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**ABORDAGEM BASEADA NA DETECÇÃO DE ANOMALIAS PARA
IDENTIFICAÇÃO DE DERRAMAMENTOS DE ÓLEO UTILIZANDO
SÉRIE DE IMAGENS SAR**

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DE DERRAMAMENTOS DE ÓLEO UTILIZANDO SÉRIE DE IMAGENS SAR**

Dissertação apresentada ao Programa de Pós-graduação do Instituto de Ciência e Tecnologia, Universidade Estadual Paulista (Unesp), Campus de São José dos Campos; Centro Nacional de Monitoramento e Alertas de Desastres Naturais (Cemaden), como requisito parcial para a obtenção do título de MESTRE.
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Orientador: Prof. Dr. Rogério Galante Negri

Coorientador: Prof.^a Dr.^a Tatiana Sussel Goncalves Mendes

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IMPACTO POTENCIAL DESTA PESQUISA

Esta pesquisa contribui diretamente para os Objetivos de Desenvolvimento Sustentável (ODS) ao melhorar a detecção de derramamentos de óleo, reforçando a preservação dos ecossistemas marinhos (ODS 14) e promovendo inovação tecnológica (ODS 9) com uso de sensoriamento remoto e aprendizado de máquina. Seus resultados apoiam políticas públicas de prevenção de desastres, fortalecendo a gestão ambiental e econômica, sobretudo no Brasil onde setores como pesca e turismo são economicamente sensíveis a desastres ambientais. A ferramenta desenvolvida tem capacidade de ser aplicada em escala global, fomentando o desenvolvimento sustentável, com impacto social e educacional significativo, capacitando futuras gerações a enfrentar desafios ambientais tão complexos como o aparecimento de manchas de óleo no mar.

POTENTIAL IMPACT OF THIS RESEARCH

This research directly contributes to the Sustainable Development Goals (SDGs) by improving oil spill detection, reinforcing the preservation of marine ecosystems (SDG 14), and promoting technological innovation (SDG 9) through the use of remote sensing and machine learning. Its results support disaster prevention policies, strengthening environmental and economic management, especially in Brazil, where sectors such as fishing and tourism are economically sensitive to environmental disasters. The developed tool has the potential for global application, fostering sustainable development with significant social and educational impact, empowering future generations to tackle complex environmental challenges, such as the appearance of oil slicks in the ocean.

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RESUMO

Os oceanos representam mais de 70% da superfície terrestre, são ricos em biodiversidade, contém vastas reservas de recursos naturais e minerais e são vitais para o transporte marítimo, bem como para a exploração de recursos. Dentre os produtos transportados e extraídos dessas águas, o petróleo representa um risco significativo quando mal manuseado, levando a uma poluição em grande escala devido a descargas ilegais ou acidentes envolvendo navios e plataformas de exploração. Diante disso, há uma crescente necessidade de soluções tecnológicas avançadas para identificar e monitorar tais desastres ambientais a fim de minimizar ou até mesmo prevenir a ocorrência destes eventos. Nesse contexto, a combinação de tecnologias de Sensoriamento Remoto com métodos de Aprendizado de Máquina demonstra ser uma combinação promissora para detectar anomalias em ambientes marinhos. Neste aspecto, esta pesquisa propõe uma abordagem baseada em uma variação do método SVM: o One-Class Support Vector Machine (OC-SVM) para a detecção de derramamentos de óleo no mar utilizando imagens de Radar de Abertura Sintética (SAR) do satélite Sentinel-1. Para testar e validar o método este trabalho apresenta um estudo de caso com experimentos realizados na região sul do Golfo do México, próximo às águas marítimas de Campeche, México, cujos resultados revelaram o potencial da abordagem proposta, alcançando níveis de precisão mais altos do que o processo de classificação tradicional.

Palavras-chave: OC-SVM; Derramamento de óleo; Sentinel-1; Google Earth Engine.

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ABSTRACT

The oceans represent more than 70% of the Earth's surface, are rich in biodiversity, contain vast reserves of natural and mineral resources, and are vital for maritime transport as well as resource exploration. Among the products transported and extracted from these waters, oil represents a significant risk when mishandled, leading to large-scale pollution due to illegal discharges or accidents involving ships and exploration platforms. In light of this, there is a growing need for advanced technological solutions to identify and monitor such environmental disasters to minimize or even prevent the occurrence of these events. In this context, the combination of Remote Sensing technologies with Machine Learning methods proves to be a promising approach for detecting anomalies in marine environments. In this regard, this research proposes an approach based on a variation of the SVM method: the One-Class Support Vector Machine (OC-SVM) for detecting oil spills at sea using Synthetic Aperture Radar (SAR) images from the Sentinel-1 satellite. To test and validate the method, this work presents a case study with experiments conducted in the southern region of the Gulf of Mexico, near the maritime waters of Campeche, Mexico, whose results revealed the potential of the proposed approach, achieving higher accuracy levels than the traditional classification process.

Keywords: OC-SVM; Oil Spill; Sentinel-1; Google Earth Engine

1 INTRODUÇÃO

Desastres naturais podem ser definidos como uma combinação de riscos naturais e vulnerabilidades que colocam em risco comunidades que são incapazes de suportar as adversidades deles decorrentes (BLAIKIE et al., 2014). Em 2023, *Emergency Events Database* (EM-DAT) (AL., 2024) registrou um total de 399 desastres relacionados a riscos naturais. Esses eventos resultaram em 86.473 fatalidades, superando a média de 20 anos de aproximadamente 367 eventos por anos com 64.148 mortes e o valor mediano de 19.290 mortes para o mesmo período. Este número de catástrofes registadas quintuplicou nos últimos 50 anos, impulsionado em parte pelas alterações climáticas induzidas pelo homem (DOURIS; KIM, 2021). Esses eventos são suficientes para motivar a realização de estudos e concentração de esforços para redução de risco (AALST, 2006)

Neste aspecto, os derramamentos de óleo no oceano representam um grave problema ambiental e econômico, causando danos significativos à vida marinha, à qualidade da água e às indústrias pesqueira e turística. Ao longo das décadas, ocorreram vários desastres envolvendo derramamentos os quais destacaram tamanha a vulnerabilidade dos ecossistemas marinhos quando expostos a este tipo de evento. Entre os incidentes mais notórios, destacam-se o derramamento do *Exxon Valdez* em 1989 (PAINE et al., 1996), que liberou aproximadamente 11 milhões de galões de petróleo no Alasca e o desastre da *Deepwater Horizon* em 2010 ((CRONE; TOLSTOY, 2010)), que resultou na liberação de cerca de 206 milhões de barris de petróleo no Golfo do México.

Mais recentemente, ocorreu no Brasil um derramamento de petróleo e óleo bruto que atingiu a costa brasileira e alcançou a faixa litorânea com uma extensão de 4.334 km em 11 estados do Nordeste e Sudeste, 120 municípios e 724 localidades até 22 de novembro de 2019 (IBAMA, 2019). O vazamento é considerado um dos maiores desastres ambientais do país, com incalculáveis impactos ambientais, econômicos e na saúde pública (RICHETTI; MILARÉ, 2021).

