

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

Version 2.0→2.1

Guideline main body																																																																															
Chapter	Item		After		Before		Remarks		Version																																																																						
All	-	-	Kako et al. 2026		Kako et al. 2025, draft paper		The bibliographic information has been updated to the latest version.		2.0→2.1																																																																						
I	1.3	-	Table 2-4. A survey example: satellite (Citing the study of Cózar et al. (2024))		Table 2-4. A survey example: satellite (Citing the study of Themistocleous et al. (2020))				2.0→2.1																																																																						
II	2.3	-	2.3 Overview of monitoring methods to meet policy-related issues. Table 6-1 shows typical policy-related issues identified by GESAMP (2019) alongside examples of remote sensing monitoring techniques that can be utilized to address them. Table 6-2 presents examples of monitoring conducted using remote sensing by local governments and other related entities.		2.3 Overview of monitoring methods to meet policy-related issues. [Addition]				2.0→2.1																																																																						
II	2.3	-	<p>Table 6-1. Examples of policy-related issues and output image using remote sensing.</p> <table border="1"> <thead> <tr> <th>Category</th> <th>What Do You Want to Know? *</th> <th>Why Do You Want to Know?</th> <th>Methods to Address Policy-Related Issues</th> <th>How to Address Policy-Related Issues</th> <th>Case Study (Numbers of Table 6-2)</th> </tr> </thead> <tbody> <tr> <td>1</td> <td>Abundance of marine litter in seas under national jurisdiction</td> <td>To manage the progress of countermeasures, to understand the impact</td> <td>-</td> <td>-</td> <td></td> </tr> <tr> <td>2a</td> <td rowspan="2">Type and origin of marine litter</td> <td rowspan="2">To develop effective and efficient mitigation measures against marine plastic pollution</td> <td>UAV @beach</td> <td>Identify litter types and abundance to estimate their sources for developing mitigation measures</td> <td></td> </tr> <tr> <td>2b</td> <td>Stationary camera @beach</td> <td>Identify litter increase / decrease trends and types to estimate their sources for developing mitigation measures</td> <td></td> </tr> <tr> <td>3</td> <td>The effectiveness of mitigation measures</td> <td rowspan="3">To assess the current status of plastic pollution, prioritize countermeasures, and promote efficient measures (including improving the efficiency of clean-up activities)</td> <td>Stationary camera @river</td> <td>Identify trends of increase/decrease in river runoff from land areas</td> <td></td> </tr> <tr> <td>4a</td> <td>Identification of accumulations</td> <td>UAV @beach</td> <td>Identify the distribution of marine plastics on major shorelines on a prefectural scale and clarify priorities for clean-up activities</td> <td>Case 1, 2, 3</td> </tr> <tr> <td>4b</td> <td></td> <td>Aircraft @beach</td> <td>Identify the distribution of marine plastics on all shorelines on a prefectural scale and clarify priorities for clean-up activities</td> <td>Case 2</td> </tr> <tr> <td>4c</td> <td></td> <td></td> <td>Stationary camera @beach</td> <td>Identify detailed litter increase/decrease trends for specific shorelines to improve the efficiency of the limited number of clean-ups</td> <td>Case 3, 4, 5</td> </tr> </tbody> </table> <p>* The left column of the table is based on GESAMP (2019).</p>	Category	What Do You Want to Know? *	Why Do You Want to Know?	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II	2.3	-	Table 6-2. Examples of remote sensing monitoring conducted to address policy-related issues		[Addition]				2.0→2.1																																																																						

