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*Communication*

# Beached and Floating Litter Surveys by Unmanned Aerial Vehicles: Operational Analogies and Differences

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**Abstract:** The abundance of litter pollution in the marine environment has been increasing globally. Remote sensing techniques are valuable tools to advance knowledge on litter abundance, distribution and dynamics. Images collected by Unmanned Aerial Vehicles (UAV, aka drones) are highly efficient to map and monitor local beached (BL) and floating (FL) marine litter items. In this work, the operational insights to carry out both BL and FL surveys using UAVs are detailly described. In particular, flight planning and deployment, along with image products processing and analysis, are reported and compared. Furthermore, analogies and differences between UAV-based BL and FL mapping are discussed, with focus on the challenges related to BL and FL item detection and recognition. Given the efficiency of UAV to map BL and FL, this remote sensing technique can replace traditional methods for litter monitoring, further improving the knowledge of marine litter dynamics in the marine environment. This communication aims at helping researchers in planning and performing optimized drone-based BL and FL surveys.

**Keywords:** Plastics; Environmental Monitoring; Beach Pollution; Ocean Pollution; Machine Learning; Drone; Coastal Monitoring

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**Citation:** Andriolo, U.; Garcia-Garin, O.; Vighi, M.; Borrell, A.; Gonçalves, G. Beached and Floating Litter Surveys by Unmanned Aerial Vehicles: Operational Analogies and Differences. *Remote Sens.* **2022**, *14*, 1336. https://doi.org/10.3390/rs14061336

Academic Editor: Weimin Huang

Received: 3 February 2022
Accepted: 9 March 2022
Published: 9 March 2022

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## 1. Introduction

The abundance of litter waste in the marine environment has been increasing globally during the last decades [1–4]. Roughly 80% of marine litter pollution originates on land, and enters the ocean via rivers [5], land-based sources [6], extreme events [7] and coastal erosion [8], among others [9]. To advance knowledge of litter abundance, distribution and dynamics on oceans and coasts, different remote sensing techniques were applied [10–12]. Images acquired by balloons [13,14], airplanes [15,16] and satellites [17–19] were exploited to detect and quantify stranded and floating litter worldwide.

In the recent years, the use of unmanned aerial vehicles (UAV, aka drones) has improved environmental monitoring surveys [20,21], since these aerial platforms (i) can operate autonomously, (ii) provide high resolution images, and (iii) are viable and affordable tools for many operational tasks. Among these, it was recently shown that UAV constitute a valid alternative to traditional litter pollution surveys in the marine environment, being feasible for detecting and mapping litter stranded on beaches [22–30] and dunes [31,32], as well as litter floating on sea [15,33,34] and river [35] waters. Regarding beached litter (BL) on the coast, drone-based surveys are advantageous in comparison with the conventional spatially limited visual census [36,37], since UAV require much less human effort in the field, and can provide deeper insights into litter dynamics [24,26]. Yet, it was shown that the integration of drone flights with traditional methods for floating litter

(FL) surveys, such as visual observations from boats and manta trawls, can improve the description of FL abundance and paths.

The operational experience gained in drone-based litter monitoring allowed us to resume in this manuscript the operational insights into both BL and FL drone-based surveys. We enumerated the analogies and differences in the use of drones for BL and FL mapping, and analysed the issues on the use of collected images for detecting and recognizing BL and FL items. Given the adaptable and multipurpose properties of UAV, we also aimed at understanding if drone flights can be integrated for a comprehensive description of both BL and FL in coastal areas, to improve the survey of marine litter dynamics in the marine environment, and support their modelling. This communication can help researchers in planning and performing optimized drone-based BL and FL surveys.

