

Ecological Informatics

A novel beach litter analysis system based on UAV images and Convolutional Neural Networks

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Abstract:	Beach litter monitoring programs play a key role in the definition of effective management actions for the conservation of the intrinsic ecological, scenic, and economic value of the coastal areas. In this study, an innovative analysis system is proposed for the automatic identification of beach litter items (dimensions > 2.5 cm) on aerial- photogrammetric images acquired by means of Unmanned Aerial Vehicles (UAV) at different elevations. The workflow is based on a Convolutional Neural Network model specifically targeted for instance segmentation and object recognition activities. Test cases were carried out along the Adriatic sector of the Apulia region (Italy), where beaches have a remarkable economic importance, attracting national and international tourists, and ecological values, hosting species of high ecological value and protected areas. The results obtained from tests performed in this study allowed defining 10 m as the optimal drone flight above ground level. In addition, encouraging results have been obtained on instance segmentation step, experimenting on real, synthetic, and mixed data, produced by using a high-resolution blending technique. In details, a beach litter density of 0.38 items m⁻² (on 0.66 items m⁻²) and a mAP of 0.67 has been achieved on real data. The proposed methodology represents a benchmark for the definition of a standardize procedure for the indirect evaluation and monitoring of the coastal environmental status. Besides allowing the investigation of large areas with limited human effort, the proposed system enables the assessment of the beach litter spatial distribution and magnitude, providing useful information for the evaluation of beach quality environmental condition.
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Response to Reviewers:	

Dear Editors of “Ecological Informatics”,

we enclose herewith the revised manuscript “***A novel beach litter analysis system based on UAV images and Convolutional Neural Networks***” written by Vincenzo M. Scarrica, Pietro P.C. Aucelli, Cosimo Cagnazzo, Angelo Casolaro, Pierpaolo Fiore, Marco La Salandra, Angela Rizzo, Giovanni Scardino, Giovanni Scicchitano, Antonino Staiano.

We are grateful for the valuable comments received, which allowed us to improve the clarity and quality of our manuscript. The main text has been carefully revised to address all the comments and revisions suggested by the reviewers. In particular, we addressed the following points: (a) the level of English throughout the paper has been improved; (b) the introductory section has been supplemented with a more extensive analysis of the state-of-the-art results; (c) comparisons between the proposed approach and current competing models in the literature have been provided, using both a standard metric and a newly defined metric; (d) a discussion section has been added to describe the results from both computational and ecological perspectives; (e) low-resolution images were removed, keeping the relevant ones at higher resolution; (f) highlights were changed to fit the guidelines and the right number of characters needed; (g) the introduction and conclusion sections were revised to better highlight the originality and relevance of our work.

We provide the manuscript with the main modified parts highlighted in yellow for easy identification.

We hope that our revisions have taken into account all comments and suggestions and that you consider our revised work suitable for publication.

Best regards.

Bari, 17/10/2022

Dr. Angela Rizzo

A handwritten signature in dark ink, reading "Angela Rizzo". The signature is written in a cursive, flowing style with a large initial 'A' and 'R'.

Dear Editors, dear Reviewers,

We would like to thank you for your further comments and suggestions, which allowed us to improve the quality of our manuscript. We tried to address all the requirements and we hope that this last version of the manuscript meets your expectations.

Please, find below our response to all your comments.

Associate Editor

Associate Editor: The paper has improved, but cannot be accepted yet. In its current state, the level of English throughout your manuscript does not meet the journal's required standard. You may wish to ask a native speaker to check your manuscript for grammar, style and syntax, or use the professional language editing options available from Elsevier Author Services: <https://webshop.elsevier.com/>. The Introduction does not cover the pertinent literature and fails to highlight the novelty of your study. The Discussion is practically non-existent and fails to draw parallels with relevant studies from the peer-reviewed literature or put the presented results into the right context. You need to add a Discussion section in your paper and evaluate your work with reference to similar studies from the field of ecological informatics. The quality of your figures is low and your Conclusions fail to highlight the key novelty of your findings and their ecological implications. Your Research Highlights should not exceed the maximum required of 85 characters, including spaces. We receive a much higher number of papers than what we can realistically publish, and the standards of the papers that are ultimately accepted are high. We hope to receive a significantly improved manuscript in the near future. Your write-up needs A LOT of work. This is not a journal that solely focuses on the technical aspects of the published scholarship, we also want to see context, broader implications of your work, critical discussion of the uncertainties etc. Please address these comments very carefully!!

Author's response:

Dear Associate Editor, first of all, thank you for your very helpful suggestions. Based on your comments, the work has been edited and intensively remodelled based on the level of English (grammar, style, nouns, etc.). We would like to have positive feedback from your next reading (together with the other reviewers) so that the work is now adjusted to the standards required by the journal.

Please, find below more details about the modifications we made:

- The introduction of the paper has been modified to clarify its actual novelty (listed in three different points: a),b),c)), and to give an overview of competing SOTA results from literature (and metrics used). In our opinion, the cited papers we have added in our introduction are among the most representative of ecological informatics (more specifically, on beach litter detection using image processing and machine learning techniques).
- As suggested, we added a discussion section (divided into paragraphs), in which an extensive comparison of F-scores, parameters, and other factors was provided to rank our model among the most relevant SOTA results. We discussed the pros and cons of our choice in terms of segmentation type (instance vs semantic) and the risks involved in choosing a specific patch size. We hope this discussion will convince you of the effectiveness of our work. We have also introduced a normalized F-score for density as a fair criterion to compare our proposal with other works, to address the problem of different beach surfaces and the litter counts among them. Although this measure is not perfectly suitable for all test cases, as it does not scale with other parameters (such as light reflection, the surface area of litter

in pixels, etc.), it could be a potential new way to standardize different results in different contexts.

- We suppressed many low-resolution images related to the results and kept the most relevant.
- We changed the “Conclusions” to stress our novelty and to group the key points of our work immediately.
- The highlights are now less than 85 characters each other (including spaces)

Reviewer #1:

The authors tried to address most of my concern. In my opinion, minor correction is necessary. The term of "Optimal" might not be appropriate, as lower altitude imagery is more costly and timely than higher altitude imagery, and "optimal" is a balance between quality and cost. I suggest the use of "desirable" or other similar words instead of "Optimal" here: Optimal shooting altitude could then be set at a height of 10 meters As a standard parameter for achieving good quality detection, as already shown in other works at the SOTA (Martin et al., 2021), compared to higher distances, i.e., as well as 20 meters and more than 20 meters (Jang et al., 2011, Duarte et al., 2020...

Author's response:

Dear reviewer, we agree with your comment and changed the term “optimal” to “desirable”. We also used this term in the highlights.

Reviewer #2:

Although the author's response is that the objective of the work was not to introduce a new SOTA method for the litter instance segmentation on sandy shore, but to propose an augmented data set (through a GP-GAN) to improve the predictive capabilities of a model when performing litter detection. However, if this study has not conducted comparative analysis with state-of-the-art methods, the superiority of the proposed method cannot be verified.

Author's response:

Dear reviewer,

From a computational point of view, the aim of our work was to introduce the concept of mask in instance segmentation for beach litter detection, since in our opinion instance segmentation could improve accuracy in detecting litter w.r.t. methods based on semantic segmentation or object detection, and also make it possible to discriminate between litter items of the same general class (e.g. “bottles”). We perfectly agree with you on the need to compare our model with competing ones from current practices. Therefore, although several difficulties to perform such a comparison due to different reasons (e.g., lack of experimental details from other scientific papers, use of different datasets, different numbers, and density per unit area of litter items, etc.), in the new revised version of our work, we performed such a comparison and, to overcome the discrepancy on the litter density per unit area among different studies, we also defined a suitable novel criterion, named DNF-score, for normalizing F-score when area surface and litter counts are different.

Indeed, the models' comparison showed that the proposed model on different test cases ranked among the best ones, in terms of both F-score and DNF-score. As described in the new results section of the manuscript. Nonetheless, we're not stating that Mask-RCNN is the SOTA model for instance segmentation, rather, that an instance segmentation model is more apt for litter recognition tasks.

In addition, a further novelty of our study consists of a dataset augmentation procedure through GP-GAN. This is because, image acquisition campaigns are costly and, the size of the (annotated) datasets is usually small to get high accuracy from Deep learning techniques.

The benefits of our augmenting approach, however, are significant only in some test cases, and we have clearly underlined this point in the new revised version of the manuscript.

We hope the analysis added in this last version of the manuscript meets your expectations.

Highlights

- Multidisciplinary framework for the indirect identification of beach litter items
- Setting of a desirable 10 m height threshold for UAV surveys
- Use of a Convolutional Neural Network for litter instance segmentation
- Data augmentation with high-resolution blending
- Introduction of a density-normalized F-score

A novel beach litter analysis system based on UAV images and Convolutional Neural Networks

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Abstract

Beach litter monitoring programs play a key role in establishing effective management measures to preserve the ecological, scenic, and economic value of the coastal areas. In this study, an innovative analysis system is proposed for the automatic identification of beach debris (> 2.5 cm) on aerial-photogrammetric images acquired by unmanned aerial vehicles (UAV) at different elevations. The workflow is based on a Convolutional Neural Network model designed for object segmentation and object recognition, and here used for instance segmentation tasks. Test cases were conducted along the Adriatic sector of the Apulia region (Italy), where the beaches have a remarkable economic importance, attracting national and international tourists, and ecological values, hosting species of high ecological value and protected areas. The results of the tests carried out in this study allowed defining 10 m as the desirable drone flight above ground. In addition, encouraging results have been obtained on the instance segmentation step, experimenting on real, synthetic and mixed data, produced by using a high-resolution blending technique. A beach litter density of 0.38 items m^{-2} (on 0.66 items m^{-2}), an F-score of 0.96 and a mAP of 0.67 has been achieved on real data. A novel metric for comparing works at the state-of-the-art (SOTA) in beach litter monitoring is also introduced, named “density-normalized F-score”. The proposed methodology represents a benchmark for the definition of a standardize procedure for the indirect evaluation and monitoring of the coastal environmental status. Besides allowing the investigation of large areas with limited human effort, the proposed system enables the evaluation of the beach litter spatial distribution and magnitude, providing useful information for the assessment of tailored beach quality indices.

