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Distinguishing Mineral Oil Slicks From Low-Wind Areas Using High-SNR Synthetic Aperture Radar

Cornelius Quigley , A. Malin Johansson , *Member, IEEE*, and Cathleen E. Jones , *Senior Member, IEEE*

Abstract—We propose a method for distinguishing oil slicks from radar-dark, oceanic low wind areas using single acquisitions of high-SNR airborne and spaceborne SAR imagery. Airborne data were acquired by DLR's F-SAR X- and L-band SAR instrument during a controlled release, oil-on-water campaign, and by NASA's unmanned aerial vehicle synthetic aperture radar (UAVSAR) L-band SAR instrument over the Aleutian Islands in Alaska and the Coal Oil Point seep field near Santa Barbara, California. The spaceborne imagery consists of five RADARSAT-2 C-band SAR scenes containing either low-wind zones or mineral and plant oil, three of which were acquired during controlled releases in the North Sea. A RADARSAT-2 scene containing grease ice is included to demonstrate the potential of the proposed method to discriminate between oil slick and other look-alike types. The proposed product, referred to as KS index maps, is based on the Kolmogorov–Smirnov test statistic and is used as a measure of separability between ensembles of pixels inside vs. outside a radar-dark area. We use the theoretical Polarimetric Two-Scale Model to interpret the physical basis on which our method distinguishes between radar-dark oil slicks and low-wind zones relative to nearby open water in higher wind areas. KS index values for oil slick are consistently between -1 and 0 , and KS index values for low-wind zones (and grease ice) are consistently between 0 and $+1$. The method is suitable for near-real-time implementation to aid oil spill response.

Index Terms—FSAR, look-alike, low wind, oil spill, synthetic aperture radar (SAR), unmanned aerial vehicle synthetic aperture radar (UAVSAR).

I. INTRODUCTION

TIMELY detection and monitoring of mineral oil discharges on the ocean surface are crucial for cleanup operations. Mineral oil slicks dampen gravity-capillary waves on the ocean surface, reducing the backscatter detected by synthetic aperture

radar (SAR) [1]. Mineral oil slicks in the ocean are easily detectable in SAR imagery as they appear radar-dark relative to slick-free water. Other natural, benign, and common phenomena like low-wind areas, natural biogenic films, grease ice, parts of shear zones, and rain cells are mineral oil look-alikes in SAR imagery [2], [3], [4].

Prior researchers have investigated methods for distinguishing mineral oil slicks from look-alikes in SAR imagery, but most work has focused on natural biogenic slicks [3]. Much effort has previously focused on the use of polarimetry for the differentiation between radar-dark features, mainly mineral oil and biogenic material [5], [6], [7], [8], [9], [10], [11], [12], [13], [14] although apparent differences in scattering mechanisms between different slick types are more likely due to the copolarization channel signals being dominated by instrument noise when satellite SARs are used [15], [16]. Large-scale experiments using airborne instruments have been conducted in which mineral oil and plant oil or biogenic simulants, such as oleyl alcohol, were discharged [8], [17], [18], [19], [20].

In the last decade, advancements have also been made using machine learning (ML) methods for the discrimination of oil slicks and look-alike phenomena. Early approaches relied on traditional feature-based classifiers such as support vector machines, random forests, and k-nearest neighbor algorithms, which typically exploit handcrafted descriptors derived from backscatter intensity, texture measures, and statistical properties of SAR imagery [19], [21], [22], [23]. More recently, supervised ML methods, such as artificial neural networks (ANNs), have been introduced to improve class separation and reduce reliance on manually engineered features. These include multilayer perceptrons and sophisticated ANN architectures that can learn hierarchical representations directly from SAR data [24], [25], [26], [27], [28]. Moreover, convolutional neural networks, can automatically learn hierarchical image features through convolutional operations [29], and are especially well suited to oil slick discrimination since it can be formulated as a spatial texture recognition problem, requiring the identification of complex patterns, shapes, and contextual features within SAR images, and has been successfully used in, e.g., [30], [31], and [32]. U-Net architecture, when it was introduced, demonstrated superior performance compared to earlier convolutional network designs and enables dense, pixel-wise predictions at the same spatial resolution as the input image, making it particularly suitable for applications requiring precise spatial delineation, such as the discrimination of oil slicks from look-alike phenomena in SAR imagery [33], and was used in, e.g., [34], [35], [36],

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Cornelius Quigley is with the Department of Environmental and Energy Sciences, Chalmers University of Technology, SE-412 96 Gothenburg, Sweden (e-mail: cornelius.quigley@chalmers.se).

A. Malin Johansson is with the Department of Physics and Technology, UiT – The Arctic University of Norway, NO-9037 Tromsø, Norway (e-mail: malin.johansson@uit.no).

Cathleen E. Jones is with the Jet Propulsion Laboratory, California Institute of Technology, Pasadena, CA 91125 USA (e-mail: cathleen.e.jones@jpl.nasa.gov).

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[37], and [38]. Despite these advances, the performance of deep learning methods remains strongly dependent on an extensive amount of training data being available. In parallel, transfer learning strategies have been explored to mitigate the limited availability of labeled datasets by adapting pretrained models to SAR-specific tasks [31], [39]. A comprehensive overview of recent developments in ML for SAR-based oil slick detection is provided in Murugan et al. [40], where additional methodological variations and application-specific considerations are discussed.

Despite a focus of research on biogenic look-alikes, low-wind over the ocean surface is the most ubiquitous look-alike phenomenon in SAR imagery. Low wind can occur in any geographical location and is less likely to be constrained by seasonal variations than, e.g., biogenic activity, which increases during sunnier and warmer months [41]. The number of studies to date that focus specifically on the low-wind look-alike is limited. Early work [42], [43] required auxiliary wind speed information. Other work that did not use wind speed information [44] had some success, but was tested on only three scenes. Quigley et al. [45] proposed a method for distinguishing mineral oil from low-wind areas based on the temporal evolution of radar-dark features in rapid repeat time-series acquired by the National Aeronautics and Space Administration (NASA) L-band Unmanned Aerial Vehicle Synthetic Aperture Radar (UAVSAR) imaging the Coal Oil Point (COP) seep field off the coast of Santa Barbara, California. However, their method required a time series of 3–5 scenes acquired over ~50–80 min, limiting its implementation to airborne instruments at present.

This study is focused on low-wind look-alikes, presenting a method using a single SAR acquisition that can reliably distinguish mineral oil slicks from low-wind areas, in both airborne and spaceborne images. Our proposed method requires a SAR sensor that meets two conditions. First, a SAR instrument with a sufficiently low noise equivalent sigma zero (NESZ), where pixels >6 dB above the noise floor of the instrument are considered to have a sufficient signal-to-noise ratio (SNR) [15], [16]. Second, a dual-copolarization SAR, i.e., one configured to acquire both the VV and HH polarization channels. Additionally, the scene must contain water pixels that are not radar-dark, i.e., zones with higher wind speed, i.e., the scene cannot contain only low wind or oil slicks. Fortunately, this is not uncommon, particularly near coasts.

The method is based on the statistics of the VV and HH normalized radar cross section (NRCS) pixels within a scene and requires no training. It operates by calculating the Kolmogorov–Smirnov (KS) test statistic between copolarization ratio values in regions-of-interest (ROIs) within a radar-dark area and those outside the radar-dark area, controlling for imaging geometry by selecting pixels in the two areas at the same incidence angle. The resulting product is an easily interpretable index, which we call the KS index.

Here, we demonstrate our method by applying it to data sets acquired by two different airborne SARs and one satellite SAR. The first airborne data set contains verified mineral oil slicks and was acquired as part of an oil-on-water campaign conducted in the North Sea in June 2019 [20]. The second airborne data set contains low-wind areas offshore of tall, mainly conical-shaped

TABLE I
PROPERTIES OF THE F-SAR ACQUISITIONS AND IN-SITU INFORMATION. NOMINAL RESOLUTION AND PIXEL SPACING VALUES ARE TAKEN FROM [47]. WIND SPEED MEASUREMENTS WERE MADE FROM A SHIP PARTICIPATING IN EXERCISE [20].

Scene ID	FSAR-L/X 1	FSAR-L/X 2
Acquisition time (UTC)	11:30	11:42
Sensor vel. [m/s]	89.85	90.43
Sensor alt. [m]	2456.3	2500.7
Age of slick [hours]	~5.50–6.00	~5.80–6.16
Slick type	Mineral oil	Mineral oil
Date	12 June 2019	
Resolution (Rg $\times$ Az) [m]	X-band: (0.2 $\times$ 0.2) L-band: (1.0 $\times$ 0.4)	
Pixel spacing (Rg $\times$ Az) [m]	X-band: (0.60 $\times$ 0.18) L-band: (0.60 $\times$ 0.36)	
Freq. of radiation [GHz]	X-band: 9.6 L-band: 1.325	
Wind speed [m/s]	12	

volcanic islands in the Aleutian Islands, Alaska, which are known to induce low wind zones with particular morphologies [46]. To assess the applicability of the method to spaceborne SAR, we apply the method to six C-band RADARSAT-2 (RS2) acquisitions. The first three acquisitions were acquired during the Norwegian Clean Seas Association for Operating Companies (NOFO) annual oil-on-water clean-up exercise held off the coast of Norway between 2011 and 2013. All three scenes contain discharges of crude oil, mineral oil emulsion, and plant oil of known quantities and material type, and two of the three scenes also contain low-wind zones. The next two RS2 scenes were acquired over the Brage oil field off the coast of Norway and contain extensive zones of low-wind as well as slicks of produced water (legal discharges of wastewater generated during oil and gas extraction) from oil platforms in the area. Lastly, as another original contribution of this work, we test our method on an RS2 scene solely containing free-floating grease ice slicks, acquired in the Kara Sea.

To evaluate the robustness of our method and its general applicability and to ensure its effectiveness, we apply it to an airborne UAVSAR time-series used in [45], acquired in a complex coastal setting containing concurrent zones of verified mineral oil slick and low-wind areas. This data was acquired as part of the National Oceanic and Atmospheric Administration (NOAA)/NASA Marine Oil Spill Thickness (MOST) project over the COP seep field near Santa Barbara, California.

II. STUDY AREAS AND DATA SETS

A. F-SAR Data: Verified Mineral Oil Slicks

Fully-polarimetric data acquired by the Deutsches Zentrum für Luft- und Raumfahrt (DLR) F-SAR X- and L-band instrument [47] during the Norwegian Radar oil Spill Experiment in 2019 (NORSE 2019) is used [20]. The instrument can acquire imagery at off-nadir look angles in the range direction from 25° to 60°. Information relating to the acquisitions can be found in Table I. The experiment was conducted in the North Sea (59° 59' N, 2° 27' E) on 12 June 2019, in which ~2 m³ of mineral oil emulsion consisting of 45% oil (10 parts evaporated Oseberg Blend and 1 part IF 380) and 55% seawater was released.

Fig. 1 shows two acquisitions of the mineral oil emulsion slick [(a) and (b)] acquired in L-band, and simultaneous X-band acquisitions of the same slick [(c) and (d)]. In the figures in this article, all F-SAR acquisitions have specific IDs, where FSAR indicates the name of the instrument used, *L* or *X* indicates the frequency band the data was acquired in, and the number indicates the n^{th} scene in the data set. Each image in Fig. 1 contains the entirety of the respective surface slick areas, with open water areas immediately adjacent to the slicks imaged at the same incidence angle. These acquisitions were chosen as the slicks are located in the far range of the scene, which ensures that pixels within the slick for the X-band acquisitions are likely to have a low-SNR, and therefore were used to evaluate the impact of instrument noise on the method. This is explained in greater detail in Sections III and IV.

All scenes in Fig. 1 are divided into a *Test area* and a *Reference area*. Fig. 1(a) shows the ROIs that are extracted from radar dark zones within the test area, indicated by the red, green, and blue boxes. The yellow ROI in the reference area is open water at the same angle of incidence as the test ROIs. The use of these ROIs in our method is explained in Section III.

Quigley et al. [48] used optical images taken from the aircraft housing the F-SAR instrument to evaluate the thickness of the mineral oil slick. They demonstrated that there are two distinct areas of different thickness within the slick, which they call the “head of the slick” and the “tail of the slick.” Using photographs and the Bonn Agreement Oil Appearance Code (BAOAC) [49], combined with the fact that 2 m³ of material was discharged, they determined that the “head of the slick” had a discontinuous true color and thickness of 151–153 μm . The “tail of the slick” was composed mostly of a silver sheen with thickness 0.04–0.3 μm . Two polygons in Fig. 1(d) outline the relative position of the two areas, with the yellow polygon being the “head of the slick” and the red polygon being the “tail of the slick.” These areas are used to evaluate our method for mineral oil slicks of different and known emulsion types and thicknesses.

B. UAVSAR Data: Low-Wind Areas Caused by Wind Shadowing

The Aleutian Islands are a chain of islands consisting of 69 volcanoes, both active and inactive, in the North Pacific stretching from the southwest tip of Alaska to the Kamchatka peninsula in the Russian Federation. In this study, we investigated all 33 available fully-polarimetric UAVSAR images acquired by NASA between July 2009 and October 2012 over the Aleutian Island chain for the presence of island-induced, low-wind phenomena caused by the island’s high conical-shaped peaks [46]. In addition, we focus our search on data that was acquired before April 2011, as UAVSAR was ~ 5 dB more sensitive before this date [50]. This is discussed further in Section IV. Here, we provide a brief description taken from [46] of three island-induced, low-wind phenomena observed in the SAR imagery used here.

Island and mountain wakes (linear wakes): Island wakes are characterized by long plumes of relatively low wind speeds that form on the lee side of islands. The most common form of island wake is a linear wake, also called a “weak wake,” which is generally narrower than the inducing peak and can be much longer

than the peak height. Plumes with widths 10s of kilometers and lengths of several hundred kilometers have been reported [46]. For the case of wind interacting with conical-shaped island bodies, the resulting wake can assume a triangular shape.

Island and mountain wakes (Kármán vortex streets): Kármán vortex streets have more complex SAR signatures and consist of trains of chevrons or spirals of alternating directions. They form when perturbations cause vortices to progressively shed on alternate sides of the island. This causes the wake to have vortices of alternating helicity extending from the island.

Mountain lee waves: When wind passes over isolated peaks or extended ranges, horizontally propagating mountain lee waves can form. These waves are easily identifiable in SAR imagery and manifest as parallel bands of fast and slow winds.

Table II contains information about the UAVSAR Aleutian Islands acquisitions as well as the relevant in-situ information about the island land masses. Figs. 2 and 3 present eight instances where low-wind phenomena are observed to be associated with land masses. In the following, all data is presented in range-doppler coordinates with the tops of the images oriented northward. All acquisitions have specific IDs, where UAVSAR indicates the name of the instrument used, AI indicates that the data was acquired in the Aleutian Islands, and the number indicates the n^{th} scene in this data set. As can be seen in Table II, most of the islands associated with the radar-dark zones in Figs. 2 and 3 have peaks that reach between 1.5 and 2 km above sea level. This indicates that the presence of the radar-dark zones in these UAVSAR imagery is likely a result of wind shadowing.

Fig. 2(a) and (b), as well as Fig. 3(a)–(e), were acquired before April 2011; Fig. 3(f) was acquired after. The imagery was acquired with UAVSAR flying in either a west-to-east or east-to-west direction. Both scenes in Fig. 2 are divided into a test area and a reference area. Fig. 2(a) demonstrates the ROIs that are extracted from radar dark zones within the test area, indicated by the red, green, and blue boxes. The yellow column indicates the pixels extracted from the reference area. All the scenes in Fig. 3 show only the test area. Figs. 2(a) and 3(a) show sidelobe artifacts that can be observed as bright linear features oriented in the azimuth direction.

As can be seen in Figs. 2 and 3, all the radar-dark areas show characteristics of the island-induced low-wind phenomena. A large, linear island wake, triangular in shape, is likely imaged in Fig. 2(a), where only the portion nearest the island can be observed due to the limited swath width of the UAVSAR. Fig. 2(b) shows three distinct radar-dark zones. The leftmost zone has the characteristic appearance of mountain lee waves, given its banded appearance. The middle is likely a linear island wake due to its triangular shape and the fact that it is adjacent to the conical-shaped volcano, Mt. Cleveland, on Chuginadak Island. The rightmost radar-dark zone is likely a linear island wake, but does not have the characteristic triangular shape due to the irregular shape of the rest of the land mass on Chuginadak Island.

