Deep learning technique for examining the mechanism, transport, and behavior of oil-related hazardous material caused by wave breaking and turbulence

Shibiao Fang\textsuperscript{1,2,3}, Mu Lin\textsuperscript{2,3,*}, Sen Jia\textsuperscript{1}, Kuan Liu\textsuperscript{1} and Darong Liu\textsuperscript{4}  

\textsuperscript{1} College of Computer Science and Software Engineering, Shenzhen University, Shenzhen 518060, People's Republic of China
\textsuperscript{2} College of Life Sciences and Oceanography, Shenzhen University, Shenzhen 518060, People's Republic of China
\textsuperscript{3} Southern Marine Science and Engineering Guangdong Laboratory (Guangzhou), Guangzhou 511458, People's Republic of China
\textsuperscript{4} College of Marine Science and Technology, China University of Geosciences, 388 Lumo Road, Wuhan 430074, People's Republic of China

\textsuperscript{*} Author to whom any correspondence should be addressed. 
E-mail: mulin@szu.edu.cn

Keywords: oil hazardous material, breaking waves, transport and behavior, submergence depth, deep learning technique

Abstract
A marine oil spill produces oil-related hazardous material (OHM) which can cause damage to the marine ecological environment, and seriously affect coastal economic development such as tourism and aquaculture. The turbulent momentum and energy generated by the wave breaking process have a significant effect on accelerating the mixing of OHM and seawater, which is one of the main factors in oil becoming sunken or submerged. In order to explore the influence of offshore wave breaking on the formation and transportation of OHM, the wave breaking process was simulated in a 2D laboratory flume, and the behavior process of OHM was identified and tracked in this paper. Five groups of breaking waves of different significant wave height (SWH) were set up in the experiment, and then OHM with the same density and mass was added, respectively, in order to observe the sinking process under the action of wave-induced turbulence. The results show that the turbulence intensity is closely related to the phase of the wave, the turbulence activity is violent at the wave crest, and the vertical distribution of the turbulent energy dissipation rate in the turbulent mixing zone remains basically unchanged. Under the actions of wave breaking and turbulence, the OHM’s submergence depth shows a good binomial growth trend. For SWH = 12.45 cm, the OHM stays under the water for nearly 2.32 s, and it reaches the deepest position of 0.165 m. Compared with SWH = 12.45 cm, the submergence depths for waves with SWHs of 20.61 cm, 26.81 cm, 32.32 cm, and 36.54 cm are increased by 8\%, 37\%, 80\%, and 159\%, respectively. Then, the submergence depths due to the other four waves are increased progressively, and the growth rates are 8\%, 26\%, 31\%, 44\%, respectively (compared with the same period of the previous wave).

1. Introduction
Oil spill pollution is one of the most frequent, widely distributed and harmful types of marine pollution (Spaulding 2017). The oil and oil-bearing substances (oil-related hazardous material (OHM)) flowing into the ocean will drift and diffuse with wind and tide. OHM drifting to the coast causes pollution hazards to beaches or coastal facilities (Johan et al 2015). When the OHM is subjected to multiple effects such as weathering and marine dynamics, some of the spilled oil sinks. Although the sunken OHM is not visible on the surface of the sea, it causes great environmental damage and economic losses to the marine ecosystem, such as the poisoning or death of fish and shellfish, pollution and damage to fishing gear, and heavy losses to fishing grounds (Loh et al 2014). Therefore, the damage of the marine ecological environment caused by OHM has become a global problem, and marine oil pollution has attracted great attention in all countries.