## 2. Flight Planning and Deployment

### 2.1. Beached and Floating Litter Survey Experiences with Unmanned Aerial Vehicles

For reporting beached litter (BL) survey characteristics, three experiences [25,26,31,32] on three beach-dune systems on the North Atlantic Portuguese coast (Table 1 and Figure 1) were considered. Different drones and camera models were adopted (Table 1), with drone flying at a variable height between 20 m and 40 m. The drone took off and landed from the beach, near the chosen area, where few Ground Control Points (GCP) and check points (CP) were placed prior to the flight. Flight missions were planned on a freeware mobile app (DroneDeploy, https://www.dronedeploy.com) to make the drone fly autonomously, and to permit the repetition of the survey of the same area over different flights. Overall, the area coverage varied between 200 m and 400 m long-shore, and between 80 and 100 m cross-shore, considering both the beach and dune environments (Table 1 and Figure 1).

For reporting floating litter (FL) survey characteristics, four experiences carried out in four maritime areas along the Mediterranean coast of Spain, in the Catalan region (Table 1 and Figure 1), namely Cap de Creus, Blanes, Barcelona, and Delta de l'Ebre [33,34], were considered. Different drones and camera models were used (Table 1), with drone flight altitude ranging between 20 and 120 m. Drones were operated from vessels, except for the experiment carried out in the waters off Blanes, where the drone took off from the beach [34]. As for BL, flights were pre-designed on the dedicated app, and planned to cover transects between 80 m and 510 m in width, and between 240 m and 1015 m in length (Table 1). Distances from the nearest shore ranged between 65 m and 22 km. Different flight heights were tested (20 m, 50 m and 120 m) in the waters off Blanes [34], while for the other surveys the flight height was set between 45 m and 65 m. These altitudes guaranteed an adequate area coverage of each transect, and a minimum GSD of 2 cm/pixel (Table 1).

Both BL and FL surveys were carried out with the camera oriented at 90 degrees, looking perpendicularly to the beach or the sea surface. The flight height was chosen to fulfil the twofold aim of (i) obtaining a suitable Ground Sampling Distance (GSD) for recognizing items on the images, and (ii) covering the target area.

For BL, other authors flew at lower height (6–10 m, e.g., [22,24]) to increase image resolution. However, obstacles such as dunes (as in the considered BL works, Table 1), trees, traffic lights and houses, among others, may endanger or make impossible a low flight. Similarly, for FL surveys, the minimum flight height was chosen considering the likely presence of ships and/or ships masts to be avoided, as well as local regulation and safety reasons.

All drone models used in our BL and FL surveys had batteries whose autonomy allowed flying for about 30 min, with some variability depending on the flight altitude set to perform the survey.