Fig. 3(a)–(d) shows triangular-shaped linear island wakes. All the associated islands, Little Sitkin Island [Fig. 3(a) and (b)], Yunaska Island [Fig. 3(c)] and Gareloi Island [Fig. 3(d)] are conical-shaped volcanoes. Fig. 3(e) likely shows a linear island wake. However, Ulak Island, which is rectangular in shape with

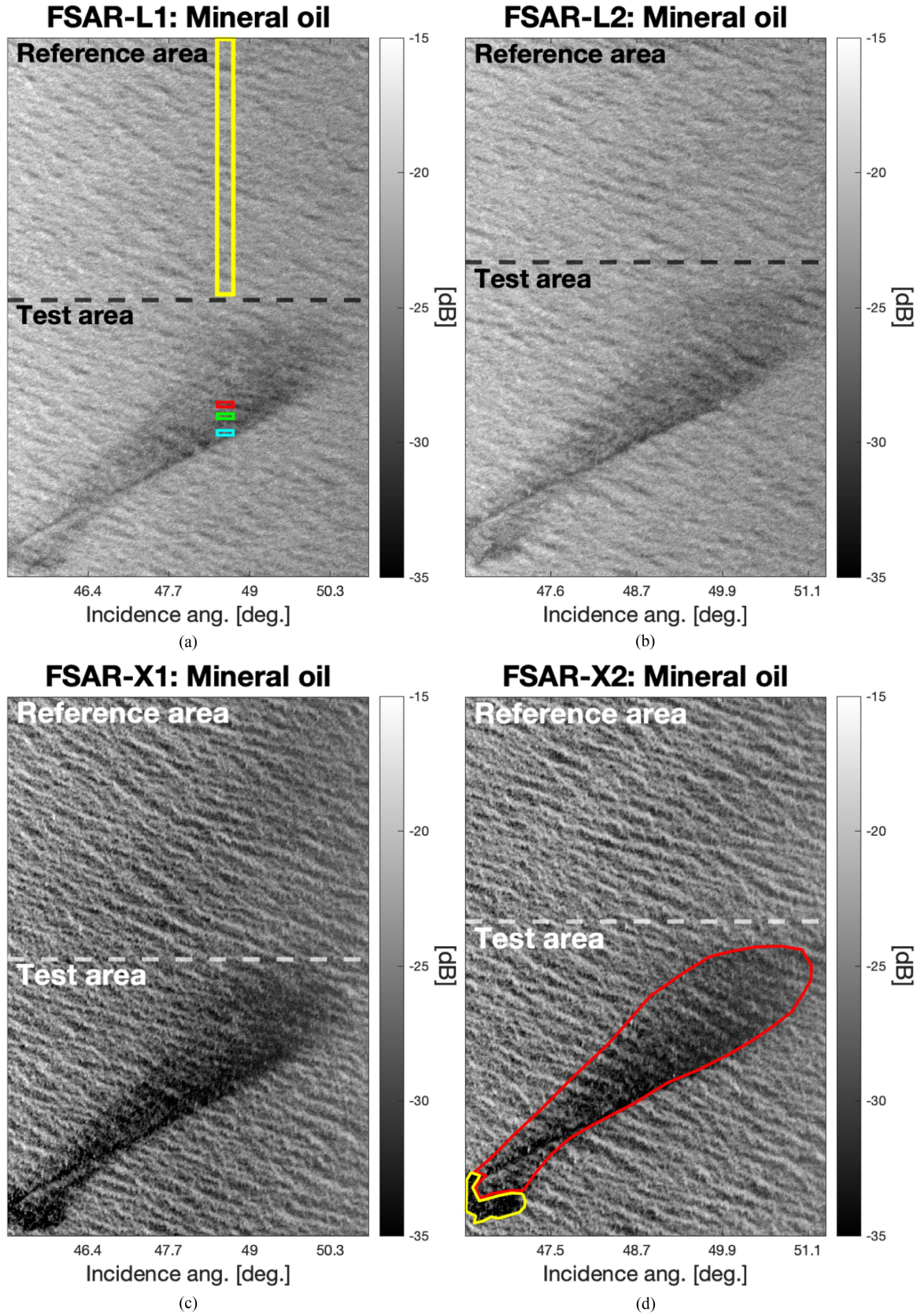


Fig. 1. (a) and (b) L-band F-SAR intensity images (σ_{VV}^0) of mineral oil and (c) and (d) simultaneous X-band F-SAR intensity images (σ_{VV}^0) of the same slicks. The images are displayed in range-doppler coordinates, multilooked by a 9×9 window. All images are divided into a “test area” containing the radar dark zone and a “reference area” containing open water. Colored ROIs in (a) are used to demonstrate the method in Section III.B. Two polygons in (d) indicate the thicker (yellow polygon) and thinner (red polygon) areas of the slick.

TABLE II
PROPERTIES OF UAVSAR ACQUISITIONS AND IN-SITU INFORMATION

Scene ID	Product name	Island name	Date	Acquisition time (UTC)	Lat, Lon of island*	Highest elevation of island (m)*
UAVSAR-AI1	aleutn_24004_10063_007_100804_L090_CX_01	Umnak Island	4 Aug. 2010	18:41	53°13'26"N 168°25'55"W	2149
UAVSAR-AI2	aleutn_24702_10063_008_100804_L090_CX_01	Chuginadak Island	4 Aug. 2010	19:16	52°50'41"N 169°49'05"W	1730
UAVSAR-AI3	aleutn_27702_09050_004_090722_L090_CX_01	Little Sitkin Island	22 Jul. 2009	21:36	51°57'07"N 178°32'18"W	1188
UAVSAR-AI4	aleutn_27702_09050_004_090722_L090_CX_01	Little Sitkin Island	22 Jul. 2009	22:09	51°57'07"N 178°32'18"W	1188
UAVSAR-AI5	aleutn_24702_10063_008_100804_L090_CX_01	Yunaska Island	4 Aug. 2010	19:16	52°38'20"N 170°38'30"W	550
UAVSAR-AI6	aleutn_25801_09050_003_090722_L090_CX_01	Gareloi Island	22 Jul. 2009	21:03	51°47'20"N 178°47'32"W	1573
UAVSAR-AI7	aleutn_07801_09051_000_090723_L090_CX_01	Ulak Island	23 Jul. 2009	00:33	52°2'35"N 175°54'05"W	unknown
UAVSAR-AI8	aleutn_24004_12088_005_121003_L090_CX_01	Unalaska Island	3 Oct. 2012	19:43	53°40'24"N 166°38'54"W	2036

*Information taken from [51].

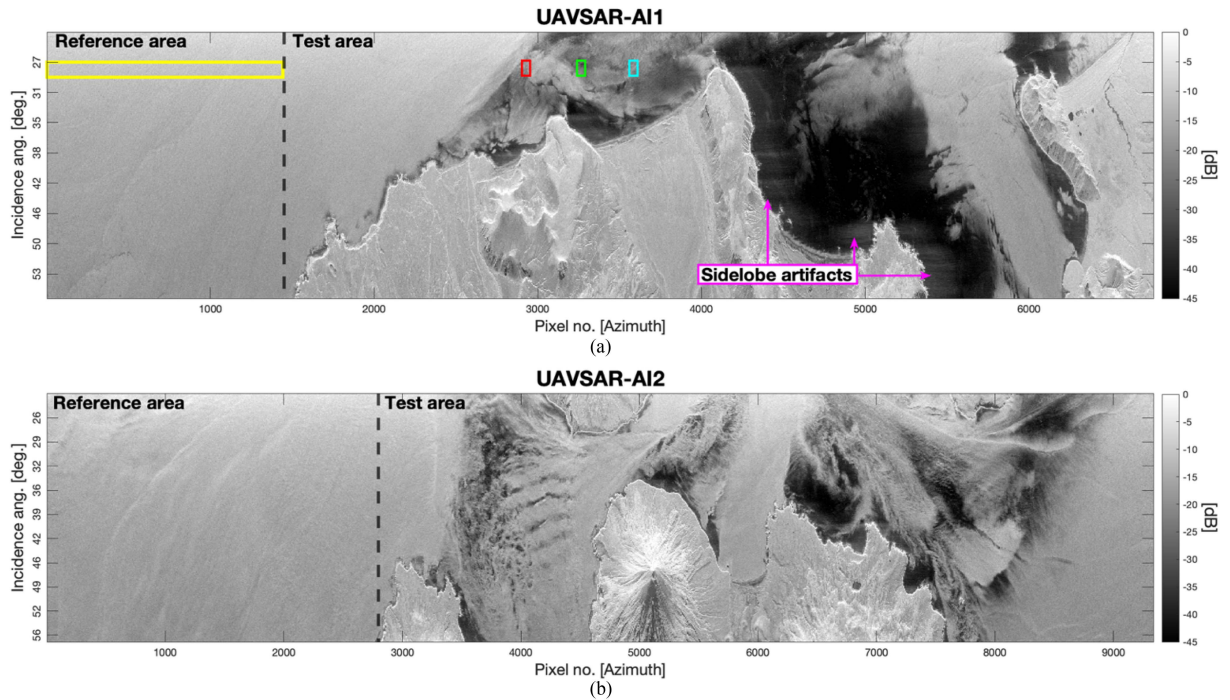


Fig. 2. (a), (b) L-band UAVSAR intensity images (σ_{VV}^0) of radar dark zones in the Aleutian Island chain containing low-wind wakes. The images are divided into a “test area” and a “reference area.” Colored ROIs in (a) are used to demonstrate the method in Section III.B. Sidelobe artifacts caused by target geometry can be seen in (a) superimposed on the radar-dark areas where the bright land along the coast contributes to the signal in the adjacent water.

a steeply sloped incline, has likely caused the wake to take on a more rectangular form. Fig. 3(f) shows a region of low-wind speed that is likely associated with a vortex shedding event like the Kármán vortex street effect. This is due to the roughly circular shape of the radar-dark region and the fact that it is not attached to a land mass.

C. UAVSAR Data: Simultaneous Acquisitions of Mineral Oil and Low-Wind Areas

UAVSAR images of the COP seep field near Santa Barbara, California, were collected on 24 June 2022. The area is a well-known natural seepage area that vents roughly 100 barrels of

crude oil per day [52], [53]. Eleven acquisitions over the course of 3.5 h were collected as part of the MOST project, and six of these are used here and shown in Fig. 5. The black rectangle in Fig. 4 indicates the area that was imaged by UAVSAR. Simultaneous wind speed measurements from the NOAA shore station NTBC1 are used for in-situ information. NTBC1 is in the Santa Barbara harbor adjacent to the UAVSAR footprint and is indicated by the cyan square in Fig. 4.

The six images used to generate the KS index maps were chosen as they contained a sufficient number of pixels containing both oil slick and low-wind zones with high-SNR. All acquisitions have specific IDs, where UAVSAR indicates the

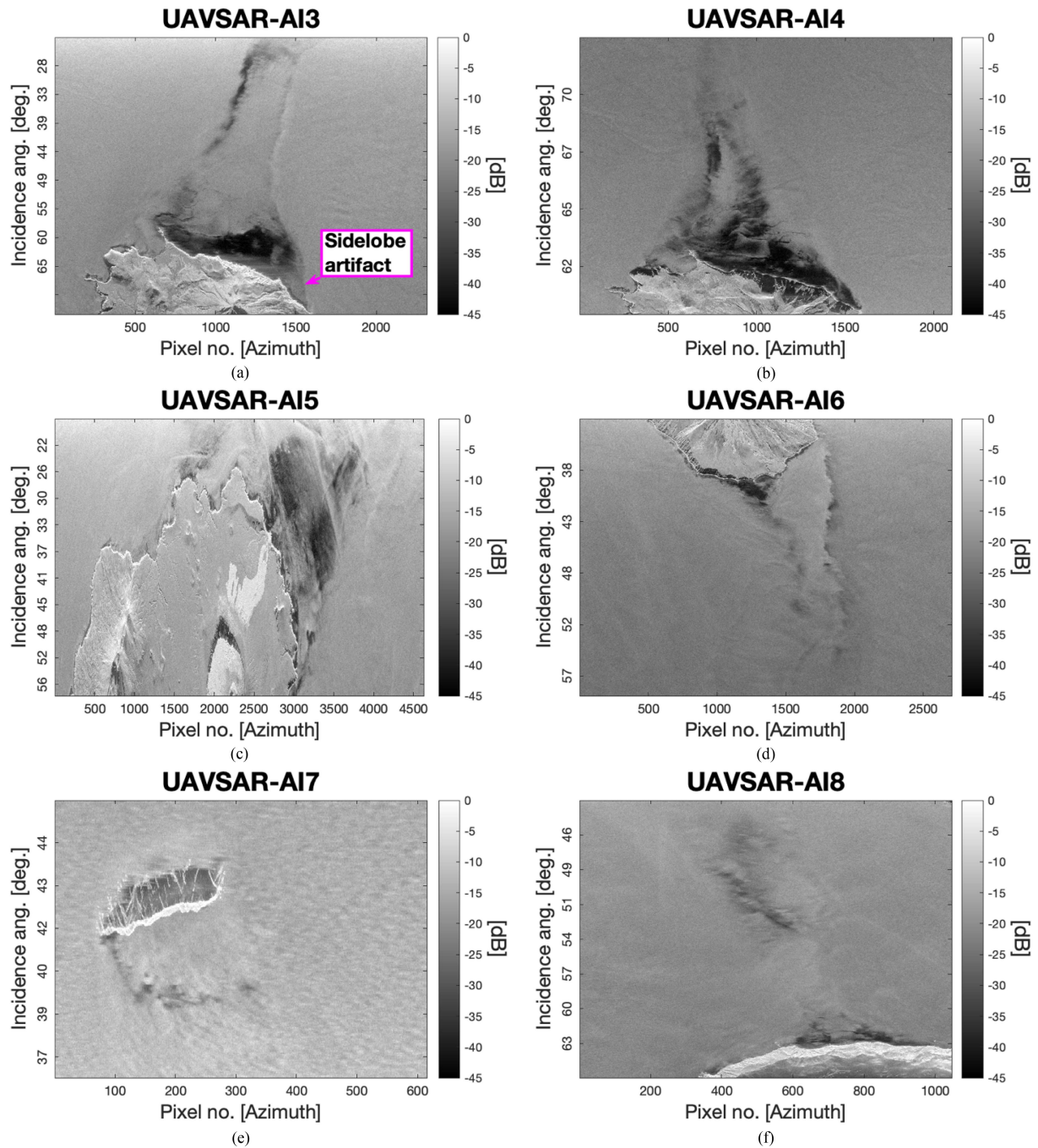


Fig. 3. (a)–(f) L-band UAVSAR intensity images (σ_{VV}^0) of radar-dark zones in the Aleutian Island chain containing low-wind wakes. Only the test areas are shown here. A sidelobe artifact can be seen in (a) superimposed on the radar dark area.

name of the instrument used, *COP* indicates that the data was acquired over the COP seep field, and the number indicates the n^{th} scene acquired in the time-series. Table III contains information about the UAVSAR COP acquisitions as well as the relevant in-situ information.

In the first three acquisitions [Fig. 5(a)–(c)], long, thin streamers of mineral oil show in the left portion of the scene. The right portion of the scene contains large patches of mineral oil, coincident with areas of low wind, as confirmed in [45] through a boat survey concurrent with UAVSAR acquisitions. During the

last three acquisitions [Fig. 5(d)–(f)], the wind speed increased from 2 m/s to roughly 6.5 m/s. In the time series of images, the low-wind area is observed to originate on the left of the scene, then gradually move to the right. Consistent with the wind speed measurements, there is more coverage by low wind areas in the first three UAVSAR-COP scenes, then a notable decrease over the course of the last three scenes.

For the UAVSAR-COP1-3, there is a time gap of 19 min between acquisitions, as is the case for UAVSAR-COP4-6, and between the two datasets, there is a 37-min gap during which

TABLE III
PROPERTIES OF UAVSAR ACQUISITIONS AND IN-SITU INFORMATION

Scene ID	Product name	Date	Acquisition time (UTC)	Wind speed [m/s]	Used to generate KS index maps	Used to generate high-confidence oil/open water maps
N/A	santab_29503_22014_003_220624_L090VVVV CX 01	24 Jun. 2022	18:25	3.1	×	✓
UAVSAR-COP1	santab_29503_22014_004_220624_L090VVVV CX 01	24 Jun. 2022	18:43	3.2	✓	✓
UAVSAR-COP2	santab_29503_22014_005_220624_L090VVVV CX 01	24 Jun. 2022	19:02	2.1	✓	✓
UAVSAR-COP3	santab_29503_22014_006_220624_L090VVVV CX 01	24 Jun. 2022	19:21	2.0	✓	✓
N/A	santab_29503_22014_007_220624_L090VVVV CX 01	24 Jun. 2022	19:39	1.5	×	✓
UAVSAR-COP4	santab_29503_22014_008_220624_L090VVVV CX 01	24 Jun. 2022	19:58	2.1	✓	✓
UAVSAR-COP5	santab_29503_22014_009_220624_L090VVVV CX 01	24 Jun. 2022	20:17	4.3	✓	✓
UAVSAR-COP6	santab_29503_22014_010_220624_L090VVVV CX 01	24 Jun. 2022	20:35	6.4	✓	✓

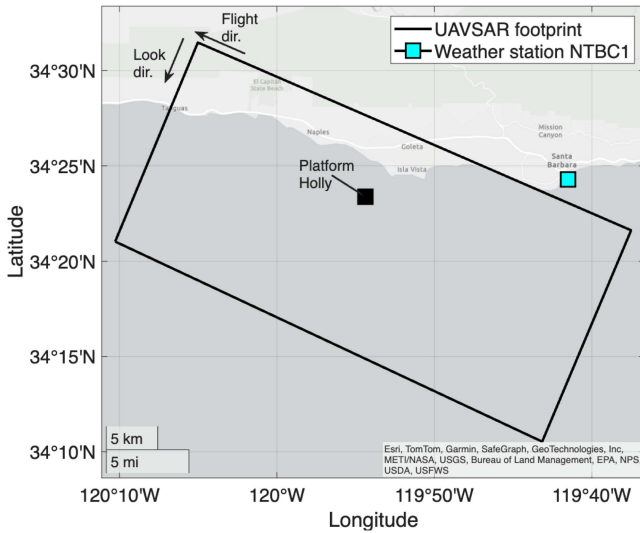


Fig. 4. Study area off the coast of Santa Barbara, California. Area imaged by UAVSAR indicated by the black rectangle. Wind speed information was taken from the weather station marked by a cyan square located in Santa Barbara harbor.

an additional acquisition was made. Another acquisition was acquired 18 min before UAVSAR-COP1. These two acquisitions are used for validation, described in Section V.C.

For the validation, georeferenced high-confidence oil/open water maps are used; as such, the UAVSAR-COP acquisitions (Fig. 5) are presented as georeferenced images. All other SAR data sets in this study are presented in range-doppler coordinates to save space in plotting.

