

# **NEURAL-BASED TECHNIQUES FOR MODELLING AND CONTROL**

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# NEURAL-BASED TECHNIQUES FOR MODELLING AND CONTROL

- The continuous growth of maritime traffic and offshore activities has increased the likelihood of incidents that pose a serious threat to the marine system;
- Accurate prediction of oil dispersion is essential for timely mitigation, but the dynamics are incredibly **complex**, governed by **winds, marine currents, and coastal morphology**.



Exxon Valdez (1989) - 42,000 m<sup>3</sup> of oil spilled



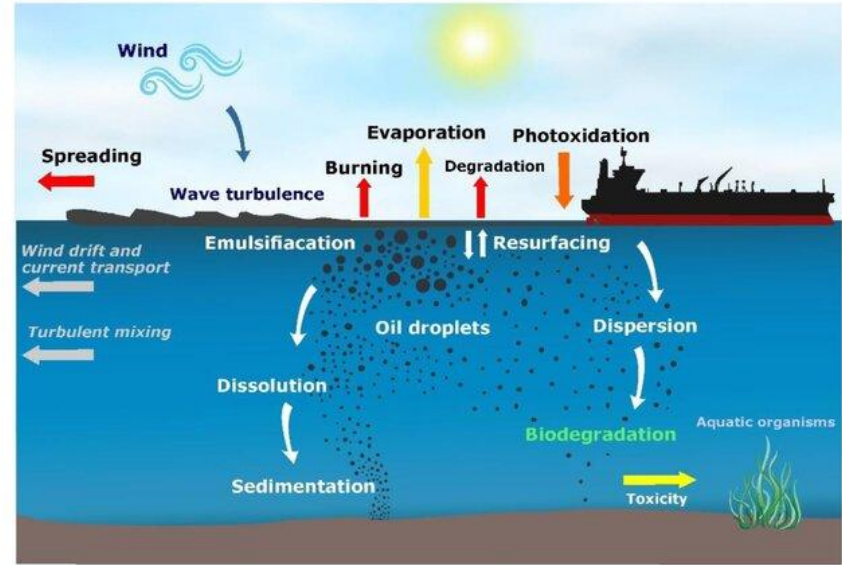
Norilsk incident (2020) - 21,000 m<sup>3</sup> of oil spilled

# NEURAL-BASED TECHNIQUES FOR MODELLING AND CONTROL

- Traditional physics-based methods rely on complex Euler Lagrangian formulations, grounded in fluid dynamics.
- These are extremely accurate, but also **computationally demanding and slow**.



**Unsuitable for real-time predictions**



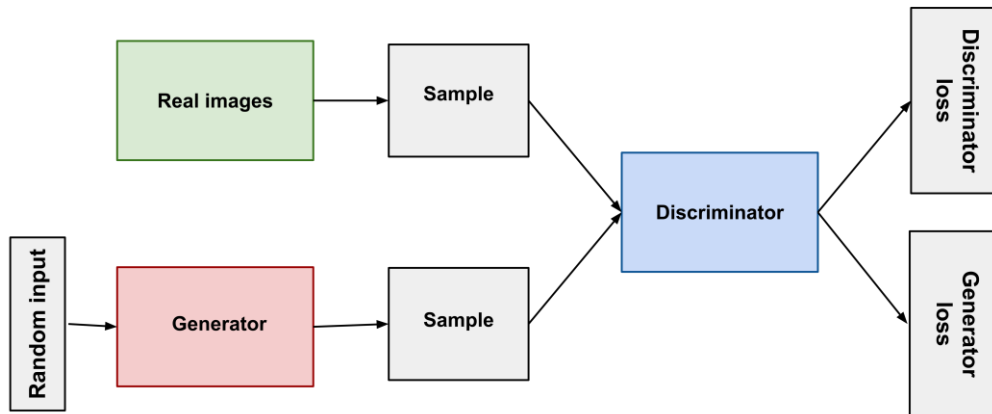
[1] Keramea, P., Spanoudaki, K., Zodiatis, G., Gikas, G., & Sylaios, G. (2021). Oil Spill Modeling: A Critical Review on Current Trends, Perspectives, and Challenges. Journal of Marine Science and Engineering, 9(2), 181. <https://doi.org/10.3390/jmse9020181>

