Drones for litter mapping: an inter-operator concordance test in marking beached items on aerial images

Abstract (max 150 words): Unmanned Aerial Systems (UAS, aka drones) are being used to map macro-litter on the environment. Sixteen qualified researchers (operators), with different expertise and nationalities, were invited to identify, mark and categorize the litter items (manual image screening, MS) on three UAS images collected at two beaches.

The coefficient of concordance (W) among operators varied between 0.5 and 0.7, depending on the litter parameter (type, material and colour) considered. Highest agreement was obtained for the type of items marked on the highest resolution image, among experts in litter surveys (W=0.86), and within territorial subgroups (W=0.85). Therefore, for a detailed categorization of litter on the environment, the MS should be performed by experienced and local operators, familiar with the most common type of litter present in the target area. This work provides insights for future operational improvements and optimizations of UAS-based images analysis to survey environmental pollution.

Keywords: Plastics, Unmanned Aerial Vehicle (UAV), Remote Sensing, Waste management, Coastal pollution

1 INTRODUCTION

The abundance of anthropogenic debris on coasts, mainly composed by plastic materials (GESAMP, 2019; IUCN and UNEP-WCMC, 2016), is dramatically increasing, and has become a global issue due to its significant potential impact on coastal systems (e.g., Islam and Tanaka, 2004), marine life (e.g., Werner et al., 2016) and human health (e.g., Bergmann et al., 2015). It is therefore crucial to plan and implement environmental monitoring strategies to support the search for suitable mitigation measures against coastal pollution (e.g., Galgani et al., 2013; OSPAR Commission, 2010).

In the recent years, unmanned aerial systems (UAS, aka drones) are being used to map macro-litter (>2.5 mm, GESAMP 2019) on coastal beaches (Bao et al., 2018; Deidun et al., 2018; Gonçalves et al., 2020b; Haseler et al., 2021; Martin et al., 2018; Merlino et al., 2020), coastal dunes (Andriolo et al., 2020a), remote islands (Fallati et al., 2019), lake beaches (Hengstmann and Fischer, 2020), sea surface (Garcia-Garin et al., 2020b, 2020a; Topouzelis et al., 2019) and river waters (Geraeds et al., 2019).

Although the visual census survey is the most common method to quantify and characterize litter on coastal and marine environments (Browne et al., 2015; Hanke et al., 2013; OSPAR Commission, 2010; Rangel-Buitrago et al., 2018; Williams and Rangel-Buitrago, 2019), it has been demonstrated that UAS permits overcoming logistical issues, reducing the human effort in the field, and geolocating the litter items to identify actual hotspots. As drones are becoming more affordable and available over the research community and general public, the technique can potentially increase the survey frequency for: i) a better description of litter variability; ii) be coupled to other environmental surveys (Andriolo et al., 2020b); iii) provide useful information to progress litter dynamic models (e.g., Cordeiro et al., 2018; Critchell

and Lambrechts, 2016; Haarr et al., 2019; Kako et al., 2018; Raimundo et al., 2020; Turrell, 2018; Yoon et al., 2010); iv) serve as tool for an optimal litter management (Rangel-Buitrago et al., 2020; Williams and Rangel-Buitrago, 2019).

For a proper application of UAS for litter detection, the manual image screening technique (hereinafter, MS) on drone images is crucial for an appropriate application of the methodology. The MS consists in visually screening the image, and marking the recognized litter items under GIS environment (or similar software) to build the litter map (Gonçalves et al., 2020c). It is therefore important to perform accurately the MS, also when automated identification of the items is chosen (Bak et al., 2019; Bao et al., 2018; Duarte et al., 2020; Fallati et al., 2019; Garcia-Garin et al., 2021; Gonçalves et al., 2020c, 2020a; Jakovljevic et al., 2020; Kataoka et al., 2012, 2018; Kataoka and Nihei, 2020; Kylili et al., 2019; Panwar et al., 2020; van Lieshout et al., 2020; Wolf et al., 2020), since machine learning and detection algorithms must be trained and/or calibrated with reliable data.

From the technical point of view, previous studies tested the reliability of drone-based litter surveys in respect to visual census conducted in the field (Fallati et al., 2019; Haseler et al., 2021; Martin et al., 2018; Merlino et al., 2020). However, as in all other related drone-based previously cited works, the MS has been performed by a single operator. Considering untrained personnel, Lo et al. (2020) proposed a photo interpretation test, with focus on how operational drone flight height and light conditions influenced the recognition of the stranded litter. Nevertheless, the MS is a highly subjective task, which also depends on the operator experience and expertise, therefore it is of interest to investigate how these factors influence the litter recognition and the marking procedure on drone images.

This work aims at investigating the agreement on MS when it is performed by different operators. Sixteen researchers with different expertise, nationalities and working in different

coastal areas were recruited to mark and categorize macro-litter on three UAS images, collected at two Portuguese and Italian beach-dune systems. An inter-operator concordance test was conducted among the group of researchers. This work intends to understand the characteristics of MS, to suggest future operational improvements and optimizations, and in general to advance the litter survey by UAS.

2 METHODS

2.1 Study sites and image dataset

2.1.1 Cabedelo beach - Portugal

Cabedelo Beach (40°08′12.8″N - 8°51′47.5″W) is a sandy coastal stretch located on the western Portuguese coast facing the North Atlantic Ocean (Fig. 1). The beach area extends for about 500 m long-shore, with a NW-SE orientation, and it is limited northwards by a 1 km-long jetty, southwards by a 90 m-long groin, backward by a dune system with alongshore height variability between 7 m and 10 m (Fig. 1). The beach shore is located southward Mondego River estuary, at a cross-shore distance of about 1 km from the spit. The tidal regime is meso-tidal, with average amplitude of the astronomical tide in the order of 2.10 m (Antunes and Taborda, 2009), while predominant waves come from NW with average significant heights of 2 m and periods from 7 s to 15 s (Fernández-Fernández et al., 2019; Oliveira et al., 2018).

