Comparing Near Coincident C- and X-band SAR Acquisitions of Marine Oil Spills

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Abstract—In this paper, we compare satellite borne C- and X-band Synthetic Aperture Radar (SAR) data for marine oil spill observation. During large scale oil-on-water exercises in the North Sea, quad-polarization Radarsat-2 (C-band) and dual-polarization TerraSAR-X (X-band) data were acquired with temporal distances of less than 24 minutes. The objective is to characterize and quantify differences in the Radarsat-2 and TerraSAR-X measurements. Three scene pairs are compared in terms of data quality and signal characteristics including statistical properties and selected multi-polarization (HH, VV) parameters. The signal characteristics are also compared among low backscatter features of various origin within the individual pairs. No viable argument for selecting one sensor above the other is identified in the data quality study. In the statistical analysis, investigation of log-cumulants indicates a larger deviation from Gaussian statistics in the TerraSAR-X data compared to in Radarsat-2 measurements. Log-cumulant diagrams are also shown to be a useful tool for discrimination between oil spills and a simulated biogenic slick in both sensors. Multi-polarization features show enhanced slick-sea contrasts and a better discrimination between mineral oil spills and other low backscatter features in Radarsat-2 compared to TerraSAR-X. The presence of a non-Bragg scattering component in the data is revealed for both sensors. The relative contribution of non-Bragg scattering to the total backscatter is found to be higher in the TerraSAR-X data than in the Radarsat-2 data. In general, the non-Bragg component is found to account for a larger part of the backscatter in slick-covered areas compared to clean sea.

Index Terms—synthetic aperture radar, frequency, polarimetry, oil spill, look-alikes, noise analysis, contrast, statistical analysis, log-cumulants, scattering mechanisms

I. INTRODUCTION

OPERATIONAL oil spill detection services work continuously to detect illegal oil releases on the ocean surface, and to assist in accidental oil spill events. Satellite borne Synthetic Aperture Radar (SAR) data are a primary tool for these services. A recent review on oil spill monitoring by SAR can be found in [1].

Over the last decades, mostly single-polarization (HH or VV) C-band SAR has been used in operational satellite based oil spill detection. However, several sensors launched in the last decade, e.g., TerraSAR-X and COSMO-SkyMed, operate in the X-band frequency range, as will some of the planned missions, including the Spanish PAZ satellite, the TerraSAR-X Next Generation [2] and the COSMO-SkyMed Seconda Generazione [3]. Incorporating X-band sensors into the operational services may improve the temporal coverage, and hence strengthen the operational applicability of SAR data for oil spill monitoring. However, more information on the use of X-band sensors compared to C-band is called for. We know from theory that the radar’s sensitivity to surface roughness of different wavelengths and to the dielectric properties is dependent on the applied radar frequency. In addition, other sensor properties such as noise floor and pixel spacing (pixel size) vary between sensors and can affect the imaging. Only a few previous studies compare C- and X-band SAR data for oil spill monitoring, e.g., [4]–[6]. In these studies, the attenuation of the backscatter signal in mineral oil slicks was investigated and found to increase with frequency. To the authors’ knowledge, no thorough analysis has been done to compare the capabilities and characteristics of operational space borne C- and X-band SAR data with respect to oil spill observation.

In this paper, detailed comparisons of dual co-polarization X-band data from TerraSAR-X (TS) and C-band observations from Radarsat-2 (RS) are presented. Our data set consists of three pairs of TS and RS scenes with large scale experimental oil slicks from deliberately released plant oil, oil emulsion and crude oil, acquired with a time difference of less than 24 minutes. The data pairs are collected under approximately the same wind conditions, but under varying incidence angles.

The main objective of this paper is to characterize and quantify differences between the RS and TS measurements. Specifically, the analysis consists of i) a data quality study in terms of signal-to-noise levels and slick-sea contrasts. Subsequently, we investigate signal characteristics including statistical properties and selected dual co-polarization parameters, which are used to infer information about scattering properties. In particular, we look at how the signal characteristics vary ii) between the two sensors and iii) between low backscatter features of various origin.

The data quality study identifies no solid reason for selecting one sensor above the other. In the statistical analysis, log-cumulants show a larger deviation from Gaussian statistics in the TS data than in the RS data. Log-cumulant diagrams are also identified as a useful tool for discrimination between oil spills and a simulated biogenic slick for both sensors. Multi-
polarization features show improved slick-sea contrast and a better separation between mineral oil spills, a look-alike and clean sea in RS compared to TS measurements. A non-Bragg scattering component is found to be present in the data. The relative contribution of the non-Bragg scattering to the total backscatter is larger in the TS data than in the RS data, and generally increases from clean sea to slick-covered areas.

This paper is organized as follows. Section II discusses some theoretical aspects related to the effects of frequency on the imaging of oil slicks. In Section III, the data set is presented, and a discussion of data quality is given in Section IV. Statistical properties are investigated in Section V, and Section VI covers the multi-polarization analysis. Further discussions are given in Section VII, and Section VIII concludes the paper.

II. REVIEW OF FREQUENCY EFFECTS IN OIL SPILL OBSERVATION

The most commonly used frequency band for operational satellite based oil spill detection has been C-band (3.75-7.5 GHz). The poor temporal coverage of individual satellites can be remedied by also including the more recently available X-band (7.5-12 GHz) sensors in the operational services. Oil spill studies using space borne SAR in the X-band frequency range are presented in, e.g., [4], [6]–[11]. The radar frequency affects the SAR imaging in several ways, as addressed in the following subsections.

A. Relative roughness and damping

In absence of long waves, the ocean backscatter within typical SAR incidence angles (\(\sim 18^\circ - 50^\circ\)) is dominated by Bragg or resonance scattering [12]. The Bragg wavelength, \(\lambda_B\), of ocean waves resulting in resonance is given by

\[
\lambda_B = \frac{n\lambda_r}{2\sin\theta}
\]  

(1)

where \(\lambda_r\) is the radar wavelength, \(\theta\) is the incidence angle and \(n = 1, 2, ...\) is the order of resonance (\(n = 1\) produces the dominant return) [13, p. 842]. From (1) it is evident that for a given \(\lambda_r\), the resonant waves are shorter at more oblique incidence angles, and at a given \(\theta\), \(\lambda_B\) increases with radar wavelength. In theory, the damping of Bragg resonant waves due to the oil is expected to be more efficient at shorter wavelengths. Hence, X-band SAR should be better for oil spill detection than C-band at fixed incidence angles and wind speed [8], [14]. Some empirical [4]–[6] and simulation [15] studies in the literature support this.

It should be noted that the Bragg scattering model in general is incomplete for describing ocean surface backscatter. On the ocean, longer waves interact with the smaller Bragg waves and affect the radar backscatter through tilt modulation, hydrodynamic modulation and velocity bunching. The two-scale approximation, where these interactions are accounted for, is a more representative scattering model [12]. However, when using these kinds of models, it has been difficult to obtain consistent characterization of the backscatter over a range of frequencies, incidence angles, polarizations and weather conditions. Inclusion of a non-Bragg component has been shown to improve the correspondence between models and measurements [16], [17]. Polarimetric indicators of non-Bragg scattering in oil slicks have been discussed in, e.g., [18]–[22], and is suggested as a tool for discriminating between oil spills and other low backscatter features such as natural biogenic films. In [23], a two-scale model is used to describe the scattering from the latter.

