DIPARTIMENTO di INGEGNERIA

LA RICERCA DENTRO UNIME

Evaluation of the propagation of oil spills in ports through Artificial Neural Networks

Giulia Bonanno

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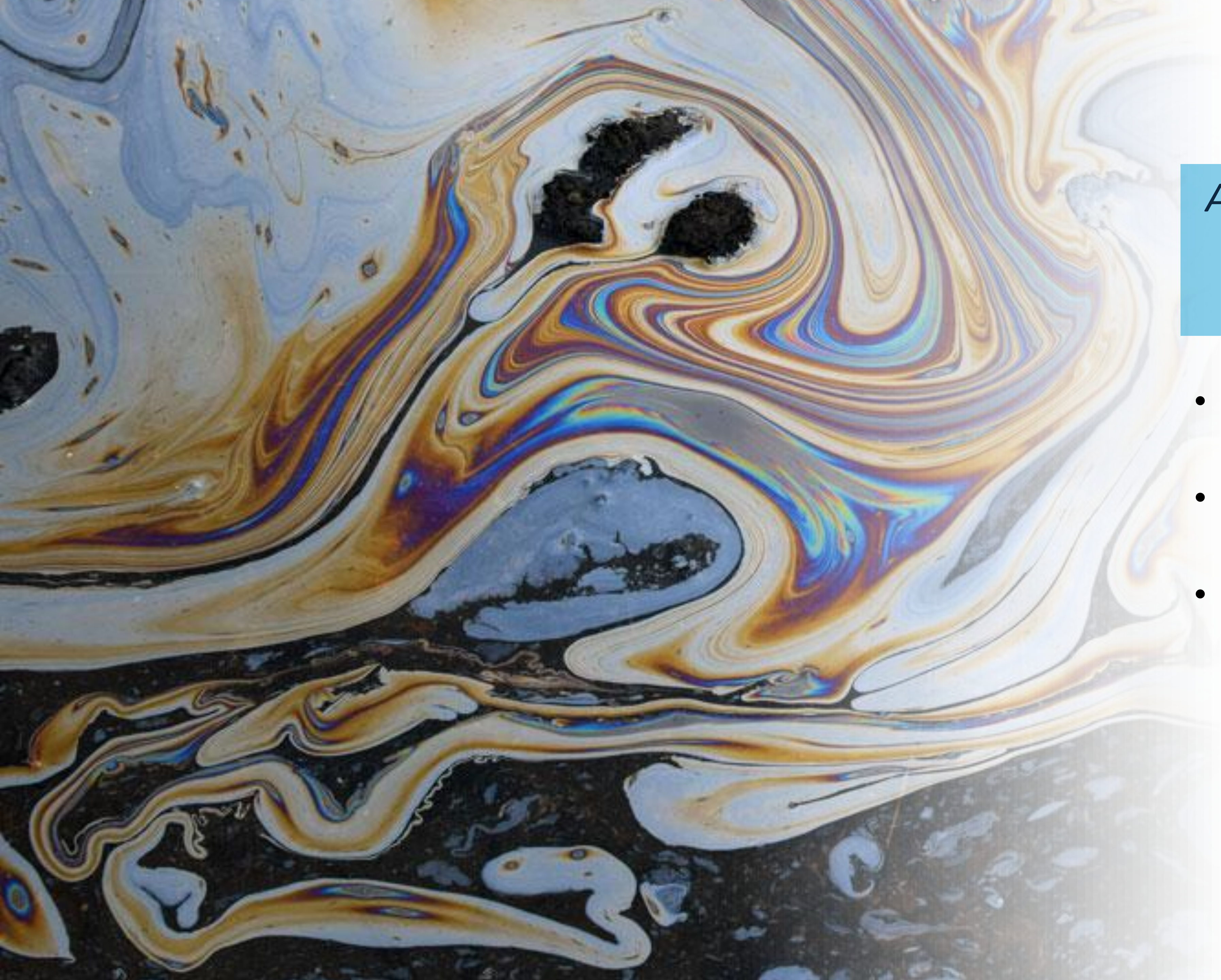


An oil spill is the release of liquid petroleum into the environment

- **Causes**: collisions, human error, weather events.
- **Environmental factors**: wind, waves, currents.
- **Weathering processes**: evaporation, emulsification, dissolution.

