# Oil spill detection from Synthetic Aperture Radar Earth observations: a meta-analysis and comprehensive review

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**ABSTRACT**

Oil spills are one of the most hazardous disasters with significant short- and long-term effects on fragile marine ecosystems. Synthetic Aperture Radar (SAR) has been considered an effective technology for mapping and monitoring oil spills in the marine environment, primarily thanks to its weather-, illumination-, and time-independent capabilities. To cope with serious oil spill threats, researchers have developed various analytical methodologies utilizing key advantages of SAR imagery to identify the occurrence of oil spills and discriminate lookalikes. Choosing the appropriate SAR specifications and investigating the effects of field conditions are challenging for oil spill monitoring and should be investigated further. This paper presents a comprehensive review study on maritime surveying and oil slick detection using SAR imagery through indexed research studies' compilation and analysis. To this end, a total of 230 peer-reviewed papers, published in various remote sensing (RS) journals and 78 conference papers in the International Society for Photogrammetry and Remote Sensing (ISPRS) archive and the IEEE International Geoscience and Remote Sensing Symposium (IGARSS) proceedings were reviewed. Our review study represents a meta-analysis investigation of these papers focusing on several features, including data, sensor type, imaging mode, microwave carrier frequency (e.g., L-, C-, and X-bands), polarization option (i.e., single-pol, dual-pol, full-pol, and compact-pol), incidence angle, and wind speed. Furthermore, it provides an overview of the RS techniques developed to deal with the oil spill detection task. This paper can be a guideline for two groups of audiences; those interested in oil spill monitoring who want to get an overview of the problem and how to address it, and those already working in the field who want to understand the scope of the work being accomplished. Consequently, the current paper contributes both to academic RS research and to practical applications.

**KEYWORDS**

Marine pollution; oil spills; satellite Earth observations; remote sensing; SAR

## 1. Introduction

Pollution of the oceans and seas from oil spills has long been a significant and unavoidable problem (Fustes et al. 2014; Bayındır, Frost, and Barnes 2018; K Topouzelis *et al*.; Ivanov 2010). Oil spills resulting from intentional or accidental release of liquid petroleum hydrocarbons into water are responsible for several ecological disasters that affect the marine life cycle and damage the quality and productivity of the marine environment (Bayındır, Frost, and Barnes 2018; Salberg, Rudjord, and Schistad Solberg 2014; Singha, Bellerby, and Trieschmann 2012). Because almost two-thirds of the Earth's surface is covered by oceans, contributing to the quality of life and economic livelihood of humans worldwide, protecting marine environments' health is of crucial importance for both short- and long-term sustainability (Lang et al. 2017).

In the marine environment, oil spills are more hazardous and destructive than those on flatter terrain. They can spread rapidly over several hundred kilometers and form a thin crust of oil, which can cover beaches. Detection and monitoring such pollution is a time-consuming and costly task. However, it is crucial to develop an immediate response program to reduce catastrophic effects (Raeisi, Akbarizadeh, and Mahmoudi 2018). A practical operation to reduce the environmental effects of oil pollution depends on the marine environment's systematic monitoring. This operation allows for the accurate estimation of oil spread areas, allowing rapid response and recovery (Keramitsoglou, Cartalis, and Kiranoudis 2006; Dutta et al. 2018). In the last decades, the detection of oil spills over oceans has received considerable attention because they pose threats to human health and have severe environmental and economic impacts on the marine environment, fisheries, wildlife, benthic communities, the human settlement on the beaches, mangrove forests, and other social interests (Anne H. Schistad Solberg 2012; Zhang et al. 2011; Dabboor et al. 2018; Nunziata et al. 2019).

As a result of increasing marine transport trade and developing marine petroleum platforms, the risk for environmental pollution due to oil discharges has been dramatically increased in the past decades. Therefore, the marine environment has become an urgent subject of public, political, and scientific concern (Liu et al. 2010; Chang et al. 2008). The exploration, production, transportation, refining, storage, distribution, and consumption of oil and petroleum products is overgrowing all over the world; consequently, the threat of destructive and hazardous effects of oil pollution increases accordingly as oil spills frequently occur in the world's marine water bodies (Caruso et al. 2013; de Oliveira et al. 2020). According to the international literature, the primary sources of oil slicks are operational/illegal discharges from vessels, platform accidents, and natural resources (Mera et al. 2012; Sharafat 2000). Although there are different sources for oil slicks on sea, ranging from human-made to natural, previous studies showed that marine tankers, offshore platforms, and large ships are major sources of oil spills in seas or oceans (Duk-jin Kim, Moon, and Kim 2010; Chen et al. 2019).

Monitoring and detecting oil slicks and predicting their trajectories play a crucial role in contingency planning for oil spills to conserve marine ecosystems and wildlife (Ceyhun 2014; Zhang et al. 2020). In order to make the proper response to environmental emergencies, effective monitoring and intervention means are required (Shu et al. 2010). Traditional ocean surveillance systems, including ships and aircrafts equipped with instruments, such as radar systems, are costly and have limitations for large areas monitoring. Therefore, given the need for near real-time detection and monitoring of oil spills, remote sensing (RS) satellite data have proven to be a suitable and efficient option that provides a cost-effective solution to accomplish such a task (Buono et al. 2019; Mera et al. 2014). Satellite RS systems improve the operational monitoring of Earth's surface by covering broad geographical areas with multi-sensor and multi- temporal data (Ivanov 2010; Li et al. 2019; Jafarzadeh and Hasanlou 2019b; Mahdianpari et al. 2020; Jafarzadeh and Hasanlou 2019a).

In the literature, several survey studies overview the oil spill issues from the RS point of view (e.g., (Fingas and Brown 2018, 2014; Leifer et al. 2012; Robbe and Hengstermann 2006; Migliaccio, Nunziata, and Buono 2015; Gens 2008)). These studies are mainly dedicated to characteristics and utilization of different sensor types, existing techniques for oil spill extraction, and applications. Brekke and Solberg (Brekke and Solberg 2005b) presented the first review of RS applications in oil spill detection. They provided a general review focusing on the detectability of oil spills using different sensor types under various conditions.

The main systems to monitor sea-based oil pollution are the use of satellites equipped with Synthetic Aperture Radar (SAR). However, a comprehensive overview and investigation of different SAR sensors' characteristics, employed SAR-based oil spill detection schemes, extracted and adopted features from SAR data, impacts of environmental conditions on SAR images, etc., is missing, and would be welcome by those who seek to learn the principles of using SAR data in oil spill detection. Thus, the current review paper aims to present a comprehensive and thorough survey of publications to point out the most successful and utilized characteristics of SAR data, plus reliable and practicable algorithms for oil spill monitoring in marine regions. Across a meta- analysis, we have recognized, categorized, and analyzed the reviewed literature. To the best of our knowledge, this is the first meta-analysis, wherein the role of SAR systems is thoroughly discussed for the oil spill detection task.

Table 1 summarizes the earlier review papers on oil spill detection using RS data. It should be noted that the available review papers are descriptive (i.e. discuss the issue of oil spills more generally and from some specific point of view) and do not convey a quantitative assessment of the oil spill detection task. Accordingly, the main goal of this study is to fill this knowledge gap by reviewing SAR-based oil spill detection papers (e.g. highlighting most commonly

**Table 1.** A summary of related surveys on remote sensing oil spill detection (the number of citations is reported by 27 September 2020, on the Web of Science database).

| No. | Title | Year | Citation | Publication | Description | Reference |
|---|---|---|---|---|---|---|
| 1 | A Review of Oil Spill Remote Sensing | 2018 | 46 | Sensors | Discusses progress in oil spill sensor development and their capabilities to apply to surveillance to oil discharges monitoring. | (Fingas and Brown 2018) |
| 2 | Oil spill detection by imaging radars: Challenges and pitfalls | 2017 | 36 | Remote Sensing of Environment | Focuses on discriminating mineral oil films and biogenic slicks. To this end, conventional methods which are widely used for discriminating purposes, critically were reviewed, and some suggestions to improve oil spill detection algorithms were given. | (Alpers, Holt, and Zeng 2017) |
| 3 | SAR polarimetry for sea oil slick observation | 2015 | 71 | International Journal of Remote Sensing | The more relevant polarimetric SAR-based approaches for sea oil spill detection were discussed. Plus, key characteristics of polarimetric SAR in terms of water-surface oil spill observation were reviewed. | (Migliaccio, Nunziata, and Buono 2015) |
| 4 | Review of oil spill remote sensing | 2014 | 211 | Marine Pollution Bulletin | The characteristics and capabilities of various measuring devices based on different regions of the electromagnetic spectrum were discussed from oil discharges detection viewpoint. | (Fingas and Brown 2014) |
| 5 | State of the art satellite and airborne marine oil spill remote sensing: Application to the BP Deepwater Horizon oil spill | 2012 | 248 | Remote Sensing of Environment | This review generally shows the specialized sensors' advantages over other technologies for observing oil spill response. | (Leifer et al. 2012) |
| 6 | Oil Spill Detection by SAR Images: Dark Formation Detection, Feature Extraction and Classification Algorithms | 2008 | 149 | Sensors | Presents an overview of the methodologies used to distinguish oil spills from other natural phenomena on SAR images. Plus, common methods to detect dark formations on the SAR images, the features which are extracted from candidate oil spill areas and the most used classifiers are also discussed. | (Topouzelis 2008) |
| 7 | Oceanographic Applications of SAR Remote Sensing | 2008 | 14 | GIScience & Remote Sensing | Provides a review of the use of SAR for oceanographic applications including oil spill detection. | (Gens 2008) |
| 8 | Oil spill detection by satellite remote sensing | 2005 | 604 | Remote Sensing of Environment | Discusses different satellite based sensors and oil spill detectability under varying conditions. In addition, oil spill detection techniques on a more general level were reviewed. | (Brekke and Solberg 2005) |
| 9 | Review of oil spill remote sensing | 1997 | 167 | Spill Science & Technology Bulletin | Gives an overview of promising role of RS technologies in oil spill detection. | (Fingas and Brown 1997) |

investigated study areas, mostly used sensor types, number of images utilized per study, frequently utilized polarization modes, most popular adopted methods, etc.).

## 2. Background

Marine oil slicks, based on spill sources, can be categorized as two main groups: (1) biogenic oil and (2) mineral oil. The former, also called surfactants, is surface films that contain surface-active organic compounds produced by marine plants (e.g., planktons) or animals (e.g., fish) or they are floating macro-algae such as sargassum and kelp (Najoui et al. 2018; Minchew, Jones, and Holt 2012). The latter contains two subcategories, including natural oil seeps that stem from sea bottom petroleum reservoirs (crude oil) and anthropogenic oil spills that discharged and leaked from ships and platforms, oil terminals, processing of industrial or urban plants (e.g., sewage plants), oil pipelines, and refineries (Najoui et al. 2018; Espedal and Johannessen 2000). It is important to note that the focus of this paper is to review the studies and advances to address the monitoring of mineral oil spills. So anywhere in the paper, the phrase "oil spill" refers to anthropogenic oil spills, not any kind of spills.

