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Table of contents

Table of figures

Table index

List of abbreviations

WP	Work Package
COCO	Common Objects in Context
CSS	Candidate Selection System
CVAT	Computer Vision Annotation Tool
DFKI	German Research Center for Artificial Intelligence
EO/IR	Electro-Optical/Infrared
EOIR AI	Electro-Optical/Infrared - Artificial Intelligence
F1	Measure of a model's accuracy (F1 score)
FastAPI	Framework für Application Programming Interfaces
GSD	Ground Sampling Distance
AI	Artificial intelligence
MNDWI	Modified Normalized Difference Water Index
NDPI	Normalized Difference Plastic Index
NDVI	Normalized Difference Vegetation Index
NIR	Near Infrared
RGB	Red-Green-Blue (Color Space)
SWIR	Short Wave Infrared
UAE	Variational Autoencoder
VIS	Visible Light
VIS AI	Visible Light - Artificial Intelligence

Introduction

This document represents the final report of the PlasticObs_plus project, which was funded by the German Federal Ministry for the Environment, Nature Conservation, Nuclear Safety and Consumer Protection (BMUV) (funding code: 67KI21014A).

The work presented includes all work carried out by DFKI in the PlasticObs_plus project. This final report follows the guidelines of the NKBF 2017. Chapter 1 gives a brief description of the project according to point I, chapter 2 presents the content developments in a detailed description according to point II. Point III (Performance Control Report) is fulfilled by a separately submitted document.

1. Abstract

1.1 Previous status and resulting task

At the beginning of the project (2022), knowledge about the distribution of plastic waste in water bodies was mainly based on selective measurements with limited spatial and temporal coverage. Studies demonstrated the use of hyperspectral remote sensing for the detection of macroplastics, but systematic monitoring of larger areas was lacking (Garaba et al., 2018). Although satellite data enable large-scale analyses, they suffer from low resolution (>10 m/pixel) and atmospheric disturbances (e.g. cloudiness), which makes it difficult to detect small plastic objects (<1 m) (Topouzelis et al., 2020). Drone-based approaches achieved a detailed recording of plastic waste with high spatial resolutions (up to 0.05 m/pixel), but were only suitable for small-scale investigations due to their limited flight range and flight time (Fallati et al., 2019). Airborne oil detection systems were established, but not optimized for plastic waste.

The aim was therefore to develop an AI-supported two-stage sensor system and integrate it into an airborne remote sensing platform for the detection and analysis of plastic waste in maritime environments. These are to take place as part of routine flight investigations, such as oil surveillance flights to detect oil spills, in order to close the gap between satellite and drone-based monitoring approaches. The resulting integrated measurement system is intended to enable standardised, both large-scale and high-resolution and regular monitoring of plastic pollution and thus further close the knowledge gaps on the sources, distribution routes and accumulation areas of plastic waste. The automatic evaluation of the remote sensing data is to be carried out using machine learning and deep learning methods. The models were to be transferred to a publicly accessible AI library, whereas the inference of selected models can be triggered and interpreted directly via a geo-portal.

1.2 Prerequisites, planning, and course of the project under which the project was carried out

The project used a flexibly equipped research aircraft (HK36 TTC-ECO) from Jade University, as well as existing sensor platforms and the expertise of the participating partners. The core scientific and technical elements were framed by stakeholder surveys at the beginning of the project. Among other things, the focus on as many areas of application as possible, interactive maps and the long-term goal of prevention was determined by the project results. The firmly scheduled regular project meetings (virtual and physical) ensure coordination, coordination, and risk monitoring in the consortium. The WP8 specifically designed for this purpose establishes public relations and knowledge transfer as an integral component. This means that the results, progress and planned campaigns are already documented and made available

during the approval period. The three milestones (1. definition of the requirements, 2. validation of the system, 3. final demonstration) structured the progress of the project and showed the most critical progress to be achieved.

1.3 Results and cooperation with other bodies

The PlasticObs_plus system implemented a two-stage AI architecture for plastic detection: In the first stage, the VIS AI analyzes the data from the VIS Line scanner in real time, while in the second stage, the EOIR AI segments and classifies the high-resolution multispectral data (3 mm/pixel at 300m altitude). The VIS AI successfully identified anomalies in Brazil and generalized across different environments, which was validated through campaigns with manual ground-truthing.

The Candidate Selection System (CSS) prioritizes possible plastic hotspots, which allows the EO/IR (Electro-Optical/Infrared) sensor technology to be efficiently aligned with hotspots. These results enable precise detection and validation of plastic waste, even in complex environments such as festival sites, salt marshes, lakes, and beaches.

The GeoNode platform integrates AI models via FastAPI interface, enables batch processing and provides the results georeferenced for subsequent visualization and export. The open-source AI library created by the project includes pre-trained models and supports global adaptations to regional waste types. Published datasets contain annotation files and include both spatially and spectrally diverse image data as a basis.

In order to strengthen the broad impact of the project, PlasticObs_plus involves national and international stakeholders in addition to the core team from research and industry. The Federal Environment Agency (UBA) contributed its expertise from the AI Lab, and the Wittbülten National Park House on Spiekeroog serves as a central point of contact in the Wadden Sea UNESCO World Heritage Site. An exchange with the Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ) and the planned cooperation with MI4People promote technology transfer and make it possible to derive political measures. These collaborations also underline the lighthouse character of PlasticObs_plus as a holistic approach to AI-supported environmental protection.

2. In-depth presentation

The following sections provide a detailed account of the activities and investigations carried out in the PlasticObs_plus project (Funding Reference 67KI21014A), as well as their results, structured by work packages. The following table lists the individual work packages and their assignment.

Table 1: Tabular overview of the work packages (WP) with lead and DFKI participation

WP	Short Title	Lead	DFKI involved
WP1	Concept and coordination phase	DFKI	Yes
WP2	Digital twin of the plastic detection system	Optimare	Yes
WP3	Sensors & Actuators	Optimare	No
WP4.1	Development of AI architectures and knowledge base	DFKI	Yes
WP4.2	Weighing system for EO/IR control	DFKI	Yes
WP4.3	Feedback loop of AI outputs	DFKI	Yes
WP4.4	Ground Truthing Model	everwave	Yes
WP5	Data management	Optimare	Yes
WP6.1	Field Experiment Drones & Application Ground Truthing	DFKI	Yes
WP6.2	Field experiment research aircraft	Jade HS	Yes
WP6.3	Field Operations Oil Surveillance Aircraft	Optimare	Yes
WP6.4	Overall assessment validation phase	everwave	Yes
WP7.1	Development, operation and further development of the Geodata Portal	DFKI	Yes
WP7.2	Development of a situation picture for the visualization of the distributions of plastic	DFKI	Yes
WP8.1	Public relations	everwave	Yes
WP8.2	Interactive science communication	everwave	Yes
WP8.3	Publications and Open-Source	DFKI	Yes
WP9.1	Administration and project coordination	DFKI	Yes
WP9.2	Reporting	DFKI	Yes

2.1 Work carried out

The following describes in detail the work packages led by DFKI in the PlasticObs_plus project. The results achieved are compared with the defined objectives.