# NEURAL-BASED TECHNIQUES FOR MODELLING AND CONTROL

Deep Learning data-driven approaches overcome the slowness of traditional techniques

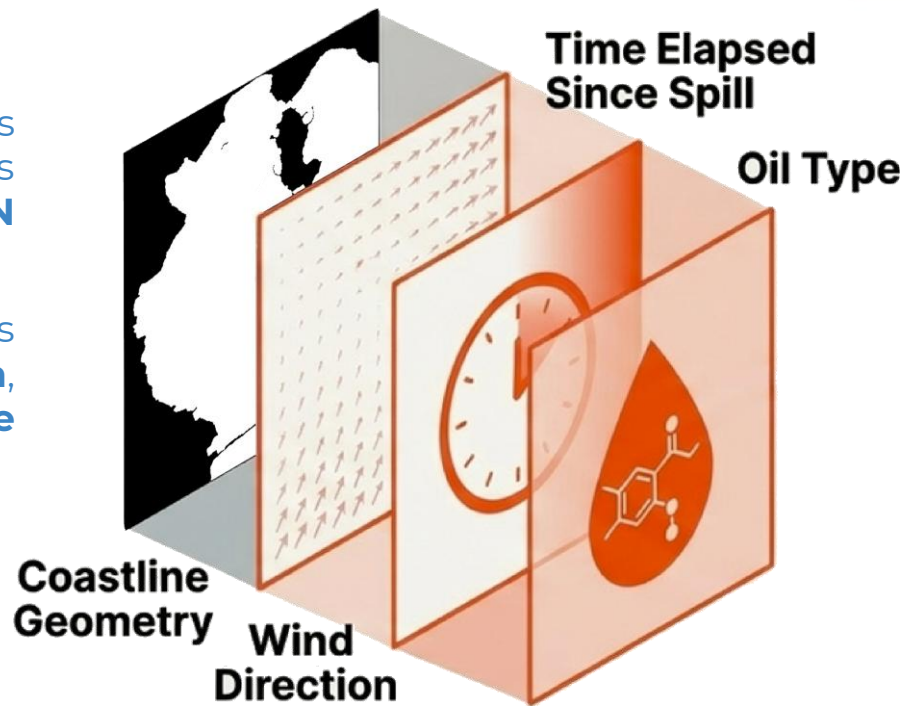
## Generative Adversarial Networks (GAN)

- The **Generator** produces synthetic samples while trying to fool the discriminator;
- The **Discriminator** attempts to distinguish between real and generated data.



# NEURAL-BASED TECHNIQUES FOR MODELLING AND CONTROL

- To ensure that the generator learns physically consistent dispersion dynamics a **Conditional Deep Convolutional GAN** has been implemented;
- The model is **conditioned** by key variables such as: **initial spill point**, **wind direction**, **coastline geometry**, **time elapsed since the spill** and the **oil type**



