

# **Deterministic short-term wave prediction for directional sea-states in real-time using Artificial Neural Network**

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# Introduction

- Deterministic short-term wave prediction is required to enhance operational efficiency, such as
  - Installation and decommissioning of marine and offshore structures
  - Active control of wave energy converters
  - Route planning for autonomous or remotely-operated vessels
- Real-time prediction is challenging, because
  - Linear model is limited to low steepness
  - Nonlinear model is limited by computational cost



Source: Golden Energy Offshore

# Objective

- Provide an approach for real-time deterministic short-term wave prediction
  - Given : Far-field waves captured by a radar on a ship
  - Predict : Near-field waves around the ship
- Establish the baseline performance
  - Linear Wave Theory (LWT) – real-time physics-based model
  - Artificial Neural Network (ANN) – real-time data-driven model

# Linear Wave Theory (LWT)

- Assume each component propagates independently
- Express the wave field as

$$\eta(\vec{x}, t) = \text{Re} \left[ \sum_{n=0}^{N-1} A_n \exp(i\vec{k}_n \cdot \vec{x} - i\omega_n t + \phi_n) \right]$$

- All parameters are computed based on measurement
- Linear dispersion relation is assumed

# Artificial Neural Network (ANN)

- A universal function  $F$  that maps input to output
  - Input: Measured surface elevation
  - Output: Reconstructed wave field
- A set of weights to be tuned using training data

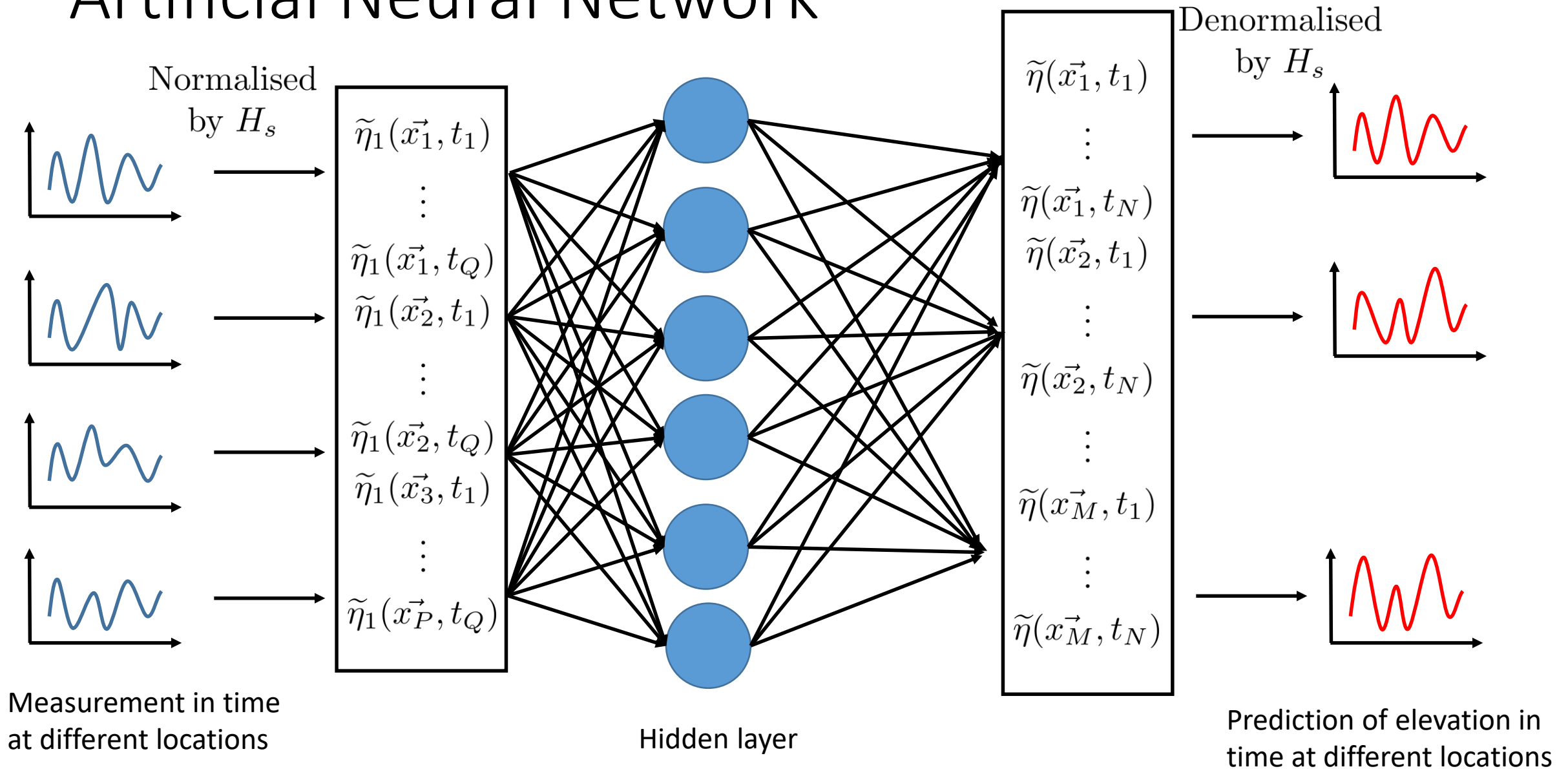
$$\{\eta(\vec{x}_i, t_j)\}_{i=m_1, m_2, \dots, m_M; j=n_1, n_2, \dots, n_N} = F(\{\eta_1(\vec{x}_i, t_j)\}_{i=p_1, p_2, \dots, p_P; j=q_1, q_2, \dots, q_Q}, \vec{w})$$

Reconstructed wave field at different locations at given t

Measured surface elevation at different locations for a given interval

Weight to be trained using training data

# Artificial Neural Network



# Prediction error

- Normalised error

$$\epsilon_n(\vec{x}, t) = \frac{|\eta_n^R(\vec{x}, t) - \eta_n(\vec{x}, t)|}{H_{s,n}/2}$$

Reference elevation  $\rightarrow$   $\eta_n^R(\vec{x}, t)$  Predicted elevation  $\rightarrow$   $\eta_n(\vec{x}, t)$

$\leftarrow$   $H_{s,n}/2$   $\leftarrow$   $H_s$  estimated based on input

- Root-mean-square (RMS) of Normalised error

$$\mathcal{E}(\vec{x}, t) = \sqrt{\frac{1}{N_s} \sum_{n=1}^{N_s} [\epsilon_n(\vec{x}, t)]^2}$$

Number of samples  
= 500 realisations

# Application on

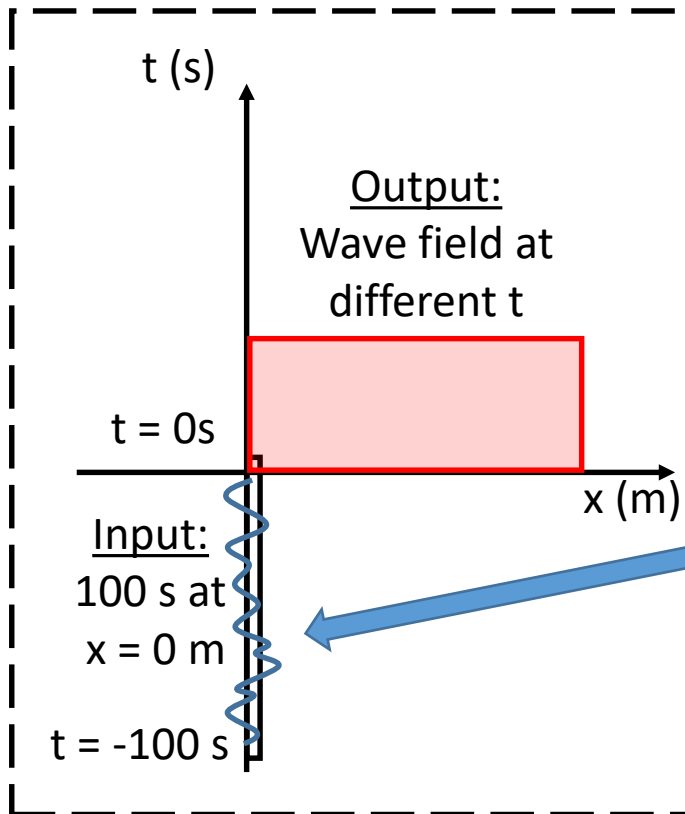
- Unidirectional Waves
- Directional Waves

