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## Data Article

# Anthropogenic litter density and composition data acquired flying commercial drones on sandy beaches along the Saudi Arabian Red Sea



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## ABSTRACT

Anthropogenic litter density and composition data were obtained by conducting aerial surveys on 44 beaches along the Saudi Arabian Coast of the Red Sea [1]. The aerial surveys were completed with commercial drones of the DJI Phantom suite flown at a 10 m altitude. The stills have a resolution of less than 0.5 cm pixels<sup>-1</sup>, hence, litter objects of few centimetres like bottle caps are easily detectable in the drone images. We here provide a subsample of the drone images acquired. To spare the time needed to visually count the litter objects in the thousands of drone images acquired, these were automatically screened using an object detection algorithm, specifically a Faster R-CNN, able to perform a binary classification in litter and non-litter and to categorize the objects in classes. The multi-class classification, however, is a challenging problem and, hence, it was conducted only on the 15 beaches that showed the highest performance after the binary classification. The performance of the algorithm was calculated by visually screening a subsample of images and it was used to correct the output of the Faster R-CNN.

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The described steps allowed to obtain an estimate of the litter density in 44 beaches and the litter composition in 15 beaches. By multiplying the relative abundance of each litter class and the median weight of objects belonging to each class, we obtained an estimate of the total mass of plastic beached on 15 beaches. Possible predictors of litter density and mass are the population and marine traffic densities at the site, the exposure of the beach to the prevailing wind and the wind speed, the fetch length and the presence of vegetation where litter could get trapped. Making such raw data (i.e. litter density and composition and their predictors) available can help building the base for a robust global estimate of anthropogenic litter in coastal environments and it is particularly important if data regards an understudied region like the Arabian Peninsula. Moreover, we share a subsample of the original drone images to allow usage from stakeholders.

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## Specifications Table

Subject	Pollution
Specific subject area	Beach anthropogenic litter and, specifically, macroplastics
Type of data	Table Image
How data were acquired	Data acquisition: aerial surveys using a drone and automatic object detection on drone images using a Faster R-CNN. Hardware and software for aerial surveys: DJI Phantom 3 Advanced and 4 Professional coupled with UgCS v.2.10 software and DJI GS Pro-app, respectively. Software for image processing (photogrammetry): PhotoScan Professional v.1.3.0 Software for Faster R-CNN: PyCharm 2019.1.3 Software for extraction of population and marine traffic density data from raster layers: QGIS v.2.18.14
Data format	Raw Analyzed
Parameters for data collection	Sites were randomly chosen among sandy beaches along the Saudi Arabian Red Sea coast. The sandy beaches had to be reachable by land or sea or had to be within the transmission range of the drone. Each drone image tested was previously cut in 12 portions to reduce the computing effort and the portions were seawater was framed for more than 3/4th of the area were excluded before automatic object detection.
Description of data collection	The drone was flown at 10 m altitude with the camera gimbal at nadir point to acquire stills of the beach. Litter objects on the drone images were automatically counted using a Faster R-CNN, an object detection algorithm. The sensitivity and positive predictive value of the Faster R-CNN were estimated by visually counting objects on a subsample of images and then used to correct the counts obtained from the algorithm. By dividing corrected counts per cumulative area of the drone pictures we estimated the litter density. A multi-class Faster R-CNN was applied to obtain litter composition data.
Data source location	Institution: King Abdullah University of Science and Technology City/Town/Region: Thuwal Country: Saudi Arabia Latitude and longitude (and GPS coordinates, if possible) for collected samples/data: From 18.1 to 29.2° N; from 34.5 to 41.6° E.

(continued on next page)

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	Primary data sources: Population density data: CIESIN, 2018. Gridded Population of the World, Version 4 (GPWv4): Population Density, Revision 11. Marine Traffic density data: <a href="https://www.marinetraffic.com">https://www.marinetraffic.com</a> Wind speed data: <a href="https://power.larc.nasa.gov/">https://power.larc.nasa.gov/</a>
Data accessibility	The dataset (table) is with the article, drone images are on a public repository Repository name: Mendeley Data Direct URL to data: <a href="http://dx.doi.org/10.17632/gpdsntb3y6.1">http://dx.doi.org/10.17632/gpdsntb3y6.1</a>
Related research article	Co-submission of: Martin, C., Zhang, Q., Zhai, D., Zhang, X., Duarte, C.M. Enabling a Large-Scale Assessment of Litter along Saudi Arabian Red Sea Shores by Combining Drones and Machine Learning, <i>Environmental Pollution</i> , 277, 116730.