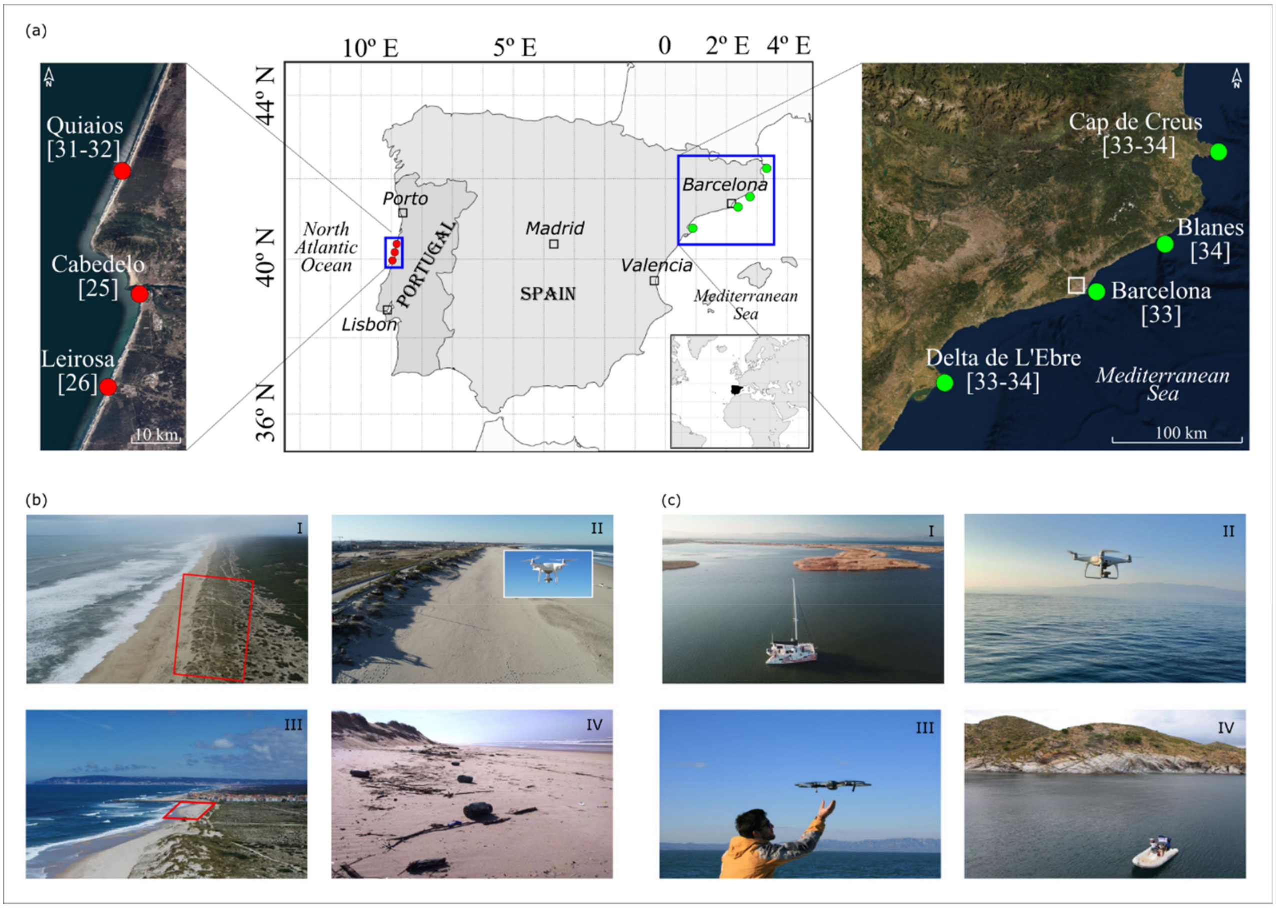


**Figure 1.** Study sites and field work experiences considered for beached (BL) and floating (FL) litter. (**a**) map of the Iberian Peninsula, with study sites locations on the Portuguese coast for BL (left), and on the Spanish coast for FL surveys (right). The number associated to the study sites indicate the related references (see reference list). (**b**) Pictures of BL surveys: (I) overview of Quiaios dunes [31,32]; (II) overview of Cabedelo beach [25], inset shows the drone; (III) overview of Leirosa beach [26]; (IV) detail of BL on Leirosa beach [26]. (**c**) Pictures of FL surveys: (I) overview of the catamaran in Delta de l'Ebre [33,34]; (II) detail of the drone flight in Barcelona [33]; (III) detail of the drone flight deployment at Delta de l'Ebre [33,34]; (IV) overview of the vessel in Cap de Creus [33,34].

**Table 1.** Operational drone flight parameters used in the experiences considered in this work for beached (BL) and floating (FL) litter.