After weathering, the OHM’s density exceeds the density of sea water, so as it can suspend in sea
water or sink onto the seabed, which are referred to as sunken and submerged oil (Akhtar et al 2012). Sunken OHM of unknown origin is a new issue in marine environmental protection (Azevedo et al 2014). The vertical transport of turbulent momentum and energy generated by the wave breaking process have a significant effect on accelerating the vertical mixing of offshore oil spill and seawater (OHM submergence), which is one of the main factors in oil becoming sunken or submerged (Dissanayake et al 2018). On the other hand, wave breaking is an important source of turbulent kinetic energy near the surface of the ocean (Fingas 2015). It plays an important role in the upper ocean process and effectively strengthens the air–sea exchange process. The study of the wave breaking process has very important reference value for marine disaster prediction and prevention. Wave breaking greatly promotes the mixing of marine OHM into the water, and the OHM can even affect the depth of effective wave height (Elliott et al 1986). Wave breaking causes a large number of bubbles to enter the ocean, changes the physical properties of the mixing layer on the ocean, and it has a significant impact on marine remote sensing and marine acoustic signal transmission. Therefore, the study of wave breaking is very necessary for the establishment of wave models and the prevention and control of OHM.

### 1.1. Novelty of this research

#### 1.1.1. Innovative oil detection method

In accordance with the conventional vision-based detection methods, since OHM is mostly observed within a regular wave, its background is simple, and it can be detected by features such as color and shape. However, in a real life scenario, oil may be completely occluded by the white spray of breaking waves. The background of the OHM in the breaking waves is more complex and the illumination varies, which further increases the difficulty of oil detection. The deep-learning-based method relies on the powerful feature extraction ability and robustness of CNN (convolutional neural network) and is an important development direction in oil detection. This paper aims to develop an innovative oil detection method based on deep learning, which can effectively and efficiently simulate and predict the formation and behavior process of OHM, so as to provide technical support for the prevention, control and treatment of OHM pollution.

#### 1.1.2. Improved algorithm for YOLO (you only look once) v4 model

Most deep learning-based methods are mainly used to detect objectives in a single image, and the huge number of parameters for the CNN make the real-time performance insufficient. It seriously affects the deployment and application of the oil detection model on small mobile terminals to some extent. In order to solve the problems of time-consumption, low detection accuracy and needing to compress the model size effectively, the real-time detection of OHM under natural environments based on YOLO v4 has been proposed in the paper. First, a dataset is constructed by acquiring moving images of OHM from laboratory experiments. Then, Labelimg software has been used to label OHM in a portion of the images in the dataset. Labelimg software is a Python-based image annotation tool, which is used to store information such as image paths, annotations, and annotation area coordinates into extensible markup language (XML) files. Then it uses a format conversion program to convert the XML file into a text format (txt) file, which contains the path, object category and coordinate information of the sample image to form a data sample (ground truth). The ground truth is divided into a test set and a training set, and the unprocessed data set (origin data) is also divided into a test set and a training set according to the same proportions. The ground truth training set and the origin data training set are imported into the YOLO v4 model. The YOLO v4 model will extract the OHM features in the origin data. After bias correction and multiple training, a feature model of the OHM is finally obtained. Finally, YOLO v4 uses the trained OHM feature model to detect the test set of the origin data, and compares the detection results with the ground truth's training set to obtain the detection accuracy to evaluate the performance of the algorithm.

### 1.2. Main contribution of the study

In contrast to previous research methods, such as using agitated vials or laboratory flasks (Shaw 2003, Reed et al 2009, Li et al 2011, Zeinstra-Helfrich et al 2015), this paper uses artificial intelligence technology and deep learning algorithms to record the movement of OHM in breaking waves. The results obtained by traditional experimental research have large errors (average precision is only 10%–20%), which limit the scientific value (Reed et al 2009). The traditional experiments on sunken and submerged oil in the laboratory entail the staff in the laboratory comparing the oil particles on the image with the ruler, and then estimating the particle size, judging by the human eye. Alternatively, researchers use particle image velocimetry (PIV) to observe the wave flow field, and then judge the motion trajectory of oil particles according to the change in flow field. These traditional detection methods are not only inefficient, but also greatly depend on the experience and theoretical level of inspectors. Working for a long time can also easily produce visual fatigue and misjudgment. However, the results obtained by the innovative detection and tracking method in the paper have high authenticity. Moreover, with a slight modification to
the YOLO v4 algorithm in the future, it can be extended to a large area of the sea, so it has extremely high application value. As such, the main contribution of this study is: Realizing the full-chain research of Formation mechanism of OHM \rightarrow Laboratory experiments and image data acquisition \rightarrow Development of oil target detection and tracking technology \rightarrow Offshore oil spill simulation and prediction.

