

Marine Oil Spill Monitoring using Sentinel-1 Dual-Pol SAR Data: An Operational GEE Framework

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Abstract—Oil Spills (OS) pose serious hazards to economies relying on the sea. Remote sensing facilitates effective offshore OS monitoring. As a result, the Sentinel-1 Synthetic Aperture Radar (SAR) missions regularly deliver open-source cloud-stored data through the Google Earth Engine (GEE) platform. This paper proposed an interactive GEE framework for operational use with Sentinel-1 Ground Range Detected (GRD) Dual-pol SAR data. An Eigen descriptor is developed to examine multiple OS incidents in GEE, and two OS from Cyprus are described in detail. OS signatures extracted from Single Look Complex (SLC) SAR and GRD are compared with the baseline Random Forest (RF) algorithm. Also, OS delineation results are showcased for the three SAR scenes reported in the literature. Qualitative outcomes show effectiveness for the GEE-based framework, whereas quantitative results are outstanding. Collectively, the proposed technique achieved an mIoU of 96%, a recall of 99%, an F1-score of 99% and accuracy of 98%. The novelty of the developed technique is an operational value of the GEE platform for Near-Real-Time (NRT) OS monitoring and actionable remote marine environment safety using SAR images as a “Black-box”.

Index Terms—SAR, Oil Spill, Polarimetry, GEE, ML

I. INTRODUCTION

OIL Spills (OS) threaten the shoreline economies, impact ecosystems, catastrophe marine habitats, affect trading and tourism sectors [1]. Therefore, marine safety and security authorities are looking for an early warning system to detect such OS incidents timely, effectively, and promptly [2]. With the use of remote sensing technology, the ability to detect OS quickly and accurately at an initial stage has been made possible in a manner that is both efficient and cost-effective [3]. One of the most valuable open data sources available for ocean remote sensing, including OS delineation, is Synthetic Aperture Radar (SAR) imaging, which includes an effective Sentinel-1 microwave Radar [4]. The C-band SAR with the dual polarizations (VV, VH) provides a fine resolution of 10m, which works anytime, day or night, and regardless of weather. Instead, optical sensors are prone to clouds, darkness, and illumination, particularly with OS.

Generally, OS reduces the Normalized Radar Cross Section (NRCS) with respect to the surrounding water area in SAR imagery. This NRCS gap is technically referred as a contrast. Scientifically, as a result of this difference, OS become black spots in the SAR images [5]. Statistical features of Radar

backscatter can discriminate between OS and other phenomena using single or dual-polarization SAR data. The Constant False Alarm Rate (CFAR) technique used for target detection [6] requires manual selection of target and clutter patches, whereas the CFAR threshold value differs for each SAR image due to contrast, hence making it impractical.

Machine Learning (ML) techniques, including Random Forest (RF) [7], Artificial Neural Networks (ANN) [8], and Genetic Algorithms (GA) [9], are applied to remote sensing images for the classification and segmentation of OS in SAR images [8]. ANN methods often use dual models for segmenting and classifying dark spots, posing challenges in detection. The arbitrary selection of inputs in ANN can hinder feature representation, while RF and GA improve feature significance but still rely on human input for feature extraction.

Deep Learning (DL) models, e.g., Convolutional Neural Networks (CNNs) [10], are mostly deployed for automatic feature extraction in SAR image classification and segmentation, including OS detection. Models such as YOLO [11] and Faster R-CNN classify dark patches in SAR images [12], while U-Net, Mask R-CNN, and DeeplabV3 enable OS delineation [13–15]. However, these models necessitate pre-identified SAR patches of OS masks, resulting in increased computational demands; furthermore, there is the risk of missing portions of large or narrow spills due to segmentation.

