



HECO: A lightweight CMEMS-based oil-spill risk-assessment tool

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ABSTRACT

Oil spills pose significant threats to marine ecosystems and coastal economies; therefore, rapid and effective emergency response is critical. Although operational forecasting models can provide highly accurate simulations, they require domain specialists to make decisions about environmental vulnerabilities. This technical barrier creates an accessibility gap that can delay situational awareness during the first hours of an emergency, particularly for local authorities without dedicated expertise. HECO (Here Comes the Oil) is an open-source, Python-based Lagrangian particle dispersion model (LPDM) powered by the Copernicus Marine Environment Monitoring Service (CMEMS). The model was evaluated through a hindcast of the August 2021 Baniyas spill, using successive Sentinel-1 SAR-derived footprints for validation. The best-performing configuration covered 86.9% of the observed area with a Jaccard index of 61.7% and a Dice similarity coefficient of 76.3%, while completing the entire simulation and output-generation workflow in less than 15 min on a standard laptop. The model also demonstrates high robustness to variations in released oil volume and perturbations in spill origin. This shows the model's significant geometric reliability for rapid hazard mapping during the early stages of an emergency response. HECO is intended for rapid, first-tier surface-hazard assessment by non-specialist users. By lowering the technical barriers to spatial hazard assessment, it enables first responders to rapidly quickly identify safe navigation zones and prioritize coastal protection strategies while awaiting more advanced operational modeling.

1. Introduction

Oil spills can cause persistent environmental, social, and economic damage (Depellegrin and Blažauskas, 2013; Saadoun, 2015; El Mous-saoui and Idelhakkar, 2023). Their recurrence, together with continuing offshore production and seaborne oil transport, makes rapid trajectory forecasting an operational requirement rather than an occasional research task (Carswell, 2018; Nelson and Grubescic, 2019). The recurrence of major spill events demonstrates that these incidents are not isolated, but are part of a persistent global pattern (Carswell, 2018). As the oil industry continues to expand into new offshore frontiers and global seaborne oil flows remain substantial, the risk of future accidents remains significant (Nelson and Grubescic, 2019). At the same time, the global energy transition is progressing unevenly across sectors and geopolitical contexts (Zhu et al., 2025). In this context, the ability to forecast the spatial and temporal evolution of oil spills is not merely a scientific endeavor, but an operational necessity to mitigate environmental and socioeconomic damage.

To mitigate the impact of these accidents, timely and reliable predictions during the early phases of an oil spill are critical to inform

containment and remediation strategies. During the first hours of an incident, even a preliminary estimate of the affected area can guide monitoring, containment, and coastal-protection priorities. However, existing forecasting systems often rely on complex hydrodynamic models that integrate wind, wave, and current data through computationally intensive numerical schemes. For instance, GNOME (General NOAA Operational Modeling Environment), provided by the National Oceanic and Atmospheric Administration, is a suite for oil spill modeling (Beegle-Krause, 2001). It has been implemented in several computational environments, including web, Python, and standalone, and it is widely used by researchers and environmental managers (Farzinger et al., 2024). *OpenDrift* is a versatile Python-based framework that simulates the paths of diverse elements ranging from oil spills, search-and-rescue targets, biological larvae and microplastics (Brekke et al., 2021). *OpenOil* is a model bundled inside *OpenDrift* used specifically for oil-spills for large-time simulation (Papaioannou et al., 2025). *MEDSLIK-II* is a simulation tool designed to track and predict the movement of oil spills by calculating how marine environments influence pollutants over time. By integrating data on wind patterns,

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water currents, and temperature, the model creates a digital recreation of how oil particles drift, evaporate, and interact with coastlines (De Dominicis et al., 2013b). OILMAP is designed for rapid response and thorough contingency planning and utilizes a comprehensive 3D model to simulate the movement and degradation of hydrocarbons across the water surface, water column, and atmosphere (Qiao et al., 2024). While the core Lagrangian simulations of established models like GNOME, OpenDrift with OpenOil or MEDSLIK-II are computationally efficient, configuring these models, harmonizing environmental forcings, and processing the outputs into actionable risk maps present a steep learning curve and require specialized expertise. In this context, the need to process and integrate raw outputs across different software environments might represent a more significant technical barrier than computational time. This steep learning curve creates an accessibility gap that can impede immediate decision-making during the critical first hours of an emergency, particularly for local authorities lacking dedicated staff (Okhariev and Pidsadnii, 2024; Merz et al., 2020; Huang et al., 2021). The ability to communicate the potentially affected areas quickly and accurately, especially in relation to weather-based forecasts, is essential for organizing timely and efficient emergency responses (Kalas et al., 2024).

Recent lightweight models, such as CranSLIK (Snow et al., 2014) and SVR-PM (Liu et al., 2023), use regression-based approaches to reduce the computational costs of oil-spill forecasting. CranSLIK is a computationally efficient statistical surrogate of MEDSLIK-II, using fitted relationships and stochastic sampling to approximate slick transport and spreading without reproducing the full model physics and state variables. Similarly, SVR-PM is a data-driven parameterization that estimates the wind-drift factor from wind conditions and integrates it into a Lagrangian oil-spill model, replacing an explicit representation of the underlying air-sea-oil interactions. However, these models have simplified physics and output. Notwithstanding the use of simpler formulations, both models require substantial expertise in forcing-data preparation, uncertainty characterization, model configuration and interpretation of the resulting forecasts. These trade-offs motivate the development of accessible, computationally efficient forecasting tools with a transparent physical basis.

In the light of the above, we introduce “HECO” (*Here Comes the Oil*), a lightweight, open-access tool for forecasting oil spills, specifically developed for integration into early-warning systems (EWS). Built upon a simplified Lagrangian Particle Dispersion Model (LPDM), HECO allows rapid simulations of pollutant drift based on real-time marine current data. The tool is designed to run efficiently even on modest hardware configurations, allowing deployment on personal laptops or low-cost servers.

What sets HECO apart is its alignment with the principles of a just transition, fostering a sustainable, inclusive, equitable, and globally accessible approach to environmental risk management. The platform integrates a web-based GIS interface that allows users to easily visualize oil spill trajectories alongside ancillary datasets (e.g. maritime traffic density, ecologically sensitive zones, and marine protected areas). By lowering technical and financial barriers, HECO extends the reach of environmental forecasting tools beyond highly specialized institutions, empowering coastal communities, public authorities, NGOs, and academic stakeholders in both developed and developing contexts (Sauer-mann et al., 2020). The model’s predictive accuracy was validated using hind-cast simulations of historical Mediterranean oil spills, with performance metrics benchmark against those of comparable forecasting systems.

In the following sections, we will introduce the integration with the kinematic forcing provided by the Copernicus Marine Environment Monitoring Services (CMEMS) and the auxiliary layers used for the output provided by the European Marine Observation and Data Network (EMODnet) (Martín Míguez et al., 2019). We also present the mathematical structure of the approximate model and the Python-based architecture that was developed. The user experience and interactive

web-GIS outputs are illustrated. After a sensitivity analysis, the model is validated against the 2021 Syrian Baniyas oil spill, and its performances are compared with the ones of existing models. Finally, a discussion and some final remarks are provided regarding tool’s strength, limitations and future developments of the proposed tool.

2. Materials and methods

This section describes the environmental datasets used to force HECO, the mathematical formulation of the Lagrangian model, and the parameterization of horizontal turbulent diffusion.

2.1. Data sources

Oil spill dispersion models are usually driven by a combination of external forcings, most commonly wind stress, Eulerian surface currents, wave-induced processes, and small-scale turbulent diffusion (Keramea et al., 2023a).

In the present work, model complexity is deliberately constrained to develop a fast and operationally accessible framework based on a single kinematic forcing. Previous studies have shown that Stokes drift and marine currents play a major role in oil slick dispersion (Drivdal et al., 2014), and either of which can be adopted as a kinematic forcing in a LPDM.

Stokes drift (Stokes, 1847) is particularly critical for accurately modeling the transport of oil spills. Traditional models often use wind-based estimates for Stokes drift, which can be inaccurate, as they may not account for ocean swell. The strong vertical shear of the drift, which diminishes rapidly with depth, further complicates the predictions for submerged oil. Advanced modeling that incorporates Stokes drift, Coriolis–Stokes forcing, and wave-enhanced mixing has been shown to significantly improve oil spill trajectory forecasts, predicting slower and more deflected drift paths compared to models that neglect wave effects (Drivdal et al., 2014). Observational studies have confirmed that in swell-dominated regions, wave-driven Stokes drift can be the main transport mechanism for low-windage oil, leading to trajectories that diverge significantly from the wind-aligned assumptions (Allshouse et al., 2017).

Marine current data are determined by solving physical ocean equations in a numerical general circulation model, constrained by real-world atmospheric forcing and assimilated observational data; these data can include satellite-altimetry time series, in situ temperature and salinity profiles, and more (Escudier et al., 2021).

