Detecting Marine Pollutants Using Sentinel-1 SAR and Sentinel-2 Optical Imagery

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Abstract

Marine pollution, including Marine Debris and Oil Spills, poses a serious environmental threat that requires systematic monitoring. Satellite observations from both passive and active sensors, combined with established machine learning techniques, have been widely used for mapping marine pollution. However, the application of cutting-edge deep learning approaches specifically tailored to this task remains limited. In this study, we use the MADOS Sentinel-2 (S2) marine pollution dataset to construct a new Sentinel-1 (S1) Synthetic Aperture Radar (SAR) dataset containing annotations for oil spills, sea surface, look-alikes (e.g., low-wind areas and internal waves), ships, and offshore oil platforms. We then train deep learning models on this Sentinel-1 dataset, including well-established architectures such as U-NET, specialized frameworks for marine pollution segmentation such as MARINEXT, and state-of-the-art approaches like SEGNEXT, and we evaluate their performance both quantitatively and qualitatively. Our findings show that MARINEXT achieves the highest F_1-macro score at 92.7%, outperforming U-NET at 70.6% and SEGNEXT at 75.9%. Qualitative evaluation using the corresponding multispectral Sentinel-2 imagery further supports these results. Finally, our analysis shows that mapping Marine Debris in SAR imagery remains particularly challenging, especially in the absence of corresponding optical observations.

1. Introduction

Protecting aquatic ecosystems is critical for global sustainability, as highlighted by the United Nations Sustainable Development Goal 14 (SDG 14). Marine Pollution, including Marine Debris and Oil Spills, continues to pose a significant environmental challenge. Synthetic Aperture Radar satellite data are widely used for monitoring marine pollutants, particularly Oil Spills, as they can detect pollutants from the sea surface under all weather and illumination conditions (Alpers et al., 2017). Recent efforts using Synthetic Aperture Radar data have also focused on the mapping of other floating matter, such as Marine Debris (Savastano et al., 2021, Simpson et al., 2023) and floating macroalgae species (Qi et al., 2022). Beyond studies that rely exclusively on Synthetic Aperture Radar data for monitoring Oil Spills, some research has combined radar with optical data to enhance temporal resolution and leverage the complementary capabilities of both sensors (Garcia-Pineda et al., 2020, Arslan, 2018).

Although Synthetic Aperture Radar imagery is widely used for Oil Spill mapping, relevant datasets remain scarce (Orfanidis et al., 2018, Blondeau-Patissier et al., 2022, Dong et al., 2023). Also, the application of state-of-the-art deep learning (DL) frameworks and foundation models remains limited (Ma et al., 2021, Ronci et al., 2020, Li et al., 2021). By incorporating datasets that include oil spills, marine debris, and look-alikes, we assess the feasibility of SAR-based monitoring for mapping diverse types of marine pollutants. In this context, we adopt and evaluate both general-purpose state-of-the-art deep learning models and those specifically designed for marine pollution segmentation tasks.

To enable a comprehensive qualitative and quantitative comparison, we construct a Sentinel-1 SAR image dataset containing samples of oil spills, low-wind areas, sea surface, ships, and offshore platforms. This is achieved by leveraging the marine pollution benchmark dataset MADOS (Kikaki et al., 2024), which includes globally distributed multispectral Sentinel-2 data. Using MADOS, we also investigate the feasibility of mapping previously reported marine debris in SAR imagery. Additionally, Sentinel-2 optical data are incorporated to provide further qualitative insights into the results.

The remainder of this paper is organized as follows: Section 2 reviews related work on Oil Spill mapping using SAR data, Section 3 outlines the dataset creation process and the adopted algorithms, Section 4 details the experiments conducted, and Section 5 discusses the results.

2. Related Work

Oil spill mapping in Synthetic Aperture Radar imagery in many approaches involves three main steps: identifying dark regions, extracting features, and performing classification (Temitope Yekeen and Balogun, 2020, Al-Ruzouq et al., 2020). Dark region identification is achieved through image segmentation techniques, ranging from traditional methods like thresholding (Conceição et al., 2021, Fan et al., 2021), to more advanced approaches such as superpixel segmentation (Zhang et al., 2020) and K-means clustering (Aghaei et al., 2022a). Feature extraction focuses on statistical, geometric, texture, contextual, and SAR-polarimetric characteristics (Al-Ruzouq et al., 2020), as well as characteristics learned through deep learning models (Song et al., 2020, Fan et al., 2021). The classification of dark spots as oil spills or non-oil categories is based on traditional classifiers like SVM (Song et al., 2020, Aghaei et al., 2022a), Random Forest (Conceição et al., 2021), and Decision Trees (Topouzelis and Psyllos, 2012), alongside advanced CNN-based methods such as U-NET (Fan et al., 2021).

