

SPATIO-TEMPORAL MONITORING OF OIL SPILLS IN THE BLACK SEA (KERCH STRAIT) USING SENTINEL-1 SAR DATA

Nataliia I. Lytvynenko, Olexander V. Korenets, Tamara M. Kurach, Iryna O. Pidlisetska

*Military Institute of Taras Shevchenko National University of Kyiv, Kyiv,
Ukrainen123n@ukr.net, korenetsaleksandr@gmail.com, tnkurach@ukr.net,
irinna2008@ukr.net*

Abstract

Oil pollution of the marine environment is one of the most hazardous forms of anthropogenic impact on ecosystems, leading to long-term environmental, economic, and social consequences. The accidental spill of fuel oil resulting from damage to Russian tankers in the Kerch Strait caused large-scale contamination of the Black Sea waters and highlighted the need for timely and objective monitoring of oil spill propagation. This study presents the results of a spatio-temporal analysis of oil pollution in the Black Sea based on Synthetic Aperture Radar (SAR) satellite imagery acquired by Sentinel-1. The research methodology is based on the processing of a time series of Sentinel-1 SAR GRD products using the ESA SNAP software. The processing workflow included radiometric calibration and geometric correction using a digital elevation model, reprojection to a common coordinate system, and elimination of geometric distortions. To improve data quality and reduce image granularity, speckle noise filtering was applied. Oil spill detection was carried out through the analysis of radar backscatter characteristics by constructing intensity profiles along the trajectories of pollution spread and examining signal variability within contaminated areas. This approach enabled the experimental determination of threshold pixel values corresponding to signal attenuation zones caused by the damping of capillary waves by the oil film. As a result, the spatial extent and temporal dynamics of oil slick propagation within the Kerch Strait and adjacent areas of the Black Sea were identified. The findings confirm the high effectiveness of Sentinel-1 SAR data for monitoring oil spills regardless of weather conditions and illumination. The proposed approach can be applied for environmental monitoring, assessment of the impacts of technogenic accidents, and support of decision-making processes in marine environmental protection.

Keywords: oil pollution, Black Sea, Kerch Strait, Sentinel-1, SAR imagery, SNAP, speckle noise, spatio-temporal analysis.

Background

On December 15, 2024, a major accident involving river–sea class tankers occurred in the Black Sea near the exit of the Kerch Strait. During a severe storm, the vessels *Volgoneft-212* and *Volgoneft-239* were damaged. The tanker *Volgoneft-212* sank, while *Volgoneft-239*, after its hull fractured, managed to approach the coast and ran aground approximately 80 meters from the shoreline. Another tanker, *Volgoneft-109*, developed a hull crack but managed to send a distress signal and was relocated to a safe area.

According to various estimates, between 2,400 and 8,000 tons of M-100 fuel oil, produced at the Saratov Oil Refinery and intended for export, entered the sea as a result of the accident. In addition to fuel oil, the vessels were carrying approximately 25 tons of diesel fuel, which is highly toxic to marine organisms.

The contamination affected extensive areas of the Kerch Strait, the eastern and southern coasts of Crimea, and subsequently the north-western part of the Black Sea. Given the complex hydrodynamics of the region, variable meteorological conditions, and the

physicochemical properties of M-100 fuel oil, there was an urgent need for operational spatiotemporal monitoring of oil spill dispersion using remote sensing methods.

One of the most effective tools for such monitoring is radar imagery from the Sentinel-1 mission operating within the Copernicus Programme. Synthetic Aperture Radar (SAR) data enable the detection of oil contamination regardless of weather conditions and time of day, which is critically important during storm events and in winter.

1. Relevance of the Study.

The relevance of this research is determined by a combination of environmental, technological, and socio-political factors. The Black Sea is a vulnerable semi-enclosed marine ecosystem with limited water exchange with the Mediterranean Sea through a system of straits. Such hydrological isolation significantly slows natural self-purification processes, contributing to the prolonged persistence of pollutants in the marine environment.

M-100 fuel oil poses a particular threat as a heavy petroleum fraction that rapidly thickens at low water temperatures (+8...+10 °C), forming dense viscous clots and aggregates. These masses may remain both on the surface and within the water column for extended periods, complicating detection and response efforts and causing long-term impacts on marine ecosystems.