Wave forcing data is obtained from the CMEMS database. In particular, the dataset *Mediterranean Sea Waves Analysis and Forecast* for Stokes drift (Clementi et al., 2023) and *Mediterranean Sea Physics Analysis and Forecast* for marine currents are considered (Escudier et al., 2020). Both datasets are provided on a regular $1/24^\circ \times 1/24^\circ$ lat-lon grid (≈ 4.6 km resolution) covering longitude 18.125–36.292 E and latitude 30.188–45.979 N. They provide two daily cycles (00 UTC and 12 UTC) that combine a 12 h analysis with a 10-day forecast, archived in a rolling two-year window. Hourly fields provide the Cartesian components of the Stokes drift and the marine current velocity. These variables enable direct reconstruction of the two-dimensional forcing vector $\vec{v} = (u, v)$ at every point in the grid and time step, thus resolving the induced full spatio-temporal variability. On the one hand integrating Stokes drift variables from CMEMS into Lagrangian oil-spill models overcomes the limitations of wind-based parameterizations. Firstly, the wave model inherently captures the propagation of the swell far from its generation area, which is a component that empirical wind-speed relations systematically neglect. Secondly, the hourly resolution and rapid updates allow Stokes drift to be coupled with co-temporal surface currents and atmospheric forcing. This preserves the critical phase relationship between waves and winds for Coriolis–Stokes feedback on drift trajectories.

Table 1
HECO's user defined input variables stored in `sim_settings.yaml`.

Variable name	Type	Unit	Range	Description
<code>credential_path</code>	<i>string</i>	–	–	Path to YAML file with username and password for CMEMS API access
<code>dataset_file_name</code>	<i>string</i>	–	–	Path and name of the NetCDF file with surface velocity forcing of the model
<code>lat0, lon0</code>	<i>degree</i>	[°]	[–180 +180]	Latitude and Longitude value of oil-spill origin, in WGS84 geographical coordinates.
<code>sim_diffusion_coeff</code>	<i>real</i>	[m ² /s]	[0–100]	Diffusion coefficient called D in Eq. (1)
<code>sim_duration_h</code>	<i>integer</i>	[h]	>0	Duration in hours of dispersion simulation to conduct.
<code>sim_particles</code>	<i>int</i>	<i>adim.</i>	>0	Number of particles to consider for LPDM, this value has an impact on computational resources needed
<code>sim_timedelta_s</code>	<i>int</i>	[s]	>0	The time step in seconds for each iteration to conduct in LPDM in discrete scenario.
<code>spill_release_duration_h</code>	<i>int</i>	[h]	>0	Parameter to perform a discrete calculation for a continued spill scenario. A value >1 distributes the spilled volume into multiple single instantaneous spills
<code>time0</code>	<i>datetime</i>	–	–	Time start of the oil-spill event, format ISO 8601: “YYYY-MM-DD HH:MM:SS”.
<code>volume_spilled_m3</code>	<i>real</i>	[m ³]	>0	Total of estimated volume of oil.

One the other hand, using a sea water velocity that can change in an LPDM solves the problem of how circular currents are usually calculated. The current vector model is defined by various components, including wind and tidal currents factors (Escudier et al., 2020). With HECO, users can choose to use either marine current data or Stokes drift data, or they can select their own custom forcing vectors.

To contextualize and assess impacts of the oil-spill on environmental and socio economic assets, the developed tool integrates auxiliary data from the EMODnet Human Activities portal, such as bathing water locations (European Environment Agency, 2024) and vessel density (European Commission. Directorate General for Maritime Affairs and Fisheries, 2023), which are embedded directly into the tool's Web-GIS interface. These data layers are utilized for visual enrichment and risk assessment, allowing users to assess the proximity of the predicted oil spill trajectories to sensitive zones and maritime traffic. These layers provide map-based intelligence to support rapid, preliminary hazard assessments and decision-making for emergency responders.

2.2. Modeling framework

As with most existing oil spill models, the core of HECO is a two-dimensional LPDM, in which buoyant particles representing oil droplets are transported by surface currents (De Dominicis et al., 2013b,a; Röhrs et al., 2018). The model solves a 2D advection–diffusion equation for each particle including diffusion represented as a random walk, as described in Eq. (1) using the explicit Euler integration method:

$$\bar{x}(t_i) = \bar{x}(t_{i-1}) + \bar{V} \cdot \Delta t + R\sqrt{2D\Delta t} \quad (1)$$

Eq. (1) describes the trajectory of individual oil particles using a two-dimensional advection-diffusion framework, solved numerically via an explicit Euler integration scheme. The model calculates the updated geographic position of a particle at the current time step, $\bar{x}(t_i)$, by displacing its previous position, $\bar{x}(t_{i-1})$, through two distinct physical mechanisms.

The first mechanism is the deterministic advection term, $\bar{V} \cdot \Delta t$, which represents the macroscopic transport of the particle driven by the two-dimensional kinematic forcing vector $\bar{V} = (u, v)$ [m/s] (e.g., surface marine currents or Stokes drift), applied over the simulation time step Δt [s].

The second mechanism, $R\sqrt{2D\Delta t}$, represents a stochastic random walk used to parameterize sub-grid scale turbulent diffusion and the horizontal spreading of the oil slick. Here, D is the horizontal diffusion coefficient [m² s^{–1}], typically ranging between 1 and 100 depending on the local hydrodynamic conditions (De Dominicis et al., 2013a), and R is a normally distributed stochastic variable. By combining these components, the model simulates both the directional drift and the continuous surface dispersion of the pollutant over time.

The horizontal diffusion coefficient parametrizes sub-grid-scale turbulent mixing and the stochastic spreading of Lagrangian particles driven by unresolved oceanic processes. No single universal open-sea LPDM diffusion coefficient exists for oil-spill forecasting. Instead, diffusion parameterizations are linked to local hydrodynamics, wind-driven mixing, and turbulence closures. Reported horizontal open-water values typically fall within the range of 1–10 m²/s, although values up to 100 m²/s have been used depending on the environmental setting. For instance, empirically calibrated horizontal diffusion values include 14 m²/s for Lake Erie (Song et al., 2025) and 10–100 m²/s for Black Sea drifter trajectories (Ivanov et al., 2021). In highly constrained coastal settings, substantially lower values, such as 0.025 [m²/s], have also been applied (Do et al., 2025).

The two-dimensional velocity field for the simulated period is provided by Stokes drift or marine currents. The values of $\bar{V} = (u, v)$ can be $VSDX, VSDY$ in the case of Stoke drift and uo, vo in case of marine currents, both of which are provided by the CMEMS data store in a NetCDF file format (Rew and Davis, 1990). At each iteration, a geospatial query selects the forcing-grid cell nearest to the particle. Optionally, the user can choose to perform a spatial, bi-linear interpolation of the forcing variable. This increases the computational effort and time, and uses the built-in Xarray Python library to read the dataset (Hoyer et al., 2024).

Because the CMEMS forcing datasets have a spatial resolution of approximately 4.6 km, their gridded velocity fields do not resolve fine-scale and sub-grid turbulent motions. In this context, D acts like a sub-grid closure parameter, representing unresolved transport and mixing processes. Its appropriate value may depend on grid resolution, local hydrodynamic conditions, and the physical processes omitted from the forcing fields; it should therefore be calibrated against suitable observations or explored through sensitivity analyses rather than assumed a priori.

