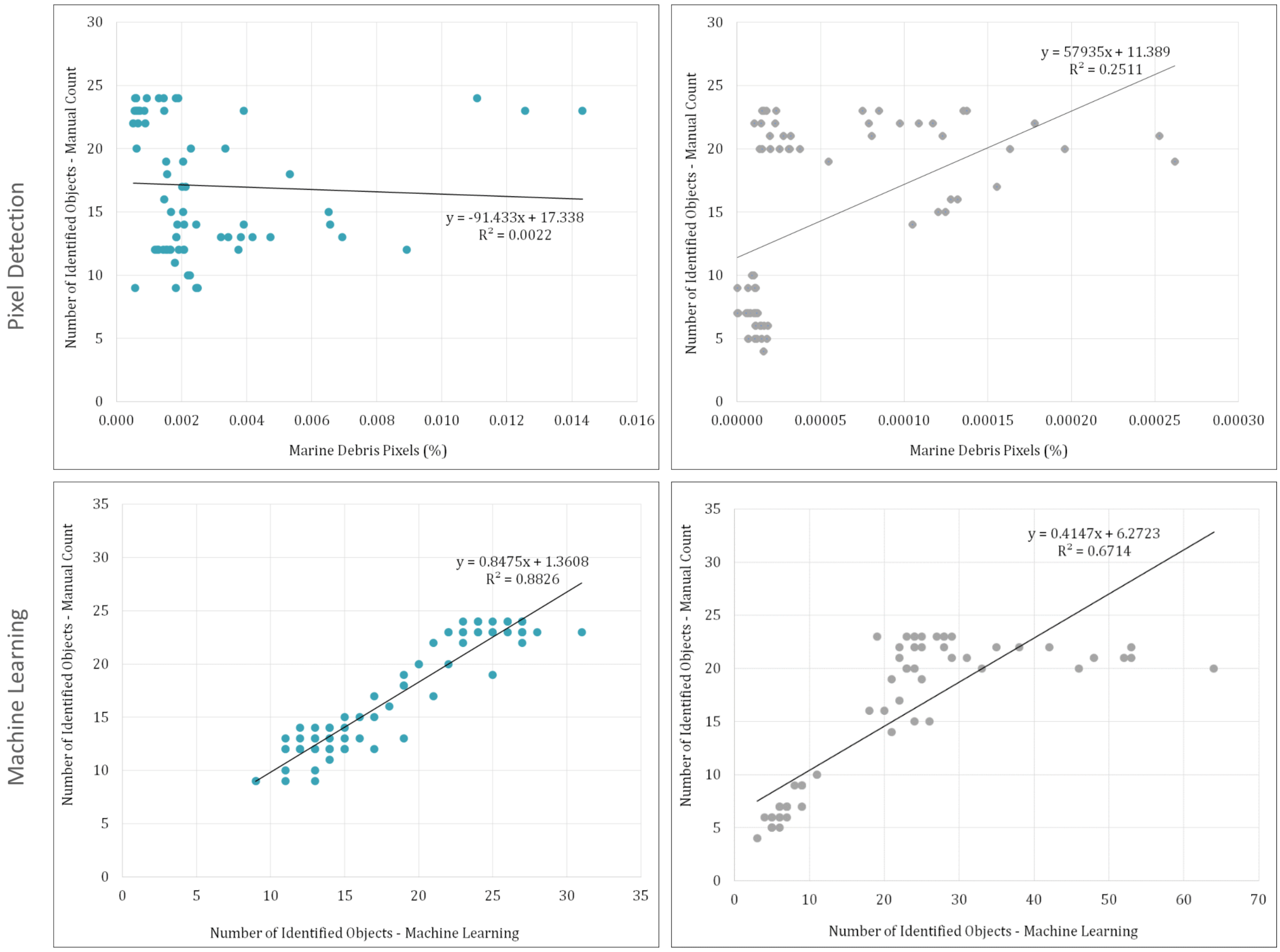

Figure 8: Linear correlation analysis between number of items per image (i.e. visually identified) and automated analysis using Pixel Detection (top) and automated object detection using Machine Learning (bottom) for the Blue Set (left) and Dark Set (right) of images.

The use of deep learning for automated detection of floating objects has a stronger performance than colour-difference based processing. As expected from the inspection of linear regressions (**Figure 8**), the range in the numbers of automatically detected objects using ML is comparable to those identified by visual inspection (**Figure 9**), particularly with normally exposed images, where medians and quartiles are very similar and there are no significant differences. Overall, ML can be used for processing large numbers of images autonomously for assessing contamination with acceptable error, however, it is important to consider processing time and implementation requirements.