III	3.2	3.2.1	<p>3.2.1 Remote sensing platforms</p> <p>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. 2026). For example, while satellites have lower spatial resolution, they can observe wide areas. In contrast, UAVs offer higher resolution but cover smaller areas compared to satellites (see Section 2.2). Thanabalan et al. (2025) demonstrated the effective use of these characteristics: they used satellite imagery to identify large-scale accumulations of debris and employed UAVs to collect detailed information on marine litter in specific areas of interest. Typical technical difficulties of remote sensing methods and future steps are shown in Table 8.</p>	<p>3.2.1 Remote sensing platforms</p> <p>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.</p>		2.0→2.1
III	3.2	3.2.2	<p>3.2.2 Image analysis</p> <p>Machine learning and deep learning-based image analysis 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.</p> <p>While manual methods can identify objects of all size ranges, image analysis methods struggle to predict relatively small or obstructed objects (Kako et al. 202). 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. 202).</p> <p>Based on image analysis AI developed using training datasets on marine litter, several automatic detection systems are now available online and can be easily used by non-experts. For example, BeachLISA (Beach Litter Image Segmentation Analysis, https://beach-ai.jamstec.go.jp/) allows users to detect and classify beach litter by simply dragging and dropping photographs into a web browser. For further details, refer to Annex Section II, 2.1.1 (2), Table 2.1.4: Examples of services for automated detection and classification of marine and river litter.</p>	<p>3.2.2 Image analysis</p> <p>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.</p> <p>While manual methods can identify objects of all size ranges, image processing methods struggle to predict relatively small or obstructed objects (Kako et al. 202 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. 202, draft paper).</p>	<p>The content described in the main body of the guidelines and in Annex Section II regarding image analysis technology has been reorganized.</p>	2.0→2.1

III	3.2	3.2.2	[Omission] *Move the content to Annex Section II	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. This 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.	(a	2.0→2.1
III	3.2	3.2.3	Table 9. Examples of applications used to collect data on litter in the environment.	Table 10. Examples of applications used to collect data on litter in the environment.		2.0→2.1
Reference	-	-	Cózar, A., Arias, M., Suaria, G., Viejo, J., Aliani, S., Koutroulis, A., Delaney, J., Bonnery, G., Macías, D., de Vries, R., Sumerot, R., Morales-Caselles, C., Turiel, A., González-Fernández, D., Corradi, P. (2024). Proof of concept for a new sensor to monitor marine litter from space <i>Nat Commun.</i> 15(1), 4637.	Themistocleous, K., Papousta, C., Michaelides, S., Hadjimistsis, D. (2020). Investigating detection of floating plastic litter from space using Sentinel-2 imagery. <i>Remote Sensing.</i> 12(16) 2648.		2.0→2.1
Reference	-	-	Kako, S., Kataoka, T., Matsuoka, D., Takahashi, Y., Hidaka, M., Aliani, S., Andriolo, U., Dierssen, H., van Emmerik, T., Gonçalves, G., Martinez-Vicente, V., Mishra, P., Monteiro, J.G., Streett, D., Konstantinos, T., Isobe, A. (2026). Remote sensing and image analysis of macro-plastic litter: A review. <i>Mar. Pollut. Bull.</i> 222, Part 1, 118630.	Kako, S., Kataoka, T., Matsuoka, D., Takahashi, Y., Hidaka, M., Aliani, S., Andriolo, U., Dierssen, H., van Emmerik, T., Gonçalves, G., Martinez-Vicente, V., Mishra, P., Monteiro, J.G., Streett, D., Konstantinos, T., Isobe, A. (2025). Advances in plastic litter diagnostics using remote sensing and image processing. (draft as of February 2025)	The bibliographic information has been updated to the latest version.	2.0→2.1
Reference	-	-	Thanabalan, P., Gayathri, K., Hidaka, M., Matsuoka, D., Mishra, P., Dierssen, H., Dash, S. K., Usha, T., Marigoudar, S. R. (2025). Monitoring of marine floating debris and beach litter using satellite and drones: a synergistic approach on policy & decision making. <i>J. Indian Soc. Remote Sens.</i> https://doi.org/10.1007/s12524-025-02332-7	[Addition]		2.0→2.1

Annex Section	Item	After	Before	Remarks	Version
II	2.1	2.1.1 (2) Automated detection (i) Types of automated litter detection methods	(2) Automated detection	The content described in the main body of the guidelines and in Annex Section II regarding image analysis technology has been reorganized.	2.0→2.1

