# Section II. Survey data analysis and publication

## 2.1 Data analysis

### 2.1.1 Detection of litter from images

(1) Manual detection
Manual detection of litter from images requires less expertise and skill than automated detection. In previous studies (Deidun et al. 2018; Andriolo et al. 2020; Escobar-Sánchez et al. 2021; Andriolo et al. 2021; Taddia et al. 2021), the images displayed on the monitor screen were zoomed in and beach litter was visually counted, such as left-to-right and top-to-bottom, marking and adding litter classification information. In the case of videos taken with a stationary camera on a river, the images are cut out from the video and the number of pieces of litter, the number of pixels of litter, and the classification are recorded for each image. In addition to using dedicated application software, it is also possible to cut out images from videos manually using video or image editing software, etc., but the latter method is inefficient and the workload is large, so it is not recommended in practice.
In addition, the use of annotation tools is also effective for manually measuring the area covered by litter and the number of items of litter in an image. Annotation tools are applications that create training data for machine learning, but they can also be used for manual detection of litter from images because they allow you to manually surround and tag objects in an image. There are several annotation tools that are available for free, and it is possible to use programming to calculate the number of pixels from the output data that has been used to mark out the area covered by litter using an annotation tool. In the demonstration experiment (Appendix 2), the litter covered area was marked out using the annotation tool Labelme (the Massachusetts Institute of Technology), and the number of pixels was calculated from the output data (extension: json) using Python. For the code to count the number of litter pixels in the output data surrounded by Labelme, please refer to the Ministry of the Environment website (BeachLitterCounter, https://www.env.go.jp/page_00929.html).
Note that previous research has shown that the detection rate for manual detection can vary depending on various factors (see Table 2.1.1).

**Table 2.1.1. Several factors related to detection rates**

| Factor [*1,2] | Note |
|---|---|
| Image resolution (GSD) | 200 pix/m (GSD = 0.5 cm) is a good solution to map plastic litter. [*3] RGB cameras with the highest possible resolution can make the GSD smaller. |
| Experience of the operator | For example, operator training should be required in order to improve their confidence with UAV-based mapping. [*3] |
| Image background | Sand, vegetation, footprints, etc. [*1] |
| Conditions of litter | Fully visible, partially buried, broken, placed close to each other etc. [*1,2] |
| Litter size | Larger items (2.5 cm <) are easier to find. [*2] |
| Litter color | For example, white, black, brown, and transparent are harder to find, while unnatural colors on the beach such as yellow, blue, pink, orange, red, and bright green are easier to find. [*2] |
| Litter shape | String/cord, lines, and squares are harder to find. [*2] |
| Environmental conditions | Coastal hinterland vegetation, weather etc. |

Notes:
*1 Andriolo et al. 2020b
*2 Escobar-Sánchez et al. 2021
*3 Taddia et al. 2021

Some studies used other information to assist with litter detection. For example, multispectral data (near-infrared (NIR) and Normalized Difference Vegetation Index (NDVI)) were used to distinguish vegetation from AMD (Taddia et al. 2021). There is also a research case study using a mobile GIS application to confirm beach litter of uncertain category in manual image screening, the result of which was edited on the mobile application during in-situ visual inspection, updating the item attributes with the category/material and color detected in-situ (Andriolo et al. 2020).

The previous studies used existing manual survey item lists (e.g., the OSPAR objects list (OSPAR Commission, 2010) and the Master List of Categories of Litter Items (European Commission, 2013)) to classify beach litter.

(2) Automated detection
If the shooting data is a video, it is necessary to extract a still image from the video and then perform automated detection.
There are two main automated data analysis methods for detecting litter from images: Object detection by bounding box (hereafter, shortened as object detection), which detects and classifies objects by bounding box, and image segmentation, which classifies objects by pixel unit of the image.

