

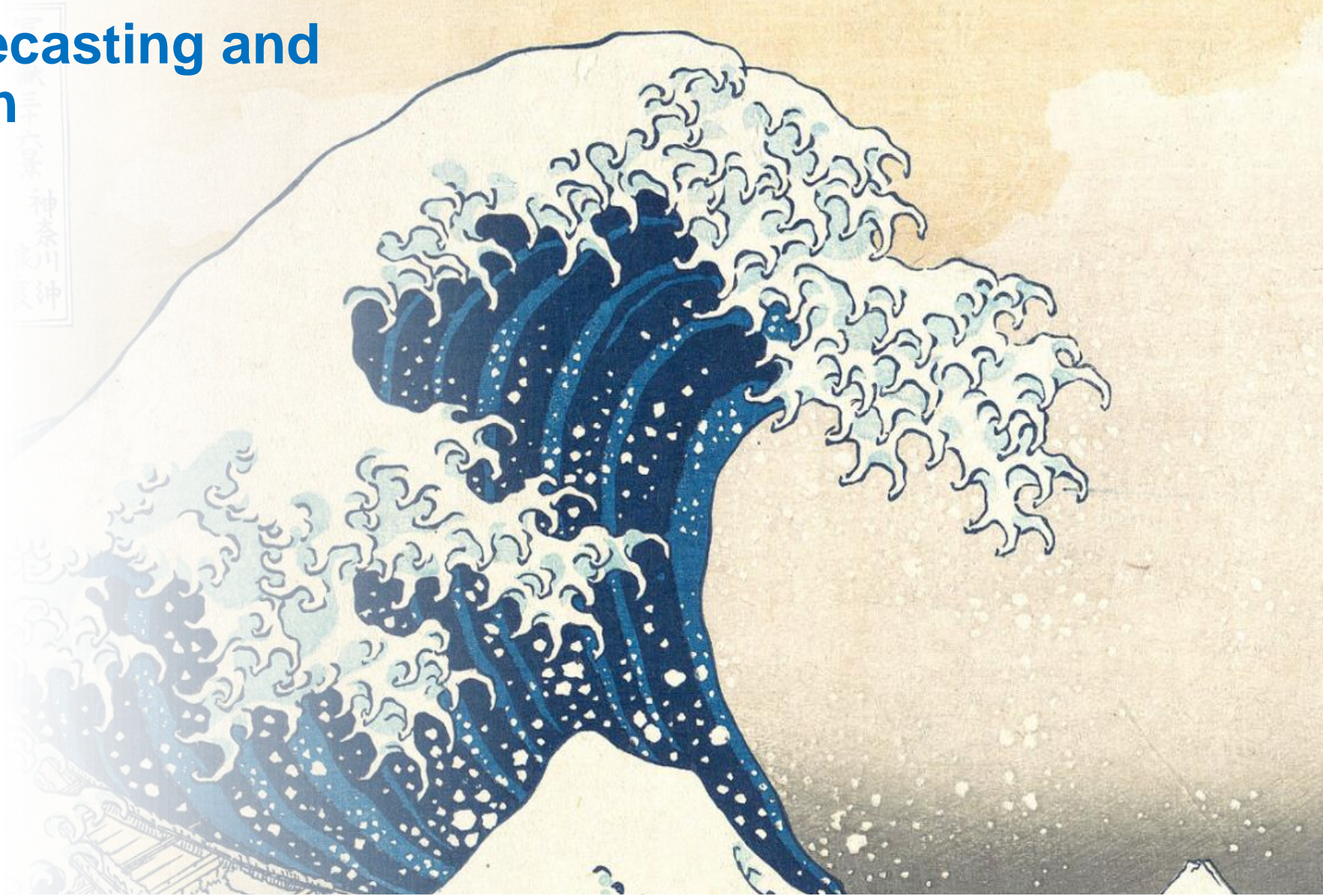
# WP3: Sea State Forecasting and Resource Evaluation

*3<sup>rd</sup> Advisory Board Meeting*

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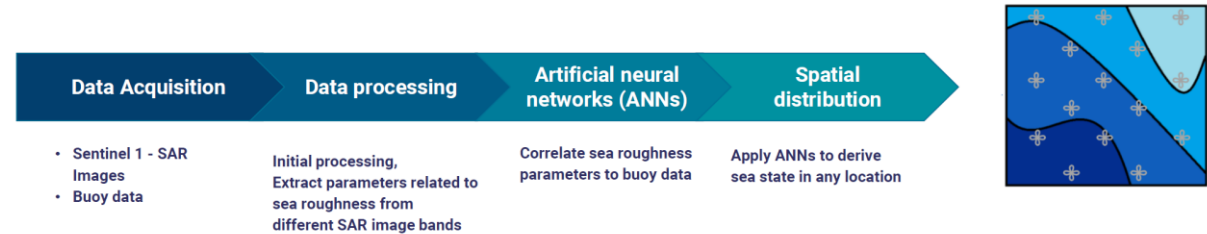
# WP3: Progress and current work

- Resource characterisation
  - SmartWave wave prediction (collaboration with Dr. Evdokia Tapoglou, *European Commission*) – a research article draft is to be submitted
  - Wave power resource evaluation in Atlantic Europe's NorthWest seas (collaboration with Dr. Charikleia Oikonomou, *Hellenic Centre for Marine Research*) – a conference paper is under preparation
  - Wave prediction via Machine Learning (collaboration with Prof. Carrie Hall, *Illinois Institute of Technology*) – the dataset is in preparation
  - Wave climate dynamics in Atlantic Europe's NorthWest seas (incl. Machine Learning) – design and theoretical part completed, numerical calculations are under preparation
  - SAR imaging of sea waves: Theoretical analysis of Sentinel 1 imagery – future work
- WEC efficiency calculations in wave tanks – a TEAMER funding application (*collaboration with National Renewable Energy Laboratory NREL*) – has been submitted
- Array effects – future work