| Reference | Survey | Site | Drone Model | Camera Resolution (px) | Flight Height (m) | Ground Sampling Distance (cm/pixel) | Area Extent (km$^2$) |
|---|---|---|---|---|---|---|---|
| [25] | BL | Cabedelo (PT) | DJI Phantom 4 Pro | 4864 × 3648 | 20 | 0.55 | 0.020 |
| [26] | BL | Leirosa (PT) | DJI Phantom 4 RTK | 5472 × 3648 | 30–40 | 0.9–1 | 0.023 |
| [31,32] | BL | Quiaios (PT) | DJI Matrix 210 RTK V2 | 4000 × 3000 | 40 | 1.2 | 0.016 |
| [33,34] | FL | Cap de Creus (ES) | DJI Phantom 3 Pro | 4000 × 3000 | 45 | 2 | 1.1 |
| [34] | FL | Blanes (ES) | Multi-rotor *Topografia* | 7952 × 5304 | 20–120 | 0.6–3.6 | 1.9 |
| [33] | FL | Barcelona (ES) | DJI Phantom 3 Pro | 4000 × 3000 | 45 | 2 | 7.9 |
| [33,34] | FL | Delta de l'Ebre (ES) | DJI Mavic Pro | 4000 × 3000 | 65 | 2 | 3.5 |

### 2.2. Environmental Constraints

The general main limitations for multirotor drone surveys in the environment are related to windy and rainy weather. The wind speed limit for drone deployment depends on the drone weight and properties, however a nominal limit for BL and FL was set to 10 knots (19 km/h).

Prior to the BL flights, besides wind speed predictions, tide must also be considered, especially on meso- and macrotidal coastal environments. Tidal excursion may indeed affect the survey assessment, since BL can be reached by swash and be moved and/or resuspended during the survey. Therefore, it was necessary to check the tidal table for operational BL survey planning, in order to perform the flight during low tide. This allowed a broader beach profile to be covered to further relate BL distribution to beach configuration [25,26]. It was also noted that spring tides can confine BL on the upper beach, therefore checking the tide table also allowed optimization of flight mission planning [25,26]. Regarding FL, the sea state can affect visibility and thus the detectability of FL items in several ways. Thus, since FL is less visible during stronger wind and in the presence of breaking waves FL surveys were conducted during Beaufort wind force scale equal or lower than 2. Moreover, as the sun reflection may have a strong influence on FL detectability, flights took place during the hours when sun glare was limited. Finally, FL surveys were performed when the sky cover was homogeneous, either with a clear or a cloudy sky, since the reflection of scattered clouds on the sea surface can also impair the detection of FL [15,38].

Fog and mist may also constitute a major constraint for BL and FL surveys, since low visibility can affect image quality and even invalidate the survey. However, conversely to tide and waves, these are often not predictable. On the North Atlantic Portuguese coast, mist is common on the beach not only during high-energy sea state in winter, but also during summer days, due to humidity and wave spray on the foreshore. In regard to FL survey, fog and mist can challenge the vessel navigation, limiting the visibility and thus the possibility to perform the survey. Finally, during BL surveys we also experienced disturbance by sea gulls during the breeding season, which may endanger the drone flight stability [25]. This was not the case for FL, as the higher flight altitude and the distance from shore allowed not intercepting any possible breeding/nesting areas.

## 3. Image Products and Analysis

From the experiences for beached litter (BL) mapping, the image block collected during the flights were used to produce two complementary geospatial products, namely the Digital Surface Model (DSM) and the related orthophoto beach map. These products were generated applying the Structure from Motion—MultiView Stereo (SfM-MVS) photogrammetric processing workflow adopting Agisoft Metashape (v1.5.3) commercial software package. In brief, the internal (lens distortions) and the external (orientation) camera parameters were found by the camera self-calibration and the Bundle Bloch Adjustment (i.e., image triangulation) methods. From the image block, the software generated a sparse 3D point cloud that was successively georeferenced by tagging Ground Control Points (GCP) on the images. Finally, the DSM was interpolated in the 3D dense point cloud generated by the MVS dense matching technique, and used for producing the orthophoto [39].

For floating litter (FL) mapping, the single images collected by drones were analysed, as it was not possible to place and tag GCP due to the constant change of the sea surface.