2.1.2 San Rossore beach - Italy

San Rossore beach (43°42'57.2" N 10°16'41.2" E) is a sandy coastal sector located at the Tyrrhenian coast of the Tuscany region, Italy (Fig. 1). The beach area extends for about 700 m long-shore, with a N-S orientation, limited southwards by a 150 m-long semi-submerged groin, backward by a dune system reaching a maximum height of about 7 m on the crest (Bertacchi, 2017). The tidal regime is micro-tidal, the wave climate is characterized by dominant southwesterly wave direction, with wave heights usually about 1 m (Bertoni et al., 2020; Bini et al., 2021). The beach is located downdrift the Arno river estuary, within the marine protected Migliarino, Massacciuccoli, and San Rossore park. The access to this area

is forbidden for recreational purposes, and only allowed for research activities upon permission.

2.1.3 Data acquisition and image dataset

At the two study sites, the same multirotor quadcopter DJI Phantom 4 Pro was used (Fig. 1), with the camera (1-inch 20-megapixel CMOS sensor, 24 mm full-frame equivalent) shooting perpendicular to the direction of the flight. Images were recorded with 80% front and 70% side overlaps, to generate the Digital Surface Model (DSM) and the orthophoto beach map applying a Structure from Motion - MultiView Stereo (SfM-MVS) photogrammetric processing on Agisoft Metashape (Gómez-Gutiérrez and Gonçalves, 2020; Gonçalves et al., 2018; Rangel et al., 2018).

The flight altitude was different at the study sites: at Cabedelo beach (Portugal), the drone was set to fly at 20 m above ground level, while the flight altitude was of 6 m at San Rossore beach (Italy). Therefore, the image nominal spatial resolution, expressed in ground sample distance (GSD), was of 0.55 cm/px at Cabedelo beach, and of 0.16 cm/px at San Rossore beach.

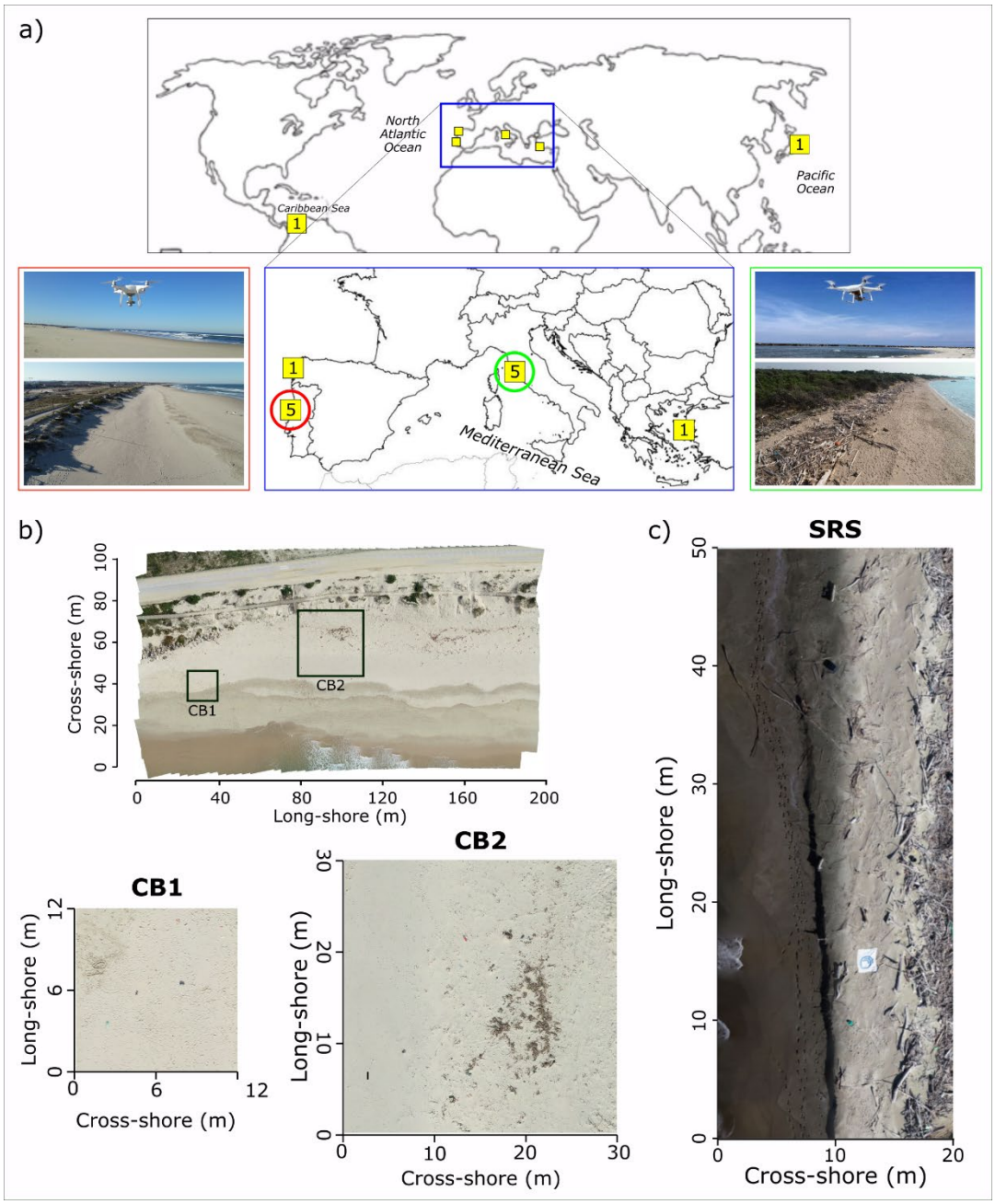

Fig. 1. Study site locations, origin of the working group (WG) and data images. a) origin of the sixteen researchers (yellow boxes with the number of researchers coming for the site). Red circle indicates the location of Cabedelo beach (Portugal), while green circle shows the San Rossore beach (Italy), with pictures taken on the fields; b) image dataset, with the orthophoto of Cabedelo beach and the two sub-images CB1 and CB2 (left), and the portion of San Rossore beach (SRS, right).

From the entire orthophoto produced at Cabedelo beach, two sub-areas were extracted (Fig. 1). The first sub-area (CB1) measured 12 m x 12 m. Three items, namely a fishing rope (~20 cm), a fishing net (~25 cm) and an octopus pot (~30 cm), were placed in this area by the drone operator prior the flight for testing the UAS technique. The second sub-area (CB2) was of 30 m x 30 m, representing the litter hotspot found on Cabedelo beach during the flight (Gonçalves et al., 2020b).