Sabendo disso, compreender e abordar estes impactos multifacetados é crucial para o desenvolvimento de medidas corretivas eficazes e para a mitigação das consequências de tais desastres ambientais nas regiões costeiras (SANTOS et al., 2022). Deste modo, busca-se cada vez mais artefatos e artifícios tecnológicos de modo a precaver e evitar este tipo de incidente. Dito isso, o Sensoriamento Remoto surge como uma ferramenta conveniente para observar e analisar a superfície da Terra, pois além de permitir registrar as informações em diferentes comprimentos de onda espectrais, os sensores remotos também permitem amplas análises espaciais e temporais (JENSEN, 2009). Em particular, o Radar de Abertura Sintética (*Synthetic Aperture Radar* - SAR) tem se mostrado altamente eficaz para a detecção e monitoramento de óleo na superfície do mar, por sua capacidade de observação diurna e noturna, pois trata-se de um sensor ativo que opera emitindo e recebendo impulsos (TONG et al., 2019; AL-RUZOUQ et al., 2020; CONCEIÇÃO et al., 2021), além da sua alta resolução e grande cobertura, o que atribui a este sensor uma

alta capacidade de observação. Nesta pesquisa o modo de imagem usado é o IW do sensor *Sentinel-1*, cujo o nível de processamento é o GRD e a aquisição da informação é realizada em três subfaixas com uma cobertura total de 250 km e uma resolução espacial de 5 x 20 m, a mais alta em comparação com outros modos (ESA, 2022).

Associado ao SAR, cada vez mais os algoritmos de Aprendizado de Máquina (*Machine Learning* - ML) têm se destacado como importantes atores no que se refere à detecção e monitoramento de manchas de óleo, pois apresentam resultados cada vez mais assertivos e auxiliam os responsáveis nas tomadas de decisões preventivas (HUANGET, 2022). Além disso, a extração de informações confiáveis das imagens SAR ganham celeridade quando estes dados são processados em plataformas em nuvem, como é o caso do *Google Earth Engine* (GEE) (CAPORUSSO; GALLO; TARANTINO, 2022), que permite aos usuários acessar, analisar e visualizar um vasto conjunto de dados geoespaciais.

Além disso, a velocidade e a eficiência na extração de informações confiáveis de imagens SAR são significativamente aprimoradas quando processadas em plataformas na nuvem, como o Google Earth Engine (GEE) (CAPORUSSO; GALLO; TARANTINO, 2022), que fornece aos usuários as ferramentas para acessar, analisar e visualizar uma vasta gama de dados geoespaciais em escala planetária. O funcionamento do GEE é baseado em três componentes principais: armazenamento de dados em nuvem, acesso aos dados e algoritmos de processamento. O catálogo de dados abriga um grande repositório de conjuntos de dados geoespaciais publicamente disponíveis, incluindo observações de uma variedade de sistemas de imagens aéreas e de satélite em comprimentos de onda ópticos e não ópticos, variáveis ambientais, previsões meteorológicas e climáticas e retrospectivas, cobertura da terra, topográficas e sócio- conjuntos de dados econômicos (GORELICK et al., 2017) Desta forma, a plataforma combina uma enorme base de dados associado a algoritmos de processamento de alta potência para fornecer uma plataforma abrangente de análise geoespacial. Tanto o acesso aos dados, quanto os processamento deles podem ser feitos na nuvem, assim como a importação/exportação de dados matriciais e vetoriais.

Neste contexto, a detecção de manchas de óleo em imagens de satélite é um campo de pesquisa que se beneficia significativamente das técnicas de ML. Métodos de aprendizado supervisionado, como Redes Neurais Convolucionais (CNN) (ZHANG et al., 2017) e *Support Vector Machines* (SVM) (XU et al., 2020), têm sido amplamente utilizados para a classificação e detecção de manchas de óleo. O SVM, em particular, apresenta algumas variantes da concepção original, dentre elas o *One Class SVM* (OC-SVM), o qual depende do problema de estimativa de quantis para detecção de anomalias, e pode ser utilizado para melhorar a precisão e eficiência de sistemas destinados a detectar contaminação de água em amostras de óleo (RADOGNA et al., 2023).

À luz das discussões apresentadas, este trabalho introduz uma abordagem automatizada baseada em ML para a detecção de derramamentos de óleo *offshore*. O método proposto utiliza SVM e OC-SVM como as principais técnicas de classificação, aplicados em todo o conjunto de

dados. Além disso, a abordagem incorpora um modelo de aprendizado por reforço para expandir o conjunto de treinamento de forma dinâmica, na forma de uma variante do OC-SVM. Esse processo começa com um conjunto de treinamento inicial, a partir do qual o classificador seleciona e adiciona as amostras mais relevantes à base de treinamento, atualizando continuamente o conjunto de referência para cada imagem. Como resultado, o classificador se torna cada vez mais preciso e eficaz na identificação de derramamentos de óleo.

A abordagem introduzida é validada por meio de um estudo de caso focado na região de Campeche, no México. Para este estudo, foram utilizadas imagens adquiridas pelo sensor SAR a bordo do satélite Sentinel-1 durante o período de abril a agosto de 2020. Os resultados alcançados demonstraram claramente a superioridade do método proposto em comparação com abordagens alternativas com um esquema de classificação semelhante, quando ao empregar um conjunto otimizado de atributos, o método proposto alcançou uma precisão de 94,5%, em contraste com o método original que alcançou uma precisão de apenas 80,4%.

Este documento está organizado da seguinte forma: no Capítulo 2 é apresentado o artigo *Study for oil spill detection using the OC-SVM method applied to Sentinel-1 radar images* e no Capítulo 3 são feitas as considerações finais acerca desta pesquisa.

2 ARTIGOS

2.1 *An anomaly detection-based approach for oil spill identification using Sentinel-1 SAR image series*

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An anomaly detection-based approach for oil spill identification using Sentinel-1 image series

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Abstract. Oceans, rich in biodiversity and vast reserves of natural and mineral resources, are vital for maritime transport and resource exploitation. Among the products transported and extracted from these waters, oil poses a significant risk when mishandled, leading to large-scale pollution from illegal discharges or accidents involving ships and exploration platforms. In light of this, there is an increasing need for advanced technological solutions to identify and monitor such environmental disasters, thereby minimizing negative impacts due to their occurrence. In this context, the combination of Remote Sensing technologies and Machine Learning methods holds great promise for detecting anomalies in marine environments. This research proposes an approach based on the One-Class Support Vector Machine (OC-SVM) method for detecting oil spills at sea, utilizing Synthetic Aperture Radar (SAR) images from the Sentinel-1 satellite. As a case study, experiments carried out in the southern region of the Gulf of Mexico, near the maritime waters of Campeche, Mexico, revealed the potential of the proposed approach, achieving higher (F1-Score of 0.945) accuracy levels than the traditional classification process based on SVM.

Keywords: OC-SVM; Oil Spill; Sentinel-1; Google Earth Engine.

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1 Introduction

Natural disasters are defined as the intersection of natural hazards and vulnerabilities that threaten communities unable to withstand the resulting adversities.¹ In 2023, *Emergency Events Database* (EM-DAT)² recorded a total of 399 disasters related to natural hazards. These events resulted in 86,473 fatalities, exceeding the 20-year average of approximately 367 events per year with 64,148 fatalities and the median value of 19,290 fatalities for the same period. Besides, the number of recorded catastrophes having increased fivefold over the past 50 years, partly due to human-induced climate change.³

Among these disasters, oil spills in the ocean represent a severe environmental and economic threat, causing significant harm to marine life, water quality, and the fishing and tourism industries. Over the past decades, several oil spill disasters have underscored the vulnerability of marine ecosystems to such events. Notable incidents include the Exxon Valdez spill in 1989,⁴ which released approximately 11 million gallons of oil in Alaska, and the Deepwater Horizon disaster in 2010,⁵ which resulted in the discharge of about 4.9 million barrels of oil into the Gulf of Mexico.