Researchers loaded VV-pol of SAR images into the Sentinel Application Platform (SNAP) for processing and relied on external tools or manual tasking, which increases the processing time [16]. Although the given descriptor has been mentioned in the literature, it has not been practically explored for a ‘cloud-based’ solution [17]. The objective of this letter is to provide fully-automatic OS detection using classical polarimetric technique. The key advantage of the proposed approach is that, even in darker SAR images, it can sense the darkest OS patches; therefore, in brighter SAR images, the proposed approach can detect OS with improved accuracy. The operational challenge or limitation is the availability of dual-pol SAR imagery. In fact, dual-pol SAR relies on polarimetric features for target characterization, making it largely independent of sample data distributions [18].

Unlike our previous work [7], which was relying on SLC data and offline processing, this letter introduces a compatible OS detector, which utilizes linear scale GRD dual-pol SAR images (like a Black-box), that enables fully operational NRT OS detection directly within Google Earth Engine (GEE), without external pre-processing or ML. Section II discusses OS detectors and accuracy metrics; Section III presents the proposed GEE-based operational framework. Results are provided in Section IV, and conclusions are made in Section V.

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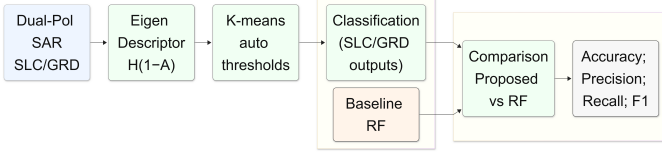


Fig. 1. Methodology: A complete flow graph followed for OS detection.

II. METHODOLOGY

Fig. 1 illustrates a complete methodology followed in the paper, proposed, $\mathcal{D}_{OS}^{GRD}$ and $\mathcal{D}_{OS}^{SLC}$ detectors are compared with baseline RF. K -means clusters provided thresholds for OS classification, and well-established analysis parameters are utilized to address the accuracy. Given a dual-polarized Sentinel-1 SAR acquisition, let S_{VV} and S_{VH} denote the linear and complex scattering elements of the GRD and SLC imagery, respectively. The covariance matrices derived from $GRD \rightarrow \mathbf{C}_2$ and $SLC \rightarrow \mathbf{C}_2$ further provide OS detectors.

A. Oil Spill Detector using GRD SAR

The polarization covariance matrix provides the scattering characteristics of the target using the scattering vector $S = [S_{VV} \ S_{VH}]^T$. The corresponding polarization covariance matrix is defined as $\mathbf{C}_2 = \langle SS^T \rangle$, where T denotes the transpose.

$$\mathbf{C}_2 = \begin{bmatrix} \langle C_{11} \rangle_{\uparrow} & \langle C_{12} \rangle_{\uparrow} \\ \langle C_{21} \rangle_{\uparrow} & \langle C_{22} \rangle_{\uparrow} \end{bmatrix}, \quad \lambda_1 = \max(\langle C_{11} \rangle_{\uparrow}, \langle C_{22} \rangle_{\uparrow}), \quad (1)$$

$$\lambda_2 = \min(\langle C_{11} \rangle_{\uparrow}, \langle C_{22} \rangle_{\uparrow}), \quad \lambda_1 > \lambda_2 > 0.$$

where $\uparrow$ is the linear scale, and $\langle \cdot \rangle$ ensemble average. Using these components of dual-pol, the proposed GRD SAR imagery-based OS detector has been developed as:

$$\mathcal{D}_{OS}^{GRD} = \left[- \left(\frac{\lambda_1}{\lambda_{\Sigma}} \log_2 \left(\frac{\lambda_1}{\lambda_{\Sigma}} \right) + \frac{\lambda_2}{\lambda_{\Sigma}} \log_2 \left(\frac{\lambda_2}{\lambda_{\Sigma}} \right) \right) \right] \times \left(1 - \frac{|\lambda_1 - \lambda_2|}{\lambda_{\Sigma}} \right), \quad \in [0, 1]. \quad (2)$$

where $\lambda_{\Sigma} = \lambda_1 + \lambda_2$, and λ_1 & λ_2 are modified eigenvalues.