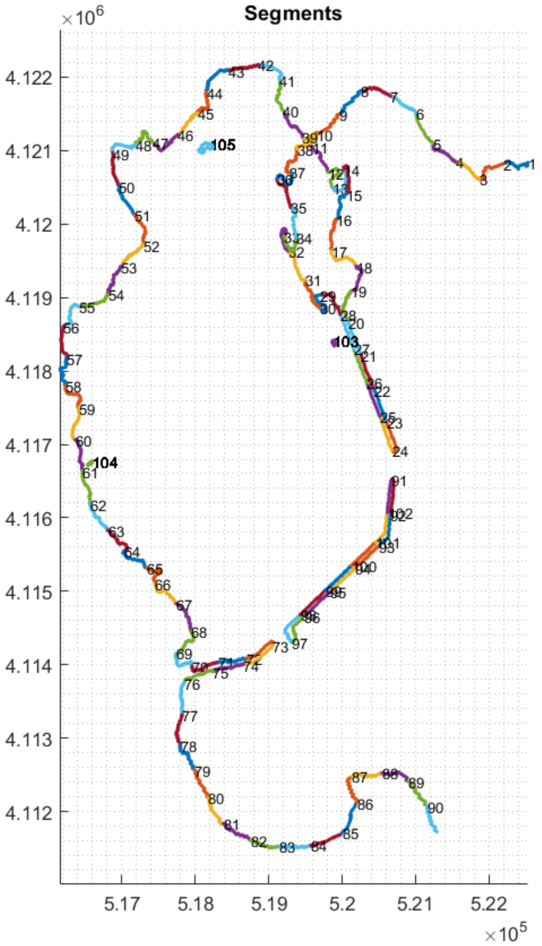
Requires flexible and dynamic modeling.

Case study

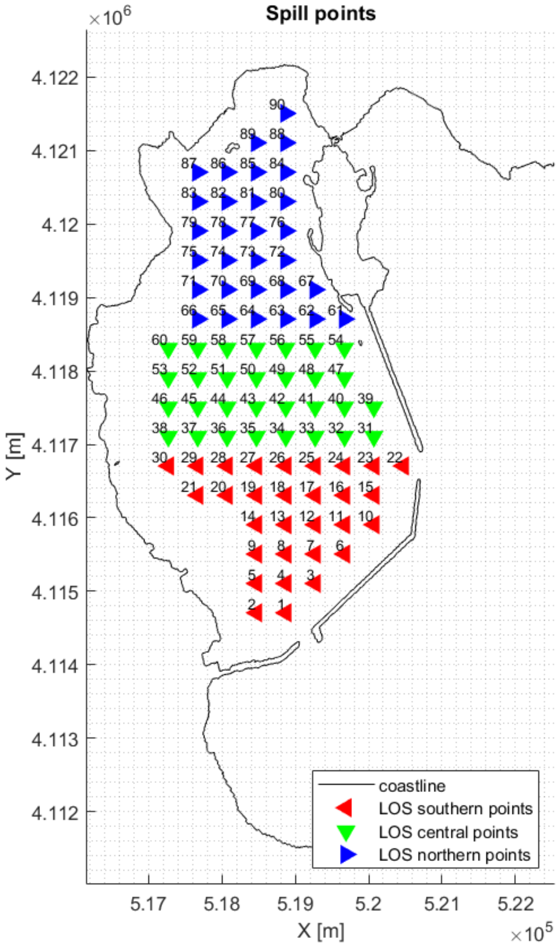
- The area is of considerable interest due to significant maritime traffic.
- The main port is protected by breakwater, but several piers are in open sea.
- The area can be divided into three subdomains:
    A. Porto Xifonio
    B. Porto Megarese
    C. Seno di Priolo

Proposed methodology

Segmentation of the area → Creation of a training database → Calibration of ANN → Assessment of the ANN performance



Step 500 m



Creation of a training database

Segmentation of the area → **Creation of a training database** → Calibration of ANN → Assessment of the ANN performance

