MINDORO OIL SPILL PROGRESS MONITORING USING SATELLITE IMAGERY

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ABSTRACT:

Oil spills in the sea pose a significant threat to marine and coastal ecosystems including corals, sea grasses, and mangroves. Responding to oil spills in the high seas can be challenging and costly, as it is difficult to survey the area using ships or planes. Timely monitoring of extents and direction of drift is costly especially when large area is involved. This study used satellite imagery to monitor the progression of an oil spill in a timely manner. Images captured by various types of sensors was used to provide an almost daily oil extent map. Combining opensource satellite imagery, contributed imagery by commercial providers, and imagery from various national space agencies enabled situational awareness during the oil spill incident. Optical and SAR images were processed by using unsupervised K-means classification, for images that undergone image segmentation, and supervised support vector machine classification. The process was used to produce 46 oil extent maps from 196 satellite images from various sources through Sentinel Asia and The International Charter Space and Major Disasters.

1. INTRODUCTION

Oil spill has profound and enduring environmental consequences, affecting the economies, human health, and living organisms in very delicate parts of marine and terrestrial environments. Oil disrupts the marine food chain by depleting and diminishing the amount of microscopic phytoplankton, the ocean's primary producer (Jha et al., 2008). It also affects the ability of larger aquatic organisms to maintain vital processes such as respiration, feeding, spawning, and thermoregulation (Thakur and Koul, 2022). Terrestrial organisms that can be in direct contact with the oil near the shores can also be negatively impacted. For instance, the insulating properties of birds' feathers and mammals' fur can be damaged by oil (Bhattacharjee and Dutta, 2022). Meanwhile, the impacts of oil spills to human population range from economic disruption of coastal communities reliant to aquatic natural resources to detrimental effects in human health including respiratory, mental, and behavioural effects (Eklund et al., 2019). The Deepwater Horizon oil spill, for example, resulted to a loss of 25,000 jobs, USD 2.3 billion industry output, and around USD 320 million tax revenue (Court et al., 2020).

Detection and delineation of oil spills in ocean waters using optical and Synthetic Aperture Radar (SAR) images is a mature area of research (Al-Ruzouq et al., 2020; Brekke and Solberg, 2005; Fingas and Brown, 2017). SAR allows for detection of oil spill under a wider range of weather conditions, whereas optical images can only capture oil spills under specific cloud-free conditions. However, SAR cannot provide accurate estimations of the thickness of the oil (Solberg, 2012). Since oil is less dense than water, oil slicks stay on the ocean surface and sometimes produce oil sheen that can be discerned visually in optical satellites. On the other hand, oil slicks that are thick enough dampens the surface of the water making it smoother compared to the surrounding water. In this case, the oil surface can be visually identified in SAR images appearing as dark slicks in the relatively brighter ocean surface. This backscatter attenuation is similarly observed in other oceanographic phenomena such as freshwater slicks, low wind activity, blooms, and upwelling regions (Hovland et al., 1994; Lin et al., 2002). Due to this similarity, the confidence of radar oil slick detection significantly decreases near areas of high productivity. Despite these drawbacks, the usability of SAR images regardless of atmospheric conditions that hinder visibility supplies invaluable contribution to oil spill monitoring.

The application of remote sensing to monitor the progression of an oil spill was recently exploited when an oil tanker, called the MV Princess Empress, was capsized in the Verde Island Passage (VIP) near Oriental Mindoro, Philippines last 28 February 2023. The ship was known to be carrying 800,000 Liters of oil (Rivas, 2023). The VIP is considered as the most critical marine biodiversity centre in the world, known for its high shore fish distributions (Carpenter and Springer, 2005). The presence of the nearby oil source posed a significant threat to the area's marine and coastal health, including reef fishes, benthic features such as corals and seagrasses, and mangrove forests. Meanwhile, in the adjacent coastal communities, the fisherfolk were substantially affected when fishing activities were immediately suspended following the oil spill incident. This led to an individual weekly income loss of USD 1300 (Agaton et al., 2023).

