Using Machine Learning to Improve Operational Wave Forecasting

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Importance of accurate wave forecasts

Many sectors rely on accurate operational wave forecasts:

- Offshore industries, e.g. side-by-side offloading, port departures, personnel transfers.
- Marine/public safety
- Coastal hazards and management

Shell

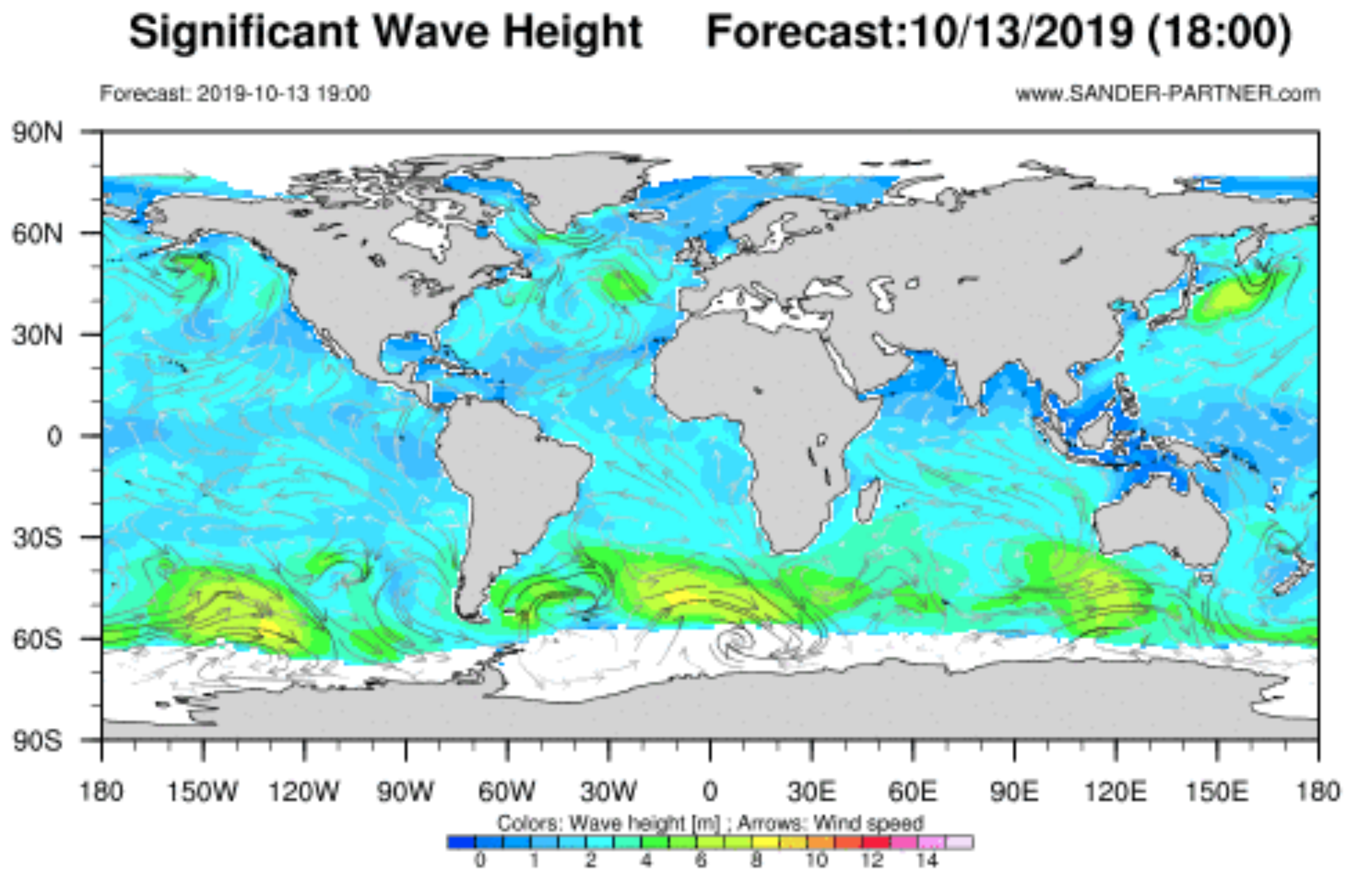
Wave impacts on offshore operations

Waves, particularly swell, can cause unsafe working conditions and damage to equipment.

