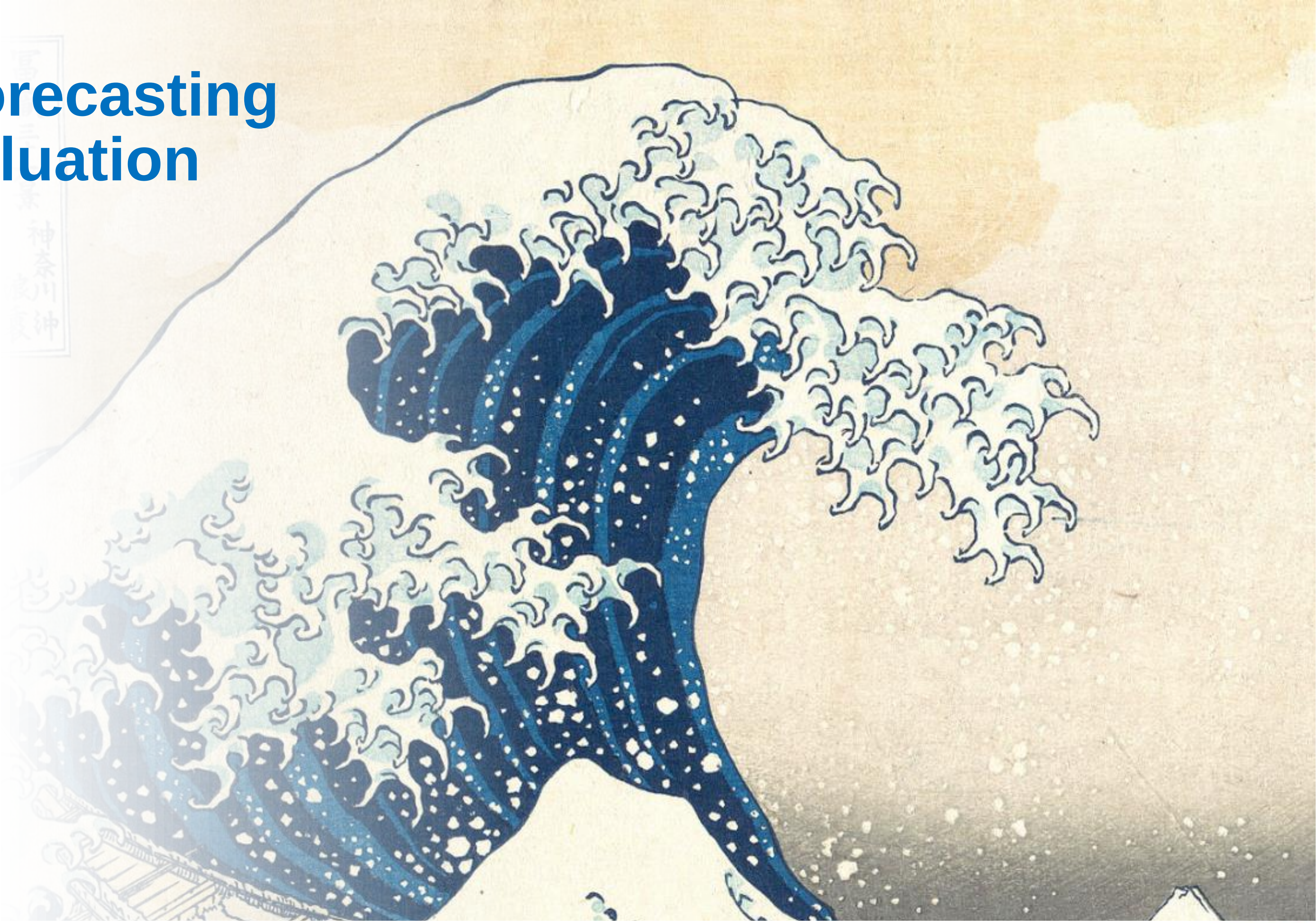
WP3: Sea State Forecasting and Resource Evaluation



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SmartWave – High accuracy & high spatial fidelity wave prediction

Motivation: Development of SmartWave to simulate parameters useful for marine renewables.

Artificial Intelligence (Artificial Neural Network – ANN and Convolutional Neural Network – CNN) will be advanced to estimate key oceanographic parameters i.e. wave height, direction, frequency, and speed. State-of-the-art remote sensing monitoring and in situ data from European Space Agency satellite Sentinel 1 (Synthetic Aperture Radar – SAR) will be utilised, whilst access to high-fidelity data from the Cefas WaveNet buoys will provide ground truth data for validation.

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Satellite SAR images

Satellite images are capable of providing hindcast information in very high resolution

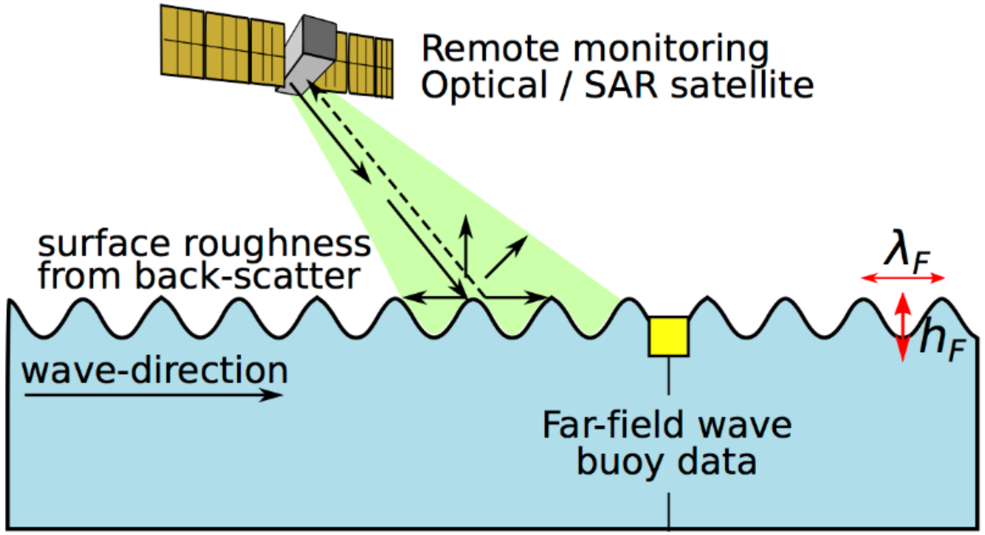
How it works:

- Radar transmits a pulse
- Some of the energy in the radar pulse is reflected back
- Every pixel of a complex SAR image contains amplitude and phase information.

