Marine Pollution Bulletin 195 (2023) 115521

Contents lists available at ScienceDirect

Marine Pollution Bulletin

journal homepage: www.elsevier.com/locate/marpolbul

Baseline

Drones for litter monitoring on coasts and rivers: suitable flight altitude and image resolution

Umberto Andriolo[a,*], Konstantinos Topouzelis[b], Tim H.M. van Emmerik[c], Apostolos Papakonstantinou[d], João Gama Monteiro[e,f], Atsuhiko Isobe[g], Mitsuko Hidaka[h,i], Shin'ichiro Kako[i], Tomoya Kataoka[j], Gil Gonçalves[a,k]

[a] INESC Coimbra, Department of Electrical and Computer Engineering, Polo 2, 3030-290 Coimbra, Portugal
[b] Department of Marine Sciences, University of the Aegean, Greece
[c] Hydrology and Environmental Hydraulics Group, Wageningen University, Wageningen, the Netherlands
[d] Department of Civil Engineering and Geomatics, University of Technology, Lemesos, Cyprus
[e] MARE – Marine and Environmental Sciences Centre/ARNET - Aquatic Research Network, Agência Regional para o Desenvolvimento da Investigação Tecnologia e Inovação (ARDITI), Funchal, Madeira, Portugal
[f] Faculty of Life Sciences, Universidade da Madeira, Funchal, Madeira, Portugal
[g] Research Institute for Applied Mechanics, Kyushu University, Kasuga, Japan
[h] Research Institute for Value-Added-Information Generation (VAiG), Japan Agency for Marine - Earth Science and Technology (JAMSTEC), Yokohama, Japan
[i] Graduate School of Science and Engineering, Department of Engineering, Ocean Civil Engineering Program, Kagoshima University, Kagoshima, Japan
[j] Department of Civil and Environmental Engineering, Graduate School of Science and Engineering, Ehime University, Matsuyama, Japan
[k] University of Coimbra, Department of Mathematics, Coimbra, Portugal

ARTICLE INFO

Keywords:
Remote sensing
Plastic
Ground Sampling Distance
Environmental pollution
UAV

ABSTRACT

Multirotor drones can be efficiently used to monitor macro-litter in coastal and riverine environments. Litter on beaches, dunes and riverbanks, along with floating litter on coastal and river waters, can be spotted and mapped from aerial drone images. Items detection and classification are prone to image resolution, which is expressed in terms of Ground Sampling Distance (GSD). The GSD is determined by drone flight altitude and camera properties. This paper investigates what is a suitable GSD value for litter survey. Drone flight altitude and camera setup should be chosen to obtain a GSD between 0.5 cm/px and 1.25 cm/px. Within this range, the lowest GSD allows litter categorization and classification, whereas the highest value should be adopted for a coarser litter census. In the vision of drawing up a global protocol for drone-based litter surveys, this work sets the ground for homogenizing data collection and litter assessments.

Marine litter consists of items that have been deliberately discarded, unintentionally lost, or transported by winds and rivers, into the sea and on coasts (UNEP (United Nations Environment Programme), 2021). Marine litter abundance in the environment is a global problem, which can affect beach and dune ecosystems, threaten marine life and harm humans (Federigi et al., 2022; Fossi et al., 2020; Menicagli et al., 2019; Panti et al., 2019). A large portion of marine pollution originates from multiple land-based sources (Andriolo and Gonçalves, 2022; Schwarz et al., 2019; Veiga et al., 2016), with rivers playing a key role in the conveyance of plastic towards the ocean (Meijer et al., 2021; Schulz et al., 2015; van Emmerik et al., 2022). Even though litter consists of various materials, plastic represents the largest proportion, composing between 61 % and 87 % of the litter bulk in the environment worldwide (Galgani et al., 2019; Morales-Caselles et al., 2021; Rangel-Buitrago et al., 2022; van Emmerik and Schwarz, 2020).

Litter monitoring strategies have been implemented over the last decades (European Commission, 2013; GESAMP, 2019; OSPAR Commission, 2010), since it is urgent to support managers and stakeholders in the search for pollution mitigation measures. Different methodologies and protocols have been specifically designed to survey micro-litter (items between 1 nm and 5 mm length), meso-litter (between 5 mm and 2.5 cm) and macro-litter (items longer than 2.5 cm) (GESAMP,

* Corresponding author.
E-mail addresses: uandriolo@mat.uc.pt (U. Andriolo), topouzelis@marine.aegean.gr (K. Topouzelis), tim.vanemmerik@wur.nl (T.H.M. van Emmerik), a.papakonstantinou@cut.ac.cy (A. Papakonstantinou), jmonteiro@mare-centre.pt (J.G. Monteiro), aisobe@riam.kyushu-u.ac.jp (A. Isobe), mitsukou@jamstec.go.jp (M. Hidaka), kako@oce.kagoshima-u.ac.jp (S. Kako), kataoka.tomoya.ab@ehime-u.ac.jp (T. Kataoka), gil@mat.uc.pt (G. Gonçalves).

https://doi.org/10.1016/j.marpolbul.2023.115521
Received 19 July 2023; Received in revised form 29 August 2023; Accepted 5 September 2023
Available online 13 September 2023

2019), by visual census on beaches and rivers, and with trawls in river and ocean waters (Galgani et al., 2013; GESAMP, 2019; OSPAR Commission, 2010). In recent years, remote sensing technologies, such as satellites and drones, have been shown to be effective in providing novel information on litter abundance and dynamics (Salgado-Hernanz et al., 2021; Veettil et al., 2022). Satellite images have been exploited to detect floating litter in ocean and rivers (Martínez-Vicente et al., 2019; Topouzelis et al., 2021), along with stranded debris on coasts (Acuña-Ruz et al., 2018). Nevertheless, the use of space images is still challenging, due to i) the low resolution of open-source satellite data, ii) the cost of commercial satellite imagery, and iii) the absence of ground truth validation (Biermann et al., 2020; Schreyers et al., 2022; Topouzelis et al., 2019).

In view of the above challenges, multirotor drones are relatively low-cost devices that can be exploited for environmental monitoring campaigns (Manfreda et al., 2018; Yang et al., 2022). Drones require small effort in the field, and are able to collect and provide high-resolution imagery. Despite being prone to a limited battery autonomy, drone flights i) are not invasive, ii) can cover large areas and remote sites, and iii) can be repeated over the same area with high frequency. Drones have been shown to be operationally suitable to survey macro-litter presence in different environments, such as beach-dune systems (Andriolo et al., 2021b; Andriolo et al., 2020b; Corbau et al., 2023; Gonçalves et al., 2020b; Taddia et al., 2021), continental shores (Bao et al., 2018; Escobar-Sánchez et al., 2021; Martin et al., 2021; Martin et al., 2018; Merlino et al., 2020), islands (Deidun et al., 2018; Fallati et al., 2019; Papakonstantinou et al., 2021; Papakonstantinou et al., 2019; Takaya et al., 2022), lake beaches (Hengstmann and Fischer, 2020) and riverbanks (Cortesi et al., 2023; Geraeds et al., 2019). Moreover, drone images have been exploited to detect floating litter on rivers (Maharjan et al., 2022; Rahmadya et al., 2022; Rocamora et al., 2021; Schreyers et al., 2021b; Wolf et al., 2020) and coastal (Almeida et al., 2023; Andriolo et al., 2022; Escobar-Sánchez et al., 2022; Garcia-Garin et al., 2021; Garcia-Garin et al., 2020a; Garcia-Garin et al., 2020b) waters.