From the orthophoto produced at San Rossore, a sub-area of 50 m x 15 m (SRS) was extracted (Fig. 1). It corresponded to half of the area surveyed by the drone, which was used to perform a comparison between UAS survey and visual census, adopting OSPAR sampling area (Merlino et al., 2020).

2.2 Manual image screening

2.2.1 Working group

Sixteen coastal researchers were invited to perform MS on UAS images. The working group (WG) was composed of five academic Professors, seven Post-Doctorates, three PhD students and one technician. The different expertise covered the disciplines involved in UAS-based litter survey on beaches, such as marine biology, geology, remote sensing, environmental engineering, oceanography, image processing and machine learning. Six nationalities and three continents were represented, including researchers working at the North Atlantic (Portugal and Spain), Mediterranean (Italy and Greece), Caribbean (Colombia) and Pacific (Japan) coasts (Fig. 1).

The WG was firstly divided in two subgroups based on the expertise (XP subgroup) and inexpertness (IP) in litter monitoring on coastal and marine environments, considering the

previous performance of both visual census and UAS-based surveys. A second classification subdivided the WG based on the territoriality (Fig. 1), grouping the researchers working at Cabedelo (PT group), at San Rossore (IT) and coming from locations different from the study sites (OS). Within each territorial group, the number of experts was roughly balanced (Table 1).

Table 1. Working group (WG) and subgroups composition, with expertise (XP) and inexpertness (IP) in surveying litter, and territorial groups (PT, IT and OS). The "expert" definition indicates researchers with experience in litter survey, both from UAS and visual census.

	WG	*Subgroups*				
		XP	**IP**	**PT**	**IT**	**OS**
Characteristics		*Expertise in litter monitoring*	*Inexpertness in litter monitoring*	*Working on the Portuguese Cabedelo beach*	*Working on the Italian San Rossore beach*	*Working on other sites*
Number of operators	16	8	8	5	5	6
Number of experts within the groups	8	8	0	3	2	3

2.2.2 Litter items shortlist

In order to suggest an adequate litter items list to support UAS-based survey and the MS, a new shortlist was provided to the WG (Fig. 2). Using a data structure similar to that proposed by UNEP for remote sensing litter record (UNEP/IOC Guidelines on Survey and Monitoring of Marine Litter, 2009), the shortlist comprised three main characteristics, namely type, material and colour. The types of litter were also characterized by their main potential source. Among the recognizable litter types, two specific categories were also included, namely

“fragments” and “undefined items”. The “fragments” were defined as pieces of an object, with undefined shape and anthropogenic origin, that could not be associated with any litter types present in the list. In the instruction of MS provided to the researchers (hereinafter, operators), it was specified that, for instance, in recognizing a broken drinking bottle, this needed to be marked as “bottles”, and not as “fragments”. “Undefined items” were instead defined as objects with distinct shape, but that could not be associated with any type of litter present in the list, for being not enough visible, and/or not recognizable due to operator inexpertness and/or low image resolution. The “undefined” category was also included in the material and colour lists, in case that these characteristics could not be precisely defined (Fig. 2).

SOURCE	code	TYPE
	0	Undefined items
	1	Fragments
CONTAINERS	2	Bottles <2L (drinking)
	3	Bottles <2 L (cleaning product)
	4	Bottles >2 L
	5	Drums and buckets
	6	Crates
	7	Other containers
FISHING & BOATING	8	Buoys
	9	Fishing nets/ropes/strings
	10	Octopus pots
	11	Other fishing & boating items
FOOD & BEVERAGE	12	Cups, chip forks, chopsticks
	13	Drink, food cans
	14	Drink package rings
	15	Tablewares
	16	Caps
	17	Other food and berage items
PACKAGING	18	Foam (insulation/packaging)
	19	Cardboards
	20	Bags
	21	Strapping
	22	Tetrapacks
	23	Other packaging
SANITARY	24	Masks
	25	Other sanitary
CLOTHING	26	Boots
	27	Shoes
	28	Gloves
	29	Other clothing
OTHERS	30	Light tubes, light globes
	31	Pallets
	32	Processed timbers
	33	Aerosol cans
	34	Tyres
	35	Magazines, newspapers
	36	Construction items

code	MATERIAL
P	plastic
R	rubber
G	glass
W	wood
M	metal
T	textile
Q	paper
C	ceramic
0 (zero)	not identified / not listed

code	COLOUR
b	blue
k	black
y	yellow
r	red
g	green
m	brown
w	white
t	transparent
0 (zero)	not identified/ not listed

Fig. 2. Litter items shortlist proposed for performing the manual image screening (MS), with the numerical codes associated to type of litter, upper case letter to materials, lower case letter to colours.

2.2.3 Manual image screening

Each image was tiled with a 3 m × 3 m squares grid to make the MS regular and organized, similarly to Andriolo et al. (2020b). The operators were asked to (i) visually screen the images, (ii) identify the litter items, (iii) add a placemark at the approximated centre of the items shape in GIS environment, and (iv) attribute the three characteristics (type, material and colour) to the objects following the provided litter shortlist (Fig. 2). In the shortlist, the code numbers identified the type, the upper and lower case letters the material and colour, respectively (Fig. 2).

A dedicated GIS package was developed and provided to the WG for performing MS, with images and point shapefiles. A brief video conference was held to train the WG, mostly dedicated to the explanation of the marking procedure with the software and the use of the shortlist. A document was also provided with the marking instruction and some general observations about the shortlist.

After the MS, each operator returned a litter map and the correspondent attribute table, with the corresponding point of localization (longitude and latitude), the type, material and colour of each item. This process was developed for each of the three used images.

2.3 Inter-operator concordance test

All data returned by the WG were used to study the level of concordance among operators and different subgroups. For CB1, we analysed how the WG marked the three known items placed in the area. Regarding CB2 and SRS, ground-truth data were missing, therefore it was not possible to measure the level of accuracy in respect to a known gold standard. For this reason, we only studied the concordance of data (number of items, type, material, colour) among the WG and subgroups.

Kendall's coefficient of concordance (W) was adopted to measure the level of agreement (Kendall, 1975; Kendall and Smith, 1939) in the number of marked items on the three images, and in assigning the litter characteristics on CB2 and SRS. Kendall's coefficient of concordance ranges from 0 (no agreement) to 1 (complete agreement). To make the comparison independent from the number of marked items, we normalized the analysis computing the percentages of type, material and colour marked and chosen by each operator on CB2 and SRS.

