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Comparative Analysis of Satellite Efficiency in Detecting Marine Pollution Within the Cleanseanet System

Abstract

CleanSeaNet is a satellite-based monitoring service operated by the European Maritime Safety Agency (EMSA), aimed at detecting oil spills and other forms of marine pollution across European Union waters. As one of the key operational tools supporting maritime surveillance and environmental protection, the service provides national authorities with near-real-time information that can be used for both immediate response and long-term policy development. This study evaluates and compares the performance of individual satellites contributing to the CleanSeaNet system, focusing on their effectiveness in identifying surface-level pollution events. Using a comprehensive dataset collected over the past five years, detected spills were categorised according to the confirmation method employed—such as aerial surveillance, vessel reports, or follow-up inspections—and subsequently classified as either real pollution events or false positives. The primary objective of this analysis is to assess the detection accuracy of each satellite across a range of spill types, while also identifying potential patterns in reliability. The findings indicate that satellite performance is not uniform. Instead, significant variations emerge that support the hypothesis that detection efficiency depends on multiple interrelated factors, including sensor technology, orbital characteristics, and prevailing environmental conditions such as sea state or wind. These insights provide valuable guidance for optimising monitoring strategies and improving the overall robustness of CleanSeaNet.

Keywords: satellite monitoring, marine pollution, CleanSeaNet, EMSA, remote sensing

1. Introduction

Marine pollution remains a significant environmental and economic challenge globally, with oil spills posing particular risks to marine ecosystems, coastal communities, and maritime activities [1, 2]. Detecting and monitoring pollution events in near real time is essential for enabling rapid response and supporting environmental protection strategies. Traditional surveillance methods, such as ship patrols or aerial observation, are effective but limited in spatial coverage and cost-efficiency [3].

Satellite-based Synthetic Aperture Radar (SAR) has become a cornerstone of operational marine monitoring, as it enables the detection of surface slicks under various weather and lighting conditions [4–7]. Comprehensive assessments of satellite and airborne remote sensing technologies have further demonstrated their effectiveness for large-scale oil spill events [8]. In Europe, the European Maritime Safety Agency (EMSA) operates CleanSeaNet, a satellite-based oil spill and marine pollution monitoring service covering the waters of EU Member States [9–11]. The service delivers near-real-time alerts to national authorities and supports both operational response and strategic environmental planning.

Multiple satellite missions contribute to CleanSeaNet, each with distinct sensor technologies, orbital characteristics, and operational roles. Understanding the performance of individual satellites is crucial for improving detection accuracy and optimizing monitoring strategies. Previous research has shown that detection efficiency is influenced by sensor properties, environmental conditions, and processing algorithms, leading to variations in accuracy between missions such as Sentinel-1, Radarsat-2, TerraSAR-X, and PAZ1 [5, 12–15].

This study evaluates the performance of four satellites contributing to CleanSeaNet over a five-year period (2019–2023), using operational detection data. The analysis focuses on temporal trends, detection category distributions, and satellite-specific performance, with particular attention to the operational use of TerraSAR-X sensor modes. The findings provide insight into how satellite characteristics affect detection reliability and offer guidance for enhancing CleanSeaNet's operational effectiveness.

2. Material and Methods

This study analysed operational data collected through the CleanSeaNet service over a five-year period (2019–2023). CleanSeaNet is operated by the European Maritime Safety Agency (EMSA) and provides satellite-based oil spill detection and monitoring across European Union waters [9–11].

2.1. Satellite Missions

The dataset includes detections from four satellite missions: Sentinel-1, Radarsat-2, TerraSAR-X, and PAZ1. These satellites differ in terms of orbital characteristics, radar frequency bands, polarimetric capabilities, and acquisition modes [12–15].

Sentinel-1, operated by the European Space Agency (ESA), provides wide coverage and frequent acquisitions. Radarsat-2, operated by the Canadian Space Agency, offers advanced polarimetric modes suitable for oil spill detection. TerraSAR-X (DLR, Germany) and PAZ1 (Hisdesat, Spain) are high-resolution X-band missions used for targeted monitoring.

2.2. Data Classification and Validation

Each satellite detection was classified into one of five categories: Mineral oil confirmed, Natural phenomena, Nothing observed, Other substance, or Unknown feature, following the standard CleanSeaNet classification scheme [9, 11]. The validation of detections was performed using aerial surveillance, vessel reports, and, when available, on-site inspections conducted by national authorities. These validation data were used to distinguish between confirmed pollution events and false positives.

