"The Guidelines for Harmonizing Marine Litter Monitoring Methods Using Remote Sensing Technologies" Comparison Table

<table>
<tr><th colspan="7">Guideline main body</th></tr>
<tr><th>Chapter</th><th colspan="2">Item</th><th>After</th><th>Before</th><th>Remarks</th><th>Version</th></tr>
<tr><td>I</td><td>1.2</td><td>-</td><td>Table 1. Number of major studies on marine litter monitoring using remote sensing technology (Kako et al. 2025, draft paper) .
<table>
<tr><th rowspan="5">Fields</th><th colspan="7">Data Acquisition Methods (Remote Sensing)</th><th colspan="4">Image Analysis Methods</th></tr>
<tr><th colspan="7">Platform</th><th rowspan="4">Manual (Visual)</th><th colspan="3">Automatic</th></tr>
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<tr><td>Beach (Dune)*2</td><td>3</td><td>22 (7)</td><td>2</td><td>2</td><td></td><td></td><td></td><td>13 (2)</td><td>6 (1)</td><td>6 (2)</td><td>10 (2)</td></tr>
<tr><td>Sea Surface</td><td></td><td>7</td><td>1</td><td>5</td><td>10</td><td></td><td>1</td><td>8</td><td>1</td><td></td><td>14</td></tr>
<tr><td>Estuary Surface</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
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<tr><td>River Surface</td><td>2</td><td>6</td><td></td><td></td><td></td><td></td><td>1</td><td>4</td><td>2</td><td>1</td><td>4</td></tr>
<tr><td>Land</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Others*3</td><td></td><td></td><td></td><td></td><td></td><td></td><td>3</td><td>3</td><td></td><td></td><td>2</td></tr>
</table>
Notes:
The numbers above are the number of papers listed as references in Kako et al. (2025, draft paper) . The numbers in this table are subject to change after the paper is published.
*1 UAV: Uncrewed Aerial Vehicle
*2 In the guidelines, the term “beach” not only refers to the area of the shoreline covered with sand or pebbles, but also includes dunes and vegetation such as mangroves. The numbers in parentheses are the number of literatures that cover dunes in the measurement area.
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<tr><td>Sea surface</td><td></td><td></td><td>1</td><td>1</td><td></td><td></td><td></td><td>1</td><td></td><td></td><td>1</td></tr>
<tr><td>Sea water column</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
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<tr><td>River surface</td><td>1</td><td>4</td><td></td><td></td><td></td><td></td><td>1</td><td>3</td><td></td><td></td><td>4</td></tr>
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*2 In the guidelines, the term “beach” not only refers to the area of the shoreline covered with sand or pebbles, but also includes dunes and vegetation such as mangroves. The numbers in parentheses are the number of literatures that cover dunes in the measurement area.
*3 At the current technical level, feasibility of measuring litter on the “sea floor” and “river floor” using remote sensing technologies is limited.</td>
<td>The "Fields" items have been revised to match Table 3.</td><td>1.0→2.0</td></tr>
<tr><td>I</td><td>1.3</td><td>-</td><td>(i) Remote sensing
Remote sensing technologies are used to gather and process information about an object without direct physical contact (ASPRES https://www.asprs.org/organization/what-is-asprs.html accessed 2024-6-30). Remote sensing platforms are defined as vehicles (Jafarbiglu and Pourreza 2022) or other stationary objects that can carry or mount sensing devices to perform remote measurement operations.
The guidelines cover remote sensing methods using the following platforms. It should be noted that the methods to be covered may change in the future.

- Stationary camera: It is defined as a camera installed in the environment, e.g., installed on a shoreline with scaffolding, fixed on a bridge, to acquire time series image data at the same location. It does not include a camera fixed on a vehicle, such as an aircraft or a vessel.
[Ommition]</td>
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The guidelines cover remote sensing methods using the following platforms. It should be noted that the methods to be covered may change in the future.