Rapid response to such environmental disasters is essential. Traditional monitoring methods, including ship surveys and aerial reconnaissance, are limited in terms of speed, spatial coverage, and weather dependence. In contrast, SAR satellite data provide observation capabilities independent of cloud cover, illumination, and adverse meteorological conditions, enabling near real-time information acquisition. This is especially critical during storms and winter periods when alternative observation methods may be ineffective or unavailable.

Furthermore, the study has a pronounced military and political context. Under conditions of prolonged regional instability, access to certain marine areas may be restricted. Satellite remote sensing methods thus serve as an independent and objective monitoring tool that does not require physical presence in the affected area, enhancing transparency and enabling international verification.

Equally important is the need for quantitative damage assessment. Determining the area and spatial configuration of oil slicks is necessary for environmental impact assessment, evaluation of damage to marine biodiversity and coastal ecosystems, and estimation of economic losses and compensation. Therefore, the application of modern satellite technologies for spatiotemporal oil spill analysis is both scientifically justified and practically indispensable.

2. Analysis of Recent Scientific Publications.

Contemporary research demonstrates a clear trend toward integrating classical radar analysis methods with machine learning and deep learning tools to improve oil spill detection accuracy and reduce false positives.

One key direction in recent years has been the application of Convolutional Neural Networks (CNNs) for segmentation and detection of oil slicks in SAR imagery. Kalogirou et al. (2025) demonstrated the effectiveness of CNN models for automated oil spill detection based on a large Sentinel-1 dataset, achieving very high classification accuracy. Cheng et al. (2026) proposed a modified U-Net architecture (NOS-Net) for more robust segmentation under varying sea state and meteorological conditions. These studies emphasize that deep neural networks can effectively capture the complex textural structure of SAR images, offering advantages over traditional threshold-based methods.

At the same time, recent studies highlight the importance of high-quality SAR data preprocessing. Particular attention is given to speckle filtering, signal normalization, and polarization analysis. For example, Chaturvedi et al. (2020) demonstrated that the VV polarization channel of Sentinel-1 provides better contrast between clean water and oil slicks compared to VH polarization. Other studies confirm that combining amplitude and intensity indicators allows more precise delineation of contaminated areas, especially under low water temperatures and variable wind conditions.

Comparative analyses of machine learning algorithms, such as Magrì et al. (2021), indicate that model selection must consider not only accuracy but also robustness to sea state variability and the presence of look-alike phenomena such as low-wind zones or biogenic films. Even advanced deep learning methods require properly prepared training datasets and careful preprocessing.

Review studies, including Fingas & Brown (2018) and Kussul et al. (2024), systematize remote sensing approaches for oil spill detection using optical, thermal, and radar sensors. SAR technology is emphasized as particularly valuable due to its independence from cloud cover and illumination. However, the physical properties of oil products and meteorological influences on radar backscatter must always be considered.

Overall, recent literature shows a transition from threshold-based and semi-automatic approaches toward comprehensive AI-driven systems, while classical techniques such as speckle filtering and profile analysis remain methodologically important.

3. Methods and Methodology.

Sentinel-1 images acquired on January 4 were selected for the study and downloaded from the Copernicus Browser platform in their original values. Two scenes were required to fully cover the southeastern coast of Crimea. Image processing was performed using SNAP software. The general workflow included: subsetting, radiometric calibration, geometric correction, mosaicking, profile construction, speckle filtering, repeated profile analysis, and masking.

4. Research Results

At the beginning of the study, a chronological reconstruction of events was established. On December 15, 2024, an accident involving the tankers *Volgoneft-212* and *Volgoneft-239* resulted in a significant release of M-100 fuel oil into the sea. Due to severe weather conditions, including strong storm winds and high waves, the main mass of the pollutant initially drifted eastward and southeastward.

During the initial stage of dispersion, wind-driven currents and storm-induced water circulation played a decisive role. Owing to intense vertical mixing of water masses, part of the fuel oil was likely distributed not only on the surface but also within the water column.

Between December 17 and 19, fuel oil was recorded along the beaches of the Krasnodar region of the Russian Federation, particularly in the areas of Veselovka, Anapa, and Blagoveshchenskaya. According to media reports, the length of the contaminated coastline ranged from 35 to 60 km.