2.3. Quantitative Analysis

The classified dataset was subjected to quantitative and comparative analyses, focusing on:

- ◊ The temporal distribution of detections (2019–2023)
- ◊ The distribution of detection categories by satellite
- ◊ The relative detection accuracy of each satellite mission.

Frequency counts, category shares, and time series were generated to identify trends and differences in detection performance. In addition, specific analyses were conducted for TerraSAR-X, examining the distribution of detections across its operational modes (Wide Scan, Strip Map, Spotlight) to better understand how sensor configuration affects detection characteristics [13].

Figure 1 illustrates the overall workflow used in this study, from data acquisition through classification, validation, and analysis.

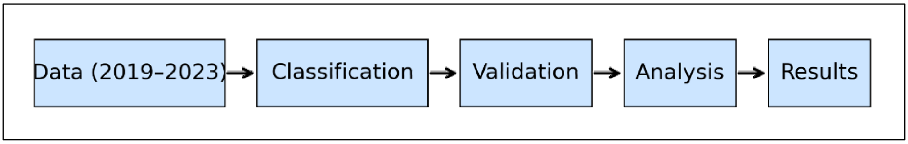

Figure 1. Methodology flowchart illustrating the main steps of the data processing and analysis, including classification, validation, and quantitative evaluation of satellite detections.

3. Results

3.1. Detection Trends (2019–2023)

During the study period, more than 11,000 satellite detections were analysed, with Sentinel-1 contributing the largest share, followed by TerraSAR-X, Radarsat-2, and PAZ1. This distribution reflects the differences in acquisition frequency and tasking strategies across the missions. The number of detections peaked in 2020, followed by a marked decline during 2021–2022 and a recovery in 2023 (Figure 2). This pattern likely reflects both operational changes in satellite tasking and the influence of environmental conditions such as wind and sea state, which affect the detectability of surface slicks. For instance, low wind speeds and seasonal variability can lead to reduced backscatter contrast and higher rates of look-alike phenomena, impacting overall detection numbers.

Sentinel-1 consistently contributed the largest share of detections each year, owing to its **systematic acquisition plan, wide swath coverage**, and **short revisit time** [12]. In contrast, Radarsat-2 and TerraSAR-X generated fewer detections annually, but their contributions remained stable over time, reflecting their **targeted acquisition strategies**. PAZ1 was introduced into operational use later in the time series, resulting in a smaller but growing contribution towards the end of the study period.

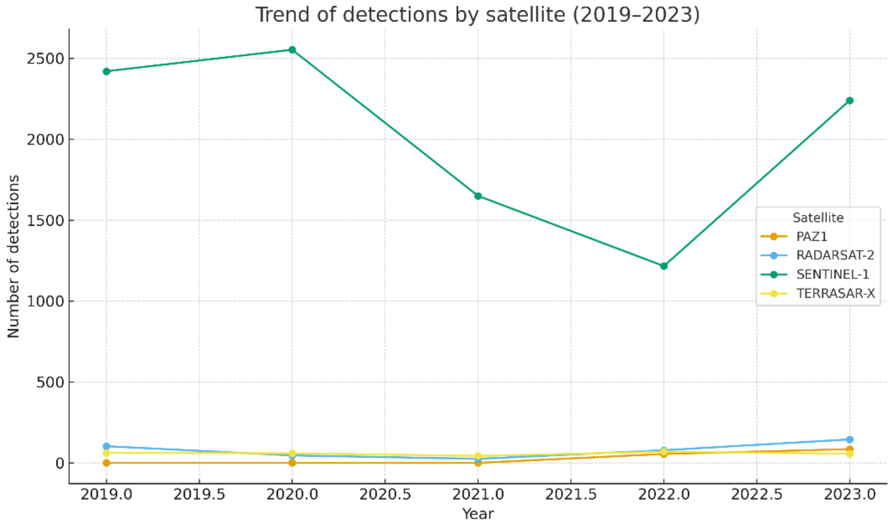

Figure 2. Temporal trend of CleanSeaNet detections by satellite (2019–2023)

The decline in detections observed in 2021 and 2022 can be partly attributed to **changes in CleanSeaNet's operational framework**, including adjustments to acquisition planning and processing routines aimed at reducing false positives. Additionally, variations in environmental conditions, such as **wind speed, sea state, and seasonal patterns**, are known to influence the detectability of slicks on SAR imagery [5–7], which may also have contributed to interannual differences.