2.1.1 WP1.2: Test plan for development results

WP1.2 aimed to create a test plan for validating the development results of the PlasticObs_plus

system, including sensor integration, data processing chain, and AI models. The detailed planning of individual test stages was not established at the start of the project but was successively reviewed and flexibly adapted to new findings or changing requirements together with all partners during the project. For example, after the test flight on Spiekeroog, the planned flight altitude for the airborne sensor system was set to 300 m to meet a requirement for the processing speed of VIS AI and the Candidate Selection System (CSS). This iterative approach ensured that current developments and challenges could be addressed promptly. Due to the lack of plastic occurrence in the North Sea, the test plan was adapted during the project period to include custom measurement setups on beaches, in salt marshes, in lakes, and the use of plastic waste occurrences at festival grounds to test the overall system.

2.1.2 WP4.1: Development of AI architectures and knowledge base

As part of WP4.1, the model originally planned as "Edge AI" has been implemented in **VIS AI** (real-time capable AI architecture for the evaluation of the RGB line scanner (VIS Line Scanner, 2025)) and **EOIR AI** (for high-resolution EO/IR sensor technology and detailed segmentation and classification using MaskRCNN).

Implementation VIS AI

The VIS AI's requirement was the speed of evaluation, i.e. the development of an AI architecture with low latency, as it must continuously provide the results and positions of possible plastic hotspots in flight for the control of the EO/IR sensors. Therefore, different architectures were developed for the planned purpose of the aircraft-based plastic detection by means of sensor fusion (see WP4.2: Weighing System for EO/IR Control , page 13). One focus was on pixel-based analysis, the results of which were published (Tholen et al., 2025). For practical testing in Brazil, the VIS AI was employed using the Variational Autoencoder Architecture (VAE), which has been specially optimized for anomaly detection in large-scale remote sensing data (Kingma and Welling, 2022). The VAE consists of an encoder that compresses input images into a latent space and a decoder that translates this representation back into a reconstructed image. This architecture allows the detection of anomalies due to deviations between the original and reconstructed image (see also Figure 1, page 11).

Originally designed for the North Sea, data collection and model validation proved to be unfeasible during the project period due to the lack of plastic waste occurrences. In order to test the overall system for general functionality and to prepare for the last practical test in Brazil, a final test campaign was carried out. on a festival site and the data obtained was successfully (details on data collection and methodology can be found in section 2.1.5, page 18).

Results VIS AI

- **Real-time capability**: The approach requires minimal computing resources, which allows it to be used on board aircraft.
- **Generalizability**: The model, trained on the images of the North Sea, shows generalizability for the data from the festival campaign
- **Field demonstration in Brazil:** Successfully detected anomalies (i.e., potential plastic hotspots).
- **Open-source contribution**: The results were incorporated into the open-source AI library, which is now available as VAE models for various environments.

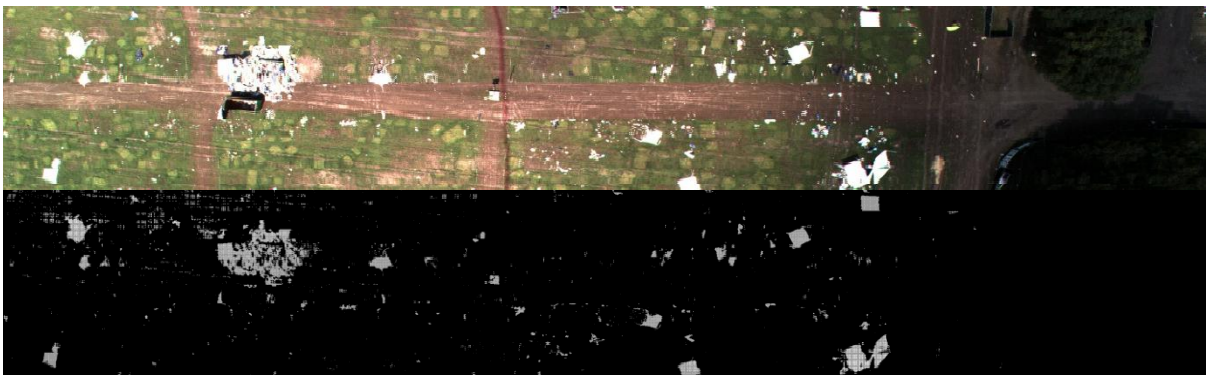

Figure 1: (Above) RGB image (composed of individual image lines) of the festival, taken with the VIS Line Scanner. (Bottom) VIS AI result image, anomalies marked by greyscale.

Implementation of EOIR AI

The EOIR AI's requirement was to evaluate high-resolution multispectral images in order to be able to quantify plastic waste more accurately and to better validate the overall system. The following points were of particular relevance for this:

- **Generation of training data**: Since the EO/IR sensor technology did not provide data until the end of the approval period, previous campaigns were implemented by drones that simulate the spatial and spectral resolution of the EO/IR sensor technology.
- **Model selection**: For instance segmentation, the Mask R-CNN model (PyTorch with ResNet50 backbone) was deliberately chosen to avoid commercial licensing restrictions of YOLO models and to preserve the open-source approach of the project.
- **Labeling process**: With the CVAT tool (Computer Vision Annotation Tool) Objects in the drone images were manually annotated (CVAT (2.16.1), 2024). The results were presented in the COCO (Common Objects in Context) format and curated (Lin et al., 2014).
- **AI inference**: The trained models provide predictions (labels, bounding boxes and confidences) that can be processed via the GeoNode platform (WP7, page 18) and can be visualized and exported.

In order to obtain image data from different altitudes, and the resulting spatial resolution, a scaling process was implemented, which was supplemented by the adaptation of annotation classes (Rettig and Becker, 2025). This enabled the greatest possible adaptability of the ground-truth data basis, also for other use cases with alternative sensors.

The EOIR AI is a central component of AI-supported sensor fusion in PlasticObs_plus for the detection and quantification of plastic waste. The successfully trained models flow into both the digital twin and the geo-portal. In the geoportal, they are accessible to stakeholders as selectable AI inferences. Via the flexibly addable FastAPI (Framework for Application Programming Interfaces) interface (see also 2.1.6 Results Platform, page 18), a pre-trained network can be adapted to local conditions (e.g. dominant waste types, sensor configurations or platforms). The created Models and Tools (Becker and Rettig, 2025), as well as datasets incl. annotations have been made publicly available (Rettig et al., 2025).