Regarding drone-based litter surveys, one of the main advantages is the provision of spatial data, since items can be detected and geolocated from drone images. Aerial surveys can provide spatial information of litter abundance and accumulation, which was limited and/or missing in the reports of traditional techniques assessments, to understand likely litter pathways and identify new pollution sources (Andriolo and Gonçalves, 2023; Galgani et al., 2013; GESAMP, 2019; OSPAR Commission, 2010). Gonçalves et al. (2022) presented a schematic framework to outline the different operational steps for a beached litter survey by multirotor drones. The framework was composed of four stages. The first stage comprised the planning of the field experience, the second stage implied the drone flight deployment, the third stage encompassed the drone image analysis, and the final fourth stage described the litter survey assessments. Even if the framework was designed for drone-based litter survey on beaches, most of the stages can be considered for the application in different environments. In particular, it is of interest to analyse the second stage regarding the drone flight setup, as this step is crucial for reliable litter survey assessments.

This baseline describes and discusses the drone flight deployment for litter surveys in the environment. The paper focuses i) on the choice of flight altitude, and ii) on the resulting image resolution, commonly expressed in terms of Ground Sampling Distance (GSD).

During drone-based litter surveys, the camera gimbal is commonly set to −90° (nadiral), to capture photos perpendicular to the flight direction (Andriolo et al., 2020a; Gonçalves et al., 2020b). Drone flight altitude and camera properties determine the pixel spatial resolution of drone images (Fig. 1a), which is expressed as Ground Sampling Distance (Driggers, 2011):

$$GSD = \frac{H^*sw}{img^*f} \tag{1}$$

where H is the flight altitude (m), sw is the sensor width (mm), img is the size of image (pixels), and f is the camera focal length (mm).

Gonçalves et al. (2022) showed the different drone flight altitudes chosen by the 15 studies that adopted the framework for drone-based litter surveys on beaches and dunes (Fig. 1b). Among works, the variation of the flight altitude was due to i) the different objectives, ii) the extent of the monitored area, and iii) the heterogeneity of beach configurations. A median value of 0.54 cm/px was found among works on beaches and dunes (Fig. 1b). Extending such analysis to drone-based litter surveys conducted on riverbanks (Cortesi et al., 2023; Geraeds et al., 2019), median value was similar (1 cm/px). Finally, considering floating litter surveys on river (Maharjan et al., 2022; Rahmadya et al., 2022; Rocamora et al., 2021; Schreyers et al., 2021b; Wolf et al., 2020) and coastal (Almeida et al., 2023; Andriolo et al., 2022; Garcia-Garin et al., 2021; Garcia-Garin et al., 2020a; Garcia-Garin et al., 2020b) waters, the adopted median GSD was of 0.6 cm/px and 0.7 cm/px,

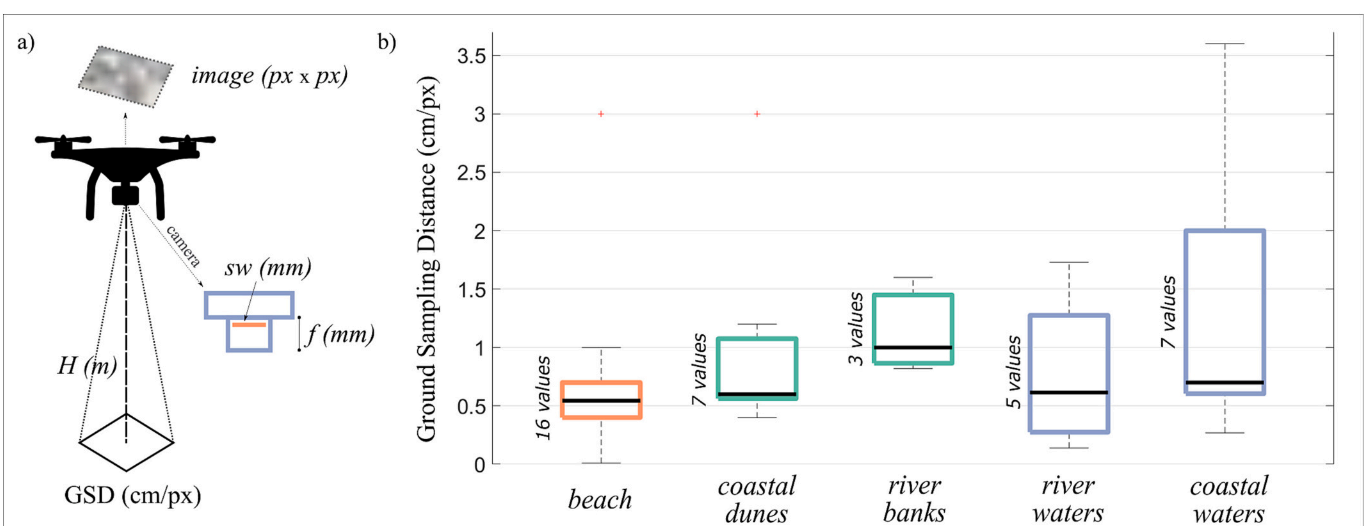

Fig. 1. Ground Sampling Distance of drone-based litter surveys. a) Schematic representation of Ground Sampling Distance (GSD) calculation. Following Eq. (1), the collected image is expressed in pixel square, sw indicates the sensor width, f the camera focal length, and H the drone flight height above the ground; b) GSD adopted by drone-based litter surveys found in the literature for different environmental domains and type of litter (blue backgrounds refer to floating litter). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

respectively, even though higher flights were tested for covering wider areas on the sea (Fig. 1b).

The GSD determines the image resolution, thus the detectable size of litter items. The minimum detectable object size can be expressed as:

$$Sz = Npx^{*}\ \mathrm{GSD} \tag{2}$$

where *Sz* (cm) is the minimum detectable object size, *Npx* (pixel) is a constant value indicating the number of pixel units representing an object, and the GSD (cm/px) is the ground area covered by a single pixel. Therefore, the suitable GSD for litter monitoring is given by:

$$\mathrm{GSD} = Sz/Npx \tag{3}$$

The parameter *Npx* is not defined a priori, and varies in general between 2 and 5 pixels (Leachtenauer et al., 1997; O'Connor et al., 2017). This parameter depends on several factors, such as sensor type, image characteristics, scene complexity, object contrast and image detection method (Leachtenauer et al., 1997; O'Connor et al., 2017), among others. Given the experiences in drone-based litter surveys and image analysis (Gonçalves et al., 2022), it can be assumed that a litter item is recognizable on drone images when it is represented by at least four pixels ($Npx = 4$). However, to be conservative and guarantee a better resolution of a single item, the value $Npx = 5$ was also considered and adopted to solve Eq. (3).

