An operational system for oil spill tracking in the probability domain. Application to the Western Mediterranean Sea.

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Abstract

An operational model for oil spill and Search and Rescue Operations is presented. The model constructs a daily database of velocity predictions provided by an Operational Forecasting System and integrates the Eulerian velocities to obtain the trajectory forward in time adding a random walk term to simulate the diffusion. The model computes the probability density function from a set of particles giving the areas of accumulated probability. Several tests are performed in order to determine the optimal numerical scheme as well as the internal computational time step. Diffusion is assessed by computing the distance between the trajectories of particles computed from model forecast and model reanalysis velocities. A total of 8 months of daily diffusion fields are averaged to get a constant in time and variable in space diffusion in the Western Mediterranean. The model is tested against the trajectory of three SVP-drifters deployed in the Balearic Sea. For these experiments, the position of the drifters laid within the curve of the 50% of
accumulated probability for the 24h forecast. For a 72h forecast the drifters fall, in the worse cases, within the contour of 90% of accumulated probability. The areas corresponding to 70% and 90% of accumulated probability are similar in shape and magnitude.

Keywords: Operational oceanography, Oil spill modelling, Search and Rescue operations, Diffusion, Mediterranean Sea.

1. Introduction

Marine pollution at sea as a consequence of accidental and or illegal spills is among the largest threats to the marine environment. Spills involving oil or hazardous materials cause every year large economical and ecological damages that, depending on the severity of the spill, its nature and the affected environment, could require decades to be recovered (Kirby and Law, 2010).

In the last years, due to the large number of incidents involving oil tankers, offshore platforms and oil pipelines, there has been an increasing concern among stakeholders and the scientific community on the prediction of the evolution of the spill in the environment. After the Sea Enterprise accident off the coast of Wales, Elliott and Jones (2000) already stated the scientific requirement in the development of oil spill models in order to forecast in a operational way the evolution of spills in the ocean from the diagnostic to forecasting approach.

To prevent the impact of oil spills in the environment, response plans recommend the combination of routinely monitoring the ocean and the use of forecasting systems based on Operational Oceanography (OO) feeding oil
spill trajectory models. Operational Forecasting Systems (OFS), as part of OO, aims to provide routinely reliable information about the ocean conditions from observations and models to provide ocean fields more accurately than those obtained by using either models or data only (Kamachi et al., 2002).

To track the fate of pollutants in the ocean surface, a Lagrangian algorithm has to be incorporated in the OFS. Tracking models of neutrally buoyant particles are a valuable tool for the study of the transport of pollutants in a fluid flow and such models have been long used for the transport of spills in the ocean (Sotillo et al., 2008; Abascal et al., 2010; Potemra, 2012). A review of numerical models used to simulate the movement and fate of oil released into the sea can be consulted in the report of the National Research Council (NRC, 2003).

Spill models are based on a trajectory package made up with forcings from winds, currents and waves that provide routinely the conditions under which the object will be transported in the ocean surface (see Fig. 1). Predictions are made by tracking a series of particles assuming that the oil spill can be modelled as the final distribution of the particles. These particles are advected by the flow together with a random walk for the description of oil droplet movement (Elliot et al., 1986; Guo et al., 2009). At each time step, the position is computed with the available currents and the final location of particles are provided. The accuracy of the final position will rely on the accuracy of the initial position (that in many cases at the initial stages is the best guess), on the ability of the OFS to provide accurate predictions and on the inclusion of the proper physical mechanisms acting on the tracked substance.
In the Mediterranean Sea, the importance of maritime traffic and the high transport density concentrated in the western and central basins abruptly increase the risk of marine accidents. The Joint Research Centre from the European Commission (EC) analysed satellite images in the whole basin from 1999 to 2004 finding more than 9000 possible spills.

A large advance in OFS was acquired in the Mediterranean after the EU funded Project “Mediterranean ocean Forecasting System-MFSTEP” which developed the core of such systems in the Mediterranean Sea (Coppini et al., 2011). Other OFS initiatives such as the Spanish ESEO Project appeared as a consequence of major marine accidents (Jordi et al., 2006; Sotillo et al., 2008).