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<tr><td>I</td><td>1.3</td><td>-</td><td>(ii) Image processing and analysis
- Image analysis
Means extracting litter information from processed images, such as identifying the types, quantities, or numbers of litter items.
In recent times, machine learning and deep learning-based image processing techniques for plastic litter quantification have emerged. These methodologies utilize large datasets to develop models capable of detecting complex features—such as colors and shapes—in images, allowing for more flexible litter detection (Kako et al. 2025, draft paper).
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Case
Kagoshima University "Research Chair of Plastic Litter Monitoring System from the City, Sea, and Space" Website. https://pmd.oce.kagoshima-u.ac.jp/ (accessed 2025-1-31)</td><td>Table 2-1. A monitoring example: stationary camera
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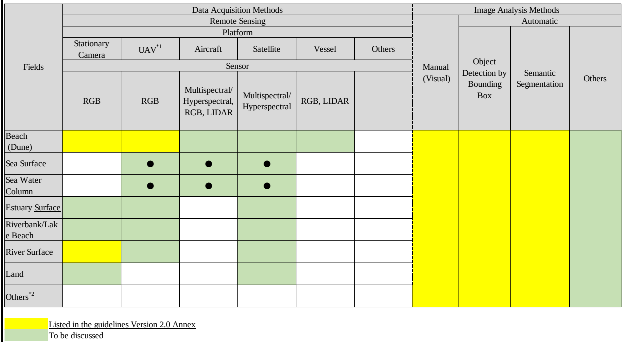
<tr><td>I</td><td>1.5</td><td>1.5.1</td><td>[Ommition]
Regarding marine area classification, the guidelines mainly cover coastal areas in order to avoid duplication with existing efforts on marine litter monitoring of other organizations such as The International Ocean Colour Coordinating Group (IOCCG).
In addition, a variety of sensors can be used on satellites, and a list of the sensors that can be installed on satellites is shown in Table 4.</td><td>[Ommition]
Regarding marine area classification, the guidelines mainly cover coastal areas in order to avoid duplication with existing efforts on marine litter monitoring of other organizations such as The International Ocean Colour Coordinating Group (IOCCG).</td><td></td><td>1.0→2.0</td></tr>
<tr><td>I</td><td>1.5</td><td>1.5.1</td><td>Figure 2. Diagram of the monitoring fields and the data acquisition methods.
Etsuary surface</td><td>Figure 2. Diagram of the monitoring fields and the data acquisition methods.
Etsuary</td><td></td><td>1.0→2.0</td></tr>
<tr><td>I</td><td>1.5</td><td>1.5.1</td><td>Table 3. The scope of monitoring fields, data acquisition methods, and image analysis methods in the guidelines.

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<tr><td>Others*2</td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
</table>
🟨 Listed in the guidelines Version 2.0 Annex
🟩 To be discussed

Notes:
Regarding plastic litter monitoring, the areas are being discussed by other initiatives (e.g., IOCCG Task Force on Remote Sensing of Marine Litter)
*1 UAV: Uncrewed Aerial Vehicle
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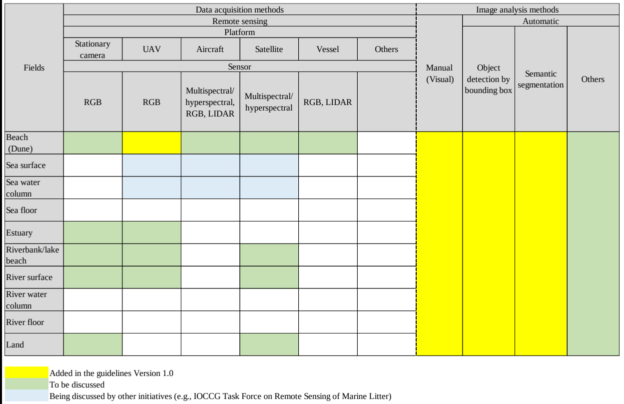
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🟨 Added in the guidelines Version 1.0
🟩 To be discussed
🟦 Being discussed by other initiatives (e.g., IOCCG Task Force on Remote Sensing of Marine Litter)

[Addition]</td><td>"Fields" where research cases have not been sufficiently confirmed are not currently considered for adding to the guidelines, and they are described as "Others" in the table. The items of the list will be reviewed depending on future technological developments.</td><td>1.0→2.0</td></tr>
</table>