The use of remotely sensed data in the past few decades has been extensively considered for tracking and detecting oil spills. Both optical and radar satellite Earth observations have been used for this application (Bayramov, Kada, and Buchroithner 2018; Jha, Levy, and Gao 2008; Xing et al. 2015). However, each option has its own advantages and disadvantages, which are briefly discussed in the following subsections.

### *2.1. Optical data*

With respect to weather conditions, the clear-sky optical imagery is challenging over the seas and oceans; thus, the use of optical products has not been as widespread as that of SAR data in oil pollution studies. Although the utilization of optical sensors is severely constrained by sun illumination and cloud-free requirements, integrating multi-sensor data can be beneficial and to some extent, compensates the limitations of visible sensors (Brekke and Solberg 2005b). Thanks to temporal resolution and spatial coverage of passive optical sensors, they could provide a unique complement to fill spatial and temporal gaps for complete coverage of an oil spill (Oscar Garcia-Pineda et al. 2020; Sun et al. 2016; Hu et al. 2009). Moreover, multispectral observations of optical images give additional information to distinguish actual oil spills from water features (e.g., algal blooms) (Brekke and Solberg 2005b; Zhao et al. 2014a). In contrast, it would be challenging to discriminate between oil slicks and such features on the SAR data since they have similar scattering properties (Zhao et al. 2014b; Bayramov, Kada, and Buchroithner 2018). However, detailed oil spectral properties may not be determined across the visible spectrum, and one could not categorically identify oil discharges using only optical range (M. Fingas and Brown 2018, 2014).

### *2.2. SAR data*

During the past decades, SAR has received considerable attention in RS communities and became an indispensable source of information in Earth observation, notably because of its broad coverage and almost all-weather and all-day imaging capabilities under the different environmental conditions at the fine spatial resolution (Arslan 2018; Bayramov, Kada, and Buchroithner 2018; El-Magd et al. 2020; Akar, Süzen, and Kaymakci 2011; Topouzelis et al. 2006). Despite some challenges of utilizing SAR in oil spill detection (as discussed in the following subsection), it has become a useful and valuable tool for rapid and accurate marine pollution monitoring (Chaudhary and Kumar 2020; Carvalho et al. 2019). Unlike optical sensors, SAR signal penetration depth through natural media and sensitivity to surface roughness, altered in an oil spill, helps observe oil pollution (Shahsavarhaghighi et al. 2013).

The primary steps in pre-processing SAR images are divided into four parts: (1) radiometric calibration, (2) geocoding, (3) filtering, and (4) land masking, and will be described briefly below. First of all, to minimize the radiometric distortions and confirm that the received signals in SAR data are associated with the sigma naught backscattering coefficient, which expresses the reflective strength of a radar target, the radiometric calibration is applied (Stussi, Amélie Beaudoin, and Gigord 1996; Frulla et al. 1998). The second step, known as SAR data geocoding, is essential, ensuring that the image displays the correct location on the Earth's surface. This step also enables integrating multi-source geospatial data to increase the accuracy of oil pollution monitoring and detection procedures in SAR data (Moreira et al. 2013; Loew and Mauser 2007). As the third step, speckle removal is crucial in pre-processing and interpreting SAR data, especially in oil spill monitoring (Shah et al. 2017). The speckle phenomenon results from the coherent interference of radar echoes from target scatters (Caruso et al. 2013). It causes a pixel-to-pixel variation of intensities that produces a "salt and pepper" appearance in SAR images (Lee et al. 1994; McCandless and Jackson 2004). The presence of SAR speckle-noise reduces the quality of images and degrades the separability between the oil spill candidate areas and the background, which seriously affects oil slicks' detection (Xu et al. 2015; Wang, Zhang, and Patel 2017; Chierchia et al. 2017).

In the reviewed literature, the following filters were employed to minimize the effects of speckle-noise and avoid producing false detections: Lee (Dutta et al. 2018; Chaudhary and Kumar 2020; Bayramov, Kada, and Buchroithner 2018; Misra and Balaji 2017; Tong et al. 2019; Song et al. 2018; Li, Jia, and Velotto 2016a), enhanced Lee (Zhang et al. 2020; Li et al. 2018), Frost (Carvalho et al. 2016), Gaussian (Shu et al. 2010; Song et al. 2018), sigma (Barni, Betti, and Mecocci 1995), Kuan (Barni, Betti, and Mecocci 1995), median (Lang et al. 2017; Cantorna et al. 2019; Konik and Bradtke 2016; Sefah-Twerefour, Wiafe, and Adu Agyekum 2012; Chang, Cheng, and Tang 2005), Gamma (Arslan 2018; Martinis, Gähler, and Twele 2012), Lopez (Li et al. 2018), boxcar (Guo, Wei, and Jubai 2018; Hassani, Sahebi, and Asiyabi 2020; Li et al. 2018; Espeseth et al. 2017; Yin, Moon, and Yang 2015), and non-local mean filters (Lang et al. 2017). Finally, land masking is a further step in the pre-processing of SAR images that contain land surfaces. This step prevents interfering of the land pixels with the detection of oil spills (Singha, Vespe, and Trieschmann 2013).

### *2.3. Challenges of utilizing SAR data*

Oil spill detection in seawater is clarified by comparing oil spectral radiance and surrounding water radiance (Araújo et al. 2004). Owing to the influence of short-wavelength gravity waves (produced on local winds and are responsible for the sea spectrum energy spreading) and capillary waves (engendered by friction and associated with wind speed and sea- surface characteristics), backscattering from the sea surface is weakened, resulting in oil slicks to appear as dark spots with complex patterns on SAR images (Guo, Wei, and Jubai 2018; Mercier and Girard-Ardhuin 2005; Arslan 2018; Li et al. 2013; Ardhuin, Mercier, and Garello 2003; Grégoire Mercier and Ardhuin 2006a; Minchew, Jones, and Holt 2012). These wind-generated waves are called "Bragg waves" (Velotto, Soccorsi, and Lehner 2014) and are directly related to the radar brightness of the sea (Perkovic et al. 2010; Shao, Sheng, and Sun 2017).

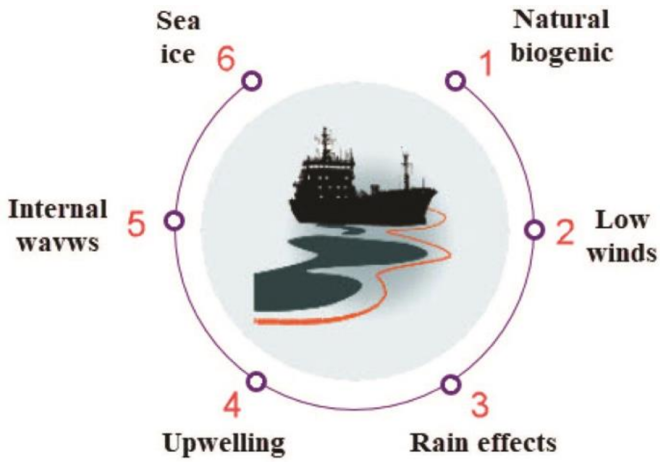
No Bragg waves are generated at very low wind speeds, causing the entire image to be dark due to specular reflection of the radar signal and rendering any slick invisible (Perkovic et al. 2010; Alpers et al. 2013). Consequently, identification of oil spills in SAR images always includes the first and essential step, which is detecting any dark-spotted areas that have high contrast relative to its surrounding (Zhang et al. 2008; Akkartal and Sunar 2008). Unluckily, several ocean phenomena and interfering substances can dampen the Bragg waves and produce low backscattering areas. They appear as dark patches (false targets) in SAR imagery, which are called lookalikes (Najoui et al. 2018).

In general, based on a comprehensive literature review, main types of oil spill lookalikes that frequently appear on SAR imagery are presented in Figure 1 (Espedal and Johannessen 2000; Holstein et al. 2018; Vijayakumar and Rukmini 2016; Carvalho et al. 2020; Chaturvedi, Banerjee, and Lele 2020; Topouzelis et al. 2007; Fingas and Brown 2018; Clemente-Colon and Yan 2000; Alpers, Holt, and Zeng 2017). A short description of each of these categories is reported in the following:

(1) Natural biogenic slicks: as discussed earlier, these are surface films produced by the decaying of marine organisms. This category is the most intricate oil spill lookalike because radar signatures of biogenic spills can

be quite similar to those of mineral oil films (Skrunes, Brekke, and Eltoft 2014; Alpers, Holt, and Zeng 2017). Since the only oil spills considered in this paper are anthropogenic ones, the natural biogenic slicks are grouped as lookalikes.

(2) Low wind zones: the surface roughness strongly depends on the wind, and variability in wind speed changes




**ure 1.** Main types of oil spill lookalikes that frequently appear on SAR images.

the backscatter level. Low wind speed (i.e., wind speed <3 m/s) produces a low backscatter area because of atmospheric circulation variation. Coastal topography and man- made obstacles also cause wind shadowing and produce dark patches (Clemente-Colon and Yan 2000).

(3) Rain effects: the atmospheric attenuation due to volume scattering in a rain system also produces a low backscatter area (Clemente-Colon and Yan 2000). This is problematic at higher frequencies (Danklmayer et al. 2009). Furthermore, rain cells hit the sea surface, resulting in turbulence in the upper water layer and dampen the Bragg waves.

(4) Upwelling: cold and nutrient-rich water reaches the surface through an oceanographic phenomenon known as upwelling. A decrease of water temperature on the sea surface alters the stability of the air–sea interface, results in lower wind stress, and reduces Bragg waves. Furthermore, the nutrient-rich waters on the water surface contribute to the formation of natural biogenic slicks (Clemente-Colon and Yan 2000).

(5) Internal waves: they affect the local sea surface velocities, cause divergent flow regimes, and alter the Bragg spectrum. Tidal flow over underwater sand banks also has a similar effect. The internal ocean waves are generated when the water density changes with depth, and strong currents interact with shallow underwater bottom topography. The SAR image of internal waves consists of adjacent bright and dark bands (Clemente-Colon and Yan 2000;
Solberg, Brekke, and Husoy 2007).

(6) Sea ice: first-year ice floes have a smooth surface and high salinity. Accordingly, they reflect the SAR signal and appear dark relative to multiyear ice in SAR imagery. Similarly, grease ice (i.e., newly formed ice composed of small millimeter-sized crystals) also dampens the Bragg waves and reduces SAR backscatter. Grease ice forms slicks, similar to those produced by mineral or biogenic surfactants (Clemente- Colon and Yan 2000).