## Numerical database

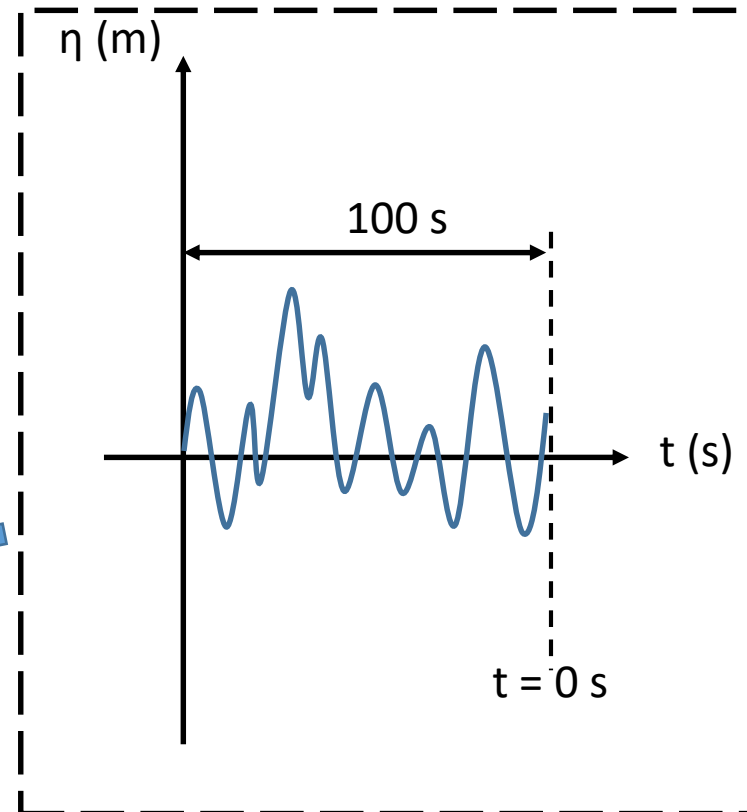
- by HOS-ocean with Jonswap spectrum assumed
- $\gamma = 3.3$
- $H_s/T_p^2 = 0.06$ , with  $T_p$  ranges from 7 s – 20 s
- Spreading =  $-45^\circ$  to  $45^\circ$  for directional wave