Premised upon the main goal of identifying and monitoring the Mindoro Oil Spill using satellite imageries, this work utilized various satellite sensors (i.e., optical and SAR) to detect and track the oil and to investigate the spatiotemporal distribution of oil spill. This work is anticipated to support ongoing initiatives for the sustainable and informed management of disasters like oil spills that have significant negative environmental impacts.

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This work is also expected to guide future efforts to monitor and contain similar disastrous incidences.

2. DATA PROVISION

2.1 Study Area

The study area is covered by the AOI provided in Figure 1 covering the (VIP) and the eastern seaboard of Mindoro Island. This is in consideration of the oil spill source where the wreck was found and the direction of wind and current in the area.

2.2 Sentinel-Asia EOR

The Philippine Space Agency (PhilSA) submitted an Emergency Observation Request (EOR) to Sentinel Asia immediately after the ship capsized due to possible oil spillage. Sentinel Asia is an initiative of the Asia-Pacific Regional Space Agency Forum (APRSAF) established in 2005 to showcase the use of Earth Observation (EO) data for disaster management in Asia Pacific Region. The Data Provider Node (DPN) members of Sentinel Asia, consisting of various space agencies in the region, conducted emergency observation on the areas provided in the EOR. Images from ALOS-2 SAR satellite of Japan Aerospace Exploration Agency (JAXA) and Formosat-5 optical satellite of Taiwan Space Agency (TASA) was provided through the EOR.

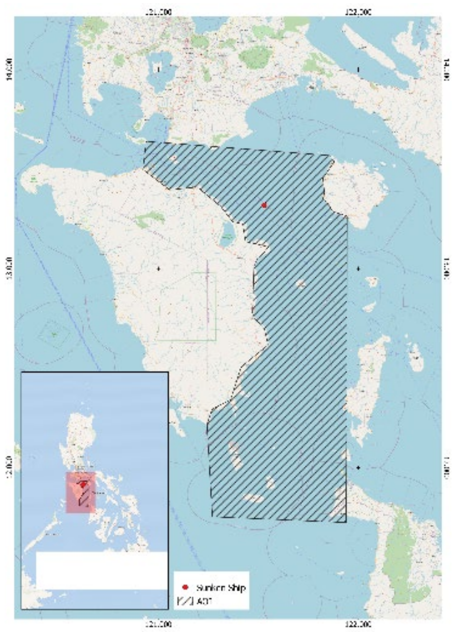

Figure 1. Location of sunken ship (red) and AOI (hashed polygon) used for satellite tasking.

2.3 International Charter Activation

Due to the potential huge environmental effect of the oil spill, the same EOR was escalated to the International Charter Space and Major Disasters (The Charter) for more EO data provision. The Charter is a unified system for the acquisition and provision of space data to areas affected by disasters (Bessis et al., 2004). EO assets of different member space agencies are combined to provide data and expertise for humanitarian purposes during major disaster situations ("About the Charter," n.d.). In this activation, the nominated Project Manager was from PhilSA. Value adders were from PhilSA, and The International Tanker Owners Pollution Federation Limited (ITOPF).

EO data provided through The Charter are listed in Table 1.

Satellite	Data Provider
Sentinel-1A	European Space Agency (ESA)
RCM-3	Canadian Space Agency (CSA)
Gaofen-3	China National Space Administration (CNSA)
RCM-1	Canadian Space Agency (CSA)
Sentinel-2B	European Space Agency (ESA)
Worldview-3	Digital Globe
Tandem-X	German Aerospace Center (DLR)
Landsat-8	US Geological Survey (USGS)
SAOCOM-1B	Argentina National Space Activities Commission (CONAE)
Landsat-9	US Geological Survey (USGS)

Table 1. List of Satellite images from The Charter

3. METHODOLOGY

Typical oil slicks in SAR imagery appear as dark formations with low backscatter mean and variance. However, various phenomena, such as regions with low wind activity, organic film accumulation, fronts, areas protected by landmasses, rain cells, areas with varying current speeds, the presence of grease ice, internal waves, upwelling and downwelling zones, as well as eddies, can all give rise to dark formations (Hovland et al., 1994). For this matter, quality control through visual indicators is performed to accurately and quickly separate oil spills from other low backscatter parcels.