D. RADARSAT-2 Data: Spaceborne Imagery of Verified Mineral Oil, Low Wind Zones, and Grease Ice

Fig. 6 shows six RADARSAT-2 acquisitions, and Table IV contains image specifics. Fig. 6(a)–(c) are of oil-on-water exercises conducted in the North Sea between the years 2011 and 2013, respectively. Similar to the NORSE 2019 exercise

outlined in Section II.A, controlled quantities of surfactant were discharged onto the ocean surface to test clean-up methods and response procedures. Wind speed information in Table IV was taken from ships participating in the exercises or from a nearby platform. The SAR and wind speed acquisitions were not coincident; however, large differences in these measurements are not expected. Table V outlines the relevant information relating to these slicks, as well as outlining some of the processes they were subjected to between the time of discharge and the time of the SAR acquisitions. All acquisitions have specific IDs, where RS indicates the name of the instrument used, i.e., RADARSAT-2, and the number indicates the n^{th} scene in this dataset.

RS-1 and RS-2 [Fig. 6(a) and (b)] contain other radar-dark areas in addition to the discharged slicks. Given that the wind speed measurements were low at the time of these acquisitions [1.6 and 4.0 m/s, respectively (see Table IV)], it is likely that these are low-wind zones. RS-4 and RS-5 [Fig. 6(d) and (e)] were acquired over the Brage oil field in the North Sea, and extensive areas of low-wind zoning were visually identified by their appearance. RS-6 [Fig. 6(f)] contains grease ice, and is included as it is a well-known oil slick look-alike [56].

III. METHODOLOGY

A. Theoretical Backscattering Model: PTSM

Numerous theoretical backscattering models have been developed to model backscatter from the ocean surface [57], [58], [59], [60], [61]. Here, the Polarimetric Two-Scale Model (PTSM) proposed by [58] is used to show how dielectric properties and large-scale roughness impact the copolarimetric ratio for the ocean surface. A brief mathematical treatment of the model is presented here, and the reader is directed to [58] for a comprehensive explanation. Additionally, the authors in [62] and [63] discuss the application of the model in determining the dielectric properties of oil slicks.

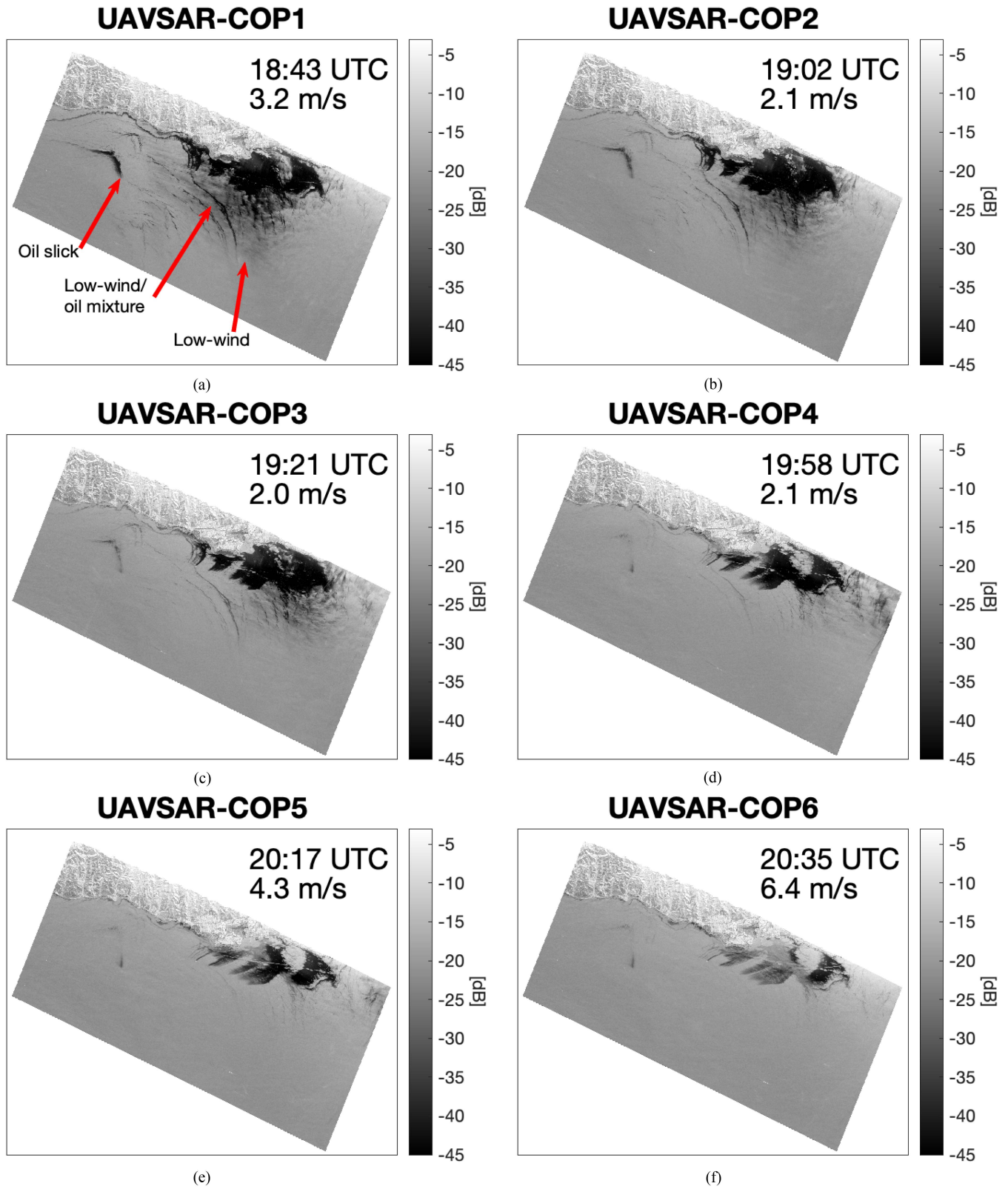


Fig. 5. (a)–(f) Georeferenced intensity images (σ_{VV}^0) for six scenes acquired on June 24, 2022, in the COP seep field. In (a)–(c), a large area of low wind and mineral oil coincides in the center of the scene. The presence of mineral oil in this area was confirmed by [45].

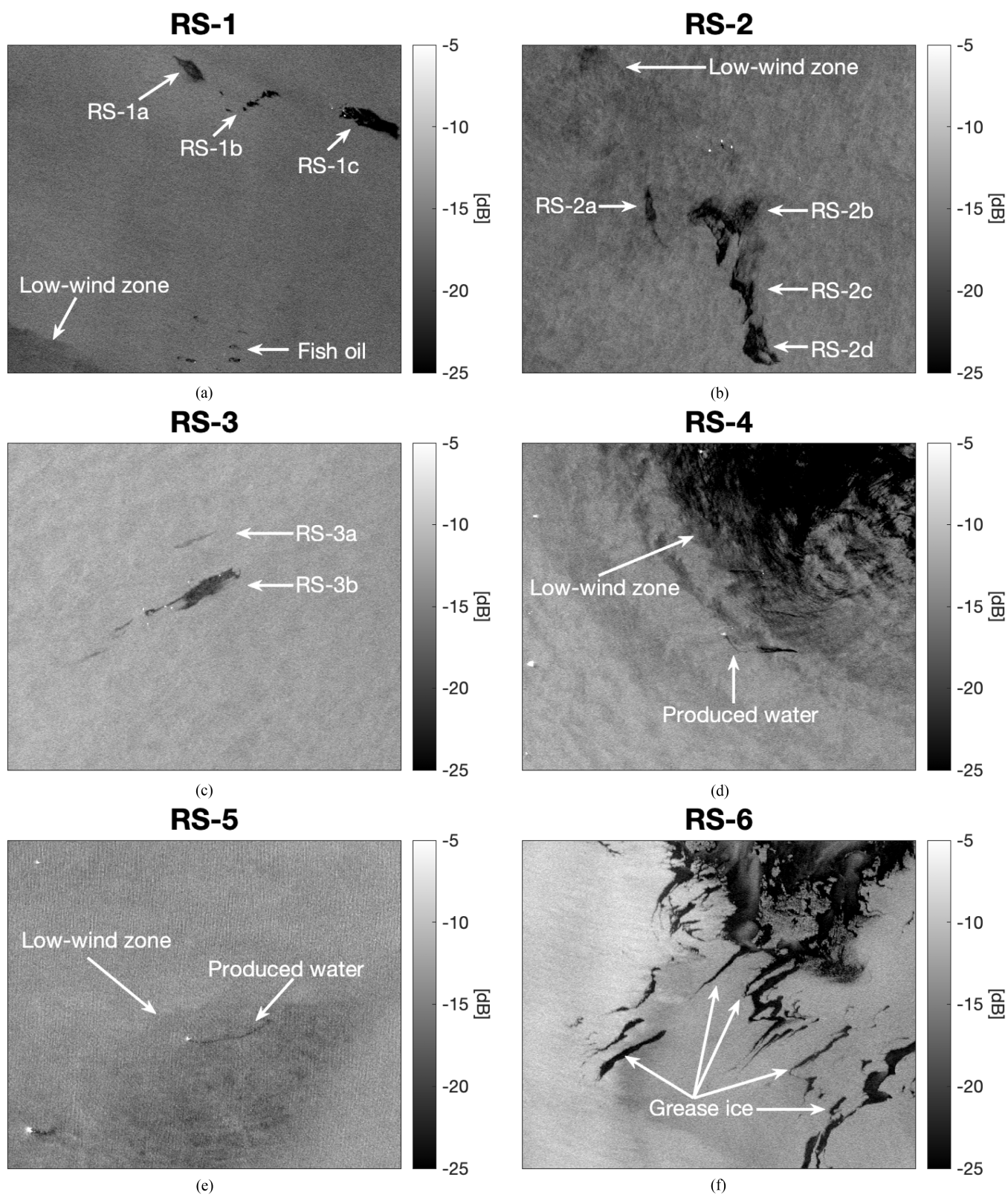


Fig. 6. (a)–(f) C-band RADARSAT-2 intensity images (σ_{VV}^0). All images are displayed in range-doppler coordinates, multilooked by a 9×9 window. (a)–(c) Images of oil-on-water campaigns. (d)–(e) Brage oil field with extensive low-wind zones present. (f) Grease ice slicks in the Kara Sea.

TABLE IV

PROPERTIES OF SAR ACQUISITION RS-1 INCLUDING WIND INFORMATION TAKEN FROM [8]. PROPERTIES OF SAR SCENES FOR RS-2 AND RS-3 ACQUISITIONS, INCLUDING WIND INFORMATION FROM [9], [18].

Scene ID	RS-1	RS-2	RS-3	RS-4	RS-5	RS-6
Date	8 Jun. 2011	15 Jun. 2012	11 Jun. 2013	23 May 2018	19 Aug. 2018	13 Nov. 2018
Time (UTC)	17:27	06:20	17:18	05:14	06:19	02:44
Mode	Fine Quad.	Fine Quad.	Fine Quad.	Fine Quad.	Fine Quad.	Fine Quad.
Incidence angle	34.5° - 36.1°	30.3° - 32.0°	28.1° - 29.9°	26.9° - 28.7°	29.2° - 30.9°	29.2° - 30.9°
Resolution (Rg x Az) [m]	5.2 × 7.6°	5.2 × 7.6°	5.2 × 7.6°	5.2 × 7.6°	5.2 × 7.6°	5.2 × 7.6°
Pixel spacing (Rg x Az) [m]	4.7 × 4.8	4.73 × 5.6	4.7 × 4.8	4.7 × 4.7	4.7 × 5.2	4.7 × 5.2
Wind speed[m/s]	1.6 - 3.3	4.0	5.0	unknown	unknown	unknown
Longitude of scene center	2°21'31"E	2°30'30"E	2°33'27"E	3°01'44"E	3°04'12"E	67°45'27"E
Latitude of scene center	59°58'05"N	59°58'17"N	60°01'08"N	60°34'11"N	60°33'37"N	75°30'32"N
Name of geographic area	North Sea	North Sea	North Sea	North Sea	North Sea	Kara Sea

TABLE V

PROPERTIES OF DISCHARGED SLICKS IN RS-1, RS-2, AND RS-3 AT TIME OF RELEASE, AND OPERATIONS PERFORMED IN THE INTERIM BETWEEN DISCHARGE AND SATELLITE ACQUISITIONS. THE AGE OF THE SLICKS AT THE TIME OF THE SAR ACQUISITIONS ARE ALSO SHOWN. (FROM [8], [9], [18], [55]).

Slick ID	Slick type	Date of release	Time of release (UTC)	Vol. (m ³)	Subjected to	Age of slick [hours]
RS-1a	Plant oil	8 June 2011	04:10	0.4	Untouched	13
RS-1b	Emulsion	7 June 2011	12:15	20	Mechanical recovery (~ 1 m ³ left on surface)	29
RS-1c	Crude oil	8 June 2011	08:23	30	Dispersion (on-going)	9
RS-2a	Plant oil	14 June 2012	16:20	0.4	Untouched	14
RS-2b	Emulsion	14 June 2012	16:20	14	Mechanical recovery (~ 12 m ³ left on surface)	14
RS-2c	Emulsion	14 June 2012	13:20	17	Mechanical recovery (~ 7 m ³ left on surface)	17
RS-2d	Emulsion	14 June 2012	20:20	10	Mechanical recovery (~ 4.8 m ³ left on surface)	22
RS-3a	Plant oil	11 June 2013	14:00	0.4	Untouched	3.5
RS-3b	Emulsion	11 June 2013	06:00	50	Mechanical recovery (~ 14 m ³ left on surface)	1

Within the PTSM, the ocean surface is modeled as a combination of large-scale roughness variations with small-scale roughness fluctuations overlaid on top. The small-scale roughness is modeled as a zero-mean stochastic process, where the height standard deviation is small relative to the electromagnetic wavelength, λ . The large-scale roughness is represented by slightly roughened, tilted facets whose slopes are normally distributed with variance, s^2 , in both range and azimuth directions.

The small-scale roughness, $\delta(x, y)$ is modeled as a band-limited *fractional Brownian motion* (fBm) process so that it has a power spectral density (PSD)

$$W(\kappa) = \frac{S_0}{\kappa^{(2+2H_t)}} = h^2 \frac{S_{0n}}{\kappa^{(2+2H_t)}} = s^2 W_n(\kappa) \quad (1)$$

where $\kappa = \sqrt{\kappa_x^2 + \kappa_y^2}$ and κ_x^2 and κ_y^2 are the Fourier transforms of x and y , respectively, and H_t is the Hurst coefficient, which is related to the fractal dimension, D , by $D = 3 - H_t$ and has a value $0 < H_t < 1$. S_0 is a quantity that is directly related

to the roughness variance, h^2 , via the dimensional facet-size-dependent constant, S_{0n} , and $W_n(\kappa)$ is the normalized PSD. For the ocean, $D = 2$ corresponds to a perfectly flat 2D surface, and higher values of D correspond to an increasingly roughened sea state. Valid values of H_t for the ocean surface range from approximately 0.65 to 0.95 [64]. In [58], it was demonstrated that the PTSM is very weakly dependent on the value of H_t , so here a nominal value of 0.9 was chosen to demonstrate the model. H_t is a frequency independent quantity.

Consider the case of the sensor illuminating an area at an incidence angle relative to a horizontal surface, v , and incident upon a single tilted facet, with facet slopes in the range and azimuth directions, respectively, given by $a = \tan(\omega)$, and $b = \tan(\gamma)$. Due to the facet tilt, the angle between the incoming radiation and the normal to the tilted facet (local incidence angle), v_l , depends on the incidence angle and facet slopes as follows:

$$\cos v_l = \frac{\cos v + b \sin v}{\sqrt{1 + a^2 + b^2}} \quad (2)$$

where a and b are assumed to be independent and identically distributed zero-mean s^2 -variance of Gaussian random variables, i.e., $a, b \sim N(0, s^2)$.

The facet tilt also causes a rotation of the local incidence plane about the look direction, $\hat{k}$, by an angle β that is related to the facet slopes and the incidence angle by

$$\tan \beta = \frac{a}{-b \cos v + \sin v}. \quad (3)$$

Using these relationships, expressions for the copolarized NRCS values for a single facet are

$$\begin{cases} \sigma_{HH}^0 = \times \left| F_H(v_l) \cos^2 \beta + F_V(v_l) \sin^2 \beta \right|^2 \\ \sigma_{VV}^0 = \times \left| F_V(v_l) \cos^2 \beta + F_H(v_l) \sin^2 \beta \right|^2 \end{cases} \quad (4)$$

where F_V and F_H are the Bragg coefficients. Full expressions can be found in [58].

Expressions for the total NRCS from an entire resolution cell can now be determined. If the large-scale-roughness height variations are greater than the emitted radiation wavelength and facet size is greater than the small-scale-roughness correlation length, returns from individual facets are uncorrelated, and the NRCS from the entire surface is obtained by averaging that of a single facet over the range of values of β and v_l . The resultant expressions are

$$\begin{cases} \sigma_{HH}^{0,a,b} = \frac{4}{s^2} \left[C_{0,0}^{HH} + \left[C_{2,0}^{HH} + 2 \frac{\text{Re}\{C_{0,0}^{HV}\} C_{0,0}^{HH}}{\sin^2 v} + C_{0,2}^{HH} \right] s^2 \right] \\ \sigma_{VV}^{0,a,b} = \frac{4}{s^2} \left[C_{0,0}^{VV} + \left[C_{2,0}^{VV} + 2 \frac{\text{Re}\{C_{0,0}^{HV}\} C_{0,0}^{VV}}{\sin^2 v} + C_{0,2}^{VV} \right] s^2 \right] \end{cases} \quad (5)$$

where s^2 is a measure of the large-scale roughness. Here, the terms $C_{k,n-k}^{pq}$ are the series expansion coefficients of the function $(k \cos v_l)^4 W F_p F_q^*$ and have the form

$$C_{k,n-k}^{pq} = \frac{1}{n!} \binom{n}{k} \frac{\partial^n \left((k \cos v_l)^4 W F_p F_q^* \right)}{\partial a^k \partial b^{n-k}} \Big|_{a=b=0}. \quad (6)$$

Expressions for $C_{0,0}^{pq}$, $C_{2,0}^{pq}$, and $C_{0,2}^{pq}$ were derived numerically. By utilizing the copolarization ratio, defined as VV/HH in this study, W cancels out, resulting in one equation with two unknowns, ε and s .