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<tr><td>I</td><td>1.5</td><td>1.5.1</td><td>Table 4 List of sensors that can be mounted on satellites to detect litter. Anomaly, plastic detection, plastic characterization of
target object as per Goddijn-Murphy et al. (2024)
[Please refer to the main text for details]</td><td>[Addition]</td><td></td><td>1.0→2.0</td></tr>
<tr><td>I</td><td>1.5</td><td>1.5.2</td><td>Table 5-1. Targeted audiences of the guidelines.</td><td>Table 4-1. Targeted audiences of the guidelines.</td><td></td><td>1.0→2.0</td></tr>
<tr><td>I</td><td>1.5</td><td>1.5.2</td><td>Table 5-2. The reasons why each technology targets the specific organizations mentioned in Table 5-1.</td><td>Table 4-2. The reasons why each technology targets the specific organizations mentioned in Table 4-1.</td><td></td><td>1.0→2.0</td></tr>
<tr><td>II</td><td>2.2</td><td>-</td><td>Figure 3-2. Examples of common images produced by each platform.
(For the suitable observation time interval of each platform: see Kako et al. (2025, draft paper).</td><td>Figure 3-2. Examples of common images produced by each platform.
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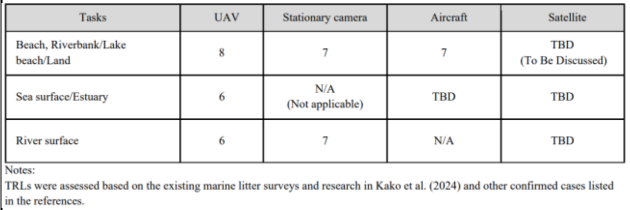
<tr><td>II</td><td>2.3</td><td>-</td><td>Table 6. Examples of policy-related issues and output image.</td><td>Table 5. The examples of policy-related issues and output image.</td><td></td><td>1.0→2.0</td></tr>
<tr><td>III</td><td>3.1</td><td>-</td><td>There are nine technological readiness levels. TRL 1 is the lowest and TRL 9 is the highest. In the guidelines, the definition of TRLs for remote sensing methods for litter monitoring was set as shown in Figure 4. TRLs of the technologies were assessed based on the existing marine litter surveys and researches referred to in Kako et al. (2025, draft paper) and other confirmed cases, under the definition in Figure 4.
As a result, the following technologies were evaluated as relatively high TRL and being highly practical: beach litter monitoring using UAVs, and beach and river surface litter monitoring using stationary cameras. These monitoring methods are described in detail in the Annex. The specific TRL figures for each platform as of April 2025 are shown on the Ministry of the Environment website (https://www.env.go.jp/page_00929.html).
For image analysis technology, Table 7 summarizes the applications (tasks) that are commonly used at this time. It should be noted that research in this field has been accelerating in recent years, and the maturity of the methods may change in the future.

* TRL is a type of indicator developed by NASA (National Aeronautics and Space Administration) to assess the maturity of technologies and is commonly applied to various technical fields.</td><td>There are nine technological readiness levels. TRL 1 is the lowest and TRL 9 is the highest. In the guidelines, the definition of TRLs for remote sensing methods for litter monitoring was set as shown in Figure 4. TRLs of the technologies were assessed based on the existing marine litter surveys and researches referred to in Kako et al. (2024) and other confirmed cases, under the definition in Figure 4 (see Table 6-1).

For image analysis technology, Table 6-2 summarizes the applications (tasks) that are commonly used at this time. It should be noted that research in this field has been accelerating in recent years, and the maturity of the methods may change in the future.

* TRL is a type of indicator developed by NASA to assess the maturity of technologies and is commonly applied to various technical fields.</td><td>As remote sensing technology for monitoring marine litter is a field in which rapid technological progress is being made, the TRL values are not fixed, but are updated frequently over time.
For this reason, rather than including the TRL evaluation values for each platform in the main body of the guidelines, we have decided to include them separately as reference information on the website introducing the guidelines, and to include only its URLs in the main body of the guidelines.
It can prevent users of the guidelines from misunderstanding the TRL as fixed values, and will also make it easier to update TRL values.</td><td>1.0→2.0</td></tr>
<tr><td>III</td><td>3.1</td><td>-</td><td>[Delete]
*Published as supplementary material on the Ministry of the Environment website.

Harmonized monitoring and data compilation of marine plastic litter
https://www.env.go.jp/page_00929.html</td><td>Table 6-1. TRL of data acquisition methods.