# SmartWave – High accuracy & high spatial fidelity wave prediction

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

## ANN based system



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

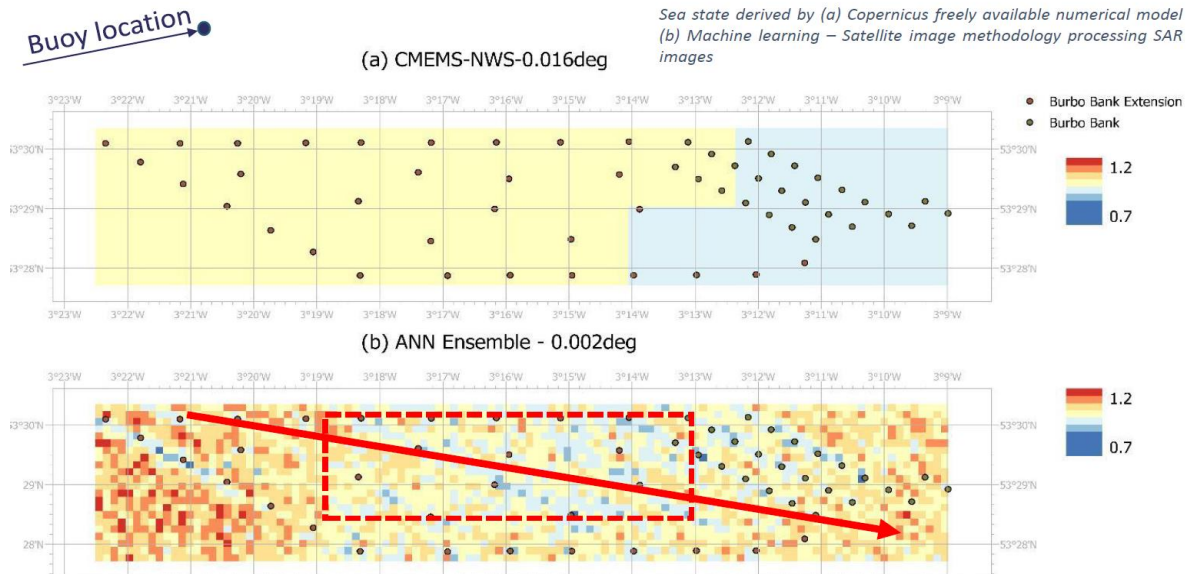
Buoy data: 0.89m (6:30am) – 1.07m (7:00am)

Numerical model at the buoy: 0.92m

ANN Ensemble: 0.95m

## Example results – Burbo Bank

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

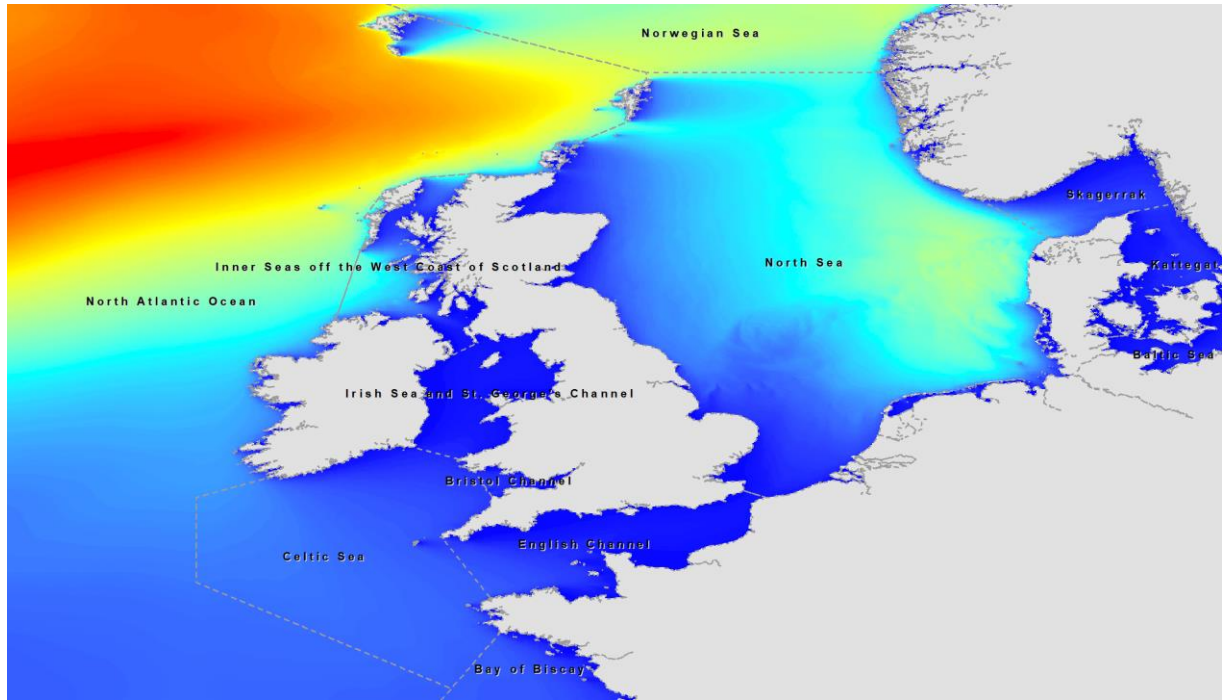


Tapoglou, E., Forster, R. M., Dorrell, R. M., & Parsons, D. (2021). Machine learning for satellite-based sea-state prediction in an offshore windfarm. Ocean Engineering, 235, 109280.