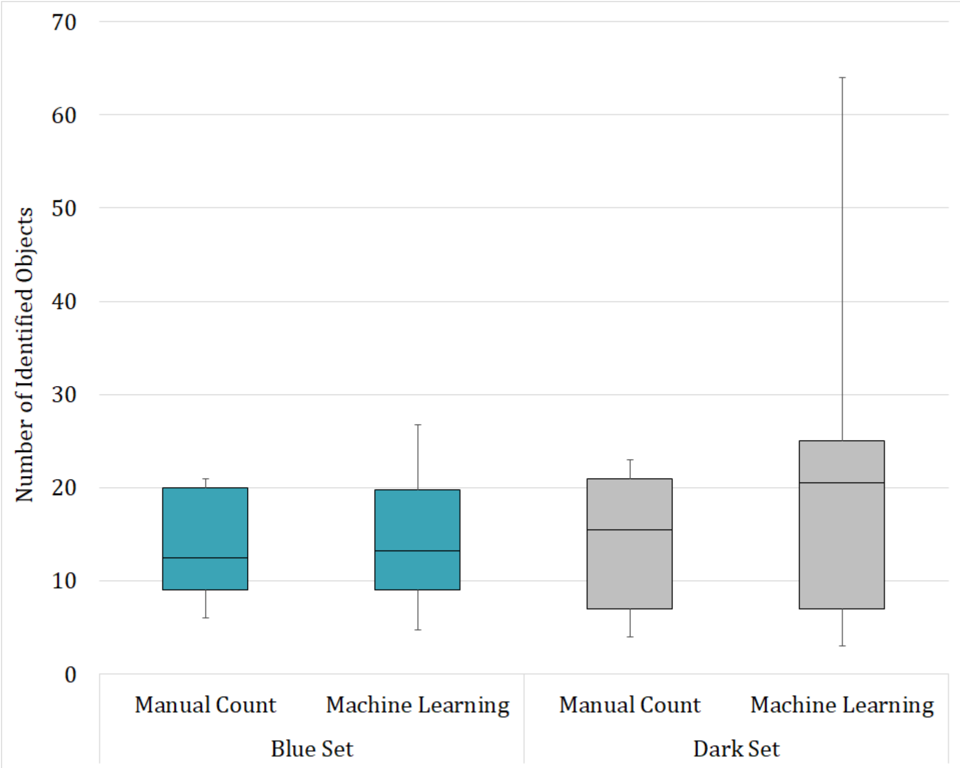

Figure 9: Box-plot of average number of identified objects on methods Manual Count and Machine Learning.

2.3.3. Assessing performance for floating litter classification

To carry out the process of deep learning classification of floating objects, it was created nine different categories: Cleaner Bottles – Containers; Drink Bottles – Green; Drink Bottles – Transparent; Drink Bottles – Large (>5L); Tetra Pak; Plastic Bags; Other Containers; Floating Fishing Gear and Other Floating Debris (**Appendix II**). The training method was already described in chapter 2.2.3 Classification Procedures.

The result of this classification was also assessed by comparing it with reference data from visual inspection. Despite variance and ranges of ML classification being comparable with that from visual inspection (**Figure 10**), ML performs differently in detecting/identifying different category objects (**Figure 11**) with major differences associated with some categories (**Figure 12**). Unlike the performance of pixel-based detection of marine debris (**Figure 8**), automated classification of floating items overall performance was better in normally exposed images (Blue Set) than that in underexposed images (Dark Set), however, both image sets overestimate and underestimate some of the item categories used (**Figure 11** and **12**)

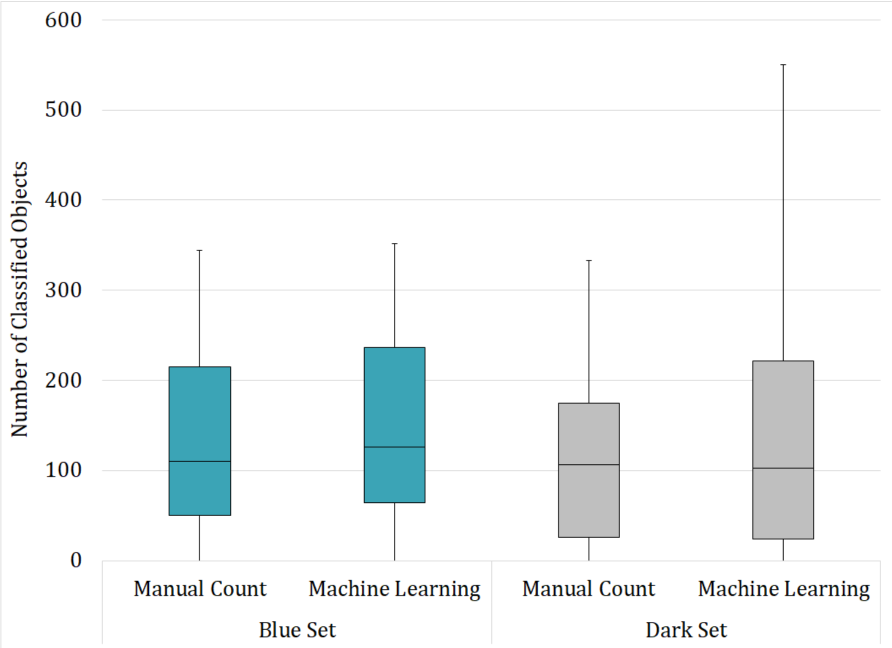

Figure 10: Box-plot of number of classified objects on methods Manual Count and Machine Learning.

In normally exposed imagery (blue set), the classes of Cleaner Bottles & Containers, Green Drinking Bottles, Floating Fishing Gear and Plastic Bags were greatly underestimated, whereas Transparent Drinking Bottles, Other Containers and Other Floating Debris was overestimated (**Figure 11**). This over estimation of these categories is likely due to backscattering light being mistakenly identified as items from these classes. The underestimation of green bottles (**Figure 12**) may be related to spectral similarity between blue background and the bottle's colour, for which the inclusion of additional multispectral data can contribute to improve object recognition.