Key words: Coastal analysis, unmanned aerial vehicles (UAVs), instance segmentation, convolutional neural networks, beach litter

Highlights

- Multidisciplinary framework for the indirect identification of beach litter items
- Setting of a desirable 10 m height threshold for UAV surveys
- Use of a Convolutional Neural Network for litter instance segmentation
- Data augmentation with high-resolution blending
- Introduction of a density-normalized F-score

1. Introduction

Marine and beach litter (BL) corresponds to all persistent, manufactured, and processed solid material discarded, disposed, or abandoned in the marine and coastal environment (United Nations Environment Programme – UNEP, 2005, 2021, OSPAR, 2010). Litter items mainly consist of plastics and polystyrene, but they include a wide range of materials such as glass, ceramics, paper, textiles, and many others. It is estimated that 70% of marine litter remains on the ocean bottoms, while the other 30% is retained equally between the water column and beaches (UNEP, 2005). Nevertheless, BL accumulation along the coasts represents an environmental and economic issue worldwide and, consequently, the global number of scientific papers, as well as grey literature, has been increasing exponentially since 2010 (Cesarano *et al.*, 2021). Several anthropogenic activities are sources of BL. Most litter elements derive from land-based sources such as villages, towns, landfills and private households and, because of improper disposal, pass through rivers and streams into the ocean (Sheavly and Register, 2007; Rech *et al.*, 2014). Litter can also be directly discarded in coastal environments by beach users (Nachite *et al.*, 2019), as well as have a marine-based origin, from recreational and fishing boats, aquaculture activities, and general shipping (Earll *et al.*, 1999; Coe and Rogers, 2012). However, the sources that determine the content and amount of BL are well known, but more attention should be paid to analyzing factors that may influence the distribution and accumulation of BL (e.g., wind direction, currents, density of beach users, and distance from rivers or urban centers) (Zielinski *et al.*, 2022).

Because of the many impacts that BL can have on natural ecosystems, economic and touristic activities, and human well-being, monitoring programs are needed to support the identification of effective coastal management strategies.

As coastal tourism is one of the main contributors to the local economies in central and south American countries, many studies have been focused on the assessment of BL distribution and density along the coasts in Colombia (Rangel-Buitrago *et al.*, 2017, 2018, 2021), Cuba (Botero *et al.*, 2017), Chile (Rangel-Buitrago *et al.*, 2019a), Ecuador (Mestanza *et al.*, 2019), and Brazil (Corraini *et al.*, 2018). Most of these studies are based on direct in situ surveys during which objects are manually identified and categorized according to international classifications. Litter magnitudes are expressed in items/m² to make the results easily comparable. As pointed out in Rangel-Buitrago *et al.* (2019b), most studies related to BL distribution, composition, and sources focus on the analysis of continental coastlines,

75 while very little work has been conducted in island areas. In addition, the results of these studies have
76 shown that in the Caribbean area, litter management is mainly related to tourism rather than
77 environmental or health purposes. Finally, plastic was found to be the most common material at almost
78 all sites analyzed, and objects from recreational activities and sanitary waste (e.g., bottles and
79 containers) accounted for the high percentage of all objects found on the analyzed beaches.

80 In Europe, great efforts have been made by several countries to assess the environmental status of the
81 European marine and coastal sectors, to comply with the requirements of the Marine Strategy
82 Framework Directive (MSFD), which identifies macro and micro-litter as major threats to marine
83 ecosystems. A recent review of literature on the BL topic showed that seven European countries were
84 found to be included in the top ten countries worldwide with the highest number of BL publications
85 indexed in Scopus (Cesarano *et al.*, 2021). As an example, the distribution of BL along the western
86 Mediterranean coast of Spain was recently analyzed by Asensio-Montesinos *et al.* (2019, 2021), who
87 found that in the investigated coastal areas, litter is essentially related to beachgoers, wastewater
88 discharges, and fishing activities. The distribution of BLs along the Atlantic coast of Andalusia has
89 been monitored since 2016 as part of several research programs (Williams *et al.* 2016; Asensio-
90 Montesinos *et al.*, 2020). Mandić *et al.* (2022) analyzed the environmental status of beaches in the
91 southern Adriatic by conducting surveys of beach litter in Albania, Italy, and Montenegro. In Italy,
92 Rizzo *et al.* (2021) analyzed the impact of BL in a coastal sector included in a Marine Protected Area
93 (MPA) and found that legal protection does not imply the achievement of high environmental standards,
94 as activities in nearby coastal areas and surrounding river basins can affect beaches located in protected
95 areas. In Portugal, several studies have analyzed different coastal areas with the aim of defining how
96 morphodynamic factors influence the distribution of BL along the beach-dune system (Gonçalves *et*
97 *al.*, 2020, Andriolo *et al.* 2021). In addition, the spatial distribution and temporal variations of BL along
98 the Mediterranean coast of Morocco, as well as main litter characteristics, were evaluated by Nachite
99 *et al.* (2018, 2019). In this case, the surveys were carried out following the UNEP guidelines and
100 considering different beach typologies (resort, village, urban, and rural beaches) in order to highlight
101 the main correlation between litter abundance distribution and beach typology.

102 The assessment of litter, in terms of the number and type of items, allows the application of customized
103 indices developed for the evaluation of the environmental status of beaches. Collected litter is generally
104 classified according to material, source, buoyancy, and potential harmfulness. Based on this type of
105 information, coastal quality can be inferred through index-based approaches, which allow the beaches
106 investigated to be ranked in terms of cleanliness, hazardousness, and litter characteristics. In this
107 context, widely used indices are the Clean Coast Index (Alkalay *et al.*, 2007; Rangel-Buitrago *et al.*,
108 2018), which quantifies the state of being litter-free, the Plastic Abundance Index (Rangel-Buitrago *et*
109 *al.*, 2021), which indicates the amount of plastic in relation with the total amount of litter, and the
110 Hazardous Anthropogenic Litter Index (Rangel-Buitrago *et al.*, 2019a), which represents the possibility
111 of being affected by hazardous objects. In addition, an integrated Beach Quality Index (BQI) was

developed by Semeoshenkova *et al.* (2017) to assess both the environmental quality and the human well-being related to recreational uses of beaches. The BQI includes an evaluation of the cleanliness indicator, which was created to assess the aesthetic quality of coastal and beach areas (Micallef and Williams, 2009).

Most BL monitoring programs are carried out with in-situ visual census approaches, following internationally proposed methodological procedures for conducting direct surveys and classifying litter objects (cf. “Guideline for Monitoring Marine Litter on the Beaches in the OSPAR Maritime Area” - OSPAR Commission, 2010, “Guidance on Monitoring of Marine Litter in European Seas” - EU MSFD TG10, 2013, “Methodology for Monitoring Marine Litter on Beaches” - Vlachogianni, 2017, “Guidelines on the monitoring and assessment of plastic litter and microplastics in the ocean” GESAMP, 2019). However, an in-situ visual census requires high human efforts and results are rather subjective, time-consuming, and spatially limited (Gonçalves *et al.*, 2020). In recent years, innovative monitoring systems have been investigated to improve traditional in-situ visual approaches, exploiting the use of images acquired from Unmanned Aerial Vehicle (UAV), automatically analyzed with Machine Learning (ML) techniques. As an example, some works have used a threshold-based segmentation algorithm to detect litter, showing quite good results (Bao *et al.*, 2018). In this case, the authors did not report any confusion matrix, but exploited the density of litter pixels over all pixels, achieving an overall accuracy of 98.6 percent over a total area of 48405 m². Turning to ML methodologies, some works have shown that ML algorithms work well on this topic, such as Random Forest (RF), Support Vector Machines (SVM) and K-Nearest Neighbours (KNN) (Hastie *et al.*, 2009). In Gonçalves *et al.* (2020), the authors intended to use the F-score to rank the algorithms: RF, SVM and KNN scored 72%, 68% and 65%, respectively. As an extension of ML, deep learning has augmented many previous results in the last decade, with the introduction of Convolutional Neural Network (CNNs) in the field of computer vision. Duarte *et al.* (2020) addressed the problem of imbalance for training ML algorithms, using DenseNet121 combined with oversampling, with an F-score of 68%. In another paper, a semantic segmentation was applied with a SegNet architecture (Bak *et al.*, 2019) while in a more recent paper, a framework based on FasterRCNN was proposed (Martin *et al.*, 2021). In Bak *et al.* (2019), the authors did not specify the metric used for their experiments, stating 98.2 % performance results, while in Martin *et al.* (2021), the authors showed an F-score of 44.2% and a beach litter density of 0.12, on average. In contrast, a domain-specific deep learning architecture called PlasticFinder was used in another work on beaches in the Republic of Maldives (Fallati *et al.*, 2019). In this case, the authors stated a 78% F-score as the best average result on Adangau Island (peaking at 81%).

In this study, a novel procedure for the automatic identification of BL objects from UAV images is proposed. The system is based on the application of a CNN model, used for *instance segmentation* and *object recognition* tasks. This approach makes it possible to identify BL objects by analyzing manually labeled photogrammetric images used to create training and validation sets. The novelty of this work can be summarized as follows: (a) the use of instance segmentation, rather than semantic segmentation

or object detection, makes it possible to segment BL object masks, reducing the signal-to-noise ratio and increasing localization accuracy; (b) transformations such as high-resolution blending and affinities can be applied to increase the size of datasets and to achieve a better generalization when only small datasets are available; (c) the introduction of a new measure, called “density-normalized F-score”, allows to compare models more fairly. Compared with previous methods (Hastie *et al.*, 2009; Gonçalves *et al.*, 2020), feature extraction is performed from the network and, to the best of our knowledge, compared with works using deep neural networks, it is one of the first to consider masks of single objects in a narrow sense rather than segmented regions of pixels (Bak *et al.*, 2019) or bounding boxes (Martin *et al.*, 2021).

UAV images were acquired in the Apulia region (southern Italy) at *Capitolo* beach (in the province of Bari), *Torre Guaceto* beach, and *Torre Canne* beach (in the province of Brindisi), where BL is a significant problem due to the remarkable landscape and environmental value of the areas and the presence of numerous attractive tourist destinations (Damiani *et al.*, 1988; Mastronuzzi *et al.*, 2015, 2020; Buongiorno and Intini, 2021). The analysis process proposed in this study includes geomorphology, photogrammetry, and machine learning, highlighting how the combination of approaches between different fields is effective in supporting the development of high-performance environmental monitoring programs, needed to meet international and national policy requirements.