On the other hand, oil slicks in optical imagery tend to have higher reflectance than the surrounding deep water due to its chemical composition and physical properties. This was similarly used to separate oil from other features present in the scene. Unlike SAR imagery, false classification emanates from cloud contamination. Quality control was similarly done by visual interpretation and segment editing.

3.1 Data Processing

There are two types of EO data provided: Optical and SAR. The general processing starts with data pre-processing which is dependent on the data type and processing level applied into the image by the data provider. After pre-processing, suspected oil slicks are visually identified from the images. A subset of the image is then selected retaining the area where oil slick is visible. This is done to reduce processing time and eliminate other areas of the image that are not necessary in delineating the oil slicks. Various algorithms are applied into the image subset to delineate the oil slick before classifying into High, Medium, and Low Confidence oil. The general processing steps are shown in Figure 2.

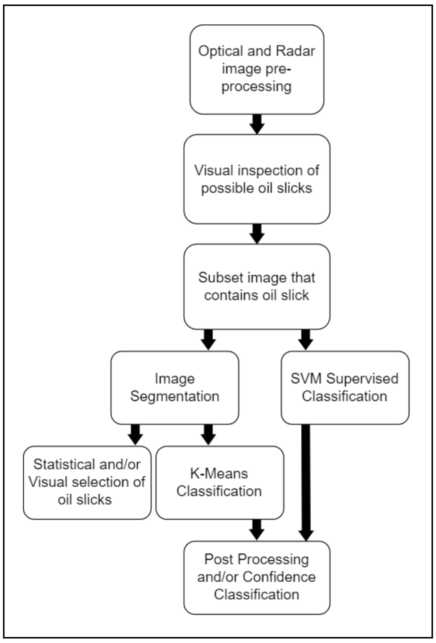

Figure 2. Processing steps in delineating oil slicks from satellite images.

3.1.1 Pre-Processing: The initial step is pre-processing of images. For SAR data, pre-processing may include a.) terrain correction, b.) speckle filtering, c.) linear-to-db conversion, depending on the processing level of the data provided. For optical images, preprocessing is limited to dark object subtraction to correct atmospheric scattering over the ocean if deemed necessary.

3.1.2 Visual Inspection of Possible Oil Slicks: Various image enhancement processes, including testing different band combinations and contrast enhancements, are implemented to locate oil slicks in an image. Analysing ocean currents from Hybrid Coordinate Ocean Model (HYCOM) and surface wind direction from NCEP Global Forecast System (GFS) can hasten the process of locating all oil spills in an image by factoring the movement of oil slicks away from the point source.

In the case of radar satellite imagery, the surface slicks effectively reduce sea surface roughness causing lower backscatter. Figure 3 shows an example of a radar acquisition by Sentinel-1 on March 18, 2023 off the coast of Mindoro.

In contrast, optical satellite images offer improved characterization capabilities by providing more visual details including spectral information about the objects of interest. This allows the distinction between thick and thin oil slicks, oil sheen, and ship wakes. Figure 4 shows an example of an optical satellite image captured by Sentinel-2 on March 8, 2023 off the coast of Mindoro.

Figure 4 illutrates different phenomena that can induce misclassification to the process. One example is ocean vessel wakes which disrupt sea surface roughness. The optical properties of oil film over water can be summarized by two key concepts, specular reflection by the surface of the oil and upwelling radiance absorption by the oil layer (Otremba and Piskozub, 2001). The prior is mainly affected by viewing and illumination geometries (Chust and Sagarminaga, 2007). This anisotropic property complicates the standardization of detection which is observed differently in both thick and/or thin oil film for different satellite acquisitions. In some cases, elevated reflectance values of oil slicks create challenges when categorizing it alongside other phenomena that also cause an increase in reflectance, such as cirrus clouds, or haze. Similarly, decreased reflectance due to dampening ocean surface waves makes it a source of misclassification as observed in boat wakes. While radiance absorption within certain spectral ranges is highly dependent on the thickness of the oil film (Otremba, 2000), assessment of different satellite sensor images suggest that observation geometries significantly influence oil slick spectral retrievals. Additionally, general cloudy conditions or even isolated clouds over areas of interests are major hindrances in optical satellite retrievals.

