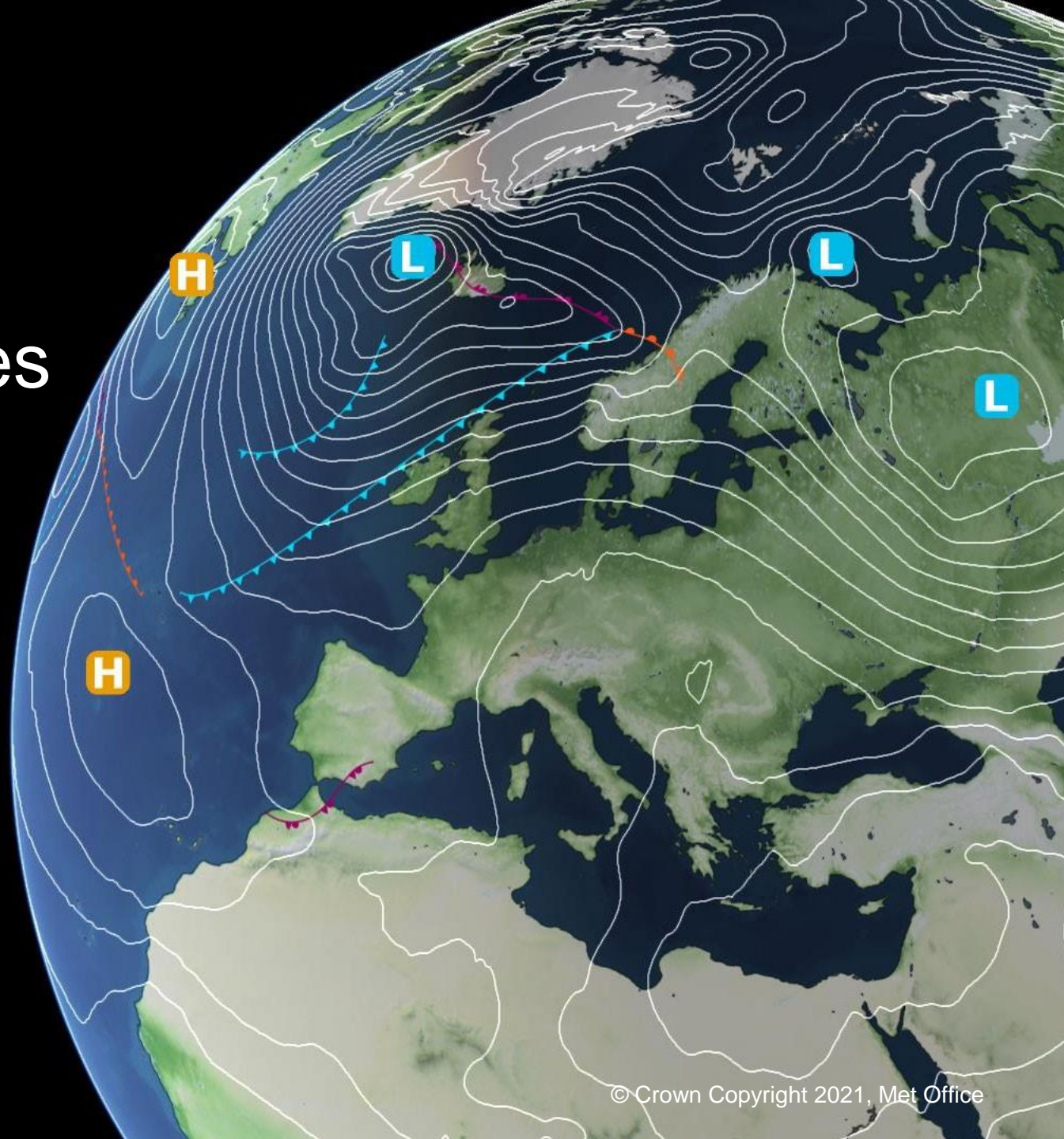


Using machine learning to project future wave climates around South Africa

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Waves SIG meeting
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Contents

- Project background and motivation
- Approach and why we chose machine learning
- Brief explanation of machine learning methods
- Results from preliminary trials
- Next steps

Motivation

Waves as a present and future hazard in South Africa:

- Coastal populations
- Coastal infrastructure and development
- Offshore industries and infrastructure
- Coastal storms - wave setup plays a large role in extreme sea level events in SA

Currently there is demand for coastal climate info and services, but not enough available resource.