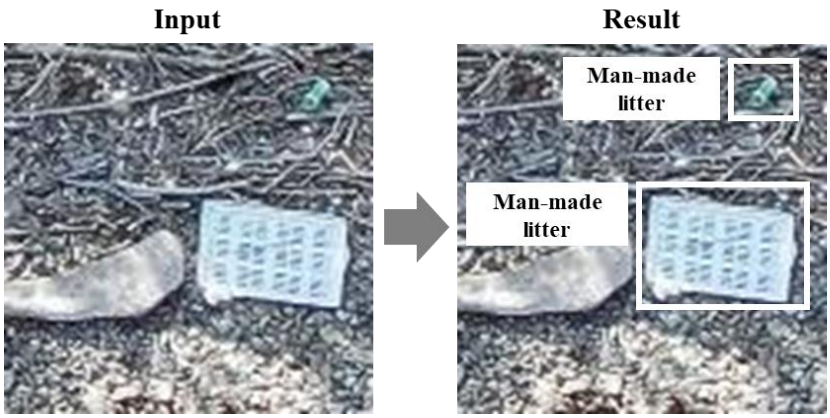


**Figure 2.1.1. Object detection**

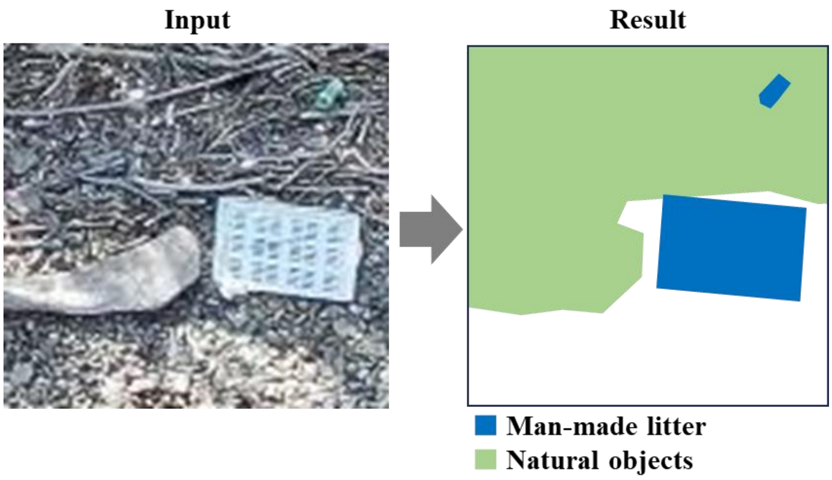


**Figure 2.1.2. Image segmentation**

Considering the characteristics of each method, the data analysis method should be selected based on the status of litter. Object detection can estimate the total number of litter pieces by detecting each individual piece of litter. It is suitable for cases where the pieces of litter are not close to each other, because the boundary of each piece of litter is clear enough to identify each individual piece.
Since semantic segmentation, a type of image segmentation can detect litter at the pixel level, its area [$m^2$] and volume [$m^3$] can be estimated by combining it with aerial images taken by UAVs and

orthorectified. This method is suitable for cases where litter is accumulated, and it is difficult to identify individual items (see Appendix 1).

Instance segmentation, which is also a type of image segmentation, can estimate the total number of pieces of litter like object detection and can detect litter at the pixel level, its area [$m^2$] and volume [$m^3$] can be estimated by using orthoimages like semantic segmentation.

For both object detection and image segmentation, image analysis techniques based on deep learning (hereinafter referred to as deep learning models) have recently been applied (e.g., Kako et al. 2020; Hidaka et al. 2022; Martin et al. 2021). The development of deep learning models requires expertise, a high-end GPU-enabled computer, and the preparation of training data (annotation work) necessary to train the models.

In particular, training data preparation is a time-consuming task and requires many images. In the case of Sugiyama et al. (2022), it took about two months and 15 staff members to prepare a Beach Litter Dataset of 3,500 images for semantic segmentation (a type of image segmentation), classifying man-made and natural litter pixel by pixel. There are also other databases, such as the Beach Plastic Litter Dataset (Hidaka et al. 2023), which extracts plastic litter from beach images taken from the ground, and the TACO Dataset (Proença and Simões, 2020), which extracts litter from beaches and classifies it into 28 categories, such as beverage cans and plastic bags. Although the datasets described above are developed from photos taken from the ground, they can also be applied to images taken by remote sensing technologies. Considering the workload, it is practical to use these existing public data as training data. However, the datasets might exhibit biases based on the region and/or substrate conditions of the litter images. Given the nearly infinite range of purposes for utilizing litter prediction models, custom datasets tailored to specific tasks are also essential.

The source code for the image analysis model is available for free and open source (see Table 2.1.2).