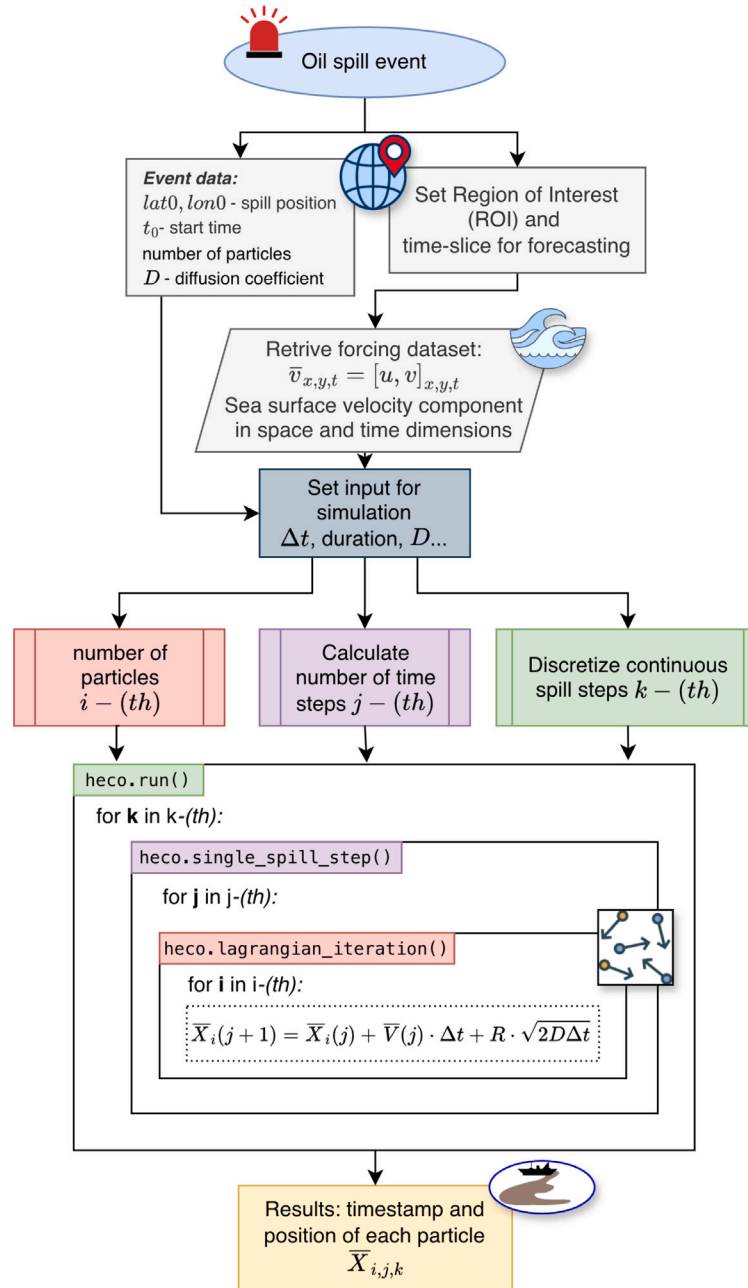


Fig. 1. Workflow of the HECO Lagrangian oil-spill diffusion estimation model. From the event descriptors — spill coordinates (lat_0, lon_0) , start time t_0 and turbulent-diffusion coefficient D — the region of interest, forecast window, and sea-surface velocity field $\vec{V}_{x,y,t} = [u, v]_{x,y,t}$ are extracted. The main routine `heco.run(yaml_file)` receives the simulation parameters (time step Δt , total duration, etc.) and launches three nested loops: k discrete release steps, j model time steps, and “ i ” Lagrangian particles. For every k -release step, `single_spill_step()` calls `lagrangian_iteration()` to update each particle position according to Eq. (1). Finally the routine returns the time-stamped trajectory matrix $X_{i,j,k}$ that records the position of every particle at every time step.

It is worth pointing out that the proposed LPDM is a simplified model, suitable for rapid assessments of oil spill dispersion in marine environments. In fact, it neglects possible vertical displacements of the oil droplets, ignoring vertical dispersion, emulsification, and vertical mixing. Moreover, it assumes that the oil spill occurs at the sea surface. However, these simplifications are acceptable for the scope of the proposed fast-computing model: specifically during the critical initial phases of an emergency where preliminary situational awareness takes precedence over long-term biogeochemical analysis. Prioritizing horizontal advection and surface transport, HECO ensures that its results represent a conservative and “worst-case” surface footprint.

2.3. Tool implementation

In accordance with the FAIR4RS principles (Wilkinson et al., 2016; Barker et al., 2022), we developed a Python tool in conjunction with Jupyter Notebook as the development environment.

HECO uses the forcing data for the diffusion vector in the LPDM and a set of parameters for simulation. All input data can be stored with specification described in Table 1 and saved in a YAML file (Predoaia et al., 2024).

Three dedicated Python functions were implemented and organized into nested iterative loops, as illustrated in Fig. 1. The computational

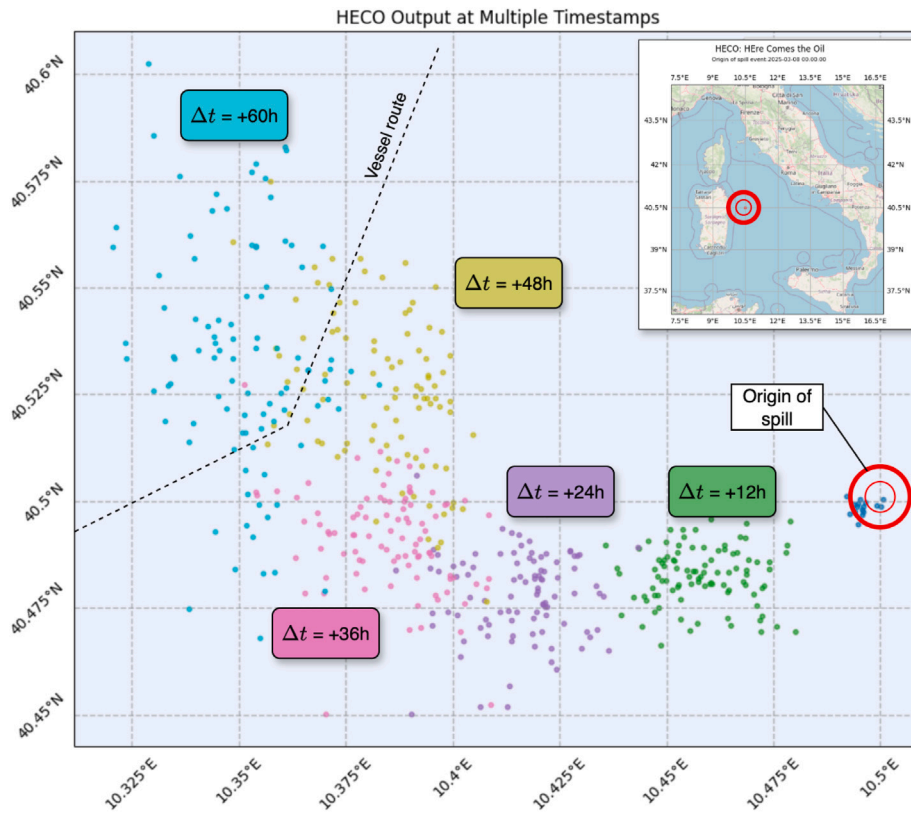


Fig. 2. Multi-temporal scatter plot of LPDM results. In this simulation example the variable used were: `dataset_file_name = HECO_TEST.nc`, `lat0 = 40.5`, `lon0 = 10.5`, `sim_diffusion_coeff = 10.0 m2/s`, `sim_duration_h = 72`, `sim_particles = 100.0`, `sim_timestep_s = 3600.0`, `spill_release_duration_h = 6.0`, `time0 = 2025-03-08 00:00:00`, `volume_spilled_m3 = 1000`.

workflow is organized into three nested functions, which track the position of each i th particle at every j th time interval and, for a continuous oil spill, repeat the simulation over k discrete release steps:

1. the core function, named as `lagrangian_iteration()`, processes the data from the forcings, the position of a i -(th) particle, and employs Eq. (1) to yield the new position of the particle after the time interval;
2. `single_spill_step()` iterates the result of previous in a finite number j -(th) of time intervals, and for a finite number i -(th) of particles;
3. a global function `heco.run(yaml_file)` incorporates the preceding functions and iterates across k -(th) spilling discrete steps.

Each iteration result is the position of a single particle after the application of forcing and time with the Lagrangian model. Fig. 1 shown the workflow of the core algorithm of HECO, from the input to output. Simulation results consist in a list of records. Each record represents the state of an individual Lagrangian tracer at a specific simulation time and is uniquely identified by the triplet (i, j, k) .

A corresponding timestamp (`time`) is provided for each entry to facilitate chronological ordering and synchronization with external forcing data. Finally, the geographical coordinates `lat` and `lon` report the particle's position in decimal degrees referenced to the WGS-84 coordinate reference system, constituting the primary output needed for subsequent visualization, statistical post-processing, or data assimilation procedures.

Established operational forecasting models provide accurate simulations of the oil spill movement, but their raw outputs, such as NetCDF or trajectory data, typically require manual processing and integration with GIS software by specialized experts to assess environmental and socio-economic vulnerabilities.

While the native outputs of many modeling systems require dedicated parsers, GIS software, or additional post-processing, HECO automatically exports the simulation results as standard, lightweight files that can be directly visualized, shared, or reused in subsequent analyses. The generated outputs comprise:

- the position of each simulated particle is stored as a point geometry for every LPDM time step which is saved into a GeoJSON file (Butler et al., 2016; Jordahl et al., 2020). It provides a simple and interoperable representation that can be directly imported into GIS software or processed using standard geospatial libraries;
- a GIF animation, that shows the temporal evolution of the particle distribution;
- a plot with multi-temporal particle distribution, that overlays particle positions from successive time steps. This output provides a concise overview of the simulated dispersion pattern, as illustrated in Fig. 2;
- A single-page web map. It includes timeline controls, base-layer selectors, informative popups, and contextual EMODnet layers retrieved through OGC-WMS calls. An Internet connection is therefore required only to retrieve these remote services, as illustrated in Fig. 3.
- the particle-distribution envelopes, which are converted from particle positions into convex-hull polygons. These geometries, also stored into a GeoJSON file, provide a computationally efficient representation of the spatial envelope of the simulated particles and can be readily shared with GIS users and map viewers.