Fig. 7 graphs the PTSM copolarization ratio for various inputs of ε and s for the conditions encountered in North Sea during the NORSE 2019 for the F-SAR acquisitions. Here, ε for open water is 74.59–60.17j using a nominal value for the salinity of the North Sea and in-situ measurements of sea surface temperature, a value that is consistent with [65]. For the frequency range of 0.1–10 GHz (F-SAR L-band has a carrier frequency of 1.325 GHz), pure mineral oil has values of ε between $2.2 + 0.02j$ and $2.35 + 0.02j$, approximately [66]. It should be noted that as mineral oil weathers and emulsifies, the complex permittivity values vary between those of pure mineral oil and pure seawater depending on the fraction of seawater in the emulsion [62], [63]. Different values for s correspond to various wind states, with low

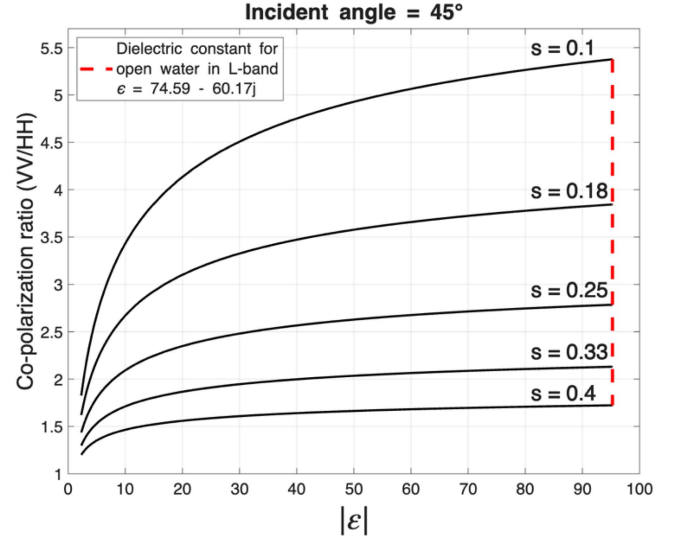


Fig. 7. PTSM curves showing the copolarization ratio (VV/HH) as a function of $|\varepsilon|$, computed for various values of s at 45° incident angle, $H_t = 0.9$, and radiation frequency of 1.325 GHz. The red dashed line indicates $|\varepsilon|$ for pure seawater.

values indicating a low degree of facet tilt due to less energy being imparted to the ocean and high values indicating greater facet tilt in the presence of higher wind speeds.

In Fig. 7, the red, dashed, vertical line indicates the value of $|\varepsilon|$ for pure seawater. As values for $|\varepsilon|$ decrease, the values for the copolarization ratio similarly decrease, implying that the presence of mineral oil can be detected by registering when copolarization ratio values are less than those of open water. In contrast, if values for $|\varepsilon|$ stay the same, but the large-scale roughness indicator s decreases, as in the case for low wind, an increase in values for the copolarization ratio can be observed. This implies that the presence of low wind can be inferred by registering when copolarization ratio values are greater than those of radar-bright, open water.

In this study, we hypothesize that the reductions in radar backscatter are induced by different physical mechanisms for low wind speeds vs. mineral oil, consistent with the analysis presented above: oil slicks cause a reduction in copolarization ratio values relative to open water, and lower wind speeds cause an increase in copolarization ratio values. If that is the case, then it is theoretically possible to differentiate the two radar dark phenomena.

We stress that the purpose of including a discussion of the PTSM is not to indicate that our method derives quantitative estimates of parameters relating to geophysical ocean surface properties. Rather, we use the model to demonstrate the qualitative relationship between the copolarization ratio and various wind states and dielectric properties of the ocean surface, specifically that lower wind speed leads to higher copolarization ratio values, and lower dielectric constant values lead to lower copolarization ratio values, both relative to open water pixels outside of low wind zones (not radar-dark). Other theoretical backscattering models predict similar qualitative behavior to the PTSM. For example, Hwang et al. [67] compared copolarization

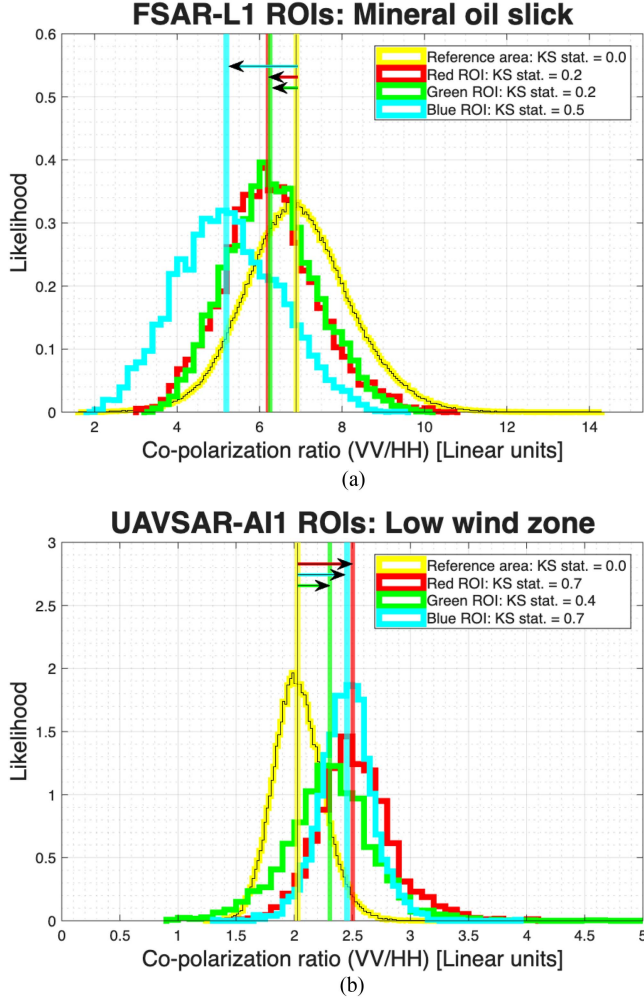


Fig. 8. (a) Histograms from red, green, and blue ROIs in Fig. 1(a) are centered to the left of the reference histogram (yellow), indicating mineral oil. (b) Histograms from red, green, and blue ROIs in Fig. 2(a) are centered to the right of the reference histogram (yellow), indicating low wind.

ratio values derived from 427 RADARSAT-2 acquisitions over open water with wind speed measurements from ocean buoys. In their study, they compared these observations to the composite surface Bragg model. Their results showed the inverse relationship between the copolarization ratio and wind speed, consistent with predictions made by the composite surface Bragg model (see Fig. 4).

B. Algorithm Description

In this section, we demonstrate how a method using relatively radar-bright open water pixels adjacent to a radar-dark zone and at the same angle of incidence can act as a discriminator on whether a radar-dark backscatter ocean surface is due to the presence of low-wind or a surfactant. This is done by performing a statistical evaluation over an ensemble of spatially correlated pixels, e.g., the test ROIs in Figs. 1(a) and 2(a).

In Fig. 8(a), normalized histograms for the copolarization ratio pixels extracted from the ROIs in Fig. 1(a) (yellow sampled from open water, red, green, and cyan sampled from oil slick)

are shown, and for Fig. 8(b) from the ROIs in Fig. 2(a). The copolarization ratio is computed from SAR pixel values in linear units, and the histograms in Fig. 8 are likewise presented in linear units. The vertical lines denote the median of the histograms and correspond to the expectation value. The x-axes of both Fig. 8(a) and (b) have been shifted so that the peaks of the yellow histograms (open water) are aligned for better visualization. As can be seen in both figures, there is a high degree of overlap between the radar dark ROIs' (red, green, and cyan) copolarization values and the corresponding open water (yellow) copolarization values.

Kolmogorov-Smirnov test statistic [KS stat., (7)] is used to measure quantitatively how separated the radar-dark and open water distributions. Consider a reference distribution $f(x)$ [copolarization ratio values from reference area (yellow in Fig. 8)] and a test distribution $g(x)$ [copolarization ratio values from test area (red, green, cyan in Fig. 8)] with cumulative distribution functions $F(x)$ and $G(x)$. The KS stat. is given as follows:

$$KS\ stat. = \sup_x |F(x) - G(x)| \quad 0 \leq KS\ stat. \leq 1 \quad (7)$$

where $\sup$ denotes the supremum (or maximum) value over all values of x . The KS test statistic will have a value of 0 if two histograms are completely overlapping, a value of 1 if there is no overlap, and intermediate values otherwise.

In addition to the KS test statistic, the median copolarization ratio position of the radar-dark test ROIs (red, green, cyan) and the reference ROI (yellow) is assessed. In Fig. 8(a), the peaks of all three radar-dark ROIs are positioned to the left of the yellow histogram's peak, which illustrates a reduction in backscatter due to the dielectric properties of the scattering medium, indicative of the presence of mineral oil. For the low-wind case [Fig. 8(b)] the median values for the radar-dark ROIs (red, green, cyan) are positioned to the right of the reference ROI values (yellow), indicating a reduction in large-scale surface roughness. From the KS stat., the KS index is now calculated as follows:

$$KS\ ind. = \text{sign}(\text{median}(f(x)) - \text{median}(g(x))) \cdot KS\ stat. - 1 \leq KS\ ind. \leq 1. \quad (8)$$

Fig. 9 outlines a flowchart diagram of the proposed method.

C. Metrics for Accuracy Assessment

To quantify the agreement between the KS index results and the corresponding high-confidence oil/open water maps, both products were thresholded to produce binary classifications of oil slick and open water. For the KS index maps, values less than zero were assigned to the oil class, while values greater than zero were assigned to the open water class. Only pixels with a high signal-to-noise ratio ($SNR > 6$ dB) were included in the analysis. The widely used Jaccard index (Intersection over Union, IoU) and the Dice coefficient were used to quantify the agreement between the segmentation outputs. These metrics are used for evaluating the spatial overlap of binary maps and are particularly well suited to threshold-based segmentation

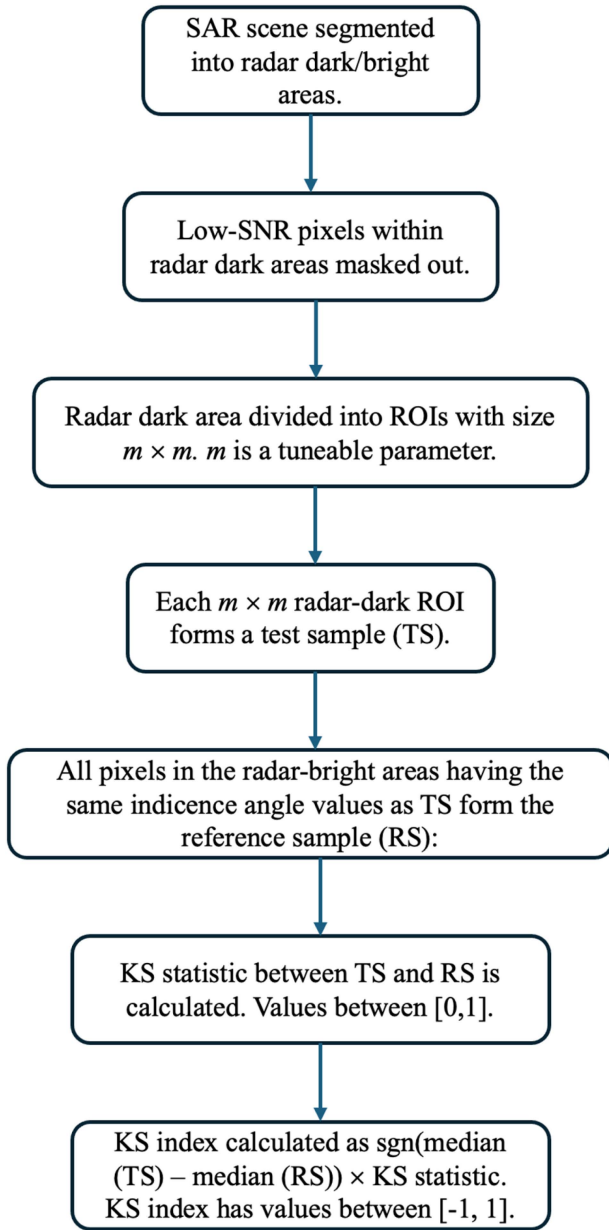


Fig. 9. Flowchart diagram of the proposed method.

problems. The Jaccard index is defined as follows:

$$J = \frac{|A \cap B|}{|A \cup B|} \quad (9)$$

where A and B represent the sets of pixels classified as the target class in the reference and derived maps, respectively. The Dice coefficient is given by

$$D = \frac{2|A \cap B|}{|A| + |B|}. \quad (10)$$

Both metrics range from 0 to 1, where 0 indicates no overlap and 1 denotes perfect agreement. While closely related, the Dice coefficient places greater emphasis on overlap and is generally less conservative than the Jaccard index.

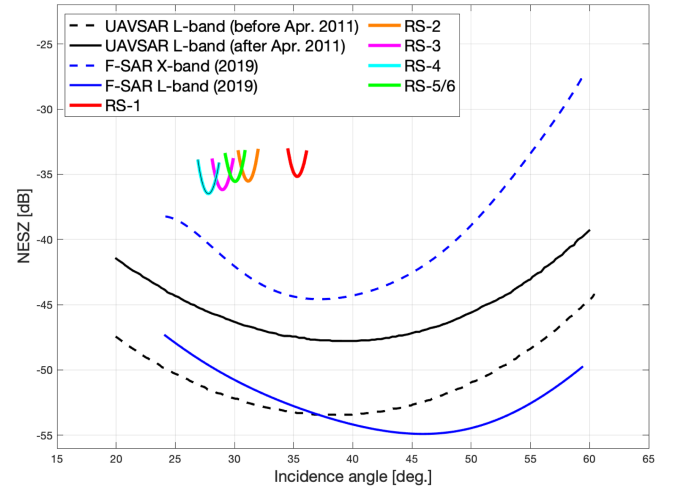


Fig. 10. NESZ curves as a function of incidence angle for UAVSAR, F-SAR, and RADARSAT-2 datasets.

IV. NOISE ANALYSIS

The PTSM predicts that when values for ε are less than that of seawater, such as the case for an oil slick, the copolarization ratio will similarly decrease, resulting in a KS index in the range of -1 to 0 . However, we hypothesize that a radar-dark area with low-SNR, whether in the form of an oil slick or low-wind, will result in low KS index values, and thus a misclassification of low-wind as oil slick. This can be expressed mathematically as follows:

$$\lim_{VV, HH \rightarrow 0} \frac{VV + N}{HH + N} = 1 \quad (11)$$

where VV and HH are the backscatter contained within the copolarization channels, and N is a noise term, commonly modeled as white Gaussian noise, affecting both polarimetric channels equally and resulting in a copolarimetric ratio of 1. Based on this, we perform a noise analysis for the airborne datasets from the F-SAR flights and the UAVSAR flights over the Aleutian Islands to identify areas that are most affected by noise, aiding in a more accurate interpretation of our results (Section V). For the UAVSAR-COP and RADARSAT-2 datasets, we mask out any noise-affected pixels in those results. This is because, as will be shown, low-SNR pixels significantly impact the final KS index values.

Fig. 10 shows the NESZ for UAVSAR (black curves) and F-SAR X-band and L-band (blue dashed and blue solid curves, respectively), with a ~ 11 dB difference between the NESZ for the F-SAR L-band and the F-SAR X-band. The UAVSAR had a NESZ ~ 5 dB lower before April 2011 [50]. For a pixel to be classified as high-SNR, we assume that it is at least 6 dB above the instrument's NESZ [15], [16], indicated in light green in Figs. 11–13 if both the VV and HH channels fulfill this criterion. Red indicates high-SNR in the VV channel only, and black indicates both the VV and HH channels have a low-SNR. For Figs. 12 and 13, a dark green color indicates a land mask. A noise analysis was carried out for the two L-band F-SAR acquisitions, and they are not shown as all pixels had high-SNR

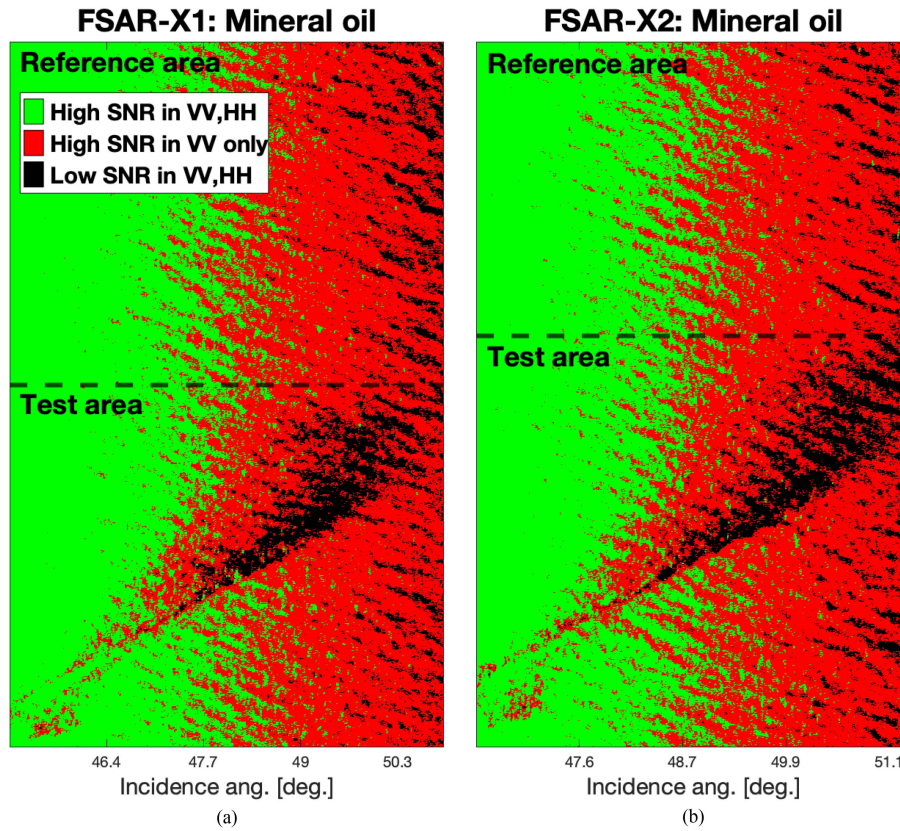


Fig. 11. (a) and (b) Noise analysis for the X-band FSAR acquisitions in Fig. 1(c) and (d) respectively. Green indicates high-SNR in both VV and HH channels, red indicates high-SNR in the VV channel only, and black indicates low-SNR in both VV and HH. High-SNR is defined as backscatter with values at least 6 dB above the NESZ.