(7) Other sources: these include dry-fallen sand banks during ebb tide, storm water that flows from land into the sea, plant oil spilled into the sea during tank cleaning of ships, transporting palm oil, fish oil, fluvial run-off, ship wakes, and coastal boating (Alpers, Holt, and Zeng 2017).

Distinguishing oil spills from lookalikes is a challenging and complex issue, which involves analysis of surface oil characteristics in the SAR images (e.g., shape, size, dB-values, gradients, and texture), environmental conditions (e.g., instantaneous wind and currents), and oil-spill prone areas (e.g., locations of oil platforms, ship lanes, and natural seepage) (Espedal 1999; Ardhuin, Mercier, and Garello 2003; Akar, Süzen, and Kaymakci 2011). Hence, choosing the appropriate SAR specifications and investigating the effects of field conditions is challenging for the oil spill monitoring task and should be explored more thoroughly.

The knowledge of wind conditions is necessary for oil spill monitoring. The detection of an oil spill is strongly dependent upon the wind speed. Many research studies investigated the relation between SAR backscatter and wind conditions in marine applications (Skrunes et al. 2018; Dagestad et al. 2013). The wind is the component that causes waves and can significantly impact oil's behavior on the ocean surface and disrupt data analysis, notably at high and very low wind speeds (Fingas 2011; Skrunes et al. 2018). Subsequently, the visibility of oil slicks is restricted to a limited range of wind speeds (Fan et al. 2015).

In addition to wind conditions, the detectability of oil spills in SAR data is a function of the sensor characteristics. Frequency is of the most fundamental characteristics of SAR imaging that encompasses the different microwave bands used in data acquisition, including L-, C- and X-bands. Notably, for L-, C-, and X-band SAR, the detectability relies on polarization, noise equivalent sigma zero (NESZ), incidence angle, swath width, and spatial resolution (Ivonin et al. 2020; Skrunes, Brekke, and Eltoft 2014; Cheng et al. 2011; Latini, Fabio, and Jones 2016).

One of the critical factors affecting surface backscattering and, consequently, oil spill characterization is the NESZ, i.e., the noise equivalent sigma zero, which measures the sensitivity of a SAR sensor. The NESZ value must be lower than the measured normalized radar cross-section (NRCS) value so that the backscattered signal from the surface will not be corrupted by noise (Skrunes, Brekke, and Eltoft 2014; Alpers, Holt, and Zeng 2017; Angelliaume et al. 2018). The NESZ and radar incidence angle have an inverse variation relationship. The increase in the radar incidence angle leads to a decrease in SAR backscattering intensity. As the backscatter decreases, the signal approaches the NESZ; therefore, causing the detection to be challenging (Skrunes et al. 2018; Marghany 2016).

Other critical elements of SAR to be considered are the swath width and the spatial resolution, which refers to the smallest discernible details on images. There is an inverse relationship between these two parameters. It makes sense to choose large swath widths for operational oil spill detection because it covers and observes large areas, although very small oil slicks will not be detected (Topouzelis 2008).

## 3. Methods

### *3.1. Bibliographic base and search query*

To prepare for this meta-analysis and comprehensive review, the Institute for Scientific Information (ISI) Web of Science and Scopus bibliographic databases were used on and up to 27 September 2020, for full- length English language papers, including journal articles and conference papers constrained to a time from 1990 to 2020. To this end, a logical literature search query was systematically developed using four sets of keywords to locate highly relevant papers in the database (see Figure 2). In order to retrieve papers that utilized SAR RS data and addressed the application of detection in the marine area, the keywords in the second, third and last columns were searched in the topic field (title/abstract/keyword). However, the first column keywords were exclusively searched in the title field to narrow the search down and make it more specific. This research obtained only the studies that analyzed the SAR data for anthropogenic oil spill detection.

Based on the search query, 1396 journal and conference papers were found in the mentioned databases. Afterward, we followed the methodology of Preferred Reporting Items for Systematic Reviews and Meta-Analyses, known as PRISMA (Moher et al. 2009) to select eligible papers to be included in our analysis. PRISMA is a checklist designed to improve the reporting standards of systematic literature reviews and meta-analyses. This reporting guideline consists of four phases flow diagram, including “identification,” “screening,” “eligibility,” and “included” (see Figure 3).

Following an initial assessment of the obtained 1396 published papers, a total of 1061 papers are selected. To be more specific, only those publications with titles and abstracts related to “oil spill detection by SAR imagery” were selected for further analysis in the next step. Moreover, only the publications that employed RS techniques based on airborne or spaceborne SAR data were selected as final items to be reviewed to maintain a controllable workload. Studies classified as review papers, book chapters, and reports were not considered in this systematic review. From the conference papers, we selected only those published in the International Society for Photogrammetry and Remote Sensing (ISPRS) archive and the IEEE International Geoscience and Remote

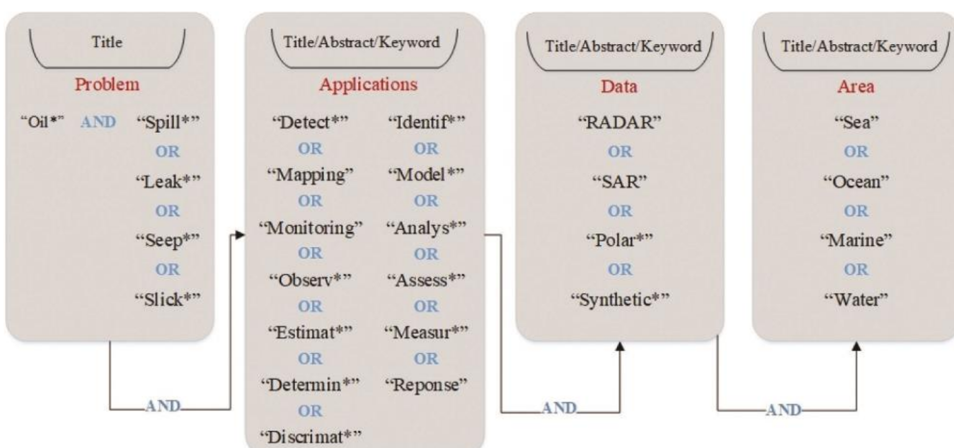



**Figure 2.** Search query criteria design for retrieving literature on SAR-based oil spill detection from WoS and Scopus databases.

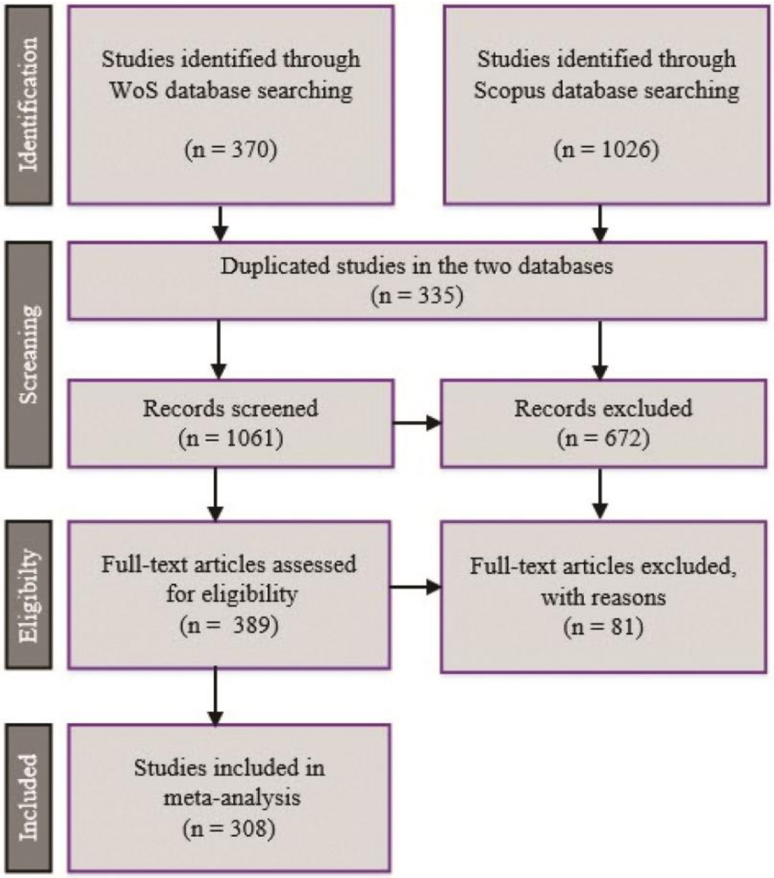



**Figure 3.** PRISMA flow diagram for manuscript selection.

**Table 2.** List of extracted attributes from the reviewed papers in the database.

| No. | Attribute | Type | Categories |
|---|---|---|---|
| 1 | Publication Title | Free text | – |
| 2 | Authors | Free text | – |
| 3 | Affiliation | Free text | – |
| 4 | Publication Year | Free text | – |
| 5 | Document Type | Classes | Article; Conference |
| 6 | Journal | Free text | – |
| 7 | Citation | Numeric | – |
| 8 | Study Area | Free text | – |
| 9 | Sensor type | Classes | ERS-1,2, JERS-1, RADARSAT-1&2, ENVISAT ASAR, ALOS-1&2 PALSAR, TerraSAR-X, Cosmo Skymed, RISAT-1, Sentinel-1 |
| 10 | Date of Data Acquisition | Numeric | – |
| 11 | Number of images | Numeric | – |
| 12 | Platform | Classes | Spaceborne; Airborne |
| 13 | Polarization Mode | Classes | Single; Dual; Full; Hybrid |
| 14 | Imaging Mode | Free text | – |
| 15 | Used frequency | Classes | L; C; X bands |
| 16 | Incident Angle | Numeric | Range of incidence angles |
| 17 | Wind Speed | Numeric | Range of wind speeds |
| 18 | Method | Classes | Classification, Segmentation, Statistical, Deep Learning |
| 19 | Research Objective | Free text | – |
| 20 | Accuracy Assessment | Numeric | Percentage |

Sensing Symposium (IEEE-IGARSS) proceedings. In addition, papers that did not contain most of the defining features listed in Table 2 were excluded. Conclusively, 308 papers were identified as eligible for our comprehensive review. A summary of manuscript selection can be seen in Figure 3.

### ***3.2. Extracted attributes from the screened records***

Table 2 includes the extracted attributes from the reviewed studies. This meta-analysis summarized these attributes to give an overview of how SAR data have been used across studies. Among these attributes, sensor type plays a crucial role in the SAR specifications, including frequency, incidence angle, and polarization. Another essential attribute is the type of Earth observation platform; airborne or spaceborne. Since airborne platforms (e.g., UAVSAR) provide lower spatial coverage than spaceborne sensors, they can be used for close analysis of relatively small case studies. On the other hand, spaceborne platforms cover a wide ground range with frequent revisit times.