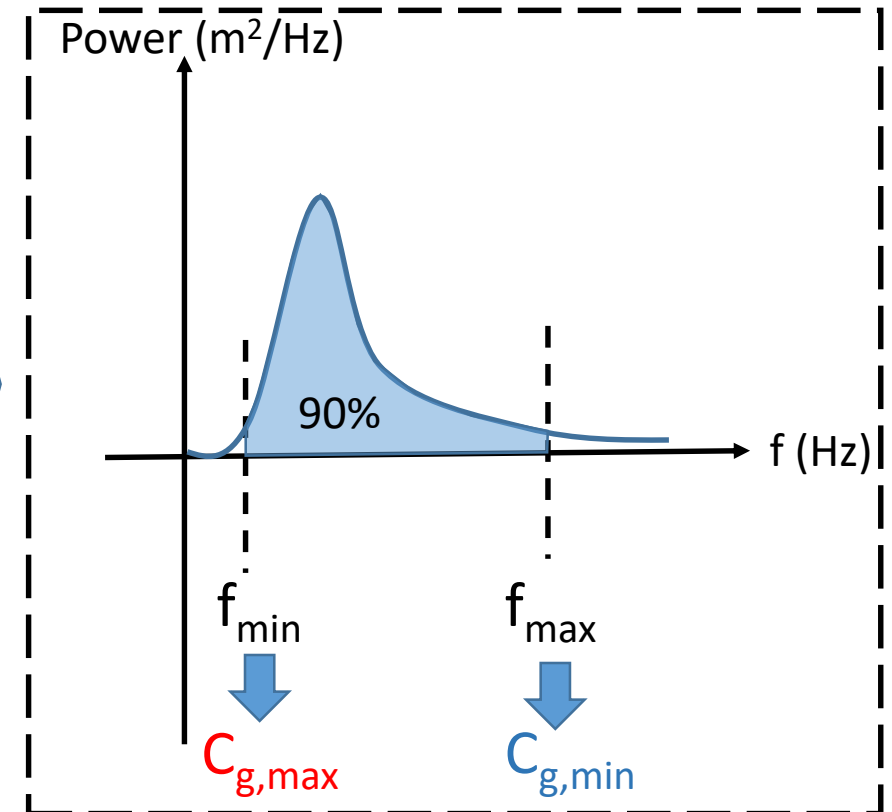
# Unidirectional Waves



Space-time  
representation

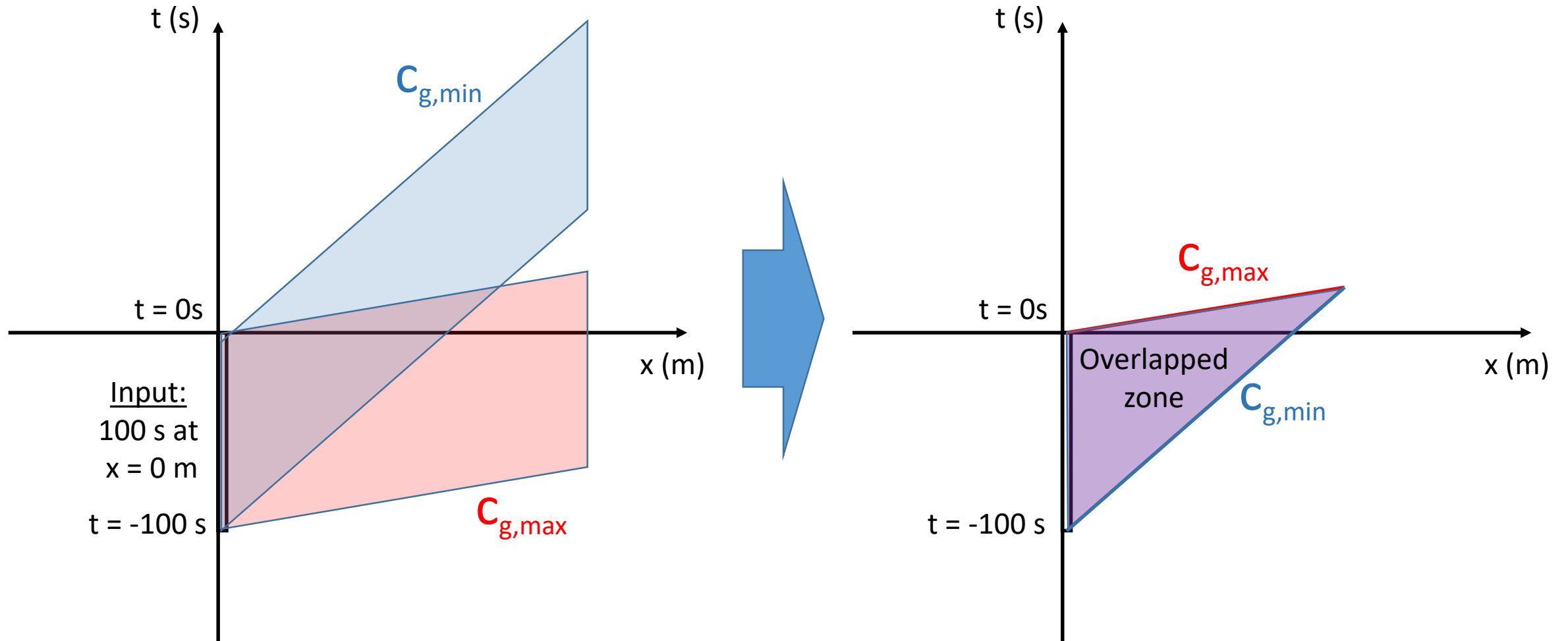


Upstream  
measurement

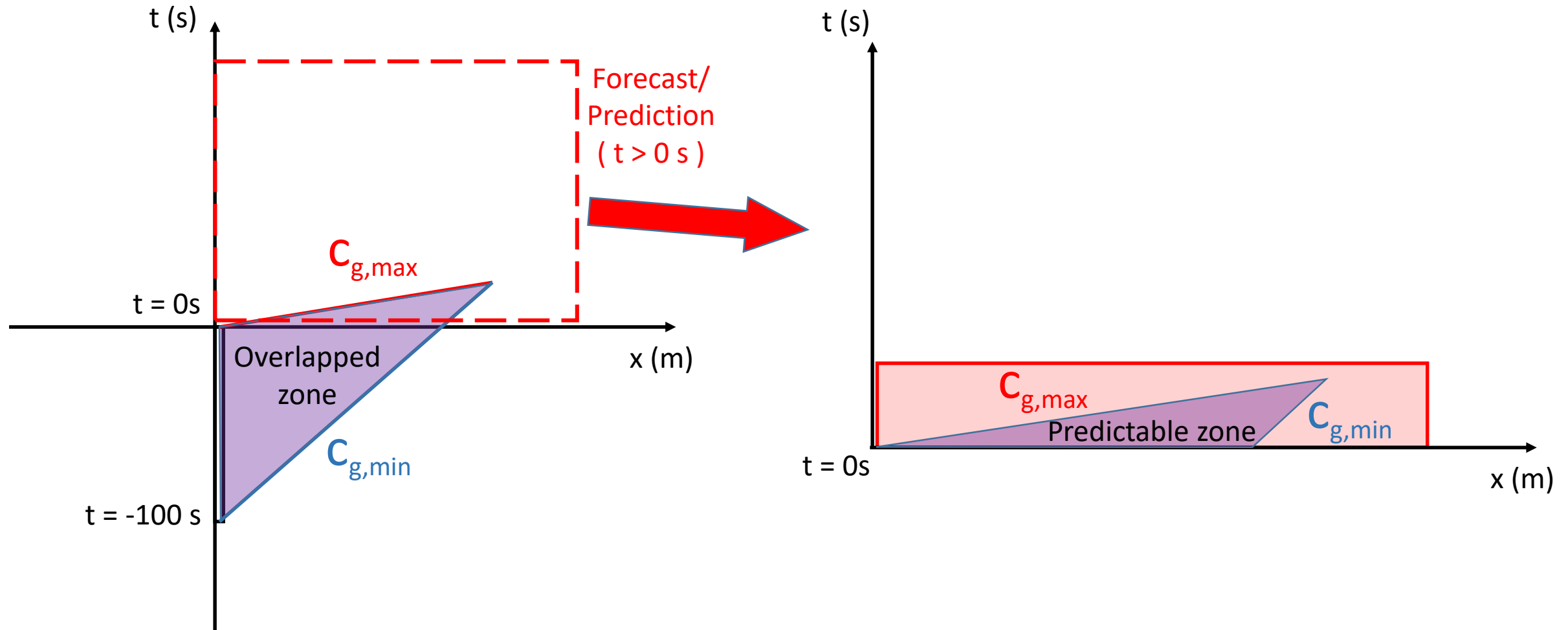


Power Spectrum

# Unidirectional Waves

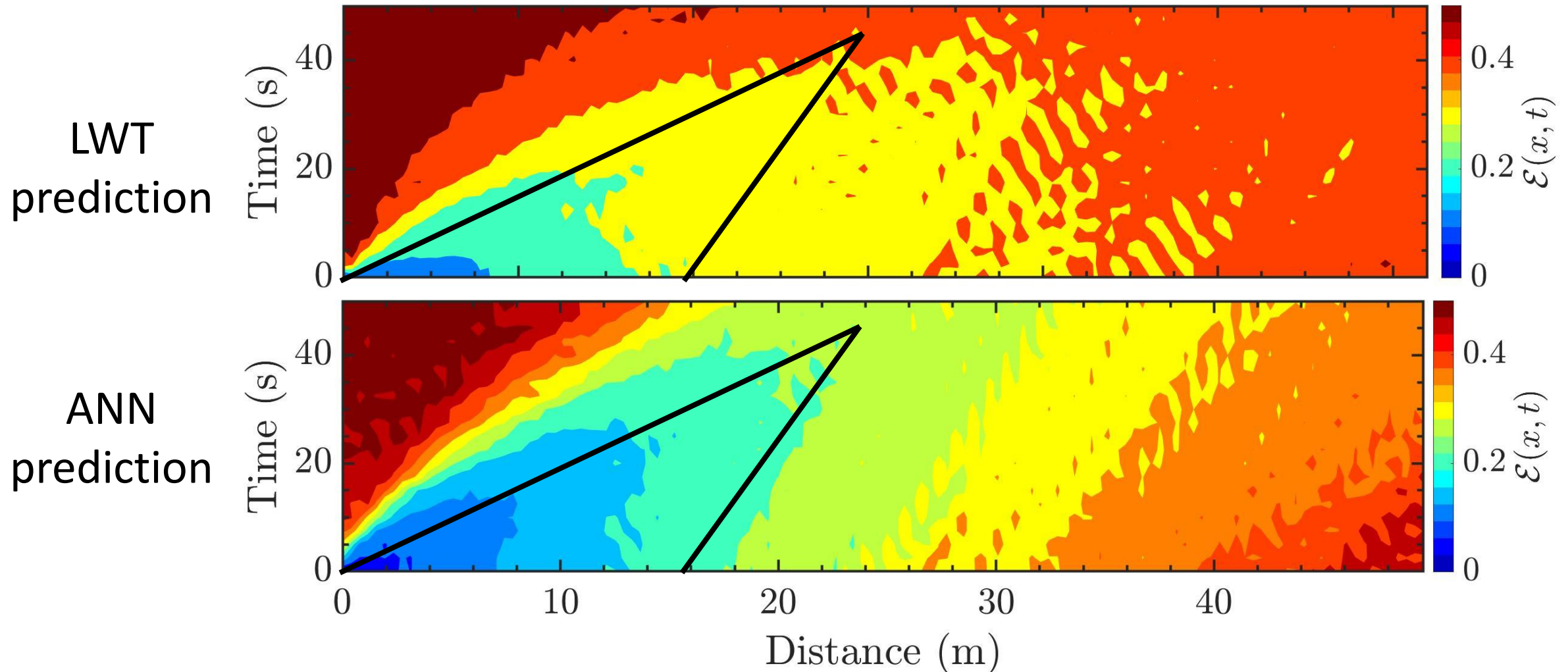


# Unidirectional Waves



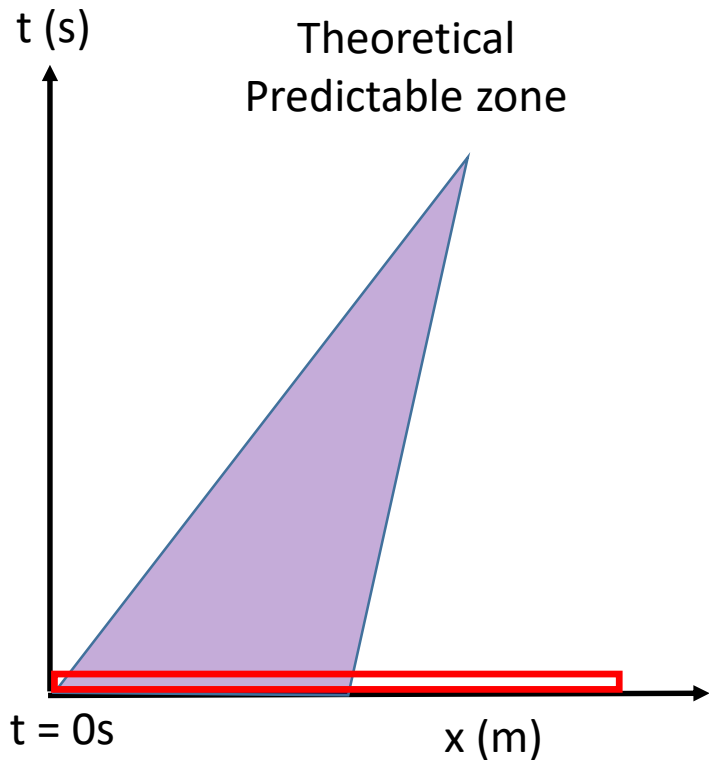