Regarding the litter minimum size *Sz*, the macro-litter minimum threshold defined in literature was of 2.5 cm, a value that is referred to the length of the longest dimension (GESAMP, 2019). However, given i) the properties of images, ii) the pixel square shape, and iii) the above observations regarding the *Npx* parameter, the minimum detectable *Sz* on drone images (Eq. (3)) should be considered as 2.5 cm × 2.5 cm (Fig. 2c). For instance, a cotton bud and/or a straw are macro-litter items, being their second dimension shorter than 2.5 cm, would not be spotted on drone images. A minimum litter size of Sz = 5 cm × 5 cm was also chosen to solve Eq. (3), as the detection and recognition of smaller items on drone images was quite challenging (Andriolo et al., 2021b; Andriolo et al., 2020b).

The solution of Eq. (3), adopting $Npx = 4$, returned a suitable GSD range of 0.62 cm/px and 1.25 cm/px, whereas for $Npx = 5$, the range resulted to be between 0.5 cm/px and 1 cm/px (Fig. 2a-b). Litter items are well detectable and identifiable on images with GSD = 0.5 cm/px, even though accumulation and/or beach wrack can make their recognitions difficult (Fig. 3a,b). Therefore, adopting a GSD lower than 0.5 cm/px would provide images with higher resolution, which perhaps would be redundant in terms of details (Fig. 2b). On images with GSD =1.25 cm/px, bigger items are still recognizable, whereas it is not possible to spot smaller items (Fig. 3b). This GSD value can be suggested for coarse litter census, and when smaller items will not be characterized in terms of categories and materials. Finally, on images with GSD higher than the proposed range, it is not possible to detect most of the litter identified in previous images, while bigger items are barely recognizable (Fig. 3b). Besides not allowing the recognition of items smaller than 5 cm × 5 cm (Fig. 2b), adopting a GSD higher than 1.25 cm/px would not provide enough resolution (Fig. 3a). Therefore, GSD values higher than 1.25 cm/px can merely be suggested for a coarse binary (litter/non-litter) detection approach (Pinto et al., 2021), when only big items will be mapped without any categorization (Fig. 3b).

In the past experiences, when the litter was marked by manual image screening (Andriolo et al., 2021a), lower GSD (higher resolution) allowed in general a better recognition of the items (Lo et al., 2020). Nevertheless, other aspects, such as operator expertise on litter and experience in image analysis, influenced the accuracy of the final assessments (Andriolo et al., 2021a; Merlino et al., 2021). When algorithms for the automated litter detection were developed (e.g., Hidaka et al., 2022; Kataoka et al., 2018; Pinto et al., 2021; Politikos et al., 2023; Wolf et al., 2020), the GSD parameter was instead not considered. It is therefore recommendable that future works devoted to automated detection techniques would consider the GSD as a crucial aspect. In fact, the transferability of machine and deep learning algorithms can be strongly dependent on the image resolution used to train the model, hence the applications on images with different GSD may be

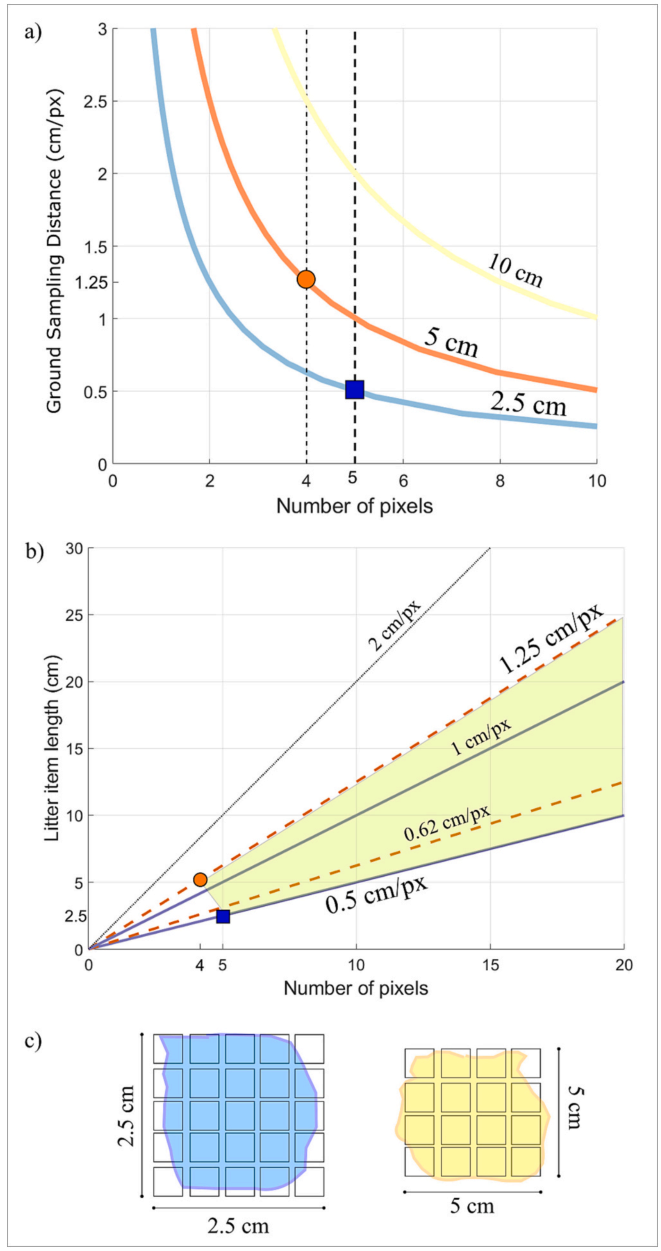

Fig. 2. Relation between Ground Sampling Distance (GSD) and size of litter (Sz). a) Blue and orange curves represent the litter size Sz (2.5 cm and 5 cm, respectively) in the graph GSD-number of pixels (Npx). The yellow curve shows a 10-cm litter size in the graph GSD-number of pixels. Black shaded lines indicate the adopted thresholds of Npx = 4 and Npx = 5; b) GSD represented in the graph litter size Sz – number of pixels (Npx). Thick blue lines indicate GSD of 0.5 cm/px and 1 cm/px, and dashed orange lines indicate GSD of 0.62 cm/px and 1.25 cm/px. For comparison purposes, dotted black lines show the GSD of 2 cm/px. Shaded area delimitates the suitable GSD range. In both graphs, blue square indicates the intersection between Npx = 5 and Sz = 2.5 cm, while orange circle the intersection between Sz = 5 cm and Npx = 4; c) examples of stylized item of 2.5 × 2.5 cm, represented by 5 × 5 pixels on an image with GSD = 0.5 cm/px (left), and stylized item of 5 × 5 cm, represented by 4 × 4 pixels on an image with GSD = 1.25 cm/px (right). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