In the same way, the Hedge's effect size *g* (Hedges, 1981; Hentschke and Stüttgen, 2011) was measured for the different subgroups in relation to the number of marked items. Although this statistic value is typically used to compare an experimental sample to a control sample, the Hedge's *g* was used to evaluate which subgroup division had more influences in the results. A value of Hedge's *g* between 0.2 and 0.5 indicates a small effect, between 0.5 and 0.8 a medium effect, while values higher than 0.8 indicate a large effect (Hentschke and Stüttgen, 2011).

3 RESULTS

3.1 Number of marked items

The number of items marked by the WG and subgroups are presented on Fig. 3. The differences found had similar magnitudes on the three images analysed, with three standard deviations below the median value, despite the distinct image resolution between CB1 and CB2 (GSD = 0.9 cm) and SRS (GSD = 0.6 cm). The XP subgroup, along with PT and IT, marked a number of items within the interquartile range, whereas the numbers returned by IP were more spread and determined the minimum and maximum scores. It is important to

note that, on the testing sub-area CB2, the automated results obtained by machine learning algorithms (Gonçalves et al., 2020c), trained with the marking of an operator belonging to PT group, were within the interquartile range (Fig. 3).

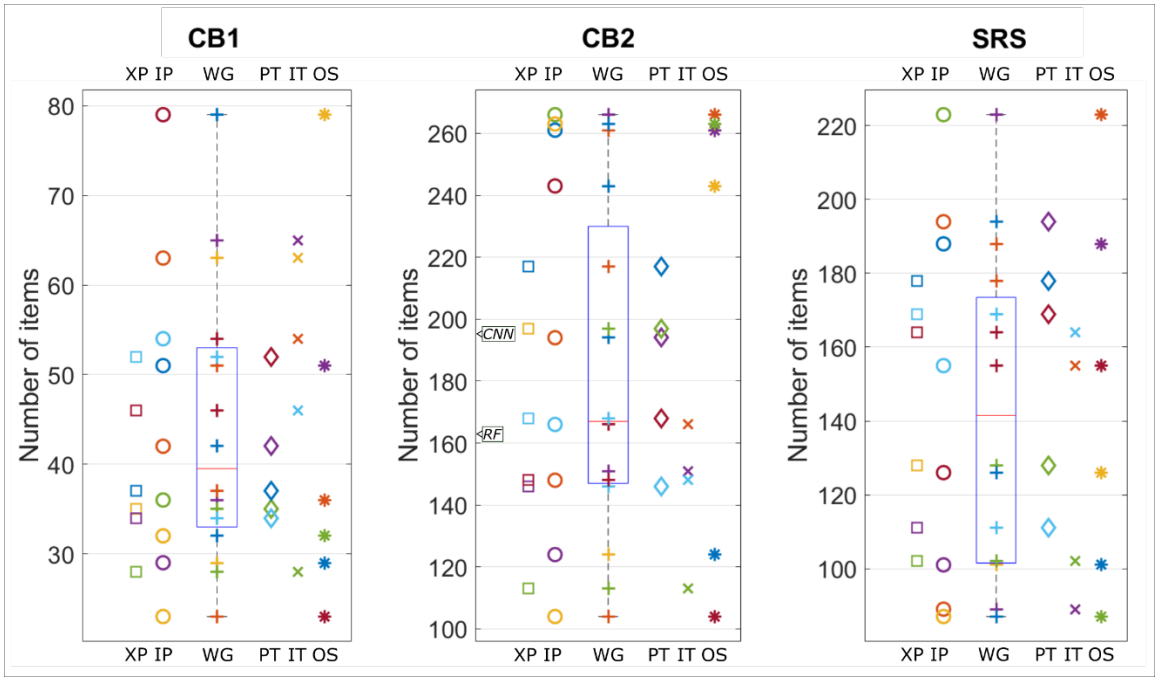

Fig. 3. Numbers of litter items marked on the two sub-areas of Cabedelo beach (CB1 and CB2) and on San Rossore (SRS). The boxplots refer to the number of items marked by the working group (WG, crosses), squares by the experts (XP), circles by the nonexperts (IP), diamonds by the Portuguese (PT), x-marks by the Italian (IT) and stars by researchers coming from other sites (OS) subgroups. On CB2, random forest (RF) and convolutional neural networks (CNN) show the results obtained by machine learning algorithms in Gonçalves et al. (2020c).

Overall, the Kendall's coefficient of concordance (W) among the components of the WG reached values between 0.51 and 0.7 (Table 2), the latest when considering together the two biggest images (CB2 and SRS). The highest concordance values were obtained among the XP group (0.77 – 0.91), while the lowest values were obtained by territorial groups in relation to the number of items marked on the three images (Table 2).

The Hedge's *g* results suggested that the territoriality (large effect > 0.8) had higher influence than the expertise (on average, < 0.5, small effect) in the number of marked litter items (Table

2). The Hedge effect was in general lower on the highest resolution SRS image, and bigger when analysing the effect between the two groups working at the study sites (PT and IT).

Table 2 Results of inter-operator concordance test. W indicates the Kendall's coefficient of concordance, g the Hedge's effect size obtained on Cabedelo beach (CB1 and CB2) and on san Rossore (SRS) images by Working group (WG) and subgroups, with expertise (XP) and inexpertness (IP) in surveying litter, and territorial groups (PT, IT and OS). Italic bold indicates the best obtained values.

Groups	Number of operators	W			Groups	Hedge's g		
		CB1+CB2	CB1+CB2+SRS	CB2+SRS		CB1	CB2	SRS
WG	16	0.66	0.51	0.70				
XP	8	**0.77**	**0.82**	**0.91**				
IP	8	0.61	0.45	0.65	**XP-IP**	0.42	0.54	0.10
IT	5	0.75	0.38	0.65	**PT-OS**	0.1	0.4	0.19
PT	5	0.55	0.62	0.75	**PT-IT**	**0.85**	**1.48**	**0.91**
OS	6	0.74	0.55	0.63	**IT-OS**	0.48	1.03	0.53

3.2 Manual image screening on CB1

On CB1 (Fig. 4), 82% of WG identified correctly the type, material (plastic) and colour (green) of the fishing net, while the rest 20% (mostly belonging to IP) still marked the item as a fishing-related object but did not indicate the correct material. Similarly, the red plastic fishing rope was characterized correctly by 70% of the WG.