**Table 2.1.2. Examples of source code and image analysis model**

| Method | Name | URL |
|---|---|---|
| Object Detection | Torchvision | https://github.com/pytorch/vision |
| | HRNet | https://github.com/HRNet/HRNet-Object-Detection |
| | YOLOv5 | https://github.com/ultralytics/yolov5 |
| Image Segmentation | Segmentation Models | https://github.com/qubvel/segmentation_models.pytorch |
| | HRNet | https://github.com/HRNet/HRNet-Semantic-Segmentation |

The Japan Agency for Marine-Earth Science and Technology (JAMSTEC) has developed a web application (BeachLISA : https://beach-ai.jamstec.go.jp/) using the semantic segmentation model developed by Hidaka et al. 2022. Since it uses a pre-trained model, it does not require coding and training of training data and models, and can detect litter in images simply by loading images using drag-and-drop operations on a web browser, making it possible to analyze images without expertise in deep learning models. Such an application has the potential to significantly reduce labor costs compared to visual image analysis (manual detection of litter from images).

The resolution of objects that a deep learning model can detect from images taken by remote sensing technology is different from that of a visual inspection (see Appendix 1, 2, 3). It also depends on the training data used to train the model. For example, in the case of the semantic segmentation model of Hidaka et al. 2022, the resolution is about 30 pixels (5 cm x 6 cm) when the GSD of the image taken by a UAV is about 1 cm (see Appendix 1). It is assumed that beach litter higher than 2-3 cm was generally detectable given the range of height error in the demonstration test cases (see Appendix 1). Regardless of the resolution, it is difficult for remote sensing technologies to detect beach litter if the litter is not visible because it is piled on top of each other.

### 2.1.2 Quantification of litter

(1) Quantification of beach litter from images taken by a UAV

While image analysis using ordinary UAV images can only determine the number and distribution of litter, orthoimages based on RTK survey results (hereinafter referred to as orthoimages) can be used to estimate the number of density [units/ $m^2$], area [$m^2$], and volume [$m^3$] of litter. To implement orthorectification, it is necessary to acquire images using ground control points (GCP) or RTK equipment as described in Section I, Survey Equipment.

Orthorectification can be implemented using Pix4Dmapper (https://www.pix4d.com/jp/product/pix4dmapper-photogrammetry-software/), Agisoft Metashape (https://oakcorp.net/ agisoft/), and OpenDroneMap (https://www.opendronemap.org/) software, etc. Terra Mapper (https://mapper.terra-drone.net/), a comprehensive platform software provided by Terra Drone Corporation, is capable of estimating the volume [$m^3$] of litter washed ashore in addition to orthorectification (see Appendix 1). Although the remote sensing and AI survey method has lower quantification accuracy than manual surveys, it is possible to cover a larger area and achieve semi-quantification.

The flowchart below summarizes the process from image capture and surveying to detection and quantification of litter washed ashore. Solid boxes in the flowchart refer to data analysis, and dotted boxes refer to data to be output.