Input data

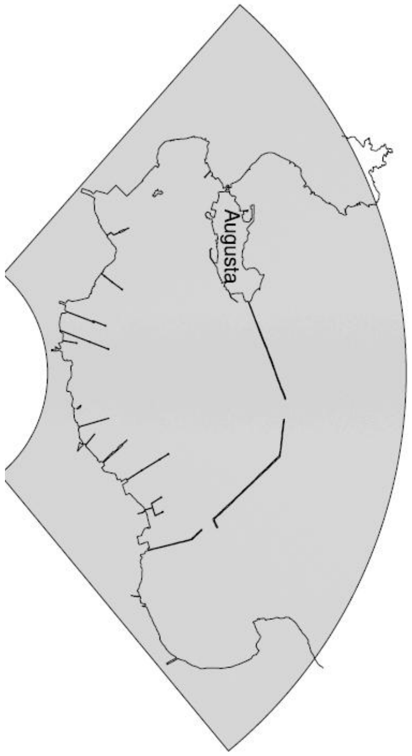
- **Wind velocity U_{10}:** 4.72 and 2.36 m/s.
- **Wind direction Dir:** 0-330° with a step of 30°.
- **Volume V:** 10000, 5000 and 2500 m^3.
- **Wind drift factor K_w:** 0.03 and 0.005.
- **Water content in the oil γ_w^F:** 0.80 and 0.06.
- **Density ρ:** between 800.85 and 954.50 kg/ m^3.

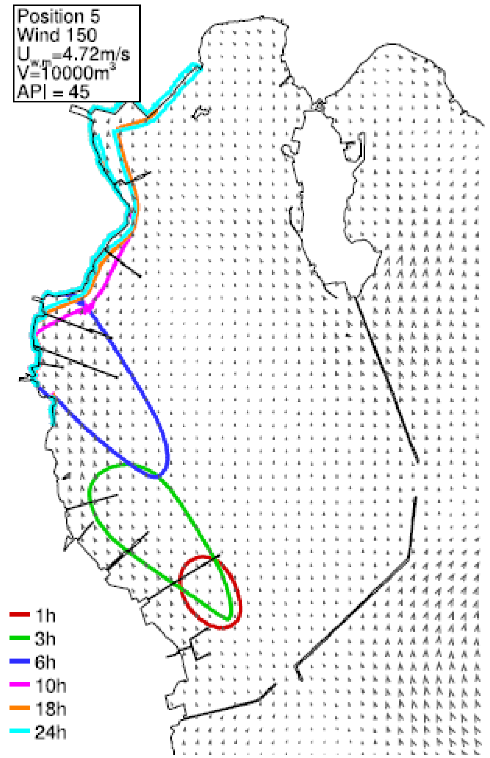
Model

The hydrodynamic field has been solved using the software DELFT3D (*Deltares,2024)* based on shallow water equations.