The octopus pot item was instead categorized properly only by the six operators (38%), all of them working at the North Atlantic coast. This item was found in great numbers in the previous UAS-based monitoring studies close to Cabedelo (Andriolo et al., 2020b; Gonçalves et al., 2020b). It is of note that IT agreed in characterizing the item as textile clothing item (three operators) and plastic container (two operators). This suggests that,

besides the fact that low image resolution affected the item recognition, the octopus pots items in use at Mediterranean coasts may have different shape and colour than the ones at the North Atlantic coast.

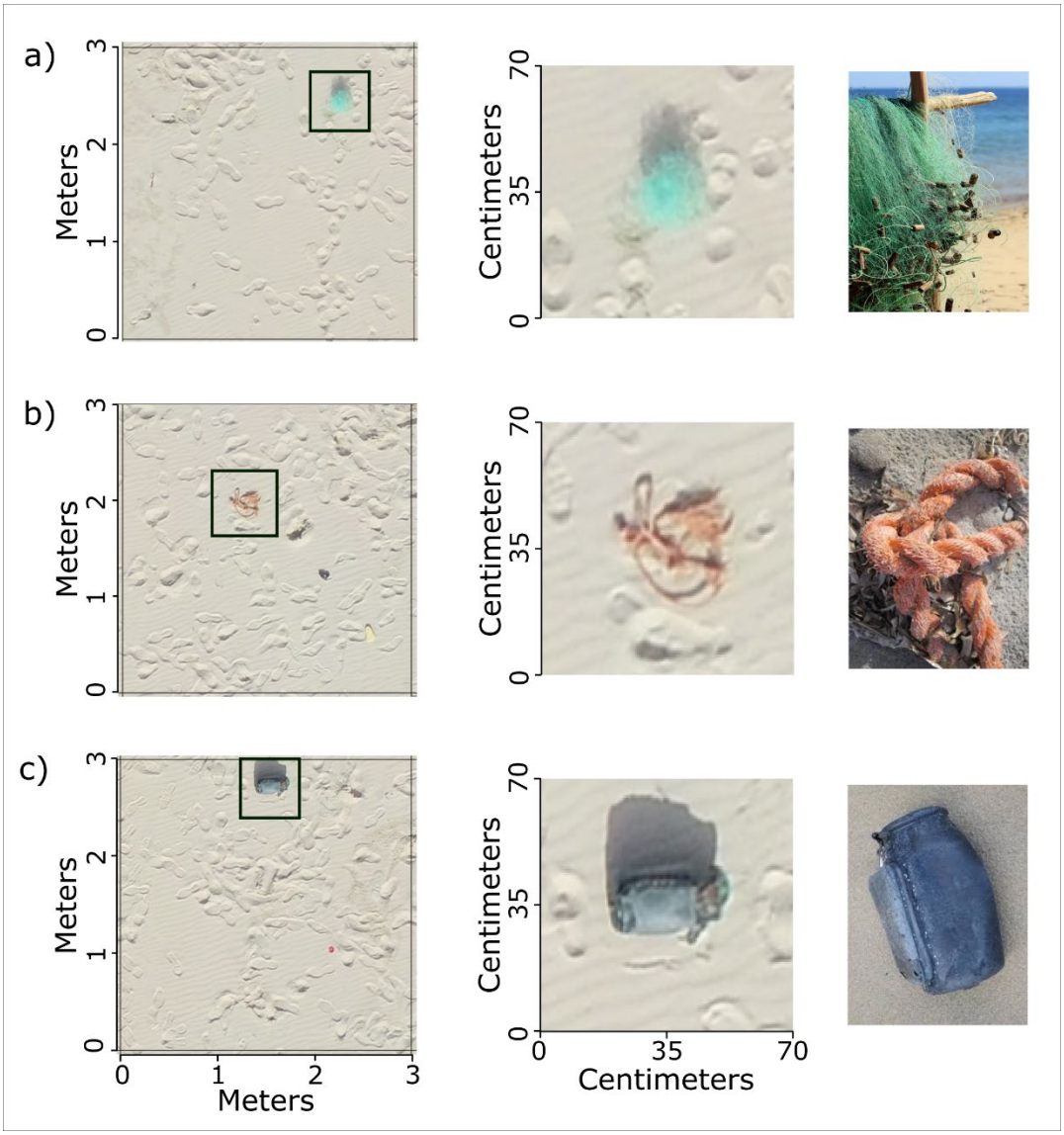

Fig. 4. Specific known items on CB1. a) Green plastic fishing net; b) red plastic fishing rope; c) black plastic octopus pot. Common to all, the left column shows the 3 m × 3 m tile extracted from CB1 and the items (black squares), the central column the items visible with a 200% zoom factor, the right column a real picture of the items.

3.3 Manual image screening on CB2 and SRS

Marking results for litter type, material and colour on CB2 and on SRS are show in Fig. 5. On CB2, among types, the fragments category was the most selected (35%, on average), the undefined items the second one (25%). The fishing-related items composed 18% of litter bulk, while all other categories were less than 10%. Considering the XP group, the results were always within the interquartile range, except for the packaging items category. The IP results were more scattered, especially for the undefined items and fragments. Considering the territorial groups, it is of note the disagreement between PT and IT, which categorized only the undefined items category with similar ratio. In general, the PT returned higher percentages of undefined items and packaging, while the IT identified higher percentages of containers and food/beverages. The percentages obtained by the OS were dissimilar to both PT and IT, as it marked the highest number of undefined categories.

Among litter materials, plastic (61%) was the most predominant, while the undefined category constituted 20%, on average. Wood, textile and other materials were lower than the 10%. It is clearly visible how the IP and OS categorized over 60% of the marked items as undefined, and that plastic was chosen for about 25% of litter (Fig. 5). Besides, the OS marked more wood and textile than the other territorial groups. The PT tended to indicate more undefined items than the IT, which chose more other materials (rubber, paper, metal and ceramic).