Within the selected flight altitudes, a distinction was made between three spectral combination classes:

- **RGB:** Classic RGB image,
- **NDVI**: NDVI (Normalized Difference Vegetation Index) – NDPI (Normalized Difference Plastic Index) - MNDWI (Modified Normalized Difference Water Index),
- **NIR**: Near Infrared-Red-Green,

and distinguish between three object classes:

- **material**: Distinction between "Plastic", "Paper", "Metal" and "Other"
- **binary**: Binary detection of objects
- **classes**: Detection with splitting of all object classes (cf. Rettig et al., 2025)

The object classes for "material" and "binary" were each clustered from the annotation for all object classes ("classes"). For example, the object classes "X…-**Plastic**-X…" have been merged into the material class "**Plastic**".

Results EOIR AI

The analysis of the F1 scores shows clear influences of spatial resolution. Models based on drone data, recorded at an altitude of 20m, corresponding to the Ground Sampling Distance (GSD = 9 mm), which is very close to the planned EO/IR sensor technology on the aircraft, show a particularly high performance. Models created with drone images at an altitude of 4 m (GSD = 2 mm) also achieve good results, especially the model 04m_binary_RGB, with an F1 score of 0.77. This suggests that segmentation approaches are less profitable at lower resolutions and that the high-resolution EO/IR sensor technology is more effective due to the two-stage process.

In the case of the last festival campaign, the tested models are less sensitive when clustering

the object classes (see Table 1, on page 33), which may be due to the lack of spectral coverage of the sensor systems in the SWIR range and the diverse structure of the clustered material classes. The exact values for all test cases can be viewed in the F1 scores table in the appendix (page 27). Figure 2 is showing the F1 scores which are based on the validation of the EOIR AI models, which, as described, are initially based only on drone data. It should be noted that there is a clear trend towards better F1 scores with decreasing altitude, i.e. increasing GSD, which is comparable to the GSD of the EO/IR sensors. These results underline that the project successfully form the basis for operational plastic detection and sensor specification for future routine flights.

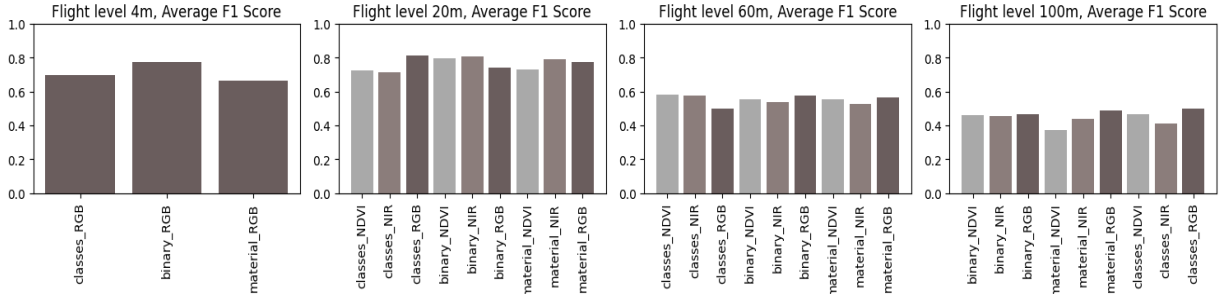

Figure 2: F1 Scores for Detection of Waste Objects

2.1.3 WP4.2: Weighing System for EO/IR Control

In order to align the EOIR sensor technology as efficiently as possible in flight, i.e. to the positions of the candidates who have been assigned a high probability of plastic hotspots by the VIS AI, a Candidate Selection System (CSS) was developed (Tholen and Wolf, 2023).

The calculation of this balancing priority will be illustrated in the following using the example of the festival flight data (for details see section 2.1.5, page 18). In the Figure 3, each point represents an anomaly detected per second or per image strip (composed of individual image lines). Due to the high swath width (i.e. the detected coverage width of the earth's surface, resulting from the opening angle of the sensor) of the VIS Line sensor system must be a large movement space for the EO/IR sensor technology can be mapped. In order to make the movement patterns of the controllable EO/IR sensors as efficient as possible, in addition to the CSS, a customizable priority approach has been implemented, which prefers the centre of the sensor and thus the sensor movement.

In the example in Figure 3 (page 14) it becomes clear that from the middle of the overflight of the festival site, the intended EO/IR movement runs more along the centre of the sensor, because there the probability of plastic waste is high over the entire swath width and thus the priority-based weighting to the centre of the sensor is more effective. This will be discussed in more detail below.

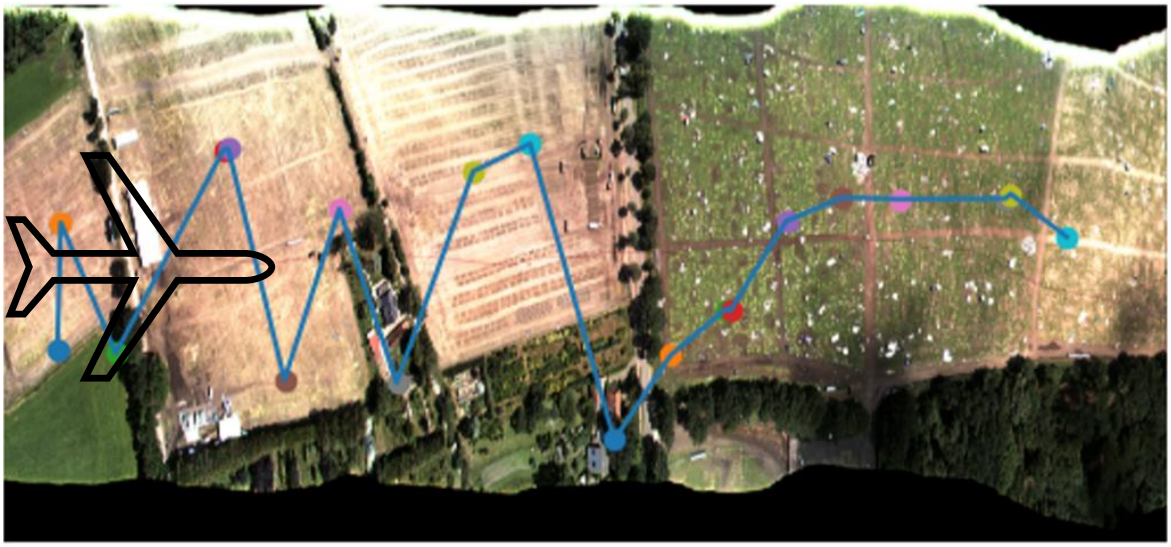

Figure 3: Simulated control for the EOIR using CSS (flight direction left to right). In addition to the probability of an anomaly, the spots with the highest priority value are displayed according to the pixel position (distance to the centre of the sensor).