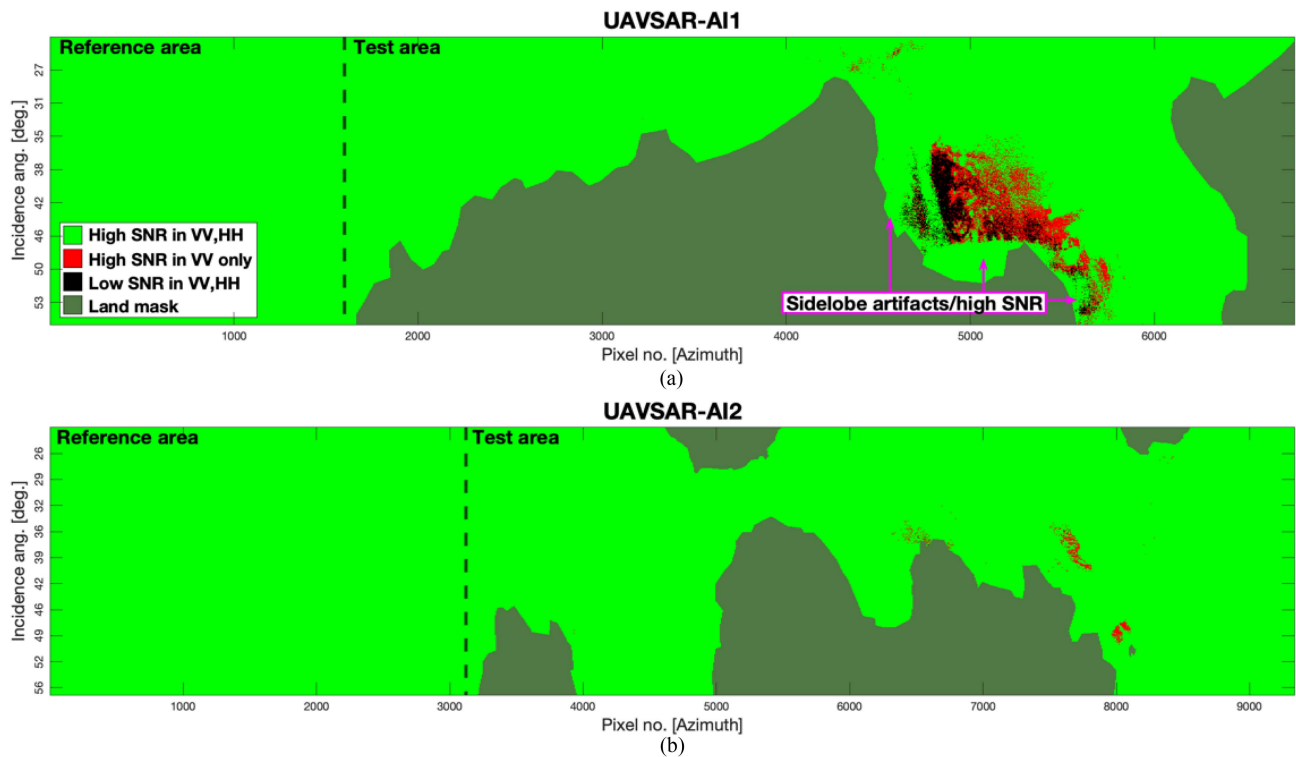


Fig. 12. (a) and (b) Noise analysis for the L-band UAVSAR acquisitions in Fig. 2 (a) and (b) respectively. Colors have the same meanings as in Fig. 11. Note that the sidelobe areas in (a) display high SNR characteristics.

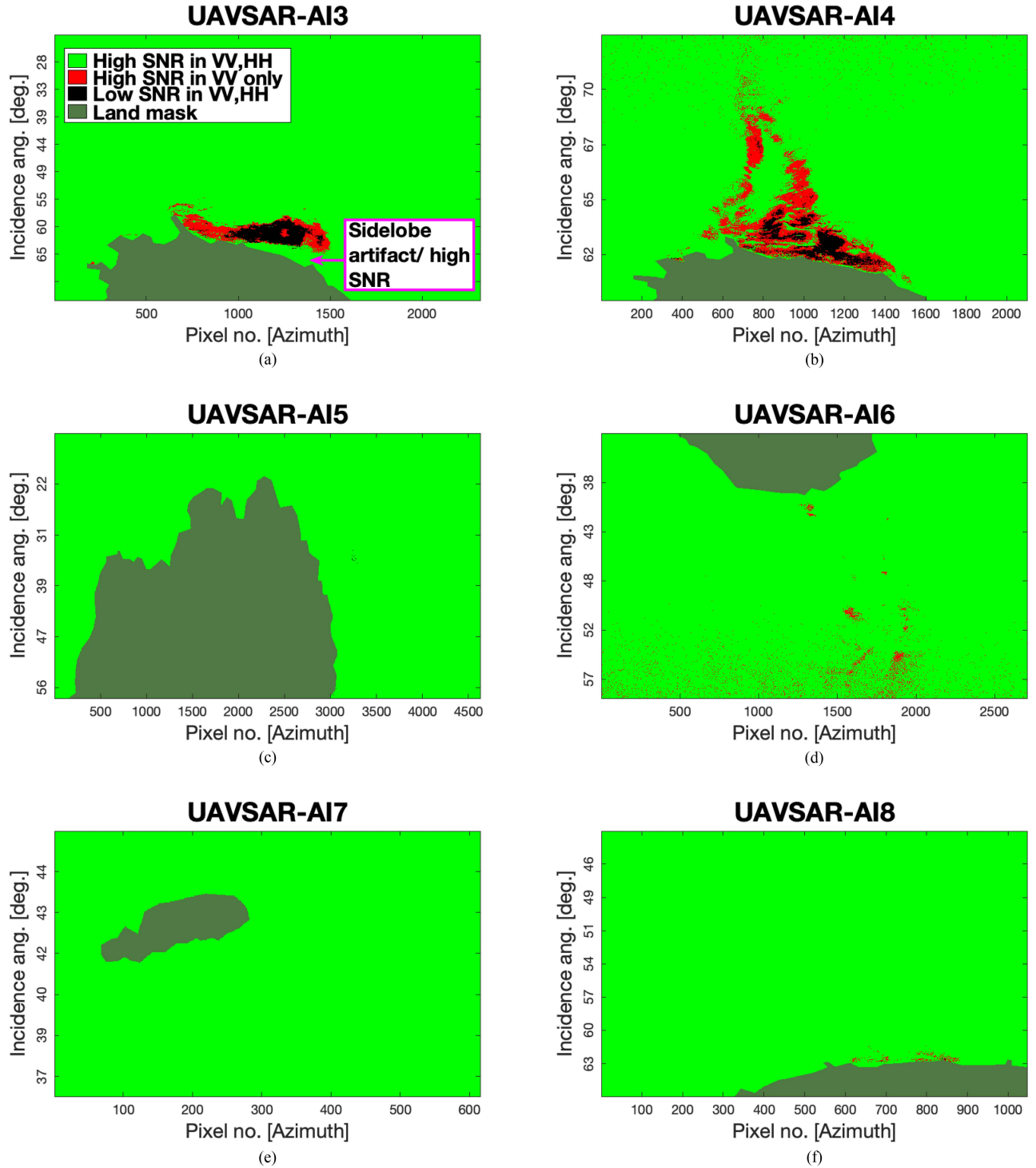


Fig. 13. (a)–(f) Noise analysis for the L-band UAVSAR acquisitions in Fig. 3(a)–(f) respectively. Colors have the same meanings as in Figs. 11 and 12. Sidelobe areas in (a) display high SNR characteristics.

in both VV and HH channels and showed no noise contrast between oil slick and open water.

For the FSAR-X1 and FSAR-X2 (Fig. 11), the oil slick area is characterized by low-SNR in either both the VV and HH channels or just the HH channel. This is expected given the relatively high noise floor in F-SAR's X-band (see Fig. 10). In Figs. 12 and 13, most areas characterized by low wind

display high-SNR characteristics. Figs. 12(a) and 13(a) and (b) display low-SNR areas close to the land masses and are likely due to extreme wind shadowing in those areas. Areas characterized by sidelobe artifacts show high-SNR in both VV and HH [Figs. 12(a) and 13(a)] and are thus denoted in light green. This will be examined in greater detail in Section V.

V. RESULTS AND DISCUSSION

Section V.A and B present the derived KS index maps for the two airborne SAR data sets used in this study, containing only oil slick and low wind areas, where the noise analysis results from Section IV are used to indicate instances where the KS index results can lead to false positives. Section V.C presents the KS index maps for the UAVSAR-COP dataset, and Section V.D presents the KS index maps for the RADARSAT-2 dataset.

A. F-SAR Data: Verified Mineral Oil Slicks

The calculation of the KS index involves comparing a $m \times m$ radar-dark ROI to radar-bright pixels at the same angle of incidence, here $m = 21$ is used to preserve the spatial information within the slick.

Fig. 14 shows the KS index results for FSAR-L1, FSAR-L2, FSAR-X1, and FSAR-X2. The L-band datasets (FSAR-L1 and FSAR-L2) had high-SNR in both VV and HH, and the KS index results show consistently negative KS index values throughout the slick, indicating a correct identification of surfactant affecting the dielectric properties of the ocean surface, i.e., mineral oil. Quigley et al. [48] analyzed photographs acquired from the aircraft carrying the F-SAR instrument and reported that the “head of the slick” (yellow polygon) exhibited a discontinuous true-color appearance, corresponding to a thickness of 151–153 μm , whereas the “tail of the slick” (red polygon) exhibited a silver sheen and ranged from 0.04 to 0.3 μm , representing a difference of 3–4 orders of magnitude. However, the KS index maps in Fig. 14(a) and (b) show no appreciable distinction between the head and tail regions. This suggests that the KS index is not sensitive to oil slick thickness, whereas it is known that the damping ratio is sensitive to relative thickness only [68].

For the FSAR-X1 and FSAR-X2 datasets, the pixels had low-SNR in either VV or HH or both (see Fig. 11) within the slick, and like the L-band acquisitions, the KS index results within the slick have negative KS index values. However, in this case, the correct identification of the oil slick is likely due to internal system noise rather than sensing a genuine alteration in the dielectric properties of the ocean surface.

The open water, KS index values for the L-band images have alternating positive and negative KS index values (represented by a mixture of blue and red) as a result of the choice of the side pixel length of the test area ROIs (21 pixels in this instance), which are smaller than the wavelength of the large-scale ocean surface waves present. This causes variations in the derived KS index values with alternating sign. To demonstrate that larger test area ROIs will converge to KS index values of 0 over open ocean, KS index maps for all 4 FSAR acquisitions, with a side length of 101×101 pixels are shown in Fig. 21 in Appendix A. Where oil slick areas retain a negative KS index, while open water areas adjacent to the slick attain values of 0.

B. UAVSAR Data: Low-Wind Areas Caused by Wind Shadowing

As stated in Section II.B, UAVSAR-AI1 [Fig. 2(a)] likely shows a linear island wake while UAVSAR-AI2 [Fig. 2(b)] likely

shows both mountain lee waves and linear island wakes, all low-wind phenomena caused by the presence of land bodies in the Aleutian Islands. Fig. 15 shows the KS index maps for both UAVSAR acquisitions, where only the test areas from Fig. 2 are shown.

Radar-dark, low-wind areas in Fig. 2 have predominantly positive KS index values in Fig. 15. The noise analysis for UAVSAR-AI1 shows a large, triangular, low-SNR zone to the east of the land mass, which corresponds to negative KS index values in Fig. 15(a). This agrees with the results for FSAR-X1 and FSAR-X2, which showed that a scattering surface would be identified as an oil slick with negative KS index values under low-SNR.

However, it should be noted that the area immediately adjacent to the land mass in UAVSAR-AI1, where sidelobe artifacts can be identified, has high SNR in Fig. 12(a). Interestingly, the KS index values in this region were also negative, as shown in Fig. 15(a). Likewise, Fig. 15(b) showed localized zones of negative KS index values associated with the island body, which had high-SNR in Fig. 12(b). This is again likely due to the presence of sidelobe artifacts. This indicates that masking pixels based solely on SNR can be insufficient for reliably distinguishing between mineral oil slicks and low-wind areas, particularly in near-coastal waters where sidelobe artifacts are more apparent. More advanced masking approaches would be required, for example, by accounting for the antenna pattern, which is beyond the scope of this study. Additional sources of high-SNR SAR artifacts include radio frequency interference (RFI) from marine radars (operating in X- and S-band) and coastal military radar installations (L-band).

UAVSAR-AI3 and UAVSAR-AI4 [Fig. 3(a) and (b)] were taken consecutively of the same island 33 min apart, with UAVSAR-AI3 being acquired in an east-to-west direction and UAVSAR-AI4 being acquired in a west-to-east direction. Hence, UAVSAR-AI3 and UAVSAR-AI4 image the same low-wind event but taken from different look directions and acquired at different incidence angles, with UAVSAR-AI3 having lower incidence angles than UAVSAR-AI4. This is evident in the noise analysis imagery in Fig. 13(a) and (b), where the latter exhibits a significantly larger low-SNR region due to the higher incidence angles at which the image was acquired. The corresponding KS index values are shown in Fig. 16(a) and (b), where low wind regions are indicated by the positive KS index values, and low-SNR areas, as well as areas with sidelobe artifacts, have negative KS index values.

The KS index maps for UAVSAR-AI5, UAVSAR-AI6, UAVSAR-AI7, and UAVSAR-AI8, shown in Fig. 16(c)–(f), have consistently positive KS index values within their radar-dark areas. No low-SNR areas were identified within these scenes, and as a result, a correct identification of low-wind areas throughout the radar dark areas.

Some open water areas in Figs. 15 and 16 deviate from 0; this is likely a consequence of the geographic distance between reference and test area ROIs, 10s–100s of km. Thus, local wind conditions, such as sporadic wind gusting or localized, island-induced wind effects, over the test area ROIs can cause roughening of the ocean surface relative to the reference ROIs,

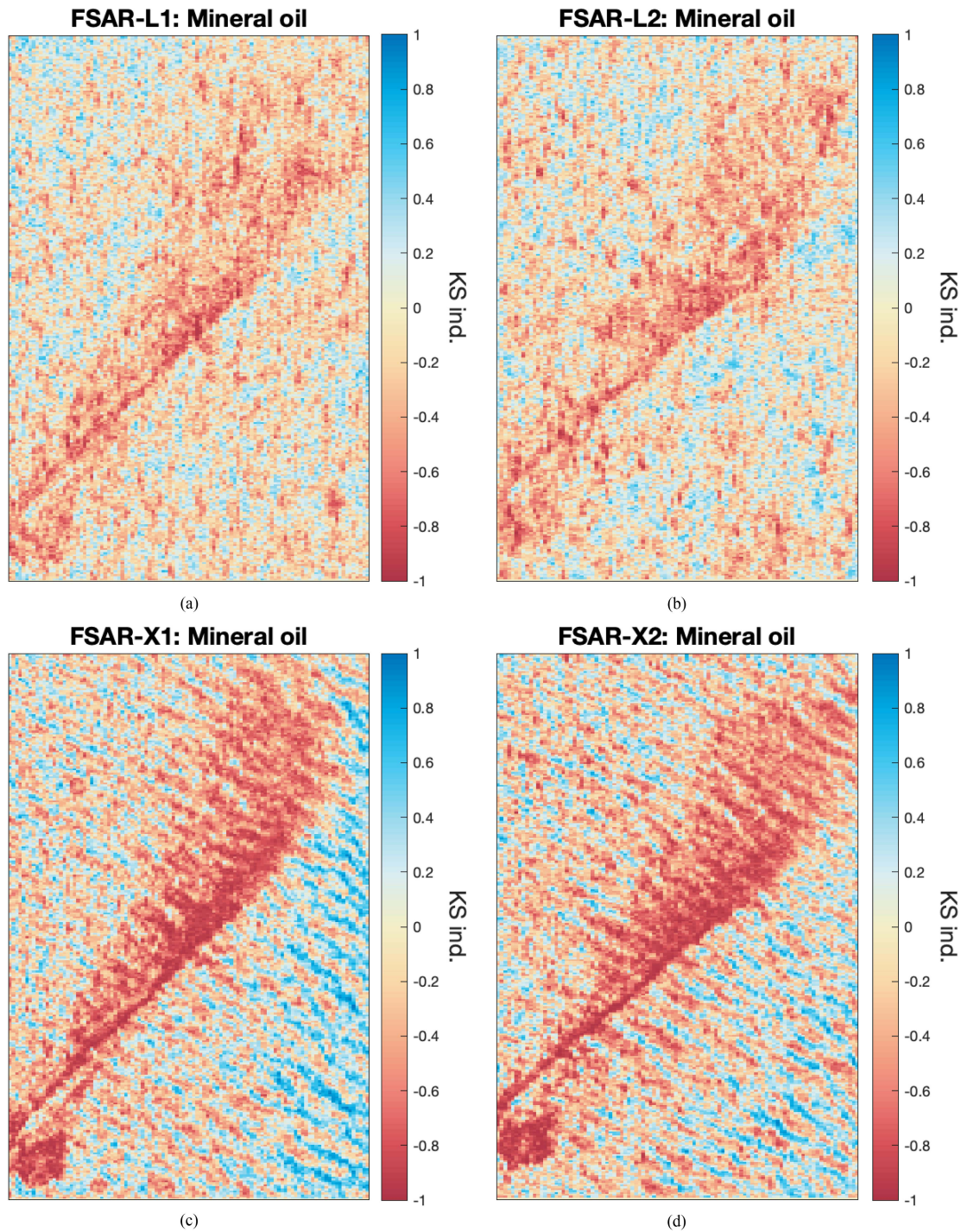


Fig. 14. (a) and (b) KS index maps for the F-SAR L-band scene with oil slicks, for which all pixels have high-SNR in both HH and VV. Here, the slicks show negative KS index values, consistent with the PTSM for oil slicks. (c) and (d) KS index maps for F-SAR X-band, for which nearly all pixels in the oil slicks have low-SNR. Oil slick areas show negative KS index values, but whether this is due to low-SNR or the lower dielectric constant is not determinable.

resulting in negative KS index values. This highlights the importance of masking out open water pixels and including them in the reference ROI for the method to work effectively.