In underexposed imagery (dark set), the Cleaner Bottles & Containers and Plastic Bags were also not recognised, making these categories completely undetected by the deep learning classification approach (**Figure 11**). Floating items on the categories Drink Bottles – Large (>5l), Other Containers and Other Floating Debris were significantly overestimated (**Figure 12**), likely due to the variability of shapes and spectral response of the training set, generating automated miss-detection of sun glint and backscatter as items from this category.

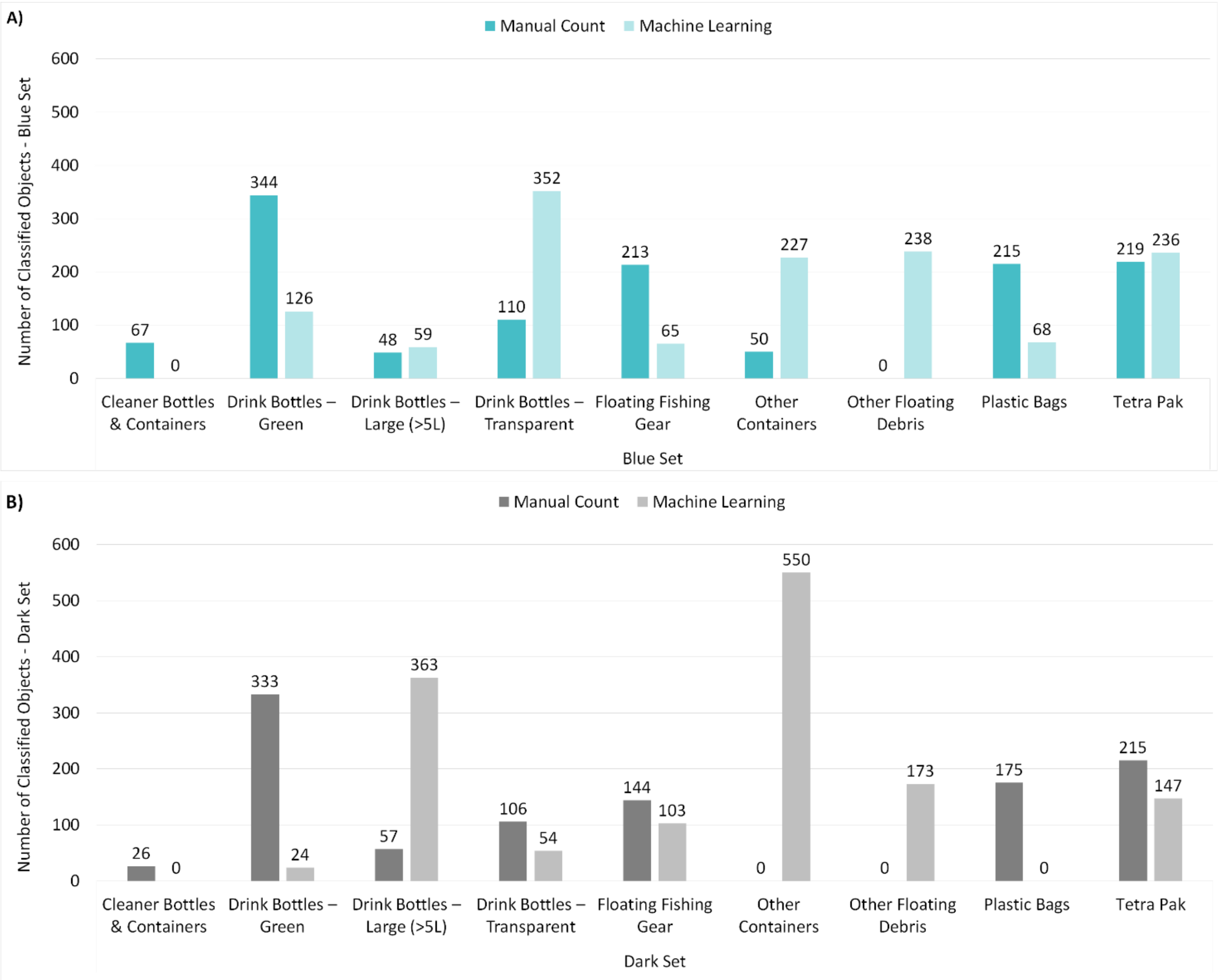

Figure 11: Comparison between the Manual Count method and Machine Learning related to the total number of objects classified per category in each different colour set.