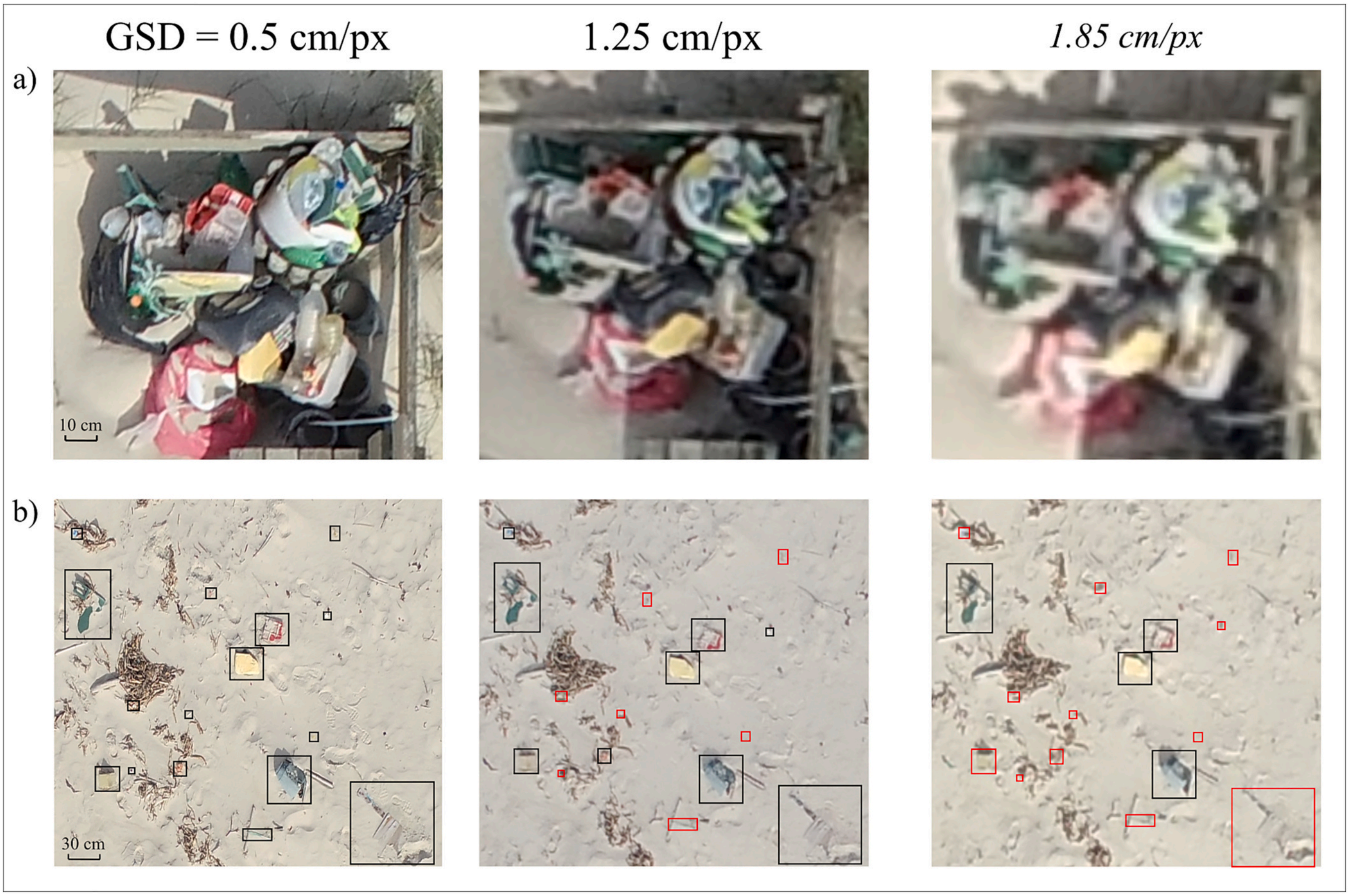

Fig. 3. Example of drone images with different Ground Sampling Distance (GSD). a) aerial picture of a recollection point close to the beach, with bins and garbage bags. Different types of plastic bottles are distinguishable on the image with GSD = 0.5 cm/px (left). On the image with GSD = 1.25 cm/px (central), items can still be counted but not recognized, whereas it is difficult to count litter on the image with GSD = 1.85 cm/px (right); b) operational assessments of litter items marked on images. On the image with GSD = 0.5 cm/px (left), several items were detected, and their material and/or category can be recognized (black boxes). On the image with GSD = 1.25 cm/px (central), the smallest items could not be detected (red boxes), while only the four biggest items could be spotted on the image with GSD = 1.85 cm/px (right). Overall, in b), black boxes bound the detected items, whereas red boxes the missed items. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

unsuccessful (Duarte et al., 2020; Gonçalves et al., 2020a, 2020c).

The representation in Fig. 2 should be considered a generalized approximation, based on a nominal and theoretical GSD. Final assessments also depend on image quality and/or field conditions, as these can influence the litter detection. For instance, items that are semi-buried (Andriolo et al., 2020b; Gonçalves and Andriolo, 2022), trapped among vegetation (Andriolo et al., 2020a; Corbau et al., 2023), and/or within beach wrack and natural wood debris (Merlino et al., 2020), can be difficult to detect and identify on coasts and on riverbanks (Fig. 3b). On river waters, the presence of natural debris and plants, such as water hyacinth (*Eichhornia crassipes*), can mutually restrain the floating litter detection (Kataoka and Nihei, 2020; Maharjan et al., 2022), and be exploited as a proxy for plastic monitoring (Schreyers et al., 2021a). On coastal waters, shoaling and breaking waves can partially hide and/or totally submerge floating litter during the image acquisition, whereas sun glitter can lower image quality and hamper litter detection (Andriolo et al., 2022; Garcia-Garin et al., 2021; Garcia-Garin et al., 2020a; Garcia-Garin et al., 2020b). Finally, the different substrates, such as sand, gravel, rock, vegetation and/or water, can affect the detection of litter items that have similar colours to image backgrounds (Fig. 3b).

Obtaining a GSD within the proposed range (Fig. 2a) may be not an easy task, as flight altitude must comply with national and local legislation, which rule the use of uncrewed aerial vehicles. Yet, the heterogeneity of coastal and riverine environments can often influence the choice of drone flight altitude. Logistical constraints, such as dunes, trees and light posts on coasts and riverbanks, along with bridges and boats on coastal and river waters, may force the selection of a specific minimum flight altitude.

To assist future drone deployments in the field, Fig. 4 shows a list of the most common multirotor drones and/or cameras currently available on the market. In order to obtain a GSD between 0.5 and 1.25 cm/px, a potential range of flight altitudes are combined with camera properties. For instance, the DJI Phantom 4 Pro, which has a built-in camera and was the most common multirotor drone used for beached litter surveys (Gonçalves et al., 2022), should fly between 18 m and 46 m above the ground. Professional drones mounting more powerful cameras have a longer range of altitudes options, and overall the possibility to fly higher, given that better visual sensors allow to collect images with higher resolution (Eq. (1)).

Final considerations regard the likely monitored area extent. It is not possible to associate here the flight altitude, and thus the GSD, with the potential coverage area. Such information is given by drone apps during the flight setup, as flight time and battery autonomy, mutually dependent, are both influenced by flight speed, image overlap, and environmental conditions.