2. Area of Study

The investigated coastal sites are located on the Adriatic side of Apulia Region (south-eastern Italy), which is characterized by about 900 km of coastal sectors, corresponding to 12% of the Italian coastline (Fig. 1a). Among all the different types of coastlines, sandy beaches are the most common (650 km in length). Several geological units are present in this area, the deposition of which is related to the past sea-level fluctuations and tectonic factors that occurred during the Middle-Late Pleistocene. The present coastal morphology is the result of Holocene marine transgression (last 12 ky BP). Holocene marine transgression produced a series of sub-circular inlets that host pocket beaches. The pocket beaches are characterized by the presence of river mouths, which developed orthogonally to the coastline during the Last Glacial Maximum (Mastronuzzi *et al.*, 2018; De Giosa *et al.*, 2019), following the regional hydrographic network, and showing characteristics of sapping processes (Mastronuzzi and Sansò, 2002a). A polyphasic dune ridge, formed by two generations of aeolian sediments, the first at ~6.0 ky BP and the second at ~2.5 ky BP, has been recognized at the edge of the pocket beaches (Mastronuzzi and Sansò, 2002b; Mastronuzzi *et al.*, 2011; Lapietra *et al.*, 2022). Beaches of this area are affected by the sediment supply of the Ofanto river, as well as by seasonally flowing streams and creeks, which carry sediment that is redistributed along the coastal areas by the predominant NW-SE longshore current (Lapietra *et al.*, 2022). This coastal sector is influenced by winds, which frequently blow from the NNW and ESE directions, strongly influencing wave patterns.

In particular, *Capitolo* beach is located in the southernmost part of the Monopoli coastline and is bordered by a dune belt covering the Middle Holocene dune and swamps that were reclaimed during urban settlements (Mastronuzzi and Sansò, 2002b). It is one of the most popular tourist destination and hosts highly exploited facilities, especially during the summer season (Fig. 1b). *Torre Canne* beach is located in the Site of Community Importance IT9140002 (“*Litorale Brindisino*”). The Torre Canne area hosts a mobile coastal system characterized by the presence of several lakes and ponds. In addition, the area has a dune belt parallel to the coast that reaches an elevation of about 17 m (Fig. 1c). *Torre Guaceto* beach is located north of the city of Brindisi (Fig. 1d) and it is included in a natural protected area established with the aim of preserve the local habitat biodiversity and to protect a wide wetland separated from the sea by the dune system. The area also belongs to the Natura 2000 ecological network as Special Protection Area (IT9140008 “*Torre Guaceto*”) and as Site of Community Importance (IT9140005 “*Torre Guaceto e Macchia San Giovanni*”). All investigated beaches play a considerable role in local environmental, economic, and social activities. According to the international guidelines (Vlachogianni, 2017), the investigated stretches have a length of 100 m and include the emerged beach from the high-water boundary to the landward edge.

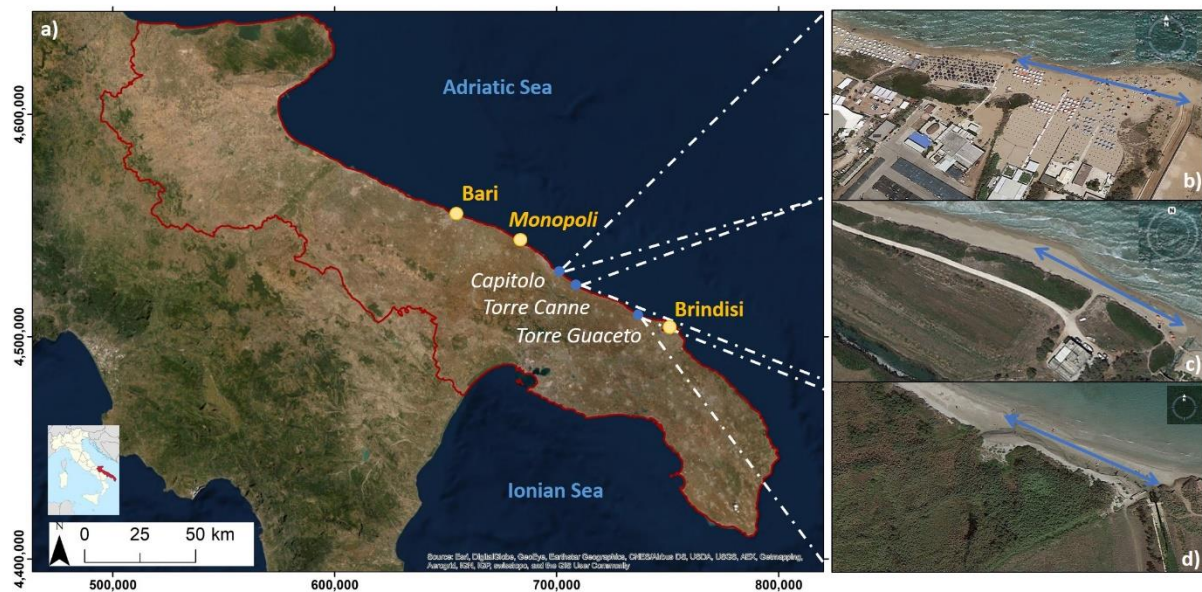


Fig. 1: a) Study area location: the Apulia region is shown in red while the blue dots identify the investigated sites; b) Capitolo beach; c) Torre Canne beach, c) Torre Guaceto beach. Images (b, c, d) are from Google Earth. The blue arrows identify the 100m long investigated beach sectors.

3. Materials and methods

This section will outline the proposed methodological framework for the automatic analysis of the photogrammetric images. The pipeline follows the order of the scheme in Fig. 2: the first phase consists of images acquisition and photogrammetric reconstruction (UAV images acquisition and post-processing); the second phase focuses on the process of datasets construction (Datasets building); the third phase describes the application of an instance segmentation technique (Instance segmentation) and, finally, the last phase consists of the evaluation of the spatial distribution of BLs.

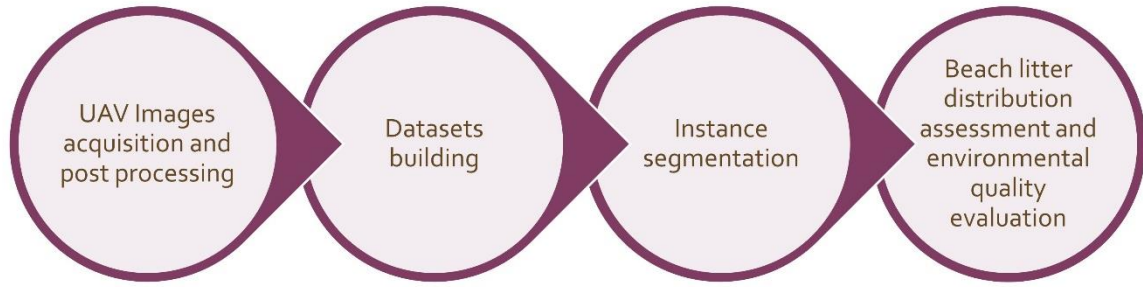


Fig. 2: Pipeline of the proposed analysis system.

3.1 UAV Images acquisition and post processing

Aerial images were acquired by using a multirotor quadcopter UAV “DJI Inspire 2” equipped with a “Zenmuse X5S” optical camera (20.8 MP, DJI MFT 15mm/1.7 ASPH supported lens, 4/3” CMOS sensor, FOV 72° and image resolution 5280 x 3956 pixel) at the beaches of *Capitolo* and *Torre Canne* (Fig. 3a, b), and a quadcopter “DJI Phantom 4 PRO” equipped with an integrated optical camera (20 MP, focal length 8.8mm, 1” CMOS sensor, FOV 84°, and image resolution 5472 x 3648 pixel) at *Torre Guaceto* beach (Fig.3c). Both UAVs are owned by the Department of Earth Sciences of the University of Bari. To investigate the beach sectors during the off-season periods, flights were carried out in February, April, and January. To define the best performing flight condition, images were collected with UAV flying heights of 10 m, 15 m, 20 m on *Capitolo* beach, 40 m on *Torre Guaceto* beach, and 45 m on *Torre Canne* beach.



Fig. 3: a, b) Drone DJI Inspire 2 flying at *Capitolo* beach; c) drone DJI Phantom 4 PRO used at *Torre Guaceto* beach. Target used to identify GCPs is shown in (c).

In the *Capitolo* and *Torre Guaceto* areas, aerial acquisitions were scheduled on “Pix4Dcapture”, a free mobile application that allows the main flight parameters to be defined: flight height of 10 m, 15 m, 20 m, and 40 m from the ground level of the UAV take-off position, flight speed of ~2 m/s, camera gimbal pitch -90°, frontal image overlap 80%, side image overlap 70%, single grid, and straight line UAV path mode. In the *Torre Canne* area, the aerial acquisition was performed with “DJI GS Pro” software with the following flight settings: flight height of 45 m from the ground level of the UAV’s take-off position, the flight speed of 5 m/s, camera gimbal pitch of -90°, frontal image overlap 90%, side image overlap 80%, UAV path mode with single grid and straight lines.

Before starting the flights, Ground Control Points (GCPs) were placed within the investigated areas to perform an accurate georeferencing process. The georeferencing process was performed through Global Positioning System - Real Time Kinematic (GPS-RTK) mode to estimate the coordinates of each GCP with a vertical accuracy of about 0.02 m and horizontal accuracy of about 0.01 m. Post-processing of the images was performed through Agisoft Metashape Professional (v. 1.6.5), which follows the principle of the Structure from Motion (SfM) process and enabled the generation of Digital Elevation Models and related RGB orthomosaics. For each orthomosaic, the Ground Sampling Distance (GSD) was calculated based pixel dimensions, camera focal length (mm), sensor width (mm) and flying height above the ground (m). The image post-processing workflow is illustrated in Fig. 4.



Fig. 4: Workflow of the procedure for the generation of the orthomosaics from UAV images.

To better design an instance segmentation process, the orthomosaics were divided into tiles of fixed size, i.e., 1000×1000 pixels. The investigated area is therefore represented as a spatial grid, and each tile is analysed in shorter time than the whole scene. In our test cases, only one type of background was considered in a single dataset, namely sandy beaches. Other types of beaches (e.g., gravel beaches) have not yet been analyzed. Backgrounds were learned from the network as an important part of the scene, as they are complementary to foreground classes and are needed to better discriminate objects. Different backgrounds introduce high variance in pixels, which can be caused by reflectance, sunlight, material composition, shadows, and occlusions. Multiple types of textures can be detected in one type of background, specifically, considering shorelines, a piece of beach and dune, and a piece of the water surface can be detected by an automatic system in one shot. The sampling step was even simplified by manually discarding the sea surface and green areas tiles so that only those on the shoreline are considered (sampling ratios are in Table 1); this leads the system to detect litter on the beach (regardless of the type of sand) but not in the green areas or in the water.