Regarding colours, white items were the most common litter (30%). As general observation, fewer differences among groups were found for the red and white litter items, whereas results were contrasting for all the other colours. For instance, the IT chose higher percentages of

blue and black items. Nevertheless, the choice of colour was much related to the type and number of items marked, besides being more subjective than the other categories.

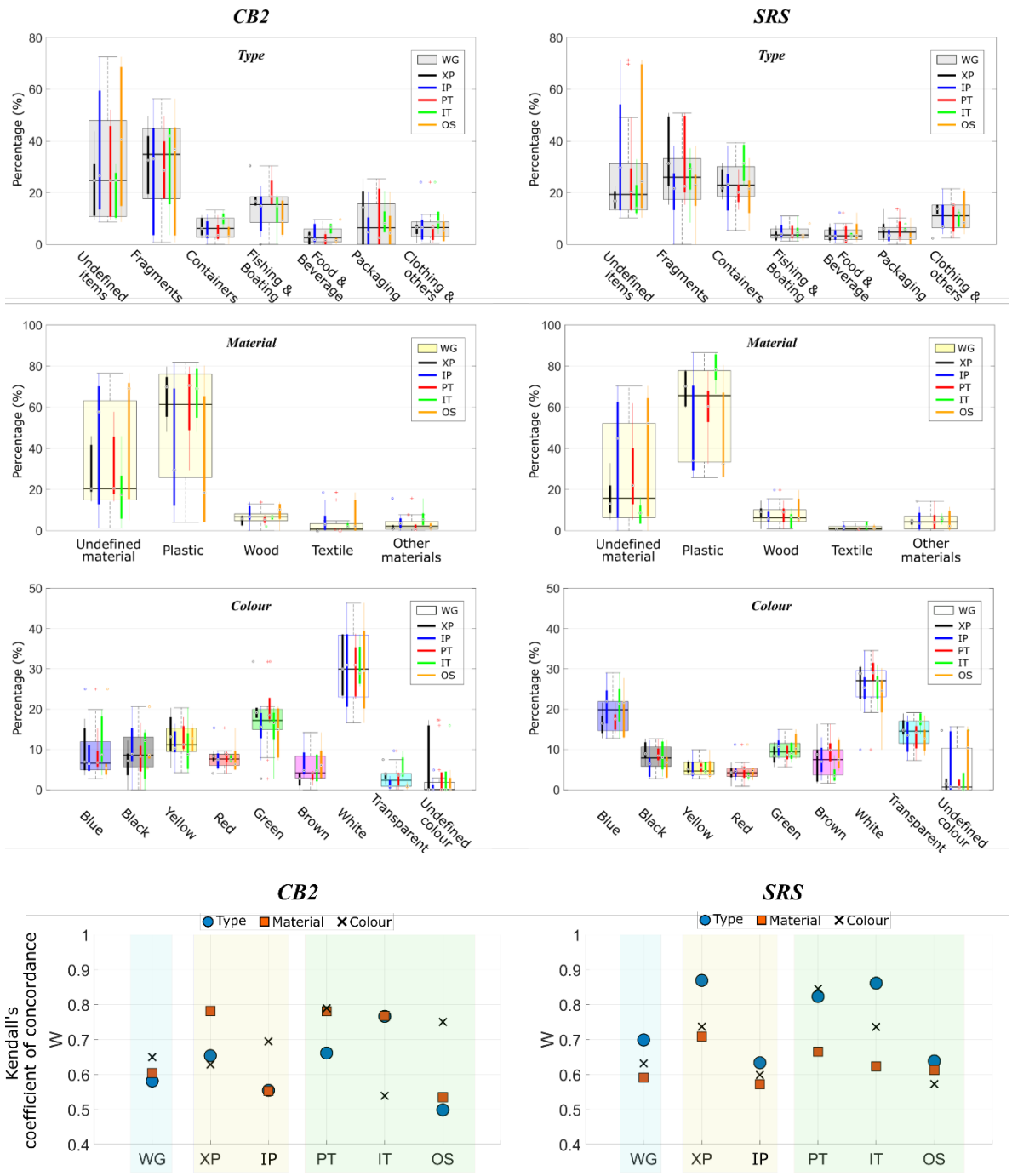

Fig. 5. Manual image screening results for CB2 and SRS. Boxplots indicate the results from the working group (WG), while coloured lines the results from the subgroups. Black lines show the results from the expert group (XP), blue lines from nonexpert group (IP), red from operators working at Cabedelo (PT), green from operators working at San Rossore (IT), and orange from operators coming from different sites (OS).

On SRS (Fig. 5), the undefined items, fragments and container types were marked with 20%. Seven other types of litter were recognized by the WG, with a percentage between 3% and 5% of the total. The fragment category was much chosen by XP and PT groups, while IP and OS opted more for the undefined item category. The choice of the type and material differed much between XP and IP, and between PT and IT, despite the higher GSD of SRS in comparison with CB2.

The material composition of litter bulk on SRS was very similar to the one found on CB2, with plastic composing 60% and wood 20%, on average. On SRS, glass, rubber and metal were found with a percentage varying between 1 % and 4 % though. The undefined materials were slightly higher (27%) than on CB2 (20%), nevertheless the marked interquartile by the WG covered the same range (15% - 60%) on both sites.

All colours were found with a percentage higher than 5%, with white (26%) and blue (18%) being the most common. On CB2, white had a similar percentage (30%), whereas green was the second most common (16%). The main differences between the two sites were in the transparent and brown items, which were recognized with higher percentages on SRS (14% and 8%, respectively) than on CB2 (4% and 2%).

3.4 Coefficient of concordance

On CB2, the average overall concordance (W) was 0.61 (Fig. 6), lowest for type (0.58) and highest for colour (0.65). Considering the subgroups, the highest agreement was for the material attribute for XP, PT and IT groups (0.76 on average), while much lower for IP and OS groups (0.54). The same observation can be done for the concordance of the type of items, which was the lowest for the OS (0.5) and maximum for the IT (0.76). The agreement for

colour depended on the objects marked, however it was always higher than 0.5 also within the subgroups, lowest for IT and highest for PT.