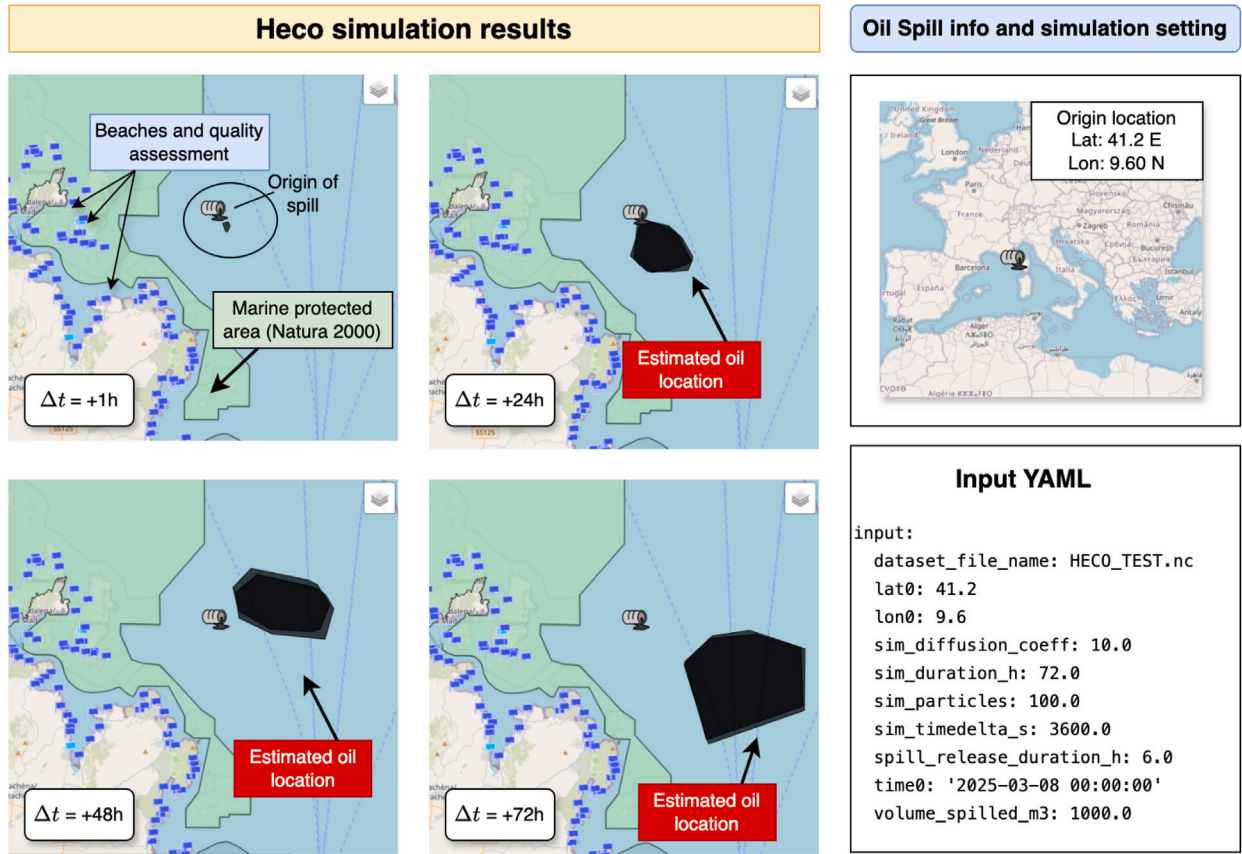


Fig. 3. Example of input data and result visualization using the *html web-map* feature. Using *convex-hull* polygon generation, it is possible to identify the envelope of the simulated particles of the oil spill.

Together, these outputs support different levels of analysis, ranging from direct access to the individual particle positions to rapid visual assessment and interactive exploration of the simulated spill trajectory. The auxiliary data layers, from EMODnet Human Activities portal (Martín Míguez et al., 2019), are listed in Table 2, they are embedded in the single-page web map output using Folium Python library and WMS client calls (Camara et al., 2021), also shown in Fig. 3. Supplementary materials provides more details model implementation and an user guide.

3. Model performance and validation

To assess the predictive accuracy and operational robustness of HECO, this section details the quantitative validation framework, performance metrics, sensitivity analysis and subsequent a real-world case-study results.

3.1. Performance metrics

To quantify the level of agreement between the modeled and observed oil spill evolution, or between different oil spill simulations, we can evaluate the consistency between the simulated convex-hull polygon and a benchmark polygon. A set of metrics can be used to score the shape, centroid location, and dimensions of the resulting polygons compared with a benchmark polygon (for eg. an observed oil slick map). The *Success Rate Area* (SRA), defined in Eq. (2), quantifies the proportion of the benchmark polygon covered by the polygon being evaluated. It is calculated by dividing their intersection area by the total area of the benchmark polygon. An SRA of 100% indicates complete coverage of the benchmark area, whereas 0 indicates no spatial overlap;

however, SRA alone does not penalize simulated area outside the observed footprint.

$$SRA = \frac{Area(B \cap E)}{Area(B)} \quad (2)$$

where “B” is the benchmark polygons, and “E” is the evaluated polygon.

The *Centroid Displacement Index* (CI) is the distance between the benchmark and simulated centroids, normalized by the diagonal of the benchmark polygon’s bounding box (Papaioannou et al., 2025).

$$CI = \frac{\Delta x}{L_{box}} \quad (3)$$

The *Jaccard* (J) index, defined in Eq. (4), is the ratio of the intersection area to the union area of the benchmark and evaluated polygons (Madhikermi et al., 2016).

$$J = \frac{Area(B \cap E)}{Area(B \cup E)} \quad (4)$$

The *Dice Similarity Coefficient* (DSC) is frequently utilized in image-processing-based validation (Rizwan I. Haque and Neubert, 2020), such as urban morphology reconstruction or medical imaging. It provides more weight to the intersection of the benchmark (“B”) and evaluated (“E”) polygons by doubling it in the numerator, is defined in Eq. (5).

$$DSC = \frac{2 \times Area(B \cap E)}{Area(B) + Area(E)} \quad (5)$$

By combining spatial overlap, boundary agreement, and positional displacement, this set of metrics ensures a comprehensive assessment of the model’s geometric sensitivity to oil spill origin location and volume, as well as of its geometric accuracy compared to observations.

Table 2

Layer list used for the Web GIS map. In this study, all WMS layers are provided by EMODnet, [Martín Míguez et al. \(2019\)](#).

Layer	Description
<i>EMODnet Human Activities:</i> Offshore oil-and gas-installations	Point features with attributes on operator, operational status, water depth and installation type. Displaying the infrastructure facilitates an assessment of both the accident's possible origin and collateral risks to neighboring energy assets.
<i>EMODnet Human Activities:</i> EMSA Route Density Map	Average ship-route density raster (1×1 km spatial resolution) of derived from AIS tracks, providing an at-a-glance representation of the principal shipping corridors intersecting the spill trajectory.
<i>EMODnet Human Activities:</i> Vessel Density Map	Monthly hours of vessel presence per grid cell (1×1 km spatial resolution) and per ship class, thereby quantifying overall traffic intensity and complementing the route-density layer for risk analysis.
<i>EMODnet Human Activities:</i> Bathing-water status	Point features representing officially monitored bathing locations and their annual quality classification under Directive 2006/7/EC. Incorporating this dataset enables the rapid appraisal of potential public-health and tourism impacts.
<i>Natura 2000 sites</i>	Polygons delimiting marine and coastal Special Protection Areas and Special Areas of Conservation throughout the EU. The layer, derived from European Environment Agency geometries, immediately indicates the presence of legally protected habitats that could be exposed to contamination.
<i>EMODnet Bathymetry</i> World Base Layer	World base-layer bathymetry — EBWBL (Thierry et al., 2019).

3.2. Sensitivity analysis

A sensitivity analysis was conducted to characterize the robustness of HECO's simulated trajectories to uncertainty in selected input parameters using a one-at-a-time perturbation approach. In particular, experiments for the perturbation of origin location and spilled volume were derived from a common benchmark configuration: a spill origin at 40.5°N , 10.5°E ; a diffusion coefficient $D = 10 \text{ m}^2/\text{s}$; 100 Lagrangian particles; a 72-h simulation duration; a 3600 s time step; a 6-h release duration; a spilled volume of 1000 m^3 and wave currents as forcing. The experiments perturbed: (i) origin location, with 298 different random origins in a 0.12° lat/lon range from benchmark, and (ii) volume spilled with 125 simulations with 25 different values ranging from 500 m^3 to 2000 m^3 in replicates test with five random seeds.