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## Value of the Data

- Despite the high throughput of papers on beach litter assessments, it is not common practice to publish raw data [2]. However, raw data can be useful, especially in combination with other datasets, to unveil patterns and anomalies otherwise hidden by a small sample size and the local scale of the surveys.
- The dataset and the drone images can be of interest to a broad audience, including marine and environmental scientists, policymakers and the general public.
- The original drone images we provide can be used as training and testing material for other object detection algorithms or to extract features other than beach litter (e.g., vegetation, animal prints, nests).
- The dataset can be used as a source of data for a global beach litter assessment, which is limited by availability of raw data, or for waste management purposes in the region.
- The methodology used to compile this dataset is relatively young. Hence, the dataset provides useful guidelines for those using the same method and thus promotes comparability of data.
- The dataset provides litter density estimates in the Arabian region, which is understudied [2].

## 1. Data Description

We provide data on 44 beach litter surveys conducted on sandy beaches along the Saudi Arabian Red Sea coast [1]. We applied an emerging methodology based on drone surveys to efficiently survey large areas in a short time coupled with the automatic detection of anthropogenic litter objects on the drone images by use of a machine learning algorithm [3–5].

The algorithm we developed can also be used as a multi-class classifier, a task that, however, involves a higher level of difficulty compared to a generic object detection [1]. For this reason, the automatic classification of litter objects was applied only on the images of the 15 beaches that resulted in the best performance of the algorithm when used for object detection.

The accumulation of anthropogenic litter on beaches is generally determined by the vicinity of sources (e.g. human settlements and shipping activities), by the circulation of winds and currents, which are carriers of litter, and by the presence of potential litter retainers like the beach vegetation [3,6,7]. Hence, for completeness, for each of the 44 surveyed beaches, we provide data on possible drivers of litter distribution too.

We provide the complete dataset and the original drone images of 5 beaches among those that resulted in the best performance of the object detection algorithm [8].

The dataset is provided as a Microsoft Excel Workbook, including 2 sheets:

**Sheet 1** reports, for each of the 44 surveyed beaches, the metadata of the beach surveyed (i.e. geographic coordinates, sampling date), specifics on the aerial surveys (i.e. the drone model used, the area covered and the number of images acquired), the output and performance of the machine learning algorithm when used for object detection, the estimates of litter density and the data on possible predictors of litter density distribution

(i.e. population and marine traffic density, exposure of the beach to the prevailing wind, wind speed, fetch length and vegetation coverage).

**Sheet 2** reports, for each of the 15 beaches tested with the multi-class classifier, the output of and performance of the classifier for each of 14 categories and the estimated anthropogenic litter composition.

The drone images are available in Mendeley Data at the following link: <http://dx.doi.org/10.17632/gpdsntb3y6.1>.

## 2. Experimental Design, Materials and Methods

We surveyed 44 sandy beaches along the Saudi Arabian Red Sea coast to estimate anthropogenic litter density and composition [1]. Surveys took place from March 2017 to April 2018 and spanned over 11° of latitude (Sheet 1). The beaches were chosen by searching for sandy coasts on the satellite images of the Red Sea available in Google Maps [9]. The beaches were hence dominated by sand with occasional rocky outcrops and/or low cliffs, and were located either on islands or along the main shore. Despite the chosen beaches were all reachable either by land or sea, the aerial survey can be completed also without accessing the beach as long as the area of interest is within the radius needed to pilot the drone.