### 3.1. Manual Image Screening

The BL items were marked through the manual image screening (MS) of the orthophoto in the Geographical Information System software (QGIS) environment [40]. The orthophoto was tiled with square grids to standardize and organize the MS, and a dedicated QGIS tool for guiding the task was developed. The operator (i) identified the litter items by zooming and panning the orthophoto, (ii) added a placemark at the approximated center of the item shape, and (iii) labelled the type of marked items. Both the OSPAR list and a simplified list conceptualized for drone-based surveys were adopted and tested [25,31] for characterizing each marked item by type, material, and colour [40]. The outputs were the BL map and the correspondent items attribute table, which included the location (longitude and latitude), type, material, and colour of each item. The MS assessed the distribution, density, and hotspot maps of BL on the monitored area, also for single materials and types of litter [26,31,32]. Eventually, the integration of the litter map with the environmental forcing and the DSM, allowed the description of BL dynamics on the shore [25,26], and the likely paths towards the dune environment [31].

The procedure of image screening for FL was performed manually by independent operators. At least one experienced operator checked each image to detect and identify the presence of FL, and a second experienced operator confirmed doubtful FL items [33,34]. As subsequent images overlapped to some extent, particular attention was given to avoid the overcounting of the same FL item in different images. FL items were classified by category and composition, according to the FL master list developed within the Marine Strategy Framework Directive by the TG Marine Litter [41], and revised during the MEDSEALITTER project (https://www.medasset.org/medsealitter-common-monitoring-protocol-for-marine-litter/). Furthermore, to automate the detection of FL, all images were labelled by the operators, as containing or not containing FL [33].

The accurate detection and identification of litter on orthophoto (BL) or on raw drone images (FL) was mainly dependent on GSD and operator experience [40]. However, image quality and the nature of litter itself also hampered the correct identification of some litter types [27,42]. Based on our BL experiences, multiple sections were needed to spot all items and optimize MS, since the task can be tedious and tiresome. In fact, the orthophoto needed to be panned and zoomed in/out continuously, and different output quality could be returned by different operators. Besides the attention given to MS task and operator expertise, final assessments were also dependent on the familiarity with BL and FL items [40]. It has also been proven that citizen science programs can contribute to the detection of litter items on drone images, upon an appropriate training plan and provision of specific tools [43].

### *3.2. Machine Learning and Automated Detection*

For both BL and FL, several techniques for automated detection of litter items on drone images were developed (Table 2). For BL automated detection on orthophotos, both pixel- and object-based approaches were tested, along with several machine learning classifiers [25,44–46]. Since a colour-based strategy was adopted, the automated recognition of BL was affected by (i) the dune vegetation, (ii) the presence of natural wood debris, and (iii) the class imbalance background/litter problem [44]. These issues generated the false positive detection that lowered the final F-score assessment (Table 2). Nevertheless, the BL density maps returned by machine learning classifiers were in line with the ones produced by the MS, suggesting that the colour-based strategy could be exploited for a coarse description of BL distribution and hotspot location [25,45,46]. Overall, the object-based approach further allowed measuring the size of litter items, which can be exploited, for instance, to compute the total area covered by litter and plastic on the beach [31], and to assess the distribution of BL based on their dimensions [32].

For FL automated detection on single images (Table 2), a pixel-based approach was used for building a deep learning model, based on a Convolutional Neural Network architecture [33]. A library called AIImagePred was developed in R [47] for an image binary classification (i.e., containing FL or not containing FL), based on the deep learning model. Furthermore, the open access web-application MARLIT was developed to detect and quantify FL in aerial images, using the Shiny package [48] through the AIImagePred R library. MARLIT allowed (i) uploading the aerial images, (ii) splitting the images into multiple cells, (iii) detecting the presence of FL in each of the cells, and (iv) quantifying FL density in relation to the covered area [33]. Given the high dynamicity of the sea surface, the main limitations of MARLIT were due to the interferences generated on the image by (i) the shadows of shoaling waves, (ii) breaking waves foam and (iii) sun glint. These conditions can partially and/or totally hide and/or submerge FL during the image acquisition. Yet, cloud shadows on the sea surface also hampered the detection of items, and misled their colour.