The mentioned complications associated with differentiating oil slicks with other oceanic or atmospheric phenomena underscore the need for prior inspection in applying necessary processing to identify oil slicks swiftly and accurately.

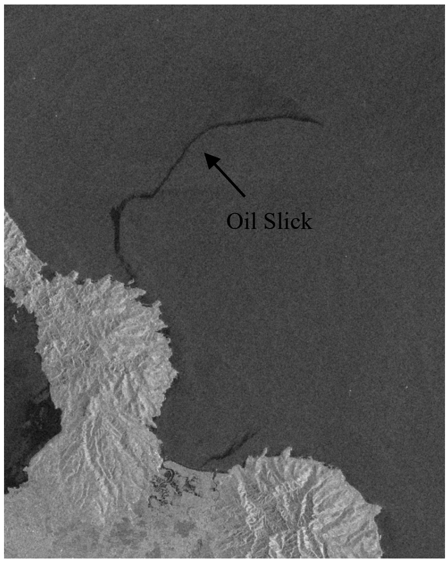

Figure 3. Sentinel-1A SAR image of oil slick captured on March 19, 2023.

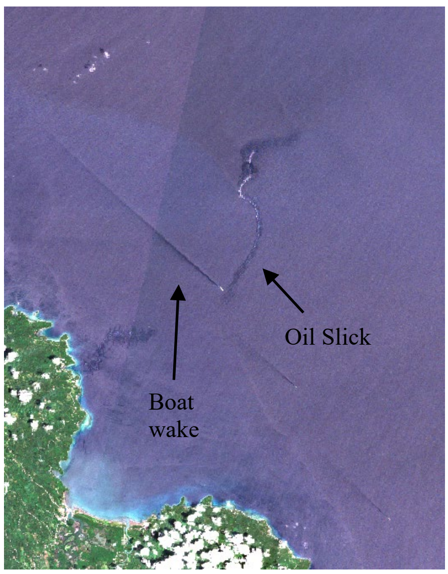

Figure 4. Sentinel-2B optical satellite image showing oil slicks and ship wakes captured on March 28, 2023.

https://doi.org/10.5194/isprs-archives-XLVIII-4-W8-2023-157-2024

3.1.3 Subsetting: Identification of possible oil slicks allows for the exclusion of unrelated image portions aside from landmasses. Narrowing down the analysis to the contaminated area not only conserves computational resources and reduces processing time but also minimizes the volume of intermediate data and final products produced, which is particularly advantageous when dealing with very high-resolution satellite imagery and its extensive data storage requirements.

3.1.4 Segmentation: Segmentation is a process applied especially to noisy optical or radar images. The application of an object-based approach considers spatial autocorrelation between neighbouring pixels, in stark contrast to the conventional pixel-based analysis. This approach enables the analysis of pixels with similar attributes as coherent objects, effectively mitigating the adverse impact of image noise.

The segmentation process is done using an existing workflow in ENVI (Jin, 2012). This involves creating gradient or intensity maps, selecting a scale level, and applying the watershed transform algorithm to delineate regions based on distinct features or intensities in the image (Roerdink and Meijster, 2000). The choice of method and scale level depends on the specific characteristics of the image and the segmentation objectives. In this scenario, oil slicks resemble more distinguishable surfaces rather than discrete objects with well-defined boundaries. As a result, the intensity method is favoured over edge detection in most cases.

After segmentation, the vector objects are either classified using unsupervised K-Means or manually selected based on statistical attributes and/or visual indicators depending on which is deemed more applicable.

3.1.5 Unsupervised K-Means Classification: K-means algorithm is a machine learning clustering algorithm that finds the minimum distance of points from the mean of each k-cluster which minimizes within class variance (Sinaga and Yang, 2020). In this method, clustering is applied on the whole segment based on zonal attributes as opposed to treating each pixel of the image as spatially independent (Mather and Tso, 2016). Figure 5 shows the clustered vector segment of the radar image in Figure 3.