Recently, deep learning frameworks have become increasingly

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prominent for Oil Spill mapping from radar data. Methods adapted for this purpose include approaches based on DeepLab (Orfanidis et al., 2018, Ma et al., 2021), U-NET (Bianchi et al., 2020, Li et al., 2023), YOLO (Yang et al., 2022), and Mask R-CNN (Yekeen et al., 2020). Furthermore, novel strategies such as those utilizing MCAN (Li et al., 2021), GAN (Ronci et al., 2020), and ShuffleNet (Aghaei et al., 2022b) have been proposed. Techniques incorporating transfer learning to enhance performance in oil spill mapping have been reported in (Yekeen et al., 2020, Zeng and Wang, 2020, Ebrahimi and Sahebi, 2024). Also, hybrid approaches that combine CNNs with vision transformers for oil spill segmentation have been explored in (Dehghani-Dehcheshmeh et al., 2023). Self-evolving frameworks have also been explored to address the challenges of this domain (Li et al., 2023).

Studies have demonstrated the effectiveness of these approaches. For example, in (Ma et al., 2021), DeepLabv3 outperformed traditional classifiers such as SVM and achieved results comparable to U-NET. Similarly, (Zeng and Wang, 2020) showed that deep-learned features provided greater benefits than handcrafted ones. YOLOv4 demonstrated competitive performance compared to Faster R-CNN, while also reducing computational overhead (Yang et al., 2022). Furthermore, MCAN surpassed both FCN and U-NET in performance, as reported in (Li et al., 2021). Additionally, (Krestenitis et al., 2019) highlighted that DeepLabv3+ excelled in both accuracy and inference time when compared to other deep convolutional neural networks (DCNNs).

3. Method

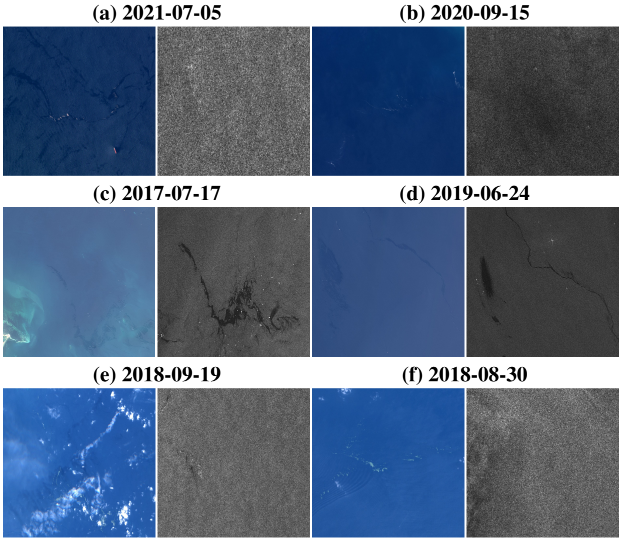
In this section, we outline the overall methodology adopted in this study for marine pollution mapping using Sentinel-1 Synthetic Aperture Radar imagery. Building upon the benchmark Sentinel-2 dataset for marine pollution, MADOS, we construct a corresponding Sentinel-1 dataset and leverage state-of-the-art deep learning frameworks (U-NET, SEGNEXT, MARINEXT) to evaluate their performance both quantitatively and qualitatively.

3.1 Dataset

For our experiments, we relied on MADOS (MArine Debris & Oil Spill) (Kikaki et al., 2024), a well-curated benchmark dataset that focuses on two major marine pollutants: floating Marine Debris and Oil Spills. MADOS consists of 174 Sentinel-2 scenes from 47 tiles acquired between 2015 and 2022. The annotated data were produced through extensive expert photo-interpretation supported by reports, field observations, and prior studies on marine pollution, resulting in approximately 1.5 M labeled pixels. The MADOS dataset spans 22 countries and contains 15 thematic classes, namely floating *dense Sargassum*, *Sparse Floating Algae*, *Natural Organic Material*, *Ship*, *Oil Platform*, *Sea snot*, *Jellyfish*, and Water-related classes such as *Marine Water*, *Sediment-Laden Water*, *Foam*, *Turbid Water*, *Shallow Water* and *Waves & Wakes*.