3.2 Dataset creation

As an annotation methodology, the labels used were of two types: “litter” and “background”, where the background class consisted of everything but the litter class. For each test set, the corresponding ground truth was considered as the comparison term for the experiments. A first dataset, called *Real*, was constructed, consisting of tiles from the beaches of *Capitolo* and *Torre Canne*. The term *Real* indicates data collected in situ, i.e., not synthetic data. To increase the number of samples in the dataset for better learning, data augmentation was applied through a high-resolution image blending technique, using the *Torre Guaceto* beach orthomosaic tiles (which do not contain visible BL) as a background, and low-resolution BLs collected from no-UAV images, through web-scraping operations. Blending was carried out using a generative machine learning model called Gaussian-Poisson Generative Adversarial

Networks (GP-GAN, Wu *et al.*, 2019; cf. Supplementary material). A Generative Adversarial Network (GAN) is a composite network, consisting of a generator and a discriminator; the discriminator classifies data produced by the generator in two classes: Fake or real. Based on this feedback, the generator learns how to improve the quality of the generated data. After the model training phase, the blended images result blurred, so GP-GAN optimizes a Gaussian-Poisson problem to increase the artifact likelihood. The resulting extended datasets were named *Synthetic* and *Synthetic3litters*, respectively. The former consists of images with an average of fifty BL items, while the latter contains images with an average of three BL items. Litters used as foreground on the background images were collected from a web-scraping operation, were manually annotated, and have a different resolution (mostly, a lower resolution) than the background of *Torre Guaceto* beach. In addition, the acquisition directions of these litters are not perpendicular to the floor, unlike the "Real" dataset. Therefore, to correctly crop and paste the litters from the scraped web images to the background images, a script was implemented to facilitate this task. All images containing litter were annotated in Common Object in Context (COCO) format (Lin *et al.*, 2014).

3.3 Instance segmentation and beach litter distribution assessment

The experiments were conducted using a Mask Region-Based Convolutional Neural Network (Mask-RCNN) (He *et al.*, 2017), an instance segmentation algorithm pre-trained on the COCO data set (Lin *et al.*, 2014). Mask-RCNN is a two-stage network: the first stage is responsible for generating proposed ROIs (regions of interest), while the second stage ranks each ROI and returns a bounding box/mask regression. The architecture is based on FasterRCNN, but it adds a parallel branch for object mask segmentation, rather than just bounding box recognition (cf. Supplementary material), and ResNet101 was used as the backbone. Each experiment was conducted by dividing each dataset into a *training set* and a *test set*, with a ratio of 8/2 (i.e., 80% for training and 20% for testing) and performing training with early stopping. Stochastic Gradient Descent (SGD) was used as the optimizer; the initial learning rate was initially set at 0.001 and an L2 regularization was applied. Performance was evaluated through Mean Average Precision using Intersection over Union (mAP@IoU*, with a 0.5 threshold) (Everingham *et al.*, 2010), and F-score*, as metrics. Afterward, the average litter density was calculated, in accordance with BL monitoring protocols. The training and test sampling ratios, measured as a percentage of the total area, are shown in Table 1, where the area is specific to each dataset. Real image datasets and mixed datasets (formed by both real and synthetic images) used in the experiments, with the corresponding number of BL items, are listed in Table 2. The suffixes 8 and 2 represent 8/10 and 2/10 of the whole amount of data, respectively. The maximum number of epochs for training is 50, and a mini-batch with one observation was used at each iteration.

The experiments were run on the Google Colab platform, harnessing the power of an Nvidia Tesla K80 GPU, with 12 GB of memory. The running time of the inference on a single sample image takes on the order of seconds.

304 **Table 1.** Sampling ratios in terms of percentage of total area.

Dataset	Training data sampling ratio	Test data sampling ratio
Real (10m)	16%	4%
Real (15m)	19%	5%
Real (20m)	6%	1%
Real (45m)	2%	0.8%
Synthetic	7%	1%
Synthetic3litters	4%	1%

305
306 *mAP@IoU: given two bounding boxes/masks, their IoU is defined as the ratio between their overlapped area
307 and their union area. Given IoU, mAP@IoU is defined as the mean of the areas under the precision-recall
308 curve, overall classes and IoU thresholds, considering true positives the instances who give IoU higher than the
309 threshold: $mAP@IoU = \frac{1}{N} \sum_{Recall_i} Precision(Recall_i)$.

310 *F-score: $\frac{2TP}{2TP+FN+FP}$ where TP are true positives, FN are false negatives, and FP are false positives.

311
312
313 **Table 2.** List of experimental data sets.

ID	Training set	#Training set BL	Test set	#Test set BL
1	Synthetic8 + Real8 (10m)	2727	Synthetic2 + Real2 (10m)	608
2	Synthetic + Real8 (10m)	3287	Real2 (10m)	48
3	Real8 (10m)	241	Real2 (10m)	48
4	Synthetic8	2486	Synthetic2	560
5	Synthetic	3046	Real	287
6	Synthetic3litters8	328	Synthetic3litters2	82
7	Synthetic3litters	410	Real	287
8	Synthetic3litters8 + Real8 (10m)	569	Synthetic3litters2 + Real2 (10m)	130
9	Synthetic3litters + Real8 (10m)	651	Real2 (10m)	48
10	Real8 (15m)	238	Real2 (15m)	53
11	Real8 (20m)	282	Real2 (20m)	78
12	Real8 (15m)	238	Real2 (10m)	48

13	Real8 (20m)	282	Real2(10m)	48
14	Real8 (45m)	283	Real2 (45m)	56
15	Real8 (10m)	241	Real2 (45m)	56
16	Real8 (15m)	238	Real2 (45m)	56
17	Real8 (20m)	282	Real2 (45m)	56
18	Real8 (45m)	282	Real2 (10m)	48

3.4 Density-normalized F-score

Comparisons among state-of-the-art models used in different works can be affected by discrepancies in the data, e.g., the total area analyzed for the test and the total number of litters considered for that test. In general, this is an issue for many scientific applications. Therefore, we propose an alternative fair criterion for evaluating different models with different data in terms of F-score, as follows:

$$\text{DNF-score} = \frac{F\text{-score} \times \frac{N}{A}}{\text{Unitary} \frac{N}{A}}$$

where N is the number of instances in the test area and A is the total surface area analyzed in the test. The *unitary* N/A corresponds to a density of one item/m², and the ratio N/A is dimensionless, so the DNF-score expresses a percentage. In this way, the F-score is normalized to the density of elements and does not strictly depend on the number of instances or the area of interest. It is worth noting, however, some limitations of our definition, i.e., light and backscatter phenomena as well as the total area of the instances are not considered, nor the number of classes customized by the model is considered. Therefore, DNF-score does not scale performance completely fairly.

3.5 Environmental quality evaluation

To provide a characterization of beaches in terms of the type and abundance of BL elements, a visual census was also carried out during the in-situ surveys. For this purpose, litter elements larger than 2.5 cm were identified, photographed, and classified according to the Master List of Categories available in the “Guidance on Monitoring of Marine Litter in European Seas developed by the European Commission” (Galgani *et al.*, 2013) and in the “Joint List of Litter Categories for Marine Macrolitter Monitoring” (Fleet *et al.*, 2021). Given the scope of the present work, this type of analysis was conducted along a representative number of transects included in the investigated coastal sectors of 100 meters in length.

4. Results

Post-processing of UAV images resulted in the orthomosaics of the investigated coastal sectors with ground sampling distance (GSD) values ranging from 0.2 to 1.2 cm (Table 3). The orthomosaics of the study areas are shown in Fig. 5. Specifically, the orthomosaic of the *Torre Canne* area, obtained from photogrammetric processing of images collected at 45 m, is shown in Fig. 5a, the orthomosaic of *Torre Guaceto* area, obtained from photogrammetric processing of images collected at 40 m, is shown in Fig.

5b, and the orthomosaics of *Capitolo* beach, obtained from photogrammetric processing of images collected at 20 m and 15 m are shown in Fig. 5c and Fig. 5d, respectively.

Table 3. List of the main fly characteristics and orthomosaic ground sampling distance.

Fly ID	Fly heights above ground level (m)	Number of images	Orthomosaic ground sampling distance (cm)
Capitolo_20	20	69	0.3
Capitolo_20	20	70	0.3
Capitolo01_10	10	35	0.21
Capitolo01_15	15	36	0.34
Capitolo02_10	10	35	0.22
Capitolo02_15	15	35	0.31
Capitolo03_10	10	37	0.23
Capitolo03_15	15	35	0.33
Capitolo04_10	10	38	0.22
Capitolo04_15	15	35	0.33
Torre Guacete01	40	332	1.1
Torre Canne01	45	289	1.2

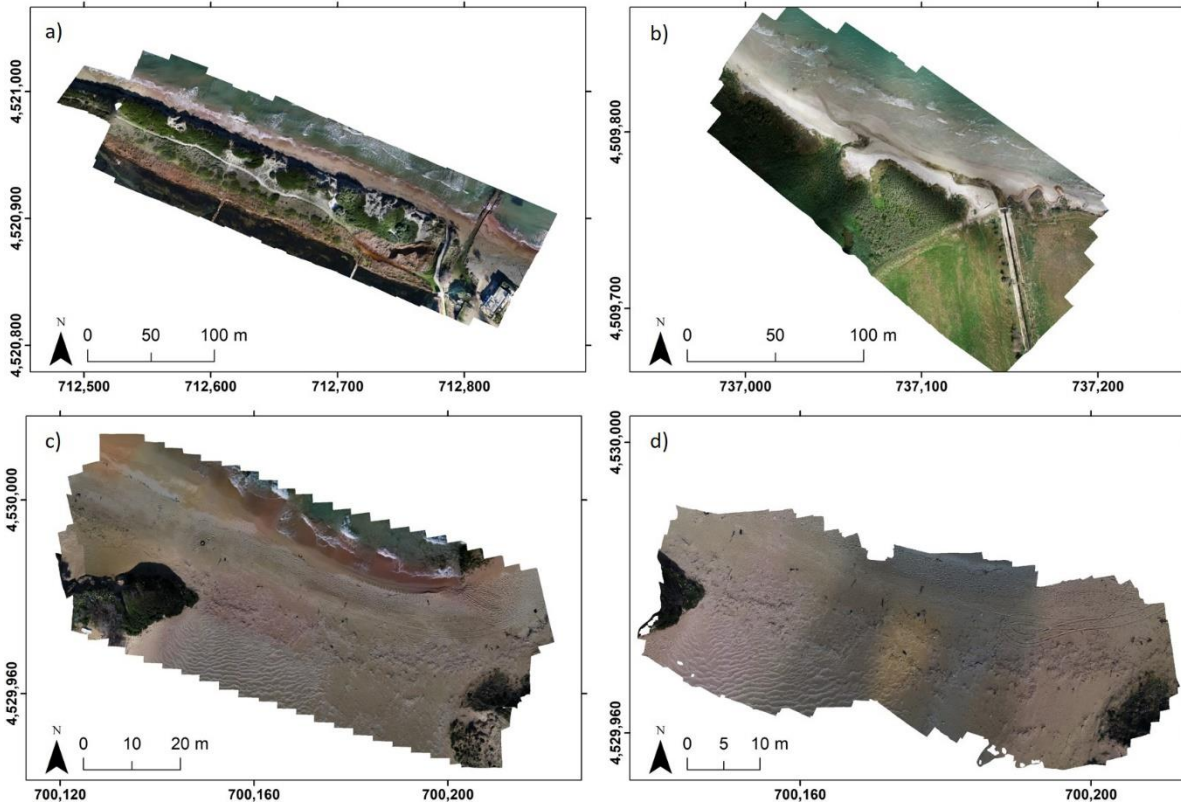


Fig. 5: Orthomosaics of the investigated coastal areas. a) Orthomosaic of *Torre Canne* area from photogrammetric images collected at 45 m. b) Orthomosaic of *Torre Guacete* area from

photogrammetric images collected at 40 m. Orthomosaics of *Capitolo* beach from photogrammetric images collected at c) 20 m and d) 15 m.