<table>
<tr><th>Tasks</th><th>UAV</th><th>Stationary camera</th><th>Aircraft</th><th>Satellite</th></tr>
<tr><td>Beach, Riverbank/Lake beach/Land</td><td>8</td><td>7</td><td>7</td><td>TBD
(To Be Discussed)</td></tr>
<tr><td>Sea surface/Estuary</td><td>6</td><td>N/A
(Not applicable)</td><td>TBD</td><td>TBD</td></tr>
<tr><td>River surface</td><td>6</td><td>7</td><td>N/A</td><td>TBD</td></tr>
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Notes:
TRLs were assessed based on the existing marine litter surveys and research in Kako et al. (2024) and other confirmed cases listed in the references.</td><td></td><td>1.0→2.0</td></tr>
<tr><td>III</td><td>3.1</td><td>-</td><td>Table 7. Correspondence table between tasks and image analysis technologies.
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*2 The classification of man-made and natural objects is accomplished, but no further detailed classification has not yet been achieved at this time (Kako et al. 2025, draft paper).</td><td>Table 7. Correspondence table between tasks and image analysis technologies.
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<table>
<tr>
<td>III</td>
<td>3.2</td>
<td>3.2.1</td>
<td>3.2.1 Remote sensing platforms
As described in Figure 3-1, the image resolution obtained by surveys and the spatial coverage of a survey area are generally inversely proportional. The major advantage of remote sensing is its ability to enable continuous observation over short periods and batch observation over wide areas, which is not practically feasible manually, although it is difficult to classify litter in as much detail as manual surveys due to the issue of image resolution. In addition, combining different platforms offers advantages in observing plastic litter across varying spatiotemporal scales (Kako et al. 2025, draft paper). Typical technical difficulties of remote sensing methods and future steps are shown in Table 8.</td>
<td>3.2.1 Remote sensing platforms
As described in Figure 3-1, the image resolution obtained by surveys and the spatial coverage of a survey area are generally inversely proportional. Remote sensing technologies can cover larger areas in less time compared to manual surveys. However, remote sensing technologies cannot classify litter in as much detail as manual surveys due to the issue of image resolution. Other typical technical difficulties of remote sensing methods and future applications based on these difficulties are shown in Table 7.</td>
<td></td>
<td>1.0→2.0</td>
</tr>
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<td>III</td>
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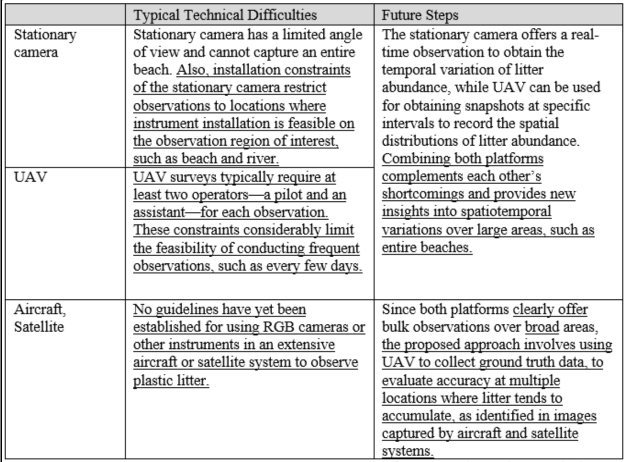
<td>Table 8. Typical technical difficulties and future steps of remote sensing methods (Kako et al. 2025, draft paper).