In the first days following the accident, storm conditions pushed water masses toward Taman, contributing to the onshore transport of part of the fuel oil. At the same time, the physicochemical properties of M-100 significantly influenced its detectability in satellite radar imagery.

M-100 is a heavy petroleum fraction. At water temperatures of +8...+10 °C, it rapidly thickens and forms dense viscous clots (“pancake-like” formations). Such aggregates may

drift within the water column rather than remain strictly on the surface. Since SAR radar primarily responds to the damping of capillary waves at the sea surface, submerged or semi-submerged oil clots are poorly detected. This explains why radar images from December 18–19 showed only minor residual manifestations of contamination near the accident site.

Between December 23 and 26, the first oil slicks were detected near Kerch and along the eastern coast of Crimea, indicating a change in the direction of pollutant transport under new hydrometeorological conditions.

At that time, a federal-level state of emergency was declared in the Russian Federation and in the occupied territories. The scale of contamination became increasingly evident, and the dispersion dynamics grew more complex and less predictable.

By the end of December, satellite imagery revealed extensive oil slicks (up to 160 km²) approximately 17 km from Cape Sarych. This was associated with changing weather conditions: currents partially lifted the fuel oil from the water column to the surface and altered its transport direction.

Following the reorganization of water circulation patterns, the fuel oil began actively drifting westward along the Crimean Mountains. A stable westward transport developed along the Southern Coast of Crimea, creating conditions for large-scale coastal contamination.

Early January marked a critical stage in the development of the environmental disaster. Fuel oil was detected in Balaklava Bay, on the “Silver” and “Golden” beaches, in Cossack Bay, and near Cape Fiolent. Due to the extent of contamination, a regional-level state of emergency was declared.

On January 4, several media outlets, including the publication “Agency,” as well as environmentalist Georgy Kavanosyan, citing satellite data, confirmed that the oil slick had reached these cities. Contamination was recorded along the stretch from Partenit to Sudak, including the waters of Alushta. The satellite image from January 4 clearly showed a large slick near Alushta, indicating the maximum concentration of fuel oil in the coastal zone during that period. Thus, January 3–4 can be considered the peak of the environmental disaster along the Southern Coast of Crimea.

Between January 9 and 12, the contamination continued spreading westward. Fuel oil was detected near Yevpatoria and Tarkhankut. Subsequently, the consequences of the accident reached the Odesa region, including the Tuzly Lagoons National Nature Park. Oil-covered dead birds were found along the coast, demonstrating the severe impact of the disaster on marine ecosystems and biodiversity.

The chronology indicates that the dispersion of fuel oil had a wave-like character strongly dependent on weather conditions. Initially, storm winds were the dominant factor; later, shifts in current directions and vertical water circulation became decisive. The specific properties of M-100 (high density, rapid thickening in cold water, and the ability to drift within the water column) complicated its remote detection at early stages.

As a result of the combination of the substance’s physical properties and changing marine hydrodynamics, the environmental disaster acquired a large-scale regional character, affecting a significant portion of the Black Sea.

To identify satellite imagery of contaminated areas, the Copernicus Browser service was used, particularly data from the Sentinel-1 radar satellite. During the analysis of the Black Sea waters throughout the drift period of the oil slick, a significant contaminated area near Alushta was identified as of January 4, 2025. Two satellite scenes were downloaded to ensure full coverage of the study area and were subsequently used for detailed processing and analysis.

Radar image processing was performed using SNAP software. The second scene contained excessive water areas, complicating processing. Therefore, subsetting was performed via Raster → Subset with selection of the VV polarization. The Amplitude_VH

data did not demonstrate clear differentiation of oil slicks, so only VV channels were used in further analysis. The image size was reduced by pixel-based cropping in the preview window by manually adjusting the boundaries. The cropped image containing part of the Southern Coast of Crimea was saved. The newly created image included only the selected area and VV polarization channels.

Radiometric calibration was performed via Radar → Radiometric → Calibrate. This procedure converted the data into physically interpretable backscatter values and eliminated system-related distortions.

Calibrated SAR images cannot be mosaicked without prior geometric correction. Therefore, geometric correction was performed using the Geolocation Grid method (Radar → Geometric → Ellipsoid Correction → Geolocation Grid), ensuring proper spatial referencing of the scenes.