# Wave power resource evaluation in Atlantic Europe's NorthWest seas

## Mapping of shallow, intermediate, and deep-water areas

122,728 modeled wave measurements ranging from 1980 to 2021

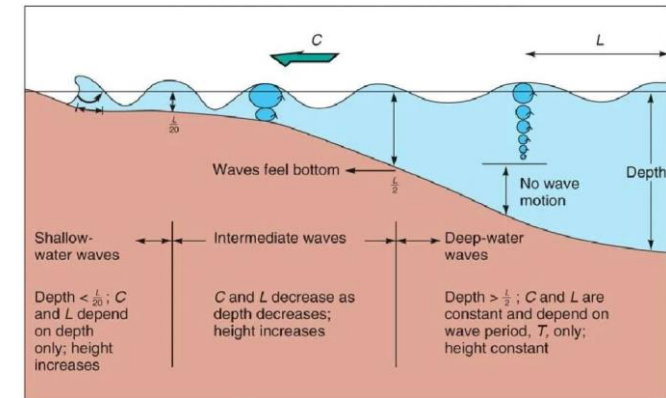


Daily mean wave power density (28.01.2022)

Bathymetry  
(EMODnet and GEBCO)

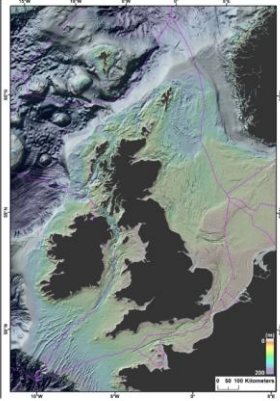
Atlantic- European NorthWest Shelf-  
Wave Physics Reanalysis  
NWSHELF\_REANALYSIS\_WAV\_004  
\_015 (Copernicus)

### Relationship between wavelength and water depth



# Wave climate dynamics in Atlantic Europe's NorthWest seas

Bathymetry offshore model of the UK (EMODnet and GEBCO)



Determination of uniform waves zones

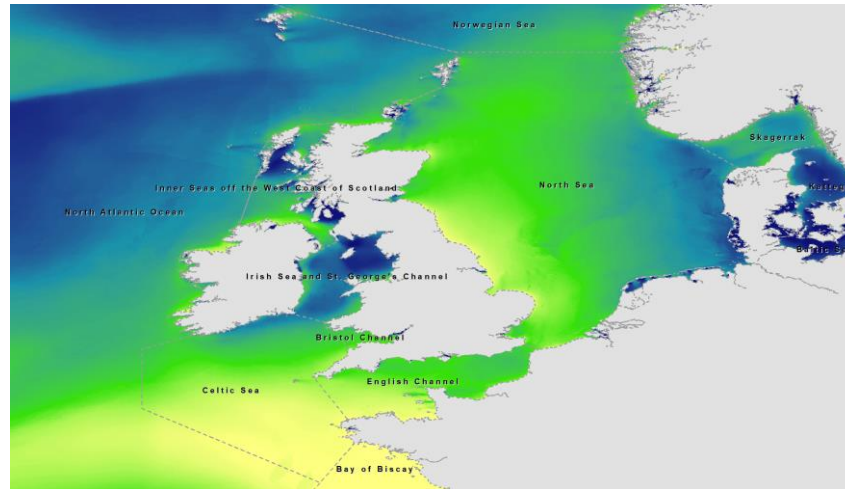


Dove, D., Bradwell, T., Carter, G., Cotterill, C., Gafeira Goncalves, J., Green, S., ... & Ottesen, D. (2016). Seabed geomorphology: a two-part classification system.

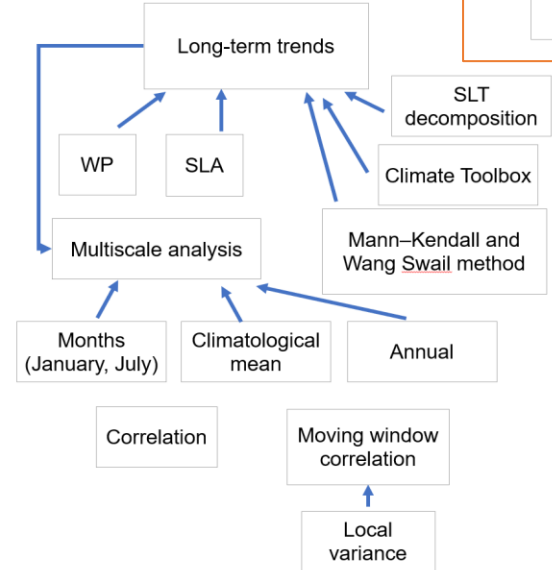
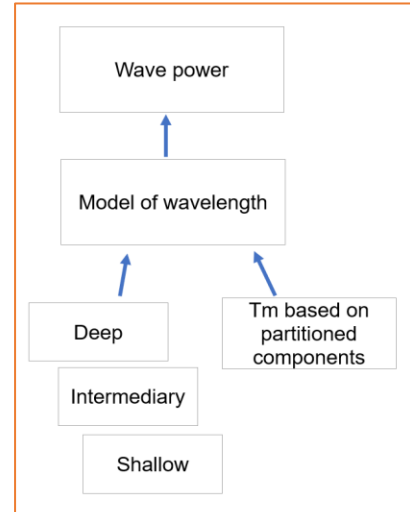
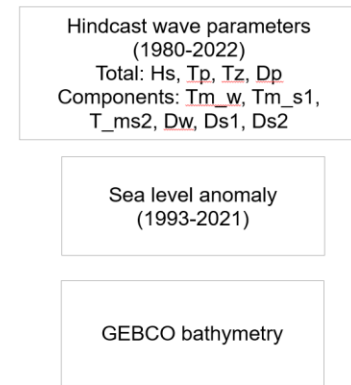
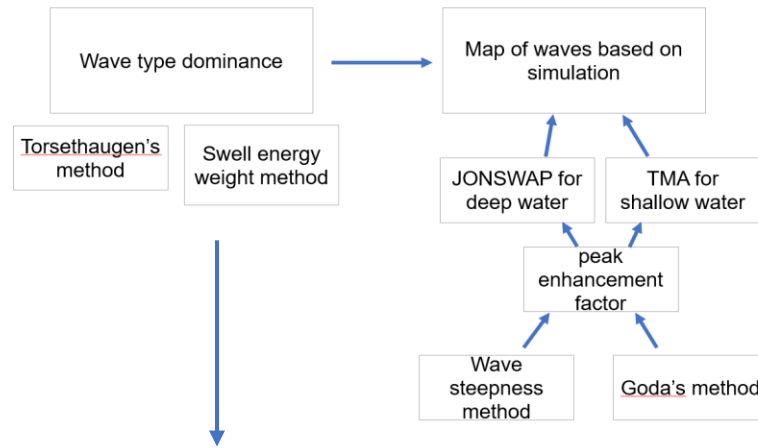
VARIABLES