Aim to help develop capability for projecting future wave climates for South Africa.



*Cape Town,
June 2017*

Images: shutterstock.com

Projecting future wave climates

Existing wave projections? No high-resolution studies for oceans around South Africa

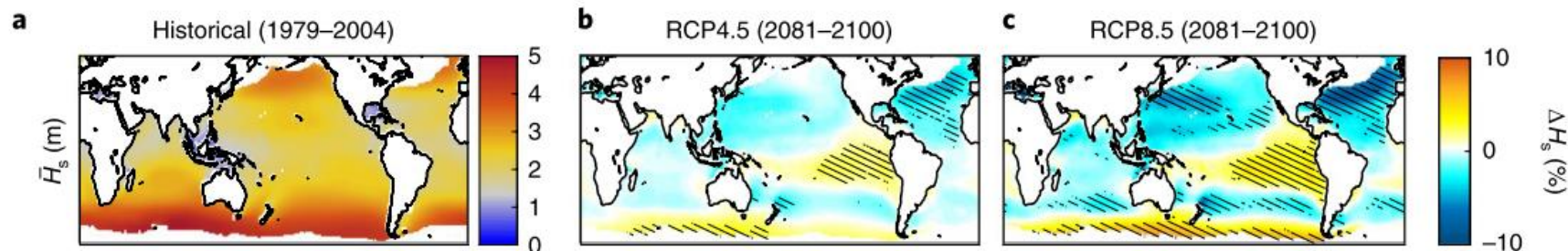
Atmospheric parameters from GCM projections can be used to force wave models

~~Dynamical methods~~

- SAWS have limited computational resource

Statistical methods

- Many of these have focused on weather-type classifications (*Camus et al., 2014, 2017; Perez et al., 2015*)
- This approach is not feasible for this project given South Africa's oceanographic setting
- **Machine learning?**



Morim et al., 2019

Why machine learning?

- Limited computational resource
- Long historical datasets available
- Existing capability within the team