The scenes were combined using Radar → Geometric → SAR Mosaic. Two calibrated images with a unified coordinate system were used as input (Fig. 1).

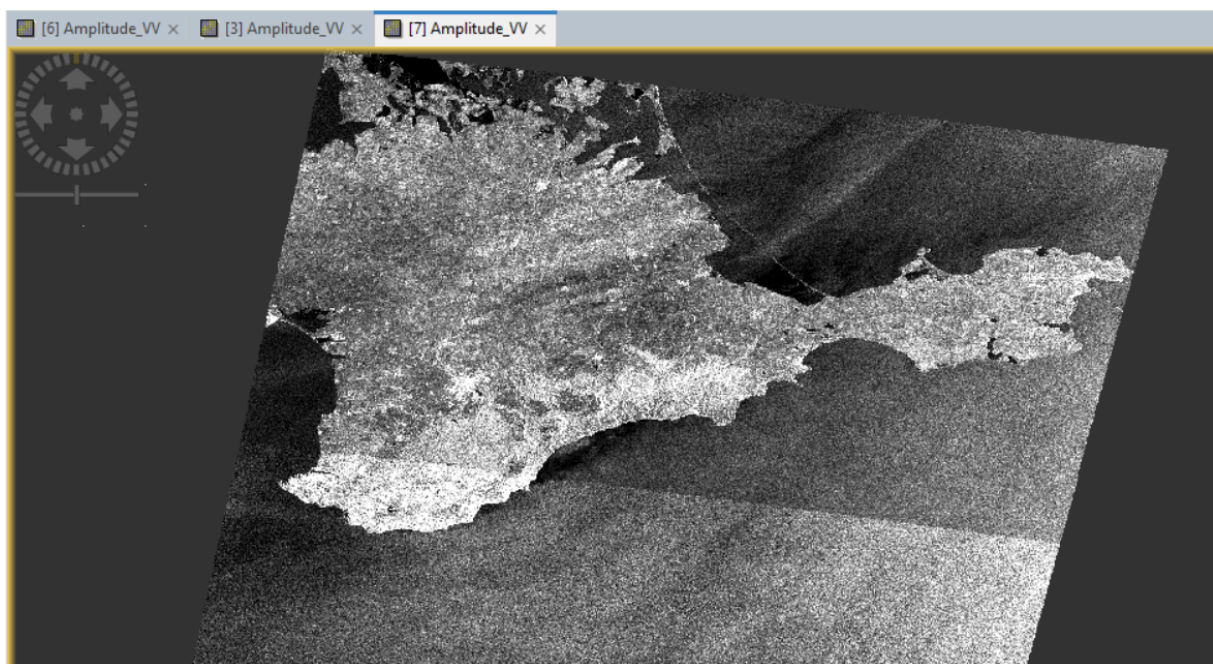
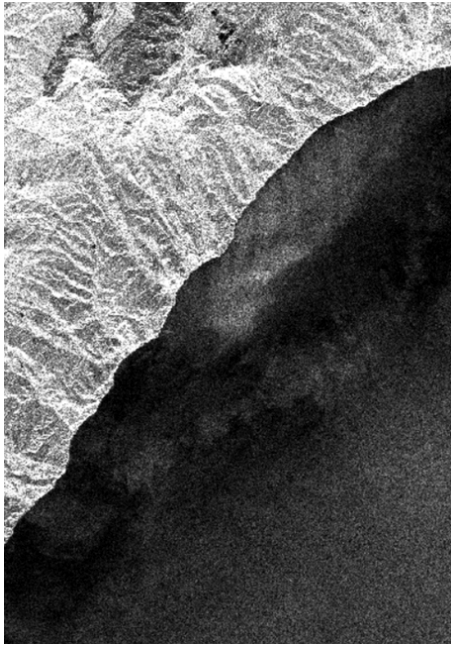