The decomposition of radar backscatter into Bragg and non-Bragg components is further addressed in Section VI-B.

![Fig. 1: Penetration depth as function of oil volume fraction (using a linear mixing model) for the frequencies of TerraSAR-X and Radarsat-2.](image)

B. Dielectric properties and penetration depth

SAR signals only penetrate a few millimeters into the sea surface, and the penetration depth depends on the dielectric properties of the sea water, which is a function of radar frequency. The complex electric permittivity is given as

\[
\epsilon(\omega) = \epsilon'(\omega) - j\epsilon''(\omega)
\]

(2)

where \(\epsilon'(\omega)\) is the real part, \(\epsilon''(\omega)\) the imaginary part, \(j = \sqrt{-1}\) and \(\omega = 2\pi f\) is the angular frequency of the incident wave with ordinary frequency \(f\) [Hz]. The relative permittivity \(\epsilon_r\) is the ratio between the material permittivity and the permittivity of vacuum, \(\epsilon_0\), i.e., \(\epsilon_r(\omega) = \epsilon(\omega)/\epsilon_0\). The term dielectric constant has been used interchangeably with the electric permittivity and also to refer to the real part of the relative permittivity, \(\epsilon_r\) [24]. We here use the term relative dielectric constant to describe the complex \(\epsilon_r\).

Over the frequency range 0.1 to 10 GHz, also covering the frequencies of RS and TS, the relative dielectric constant for sea water (salinity 32.54 \(\%\)) has a real component greater than \(\sim 40\) at a temperature of \(0^\circ\)C and greater than \(\sim 55\) at \(20^\circ\)C. The absolute value of the imaginary component is greater than \(\sim 40\) and \(\sim 30\) for \(0^\circ\)C and \(20^\circ\)C respectively [25, p. 2023]. In the same frequency range, biogenic and mineral oils have real components in the range 2.2 - 2.35 and imaginary components less than 0.02 [26], [27].
The ability of a SAR sensor to detect changes in the dielectric constant due to presence of oil depends on the thickness of the oil layer relative to the radar wavelength. In the case of a sufficiently thick layer of oil, or if oil is mixed with water in high enough concentrations in a layer below the surface, the reduction in effective dielectric constant can lead to a decrease in backscattered energy. This is addressed in [28], where a method for decoupling the effects of reduced dielectric constant and damping of surface roughness is described. In [26], the authors find that the reduction in backscatter over the Deepwater Horizon oil slick is at least partly caused by differences in dielectric constant by evaluating the copolarization ratio.

The dielectric properties of an oil spill can change with time as the slick is exposed to various weathering processes, e.g., evaporation, emulsification and dispersion. In the emulsification process, water is mixed into the oil. By using a mixing model, the dielectric constant of an oil-in-water emulsion may be estimated. Here, the relative dielectric constant of an emulsion, \( \epsilon_{em} \), is computed as

\[
\epsilon_{em}^\alpha = \epsilon_{sw}^\alpha + \nu_{oil}(\epsilon_{oil}^\alpha - \epsilon_{sw}^\alpha)
\]

where \( \epsilon_{sw} \) and \( \epsilon_{oil} \) are the relative dielectric constants of sea water and oil respectively, and \( \nu_{oil} \) denotes the volume fraction of oil in the emulsion [25], [29]. We use \( \alpha = 1 \), which is known as the linear model. The relative dielectric constant of sea water is here set to \( \epsilon_{sw} = 60 - j35 \) for RS and \( \epsilon_{sw} = 50 - j35 \) for TS based on [25, Fig. E.1] (salinity 32.54 \%, temperature \( \sim \) 10°C). For oil, \( \epsilon_{oil} = 2.3 - j0.02 \) (as used in [26], [29]) is applied, which is in accordance with the values given above.

The dielectric properties affect how far into the sea water column the signal can penetrate. The penetration depth \( \delta_p \) is defined as the depth where the power of the propagating electric field is attenuated by a factor \( 1/e \), and is defined as

\[
\delta_p = \frac{1}{2k_0\Im(y_{t_e})}
\]

where \( k_0 \) is the wave number and \( \Im \) denotes the imaginary part [30]. Eqs. (3) and (4) are applied to investigate the difference in the penetration depth for C- and X-band frequencies for varying oil volume fraction in the oil-in-sea-water mixture. Results are shown in Fig. 1. It is seen that the penetration depth is quite small, and that it increases with oil volume content. For \( \nu_{oil} < 0.8 \), \( \delta_p < 0.25 \) cm for X-band and \( \delta_p < 0.48 \) cm for C-band are found.

C. Resolution and speckle

The theoretical spatial resolution of a SAR sensor is not directly related to frequency. Table I, where sensor properties are summarized, shows the difference in resolution between RS and TS, which is particularly large in the range direction. Slant range resolution, \( \delta_{sr} \), is given by

\[
\delta_{sr} = \frac{c}{2B}
\]

where \( c \) is the speed of light and \( B \) is the pulse bandwidth [31]. The 150 MHz bandwidth of TS allows for a finer resolution compared to RS, which operates with a bandwidth of 30 MHz.

One important factor for the SAR image quality is the speckle, which is a granular pattern due to pixel-to-pixel variation in intensity. The variation is caused by constructive and destructive interference between returns from the many elementary scatterers within the same resolution cell. For a rough homogenous surface with a large number of scatterers present within each resolution cell, the sum of the reflected waves can be assumed to have a phase uniformly distributed between \( -\pi \) and \( \pi \). This is referred to as fully developed speckle. From the central limit theorem, the real and imaginary parts of the sum are independently and identically Gaussian distributed with zero mean. Further, the amplitude will have a Rayleigh distribution and the intensity will follow a negative exponential distribution [31]. High resolution data products can have fewer scatterers within each resolution cell, and fully developed speckle may not be obtained. This is here referred to as partially developed speckle. A higher level of pixel-to-pixel variation can be expected for these products. To reduce speckle, both fully and partially developed, multi-looking techniques are often applied, at the cost of reduced resolution. If it is desired to keep the full resolution, speckle modeling can be applied, as discussed in, e.g., [32].

D. Weather limitations

Oil spill observation by SAR is restricted by the wind speed range in which detection is possible. The minimum wind speed for generating measurable Bragg waves varies with frequency. At an incidence angle of 20°, \( \sim 2.5 \) m/s and \( \sim 2.2 \) m/s are the thresholds for X- and C-band respectively. The threshold increases slightly with incidence angle [12], [33]. Very low wind speeds may not provide enough contrast in surface roughness between slick-free and slick-covered surfaces for slick detection to be possible. On the other hand, very strong
winds may mix the oil into the subsurface waters. According to [34], efficient oil spill detection at C-band frequency requires wind speeds in the range 2-3 m/s to 10-14 m/s.