The drones used are commercial drones of the DJI Phantom suite. Specifically, the DJI Phantom 3 Advanced (Adv) was used to complete the surveys in March 2017, while later we purchased a DJI Phantom 4 Professional (Pro) to complete the surveys from November 2017 to April 2018. Due to legal restrictions on the use and import of drones in Saudi Arabia, we initially used the Phantom 3 Adv, being available to us, and switched to a Phantom Pro-once government permits to import the new model became available. Both drone models are quadcopters, hence do not require large take-off platforms, they are lightweight ( $< 1.5$  kg), thus easy to carry in the field, and they are relatively cheap ( $< 2000$  USD). The DJI Phantom 4 Pro-has a longer battery lifetime than the DJI Phantom 3 Adv (30 min instead of 23 min), sensors for obstacle avoidance, a longer transmission distance with the controller (7 km instead of 5 km) and it is coupled with a higher resolution camera (20 MP instead of 12 MP). To survey the beaches, we flew the drones in the automated mode, in order to maintain a constant height and speed of the aircraft and in order to acquire stills at regular time intervals. The automatic flights were planned using UgCS v.2.10 [10] and the DJI Ground System (GS) Pro-app [11] when flying the DJI Phantom 3 Adv and 4 Pro, respectively. When planning a flight with UgCS, the maximum transmittance radius between controller and aircraft drops to 500 m. The missions were designed to cover, by mean of parallel transects, the entire area between the swash zone, where waves break on the beach, and the dunes and they were planned in order to consume only one battery for each beach. The drones were flown at a 10 m altitude with a nadir pointing camera, which results in a footprint of  $13 \times 17$  m and a resolution of  $0.5 \text{ cm pixel}^{-1}$  for images acquired with the DJI Phantom 3 Adv and a  $9 \times 16$  m footprint and  $0.3 \text{ cm}^{-1}$  resolution for those acquired with the DJI Phantom 4 Pro. The altitude was chosen to be able to detect, on the drone images, objects down to 2.5 cm, the lower limit of the macro-litter. The aircraft speed was kept at approximately  $2 \text{ m s}^{-1}$  and stills were acquired every 2 s, which allowed to obtain images with a 70% front and side overlap. Thanks to the overlap, drone images, that are also georeferenced, can be combined into an orthomosaic, which we produced in PhotoScan Professional v.1.3.0 [12], also used to measure the area of the beach covered by the survey (Sheet 1).

Since not all the objects are visible from the drone images (e.g. small objects with undefined shapes and items half-buried in the sand or hidden by vegetation), a ground truth assessment is needed to account for the underestimation. Briefly, after the drone survey on a beach was completed, a section of the beach was delimited and objects in it were counted and classified. Later, the drone was flown again to take a picture of the delimited section at a 10 m altitude. This allows to estimate the proportion of objects visible in a 10 m-drone image compared to those effectively present on the beach. In the dataset, we provide the average value of the proportion

of objects detectable from drone images acquired with the DJI Phantom 4 Pro, obtained after conducting 12 ground truth assessments [1] and the value for drone images acquired with the DJI Phantom 3 Advanced obtained from Martin et al. [3].

The set of images acquired during the drone survey covering the entire beach area were automatically screened to detect and classify anthropogenic litter objects. To this end, we developed a machine learning algorithm, specifically a Faster R-CNN. In an automatic detection of objects, the image, in this case the one acquired with the drone, is entirely scanned by mean of a multi-scale window, with adaptable size and frame ratio, hence, able to detect objects of different dimensions. While scanning, visual features are extracted to provide a representation of the image portion framed by the sliding window. Based on the visual features, the framed portion is classified in 'positive' (i.e. the object of interest) or 'negative' (i.e. the background), when doing a binary classification, or in types, when doing a multi-class classification [13]. A Faster R-CNN is composed of two networks, a Regional Proposal Network (RPN) that generates boxes around possible objects of interest and provides the probability that the framed object is a 'positive', and the detection network that classifies the objects proposed by the RPN as 'positive' into types [14].

However, the algorithm needs to be first trained to distinguish the feature of the objects of interest from the background or from other objects. The training occurs providing examples of the objects of interest, in our case anthropogenic litter items. To do so, we selected the drone images of two beaches that have uniform backgrounds (station n. 30 and 40, Sheet 1), which facilitates the extraction of the object visual features. Indeed, the two selected beaches do not have vegetation, rocks or other natural elements and the contrast between the litter objects and the bare background is thus enhanced. The images of the two beaches are available at <http://dx.doi.org/10.17632/gpdsntb3y6.1>. Since each drone image sizes 6 MB, the images were first cut in 12 non-overlapping portions each to reduce the computing effort while training the algorithm. From the high throughput of portions obtained cutting the hundreds of drone images of the two beaches, we selected 750 portions and we labelled all the litter objects they contained, by using the freely-available software Labellmg [15]. We labelled 1608 objects by classifying them in 14 categories [1] (Sheet 2). Labellmg produces one .xlm file for each labelled portion of drone image and each .xlm file contains the cartesian coordinates of the litter objects in the corresponding image portion and the label assigned to them. The portions of the drone images and the corresponding .xlm file are both used to train the algorithm that learns how to distinguish anthropogenic litter items from the background. We used the toolkit API in Tensorflow as implementation medium and we set the learning rate to 0.0001. The batch size was 100 and training epochs were 3000. We used cross entropy loss and Adam optimizer as cost function and optimizer, respectively.