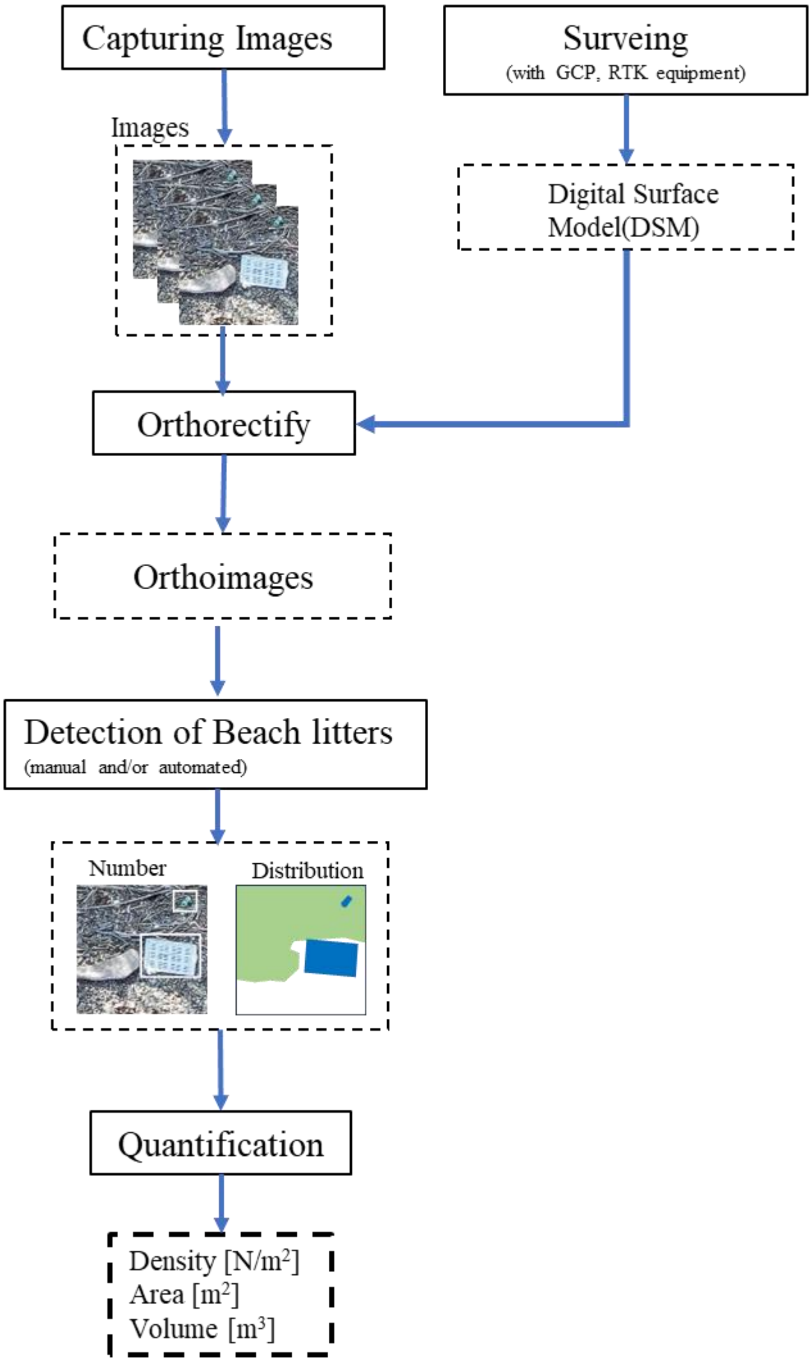


**Figure 2.1.3. Flowchart of the process from image capture by UAVs and surveying to detection and quantification of beach litter**

(2) Quantification of beach litter from images taken by a stationary camera
The number of pixels occupied by litter can be obtained from the analysis of stationary camera images. When the beach is photographed from an angle using a stationary camera, the litter in the front appears larger and the litter in the back appears smaller, and there is a difference in the number of pixels.
In order to correct this and more accurately represent the amount of litter, one method involves performing a projection transformation to convert oblique images into a top-down view, followed by calculating the covered area based on the number of pixels. However, projection transformation requires conducting surveys to measure the distance of the bottom and top edges of the ground image, as well as the camera angle. This process demands specific expertise, skills, and effort due to the need for measurements such as surveying and camera angle calculation.
From the results of demonstration tests, the correlation coefficient between the time-series variation in the area of coverage and the time-series variation in the number of pixels that had not been subjected to a projection transformation was significant ($p < 0.01$, see Appendix 2), so it is thought that it may be possible to grasp the approximate time-series variation in the amount of litter from the number of pixels of litter identified from images that have not been subjected to a projection transformation. However, it is important to note that if there is a difference in the amount of litter between the front and back of the image, there is a possibility that the amount of litter and the number of pixels will not be in a proportional relationship.
When litter is detected automatically from images, there are cases where the camera lens fogging or sunlight glints are misdetected. However, in the case of time series data, it is thought that the influence of such outliers can be reduced by calculating the 7-day moving average of the data (see Appendix 2).

**Figure 2.1.4. Image of the beach taken by a stationary camera (left) and image after projection transformation (right)**

(3) Quantification of river litter from images taken by a stationary camera
By imaging the video taken by a stationary camera of litter floating down the river, and then analyzing each image, it is possible to obtain the number of pieces of litter in each image, as well as the number of pixels that the litter occupies. The number of pixels can be used to calculate the area of the litter, but the actual length of each pixel varies depending on the water level of the river, which is the distance from the camera to the water's surface, so it is necessary to understand the relationship between the water level of the river and the length of one pixel above the water's surface in advance. For information on how to calculate the relationship formula, please refer to Section I, 1.3.2 (2).
In addition, by understanding the relationship between the area and weight of litter in advance during the field survey, it is possible to convert the area obtained through image analysis into weight. The weight per unit area differs depending on the type of litter, so measurements should be taken for each category of litter.