SAR sensors, operating in the microwave frequency range, are generally considered independent of weather conditions. However, heavy rain may attenuate the signals, and produce image artifacts and oil spill look-alikes. This problem is more pronounced at higher frequencies, hence X-band is more prone to this than C-band [35].

III. EXPERIMENTAL SETUP AND DATA ACQUISITION

In June 2011 and June 2012, oil-on-water exercises were conducted by the Norwegian Clean Seas Association for Operating Companies (NOFO) in the North Sea (N 59° 59', E 2° 27'). Different substances, i.e., crude oil, oil emulsion and plant oil were released onto the sea surface for the purpose of equipment and procedure testing, providing unique opportunities to collect remote sensing data of oil spills and look-alikes. Data were collected by Radarsat-2 (C-band) in Fine quad-polarization mode and TerraSAR-X (X-band) in dual co-polarization (HH, VV) Stripmap mode. Sensor properties are presented in Table I specifically for the modes investigated here.

<table>
<thead>
<tr>
<th>Radarsat-2 (Fine Quad-pol., SLC)</th>
<th>TerraSAR-X (Dual-pol. Stripmap, SSC)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Owner/Operator</td>
<td>CSA/MDA</td>
</tr>
<tr>
<td>Launch year</td>
<td>2007</td>
</tr>
<tr>
<td>Frequency</td>
<td>5.41 GHz (C-band)</td>
</tr>
<tr>
<td>Polarization</td>
<td>Quad-pol.</td>
</tr>
<tr>
<td>Resolution (Rg × Az)</td>
<td>5.2 m × 7.6 m</td>
</tr>
<tr>
<td>Scene size (Rg × Az)</td>
<td>25 km × 25°° km</td>
</tr>
<tr>
<td>Incidence angle</td>
<td>18° - 49°°°</td>
</tr>
<tr>
<td>NESZ</td>
<td>-33.5 dB - 39.5 dB</td>
</tr>
<tr>
<td>Bandwidth</td>
<td>30 MHz</td>
</tr>
<tr>
<td></td>
<td>DLR</td>
</tr>
<tr>
<td></td>
<td>2007</td>
</tr>
<tr>
<td></td>
<td>9.65 GHz (X-band)</td>
</tr>
<tr>
<td></td>
<td>Dual-pol. (HH/VV, HH/HV or VV/VH)</td>
</tr>
<tr>
<td></td>
<td>1.2 m × 6.6 m</td>
</tr>
<tr>
<td></td>
<td>15 km × 50 km</td>
</tr>
<tr>
<td></td>
<td>20° - 45°°°</td>
</tr>
<tr>
<td></td>
<td>-19 dB</td>
</tr>
<tr>
<td></td>
<td>150 MHz</td>
</tr>
</tbody>
</table>

From Table I, it is seen that TS can provide dual-polarization data with the preferred channel combination for oil spill observation, i.e., HH and VV [12]. In order to obtain this polarization combination in RS, quad-polarization data must be acquired. TS has a higher noise floor than RS (see Table I), which could be a disadvantage, as is further discussed in Section IV-A. A difference in the resolution between the two sensors is seen in Table I, with a finer resolution in TS, particularly in the range direction.

Properties of the different releases are given in Table II. The plant oil is Radiagreen ebo and the crude oil is evaporated Balder oil. The emulsion released in the 2011 exercise is Oseberg blend crude oil mixed with 5% IFO380°°, with a water content of 69%. Emulsion of Oseberg blend was also released during the 2012 exercise, with an initial water content of 58%. Further information on the oil properties is provided in [39].

Three pairs of near coincident C- and X-band scenes are investigated in this paper. An overview of the data is given in Table III, and intensity images are shown in Figs. 2 - 4. The dark regions of interest are indicated, with E, C, P and N denoting emulsion, crude oil, plant oil and natural phenomenon, respectively. The images in Figs. 2 - 4 have been resized for visual purposes, to account for the difference in pixel size and avoid distortions. However, note that in the data analysis, the original data are used, as it is important for this study to conserve the statistical properties of the data, and less important to have pixels of comparable ground sizes.

![Intensity image [dB] for scene pair b (multi-looked by 9 × 9 window). (a) Rsb. (b) Tsb.](image-url)
TABLE II: Properties of the releases. 'Ws', 'Tmp' and 'Wh' denotes the wind speed, air temperature and wave height around the time of release. Measurements within parentheses are obtained at the closest platform, whereas the rest is measured at ships participating in the exercise. NA denotes not available data.

<table>
<thead>
<tr>
<th>Slick</th>
<th>Substance</th>
<th>Viscosity [mPa·s]</th>
<th>Density [kg/L]</th>
<th>Volume of release</th>
<th>Subjected to</th>
<th>Ws Tmp Wh Age</th>
</tr>
</thead>
<tbody>
<tr>
<td>RSa_P</td>
<td>Radiagreen ebo</td>
<td>6.92²⁶</td>
<td>0.865²⁶</td>
<td>0.4 m³</td>
<td>None</td>
<td>1.6 - 3.3 m/s 12°C, (1 m)</td>
</tr>
<tr>
<td>TSB_P</td>
<td>Emulsion of Oseberg blend (69% water)</td>
<td>4860²⁶</td>
<td>NA</td>
<td>20 m³</td>
<td>Mechanical recovery (~1 m³ left on surface)</td>
<td>1.6 - 3.3 m/s 16°C, (0.5 m)</td>
</tr>
<tr>
<td>RSb_E</td>
<td>Balder crude oil</td>
<td>219²⁶</td>
<td>0.914²⁶</td>
<td>30 m³</td>
<td>Dispersion (ongoing)</td>
<td>1.6 - 3.3 m/s 11°C, (1 m)</td>
</tr>
<tr>
<td>TSB_E</td>
<td>Emulsion of Oseberg blend (58% water)</td>
<td>1234⁶¹</td>
<td>0.965⁶¹</td>
<td>17 m³</td>
<td>Mechanical recovery (&gt;7 m³ left on surface)</td>
<td>5 m/s 6 m/s 8°C, 1.5 - 2 m</td>
</tr>
<tr>
<td>RSc_E1</td>
<td>Emulsion of Oseberg blend (58% water)</td>
<td>1234³</td>
<td>0.965³</td>
<td>17 m³</td>
<td>Mechanical recovery (&gt;4.8 m³ left on surface)</td>
<td>5 m/s 6 m/s 8°C, 1.5 - 2 m</td>
</tr>
<tr>
<td>RSc_E2</td>
<td>Balder crude oil</td>
<td>219⁶³</td>
<td>0.914⁶³</td>
<td>30 m³</td>
<td>Dispersion (ongoing)</td>
<td>5 m/s 5 m/s 8°C, 1.5 - 2 m</td>
</tr>
</tbody>
</table>

²⁶ From a density of 865 kg/m³ (20°C) and kinematic viscosity ~8 mm²/s (40°C) ²⁷ At 20°C ²⁸ At 15°C ²¹ From a laboratory study of Balder 2001 [38] ²³ At shear rate 10 s⁻¹, 13°C ²⁹ At 20°C ²⁷ From a laboratory study of Balder 2001 [38] ²⁸ At 15°C ²⁹ At 20°C

TABLE III: Properties of the SAR scenes. Wind measurements within parentheses are obtained at the closest platform, whereas the rest is measured at ships participating in the exercise. ‘Var.’ denotes variable wind direction.