Can provide information about the sea roughness

Using SAR images has benefits:

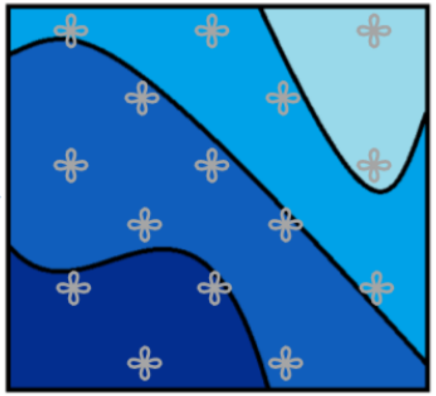
- Unaffected by weather
- Unaffected by cloud cover
- Larger datasets



How it works

ANN based system

Data Acquisition → **Data processing** → **Artificial neural networks (ANNs)** → **Spatial distribution**



Data Acquisition

- Sentinel 1 - SAR Images
- Buoy data

Data processing

Initial processing,
Extract parameters related to sea roughness from different SAR image bands

Artificial neural networks (ANNs)

Correlate sea roughness parameters to buoy data

Spatial distribution

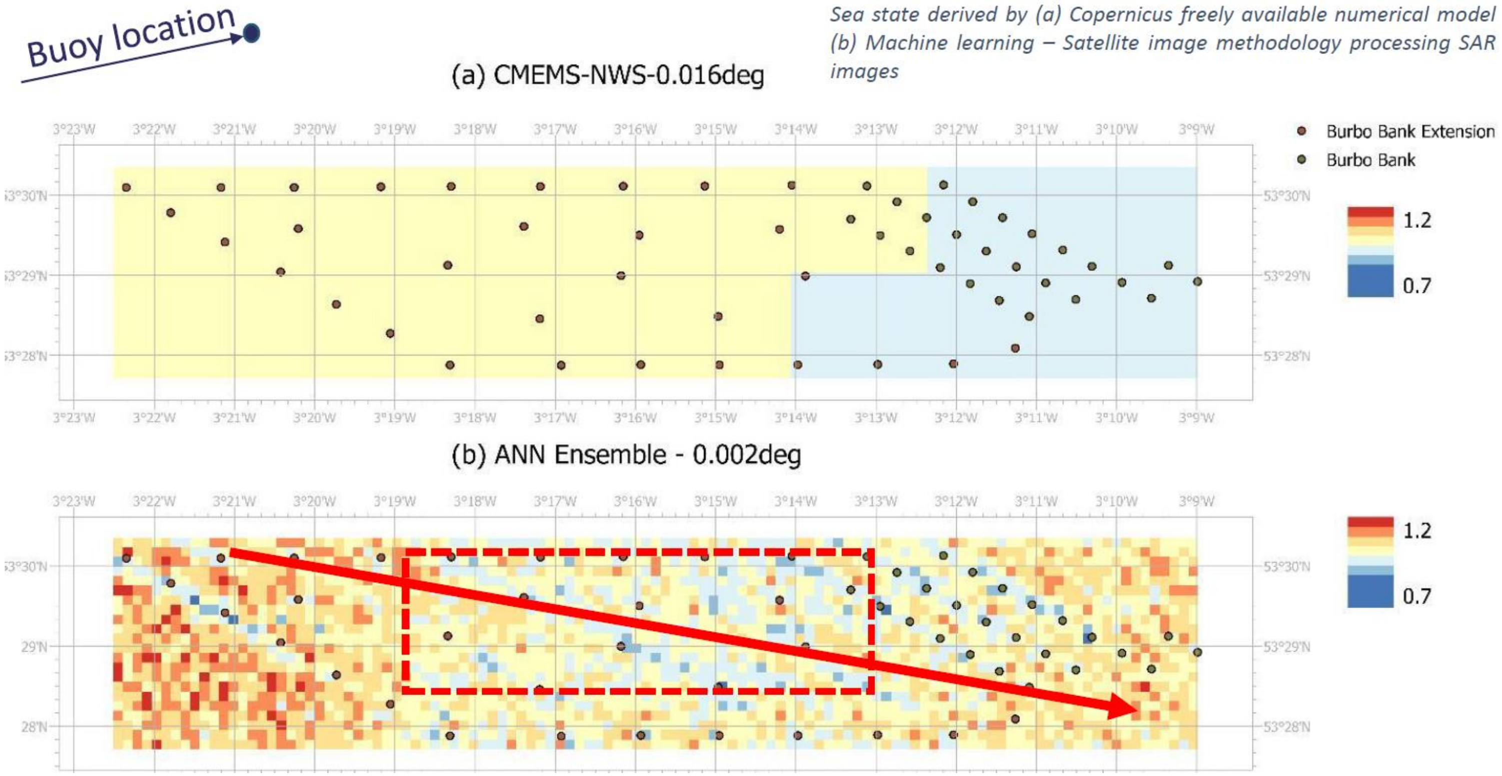
Apply ANNs to derive sea state in any location

Example results – Burbo Bank

Comparison of Sea state conditions at 2/4/2019 06:32:16am

Buoy data: 0.89m (6:30am) – 1.07m (7:00am)	Numerical model at the buoy: 0.92m	ANN Ensemble: 0.95m

- Same trend of significant wave height for both hindcasts
- Higher resolution for machine learning-satellite image methodology
- Possible to identify pattens like sheltering in the inner wind turbines compared to the ones that are at the edge of the wind farm.



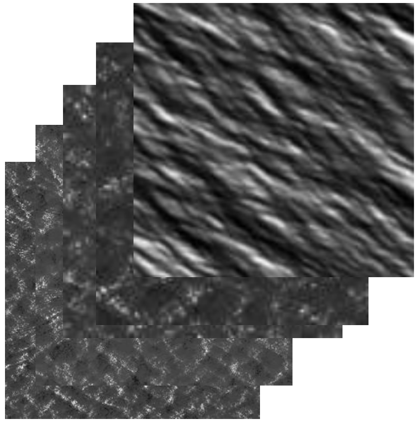
Sea state derived by (a) Copernicus freely available numerical model (b) Machine learning – Satellite image methodology processing SAR images

Tapoglou, E., Forster, R. M., Dorrell, R. M., & Parsons, D. (2021). Machine learning for satellite-based sea-state prediction in an offshore windfarm. Ocean Engineering, 235, 109280.