# Unidirectional Waves

## - RMS Normalised Error

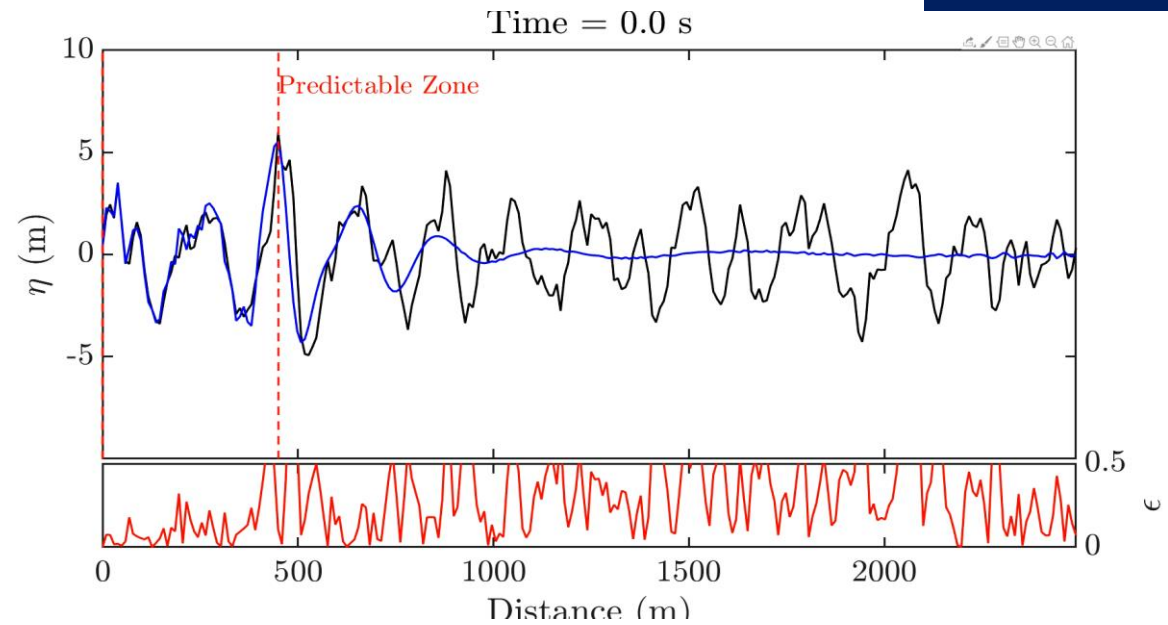




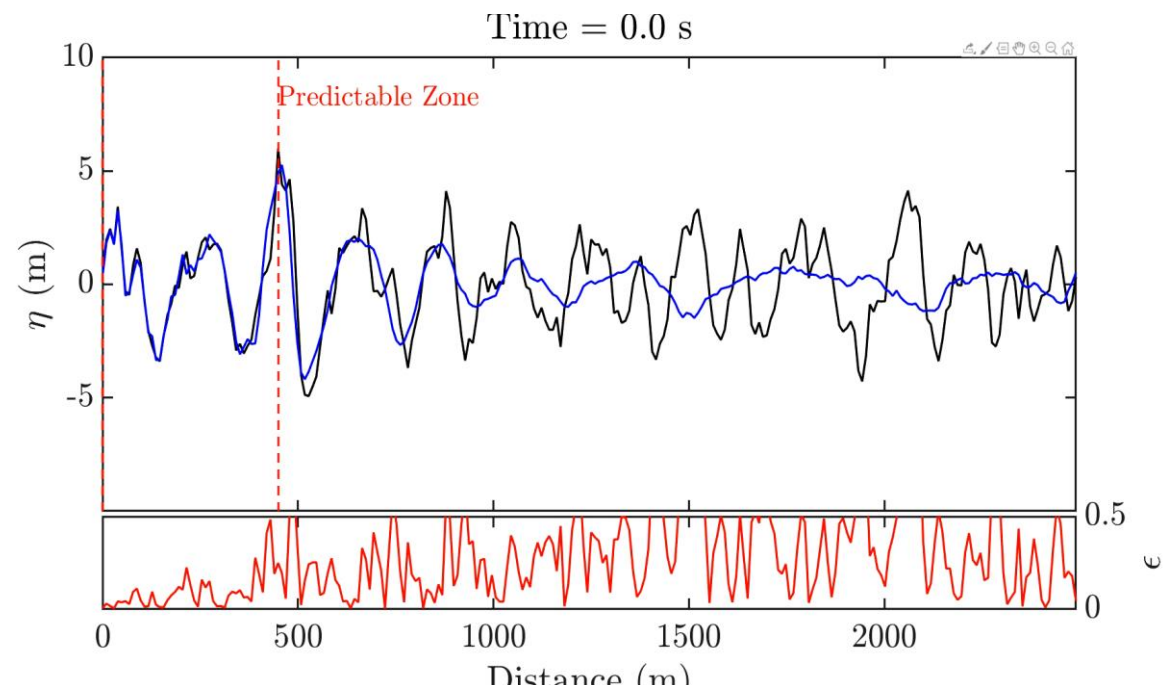
# Unidirectional Waves



LWT prediction



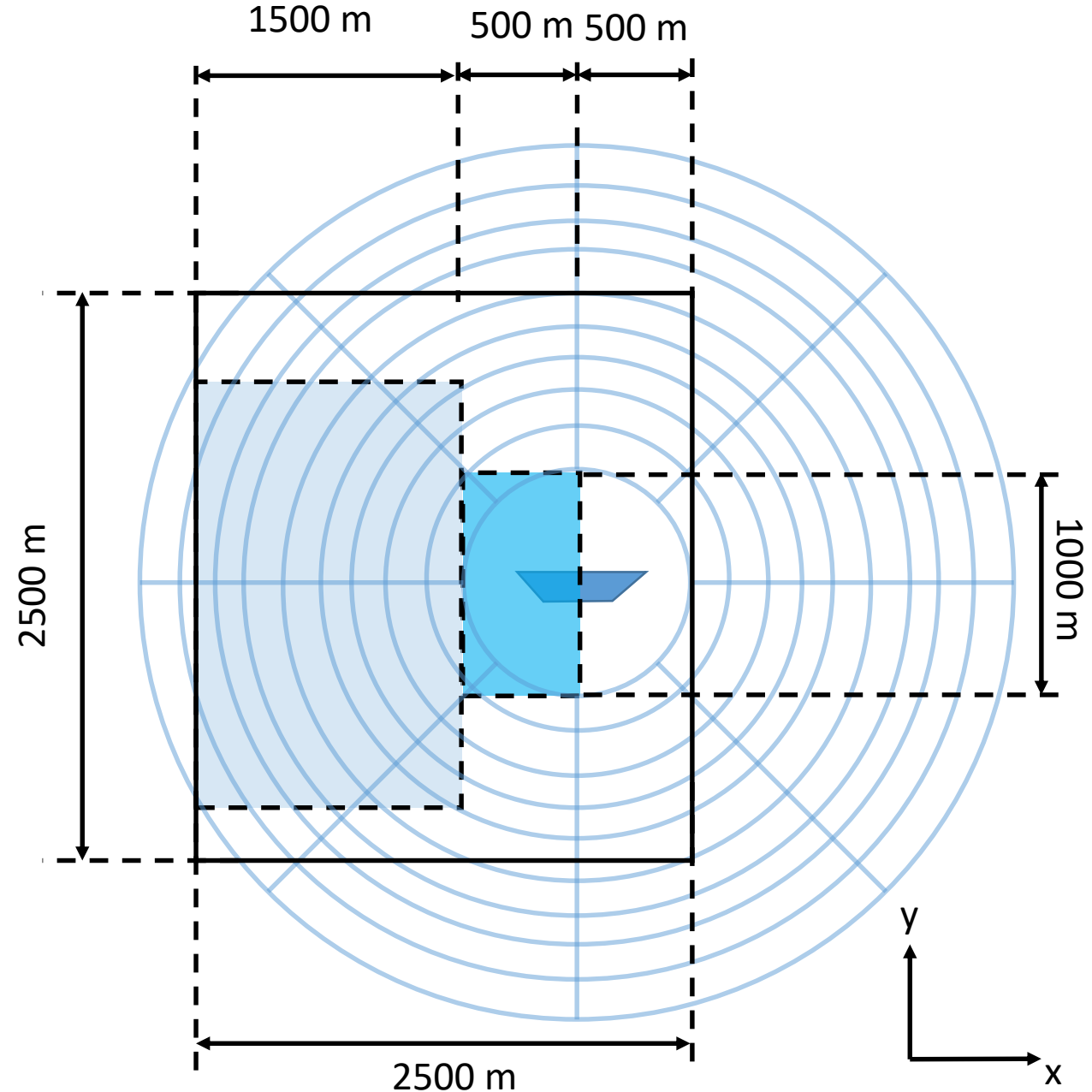
ANN prediction



Prediction of LWT and ANN for a realisation

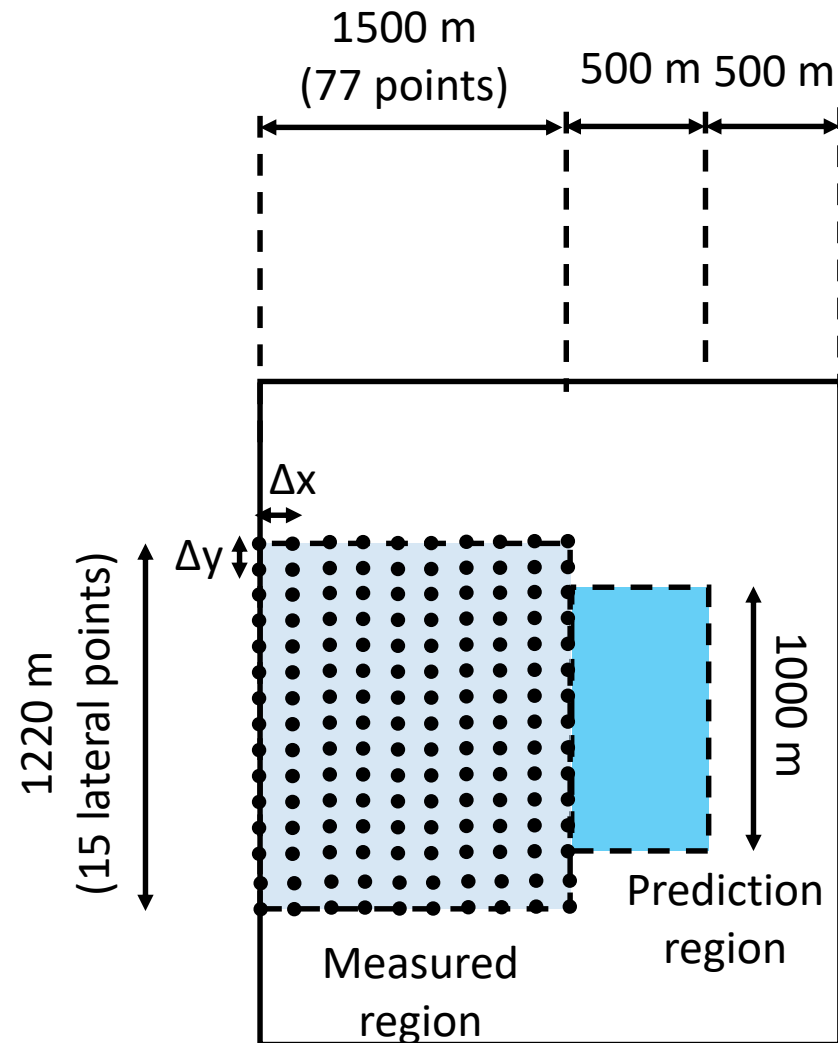
# Directional Waves

- Assuming a radar is installed on a ship
  - Covering 0.5km – 2km
  - Angular resolution of  $2.5^\circ$   
( $\Delta y = 88$  m at 2km distance)
  - Radial resolution of  $\sim 20$ m  
( $\Delta x = 20$  m)
  - Sampling rate of 24 RPM  
( $\Delta t = 2.5$  s)
- To predict wave field in front of the ship