<table>
<thead>
<tr>
<th>Date</th>
<th>Time</th>
<th>θ</th>
<th>Pass direction</th>
<th>Look direction</th>
<th>Measured wind</th>
<th>SAR wind</th>
<th>Pixel spacing</th>
<th>Beam</th>
</tr>
</thead>
<tbody>
<tr>
<td>RSa</td>
<td>08.06.11 05.59</td>
<td>46.1° - 47.3°</td>
<td>Desc.</td>
<td>Right</td>
<td>1.6 - 3.3 m/s ESE</td>
<td>3.4 m/s / 6.2 m/s</td>
<td>4.73 m x 4.73 m</td>
<td>FQ28</td>
</tr>
<tr>
<td>Tsa</td>
<td>08.06.11 06.23</td>
<td>27.3° - 29.0°</td>
<td>Desc.</td>
<td>Right</td>
<td>1.6 - 3.3 m/s ESE</td>
<td>5.9 m/s / 7.9 m/s</td>
<td>0.91 m x 2.42 m</td>
<td>StripNear_006</td>
</tr>
<tr>
<td>RSB</td>
<td>08.06.11 17.27</td>
<td>34.5° - 36.1°</td>
<td>Asc.</td>
<td>Right</td>
<td>1.6 - 3.3 m/s Var. (E)</td>
<td>5.9 m/s / 7.9 m/s</td>
<td>4.73 m x 4.82 m</td>
<td>FQ15</td>
</tr>
<tr>
<td>TSB</td>
<td>08.06.11 17.11</td>
<td>19.9° - 21.7°</td>
<td>Asc.</td>
<td>Right</td>
<td>1.6 - 3.3 m/s Var. (E)</td>
<td>5.9 m/s / 7.9 m/s</td>
<td>0.91 m x 2.40 m</td>
<td>StripNear_003</td>
</tr>
<tr>
<td>RSC</td>
<td>15.06.12 17.48</td>
<td>48.3° - 49.5°</td>
<td>Asc.</td>
<td>Right</td>
<td>3 m/s (NE)</td>
<td>6.9 m/s / 7.9 m/s</td>
<td>4.73 m x 5.12 m</td>
<td>FQ31</td>
</tr>
<tr>
<td>TSc</td>
<td>15.06.12 17.28</td>
<td>40.9° - 42.1°</td>
<td>Asc.</td>
<td>Right</td>
<td>3.5 m/s (NE)</td>
<td>6.9 m/s / 7.9 m/s</td>
<td>0.91 m x 2.30 m</td>
<td>StripFar_012</td>
</tr>
</tbody>
</table>

Weather measurements included in Figs. 2 - 4, Table II and Table III are mainly from ships participating in the exercises. Observations from the closest platform are used to supplement where information from ships are not available (indicated by parentheses). In the cases where a range is given for the wind speed, the measurements were logged by the source on the Beaufort scale, and translated to m/s by us. The measured wind speeds at the time of acquisitions are low in all three cases, around the lower threshold for oil detection (see Section II-D). Some uncertainty applies to these measurements due to temporal and spatial distances between satellite passes and weather measurements. For comparison, wind retrieval was performed on the RS acquisitions by scientists at the Northern Research Institute (Norut) using the CMOD Ifremer 2 model. Mean SAR wind for each scene is included in Table III. Higher wind speeds, compared to the observations, are obtained from the SAR scenes. In case a and case c, there is a large uncertainty in the obtained wind speed due to the high incidence angles. The large θ may also cause the higher difference between HH and VV in case a. The measured wind direction is used as input for the SAR wind retrieval, and also induces some uncertainty. For the study presented in this paper, the absolute wind speed is not very important. In all scene pairs, the temporal differences between C- and X-band acquisitions are small (16-24 minutes). Hence, the meteorological conditions are assumed the same within each pair, and a reasonable fair comparison is possible. For a frequency comparison, this data set is close to optimal with the currently available space borne SAR sensors.

One important problem for oil spill observation by SAR is natural phenomena that produce similar SAR signatures as oil spills. These are called look-alikes, and include natural films produced by marine organisms, low wind areas, grease ice, rain cells, shear zones, internal waves and ship wakes [40]. The plant oil released during the oil-on-water exercises is expected...
to form a monomolecular film, similar to the films produced naturally by marine organisms [39], and is here treated as a substitute for natural biogenic slicks. Hence, in scene pair b, dark patches of various origin, i.e., mineral oil spill, simulated biogenic slick and a natural phenomenon can be compared. Note that the geometric properties of the simulated biogenic slick may not be representative of naturally occurring slicks.

IV. DATA QUALITY ASSESSMENT

A discussion of different quality measures for oil spill detection is given in [41]. In the following, the data quality of TS and RS scenes is analyzed in terms of signal-to-noise levels and contrasts.

A. Noise analysis

The usefulness of SAR imagery for oil slick observation is highly affected by the noise equivalent sigma zero (NESZ) of the system, which is the value of the backscatter coefficient that would give a signal level equal to the receiver noise level [41]. The NESZ must be lower than the measured normalized radar cross section (NRCS) to make sure that the signal is not corrupted by noise. Oil slicks and look-alikes are low backscatter features, and the signals may in some cases lie below the sensor noise floor. A signal-to-noise analysis is therefore important, especially if slick characterization, i.e., the discrimination between oil spills and look-alikes, and the extraction of slick properties, is desired in addition to slick detection.

The NESZ of TS lies between -19 dB and -26 dB, depending on the incidence angle, with an average of -21 dB [37]. RS quad-polarization modes have NESZ values in the range -27.5 dB to -43 dB [36]. The proximity of the backscatter signal to the sensors noise floor have been evaluated for the scenes described in Table III, and the results are presented in Fig. 6. The figure shows the mean and standard deviation of the backscatter computed within a box of 20 × 20 samples within a given region of interest. The signal levels are compared to the sensor noise floor, which is plotted as function of incidence angle. Even though the RS data are quad-polarization measurements, only the co-polarization channels are investigated in this study. The cross-polarization channels were in [39] found to be severely contaminated by noise, and are excluded from the present study. For RSa (Fig. 6(a)), the majority of mean VV signals in the slicks lie slightly above the noise floor, while the mean HH signals are found on or below the NESZ. For TSa (Fig. 6(d)), HH and VV have similar mean values that are close to the noise floor for the slick-covered areas. For case b (Fig. 6(b) and Fig. 6(e)), the backscatter signals lie mainly within one standard deviation above the noise floor for both sensors, with TSb being somewhat less affected by the noise than RSb. The natural phenomenon and the plant oil have signal values closer to the clean sea than the mineral oils (emulsion and crude oil). In RSc (Fig. 6(c)), mean signal values lie less than one standard deviation above the noise floor.
Fig. 6: Signal-to-noise analysis of HH and VV channels. Each vertical line shows the mean ± one standard deviation of the backscatter signal in selected regions of size 20 × 20 pixels. (a) RSA. (b) RSB. (c) RSC. (d) TSA. (e) TSB. (f) TSC.