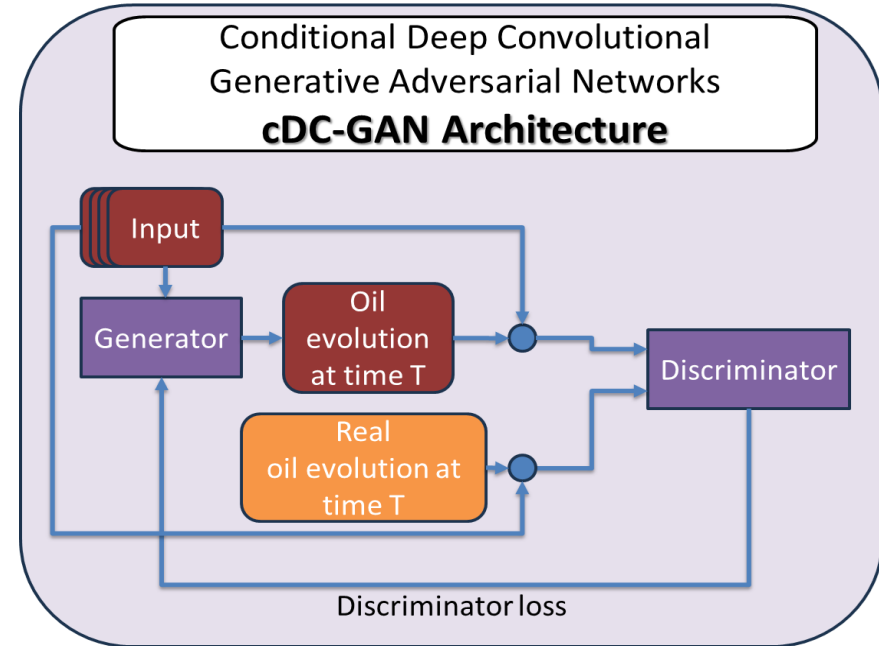
# NEURAL-BASED TECHNIQUES FOR MODELLING AND CONTROL

- **Binary Cross-Entropy (BCE)** is used as loss for both Discriminator and Generator;



$$L_n = -w_n [y_n \cdot \log x_n + (1 - y_n) \cdot \log(1 - x_n)]$$

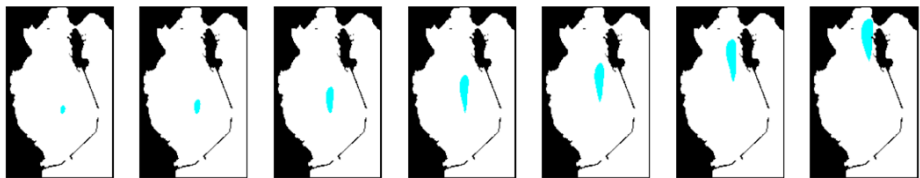
- A weight  $w_n$  is used to balance the effect of black and white pixels in the loss function  $L_n$ ;
- To increase model's sensitivity to the pixel representing the crude oil  $w_n$  is set to 10 for the black pixels and 1 otherwise (**W-BCE**)



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- The case study taken into account was the harbour of **Augusta, Sicily** which handled over **6 million tons of crude oil** and more than **13 million tons of liquid petroleum products** in 2024 [3];
- Two dataset based on Eulerian Navier–Stokes numerical simulations and with different oil types were derived from [4]

Example of a sequence in the dataset



[3] Statistics of the Augusta port- Autorit`a di Sistema Portuale del Mare di Sicilia Orientale — adspmaresiciliaorientale.it <https://www.adspmaresiciliaorientale.it/numeri/statistiche/>. [Accessed 11-07-2025]

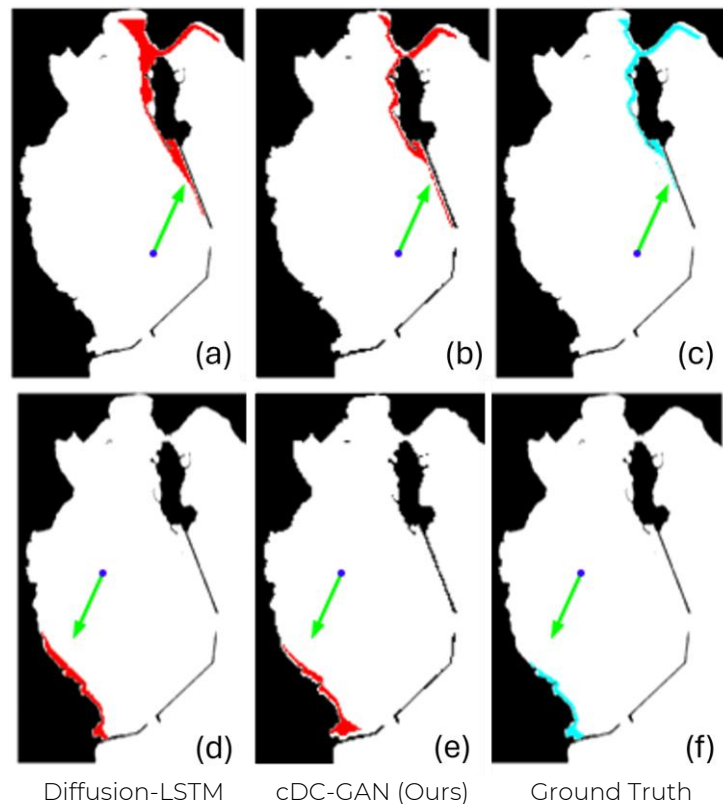
[4] Roman, F. and Cavallaro, L. (2025). Numerical analysis of oil spill scenarios in harbour areas with an eulerian approach: The augusta case. Ocean Engineering, 318, 120130.