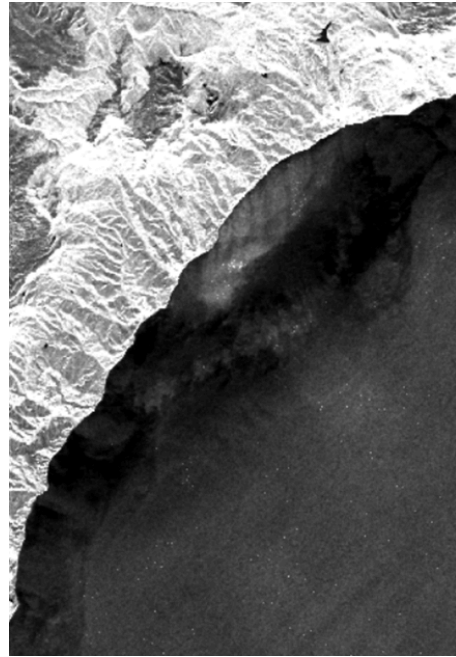
Fig. 1. Result of SAR Mosaic operation

The next preprocessing stage involved speckle filtering — the removal of granular noise characteristic of SAR imagery caused by interference of reflected radar signals. For Sentinel-1 data, this processing is essential, as unfiltered images exhibit significant brightness variability even within homogeneous areas. In studies of areal phenomena such as oil contamination, speckle filtering is particularly important. Oil slicks appear as zones of reduced backscatter due to capillary wave damping. However, speckle noise may generate local dark or bright pixels that can be misinterpreted as contamination. Filtering therefore reduces random signal fluctuations, increases homogeneity of clean water areas, enhances contrast between contaminated and uncontaminated zones, and improves classification reliability.

Speckle filtering was performed via Radar → Speckle Filtering → Single Product Speckle Filter with parameters: Window Size 11×11 and Target Window Size 5×5. The filter significantly reduced image granularity and increased both visual and statistical contrast between clean and contaminated water surfaces (Fig. 2).



Before filtering



After filtering

Fig. 2. Contaminated area of the south-eastern coast of Crimea after applying the filtering procedure.

Although visual improvement was evident, quantitative assessment was conducted using profile analysis. A profile represents the distribution of amplitude or intensity values along a line or curve crossing different surface types. The Line Drawing Tool was used to draw a line across contaminated and clean water areas on the unfiltered Amplitude_VV image. For more complex trajectories, the Polyline Drawing Tool was applied (Fig. 3).

Profile analysis was performed via Analysis → Profile Plot after selecting the profile using the Selection Tool. The same procedure was repeated for the filtered image, allowing comparison.