By dividing the number of pieces of litter obtained through image analysis and the weight converted from the litter area by the width of the shooting range and the shooting time of the video, it is possible to calculate the amount of litter flowing down per unit time (flux).
The flow from image shooting to detection and quantification of litter flowing down the river is summarized in the following flowchart. The solid rectangles in the flowchart represent data analysis, and the dotted lines represent the data output.

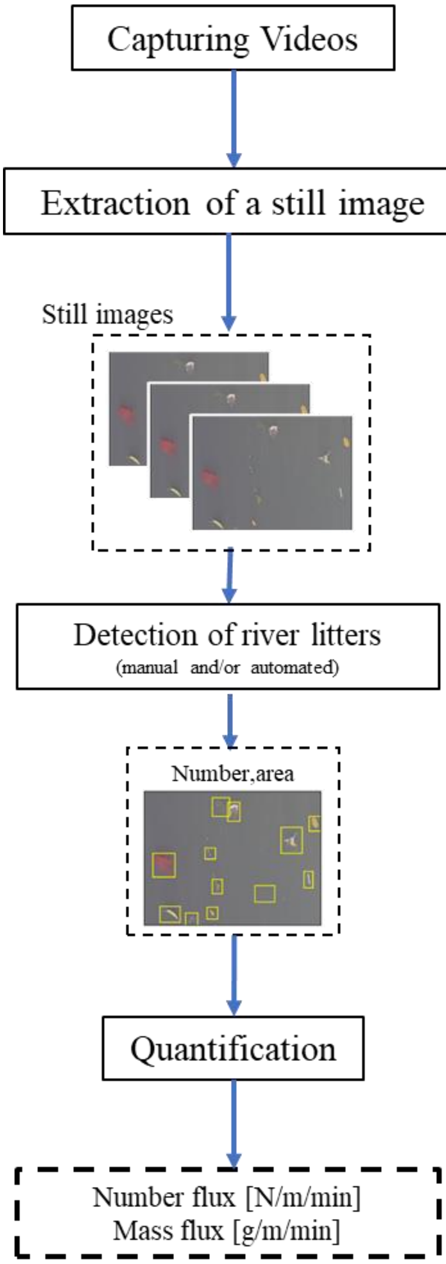


**Figure 2.1.5. Flowchart of the process from video capture by stationary cameras and surveying to detection and quantification of river litter**

Image source: Automated River Plastic Monitoring Using Deep Learning and Cameras（2020）
Colin van Lieshout, Kees van Oeveren, Tim van Emmerik, Eric Postma
https://agupubs.onlinelibrary.wiley.com/doi/full/10.1029/2019EA000960

## 2.2 Data publication

### 2.2.1 Unit of data publication

According to the inquiry results about UAVs, Table 2.2.1 shows the units of data used in the survey results and the reasons for selecting these units. The most common response was "the quantity of litter," followed by "

Litter covered area" and "Number density of litter (see Figure 2.2.1). Using the quantity of litter per survey and survey area, a density of litter by number can be estimated. The area covered by litter is obtained by image segmentation or counting pixels of the detected litter in the bounding box. Litter volume can be estimated as the demonstration test (see Appendix 1).
In the case of the survey of beach litter using a stationary camera, the number of pixels and the area covered by the litter in the images were used in previous surveys (Kako et al. 2010). In the demonstration experiment, the number of pixels, the number of items, and the volume of beach litter were calculated by manual detection, and the number of pixels and the area covered by the beach litter were calculated by automatic detection (see Appendix 2).
In previous cases of litter surveys in rivers using stationary cameras, the number of pieces of litter and the area covered were calculated from the video footage (Kataoka et al. 2020, Lieshout et al. 2020). Furthermore, by dividing these by the width of the shooting range and the shooting time of the video, it is possible to obtain the flux of litter in units of number or area ([N/m/min][$m^2$ /m/min]) (Kataoka et al. 2020). It is also possible to estimate the weight flux [g/m/min] by measuring the weight of each type of litter in the field beforehand (Kataoka et al. 2020, Appendix 3).