B. Oil Spill Detector using SLC SAR

The covariance matrix from SLC dual-pol SAR is given as:

$$\mathbf{C}_2 = \begin{bmatrix} \langle S_{VV}^2 \rangle & \langle S_{VV} S_{VH}^* \rangle \\ \langle S_{VH} S_{VV}^* \rangle & \langle S_{VH}^2 \rangle \end{bmatrix}, \quad \in \mathbb{C} \quad (3)$$

where $\mathbb{C}$ corresponds to complex numbers and $*$ represents the complex conjugate. Once the eigenvalues of $\mathbf{C}_2$ the matrix are computed, key scattering characteristics can be derived. The entropy ($\mathcal{H}$) quantifies the randomness in the scattering process, is calculated as follows:

$$\mathcal{H} = - \sum_{i=1}^2 p_i \log_2(p_i), \quad \in [0, 1], \quad \text{and, } p_i = \frac{\lambda_i}{\lambda_{\Sigma}}. \quad (4)$$

where ' i ' is the rank of the matrix. The anisotropy ($\mathcal{A}$), complementing $\mathcal{H}$, describes the relative difference between the two eigenvalues and is defined as:

$$\mathcal{A} = \frac{\lambda_1 - \lambda_2}{\lambda_1 + \lambda_2}, \quad \mathcal{A} \in [0, 1] \quad (5)$$

After multiple experiments with polarimetric descriptors mentioned in [19] to assess the scattering characteristics, we identified that the combination of eigen descriptors given below provides an optimal detection and classification of OS:

$$\mathcal{D}_{OS}^{SLC} = \mathcal{H} (1 - \mathcal{A}), \quad \in [0, 1] \quad (6)$$

Both detectors' qualitative results demonstrate a high degree of accuracy. GRD serves as an actionable source for OS detection since SLC data is not available in GEE. The proposed eigen-descriptors have a wide dynamic range for three classes (0 – 1). The categorization utilizes the empirical distribution span of K -means [20] to automatically identify thick oil, thin oil, and sea, showing consistency across both descriptors and SAR OS scenes analogies.

C. OS Classification Accuracy Analysis Metrics

Accuracy for the use of SLC and GRD detectors is essential for effective identification of OS delineation. The metrics for OS detection and classification analysis are summarized as:

- 1) To achieve higher classification Overall Accuracy (OA), the Cost (C) of the i^{th} solution is calculated as [21]:

$$C_i = 1 - \frac{OA_i}{100} \quad (7)$$

This cost function verifies the accuracy of the developed OS detectors and demonstrates the robustness and potential of the presented $\mathcal{D}_{OS}^{SLC}$ and $\mathcal{D}_{OS}^{GRD}$ for OS detection.

- 2) K -means clustering algorithm is an unsupervised, non-deterministic iterative method that is widely used in large-scale dataset clustering problems [22]. It is incorporated to find the best threshold spans for the two or three OS classes from the detectors of the i^{th} solutions (SLC and GRD). This algorithm divides data into K classes, ensuring minimum similarity within classes through iterative processes.
- 3) OS extent is determined by integrating pixels across regions identified as thick and thin oil in spatial domain Ω ; thus, OS area estimation is provided as:

$$OS_{km^2} = \sum_{(x,y) \in \Omega} \left[OS(x,y) \right] \frac{\mathcal{G}_{\text{pixel}}(x,y)}{10^6} \quad (8)$$

where $\mathcal{G}_{\text{pixel}}$ presents the geometry, and the expression combines segmentation and area computation to provide a quantitative estimate of the detected OS in the polygon.

- 4) Since pixel-level ground truth is unavailable, the RF-based delineation and literature-reported spill extents are used as reference benchmarks for comparative accuracy analysis [7].
- 5) Quantitative analysis of detected OS is done by metrics; Precision, Recall, F1-Score, and mIoU [10, 12, 13].