<table>
<tr><th></th><th>Typical Technical Difficulties</th><th>Future Steps</th></tr>
<tr><td>Stationary camera</td><td>Stationary camera has a limited angle of view and cannot capture an entire beach. Also, installation constraints of the stationary camera restrict observations to locations where instrument installation is feasible on the observation region of interest, such as beach and river.</td><td rowspan="2">The stationary camera offers a real-time observation to obtain the temporal variation of litter abundance, while UAV can be used for obtaining snapshots at specific intervals to record the spatial distributions of litter abundance. Combining both platforms complements each other's shortcomings and provides new insights into spatiotemporal variations over large areas, such as entire beaches.</td></tr>
<tr><td>UAV</td><td>UAV surveys typically require at least two operators—a pilot and an assistant—for each observation. These constraints considerably limit the feasibility of conducting frequent observations, such as every few days.</td></tr>
<tr><td>Aircraft, Satellite</td><td>No guidelines have yet been established for using RGB cameras or other instruments in an extensive aircraft or satellite system to observe plastic litter.</td><td>Since both platforms clearly offer bulk observations over broad areas, the proposed approach involves using UAV to collect ground truth data, to evaluate accuracy at multiple locations where litter tends to accumulate, as identified in images captured by aircraft and satellite systems.</td></tr>
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Reference: Kako et al. 2025, draft paper</td>
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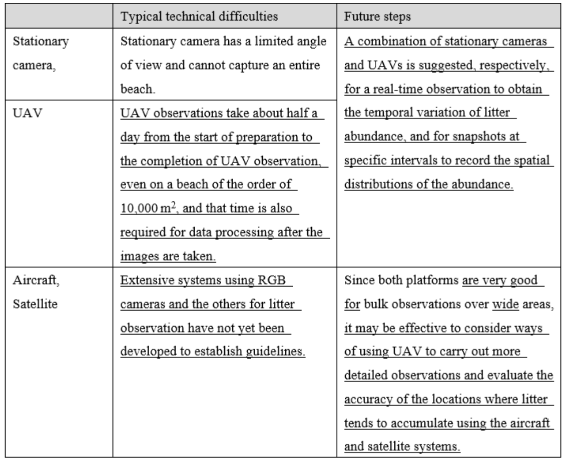
<table>
<tr><th></th><th>Typical technical difficulties</th><th>Future steps</th></tr>
<tr><td>Stationary camera,</td><td>Stationary camera has a limited angle of view and cannot capture an entire beach.</td><td rowspan="2">A combination of stationary cameras and UAVs is suggested, respectively, for a real-time observation to obtain the temporal variation of litter abundance, and for snapshots at specific intervals to record the spatial distributions of the abundance.</td></tr>
<tr><td>UAV</td><td>UAV observations take about half a day from the start of preparation to the completion of UAV observation, even on a beach of the order of 10,000 m^2, and that time is also required for data processing after the images are taken.</td></tr>
<tr><td>Aircraft, Satellite</td><td>Extensive systems using RGB cameras and the others for litter observation have not yet been developed to establish guidelines.</td><td>Since both platforms are very good for bulk observations over wide areas, it may be effective to consider ways of using UAV to carry out more detailed observations and evaluate the accuracy of the locations where litter tends to accumulate using the aircraft and satellite systems.</td></tr>
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<td></td>
<td>1.0→2.0</td>
</tr>
<tr>
<td>III</td>
<td>3.2</td>
<td>3.2.1</td>
<td>Column: Current Status and Future Prospects of Marine Litter Monitoring Using Satellites
[Please refer to the main text for details]</td>
<td>[Addition]</td>
<td></td>
<td>1.0→2.0</td>
</tr>
<tr>
<td>III</td>
<td>3.2</td>
<td>3.2.2</td>
<td>Machine learning and deep learning-based image processing model was developed, which utilizes large datasets and can detect complex features—such as colors and shapes—in images, allowing for more flexible litter detection. Details on image analysis methods and data disclosure are provided in Annex Section II of these guidelines.
While manual methods can identify objects of all size ranges, image processing methods struggle to predict relatively small or obstructed objects (Kako et al. 2025, draft paper).
The development of image analysis technology based on deep learning requires specialized knowledge and the preparation of data to be used for training, and the assignment of information such as the location and classification of marine litter to that data (annotation work). Since current image analysis requires manual verification and annotation of all collected data and given the significant time and cost associated with creating training data, it is essential to share these datasets regardless of the remote sensing platform (Kako et al. 2025, draft paper).</td>
<td>Machine learning and deep learning-based image processing model was developed, which utilizes large datasets and can detect complex features—such as colors and shapes—in images, allowing for more flexible litter detection. However, given the high cost associated with creating training data, it is essential to share these datasets regardless of the platform. In addition, manual methods can identify objects of all size ranges, whereas image processing methods struggle to predict relatively small or obstructed objects (Kako et al. 2024).</td>
<td></td>
<td>1.0→2.0</td>
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			Regarding the sharing of datasets, there are examples of the use of cloud computing (a technology for sharing work and data via the Internet) for annotation in the field of marine ecology. For example, the web applications shown in Table 9 are provided to experts partly free of charge. Some services are equipped with programs that automatically detect objects in uploaded images and classify them by pixel unit through image segmentation. Users of such a service can upload images onto a web application, annotate them with the automatically detected objects, and share them online. Shared label data can be reclassified to ensure consistency in data classification. The above applications are also used in the marine litter. Specifically, BIIGLE, shown in Table 9, has been used in research to analyze the spatial and temporal variability of litter accumulated on the sea floor, and marine litter label data has been shared (Tekman et al. 2017). Once marine litter label data is shared, the collection and accumulation of data necessary for image analysis and automatic object detection of litter by AI will take place through the application. It would facilitate data integration across different remote sensing platforms, as the collected label data could be reclassified. The data accumulated through the application can be used to create and develop AI that automatically detects and classifies litter in images or videos collected by remote sensing. Table 9 Examples of cloud computing services for annotation [Please refer to the main text for details]	[Addition]		
III	3.2	3.2.3	3.2.3 Continuous collection of training data using smartphone applications [Please refer to the main text for details]	[Addition]		1.0→2.0
III	3.2	3.2.4	3.2.4 Overall monitoring using remote sensing technologies	3.2.3 Overall monitoring using remote sensing technologies		1.0→2.0
Ⅲ	3.3	-	3.3 Future revision of the guidelines The guidelines will be updated periodically in line with the development of remote sensing technologies. As shown in Table 3, the technical details on platforms other than UAVs and stationary cameras will be added to the Annex as necessary.	3.3 Future revision of the guidelines The guidelines will be updated periodically in line with the development of remote sensing technologies. As shown in Table 3 and Table 6-1, we plan to add Annex for stationary camera, aircraft, and satellite in the future.		1.0→2.0