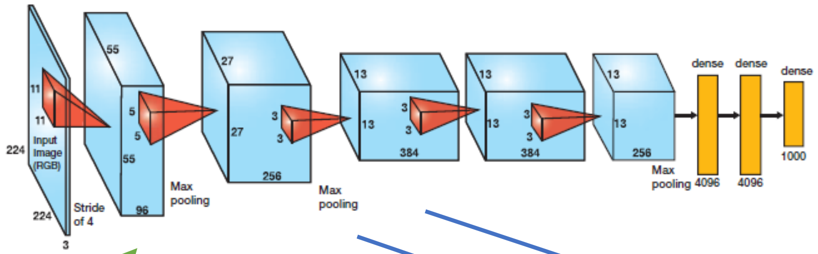
CNN based system

Deep learning

SAR imagery synthetic database creation
Different parameters:
wind directions
wind speeds
fetch size
incidence angles
polarizations

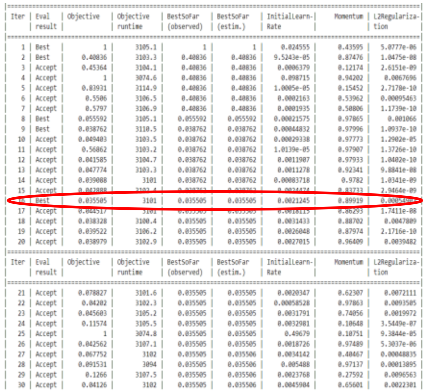


Training CNN (AlexNet)

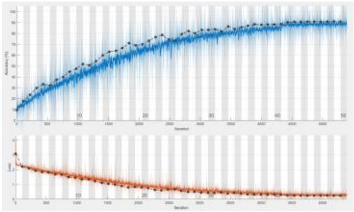


Strategies:
Training from scratch
Transfer learning with real data

Automated classification and estimation of sea state parameters:
wave height
direction
frequency
speed

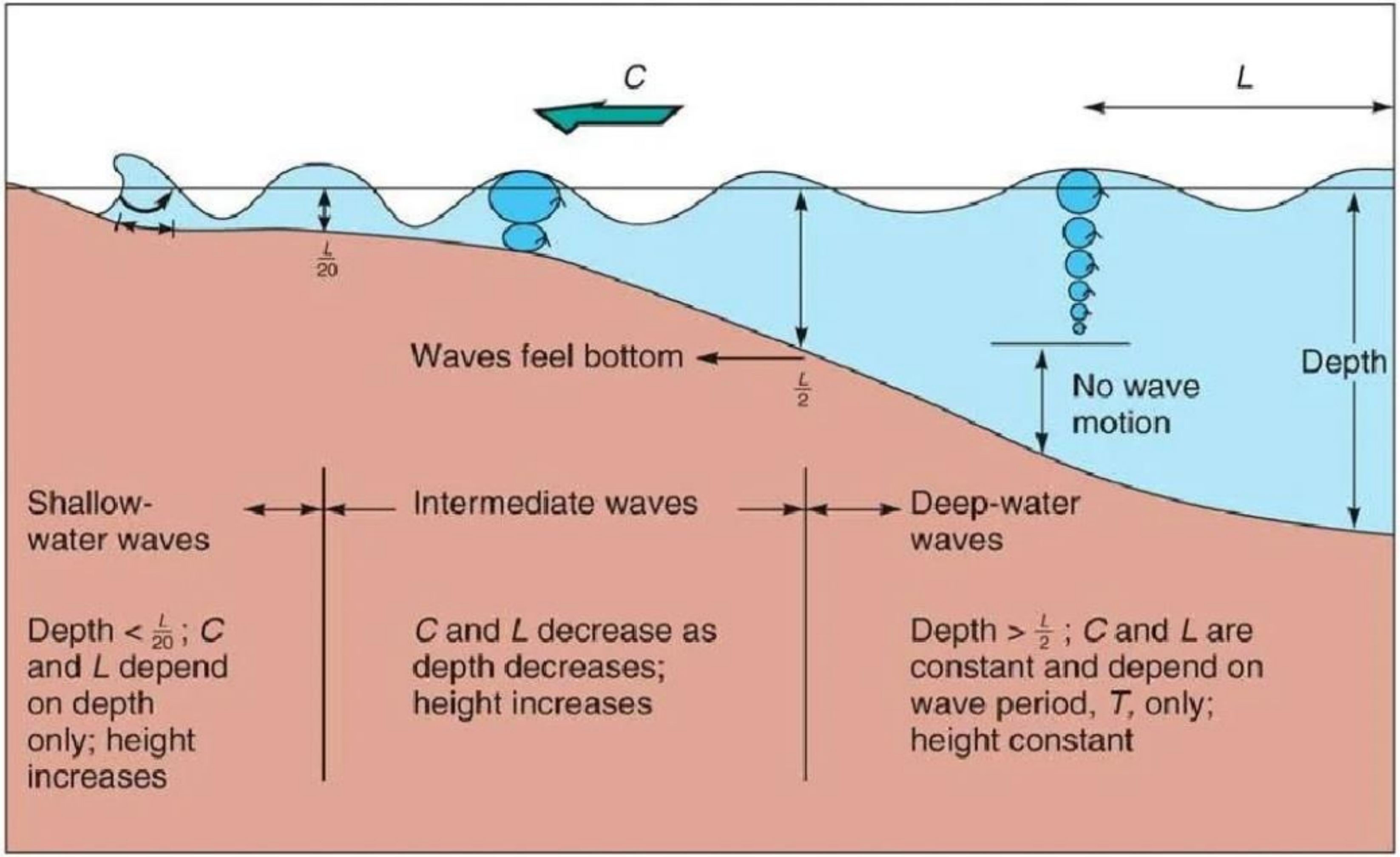


Iter	Eval result	Objective	Objective runtime	BestSoFar (observed)	BestSoFar (estim.)	InitialLearn-Rate	Momentum	L2Regulariza-tion
1	Best	1	3105.1	1	1	0.024555	0.43595	5.0777e-06
2	Best	0.40836	3103.3	0.40836	0.40836	9.5243e-05	0.87476	1.0475e-08
3	Accept	0.45364	3104.1	0.40836	0.40836	0.0006379	0.12174	2.6151e-09
4	Accept	1	3074.6	0.40836	0.40836	0.098715	0.94202	0.0067696
5	Accept	0.83931	3114.9	0.40836	0.40836	1.0005e-05	0.15452	2.7178e-10
6	Accept	0.5506	3106.5	0.40836	0.40836	0.0002163	0.53962	0.00095463
7	Accept	0.5797	3106.9	0.40836	0.40836	0.0001935	0.50806	1.1739e-10
8	Best	0.055592	3105.1	0.055592	0.055592	0.00021575	0.97865	0.001066
9	Best	0.038762	3110.5	0.038762	0.038762	0.00044832	0.97996	1.0937e-10
10	Accept	0.049403	3103.5	0.038762	0.038762	0.00029338	0.97773	1.2902e-05
11	Accept	0.56862	3103.2	0.038762	0.038762	1.0139e-05	0.97907	1.3726e-10
12	Accept	0.041585	3104.7	0.038762	0.038762	0.0011907	0.97933	1.0402e-10
13	Accept	0.047774	3103.3	0.038762	0.038762	0.0011278	0.92341	9.8841e-08
14	Accept	0.039088	3101	0.038762	0.038762	0.00083718	0.9782	1.0341e-09
15	Accept	0.042888	3102.4	0.038762	0.038762	0.0024474	0.83733	2.9464e-09
16	Best	0.035505	3101	0.035505	0.035505	0.0021245	0.89919	[illegible]
17	Accept	0.044517	3101	0.035505	0.035505	0.0018115	0.86293	1.7411e-08
18	Accept	0.038328	3100.4	0.035505	0.035505	0.0031433	0.88702	0.0047809
19	Accept	0.039522	3106.2	0.035505	0.035505	0.0026048	0.87974	2.1716e-10
20	Accept	0.038979	3102.9	0.035505	0.035505	0.0027015	0.96409	0.0039482
Iter	Eval result	Objective	Objective runtime	BestSoFar (observed)	BestSoFar (estim.)	InitialLearn-Rate	Momentum	L2Regulariza-tion
21	Accept	0.078827	3101.6	0.035505	0.035505	0.0020347	0.62307	0.0072111
22	Accept	0.04202	3102.3	0.035505	0.035505	0.00058528	0.97863	0.0093505
23	Accept	0.045603	3105.2	0.035505	0.035505	0.0031791	0.74056	0.0019972
24	Accept	0.11574	3105.5	0.035505	0.035505	0.0032981	0.10648	3.5449e-07
25	Accept	1	3074.8	0.035505	0.035505	0.49679	0.10751	9.3844e-05
26	Accept	0.042562	3107.1	0.035505	0.035505	0.0018726	0.97489	5.3037e-06
27	Accept	0.067752	3102	0.035505	0.035506	0.0034142	0.40467	0.00048835
28	Accept	0.091531	3094	0.035505	0.035506	0.005488	0.97137	0.00013895
29	Accept	0.1266	3107.5	0.035505	0.035506	0.0023768	0.27592	0.0096563
30	Accept	0.04126	3102	0.035505	0.035506	0.0045904	0.65601	0.0022301