III. INTERACTIVE GEE PLATFORM FOR OS DELINEATION

A user-friendly, dashboard-oriented framework is designed in the GEE environment, enabling interactive monitoring of potential marine OS incidents utilizing Sentinel-1 SAR GRD data. The framework collects data, dual-polarization processing, mask generation, pixel-level classification, and

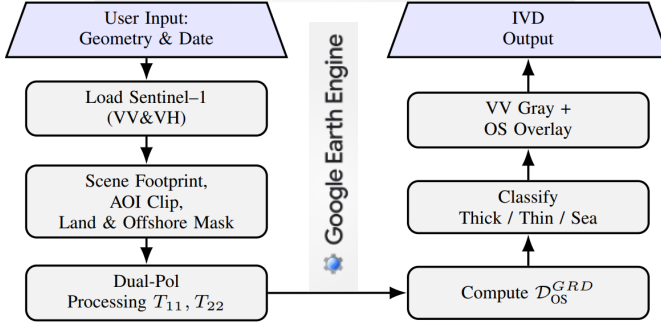


Fig. 2. Key steps for OS detection and classification in the GEE.

visual analysis into a single interface. The key steps used for OS detection and classification in the GEE platform are given in Fig 2. At first Sentinel-1 IW acquisition is selected according to the user-defined geometry and date range. The associated scene footprint is retrieved and clipped to the Area of Interest (AoI). To ensure that only open-water pixels are evaluated, a buffered land-sea mask is applied, expanded by a configurable offset to suppress mixed land-sea transitions. The offshore mask is then used to restrict all subsequent polarimetry processing steps to marine regions.

Dual-polarization channels are incorporated through a simplified covariance model in which the local diagonal terms are obtained from neighborhood averages of the VV and VH linear scale images, as mentioned in Eq. 2. These components, interpreted as two effective eigenvalues, form the basis for deriving the normalized spectral weights and the OS detection quantity as discussed above. The metric combines the entropy of the eigenvalue distribution with a contrast term penalizing large disparities between λ_1 and λ_2 . An additional span-based signal-to-noise mask (-40 dB) is applied to exclude low-backscatter areas where the estimation becomes unpredictable. OS is classified into three classes to delineate thick oil, thin oil, and seawater. The classes are visualized on top of the grayscale VV image, offering both context and interpretability. The final interface operates completely in the GEE, permitting users to inspect SAR scenes of their AoI, verify classification outputs, and perform region-specific assessments without external pre-processing or local computation.

IV. EXPERIMENTAL RESULTS AND DISCUSSION

In this manuscript, SAR data from SLC and GRD are employed to implement dual-pol OS Eigen descriptors. The methods are evaluated using Cyprus OS incident to enhance the detection of OS in Sentinel-1 SAR imagery and identify

TABLE I
SENTINEL-1 OS SAR SCENE SOURCES OVER THE DIFFERENT AOI

Scene	Place	Acquisition Date	Reference	Type
1	Cyprus	29 - 08 - 2021	[7]	SLC & GRD
2	Cyprus	30 - 08 - 2021	[7]	SLC & GRD
3	Port Said	04 - 10 - 2014	[23]	GRD
4	UAE	08 - 03 - 2017	[18]	GRD
5	Kuwait	10 - 08 - 2017	[24]	GRD

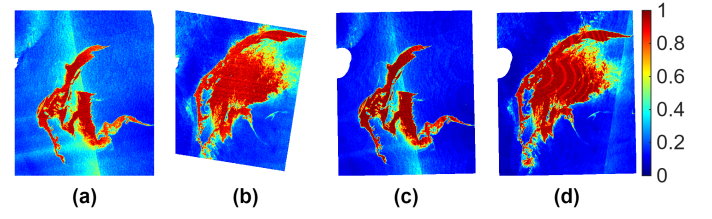


Fig. 3. For OS reported in [7], Panels (a) and (b) show the spatial signatures computed from SLC SAR using Eq. 6. Panels (c) and (d) show the corresponding spatial signatures retrieved from GRD SAR using Eq. 2.