2. Material and methods

2.1. Experimental setup

In order to study the oil diffusion situation and diffusion law under the action of breaking waves with different energies, the experiments were divided into six groups, namely six breaking waves with significant wave heights (SWHs) of 12.45 cm, 20.61 cm, 26.81 cm, 32.32 cm, 36.54 cm and 39.83 cm in the laboratory. The density of each oil mass used in this research was 0.89 g cm$^{-3}$, and the weight of each oil mass was 100 g. The hazardous material (HM) transport hydrodynamic simulation tank (length 32 m, width 0.8 m, depth 2 m, seawater depth 1.014 m) is shown in figure 1.

The experiment procedure is shown in the following:

(a) The HM transport hydrodynamic simulation tank produced breaking waves with wave heights of 12.45 cm, 20.61 cm, 26.81 cm, 32.32 cm, 36.54 cm and 39.83 cm respectively, and then released the experimental oil at the broken position of the wave-making. The wave-making process is shown in figure 2.

(b) The experimenter turned on the camera, observed and recorded from the perspective of the top shot and the side shot, respectively. A picture was taken every 0.04 s. The camera and the PIV are shown in figure 2.

(c) According to the acquired image data, the experimenter selected photos of a period before and after the generation of the breaking wave, identified and converted them through a computer, and obtained oil pixels.

(d) During the experiments, some water tank structures and light and shadow changes may be recognized as oil droplets by the computer, so the converted data needs to be corrected (for example, the interference pixels are excluded). After correcting the data, the lateral and vertical oil film diffusion velocities were calculated.

(e) Finally, we analyzed and discussed the oil diffusion situation and diffusion law.

(f) In figure 2, a tantalum wire wave gauge and acoustic doppler velocimetry (ADV) were used to measure the changes in amplitude and velocity during wave breaking.

2.2. Data processing

Analyze the time series of wave height to obtain the wave spectrum:

$$S(\omega) = \frac{2}{\pi} \int_0^{\infty} R(\tau)e^{-i\omega \tau} d\tau \quad (1)$$

where $S(\omega)$ is ocean wave spectrum, $\omega$ is frequency, $R(\tau)$ is the correlation function, and $\tau$ is the different moments.

Compared with the classical wave breaking theory, the average period is calculated by the Stokes wave dispersion relationship to calculate whether each wave is broken. For more complex cases, the accuracy is low, so the wave surface height $\zeta (t)$ is introduced in this paper. The Hilbert transform method of $\zeta (t)$ calculates the wave velocity at each time, and determines the occurrence of wave breaking by comparing whether the wave breaks at each time. Compared with the original wave breaking criterion under the average period, the current measurement accuracy can be greatly improved (Wu and Nepf 2002). The calculation principle is that any wave surface can be expressed as:

$$\zeta (t) = \text{Re} \left[ A(t)e^{-i\Phi(t)} \right] \quad (2)$$

where $A(t)$ and $\Phi(t)$ represent the amplitude function and phase function of a wave, respectively. $\text{Re}$ is the real part, and $\Phi(t)$ is obtained by Hilbert transform. Then the wave velocity $c(t)$ can be calculated:

$$c(t) = \frac{-g}{\partial \Phi(t)/\partial t} \quad (3)$$

where $g$ is the gravitational acceleration.

The wave velocity and wave surface equation satisfy:

$$r(t) = \left| -\frac{\partial \zeta(t)}{\partial t} \right| > C_r = 0.586c. \quad (4)$$

This point is the breaking point on a wave surface.

The breaking criterion $C_r$ represented by equation (4) is still the standard theoretical criterion, and $r(t)$ is the wave surface height $\zeta (t)$ derivative of $t$. We only enhance the accuracy of the calculation results by improving the calculation method in this process. The calculation process is to compare the size of $r(t)$ and $C_r$ in the experiment for the wave surface data at each time. When the relationship between them meets equation (4), it is marked as the breaking point. As long as there are one or more breaking points in a complete wave, it is regarded as the breaking wave. After the test of the experimental results, the judgment accuracy of this method meets the requirements.