Annex						
Section	**Item**		**After**	**Before**	**Remarks**	**Version**
I	1.1	1.1.2	1.1.2 Survey implementation (7) Data needed for quantification of beach litter Record [Please refer to the main text for details]	[Addition]	The items in 1.2 and 1.3 have been aligned, and items have been added to provide useful data for considering beach litter.	1.0→2.0
I	1.1	-	Figure 1.1.1 Table 1.1.1 [Same modifications are applied for other chart numbers]	Figure 1 Table 1	The numbering of figures and tables has been changed to reflect the addition of the annex.	1.0→2.0
I	1.2	-	1.2 Beach litter monitoring survey using stationary camrera [Please refer to the main text for details]	[Addition]		1.0→2.0
I	1.3	-	1.3 River litter monitoring survey using stationary camrera [Please refer to the main text for details]	[Addition]		1.0→2.0

<table>
<tr>
<td>II</td>
<td>2.1</td>
<td>2.1.1</td>
<td>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 litter covered area 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 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 (Wada, 2016), 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
Note that previous research has shown that the detection rate for manual detection can vary depending on various factors (see Table 13).</td>
<td>2.1.1 Detection of beach litter from images
(1) Manual detection
Manual detection of beach litter from images requires less expertise and skill than automated detec-tion. 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.
According to the previous studies, detection rates are valuable for several factors (see Table 13).</td>
<td>Whereas Annex Section I was limited to monitoring of beach litter by UAVs in Version 1.0 of the guidelines, Version 2.0 added content on monitoring of beach and river litter by stationary cameras.
In line with this, the contents of Section II was also expanded to cover a wider range of remote sensing technology-based monitoring of litter, rather than being limited to monitoring of beach litter by UAVs.

In addition, methods for cut out images from videos and analysing them, as well as a mtethod that can be used for manual detection of litter from images.</td>
<td>1.0→2.0</td>
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<tr>
<td>II</td>
<td>2.1</td>
<td>2.1.1</td>
<td>Table 13. Several factors related to detection rates
<table>
<tr><th>Factor [*1,2]</th><th>Note</th></tr>
<tr><td>Image resolution (GSD)</td><td>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.</td></tr>
<tr><td>Experience of the operator</td><td>For example, operator training should be required in order to improve their confidence with UAV-based mapping.[*3]</td></tr>
<tr><td>Image background</td><td>Sand, vegetation, footprints, etc.[*1]</td></tr>
<tr><td>Conditions of litter</td><td>Fully visible, partially buried, broken, placed close to each other etc.[*1,2]</td></tr>
<tr><td>Litter size</td><td>Larger items (2.5 cm <) are easier to find.[*2]</td></tr>
<tr><td>Litter color</td><td>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]</td></tr>
<tr><td>Litter shape</td><td>String/cord, lines, and squares are harder to find.[*2]</td></tr>
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<td>1.0→2.0</td>
</tr>
<tr>
<td>II</td>
<td>2.1</td>
<td>2.1.1</td>
<td>Some studies used other information to assist with litter detection.
[Ommition]</td>
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[Ommition]</td>
<td></td>
<td>1.0→2.0</td>
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<tr>
<td>II</td>
<td>2.1</td>
<td>2.1.1</td>
<td>(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.</td>
<td>(2) Automated detection

There are two main automated data analysis methods for detecting beach 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.</td>
<td></td>
<td>1.0→2.0</td>
</tr>
</table>