In literature, other numerous approaches have been proposed for BL and FL automated detection by machine learning and other image processing techniques. However, most of them were (i) based on synthetic examples, (ii) considered a limited number of items and/or (iii) did not perform an operational BL and/or FL survey. For a comprehensive review of the automated algorithms developed for litter detection, see Pinto et al. [45] and reference therein.

Overall, performances for FL were higher than for BL, perhaps because the sea water constitutes a more homogeneous background in comparison to sand, when the above cited interferences are limited. In fact, most of the issues in the automatic detection of BL were due to footprints [49], and items trapped among wood and vegetation [46].

It would be interesting to test if the several developed classifiers would be applicable in the different images collected for BL and FL detection. Even though automated object detection assessments depend on the image background. Future works may aim to achieve this objective.

**Table 2.** Different approaches developed for automated image detection of beached (BL) and floating (FL) litter items. Machine learning classifiers include random forest (RF), Convolutional Neural Network (CNN), Support vector machine (SVM), k-nearest neighbors (KNN), and neural network (NN). Both pixel-based (Px) and object-based (Ob) approaches were tested. Assessments for the binary approach (litter/non-litter identification) are reported in terms of precision (P), recall (R) and F-score.

| Reference | Method | | Type of Litter | Binary Approach | | | UAV Flight Altitude (GSD) |
|---|---|---|---|---|---|---|---|
| | | | | P (%) | R (%) | F-Score (%) | |
| [25] | RF | Px | BL | 73 | 74 | 75 | 20 m (0.55 cm/pixel) |
| [44,46] | RF<br>CNN | Px | BL | 70<br>55 | 71<br>65 | 70<br>60 | 20 m (0.55 cm/pixel) |
| [50] | RF<br>SVM<br>KNN | Ob<br>Ob<br>Ob | BL | 75<br>76<br>68 | 68<br>62<br>62 | 72<br>68<br>65 | 20 m (0.55 cm/pixel) |
| [33] | CNN | Px | FL | 79 | 94 | 86 | 20–120 m (0.6–3.6 cm/pixel) |
| [45] | NN | Px | BL | 80 | 67 | 73 | 30 m (0.9 cm/pixel) |

## 4. Discussion

Beached litter (BL) surveys have been shown to be effective for evaluating the level of beach contamination and for improving the knowledge on BL dynamics on the shore [25,26]. In addition, drones offer a valuable solution for a non-intrusive mapping of BL on coastal dunes, where trampling may endanger the delicate equilibrium of these ecosystems [31,32]. On the other hand, floating litter (FL) surveys have proven to be at least as effective, if not more effective, than observer-based surveys to detect floating items at sea [34].

A common constraint for performing drone-based BL and FL surveys was related to weather conditions, since drone deployment required calm wind, along with the absence of fog, mist, or rain, to fly and/or collect good quality images. However, in comparison to FL, BL surveys were less affected by environmental conditions, such as the perturbations of the sea surface caused by wind or sun glint. On top of this, the risk of losing the drone was higher when flying over the sea surface, therefore the range of optimal environmental conditions to perform drone-based FL surveys was more limited. Yet, flights for BL mapping were logistically easier to perform, as they did not require the expensive use of a vessel. For these reasons, the developments of drone-based BL surveys are somehow more advanced than that of drone-based FL surveys, whose application has been less adapted yet.

Although for FL the chosen drone flight altitude was higher than for BL (Table 1), this parameter may be easily adapted for a potential BL and FL combined survey over the coastal area. However, the autonomy of drone batteries determines the main issue for such integration: whatever the chosen drone flight height, the autonomy of multirotor drones is still limited in time today, restricting surveys to a limited area.