## 4. Results

As mentioned earlier, based on the criteria outlined in the previous section, a total of 308 articles were selected. Several data categories have been extracted based on the review of journal and conference papers related to oil spill detection. In this section, detailed results of the systematic review will be presented. To this end, first, the articles' general characteristics, including the journals, the number of published papers per year, and the study areas, are presented. Afterward, study regions, SAR sensor types used in the literature and their characteristics such as frequency and polarization mode, the number of images utilized per study, and different types of methods employed in oil spill detection were discussed in detail. Finally, the reported accuracies in studies that used different types of SAR polarizations were assessed. Quantitative and qualitative results of the current meta-analysis are presented in the remainder of this section.

### *4.1. General characteristics in oil spill detection studies*

Figure 4 indicates the publication trends among 308 papers reviewed using PRISMA and illustrates the number of major oil spill events within the period 1990–2020. The increasing trend of publications in Figure 4 emphasizes the importance of oil spill detection for the scientific community. Given the increasing number of SAR sensors and their promising performance in oil spill detection, about 42% of the papers were published in recent years (2016–2020). The fact that 42% of the papers were published between 2016 and 2020 could also be related to the European Space Agency's open data policy (ESA) adopted for Sentinel- 1 data, making it easier to access SAR data. According to reports published by (ITOPF 2020), there has been a marked downward trend in the number of oil spill events over the last few decades. The frequency of oil spills greater than 700 tones has been shown in Figure 4.

Overall, the reviewed papers in our study were published in 89 different journals and two conferences, revealing the wide breadth of disciplines interested in the oil spill monitoring theme. We found that 70 of these journals have published only one or two papers in the field of oil spill detection. Only journals and conferences published more than two oil spill papers are included in Figure 5.

As shown in Figure 5, the highest number (top seven) of publications associated with oil spill detection occurs in

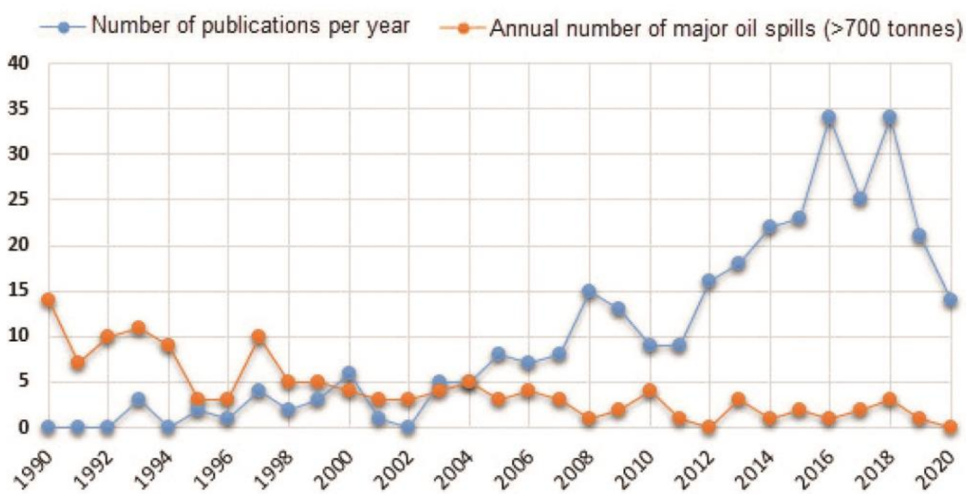



**Figure 4.** The fluctuation and the total number of publications per year, and the annual number of major oil spills from 1990 to 2020.

the IEEE-IGARSS archive, International Journal of Remote Sensing (IJRS), IEEE Transactions on Geoscience and Remote Sensing (IEEE-TGRS), IEEE Journal Selected Topics in Applied Earth Observation and Remote Sensing (IEEE-JSTARS), Remote Sensing (MDPI), ISPRS archives, and Remote Sensing of Environment (RSE).

Figure 6 illustrates the published papers' global geographical coverage based on the articles' reported research institutions. In 20 countries, three or more papers were published. As illustrated, researchers affiliated with institutions in China account for the bulk of oil spill studies with 61 articles, followed by 46 articles in Italy. The articles from China and Italy consisted of about 34% of the studies. This number of publications may be due to the universities' and

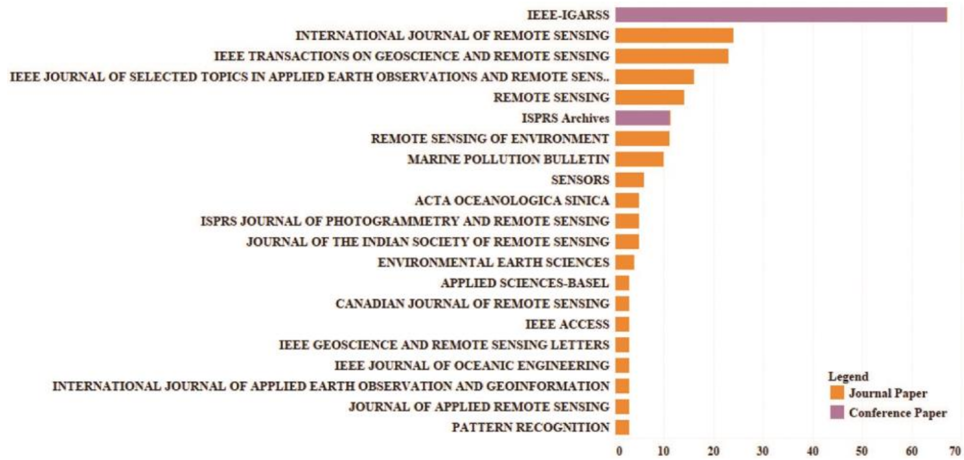



**Figure 5.** The number of oil spill detection papers published per journal (only those journals published three or more papers are included).

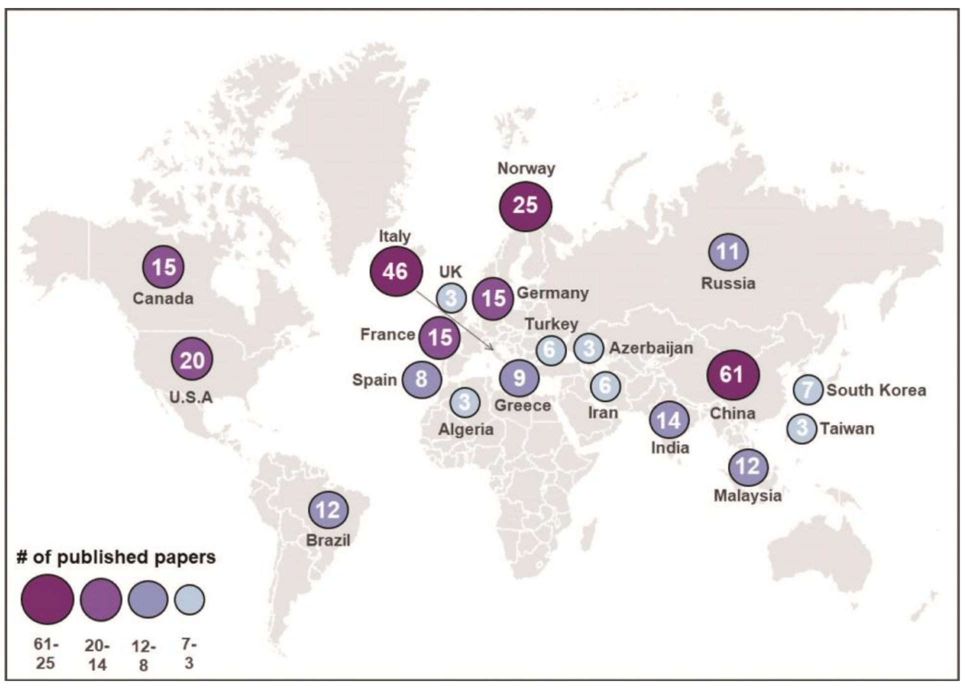



**Figure 6.** Distribution and frequency of published papers per country, according to the country reported in the papers.

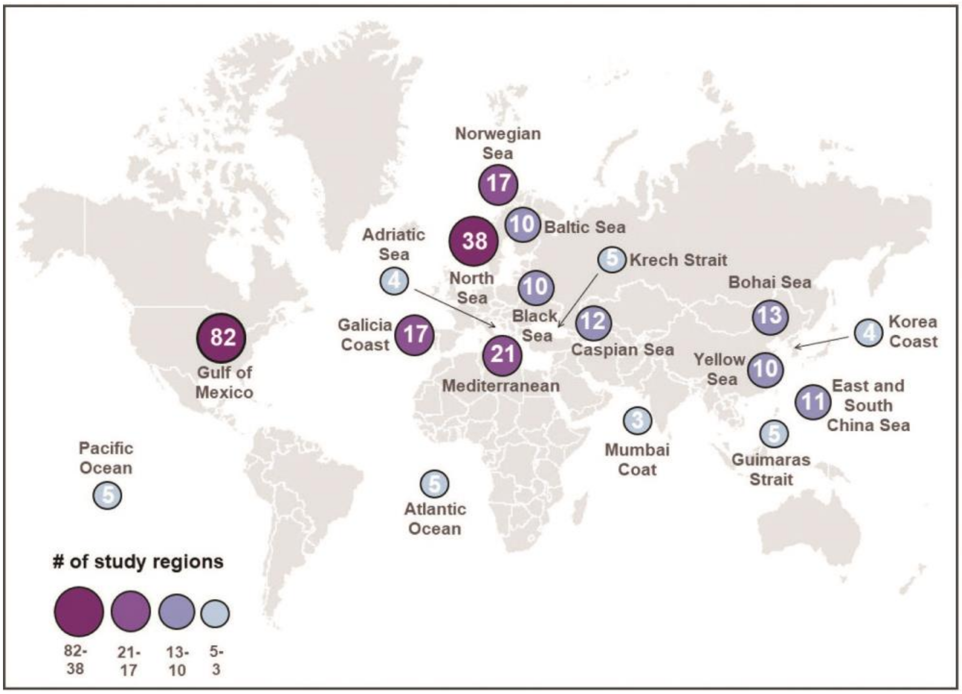



**Figure 7.** The global distribution and counts of study regions from all reviewed oil spill studies.

institutions' extensive scientific studies located in these countries. It could also be a result of the higher interests in marine pollution monitoring in these countries. The remaining countries in which more than three oil spill studies have been published are Norway (25), USA (20), Canada (15), France (15), Germany (15), India (14), Brazil (12), Malaysia (12), Russia (11), Greece (9), Spain (8), South Korea (7), Iran (6), Turkey (6), Algeria (3), Azerbaijan (3), Taiwan (3), and United Kingdom (3).