After the probability of an anomaly (in our case a potential plastic hotspot) was not considered sufficiently efficient as a criterion in the system, the criterion was supplemented by a priority value ($prio$). Figure 4 (page 15) shows the calculation of priority, taking into account the position of the anomaly relative to the centre of the sensor and the probability that it is a significant anomaly. The red X-axis represents the pixel position of the anomalies. The probability of an anomaly is represented on the green Y-axis on a scale from 0 to 1, with 1 being the highest value. The blue Z-axis represents the assigned priority value. Larger priority values therefore describe an advantageous hotspot. Consequently, all other hotspots located further from the sensor centre ($fullRes/2$) are rated progressively lower. The following equations show the calculations for the weighted distance to the centre of the sensor (1) and the priority value (2). By iteratively testing the exponents 2, 4, and 6 graphically, the most suitable value for our study area was determined to be 4 for the function defined in Equation (1). Key factors in selecting the exponent value were its even-numbered parabolic behavior and the sufficient prioritization of pixels near the sensor centre. The normalization of the $dist$ and $probability$ factors in Equation (2), along with scaling by a factor of 10, enables:

- Efficient system integration via integer representation of priority values,
- Interoperability between components of the decision-making system,
- Comparability of results across heterogeneous environments.

$$dist = -\left(\frac{2}{fullRes}\right)^4 * \left(pixel\_id - \frac{fullRes}{2}\right)^4 + 1 \quad (1)$$

$$prio = \left(\frac{1}{dist} * \frac{1}{probality} - 1\right) * 10 \quad (2)$$

- **fullRes**: Refers to the full resolution of an image line from the VIS AI model
- **pixel_id**: Denotes the specific pixel within the image in which the anomaly was detected.
- **probability**: The probability of anomaly at the specific pixel position.
- **dist**: The distance of the anomaly to the centre of the sensor
- **prio**: The priority for targeting the anomaly

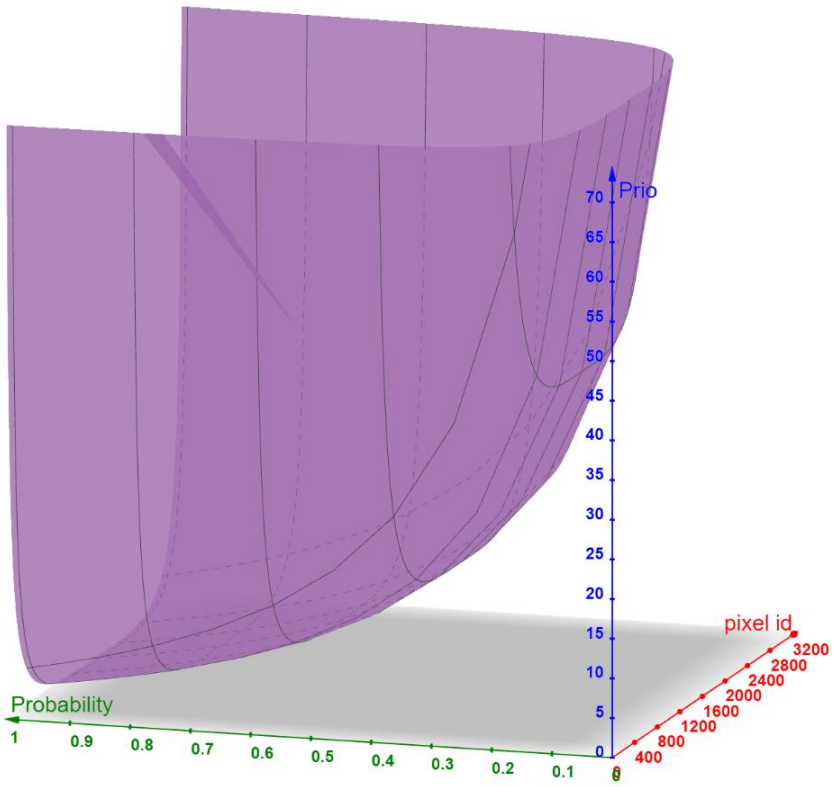

Figure 4: Visualization of priority calculation (z, blue), as a function of pixel position (x, red) and probability (y, green) of an anomaly

2.1.4 WP4.3: Feedback loop of AI outputs

The feedback loop is based on data from past, already completed flight missions. During the flight, data are written into a database using container management tools and can subsequently be retrieved from the database (MariaDB software) via SQL queries.

The purpose of the feedback loop is to validate the VIS AI and enable continuous optimization. In this way, the data foundation can be regularly expanded or updated and adapted to specific regional conditions in order to increase detection accuracy. This concept is particularly effective, as it purposefully supports the autonomous operation of VIS AI and enables a continuously operational system in as many regions as possible under changing environmental conditions.

For this purpose, a script was developed in cooperation with Optimare, which enables validation by experts based on database entries from past routine flights. The script reads composite image lines from the database and displays them to the experts. In the visualization, detected anomalies are shown as points in the image, with a reference to the EOIR video, so that the anomaly can be validated at higher resolution. The experts annotate the image strips in which anomalies were correctly detected (true positives), which are then not used for retraining VIS AI. The remaining image strips, in which no anomalies were detected (true negatives) or in which one or more anomalies were incorrectly detected (false positives), are subsequently passed to VIS AI for training.

The following figures (Figure 5 – Figure 6, page 17) illustrate the described functionality with screenshots of the feedback loop tool. The first figure shows the automatic playing of a video for a detected anomaly shown. It should be noted that, according to the VAE architecture, an anomaly is initially defined as any feature or structure that does not correspond to the reconstructed image (cf. VIS AI, section 2.1.2, page 10). Only through the subsequent validation can the goal, plastic waste detection, be met.