More recently, Brazil experienced an oil spill that affected its coastline, impacting a stretch of 4334 km across 11 states in the Northeast and Southeast, encompassing 120 municipalities and 724 localities by November 22, 2019.⁶ This spill is considered one of the largest environmental disasters in the country, with significant environmental, economic, and public health impacts.⁷

Given these considerations, understanding and addressing these multifaceted impacts is essential for developing effective mitigation strategies and corrective measures for environmental disasters in coastal regions.⁸ As a result, there is a growing emphasis on the use of technological tools and strategies to monitor and mitigate such incidents.

In this context, Remote Sensing stands out as a powerful tool for observing and analyzing the Earth's surface. In addition to recording information across different spectral wavelengths, remote sensors facilitate extensive spatial and temporal analyses.⁹ Specifically, Synthetic Aperture Radar (SAR) has proven highly effective in detecting and monitoring oil spills on the sea surface due to its ability to provide day and night observations. As an active sensor that operates by emitting and receiving pulses, SAR offers high resolution and wide coverage, making it a valuable tool for comprehensive monitoring.^{10–12}

In conjunction with SAR, Machine Learning (ML) algorithms have increasingly become key players in oil spill detection and monitoring, offering enhanced accuracy and aiding decision-

makers in implementing preventive measures.¹³ Moreover, the speed and efficiency of extracting reliable information from SAR images are significantly improved when processed on cloud platforms such as Google Earth Engine (GEE),¹⁴ which provides users with the tools to access, analyze, and visualize a vast array of geospatial data.

The detection of oil spills using satellite images is a research field that greatly benefits from ML techniques. Supervised learning methods, such as Convolutional Neural Networks (CNN)¹⁵ and Support Vector Machines (SVM),¹⁶ have been widely employed for the classification and detection of oil spills. The SVM, particularly, includes variants like the One-Class SVM (OC-SVM), which is utilized for anomaly detection by addressing the quantile estimation problem. This approach can enhance the accuracy and efficiency of systems designed to detect water contamination in oil samples.¹⁷

In light of the discussions presented, this work introduces an automated ML-based approach for detecting offshore oil spills. The proposed method utilizes SVM and OC-SVM as the primary classification techniques, with the OC-SVM applied across the entire dataset. Additionally, the approach incorporates a reinforcement learning model to expand the training set dynamically. This process begins with an initial training set, from which the classifier selects and adds the most relevant samples to the training base, continuously updating the reference set for each image. As a result, the classifier becomes increasingly accurate and effective in identifying oil spills.

The introduced approach is validated through a case study focused on the Campeche region in Mexico. For this study, images acquired by the SAR sensor onboard the Sentinel-1 satellite during the period from April to August 2020 were utilized.

This paper is organized as follows: Section 2 introduces the basic notations, the ML model, the SAR image processing, and the radiometric indices. The proposed approach is outlined in

Section 3. Section 4 provides details about the study area and datasets, experimental design and the results achieved. Finally, Section 5 discusses the main findings and conclusions of this research.

2 Theoretical Aspects and Background

2.1 Preliminary notations

Let $\mathcal{I}$ represent the matrix of an image obtained through Remote Sensing. Each position within $\mathcal{I}$ corresponds to a pixel s , which is defined over a regular grid $\mathcal{S} \subset \mathbb{N}^2$. A pixel s is associated with a specific geographic location. The measurement captured by the remote sensor at each pixel is denoted by the vector $\mathbf{x} \in \mathcal{X}$, where $\mathcal{X}$ is the data attribute space. Thus, $\mathcal{I}(s) = \mathbf{x}$ indicates that the characteristics of $\mathcal{I}$ at position s are described by the components of a d -dimensional vector $\mathbf{x} = [x_1, x_2, \dots, x_d]$.

In various applications that utilize satellite images, distinguishing between different targets on the Earth's surface is a common and essential task. To achieve this, classification techniques are employed. The classification process involves applying a function $F: \mathcal{X} \rightarrow \mathcal{Y}$ to the attribute vector $\mathbf{x}$ of each pixel $s \in \mathcal{S}$, thereby associating it with a class label $y \in \mathcal{Y} = \{1, \dots, c\}$. We denote the classification $\mathcal{C}$ as the result of applying F to each position s of $\mathcal{I}$.

The numerous image classification techniques proposed in the literature offer different approaches to modeling the function F . Examples of such techniques include the SVM¹⁸ and the OC-SVM.¹⁹

2.2 Support Vector Machine

Among the various techniques in the field of ML, the SVM is particularly popular in Remote Sensing applications. This popularity is due to its robust mathematical foundation, straightforward

99 algorithmic structure, and high generalizability.²⁰

100 In essence, SVM works by identifying a binary separating hyperplane between training sam-
 101 ples that maximizes the margin between two classes. Formally, given the training set $\mathcal{D} =$
 102 $\{(\mathbf{x}_i, y_i) \in \mathcal{X} \times \mathcal{Y} : i = 1, \dots, m\}$, with $\mathcal{Y} = \{-1, +1\}$ expressing class-indicators, the separat-
 103 ing hyperplane corresponds to the geometric location where the following linear function equals
 104 zero:

$$F(\mathbf{x}) = \langle \mathbf{w}, \mathbf{x} \rangle + b, \quad (1)$$

105 where $\mathbf{w}$ represents the orthogonal vector to the hyperplane $F(\mathbf{x}) = 0$, $b/\|\mathbf{w}\|$ is the distance from
 106 the hyperplane to the origin, and $\|\mathbf{w}\|$ is the Euclidean norm of $\mathbf{w}$. The parameters of Eq. (1) are
 107 obtained by solving the following optimization problem:²¹

$$\begin{aligned} \min_{\lambda} \quad & \sum_{i=1}^m \lambda_i - \frac{1}{2} \sum_{i=1}^m \sum_{j=1}^m \lambda_i \lambda_j y_i y_j \langle \mathbf{x}_i, \mathbf{x}_j \rangle \\ \text{subject to:} \quad & \begin{cases} 0 \leq \lambda_i \leq C, i = 1, \dots, m \\ \sum_{i=1}^m \lambda_i y_i = 0. \end{cases} \end{aligned} \quad (2)$$

108 where λ are Lagrangian multipliers upper bounded by C , a real parameter that acts as a penalty for
 109 misclassifications.

110 Consequently, based on the support vectors set SV , which stands for the samples $\mathbf{x}_i$ such that
 111 $\lambda_i \neq 0$, are computed $\mathbf{w} = \sum_{\forall \mathbf{x}_i \in SV} y_i \lambda_i \mathbf{x}_i$ and $b = \frac{1}{\#SV} \left(\sum_{\mathbf{x}_i \in SV} y_i + \sum_{\mathbf{x}_i \in SV} \sum_{\mathbf{x}_j \in SV} \lambda_i \lambda_j y_i y_j \langle \mathbf{x}_i, \mathbf{x}_j \rangle \right)$.
 112 Once computed such parameters, for a given $\mathbf{x}$, it is assigned to the class “+1” whether $F(\mathbf{x}) \geq 0$,
 113 otherwise, it is assigned to the class “-1”.