Structured grid with a circular sector discretised into 480 × 720 cells

Total number of simulated scenario: 14040

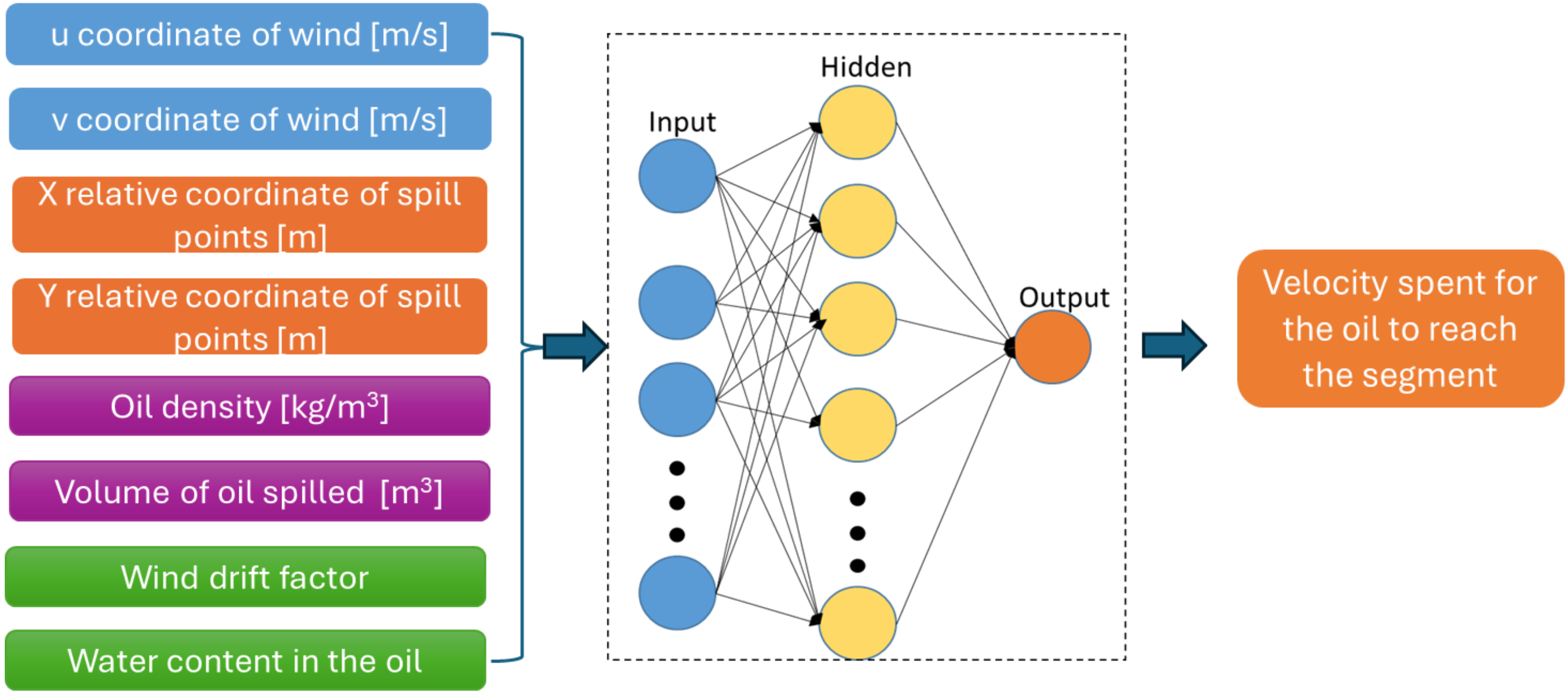




Calibration of ANN

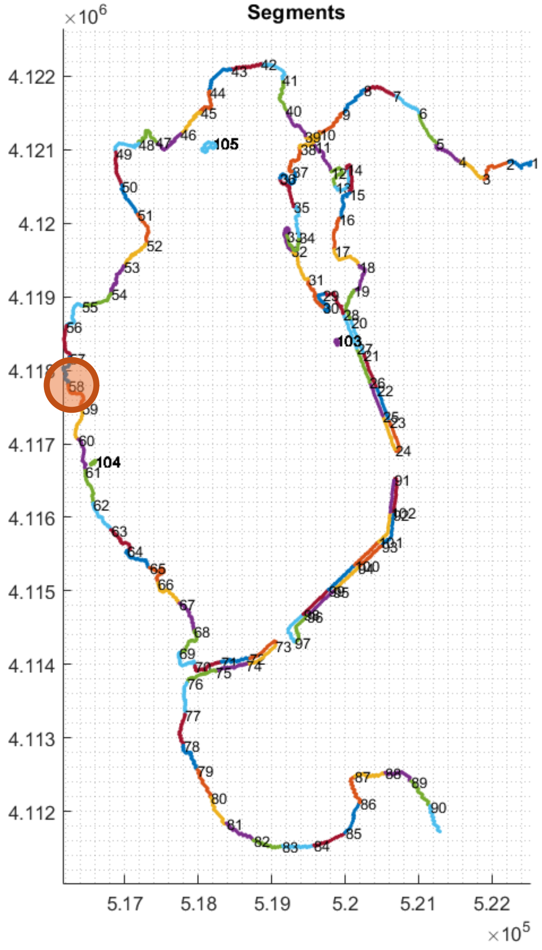
Segmentation of the area → Creation of a training database → **Calibration of ANN** → Assessment of the ANN performance

- **Architecture**:
  - 8 input
  - 2 hidden layers
  - 1 output
- input data **normalized** with z-score standardization
- **Fully connected dense** layers
- Activation function: **ReLU**
- Optimization: **Adams**



Workflow for the ANN

Segmentation of the area → Creation of a training database → Calibration of ANN → Assessment of the ANN performance



Step 1 – Local optimization

- Select a representative (central) segment of the bay
- Train and optimize the neural network on this segment