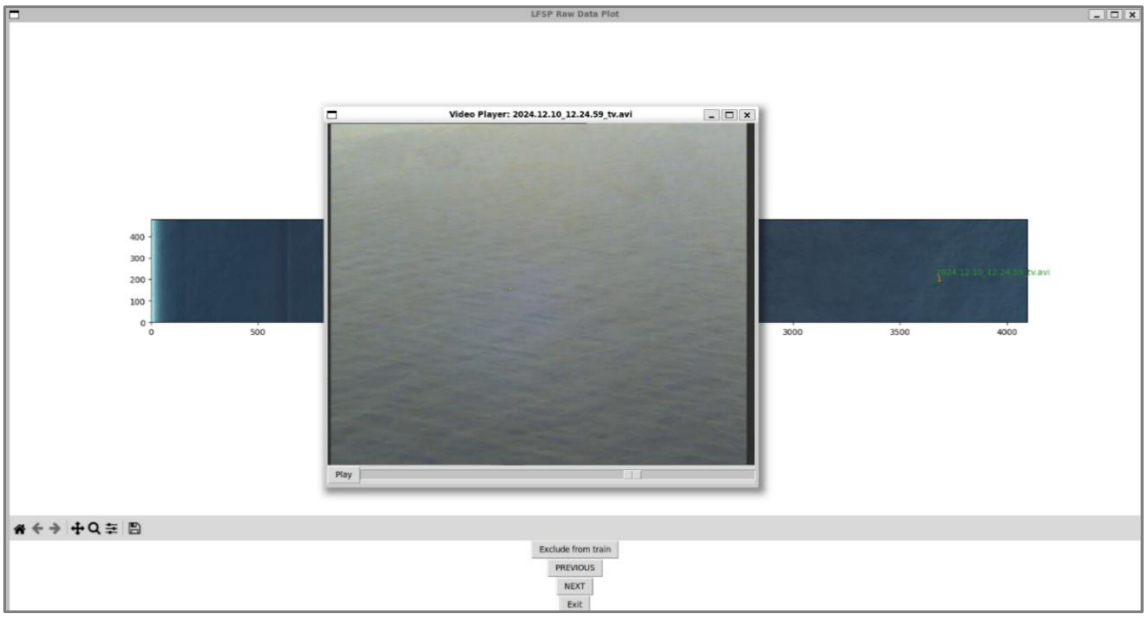

Figure 5: Automatically play a video for the anomalies found

In the activity diagram below (Figure 6, page 17) shows the flow for the feedback loop application. If an anomaly is detected in the image strips, the video name is read from the database and the corresponding video is played. This allows for detailed verification and validation of the anomaly. In the event of an anomaly, it checks whether it is a true positive and the image strip is then written to a CSV file. This step is crucial to ensure that the identified anomaly is actually relevant and correct in order to exclude it from subsequent training.

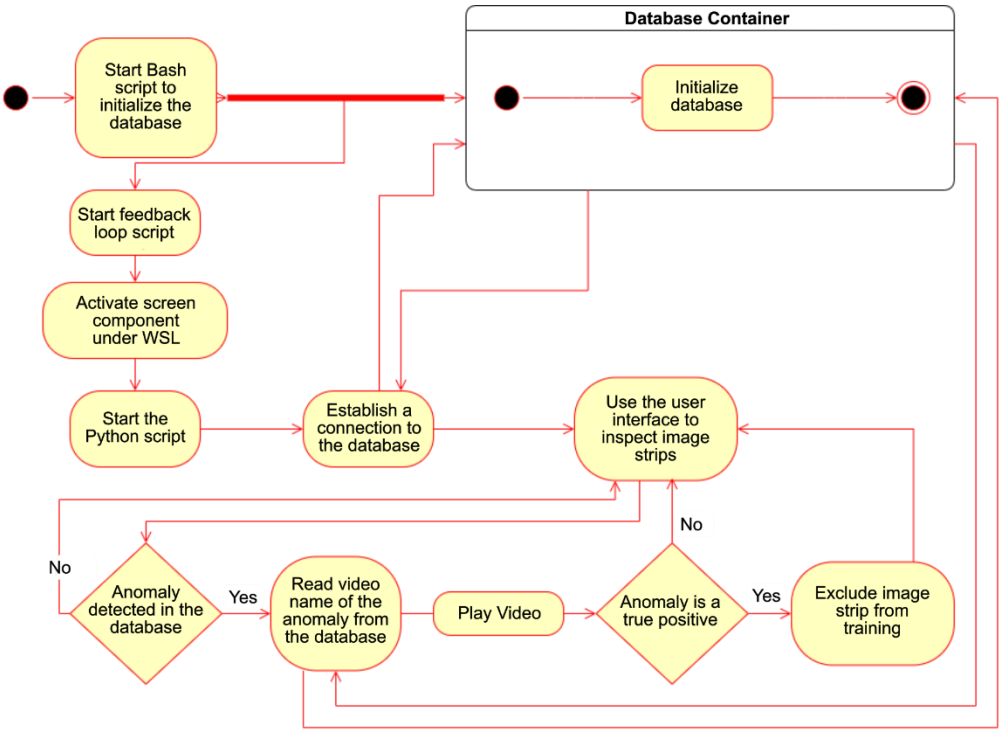

Figure 6: Activity diagram for the Feedbackloop application

2.1.5 WP6.1: Field Experiment Drones & Application Ground Truthing

Within WP6.1, drones were specifically deployed to generate datasets for testing and simulating the technical aspects of the project. The first deployment took place in 2023 on the island of Spiekeroog, where drones flew at altitudes between 15 and 100 meters over specially prepared test plots on the beach and in salt marshes to detect different types of plastics. Further deployments were conducted near Friedeburg, where artificial waste patches were placed on a lake and surveyed by drones. In addition to these field deployments, the detectability of waste hotspots was also examined at two festivals to systematically record and map the typical quantities of plastic waste that occur after large events.

A central element was ground truthing: Over the first three days on the second festival campaign in June 2024, 432 test plots were surveyed for the weight and volume of waste, with image data collected via smartphones, drones, and the research aircraft (Rettig et al., 2025). The interplay between drone and aircraft data enabled the verification of transferability and scalability of the methods. While the aircraft, equipped with a VIS line scanner, provided large-area overviews at a 15 cm resolution, the drones enabled detailed analyses on selected plots. By combining both platforms, the strengths—rapid area coverage and high level of detail—could be optimally tested.

2.1.6 WP7: Platform for Results (WP7.1 and WP7.2)

In the project, GeoNode was preferred as the platform for the results. Supported by an active community and seamless integration with other open-source projects, GeoNode offers a comprehensive and secure solution for geospatial data management. GeoNode is primarily an open-source platform for managing and publishing geodata, which is particularly suitable for local hosting, without license fees. The platform is characterized by customizability, as developers can modify the source code and integrate additional features to meet specific requirements. Local hosting also gives organizations full control over their data, which is especially important for sensitive information. The open-source implementation using GeoNode (geonode.org), global usability also enables future potential adaptations to technical necessities or regional conditions. The subcontractor 52°North has specially developed the GeoNode platform for this project (Bredel, 2025).

Key Functionalities achieved for Platform:

- **Batch Processing**:

  The platform enables batch processing of large datasets for users with the according status, allowing for efficient handling of extensive remote sensing data (see Figure 7, page 19).

Figure 7: Batch Processing in GeoNode

- **API Integration**:

  The interaction between GeoNode and the AI API is illustrated in a sequence diagram (see Figure 8). The FastAPI (Framework for Application Programming Interface) allows for the integration of trained AI models (developed within the project and further) and the adaptation of models to local conditions (e.g., dominant waste types, sensor configurations, or platforms).