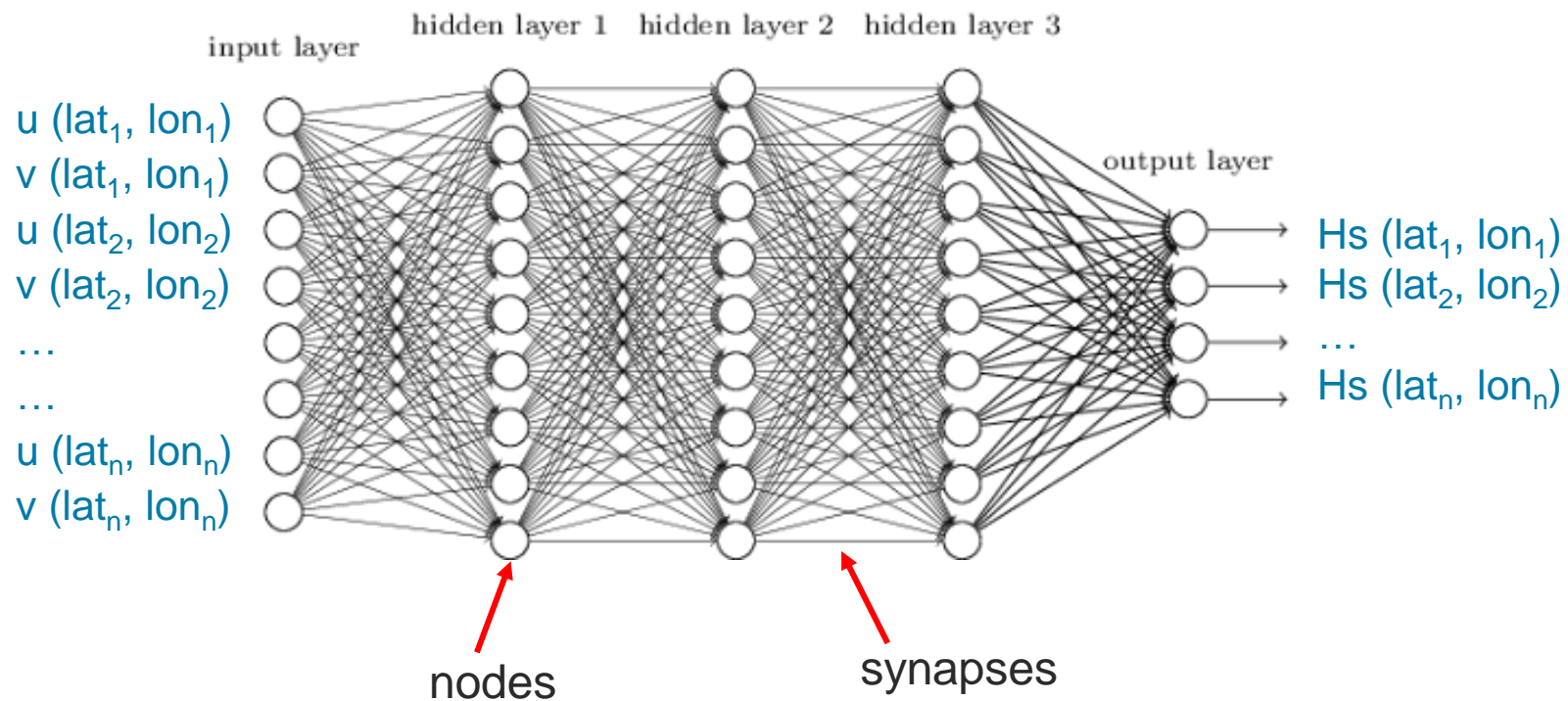


machine learning well suited

Machine learning approach

- Understand different ML techniques and what is suited to our problem
- Artificial Neural Network (ANN) determined to be most suitable method
 - Suited for regression rather than classification
 - Has ability to extrapolate
 - Can be seen as a black box – need to work on interpretability and explainability
- Considered 2 different types of ANN for this work:
 - Basic ANN
 - Convolutional Neural Network (CNN)

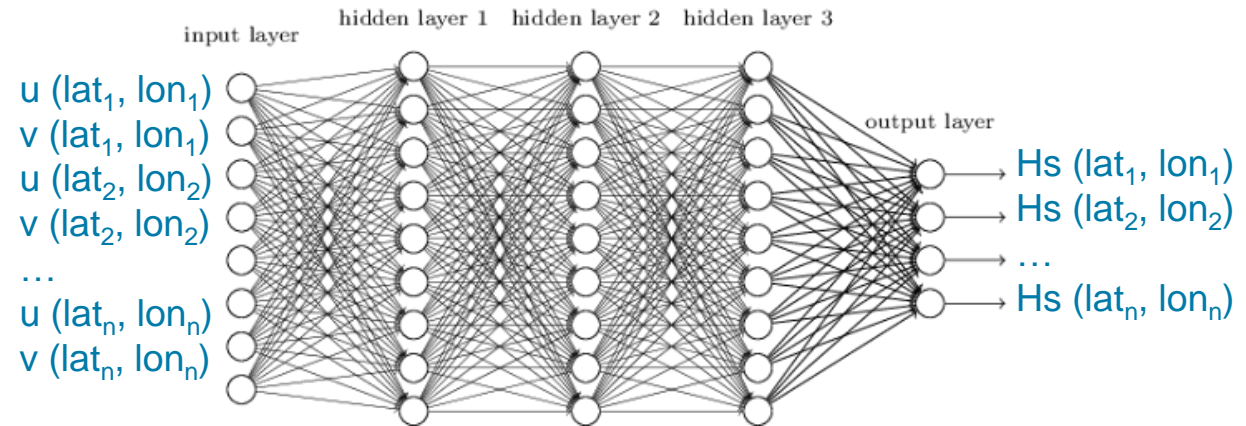
Artificial Neural Networks



Adapted from towardsdatascience.com

Artificial Neural Networks

- Relatively straight-forward to set up and start running
- Easy to test different inputs and explore feature importance
- Easy to change and test model architectures
- Model itself has no inbuilt spatial understanding - each grid point is a separate feature
- Model has no inbuilt temporal understanding - to consider previous time steps we add time-lagged inputs as additional features