Based on the MADOS Sentinel-2 dataset, we constructed a Sentinel-1 Synthetic Aperture Radar dataset focused on marine pollutants. This was achieved by collecting Sentinel-1 images available within a ± 1-day temporal window of the MADOS entries. The dataset was further enriched with additional oil spill events identified and interpreted by experts, originating either from MADOS-detected cases or from independent sources. We utilized the Sentinel-1 IW GRD product and applied widely adopted preprocessing steps using SNAP (Filipponi, 2019). The selected images target documented pollution events, and the annotations were produced by two photo-interpretation experts using VV-polarized data, as VV polarization is well-suited for differentiating oil spills (Mera et al., 2012) and other floating features (Qi et al., 2022) on the sea surface.

Figure 1 presents representative cases of marine pollution and sea surface features observed in Sentinel-2 images along with the corresponding Sentinel-1 SAR images. Specifically, examples are shown from the Gulf of Honduras (Figure 1a, e, f), the Arabian Gulf (Figure 1c, d), and the Gulf of Port-au-Prince (Figure 1b). Marine debris and *Sargassum* in Synthetic Aperture Radar images may appear as positive-contrast formations (Qi et al., 2022), as illustrated in Figure 1a, e. In contrast, Oil Spills typically appear as negative-contrast formations (Figure 1c, d). Despite the availability of near-simultaneous Sentinel-1 images and corresponding MADOS entries, experts consistently struggled to identify Marine Debris in Synthetic Aperture Radar imagery (Figure 1b). This is consistent with prior findings on the difficulty of discriminating floating materials in multispectral imagery (Mikeli et al., 2022), leading to the exclusion of Marine Debris from the final dataset.



(a) 2021-07-05 **(b) 2020-09-15**
(c) 2017-07-17 **(d) 2019-06-24**
(e) 2018-09-19 **(f) 2018-08-30**

Figure 1. Examples of sea surface features observed in Sentinel-2 and corresponding Sentinel-1 images from the same date. (a) Marine Debris appears as positive contrast in S1. (b) Marine Debris in S2 lacks corresponding positive contrast in S1. (c) and (d) show Oil Spills similarly visible in both S2 and S1, with negative contrast in S1 as expected. (e) *Sargassum* appears as positive contrast in S1, while (f) shows no such confirmation.

Our final dataset comprises 65 unique Sentinel-1 acquisition dates, of which 22 correspond to Oil Spills with same-day Sentinel-2 imagery, while 26 correspond to Sentinel-2 images within a ± 1-day window. The dataset is organized into four superclasses: *Oil Spill* (42,187,435 pixels), *Sea* (14,885,243 pixels), *Manmade* objects (e.g., ships and offshore platforms 58,950 pixels), and *Lookalikes* (e.g., low wind areas and currents/internal waves 37,993,089 pixels).

3.2 Models

In this subsection, we describe the well-established and state-of-the-art deep learning (DL) models employed in our experiments for the task of marine pollution segmentation.

3.2.1 U-Net: We include U-Net, a widely used encoder-decoder convolutional architecture developed for semantic segmentation (Ronneberger et al., 2015). For this study, we adopt the implementation provided in (Kikaki et al., 2022).

3.2.2 SegNeXt: We also employ SegNeXt (Guo et al., 2022), a state-of-the-art encoder-decoder architecture. Its encoder follows a four-stage pyramid structure known as the Multi-Scale Convolutional Attention Network (MSCAN), where each stage comprises a down-sampling operation followed by multiple blocks. These blocks are inspired by Vision Transformers (ViTs) (Dosovitskiy et al., 2020), where the self-attention module is replaced by Multi-Scale Convolutional Attention (MSCA).

3.2.3 MariNeXt: MariNeXt is a state-of-the-art semantic segmentation framework specifically designed for mapping marine pollution using multispectral imagery. In (Kikaki et al., 2024), they adopt the SegNeXt architecture (Guo et al., 2022) and introduce improvements in three directions: modeling (1st-stage higher-resolution features), training (Very Simple Copy-Paste data augmentation), and testing (Test-Time Augmentation strategy). MariNeXt outperforms all baseline models in terms of F_1-score and mIoU.

4. Experiments

In this section, we describe our experimental design as well as evaluate the performance of the applied models both qualitatively and quantitatively.

In order to train and assess models, we split our dataset into three disjoint subsets: a training set (50 unique dates), a validation set (9 unique dates) and a test set (6 unique dates, aligned with the Sentinel-2 dataset). For the quantitative evaluation of the models' performance in the semantic segmentation task, we calculated four performance metrics per class: (i) Jaccard Index or Intersection-over-Union (IoU), (ii) Recall, (iii) F_1-score, and (iv) Precision. Additionally, based on the per-class metrics, we determined the following overall performance metrics for each model: (i) mean Recall (mRec), (ii) mean Jaccard Index or Intersection-over-Union (mIoU), (iii) Overall Accuracy (OA), and (iv) macro F_1-score. For the qualitative evaluation, we visually inspected the prediction maps generated by the models on the test set, which included various instances of Oil Spills. To ensure a more comprehensive assessment, the results of the models were also evaluated along with the corresponding Sentinel-2 imagery.