### *4.2. Study regions and oil spill-prone areas*

The worldwide distribution of study regions is shown in Figure 7. As shown, most studies were conducted in the Gulf of Mexico (82). Furthermore, the 38 and 21 studies performed over the North Sea and the Mediterranean Sea represent the strong attention of researchers on those areas. Moreover, the number of remaining study areas that were studied three or more times in the reviewed literature are as follows: Galicia coast (17), Norwegian Sea (17), Bohai Sea (13), Caspian Sea (12), East and South China Sea (11), Baltic Sea (10), Black Sea (10), Yellow Sea (10), Atlantic Ocean (5), Pacific ocean (5), Guimaras Strait (5), Kerch Strait (5), Adriatic Sea (4), South Korea coast (4), and the coast of Mumbai (3).

Sea-based offshore platforms can be the primary source of marine oil pollution. An offshore oil and gas platform includes facilities to explore, extract, store, and process petroleum and natural gas through drilled wells, increasing the risk of oil spills ruining and poses devastating effects on the marine environment. As seen in Figure 8, the North Sea and the Gulf of Mexico (United States) can be classified as the most prone oil spill zones because of the large number of installed offshore drilling rigs, totaling 184 and 175 rigs, respectively (Fazeres-Ferradosa et al. 2019). In addition, the significant number of oil platforms in the Persian Gulf (159), far east Asia (155), and southeast Asia (152) may also contribute and pose a threat to the marine environment.

Accidents involving ships or oil rigs and platforms, breaking of outdated and damaged facilities, human mistakes, and wars make the ocean water became contaminated by liquid petroleum hydrocarbon, which would cause damages to the marine environment for decades. In some cases, a vast range of polluted marine environment with a massive release of tens of millions of oil gallons, resulting in substantial effects from injured wildlife to the loss in tourism revenue. Examples of historical major oil spills are listed in Table 3 (Hoffman and Devereaux Jennings 2011; O'Rourke and Connolly 2003; Congress 1991; Chen et al. 2019).

### *4.3. SAR sensors used for oil spill detection*

In the current meta-analysis, satellite-borne SAR has been proven as a useful and indispensable source of

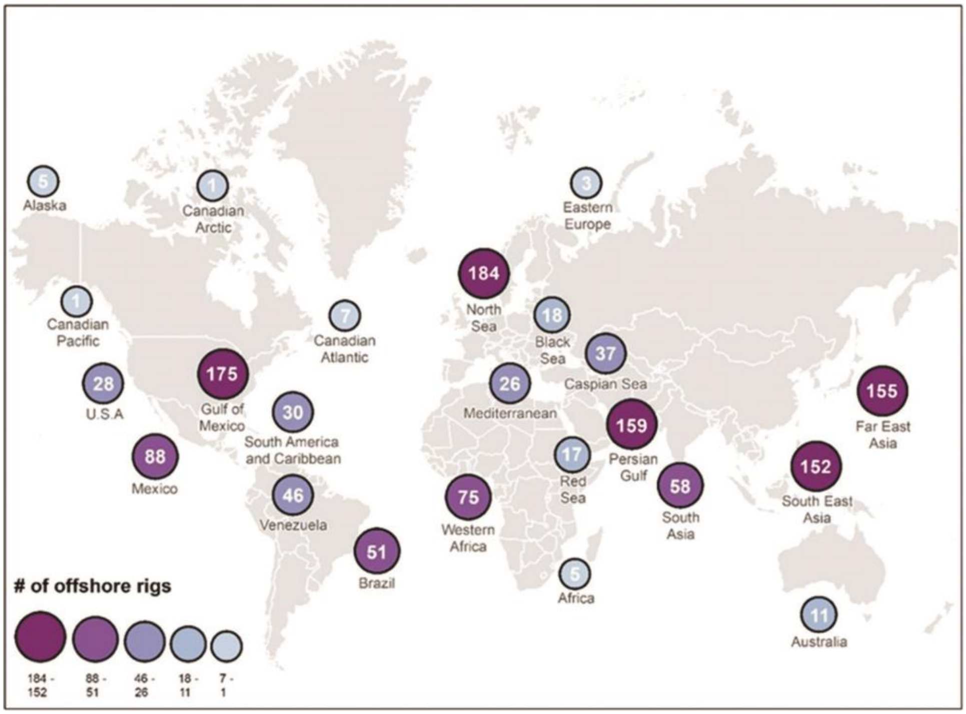



**Figure 8.** Location and distribution of offshore oil rigs worldwide.

**Table 3.** Major oil spill disasters in the world history ranked by the amount of spill size.

| No. | Spill/Tanker | Location | Date | Amount Spilled (million gallons) |
|---|---|---|---|---|
| 1 | Gulf War oil spill | Persian Gulf, Kuwait | 19 January 1991 | 380–520 |
| 2 | Deepwater Horizon | Macondo Prospect, Central Gulf of Mexico | 22 April 2010 | 206 |
| 3 | Ixtoc-I Oil Spill | Bay of Campeche off Ciudad del Carmen, Mexico | 3 June 1979 | 140 |
| 4 | Atlantic Empress Oil Spill | Off the coast of Trinidad and Tobago | 19 July 1979 | 90 |
| 5 | Kolva River Oil Spill | Kolva River, Russia | 6 August 1983 | 84 |
| 6 | Nowruz Oil Field Spill | Persian Gulf, Iran | 10 February 1983 | 80 |
| 7 | Castillo de Bellver Oil Spill | Off Saldanha Bay, South Africa | 6 August 1983 | 79 |
| 8 | Amoco Cadiz Oil Spill | Portsall, France | 16 March 1978 | 69 |
| 9 | ABT Summer Oil Spill | About 700 nautical miles off the coast of Angola | 28 May 1991 | 51–81 |
| 10 | M/T Haven Tanker Oil Spill | Genoa, Italy | 11 April 1991 | 45 |
| 11 | Odyssey Oil Spill | Off the coast of Nova Scotia, Canada | 10 November 1988 | 40.7 |
| 12 | The Sea Star Oil Spill | Gulf of Oman | 19 December 1972 | 35.3 |
| 13 | The Torrey Canyon Oil Spill | Scilly Isles, U.K. | 18 March 1967 | 25–36 |
| 14 | Sanchi | Off Shanghai, China | 6 January 2018 | 34 |
| 15 | Irenes Serenade | Navarino Bay, Greece | 23 February 1980 | 30 |
| 16 | Urquiola | La Coruna, Spain | 12 May 1976 | 30 |
| 17 | Hawaiian Patriot | 300 nautical miles of Honolulu | 23 February 1977 | 30 |
| 18 | Independenta | Bosphorus, Turkey | 15 November 1979 | 28.9 |
| 19 | Jakob Maersk | Oporto, Portugal | 25 January 1975 | 26.4 |
| 20 | Braer | Shetland Islands, UK | 5 January 1993 | 25.5 |

data for oil spill detection. Table 4 lists some of the well-known SAR-equipped satellite missions widely employed in the reviewed literature along with their life span, repeat cycle, wavelength, frequency, polarization, and orbital inclination.

From the RS platform viewpoint, 291 publications have applied satellite-borne SAR images. Sensor types included in these studies are shown in Figure 9. As shown, ENVISAT, RADARSAT-2, and ERS-2 are the most frequently employed data sources and were used in 84, 82, and 69 studies, respectively. Moreover, the number of remaining types of SAR sensors studied oil spill detection are as follows: ERS-1 (52), RADARSAT-1 (45), TerraSAR-X (40), ALOS-PALSAR (29), UAVSAR (20), COSMO-SkyMed (20), SIR-C/X-SAR (14), Sentinel 1A/ B (13), RISAT-1 (5). Note that sensors used five times or more in the literature are included in Figure 9.

Figure 10(a and b) indicates that about 93% of papers used spaceborne SAR data, and the remaining 7% applied airborne SAR data in oil spill studies. The satellite broad coverage capabilities should be the primary motivation that most reviewed studies employed spaceborne data sets. The presence of oil spills may appear differently when different SAR imaging sensors are used because surface characteristics can vary based on wavelength, frequency, polarization, and incidence angle. SAR sensors operate at different frequencies. Based on the reviewed literature, L-, C-, and X-band at a wavelength of 24, 6, and 3 centimeters, respectively, are the most used microwave bands for oil spill monitoring.

Regarding the choice of sensor, the reliability of detection is mainly subject to the frequency band and the sensor noise floor. Gade *et al*. in (Gade et al. 1998) proved that SAR images acquired at high frequency (i.e., X-band or C-band) are preferable to those acquired at a lower frequency (i.e., L-band) for oil slick detection. The damping ratio – a measure of the difference in spectral energy density of the ocean surface waves between oil-free and oil-covered surfaces (Wismann et al. 1998) – increases at higher frequencies, so the contrast between oil spills and clean sea is reported to be highest in X-band, moderate in C-band, and lowest in L-band (Marzialetti and Laneve 2016; Fingas and Brown 2018; Skrunes et al. 2015), and that is why X and C-band is superior to L-band (Vespe and Greidanus 2012; Marzialetti and Laneve 2016). However, it is also demonstrated in (Minchew, Jones, and Holt 2012b) that low noise L-band SAR systems can provide helpful oil spill data and identify oil slick successfully.