In the vision of drawing up a protocol for drone-based litter survey, this baseline sets the ground for the proposal of a single GSD value, or at least a short range of GSD, to homogenize data collection among works. The protocol should promote the use of drones i) to increase the frequency and locations of litter surveys, ii) to provide spatial information

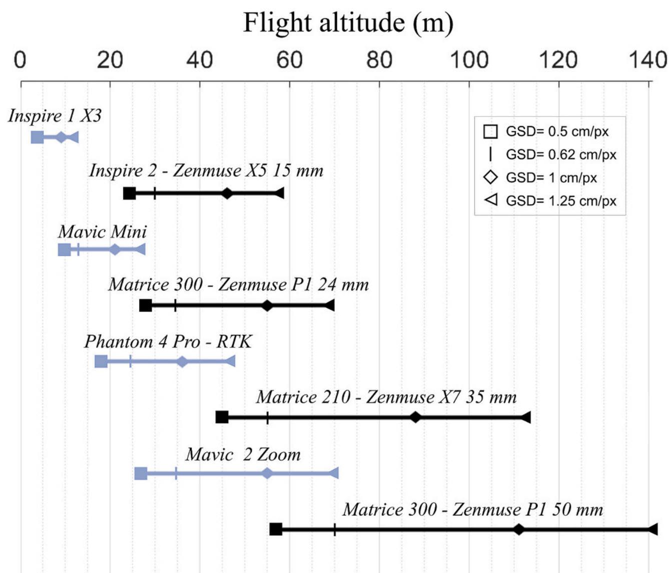

Fig. 4. List of drones and relative flight altitudes to obtain a Ground Sampling Distance (GSD) of 0.5 cm/px (squares), 0.62 cm/px (vertical line), 1 cm/px (diamond) and 1.25 cm/px (left triangle). The list comprises drones mounting a built-in camera (blue) and drones with specific (and exchangeable) onboard cameras (black). Data were retrieved from https://www.heliguy.com/pages/gsd-calculator. Data can slightly change depending on the image size chosen by the operator (Eq. (1)). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

on litter abundance, location and accumulation over longer and wider areas, and iii) to advance knowledge on litter dynamics both on coastal and riverine environments.

CRediT authorship contribution statement

Umberto Andriolo: Conceptualization, Methodology, Validation, Formal Analysis, Investigation, Resources, Data curation, Writing-Original draft preparation, Writing – Review & Editing, Visualization, Supervision.

Konstantinos Topouzelis Conceptualization, Methodology, Formal Analysis, Investigation, Resources, Writing – Review & Editing, Supervision.

Tim van Emmerik Methodology, Investigation, Resources, Writing – Review & Editing, Supervision.

Apostolos Papakonstantinou Conceptualization, Methodology, Formal Analysis, Writing – Review & Editing.

Joao Gama Monteiro Methodology, Investigation, Resources, Writing – Review & Editing.

Atsuhiko Isobe Methodology, Writing – Review & Editing, Project administration, Funding Acquisition.

Mitsuko Hidaka Methodology, Writing – Review & Editing, Project administration, Funding Acquisition.

Shin'ichiro Kako Methodology, Writing – Review & Editing, Project administration, Funding Acquisition.

Tomoya Kataoka Methodology, Writing – Review & Editing, Project administration, Funding Acquisition.

Gil Gonçalves: Conceptualization, Methodology, Formal Analysis, Investigation, Resources; Writing- Reviewing and Editing, Supervision, Project administration, Funding Acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgments

This work was supported by the Portuguese Foundation for Science and Technology (FCT) in the framework of UIDB/00308/2020.

This research was performed by the Environment Research and Technology Development Fund (JPMEERF20231004) of the Environmental Restoration and Conservation Agency provided by the Ministry of the Environment of Japan. This work was also supported by JSPS KAKENHI Grant Number 23H03527.

The work of TvE was supported by the Veni Research Program, the River Plastic Monitoring Project with project number 18211, which was (partly) financed by the Dutch Research Council (NWO).

JGM is funded by national funds through FCT Fundação para a Ciência e a Tecnologia, I.P., under the Scientific Employment Stimulus—Institutional Calls—(CEECINST/00037/2021). JGM work was partly supported by the projects: CleanAtlantic (EAPA-46/2016), INTERREG Atlantic Area Program and Oceanlit (MAC2/4.6d/302), INTERREG-Mac Program.

References

Acuña-Ruz, T., Uribe, D., Taylor, R., Amézquita, L., Guzmán, M.C., Merrill, J., Martínez, P., Voisin, L., Mattar, B.C., 2018. Anthropogenic marine debris over beaches: spectral characterization for remote sensing applications. Remote Sens. Environ. 217, 309–322. https://doi.org/10.1016/j.rse.2018.08.008.

Almeida, S., Radeta, M., Kataoka, T., Canning-Clode, J., Pessanha Pais, M., Freitas, R., Monteiro, J.G., 2023. Designing unmanned aerial survey monitoring program to assess floating litter contamination. Remote Sens. https://doi.org/10.3390/rs15010084.

Andriolo, U., Gonçalves, G., 2022. Is coastal erosion a source of marine litter pollution? Evidence of coastal dunes being a reservoir of plastics. Mar. Pollut. Bull. 174, 113307 https://doi.org/10.1016/j.marpolbul.2021.113307.

Andriolo, U., Gonçalves, G., 2023. The octopus pot on the North Atlantic Iberian coast: a plague of plastic on beaches and dunes. Mar. Pollut. Bull. 192, 115099 https://doi.org/10.1016/j.marpolbul.2023.115099.

Andriolo, U., Gonçalves, G., Bessa, F., Sobral, P., 2020a. Mapping marine litter on coastal dunes with unmanned aerial systems: a showcase on the Atlantic Coast. Sci. Total Environ. 736 https://doi.org/10.1016/j.scitotenv.2020.139632.

Andriolo, U., Gonçalves, G., Sobral, P., Fontán-Bouzas, Á., Bessa, F., 2020b. Beach-dune morphodynamics and marine macro-litter abundance: an integrated approach with unmanned aerial system. Sci. Total Environ. 749, 141474 https://doi.org/10.1016/j.scitotenv.2020.141474.

Andriolo, U., Gonçalves, G., Rangel-Buitrago, N., Paterni, M., Bessa, F., Gonçalves, L.M.S., Sobral, P., Bini, M., Duarte, D., Fontán-Bouzas, Á., Gonçalves, D., Kataoka, T., Luppichini, M., Pinto, L., Topouzelis, K., Vélez-Mendoza, A., Merlino, S., 2021a. Drones for litter mapping: an inter-operator concordance test in marking beached items on aerial images. Mar. Pollut. Bull. 169 https://doi.org/10.1016/j.marpolbul.2021.112542.

Andriolo, U., Gonçalves, G., Sobral, P., Bessa, F., 2021b. Spatial and size distribution of macro-litter on coastal dunes from drone images : a case study on the Atlantic coast. Mar. Pollut. Bull. 169, 112490 https://doi.org/10.1016/j.marpolbul.2021.112490.