The turbulent fluctuation velocity in the experiment is mainly calculated by the following methods:
PIV flow field velocity includes average flow velocity \( \bar{u} \), periodic motion velocity \( \tilde{u} \) and turbulent motion velocity \( u' \):

\[
    u = \bar{u} + \tilde{u} + u'.
\]

In equation (5), the average velocity is obtained by time averaging the velocity time series, and the periodic motion velocity is obtained by the measured velocity band-pass filtering, with a band-pass filtering range of 0.45–0.6 Hz.

The expression of turbulent horizontal fluctuation velocity is:

\[
    u' = u - \bar{u} - \tilde{u}.
\]

Similarly, the vertical fluctuation velocity of turbulence is calculated according to the same method. The dissipation rate of turbulent energy per unit mass can be expressed as:

\[
    \varepsilon = \left\langle \frac{1}{\rho} \frac{\tau_{ij}}{s_{ij}} \right\rangle
\]

where \( \tau_{ij}' \) is the viscous stress pulsation and \( s_{ij}' \) is the strain rate pulsation, \( \langle \rangle \) is the time average.

Therefore, the turbulent energy dissipation rate \( \varepsilon \) is:

\[
    \varepsilon = \left\langle \frac{\partial u_i'}{\partial x_j} \left( \frac{\partial u_i'}{\partial x_j} + \frac{\partial u_j'}{\partial x_i} \right) \right\rangle
\]
where $u'_i$ and $u'_j$ are the turbulent pulsation velocities in different directions, $x_i$ and $x_j$ are the coordinates in different directions, and $\nu$ is the kinematic viscosity coefficient.

The above formula is still complex. Therefore, assuming that the turbulence is isotropic, and the energy dissipation rate formula of 2D plane turbulence is simplified as (Doron et al 2001):

$$\varepsilon = 3\nu \left[ \left( \frac{\partial u'}{\partial x} \right)^2 + \left( \frac{\partial w'}{\partial z} \right)^2 + \left( \frac{\partial u'}{\partial z} \right)^2 + \left( \frac{\partial w'}{\partial x} \right)^2 + 2 \left( \frac{\partial u'}{\partial x} \frac{\partial w'}{\partial x} \right) + \frac{2}{3} \left( \frac{\partial u'}{\partial x} \frac{\partial w'}{\partial z} \right) \right]$$

(9)

where $u'$ and $w'$ are the turbulent horizontal and vertical fluctuating velocities, $x$ and $z$ are the horizontal and vertical coordinates, respectively.

In this paper, the vertical turbulent diffusion coefficient is calculated based on turbulent diffusion theory, which is determined by formula (10). After transformation, it is calculated by equation (11) (Thomson et al 2009):

$$u'w' = K_w \frac{\partial u'}{\partial x}$$

(10)

$$K_w = \beta w'^2 \int_0^\infty R(\tau) d\tau$$

(11)

where $K_w$ is the vertical turbulent diffusion coefficient, $\beta$ is the proportional parameter, $u'$ and $w'$ are the turbulent horizontal and vertical fluctuating velocities, and $R(\tau)$ is the Euler turbulence autocorrelation function.

According to Taylor’s freezing hypothesis, the relationship between time (frequency $\omega$), space (wave number $K$) and average velocity $U$ is:

$$\omega = KU.$$  

(12)

Thus, the wave number spectrum can be transformed into the frequency spectrum. The final calculation formula of the turbulent energy dissipation rate is:

$$\varepsilon = \frac{55}{18} AU^{-1} \left[ S(f) f^{5/3} \right]^{3/2}$$

(13)

where $f$ is the frequency range and $A$ is the universal constant, taking 0.95 and 0.62 respectively (corresponding to the horizontal and vertical velocity spectra).