114 An essential characteristic of kernel-machines like SVM is the possibility of using kernel
 115 function. By using such artifact, which stands for substituting the inner product (i.e., $\langle \cdot, \cdot \rangle$) in

116 Eqs. (1) and (2) by $K(\cdot, \cdot)$. A typical example of kernel function is the radial basis function (RBF)
 117 $K(\mathbf{x}_i, \mathbf{x}_j) = e^{-\psi \|\mathbf{x}_i - \mathbf{x}_j\|^2}$, with $\psi \in \mathbb{R}_+$. Further details on kernel functions are discussed in
 118 Shawe-Taylor et al.²²

119 2.3 One-Class Support Vector Machine

120 From the original conception of the SVM method, several variants have been proposed, includ-
 121 ing the OC-SVM,²³ which is specifically designed for quantile estimation and anomaly detection.
 122 Conceptually, starting from a set of observations $\mathcal{Z} \subset \mathcal{X}$, the OC-SVM method provides a model
 123 capable of classifying the objects as part of a set of non-anomalous elements according to a prob-
 124 ability ν of false-positive occurrence.

125 Formally, we may express the function $F: \mathcal{X} \rightarrow \{+1, -1\}$, where the output $+1$ implies that
 126 the data input is in $\mathcal{Z}$, and -1 otherwise. The decision function F is given by:

$$F(\mathbf{x}) = \text{sgn} \left(\sum_{i=1}^n \alpha_i K(\mathbf{x}, \mathbf{x}_i) - b \right) \quad (3)$$

127 where $b = \sum_{j=1}^n \alpha_j K(\mathbf{x}_i, \mathbf{x}_j)$ to some $\mathbf{x}_i \in \mathcal{Z}$, and $K(\cdot, \cdot)$ stands for a kernel function. The
 128 coefficients α_i , with $i = 1, \dots, n$, are obtained by solving the following optimization problem:

$$\begin{aligned} & \min_{\alpha} \sum_{i,j=1}^n \alpha_i \alpha_j K(\mathbf{x}_i, \mathbf{x}_j) \\ & \text{subject to: } \begin{cases} \alpha_i \in [0, \frac{1}{\nu n}] \\ \sum_{i=1}^n \alpha_i = 1 \end{cases} \end{aligned} \quad (4)$$

129 It is worth noting that the OC-SVM is parameterized by $\nu \in [0, 1]$ and other parameters related
 130 to the adopted kernel function.

Additionally, this learning model can also operate based on a reinforcement scheme. Suppose an image series $\mathcal{I}^{(\ell)}$, with $\ell = 1, \dots, T$ representing images acquired at distinct time instants. Starting with an initial training set $\mathcal{D}^{(1)}$, the classifier $F^{(1)}$ is trained and then applied to classify the first image $\mathcal{I}^{(1)}$. In this process, highly reliable classified samples/examples (i.e., $\mathbf{x}$ vectors with high values for $|F(\mathbf{x})|$) in the output map $\mathcal{C}^{(1)}$ are selected and added to the training base, resulting in the updated training set $\mathcal{D}^{(2)}$. This process is iteratively repeated for each image $\mathcal{I}^{(\ell)}$, with $\ell = 1, \dots, T$, leading to progressively more adapted and reliable classifiers. Further details on how this process is employed in the proposed approach are discussed in Section 3.

2.4 SAR data pre-processing for oil-spill detection

A key element in marine remote sensing using SAR is the observation of backscattering resulting from the interaction between microwaves and short-gravity capillary waves on the sea surface. The recorded backscattered signal is described by the coefficient σ^0 (sigma zero), which represents the normalized Radar cross-section.²⁴ However, beyond the σ^0 values, which represent the backscatter per unit area in the ground range, the signal can also be described using γ^0 (gamma zero), which expresses the backscatter per unit area perpendicular to the line of sight.²⁵ The geometric relationship between σ^0 and γ^0 is given by $\gamma^0 = \sigma^0 \cos \theta$, where θ is the local incidence angle.

Recent studies suggest that “polarization indices” can offer better support for research involving ML models applied to SAR data.^{26,27} Table 1 presents examples of polarization indices derived from dual-polarized SAR data. The “Polarized Ratio” ($VHrVV$) was effective in separating open water from deep or shallow marsh areas²⁸ and reducing systematic errors associated with acquisition systems.²⁹ The “Normalized Difference Polarized Index” ($NDPI$) was adopted for analyzing forest degradation.^{30,31} The “Normalized VH and VV Indices” ($NVHI$ and $NVVI$) were adapted

from the “Radar vegetation index”, to reflect the level of vegetation growth.^{32,33}

In addition to these indices, Afgatiani et al.³⁴ show that other indices from VV and VH backscatters (i.e., no transformation needed) favor oil spill detection. Such alternative indices comprises the mean (i.e., $\frac{VH+VV}{2}$), product (i.e., $VH \cdot VV$), division (i.e., VV/VH) and difference between VV and VH (i.e., $VV - VH$).

Table 1 Polarized indices for dual-polarized SAR data. γ_{VH}^0 and γ_{VV}^0 stand for the γ_{VH}^0 computed for VH and VV polarization backscatters, respectively.

Index	Expression	References
Polarized Ratio (VH to VV)	$VHrVV = \frac{\gamma_{VH}^0}{\gamma_{VV}^0}$	Brisco et al. ²⁸
Normalized Difference Polarized Index	$NDPI = \frac{\gamma_{VV}^0 - \gamma_{VH}^0}{\gamma_{VV}^0 + \gamma_{VH}^0}$	Mitchard et al. ³⁰
Normalized VH Index	$NVHI = \frac{\gamma_{VH}^0}{\gamma_{VV}^0 + \gamma_{VH}^0}$	McNairn & Brisco ³²
Normalized VV Index	$NVVI = \frac{\gamma_{VV}^0}{\gamma_{VV}^0 + \gamma_{VH}^0}$	McNairn & Brisco ³²
Polarization Mean	$Mean = \frac{VH+VV}{2}$	Afgatiani et al. ³⁴
Polarization Product	$Prod = VH \cdot VV$	Afgatiani et al. ³⁴
Polarization Division	$Div = VV/VH$	Afgatiani et al. ³⁴
Polarization Difference	$Diff = VV - VH$	Afgatiani et al. ³⁴

In addition to backscatter-derived indices, speckle filtering is a crucial component of SAR image pre-processing. Among the various methods available in the literature,^{35–38} the Sigma Lee filter³⁹ stands out as a promising and practical option for processing SAR image series. For this study, we employed the implementation of this filtering process with a 7×7 kernel size, as proposed by Mullissa et al.⁴⁰

3 Proposed approach for oil spill detection

Figure 1 provides an overview of the proposed approach for oil spill detection. A detailed discussion of this approach is presented below.