As shown in Figs. 15 and 16, the KS index method demonstrates strong performance in accurately identifying areas of low wind. However, applying the KS index method requires the user to select a value for m , the pixel side length of the test-area ROIs, which is a user-defined parameter that governs

the trade-off between spatial resolution and computational cost. Smaller values of m produce more detailed KS index maps, but at the expense of increased processing time. In this study, a value of $m = 21$ was selected primarily for the airborne SAR datasets for visual clarity of the resulting images. In practical applications, however, end users may wish to adjust this parameter depending on their specific needs and computational constraints. An evaluation of different values of m is provided in Appendix A,

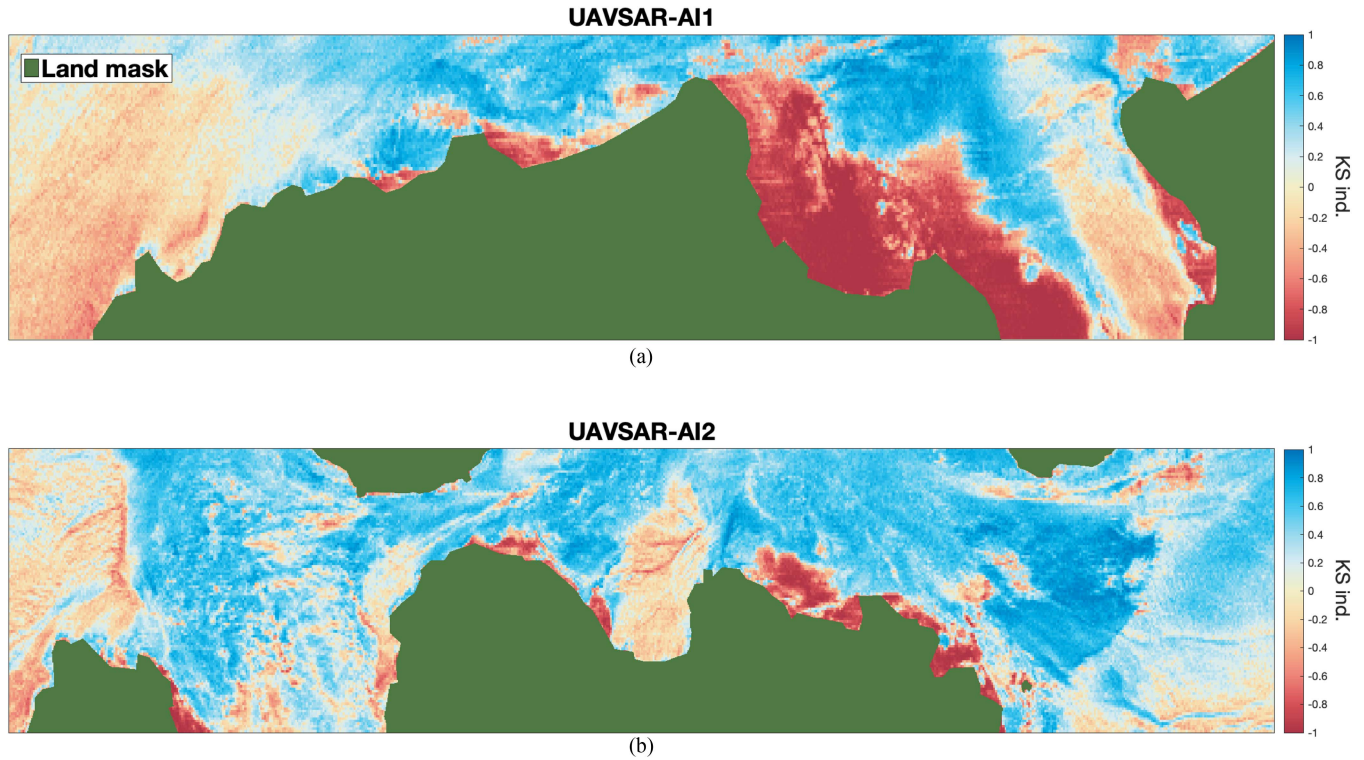


Fig. 15. (a) and (b) KS index maps for UAVSAR imagery acquired in the Aleutian Islands, shown in Fig. 2. Positive KS index values indicate the presence of low wind zones. Negative KS index values correlate to low-SNR values (Fig. 12) and sidelobe artifacts (Fig. 2). Only test areas from Fig. 2 are shown. Land (green) is masked out.

which demonstrates that variations in m do not significantly affect the classification accuracy for identifying low-wind zones associated with positive KS index values.

C. UAVSAR Data: Simultaneous Acquisitions of Mineral Oil and Low-Wind Areas

The UAVSAR-COP time series was included in this study to demonstrate a real-world scenario where low-wind events coincide with an oil slick in a coastal environment. Fig. 17 presents the KS index maps for the UAVSAR-COP time series, where pixels < 6 dB above the NESZ (solid black curve in Fig. 10) were excluded from analysis and are depicted in grey.

The damping ratio (DR), derived using the method in [68], is commonly used in operational applications to provide a first-order estimate of relative slick thickness. It is computed from the contrast between in-slick NRCS values and open-water pixels at the same incidence angle. In this study, the DR was used to segment the scene into radar-dark areas (oil slick or low wind, $DR > 1$) and radar-bright open water ($DR \approx 1$). Accordingly, Fig. 17 shows KS index values only for radar-dark regions, while radar-bright areas are set to zero (yellow).

The KS index maps for UAVSAR-COP1, UAVSAR-COP2, and UAVSAR-COP3 show extensive low-wind zones, as indicated by the positive KS index values, while the streamers to the left of the images are correctly identified by negative KS index values. It should be noted that large portions of these scenes are affected by low-SNR, and that these low-SNR regions reduce

in size in UAVSAR-COP4-6 and indicate negative KS index values as the wind speed increases and the low-wind zones disappear.

To validate the KS index values for UAVSAR-COP1, UAVSAR-COP2, and UAVSAR-COP3, they are compared with high-confidence oil/open water maps using the method outlined in Quigley et al. [45]. These maps are derived by calculating the standard deviation of the VV-pol NRCS for ensembles of pixels across a rapid-repeat time series. Specifically, the ensembles are created by extracting a $m \times m \times k$ set of pixels across the scene and time-series, where, like the KS index m is a tunable parameter and k is the number of scenes considered in the time series. In this study, the maps are created by setting m to 21 and k to 3. The approach operates directly on NRCS backscatter rather than on the copolarization ratio. The underlying rationale is that low-wind conditions are likely to be more spatially and temporally variable, leading to greater fluctuations between the acquisitions, compared to oil slicks that have less spatial variability over the same time scale. As a result, this approach has proven effective in distinguishing oil slicks from low-wind areas in rapid-repeat time-series data [45].

The maps are shown in Fig. 18 and were derived using three (i.e., $k = 3$) consecutive scenes acquired over the span of 38 min. In summary, the KS index map for UAVSAR-COP1 is derived using UAVSAR-COP1, and for the corresponding high confidence oil/open water map, UAVSAR-COP1, as well as a scene acquired just before UAVSAR-COP1 and a scene just after UAVSAR-COP1, is used, etc. As UAVSAR-COP6 was

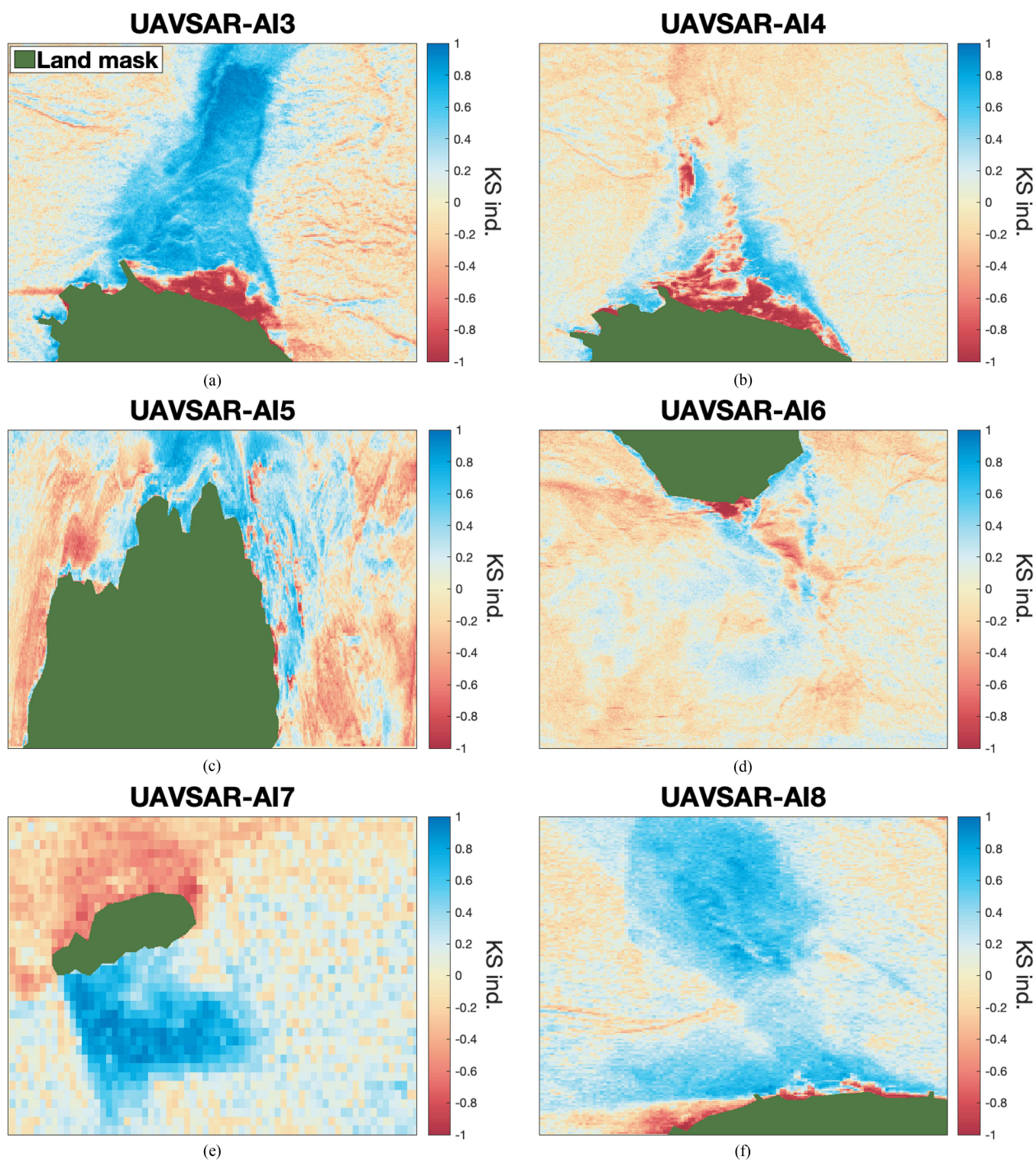


Fig. 16. (a)–(f) KS index maps for UAVSAR imagery acquired in the Aleutian Islands, shown in Fig. 3. Positive KS index values indicate the presence of low wind zones. Negative KS index values correlate to low-SNR values (Fig. 13) and sidelobe artefacts (Fig. 3). Land (green) is masked out.

the last scene acquired in this time series, the high confidence oil/open water map in Fig. 18(f) was derived using UAVSAR-COP6 plus two scenes acquired before UAVSAR-COP6, i.e., the same scenes used to generate the map shown in Fig. 18(e) are used.

For all three KS index maps in Fig. 17(a)–(c), areas of low wind (blue colored, positive KS index values) correspond to high standard deviation values in Fig. 18(a)–(c), similar to the surrounding open ocean. Likewise, areas of oil slick in Fig. 17(d)–(f) (red colored, negative KS index values)

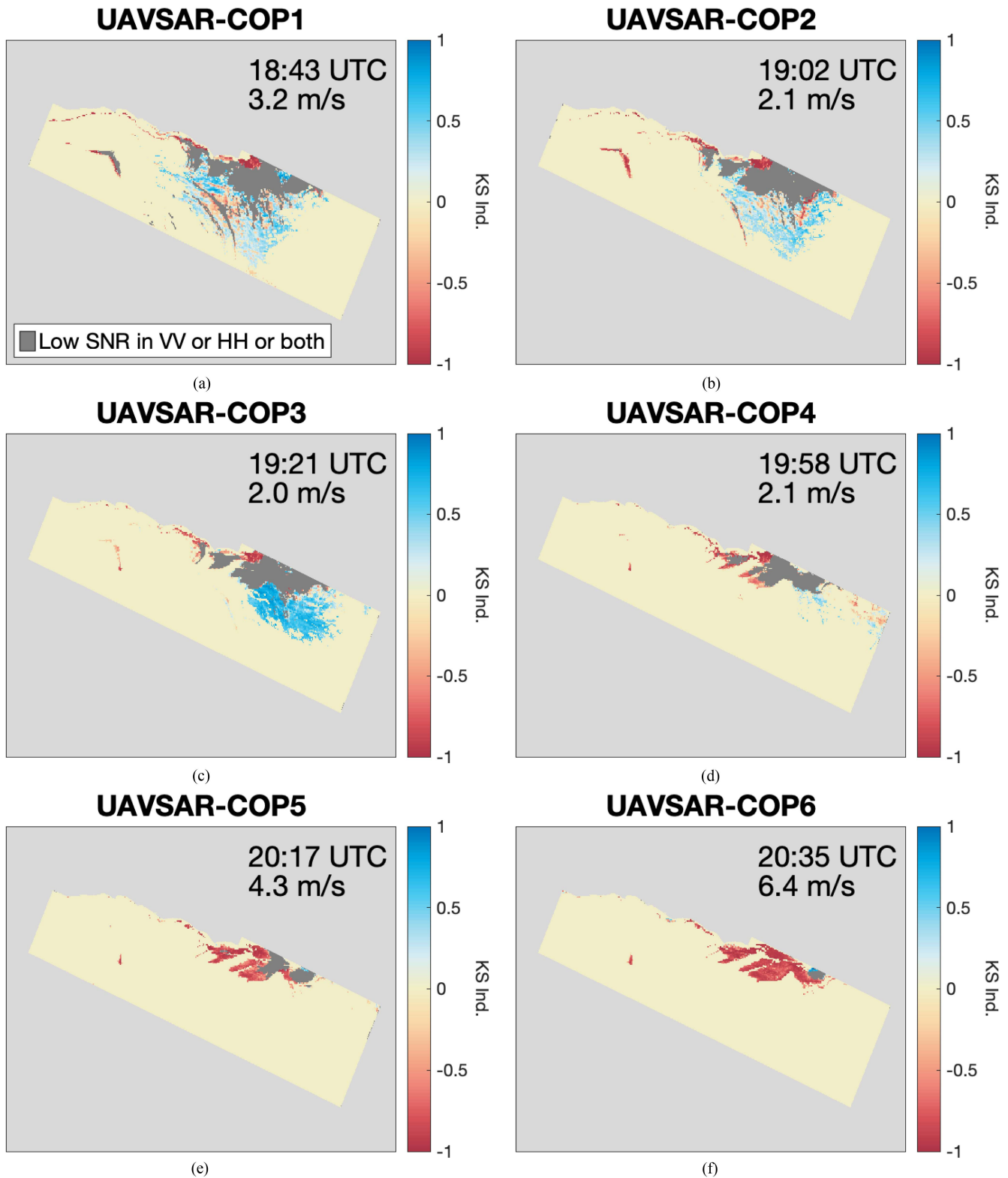


Fig. 17. (a)–(f) KS index maps for UAVSAR imagery acquired in the COP seep field shown in Fig. 5. Open water pixels are assigned a value of 0. Pixels with low-SNR (VV or HH) are also masked out and are indicated in dark grey. Low wind areas (positive KS index values) can be seen in (a)–(c). Low wind areas reduce in extent and disappear in (d)–(f) along with increased backscatter (higher SNR) in oil slick areas and the disappearance of streamers to the left of the images. This correlates to a rise in wind speed at the time of acquisition (see Fig. 5).