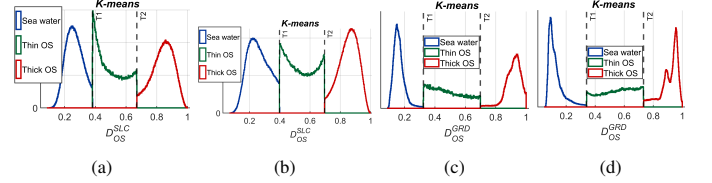


Fig. 4. Distributions of K -means clusters with threshold values corresponding to the spatial signatures shown in Fig. 3(a)-(d). Panels (a)-(d) show the threshold distributions for the respective SLC and GRD OS Descriptors.

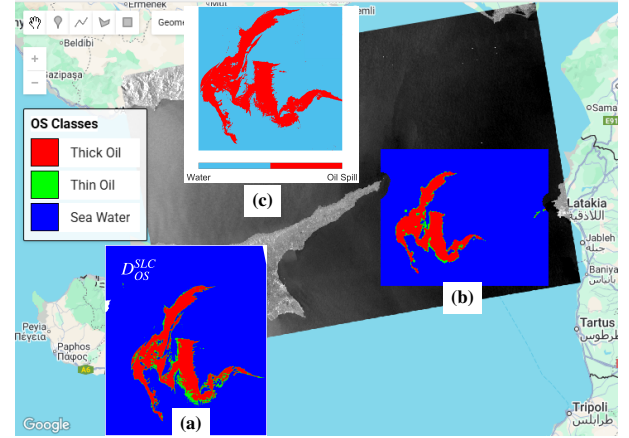


Fig. 5. SAR Scene-1. (a) OS extracted by D_{OS}^{SLC} , (b) OS detected by D_{OS}^{GRD} in GEE, and (c) OS delineated by baseline method RF [7].

best candidate for an operational framework. Table I presents SAR scenes, where 1 and 2 are sourced from Cyprus while 3–5 are obtained from various locations as documented in the literature. The signatures of the OS detector from SLC Eq. 6 for SAR scenes 1 and 2 are shown in Figs 3 (a) and (b). The corresponding signatures of the GRD OS detector for these scenes are illustrated in Figs 3 (c) and (d), which are acquired from the GEE platform using Eq. 2.

The dynamic range of SLC and GRD OS detectors is 0–1. Compared to other polarimetric techniques, the dual-pol eigen descriptor provides sufficient contrast for K -means clustering, enabling an unsupervised grouping of data points into K -classes based on their class measures. Figs 4 (a) and (c) describe K -means thresholds for SAR scene-1 by using the output of D_{OS}^{SLC} and D_{OS}^{GRD} , respectively. Figs 4 (b) and (d) describe K -means threshold spans for scene-2 discretely.

Given SAR **Scene-1**, OS classification results utilizing the thresholds of K -means for SLC and GRD descriptors are shown in Figs. 5 (a) and (b); moreover, logical OS mask obtained by RF is depicted in Fig. 5 (c). For SAR **Scene-2**,

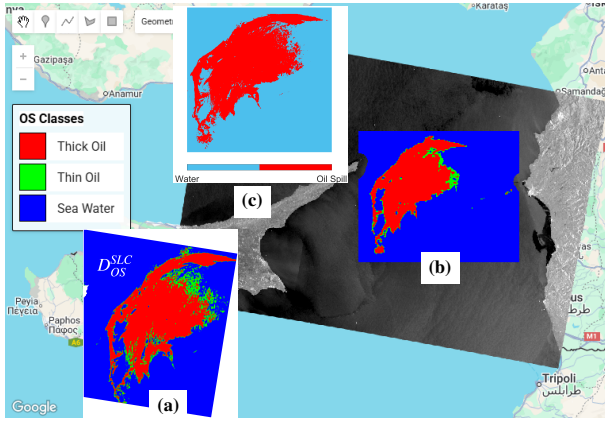


Fig. 6. SAR Scene-2. (a) OS extracted by D_{OS}^{SLC} , (b) OS detected by D_{OS}^{GRD} in GEE, and (c) OS delineated by baseline method RF [7].