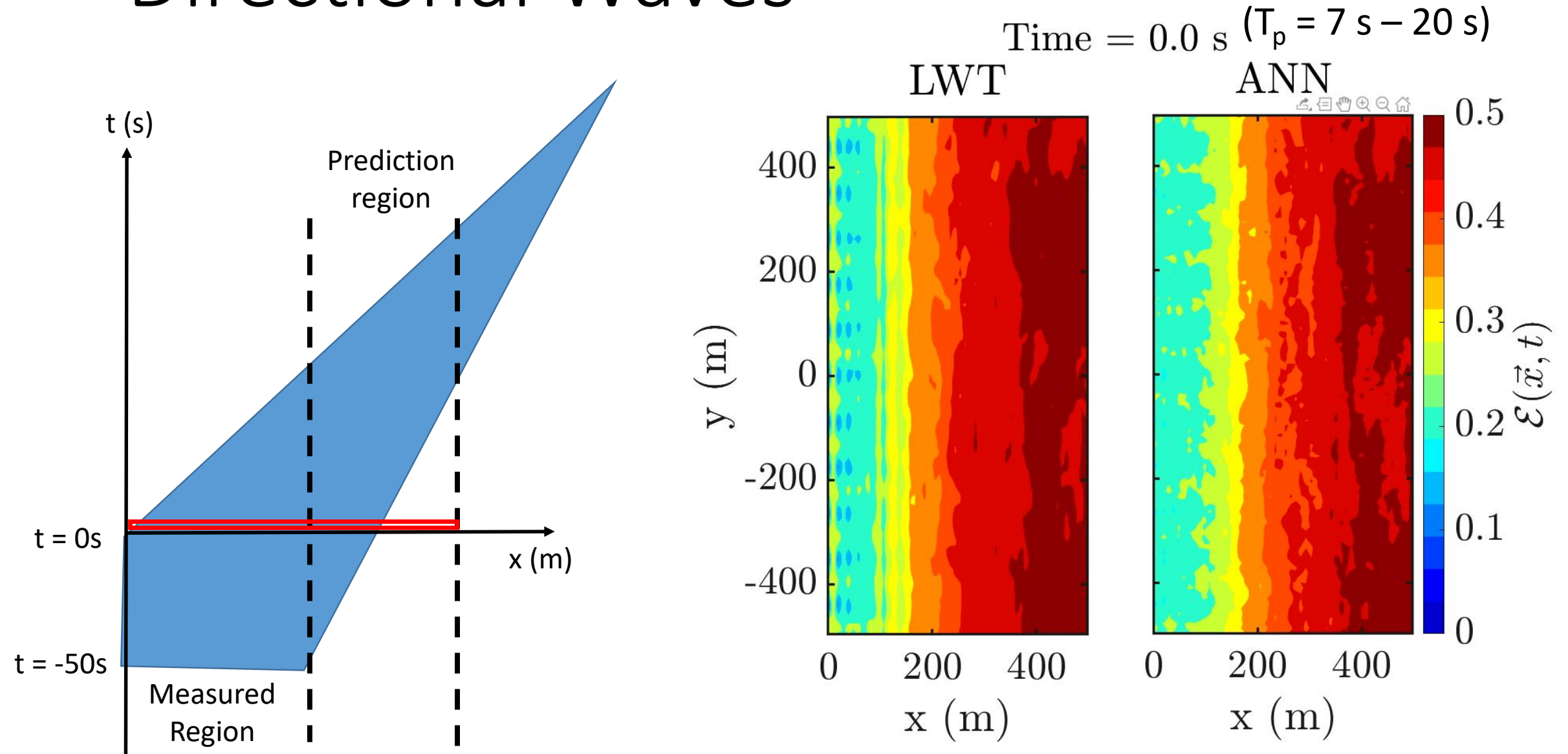


# Directional Waves

- Simplify to rectangular domain
- Input
  - 15 x 77 grid points
  - Elevation measured from  $t = -25$  s to 0 s
- Output
  - Wave field predicted from  $t = 0$  s to 120 s

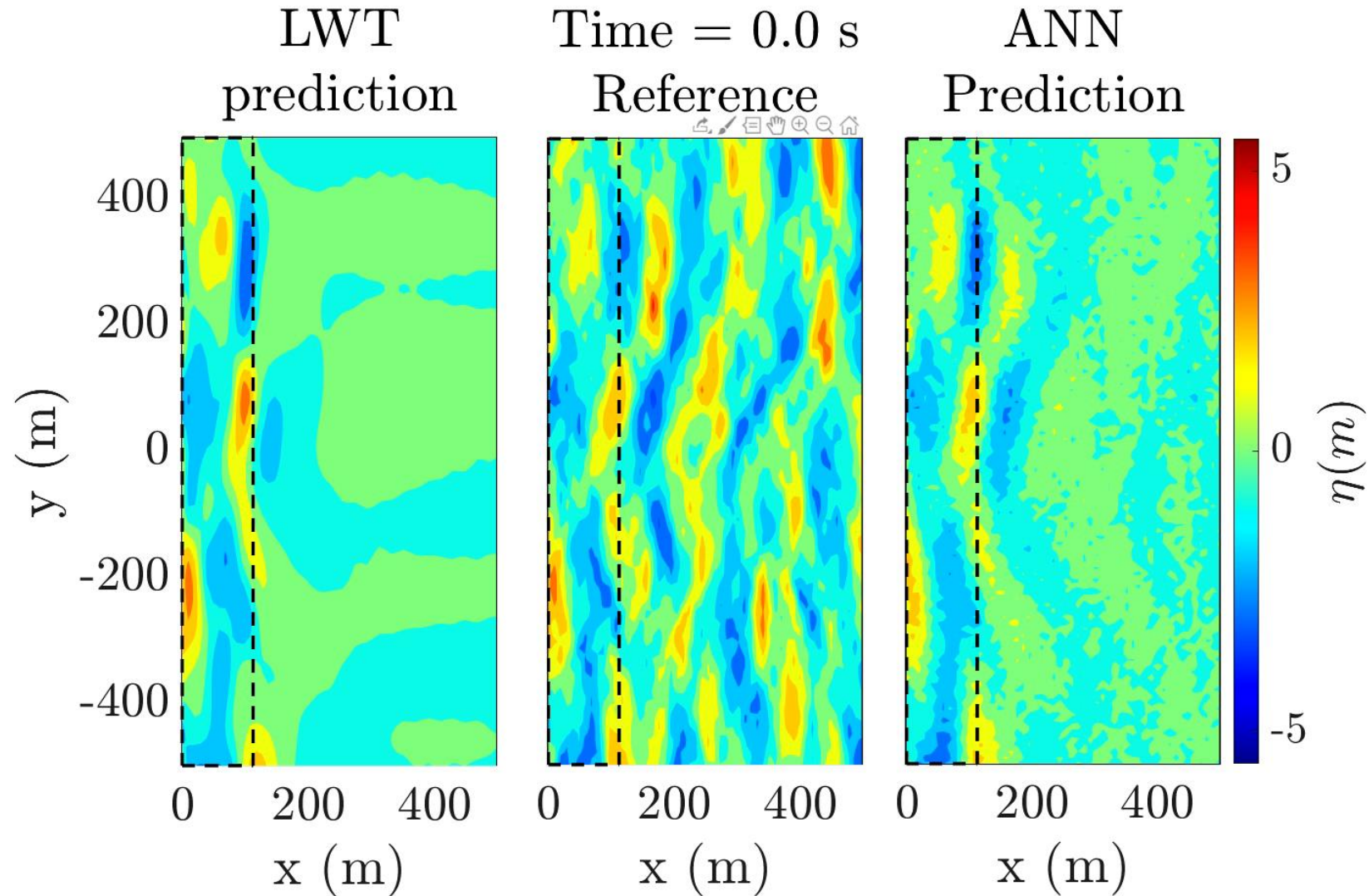


# Directional Waves





# Directional Waves



# Summary

- A data-driven approach of real-time deterministic short term wave prediction is established
  - Based on numerical data generated using HOS-ocean
  - Data-driven model using ANN
  - Better performance compared to LWT
- Limitation of current ANN model
  - Network size become very large for larger coverage
  - Accuracy within predictable zone still need to be improved
- Extension to current ANN model
  - Explore different ANN configuration (convolutional, recurrent)
  - Include physics in ANN model to improve accuracy