In this work, we present an operational system to track oil spills in the probability domain. The core of the system is based on the wind and ocean currents of an OFS linked with a tracking algorithm which transports virtual and neutrally buoyant particles to estimate the probability density function of the spill using a kernel estimator from their final positions. Several tests are made to obtain the internal computational time step in the Lagrangian tracking algorithm as well as to identify a proper numerical algorithm to be used. The system is applied in the Western Mediterranean Sea in the frame of the EU funded TOSCA Project to provide operational forecasts for oil spill accidents. In the present version, the OFS component is composed by the Western Mediterranean Operational Forecasting System (WMed) which routinely provides ocean fields from ROMS forced by the HIRLAM atmospheric model.
2. Data and Methods

Trajectories of neutrally buoyant Lagrangian particles will be derived from the Eulerian velocity field plus a random walk contribution term related to the eddy diffusivity (Proehl et al., 2005).

A particle \( p \) at the ocean surface will be transported by the fluid velocity governed by,

\[
\dot{x}_p(x, t) = u_{adv}^p(x, t) + u_{dif}^p(x, t),
\]

where \( \dot{x}_p = \frac{dx_p}{dt} \) is the total velocity and \( u_{adv}^p \) and \( u_{dif}^p \) are the advective and diffusive components of the velocity field. The advective component of the Eulerian velocity is obtained from the OFS as a linear combination of surface ocean currents \( (u_{curr}^p) \), wave induced currents \( (u_{waves}^p) \) and wind speed \( (u_{wind}^p) \) (Abascal et al., 2009)

\[
u_{adv}^p = u_{curr}^p + u_{waves}^p + \gamma u_{wind}^p.
\]

The above can be applied for forecasting or for diagnostic purposes and consequently, ocean currents, wave induced currents and wind speed will be obtained from predictive or observational systems respectively. The effect of the wind is parametrized through the coefficient \( \gamma \) also known as wind drag coefficient in the literature which, depending on the spill type, shape of the spill, wind intensity and accuracy of ocean currents takes a value between 0.025 to 0.044 with a mean value of 0.03 (ASCE, 1996)

The wave induced currents are derived from the Stokes drift, which is a second order effect of the linear theory. Assuming that wave height is finite (but not zero), the Stokes drift is,

\[
u_{waves}^p(x_p) = \frac{H^2 \omega^2}{8c} k.
\]
where $H$ is the wave height, $\omega = 2\pi / T$ the wave frequency, $c = \omega / k$ the wave celerity, $k$ is the vector wave number and $k$ the wave number module. In the area of study, the wave induced currents is negligible compared to the other two terms and therefore as shown later will be dismissed.

Under this deterministic approach, the two-dimensional position of the particle at the ocean surface is tracked by integrating the velocity given by Eq. (1), i.e.,

$$x_p(t + \delta t) = x_p(t) + \int_t^{t+\delta t} u_p^{adv}(x_p, t) dt + \int_t^{t+\delta t} u_p^{dif}(x_p, t) dt,$$

(4)

where $x_p = (lat, lon)$ with $lat$ and $lon$ standing for the position of the particle $p$. The last term in the RHS of Eq. (4) represents the diffusive component of the velocity field and is related to turbulent processes of unresolved scales. In our approach we are introducing all the uncertainties (error in models, initial conditions, etc.) in this diffusive velocity. Following (Ross and Sharples, 2004; Marinone et al., 2006, 2011) this term can be computed as,

$$\int_t^{t+\delta t} u_p^{dif}(x, t) dt = R\sqrt{6D\delta t},$$

(5)

with $R(x, t)$ being random numbers in $[-1, 1]$ and $D(x)$ the diffusivity to be empirically determined.