Step 2 – Generalization test

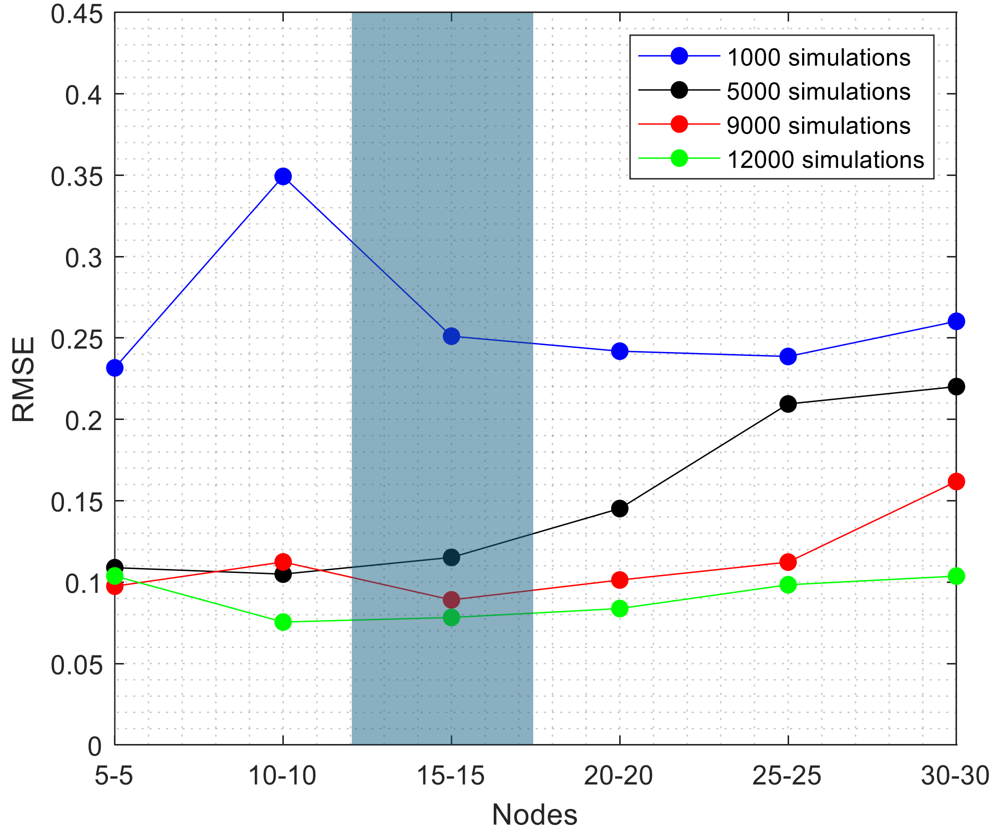
- Apply the optimized configuration to the entire internal bay
- Evaluate model performance segment by segment
- Compare error distribution across the bay.

Step 3 – Analysis of results

- Check consistency of errors among segments.
- Identify areas (upper/lower bay) where the model fails to generalize.
- Assess whether local optimization captures global variability.

Step 1 – Local optimization

Segmentation of the area → Creation of a training database → **Calibration of ANN** → Assessment of the ANN performance



Performance indexes for the ANN trained with 15 neurons in the two hidden layers.

15-15 NODES			
Input data	RMSE unseen [m/s]	d unseen	R^2 unseen
1000	0.251	0.848	0.947
5000	0.115	0.958	0.983
9000	**0.089**	**0.972**	**0.989**
12000	0.078	0.981	0.993