2.3. Method

The YOLO network is a one-stage object detection algorithm. It uses a single CNN to process images and can directly calculate the classification results and position coordinates of objects. With the end-to-end object positioning and classification, the detection speed has been greatly increased (Redmon et al 2016). Compared with YOLO v3, YOLO v4 introduced mosaic data enhancement in data processing. In addition, the backbone, network training, activation function, and loss function were optimized, which made YOLO v4 faster and achieved the best balance between the accuracy and speed in these real-time object detection algorithms (Bochkovskiy et al 2020). Figure 3 is the technical road map showing the framework and workflow of YOLO v4 combined with experiments. The YOLO v4 network utilized CSPDarknet53, an open source neural network framework, as the main backbone network to train and extract image features (Bochkovskiy et al 2020); then path aggregation network was employed as the neck network to achieve better fusion of the extracted features; and the head exploited YOLO v3 to realize object detection. In the structure of the oil detection model based on YOLO v4, the composition and functions of the main modules are as follows:

- The CBL (convolution, batch normalization and leaky-ReLU) was a module composed of a convolution layer, a batch normalization layer and a
Leaky-ReLU activation function. It was the most frequently seen structure in the YOLO v4 network.

- The CBM (convolution, batch normalization and a self regularized non-monotonic neural activation function (MISH)) module and CBL were both used for feature extraction. The difference between the two was that the activation function of the CBM used MISH instead of Leaky-ReLU.
- The SPP (spatial pyramid pooling) was a SPP layer, which mainly transformed convolution features of different sizes into pooled features with the same length.
- The CSP (center and scale prediction) module could enhance CNN’s learning ability by dividing low-level features into two parts and then fusing cross-level features.

3. Results

3.1. Spatial distribution of turbulent energy dissipation rate for different situations

According to the calculation results of the SWH, this study calculated the time series of the turbulent energy dissipation rate under the breaking wave (see figures 4–9), and found that the occurrence time of the breaking wave has a certain law, that is, the turbulent flow mixing is mainly concentrated in the break-out period. However, in the nonbreaking period, the changes of seawater turbulence and the background turbulence field at the bottom of the tank have little change. By comparing the time series of the turbulent energy dissipation rate of different groups, this study found that with the rapid increase in the number of breaking waves, the larger the area of the whole wave image, the larger the area of the turbulent energy dissipation rate, and the greater the effect of turbulence in the water–air exchange. In the figures, $t$ represents time (s) and $T$ represents one period.

Figure 10 shows the change in the spatial average value of turbulent energy dissipation rate in the whole turbulence affected area at different times. According to the analysis of the distribution of turbulent energy dissipation rate, the turbulent dissipation rate at the wave crest reaches the maximum, which is two to five times higher than that at the wave trough. This shows that the mixing of breaking waves is mainly concentrated at the crest, and the turbulence at the trough is affected by turbulent diffusion and wave nonlinearity, so the influencing factors are more complex. Therefore, the generation and evolution mechanism of turbulence at the crest is mainly discussed below.

3.2. Relationship between turbulent dissipation and OHM under action of breaking waves

In this paper, five breaking waves (SWH = 12.45 cm, 20.61 cm, 26.81 cm, 32.32 cm, 36.54 cm) were selected for analysis, because the sinking processes in these five waves were very clear. The oil (density of 0.89 g cm$^{-3}$, mass of 100 g) was transported by the waves, forming OHM. The simulation of the behavior process of
Figure 5. Spatial distribution of turbulent dissipation rate for $\text{SWH} = 20.61 \text{ cm}$.

Figure 6. Spatial distribution of turbulent dissipation rate for $\text{SWH} = 26.81 \text{ cm}$.
Figure 7. Spatial distribution of turbulent dissipation rate for SWH = 32.32 cm.

Figure 8. Spatial distribution of turbulent dissipation rate for SWH = 36.54 cm.
Figure 9. Spatial distribution of turbulent dissipation rate for $\text{SWH} = 39.83$ cm.

Figure 10. The space-averaged turbulent dissipation rate at various moments for different experiments.
Figure 11. Overall trajectory of OHM under 12.45 cm breaking wave.

Figure 12. Overall trajectory of OHM under 20.61 cm breaking wave.