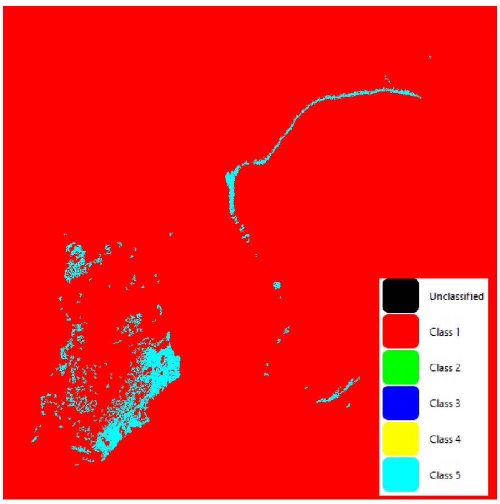

Figure 5. Unsupervised K-Means clusters showing mis-classified oil class on the lower-left portion of the image.

It can be observed in the sample image that Class 5, which includes the actual oil spill, mis-classified the dark areas inside the lake. The final classification should be interpretation by the processor.

3.1.6 Statistical/Visual Selection of Oil Segments: After segmentation, manual selection or zonal attribute-based thresholding may be applied when it is feasible and more convenient to manually identify segments corresponding to oil slicks, rather than subjecting them to unsupervised classification. This approach ensures that selected segments exhibit a higher level of confidence depending on interpreter expertise. It also requires less post-processing and quality assurance out of the other paths of processing.

3.1.7 Supervised Support Vector Machines Classification: Supervised classification is used mainly on optical image to take advantage of the spectral information that can be derived from the image, enhancing the ability to distinguish oil features from non-oil features more effectively. Training samples from multiple features present in the subset are selected with emphasis on separating thick oil and thin oil from similar features such as thin clouds and haze. Support Vector Machine is the algorithm of choice for this application because of its consistent performance and its ability to deliver satisfactory results across a broad spectrum of applications (Sheykhmousa et al., 2020). Figure 6 shows a sample result of a SVM classification on oil spill delineation.

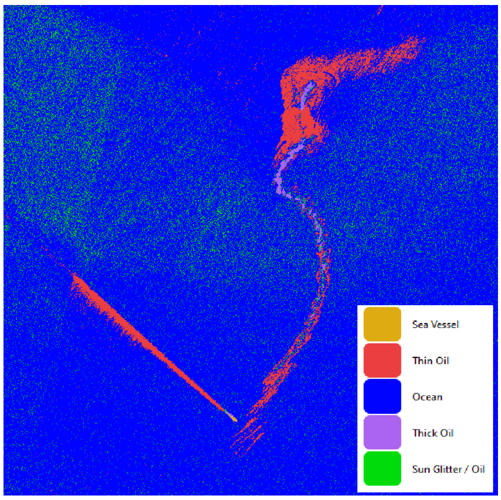

Figure 6. SVM classification results which classified the ship wake as thin oil.

It is apparent in Figure 6 that the ship wake is misclassified as thin oil but since these two classes are spatially disjoint, it is easily amendable in the post-processing stage. IT can also be observed that the actual oil slick follows a winding pattern compared to the straight pattern exhibited by the ship wake. The result of the classification is primarily concerned with the omission and commission accuracy of oil features against other non-oil features. If oil classes accuracy does not meet the desired standard, reprocessing may be undertaken to further refine the results. This can include parameter optimization, revising the training data set, and image transformation (Cervantes et al., 2020). In parallel, other branching methods explained in this research can be explored to see which best gives us the required result.

3.1.8 Post Processing and/or Confidence Classification: Post-processing for clustered images using K-Means classification includes the critical steps of pruning to address misclassifications and object selection to rectify omissions. In contrast, for manually selected segments determined through statistical and visual assessment, minimal intervention is necessary. Oil slicks classified through segmentation after quality assessment are simplified using vector smoothing. Post-processing for pixel-based classification using SVM undergo noise reduction by isolating oil slick classes and applying clumping and sieving.

Post-processing techniques applied to specific branches of the methodology exhibit minor variations, yet their overarching goal remains consistent: to generate a practical and usable product that end users can use for knowledge-based approach on the ongoing issue.

The classifications are then reclassified into High, Medium, and Low Confidence oil slicks when applicable. The area of oil slicks is calculated using a GIS software and the results are presented in maps released to relevant government agencies and to the public. Figure 7 and 8 shows sample delineations for optical and SAR images indicating the area of the oil slick and the different confidence levels based on the interpretation of remote sensing experts of PhilSA.