Thank You

TCOMS

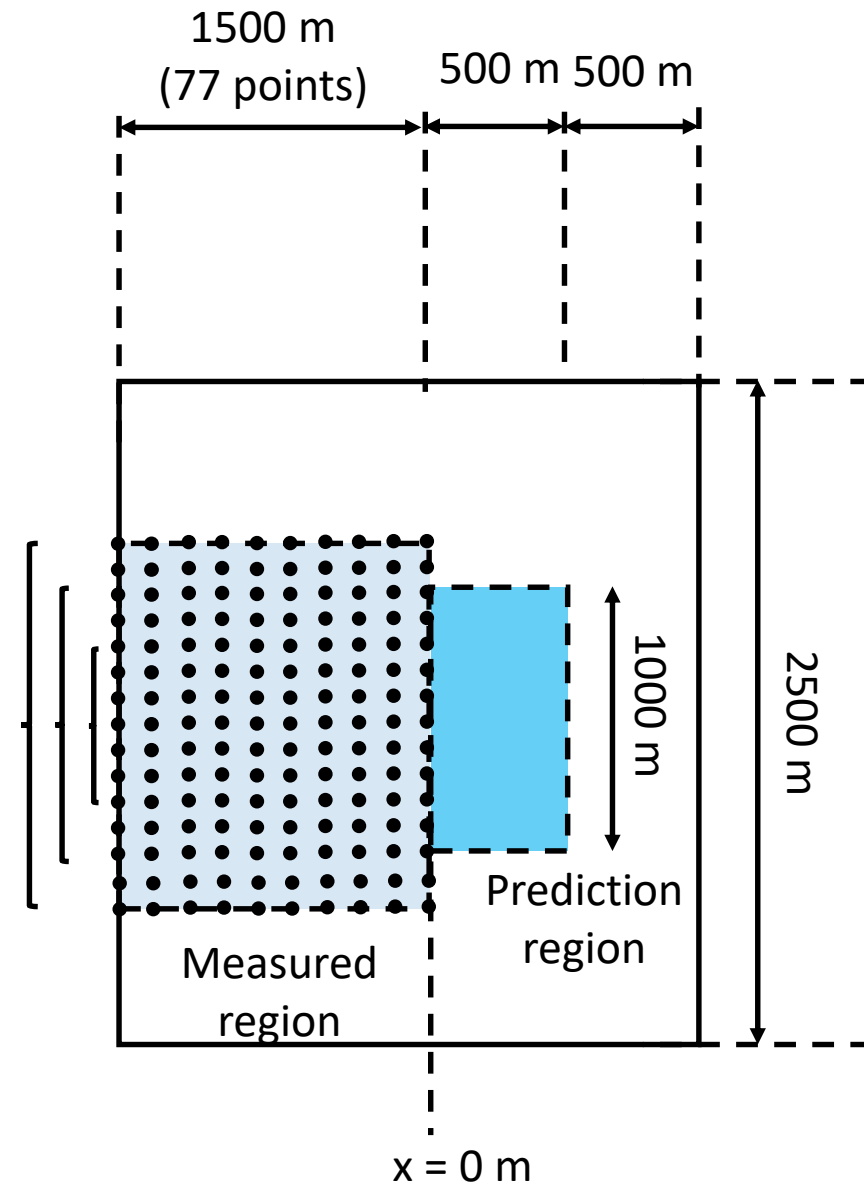
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12 PRINCE GEORGE'S PARK, SINGAPORE 118411



# Directional Waves

- First step is to determine width of the measured region required
- Input:
  - Varying width of measured region
  - Elevation measured from  $t = -25$  s to  $0$  s
- Output:
  - Wave field predicted at  $t = 60$  s