Figure 13. Overall trajectory of OHM under 26.81 cm breaking wave.
Figure 14. Overall trajectory of OHM under 32.32 cm breaking wave.

Figure 15. Overall trajectory of OHM under 36.54 cm breaking wave.

OHM in waves is shown in figures 11–15. The straight line represents the initial water surface of the experimental flume (water depth = 1.014 m).

As shown in figure 16, the submergence depth shows a good binomial growth trend. Compared with the SWH = 12.45 cm, the submergence depths for waves with SWHs of 20.61 cm, 26.81 cm, 32.32 cm, and 36.54 cm are increased by 8%, 37%, 80%, and 159%, respectively. Then, the submergence depth for SWH = 12.45 cm is 0.165 m, and the other four waves’ submergence depths increase progressively, and the growth rates are 8%, 26%, 31%, 44%, respectively (compared with the same period of the previous wave).
4. Discussion and conclusions

An oil spill may cause the disappearance or decrease of some oil-sensitive species in the ecological community, and the increase of some pollution-loving species, resulting in the destruction of the food chain of marine organisms in local sea areas. The work in this paper helps to trace oil pollution so as to quickly eliminate OHM: Formation mechanism of OHM → Laboratory experiments and image data acquisition → Development of oil target detection and tracking technology → marine environment protection.

In the upscaling application of the results of this research, the vertical diffusion coefficient obtained in this study and the relationship between dissipation rate and the oil’s submerged depth can be used in future to determine the turbulent diffusion coefficient of the sea area, thus more intuitively showing the actual situation of the diffusion of pollutants (sunken and submerged oil, OHM) in the sea area. The vertical diffusion coefficient is an important parameter in the oil spill simulation model. The turbulence caused by wave breaking makes the oil (less dense than seawater) sink, mainly because the mixing coefficient increases, which is the expansion of...
vertical diffusion coefficient. In the general numerical model, the vertical diffusion coefficient describing the approximate tracer such as oil spill takes a constant value or directly uses the vertical vortex viscosity coefficient in the hydrodynamic model (calculated by vertical closed parameterization schemes such as key performance parameter(KPP)). However, in this study, the vertical diffusion coefficient can be clearly obtained in the experiment, and the relationship between dissipation rate and the oil’s submerged depth can guide the setting of model parameters in the simulation of a large-scale oil spill or submerged oil accidents at sea. As such, in practical applications to real-life settings, the results of this paper can effectively reduce the cost of the macro-sea pollution movement process detection, and greatly enhance the calculation speed and accuracy of the marine oil spill numerical model.

Regarding the detection accuracy of this innovative method in comparison to other methods, this paper compared the ‘YOLO v4’, ‘CenterNet’, ‘YOLO v3’, and ‘SSD’. The results show that the average detection speed values of ‘YOLO v4’, ‘CenterNet’, ‘YOLO v3’, and ‘SSD’ are 42.47 frames per second, 26.80 frames per second, 35.37 frames per second, and 38.90 frames per second, respectively. In terms of detection accuracy, the ‘YOLO v4’ algorithm exceeds the other three algorithms by 10.59%, 22.62%, and 31.69%, respectively.

Then, the main conclusions are the following.

(a) The submergence depth for a breaking wave in this research shows a good binomial growth trend. For SWH = 12.45 cm, the OHM stays under the water for nearly 2.32 s, and the OHM reaches the deepest position of 0.165 m. Compared with the SWH = 12.45 cm, the oil's submergence depths for waves with SWHs of 20.61 cm, 26.81 cm, 32.32 cm, and 36.54 cm are increased by 8%, 37%, 80%, and 159%, respectively. Then, the submergence depths of the other four waves are increased progressively, and the growth rates are 8%, 26%, 31%, 44%, respectively (compared with the same period of the previous wave).