2.1. Ocean modelling subsystem

Currents are provided operationally in the frame of EU Med project TOSCA. The system known as BALOP (BAlearic OPerational system) is operated by the Balearic Islands Coastal Observing System (SOCIB) and is part of its forecasting facility component.
The ocean model is the Regional Ocean Modelling System (ROMS), a three-dimensional free-surface, sigma coordinate, split-explicit equation model with Boussinesq and hydrostatic approximation. The reader is referred to the work of Shchepetkin and McWilliams (2005) for a more complete description of the numerical code.

The area under study covers the Balearic Sea extending from 1°W to 5°E and from 38°N to 44°N. The grid is 256 × 320 (N_x, N_y) points with a resolution of ∼1.8 km, which allows a good sampling of the first baroclinic Rossby radius of deformation (about 10 – 15 km) throughout the whole area (Send et al., 1999) and 30 vertical levels. The vertical σ-coordinate is stretched to account for boundary layers. Bottom topography is derived from a 1 minute resolution database, ETOPO1 (Smith and Sandwell, 1997). The model is daily initialized using temperature, salinity, horizontal velocities, and Sea Surface Height (SSH) from previous restart at t = −24 hours (Oddo et al., 2009). At the two lateral open boundaries (South and East) an active, implicit, upstream biased, radiation condition connects the model solution to the surrounding ocean (Marchesiello et al., 2001). The daily MFS fields are used to infer the thermodynamics at the open boundaries. The atmospheric forcing is obtained from AEMET/Hirlam model with a spatial resolution of ∼5 km at an hourly temporal resolution (Unden et al. and others, 2002).

2.2. Trajectory matrix

BALOP-OFS provides surface currents and wind fields for the next 3 days at a 3 hours interval. The system is initialized daily with the re-analysed fields of the previous 24 hours. The velocity fields (ocean surface currents and wind speed) are arranged daily in a cube of dimensions (N_x, N_y, N_t),
where \( N_t = 25 \) correspond to the forecasting times of \( t(\text{hours}) = 0, 3, 6, ..., 72 \), provided by BALOP-OFS.

An hypothetical spill occurring at a certain time \( T \) and in a location \((\text{lon}, \text{lat})\) is represented by a point inside the cube with 8 neighbouring vertexes with velocities \( u_i, \{i = 1 : 8\} \) provided by BALOP-OFS, \( (i.e., \) the closest spatial model grid points for the past and future time steps). The advective component of the velocity field is obtained at the spill location by,

\[
\mathbf{u}_{p}^{\text{adv}}(\text{lon}, \text{lat}, T) = \sum_{i=1}^{8} w_i u_i. \tag{6}
\]

Above, \( w_i \), are weighting coefficient that are computed as \( V_i / V_T \) (see Fig. 2).

This method allows a very fast computation of the velocity field beside including Lagrangian information since uses past and future velocity fields. After a time \( T + \tau \) the position of the spill is obtained after integrating Eq. (4) with the velocity Eq. (6) and new weighting coefficients computed with the new particle position as previously described. We remark that the velocities \( u_i \) will change either when the spill crosses the OFS grid or when a new field is required as the time evolves. Otherwise, only coefficients \( w_i \) are modified at each computational time step.

2.3. Lagrangian numerical scheme

A strong constrain in any OFS is the time required to get the predictions. Therefore efficient numerical schemes are to be implemented without sacrificing the accuracy of the forecast.

To assess the best numerical scheme to be implemented in the Lagrangian model in terms of accuracy in predictions, we performed a numerical ex-
periment using analytical currents derived from a streamline function $\Psi(x)$ randomly generated from a specific isotropic spectrum with random phases (Garau et al., 2005). The spectrum is generated so as the peaks are separated at a specific spatial scale in order to obtain homogeneous eddies. Velocity field is generated on a mesh of $200 \times 200$ and is derived from the streamline function as,

$$u = -\frac{\partial \Psi}{\partial y}; \quad v = \frac{\partial \Psi}{\partial x},$$