The results and discussion of the instance segmentation experiments are shown below, with some visual outputs. The proposed model achieved high average accuracies on the *Real* dataset, as shown in Table 4 (No. 3), and in Fig. 6, which depicts the loss plot providing information on the expected generalization error of experiment No. 3, concretely, at the 11-th epoch, the minimum error value is reached, thus at that point the model was frozen for the final inference. Furthermore, from different tests (experiments No. 3, 10, 11 in Table 4), it can be derived that 10 meters is a desirable distance for data acquisitions, as the performance decreases by elevating the drone camera. This thesis is also confirmed by experiments No. 12, 13, and 18 (Table 4), as they were carried out to compare the learning ability at different heights with a test at 10 meters height. Indeed, as expected, no model is better than the one trained at 10 meters, since the resolutions are very different from each other and provide different information content, with performance that degrades with increasing height. Experiments No. 14, 15, 16, and 17 (Table 4) involve models trained at different heights and tested at 45 meters height. As it can be seen, the closer the height is to 45 meters, the better the inference of the model. In fact, the worst performance corresponds to training at 10 meters height and testing at 45 meters height. The best performance, as expected, corresponds to training at 45 meters height and testing at 45 meters height. The performance of the models trained on 15 and 20 meters heights lies in between. These experiments show a crucial issue, it is difficult to achieve a perfect trade-off between cost and quality, as higher flights are inexpensive but produce poor performance, and at the same time, it has been shown that good quality trained models (starting at 10 meters) do not perform as well on higher elevation data (starting at 45m), which are cheaper to test. These behaviors show how the height parameter may be critical in the test campaign, since even if with higher elevations a single image can detect more litter, at the same time, there may be a loss of accuracy. The BL density was computed only on the in situ data, referring to the test set of experiment No. 3. The total number of test images is 18 and the total covered area is 72 m², yielding a BL density of 0.66 objects m⁻². As the number of true positive patterns is 27 (while false positives and false negatives are both one), the expected BL density is 0.38 elements m⁻² and the F-score is 0.96 (96%).

Table 4. Performance of Mask-RCNN on the experiments, measured in mAP@0.5

Experiment ID	mAP@0.5
1	0.64
2	0.37
3	0.67
4	0.70
5	0.23
6	0.83
7	0.25
8	0.70
9	0.43
10	0.52
11	0.42
12	0.65
13	0.55
14	0.48
15	0.20
16	0.38
17	0.37
18	0.45

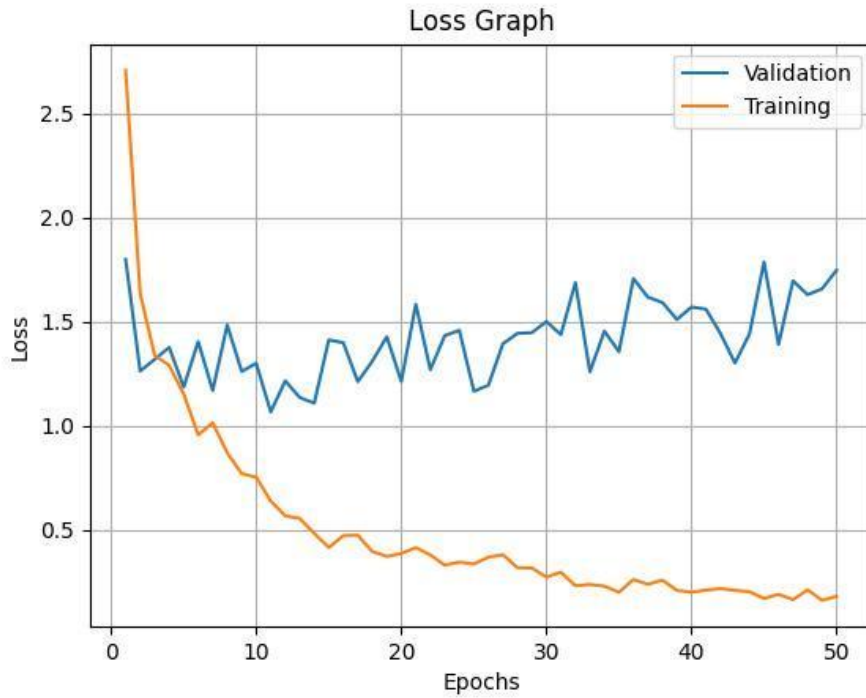


Fig. 6: Mask-RCNN training (orange curve) and validation (blue curve) losses, from experiment No. 3.

Regarding experiments on *Synthetic*, *Synthetic3litters*, and mixed experiments, some considerations can be made. As shown in Table 4, when datasets are homogeneous (e.g., only *Synthetic* or *Real*, i.e., experiments No. 2, 4, 6, 10, 11) or symmetrically mixed (e.g., half *Synthetic* and half *Real*, i.e., experiments No. 1 and 8) performance are reasonable. However, this does not happen when training sets are mixed, and the test is homogeneous (experiments No. 2 and 9). The reason may be the difference in resolution between foreground and background in *Real* (i.e., very low difference) and in *Synthetic* (i.e., very high difference) datasets. Those differences affect the accuracy of corresponding test sets. The symmetrically mixed experiment with synthetic data having an average of three litters per image (experiment No. 8 in Table 4) gains in accuracy over the mixed with an average of 50 litters (experiment No. 1 in Table 4). The motivation can be the homogeneous number of instances in a single image (for experiment No. 8 in Table 4) since real data have a lower number of instances. Moreover, the unbalanced number of instances between training and test sets in some experiments has certainly affected performance (as in experiments No. 2 and 9 in Table 4). Surprisingly, the experiment No. 6 in Table 4 reaches the highest accuracy, confirming the goodness of the augmented *Synthetic3litters* data set. The worst results were obtained in experiments No. 5 and 7 in Table 4 since in these experiments the training set consists of synthetic data and the test set consists of real data. Visual results of experiment No. 3 are shown in Fig. 7 (a, b, c, d).

Table 5. SOTA benchmarks (F-score) for beach litter detection and comparison with the proposed approach.

Methodology	RF (Gonçalves <i>et al.</i> , 2020)	SVM (Gonçalves <i>et al.</i> , 2020)	KNN (Gonçalves <i>et al.</i> , 2020)	DenseNet121 (Duarte <i>et al.</i> , 2020)	FasterRCNN (Martin <i>et al.</i> , 2021)	PlasticFinder (Fallati <i>et al.</i> , 2019)	Mask- RCNN (this study)
F-Score	72%	68%	65%	68%	44%	78%	96%

Comparisons were made only with methods for which details on metrics and results were available. It is worth noting that all mentioned experiments have different total and litter areas; in other words, the corresponding works report heterogeneous beach data, with different transect sizes and different conditions (litter type, backgrounds, light conditions, etc.). In addition, classification tasks also differ: the work by (Gonçalves *et al.*, 2020) is based on a four-class membership problem, where litter is the main class and three backgrounds are subclasses (VegDeb, Sand, and Shadow); (Martin *et al.*, 2021) divides litter into 14 classes, while (Fallati *et al.*, 2019) considers 5 main classes (AMD, Sea, Vegetation, Sand, Other), where the AMD class (plastic objects) is further composed of 10 subclasses. The proposed approach is mainly based on a two-class detection problem, as in (Duarte *et al.*, 2020). As Table 5 shows, our model achieves superior performance. As suggested by (Gonçalves *et al.*, 2020), these results are partly motivated by the smaller number of classes adopted, since a smaller number of categories implicitly compresses data that share the same properties (i.e., garbage, background, and non-waste objects). Finally, it should be noted that all the cited works analyzed different coastal areas, e.g., (Martin *et al.*, 2021) analyzed 44 beaches on the Red Sea coast of Saudi Arabia, whose density of litter on the beach changes abruptly (from 0.1 to 0.5 objects per m^{-2}). As for our case study, data were collected only from the *Capitolo* beach area, where the beach litter density is much higher (0.66 objects per m^{-2}). Therefore, to account for the differences in density between studies, the results were compared based on the DNF score normalized for density (Table 6).

Table 6. SOTA Benchmarks (DNF-score) for beach litter detection and comparison with the proposed approach.

Methodology	RF (Gonçalves <i>et al.</i> , 2020)	SVM (Gonçalves <i>et al.</i> , 2020)	KNN (Gonçalves <i>et al.</i> , 2020)	DenseNet121 (Duarte <i>et al.</i> , 2020)	FasterRCNN (Martin <i>et al.</i> , 2021)	PlasticFinder (Fallati <i>et al.</i> , 2019)	Mask- RCNN (this study)
DNF-score	10,9%	10,3%	9,8%	44,1%	5,6%	14,3%	37,3%

Specifically, Table 6 was deduced by considering, for each cited work, the total areas and the number of litter items used for testing. Concretely, (Duarte *et al.*, 2020) analyzed a validation set consisting of 13345 patches of 64x64 pixels with a GSD of 5.5 mm/pixel, resulting in an area of 300.64 m^2 (A). Now, since the number of litter items in their ground truth (N) is 194, the resulting density is 0.64 m^{-2} objects.

In (Gonçalves *et al.*, 2020), the values of A and N are 1593.8 m² and 242 liters, respectively, with a density of about 0.15 m⁻² objects. The same counting operation was performed for the remaining works shown in Table 6. In terms of DNF-score, DenseNet121 (Duarte *et al.*, 2020) ranked first, just ahead of our proposed Mask-RCNN-based approach. It is worth noting, however, that the DFN-score does not consider any information, such as illumination phenomena, reflection, number of classes, litter area, and other parameters. As a result, the comparison is made only on a normalized density basis, which is not the fairest scale. However, F-score and DNF-score provide us with evidence of the effectiveness of the proposed approach.