Once trained, the algorithm was applied to detect and hence count litter objects on the pictures of all the 44 beaches, including stations 30 and 40, since not all their drone images were used for the training phase. The drone images of a subsample of stations (i.e., 21, 23, 30, 40 and 44) are available at <http://dx.doi.org/10.17632/gpdsntb3y6.1>. To reduce the computing effort, all the drone images were cut each in 12 non-overlapping portions and the portions that were framing seawater for more than 3/4th of their area were excluded since the focus of the study is on beach litter. The Faster R-CNN was applied on the set of images of one beach at a time in order to obtain, as output, the total number of litter objects in each beach. Indeed, the algorithm first draws boxes around the objects that it has classified as 'positive' and then counts them.

To estimate the performance of the algorithm, we randomly selected 10 drone images per beach and we manually counted the true and false positives and the false negatives in the corresponding cut portions. The true positives are the objects that were framed as 'positive' by the algorithm and that are indeed anthropogenic litter objects, the false positives are background or natural objects that were wrongly proposed as 'positive' by the algorithm and the false negatives are anthropogenic litter objects that were not considered by the algorithm. True and false positives and false negatives are used to calculate performance parameters like sensitivity, that indicates the fraction of anthropogenic litter objects present in the image and that the algorithm

was able to detect, the Positive Predictive Value (PPV), which is the fraction of 'positives' that are actually anthropogenic litter objects, and the F-score which is a measure of the overall goodness of the Faster R-CNN. These are calculated as follows:

$$\text{Sensitivity} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

$$\text{Positive Predictive Value (PPV)} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

$$F - \text{score} = \frac{2 * \text{Sensitivity} * \text{PPV}}{\text{Sensitivity} + \text{PPV}}$$

If, for example, Sensitivity is 60%, it means that the algorithm can detect 60% of the anthropogenic objects present in the drone images, hence, it is underestimating the number of objects. If the PPV is 60% however, it means that only 60% of the objects that were counted as 'positives' by the algorithm are indeed anthropogenic objects, hence the algorithm is, in this case, overestimating. The calculated Sensitivity and PPV of the 10 drone images were averaged and used to correct the output of the algorithm for each beach  $i$  as follows:

$$N. \text{ of objects (corrected)}_i = \frac{N. \text{ of detected objects}_i * \overline{PPV}_i}{\overline{Sensitivity}_i}$$

where  $\overline{PPV}_i$  and  $\overline{Sensitivity}_i$  are the mean values of PPV and Sensitivity calculated for the 10 randomly selected drone images per beach and provided in Sheet 1.

This value, however, is an estimate of the number of objects detectable in a drone image, which, as we explained before, is an underestimation due to the challenge of seeing, in a drone image, the smaller and half-hidden objects that are on the beach. To correct for this underestimation, the value above has to be further divided for the proportion of objects on the beach that can be seen in a drone image, proportion that we obtained with the ground truth assessment (Sheet 1). The whole calculation is provided as formula in Sheet 1, Column O. The corrected number of objects obtained as described is then divided for the total area of the drone images of each beach in order to obtain the estimate of the anthropogenic litter density per beach (Sheet 1). The total area of the images is obtained multiplying the number of drone images per the image footprint, namely the area of beach covered by each image. It should be noted that the total area of the images is much larger than the area of beach surveyed because of the 70% side and front overlap between acquired images.

The calculated mean F-score value per beach (Sheet 1) was used to select the best performing beaches and apply the multi-class classifier. We selected the 15 beaches with the best F-score. In this case, the output of the Faster R-CNN is the number of objects per each category per beach. The algorithm draws boxes around the objects that it proposes as 'positives' and labels them with the name of one of the 14 categories, listed in Sheet 2. We calculated the performance of the multi-class classifier similarly to what done for the binary classification. We randomly selected 10 drone images per beach and counted the true and false positives and false negatives per each category and calculated Sensitivity and PPV per category per beach. We had to randomly select 20 drone pictures for stations n. 21, 23, 26, 34, 38 and 40 because of the scarcity of objects in the first 10 images that did not allow to calculate Sensitivity and PPV for each category. However, some categories were still under-represented in the selected images and it was not possible to calculate the values of Sensitivity and PPV of those categories for some of the beaches. In that case, we averaged the available values of Sensitivity and PPV of those categories across beaches and reported the average instead in Sheet 2. Sensitivity and PPV for each category and beach were used to correct the output of the Faster R-CNN as follows:

$$N. \text{ of objects (corrected)}_{j,i} = \frac{\frac{N. \text{ of detected objects}_{j,i} * \overline{PPV}_{j,i}}{\overline{Sensitivity}_{j,i}}}{P(\text{detection})_j}$$

Where  $i$  indicates the beach,  $j$  the category,  $\overline{PPV}_{i,j}$  and  $\overline{Sensitivity}_{i,j}$  are the mean values of PPV and Sensitivity per category per beach.  $P(detection)_j$  indicates the probability of detecting the beach litter objects of a category  $j$  from a drone image, obtained from the ground truth assessment and provided in Sheet 2.