(7) which immediately holds incompressibility of the flow (i.e. $\nabla \cdot \mathbf{v} = 0$). The grid size is 1 km in both $x$ and $y$ directions. The fields evolve in time by using the potential barotropic vorticity equation (Gill, 1992). These fields have been chosen so as they have similar characteristic values than those in the study area. Velocity fields are generated every 6 minutes for a total of 75 hours and stored following the methodology described in Section 2.2. A set of particles are launched at random positions and their trajectories integrated in time with a Cooper-Verner algorithm of eighth order (hereinafter CV8). The trajectory of particles obtained by this method will constitute our reference path. We note that this integration method is computationally expensive and its application is not recommended for an OFS. Three additional numerical schemes were also implemented: an explicit Euler scheme (ES), a 4$^{th}$ order Runge-Kutta (RK4) and a 5$^{th}$ − 4$^{th}$ order Runge-Kutta-Felhberg with an adaptative time step (RKF54). The error, defined as the separation in meters after 75 hours of simulation, between the final position of particles for the three numerical schemes relative to the position given by the CV8 method is presented in Fig. 3 for 10 random initial positions. The internal computational time step $\Delta t$ has been set equal to $\Delta t = 6$ minutes for all
numerical schemes. As expected, the largest deviations are presented when
the ES is used with an average error of $10^3$ m. In ocean flows with rapid
variations or strong gradients this method could provide large deviations in
the final position of the advected particles. The other two methods, RKF54
and RK4 give similar with deviations respect CV8 below 1 meter with less
computational cost for RK4. Therefore in this work we adopted RK4.

In order to get an insight for the optimal integration time step to be used
in the RK4 for the Lagrangian algorithm, using the above synthetic fields,
we have considered $\Delta t_{\text{min}} = 6, 12, 18, 24, \ldots, 180$. For each different time
step length $\Delta t$ we deploy at the same position 20 particles and the final
position after 75 hours compared against the trajectory computed using the
CV8 method (with $\Delta t = 6$ minutes). The average error for all 20 particles
computed for the different computational time steps are displayed in Fig.
4. The error is below 2% for integration time steps up to 30 minutes and
increases up to a 15% for integration time steps of 180 minutes. Based on
those results, the integration time step for the Lagrangian integration was
set to 30 minutes. This result is in accordance with the time step used in
Abascal et al. (2010) where the time step was imposed to ensure particles to
remain within the same grid point at each computational time step.

3. Probability contours

Oil spill models predict the trajectory of a set of neutrally buoyant par-
ticles including in some cases, chemical and weathering processes to account
for the oil aging in the ocean surface (Castanedo et al., 2006; GNOME,
2002). Uncertainty in predictions are parametrized by imposing a random
walk Monte-Carlo technique for a set of particles around the spill location.

The chaotic nature of ocean will result in inaccuracies of the predicted fields from the OFS. Besides, at the initial stages of spill accidents the exact spill location is not always well determined resulting in large errors in predictions due to this chaotic nature. To delimit this constrain, the present approach display the area of probability of the final positions of a set of particles instead of providing the individual track of them. Expressed in short, a set of particles is distributed around the initial spill location in a circle of small radius (4 km) and their path solved after integration of Eq. (4). After a certain time of simulation, the probability density function of particles is computed by a Gaussian kernel estimator (Martinez and Martinez, 2002),

$$\hat{f}_{ker}(x,y) = \frac{1}{2\pi N h_x h_y} \sum_{i=1}^{N} \prod_{j=1}^{2} \exp \left( -\frac{1}{2} \left( \frac{x_j - X_{ij}}{h_j} \right)^2 \right),$$  

where $N$ is the number of particles launched, $x_j$ are the final position ($j = 1$ longitude and $j = 2$ latitude) of the particles, $X_{ij}$ are the $j$-component of the $i$ observation and $h_x, h_y$ are the bin width given by the normal reference rule, e.g.,