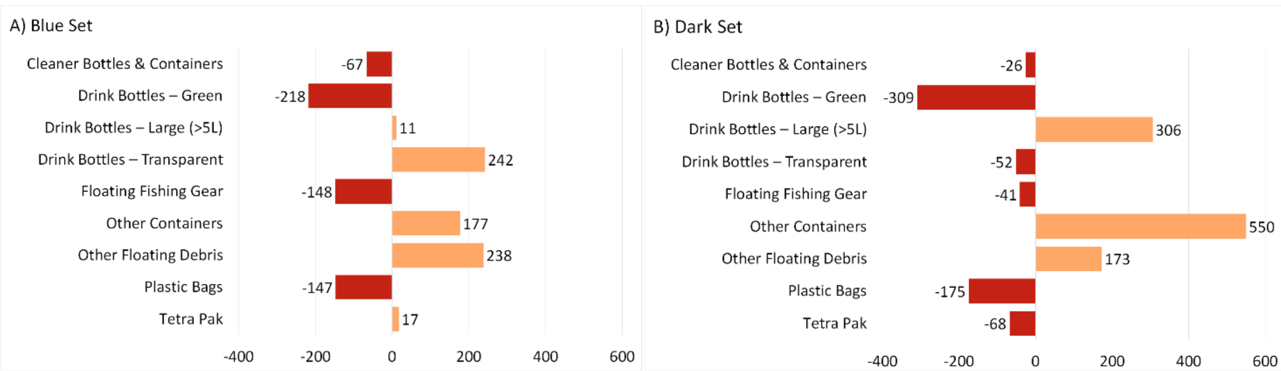

Figure 12: Differences per category on the number of classified objects between Manual Count (i.e. visually inspection) and Machine Learning assisted automated detection/classification in the blue set (left) and dark set of images (right). Negative values (red) represent the total number objects missed by automated detection/classification (false negatives), whereas positive values (orange) depict the total number of false detections per category (false positives).

The category Drink Bottles – Green and Plastic Bags, had a comparable underestimation in both data sets. Similarity in the light reflectance and spectrum between the blue sea and the translucid green of the bottles could have hampered the detection and classification of these items. In the class of plastic bags, as they present different shapes in each image, automated detection may have been negatively affected, as the shape of an object can be a relevant criterion for the classification success. The flexibility and mutable shape of plastic bags creates a handicap for automatic detection of this item class.

Other Containers and Other Floating Debris categories, in both data sets, were overestimated with many false positives being classified within these two categories. Other containers over estimation may be an artifact from the use of a single object within this category: a black container that would float under the sea surface. The use of a single object, combined with the lensing effect of water over the partially submerged object, may have contributed for the misclassification of shadows and areas of images with high contrast as an object. As for the Other Floating Debris category, this was a dummy category created to enable the algorithms to identify floating objects that could not be classified as one of existing categories. The generated false positives are mostly produced by high reflectance backscatter that produce white "false objects" at the sea surface.

Transparency of the objects classified as Drink Bottles – Transparent, have likely influenced the over estimation of these objects in the blue set, as differences in light and colour profile are reduced by transparency. The use of low exposure images (i.e. dark set) appears to produce some mitigating effects, producing a lower under estimation than the overestimation produced with imagery and training sets from the Blue Set.

One of the main reasons to carry out this experiment with two image sets using different exposures (i.e. Blue Set vs Dark Set) was to understand how differences in exposure and contrast affect the reliability of the automated classification models. One of the biggest problems with NADIR images collected over the ocean is the glare/reflection you get from sunlight backscatter, resulting in "specs" of high reflectance that can be misidentified as (white) floating objects. For some object categories (e.g. cleaner container bottles, fishing gear), using low exposed, high contrast images in training and analysis, seems to perform better and produce lower errors (under or overestimation) than normally exposed imagery. However, models trained using these latter images seem to perform better in detecting objects in some other categories (e.g. large drink bottles and other containers), suggesting further research is needed to combine the use of multiple exposure images or multiple individual spectra analysis.

2.4. Final Considerations

Flight parameters selected for this case study have influenced the final result and the detection capability. Since flight height, light exposure and even the direction in relation to the light source, among others, affect the image quality and the perception of some physical characteristics of the objects to be classified, including: colour reflectance (translucid vs opaque objects or reflected spectral profile of the material); the definition of object contours (well-defined vs blurred), and the size of objects. Flights at higher altitudes generate smaller, lower resolution objects on the collected image. The size and shape of objects to classify are thus conditioned by pixel size and resolution, becoming more blurred and smaller with altitude, but, in turn, the higher the altitude the bigger the area covered by each image, enabling an increase in sampled area. Flights at lower altitudes between 15 to 30m cover relatively lower areas than those at higher altitude, but they considerably improve the image resolution and enable the detection of small sized items (approx. 10 cm). Flight parameters such as altitude must be custom defined to best balance image resolution and covered area. Similarly, determining light conditions by choosing the time of day (8 to 10 am and 16 to 18 pm) and the direction of flight paths helps to enhance image quality by minimizing the sun reflection and backscatter over the sea. In turn, this minimizes sun speckles on the image - high reflectance whites spots of undefined shapes that create visual noise and hamper manual and automated analysis

For the purposes of this case study, three major aspects were considered in comparing methods: i) average time required to inspect and process each image; ii) ability to adequately assess floating litter contamination, and; iii) skills and logistical requirements for implementing a monitoring program using each method.

As the approaches differ on the output, simple descriptive statistics were applied to compare outputs whereas standard metrics were used to assess deep learning classification models. Finally, an evaluation of requisites such as computational infrastructures and skills for each analytical approach must be considered, as to determine feasibility of a monitoring program that relies on imagery analysis, **Table 1**.

The average time required for each image to be processed was considered an essential indicator for determining adequate methods and analytical approaches, as some require a user to inspect and make annotations on each single image, whereas automated methods may require initial annotations or user interaction, but will then be able to process a large number of images automatically. Despite the low times required for visual inspection and identification of floating objects (<30s) or classification (<55s) (**Table 1**), the Manual Count processing option is still tedious and may hamper scaling up imagery collection and efforts. The Pixel Base Detection method allows us to know the percentage level of general contamination of a given area less than 45 s (**Table 1**). This method is useful in scenarios where it is necessary to find places of concentration or sources of contamination by marine litter in a large volume of images and/or with different areas. In the Machine Learning method, the average time used by the model to classify objects on each image is less than 160s (**Table 1**). The model requires considerably more time to provide information on the number of different objects than that taken by a user to visually inspect an image and tag the multiple objects, however, this process can be done with no user interaction.