Once we obtained the litter density and composition at a beach, we could estimate the stocks ( $s_i$ ) of plastic litter in  $g\ m^{-2}$ , as follows:

$$s_i = \Sigma (d_i * p_{j,i} * \tilde{w}_j)$$

Where  $\Sigma$  is the sum,  $d_i$  is the density of all litter objects (items  $m^{-2}$ ) in each beach  $i$ ,  $p_{j,i}$  is the relative abundance of objects of each category  $j$  in each beach  $i$  and  $\tilde{w}_j$  is the median weight (g) of objects of each category  $j$ , excluding categories of non-plastic objects (i.e. “glass”, “metal” and “anthropogenic wood”). We concentrated on plastic litter only being the most abundant on the surveyed beaches [1] and because the median weights of non-plastic objects was not available. The median weights of plastic objects from each of the 14 categories were obtained from Martin et al. [16]. In Sheet 1, we provide the stock values ( $s_i$ ) at the 15 beaches for which litter composition data were estimated.

In Sheet 1, we provide data on possible predictors of anthropogenic litter density distribution on sandy beaches. Population density data were obtained from the NASA Socioeconomic Data and Applications Center (SEDAC) website [17]. We specifically downloaded the raster layer of Population Density, v4.11 (2000, 2005, 2010, 2015, 2020) and we extracted, by using the Point Sampling Tool plug-in of QGIS v.2.18.14 [18], the population density values from 2015 to 2020 at the 44 sampling points, at 3 resolutions, i.e. 5, 30 and 110  $km\ pixel^{-1}$ . We then averaged the values from 2015 to 2020 at each sampling point and resolution to obtain an estimate of the population density in 2017–2018, when the surveys took place.

We obtained a color-coded map of marine traffic densities in the Red Sea for year 2017 from <https://www.marinetraffic.com> [19]. By using the Zonal Statistics plug-in QGIS, we extracted the mean RGB values from the marine traffic density map in a radius of 5, 30 and 110 km from the sampling points. To convert the RGB values to marine traffic density values (in number of routes  $km^{-2}\ y^{-1}$ ), we used the color bar of the density map. Specifically, we compared the marine traffic density values provided in the map color bar and the corresponding values of the RGB spectra and we found that the blue values of the RGB spectra are exponentially proportional to the marine traffic density values. Therefore, the blue values of the RGB spectra at the 44 sampling points were converted accordingly to number of routes  $km^{-2}\ y^{-1}$  at the 3 resolutions (Sheet 1).

Wind speed data were obtained from <https://power.larc.nasa.gov/> [20]. For each sampling point, we downloaded the monthly wind speed ( $m\ s^{-1}$ ) at 10 m altitude for the year preceding the sampling date and the daily wind speed data for the 30 days preceding the sampling date. The monthly wind speed data were averaged to provide an estimate of the wind speed in the year preceding the sampling, while the daily speed data were averaged to provide an estimate of the wind speed in the month and in the week preceding the sampling (Sheet 1). We provide also the wind speed value on the day of the sampling for each sampling point (Sheet 1).

The fetch length, the linear distance travelled by winds without encountering obstacles, was measured in Google Maps for each sampling point as the perpendicular linear distance between the beach line and the closest land mass.

The exposition of the beach is provided in Sheet 1 as cardinal point and deviance angle to the prevailing wind. Particularly, for each beach, we indicated the closest between 8 cardinal points (N, NE, E, SE, S, SW, W, NW). For instance, if the beach faces NNE, we indicated either N or NE as the closest cardinal point, depending on the angle of the exposure. If the beach is not linear (e.g. station n. 7) and has two exposures, we indicated both. The deviance angle, instead, is calculated as the angle between the prevailing wind and the  $90^\circ$  angle to the beach line. In winter months, when the surveys occurred, the prevailing wind comes from NW. Therefore, deviance angles between  $0$  and  $90^\circ$  mean that the beach is exposed to the prevailing wind, while deviance angle  $> 90^\circ$  mean that the beach is sheltered.