For the three TS scenes, the noise contamination is seen to increase with incidence angle. This is not surprising, as the signal level is expected to decrease with increasing incidence angle. For RS, RSc has somewhat higher signal levels than RSA, even though the incidence angle is slightly larger. This may be related to slick properties such as age or different level of weathering due to different wind conditions between release time and time of image acquisition. For both sensors, the signal is generally stronger in VV than in HH, and the difference between the two channels increases with increasing incidence angle as expected [42].

The results presented in Fig. 6 do not give any solid reason for using one sensor above the other. As noted in Section III, the higher noise floor of TS would in general be a disadvantage for this sensor, but Fig. 6 show that this is compensated for by the higher signal values in this sensor. As the backscatter decreases with increasing incidence angle, a different result may be obtained if data with more similar θ were available.

B. Contrast

For a given parameter \( F \), the contrast between slick-free and slick-covered surfaces in SAR imagery, \( \zeta \), can be defined as the ratio of the mean value of a slick-free background sample \( \langle F_{\text{sea}} \rangle \) to the mean value of a sample extracted from the slick-covered region \( \langle F_{\text{slick}} \rangle \):

\[
\zeta = \frac{\langle F_{\text{sea}} \rangle}{\langle F_{\text{slick}} \rangle}.
\]

In this section, the contrast is computed and compared between RS and TS scenes. We evaluate \( \zeta \) with respect to the calibrated backscatter intensity \( I \) (in linear units), hence

\[
\zeta_I = 10 \log_{10} \left( \frac{\langle F_{\text{sea}} \rangle}{\langle F_{\text{slick}} \rangle} \right).
\]

Both measured and simulated slick-sea contrasts are reported to decrease with increasing wind speed and to increase with frequency (Bragg wavenumber), oil viscosity and thickness [4]–[6], [15], [43]. For moderate incidence angles, the contrast was found to increase with incidence angle in [15], [26]. In [5], contrast values were found to be independent of radar look direction relative to the wind for wind speeds of 6 - 10 m/s. In several studies, no dependency on polarization was found [5], [6], [44], whereas other studies reported enhanced contrast in VV compared to HH [4], [15], [26], [45]. VV seems to be perceived as the preferred polarization channel for oil spill detection [14], [34], and has the advantage of being less affected by the noise as noted in the previous section.

Table IV presents the mean and standard deviation of \( \zeta_I \) from the different regions in our data set. The calculations
are based on the backscatter intensity in VV polarization for selected slick regions of size 20 × 20 pixels, and similar sized areas from the clean sea at the exact same range positions. Only the regions present in both RS and TS scenes are included. The Bragg wavenumber given in Table IV is defined as $k_B = 2\pi/\lambda_B$. For case $a$, the mean $\zeta_I$ is slightly higher in TS compared to RS. For case $b$ and $c$ on the other hand, the mean slick-sea contrast is better in the RS data than in the TS data. The difference between the sensors is largest in case $b$. Similar trends as for VV were observed in HH, but with generally lower contrasts in all cases except for the natural phenomenon. The lower contrasts in HH may be related to the closer proximity to the noise floor, compared to VV. The differences between HH and VV were larger in the RS data than in the TS data in all cases. Table IV shows that the simulated biogenic slick and the natural phenomenon present in case $b$ produce lower contrasts than the mineral oils in both scenes, with a larger difference in RSb than in TSb.

In the literature, the contrast between mineral oil spills and clean sea is reported to be higher in X-band than C-band, and to increase with Bragg wavenumber. The results presented in Table IV do not show a consistent increase in $\zeta_I$ with frequency or with $k_B$. It should be noted that for TSb, the very low incidence angles may cause specular reflection to take place, hence the observed findings may be related to other effects than damping of the small waves.

### V. Statistical Analysis

In this section, we focus on single channel (VV polarization) single-look intensity (SLI) data. From the central limit theorem, fully developed speckle has Gaussian distributed real and imaginary parts and negative exponential distributed SLI (see Section II-C). We here investigate the statistical properties of the measurements and examine how well the data actually follow a Gaussian distribution. Furthermore we would like to see if there are any frequency dependent differences in the statistical characteristics of the various regions.

The product model is commonly used to describe non-Gaussian statistics. Under this model, the observed intensity $I$ can be expressed as the product of two separate processes; the underlying radar cross section, represented by the random variable $\tau$ with an undefined probability density function (pdf), and an uncorrelated speckle contribution, represented by the random variable $X$: $I = \tau X$. (6)

In the SLI case, $X$ will be exponentially distributed. $\tau$ is referred to as texture, and various theoretical models for this parameter will be given in this section [46].

Statistical properties of slicks were also evaluated in [32], where the generalized K-distribution was used to model the measurements. A larger deviation from Gaussian statistics was observed in low backscatter features, but discrimination among oil spills and other dark regions were not possible [32].

Here, the deviation from Gaussian statistics due to the presence of texture is evaluated by means of log-cumulants. Log-cumulants were described by Nicolas in [47], [48] as cumulants derived in the log-domain. The second- and third-order log-cumulants, $\kappa_2$ and $\kappa_3$, represent variance and skewness in the log-domain respectively and are computed from the log-moments as

$$\kappa_2 = m_2 - m_1^2 \tag{7}$$

$$\kappa_3 = m_3 - 3m_1m_2 + 2m_1^3 \tag{8}$$

where $m_\nu$ is the log-moment of order $\nu$ of a sample of $N$ intensities $I$: $m_\nu = \frac{1}{N} \sum_{i=1}^{N} (\log I)^\nu \ [47], [48]$. The log-cumulant diagram, where $\kappa_2$ and $\kappa_3$ are plotted against each other, is a visualization tool that can be used to compare measurements with theoretical distribution models [49], [50].

Log-cumulants are computed from our data by manually drawing polygons around each of the dark ocean features, and subsequently calculating $\kappa_2$ and $\kappa_3$ from a random sample of size 4000 drawn from these selected regions. For each region, the calculation is repeated 200 times. Within each scene pair, boxes of clean water sections are selected from approximately the same area in the RS and TS scenes. For the crude oil slick in RSb, the polygon is chosen to cover a similar area as that in TSb, i.e., the rightmost part is cut out (see Fig. 3).