Considering the purpose of estimating the flow of waste plastic, 3D information can only be obtained accurately from UAVs, a potential approach for linking the information obtained from various locations may be to select a photography method that can estimate the area covered by beach litter and the number of items per unit area or per unit time (flux) in the target area (Deidun et al. 2018). It is important to save raw data such as orthoimages for reanalysis, as future technological developments may make it possible to estimate the amount of litter in other units.

■ Point
From the perspective of data comparison, the recommended data units are the density of litter by number, and litter coverage area. Volume is another optional data unit.

**Table 2.2.1. The inquiry results_Data unit about UAV surveys**

| Case No. | What are the units used to quantify litter? | Please tell us why you chose the units on the left. |
|---|---|---|
| 1 | Quantity of litter, Number density of litter, Litter covered area | Marine litter abundance, hotspots location, clean coast index, clean-up operations |
| 2 | Quantity of litter, Litter covered area, size of litter | Traditionally we worked with Quantity of litter, size of litter, area covered. I believe that drone based survey can and should also compute weight and volume (we are working to test the last two parameters) |
| 3 | Quantity of litter, Number density of litter | They are the most representative. |
| 4 | Volume, Litter covered area | For use in simulations |
| 5 | Volume, Quantity of litter | - |
| 6 | Quantity of litter, Number density of litter, Litter covered area | Weight and volume impossible to measure |
| 7 | Quantity of litter, Number density of litter, Litter covered area | - |
| 8 | Quantity of litter, Number density of litter, Litter covered area | The used units have been selected to be comparable with the ones we obtain from the “real survey” conducted on the field, from which we will compare our data. The volume or weight of the recovered material, considered all together, does not allow a subsequent classification based on type, which we are interested in doing. |
| 9 | Volume, Litter covered area | Because it is easy to calculate. |
| 10 | Quantity of litter, Number density of litter, Litter covered area | These are the most relevant ones for our purpose, which is detecting where litter accumulates and overall litter pollution. |
| 11 | Quantity of litter, Number density of litter | - |
| 12 | Quantity of litter, Number density of litter, Litter covered area | - |
| 13 | Quantity of litter, Number density of litter | Same as validation data |
| 14 | Litter covered area | Matching the artificial targets that we used in this particular experiment |
| 15 | Quantity of litter, Litter covered area | To quantify and classify the litter both spatially and temporally |
| 16 | Quantity of litter, Number density of litter, Litter covered area | - |

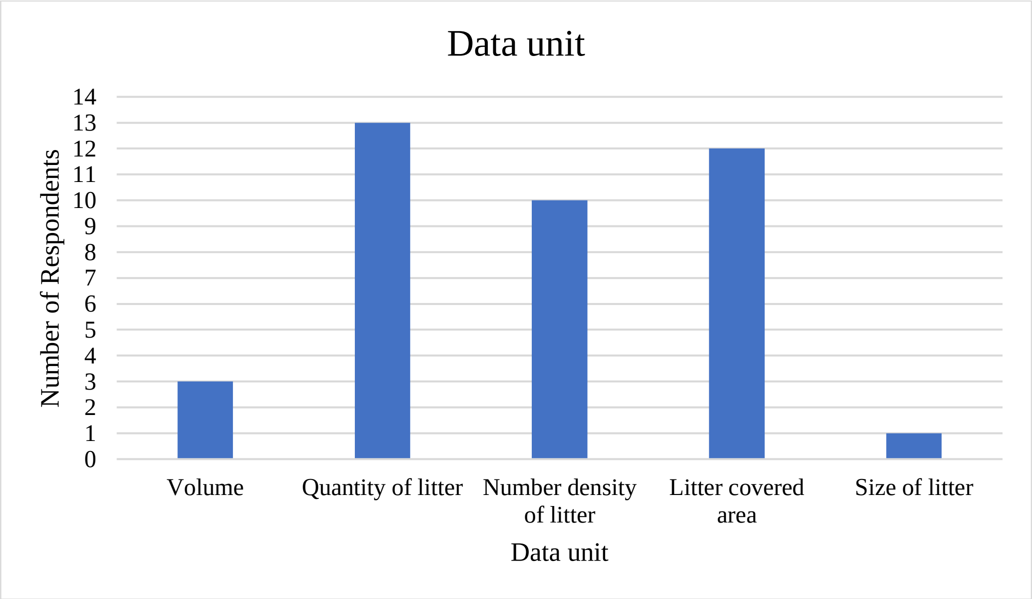


**Figure 2.2.1. The inquiry results_Data unit about UAV surveys**

### 2.2.2 Content of the data to be published

The information published as survey results includes Quantity of litter, Percentage of litter composition, Distribution map of litter amount, Distribution map of litter types (see Appendix 1), DSM, etc. (see Table 2.2.2).