Spatial resolution and integration time step were not varied independently in the present sensitivity analysis. All experiments employed the native CMEMS spatial and temporal resolution. Consequently, the reported results apply to this numerical configuration. Sensitivity to forcing resolution and integration time step remains to be evaluated through a dedicated spatial and temporal convergence analysis.

3.2.1. Origin location

The spatial sensitivity of HECO was evaluated by perturbing the initial spill coordinates within the intervals $40.44\text{--}40.56^\circ\text{N}$ and $10.44\text{--}10.56^\circ\text{E}$, corresponding to maximum coordinate offsets of approximately $\pm 0.06^\circ$ from the reference origin (40.50°N , 10.50°E). The resulting distances from the benchmark ranged from 0.14 to 8.75 km.

[Fig. 4](#) shows a pronounced reduction in agreement with increasing origin displacement. Perturbations aligned within 30° of the NE–SW direction (parallel to the forcing ocean current used) have a better performances with SRA and DSC upper than 56%. In comparison, perturbations oriented $60\text{--}90^\circ$ from the current axis have lower performances

with SRA and DSC lower than 10%. Thus, origin displacement is an important control on model agreement, but its effect is strongly direction-dependent. The NE–SW elongation of the high-agreement region is consistent with the forcing-current field, indicating greater robustness for perturbations aligned with the prevailing transport pathway than for similarly distant cross-current perturbations.

3.2.2. Spilled volume

A baseline simulation, hereafter referred to as the benchmark, was established using a reference configuration with a spill volume of 1000 m^3 . The sensitivity analysis covered volumes between 500 and 2000 m^3 , sampled at 62.5 m^3 intervals. This produced 25 volume levels, including the benchmark. Because spilled volume is not used directly by HECO's particle-trajectory calculations, its effect was represented by varying the number of released particles while maintaining a constant represented volume.

Each volume scenario was simulated using five independent random seeds. Within each replicate, the same seed was applied to the benchmark and to every tested volume, thereby implementing a common-random-number design intended to reduce variability arising from stochastic forcing. In total, 125 HECO simulations were performed: five benchmark simulations and 120 sensitivity simulations. All parameters other than the represented spill volume and corresponding particle count were held constant. At each simulation time, particle positions were converted into convex-hull polygons.

Sensitivity was evaluated at the final common timestamp by comparing each simulated footprint with the corresponding same-seed benchmark footprint.

Spatial agreement was quantified using the Success Rate Area, Jaccard similarity, Dice similarity coefficient, and Centroid Index. Higher values indicated greater agreement for the first three metrics, whereas lower Centroid Index values indicated closer alignment between polygon centroids. For each tested volume, the five replicate scores were summarized using their arithmetic mean and sample standard deviation.

This experiment measures the sensitivity of the particle-sampled convex-hull footprint to the number of particles used to represent the spill.

As shown in [Fig. 5](#), similarity scores remain highly stable across the entire volume spectrum, substantially without geometric degradation. While initial volume dictates in internal concentration and mass balance, it minimally impacts the slick's outer boundary and trajectory within HECO's Lagrangian framework. Therefore, the results demonstrate that the HECO model's simulations are highly robust to variations in the initial spilled volume parameter. The average score of SRA, J, and DSC remain constant up to a score of 70%, and the CI remains below 10%. This confirms the model's geometric reliability for rapid hazard mapping during the critical first hours of an emergency, even when the exact spill size is uncertain.

3.3. Model validation

To validate HECO under a documented historical scenario, a hind-cast was performed for the August 2021 Baniyas oil spill in the eastern Mediterranean Sea. On 23 August 2021, a ruptured tank released more than 10,000 tonnes of heavy fuel oil into the Mediterranean, creating a massive slick that contaminated hundreds of kilometers of the Syrian coastline before spreading both North and West, threatening the shores of Turkey and Cyprus ([Keramea et al., 2023b](#)). Oil-slick extents interpreted from Sentinel-1 SAR imagery ([Chaturvedi et al., 2020](#)) were obtained from [Abou Samra and Ali \(2024\)](#) for two acquisition times: 29 August 2021 at 16:36 UTC and 30 August 2021 at 10:58 UTC.

The two observations had distinct roles in the validation process: the 29 August footprint was used to define the dispersed initial condition, whereas the last footprint was reserved as the spatial verification target.

Because HECO represents releases as point sources, the 29 August SAR-derived footprint was discretized into 52 virtual sources located at the centroids of all forcing-grid cells intersecting the footprint.

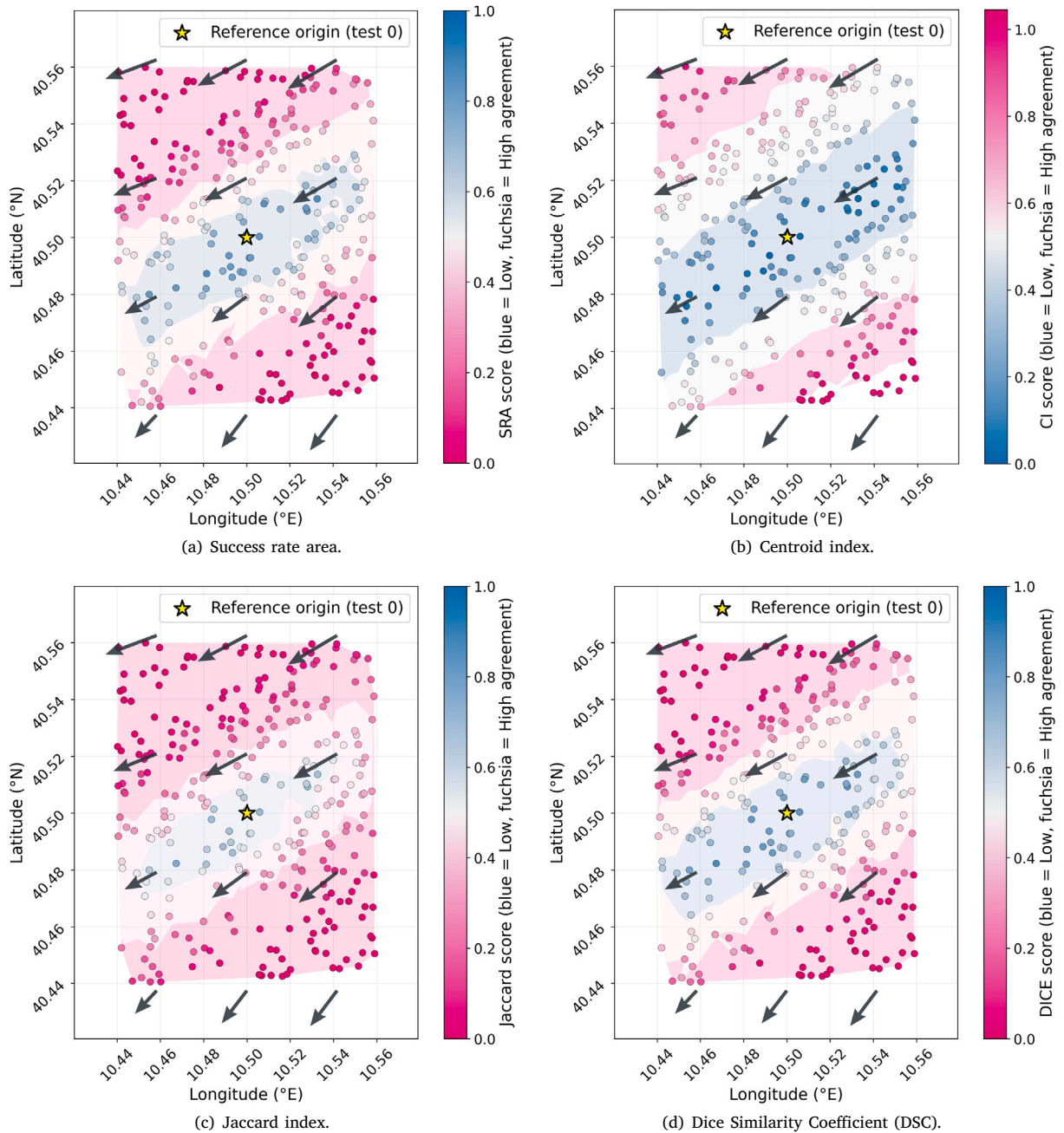


Fig. 4. Final-iteration spatial sensitivity of HECO to perturbations of the spill origin location. The panels show (a) SRA, (b) CI, (c) Jaccard and (d) DSC scores for 298 perturbed simulations relative to the reference simulation, whose origin is indicated by the yellow star (benchmark). Blue was used for the low agreement scores and fuchsia for the high ones. Agreement generally decreases with distance from the benchmark, but the response is anisotropic: origins aligned with the NE-SW current axis retain substantially higher agreement than similarly distant cross-current origins. The arrows represent the marine-current field at the initial simulation time. Variations in the scores are more strongly influenced by the proximity of the perturbed locations to different current regimes and circulation patterns than by their distance from the reference location.