5.1 Other parameter settings

Our results suggest, for image acquisition, a desirable shooting altitude of 10 meters as a standard parameter for obtaining good quality detections, as also demonstrated in other works (Martin *et al.*, 2021, Fallati *et al.*, 2019) that report good accuracies. In addition, there are also other factors that influence the performance of a model. First, camera resolutions. *Capitolo* and *Torre Canne* images were acquired at 20.8 MP, while (Martin *et al.*, 2021, Bao *et al.*, 2018, Gonçalves *et al.*, 2020) used a resolution of 20 MP, and (Fallati *et al.*, 2019) a lower resolution of 12.4 MP. A flight speed of about 2 m/s as in the *Capitolo* and *Torre Guaceto* campaigns, as well as in some other study areas (Martin *et al.*, 2021), seems to be an optimal standard speed for obtaining quality results. Overlap for orthomosaic reconstruction plays an important role. In the *Torre Guaceto* and *Capitolo* areas, the overlap coefficients for the frontal and lateral parts were 80% and 70%, respectively, as well as in (Gonçalves *et al.*, 2020). In the *Torre Canne* area, the coefficients are even higher (90% and 80%, respectively), and this is due to a higher flight speed (which can lead to a loss of accuracy in the reconstruction if the overlap is not high enough).

In addition, the resolution of the tiles deserves to be discussed. In our work, although a size of 1000×1000 pixels was used for each input, it did not prove to be an optimal choice. In fact, an instance segmentation algorithm, such as Mask R-CNN, works to learn the proportions between object scales and aspect ratios (in our study 5 and 3, respectively), which are highly dependent on image resolution. To obtain a complete landscape, other works refer to different resolutions for patches (not whole frames), i.e., 64 x 64 pixels (Duarte *et al.*, 2020). Fixing the patch size might be a good option considering the average ratio of height to litter size given the height, however, it is not a scalable choice because if the height or average litter size changes, the patch would have to be redefined. Compared to (Duarte *et al.*, 2020), our approach is holistic, that is, a kernel scans each frame and searches for candidates. Finally, as the resolution is reduced, some objects in the scene are eliminated or made invisible, while others are included but enlarged, whereas as the resolution is increased, more litter is taken but will appear smaller. This implies a scaling of the size and aspect ratios of the bounding boxes/masks on which the network is trained, which can lead to both improved accuracy and loss of generalization. Indeed, a larger number of pixels in a mask may discriminate it better, but at the same

time, if the algorithm learns only large masks, it may not be able to generalize. Compared to the semantic segmentation used in (Bao *et al.*, 2018), instance segmentation techniques have a bottleneck in choosing the right aspect ratios and scaling factors; however, it is the price to pay to be able to label different types of objects and backgrounds (unlike semantic segmentation), which could be crucial for litter classification. Experimenting with different resolutions before the actual scaling of the network could be an important topic to investigate.

5.2 Litter types, composition, and future directions

From the analysis of litter larger than 2.5 cm collected along representative transects of the investigated beaches, it was possible to assess the most abundant categories of BL and define its main characteristics in terms of buoyancy, harmfulness, and potential source. Figs. 8a and 9a show the percentages of each BL element identified in Capitolo beach and Torre Guaceto beach. The elements are classified according to the codes provided in the European master list by the European Commission (Galgani *et al.*, 2013; Fleet *et al.*, 2021). The analysis shows that the most representative BL categories identified in Capitolo are plastic beverage and food caps and lids (code G21 - Fig. 8b), nets and pieces of netting (code G53 - Fig. 8c), and pieces of plastic with dimensions less than 50 cm (code G79). Other BL objects are cotton bud sticks (Code G95) and other plastic objects (Code G124) represented mainly by umbrella tips (Fig. 8d). The most identified objects belong to the class of artificial polymeric materials and are characterized by persistent buoyancy. Considering their potential origin, they are mostly related to recreational and beach fishing activities. In addition, the presence of cotton bud sticks points to the presence of sewage-related debris, probably due to broken pipes or direct discharge into the marine environment from sewage collectors located near the investigated site. Regarding the analysis of the data collected at Torre Guaceto beach (Fig. 9a), the most representative category identified at Torre Guaceto beach is plastic beverage and food caps and lids (Code G21) and beverage bottles (Code G7 – Fig. 9b), as occurred at Capitolo beach. Different objects related to the recreational activities are also identified (Fig. 9c, d).

Regarding the characterization of BL objects identified at Torre Canne beach, Cagnazzo *et al.* (2021) showed that plastic and glass bottles, rubber soles, and plastic bags were the most abundant objects recognized during the field survey. This type of characterization allows us stating that although local factors such as coastal morphology and degree of exposure to wind and waves, in theory, influence the distribution of BLs (Williams *et al.*, 2017), the environmental quality of Apulian beach sectors is strongly impacted by human recreational uses, as also evidenced along other Italian coastal sectors (e.g., Poeta *et al.*, 2014, 2016; Giovacchini *et al.*, 2018).

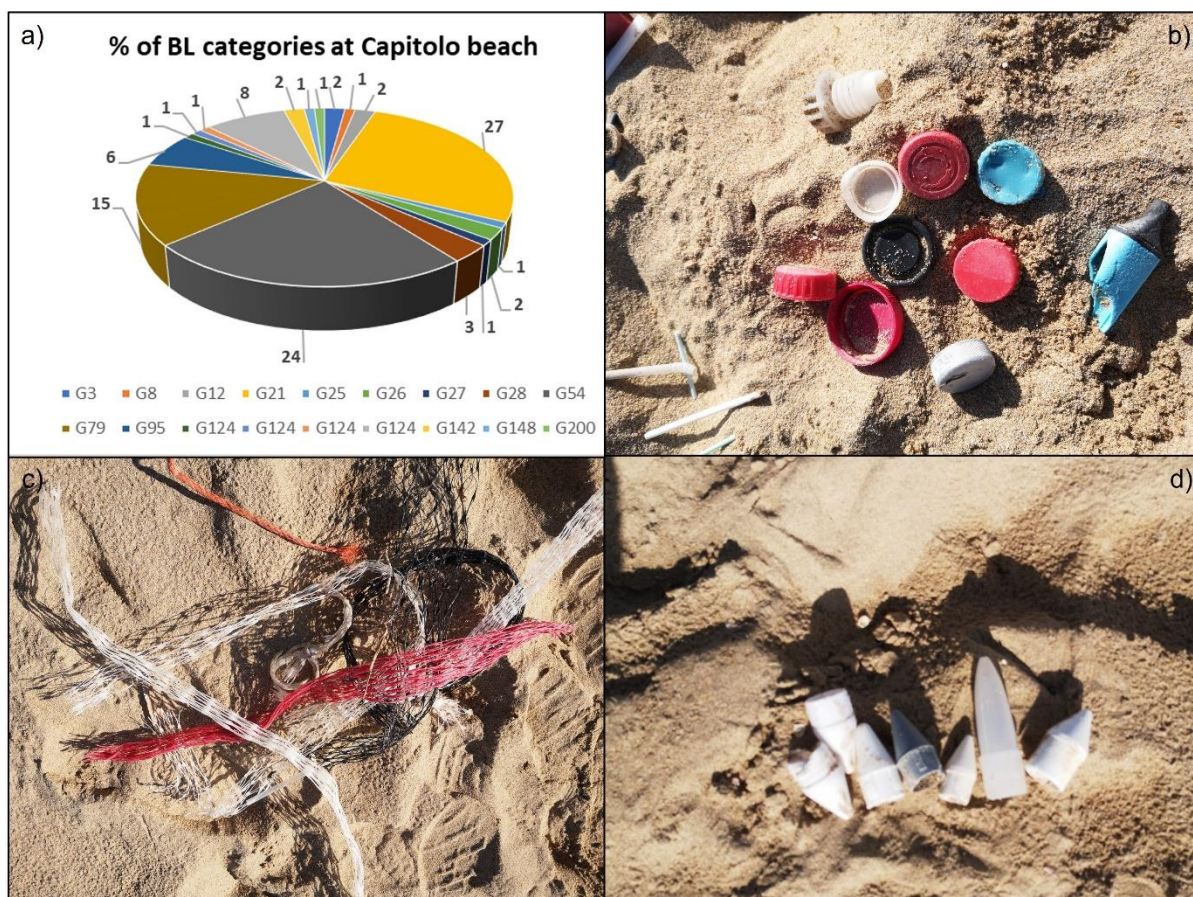


Fig. 8: BL items identified along representative transects at *Capitolo*: a) percentage distribution shown by considering the European code (EC, 2013). b) examples of objects belonging in the G21 category; c) examples of objects belonging in the G53 category; d) examples of objects belonging in the G124 category.

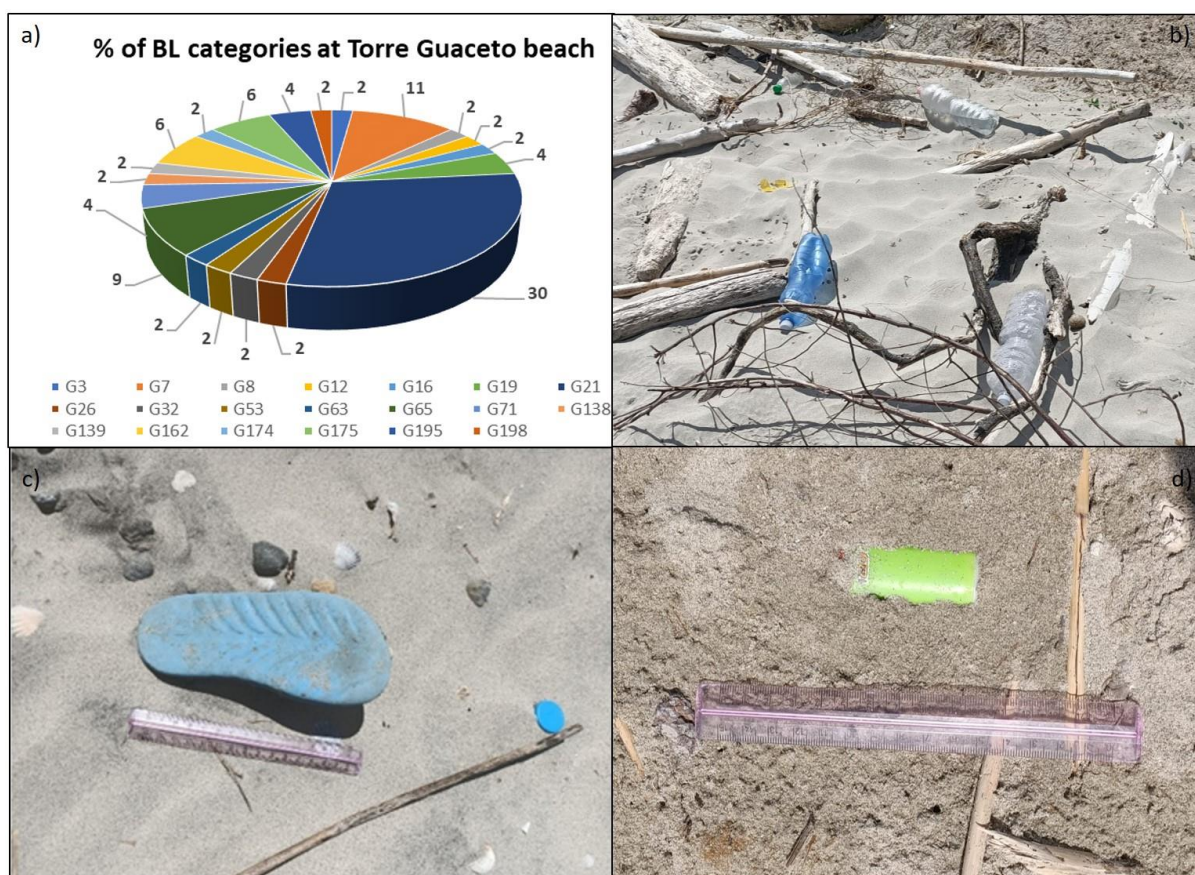


Fig. 9: BL items identified along representative transects at *Torre Guaceto*: a) percentage distribution shown by considering the European code (EC, 2013). b), c), d) examples of objects whose origin is mainly related to anthropogenic recreational activities.