It is not a question of which is better, or which should be standardized; rather, it is important to properly quantify the information according to the purpose (Kako et al. 2024) (see Table 2.2.3).

When publishing survey data, it is useful to visualize the data so that it can be easily compared with data from other locations and easily understood by non-experts. In the case of Gonçalves et al. (2022), the density of litter by number, and litter coverage area are visualized using grid maps (see Figure 2.2.2). For publishing the grid map, web GIS services (e.g., INSPIRE (https://inspire-geoportal.ec.europa.eu/), Coastal Marine Litter Observatory (CMLO, https://cmlo.aegean.gr/)) can be useful. In terms of unifying the units for evaluating global quantities, it will be important to construct a system that allows data sharing so that such analysis can be performed in image analysis (Kako et al. 2024). There are various grid sizes (5 m x 5 m, 10 m x 10 m, etc.), but any size is considered acceptable as long as the data is compatible with other grid survey data by rescaling.

In the case of stationary camera surveys on beaches, it is often the case that data is collected over a long period of time, and so data on temporal changes is sometimes published. In the case of Kako et al. (2010), temporal changes in the area covered by litter are shown (see Figure 2.2.3). In other cases, the results are shown as temporal changes in the number of pixels in the image that are occupied by litter (see Appendix 2).

In the case of stationary camera surveys of rivers, there are examples where the results are shown as the number of pieces of litter, and the flux of litter based on the number of pieces, coverage area, and weight ([N/m/min], [$m^2$/m/min], [g/m/min]) (Kataoka et al. 2020, Lieshout et al. 2020, Appendix 3). Furthermore, there are also examples of calculating and showing the number of items of litter washed down the river in the survey target river per year based on river flow, and examples of calculating and showing the amount of litter washed down from the entire wide area, such as regional administrative divisions (Ministry of the Environment, Manual for the Survey of the Actual Situation of Plastic Litter Flowing into the Seto Inland Sea, 2024). For information on the method of calculating the number of items washed down per year, etc., please refer to Appendix 3.

For the data publication, it is also recommended to provide information necessary for data comparison (e.g. lower detection limit of litter, etc.).

**Table 2.2.2. The inquiry results _how to publish survey results**

| Case No. | Information Published as Survey Results |
|---|---|
| 1 | Number of items per square meter |
| 2 | "Amount of litter": we used tables with number of objects and percentages.<br>Regarding "Distribution map of litter amount", we used grids of 5m x 5m, and showed the percentages of occupancy (or number of items) in the single cells. However, this approach was just a test/example, and should be better defined. |
| 3 | 10m x 10m, number of items in the area |
| 4 | - |
| 5 | g/100m2. Because the survey of beach litter is determined to be 10m x 10m and conducted. |
| 6 | Items m2 |
| 7 | Amount of litter, Percentage of litter composition, Distribution map of litter amount, Distribution map of litter types, DSM |
| 8 | Amount of litter: we normally use the Quantity of litter / square meter on the surveyed area. It is also possible to calculate the linear amount of litter (Quantity of litter / /m), considering the extension of the beach.<br>Distribution map: we divide the areas into a small "square" with a grid, and we calculate the Quantity of litter found in these sub-areas. After that, we define a graduate scale of "litter density", assigning a "scale" of color to each interval of this value. The final map visualizes the density with the intensity/nuance of the colors. It is possible to do that also for ONLY one type of litter, or type of material, so visualize difference in density distribution depending on the litter type/material. |
| 9 | Volume and Coverage Area |
| 10 | These are included in the report as average litter density for each beach and accumulation areas using heat maps. Characterization and composition are generated from an in-situ survey of a smaller area (sub-sampling and extrapolation). This characterization is in-situ as it is mandatory for compliance with EU-regulations and/or programs. Flights are used to survey larger areas and provide insight on accumulation, abundance, and density of marine litter pollution. |
| 11 | Amount of litter, Distribution map of litter amount |
| 12 | Distribution map of litter amount, Distribution map of litter types |
| 13 | Items/m2 surface |
| 14 | Percentage of litter composition |
| 15 | Percentage of litter composition, Distribution map of litter types, DSM |
| 16 | Amount of litter, Percentage of litter composition, Distribution map of litter types, DSM |