- sea\_surface\_wave\_significant\_height (SWH)
- sea\_surface\_wave\_mean\_period\_from\_variance\_spectral\_density\_second\_frequency\_moment (MWT)
- sea\_surface\_wave\_period\_at\_variance\_spectral\_density\_maximum (MWT)
- sea\_surface\_wave\_mean\_period\_from\_variance\_spectral\_density\_inverse\_frequency\_moment (MWT)
- sea\_surface\_wave\_from\_direction (VMDR)
- sea\_surface\_wave\_from\_direction\_at\_variance\_spectral\_density\_maximum (VMDR)
- sea\_surface\_wave\_stokes\_drift\_x\_velocity (VSDXY)
- sea\_surface\_wave\_stokes\_drift\_y\_velocity (VSDXY)
- sea\_surface\_wind\_wave\_significant\_height (WW)
- sea\_surface\_wind\_wave\_from\_direction (WW)
- sea\_surface\_wind\_wave\_mean\_period (WW)
- sea\_surface\_primary\_swell\_wave\_significant\_height (SW1)
- sea\_surface\_primary\_swell\_wave\_mean\_period (SW1)
- sea\_surface\_primary\_swell\_wave\_from\_direction (SW1)
- sea\_surface\_secondary\_swell\_wave\_mean\_period (SW2)
- sea\_surface\_secondary\_swell\_wave\_from\_direction (SW2)
- sea\_surface\_secondary\_swell\_wave\_significant\_height (SW2)

TEMPORAL COVERAGE from 1980-01-01 to present  
 TEMPORAL RESOLUTION 3 hourly instantaneous  
 SPATIAL RESOLUTION 0.017° × 0.017°



Daily mean sea state dominance (28.01.2022)



# SAR imaging of sea waves: Theoretical analysis of Sentinel 1 imagery

SLC products are generated for all acquisition modes:

- StripMap SLC
- Interferometric Wide swath SLC
- Extra Wide swath SLC
- Wave SLC

### Stripmap SLC

Beam	S1	S2	S3	S4	S5	S6
Spatial Resolution rg x az m	1.7 x 4.9	2.0x4.9	2.5x4.9	3.3x4.9	3.3x3.9	3.6x4.9
Pixel spacing rg x az m	1.5x3.6	1.8x4.2	2.2x3.5	2.6x4.1	2.9x3.6	3.1x4.1
Incidence angle °	22.3	25.6	31.2	36.4	41.0	43.8

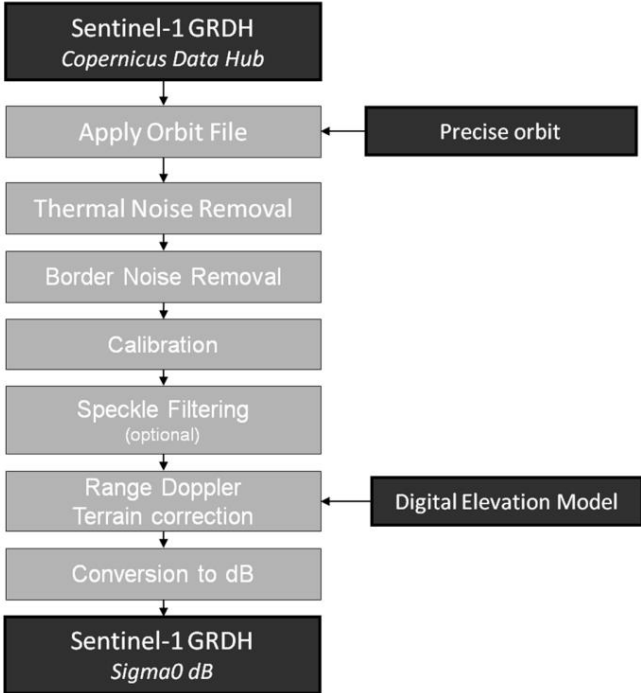
### Interferometric Wide Swath SLC

Beam ID	IW1	IW2	IW3
Spatial Resolution rg x az m	2.7x22.5	3.1x22.7	3.5x22.6
Pixel spacing rg x az m	2.3x14.1	2.3x14.1	2.3x14.1
Incidence angle °	32.9	38.3	43.1

### Wave SLC

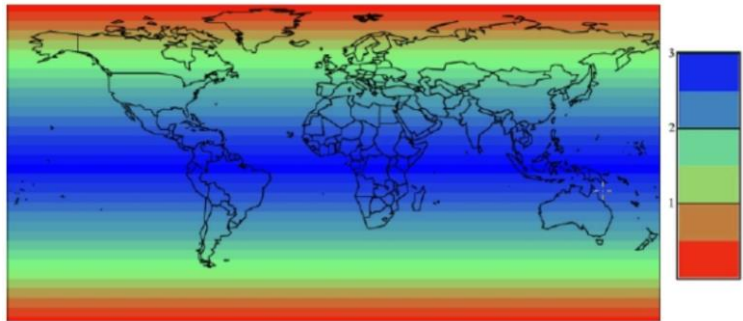
Beam ID	WV1	WV2
Spatial Resolution rg x az m	2.0x4.8	3.1x4.8
Pixel spacing rg x az m	1.8x4.1	2.7x4.1
Incidence angle °	23.4	36.4