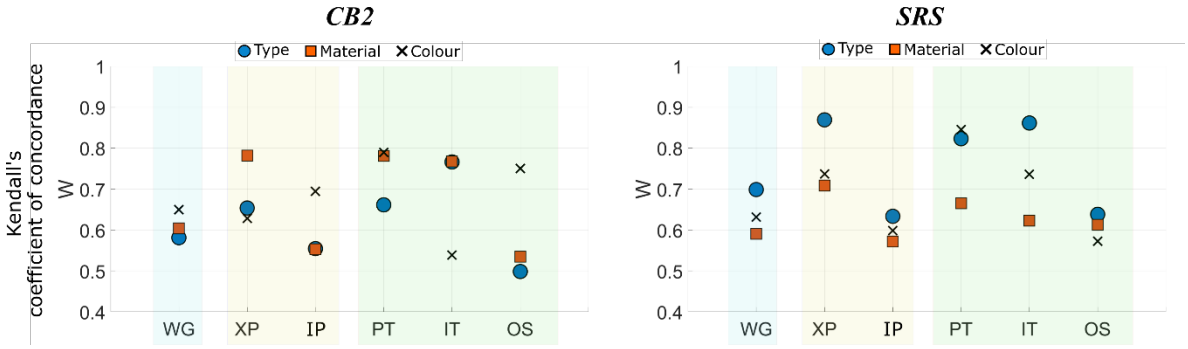

Fig. 6. Kendall's coefficient of concordance results for CB2 and SRS. Blue circles refer to type of litter, orange squares to material, black crosses to colour. Coloured panels are related to the subdivisions of the working group (WG, blue panel) into subgroups based on expertise in litter survey (XP and IP, yellow panel), and on the territoriality (PT, IT and OS, green panel).

On SRS, the average overall concordance was 0.6 (Fig. 6), lowest for material (0.58) and highest for type (0.7). The XP, PT and IT subgroups had high concordance in categorizing the type of items (0.85, on average), whereas for IP and OS was lower (0.65). In general, the concordance for type of items was higher than CB2 (+0.1 on average), whereas for materials was slightly lower for IP, PT and IT. This suggests that the higher resolution SRS image allowed a better and clearer recognition of type of litter.

4 DISCUSSION

4.1 Inter-operator concordance

The number of items marked on the images depended more on the territoriality than on the expertise, as the Hedge *g* effect size (Table 1) was highest for the subgroups PT and IT on their respective sites. This suggests that the simple marking of items, without attributing any detail, could be performed by trained personnel of different expertise, better if familiar with

the working area, to produce the litter abundance map from the UAS survey. The geolocation of the items can be used, for instance, to find hotspots and litter pathways (e.g., Andriolo et al., 2020a; Gonçalves et al., 2020b), in order to understand the role of environmental forcing and/or support the litter dynamic models (e.g., Cordeiro et al., 2018; Critchell and Lambrechts, 2016; Haarr et al., 2019; Kako et al., 2018; Raimundo et al., 2020; Turrell, 2018; Yoon et al., 2010). It was beyond the scope of this work to define a proper level of training required for MS, hence to propose a training framework, therefore future work may be dedicated to these subjects, also considering that citizen science may contribute to MS performance and in general support UAS-based surveys (e.g., Haseler et al., 2018; Papakonstantinou et al., 2021; van Emmerik et al., 2020).

The coefficient of concordance (W) analysis showed that operators tended to agree within each territorial group (Table 2 and Fig. 6), whilst the comparison between XP and IP suggested that the expertise in litter is required for a more detailed characterization of the litter type and material. This was clear, for instance, when we analysed the characterization of the items present on CB1 (Fig. 4), marked correctly only by the operators involved in the previous UAS-based survey on the study site.

Analysing the outputs, it was found that the highest number of items, and in general more detailed MS, was returned by who spent more effort in using the zoom tool for magnifying the images. Although during the briefing the operators were invited to use the zoom tool in a dynamic way, some operators reported that they kept the zoom fixed, and/or missed items because they span the images with high zoom factor. Therefore, the correct use of the zoom tool may be a critical point for spotting, marking and categorizing the items. This elucidates that the different number of marked items returned by the operators for the three images did not depend exclusively on the GSD and on the operator expertise, but also on the attention

given in using the zoom dynamically. In fact, the main differences among the operators were due to the marking of small fragments and uncategorized items, which were difficult to spot with low zoom factor and /or because in the shadow, and/or semi-buried, and/or among woody debris. Perhaps, in the perspective of standardizing the MS accuracy among different works and operators, an operational zoom range may be set and recommended based on the image GSD.

It is of note that the attention and effort given during the MS by each operator is a difficult factor to weight. This is due to the alienating and tedious nature of the MS, which brings to lose concentration, and thus accuracy. Feedbacks from the WG advised that it was beneficial to schedule the MS in different steps, limiting the time spent in marking. It was also reported that repeating the MS, and/or re-screening the image after a first marking performance, improved the accuracy and augmented the number of marked items.

4.2 Litter items shortlist

The new litter items shortlist was proposed to simplify and standardize the MS, as previous works noted that adopting the OSPAR list to categorize the items on UAS-based images was problematic and difficult (e.g., Andriolo et al., 2020a; Gonçalves et al., 2020b).

The structure of the shortlist showed to be efficient for the litter mapping using UAS images, providing the necessary information to describe the composition and possible sources of the litter bulk. The introduction of the “undefined” category, for all the three attributes, was particularly effective and appropriate due to the nature of MS and images. In fact, although it was often not possible to assign a specific category to the item, some other attributes could be assigned, keeping some of the information available. In this regard, it was interesting to

observe how the XP group had greater agreement in choosing between fragments and undefined items categories.

It is important to include the colour information, as this property has arisen as important in many aspects of coastal and marine pollution (Martí et al., 2020), and can improve the automated detection of litter items (Bao et al., 2018; Gonçalves et al., 2020c, 2020a; Kataoka et al., 2012). The item size information could also be added, although the digitalization of objects in GIS environment requires intense human effort. The semi-automated application of an image segmentation software can allow a fast and easy computation of item size.