# NEURAL-BASED TECHNIQUES FOR MODELLING AND CONTROL

- The cDC-GAN approach was compared to a baseline method made by a Diffusion model combined with an LSTM;
- **Outperforming the baseline** on both datasets for every considered metrics;
- Inference time is significantly reduced **from 9 seconds per image (Diffusion-LSTM) and 5/10 minutes** (Eulerian Navier–Stokes numerical simulations) **to 27.7 ms per sequence**;

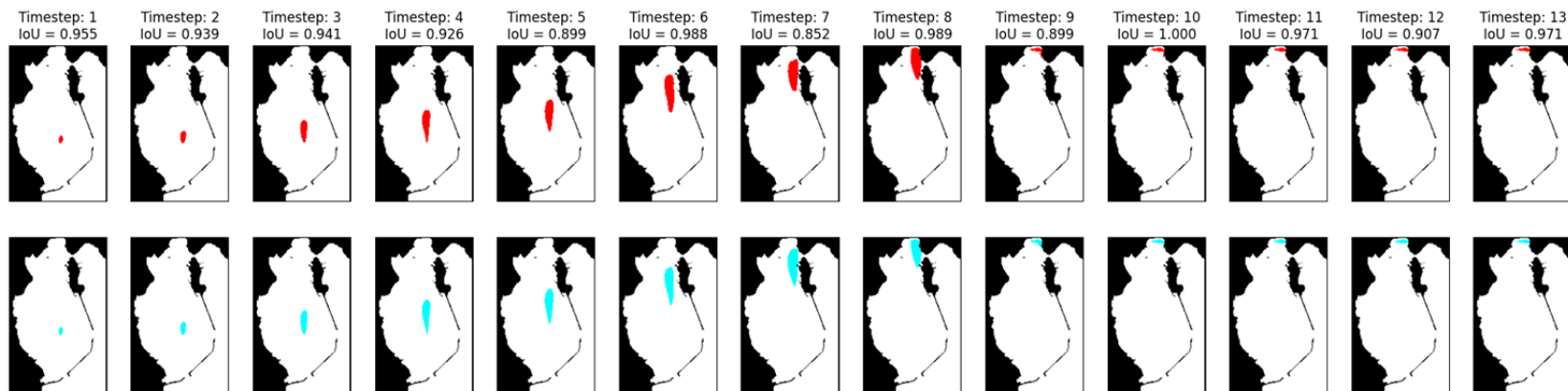
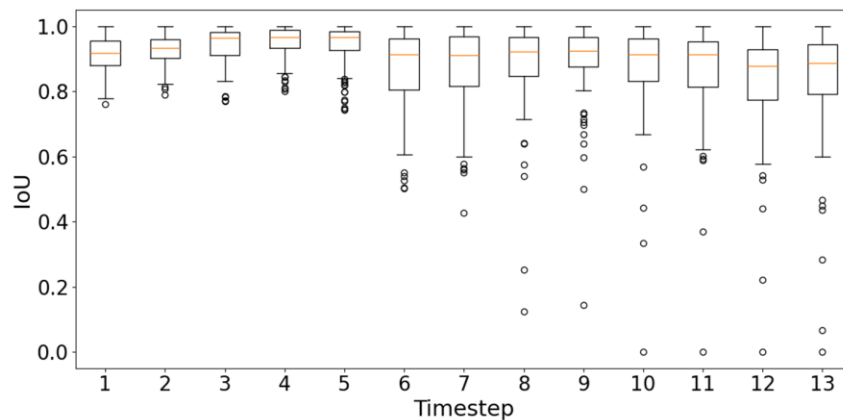
Technique	IoU $\uparrow$	MSE $\downarrow$	SSIM $\uparrow$	PSNR $\uparrow$	FID $\downarrow$
DiffusionLSTM (DB1)	$7.70 \times 10^{-1}$	$16.1 \times 10^{-3}$	$9.94 \times 10^{-1}$	19.94	3,47
DiffusionLSTM (DB3)	$8.38 \times 10^{-1}$	$1.80 \times 10^{-3}$	$9.90 \times 10^{-1}$	31.69	1.38
FC & W-BCE (DB1)	$9.21 \times 10^{-1}$	$1.52 \times 10^{-3}$	$9.94 \times 10^{-1}$	36.15	1.07
FC & W-BCE (DB3)	<b><math>9.55 \times 10^{-1}</math></b>	<b><math>0.57 \times 10^{-3}</math></b>	<b><math>9.96 \times 10^{-1}</math></b>	<b>43.22</b>	<b>0.61</b>