Table 1: Summary comparison in different performance indicators for the use of Manual count, Pixel Base detection and Machine Learning to detect and assess floating litter contamination using UAS-remote sensing to collect aerial imagery (Blue and Dark sets). **$\bar{x}$**, average; **σ**, standard deviation; **Precision**, indicates the ratio of the correctly segmented classes that are positive for each class; **Recall**, is the ratio of the correctly classified positive classes. It is also referred as to sensitivity; **F1**, is the harmonic mean witch indicates the extent alignment of the predicted boundary with ground truth boundary. Evaluates the balance between precision and recall values. For Precision, Recall and F1 the higher is the value, the better is the performance.

Methods			Manual Count		Pixel Base Detection		Machine Learning	
DataSet			**Blue**	**Dark**	**Blue**	**Dark**	**Blue**	**Dark**
Performance Evaluation	Process Time (s) (Average)	Identification	26 s	22 s				
		Classification	52 s	40 s				
		Processing			43 s	26 s		
		Object Classification					159 s	135 s
	Number of Objects Classified	$\bar{x}$	141	117			152	157
		σ	112	112			116	187
		% of pixels detected			0.0025%	0.000049%		
		Estimated area			5.31	0.089		
	Performance from ML method						Precision: 63.59% Recall: 78.27% F1-score: 56.33%	Precision: 77.62% Recall: 77.71% F1-score: 66.15%
Work Interface			- DotDotGouse		- Workflow who to generate new Algorithm		- Supervisely - Goolge Collab GPU - Python AID	
Requests			- Informatic skills		- Programming skills - Knowledge in processing colour images		- Programming skills - Knowledge in deep learning	

The statistical validation results of the ML method are considered acceptable (Gonçalves et al., 2020; Jakovljevic et al., 2020) Blue Set: Precision = 64%, Recall = 78%, F1-score = 56%; Dark Set: Precision = 78%, Recall = 78%, F1-score = 66 %; **Table 1**), taking into account the experimental character of this type of methodology. It is expected that with the evolution of the applied model, the statistical validation values are increasingly closer to the theoretical optimum. Regarding Object Identification, the ML method has an average error of over 11 objects per image in Blue Set and 40 per image in Dark Set, when compared with the Ground Truth Values (i.e., Manual Count data). The experiment carried out between Blue and Dark set highlighted relevant findings concerning the type of object versus the environment in which it is, against the ability to be detected by the operator and/or automatically detected (Appendix II). A SWOT analysis summarizes key findings and the advantages/disadvantages of using normal exposed and low exposed imagery (**Table 2**).

Despite the general advantage for automated image annotation processes, these generally have errors associated to the critical discrimination of objects, leading to the need of evaluating how good the approach is in assessing floating debris contamination or in classifying floating objects. The time and effort dedicated and the knowledge and skills required to optimise and routinely apply Machine Learning is often compensated for being a single initial effort to acquire knowledge and train the model. After this laborious process, the model is continuously self-training and fed by the images that the user asks the model to use, that is, if it keeps the classification classes constant. This is one of the most significant differences to be highlighted between the analysed methods. In the Manual Count method, the dedication and time spent by users are proportionally and constantly increased by the number of images to process, however, the level of expertise required is minimal, as it only needs the user to inspect each image and tag visible litter items. As such, monitoring programs that aim to use UAS-based remote sensing should consider the frequency and total number of images that will be processed, when selecting which analytical method suits them best. Special considerations should also be given to available human resources and their skillset. Annual programs with 0-1000 images to process can consider using visual inspection and manual identification or categorization, as they will require low expertise and a total processing time of 9-18 hours per year. Large scale efforts with thousands of images from different sources or with higher frequency should consider implementing an automated classification system using deep learning.

Table 2: SWOT analysis of using normal and low exposed aerial imagery for monitoring floating litter objects

	Data Set	
	Blue	**Dark**
Strengts	Visible spectrum common to any standard commercial drone. No specific and expensive equipment is required to perform the Survey.	Minimizes "noise" over the ocean surface, which in turn minimizes classification errors.
Weaknesses	Glare, reflections, scum, wave foam are examples of phenomena that would want to "noise" in the RGB images to be analyzed.	Dark or transparent objects are challenging to classify.
Oportunites	The methodologies created can be applied anywhere in the world for marine debris monitoring.	Exploration of other colour spectrum (such as NIR), to test the behaviour of the models.
Threats	The theoretical and technical knowledge of other teams to have the sensitivity to adjust the methodology to their monitoring areas.	The theoretical and technical knowledge of other teams to have the sensitivity to adjust the methodology to their monitoring areas.

Overall, trial data suggests that UAS remote sensing can be effectively used for floating litter monitoring in two main fashions: i) by visually inspecting each image and identifying or classifying images, or; ii) by using deep learning to detect floating items without classifying them. Automated classification is also possible to become more accurate and reliable, but it still requires further research and development in: using multi camera or multi spectral systems, optimising model training and creating a multi-step workflow for the classification. The use of colour difference debris pixel detection also requires additional optimization and development to reduce error, namely by integrating additional multispectral data and/or hyperspectral data.