Scikit learn MLPRegressor

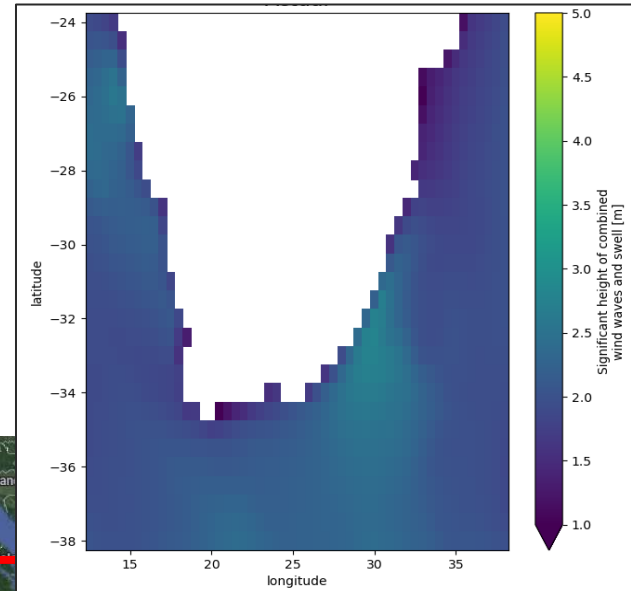
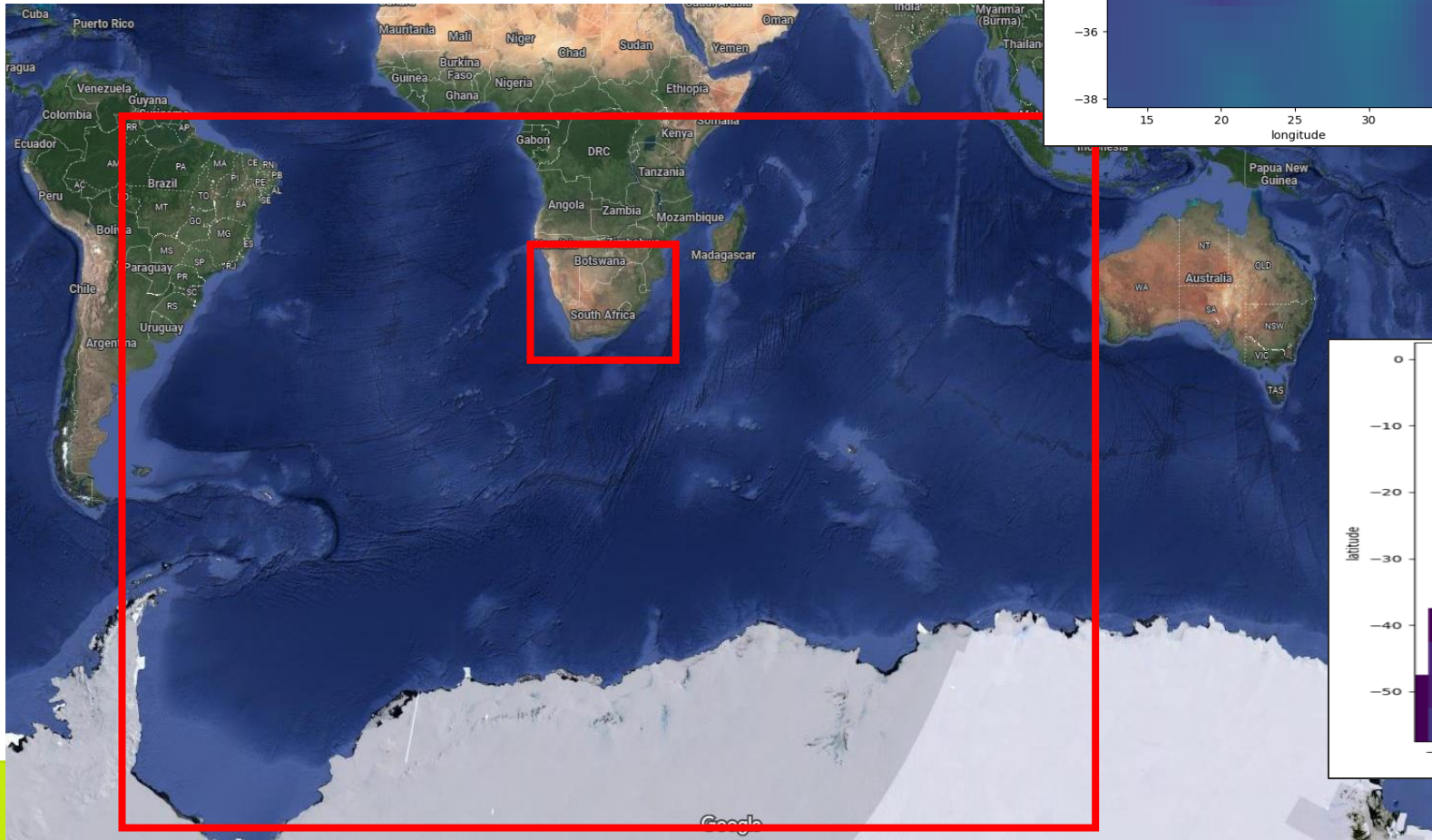
Adapted from towardsdatascience.com