# NEURAL-BASED TECHNIQUES FOR MODELLING AND CONTROL

High performances not only at the final step (24 hours after the spill), but also in every intermediate timestep in the dataset



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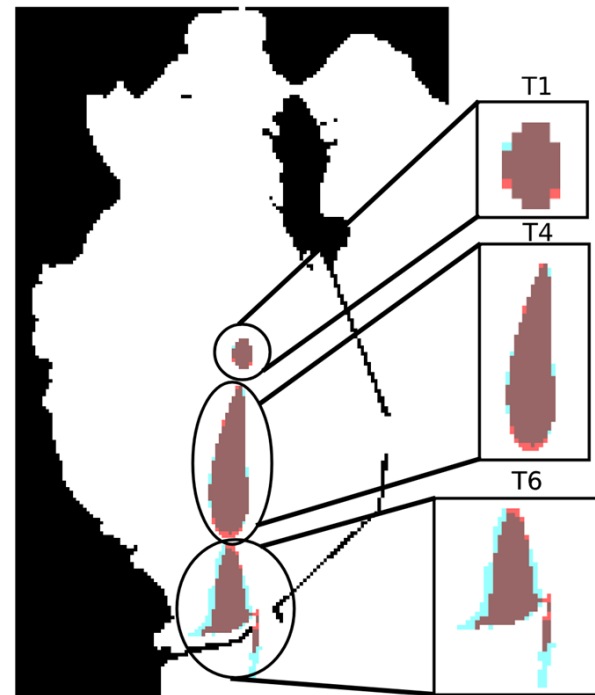
Predicted Evolution



Real Evolution



Combined Evolution



# NEURAL-BASED TECHNIQUES FOR MODELLING AND CONTROL

- The proposed cDC-GAN provides an **accurate, fast, and flexible** tool for predicting oil spill diffusion in harbour areas;
- The architecture's modular design allows integration of **further conditioning inputs** and **different coastline maps**;
- Future works will focus on extending the model to include additional conditioning variables such as wave height and to sample at intermediate timesteps between those present in the datasets.

Patanè, Luca and Maio, Antonino and Faraci, Carla and Iuppa, Claudio and Cavallaro, Luca and Roman, Federico and Xibilia, Maria Gabriella, Predicting oil spill diffusion through Generative Adversarial models. Submitted to [IFAC World Congress](#) 2026.

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**Thank you !**

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