Despite the preliminary positive feedbacks by the operators, more efforts must be spent in the search for an optimal shortlist for the standardization of MS, especially regarding the type of items. First, a site-dependent shortlist, built with the most common items found in the area, could make the MS easier and faster, along with homogenizing the results of different operators. As seen in Fig. 5, the concordance in choosing the types and materials was much dependent on the territoriality. At the same time, a site-dependent list may compromise the comparison among surveys on different coastal areas. Second, a shortlist should also consider the (average) size of the items, as for instance some objects may not be properly recognized due to the image resolution resulting from drone flight height (GSD). Third, the shortlist should avoid voices that are in conflict and that may generate difficulties in the choice. In our case, for instance, the fish crates in polystyrene could be categorized as crates (container), fishing-related items, and as foams (packaging). Fourth, it is necessary to consider that the UAS-based survey may not reach the level of details provided by the visual census, independently on drone flight height and image GSD, as MS relies on visual screening of the image and not on the physical handling of the items. On the other hand, the shortlist should consider that UAS-based surveys can provide different and valuable information, such as the

position of hotspots, the litter location over wider areas, the likely pathways of the accumulated items, the total area covered by plastic litter, among others.

Finally, to keep the MS and the remote classification simple, the shortlist needs to be relatively easy to be used and consulted, as the main attention must be spent in marking and categorizing the litter items during the image screening.

4.3 Limitations and observations

The main limitation of this work lies on the missing ground-truth data, which did not allow to clearly understand which operator and subgroup marked better and/or correctly categorized litter on CB1 and SRS. Future work should set a controlled and punctual comparison between UAS survey and visual census on the ground. In fact, despite the efforts spent by previous works in comparing MS results versus visual census on beaches (Haseler et al., 2021; Martin et al., 2018; Merlino et al., 2020), it is still not clear where and which litter items were not detected and/or correctly categorized, as comparisons regarded the whole surveyed area by visual census and the entire litter bulk present on the beach. Yet, placing items artificially, as done for instance in CB1 (Fig. 4), does not properly represent the actual challenge of MS, since items can be semi-buried, shadowed, less visible within woody debris. Defining sub-areas on the beach within the whole monitored area, prior the UAS flight, may allow to locally compare the actual number and type of items found on the ground during the visual census, and the ones marked on the images. This would allow understanding which items are more difficult to be recognized, and which external conditions affect most the accuracy of the UAS survey.

Although this work implied the execution of the MS on images with two different pixel resolutions, we did not investigate in details the influence of GSD and image quality in litter

items detection. Based on their image interpretation test, Lo et al. (2020) recommended to fly the drone at maximum 10 m height during a sunny day to optimize the resolution (not specified in terms of GSD) and the accuracy in beach litter identification. However, the minimum operational drone flight altitude depends also on the logistics, as for instance the presence of obstacles (e.g., houses, poles, boats, trees) and the dune height on beach-dune systems (Andriolo et al., 2020b; Gonçalves et al., 2020b) may impose a certain minimum altitude (higher than 10 m) for drone safety. Besides, sunny conditions may affect the detection of white and transparent items (Lo et al., 2020). Future work should investigate how the combination environmental conditions during the flight (e.g., light intensity), image resolution (GSD) and image quality parameters (e.g., noise, blurring, ringing), along with operator experience and expertise, influence the accuracy of the litter detection on beaches with different substrates. As drones are being used also to detect and map on water rivers and sea surface (Garcia-Garin et al., 2020a; Geraeds et al., 2019; Topouzelis et al., 2019), this combined analysis may also be carried out for floating litter UAS surveys.

5 CONCLUSIONS

Sixteen coastal researchers (operators) were invited to identify, mark and categorize litter items on unmanned aerial system (UAS, aka drone) images collected at two beaches, in order to suggest future operational improvement of the manual image screening (MS). Three orthophotos from two beaches in Portugal and Italy were considered, with different image nominal spatial resolution, expressed in ground sample distance (GSD).

The number of items marked on images depended more on the territoriality than on the expertise of the operators working group (WP), suggesting that the UAS-based litter

abundance map could be produced by briefly trained personnel, such as operators recruited from emerging citizen science projects.

The Kendall coefficient of concordance (W) among the components of the WG was between 0.5 and 0.7, depending on the number of items and categories considered. Highest agreement was obtained for the type of items marked on the highest resolution Italian image, among operators with expertise in litter surveys (0.86). Nevertheless, high agreement was also registered within territorial subgroups (0.85), which were composed of half of nonexperts in marine litter. Therefore, for a detailed categorization of litter type and material, the MS should be performed by expert personnel in litter monitoring, however nonexpert operators familiar with the most common litter items present in the study area may be recruited for the MS procedure.

From the feedback and observations of the WG, it was found that also the zoom factor was an important parameter, regardless of the resolution of the two different images used in this work. Thus, for obtaining robust and standardized MS results by different operators, an operational zoom range should be set and recommended for future works, based on image quality and GSD.

This work represents the first the inter-operator agreement analysis for detecting litter on UAS images. It provided useful information for future operational improvements of UAS-based images analysis to survey litter in the environment.

Acknowledgments

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 and the research project UAS4Litter (PTDC/EAM-REM/30324/2017). U.A. and G.G. thank all the co-authors for the commitment in participating in this work, and for providing the high quality data necessary to perform the inter-operator concordance test. S.M. and M.P thank the Park of Migliarino, Massacciuccoli and San Rossore for the permission to access the protected area and performing the field experience.

The work of F.B. was supported by the University of Coimbra through contract IT057-18-7252. F.B. and P.S. acknowledge FCT, I.P. through the strategic project UIDB/04292/2020 granted to MARE.

Luís Pinto was partially supported by the Centre for Mathematics of the University of Coimbra - UIDB/00324/2020, funded by the Portuguese Government throughFCT/MCTES. A. F.-B. is supported by a Post-Doc Fellowship (ED481D2019/028) awarded by Xunta de Galicia (Spain). Thanks are also due to FCT/MCTES for the financial support to CESAM (UIDP/50017/2020 + UIDB/50017/2020), through national funds.

Diogo Gonçalves was supported by the grants UI0308/UArribaS.1/2020 and UI0308-D.Remota1/2020 funded by the Institute for Systems Engineering and Computers at Coimbra (INESC Coimbra) with the support of Portuguese Foundation for Science and Technology (FCT) through national funds (PIDDAC) in the framework of UIDB/00308/2020.

This paper was supported by a project (JPNP18016) commissioned by the New Energy and Industrial Technology Development Organization (NEDO) and the River Fund of the River Foundation (Grant Number: 2020-5211-041), Japan.

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