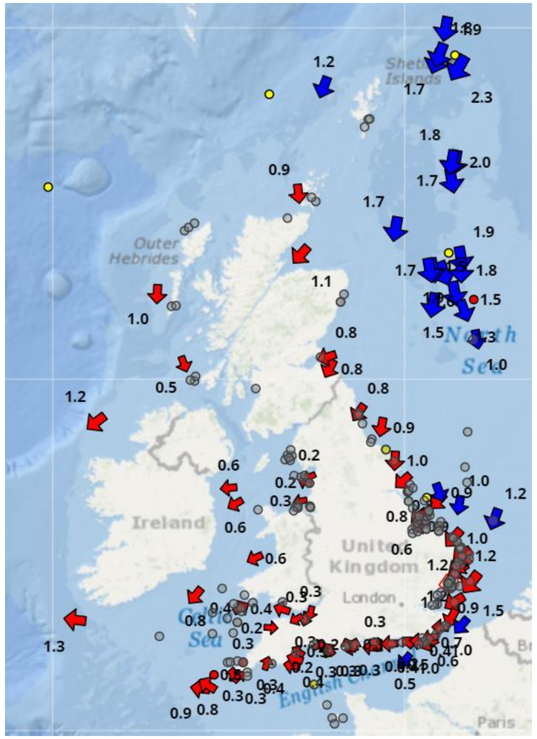
Bayesian optimization to find optimal network hyperparameters

Relationship between wavelength and water depth

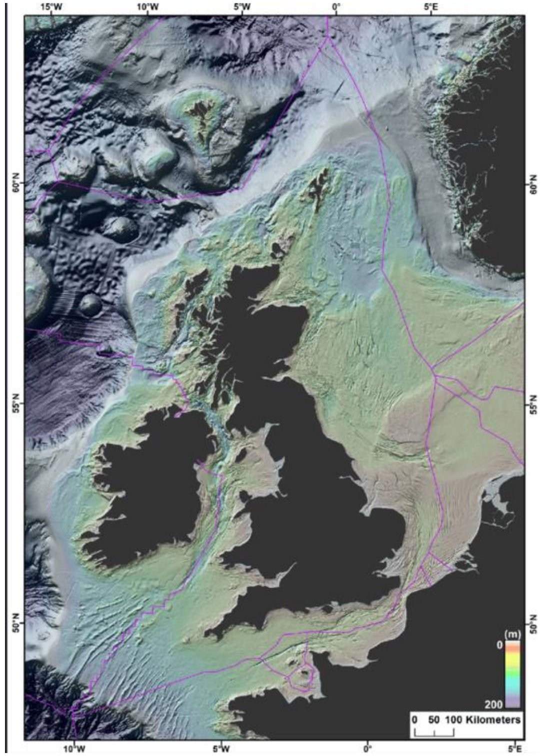


Mapping of shallow, intermediate, and deep-water areas

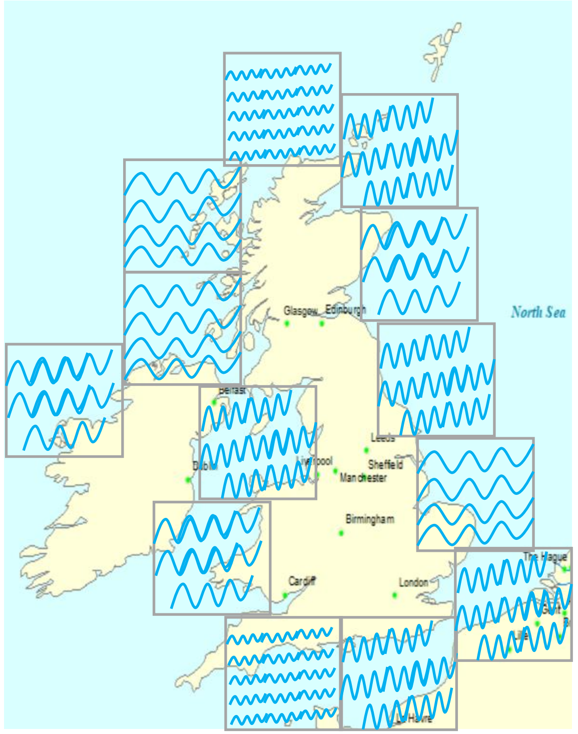
Cefas WaveNet buoys



Bathymetry offshore model of the UK (EMODnet and GEBCO)



Determination of uniform waves zones



Dove, D., Bradwell, T., Carter, G., Cotterill, C., Gafeira Goncalves, J., Green, S., ... & Ottesen, D. (2016). Seabed geomorphology: a two-part classification system.