(b) Under the action of breaking waves with SWHs of 12.45 cm and 20.61 cm, the OHM continues to sink after wave breaking, and it does not reach the maximum depth in one cycle. Under the action of breaking waves with SWHs of 26.81 cm, 32.32 cm, and 36.54 cm, the OHM quickly reaches the maximum depth in one cycle. However, the speed values of sinking for these waves are 0.208 m s⁻¹, 0.222 m s⁻¹, 0.212 m s⁻¹, 0.359 m s⁻¹, and 0.303 m s⁻¹, respectively. This is because the period becomes larger with the increase of the SWH, which buys time for the OHM to sink in a period.

Data availability statement

All data that support the findings of this study are included within the article (and any supplementary files).

Acknowledgments

This work was supported by the National Natural Science Foundation of China (Grant No. U2006210), the Key Special Project for Introduced Talents Team of the Southern Marine Science and Engineering Guangdong Laboratory (Guangzhou) (Grant No. GML2019ZD0604), and the Shenzhen Fundamental Research Program (Grant No. JCYJ20200109110220482).

ORCID iD

Darong Liu https://orcid.org/0000-0001-7581-6192

References

Akhtar J, Bjornskau T and Jean-Hansen V 2012 Oil spill risk analysis of routing heavy ship traffic in Norwegian waters WMU J. Marit. Aff. 11 233–47

Azevedo A, Oliveira A, Fortunato A B, Zhang J and Baptista A M 2014 A cross-scale numerical modeling system for management support of oil spill accidents Mar. Pollut. Bull. 80 132–47

Bochkovskiy A, Wang C Y and Liao H Y M 2020 YOLOv4: Optimal Speed and Accuracy of Object Detection (Vancouver: CVPR)

Dissanayake A L, Gros J and Socolofsky S A 2018 Integral models for bubble, droplet, and multiphase plume dynamics in stratification and crossflow Environ. Fluid Mech. 18 1167–202

Doron P, Bertuccioli L, Katz J and Osborn T R 2001 Turbulence characteristics and dissipation estimates in the coastal ocean bottom boundary layer from PIV data J. Phys. Oceanogr. 31 2108–34

Elliott A J, Hurford N and Penn C J 1986 Shear diffusion and the spreading of oil slicks Mar. Pollut. Bull. 17 308–13

Fingas M A 2015 Review of Natural Dispersion Models. Handbook of Oil Spill Science and Technology (Edmonton: Wiley)

Johan B P, Umer F and John D E 2015 Subsurface oil releases-experimental study of droplet size distribution phase 2 Riv. Dibiol. 1 235–50

Li Z, Lee K, Kepkey P E, Mikkelsen O and Pottsmith C 2011 Monitoring dispersed oil droplet size distribution at the gulf of Mexico deepwater horizon spill site Int. Oil Spill Conf. Proc. 2011 abs377

Loh A, Shin W J, Ha S Y and Yim U H 2014 Oil-suspended particulate matter aggregates: for motion mechanism and fate in the marine environment Ocean Sci. J. 49 329–41

Redmon J, Divvala S, Girshick R and Farhadi A 2016 You only look once: unified real-time object detection 2016 IEEE Conf. on Computer Vision and Pattern Recognition (CVPR) (27–30June) (Las Vegas, NV: IEEE Press) pp 779–88

Reed M, Johansen Ø, Leirvik F and Brors B 2009 Numerical Algorithm to Compute the Effects of Breaking Wave on Surface Oil Spilled at Sea (Trondheim: SINTEF)

Shaw J M 2003 A microscopic view of oil slick break-up and emulsion formation in breaking waves Spill Sci. Technol. Bull. 8 491–501
Spaulding M L 2017 State of the art review and future directions in oil spill modeling Mar. Pollut. Bull. 115 7–19
Thomson J, Gemmrich J R and Jessup A T 2009 Energy dissipation and the spectral distribution of whitecaps Geophys. Res. Lett. 36 L11601
Wu C H and Nepf H M 2002 Breaking criteria and energy losses for three—dimensional wave breaking J. Geophys. Res. 107 41–1–18
Zeinstra-Helfrich M, Koops W, Dijkstra K and Murk A J 2015 Quantification of the effect of oil layer thickness on entrainment of surface oil Mar. Pollut. Bull. 96 401–9