3.3.1. Diffusion coefficient calibration

To evaluate the HECO model's response to turbulent mixing parameterizations, an event-specific calibration analysis was conducted focusing on the horizontal diffusion coefficient. For each of 52 distinct spatial origins, an iteration of 150 baseline simulations was executed. Across these iterations, the diffusion coefficient was systematically perturbed, scaling linearly from a minimum of 5.0 to a maximum of 80.0. Other configuration parameters were: simulation timestep = 3600 s, Volume spilled 100 m³ for each point, spill release duration = 1 h, start-time = 2021-08-29 16:36:07, duration 19 h. As shown in Fig. 6,

the calibration produced three distinct optimal values of D , one for each metric score. The highest SRA, 96.3%, was obtained for $D = 77.48$ m²/s, while the minimum CI, 0.069, occurred at $D = 78.49$ m²/s. In contrast, both overlap-based metrics selected a substantially lower coefficient, $D = 10.03$ m²/s, yielding a maximum Jaccard index of 63.9% and a corresponding DSC coefficient of 77.9%.

The calibration analysis shows that D affects HECO differently depending on the metric. As D increases, SRA rises from about 81% to above 95%, indicating that the simulated plume covers a larger fraction of the observed footprint. However, because SRA does not

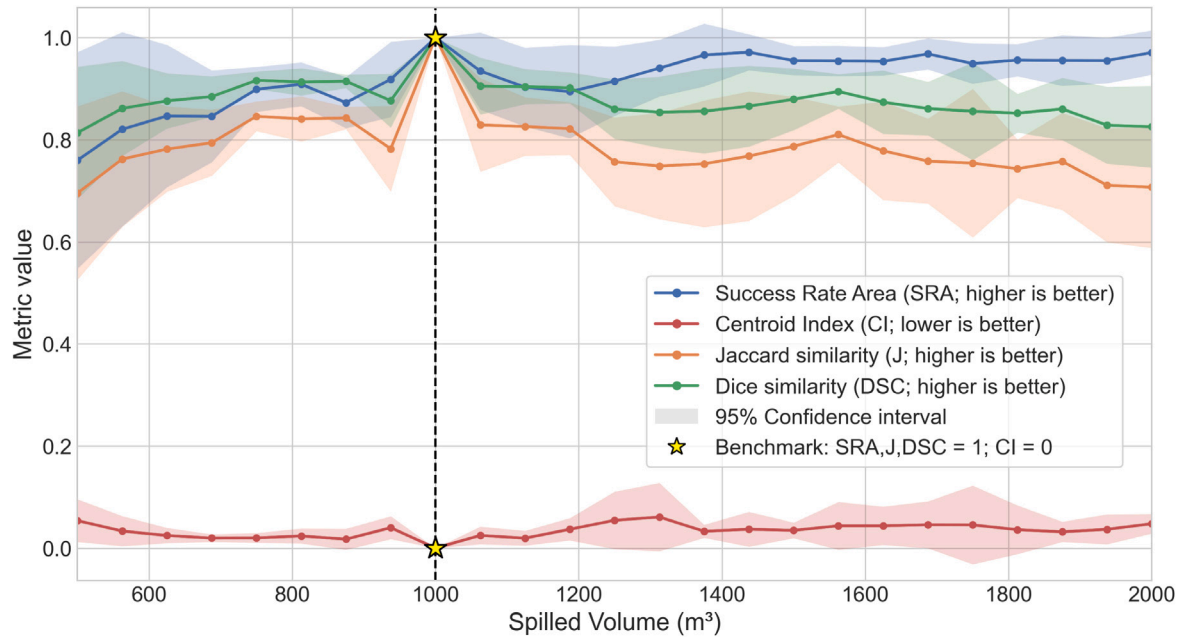


Fig. 5. Sensitivity analysis of the spilled volume for spatial similarity metrics. Success Rate Area (SRA — Eq. (2)), Centroid Index (CI — Eq. (3)), Jaccard Index (Eq. (4)), and Dice Similarity Coefficient (DSC — Eq. (5)) are reported. Final-iteration scores across simulated volumes exhibit an approximately horizontal trend, indicating negligible sensitivity to spill volume. The absence of systematic degradation demonstrates that the HECO model produces spatial boundaries and centroid displacements that remain geometrically stable even under substantial variations in the initial spill volume.

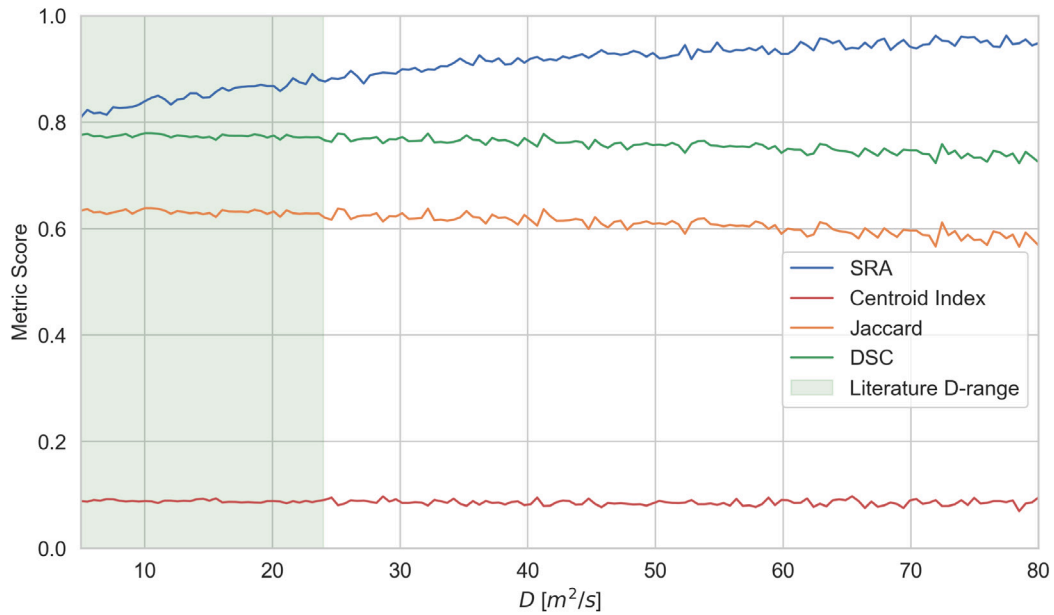


Fig. 6. Response of the spatial-agreement metrics to variations in the horizontal diffusion coefficient D . Success Rate Area (SRA — Eq. (2)), Centroid Index (CI — Eq. (3)), Jaccard Index (Eq. (4)), and Dice Similarity Coefficient (DSC — Eq. (5)) are reported. Higher SRA, Jaccard Index, and DSC values indicate better agreement, while lower CI values indicate better agreement. It is also reported the range of D used for similar sea conditions (Song et al., 2025). The SRA index consistently improves its score because as diffusivity increases, the overall size of the enclosing polygon also increases. Thus, it always encompasses the observed polygon. The Jaccard and DSC indexes both show a decline after $D=10$, which indicates that values of D that are too high are not supported by the literature for this particular case.

penalize simulated area outside the observed polygon, this increase should not be interpreted alone as improved overall spatial agreement. Conversely, Jaccard and DSC slightly decrease as stronger diffusion enlarges the simulated plume and increases the excess area outside the observed footprint, thereby reducing the normalized spatial overlap. CI is substantially constant, suggesting that plume displacement is also influenced by stochastic dispersion and transport.

After this preliminary event-specific calibration, the optimal value for the diffusivity coefficient can be estimated. Within the range indicated in the literature, the best performance is observed with a value of $D = 20 \text{ m}^2/\text{s}$, considering all the metrics.

3.3.2. Simulation using different forcings

Considering the diffusion coefficient $D = 20 \text{ m}^2/\text{s}$, two simulation were conducted using different forcing vectors: Test#1 used Stokes

Table 3
Spatial comparison results.

Metric	Unit	Test #1	Test #2
Area measures			
Area O (observed)	km ²	2092.7	2092.7
Area S (simulated)	km ²	2671.4	2422.4
Area $(O \cap S)$ (intersection)	km ²	1818.5	1595.6
Area $(O \cup S)$ (union)	km ²	2945.5	2919.4
Centroid distance Δx	km	9.8	9.3
Bounding-box diagonal L_{box}	km	104.6	104.6
Benchmark metric scores			
Success Rate Area (SRA)	%	86.9	76.24
Jaccard similarity Index (J)	%	61.7	54.7
Dice Similarity Coefficient (DSC)	%	76.3	70.7
Centroid Index (CI)	–	0.0938	0.0885

drift, and Test#2 used marine currents. All other parameters were the same: simulation timestep = 3600 s, Volume spilled 100 m³ for each point, spill release duration = 1 h, start-time = 2021-08-29 16:36:07, duration 19 h.