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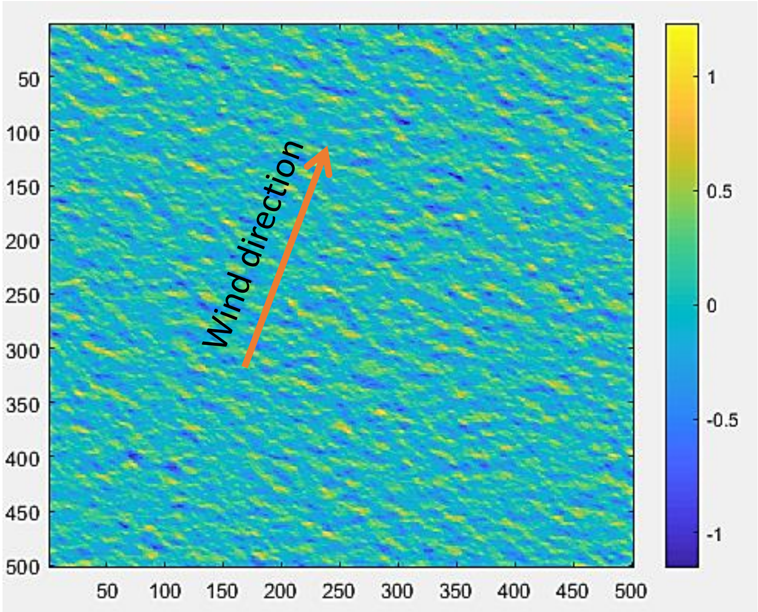
Sea Surface Modelling - Linear theory

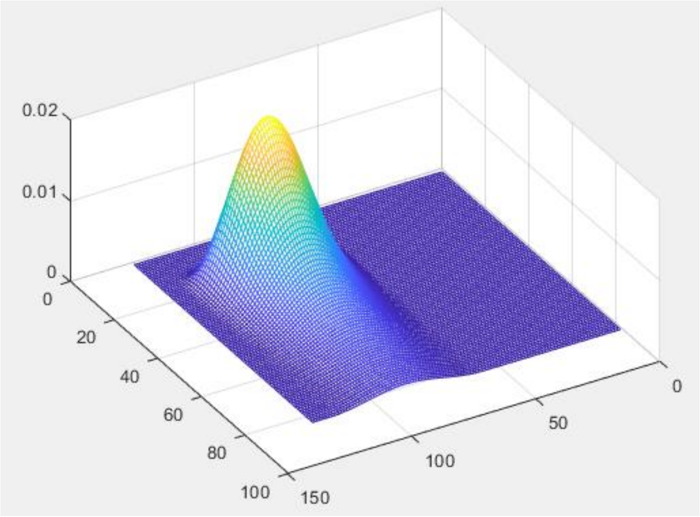
The irregular sea surface elevation model can be expressed as:

$$Z_{sea}(x, y, z, t) = \sum_i \sum_j A_{ij} \cos\left[k_i\left(x\cos\theta_j + y\sin\theta_j\right) - \omega_i t + r_{ij}\right]$$

$$A_{ij} = \sqrt{2S(k_i)D(k_i,\theta_j)dk_i d\theta_j}$$

Wind speed Vw = 7 m/s

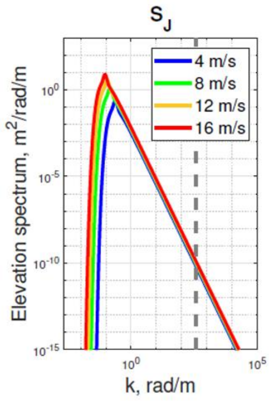




Omnidirectional spectrum

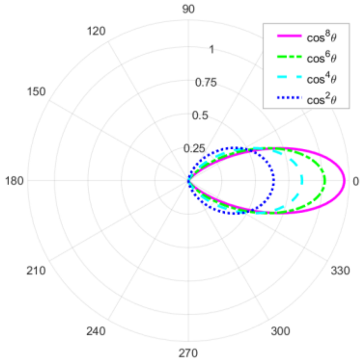
Joint North Sea Wave Project (JONSWAP)

$$S(k_i) = \frac{\alpha}{2} k_i^{-3} \exp\left[-1.25\left(\frac{k_i}{k_p}\right)^{-2}\right]$$
$$\exp\left\{\ln\gamma \exp\left[-\frac{\left(\sqrt{k_i/k_p} - 1\right)^2}{2\sigma^2}\right]\right\}$$



Directional spreading function

$$D(\theta_j) = \begin{cases} \frac{2}{\pi}\cos^2\theta_j & |\theta_j| \le 90^0 \\ 0 & |\theta_j| > 90^0 \end{cases}$$



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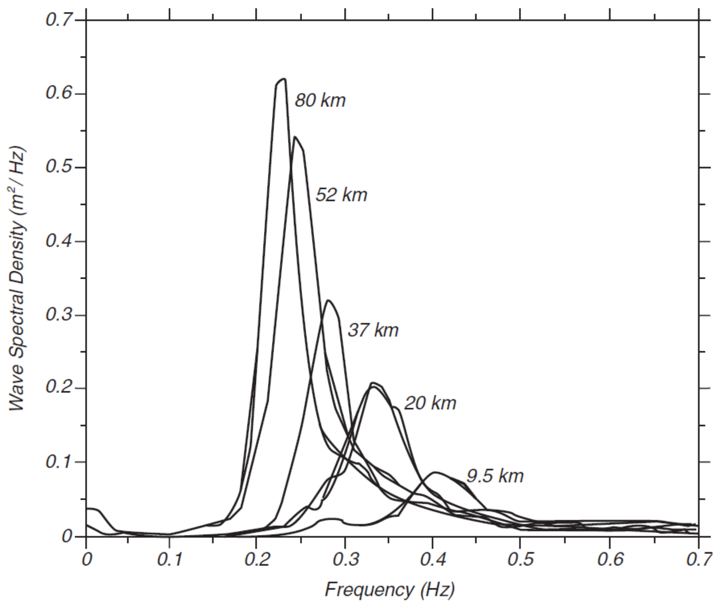
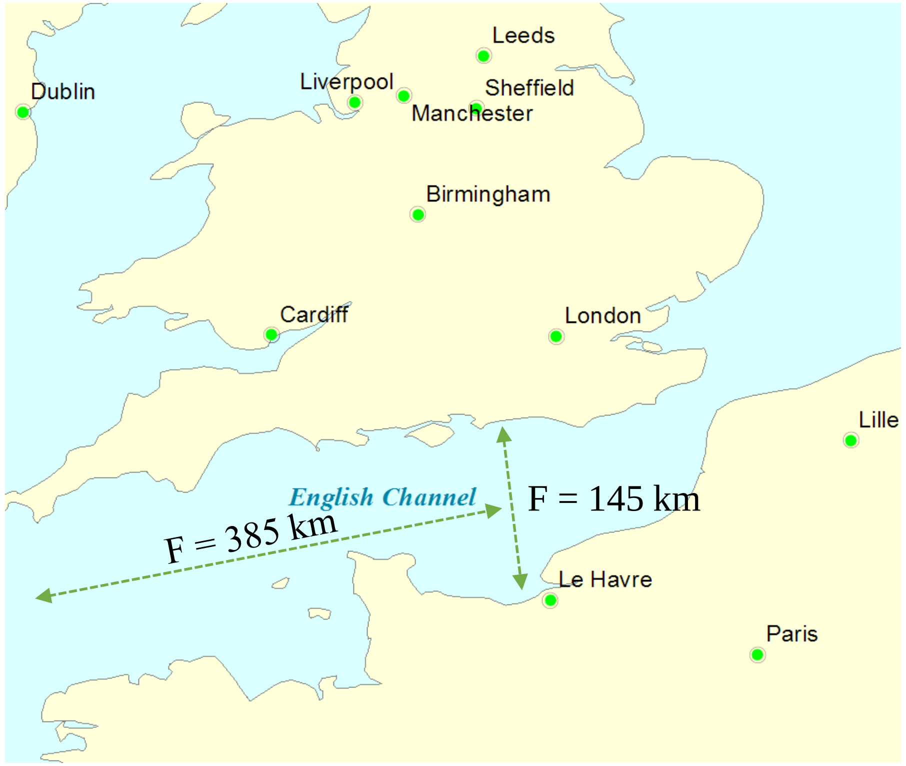
Sea Surface Modelling – Fetch length