Neural Network trials

Results from trial run with basic ANN looking at ability to predict waves for historic period

ERA5 datasets

- Winds: u and v wind components
- Waves: significant wave height (Hs) (Tp, dir)

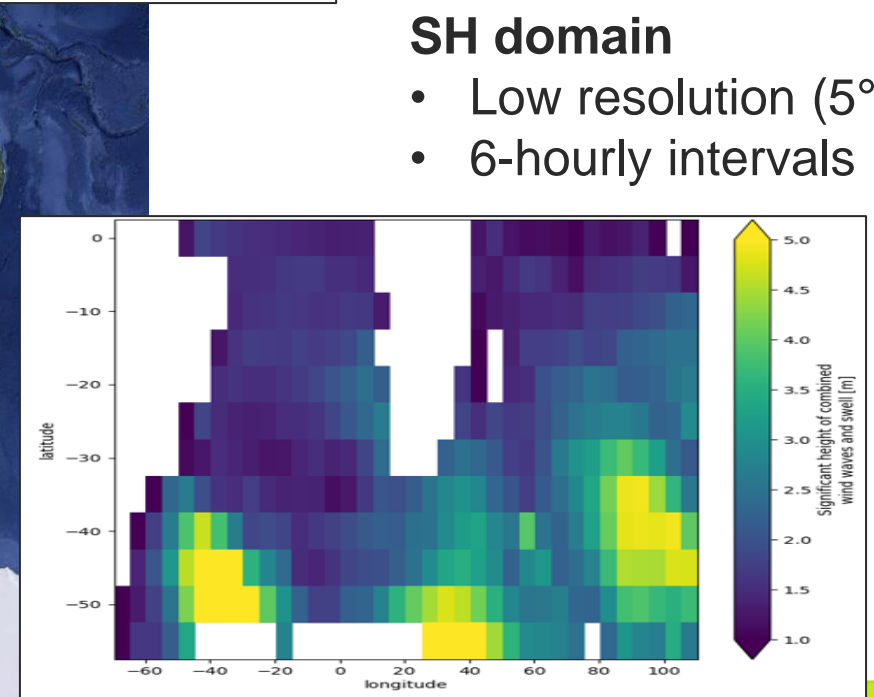


SA domain

- Same area as covered by SAWS hindcast
- High resolution (0.5°)
- 6-hourly intervals