Drone-based BL and FL surveys have the common advantage of requiring less human and logistical efforts than the respective traditional survey methods (Table 3). Beached litter drone-surveys can potentially be performed by a single operator, since just drone deployment and (optional) GCPs and CPs placement are required. As they are mostly performed from a boat, FL drone-surveys need instead at least two operators: one person in charge of operating the drone, while the other is manoeuvring the vessel. The BL map of a 0.02 km$^2$ beach area, and transect of 0.16 km$^2$ for FL survey, were assessed in about one working day (Table 3). These logistic advantages can allow increasing the monitoring frequency [24,26] and the target area extent of both BL and FL [22]. Yet, drone-based surveys can improve the knowledge on BL and FL characteristics and dynamics, since additional information such as the size [32], paths [31], and hotspot locations [25] can be obtained. This is fundamental to provide better data for understanding and improving the modelling of both BL and FL dynamics. Finally, drone-based surveys assessments may also potentially improve litter cleaning operations, support the search for proper cleaning strategies, and optimize the cleaning paths [51,52].

Overall, the difficulty in recognizing litter type and composition from the visual screening of drone images was common to both BL and FL surveys. This was due to the nature of RGB images and the countless types of litter that may be found in the environment. Semi-buried items on beaches (BL), and/or trapped by dune vegetation (BL), algae (FL) and natural wood debris (BL and FL) additionally hampered litter characterization. Further advances are needed, and the recent applications of multi- and hyperspectral cameras seem promising in this regard, since different materials produce different spectral responses [16,53]. An online platform for sharing drone images from both BL and FL surveys would be beneficial for further development of automated solutions. Yet, citizen science programs have proven to be helpful for both collecting and screening the images obtained in the field [30,43,54], therefore such shared platform may be valuable both for uploading images and training citizen science operators.

**Table 3.** Approximate time required to assess a drone-based survey of beached (BL) and floating (FL) litter survey. Main tasks are divided into fieldwork and image post-processing. The different steps to carry out the final assessments, as well as the required tools and software for the aim, are indicated in the sub-tasks.

| | Task | Sub-Task | Time Required (h) | Tools/Logistics Required | Minimum Number of Operator(s) Required |
|---|---|---|---|---|---|
| **BL** | Fieldwork | Flight planning | 0.5 | Drone + dedicated app | 1 |
| | | Drone deployment | 1 | Drone | |
| | | GCP placing | 0.5 | GCP | |
| | Post-processing | Image organization | 1 | Computer + image processing and QGIS software | 1 |
| | | Manual image screening | 4 | | |
| | | QGIS map | 2 | | |
| **FL** | Fieldwork | Flight planning | 0.5 | Drone + dedicated app | 2 (1 vessel driver + 1 drone oper-ator) |
| | | Vessel preparation + navigation to survey area | 1–2 | Vessel | |
| | | Drone deployment | 2 (6 transects, 20 min each) | Drone/Vessel | |
| | Post-processing | Image organization | 1 | Computer + image processing and QGIS software | 1 |
| | | Manual image screening | 4 | | |

It is of interest to underline that both BL and FL drone-based surveys can be integrated with other types of environmental investigations that exploit drone images for different purposes. Conversely, drone images of litter could be collected by researchers who are deploying drones on coasts or at sea for other studies. For instance, BL drone surveys can be coupled to beach-dune morphodynamic studies [26,55–61], coastal cliffs 3D reconstructions [39,62], and dune vegetation census [63,64], among others. Drone-based FL surveys can be combined with drone flights aiming at monitoring marine fauna [65,66], sargassum and seagrass [67–69], as well as documenting human activities at sea [70,71], possible illegal activities [72] and oil spills [73].