In Table 1, we demonstrate the overall performance of the evaluated models. While U-Net is the fastest and simplest model, it delivers the weakest performance. Among the three models, MariNeXt consistently achieves the highest scores across all metrics, with an mRec of 96.2%, mIoU of 86.8%, OA of 96.0%, and F_1-macro of 92.7%. SegNeXt also performs well, showing notable improvements over U-Net, particularly in mRec, mIoU and F_1-macro score.

According to Table 2, MariNeXt achieves the highest metrics for the *Oil Spill* class, with an IoU of 77.3%, Recall of 93.2%, F_1-score of 87.2%, and Precision of 81.9%, followed by SegNeXt with differences ranging from 2.3% to 7.1% across all metrics. Regarding *Sea* and *Manmade* classes, MariNeXt outperforms both SegNeXt and U-Net for the *Manmade* and *Sea* (with the exception of Recall for *Sea*, where it matches U-Net). For the *Lookalike* class, however, SegNeXt appears to be better closely followed by MariNeXt and U-Net.

mRec	mIoU	OA	F_1-macro
U-Net			
85.4	61.2	93.1	70.6
SegNeXt			
93.4	67.8	95.6	75.9
MariNeXt			
96.2	**86.8**	**96.0**	**92.7**

Table 1. Mean evaluation scores obtained by U-Net, SegNeXt and MariNeXt.

Method	U-Net				SegNeXt				MariNeXt			
	IoU	Recall	F_1	Prec.	IoU	Recall	F_1	Prec.	IoU	Recall	F_1	Prec.
Oil Spill	57.2	74.6	72.8	71.0	70.6	86.1	82.7	79.6	**77.3**	**93.2**	**87.2**	**81.9**
Sea	81.3	**97.1**	89.7	83.3	87.7	94.8	93.4	92.1	**95.4**	**97.1**	**97.6**	**98.2**
Lookalike	92.8	95.5	96.3	97.1	**95.4**	**97.0**	**97.7**	98.3	95.3	96.4	97.6	**98.8**
Manmade	13.4	74.4	23.6	14.0	17.6	95.7	29.9	17.7	**79.3**	**98.2**	**88.5**	**80.5**

Table 2. Evaluation scores obtained by U-Net, SegNeXt and MariNeXt for each class.

We visually inspected the produced prediction maps and compared them to the corresponding Sentinel-1 and Sentinel-2 images (Figure 2). U-Net appears to underestimate the presence of *Oil Spill* in Figure 2b, c, and e, and in some cases, it fails to map it entirely (Figure 2d). MariNeXt consistently captures the boundaries of *Oil Spill* in detail, as demonstrated in Figure 2a, b, c, and e. SegNeXt seems to be less consistent in extracting the faintest parts of the *Oil Spill* (Figure 2a, d), and in specific cases, it fails even to segment wide areas of the *Oil Spill* (Figure 2e). In the example shown in Figure 2c, both U-Net and SegNeXt mistakenly identify a *Lookalike* area as an *Oil Spill*.

5. Discussion & Conclusion

In this study, we constructed a new Sentinel-1 dataset focused on marine pollution and employed both state-of-the-art and well-established deep learning models to quantitatively and qualitatively evaluate their performance in mapping marine pollution.

The Sentinel-1 dataset was generated based on the MADOS Sentinel-2 dataset (Kikaki et al., 2024) by collecting Sentinel-1 images within a ± 1-day window of the corresponding Sentinel-2 entries, providing a stronger ground truth for evaluation. During dataset construction, we observed, as previous studies have suggested, that while oil spills can be distinguished from the sea surface in Sentinel-1 as negative-contrast formations, other floating matters are challenging to differentiate in Synthetic Aperture Radar imagery and were therefore excluded from the final dataset.