The span of some well-known texture models in the $\kappa_2$-$\kappa_3$ space is indicated in Fig. 7. Their dimension depends on the number of free parameters in the pdf of $\tau$. The point in magenta at the intersection of the texture distributions indicates no textural variation (delta function), i.e., Gaussian statistics. The two curves in the log-cumulant diagram represent pdfs with one texture parameter. The one to the left corresponds to Gamma and the one to the right corresponds to Inverse Gamma distributed texture variables. The Fisher, Beta and Inverse Beta models each have two texture parameters and are hence represented by surface regions as indicated by the legends in Fig. 7. The log-cumulants determine the shape of the distributions, with more heavy-tailed distributions found on the right side of the diagram.
Fig. 7 also shows log-cumulants based on samples from the TSb and RSB scenes. Each region type (crude oil, emulsion, plant oil and natural phenomenon) is plotted in separate panels along with samples from the clean sea. The ellipses are located at the mean and indicate two standard deviations from the mean, of the $\kappa_2$ and $\kappa_3$ within the relevant region type and sensor. The ellipse of the theoretical negative exponential distribution is included for comparison. The only regions in Fig. 7 that lie close to the theoretical exponential distribution, i.e., with ellipses containing the delta-function (no texture), are the slick-free regions in RS. All regions in TS, and the slick-covered areas (including the plant oil) in RS lie higher up in the diagram, indicating a presence of texture and non-Gaussian statistics. Larger deviation from Gaussian statistics in slick-covered regions compared to clean sea is in accordance with the findings in [32]. For all regions, TS data are found further up in the diagram in Fig. 7 than corresponding RS data, and hence deviate more from the Gaussian statistics.

Another interesting observation in Fig. 7 is the difference in the log-cumulants from the plant oil look-alike and the natural phenomenon to the two mineral oil slicks. A higher texture is observed in the latter for both sensors. A slightly larger difference between the log-cumulants of emulsion and the look-alike is found in RSB compared to TSb. The variation in log-cumulants between the crude oil slick and the look-alike are similar in RSB and TSb.

A similar investigation as presented in Fig. 7 has been carried out for the other two scene pairs, with similar findings. Higher texture is observed in the TS data than in the RS data in all cases. The difference in log-cumulants between the sensors is smallest in case c, where some overlap between the respective ellipses is found. For RSB, a difference in texture between the plant oil and emulsion is found, similar to that seen in RSB and TSb.

This study indicates that there are differences in the statistical characteristics of data from the different regions and between sensors. The log-cumulant diagram is here shown to be a useful tool to discriminate between mineral oils and a biogenic slick in both RS and TS acquisitions. This will be further discussed in Section VII. The ability to distinguish mineral oil from look-alikes is also investigated in the next section, where multi-polarization techniques are addressed.

VI. ANALYSIS OF MULTI-POLARIZATION FEATURES AND SCATTERING PROPERTIES

TS and RS measure either two or four of the elements in the full scattering matrix $S$:

$$
S = \begin{bmatrix}
S_{HH} & S_{HV} \\
S_{HV} & S_{VV}
\end{bmatrix} = \begin{bmatrix}
|S_{HH}| e^{j\phi_{HH}} & |S_{HV}| e^{j\phi_{HV}} \\
|S_{HV}| e^{j\phi_{HV}} & |S_{VV}| e^{j\phi_{VV}}
\end{bmatrix}.
$$

(9)

The matrix elements represent the measured complex scattering coefficients with amplitude $|S_{pq}|$ and phase $\phi_{pq}$. The first and second subindices refer to the polarization of the transmitted and received signals respectively, where H denotes horizontal and V vertical polarization. RS offers quad-polarization acquisitions, in addition to dual-polarization measurements as combinations of co- and cross-polarization channels (HH/HV and VV/VH). TS only provides an experimental
quad-polarization mode, but offers the HH/VV combination in addition to the co- and cross-polarization options in the dual-polarization case [36], [37]. The various polarization channels are sensitive to different characteristics of the observed surface, and by combining the channels, information related to physical properties and scattering behavior can be obtained.

In this paper, multi-polarization refers to combinations of two or more polarization channels.

Conventional oil spill detection services are based on single-polarization (HH or VV) data. However, multi-polarization techniques have received more attention over the last decade, and are exploited for oil slick characterization in, e.g., [11].
A. Two powerful multi-polarization features for slick characterization

In [39], a comparison of eight well-known multipolarization features was carried out, aiming to identify the most useful features for oil versus look-alike discrimination. Only co-polarization measurements (HH and VV) were included in the features, as a noise analysis in the same study found the cross-polarization channels in RS data to be severely contaminated by noise [39]. The two features identified as the most discriminative were the real part of the co-polarization cross product, \( r_{CO} \), and the geometric intensity, \( \mu \):

\[
r_{CO} = |\Re(\langle S_{HH}S_{VV} \rangle)| \tag{10}
\]

\[
\mu = (\det(T_{\text{sub}}))^{1/2} \tag{11}
\]

where \( \Re \) denotes the real part, \( \ast \) is the complex conjugate and \( \det(\cdot) \) is the determinant. The 2 × 2 matrix \( T_{\text{sub}} \) is given by (12) and is a submatrix of the coherency matrix (see, e.g., [31]), in which the cross-polarization terms are discarded.

The geometric intensity \( \mu \) is a measure of the combined intensity in the co-polarization channels. It is similar to the span, but is computed as the geometric mean of the eigenvalues, rather than the sum, and contains information about the cross-products in addition to the intensities used in the span. Lower values of \( \mu \) in slicks compared to the adjacent clean sea have been observed due to damping of the capillary and short gravity waves (and possibly also due to a reduction in dielectric constant) [39]. \( r_{CO} \) was proposed for oil spill versus look-alike discrimination in [19], [21]. In these papers, it was argued that \( r_{CO} \) has the ability to distinguish slick-covered areas characterized by a non-Bragg scattering mechanism from clean sea and look-alikes where Bragg scattering is present.

In [39], RSb was investigated. An analysis similar to that presented in [39] has also been carried out for TSc, comparing the same eight multi-polarization features in terms of discrimination ability. It was found that also for TSc, \( \mu \) and \( r_{CO} \) gave better results compared to the other features.

Now, we compare \( \mu \) and \( r_{CO} \) within all the three scene pairs described in Table III, to evaluate the slick detection and characterization potential. The \( r_{CO} \) computed from each scene using a 9 × 9 pixels sliding window is presented in Fig. 8. For TSc, only the area containing the slick regions that are also present in RSc is shown. In all scenes, oil covered areas are found to produce lower values of \( r_{CO} \) compared to the adjacent clean water. In [21], the reduction in \( r_{CO} \) in oil spills is explained by the presence of a non-Bragg scattering mechanism within these regions. The plant oil slick and the natural phenomenon in case b are observed to give feature values more similar to the clean sea compared to the mineral oils. A comparison between the RS and TS data in terms of multi-polarization features is carried out. For case a (Fig. 8(a) and Fig. 8(b)), the visual results are seen to be quite similar. Some internal slick variations are observed in both scenes, slightly more pronounced in RSA. In case b (Fig. 8(c) and Fig. 8(d)) and case c (Fig. 8(e) and Fig. 8(f)), the various dark ocean features seem to have better defined boundaries, more homogeneous regions and partly higher contrasts to the clean sea in the RS scenes compared to the TS scenes. The TS scenes also have a more speckled appearance than the RS scenes, probably related to the finer resolution of the former.