Preprocessing



Using SAR images has benefits:

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



Revisit frequency ~ 2 days (IW mode)

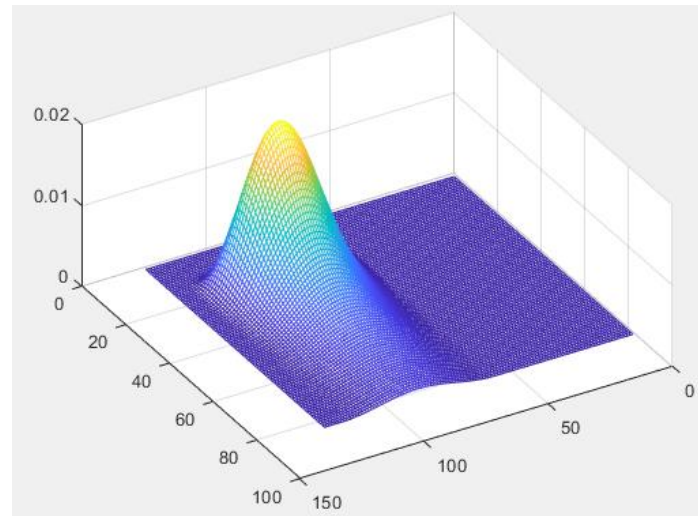
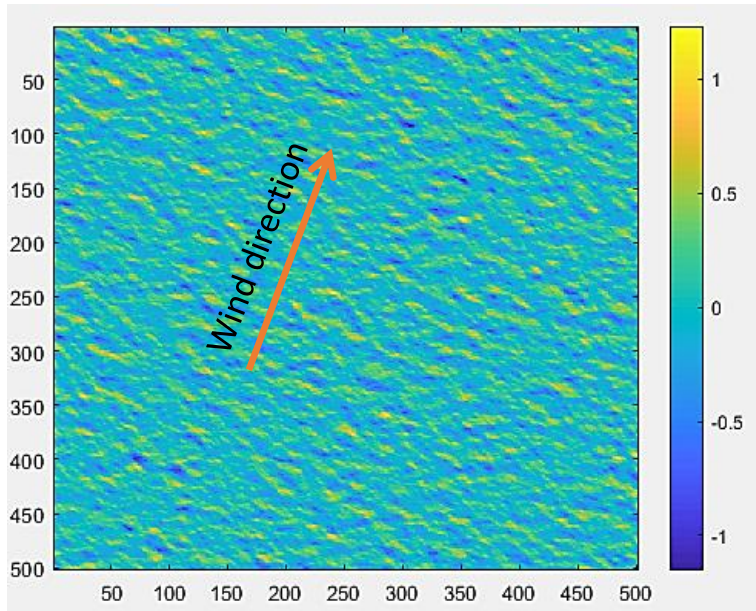
# Sea Surface Modelling - Linear theory

The irregular sea surface elevation model can be expressed as:

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

Wind speed  $V_w = 7$  m/s

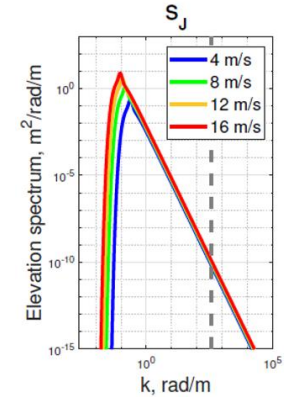
$$A_{ij} = \sqrt{2S(k_i)D(k_i, \theta_j)dk_i d\theta_j}$$



Omnidirectional spectrum

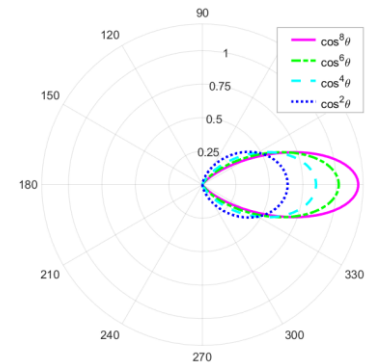
Joint North Sea Wave Project (JONSWAP)