Andriolo, U., Garcia-Garin, O., Vighi, M., Borrell, A., Gonçalves, G., 2022. Beached and floating litter surveys by unmanned aerial vehicles: operational analogies and differences. Remote Sens. 14, 1336. https://doi.org/10.3390/rs14061336.

Bao, Z., Sha, J., Li, X., Hanchiso, T., Shifaw, E., 2018. Monitoring of beach litter by automatic interpretation of unmanned aerial vehicle images using the segmentation threshold method. Mar. Pollut. Bull. 137, 388–398. https://doi.org/10.1016/j.marpolbul.2018.08.009.

Biermann, L., Clewley, D., Martinez-Vicente, V., Topouzelis, K., 2020. Finding plastic patches in coastal waters using optical satellite data. Sci. Rep. https://doi.org/10.1038/s41598-020-62298-z.

Corbau, C., Buoninsegni, J., Olivo, E., Vaccaro, C., Nardin, W., Simeoni, U., 2023. Understanding through drone image analysis the interactions between geomorphology, vegetation and marine debris along a sandy spit. Mar. Pollut. Bull. 187, 114515 https://doi.org/10.1016/j.marpolbul.2022.114515.

Cortesi, I., Mugnai, F., Angelini, R., Masiero, A., 2023. Mini UAV-based litter detection on river banks. In: ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences. https://doi.org/10.5194/isprs-annals-X-4-W1-2022-117-2023.

Deidun, A., Gauci, A., Lagorio, S., Galgani, F., 2018. Optimising beached litter monitoring protocols through aerial imagery. Mar. Pollut. Bull. 131, 212–217. https://doi.org/10.1016/j.marpolbul.2018.04.033.

Driggers, R.G., 2011. Encyclopedia of Optical Engineering. Marcel Dekker, New York. https://doi.org/10.1081/e-eoe.

Duarte, D., Andriolo, U., Gonçalves, G., 2020. Addressing the class imbalance problem in the automatic image classification of coastal litter from orthophotos derived from Uas imagery. In: ISPRS Ann. Photogramm. Remote Sens. Spat. Inf. Sci., V-3–2020, pp. 439–445. https://doi.org/10.5194/isprs-annals-v-3-2020-439-2020.

Escobar-Sánchez, G., Haseler, M., Oppelt, N., Schernewski, G., 2021. Efficiency of aerial drones for macrolitter monitoring on Baltic Sea beaches. Front. Environ. Sci. 8, 1–18. https://doi.org/10.3389/fenvs.2020.560237.

Escobar-Sánchez, G., Markfort, G., Berghald, M., Ritzenhofen, L., Schernewski, G., 2022. Aerial and underwater drones for marine litter monitoring in shallow coastal waters: factors influencing item detection and cost-efficiency. Environ. Monit. Assess. 194 https://doi.org/10.1007/s10661-022-10519-5.

European Commission, 2013. MSDF Guidance on Monitoring Marine Litter, JRC Scientific and Policy Reports. https://doi.org/10.2788/99475.

Fallati, L., Polidori, A., Salvatore, C., Saponari, L., Savini, A., Galli, P., 2019. Anthropogenic marine debris assessment with unmanned aerial vehicle imagery and deep learning: a case study along the beaches of the Republic of Maldives. Sci. Total Environ. 693, 133581 https://doi.org/10.1016/j.scitotenv.2019.133581.

Federigi, I., Balestri, E., Castelli, A., De Battisti, D., Maltagliati, F., Menicagli, V., Verani, M., Lardicci, C., Carducci, A., 2022. Beach pollution from marine litter: analysis with the DPSIR framework (driver, pressure, state, impact, response) in Tuscany, Italy. Ecol. Indic. 143, 109395 https://doi.org/10.1016/j.ecolind.2022.109395.

Fossi, M.C., Baini, M., Simmonds, M.P., 2020. Cetaceans as ocean health indicators of marine litter impact at global scale. Front. Environ. Sci. https://doi.org/10.3389/fenvs.2020.586627.

Galgani, F., Hanke, G., Werner, S., De Vrees, L., 2013. Marine litter within the European Marine Strategy Framework Directive. ICES J. Mar. Sci. 70, 1055–1064. https://doi.org/10.1093/icesjms/fst122.

Galgani, L., Beiras, R., Galgani, F., Panti, C., Borja, A., 2019. Editorial: "impacts of marine litter.". Front. Mar. Sci. 6, 4–7. https://doi.org/10.3389/fmars.2019.00208.

Garcia-Garin, O., Aguilar, A., Borrell, A., Gozalbes, P., Lobo, A., Penadés-Suay, J., Raga, J.A., Revuelta, O., Serrano, M., Vighi, M., 2020a. Who's better at spotting? A comparison between aerial photography and observer-based methods to monitor floating marine litter and marine mega-fauna. Environ. Pollut. 258 https://doi.org/10.1016/j.envpol.2019.113680.

Garcia-Garin, O., Borrell, A., Aguilar, A., Cardona, L., Vighi, M., 2020b. Floating marine macro-litter in the North Western Mediterranean Sea: results from a combined monitoring approach. Mar. Pollut. Bull. 159 https://doi.org/10.1016/j.marpolbul.2020.111467.

Garcia-Garin, O., Monleón-Getino, T., López-Brosa, P., Borrell, A., Aguilar, A., Borja-Robalino, R., Cardona, L., Vighi, M., 2021. Automatic detection and quantification of floating marine macro-litter in aerial images: introducing a novel deep learning approach connected to a web application in R. Environ. Pollut. 273 https://doi.org/10.1016/j.envpol.2021.116490.

Geraeds, M., van Emmerik, T., de Vries, R., bin Ab Razak, M.S., 2019. Riverine plastic litter monitoring using unmanned aerial vehicles (UAVs). Remote Sens. 11 https://doi.org/10.3390/rs11172045.

GESAMP, 2019. Guidelines for the Monitoring and Assessment of Plastic Litter in the Ocean by Joint Group of Experts on the Scientific Aspects of Marine Environmental Protection, Gesamp https://doi.org/ISSN: 1020-4873.

Gonçalves, G., Andriolo, U., 2022. Operational use of multispectral images for macro-litter mapping and categorization by Unmanned Aerial Vehicle. Mar. Pollut. Bull. 176, 113431 https://doi.org/10.1016/j.marpolbul.2022.113431.

Gonçalves, G., Andriolo, U., Gonçalves, L., Sobral, P., Bessa, F., 2020a. Quantifying marine macro litter abundance on a sandy beach using unmanned aerial systems and object-oriented machine learning methods. Remote Sens. 12, 2599. https://doi.org/10.3390/rs12162599.

Gonçalves, G., Andriolo, U., Pinto, L., Bessa, F., 2020b. Mapping marine litter using UAS on a beach-dune system: a multidisciplinary approach. Sci. Total Environ. 706 https://doi.org/10.1016/j.scitotenv.2019.135742.