Forcing velocities were sampled at particle locations using nearest-neighbor cell selection (without bi-linear interpolation of location coordinates), consistent with the hourly CMEMS forcing interval. At the verification time, particle positions from the 52 releases were converted into source-level hulls and then dissolved to define the simulated footprint. Two otherwise identical configurations were evaluated: Test #1 used Stokes drift components from the CMEMS Mediterranean Waves Reanalysis (E.U. Copernicus Marine Service Information (CMEMS), 2024), whereas Test #2 used marine current components from the CMEMS Mediterranean Sea Physics Reanalysis (Escudier et al., 2020).

The forecast oil-slick coverage was compared with SAR-detected observations (Abou Samra and Ali, 2024) using the performance metrics introduced in Section 3.1. For instance, Fig. 7 illustrates inputs used and result for two time steps for Test #2; at $t = +4$ h and $t = +19$ h. Fig. 8 compares the SAR-derived reference footprint with the simulated footprints obtained using Stokes drift and marine current forcing.

The spatial performance of the two model configurations was evaluated through the set of area-based and shape-similarity metrics defined earlier, with results summarized in Table 3. Both tests use the same observed domain of 2092.7 km², allowing for a direct and unbiased comparison of simulated outputs.

As reported in Table 3, in Test #1 the area under consideration encompasses an expanse of 2671.4 square kilometers. This calculation results in an estimated overestimation of approximately 27.7% with respect to the observed extent. Test #2 yields a reduced simulated area of 2422.4 km², corresponding to a lower overestimation of roughly 15.8%. Regarding spatial coincidence, Test #1 achieves a Success Rate Area of 86.9%, a Jaccard Similarity Index of 61.7%, and a Dice Similarity Coefficient of 76.3%, all of which indicate a satisfactory degree of overlap between observed and simulated extents. In contrast, Test #2 yields lower values across all three indices (SRA = 76.2%, J = 54.7%, DSC = 70.7%). The Centroid Index, which quantifies the normalized displacement between the centroids of the observed and simulated extents, shows a marginal difference from 0.0938 for Test #1 to 0.0885 for Test #2. Both CI values are below 0.1, indicating a relatively small centroid separation after normalization by the observed bounding-box diagonal. CI measures displacement magnitude and does not, by itself, demonstrate the absence of directional bias. The identical value of L_{box} (104.6 km) reflects the use of the same observed reference polygon in both comparisons; differences in the metrics therefore arise from differences between the two simulated footprints and their overlap with that reference.

The findings reveal a good agreement between the results obtained from Test#1 and Test#2 with the SAR-detected observations (considered as “marine truths” or benchmark) derived by the cited study (Abou Samra and Ali, 2024).

Overall, Test #1 demonstrates superior performance in terms of spatial overlap metrics, whereas Test #2 offers a geometrically tighter simulation with reduced areal overestimation and marginally better centroid alignment. Ocean surface currents (used for Test #1) should be preferred when maximizing the coverage of the observed spill area and minimizing missed detections are the primary objectives. Conversely, Stokes drift (used for Test #2) may be more suitable when reducing false-positive areas and improving spatial accuracy through lower excess simulated area and reduced centroid displacement are more critical, such as in risk mapping or damage assessment applications. However, the optimal configuration is not universal and should be selected considering the local hydrodynamic conditions and circulation regime of the area of interest. Regions dominated by large-scale surface currents may benefit more from ocean-current forcing, whereas areas where wind-driven transport significantly affects surface dispersion may show improved performance when Stokes drift is included. Therefore, the choice between configurations should account for both the operational consequences of missed areas versus false alerts and the prevailing physical mechanisms governing oil transport.

4. Discussion

The validation described in Section 3.3 concerns one event and one later verification footprint. It demonstrates case-study hindcast skill and workflow feasibility rather than general predictive accuracy. Mainly arises from SAR delineation, temporal matching, convex-hull representation, forcing resolution, stochastic diffusion, and omitted physical processes. Table 4 compares the HECO validation scores with the best performance values reported for OpenOil, SVM-PM, and CranSLIK. The scores from this HECO case-study fall within the ranges reported by similar published studies; these comparisons should be interpreted only as contextual benchmarks, since the underlying spill events, observations, forcing datasets, and validation protocols differ among studies. In particular, the OpenOil 3D model (Papaioannou et al., 2025), in its validation against the 2024 Tobago shipwreck spill achieved SRA values ranging from 71% to 85%. The SVM-PM model proposed by Liu et al. in 2023 (Liu et al., 2023) achieve a fit of 70% in its validation against the 2018 Sanchi oil tanker spill, and the 2011 Penglai oil spill, (that we can consider the same as SRA). The CranSLIK model (Snow et al., 2014) achieved an SRA value of 80%. In comparison, HECO achieved an SRA of 86.9% for the 2021 Syrian Baniyas oil spill case study.

For centroid displacement, the OpenOil validation reported CI values ranging from 0.0151 to 0.103, while the SVM-PM validation reported a CI value of 0.94. HECO achieved CI values of 0.089–0.094, which are significantly lower than the value reported for SVM-PM and indicate improved centroid localization accuracy and falls within the range reported for OpenOil.

A key operational advantage of HECO is its computational efficiency. During the validation tests, the model was run on a MacBook Pro equipped with an Intel i5 CPU. When using a locally stored forcing dataset, the complete computation and output-generation workflow required less than 15 min. By contrast, retrieving data through the CMEMS API during the simulation substantially increased the execution time, as each LPDM iteration required a separate web request. This finding highlights the importance of pre-downloading the required forcing data when HECO is used for rapid emergency assessment.

While comprehensive systems like MEDSLIK-II (De Dominicis et al., 2013a) are indispensable for calculating the precise, long-term biogeochemical fate of oil needed for extensive clean-up operations, HECO fills a vital operational gap. It sacrifices some physical realism in exchange for rapid, accessible, low-barrier hazard mapping that empowers local first responders during the critical first hours of an emergency.

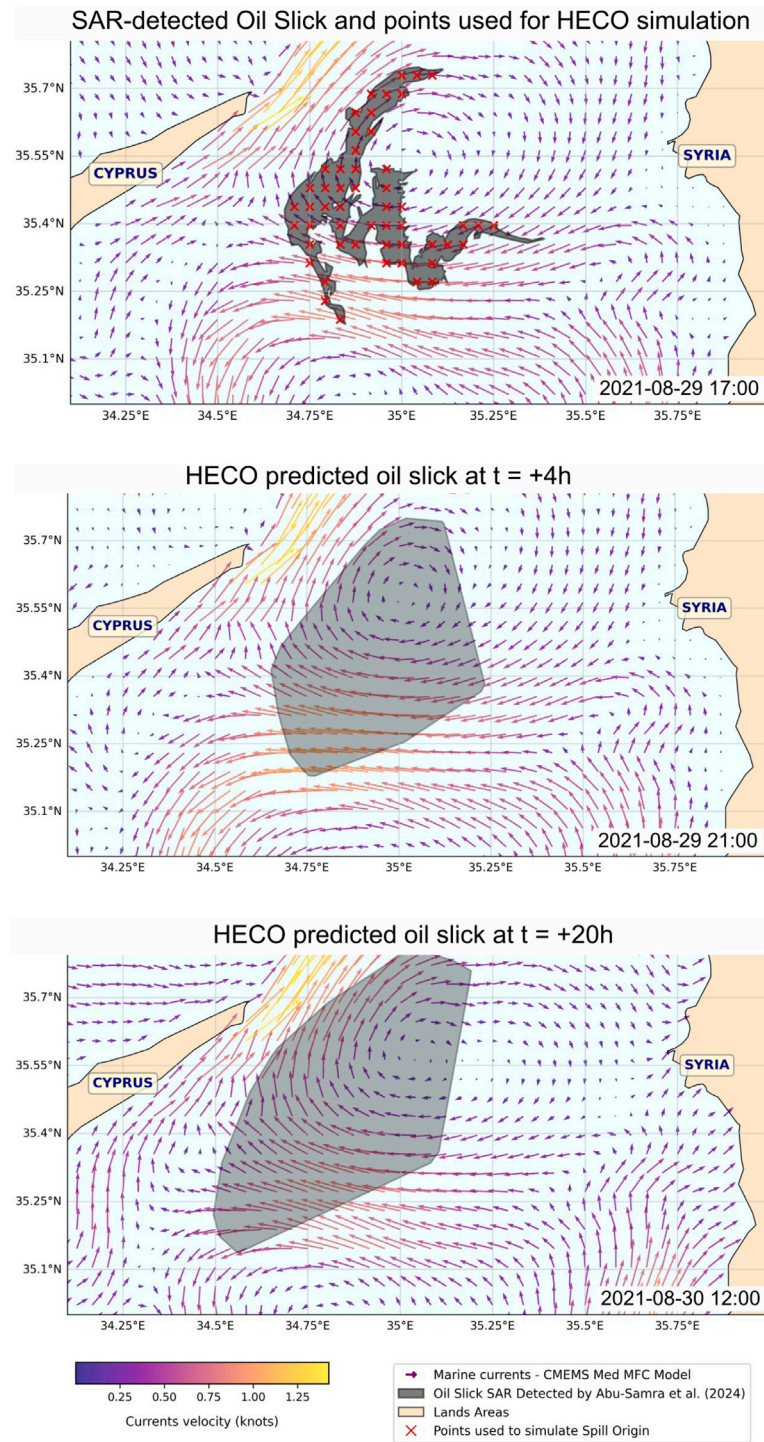


Fig. 7. Evolution of the HECO simulation for Test #2 using CMEMS surface-current forcing. The first panel shows the virtual source locations used to represent the initial SAR-derived slick, indicated by red crosses. The remaining panels show the simulated particle distributions at $t = +4$ h and $t = +19$ h.