The fetch is a significant factor in the development of wind waves

JONSWAP wave spectrum for different fetches



Stewart, R. H. (2008). *Introduction to physical oceanography*.



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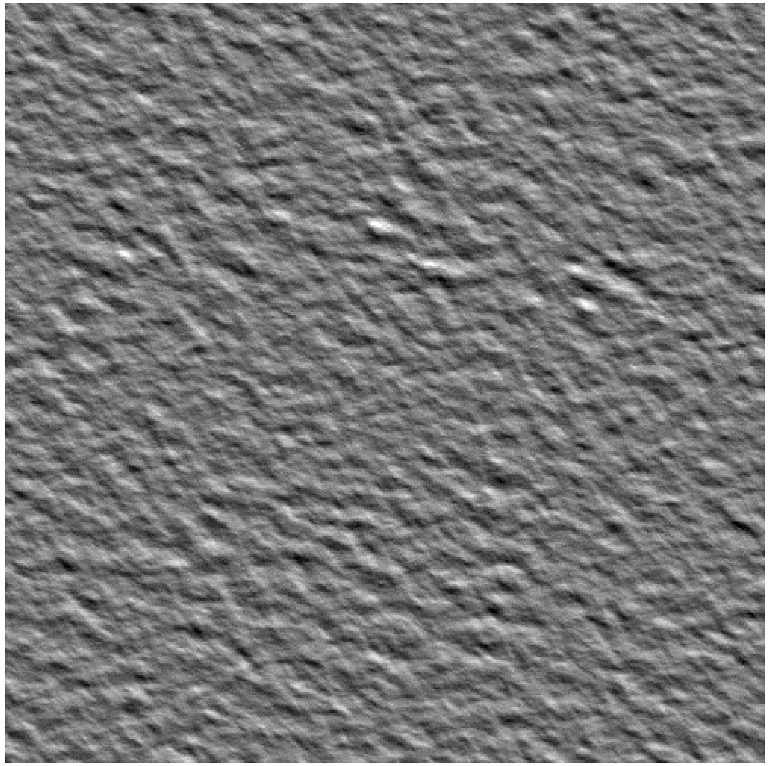
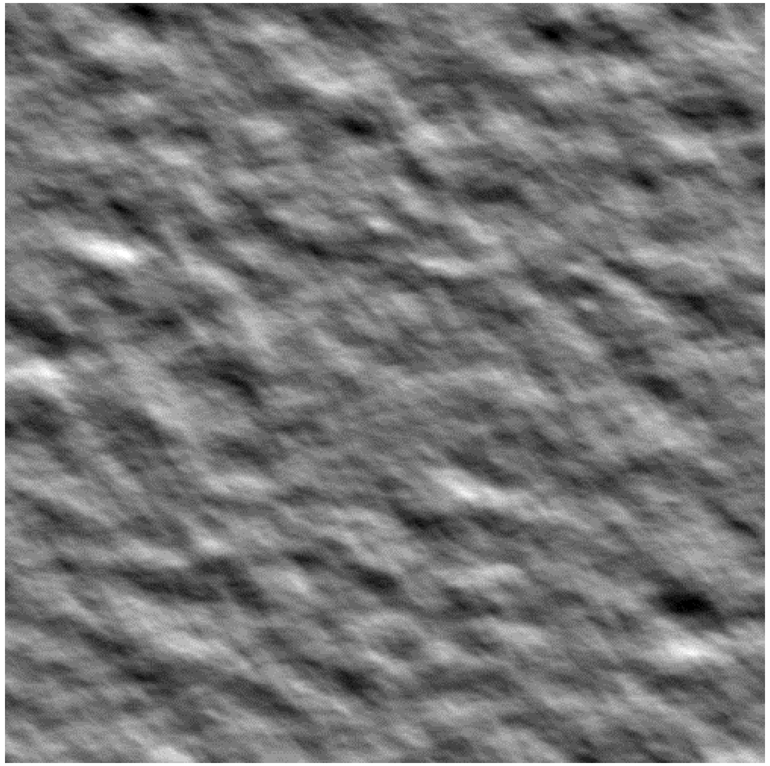
Sea Surface Modelling – Time domain

Vw = 7 m/s, F = 20 km

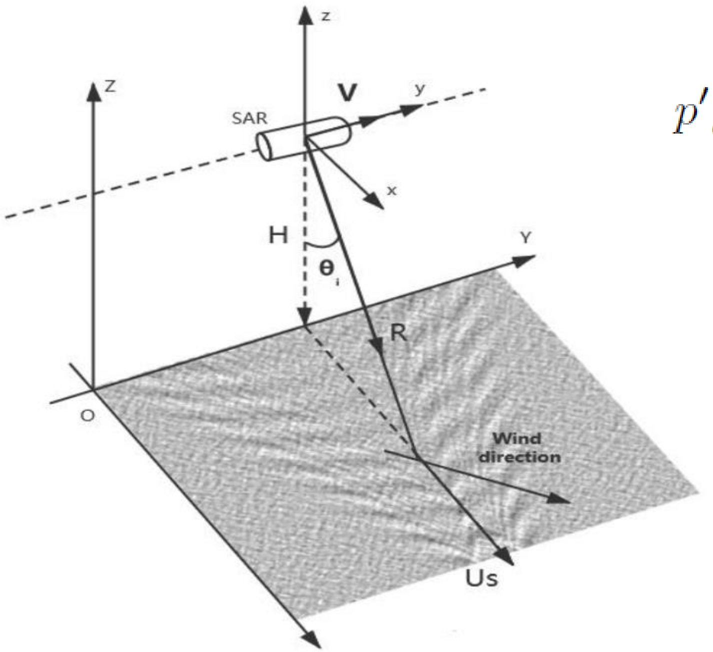


Vw = 7 m/s, F = 105 km



SAR image simulation – velocity bunching of gravity waves

$$I(x,y) = \frac{\pi T_i}{2V} \iint \delta(y - y_0) \frac{\overline{\sigma}(x_0, y_0)}{p_a^1(x_0, y_0)} \times \exp\left\{-\pi^2 \left[\frac{x - x_0 - \frac{R}{V} u_r(x_0, y_0)}{p_a^1(x_0, y_0)}\right]^2\right\} dx_0 dy_0$$