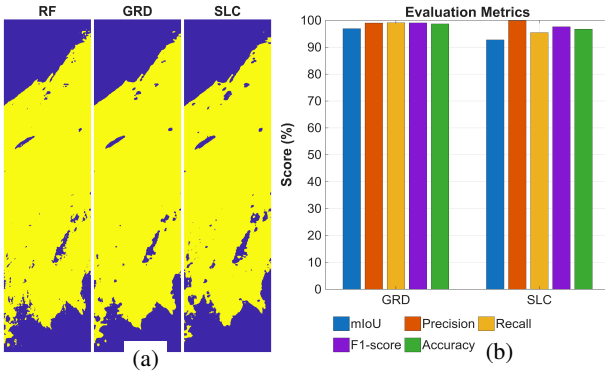


Fig. 7. (a) Patches of OS extracted from RF, D_{OS}^{GRD} , and D_{OS}^{SLC} , (b) Evaluation metrics including mIoU, precision, recall, F1-score, and Accuracy.

TABLE II
 U_{10} , COST, AREA OF OS DETECTION, AND PROCESSING TIME.

Scene	Type	U_{10} (m/s)	Cost C_i	Area Km ²	Tp
1	SLC	-	0.1070	906	35 min
1	GRD	0.4 - 6.4	0.0925	809	10s
2	SLC	-	0.0924	2090	50 min
2	GRD	0.6 - 8.9	0.0419	1910	12s

the three extracted classes are depicted in Figs. 6 (a) and (b) for SLC and GRD, respectively; further, the binary OS mask obtained by RF is shown in Fig. 6 (c). In the GEE windows, red indicates thick or central OS, green represents thin OS, and blue signifies seawater. Both D_{OS}^{SLC} and D_{OS}^{GRD} effectively classify SAR scenes into thick OS, thin OS, and seawater classes using K -means clustering. This classification uses distinct normalized dynamic ranges from 0 to 1, represented by T_1 and T_2 in Fig. 4.

The qualitative and quantitative analyses for SLC and GRD are shown in Figs. 7(a) and (b), respectively. The metrics, including mIoU, precision, recall, F1-score, and accuracy, are represented by different colored bars, with the corresponding values shown on the y-axis for each metric. The SLC and GRD detectors are compared with the baseline RF algorithm. These results show that D_{OS}^{GRD} achieves higher accuracy (98%) than D_{OS}^{SLC} (96%), thereby supporting its selection in GEE as a reliable product for OS delineation. To find the best candidate,

TABLE III
SLC AND GRD DETECTOR COMPARISON WITH BASELINE RF USING EVALUATION METRICS.

Comparison	mIoU	Precision	Recall	F1-score	Accuracy
SLC vs RF	92.74	99.91	95.44	97.62	96.74
GRD vs RF	96.91	99.01	99.11	99.06	98.68