II	2.1	2.1.1	Considering the characteristics of each method, the data analysis method should be selected based on the status of litter washed ashore. 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 iden-tify 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 diffi-cult to identify individual items (see Appendix 1). Instance segmentation, which is also a type of image segmentation, can estimate the total number of litter pieces 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. [Ommition]	Considering the characteristics of each method, the data analysis method should be selected based on the status of litter washed ashore. Object detection can estimate the total number of pieces of beach litter 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 iden-tify each individual piece. Since semantic segmentation, a type of image segmentation can detect beach 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 beach litter is accumulated, and it is diffi-cult 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 beach litter like object detection and can detect beach litter at the pixel level, its area [m^2] and volume [m^3] can be estimated by using orthoimages like semantic segmentation. [Ommition]		1.0→2.0
II	2.1	2.1.1	Although the datasets de-scribed 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 14).	Although the datasets de-scribed above are developed from photos taken from the ground, they can also be applied to aerial images taken by UAVs. 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 14).		1.0→2.0
II	2.1	2.1.1	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 pretrained 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 a 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 segmen-tation 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, 2, 3). 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.	The Japan Agency for Marine-Earth Science and Technology (JAMSTEC) is developing a web application (will open to the public in 2024) using the semantic segmentation model developed by Hidaka et al. 2022. Since it uses a pretrained 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 beach litter from images). The resolution of objects that a deep learning model can detect from images taken by a UAV is different from that of a visual inspection (see Appendix 1). 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 UAVs to detect beach litter if the litter is not visible because it is piled on top of each other.		1.0→2.0

II	2.1	2.1.2	2.1.2 Quantification of litter (1) Quantification of beach litter from images taken by a UAV [Ommition]	2.1.2 Quantification of beach litter [Ommition]	The contents for the quantification of images of litter using stationary cameras were added in (2) and (3). In line with the addition, the title has been added for the contents of the quantification of beach litter from images taken by a UAV, which was described in the Guidelines version 1.0.	1.0→2.0
II	2.1	2.1.2	Figure 11. Flowchart of the process from image capture by UAVs and surveying to detection and quantification of beach litter	Figure 11. Flowchart of the process from image capture and surveying to detection and quantification of beach litter		1.0→2.0
II	2.1	2.1.2	(2) Quantification of beach litter from images taken by a stationary camera [Please refer to the main text for details]	[Addition]		1.0→2.0
II	2.1	2.1.2	(2) Quantification of river litter from images taken by a stationary camera [Please refer to the main text for details]	[Addition]		1.0→2.0
II	2.2	2.2.1	2.2.1 Unit of data publication According to the inquiry results about UAVs, Table 15 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 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 past 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.	2.2.1 Data unit According to the inquiry results, Table 15 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 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). However, 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 in the target area. 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.	Descriptions of the units of data used in the surveys of beach litter and river litter using stationary cameras have been added.	1.0→2.0
II	2.2	2.2.1	Table 15. The inquiry results_Data unit about UAV surveys.	Table 15. The inquiry results_Data unit.		1.0→2.0
II	2.2	2.2.1	Figure 14. The inquiry results_Data unit about UAV surveys.	Figure 12. The inquiry results_Data unit.		1.0→2.0

II	2.2	2.2.2	2.2.2 Content of the data to be published [Ommition] 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 13). 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 con-struct 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 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 calcu-lating 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 compari-son (e.g. lower detection limit of litter, etc.).	2.2.2 Data publication [Ommition] 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 13). 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 con-struct 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. For the data publication, it is also recommended to provide information necessary for data compari-son (e.g. lower detection limit of litter, etc.).	Descriptions of the units of data used in the surveys of beach litter and river litter using stationary cameras have been added.	1.0→2.0
II	2.2	2.2.2	Figure 15. Example of drone-based litter survey outcomes based on grid map production.	Figure 13. Example of drone-based litter survey outcomes based on grid map production.		1.0→2.0
II	2.2	2.2.2	Figure 16. 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).	[Addition]		1.0→2.0

Appendix

Appendix	Item		After	Before	Remarks	Version
2	-	-	Appendix 2 Result of demonstration test for beach litter survey using stationary camrera [Please refer to the main text for details]	[Addition]		1.0→2.0
3	-	-	Appendix 3 Result of demonstration test for river litter survey using stationary camrera [Please refer to the main text for details]	[Addition]		1.0→2.0