$$h_{x,y} = \left( \frac{1}{N} \right)^{1/6} \sigma_{x,y},$$

with $\sigma_{x,y}$ is the standard deviation of the final points in latitude and longitude respectively. With this methodology, we can provide the user with the contours of accumulated probability provided at the desired interval (e.g., 90%, 75%, 50%). These contours coincides with the isolines of the kernel. Several tests have been made to estimate the optimal number of particles finding that no significant changes on the shape of the density contours are usually appreciable over 200 particles.
The contours of accumulated probability of 50%, 70% and 90% for 200 particles launched at a random position in the above analytical fields are displayed in Fig. 5 for a 24 h prediction (left), 48 h prediction (center) and 72 h prediction (right). It is remarkable that in spite of no diffusion was considered in those simulations, bimodal distribution of the density of probability can be obtained (see Fig. 5, right) as a result of the chaotic nature of the oceanic flows.

4. Results and Discussion

In September 2011, three Surface Velocity Program (SVP) ClearWater drifters were deployed in the study area to measure surface currents. Each drifter was composed of a surface buoy with subsurface drogue attached and centered at 15 meters depth that guaranteed the flow of the drifter with the ocean currents. A transmitter inside the surface buoy sent positioning periodically for tracking surface ocean trajectories. The communication system used for these drifters was Argos-2 and the system was configured to transmit hourly position. Positioning time series from drifters were linearly interpolated.

The Balearic Islands are located in the Western Mediterranean Sea, 200 km East the coast of Spain (see Fig. 7). The largest island, Mallorca, is separated from the southern island, Ibiza, by the Mallorca Channel that can reach depths of 800 m. The shelf around Mallorca extends roughly 10 km both east and west and connects with a common shelf with the northern Island Menorca. This geological frame provides a geometry favourable for the generation and amplification of trapped and long waves (Liu et al., 2002;
Orfila et al., 2011). The southern shelf of the Balearic Islands is influenced by the dynamics of the Algerian basin (Perkins and Plset, 1990; Millot, 1991) where the unstable nature of the Algerian current generates long-lived anticyclonic eddies. The presence of older offshore eddies can deflect the Atlantic waters of the Algerian current seaward reaching the vicinity of the Balearic Sea. Werner et al. (1993) studied the circulation of the southern coast of the island of Mallorca from a 3-D finite element model under wind driven and remotely forced conditions pointing out the role of the diurnal sea breeze in the generation of currents in the shelf of the Island.

To explore the ability of the model in tracking accurately the path of surface spill under different dynamics, two different areas were selected for the deployment. On September 11th, 2011, two SVP were launched in the vicinity of Cabrera Islands (southwestern side of Mallorca Island) at location (3°, 39°) and (2° 51′, 39° 10′). This area can be under the influence of the deflected flow from the Algerian current and is driven by the diurnal sea breeze. On September 26th, a third drifter was deployed at (3° 33′, 39° 14′) on the eastern shelf of Mallorca.

The module of surface current, wind speed ($\gamma = 0.03$) and Stokes drift at (2°6′, 39°36′) for September 2011 are shown in Fig. 6. Waves were acquired from the WAM operational model for the Western Mediterranean Sea operated by SOCIB (Ponce de Leon et al., 2012) and Stokes drift calculated from Eq. (3). As seen, while surface currents and wind speed are of the same order of magnitude, the value of the Stokes drift is one order lower.
Eddy diffusivity

To solve the random walk term in Eq. (5) we have to determine the value of the eddy diffusivity at the ocean surface which is not an easy task. This term is usually taken spatially and temporally constant and different values can be found in the literature for the eddy diffusivity for an specific area. The horizontal diffusivity can be inferred by Okubo’s empirical formula which relates the eddy-diffusion, $D$ with the spatial scale $l$ (Okubo, 1971) as,

$$D(l) = 2.055 \cdot 10^{-4} l^{1.15}.$$  

(10)

Recently (Hernandez-Carrasco et al., 2011) analysed the role of diffusion in the Western Mediterranean by measuring the error in the computation of Finite Size Lyapunov Exponents by changing the resolution of the model data. These authors found that diffusion introduces small scale irregularities on the trajectories, and also substantial dispersion at large scales.