II	2.1	2.1.1	(ii) Development of automated analysis technologies for marine litter The development of deep learning models requires expertise, a high-end GPU-enabled computer, and the preparation of training data necessary to train the models. This involves annotating the data with information such as the location and classification of marine litter. In particular, training data preparation is a time-consuming task as it requires many images and annotation work	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		2.0→2.1
II	2.1	2.1.1	There are also other databases, such as the Beach Plastic Litter Dataset (Hidaka et al. 2023; Hidaka et al. 2025), which extracts plastic litter from beach images taken from the ground, and the TACO Dataset (Pro-ença and Simões, 2020), which extracts litter from beaches and classifies it into 28 categories, such as beverage cans and plastic bags.	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 (Pro-ença and Simões, 2020), which extracts litter from beaches and classifies it into 28 categories, such as beverage cans and plastic bags.		2.0→2.1
II	2.1	2.1.1	Given the significant time and cost associated with creating training data, it is essential to share these existing public datasets (Kako et al. 2026)	Considering the workload, it is practical to use these existing public data as training data.		2.0→2.1
II	2.1	2.1.1	Regarding the sharing of datasets, there are examples of the use of cloud computing 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 2.1.3 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 marine litter. Specifically, BIIGLE, shown in Table 2.1.3, 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 2.1.3. Examples of cloud computing services for annotation.	[addition] *Content from the main body of the guidelines has been moved to this part		2.0→2.1
II	2.1	2.1.1	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.	[Addition] *Location changed		2.0→2.1

II	2.1	2.1.1	<p>(iii) Application of automated analysis technologies</p> <p>Image analysis AI systems, built using training data annotated by experts, are now publicly available online (see Table 2.1.4). These systems use pre-trained models, eliminating the need for users to prepare training data, write code, or train models themselves. Users can simply upload images or videos through basic mouse operations, making it possible to detect litter in images without requiring any specialized knowledge of deep learning.</p> <p>Compared to manual visual inspection (i.e., detecting litter by hand from images), these applications can significantly reduce the time and effort required. In addition, because the results are more objective, they are likely to show less variability in accuracy.</p> <p>Automatic image analysis technologies for marine litter have rapidly advanced in recent years, and further developments and new systems are expected in the future.</p>	<p>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).</p>	2.0→2.1	
II	2.1	2.1.1	<p>[Omission]</p> <p>*Location changed</p>	<p>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.</p>	2.0→2.1	
II	2.1	2.1.1	<p>Table 2.1.4 Examples of services for automated detection and classification of marine and river litter</p>	<p>[Addition]</p>	2.0→2.1	
II	2.1	2.1.1	<p>Column</p> <p>BeachLISA: Image Analysis of Marine Litter on Beaches</p>	<p>[Addition]</p>	2.0→2.1	
Reference	-	-	<p>Kako, S., Kataoka, T., Matsuoka, D., Takahashi, Y., Hidaka, M., Aliani, S., Andriolo, U., Dierssen, H., van Emmerik, T., Gonçalves, G., Martinez-Vicente, V., Mishra, P., Monteiro, J.G., Streett, D., Konstantinos, T., Isobe, A.(2026). Remote sensing and image analysis of macro-plastic litter: A review, Mar. Pollut. Bull. 222, Part 1, 118630.</p>	<p>Kako, S., Kataoka, T., Matsuoka, D., Takahashi, Y., Hidaka, M., Aliani, S., Andriolo, U., Dierssen, H., van Emmerik, T., Gonçalves, G., Martinez-Vicente, V., Mishra, P., Monteiro, J.G., Streett, D., Konstantinos, T., Isobe, A.(2025). Advances in plastic litter diagnostics using remote sensing and image processing. (draft as of February 2025)</p>	<p>The bibliographic information has been updated to the latest version.</p>	2.0→2.1
Reference	-	-	<p>Hidaka, M., Murakami, K., Kawahara, S., Sugiyama, D., Kako, S., Matsuoka, D. (2025). Updating “BePLi Dataset v1: Beach Plastic Litter Dataset version 1, for instance segmentation of beach plastic litter” with 13 object classes. Data in Brief. 61, 111867.</p>	<p>[Addition]</p>	2.0→2.1	