Table 4

Contextual comparison with performance values reported in other validation studies.

Parameter	HECO Test#1	HECO Test#2	OpenOil (Papaioannou et al., 2025)	SVM-PM (Liu et al., 2023)	CranSLIK (Snow et al., 2014)
$SRA_{(Eq. (2))}$	86.9%	76.24%	71%–85%	70%	80%
$CI_{(Eq. (3))}$	0.0938	0.0885	0.074	0.94	n.a.
$J_{(Eq. (4))}$	61.7%	54.66%	66.9%	n.a.	n.a.
$DSC_{(Eq. (5))}$	76.34%	70.68%	80.2%	n.a.	n.a.

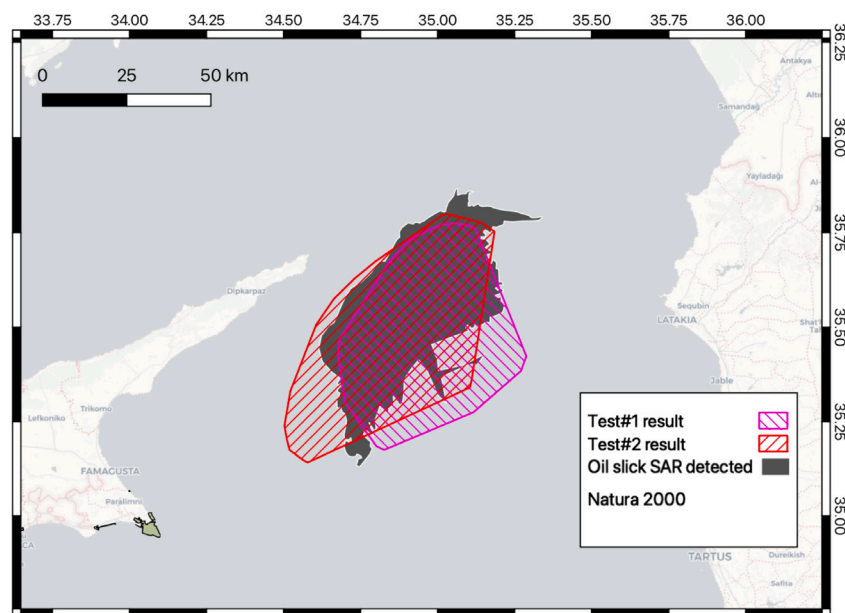


Fig. 8. Spatial comparison between the 30 August SAR-derived oil-slick footprint and HECO hindcasts. Test #1 uses Stokes drift forcing and has SRA = 86.9%; Test #2 uses marine-current forcing and has SRA = 76.24%. Full metrics are reported in [Table 3](#).

5. Conclusions

The first hours after oil spill accidents require rapid and accessible decision tools in emergency scenario. The need for specialized GIS skills and substantial computational resources can hinder rapid response because of steep learning curves. To bridge this gap, this study introduces HECO (Here Comes the Oil!), a lightweight, open-source, first-tier simulator for oil slick dispersion in open water using CMEMS current forecasting data. The tool, developed in Python and easily deployable in widely used web-services such as EDITO DataLab, is designed as a risk-assessment tool suitable for execution on standard personal computers.

A primary scientific contribution of HECO is the automation of the risk-communication pipeline. Rather than requiring specialized personnel to process raw output files, HECO automatically translates simulation results into a self-contained, interactive HTML Web-GIS application. By overlaying the projected spill trajectories with socio-environmental vulnerability datasets from EMODnet, such as Natura 2000 protected sites, bathing water status, and vessel density. HECO delivers immediate, map-based situational awareness directly to non-specialist decision-makers and local first responders.

The model's performance was successfully validated against the historical 2021 Syrian Baniyas oil spill using SAR satellite observations. The simulations demonstrated a strong spatial congruence with the observed spill, achieving a Success Rate Area (SRA) of up to 86.9%. This result supports the tool's potential for rapid preliminary hazard mapping, while broader multi-event validation is still required before general operational reliability can be established.

The capacity of HECO to deliver simulation results in seconds to minutes constitutes a critical operational advantage. This rapid turnaround directly addresses the often prohibitive computational demands of traditional oil spill models, which can impede timely responses during the critical initial phase of an incident. The provision of simulation results through an intuitive Web-GIS interface is a key feature enhancing HECO's practical utility for non-specialist users. This approach effectively translates complex numerical model outputs into readily interpretable map-based visualizations, which are fundamental for effective communication in early warning systems. By presenting predicted oil dispersion patterns overlaid with relevant contextual

EMODnet data layers, such as vessel density or bathing water status (as detailed in [Table 2](#)), the tool provides actionable intelligence directly to emergency managers and decision-makers.

The predictive accuracy of HECO is intrinsically linked to the quality, resolution, and timeliness of the *external oceanographic forecasting datasets* it employs, such as the CMEMS products for Stokes drift velocities and marine currents. As a data-driven model, any inaccuracies, biases, data gaps, or delays present in these forcing input data will inevitably propagate through the simulation, directly affecting the reliability and credibility of HECO's trajectory predictions.

Unlike other comprehensive operational systems (e.g., MEDSLIK-II) that calculate the precise biogeochemical fate of oil for long-term clean-up operations, HECO serves as a preliminary "first-tier" risk assessment tool. HECO is designed to complement them by filling the gap in immediate, localized, non-expert response in developing regions or small municipalities where deploying complex systems immediately is impractical. By deliberately excluding weathering processes like evaporation, HECO provides a conservative, "worst-case" maximum surface footprint. This intentional simplification is scientifically justified for the immediate early-warning phase (the first few hours post-spill), where the primary objective is to rapidly establish navigation exclusion zones and identify threatened coastal socio-economic assets before specialized modelers arrive. These simplifications make HECO a robust tactical tool for conducting a preliminary hazard assessment. It also provides a necessary "worst-case" scenario for immediate emergency mobilization.

The performance results from the tests conducted and the sensitivity analyses of the key input data place the HECO model on par with the most widely used software. The result, therefore, is to help the adoption of predictive models for the dispersion of pollutants in the open-sea, promoting both greater awareness of the risks and the widespread use of data-driven decision-making by authorities and businesses in the blue economy.

Some potential enhancements for HECO include: (i) improvement of the algorithm to include other physical components such as oil weathering, evaporation, and emulsification; (ii) extension of the simulation to the 3D domain with vertical mixing; (iii) better integration with the CMEMS and EDITO frameworks; (iv) improving spatial resolution through higher-resolution forcing datasets, local or nested

hydrodynamic products, and refined interpolation schemes, particularly in coastal areas; and (v) complete development of the software for distribution to users with a practical GUI to improve the user experience.

CRedit authorship contribution statement

Gianfranco Di Pietro: Writing – original draft, Software, Methodology, Conceptualization. **Massimiliano Marino:** Writing – review & editing, Methodology, Formal analysis, Data curation, Conceptualization. **Martina Stagnitti:** Software, Methodology, Investigation, Formal analysis. **Elisa Castro:** Software, Methodology, Data curation, Conceptualization. **Sofia Nasca:** Software, Resources, Data curation. **Luca Cavallaro:** Supervision, Formal analysis, Conceptualization. **Enrico Foti:** Supervision, Resources, Methodology. **Rosaria Ester Musumeci:** Supervision, Formal analysis, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at <https://doi.org/10.1016/j.ocecoaman.2026.108378>.

Data availability

HECO python tool are available in a GitHub repository at URL <https://github.com/SeaQuestTeam/HECO>. Test and validation data will be made available on request.

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