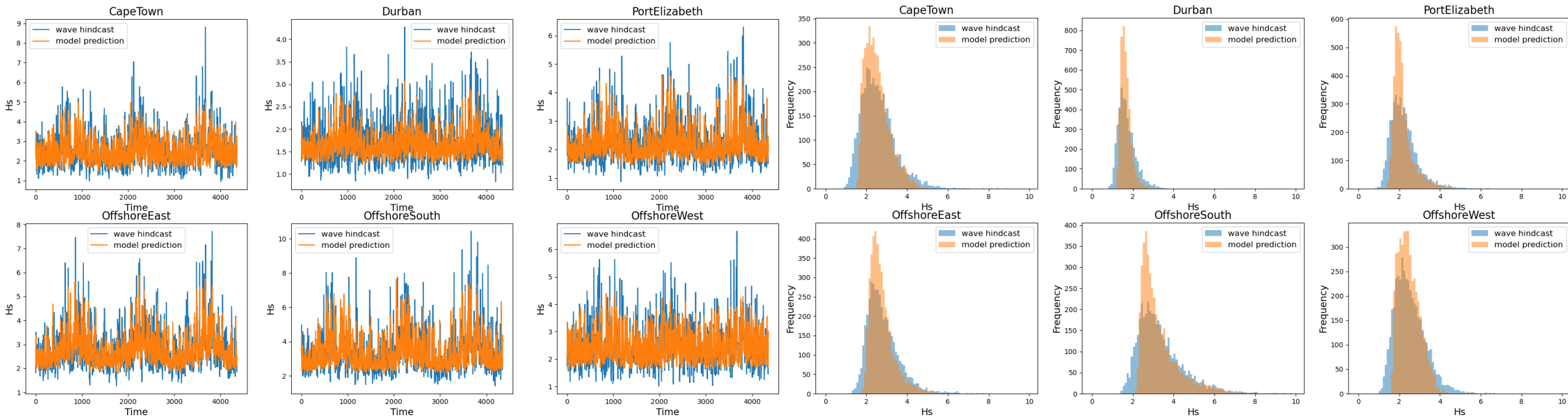
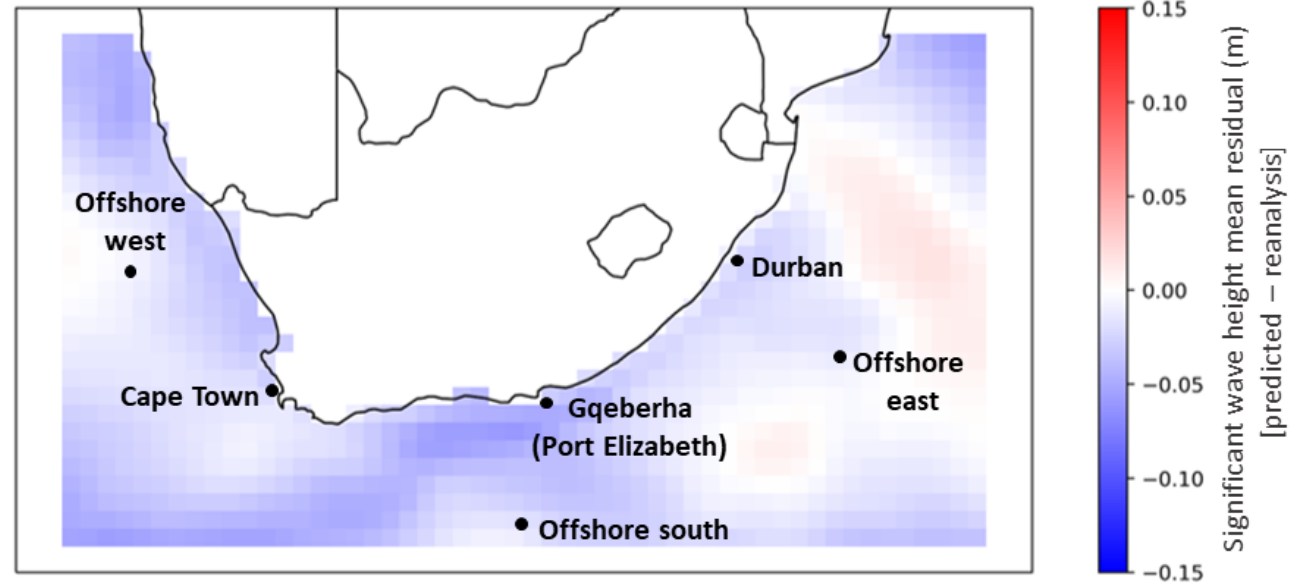
SH domain