4. RESULTS AND DISCUSSION

The Mindoro Oil Spill extent was monitored through time using EO data. Through EOR of Sentinel Asia and Charter activation of International Charter Space and Major Disasters, satellite images were provided. Though many of those provided, especially optical images from the charter were not used due to cloud cover, twenty-nine (29) value added products were produced by PhilSA from March 2 to April 24, 2023. There were forty-six (46) products in total from the charter activation derived from one hundred ninety-two (192) satellite data acquisitions. The acquisitions include pre-event images provided by charter members.

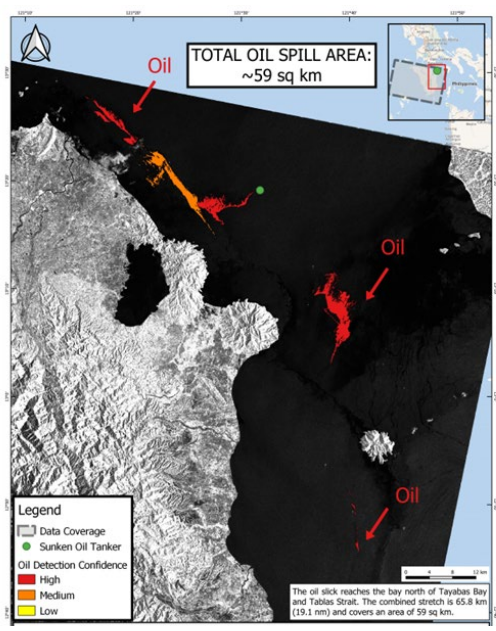

Figure 7. Classified Sentinel-1A SAR image captured on 31 March 2023 showing High, Medium, and Low Oil detection confidence.

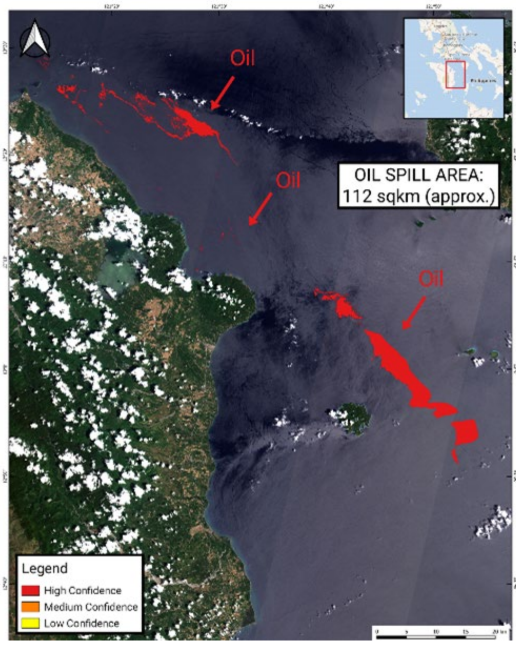

Figure 8. Classified Sentinel-2 optical image captured on 02 April 2023 showing High oil detection confidence.

Using the workflow described in this paper, the Philippine Space Agency was able to provide an almost daily monitoring of the oil spill. Due to the activation of Sentinel Asia and the Charter, almost daily monitoring of oil extents including its covered area was provided.

5. FUTURE WORK AND OPERATIONALIZATION

Various satellite imageries such as optical and SAR were utilized to identify and monitor the spatiotemporal distribution of Mindoro Oil Spill. For both image types, the general procedure consists of segmentation to identify and delineate the oil in the water surface, unsupervised K-means classification to cluster the images into different classes, and then visual selection of the oil segments. In certain circumstances, supervised support vector machines classification was employed on optical images to take advantage of the spectral signatures of oil. This work underscores the importance of using satellite imageries in detecting and tracking the evolution of oil spills and how future developments in machine learning and image processing techniques will further enhance these capabilities.

For future works, it is intended to improve the design and implement machine learning algorithms to provide a more rapid and efficient response to oil spill events. Such improvement includes reducing the time it takes to detect and respond to oil spills and making the entire monitoring operation more effective.

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