3. Selecting most suitable analysis methods

The purpose of this case study is to provide a comparison rationale that can be used to assess overall advantages and disadvantages of different analytical and classification approaches in order to design floating litter monitoring programs with UAS-based remote sensing that can be adjusted to fit different conditions, skills, expertise and available resources.

When choosing which method is most suitable, selection criteria can often be narrowed down to the following questions: i) what is the complexity of the workflow we will be applying?; ii) what is the time required to effectively produce results?; iii) what are the operational and equipment costs?; iv) what is the size, level of expertise and skill set of the team required for such a method?; v) what is the detail, quality and accuracy of the produced data and outputs?; and vi) can the methods be implemented and used in the target monitoring area or region?

Based on the present dataset and pilot study, the use of machine learning and artificial intelligence to detect or classify floating objects still presents itself with higher levels of complexity, more demanding equipment requirements and a larger team that includes expertise in programming and in implementing ML. In addition, inaccuracies and errors make visual inspection and object tagging a more precise solution. As such, the operational solution that works best in most scenarios will be based manually tagging items (ideally, with online co-working and using shared access to cloud storage or servers). A SWOT analysis of these methods (Table 3), provides further details on the advantages and disadvantages of each of the strategies used for processing imagery.

Table 3: SWOT analysis of different processing strategies used for monitoring floating litter from aerial imagery.

	Methods Manual Count	 Pixel Base Detection	 Machine Learning
Strengts	The simplicity of the Methodology. Basic knowledge in informatics.	Quickness in identifying contaminated areas.	After the first trained process, the time required to the operator is only to feed it new data for training.
Weaknesses	Time request to the operator to process one big volume of data.	Learning curve. Time and knowledge are required for the creation and maintenance of the methodology. Non-classification of the affected area by the type of the contaminant.	Learning curve. Time and knowledge are required for the creation and maintenance of the methodology.
Oportunites	Expert in Marine Litter classification with MSDF. Effortless to replicate by other research teams.	Applicability in different environments and contaminant types. Creation of a user-friendly interface with the developed methodology.	Creation of a user friendly interface and Data Base increment. Innovatived methodology and aligned with the developments of Artificial Intelligence. Open-source.
Threats	Method out of the new digital era.	Knowledge of programming and image.	Specific knowledge in python and deep leaning. Competition with the rest of the scientific community. The complexity of the methodology to be replicated by external teams.

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Appendix

Appendix I

Appendix I – Remote sensing and aerial surveys for monitoring floating litter with Unmanned Aerial Systems (UAS): general protocol guidelines for vessel and shore-based operations.

Fluxes of floating litter at sea vary depending on the proximity to shore, urban activities, coastal uses, wind and ocean currents. These factors can promote the accumulation of marine floating litter in convergence zones. Due to the spatial and temporal variability and dynamic nature of floating marine litter, it is crucial to develop a standard, cost-effective, repeatable and fast method that estimates its amount and distribution. Estimating litter trends over time is needed for efficient monitoring programs, management and reduction measures.

The use of remote sensing from "Unmanned Aircraft Systems"(UAS) from shore and vessels allows the detection of floating litter and the collection of spatially explicit information, enabling efficient comparable assessments of floating litter contamination in coastal and open waters. With adequate design and workflows, UAS-based remote sensing allows the identification of floating objects and assessing contamination levels with reduced sampling effort. The following guidelines for using drone-based aerial surveys from land-base and vessels intend to enhance the monitoring capabilities and standardization of floating litter detection methods and protocols.

1. Mandatory requirements

Fulfilment with the legislation and regulations in force for flight operations with drones and image collection. Namely:

- UAS, operator and pilot registration with the Civil Aviation Authority;
- Adequate legal certification for carrying out the operations;
- Civil liability insurance;
- Applicable authorizations for aerial image collection and flight;
- Compliance with privacy and data protection international, national and local legislation and regulations.

2. Equipment and Applications

Monitoring of marine litter by aerial remote sensing using unmanned aircraft requires an Unmanned Aerial System (also known as drone) equipped with camera, GPS and operational capacity for programmable flight. It also requires a controller or ground flight station and flight programming software for image collection. For floating litter monitoring activities, we recommend:

- Unmanned aircraft: multirotor drone with manual or pre-program flight planning equipped with RGB camera with manual settings (optional: additional multispectral or thermal camera). For vessel-based operations select a drone with a design and flight stability for a user to safely hold it in hands for deployment and retrieval (e.g. DJI Phantom series - **Figure 1**). Large drones are very hard to land on vessels and increase danger for crew and pilot. Smaller drones can be used, but special care must be given when grabbing aircraft.

- Flight planning controller and software with camera live view and telemetry and that enables pausing and continuing survey, even when turning off aircraft for battery replacement.

Figure 1: Example of one UAV how was design to safely hold it in hands by the operator, e.g. DJI Phantom series.

3. Flight planning (general):

A. Evaluate operational risks: prior assessment of airspace and characteristics of target areas to identify potential risks and hazards, including: proximity to airports or other fly zones with air traffic, obstacles and infrastructure, terrain topography and other eventual hazards and restrictions to operations. Establish maximum flight altitude and survey area give the site characteristics.