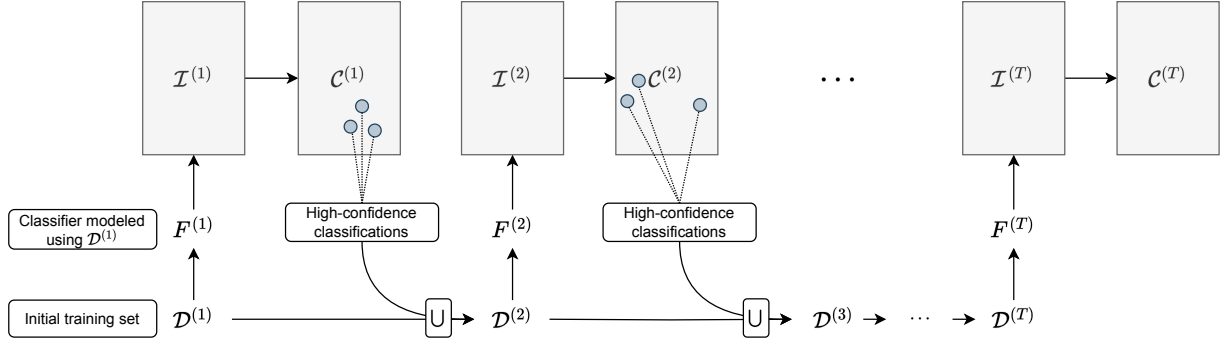


Fig 1 Flowchart of the proposed method for oil spill detection.

Suppose an image series $\mathcal{I}^{(1)}, \dots, \mathcal{I}^{(T)}$, representing a region affected by oil spills over the analyzed period, and a training set $\mathcal{D}^{(1)}$ containing examples of both oil spills and water. Using $\mathcal{D}^{(1)}$ to train a classifier $F^{(1)}$, its application to $\mathcal{I}^{(1)}$ generates a water-oil classification map $\mathcal{C}^{(1)}$. By selecting the highly reliable classified elements and adding them to $\mathcal{D}^{(1)}$, the training set is expanded to form $\mathcal{D}^{(2)}$. This expanded training set is then used to train a second classifier $F^{(2)}$, which, when applied to $\mathcal{I}^{(2)}$, produces a new water-oil classification map $\mathcal{C}^{(2)}$. This process is repeated iteratively for each image $\mathcal{I}^{(\ell)}$, with $\ell = 1, \dots, T$, leading to progressively refined classifiers and corresponding water-oil classification maps. Moreover, it is also important to note that the classification maps $\mathcal{C}^{(1)}, \dots, \mathcal{C}^{(T)}$ can be analyzed either separately or jointly. It is worth highlighting that as the training set expands over time, approaching $\ell \rightarrow T$, the resulting classifier $\mathcal{D}^{(\ell)}$ is expected to yield more accurate classifications for the corresponding $\mathcal{C}^{(\ell)}$.

Concerning the classification models $F^{(\ell)}$, the OC-SVM method is adopted. This choice is reasonable considering the method's robustness and suitability for binary classification problems where the primary focus is on a particular class (e.g., oil). Additionally, the OC-SVM offers a convenient way to identify high-confidence classifications of inliers and outliers, with $F^{(\ell)}(\mathbf{x})$ tending towards large positive and negative values, respectively. Furthermore, to ensure spatial consistency, high-confidence classification examples are restricted to cases where all the neighboring pixels in

a 3×3 neighborhood are assigned to the same class. Conversely, classifications near the separation hyperplane, where $|F^{(\ell)}(\mathbf{x})| < 1/d$ with d representing the attribute space dimension, indicate less confident classifications.

Based on the formalization described above, the proposed approach is referred to as “Incremental Oil Classification with OC-SVM” (InOC2-SVM). This approach was implemented using the Google Earth Engine platform.⁴¹ Further details regarding code availability can be found in the *Data, Materials, and Code Availability* section.

4 Experiment and results

The effectiveness of the approach proposed in Section 3 is demonstrated throughout a study case carried out along this section. Details regarding the study area and data are presented in Sections 4.1 and 4.2. The experimental design is discussed in Section 4.3, followed by results and discussions in Section 4.4.

4.1 Study area

The study area for this research is situated within the Gulf of Mexico (Figure 2), a smaller part of the Atlantic Ocean and the ninth largest body of water in the world. The Gulf is located between North and Central America, covering approximately 1.6 million km^2 . It spans roughly 1600 km from east to west and 900 km from north to south, with a geological composition primarily consisting of sedimentary rocks and debris. The Gulf’s deepest point reaches 4384 m in the Sigsbee Deep.

The specific study area lies within the maritime waters of the Mexican state of Campeche, characterized by a tropical climate with more rainfall during the summer than in winter. According to

the Köppen-Geiger classification, Campeche has a tropical savanna climate (Aw), with an average temperature of 26.9 °C and an annual average rainfall of 854 mm.⁴²

The local economy is driven by several sectors, including fishing, agriculture, tourism, maritime transport, and mineral exploration. Among these, oil extraction from the surrounding waters stands out as the region’s primary and most influential activity.⁴³ This significant focus on oil extraction often results in the presence of oil slicks on the ocean surface, stemming from both natural and anthropogenic causes.⁴⁴

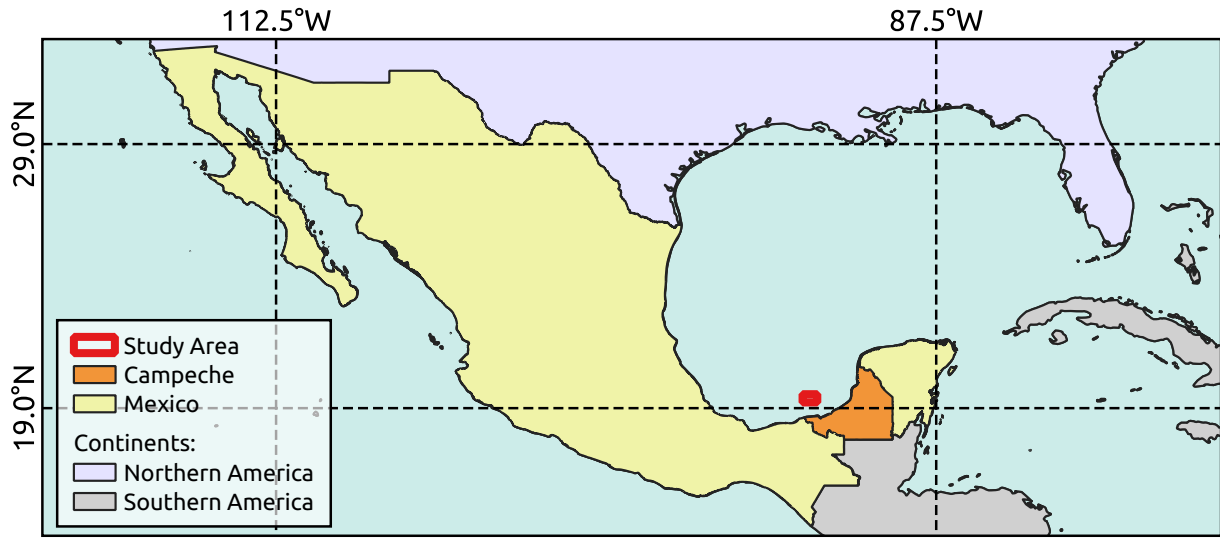
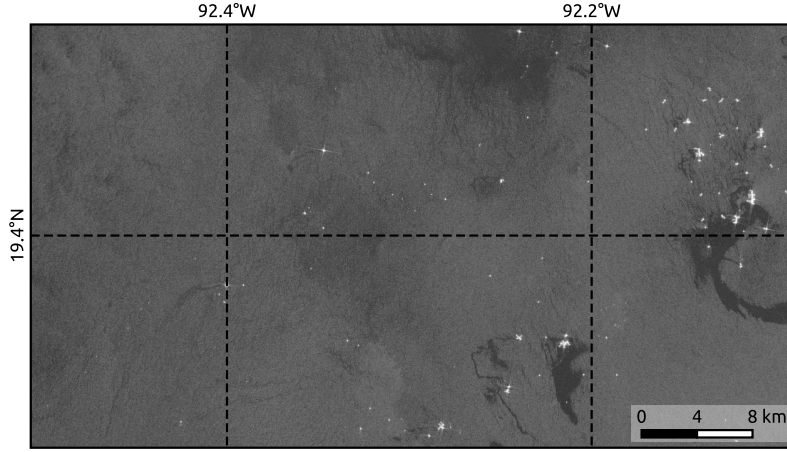


Fig 2 Study area location.