Varying width of measured region

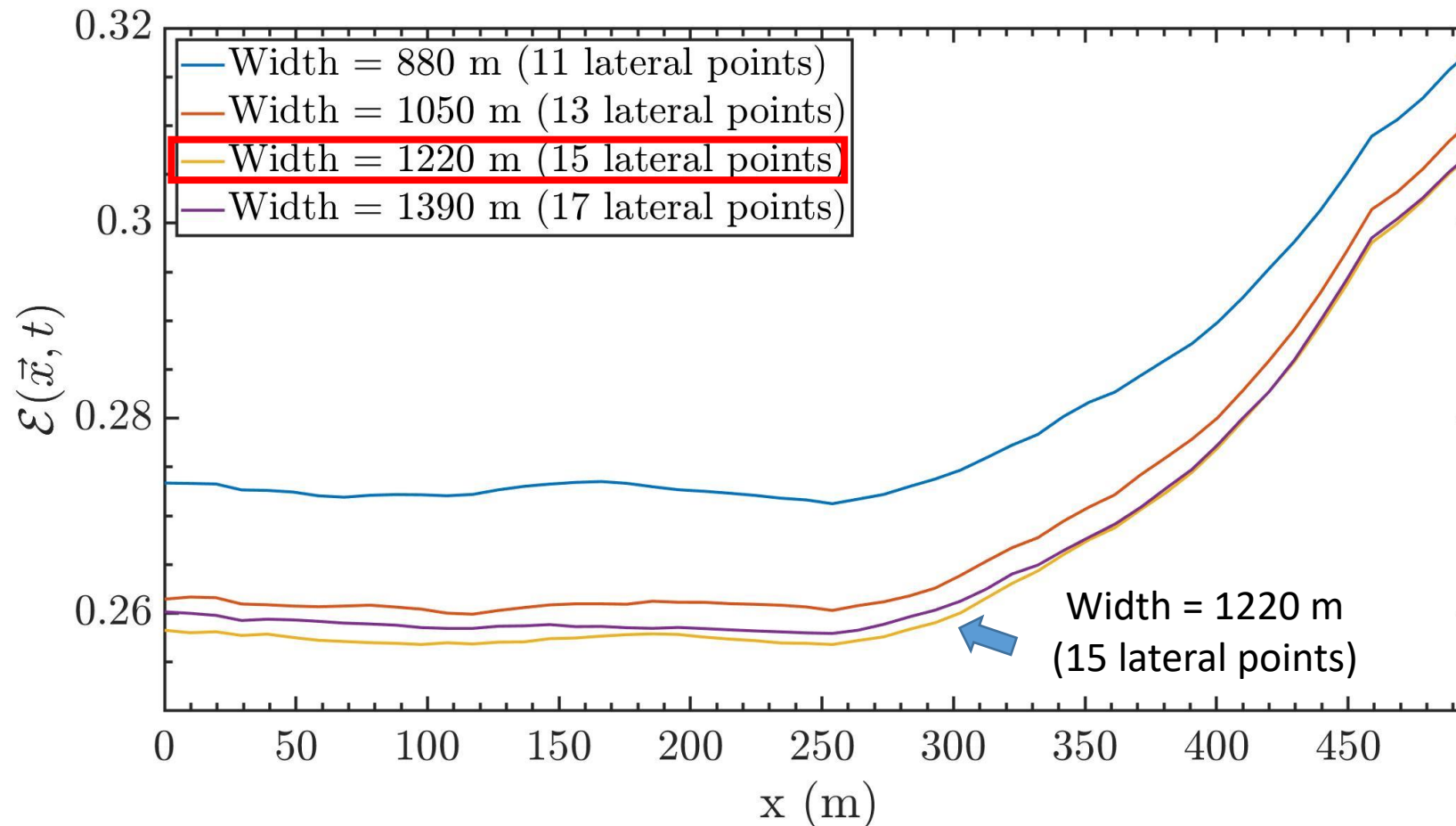




# Directional Waves

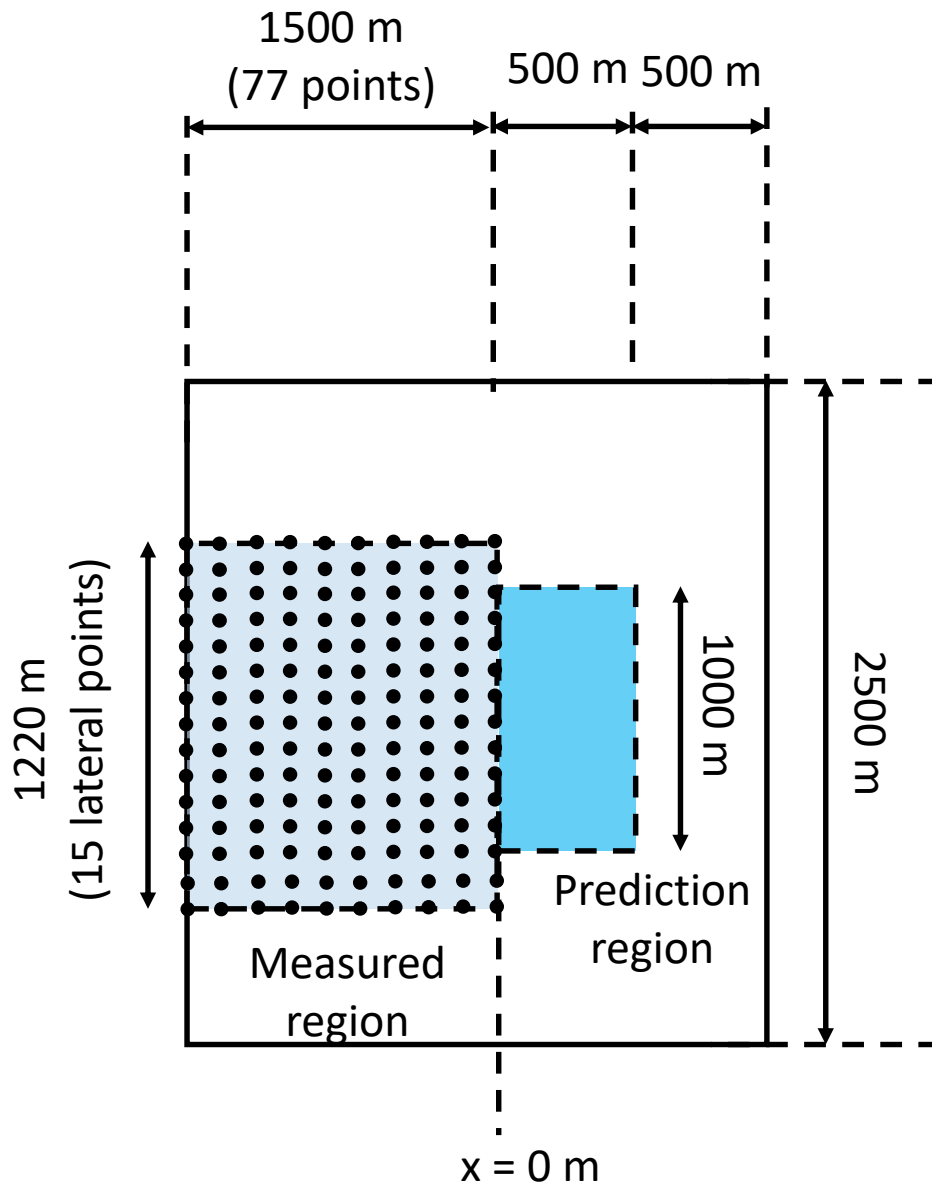
- ANN Prediction Error in the prediction region

Mean error along x in prediction region



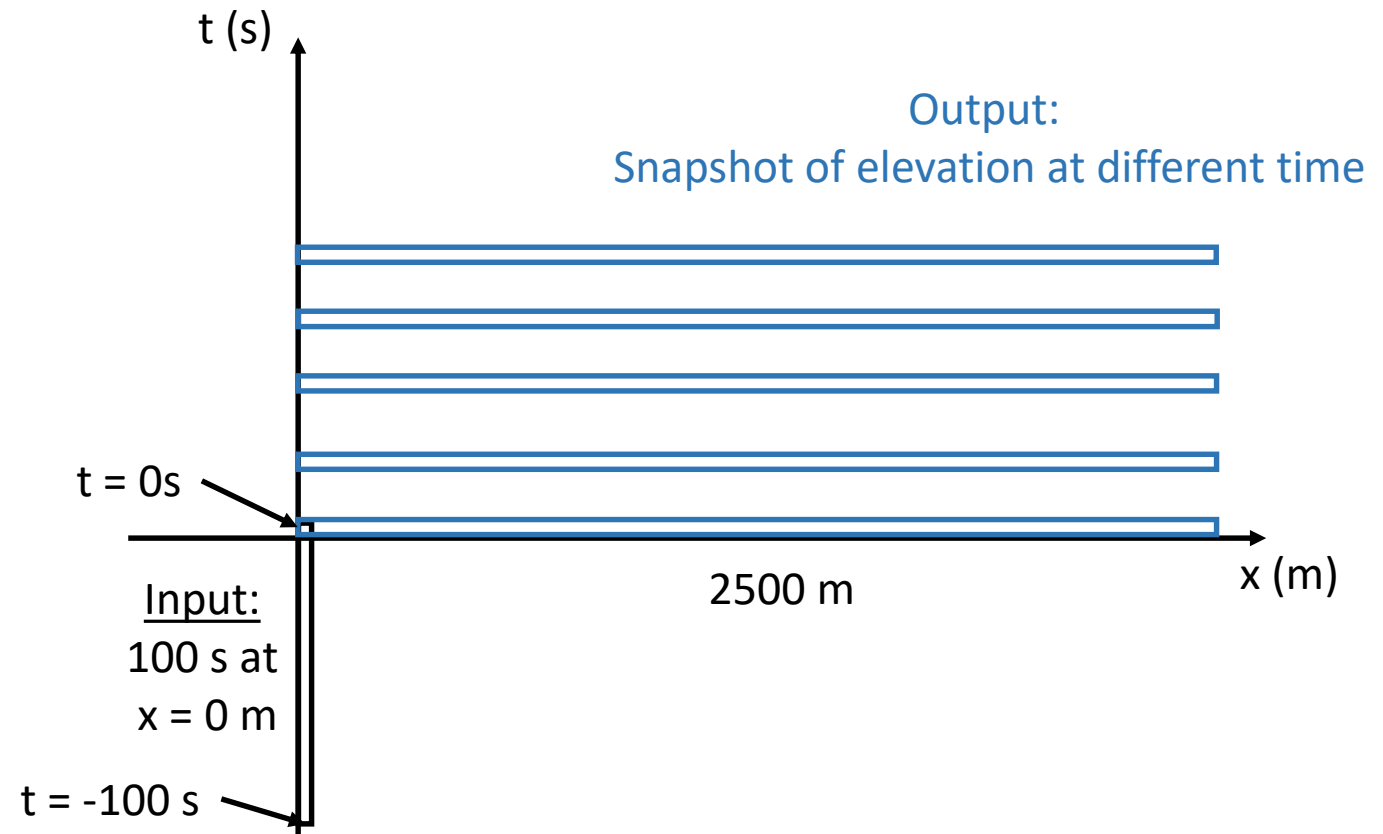
# Directional Waves

- Predict wave field in prediction region
- Input:
  - 15 x 77 grid points
  - Elevation measured from  $t = -25$  s to  $0$  s
- Output:
  - Wave field predicted from  $t = 0$  s to  $180$  s, at 5 s interval



# Unidirectional Waves

- Input
  - Elevation at  $x = 0$  m, collected from  $t = \underline{-100}$  s to  $\underline{0}$  s
- Output
  - Snapshot of elevation ( $x = 0 - 2500$  m) at different time



# Outline

- Models for real-time prediction
  - Linear Wave Theory (LWT)
  - Artificial Neural Network (ANN)
- Quantification of prediction error
- Application on
  - Unidirectional waves
  - Directional waves
- Future Work

# Models for real-time prediction

- Linear Wave Theory (LWT)
- Artificial Neural Network (ANN)



# Linear Wave Theory (LWT)

- Given measurements of wave field in space, 2D FFT is conducted to extract the information of each wave number
- Each wave component is propagated independently in time by multiplying
- Linear dispersion relation is assumed

$$\eta(\vec{x}, t) = \text{Re} \left[ \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} A_{mn} \exp(i\vec{k}_{x,m} \cdot \vec{x} - i\omega_n t + \phi_n) \right]$$