As shown in Figure 10(a), C-band appears to be the primary SAR wavelength for oil spill detection with 236 studies, followed by X-band (48 studies) and L-band (31 studies). This fact could be triggered by the higher number of SAR satellites operating in the C-band than the X- and L-bands (refer to Table 4). According to Figure 10(b), L-band airborne SAR data has been used in 25 studies in the reviewed literature. Some studies employed a multi-frequency dataset

**Table 4.** Characteristics of well-known SAR-equipped satellite missions utilized in the oil spill detection community. The columns "WL," "Pol" and "OI" indicate wavelength, polarization and orbital inclination, respectively.

| Satellite Mission (Sensor) | Life Span | Repeat Cycle (days) | WL (cm)/Band | Pol. | OI (deg.) | Ref. |
|---|---|---|---|---|---|---|
| ERS-1 | 1991–2000 | 35, 3, 168 | 5.66/C-band | Single-VV | 98.52 | (Singha, Bellerby, and Trieschmann 2012; Bayramov, Kada, and Buchroithner 2018; Chehresa et al. 2016) |
| JERS-1 | 1992–1998 | 44 | 23.5/L-band | Single-HH | 97.7 | (Garcia-Pineda et al. 2020; MacDonald et al. 2015) |
| SIR-C/X-SAR | 1994–1994 | 1 | 23.5, 5.8 /L-,C-band 3.1/X-band | Quad Single-HH | 57 | (Zhang et al. 2020; Yin et al. 2020; Zheng et al. 2017; Bandiera, Masciullo, and Ricci 2014) |
| ERS-2 | 1995–2011 | 35 | 5.66/C-band | Single-VV | 98.52 | (Liu et al. 2010; Chehresa et al. 2016; Garcia-Pineda et al. 2017; Asl et al. 2017) |
| RADARSAT-1 | 1995–2013 | 24 | 5.66/C-band | Single-HH | 98.6 | (Bayramov, Kada, and Buchroithner 2018; Cao, Linlin, and Clausi 2017; Xu, Jonathan, and Brenning 2014; Dabboor et al. 2019) |
| ENVISAT (ASAR) | 2002–2012 | 35 | 5.63/C-band | Dual | 98.55 | (Mera et al. 2012; Mera et al. 2014; Bayramov, Kada, and Buchroithner 2018; Wang et al. 2015; Akar, Süzen, and Kaymakci 2011) |
| ALOS (PALSAR) | 2006–2011 | 46 | 23.6/L-band | Quad | 98.16 | (Ozkan et al. 2012; Cheng et al. 2011; Wang et al. 2019) |
| RADARSAT-2 | 2007–Present | 24 | 5.55/C-band | Quad | 98.6 | (Ozkan et al. 2012; Zou et al. 2016; Carvalho et al. 2018; Song et al. 2017; Singha, Vespe, and Trieschmann 2013) |
| TerraSAR-X | 2007–Present | 11 | 3.11/X-band | Quad | 97.2 | (Nunziata et al. 2019; Singha et al. 2016; Kim and Jung 2018) |
| Cosmo-Skymed | 2007–Present | 1–8 | 3.1/X-band | Dual | 97.86 | (Nunziata, Buono, and Migliaccio 2018; Lupidi et al. 2017; Vespe et al. 2011) |
| RISAT-1 | 2012-Present | 25 | 5.3/C-band | Quad | 97.55 | (Dutta et al. 2018; Chaudhary and Kumar 2020; Vanjare et al. 2019) |
| Sentinel-1A Sentinel-1B | 2014-Present 2016-Present | 6 | 3.1/C-band | Dual | 98.18 | (Arslan 2018; Bayramov, Kada, and Buchroithner 2018; Chaturvedi, Banerjee, and Lele 2020; Cantorna et al. 2019) |

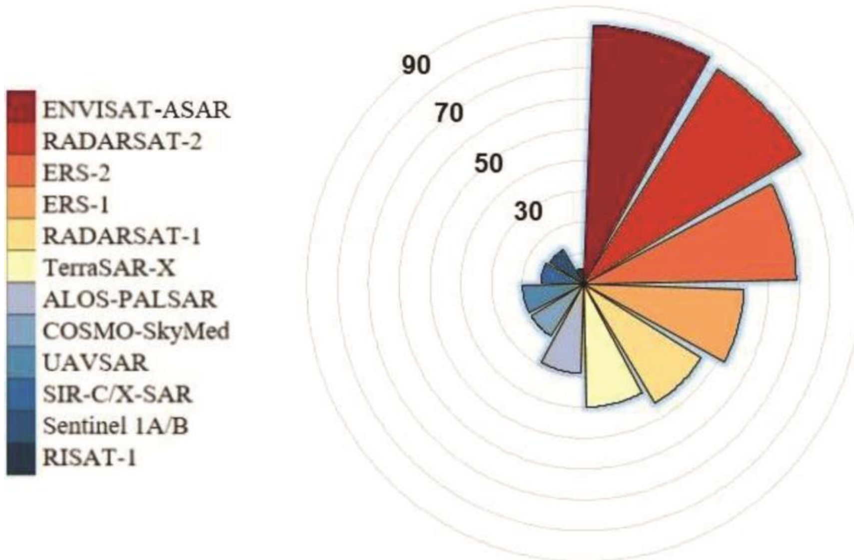



**Figure 9.** Distribution of employed sensor types in oil spill detection studies. The numbers on the graph indicate the frequency of sensors' usage in the reviewed literature.

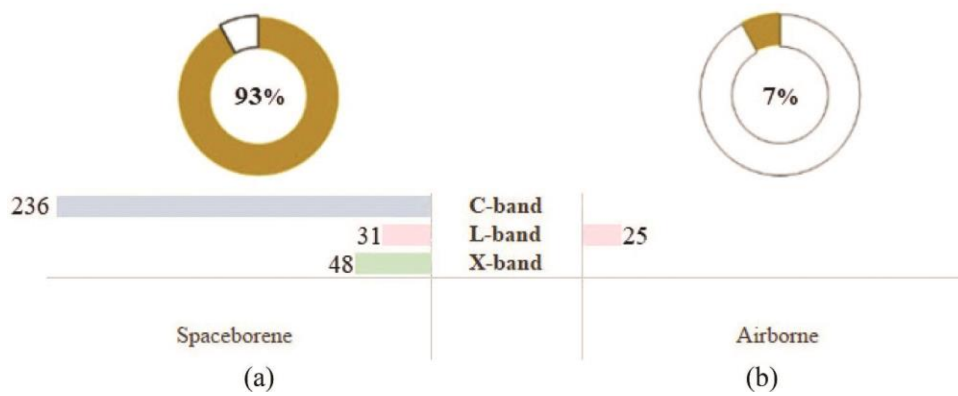



**Figure 10.** The usage of spaceborne and airborne SAR imagery; and X-, C-, and L-band in oil spill detection studies.

(combinations of X-, C-, and L- bands) for oil spill detection. The relative detection capacities of SAR are strongly connected with the frequency of used instruments, depending on the different penetration capabilities. Because SARs of different microwave frequency bands (L-, C-, X-band) interact with different components of the ocean wave spectrum, an approach involving multi-frequency characteristics of SAR can offer further information about the damping behavior of oil spills (Latini, Fabio, and Jones 2016). For operational purposes, concurrent acquisition (or near temporal overlap) of SAR images at L-, C-, and X-band over the same regions may require better examination. Considering the potentials of SAR systems acquiring data over the same spill and at the same time, the studies adopted a combination of SAR bands less often. As seen in Figure 11, studies combining C- and L-bands are the most common (18 studies). There are 11 studies in the reviewed literature that combined all three mentioned bands. In addition, 10 papers utilized the combination of X- and C-bands SAR data and just one study established a method for the oil spill detection task based on X- and L-band SAR jointly.

### *4.4. Number of SAR images used in different studies*

The statistical results shown in Figure 12 demonstrate the number of spaceborne or airborne images used in a specific period per paper. As shown in Figure 12,

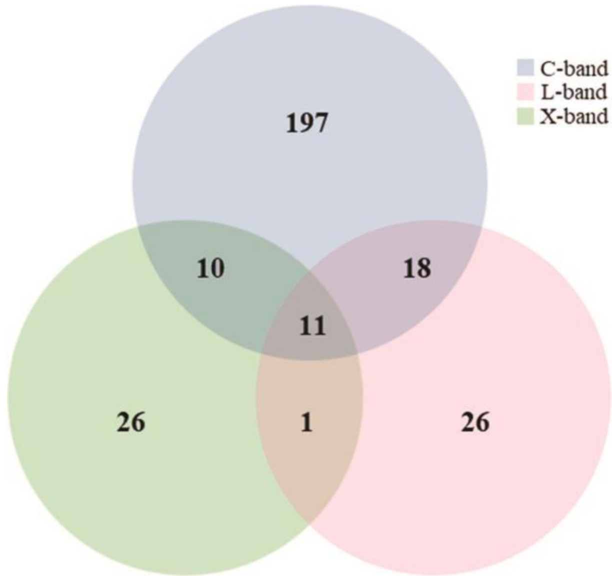



**Figure 11.** Combination of L-, C-, and X-band radar backscatter data used in the reviewed literature on oil spill detection.

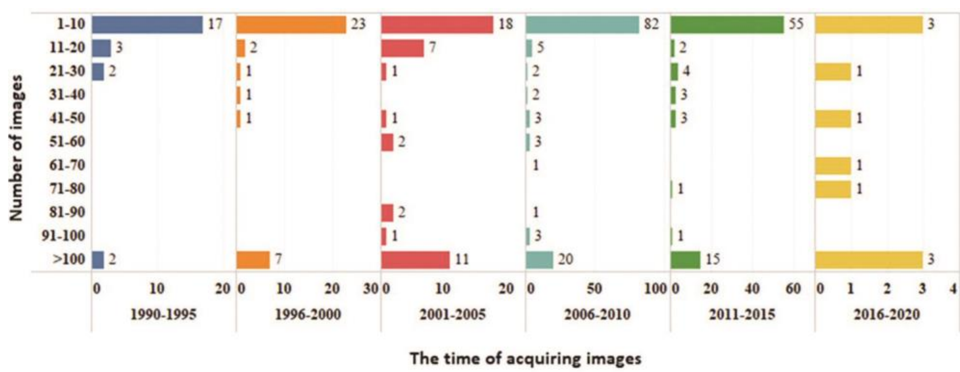



**Figure 12.** Distribution of the number of spaceborne and airborne images per time period.

most of the reviewed studies employed the images acquired during 2006–2010, mostly related to the Deepwater Horizon oil spill in the Gulf of Mexico, as indicated in Figure 7.

### ***4.5. SAR polarization modes used in oil spill detection***

The availability of advanced polarimetric SAR sensors and the generation of various polarization options allow users to select the most suitable SAR observations for oil pill detection in various ocean conditions. Polarization options could be single-pol, dual-pol, quad-pol, and hybrid/compact-pol. The single-pol SAR provides one channel of SAR data in either HH, HV, VH, or VV. Different polarizations make it possible to observe different features. For example, from an oil spill detection viewpoint, an oil spill incident can easily be observed in the VV SAR polarization, while other corresponding polarizations may not observe it in such an obvious way. SAR images obtained in single-pol HH or VV are widely used in operational services (Ivonin et al. 2020).

A linear dual-pol SAR system transmits one polarization and receives two, resulting in either HH/HV or VH/VV imagery. A dual-pol SAR system provides additional information about surface features through the different and complementary echoes compared to a single-pol system. A quad-pol system would alternate between transmitting H and V radar signals and coherently receive both H and V, resulting in HH, HV, VH, and VV imagery. Finally, a hybrid-pol transmits a circularly polarized radar signal (right or left) and coherently receives H and V, also known as compact- pol.

The backscattered signal level from the ocean surface is higher for single-pol VV than for HH-pol (Valenzuela 1978). Therefore, the VV channel is often preferred to HH for oil spill monitoring (Angelliaume et al. 2018). As presented in Figure 13, 133 papers have used single-pol SAR data from all the screened studies. In these studies, 44 and 89 papers have used HH and VV polarization, respectively. This result is expectable since VV polarization is favorable for marine SAR applications.