B. Updates and Calibration: Inspect batteries for signs of damage or swelling. Check and update firmware and software and test connectivity. Calibrate aircraft instruments and sensors. Check **batteries, remote and tablet or phone are charged and available free space in memory card.**

C. Assessment of atmospheric conditions: Assess weather forecasts and sea conditions to verify suitable conditions for operations with the aircraft, including:

- No precipitation;
- Low wind (winds below 10 knots, however, it will depending on specifications of the drone in use);
- Calm sea;
- Ambient temperature between 10 to 40 °C.

D. Light conditions: for optimal results, plan flight operations for clear skies and sun at angles between 10º and 45º, as to obtain better contrast and minimize light backscatter.

E. Distance and target survey area: Unlike surveys over land, overlapping aerial imagery from open waters lack matching landmarks to produce quality mosaics. As such, floating litter monitoring from aerial imagery must rely collection and processing of multiple images with no overlap. Altitude and image sensor size will determine image footprint area, which can be easily estimated.[4]

[4] https://support.pix4d.com/hc/en-us/articles/202560249-TOOLS-GSD-calculator

4. Aerial surveys:

A. **Survey Area:** The objective is to collet imagery at a pre-defined altitude, over transect(s) perpendicular or parallel to the shore line. Fly, for example, 1 km (or more) in a straight line The transect length and total flight distance will depend on the drone's autonomy and the range signal between the drone and the controller. This means that transect length and scanning area must me adjusted to the drone in use:

- Manual operated flights, with automated image capture are recommended to enable pilot control, but pre-programmed waypoints can also be used.
- Flight direction may vary from strictly perpendicular or parallel to shore, which can be set to minimise backscatter by taking a heading away from the sun.

B. **Altitude:** Altitude should be set between 10 - 30 meters depending on user preference. Low altitude provides higher resolution but lower area coverage).

C. **Camera settings:** camera should be set in Manual mode, with a minimum shutter speed of 200. Aperture should be set to minimise backscatter (EV -1.0 to -0.3 depending on conditions and preferred analysis method). Polarising filters are recommended in RGB cameras. Camera capture interval should be set depending on objectives and the minimum images required per transect. We recommend setting it every 5-10 seconds. When manually flying, maintain slow speeds and stop for the capture of imagery (i.e. use countdown and stop any movement 1-2 seconds before it reaches zero and captures an image). Lastly, camera angle should be set to 90° but can also be used with a slightly lower angle to minimise backscatter and sun glitter if image analysis will use manual annotation or machine learning for automated annotation and object detection (we recommend not to go lower than 80°). It is recommended to do a manually operated hover flight at the desired altitude and visually inspect live feed to adjust aperture and shutter speed for optimal image contrast and results.

D. Keep track of each transect when doing more than one per flight (e.g. use a front facing image capture to separate imagery of each transect).

4.1. Land-based survey

No special considerations are required for flying from shore or land. Be aware of marine traffic and flight altitude and of people in the shore line during operations. Considering the need of flying in line of sight, we recommend flying 1 km in a straight line perpendicular to shore, 0,5 to 1 km parallel to shore and return straight line perpendicular to shore (**Figure 2**). Flight path does not have to be strictly perpendicular. The drone's flying distance will depend on the drone's autonomy and the range signal between the drone and the controller. This means that transect length and scanning area must be adjusted to the drone in use.