SAR scanning geometry

$$p'_a(x,y) = N_l p_a \left[1 + \frac{\pi^2 {T_i}^4}{{N_l}^2 \lambda^2} \bar{A}_r(x,y) + \frac{1}{{N_l}^2} \frac{{T_i}^2}{{\tau_c}^2}\right]^{1/2}$$

Degraded azimuthal resolution

$$p_a = \frac{\lambda R}{2 V T_i}$$

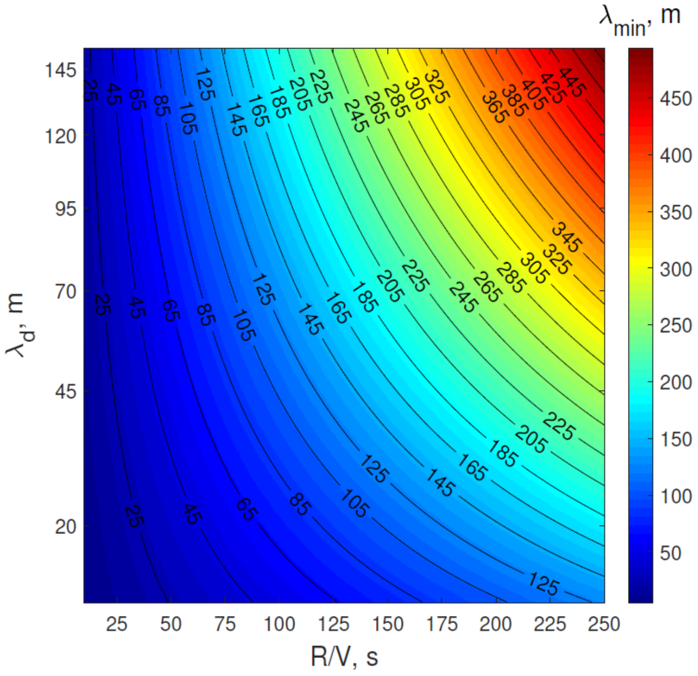
Single-look azimuthal resolution

R/V is the range-to-velocity ratio

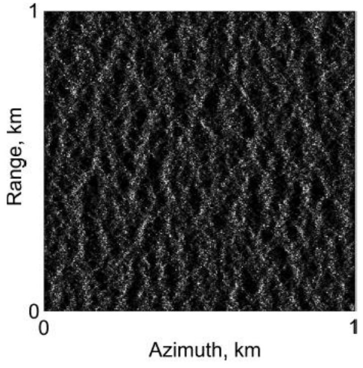
SAR simulation

The important limitation of SAR imaging of waves moving in flight direction which is associated with the velocity bunching is the azimuthal cut-off effect.

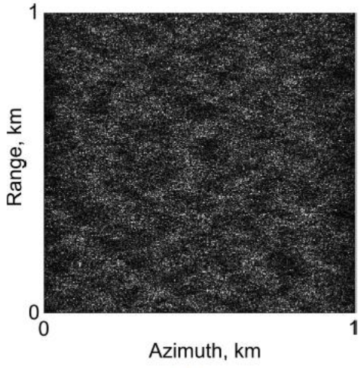
The minimal detectable wavelength of the surface waves can be approximated as $\lambda_{\min} = C_0 \frac{R}{V} \sqrt{H_s}$



(a)



(b)

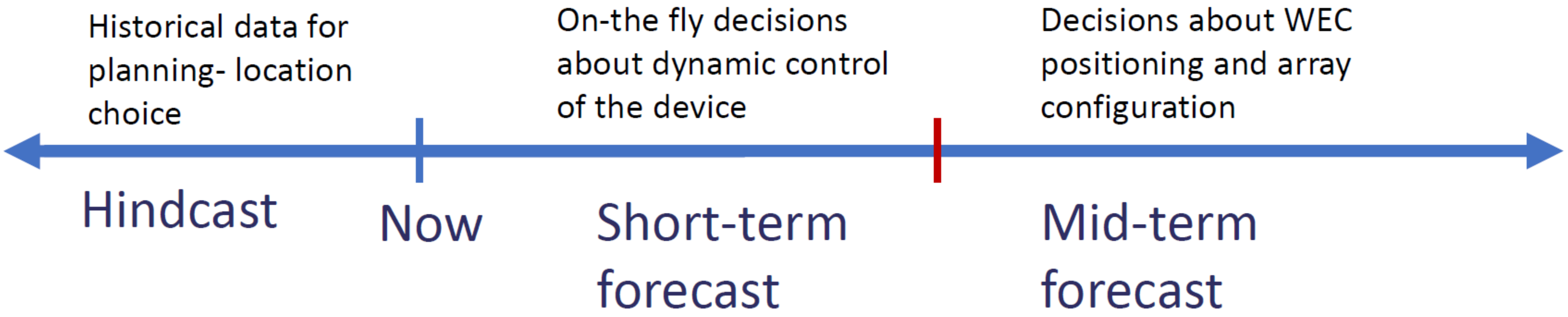


(c)

Simulated SAR images of the sea surface with Vw = 10.7 m/s and λd = 95.5 m for (b) airborne (R/V = 23.1 s) and (c) satellite (R/V = 107.1 s) platforms.

Rizaev, I. G., Karakuş, O., Hogan, S. J., & Achim, A. (2022). Modeling and SAR Imaging of the Sea Surface: a Review of the State-of-the-Art with Simulations. ISPRS Journal of Photogrammetry and Remote Sensing, 187, 120-140.