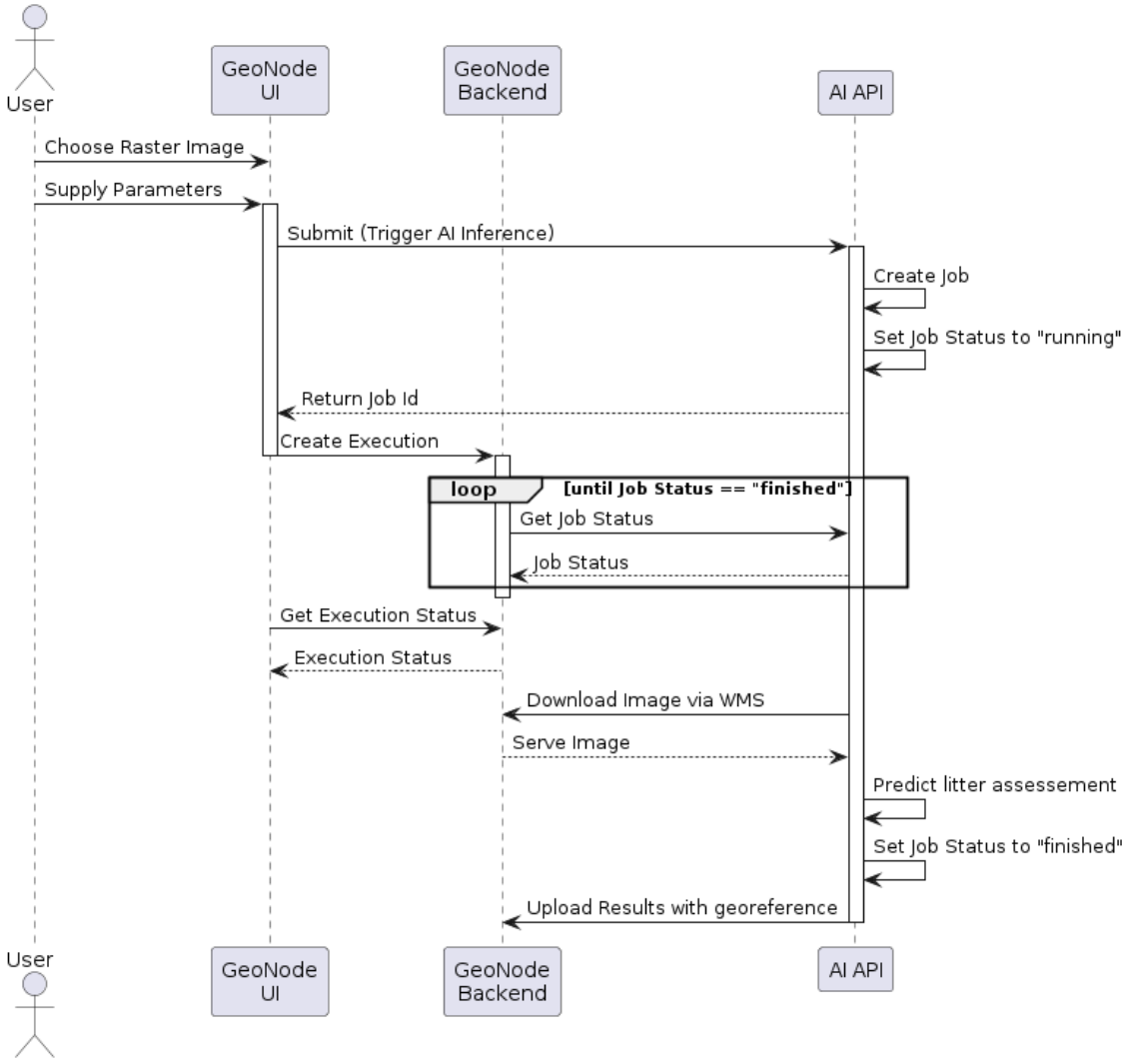

Figure 8: Sequence diagram of the interaction between GeoNode and the AI API

- **Visualization and Export**:

  The inference results from the API are displayed in the attribute table and can be visualized as shapefiles over the original image (e.g., as transparent bounding boxes), enabling both detailed and overview maps for further analysis (see Figure 9).

- **Open Access**:

  The platform is designed as an open-source solution, allowing for global adaptation and integration into existing monitoring workflows. Results can be made available as web map services (WMS) for both the public and relevant stakeholders and authorities.