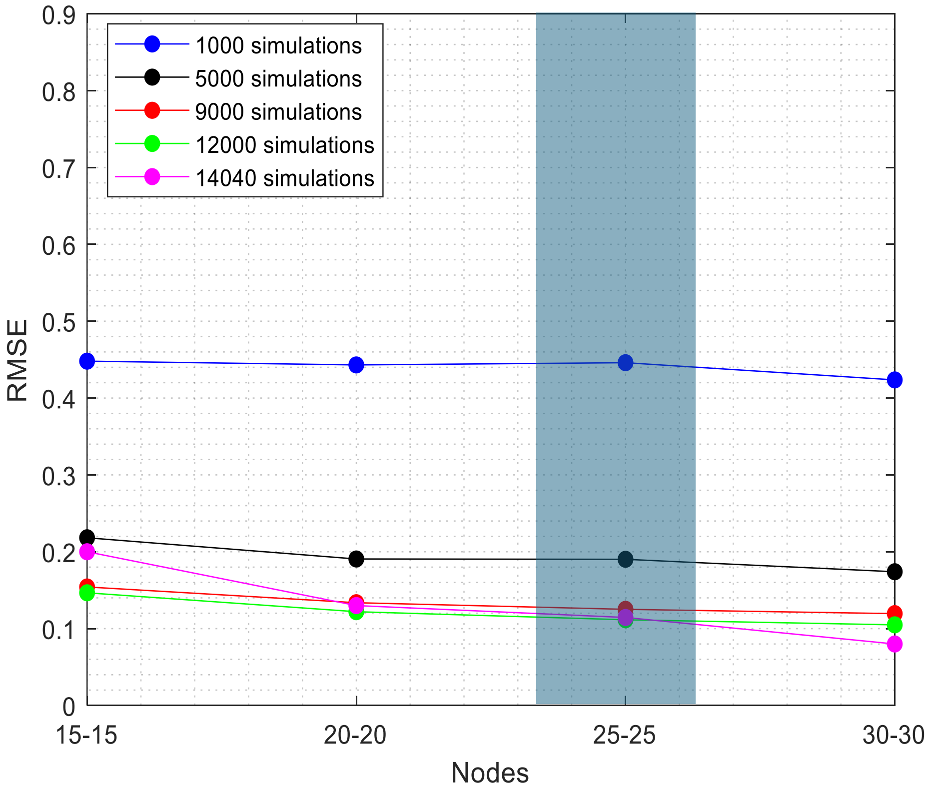
$$RMSE = \sqrt{\sum \frac{(O-P)^2}{n}} \qquad R^2 = \left(\frac{\sum(O-\bar{O})(P-\bar{P})}{\sqrt{\sum(O-\bar{O})^2}\sqrt{\sum(P-\bar{P})^2}}\right)^2$$

$$d = 1 - \frac{\sum(O-P)^2}{\sum\left(|O-\bar{O}| + |P-\bar{P}|\right)^2}$$

O is the array of observed values and $\bar{O}$ is its mean
P is the array of predicted value and $\bar{P}$ is its mean

Step 2 – Generalization

Segmentation of the area → Creation of a training database → **Calibration of ANN** → Assessment of the ANN performance



Performance indexes for the ANN trained with 25 neurons in the two hidden layers.

15-15 NODES

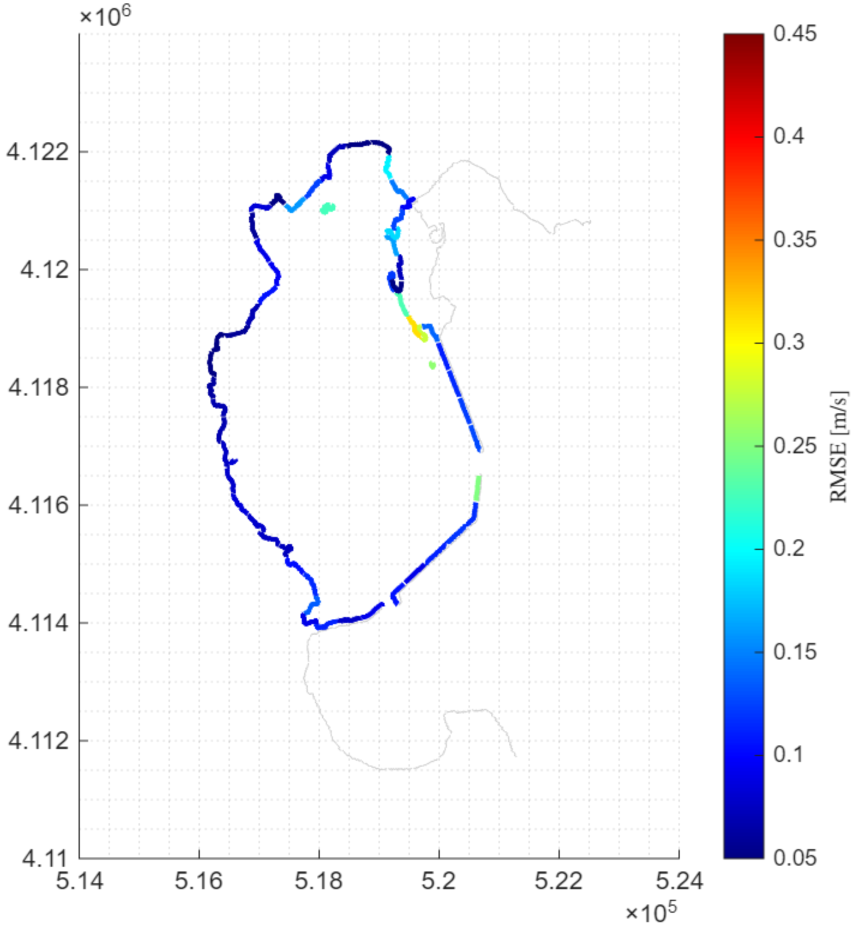
Input data	RMSE unseen [m/s]	d unseen	R^2 unseen
1000	0.251	0.848	0.947
5000	0.115	0.958	0.983
9000	**0.089**	**0.972**	**0.989**
12000	0.078	0.981	0.993