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



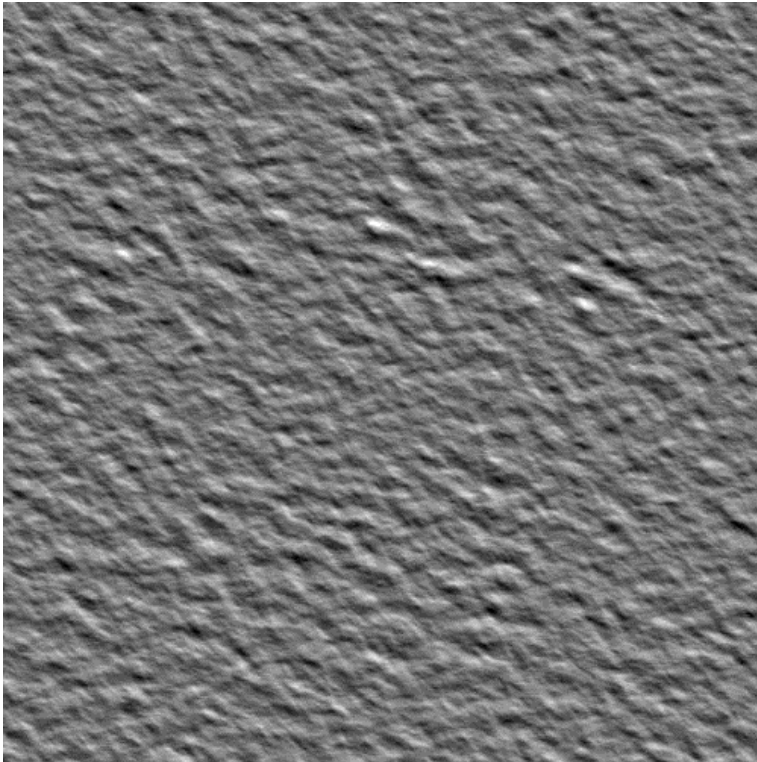
Directional spreading function

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

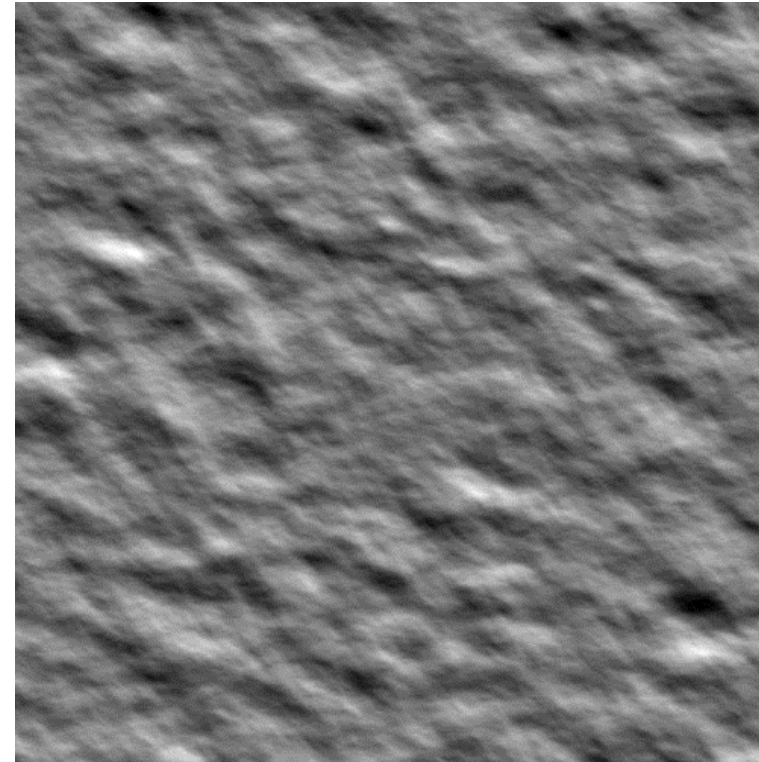


# Sea Surface Modelling – Time domain

$V_w = 7 \text{ m/s}$ ,  $F = 20 \text{ km}$



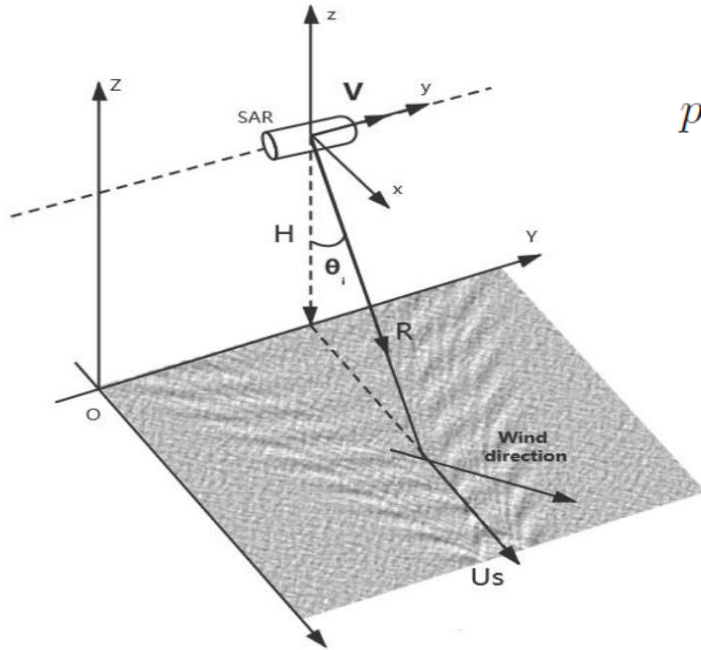
$V_w = 7 \text{ m/s}$ ,  $F = 105 \text{ km}$