Gonçalves, G., Andriolo, U., Pinto, L., Duarte, D., 2020c. Mapping marine litter with Unmanned Aerial Systems: a showcase comparison among manual image screening and machine learning techniques. Mar. Pollut. Bull. 155, 111158 https://doi.org/10.1016/j.marpolbul.2020.111158.

Gonçalves, G., Andriolo, U., Gonçalves, L.M.S., Sobral, P., Bessa, F., 2022. Beach litter survey by drones: mini-review and discussion of a potential standardization. Environ. Pollut. 315, 120370 https://doi.org/10.1016/j.envpol.2022.120370.

Hengstmann, E., Fischer, E.K., 2020. Anthropogenic litter in freshwater environments – study on lake beaches evaluating marine guidelines and aerial imaging. Environ. Res. 189 https://doi.org/10.1016/j.envres.2020.109945.

Hidaka, M., Matsuoka, D., Sugiyama, D., Murakami, K., Kako, S., 2022. Pixel-level image classification for detecting beach litter using a deep learning approach. Mar. Pollut. Bull. https://doi.org/10.1016/j.marpolbul.2022.113371.

Kataoka, T., Nihei, Y., 2020. Quantification of floating riverine macro-debris transport using an image processing approach. Sci. Rep. 10 https://doi.org/10.1038/s41598-020-59201-1.

Kataoka, T., Murray, C.C., Isobe, A., 2018. Quantification of marine macro-debris abundance around Vancouver Island, Canada, based on archived aerial photographs processed by projective transformation. Mar. Pollut. Bull. 132, 44–51. https://doi.org/10.1016/j.marpolbul.2017.08.060.

Leachtenauer, J.C., Malila, W., Irvine, J., Colburn, L., Salvaggio, N., 1997. General image-quality equation: GIQE. Appl. Opt. 36, 8322. https://doi.org/10.1364/ao.36.008322.

Lo, H.S., Wong, L.C., Kwok, S.H., Lee, Y.K., Po, B.H.K., Wong, C.Y., Tam, N.F.Y., Cheung, S.G., 2020. Field test of beach litter assessment by commercial aerial drone. Mar. Pollut. Bull. 151 https://doi.org/10.1016/j.marpolbul.2019.110823.

Maharjan, N., Miyazaki, H., Pati, B.M., Dailey, M.N., Shrestha, S., Nakamura, T., 2022. Detection of river plastic using UAV sensor data and deep learning. Remote Sens. 14 https://doi.org/10.3390/rs14133049.

Manfreda, S., Mccabe, Matthew F., Miller, Pauline E., Lucas, R., Pajuelo, V.M., Mallinis, G., Dor, E. Ben, Helman, David, Estes, L., Ciraolo, G., Müllerová, J., Tauro, F., Lima, M.I. De, Lima, J.L. De, Frances, F., Caylor, K., Kohv, M., Maltese, A., Perks, M., Ruiz-Pérez, G., Su, Z., Vico, G., Toth, B., 2018. Use of unmanned aerial Systems for Environmental Monitoring. Remote Sens. 10 (4), 641. https://doi.org/10.3390/rs10040641.

Martin, C., Parkes, S., Zhang, Q., Zhang, X., McCabe, M.F., Duarte, C.M., 2018. Use of unmanned aerial vehicles for efficient beach litter monitoring. Mar. Pollut. Bull. 131, 662–673. https://doi.org/10.1016/j.marpolbul.2018.04.045.

Martin, C., Zhang, Q., Zhai, D., Zhang, X., Duarte, C.M., 2021. Enabling a large-scale assessment of litter along Saudi Arabian red sea shores by combining drones and machine learning. Environ. Pollut. 277, 116730 https://doi.org/10.1016/j.envpol.2021.116730.

Martínez-Vicente, V., Clark, J.R., Corradi, P., Aliani, S., Arias, M., Bochow, M., Bonnery, G., Cole, M., Cózar, A., Donnelly, R., Echevarría, F., Galgani, F., Garaba, S. P., Goddijn-Murphy, L., Lebreton, L., Leslie, H.A., Lindeque, P.K., Maximenko, N., Martin-Lauzer, F.R., Moller, D., Murphy, P., Palombi, L., Raimondi, V., Reisser, J., Romero, L., Simis, S.G.H., Sterckx, S., Thompson, R.C., Topouzelis, K.N., van Sebille, E., Veiga, J.M., Vethaak, A.D., 2019. Measuring marine plastic debris from space: initial assessment of observation requirements. Remote Sens. 11, 8–14. https://doi.org/10.3390/rs11202443.

Meijer, L.J.J., van Emmerik, T., van der Ent, R., Schmidt, C., Lebreton, L., 2021. More than 1000 rivers account for 80% of global riverine plastic emissions into the ocean. Sci. Adv. https://doi.org/10.1126/sciadv.aaz5803.

Menicagli, V., Balestri, E., Vallerini, F., Castelli, A., Lardicci, C., 2019. Adverse effects of non-biodegradable and compostable plastic bags on the establishment of coastal dune vegetation: first experimental evidences. Environ. Pollut. 252, 188–195. https://doi.org/10.1016/j.envpol.2019.05.108.

Merlino, S., Paterni, M., Berton, A., Massetti, L., 2020. Unmanned aerial vehicles for debris survey in coastal areas: long-term monitoring programme to study spatial and temporal accumulation of the dynamics of beached marine litter. Remote Sens. 12, 1260. https://doi.org/10.3390/RS12081260.

Merlino, S., Paterni, M., Locritani, M., Andriolo, U., Gonçalves, G., Massetti, L., Zou, Q., 2021. Citizen science for marine litter detection and classification on unmanned aerial vehicle images. Water (Switzerland) 13, 3349. https://doi.org/10.3390/W13233349.

Morales-Caselles, C., Viejo, J., Martí, E., González-Fernández, D., Pragnell-Raasch, H., González-Gordillo, J.I., Montero, E., Arroyo, G.M., Hanke, G., Salvo, V.S., Basurko, O.C., Mallos, N., Lebreton, L., Echevarría, F., van Emmerik, T., Duarte, C. M., Gálvez, J.A., van Sebille, E., Galgani, F., García, C.M., Ross, P.S., Bartual, A., Ioakeimidis, C., Markalain, G., Isobe, A., Cózar, A., 2021. An inshore–offshore sorting system revealed from global classification of ocean litter. Nat. Sustain. 4, 484–493. https://doi.org/10.1038/s41893-021-00720-8.

O'Connor, J., Smith, M.J., James, M.R., 2017. Cameras and settings for aerial surveys in the geosciences: optimising image data. Prog. Phys. Geogr. 41, 325–344. https://doi.org/10.1177/0309133317703092.

OSPAR Commission, 2010. Guideline for Monitoring Marine Litter on the Beachs in the OSPAR Maritime Area. OSPAR Comm.

Panti, C., Baini, M., Lusher, A., Hernandez-Milan, G., Bravo Rebolledo, E.L., Unger, B., Syberg, K., Simmonds, M.P., Fossi, M.C., 2019. Marine litter: one of the major threats for marine mammals. Outcomes from the European Cetacean Society workshop. In: Environmental Pollution, pp. 72–79. https://doi.org/10.1016/j.envpol.2019.01.029.