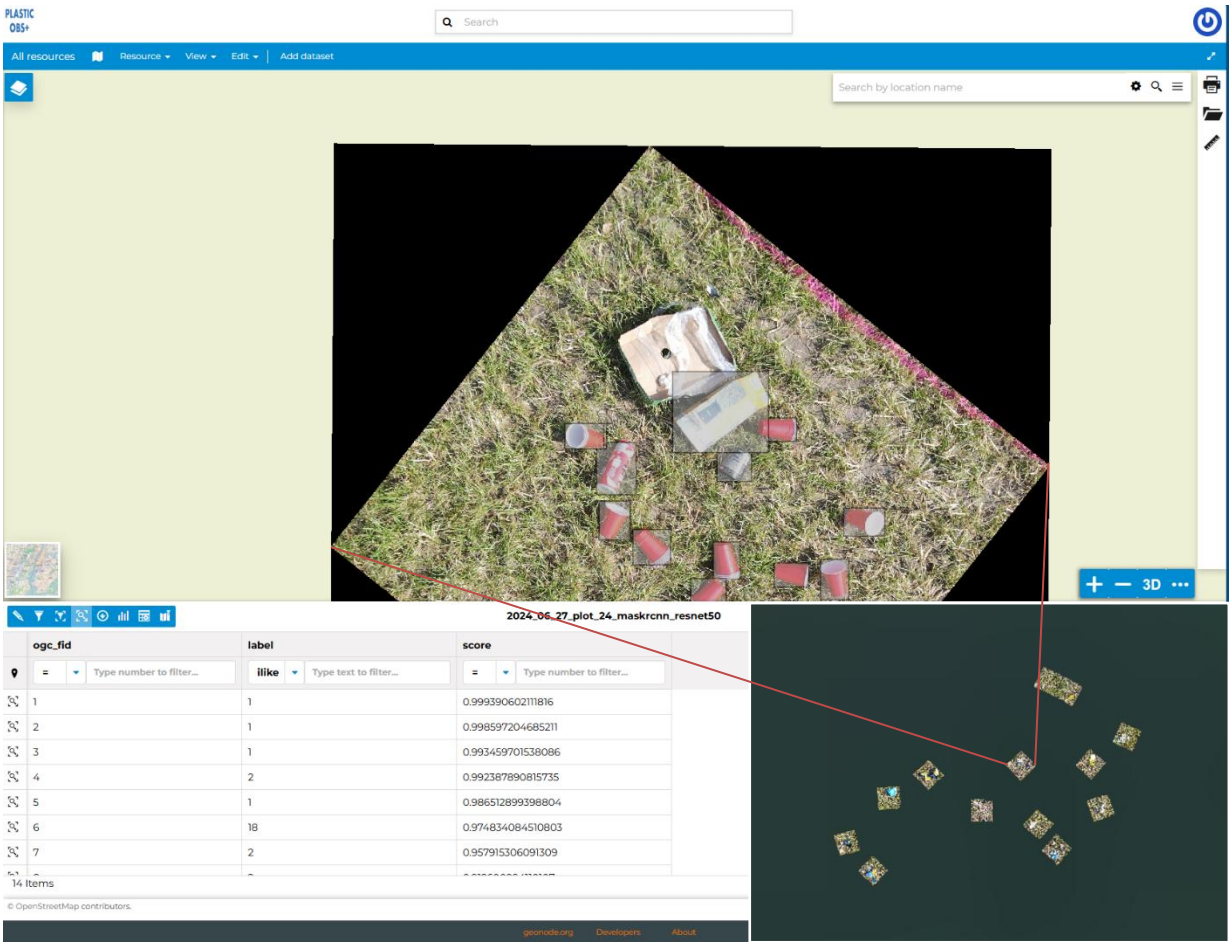

Figure 9: Representation of the inference result of the API. Detections in detail as transparent bounding boxes, with other results also in an overview map.

2.1.7 WP8.3: Publications and Open-Source

This work package encompasses the dissemination of project results through scientific publications, open-source software, and the release of data. The project produced several peer-reviewed articles, conference presentations, and open datasets to promote transparency and foster further research in AI-based plastic detection.

Key outputs include:

- Scientific articles published in journals and at conferences.
- Open-source AI libraries and tools made available via platforms such as GitHub.
- Public datasets with annotations for training and validation.
- Presentations at scientific and industry forums.

For a detailed list of publications, see 2.6 Publications (page 25)

2.1.8 WP9.1: Administration and Project Coordination

Within this work package, the project schedule and execution of the individual work packages, as well as communication with the funding agency and project sponsor, were ensured. Required documentation was reported, and project budget management was continuously performed. Project control was carried out through regular virtual meetings and semi-annual in-person meetings. These meetings and the reporting (WP9.2) provided quality control over the progress of the individual work packages. Project risks were managed and minimized as much as possible.

2.1.9 WP9.2: Reporting

The preparation of interim and final reports was completed on schedule. Due to delays in achieving milestones 2 and 3, the presentation of project results was moved to the project's end. As a substitute, low-threshold virtual meetings with stakeholders (e.g., with GIZ and MI4People) and the final event in February 2025, in collaboration with everwave, were organized to enable stakeholder interaction.

2.2 Main items of the numerical record

DFKI has achieved the goals set out in the project plan while adhering to the schedule and budget. Details can be found in the numerical proof of use.

Table 2: Main items of numerical proof

Cost	VK	VN	Difference	**Deviation VK to VN in %**
Material	1.776,46 €	2.000,00 €	- 223,54 €	-11%
External services	50.400,00 €	50.400,00 €	-	0%
Total personnel costs	465.962,78 €	466.328,70 €	- 365,92 €	0%
Travelling expenses	12.348,87 €	13.800,00 €	- 1.451,13 €	-11%
Depreciation and amortization of project-specific assets	3.322,85 €	3.859,04 €	- 536,19 €	-14%
Depreciation and amortization of other fixed assets	-	-	-	0%

Other direct project costs	937,82 €	5.188,00 €	- 4.250,18 €	-82%
Total direct project costs	**534.748,78 €**	**541.575,74 €**	**- 6.826,96 €**	**-1%**
In-house services	-	-	-	0%
Administrative costs	231.800,09 €	221.706,15 €	10.093,94 €	5%
Cost	**766.548,87 €**	**763.281,89 €**	**3.266,98 €**	0%

The material costs amounted to € 1,776.46 and were thus 11% below the planned budget. For external FE services, the estimated € 50,400.00 was fully exhausted. The total of personnel costs amounted to € 465,962.78 and was thus almost within budget. Depreciation and amortization of project-specific assets amounted to € 3,322.85 and was thus 14% below the estimate. € 937.82 was spent on other direct project costs, which were significantly below budget. The reason for this is the incomplete utilization of funds allocated for open-source publications during the funding period, which are, however, still being actively planned and implemented with some delay. The total of the direct project costs amounted to € 534,748.78 and was thus only 1% below the planned value. No costs were charged for in-house services. Administrative costs amounted to € 231,800.09 and were thus 5% above the planned budget. The cost price totalled € 766,548.87 and was thus largely in line with the plan.

2.3 Necessity and appropriateness of the work done

The work carried out within the framework of PlasticObs_plus proved to be necessary and appropriate. The development of an AI-supported sensor system with real-time capability enabled the airborne detection of plastic waste in marine ecosystems while maintaining scalability. The adequacy of the methodology is underlined by the successful generalization and transferability of the models and other technical results, as well as the validation by ground-truthing in complex environments. The project-related integration of stakeholders from the environmental protection sector, as well as the open-source approach (publications, datasets, GitHub and GeoNode) also demonstrate the operational relevance and global adaptability of the solutions.

2.4 Applicability

2.4.1 Economic prospects of success

Although DFKI does not pursue economic development directly, the economic prospects for AI-based plastic detection are promising. Startups developing integrated solutions for monitoring and removal are indirectly supported by the open-source strategy. The combination of precise detection and targeted cleanup offers valuable use cases for environmental protection and waste management stakeholders through cost-efficient solutions.

2.4.2 Prospects of scientific success

The scientific prospects for success of the PlasticObs_plus system are founded on its technological transferability, methodological innovation, and strategic integration into international research networks. The developed AI models for plastic detection are not only characterized by their transferability into diverse environments but are also versatile in application due to their modular architecture. They can be potentially tested for their transferability to other ecosystems (e.g., coral reefs, seagrass meadows) and, when combined with alternative sensor technologies, extended to address advanced challenges such as assessing plastic quality (e.g., pollution levels). Building on these project outcomes, applications were submitted for the following international research initiatives:

- **SeaCaire**: SEA and Coastal-based monitoring strategies – employing AI to protect threatened Ecosystems
- **RED-SAIL**: Robotics and Environmental Detection: Surveillance and Identification of Aquatic Litter
- **pAIro**: pAIrolysis-to-CNTs: Sensor-based plastic quality assessment and AI predictive model for product yield optimization

Additionally, a proposal was submitted for a national research transfer project (**Green AI Hub Mittelstand**) in collaboration with Procertus GmbH, a cleanup service provider for large-scale events.