Gap resonance example during side-to-side operations

Modern wave forecasting

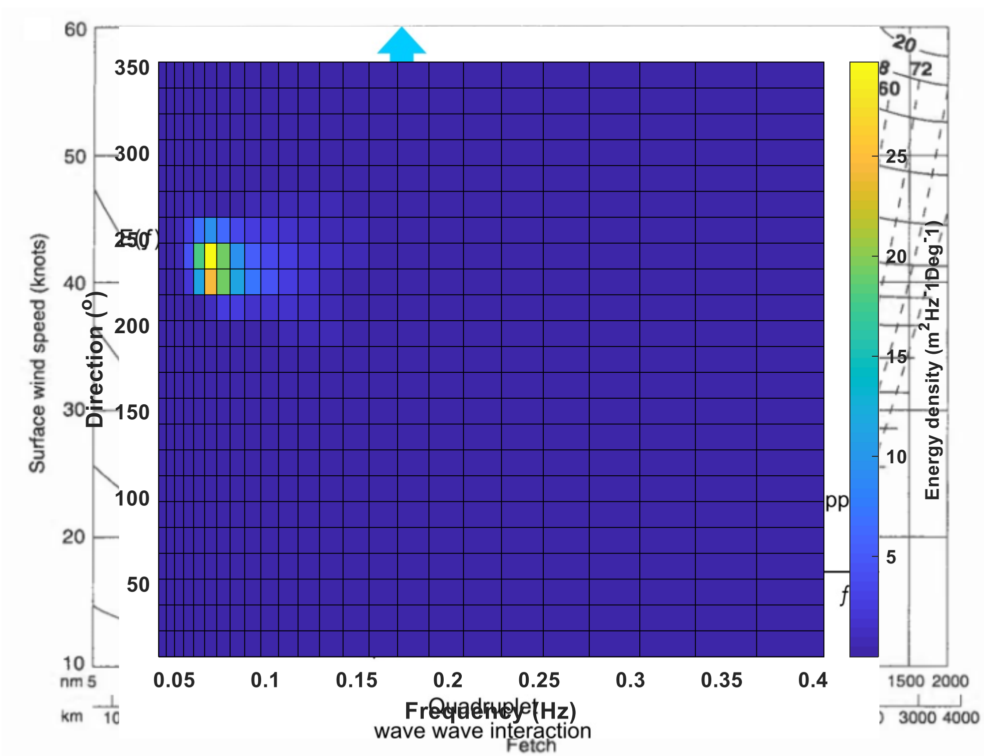
A vast majority of operational wave forecasts rely on "third-generation" spectral (phase-averaged) wave models run over global and/or continental/ocean basin scales.



Limitations of spectral wave forecast

Despite mostly producing very good forecasts, spectral wave models (e.g. Wavewatch III) have a number of innate limitations based on their numerics or physics, for example:

- Wind wave growth is mostly based on empirical parameterizations.
- They crudely handle redistribution of energy across the spectrum.
- Rely on wind fields from atmospheric models.
- Have relatively coarse resolution in space, frequency, and direction.