Papakonstantinou, A., Topouzelis, K., Doukari, M., Andreadis, O., 2019. Mapping refugee litters in the eastern coast of Lesvos using UAS, an emerging marine litter problem. Abstr. ICA 1, 1–2. https://doi.org/10.5194/ica-abs-1-290-2019.

Papakonstantinou, A., Batsaris, M., Spondylidis, S., Topouzelis, K., 2021. A Citizen Science Unmanned Aerial System Data Acquisition Protocol and Deep Learning Techniques for the Automatic Detection and Mapping of Marine Litter Concentrations in the Coastal Zone.

Pinto, L., Andriolo, U., Gonçalves, G., 2021. Detecting stranded macro-litter categories on drone orthophoto by a multi-class Neural Network. Mar. Pollut. Bull. 169, 112594 https://doi.org/10.1016/j.marpolbul.2021.112594.

Politikos, D.V., Adamopoulou, A., Petasis, G., Galgani, F., 2023. Using artificial intelligence to support marine macrolitter research: a content analysis and an online database. Ocean Coast. Manag. 233, 106466 https://doi.org/10.1016/j.ocecoaman.2022.106466.

Rahmadya, A., Hidayat, Aisyah, S., Husrin, S., Olsen, M., 2022. Monitoring of plastic debris in the lower Citarum River using Unmanned Aerial Vehicles (UAVs). In: IOP Conference Series: Earth and Environmental Science. https://doi.org/10.1088/1755-1315/950/1/012080.

Rangel-Buitrago, N., Neal, W., Williams, A., 2022. The Plasticene: time and rocks. Mar. Pollut. Bull. 185, 114358 https://doi.org/10.1016/j.marpolbul.2022.114358.

Rocamora, C., Puerto, H., Abadía, R., Brugarolas, M., Martínez-Carrasco, L., Cordero, J., 2021. Floating debris in the low Segura river basin (Spain): avoiding litter through the irrigation network. Water (Switzerland) 13, 1–18. https://doi.org/10.3390/w13081074.

Salgado-Hernanz, P.M., Bauzà, J., Alomar, C., Compa, M., Romero, L., Deudero, S., 2021. Assessment of marine litter through remote sensing: recent approaches and future goals. Mar. Pollut. Bull. 168 https://doi.org/10.1016/j.marpolbul.2021.112347.

Schreyers, L., van Emmerik, T., Nguyen, T.L., Castrop, E., Phung, N.A., Kieu-Le, T.C., Strady, E., Biermann, L., van der Ploeg, M., 2021a. Plastic plants: the role of water

hyacinths in plastic transport in tropical rivers. Front. Environ. Sci. 9 https://doi.org/10.3389/fenvs.2021.686334.
Schreyers, L., van Emmerik, T., Nguyen, T.L., Phung, N.A., Kieu-Le, T.C., Castrop, E., Bui, T.K.L., Strady, E., Kosten, S., Biermann, L., van den Berg, S.J.P., van der Ploeg, M., 2021b. A field guide for monitoring riverine macroplastic entrapment in water hyacinths. Front. Environ. Sci. 9, 1–18. https://doi.org/10.3389/fenvs.2021.716516.
Schreyers, L., Van Emmerik, T., Biermann, L., Van Der Ploeg, M., 2022. Direct and indirect river plastic detection from space. In: International Geoscience and Remote Sensing Symposium (IGARSS), pp. 5539–5542. https://doi.org/10.1109/IGARSS46834.2022.9883379.
Schulz, M., Clemens, T., Förster, H., Harder, T., Fleet, D., Gaus, S., Grave, C., Flegel, I., Schrey, E., Hartwig, E., 2015. Statistical analyses of the results of 25 years of beach litter surveys on the south-eastern North Sea coast. Mar. Environ. Res. 109, 21–27. https://doi.org/10.1016/j.marenvres.2015.04.007.
Schwarz, A.E., Ligthart, T.N., Boukris, E., van Harmelen, T., 2019. Sources, transport, and accumulation of different types of plastic litter in aquatic environments: a review study. Mar. Pollut. Bull. https://doi.org/10.1016/j.marpolbul.2019.04.029.
Taddia, Y., Corbau, C., Buoninsegni, J., Simeoni, U., Pellegrinelli, A., 2021. UAV Approach for Detecting Plastic Marine Debris on the Beach: A Case Study in the Po River Delta (Italy), pp. 1–18.
Takaya, K., Shibata, A., Mizuno, Y., Ise, T., 2022. Unmanned aerial vehicles and deep learning for assessment of anthropogenic marine debris on beaches on an island in a semienclosed sea in Japan. Environ. Res. Commun. 4 https://doi.org/10.1088/2515-7620/ac473b.
Topouzelis, K., Papakonstantinou, A., Garaba, S.P., 2019. Detection of floating plastics from satellite and unmanned aerial systems (Plastic Litter Project 2018). Int. J. Appl. Earth Obs. Geoinf. 79, 175–183. https://doi.org/10.1016/j.jag.2019.03.011.
Topouzelis, K., Papageorgiou, D., Suaria, G., Aliani, S., 2021. Floating marine litter detection algorithms and techniques using optical remote sensing data: a review. Mar. Pollut. Bull. https://doi.org/10.1016/j.marpolbul.2021.112675.
UNEP (United Nations Environment Programme), 2021. From Pollution to Solution: A Global Assessment of Marine Litter and Plastic Pollution. New Scientist.
van Emmerik, T., Schwarz, A., 2020. Plastic debris in rivers. Wiley Interdiscip. Rev. Water 7, 1–24. https://doi.org/10.1002/wat2.1398.
van Emmerik, T., Mellink, Y., Hauk, R., Waldschläger, K., Schreyers, L., 2022. Rivers as plastic reservoirs. Front. Water 3. https://doi.org/10.3389/frwa.2021.786936.
Veettil, B.K., Hong Quan, N., Hauser, L.T., Doan Van, D., Quang, N.X., 2022. Coastal and marine plastic litter monitoring using remote sensing: a review. Estuar. Coast. Shelf Sci. 279, 108160 https://doi.org/10.1016/j.ecss.2022.108160.
Veiga, J.M., Fleet, D., Kinsey, S., Nilsson, P., Vlachogianni, T., Werner, S., Galgani, F., Thompson, R.C., Dagevos, J., Gago, J., Sobral, P., Cronin, R., 2016. Identifying sources of marine litter. In: JRC Technical Report.
Wolf, M., van den Berg, K., Garaba, S.P., Gnann, N., Sattler, K., Stahl, F.T., Zielinski, O., 2020. Machine learning for aquatic plastic litter detection, classification and quantification (APLASTIC–Q). Environ. Res. Lett. https://doi.org/10.1088/1748-9326/abbd01.
Yang, Z., Yu, X., Dedman, S., Rosso, M., Zhu, J., Yang, J., Xia, Y., Tian, Y., Zhang, G., Wang, J., 2022. UAV remote sensing applications in marine monitoring: knowledge visualization and review. Sci. Total Environ. https://doi.org/10.1016/j.scitotenv.2022.155939.