Histograms of the \( r_{CO} \) values within selected regions in case b are shown in Fig. 9. For RSb (Fig. 9(a)), we see that the crude oil and emulsion have a large degree of overlap, but they are quite well separated from the clean sea. The plant oil distribution lies between the mineral oils and the clean sea, overlapping somewhat with both. For TSc (Fig. 9(b)), the relative positions of the distributions are similar to those for RSb, but a higher degree of overlap between the regions is found. Hence, in this data set, RS gives a better discrimination between mineral oils, biogenic slick and clean sea. Similar findings as for \( r_{CO} \) (as those shown in Fig. 8 and Fig. 9) are found for \( \mu \).
Finally, we note that RSb and TSb have previously been compared in a preliminary analysis presented in [54]. In this study, a classification based on a feature vector consisting of $\mu_r, r_{co}$ and the standard deviation of the co-polarized phase difference was carried out. A better separation between the slick types was found in the RS data compared to the TS data. In that study we also found that the classifications of RSb showed some interesting internal variations, which could be related to thickness inhomogeneities in the oil slick.

B. Scattering analysis

Sea surface scattering models were briefly discussed in Section II-A. In this section, surface scattering mechanisms are further investigated based on the model presented in [55]. The aim is to compare the scattering properties of the various dark ocean features, and to evaluate whether the scattering behavior varies between the sensors.

In [55], the radar cross section was represented as the sum of one polarized scattering component associated with conventional two-scale Bragg scatter (Bragg waves superposed on longer waves), $\sigma_{BB}^{PP}$, and one nonpolarized (NP) scattering component due to non-Bragg scattering, $\sigma_{NP}$:

$$\sigma_{OP}^{PP} = \sigma_{NP} + \sigma_{BB}.$$

The NP component is assumed to be the same for both polarizations, and can in theory be removed by computing the polarization difference (PD)

$$PD = \sigma_{VV} - \sigma_{HH} = \sigma_{OP}^{VV} - \sigma_{OP}^{HH}. \quad (14)$$

PD is controlled by the surface roughness produced by wave components close to the Bragg wave number, and should reveal near-surface wind variability and presence of slicks [55]. The NP component is expressed as

$$NP = \sigma_{ONNP} + \sigma_{BB} - PD/(1-p_B). \quad (15)$$

where $p_B = \sigma_{BB}^{HH}/\sigma_{BB}^{VV}$ is the polarization ratio for the two-scale Bragg scattering model [55]. The $p_B$ is independent of surface roughness, and is a function of only the dielectric constant and the incidence angle [56]. NP is interpreted to be caused by wave breaking from steep and rough patches on the surface [55] and other phenomena that can cause non-Bragg scattering. Finally, the polarization ratio (PR) is defined as

$$PR = \frac{\sigma_{HH}}{\sigma_{VV}^{OP}} = \frac{\sigma_{BB}^{HH} + \sigma_{ONNP}}{\sigma_{BB}^{VV} + \sigma_{ONNP}}. \quad (16)$$

The three parameters PD, NP and PR are used to analyze the scattering from the sea surface. The PD and NP contain information about the Bragg and non-Bragg scattering mechanisms, respectively. As can be seen in the right-hand side of (16), the non-Bragg component in the cross section terms allows PR to evaluate departure from Bragg scattering [16], [55]. In [55], a slick was found to be clearly visible in the PD image while almost not detectable in NP. The PD was seen to be more sensitive to slicks than $\sigma_{VV}^{OP}$ which was explained by the removal of the NP component. Further, it was noted that the PR component may be useful for discrimination between oil slicks and look-alikes such as low wind areas and surface currents.

In the following, PD, PR and NP are analyzed for our data set. The three parameters are calculated from $\sigma_{VV}^{OP}$ and $\sigma_{HH}^{OP}$ after subtraction of the noise floor (i.e., the range dependent NESZ on linear scale). The resulting PD is shown in Fig. 10. Note that ships are masked out for visual purposes. In the RS scenes, the various dark ocean features are clearly detected as areas of reduced PD. This reduction in PD is probably caused by the suppression of surface roughness [55]. The visual contrasts between slicks and clean sea are poorer in the TS images compared to the RS scenes in Fig. 10. The lowest contrasts are found in TSb, probably due to the very low incidence angles for this scene ($19.9^\circ - 20.7^\circ$). For low incidence angles, the backscatter values of the HH and VV channels are expected to be very similar, as is seen for TSb in Fig. 6(e).

Fig. 11 and Fig. 12 show the contrast $\zeta$ in PD, PR and NP, computed from (5), along profile lines traversing the regions of interest (the line positions are indicated in Fig. 10) for RSb and for case c, respectively. A line width of 20 pixels in the range direction is used, and the values are averaged over 20 pixels in the azimuth direction along the profile lines. The contrasts of $\sigma_{HH}^{OP}$ and $\sigma_{VV}^{OP}$ are included for comparison. The positions of the relevant regions along the profiles in Fig. 11 and Fig. 12 are indicated by black vertical lines. For the RS data, a clear reduction in PD and NP are observed in Fig. 11 and Fig. 12 for all dark ocean features. The contrast in PD is found to exceed that of $\sigma_{VV}^{OP}$, which was also observed in [55]. The reduction in NP over the slick-covered regions in Fig. 11 and Fig. 12 indicates that the non-Bragg component is also affected by the oil films, contradicting the findings in [55]. Fig. 11 and Fig. 12 show that the PR feature detects the slicks as areas of increased values, but this feature gives a lower slick-sea contrast compared to PD and NP. According to [55], an increase in PR in slick areas can be interpreted as the non-Bragg scattering component being more dominating here. The slicks dampen the resonant Bragg waves, which reduces the Bragg scatter component, whereas the longer waves responsible for $\sigma_{ONNP}$ are less dampened. Hence, the total effect is that we see a slight increase in PR. Note that, if the slick is thick enough, the change in PR could also be related to a change in the dielectric properties (see Section II-B). When comparing the different regions in RSb (Fig. 11), the contrast is seen to increase from the natural phenomenon to plant oil, to emulsion/crude oil for all parameters. The differences between the regions are largest in PD. For TSc (Fig. 12(b)), large variations are observed in...
Fig. 10: Polarization difference, PD. Positions of profile lines in the azimuth direction are indicated by black lines. (a) RSA. (b) TSA. (c) RSB. (d) TSB. (e) RSC. (f) TSC.

the contrast along the profile line. A variation between the slick-free and slick-covered area is discernible, however the identification of the slick region is not nearly as clear as in the RS data.

In (13), the backscatter is represented as a sum of a Bragg component, $\sigma_{BB}^0$, and a non-Bragg component, $\sigma_{0nB}$. Next, the relative contributions of these two mechanisms are compared between the sensors and between the various dark ocean features. In Fig. 13, the contribution of the Bragg and non-Bragg components are evaluated along the profile lines indicated in Fig. 10 for case c. In the panels on the left hand side of the figures, each scattering contribution and the total $\sigma_{VV}^0$ are plotted, whereas the relative contributions of each mechanism, i.e., $\sigma_{0nB}^V/\sigma_{VV}^0$ and $\sigma_{0B}^V/\sigma_{VV}^0$, are presented in the panels on the right hand side. For RSC (upper part of Fig. 13), the backscatter is dominated by the Bragg component in the clean sea. In the slick area, reductions in both scattering components are seen, but with a smaller decrease in the non-
Bragg case. Hence, non-Bragg scattering contributes relatively more with respect to the total backscatter in the slick areas compared to the clean sea. From Fig. 13(b) it can be seen that the non-Bragg contribution actually exceeds that of the Bragg component in parts of the slick. The TSc (lower part of Fig. 13) on the other hand, shows a more equal contribution of the two mechanisms in both the slicks and the clean sea. Hence, a larger part of the total backscatter is caused by non-Bragg scattering in the TS data, compared to the RS data. This is in accordance with the observations in [16]. Again, much more variation along the profile lines is seen in TSc compared to RSc.