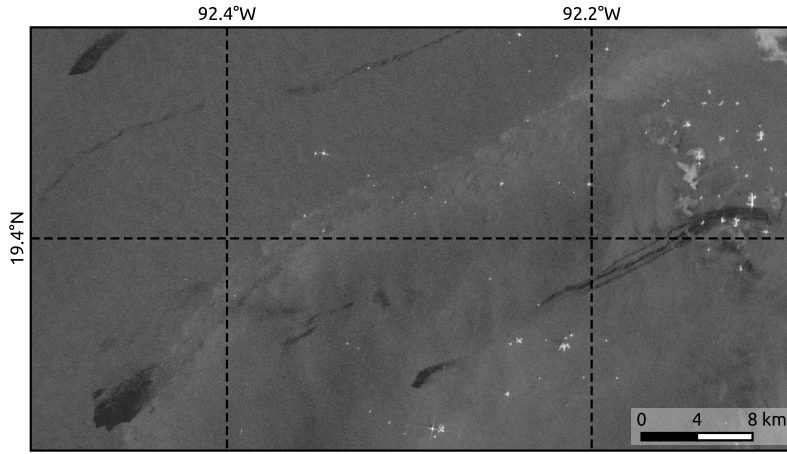
4.2 Dataset

The dataset used in these experiments consists of a series of SAR images acquired by the Sentinel-1 satellite, along with a set of water-oil reference examples corresponding to the first instance of the image series. The image series spans the period between April 25th and August 23rd 2020. Figure 3 presents the initial and final instants of the considered image series.

An initial training set with 409 validated oil samples was compiled from the reference examples, specifically observed at the first instance of the image series, dated April 25th, 2020. These



(a) April 25th 2020.



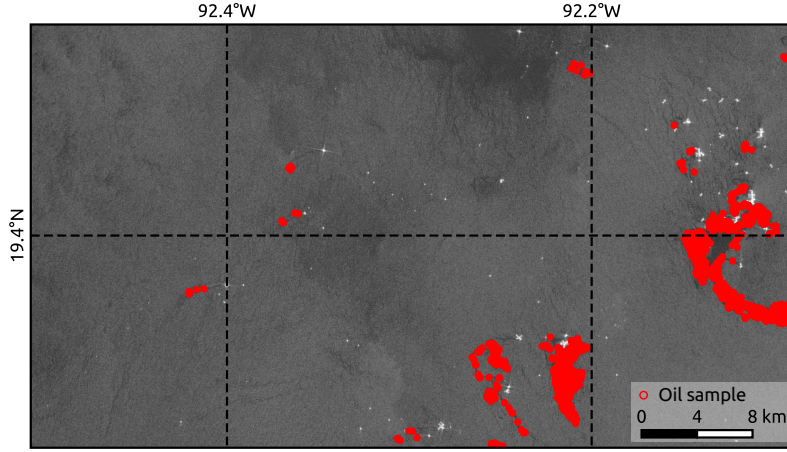
(b) August 23rd 2020.

Fig 3 Initial and final instants of the SAR image series considered in VV polarization.

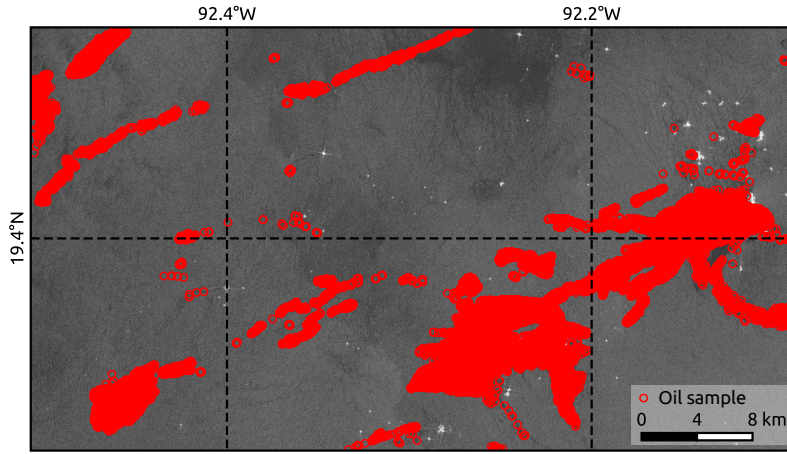
218 samples, employed to train the proposed approach (InOC2-SVM), were collected with the under-
 219 standing that oil spills typically appear as dark, homogeneous areas in SAR images and exhibit a
 220 distinct texture compared to their surroundings. Figure 4(a) illustrates the aforementioned example
 221 dataset.

222 Additionally, a comprehensive set of reference samples spanning the entire analysis period
 223 was compiled to train the SVM (binary approach – water and oil classes) and OC-SVM (single-
 224 class approach – oil class only). Figure 4(b) presents the described training set with respect to oil
 225 samples. Finally, a test set expressing the oil spills occurrence in the last instant of the image series

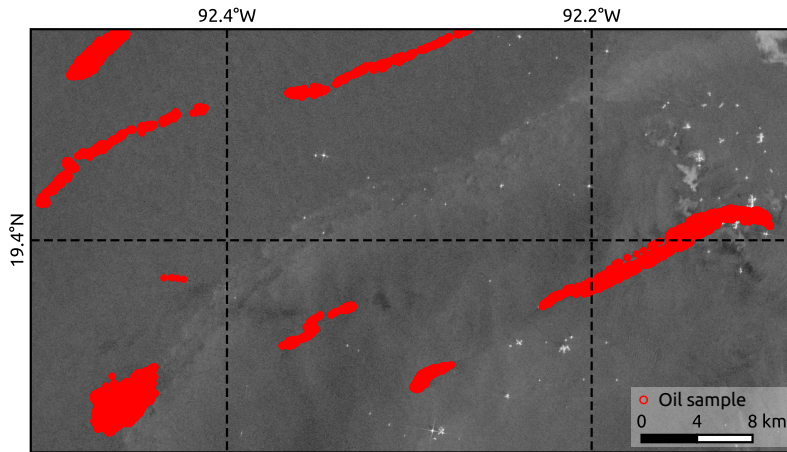
²²⁶ (August 23rd 2020) is depicted in Figure 4(c).



(a) Initial training set.



(b) Complete period examples.



(c) Test samples.

Fig 4 Oil reference samples with a VV polarization background image from April 25th, 2020 in (a) and (b), and from August 23rd, 2020 in (c). Water samples, being complementary to oil occurrences, were omitted to enhance visualization.

4.3 Experimental design

The following details comprises the experiment design considered to assess and verify the effectiveness of the proposed approach. Such details comprises: (i) the considered data attributes; (ii) baseline methods; (iii) hyperparameter tuning process; and (iv) the adopted accuracy measures.