The dataset is organized into four classes: *Oil Spill*, *Lookalikes*, *Manmade* objects, and the *Sea*. Quantitative and qualitative analyses indicate that all three models successfully map the densest regions of oil spills, with MariNeXt consistently delineating oil spill boundaries more accurately, even capturing

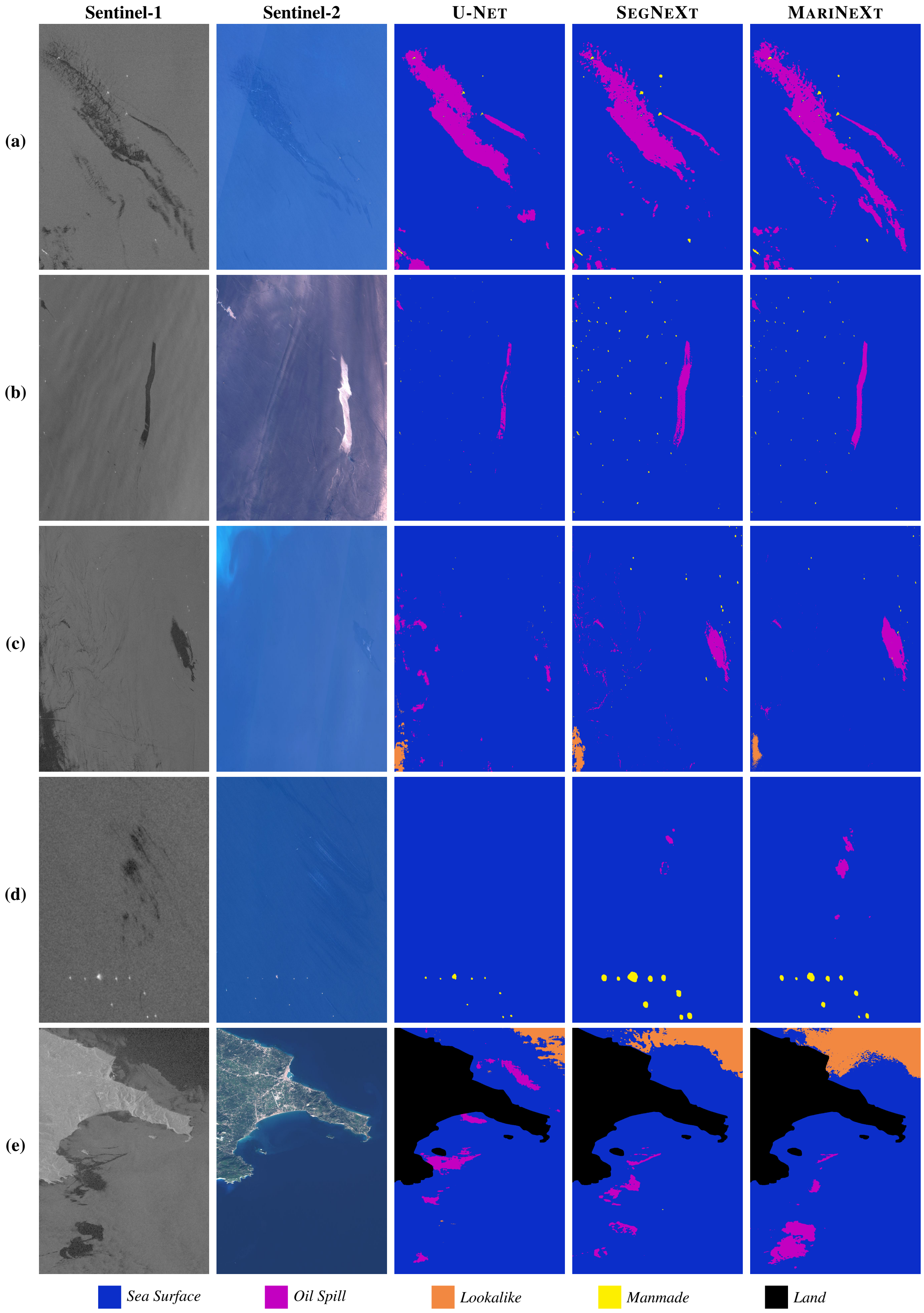


Figure 2. Prediction results by U-NET, SEGNEXT, and MARINEXT. Selected indicative examples from the model outputs, shown alongside corresponding Sentinel-1 VV (SNAP-processed) and Sentinel-2 RGB patches for Arabian Gulf (a-d) and Ionian Sea (e) for the following unique acquisition dates: (a) 2018-04-18, (b) 2018-07-14, (c) 2018-08-16, (d) 2020-08-17, and (e) 2018-10-26.

the faintest regions. While manmade objects such as ships and oil platforms can be reliably identified in Sentinel-1 imagery, the identification of Marine Debris remains notably challenging.

The dataset could be further expanded to include additional floating matters (e.g., macroalgae such as *Sargassum*, *Sea snot*, and *Marine Debris*) and environmental variables (wind, currents, and other oceanographic factors) to improve model accuracy and generalization for SAR-based marine pollution monitoring.

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