Fig. 14 shows the relative contribution of the two scattering mechanisms in the different regions of RSc. Non-Bragg contribution is seen to surpass the Bragg scattering in all three slicks. On the contrary, in the area where the natural phenomenon is present (Fig. 14(d)), Bragg scattering is still dominating. A similar scattering analysis for TSc show that all regions are dominated by non-Bragg scattering. From (15), we note that \( \sigma_{\text{PP}} \rightarrow \sigma_0^{\text{NP}} \) when \( \theta \rightarrow 0 \) (HH = VV). This is expected to be the case in TSc due to the very low incidence angles.

The contrasts in case a show a similar behavior as in case c in Fig. 12. RSc shows similar Bragg versus non-Bragg scattering contributions as RSc in Fig. 13, whereas TSc shows a domination of non-Bragg scattering in both slicks and clean sea.

This study shows that the relative contribution of non-Bragg scattering to the total backscatter in general increases
from slick-free to slick-covered areas, and from RS to TS measurements. These results are further discussed in the next section.

VII. DISCUSSION

Two interesting differences observed between the RS and TS data are the difference in texture shown in Section V and the difference in scattering properties found in Section VI-B. We also observe that there are significant variations in texture and scattering properties between the various slick regions. These findings are further discussed in this section.

A. RS versus TS

In Section VI-B, a larger contribution of non-Bragg scattering in the TS data compared to the RS data is observed. This may, at least partly, be related to an increased contribution of specular reflection in the TS data due to low incidence angles, particularly for TSb with $\theta \sim 21^\circ$. The other two scene pairs are acquired at larger incidence angles, where Bragg scattering is considered to be dominant. However, the lower incidence angle in TS relative to RS in each scene pair could have some effect on the observed scattering differences between the sensors. The smallest difference in incidence angle between RS and TS acquisitions ($\sim 8^\circ$) is found in case c, where we also have the largest incidence angles ($\sim 49^\circ$ in RSc and $\sim 41^\circ$ in TSc). Also in this case, a higher contribution of non-Bragg scattering is observed in the TS measurements.

The difference in scattering properties observed between the sensors may affect the statistical properties of the data. A higher texture (i.e., a larger deviation from Gaussian statistics) is found in the TS data compared to the RS data in Section V. This could be related to the presence of more specular reflections in the TS measurements. However, several other factors can also cause increased texture. One factor is the finer resolution of TS compared to RS. The smaller resolution cells in TS will contain a lower number of wave trains, which can give more inhomogeneous regions and partially developed speckle, increasing the texture. Another possible cause for the texture differences between sensors is the variation in the relative roughness described in Section II-A.

B. Mineral oil versus clean sea and look-alike

In Section VI-B, a relatively larger contribution of non-Bragg scattering is observed in the slicks (including the plant oil) compared to the clean sea (including the natural phenomenon). Within the individual scenes, variations in sensor properties and environmental conditions are negligible. Hence, the differences between the regions are likely to be related to the presence of the slicks, and their induced changes to the surface characteristics.

It is interesting to see that whereas the plant oil shows a similar increase in the non-Bragg contribution as observed in the mineral oils, it is separated from the emulsion and crude oil in the log-cumulant diagram. Hence, neither the sensor properties nor the relative contribution of Bragg/non-Bragg scattering should cause the observed difference in texture between the plant oil and the mineral oil slicks. This suggests that the textural differences in the mineral oils versus the clean sea and look-alike are related to actual physical variations within the mineral oil slicks. Whereas the plant oil is expected to form a homogeneous monomolecular film [39], with little internal variations, the mineral oils are likely to contain physical variations from, e.g., inhomogeneous distribution of oil and variations in slick thickness and/or dielectric properties. This could produce the observed difference in the texture. As noted, discrimination between mineral oils and look-alike phenomena is highly desirable. Based on the results presented in this paper, the log-cumulants (particularly the $\kappa_2$) seem to be a useful tool for this purpose. This should be further investigated in the future.

VIII. CONCLUSION

Near coincident multi-polarization RS (C-band) and TS (X-band) data, containing experimental oil spills and other dark ocean features are compared. Both sensors detect the slicks in the given conditions, at incidence angles $\sim 35^\circ - 50^\circ$ for RS and $\sim 20^\circ - 42^\circ$ for TS.

The data quality is examined by evaluating the slick-sea contrasts and the proximity of the backscatter signal to the sensors noise floor. No viable argument for selecting one sensor above the other is identified in this analysis.

In the statistical analysis, log-cumulants are investigated to evaluate how well the data from TS and RS follow a Gaussian distribution. A larger deviation from Gaussian statistics (higher texture) is found in the TS data compared to the RS data. This may be related to the smaller pixel spacing of TS, to variation in relative roughness due to a higher frequency, or to a difference in scattering properties. The log-cumulant diagram (in particular $\kappa_2$) is shown to be a useful tool for discrimination between oil spills and a simulated biogenic slick for both sensors. Physical variations within the mineral oil slicks may cause the increased texture observed in these areas.

Multi-polarization features are investigated in order to evaluate the sensors ability to detect and characterize slicks, and to examine the scattering properties of the data. Enhanced slick-sea contrasts and a better discrimination between mineral oil spills and the simulated look-alike are found for RS compared to TS. The presence of a non-Bragg scattering component is revealed in the measurements from both sensors. However, a relatively higher contribution of the non-Bragg component to the total backscatter is found in the TS data compared to the RS data. A general increase in the non-Bragg contribution in the slicks compared to the clean sea is also observed. We find that the polarization ratio can be used to suppress the natural phenomenon, and that the polarization difference considerably enhances the slick-sea contrast.

In summary, this empirical study obtains, to a certain degree, better results for RS compared to TS. However, future work should cover a larger range of weather conditions and slick properties, to draw more firm and general conclusions.

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Fig. 13: Contribution of Bragg versus non-Bragg scattering along the profile lines indicated in Fig. 10 in case c. Vertical black lines indicate the position of the emulsion slick. (a) Backscatter, RSc. (b) Relative contribution, RSc. (c) Backscatter, TSc. (d) Relative contribution, TSc.

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Fig. 14: Relative contribution of Bragg versus non-Bragg scattering in RSb along the profile lines indicated in Fig. 10(c). Vertical black lines indicate the positions of the relevant regions. (a) Emulsion. (b) Crude oil. (c) Plant oil. (d) Natural phenomenon.


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