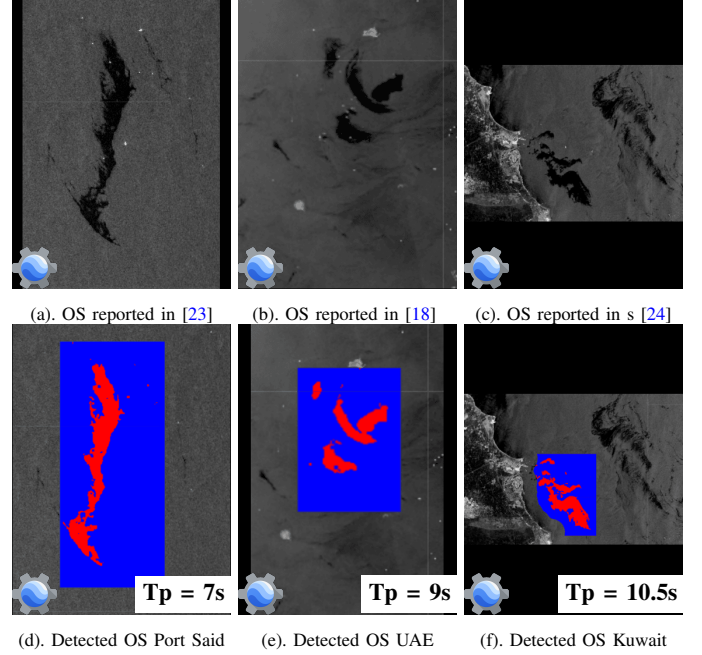


Fig. 8. OS incidents reported in the literature were used to compare the performance of the proposed GEE-based D_{OS}^{GRD} OS Detector.

as depicted in Table II, the GRD product has lower C_i in both SAR scenes, indicating greater overall accuracy and class consistency than SLC. Wind speed in both SAR AoI ranges from 0.5 to 5 ms^{-1} around OS. As described in [15] that, the precision and recall of OS localization and segmentation versus wind speeds in this range are nominal.

The GRD-based detector is well-suited for cloud-based OS hazard monitoring due to its open-source data, GEE-integration, rapid processing time 'Tp' of 10-12 seconds, and effective categorization. In GEE we kept 100 meters pixel-area integration to determine the total spill area in square kilometers as discussed in Eq. 8, generates an OS mask from the thick and thin classes, and permits segmented oil spill region analysis and visualization. The calculated OS areas for scenes 1 and 2 using SLC and GRD SAR are given in Table II; while comparing with [16], the proposed GRD detector in GEE shows great accuracy for segmentation, provided that different scales are used in reference. Table III reports the mIoU, precision, recall, F1-score, and accuracy of the SLC and GRD detectors compared with the baseline RF mask. The GRD detector achieves higher mIoU, recall, F1-score, and accuracy, with an overall accuracy of 98%, compared with 96% for SLC. Although SLC shows slightly higher precision, GRD provides better overall agreement with the RF baseline, demonstrating its effectiveness for OS delineation using dual-pol SAR images without ML, directly in GEE.

Additionally, $\mathcal{D}_{OS}^{GRD}$ is applied to detect OS in SAR scenes from 'Port Said,' 'UAE,' and 'Kuwait' that are listed in Table I. The OS masks results of SAR scenes 3—5 further confirm that the GEE-based OS detector achieves superior performance, even though these OS events have been segmented by different techniques in the literature. The three SAR OS incidents reported in [23], [18], [24] are shown in Figs 8(a)–(c), while Figs 8(d)–(f) show the corresponding OS detections obtained by the GEE-based GRD detector combining thick and thin OS classes to show the cumulative OS mask.

V. CONCLUSIONS

In this paper, we evaluated descriptors from dual-pol SLC and GRD SAR for detecting OS in Sentinel-1 SAR imagery. The well-documented OS incidents, including two OS from Cyprus and three OS from the Gulf regions, are examined. To classify these OS types, we use the K –means unsupervised algorithm with automatic thresholds selection. The overall accuracy for the Cyprus SAR scenes is computed, and the cost C_i function for both detectors are evaluated. The OS results of GRD and SLC detectors are compared with the RF baseline algorithm. The OA, C_i , area comparisons, recall, F1-score, mIoU, and associated merits discussed above reveal that the GEE-based $\mathcal{D}_{OS}^{GRD}$ detector achieves overall accuracy exceeding 98% and is well suited for detecting central OS over user-defined geometry. The outcome of this research provides an operational GEE framework for OS detection, classification and segmentation using SAR data for marine safety and security. Future work will apply tile-computing-based deep learning models for pixel-level OS segmentation.

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