- Low resolution (5°)
- 6-hourly intervals



ANN

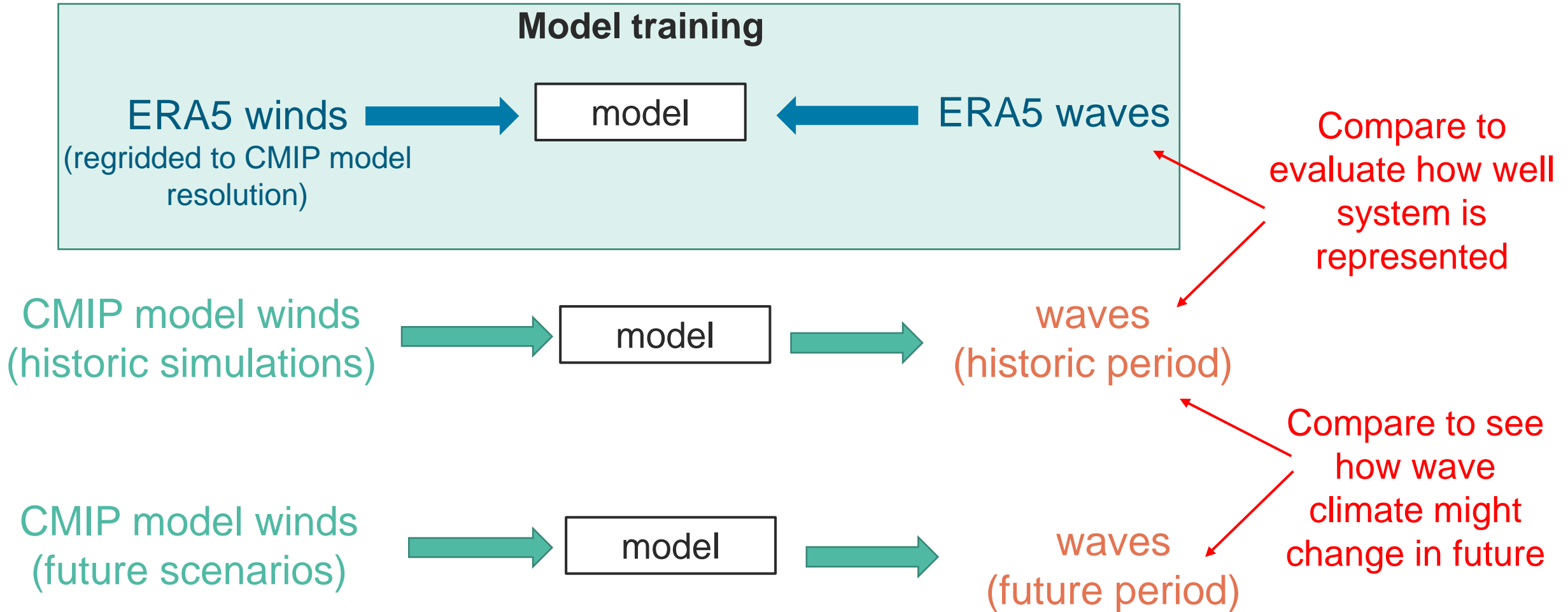
- Train with 39 years (1979-2017)
- Test with 3 years (2018-2020)
- 7 days time-lagged inputs



Next steps

- Taking our ANN model forward
- Run trained ANN model with CMIP historical and future scenarios
- Compare output with other wave projections (COWCLIP)

Application with CMIP datasets



Summary

- Machine learning can be a useful tool to study waves
 - Computationally lightweight tool, easily adaptable
 - Need to understand what model is appropriate for specific problem
 - Time required for initial setup, but very rapid to run
- Promising initial results for ANN approach in predicting wave climates around South Africa
 - Good at predicting average Hs, but less skilled in identifying extremes
- Next step is application with CMIP atmospheric outputs

Questions?

For more information please contact

 www.metoffice.gov.uk/research/approach/collaboration/newton/wcssp-southafrica

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