3.2. Detection Categories

All detections were classified into one of five categories following CleanSeaNet procedures: *Mineral oil confirmed*, *Natural phenomena*, *Nothing observed*, *Other substance*, and *Unknown feature* [7, 10].

The analysis of category distributions across satellites reveals marked differences in detection reliability (Figure 3). Across all missions, the category "Nothing observed" accounts for a substantial proportion of detections, reaching approximately two-thirds for Sentinel-1 and TerraSAR-X, while remaining noticeably lower for PAZ1 and Radarsat-2. This pattern reflects the well-known challenge of distinguishing oil spills from look-alike phenomena, such as wind slicks or biogenic films, particularly in wide-swath acquisitions where reduced spatial resolution can hinder discrimination.

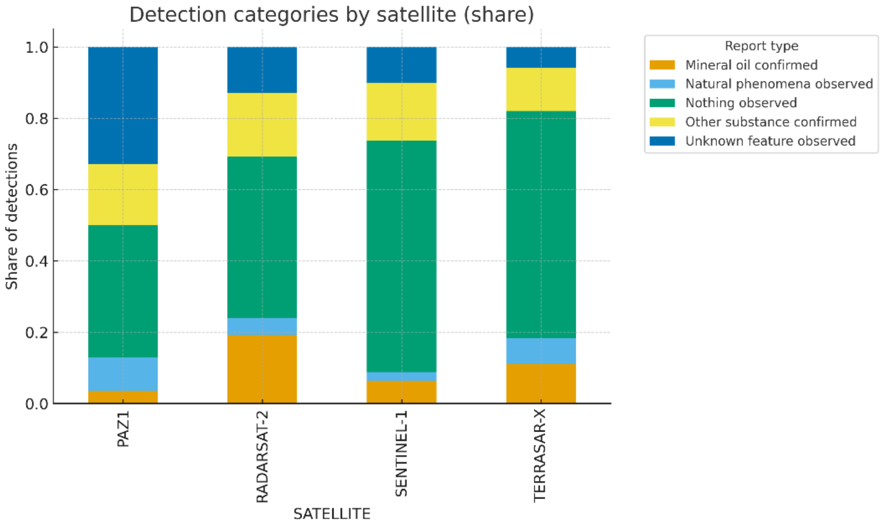

Figure 3. Distribution of detection categories by satellite

In contrast, Radarsat-2 exhibits the highest proportion of "Mineral oil confirmed" detections, suggesting improved capability in identifying true spills, whereas PAZ1 shows a comparatively large share of "Unknown feature observed," indicating greater ambiguity in classification. The "Natural phenomena observed" category remains relatively limited across all sensors but appears somewhat more pronounced for PAZ1 than for the others.

3.3. Satellite Performance

Beyond categorical distributions, detection performance was assessed in terms of confirmed mineral oil detections, representing validated pollution events. Radarsat-2 exhibited the highest confirmation rate, with 19 % of its detections classified as mineral oil, compared to 6 % for Sentinel-1 and 11 % for TerraSAR-X. These differences are attributable to variations in sensor characteristics, including frequency band, polarimetric capabilities, and spatial resolution [12–14]. Radarsat-2's fully polarimetric C-band system provides richer information for oil–water contrast analysis, improving the reliability of automated detection algorithms.

Sentinel-1, despite its broad coverage and frequent acquisitions, had a lower confirmation rate due to its operational IW mode (Interferometric Wide Swath) with dual-polarisation. While this mode allows for efficient monitoring of large areas, it is less optimal for differentiating oil spills from look-alikes compared to fully polarimetric modes [5]. TerraSAR-X, operating in X-band, offers high-resolution imagery that is useful for the detailed characterisation of slicks, but environmental factors and acquisition mode choices still influence detection outcomes.

PAZ1, which entered operational service later in the time series, contributed fewer detections overall. However, its data were used mainly for targeted monitoring in specific areas of interest, often complementing acquisitions from other satellites. This highlights the importance of using multiple satellite missions in tandem to achieve both wide-area coverage and targeted precision.