Errors in the prediction of trajectories obtained by the Lagrangian model will be mainly due to wrong or poorly solved ocean fields provided by the OFS. Therefore, it is reasonable to compute diffusion from these data. In this work we estimate the diffusivity directly from model data as follows. From January to August 2011 at each model grid point particles were advected using the forecast fields from BALOP-OFS for a 24 hours period. A second set of particles were also advected using the reanalyzed fields and the separation $L$ in meters among final distances computed for each model grid point. Diffusion $D(x)(m^2/s)$ is readily obtained for each day as, y

$$D(x) = \frac{L^2(x, y)}{86400}$$  

(11)
The eight months (January-August) averaged values of $D(x) (m^2/s)$ for the Western Mediterranean area are shown in Fig. 7. By doing so, we are including a pseudo-diffusion of particles as the result of numerical uncertainties and not trying to solve real ocean diffusion. When a spill is modelled, a set of 200 particles is placed inside a circle of radius $R = 4 km$ centred at the spill location and each particle tracked by solving with a RK4 method Eq. (4). For the diffusion term the model generates at each computational time step, random numbers with a Gaussian distribution with zero mean (Hunter et al., 2003) taking the value of $D(x)$ for the specific time step.

The first drifter simulated an spill occurring at $(3^\circ, 39^\circ)$ on September 11th (displayed by a cross in Fig. 8). In the same figure are shown model results corresponding to the accumulated probability density contours of the 50% (black line), 70% (gray line) and 90% (gray dashed). Model results are displayed for 24 hours forecast (i.e. September 12th) (Fig 8, left panel), 48 hours forecast (i.e. September 13th (Fig 8, center) and for 72 hours forecast (i.e. September 14th (Fig 8, right panel). The trajectory of the drifter is depicted by a gray line whereas the position at each snapshot is depicted as a black. As seen the SVP position lies between the curves representing the 50% and 70% of accumulated probability, the drifter travelled 14, 10 and 20 nautical miles during the 12th, 13th and 14th respectively. Note that for this simulation Lagrangian particles travel from areas of eddy diffusivity of $D \sim 10 \ m^2/s$ to areas of $D \sim 5 \ m^2/s$.

A second experiment simulated a spill occurring on the East coast of Mallorca at the edge of the shelf. Drifter was deployed on September 26th at $(3^\circ 33', 39^\circ 14')$ (cross in Fig. 9). Again, in the same figure we show model
results of the accumulated probability density contours of the 50% (black line), 70% (gray line) and 90% (gray dashed). Model results are at 24 hours forecast (Fig 9, left panel), 48 hours forecast (Fig 9, center) and for 72 hours forecast (Fig 9, right panel). As seen the Lagrangian model model is able to reproduce the position of the drifter within the 50% of accumulated probability for the first 24 hours forecast and needing to use wider contours for the following days (70% and 90% for +48 h and +72 hours respectively).

Since a typical forecasting horizon in an emergency oil spill response is 24 hours, we performed a third experiment by comparing the trajectory during 6 days of a third drifter launched on September 11th at (2° 51’, 39° 10’) with the model using only 24 hours of forecast (Fig. 10 where the contours of the 50%, 70% and 90%) of accumulated probability are shown at 24 hours interval. The initial position of the SVP-drifter for each snapshot is depicted by a cross and the final position by a dot. For completeness, the path travelled is also displayed by the gray line (dashed for the past and solid by the last 24 hours forecast). Not surprisingly, using the daily forecast to perform daily forecast result in a reduction of the area covered by the accumulated probability.

5. Conclusions

An operational model to simulate Oil Spill Trajectories and for Search and Rescue Operations has been presented. Two innovations differ from previous operational models. First, we propose the use of numerical simulations to infer the diffusivity of the area. Second, the model rather than providing the final position of particles, provides the contours of accumulated probability of particles transported by the flow. As previous models, we use the forecast
fields of winds and currents to estimate the final position of a relatively small number (\(\sim 200\)) of neutrally buoyant particles at the ocean surface to compute the percentage of them on specific areas through a density kernel estimator. Finally, the curves of accumulated probability are displayed. The distribution of the curves of probability, as shown, can be multi-modal which in SAR operations could help to optimize the available searching resources.