Despite the versatility of drone surveys, and given the review of analogies and differences among BL and FL surveys, it seems difficult to combine BL and FL surveys in the coastal environment, at least at high-energy sites such as the North Atlantic Portuguese coast. There, the turbulence generated by breaking waves and the resident foam in the nearshore would not allow identifying FL items. On the other hand, the limited battery autonomy of multirotor drones would limit the target area in calmer seas such as the Mediterranean. The evolution of drone technology and the increase of battery autonomy may perhaps allow integrating beach and marine litter surveys in further areas in the next future. Nevertheless, the techniques outlined in this work can be combined for surveys of litter stranded along river banks and floating in river waters, as well as in estuaries, deltas, and lagoon environments, where litter items strand in intertidal flats, sandbars and salt march, and/or float on the calm/still waters. As these domains are smaller, the same drone flight can be used for both BL and FL surveys.

## 5. Conclusions

Images collected by Unmanned Aerial Vehicles (UAV, aka drones) are highly efficient to map and monitor beached (BL) and floating (FL) marine litter items. In this work, the operational procedures to carry out both BL and FL surveys using UAV were described and commented in detail.

Based on our previous experiences, drone deployment and logistics constitute the main differences between BL and FL surveys. For BL, environmental conditions for data collection were stricter than for FL surveys, since tide and wind needed to be considered prior to fieldwork. Overall, logistics was more demanding for FL, as the use of vessel and more human operators were required for offshore surveys.

The procedure of manual litter detection on images was very similar for both surveys, even though orthophoto and raw drone images were used for BL and FL, respectively. However, litter automatic detection on images still represents a technological challenge, and further research is needed to improve the effectiveness of current automated algorithms.

In terms of advantages, UAV-based surveys are more effective than the traditional techniques for both BL and FL surveys, can be integrated with other different drone-based studies, and allow improving knowledge on litter dynamic in the marine environment.

**Author Contributions:** Conceptualization, U.A., O.G.-G., M.V. and G.G.; methodology, U.A., O.G.-G., M.V. and G.G.; software, U.A., O.G.-G., M.V. and G.G.; validation, U.A., O.G.-G., M.V. and G.G.; formal analysis, U.A., O.G.-G., M.V. and G.G.; investigation, U.A., O.G.-G., M.V., A.B. and G.G.; resources, U.A., O.G.-G., M.V., A.B. and G.G.; data curation, U.A., O.G.-G., M.V., A.B. and G.G.; writing—original draft preparation, U.A., O.G.-G., and M.V.; writing—review and editing, U.A., O.G.-G., M.V., A.B. and G.G.; visualization, U.A., O.G.-G., M.V., A.B. and G.G.; supervision, U.A., O.G.-G., M.V., A.B. and G.G.; project administration, M.V., A.B. and G.G.; funding acquisition, U.A., A.B. and G.G. All authors have read and agreed to the published version of the manuscript.

**Funding:** This work was supported by the Portuguese Foundation for Science and Technology (FCT) and by the European Regional Development Fund (FEDER) through COMPETE 2020, Operational Program for Competitiveness and Internationalization (POCI) in the framework of UIDB 00308/2020, the research project UAS4Litter (PTDC/EAM-REM/30324/2017), and the project MEDSEALITTER (1MED15_3.2_M12_334; European Union- European Regional Development Fund- Interreg MED). We thank the MCIN/AEI/10.13039/501100011033 and FSE "El FSE invierte en tu futuro" for supporting O. Garcia-Garin with a Ph.D. FPU scholarship (FPU17/00073).

**Data Availability Statement:** Not applicable.

**Acknowledgments:** U.A. and G.G. would like to thank Filipa Bessa, Paula Sobral and Luisa Gonçalves, for the participation in the project; Luis Pinto, Diogo Duarte for machine learning development; Angela Fontan-Bouzas for the help in beach morphodynamic analysis. O. G.-G., M.V. and A.B. would like to thank Eduard Degollada, Bertrand Bouchard, Alex Aguilar, Luis Cardona, Antonio Monleón-Getino, Pere López-Brosa, and Ricardo Borja-Robalino for the participation in the project, help in the fieldwork and in the deep learning development.

**Conflicts of Interest:** The authors declare no conflict of interest.

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