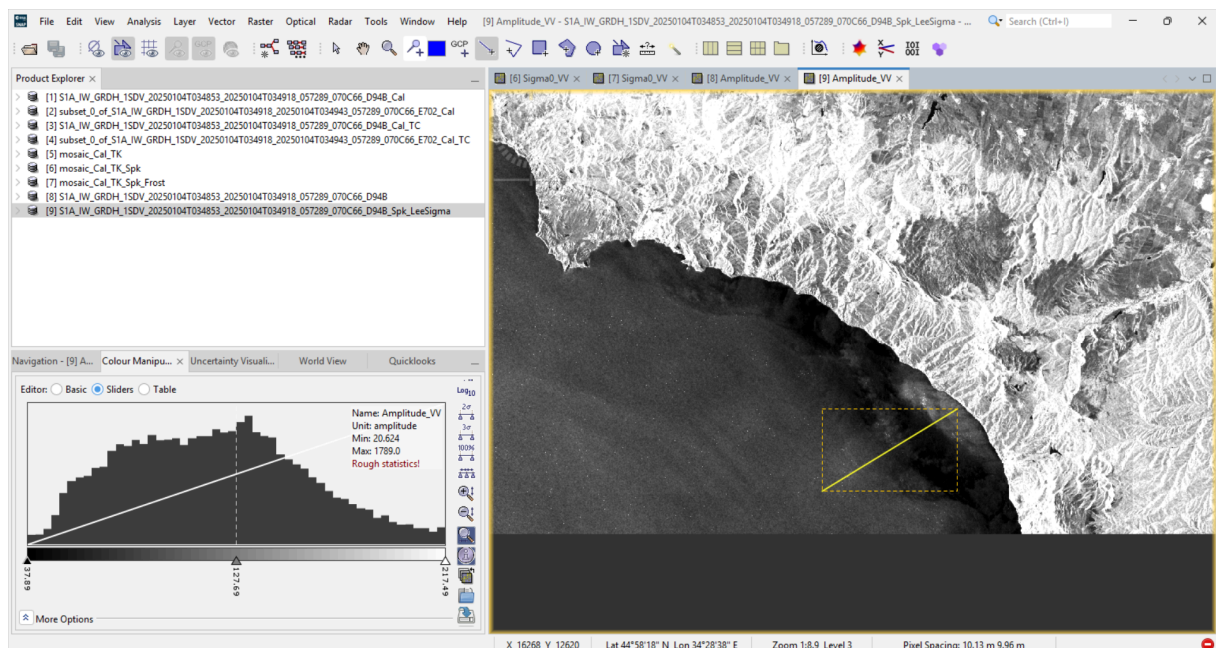


Fig. 3. Drawing a line to build a profile

The results showed that unfiltered data exhibited much higher dispersion within both clean and contaminated areas. Signal fluctuations were chaotic, complicating threshold determination. In the unfiltered image, the difference between minimum values of clean water and maximum values of contaminated areas was approximately 120 versus 45. After filtering, the values became smoother and more contrasted — 60 versus 15 — significantly improving class separability.

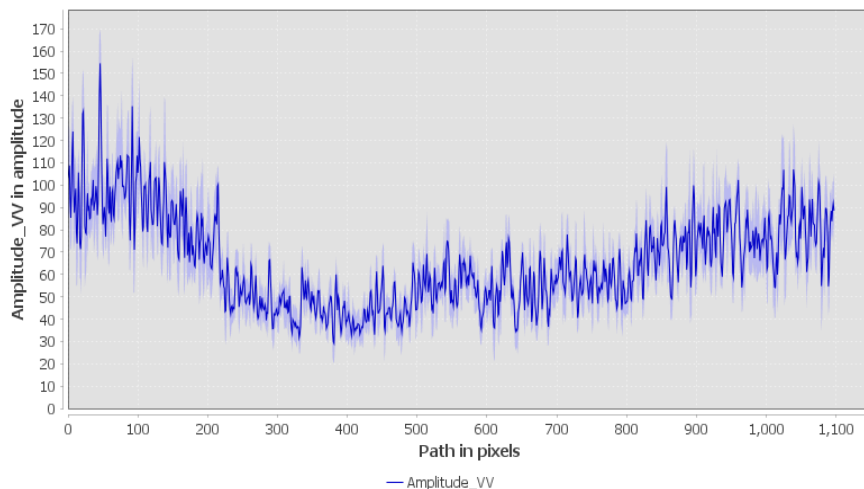
Thus, speckle filtering substantially reduced statistical noise and improved the suitability of radar data for thematic interpretation.

The next stage involved determining threshold values and creating a contamination mask. To delineate oil slicks, it was necessary to identify radar signal thresholds separating contaminated from clean water. Profiles were constructed within contaminated areas using two channels: Amplitude_VV and Intensity_VV. Profile analysis indicated that contaminated areas had values below 75 for Amplitude_VV and below approximately 6000 for Intensity_VV. These initial thresholds required refinement (Fig. 4).

The mask was created in the Mask Manager using Create a new mask based on logical band math expression. The initial condition was:

(Amplitude_VV < 75) and (Intensity_VV < 6000)