In addition, a total of 40 papers utilized dual-pol SAR imagery, of which HH-VV, HH-HV, and VV-VH were used 32, 3, and 5 times, respectively. Moreover, a total of 81 and 29 papers used full and hybrid polarization, respectively. Since most of the available spaceborne SAR sensors have a moderate noise floor (refer to Table 5), the cross-polarization (HV or VH) channels have the most negligible share in the detection of oil slicks (Angelliaume et al. 2018).

### *4.6. SAR polarization modes and their detection accuracy*

To evaluate and compare the effects of different types of SAR polarizations on the overall accuracy (OA) of oil spill detection schemes, the OA's boxplots were calculated and presented in Figure 14. Herein, the median OA for all types of polarization is more than 87%. The median OA of full-pol data is nearly 94%, and the lower and upper whiskers extend from 83% to 99%. The more utilization of single-pol data has made the results less consistent, and their accuracies depend on the applied methods and marine conditions. The median OA of single-pol data is around 91%, and the lower and upper whiskers extend from 70% to 99%. Furthermore, the median accuracies of dual-pol and hybrid data are 87.6% and 93%, respectively. According to Figure 14 and the reviewed literature (e.g., (Ferdinando Nunziata, Gambardella, and Migliaccio 2008; Velotto et al. 2011; Shirvany, Chabert, and Tourneret 2012; Nunziata, Gambardella, and Migliaccio 2013; Skrunes, Brekke, and Eltoft 2014; Salberg, Rudjord, and Schistad Solberg 2014)), quad- pol data can improve the detection capability of slicks compared to dual-pol data. It should be kept in mind that operational costs will be considerably high when using multi-channel SAR systems.

### *4.7. The effects of NESZ and incidence angle*

We know from the theories mentioned above that the NESZ and incidence angle are inversely related. According to (Skrunes et al. 2018), for incidence angles above 30°, the VV channel provides higher backscattering values, followed by the HH channel. The HV channel provides the lowest backscattering. In (Espeseth et al. 2019), the authors found that a signal- to-noise ratio (SNR) of at least 10 dB is required to ensure that the scattering properties are not affected by noise. Hence, investigating the marine surface's signal level relative to the noise floor is crucial for oil spill monitoring (Tong et al. 2019).

As mentioned in the current meta-analysis, the UAVSAR system is widely studied for oil spill detection due to its very low NESZ (−53 dB). The available satellite-based SAR sensors have higher noise floors (Skrunes, Brekke, and Eltoft 2014; Brent Minchew, Jones, and Holt 2012). The acquisition mode, incidence angle, and NESZ values of typical spaceborne SAR sensors are listed in Table 5 for a more comprehensive understanding and better comparison.

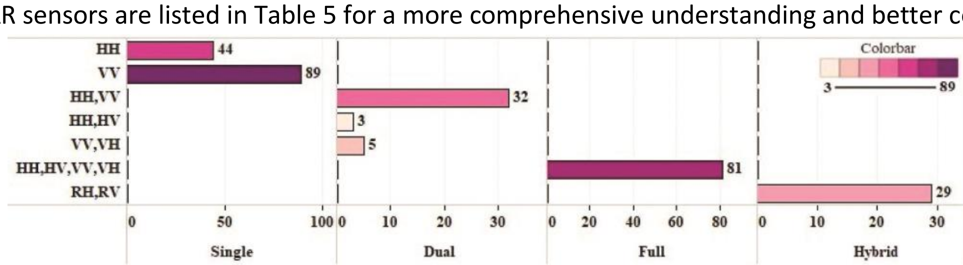



**Figure 13.** The number of oil spill monitoring studies that used each type of SAR polarization.

**Table 5.** The acquisition mode, incidence angle, and NESZ values of satellite-borne SAR sensors.

| Satellite mission | Acquisition Mode | NESZ (dB) | Incidence Angle (deg) | Number of reviewed studies with imaging mode |
|---|---|---|---|---|
| ERS-1,2 | Stripmap | −21 to −24 | 20–26 | 14 |
| JERS-1 | Stripmap | <−20.5 | 35 | – |
| SIR-C/X-SAR | fine quad | −22 to −35 | 15–55 | 3 |
| RADARSAT-1 | Fine | −21 | 37–47 | 2 |
| | Standard | −21 | 20–49 | 7 |
| | Wide | −21 | 20–45 | 12 |
| | ScanSAR narrow | −21 | 20–49 | 13 |
| | ScanSAR wide | −21 | 20–49 | 9 |
| | Extended High | −21 | 52–58 | – |
| | Extended Low | −21 | | 1 |
| ENVISAT ASAR | Image | −20 to −22 | 15–45 | 14 |
| | Alternating polarization, | −19 to −22 | 15–45 | 1 |
| | wave, Wide | −20 to −22 | 15–45 | – |
| | swath, | −21 to −26 | 17–42 | 44 |
| | Global monitoring | −32 to −35 | 17–42 | - |
| ALOS PALSAR | Fine 1 | <−23 | 8–60 | 3 |
| | Fine 2 | <−25 | 8–60 | 2 |
| | Polarimetry | <−29 | 8–30 | 1 |
| | ScanSAR | <−25 | 18–43 | 3 |
| RADARSAT-2 | Fine | −28 | 20–52 | 1 |
| | Standard | −31 | 20–45 | 3 |
| | Wide | −23 | 20–46 | 14 |
| | ScanSAR narrow | −23 | 20–49 | 5 |
| | ScanSAR wide | −23 | 49–60 | – |
| | Extended High | −27.5 to −43 | 18–49 | 39 |
| | Fine Quad- polarization | | | |
| TerraSAR-X | Spotlight (LR) | −23 | 20–55 | – |
| | Spotlight (HR) | −23 | 20–55 | – |
| | Stripmap | −22 | 20–45 | 15 |
| | ScanSAR | −21 | 20–45 | 14 |
| Cosmo Skymed | ScanSAR wide region | −21 | 18.4–59.9 | 2 |
| | ScanSAR huge region | −21 | 18.4–59.9 | 4 |
| RISAT-1 | CRS ScanSAR | −18 | 12–34 | – |
| | MR ScanSAR | −18 | 12–55 | 1 |
| | FR Stripmap1 | −18 | 12–55 | 3 |
| | FR Stripmap2 | −18 | 12–55 | - |
| Sentinel-1 | Stripmap | −22.2 | 18.3–46.8 | – |
| | Interferometric wide swath | −23.7 | 29.1–46 | 8 |
| | Extra wide swath | −23.1 | 18.9–47 | 1 |
| | Wave | −26.3 | 21.6–38 | - |

Besides, the number of reviewed studies utilized each type of imaging mode is provided.

### ***4.8. The effect of wind speed***

As investigated in the reviewed literature, the most favorable wind speed range for monitoring oil slicks in SAR images is approximately between 4 m/s and 10 m/s (Espedal et al. 1998; Espedal 1999; Wismann et al. 1998). It is also clear from Table 6 that most of the oil spill studies have been done under favorable wind and sea-state conditions. The wind speed conditions listed in Table 6 are reported in reviewed papers, based on Quick Scatterometer (QuikSCAT)-

**Table 6.** Oil Slick response according to wind speed obtained from reviewed studies.

| Wind Speed (m/s) | Oil slick signature | Number of reviewed studies |
|---|---|---|
| 0–2 | Oil slick detection is impracticable. The term “glassy sea” is used for such condition. | 36 |
| 2–4 | No impact of the wind on oil slicks. The detection of hydrocarbons is not easy given the increased lookalikes. | 79 |
| 4–7 | Relatively desirable condition. The wind speed does not have any significant effects on oil slicks. Plus, there are much fewer lookalikes. | 115 |
| 7–10 | Oil slicks begin to be affected by the chop, and Oil-polluted areas gradually disappear from the sea surface water as they are “washed down” by breaking waves. | 71 |
| 10–12 | Due to the dispersion of thin spills, only the thickest oil spills are detectable. | 27 |
| >12 | Oil slicks are broken up and dispersed, making it difficult and almost impossible to detect, even the thick ones. | 12 |

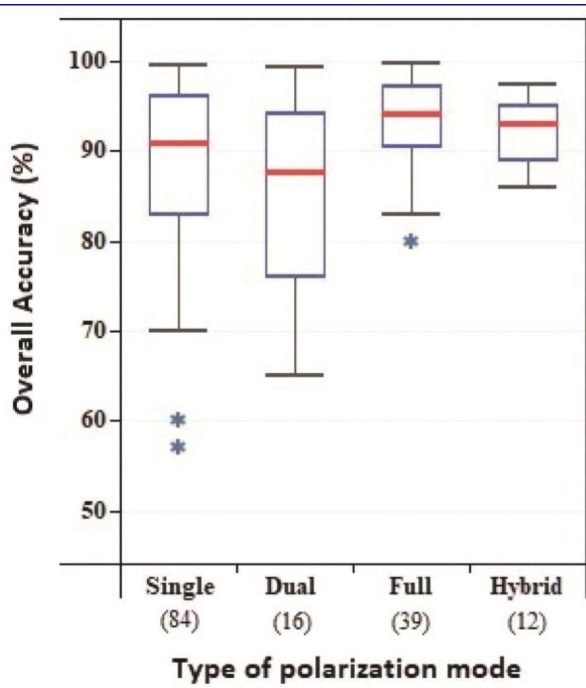



**Figure 14.** Box-and-whisker plots displaying the effect of different SAR polarizations on the OA.

SeaWinds observations (Mercier and Girard-Ardhuin 2005; Quintero-Marmol et al. 2003; Migliaccio et al. 2007; Shao et al. 2008; Mercier and Ardhuin 2006b), underwater gliders for in-situ ocean measurements, and Cross Calibrated Multi-Platform (CCMP) wind data (Tian, Huang, and Hongga 2017). Moreover, in some of the papers, these conditions were estimated and retrieved from SAR images using the CMOD4/5 model (CMOD is a C-band geophysical model that provides an empirical relation between the radar backscatter sensed from the roughened sea surface and wind speed) (Najoui et al. 2018; Vijayakumar and Rukmini 2016; Mera et al. 2017; Hersbach, Stoffelen, and de Haan 2007; Garcia-Pineda et al. 2013; Kim et al. 2015).

### *4.9. Different analytical oil spill detection methods*

The detection of oil spills in SAR data generally comprises segmentation, feature extraction, and classification procedures (Brekke and Solberg 2005a; A. H. S. Solberg, Brekke, and Husoy 2007). Different algorithms have been presented in the literature for the detection of oil spills. In the current meta-analysis, we summarized the common and widely used oil detection methods into four categories: traditional machine learning approaches, deep learning (DL) methods, threshold and segmentation techniques, and statistical algorithms.