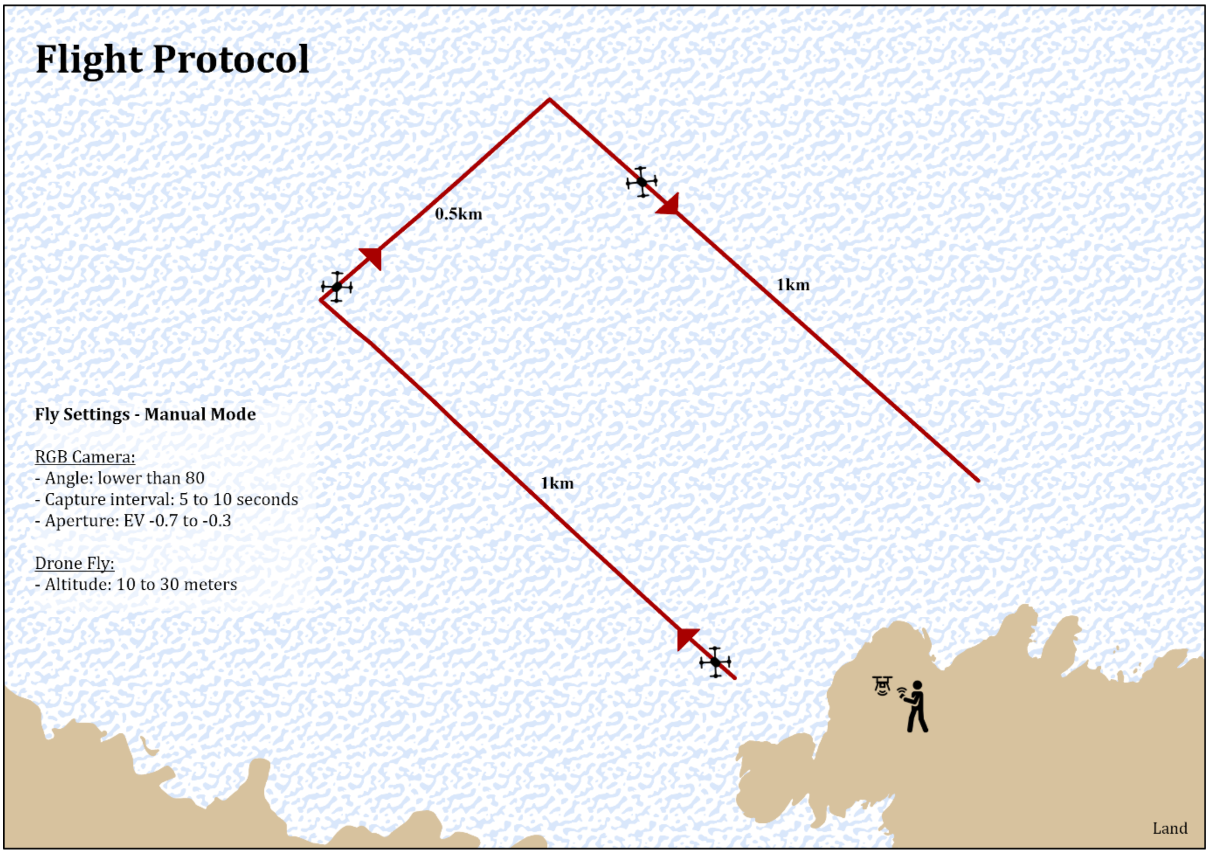

Figure 2: Summary of basic flight operations for land-based transect survey for monitoring floating litter contamination (transect distance and values used on Mavic 2 Pro quadcopter; adapt depending on drone model, sensor size, camera and range).

4.2. Vessel-based survey

It is important to have in consideration that drone operations from vessels have multiple particularities, including safety in launch and retrieval and possible sources of interference:

- For launch and retrieval, it is recommended that users are able to hold the drone in hand for launch and retrieval or to have a large deck for safe take-off and landing. Some drones can land in water, making this an additional option for retrieval;
- In vessels equipped with electronics like AIS and radar, interference may be an issue, for which it is suggested for them to be switched off when possible;
- Compass and drone positioning systems have issues due to magnetic interference and/or boat movement during drone boot. To minimise it, switch the drone on while holding it in hand and try to maintain it steady and away from sources of magnetic interference.

Take in consideration the specificities of vessel-based operations when selecting **drone model**:

- Multirotor drone with manual and pre-program flight planning equipped with RGB camera with manual settings (optional: additional multispectral or thermal camera);
- A drone with a design and flight stability for a user to safely hold it in hands for deployment and retrieval (e.g. DJI Phantom series) (**Figure 1**).

Vessel-based operations can be done from stationary position, drifting or with the vessel following the UAS. Depending on vessel and scenario, some considerations are recommended:

- From large ships and vessels with automatic positioning capabilities, plan flight paths and transects as from land-based operations;
- From large ships and vessels that are not actively maintaining stationary positioning (ie.; drifting), make sure to adjust flight course considering the drifting of your ground station. For safety, general precaution dictate that flight course is down current and in the same direction than vessel drift, however, other options are possible under slow drifts: for example, fly 1 km perpendicular to current and drifting direction, 1km down current and 1 km back to the vessel;
- From small vessels (e.g., rib boats), we recommend that transects and flight course is upwind, with manual flight operations and for the vessel to follow the UAS. Transects can generally be longer than 1 km, as you do not have to return to launch site (e.g., the UAS can be recovered from pursuing vessel).

5. Safety recommendations:

- During flight operations, it is necessary to ensure real-time monitoring of the status of the UAS (e.g., flight time and battery; loss of signal between drone and controller; changes to the predefined flight paths; approach of obstacles (birds, other UAS equipment);
- In the event of an unforeseen risk being identified or an incident or anomaly, it is necessary to interrupt the flight;
- If the battery reaches 25% charge, it is recommended to pause the mission, return to home, land and replace the battery before summarizing the mission;
- Flight operations should be done in good weather conditions, with low wind and waves and when the sun is not very high (also to minimise backscatter);
- make sure to comply with regulations and legislation for drone operations.

Appendix II

Appendix II – Categories of Classification

Table 1: Floating litter category classes used in image annotation and automated object classification.

Name	Description	Blue Set Image (150x150 pixels)	Dark Set Image (150x150 pixels)
Cleaner Bottles - Containers	Cleaner Bottles and Containers. Artificial polymer materials. Monitoring Guidance for Marine Litter in European Seas.		
Drink Bottles – Green	Green drink Bottles. Artificial polymer materials. Monitoring Guidance for Marine Litter in European Seas.		
Drink Bottles – Transparent	Transparent drink bottles. Artificial polymer materials. Monitoring Guidance for Marine Litter in European Seas.	 	 
Drink Bottles – Large (>5L)	Large drink bottles, more than 5L. Artificial polymer materials. Monitoring Guidance for Marine Litter in European Seas.		
Tetra Pak	Tetra Brik Aseptic Packaging Components (polyethylene, aluminum, paper). Monitoring Guidance for Marine Litter in European Seas.		
Plastic Bags	Plastic Bags. Artificial polymer materials. Monitoring Guidance for Marine Litter in European Seas.		
Other Containers	Other Containers. Diferentes tipes of marine litter (plastic or others materials).		
Floating Fishing Gear	Floating Fishing Gear: nets, lines, buoys, etc		
Other Floating Debris	Other Floating Debris. Represents something, a good image but you don't know what it is.