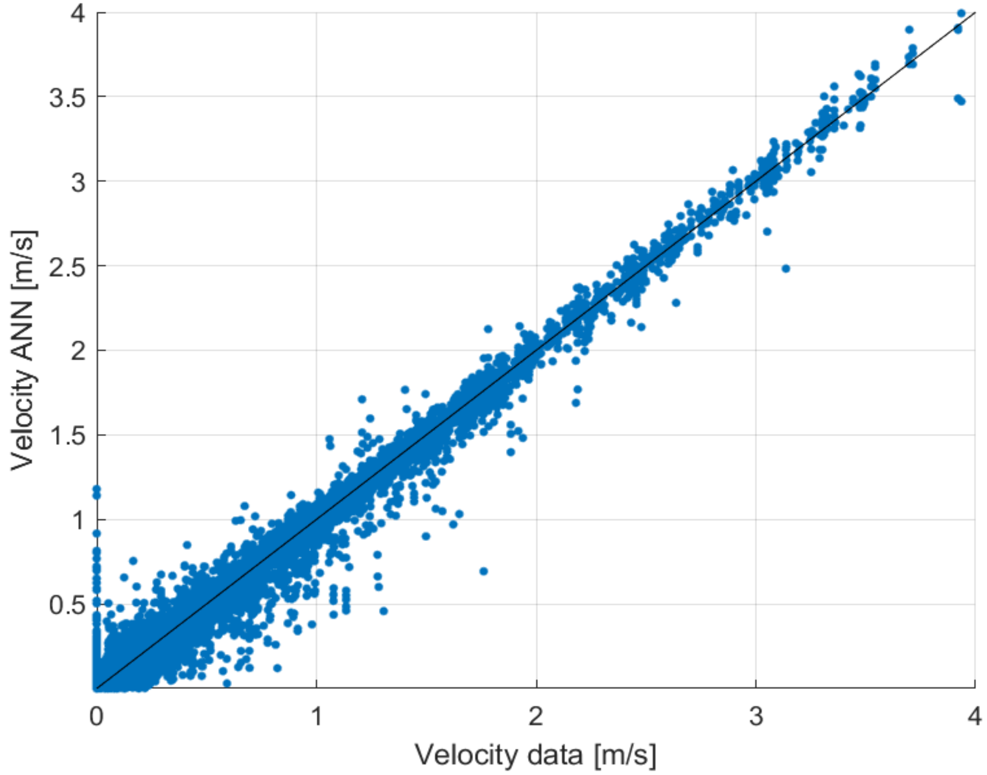
25-25 NODES

Input data	RMSE unseen [m/s]	d unseen	R^2 unseen
1000	0.449	0.947	0.888
5000	0.164	0,991	0.965
9000	0.126	0.996	0.986
12000	**0.11**	0.997	0.990
14040	0.09	0.998	0.991

Step 3 – Analysis of results

Segmentation of the area → Creation of a training database → Calibration of ANN → **Assessment of the ANN performance**





Nodes	Input data	RMSE	R^2	d	bias
25-25	12000	0.11	0.991	0.997	0.001

Conclusion

- The ANN demonstrated strong predictive capabilities achieving low RMSE and high R^2 values even on unseen data.
- The second configuration, with 25 neurons per hidden layer and 12000 training simulations, provided the optimal trade-off between accuracy and computational efficiency.
- Further increases in network complexity or dataset size yielded only marginal gains, confirming the robustness of the selected configuration.
- The ANN is much faster than traditional numerical models, and it achieves these results without losing accuracy.
- That kind of computational speed is crucial for early warning systems, where rapid response and timely prediction can make a real difference in managing oil spills effectively.

Thank you for your kind attention!