Table 7. Example of polymers and related identified items.

Polymer	Item
Polystyrene	Glasses
Polypropylene	Ropes, plugs
Polyethylene	Bags
Styrene-Butadiene	Tyres
Nylon	Nets
Polyvinyl Chloride	Envelopes
Polyurethane	Sponges
Cellulose Acetate	Cigarettes
Polyethylene Terephthalate	Bottles

To be able to recognize instances of each waste category with high accuracy, a twofold problem needs to be addressed: having objects with the same colors may affect the learning model by making it learn the color and not the actual composition; a similar problem arises for objects with the same 2D shape. Therefore, it would be desirable to integrate different approaches. A possible solution (not cheap, however) could be the use of hyperspectral cameras, to obtain information about polymers. As shown in Table 7, every item is listed according to its own plastic composition (Uhrin *et al.*, 2019). Polymers may make them more distinguishable. For instance, if in a training set envelopes on the ground have

the same pixel intensity as bags, it may be likely that a model would learn to associate them to the same category (that is, “envelope” or “bag”), due to similarities on their 2D shape; in this case, by analyzing other bands out of the visible one, polymer and visual information can be integrated for correctly establishing the class of membership. To this end, Fourier Transform Mass Spectroscopy (FTIR), Raman spectroscopy, and Energy dispersive X-ray are techniques that exploit the information of the reflectance and transmittance information for characterizing the litter chemical composition (Uhrin *et al.*, 2019). As highlighted in Salgado-Hernanz *et al.* (2021), compared to other remote-sensing techniques, the operability of UAV-based surveys results to be more cost efficient. Nevertheless, one of the main limitations is related to the drone flight autonomy, which allows surveying a limited study area. The use of high-resolution multispectral satellite imagery can be considered a useful way to regularly monitor larger areas, thus providing repeatable information. Nonetheless, the pixel spatial resolution of satellite image is lower than the one achievable by using UAV systems. For this reason, further applications will be devoted to exploring possible applications of open access satellite images for BL automatic detection purpose, as already done for floating plastics monitoring (Topouzelis *et al.*, 2019, 2021).

6. Conclusions

This study presents preliminary results obtained through an analysis pipeline in which an automated CNN model was used to detect BL features on UAV images collected along the beaches of *Capitolo*, *Torre Canne*, and *Torre Guaceto*, Apulia. Data augmentation was applied through high-resolution blending technique to extend the data sets. This procedure showed that experiments with symmetric mixtures performed better than homogeneous mixtures when synthetic data with an average of three litter were used. The analysis allowed the definition of a desirable drone flying height at 10 meters and the proposal of a new dataset of BL objects to be made available for further ML applications, on which the instance segmentation experiments showed encouraging outcomes. The results showed an average precision on equally mixed synthetic data of 0.70 and of 0.67 on real data (with a beach litter density of 0.38 items m^{-2} out of 0.66 items m^{-2}) while the maximum precision value (0.83) was obtained on homogeneous synthetic data. The F-score on real data is 96%. A more reliable definition of F-score (normalized on litter density per test area), called DNF-score, was introduced and a set of SOTA methodologies based on this criterion was compared. The study also made it possible to characterize the environmental quality of the investigated beaches, showing that beach users’ activities, along with fishing and sewage discharge, are the main source of BL. The results of this research represent a starting point for the development of a high-performance automatic BL monitoring system. At present, the framework is unable to classify waste types and backgrounds, so it is limited to locating waste (without classes) on a single background type, i.e., sandy beaches. In a future version, the system will be able to recognize different types of coastal backgrounds, including water and green areas, so it will automatically consider only tiles referring to the backshore sector. In addition, at this state, the algorithm has been tested by using UAV images acquired in a context with similar morphodynamic

characteristics. With the aim of progressively enhance the performance of the proposed algorithm, further research activities will be focused on the application of the proposed analysis system in coastal areas with different morphodynamic characteristics (e.g., mesotidal conditions, coarse and very coarse sand and gravel beaches, presence of woody debris). To support the identification of potential litter sources and the definition of the main distribution pathways, further activities will be focused on BL classification in terms of composition material using hyperspectral images. Finally, the results of the BL composition are the starting point for the calculation of specific environmental quality indices whose results represent a suitable set of information for the identification of tailored management strategies. This latter aspect will require the definition of monitoring programs which will be based on the acquisition of data with specific seasonal time frames.

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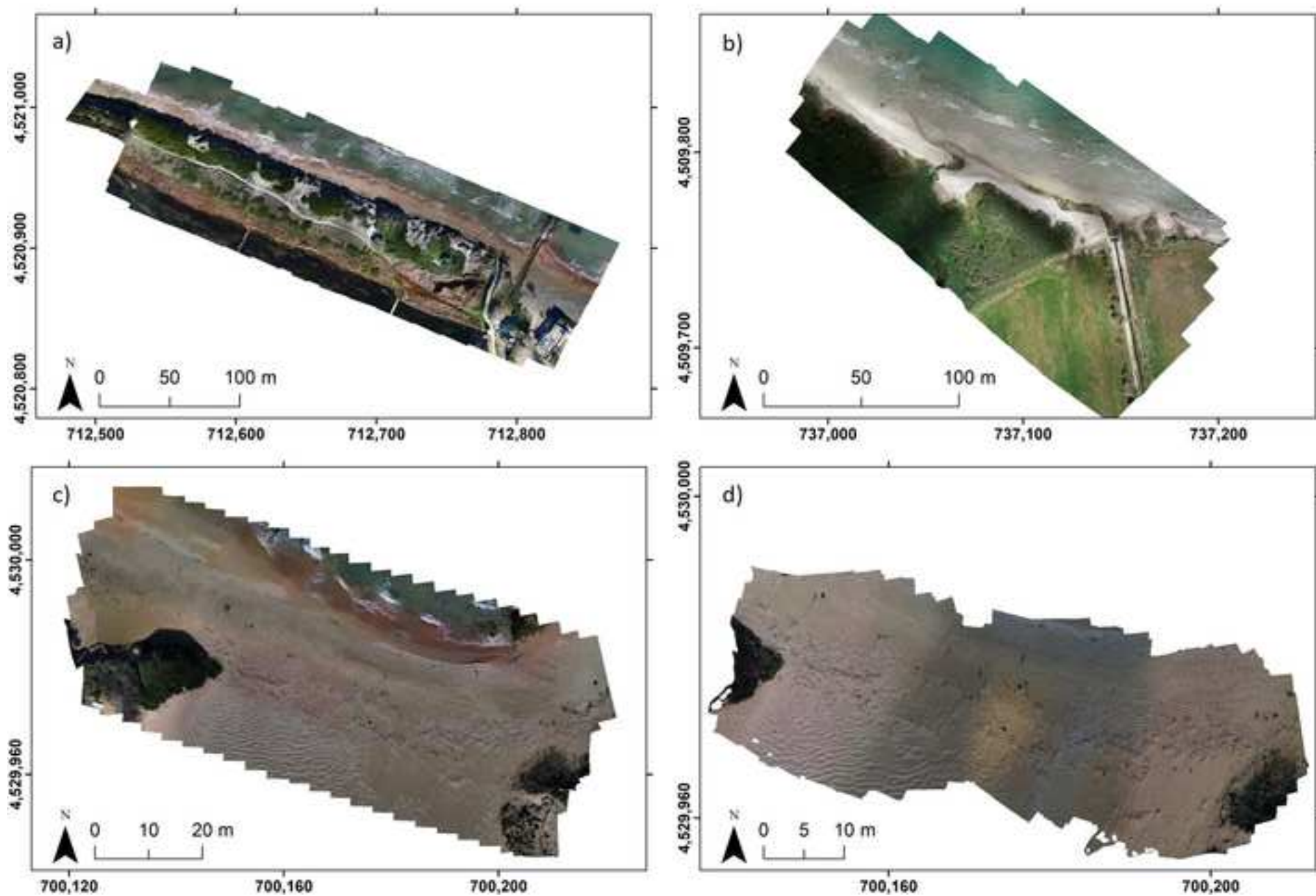
Figure 01