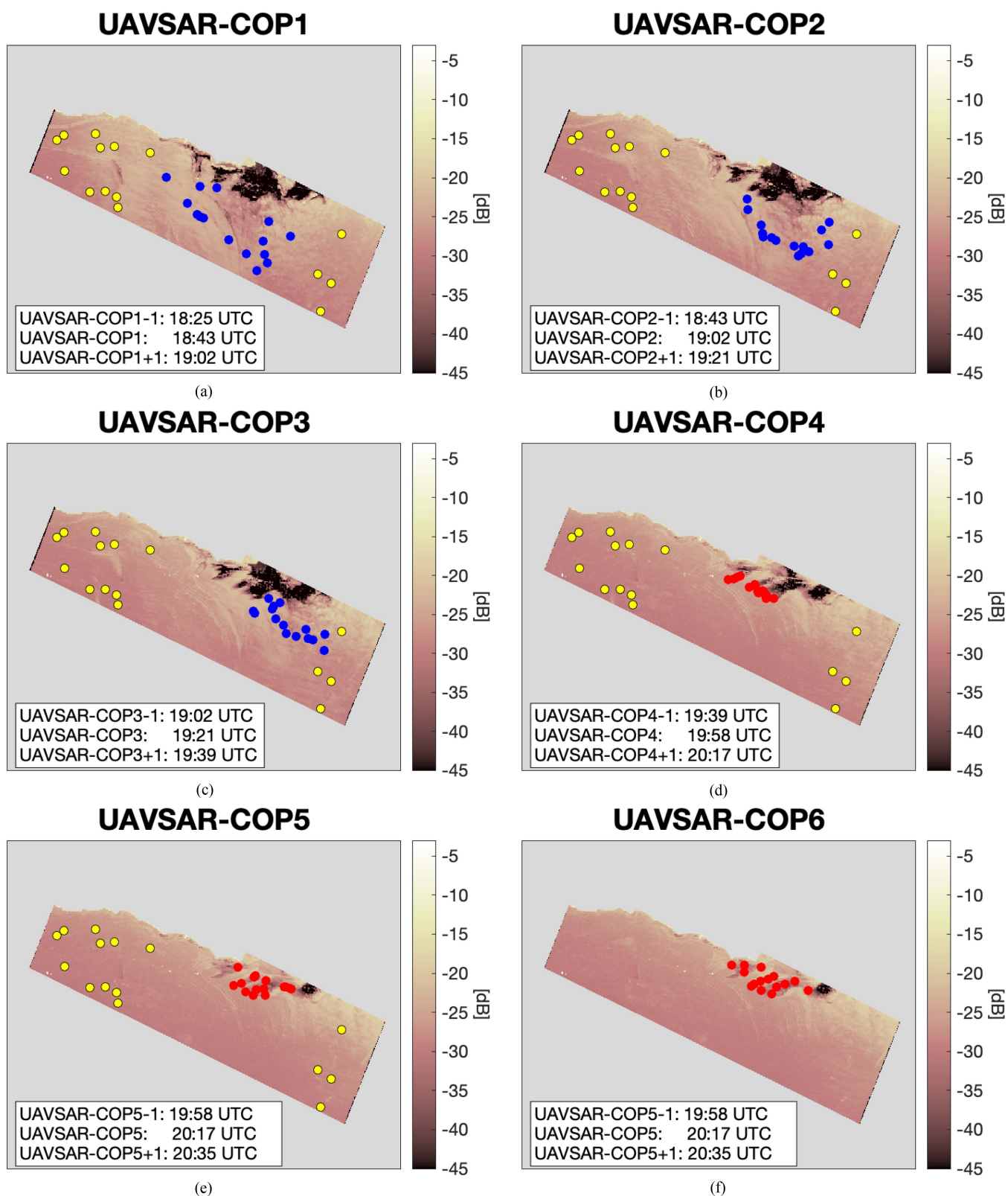


Fig. 18. High-confidence oil/open water maps corresponding to UAVSAR-COP1 - UAVSAR-COP6 [Fig. 17(a)–(f)]. Each map is made using three consecutive rapid-repeat images following the method outlined in [45]. Low wind areas in Fig. 17(a)–(c) correspond to open water areas in each of the maps. The coincident oil slick areas are clearly delineated. Colored points correspond to the location of sampled pixels from the KS index maps in Fig. 17.

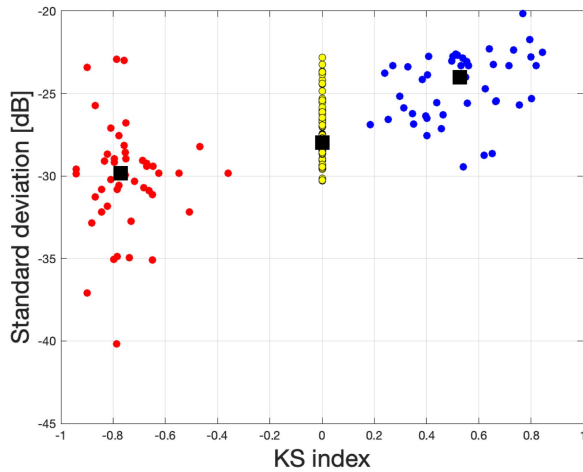


Fig. 19. Scatter plot of KS index values vs. standard deviation values corresponding to the colored points in Fig. 18.

correspond to low standard deviation values in Fig. 18(d)–(f). For a quantitative comparison, 15 areas of positive and negative values in the KS index maps were extracted and compared with the overlapping values from the high confidence oil/open water maps. The areas were sampled away from the land to avoid side-lobe artifacts or areas that may correspond to kelp beds in the area. In addition, areas with streamers in the left portion were avoided, as [45] showed that the high-confidence oil/open water map method does not handle long, thin, linear, radar-dark features very well. Additionally, 15 areas were sampled from radar-bright open water regions, with standard deviation values corresponding to a KS index of 0. The location of these points can be seen in Fig. 18 as either red (positive KS ind.), blue (negative KS ind.), or yellow (KS ind. = 0) circles.

Fig. 19 shows a scatter plot of these sampled points, with the black squares being the centroid of each cluster and calculated using the median. There is a high degree of separability between these clusters, with the oil slick samples having the greatest skew toward lower high-confidence oil/open water values. The median high confidence oil/open water value corresponding to the low wind areas was -24.0 dB, the water -28.8 dB, and the oil -29.9 dB. Only pixels that had high-SNR were used from the KS index maps; thus, using an instrument with a lower noise floor would likely result in a greater separability between the oil class and the low-wind and open water classes.

The Jaccard index and the Dice coefficient were calculated for the thresholded KS index results and thresholded high confidence oil/open water maps for UAVSAR-COP1, UAVSAR-COP2, and UAVSAR-COP3 (Figs. 17 and 18, respectively). Appendix A (Fig. 23) shows the thresholded images. We observe high correspondence for the low-wind open water class (Jaccard = 0.7760, Dice = 0.8739) and lower correspondence for the oil class (Jaccard = 0.2118, Dice = 0.3495). Overall, the results indicate that the proposed method is highly reliable for delineating open water areas experiencing low-wind conditions. The relatively low scores for the oil slick class are

likely attributable to the limited availability of mineral oil pixels satisfying the SNR criterion, as well as potential masking effects. This suggests that improved masking of erroneously included low-SNR pixels may be required to enhance oil slick delineation performance.

D. RADARSAT-2 Data: Spaceborne Imagery of Verified Mineral Oil, Low Wind Zones, and Grease Ice

The RADARSAT-2 dataset was included to demonstrate the applicability of the method to spaceborne SARs, which generally have higher noise floors than their airborne counterparts (see Fig. 10). The images were acquired 100s of km away from land, ensuring that any wind-induced low-wind zones present are due purely to atmospheric effects, and not due to wind shadowing from land bodies or other coastal phenomena. For the KS index maps in Fig. 20, a box size of 51×51 pixels is applied, a value of 0 for radar-bright open water areas, pixels <6 dB above the NESZ in both the HH and VV channels were excluded from the analysis and are depicted in grey. A larger box size was selected due to the coarser spatial resolution of the RADARSAT-2 imagery relative to UAVSAR. This choice also facilitates clearer visual presentation of the results, although, as shown in Appendix A, the method is not sensitive to the selection of m . The mineral oil slicks have negative KS index values, and the low wind areas have positive KS index values, consistent with the results from Section V.A and B.

The plant oil slicks in RS-1 and RS-2 (RS-1a and RS-2a, respectively) also have negative KS index values. As biogenic materials often consist of fatty acids, proteins, and other biomolecules with long molecular chains, containing both hydrophobic and amphiphilic parts, they tend to orient themselves on the ocean surface and form monomolecular slicks. Thus, KS index values of 0 are expected, as monomolecular slicks will dampen small-scale capillary waves while not having significant effects on the dielectric properties of the scattering surface.

Using SAR images from the 2015 NOFO oil-on-water campaign, where the same plant oil type was released as imaged in the RADARSAT-2 images used here, Jones et al. [69] modeled the vertical transport of a discharged plant oil slick, as well as three mineral oil emulsion slicks with water contents of 40%, 60%, and 80%. They found that the discharged plant oil was entrained more quickly and mixed much deeper into the water column than discharged mineral oil emulsions. This may affect the dielectric constant of the ocean surface and is likely why negative KS index values are attained for the plant oil in this case.

Extensive low wind zones are shown in Fig. 20(d) and (e) where most pixels were correctly classified with positive KS index values, consistent with the findings in Section V.B. Some pixels have negative KS index values, despite having a relatively high-SNR, likely due to masking issues whereby some radar-bright, open water pixels are included in the test area ROI, as can be seen in Fig. 6(d). This is also consistent with the KS index results for the open water areas presented in Figs. 15 and 16 for the UAVSAR-AI dataset in Section V.B.

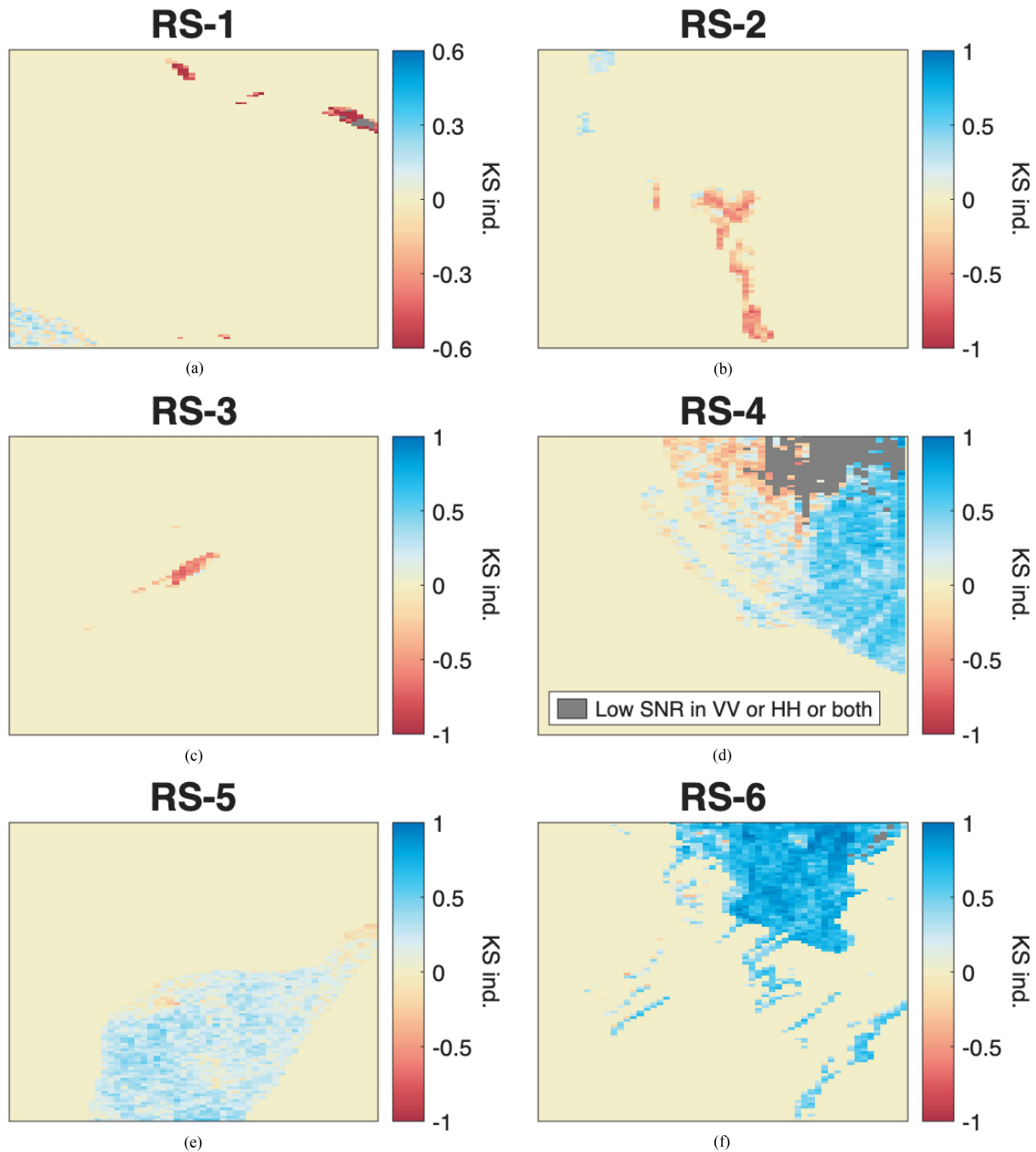


Fig. 20. (a)–(f) KS index maps for RADARSAT-2 imagery shown in Fig. 6. Positive KS index values indicate the presence of low wind zones. Negative KS index values indicate the presence of mineral oil slicks. KS index map in (a) scaled to $[-0.6, 0.6]$ for better visualization.

These results represent an advancement over Quigley et al. [45], where discrimination between oil slicks and low-wind areas required multiple images of rapid-repeat SAR acquisitions (Fig. 18). The reliance of [45] on multitemporal data limited that approach primarily to airborne SAR systems. In contrast, the RADARSAT-2 KS index maps, shown in Fig. 20, demonstrate that with this new method discrimination can be achieved using a single SAR acquisition, thereby enabling operational implementation with spaceborne SARs.

In Fig. 6(f), grease ice is dominating the radar-dark areas and, by their appearance, closely resembles typical mineral oil slicks. As the grease ice is highly saline, KS index values of 0 were expected. However, KS index values similar to those of low wind areas were obtained [Fig. 20(f)]. Since the scene was acquired in relatively calm conditions, it is suggested that this allowed the ice to raft on the water surface and thus suppressed some of the large-scale surface waves relative to the open water. These results are preliminary and from only one scene, but they suggest

that the proposed approach may have applicability beyond oil slick discrimination from low wind. However, this interesting observation requires further investigation and validation to determine whether this is a reliable method for distinguishing grease ice from mineral oil.

VI. CONCLUSION

The primary objective of this study was to develop a method to differentiate oceanic oil slicks from low-wind areas in single scene SAR imagery. A unique aspect of this study involved testing the method on a UAVSAR dataset of the Aleutian Islands that exclusively contains low-wind zones, an inherently challenging task since low-wind conditions cannot be predetermined. Using a theoretical backscattering model, we were able to predict positive KS index values over low-wind areas provided that the data had a high SNR. These low-wind area predictions were confirmed in all eight UAVSAR-AI images. We note that SAR imagery can also be exploited to derive wind speed fields using established approaches such as geophysical model functions [70], [71], [72], [73] and azimuth cut-off techniques, particularly for spaceborne systems. Such wind information can provide independent support for the interpretation of the results in an operational context.

Although this study showed promising results, we emphasize that one of the key requirements for the proposed technique is a dual copolarimetric SAR capable of capturing high-SNR pixels within the radar-dark areas. Currently, publicly available SAR datasets, such as Sentinel-1, provide data only in either VV/VH or HH/HV polarimetric channels and have relatively high noise floors, making them unsuitable for this application.

In this study, we also applied the method to spaceborne SAR data sets of verified mineral and plant oil slicks. We used six spaceborne C-band fine-quad polarimetric RADARSAT-2 acquisitions, all acquired with high-SNR across most pixels in both the VV and HH polarimetric channels. Within these scenes, all marine slicks were associated with negative KS index values, and all tested instances of low-wind zones were associated with positive KS index values. The plant oil slicks were expected to yield KS index values of zero, as such biogenic material tends to form monomolecular slicks, which are not expected to affect the dielectric properties of the ocean surface. However, water column entrainment may be the reason for the negative KS index values.

We also note the proposed method requires the presence of open-water/non-low-wind pixels in the scene (and at similar incidence angles) to provide contrast for the radar-dark area and enable robust statistical estimation. In the case of RADARSAT-2 fine quad-pol data, the typical $25 \text{ km} \times 25 \text{ km}$ coverage may limit operational applicability for extended low-backscatter regions that reduce the availability of suitable reference pixels. Future and new missions such as Sentinel-1 Next Generation and NISAR provide much wider swath coverage, which may better support such applications at scale. In addition, these requirements highlight the importance of appropriate mission

design for operational oil spill and radar-dark feature monitoring that employs our method.

As a final contribution, we applied the method to a SAR scene containing grease ice, which is radar-dark and was expected to exhibit KS index values of zero, similar to open water, due to its high salinity. However, the results showed a clear separability, with positive KS values. Although studies focusing on distinguishing grease ice from mineral oil slicks in SAR imagery are limited [56], [74], these findings suggest the method's potential for separation of the two in spaceborne SAR. Further validation is needed, particularly for varying Arctic conditions where such discrimination will become increasingly important due to changing sea ice coverage and increasing maritime activity [75], [76].

The proposed method shows promise for the detection and separation of low-wind areas and mineral oil slicks, though to operationalize it, some further additions could be considered, as outlined in the following.