Regarding the attributes, it was considered for distinct set that combines original and polarization indices. More precisely, “Set 1” stands for the attribute set $\{\gamma_{VV}^0, \gamma_{VH}^0\}$; “Set 2” for $\{\gamma_{VV}^0, \gamma_{VH}^0, NDPI, NVHI, NVVI, V HrVV\}$; “Set 3” for $\{Mean, Prod, Dif\}$; and “Set 4” for $\{Div, Prod, Dif\}$.

To enable comparisons with alternative approaches, the original versions of SVM and OC-SVM were used as baseline methods. The SVM was trained using an extensive dataset containing oil-water examples observed throughout the entire image series, excluding the last instance (i.e., the image acquired on August 23rd, 2020), which was then classified to produce a map of oil occurrence. Similarly, the OC-SVM was trained using the same dataset but limited only to oil examples. A map of oil occurrence was then generated by applying this model to the last instance of the image series.

The Grid-Search⁴⁵ process with 10-fold cross-validation process was adopted for automatic tuning of the SVM and OC-SVM hyperparameters. Concerning the SVM, the space-search for the penalty and the RBF kernel parameters were $C = \{10^{-2}, 10^{-1}, 1, 10, 100\}$ and $\psi = \{10^{-4}, 10^{-3}, 10^{-2}, 10^{-1}, 1/d, 1\}$, respectively. For OC-SVM, was considered $\nu = \{0.005, 0.05, 0.1\}$ and the same set of ψ adopted for the SVM. The accuracy of the results were measured in terms of F1-Score.⁴⁶

4.4 Results and discussions

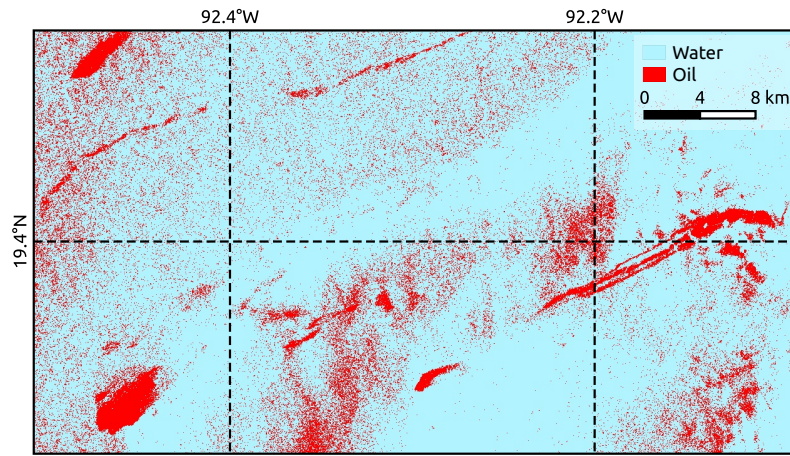
According to the experimental details presented in Section 4.3, a series of results were obtained by the proposed and alternative methods for mapping oil spills in the study area over the analyzed period. Table 2 presents the F1-Score values recorded for each result. Additionally, the best classifications from each method are shown in Figure 5.

Table 2 Summary of F1-Score values, obtained from the experiments. Highlighted values represent the highest results per attribute set

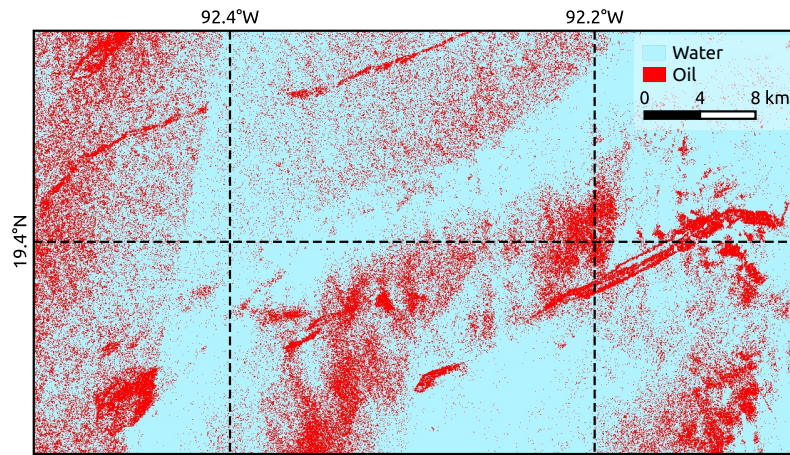
	Attributes			
	Set 1	Set 2	Set 3	Set 4
SVM	0.729	0.765	0.804	0.780
OC-SVM	0.929	0.909	0.928	0.930
InOC2-SVM	0.923	0.930	0.945	0.945

Initially, when evaluating the input datasets, higher accuracy values were achieved using the non-transformed data (i.e., Sets 3 and 4). These findings align with those reported by Afgatiani et al.³⁴

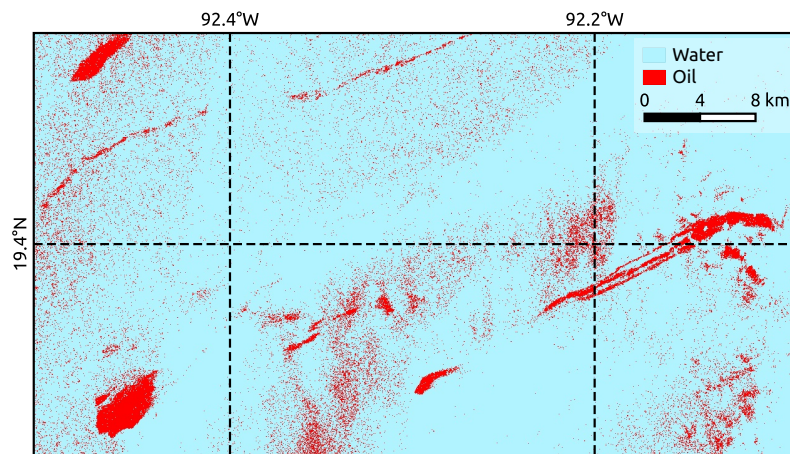
The results obtained from the application of the proposed method demonstrated a significant improvement in detecting oil slicks in the ocean compared to traditional methods. Specifically, the proposed approach achieved a detection accuracy of 0.945 when using attribute Sets 3 and 4, surpassing the SVM method, from which the InOC2-SVM was derived. The best F1-Score recorded for the SVM in this study was 0.804, using attribute Set 3. This substantial increase in accuracy is highly relevant, as it enables more precise identification, ranging from small oil concentrations (seepage slicks), which are often overlooked by traditional algorithms, to large spills. Qualitatively, the SVM method tended to produce less regularized (i.e., noisier) maps compared to InOC2-SVM (see Figs. 5(a) and 5(b)). On the other hand, the OC-SVM method achieved F1-Score values close to the proposed method when considering attribute Set 4. However, the OC-SVM method



(a) SVM (Set 3, $C = 10^{-2}$, $\psi = 4.10^{-1}$). F1-Score = 0.804



(b) OC-SVM (Set 3, $\nu = 10^{-1}$, $\psi = 10^{-4}$). F1-Score = 0.930.



(c) InOC2-SVM (Set 3, $C = 10^{-1}$, $\psi = 10^{-3}$). F1-Score = 0.945.

Fig 5 Best classifications achieved by each analyzed method.

frequently misclassified oil detections (Fig. 5(b)).