3.4. TerraSAR-X Sensor Modes

The analysis of TerraSAR-X acquisition modes revealed that Wide Scan mode dominated operational use throughout the study period. This mode offers larger coverage at moderate resolution, making it suitable for routine monitoring. Strip Map and Spotlight modes were used less frequently, but primarily for targeted verification of suspected pollution events detected by other missions. The higher spatial resolution of Spotlight mode enables detailed analysis of slick morphology and structure, which can support decision-making during follow-up operations [13].

The distribution of TerraSAR-X modes illustrates the operational trade-off between spatial resolution and areal coverage. While Wide Scan enables efficient routine surveillance, higher-resolution modes are essential for detailed verification. This complementary use of modes mirrors the multi-sensor strategy within CleanSeaNet, where broad-coverage acquisitions from Sentinel-1 are complemented by targeted acquisitions from high-resolution missions.

4. Discussion

The comparative analysis of CleanSeaNet detections between 2019 and 2023 reveals significant variations in satellite performance, shaped by differences in sensor technology, acquisition strategies, and environmental conditions. Sentinel-1 stands out for its exceptional spatial and temporal coverage, but its dual-polarisation IW mode remains less reliable for distinguishing oil spills from look-alike phenomena [5, 7]. This limitation is well documented in the SAR literature, which highlights the influence of polarimetric configuration and environmental factors on detection reliability [16–20]. By contrast, Radarsat-2 achieved the highest detection accuracy due to its fully polarimetric C-band capabilities [14], while TerraSAR-X and PAZ1 contributed fewer but higher-resolution acquisitions that proved valuable for targeted verification.

These findings confirm that no single SAR mission can meet the diverse operational requirements of large-scale marine pollution monitoring [5, 7, 18, 21]. A multi-sensor strategy, in which Sentinel-1 provides the baseline wide-area coverage and higher-precision missions such as Radarsat-2, TerraSAR-X and PAZ1 are used selectively for validation and detailed analysis, offers a more robust operational framework. Such an approach exploits the complementary strengths of different sensors, improving both detection coverage and reliability.

Environmental factors—including wind speed, sea state, and biogenic slicks—play a crucial role in shaping detection outcomes [4–6]. Integrating auxiliary datasets such as AIS vessel traffic information and meteorological data could support better contextual interpretation of SAR detections and reduce false positives [22]. These directions, together with advances in machine learning methods [23], offer promising pathways for enhancing the future performance of CleanSeaNet.

5. Conclusions

This study assessed the performance of four satellite missions—Sentinel-1, Radarsat-2, TerraSAR-X, and PAZ1—within the CleanSeaNet framework over a five-year period (2019–2023). By analysing temporal trends, detection categories, and satellite-specific confirmation rates, the research provides a clearer understanding of how different sensor technologies contribute to operational marine pollution monitoring.

The findings confirm that each satellite plays a distinct role. Sentinel-1 offers unmatched spatial and temporal coverage, making it the primary tool for wide-area surveillance, while Radarsat-2 delivers higher detection accuracy through its polarimetric capabilities. TerraSAR-X and PAZ1, though contributing fewer detections, provide high-resolution acquisitions that are particularly valuable for targeted verification. These complementary strengths demonstrate the need for a coordinated multi-sensor strategy to improve both detection coverage and reliability.

Looking ahead, future research should concentrate on three complementary directions. First, developing data fusion approaches that combine SAR with optical and thermal data may improve the discrimination between oil spills and natural phenomena under complex environmental conditions. Second, integrating near-real-time environmental information, such as wind fields and oceanographic data, could support adaptive detection algorithms that account for dynamic conditions. Third, the operational implementation of machine learning and deep learning methods on large historical datasets has the potential to improve classifier robustness, reduce operator workload, and enhance overall detection confidence.

Overall, the study successfully achieved its objective of assessing and comparing the performance of four satellite missions within the CleanSeaNet framework over a five-year period. By analysing temporal trends, detection categories, and satellite-specific confirmation rates, the research provides a clearer understanding of the respective roles and strengths of different SAR missions in operational marine pollution monitoring. These insights can support future improvements in satellite tasking and methodological approaches, contributing to the continued development of CleanSeaNet as a key operational service for protecting the marine environment.

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