Profile Plot for Amplitude_VV



Profile Plot for Amplitude_VV

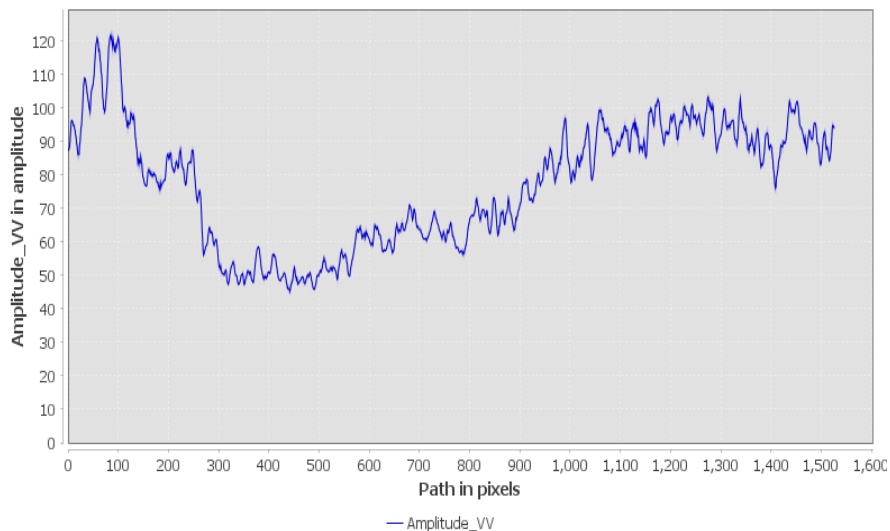


Fig. 4. Constructed the profiles

After application, numerous noise pixels were detected. The Pixel Info tool was used to analyze pixel values in specific areas, leading to threshold refinement. The final expression was:

$(\text{Amplitude_VV} < 67) \text{ and } (\text{Intensity_VV} < 4000) \text{ and } (\text{Intensity_VV} \neq \text{NaN})$

The last condition excluded areas outside the study region that were formally included in the raster image.

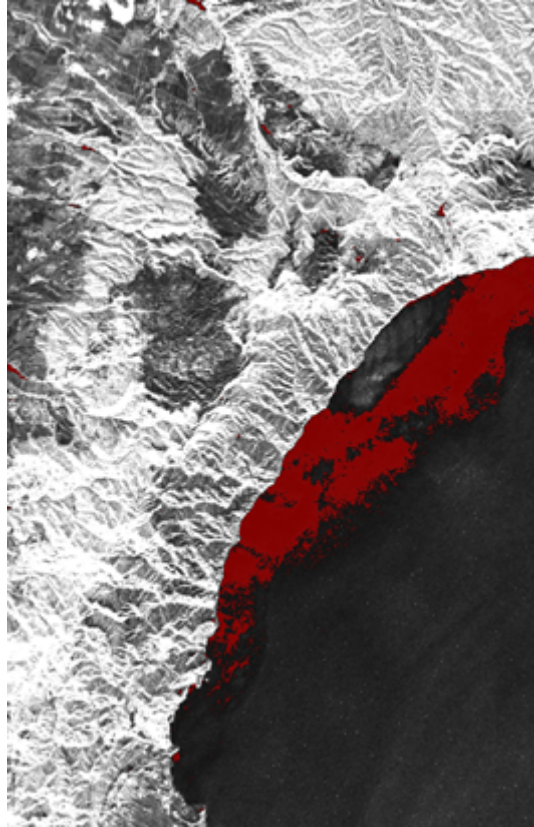


Fig. 5. Correct oil spill mask

The oil slick was digitized using the Polygon Drawing Tool. The resulting vector geometry was exported via Vector → Export → Geometry as Shapefile. The shapefile was opened in Google Earth, where the contaminated area was calculated in the “Properties” tab.

The results showed that the contaminated water surface area as of January 4, 2025, was approximately 270 km².

Conclusions and recapitulations

The study confirmed the high effectiveness of Sentinel-1 SAR data for oil spill monitoring under complex hydrometeorological conditions. VV polarization provides clearer oil slick identification compared to VH. Speckle filtering significantly improves image quality and classification reliability. Threshold masking proved to be a practical tool for delineating contamination boundaries and estimating spill area.

The spatiotemporal analysis revealed a wave-like dispersion pattern strongly dependent on meteorological and hydrodynamic conditions. The combined use of speckle filtering, profile analysis, logical masking, and vectorization enabled a quantitatively substantiated assessment of oil pollution extent. SAR-based satellite monitoring thus

represents a reliable, operational, and practical tool for environmental control and can be recommended for implementation in marine emergency response systems in the Black Sea region.

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Natalia Lytvynenko, PhD (Technical), Senior Researcher
ORCID ID: 0000-0002-2203-2746
n123n@ukr.net

Oleksandr Korenets, PhD (Geography)
ORCID ID: 0000-0001-6352-9591
e-mail: oleksandr.korenets@knu.ua

Tamara Kurach, PhD (Geography), Assoc. Prof.
ORCID ID: 0000-0002-5989-9431
e-mail: kurachTM@knu.ua

Iryna Pidlisetska, PhD (Geography), Assoc. Prof.
ORCID ID: 0000-0001-6724-2379
e-mail: Irinna2008@univ.net.ua

Military Institute of Taras Shevchenko National University of Kyiv