Figure 6 illustrates the True/False Positive/Negative rates for the oil-water maps presented in Figure 5. From these rates, it is evident that the proposed model achieves a high True Negative detection rate, which reflects its superior ability to accurately identify water regions. Although the OC-SVM method demonstrates higher True Positive rates (i.e., better ability to detect oil) compared to InOC2-SVM, this elevated rate is a side effect of OC-SVM, resulting from its tendency to overestimate the presence of oil, as can be seen in Figure 5(b). The highest false detection rates are observed in the results produced by the SVM method.

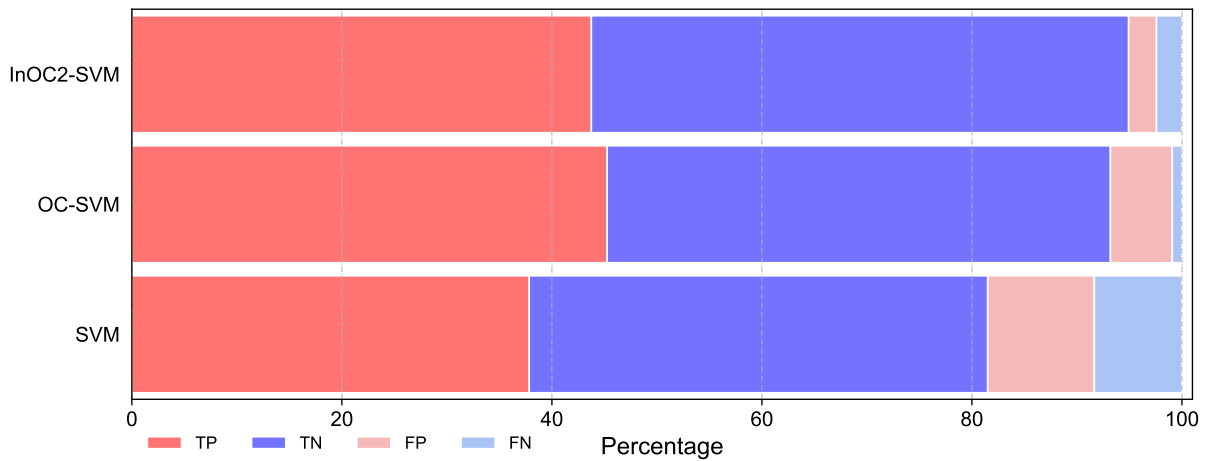


Fig 6 True Positive (TP), True Negative (TN), False Positive (FP) and False Negative (FN) rates related to the best results of each analyzed method.

In summary, the InOC2-SVM model demonstrated a reduction in False Positive rates by approximately 74% compared to the SVM method and 55% compared to the OC-SVM method, thereby minimizing unnecessary alerts and optimizing resources allocated for on-site verification. This improved efficiency clearly shows that the proposed model not only enhances detection capabilities but also contributes to a more effective response in the event of an oil spill.

5 Conclusions

This work proposed a novel approach for detecting and mapping oil spills in offshore regions. The approach involves an incremental classification scheme of a series of SAR images, where an initial set of examples is progressively expanded with high-confidence classified samples. This iterative process culminates in a robust and accurate oil-water classification map by the final instant of the analyzed image series.

To demonstrate the effectiveness of the proposed approach, an experiment was conducted using Sentinel-1 images acquired between April 25th and August 23rd, 2020, over a region in the Gulf of Mexico. The results clearly demonstrate the superiority of the proposed method compared to alternative approaches with a similar classification scheme. In summary, by employing a convenient set of attributes, the proposed method achieved an F1-Score value of 0.945. In contrast, the original alternative method achieved an value of 0.804.

Concerning future perspectives for this research, it should explore the inclusion of additional attributes and their respective combinations, a more refined exploration of the types of preprocessing of the image data, since these parameters shown a strong influence on the results achieved. In addition, performing these tests in other wavelengths besides the C-band, extending the proposed approach to other classification models and conducting additional analyses in different regions can also offer a great contribution to a better classification of the images.

Disclosures

The authors declare that they have no conflict of interest.

Code and Data Availability

Data are available from the authors upon request at j.silva-junior@unesp.br. Code are available at <https://github.com/.../InCO2SVM/>. (available after accepted for publishing)

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3 CONSIDERAÇÕES FINAIS

A exploração e o transporte de óleo *offshore* são atividades essenciais para a economia global, mas também apresentam riscos significativos para o meio ambiente marinho. Surgimentos e derramamentos de óleo podem ter impactos devastadores sobre os ecossistemas, afetando a fauna, a flora e as comunidades costeiras. Neste contexto, a detecção precoce e o monitoramento eficiente de manchas de óleo são cruciais para mitigar os efeitos adversos desses incidentes.

Diante disso, este trabalho propôs uma nova abordagem para a detecção e mapeamento de derramamentos de óleo em regiões *offshore*. A abordagem envolve a classificação incremental de uma série de imagens SAR, onde um conjunto inicial de exemplos é progressivamente expandido com amostras classificadas com alta confiança. Este processo iterativo culmina em um mapa robusto e preciso de classificação óleo-água no instante final da série de imagens analisada. A abordagem proposta é derivada da concepção original do SVM e é referenciada neste artigo como InOC2-SVM (*Incremental Oil Classification with OC-SVM*).

Para demonstrar a eficácia da abordagem proposta, foi realizado um experimento utilizando imagens do Sentinel-1 adquiridas entre 25 de abril e 23 de agosto de 2020, em uma região do Golfo do México. Os resultados corroboraram com a hipótese inicial de que o InOC2-SVM demonstra um desempenho superior e é uma ferramenta promissora para a prevenção de desastres ambientais ao evidenciar a superioridade do método proposto em comparação com abordagens alternativas com um esquema de classificação semelhante. Em resumo, empregando um conjunto otimizado de atributos, o método proposto alcançou um valor *F1-score* de 94,5%. Em contraste, o método original alcançou um valor de apenas 80,4% medido também pelo *F1-score*.

Dito isto, os resultados apresentados mostraram que, ao treinar o modelo apenas com dados da classe óleo e reforçando os dados amostrais, o classificador pode identificar de forma eficiente padrões que se desviam do normal, distinguindo de forma precisa entre óleo e outros alvos (água marítima, plataformas, costa etc.). Desta forma, combinação de técnicas avançadas de aprendizado de máquina com dados de alta resolução do Sentinel-1, aliado à uma ferramenta poderosa para observação e análise da superfície terrestre como o *Google Earth Engine* oferece uma solução eficaz para a detecção precoce e o monitoramento de manchas de óleo, contribuindo não apenas para a precisão da detecção, mas também para a proteção dos ecossistemas marinhos e a mitigação de desastres ambientais.

Por fim, os resultados alcançados neste trabalho abrem caminho para futuras pesquisas, quando se pode ainda explorar a inclusão de atributos adicionais e suas respectivas combinações, uma exploração mais refinada dos tipos de pré-processamento dos dados de imagem, visto que esses parâmetros mostraram ter grande influência nos resultados alcançados. Além disso, realizar esses testes em outras bandas de frequência além da banda C, estender a abordagem proposta a outros modelos de classificação e conduzir análises adicionais em diferentes regiões também podem oferecer uma grande contribuição para uma melhor classificação das imagens.

Em suma, entende-se que a adoção e exploração deste método em sistemas de monitoramento oceânico poderia representar um avanço substancial na proteção dos ecossistemas marinhos, oferecendo uma solução mais robusta e confiável para a detecção precoce de manchas de óleo, minimizando assim os desafios ambientais associados à exploração e ao transporte de óleo *offshore*, promovendo a sustentabilidade e a proteção dos oceanos.

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