The main common traditional and machine learning methods employed for detection of oil spills are as follows: support vector machine (SVM) (Hassani, Sahebi, and Asiyabi 2020; Cao, Linlin, and Clausi 2017; Xu, Jonathan, and Brenning 2014; Zhang et al. 2017; Mera et al. 2017; Zou et al. 2016), Decision Tree (Topouzelis and Psyllos 2012; Mihoub and Hassini 2014; Konik and Bradtke 2016; Akar, Süzen, and Kaymakci 2011), Maximum likelihood (Zhang et al. 2017; Misra and Balaji 2017), Naïve Bayes (Chehresa et al. 2016), Mahalanobis distance (Yang, Ying, and Zhu 2017), Random forest (RF) (Tong et al. 2019), k-means (Skrunes, Brekke, and Eltoft 2014), Classification And Regression Trees (CART) (Mera et al. 2014) and Artificial Neural Networks (ANNs). Moreover, the most conventional deep Learning (DL) methods in oil spill detection scheme include convolutional neural network (CNNs) (Guo, Wei, and Jubai 2018; Temitope Yekeen, Balogun, and Wan Yusof 2020; Cantorna et al. 2019; Zeng and Wang 2020), Generative Adversarial Networks (GANs) (Yu et al. 2018), deep belief networks (DBNs) (Chen et al. 2017), and Autoencoders (AEs) (Chen et al. 2017). Widely used statistical approaches include statistical region-based classifier (Genovez et al. 2019), Markov chain (Yao et al. 2014; Mercier et al. 2003), region- based generalized likelihood ratio test (GLRT) (Chang et al. 2008; Chang, Cheng, and Tang 2005), logistic regression (Cantorna et al. 2019). Threshold and segmentation methods mainly consist of adaptive and hysteresis thresholding, edge detection, and entropy approaches such as the maximum descriptive length algorithm (Montali et al. 2006; Galland, Refregier, and Germain 2004; Pelizzari and Bioucas-Dias 2007; Yu et al. 2017; Li, Jia, and Velotto 2016b).

As displayed in Figure 15(a), about 103 studies adopted traditional machine learning approaches in the reviewed literature. In addition, the number of segmentation techniques, statistical methods, and DL algorithms were 82, 61, and 26, respectively.

Moreover, feature (parameters of the dark formations) extraction is a critical step in the oil spill detection schemes, making it possible to use a group of features to distinguish oil slicks and lookalikes. Figure 15(b) presents the more common features

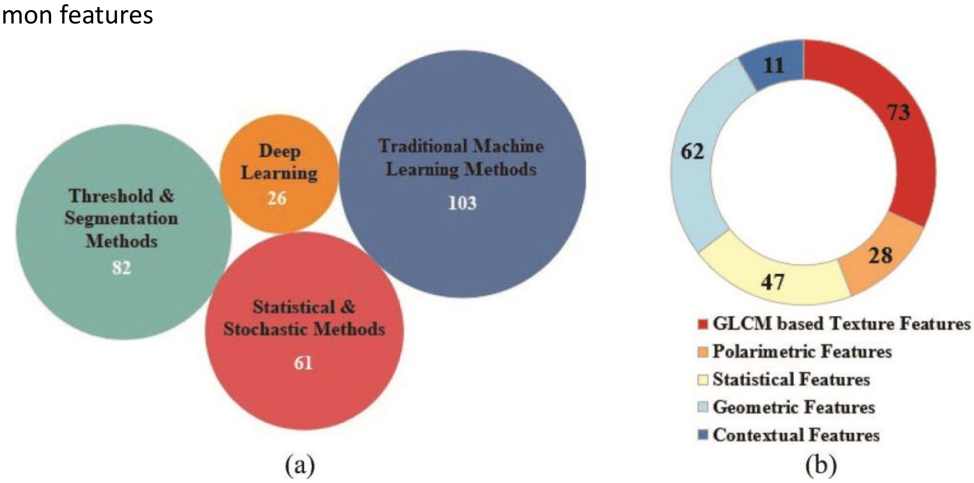



**Figure 15.** (a) The number of studies associated with each oil detection strategy. (b) The number of publications associated with different types of features extracted from SAR data.

adopted in oil spill detection studies. These features can be separated into five major groups: (1) features referring to the geometrical properties of dark formations (e.g., area, perimeter, shape) (Karathanassi et al. 2006; Brekke and Solberg 2005b), (2) features concerning the physical/statistical behavior of oil spills (e.g., mean, max, standard deviation, and ratios of backscattering coefficient values) (Karathanassi et al. 2006; Topouzelis 2008), (3) features denoting to the oil spill context (e.g., presence of rig/ship, distance to ship) (Brekke and Solberg 2005b; Topouzelis, Stathakis, and Karathanassi 2009; Chehresa et al. 2016), (4) derivatives of gray-level co-occurrence matrix known as GLCM-based texture features (e.g., contrast, correlation, entropy, energy) (Chehresa et al. 2016; Yang, Ying, and Zhu 2017; Guo, Danni, and Jubai 2017), and (5) features extracted from different polarimetric SAR images (e.g., degree of polarization, alpha angle) (Song et al. 2017; Zhang et al. 2017; Li et al. 2018).

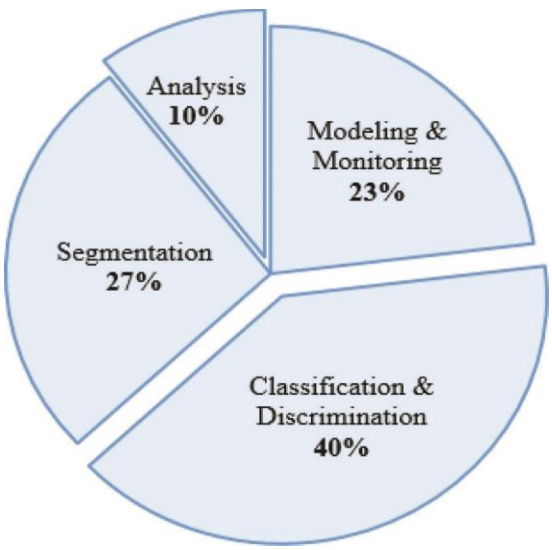



**Figure 16.** Different strategies in oil spill detection.

***4.10. Strategies in oil spill detection studies***

As discussed earlier, the reviewed papers used different methods to deal with oil spill detection issues. In general, these methods follow related sub-objectives in line with the primary objective (i.e., oil spill detection). Figure 16 illustrates the different types of sub-objectives considered in the reviewed studies. As shown, 40% of studies were benefited from "classification and discrimination" strategies followed by "modelling and monitoring," which accounts for 23% of the studies. The "modelling and monitoring" group includes various strategies, including monitoring the spatial distribution and primary sources of oil spills, visual interpretation, contamination probability modeling and assessment, time series analysis and oil spill frequency modeling, numerical simulations to simulate the trajectories of the oil spills, oil slick trajectory forecasting model, and characterizing oil- water mixing.

Based on Figure 16, 27% of the studies adopted their strategies based on image segmentation. Furthermore, only 10% of studies are categorized as “analysis” group, mainly focused on interpreting SAR backscattering mechanisms over oil-covered waters, oil-polluted areas’ backscattering simulation, characterizing the scattering from oil spills and biogenic surface films under different wind conditions, and assessment of experience from a field experiment. Studies associate with multi- sensor, multi-polarization and multi-frequency analyses of different SAR systems in oil spill events and their response in oil-polluted areas are also involved in this group.

## 5. Conclusions and future research needs

In this paper, we presented a comprehensive review and meta-analysis of oil spill detection studies. Our research provides a systematic investigation of indexed research studies’ compilation and analysis, focusing on several features, such as data, platform, and sensor type, SAR imaging mode, microwave carrier frequency (e.g., L-, C-, and X-bands), polarization option (i.e., single-pol, dual-pol, full-pol, and compact- pol), incidence angle, and wind speed condition. Furthermore, it gives a comprehensive overview of the approaches established to deal with the oil spill detection task through SAR imagery. The current meta-analysis is the only research conducted to provide both descriptive and quantitative investigation of oil spill studies using a database containing 308 eligible papers, of which 230 are journal papers and 78 are conference papers. A summarization of the paper’s content and crucial findings are given in the following:

- The summarized papers in the present meta- analysis have been published in 89 different journals and two conferences. From all of these publications, about 42% of them were published from 2016 to 2020.
- Researchers affiliated with institutions in China and Italy account for the bulk of oil spill studies with nearly 20% and 15% of the database, respectively. Consequently, a significant part of this review study is conducted in either of these two countries, followed by Norway (8%), USA (7%).
- Since the coverage of the spaceborne missions is much more extensive than that of the airborne missions, most of the reviewed studies employed spaceborne data sets in maritime oil spill detection with a 93% share.
- In terms of sensor type, ENVISAT (84 studies), RADARSAT-2 (82 studies), ERS-2 (69 studies), ERS-1 (52 studies), RADARSAT-1 (45 studies), and TerraSAR-X (40 studies) are the most frequently studied data sources.
- Most of the reviewed studies employed the images acquired during 2006–2010, which could be related to the Deepwater Horizon oil spill in the Gulf of Mexico.
- From the polarization perspective, single-pol (133 studies) and full-pol (81 studies) SAR data have a significant share in the reviewed literature with a median overall accuracy of 94% and 91%, respectively. Furthermore, the median accuracy of dual-pol (40 studies) and Hybrid (29 studies) data are 87.6% and 93%, respectively.
- Reviewed studies indicated that C-band radar had been used widely in the oil spill detection task with 236 studies, followed by L-band (56 studies) and X-band (48 studies).
- From a methodology point of view, about 103 studies adopted different traditional classification methods in the reviewed literature. Additionally, the number of studies that utilized segmentation methods, statistical methods, and DL algorithms were 82, 61, and 26, respectively.
- Environmental wind speed condition measurements play a significant role in oil spill detection. About 68% of reviewed papers adopted these measurements.

SAR sensors are efficient RS tools for oil spill detection, and various techniques have been proposed to cope with the monitoring of oil pollution using SAR data in recent decades. Nevertheless, there is a need to develop real-time monitoring systems. Providing techniques based on cloud computing services and proposed automatic DL models, considering the continuous development in computer vision will significantly increase the success in this area. In addition, it is still necessary to extensively explore the potential of compact hybrid polarization, which is currently provided operationally by the RADARSAT Constellation Mission, for oil spill monitoring. It is also expected from the scientific community, i.e., from RS experts to environmental monitoring specialists, to access various multi-sensor images collected over different locations and open-source annotated datasets related to oil spill events. This will increase the speed of achieving new detection algorithms that are desperately needed to protect the marine environment. A detailed investigation and review of oil spill detection methods in the literature is also absent.

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