The GeoNode platform forms the technological basis for future projects: as an open-source GIS, it enables the integration of multi-scale remote sensing data with in-situ measurements. The FastAPI interface allows direct integration of AI models into existing monitoring workflows, for example, for quantifying plastic sinks in coral reefs. The platform also supports potential citizen science approaches, enabling the public to validate detection results.

Future research projects can build on the multi-sensor database and expand it with hyperspectral sensor data, LiDAR, radar, and polarimetric measurements to create a globally

referenceable "plastic fingerprint catalog". The developed technology and results can also be incorporated into harmonized monitoring protocols that unify satellite-, aircraft-, and drone-based data to support a digital representation of the oceans.

In summary, PlasticObs_plus, through its interdisciplinary orientation and open architecture, bridges the gap between basic research and applied environmental monitoring—a prerequisite for securing future third-party funding projects in the context of the UN Sustainable Development Goals.

2.5 Progress that has become known

During the approval period, significant advances were made in remote sensing technology for detecting plastic waste in marine ecosystems. Scientific breakthroughs include improved detection accuracy, machine learning, and hyperspectral sensors, while startups (e.g., scidrones.com) are developing integrated solutions for monitoring and remediation.

Research from the University of Minnesota demonstrated for the first time that spectral reflectance properties in the visible and infrared spectrum can distinguish plastic from natural materials such as algae or driftwood in rivers (Olyaei et al., 2024). In parallel, experiments in the Deltares test basin showed that microwave sensors (X- and Ku-band) reliably identify plastic at concentrations of at least 1 unit/m², even under wave conditions (De Fockert et al., 2024).

Italian researchers combined hyperspectral remote sensing with real-time ML algorithms to detect plastic in different environments (Balsi et al., 2025). These systems analyze spectral "fingerprints" of polymers that remain unambiguous even in the presence of biofilm growth. However, projects like this one, which show that polymers such as PET and PE have unique optical signatures that are potentially detectable in satellite data, are still highly dependent on the concentration of the plastic parts and sensor resolution (De Fockert et al., 2024).

2.6 Publications

Publications

- Tholen, C., Wolf, M., Leluschko, C., Zielinski, O., 2023. Machine learning on multisensor data from airborne remote sensing to monitor plastic litter in oceans and rivers (PlasticObs+), in: OCEANS 2023 - Limerick. Presented at the OCEANS 2023 - Limerick, IEEE, Limerick, Ireland, pp. 1–7. https://doi.org/10.1109/OCEANSLimerick52467.2023.10244528
- Tholen, C., Wolf, M., 2023. On the Development of a Candidate Selection System for Automated Plastic Waste Detection Using Airborne Based Remote Sensing, in: Bramer, M., Stahl, F. (Eds.), Artificial Intelligence XL, Lecture Notes in Computer Science. Springer Nature Switzerland, Cham, pp. 506–512. https://doi.org/10.1007/978-3-031-47994-6_45
- Leluschko, C., Tholen, C., 2023. Goals and Stakeholder Involvement in XAI for Remote Sensing: A Structured Literature Review, in: Bramer, M., Stahl, F. (Eds.), Artificial Intelligence XL, Lecture Notes in Computer Science. Springer Nature Switzerland, Cham, pp. 519–525. https://doi.org/10.1007/978-3-031-47994-6_47
- Binkele, T., Hengstermann, T., Schmid, T., Wellhausen, J., Leluschko, C., Tholen, C., 2024. Automatic litter detection using AI in environmental surveillance aircraft, in: Hou, W., Mullen, L.J. (Eds.), Ocean Sensing and Monitoring XVI. Presented at the Ocean Sensing and Monitoring XV, SPIE, National Harbor, United States, p. 11. https://doi.org/10.1117/12.3013922
- Tholen, C., Rodenbäck, E., Nolle, L., Rettig, R., Stahl, F., 2025. On the Development of a Pixel-Wise Plastic Waste Identification System for Multispectral Remote Sensing Applications, in: Bramer, M., Stahl, F. (Eds.), Artificial Intelligence XLI, Lecture Notes in Computer Science. Springer Nature Switzerland, Cham, pp. 47–60. https://doi.org/10.1007/978-3-031-77915-2_4

Datasets

- Rettig, R., Becker, F., Berghoff, A., Binkele, T., Butter, M.W., Floehr, T., Kumm, M., Leluschko, C., Littau, F., Reinders, E., Rodenbäck, E., Schmid, T., Schründer, S., Schweigert, S., Sinhuber, M., Tholen, C., Wellhausen, J., Stahl, F., 2025. Multiscale_Waste_PlasticObs_plus. https://doi.org/10.5281/ZENODO.14844219Multiscale_Waste_PlasticObs_plus

GitHub-Repositories:

- **Adapting_Annotation_Datasets** (Rettig and Becker, 2025)
- **Plasticobs-GeoNode** (Bredel, 2025)
- **AI Library** (Becker and Rettig, 2025)
  - **EOIR:** Training and Test Scripts
  - **VIS AI + CSS:** VIS AI and CSS as used in Brazil
  - **VIS AI Training:** Docker environment for VIS AI training
  - **Feedback loop:** General information about the feedback loop
  - **FastAPI:** AI API for the GeoNode platform

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Appendixes

Table 3: F1 scores for the detection of plastic waste

Test Category	F1 Score
04m_all_classes_RGB	0,6993
04m_binary_RGB	0,7718
04m_material_RGB	0,6641
20m_binary_RGB	0,7414
20m_material_RGB	0,7731
20m_material_NIR	0,7890
20m_material_NDVI	0,7297
20m_binary_NIR	0,8058
20m_binary_NDVI	0,7973
20m_all_classes_RGB	0,8153
20m_all_classes_NIR	0,7123
20m_all_classes_NDVI	0,7223
60m_binary_RGB	0,5734
60m_material_NDVI	0,5530
60m_binary_NIR	0,5389
60m_material_NIR	0,5250
60m_material_RGB	0,5634
60m_all_classes_NDVI	0,5820
60m_all_classes_NIR	0,5739
60m_all_classes_RGB	0,5016
60m_binary_NDVI	0,5561
100m_all_classes_NDVI	0,4672
100m_binary_NDVI	0,4598
100m_material_RGB	0,4862
100m_material_NIR	0,4385
100m_material_NDVI	0,3748
100m_binary_RGB	0,4658
100m_binary_NIR	0,4543
100m_all_classes_NIR	0,4109
100m_all_classes_RGB	0,4996