# SAR image simulation – velocity bunching of gravity waves

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



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

$$p_a = \frac{\lambda R}{2VT_i}$$

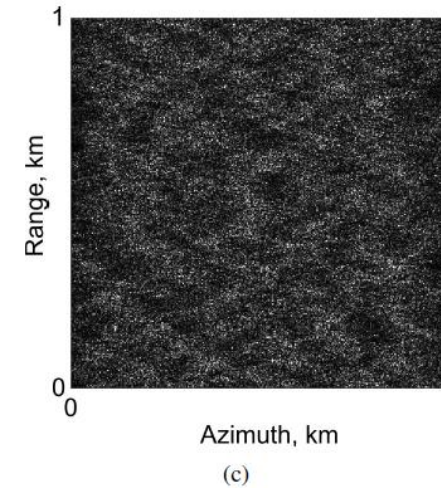
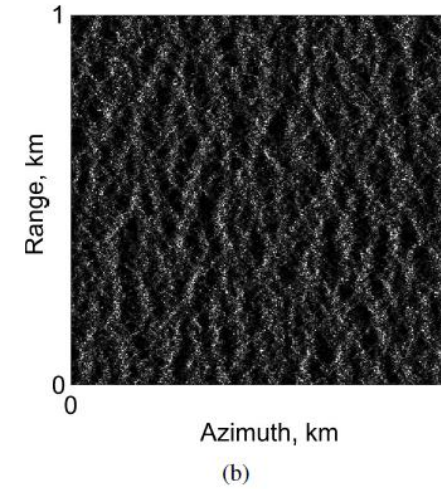
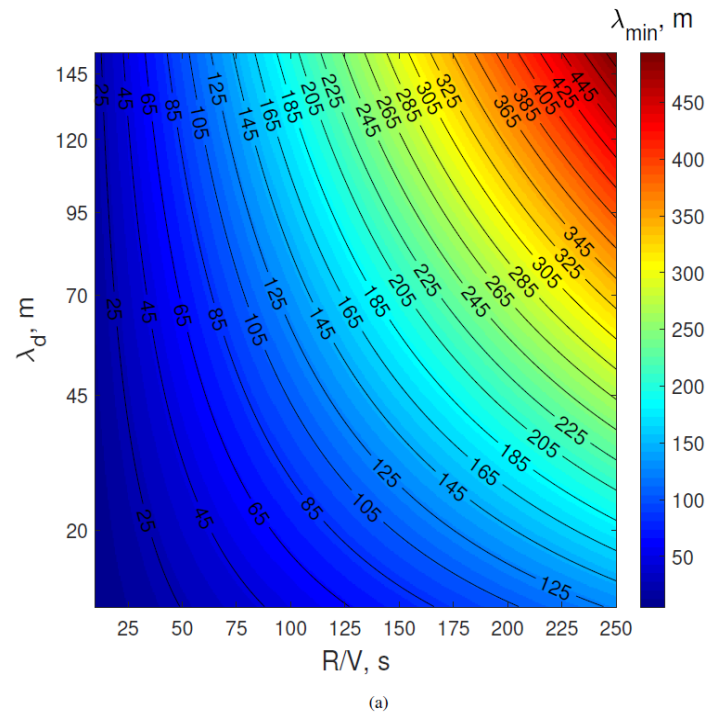
Single-look azimuthal resolution

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  $\lambda_{\min} = C_0 \frac{R}{V} \sqrt{H_s}$



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

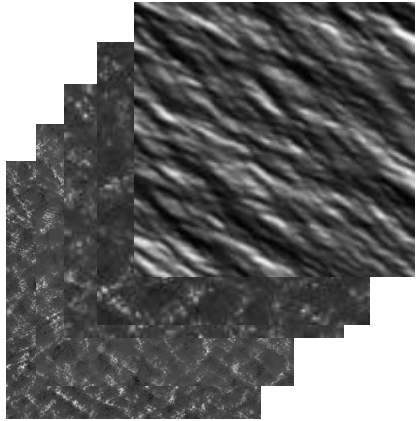
Rizaev, I. G., Karakuş, O., Hogan, S. J., & Achim, A. (2022). Modeling and SAR Imaging of the Sea Surface: a Review of the State-of-the-Art with Simulations. ISPRS Journal of Photogrammetry and Remote Sensing, 187, 120-140.

# CNN based system

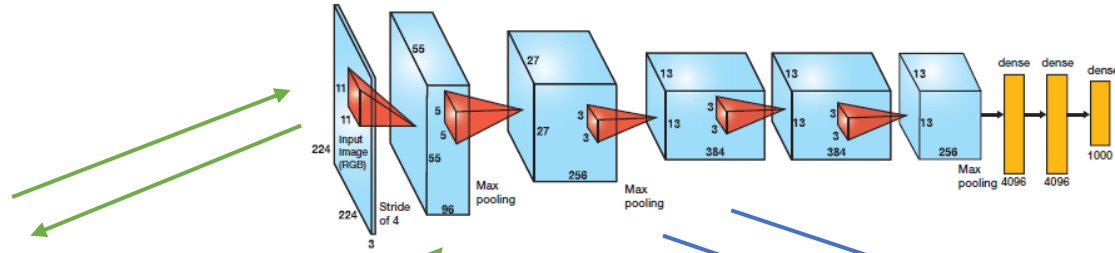
## Deep learning

### SAR imagery synthetic database creation

- Different parameters:
- wind directions
  - wind speeds
  - fetch size
  - incidence angles
  - polarizations