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Figure 05

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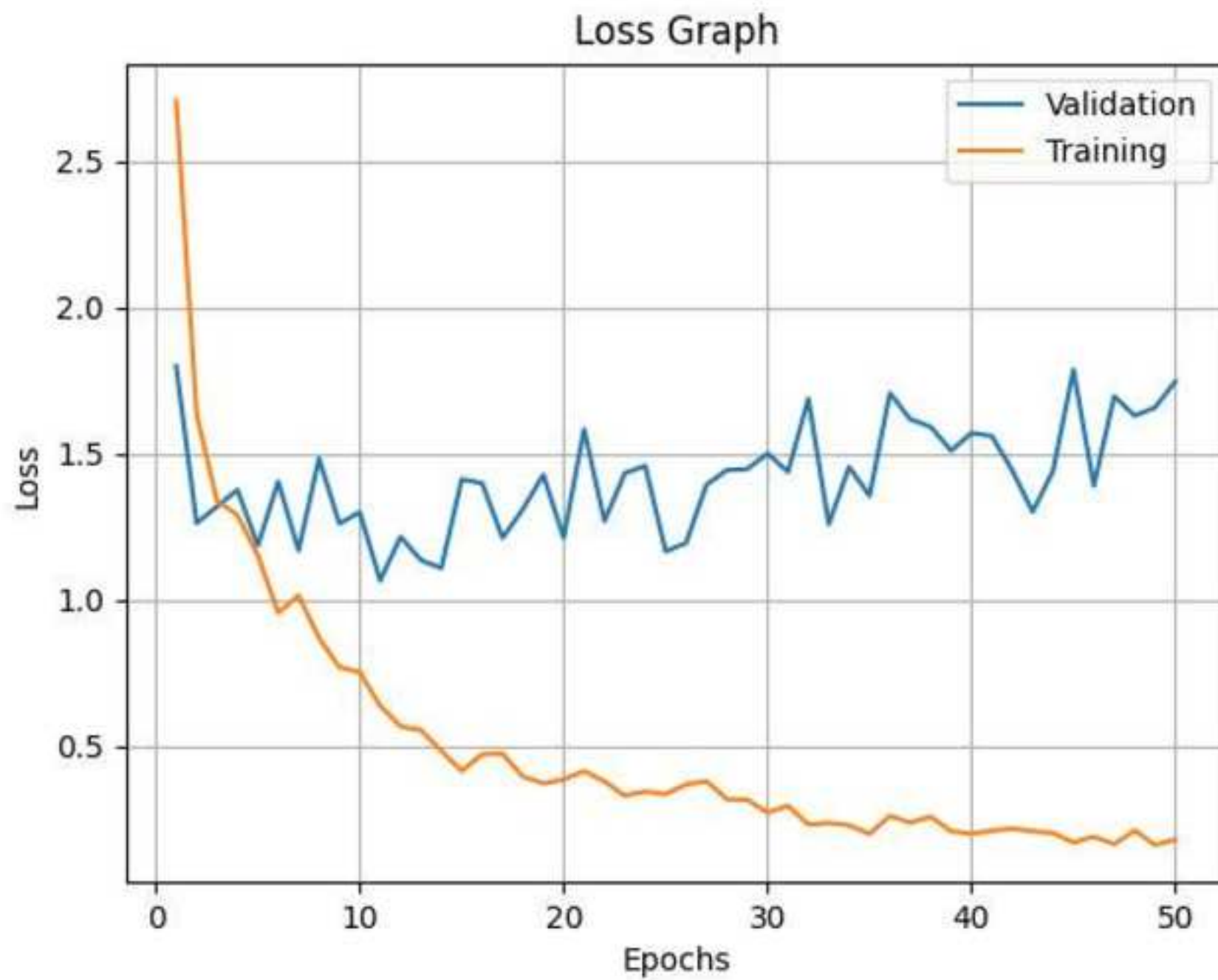
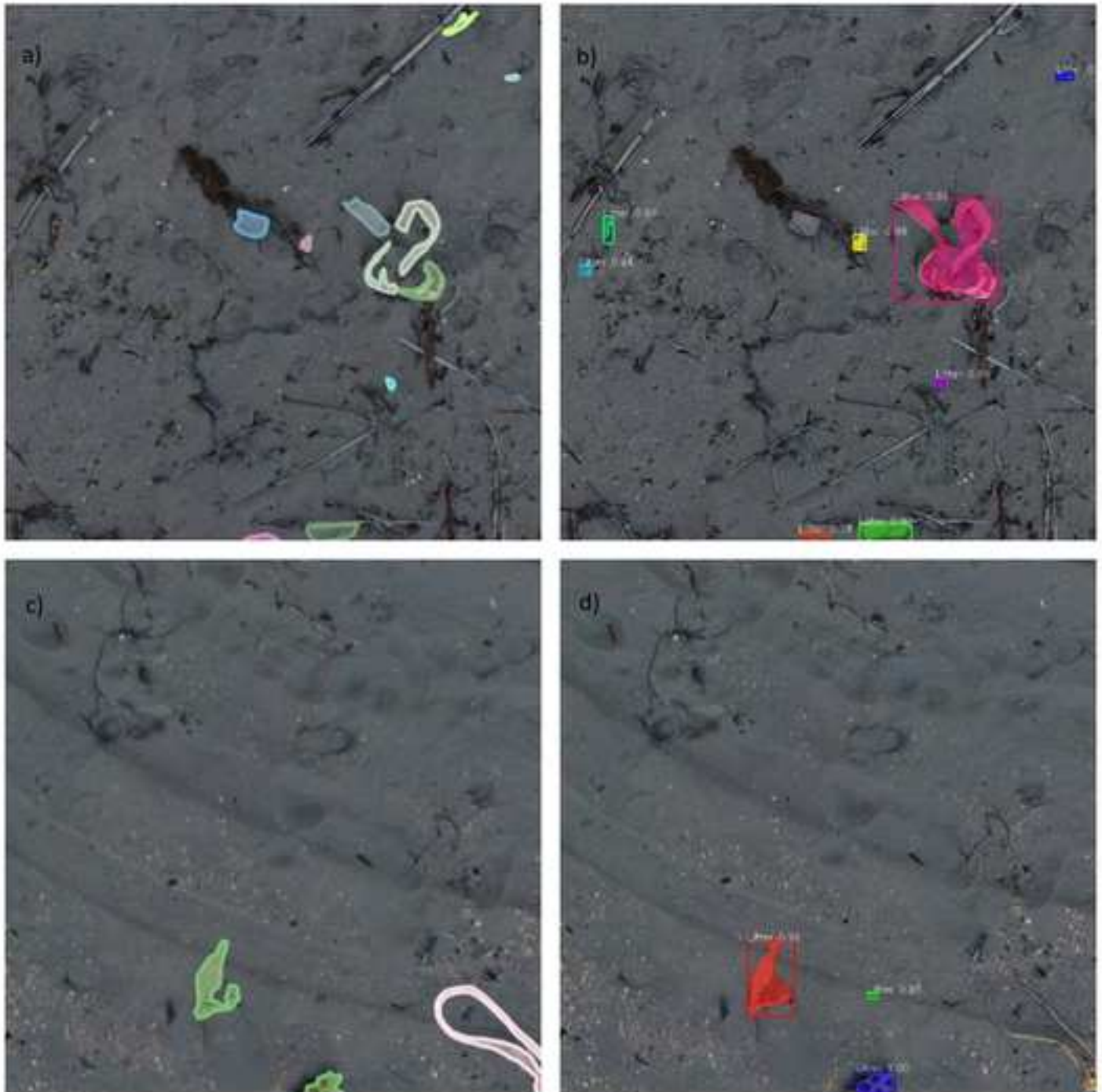
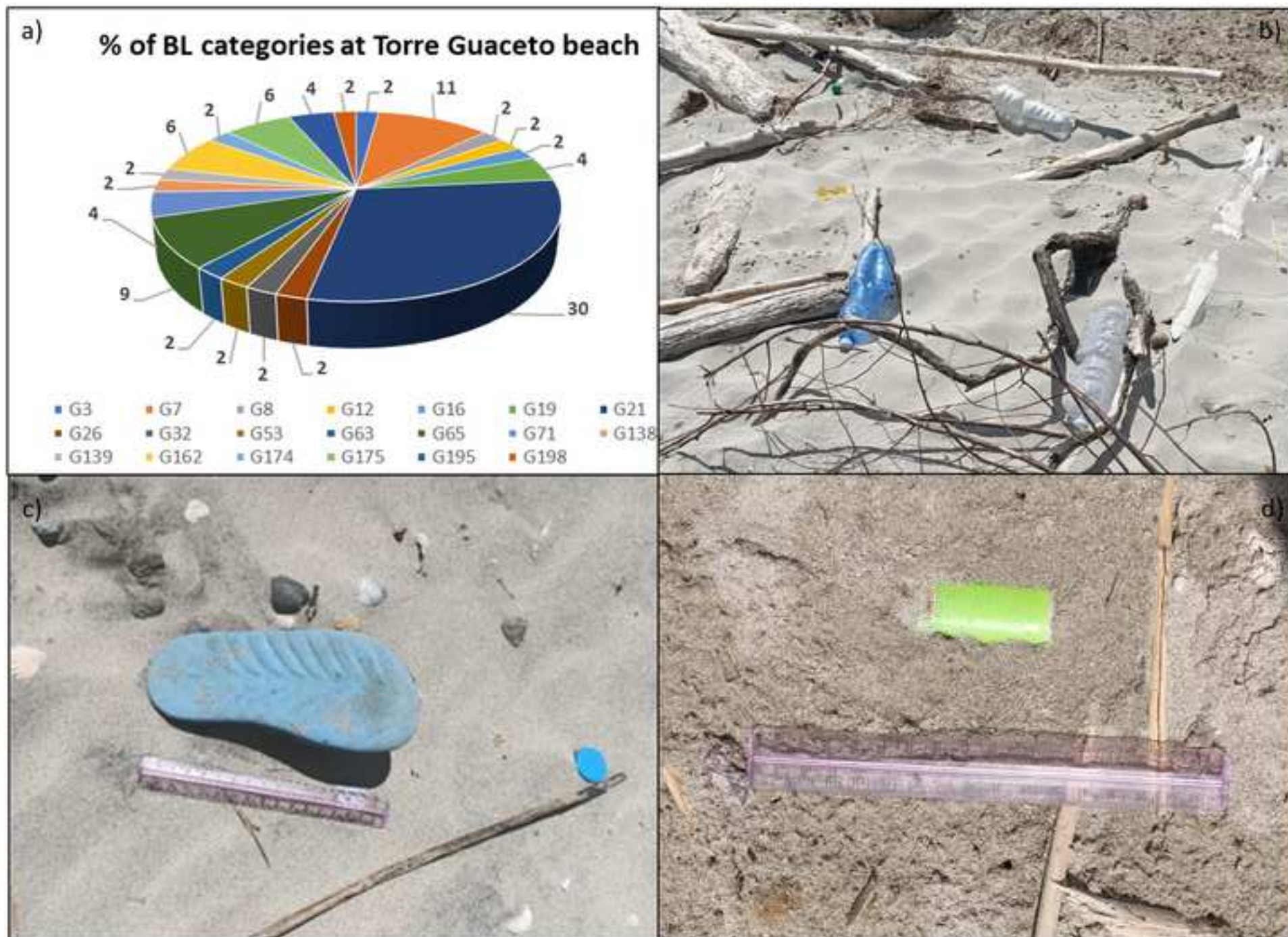


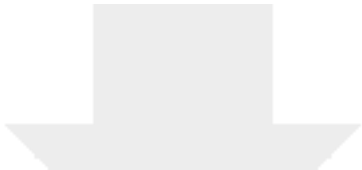
Figure 07

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