The relative vegetation coverage is obtained as the area covered by vegetation divided per area of the beach surveyed, both measured on the orthomosaics of the beaches using Photoscan Pro.

## Ethics Statement

This work did not involve use of human subject, animal experiments or social media data.

## CRedit Author Statement

**Cecilia Martin:** Conceptualization, Methodology, Investigation, Validation, Writing - Original draft preparation; **Qiannan Zhang:** Software, Writing - Reviewing and Editing; **Dongjun Zhai:** Software, Writing - Reviewing and Editing; **Xiangliang Zhang:** Supervision, Funding acquisition, Writing - Reviewing and Editing; **Carlos M. Duarte:** Conceptualization, Supervision, Funding acquisition, Writing - Reviewing and Editing.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships which have or could be perceived to have influenced the work reported in this article.

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## Supplementary Materials

Supplementary material associated with this article can be found in the online version at doi:[10.1016/j.dib.2021.107056](https://doi.org/10.1016/j.dib.2021.107056).

## References

- [1] C. Martin, Q. Zhang, D. Zhai, X. Zhang, C.M. Duarte, Enabling a Large-Scale Assessment of Litter along Saudi Arabian Red Sea Shores by Combining Drones and Machine Learning, *Environ. Pollut.* 277 (2021) 116730.
- [2] C. Serra-Gonalves, J.L. Lavers, A.L. Bond, Global review of beach debris monitoring and future recommendations, *Environ. Sci. Technol.* 53 (21) (2019) 12158–12167.
- [3] C. Martin, S. Parkes, Q. Zhang, X. Zhang, M.F. McCabe, C.M. Duarte, Use of unmanned aerial vehicles for efficient beach litter monitoring, *Mar. Pollut. Bull.* 131 (2018) 662–673.
- [4] L. Fallati, A. Polidori, C. Salvatore, L. Saponari, A. Savini, P. Galli, 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 (2019) 133581.
- [5] G. Gonalves, U. Andriolo, L. Pinto, F. Bessa, Mapping marine litter using UAS on a beach-dune system: a multidisciplinary approach, *Sci. Total Environ.* 706 (2020) 135742.
- [6] UNEP (2005). Marine litter: an analytical overview. UNEP.
- [7] M. Bergmann, L. Gutow, M. Klages, *Marine Anthropogenic Litter*, Springer Nature, 2015.



- [8] C. Martin, Q. Zhang, D. Zhai, X. Zhang, C.M. Duarte, Drone images of sandy beaches and anthropogenic litter along the Saudi Arabian Red Sea, Mendeley Data V1 (2021), doi:10.17632/gpdsntb3y6.1.
- [9] Satellite images of the Saudi Arabian Red Sea coast, google maps, accessed in 2017 and 2018, <https://www.google.com/maps>.
- [10] Ground station software, UgCS v.2.10 (2017), <https://www.ugcs.com>.
- [11] DJI Ground Station (GS) Pro (2018), <https://www.dji.com/ground-station-pro>.
- [12] Agisoft photoscan professional (Pro) v.1.3.0 (2018), <https://www.agisoft.com>.
- [13] Z.Q. Zhao, P. Zheng, S.T. Xu, X. Wu, Object detection with deep learning: a review, *IEEE Trans. Neural Netw. Learn. Syst.* 30 (2019) 3212–3232.
- [14] S. Ren, K. He, R. Girshick, & J. Sun (2015). Faster r-cnn: towards real-time object detection with region proposal networks, in: *Advances in neural information processing systems*. pp. 91–99.
- [15] Tzatalin. Labellmg. Git code (2015), <https://github.com/tzatalin/labellmg>
- [16] C. Martin, H. Almahasheer, C.M. Duarte, Mangrove forests as traps for marine litter, *Environ. Pollut.* 247 (2019) 499–508.
- [17] CIESIN (2018). Gridded population of the world, version 4 (GPWv4): population density, revision 11, <https://sedac.ciesin.columbia.edu/data/set/gpw-v4-population-density-rev11>.
- [18] QGIS v.2.18.14 (2017), <https://www.qgis.org/en/site>.
- [19] Density map of 2017, accessed in April 2020, <https://www.marinetraffic.com>.
- [20] Wind Speed At 10m altitude from MERRA-2 (The Modern-Era Retrospective analysis for research and applications), an Assimilation model of the NASA's Global Modeling and assimilation office (GMAO), accessed in April 2020, <https://power.larc.nasa.gov/data-access-viewer/>