**Table 2.2.3. Example of how to use survey results information**

| Survey Results Information | Uses of the Information (Kako et al. 2024) |
|---|---|
| Quantity of litter per item type | It facilitates formulation of policies that contribute to the reduction of plastic litter, for example, by restricting the use of certain products. |
| Spatial distribution of litter | It can be used to identify areas in need of intensive cleaning. |
| Volume and weight estimates | They provide very important information in the calculation of disposal costs. |

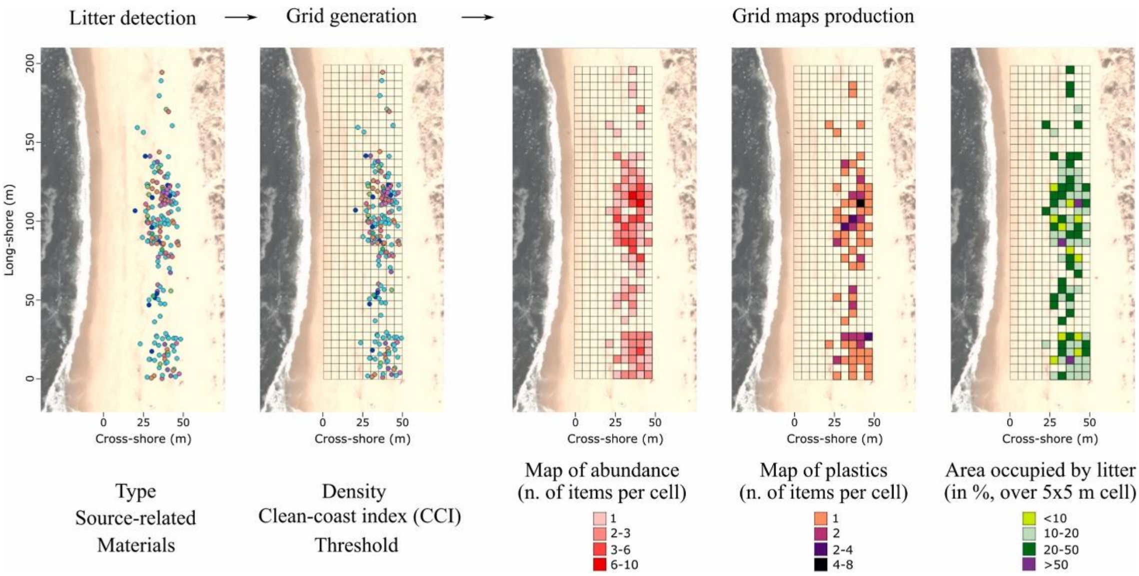


**Figure 2.2.2. Example of drone-based litter survey outcomes based on grid map production.**
a) Detected litter items on orthoimage. Colors can indicate different type, source and/or material; b) grid (in the example, 5 m x 5 m) generation allows counting of the desired category within each cell. For instance, thematic map of litter abundance (c), map of types and/or materials, such as plastic (d), distribution of the size and the actual area occupied by litter (e), among others, can be generated from the points dataset. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.) (Gonçalves et al. 2022)

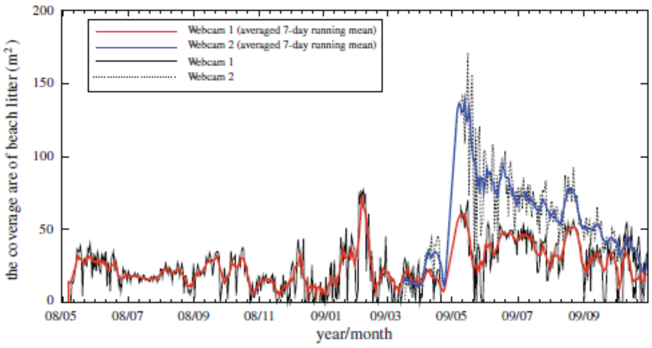


**Figure 2.2.3. Example of the results of a time-series survey of litter washed up on the beach using a stationary camera**

Time series of the area of beach litter on the Ohgushi Coast. Background values are 30% or more. See the top left for the meaning of each curve. Missing values are interpolated with a straight line (Kako et al. 2010).

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