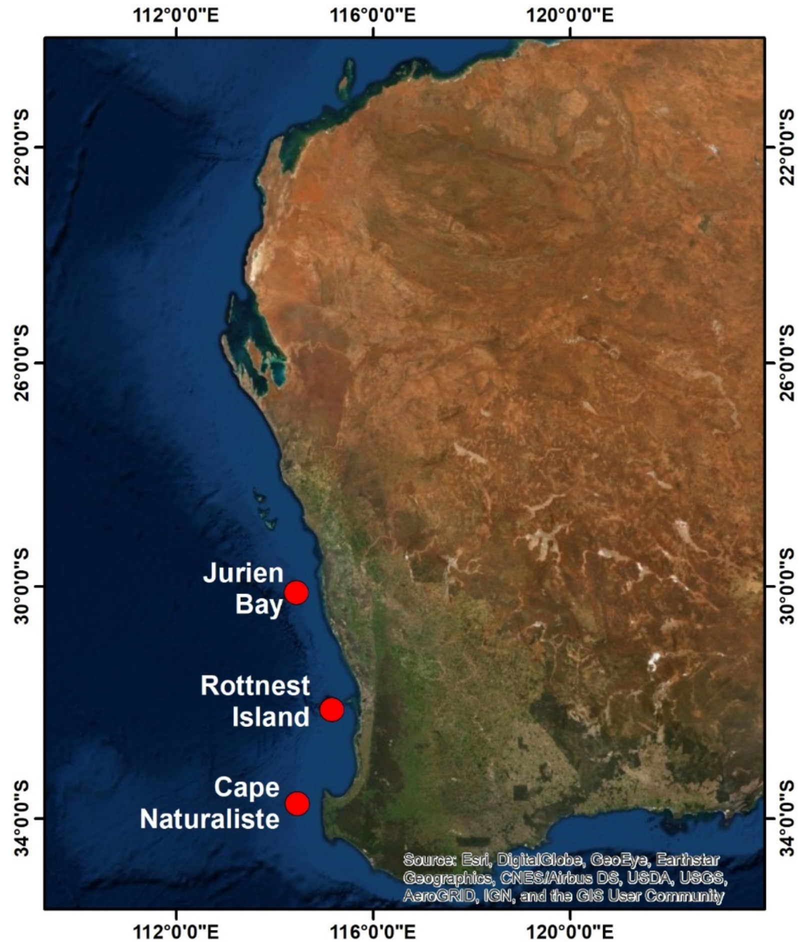


Can machine learning be used to improve operational wave forecasts?

We examine the feasibility of using machine learning algorithms to bias-correct BOM AUSWAVE forecast.

- Machine learning is used to bias-correct, not make the forecast. i.e. a "grey box" not a "black box".

Method applied as a pilot study using BOM forecasts and observations from WA Department of Transport wave buoys at Cape Naturalist, Rottnest Island, Jurien Bay.



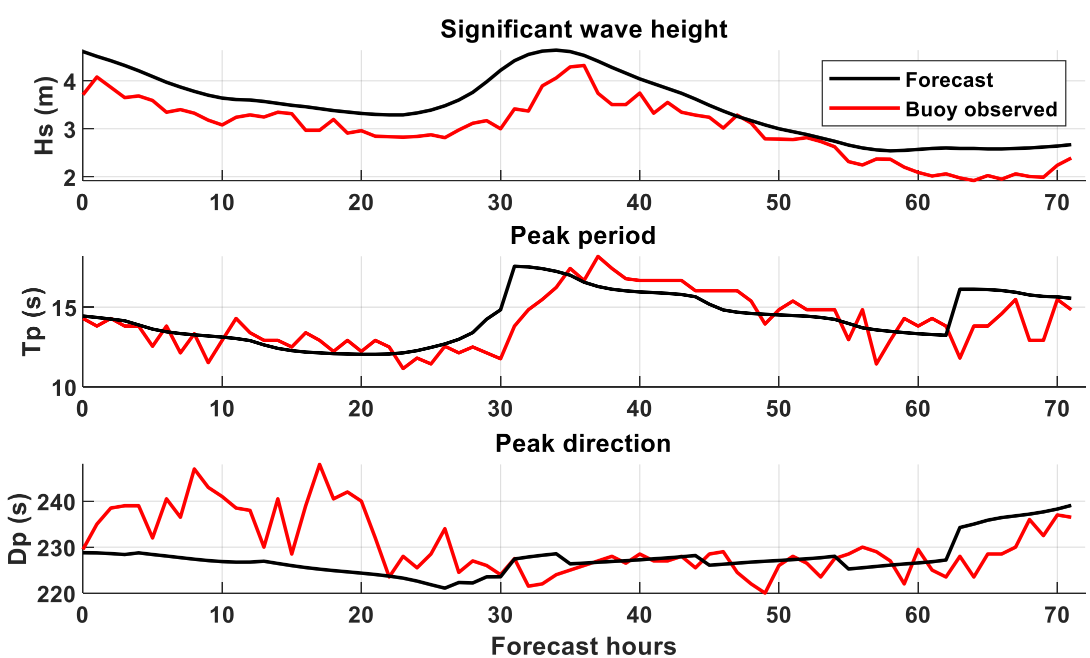
Methodology

A Recurrent Neural Network (RNN) was trained using 18 months of:

- BOM AUSWAVE-R 72 hour forecasts (1 hour interval updated every 12 hours)
- Hourly bulk statistics from the wave buoys (some missing data)

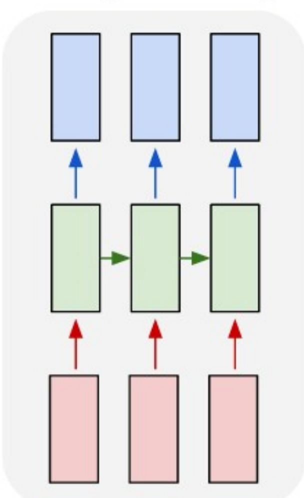
A random 20% of the training data set was withheld for performance evaluation (data not used for training).