- 1) SAR artifacts in radar-dark areas often arise from range and azimuth sidelobe ambiguities in waters adjacent to radar-bright objects and areas. These artifacts are common along shorelines and can compromise derived KS index results, particularly near shore. Methods to exclude contaminated pixels should be explored.
- 2) In this study, we utilized the DR and manually segmented radar-dark areas by setting a threshold. More sophisticated and automated techniques to exclude open water pixels from the low-backscatter ROIs should be investigated.
- 3) Further work should be conducted to evaluate the robustness of the proposed method and its application to other mineral oil slick look-alikes. Applying the method to other potential coastal look-alike phenomena, e.g., coastal upwelling, estuarine plumes, oceanic eddies, and biogenic slicks, could be explored.
- 4) Further investigation into the applicability of the proposed method to other domains would be valuable. One potential application is SAR-based ship detection, where the objective is to distinguish targets from background sea clutter. The methodology presented in this study constructs a statistical distribution from open-water pixels and evaluates deviations within a selected ROI. If the ROI contains a spatially localized target, such as a ship, the resulting statistical deviation may produce a negative KS index, potentially enabling positive target detection. A similar approach has previously been explored by [77], where KS statistics were employed to distinguish ships from surrounding sea ice in ice-infested waters. For a comprehensive overview of SAR-based target detection methods, the reader is referred to [78].

We highlight the finding that negative KS index values were consistently observed between mineral oil emulsions of markedly different thicknesses in L-band, which indicates that even thin sheens of mineral oil can be classified using the proposed approach. Further work should be undertaken to verify these results, e.g., multifrequency studies with coincident optical imagery.

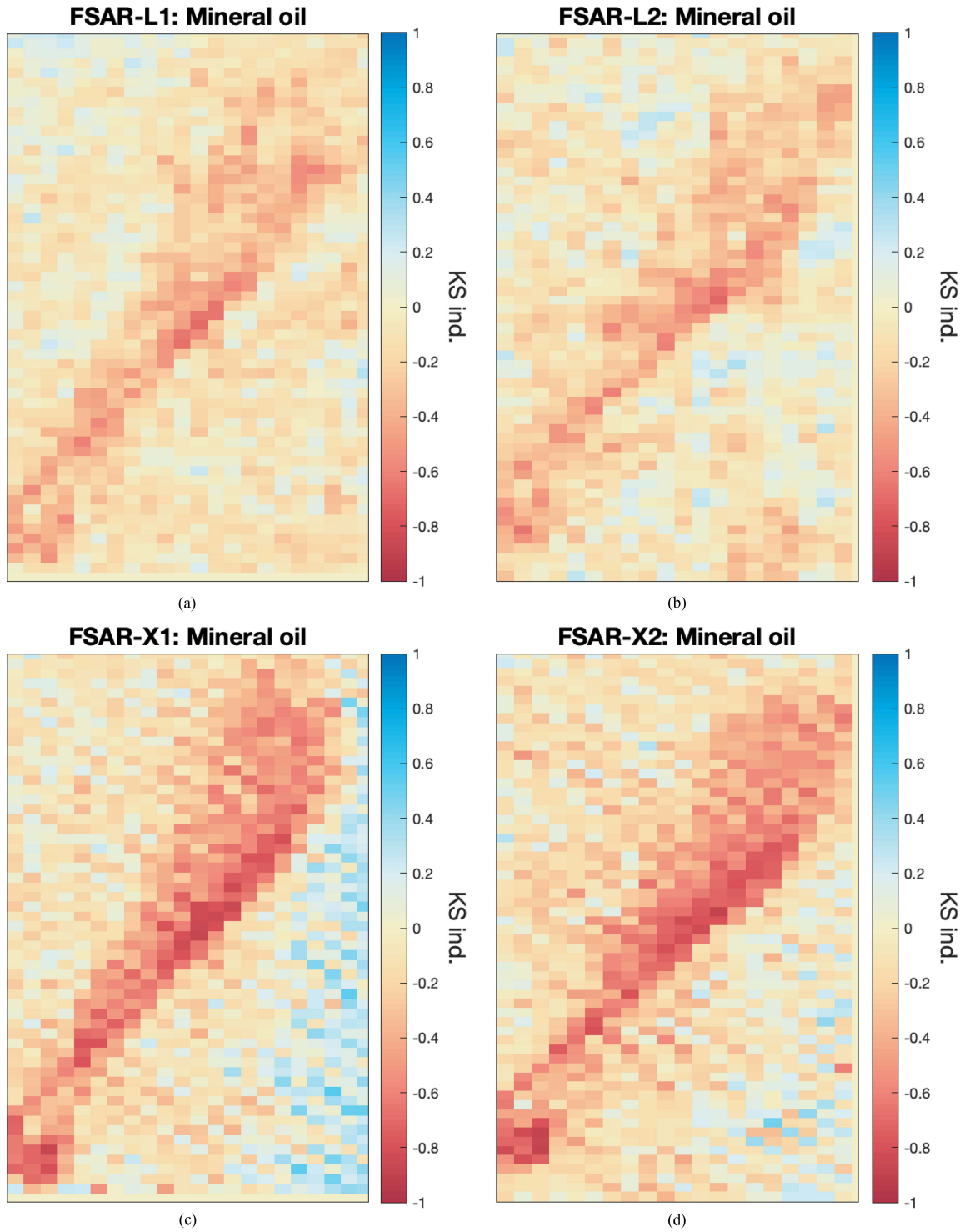


Fig. 21. Same as in Fig. 14 but with a box size of 101×101 pixels. KS index values for open water areas assume a value of 0.

APPENDIX A

Here, we assess the impact of varying values of m on the classification accuracy of the different scattering surfaces observed in the SAR imagery.

First, we reapply the method to all four F-SAR images in Fig. 2 using a box size of 101×101 pixels. The results are shown in

Fig. 21. As can be seen, negative KS index values are achieved for the L-band acquisitions in (a) and (b). Similarly, negative KS index values are achieved for the X-band acquisitions in (c) and (d), due to low SNR in this instance. In contrast to the F-SAR KS index maps shown in Fig. 14, the ocean areas now register KS index values of zero, indicated by a yellow color. This is due

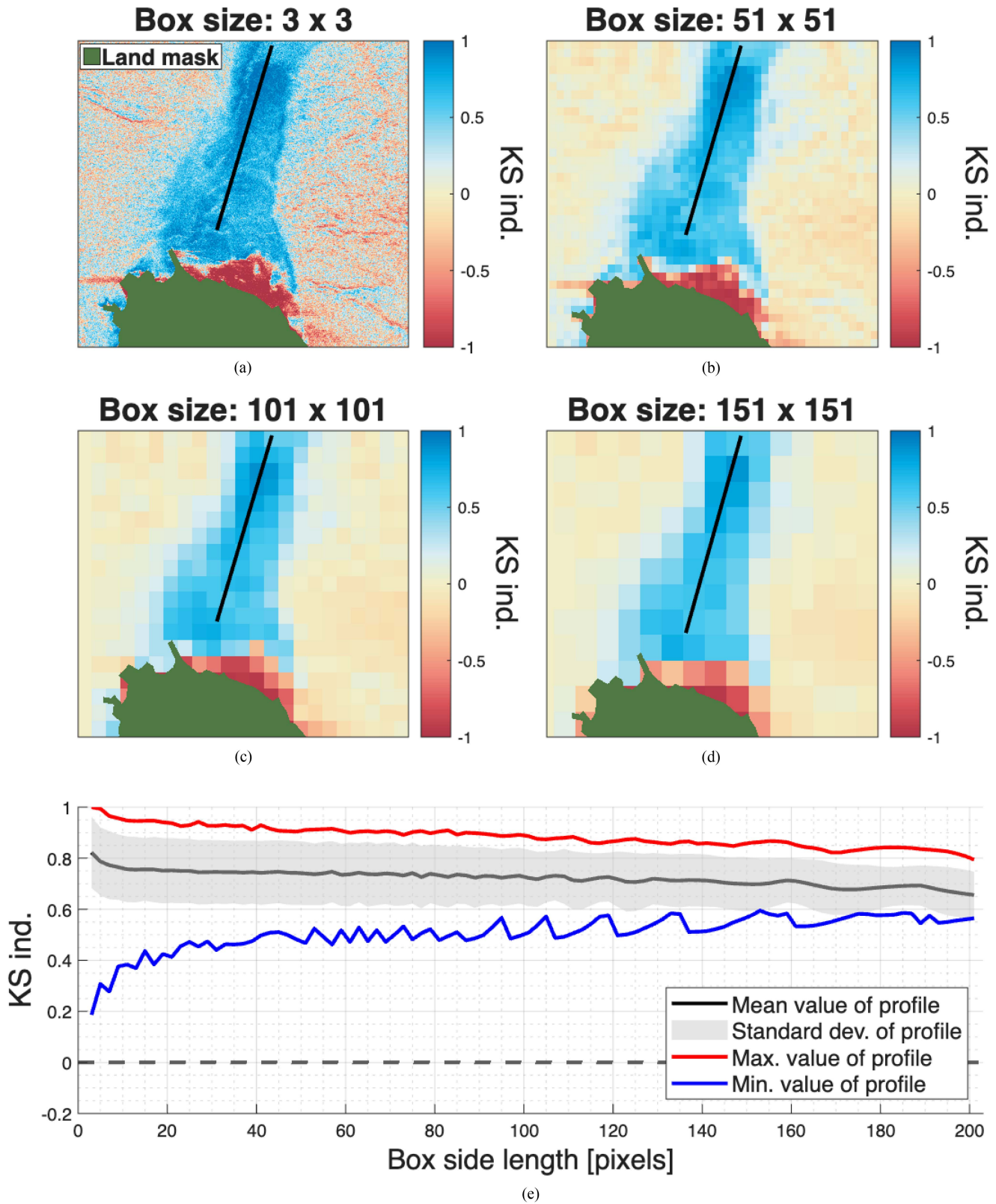


Fig. 22. (a)–(d) KS index maps for UAVSAR-AI3 reanalyzed using different ROI pixel side lengths. The black line shows the sample profile. (e) Mean and standard deviation of KS index values (black and gray, respectively) from the sample profile for different box side lengths. The mean value is approximately 0.7 for all box side lengths. The maximum and minimum values along the profile also remain within the positive KS index range.

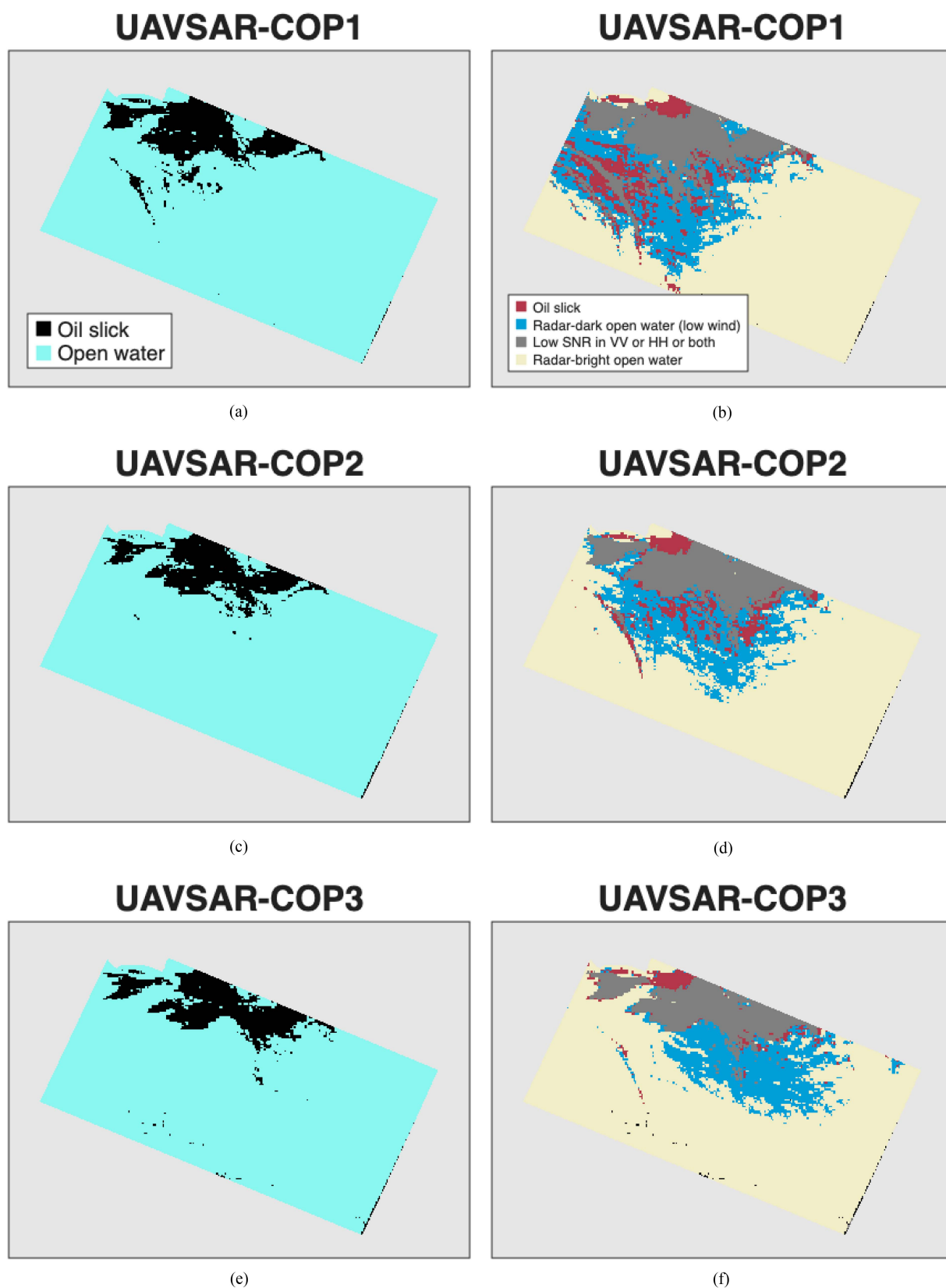


Fig. 23. (a), (c), and (e) High confidence oil/open water maps with a -31 dB threshold applied. (b), (d), and (e) KS index maps thresholded at KS index = 0.

to the larger box size used to derive these results as opposed to the box size used for the results in Fig. 14 (21×21 pixels).

Second, to demonstrate that the classification accuracy for low-wind areas is not dependent on the choice of m , we reapply the method to a low-wind zone with extensive areal coverage. Specifically, the method is applied to UAVSAR-AI3 [Fig. 3(a)], while allowing m to vary from 3 to 201. Fig. 22(a)–(d) shows the resulting KS index maps for box side lengths of 3, 51, 101, and 151, respectively. Although it is unlikely that an end user would select a value as large as $m = 201$, it is included here for demonstration purposes. For each iteration, a profile of KS index values is sampled along the center of the low-wind zone [black line in Fig. 22(a)–(d)]. The center is chosen because the low-wind zone has not been explicitly masked, and this avoids contamination from open-ocean pixels, particularly for larger values of m . Fig. 22(e) presents the mean KS index value along the profile (black line), with the shaded region indicating ± 1 standard deviation. As shown, the mean KS index values remain positive across all box sizes and have a value of roughly 0.7 for all side lengths. Additionally, the maximum and minimum values along each profile are plotted (red and blue, respectively), and these also remain within the positive KS index range. This demonstrates that the KS index method is robust and not sensitive to the choice of m .

APPENDIX B

The high-confidence oil/open-water maps corresponding to UAVSAR-COP1 to UAVSAR-COP3 were thresholded to produce classified maps distinguishing open water from mineral oil slicks. An empirically determined threshold of -31 dB was used, and applied to the UAVSAR-COP1 to UAVSAR-COP3 maps [Fig. 18(a)–(c)] as they contained low-wind zones and are shown in Fig. 23(a), (c), and (e). The corresponding KS index maps, thresholded at a KS index value of 0, are presented in Fig. 23(b), (d), and (f). Specifically, KS index values greater than 0 are shown in blue, values less than 0 are shown in red, and low-SNR regions are shown in gray and excluded from the analysis.

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Cornelius Quigley received the bachelor's degree in physics from the Department of Physics, National University of Ireland, Cork, Ireland, in 2013, the master's degree in remote sensing of seaice using synthetic aperture radar from the Department of Physics and Technology, UiT – The Arctic University of Norway, Tromsø, Norway, in 2017, and the Ph.D. degree in remote sensing of mineral oil slicks using synthetic aperture radar from the Center for Integrated Remote Sensing and Forecasting for Arctic Operations (CIRFA), Tromsø, Norway, in 2021.

He is currently a Postdoctoral Researcher with the Department of Environmental and Energy Sciences, Chalmers University of Technology, Gothenburg, Sweden. He was subsequently a Postdoctoral Researcher with CIRFA until December 2023. He was a Postdoctoral Researcher with the Department of Exploration, Helmholtz-Zentrum Dresden-Rossendorf (HZDR), Freiberg, Germany, until May 2026, where his research focused on the application of SAR technology for monitoring tailings storage facilities to improve safety in the mining industry. His research interests include multifrequency remote sensing of sea ice and oil spills.



Technology, Gothenburg, Sweden. Her research interests include multifrequency remote sensing of sea ice, oil spills, and permafrost.

A. Malin Johansson (Member, IEEE) received the M.Sc. degree in physical oceanography from Gothenburg University, Gothenburg, Sweden, in 2005, and the Ph.D. degree in remote sensing from Stockholm University, Stockholm, Sweden, in 2012.

She is currently an Associate Professor with the Department of Physics and Technology, UiT – The Arctic University of Norway, Tromsø, Norway, which she joined in 2014. She was a Postdoctoral Researcher with the Radar Remote Sensing Group, Department of Earth and Space Sciences, Chalmers University of Technology, Gothenburg, Sweden. Her research interests include multifrequency remote sensing of sea ice, oil spills, and permafrost.



Cathleen E. Jones (Senior Member, IEEE) received the B.S. degree in physics from Texas A&M University, College Station, TX, USA, in 1982, and the Ph.D. degree in physics from the California Institute of Technology, Pasadena, CA, USA, in 1991.

She is currently a Senior Research Scientist with the NASA Jet Propulsion Laboratory, California Institute of Technology, where her main research is focused on the development of methods for determining oil slick characteristics, monitoring subsidence and critical infrastructure, and understanding land

building/loss in deltas. She is the Applications Co-Lead of the NASA NISAR Science Team.