To solve the Lagrangian algorithm we have used a Runge-Kutta of the 4\(^{th}\) order which provides similar results than a variable time step method (\(e.g.\) RKF54) when compared with an 8\(^{th}\) order Cooper-Verner method. Regarding the computational time step, we found that 1800 seconds is a good commitment between accuracy and computational efficiency. Regarding interpolation of the OFS currents we use past and future wind and currents fields to obtain the Eulerian velocity at the desired location using eight known velocities capturing at each time step Lagrangian information of the flow.

Research is devoted to include improvement in the model both for oil spill modelling as well as for the use for SAR operations. Regarding oil spill, a database for different oil are being compiled to include the evaporation as well as the mechanical spreading. So far, the eddy diffusivity implemented is fickian (\(e.g.\) white noise) but as recently stated a non-fickian distribution for the random term is more suitable and will be implemented. Regarding SAR, analysis of the wind drag coefficient \(\gamma\) have to be done with in situ measurements with dummies.

The spill has been modelled by deploying a number of particles in a circle around the spill position. To include the gathering of the oil in a three dimensional model, different topologies have to be included to compute the
density of oil and its corresponding equilibrium depth. The accumulated probability contours are a very suitable concept for SAR operations since it can provide several areas of search by the multimodal distribution of the probability kernel.

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Figure 1: Schematic diagram of an OFS for oil spills. Blue boxes indicate the numerical component while brown boxes the observational component.
Figure 2: Schematic view of the trajectory matrix. Each $N_x \times N_y$ layer consists on the output of the OFS. The cube has $N_t$ forecast fields in the third dimension. A spill position with coordinates $(\text{lon}, \text{lat}, T)$ occupies a point within the volume that has eight neighbour vertexes with given velocities. The weighting parameters relate the known velocities with the unknown velocity at the spill position by rating the corresponding volume $V_i$ given by the node $i$ and the total volume $V$. 
Figure 3: Error in meters for 10 random positions between the trajectories computed with the ES (circles), RK4 (squares) and RKF54 (triangles) and those obtained by the CV8 method.
Figure 4: Error after 75 hours between the CV8 and the RK4 method for different temporal time steps.

Figure 5: Contours of accumulated probability for 200 particles deployed in a circle of 8 km around the initial location (point) after 24h (left), 48h (center) and 72h (right) forecast. Only one every 6 velocity vectors have been drawn.
Figure 6: Time series of surface currents (gray), wind speed -weighted by 0.03- (black dashed) and Stokes drift (black solid) at (2° 6′, 39° 36′) for September 2011. The dark boxes indicate the periods of the SVP experiments.
Figure 7: Average eddy diffusivity for the Balearic Sea for the period January-August 2011.
Figure 8: Contours of 50 (black), 70 (gray) and 90 (gray dashed) accumulated probability of spill incidence for a spill occurring on September 11th initially located at (3°, 39°). Each plot correspond for a 24 hours forecast. The trajectory of the SVP drifter is displayed as the gray solid line where the position corresponding to September 12th, 13th and 14th as black dot (left, center and right panels respectively).
Figure 9: Contours of 50 (black), 70 (gray) and 90 (gray dashed) accumulated probability of spill incidence for a spill occurring on September 26th initially located at (3° 33′, 39° 14′).

Each plot correspond for a 24 hours forecast. The trajectory of the SVP drifter is displayed by the gray solid line where the position corresponding to September 27th, 28th and 29th as black dot (left, center and right panels respectively).
Figure 10: Daily forecast of contours of 50 (black), 70 (gray) and 90 (gray dashed) accumulated probability of spill incidence for a spill occurring on September 11th initially located at \( (2^\circ 51', 39^\circ 10') \).