Uses of SmartWave



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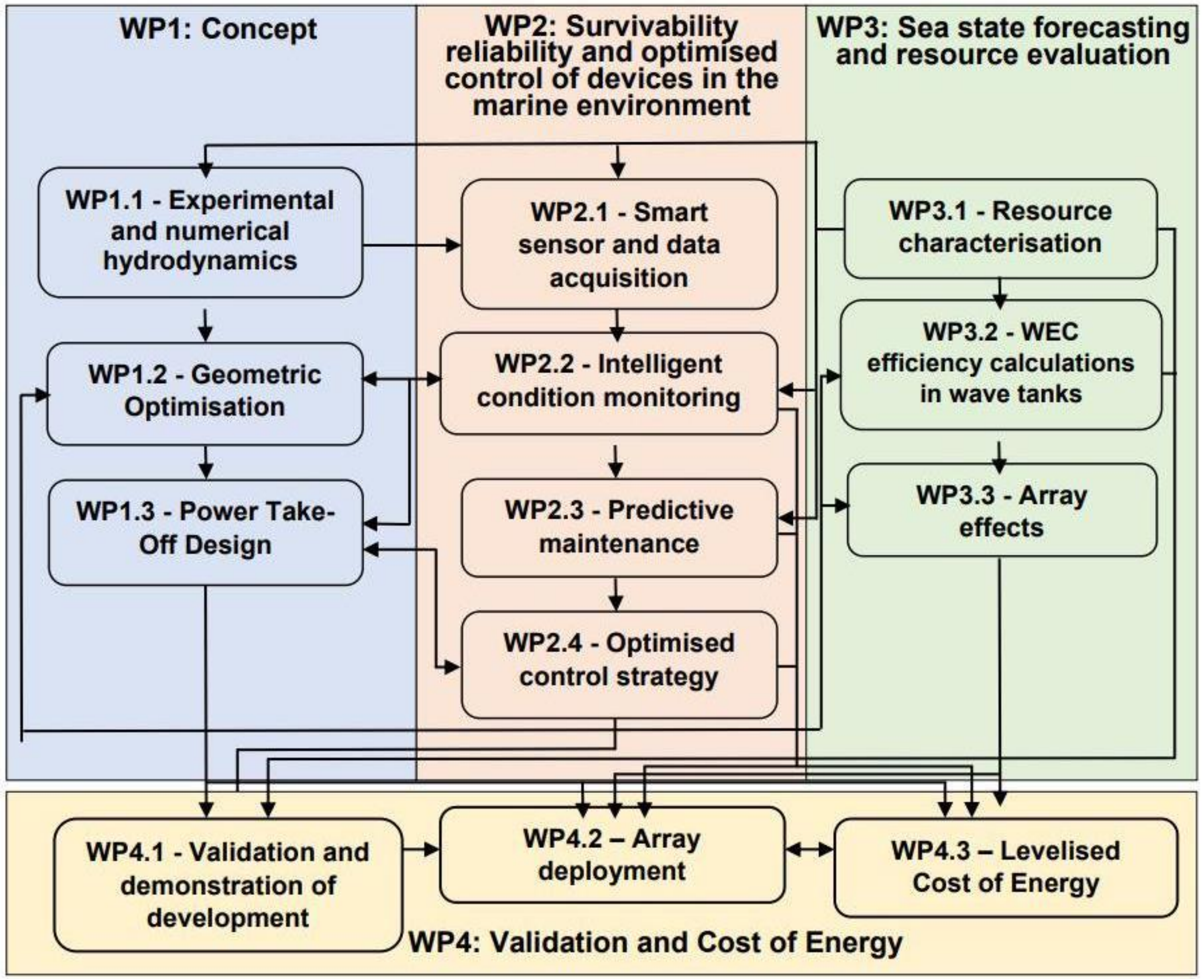
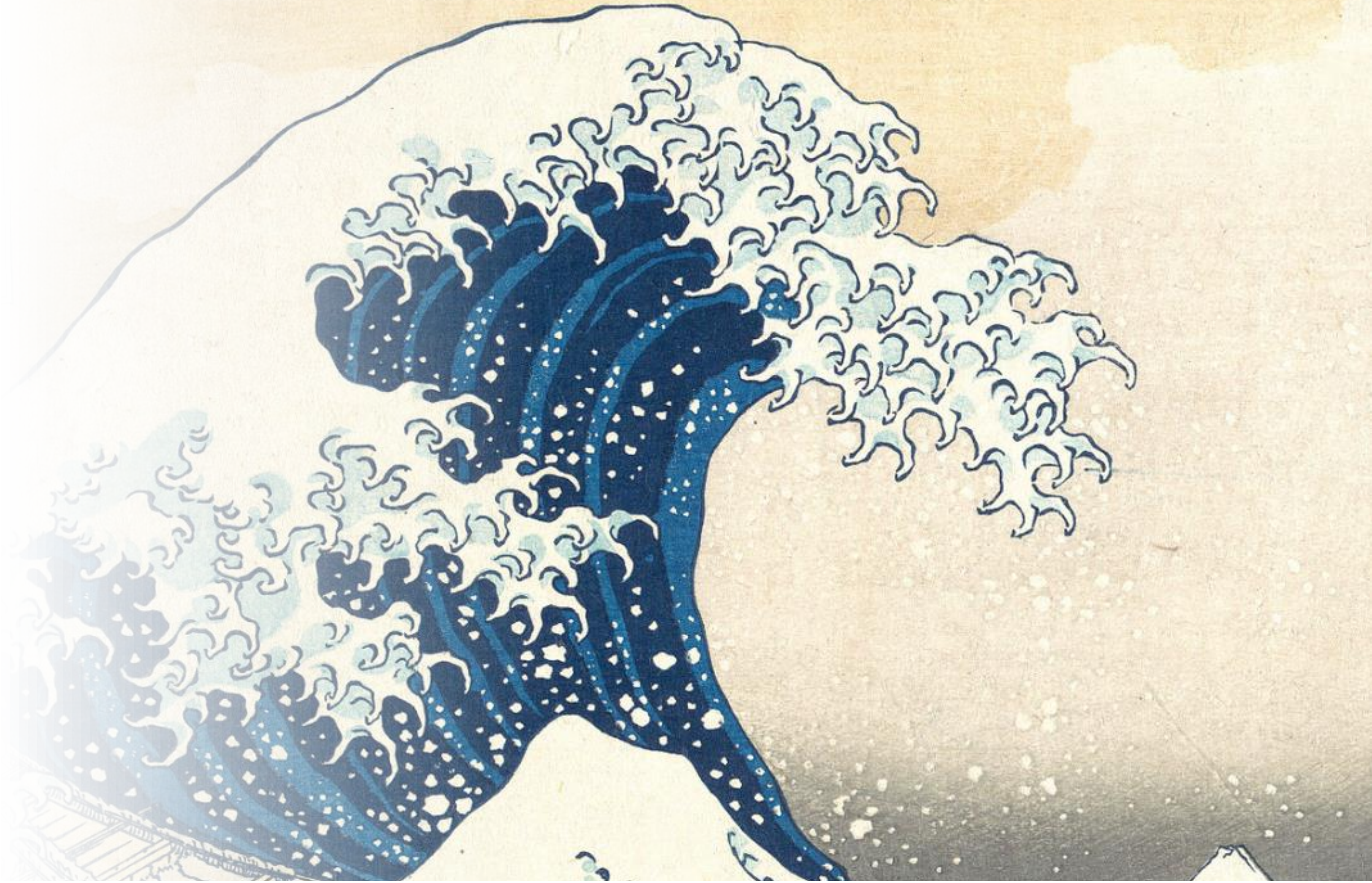
Interaction with other WPs



Thank you!



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