### Training CNN (AlexNet)

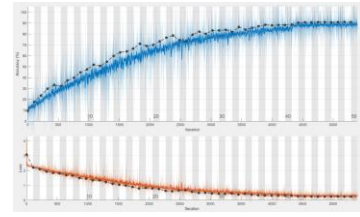


### Strategies:

- Training from scratch
- Transfer learning with real data

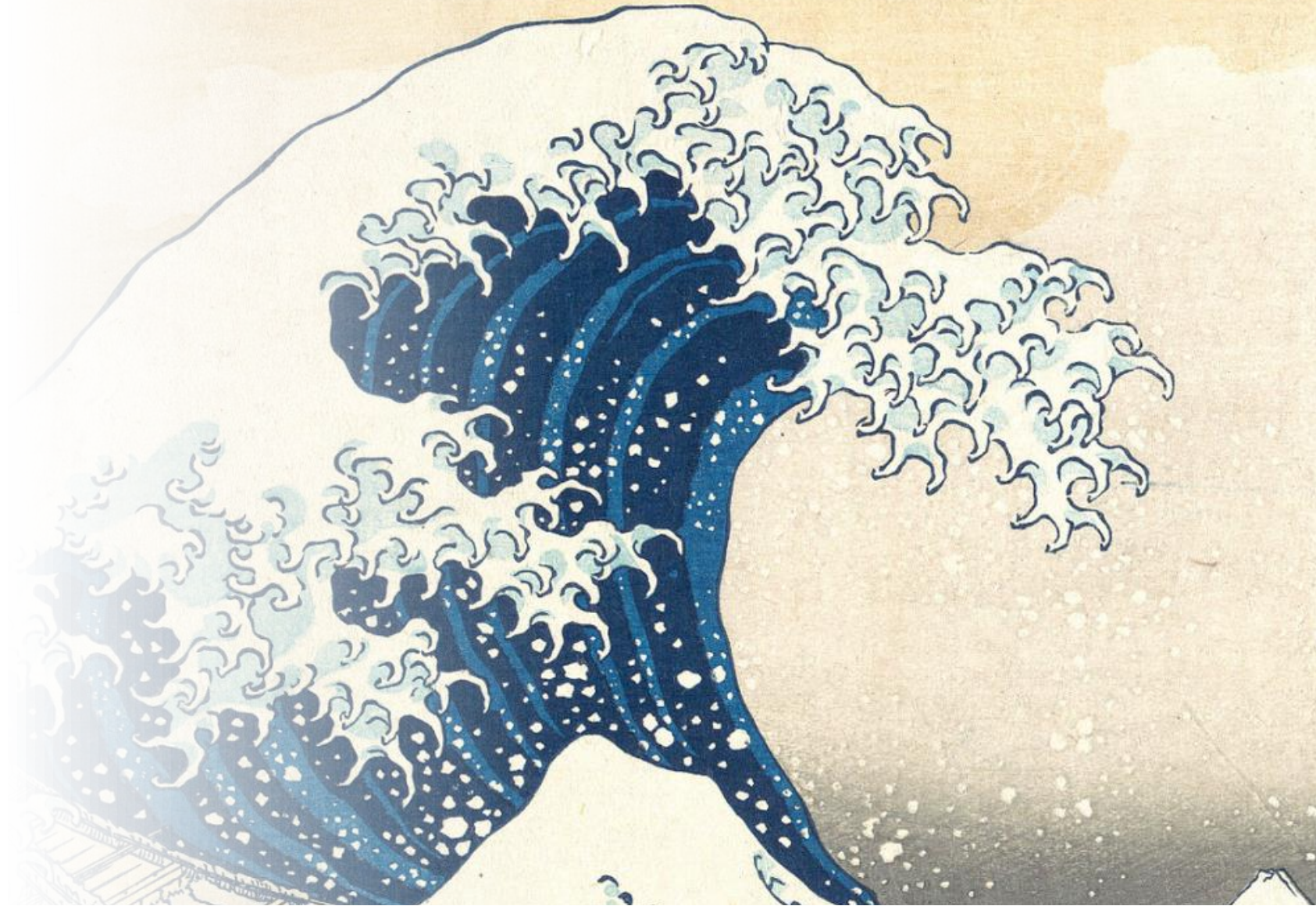
Automated classification and estimation of sea state parameters:  
 wave height  
 direction  
 frequency  
 speed

Iter	Eval	objective	objective	BestSoFar	BestSoFar	InitialLearn-	momentum	L2Regulariza-
	result		runTime	(observed)	(estim.)	rate		tion
1	Best	3	3385.3	1	1	0.024555	0.43595	5.0777e-08
2	Best	0.48836	3383.2	0.48836	0.48836	0.5450e-05	0.82426	5.0465e-08
3	Accept	0.45364	3384.1	0.48836	0.48836	0.006379	0.12174	2.051e-09
4	Accept	3	3074.6	0.48836	0.48836	0.009715	0.94202	0.0057099
5	Accept	0.49311	3384.9	0.48836	0.48836	1.0006e-05	0.54542	2.7273e-10
6	Accept	0.5596	3386.5	0.48836	0.48836	0.002163	0.53962	0.00095463
7	Accept	0.5797	3386.9	0.48836	0.48836	0.0039355	0.58886	1.1779e-10
8	Best	0.49592	3385.1	0.49592	0.49592	0.0021973	0.97805	0.0038464
9	Best	0.49782	3318.5	0.49782	0.49782	0.0044432	0.97996	1.0937e-10
10	Accept	0.48688	3387.5	0.49782	0.49782	0.0029138	0.97773	1.2902e-08
11	Accept	0.5082	3383.2	0.49782	0.49782	1.0130e-05	0.97907	1.1726e-10
12	Accept	0.461585	3384.7	0.49782	0.49782	0.0019007	0.97933	1.0402e-10
13	Accept	0.461774	3383.3	0.49782	0.49782	0.0022728	0.93341	0.0041e-08
14	Accept	0.49088	3381	0.49782	0.49782	0.0003718	0.9782	1.051e-09
15	Accept	0.49088	3384.4	0.49782	0.49782	0.004424	0.9331	2.7624e-07
16	Accept	0.49595	3381	0.49595	0.49595	0.0021441	0.9858	0.0009
17	Accept	0.48537	3382	0.49595	0.49595	0.0049715	0.95295	1.741e-08
18	Accept	0.49128	3380.4	0.49595	0.49595	0.0013433	0.98702	0.0047009
19	Accept	0.49522	3382.4	0.49595	0.49595	0.0020648	0.97814	1.1716e-10
20	Accept	0.49879	3382.9	0.49595	0.49595	0.0027015	0.96489	0.003482
21	Accept	0.47827	3381.6	0.49595	0.49595	0.0030347	0.62307	0.0072111
22	Accept	0.48282	3382.3	0.49595	0.49595	0.0038528	0.97863	0.0093585
23	Accept	0.48569	3385.2	0.49595	0.49595	0.0021591	0.74856	0.0010573
24	Accept	0.49374	3385.5	0.49595	0.49595	0.0032081	0.18648	3.5450e-07
25	Accept	3	3074.4	0.49595	0.49595	0.49079	0.10731	9.3844e-05
26	Accept	0.48256	3387.1	0.49595	0.49595	0.0037028	0.97489	5.3037e-08
27	Accept	0.48752	3382	0.49595	0.49595	0.0041442	0.48467	0.00048835
28	Accept	0.49531	384	0.49595	0.49595	0.40548	0.9717	0.0001895
29	Accept	0.4366	3387.5	0.49595	0.49595	0.0027018	0.2792	0.0027018
30	Accept	0.48126	3382	0.49595	0.49595	0.0049304	0.65601	0.0022381



Bayesian optimization to find optimal network hyperparameters

# Thank you!



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