The data from all locations was combined to maximize the training data set



Recurrent Neural Networks

Recurrent Neural Networks are modified versions of traditional neural networks and are used for data sets where sequences are important, e.g. speech, handwriting, time series.



In a standard neural network, the history is not important

In RNN the history is used based on previously seen sequences (basically a neural network in a loop)

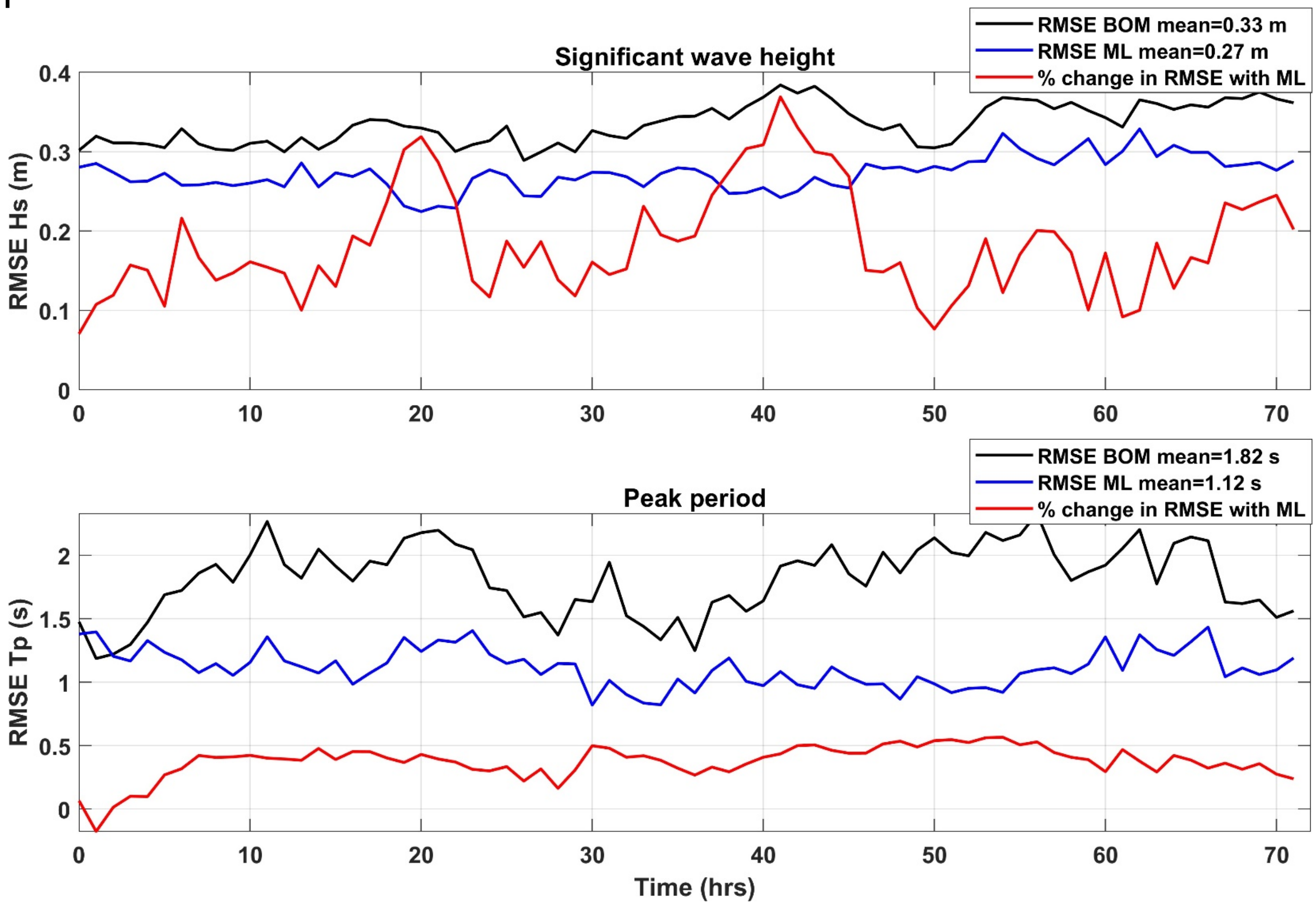
Inputs

ML model

Outputs

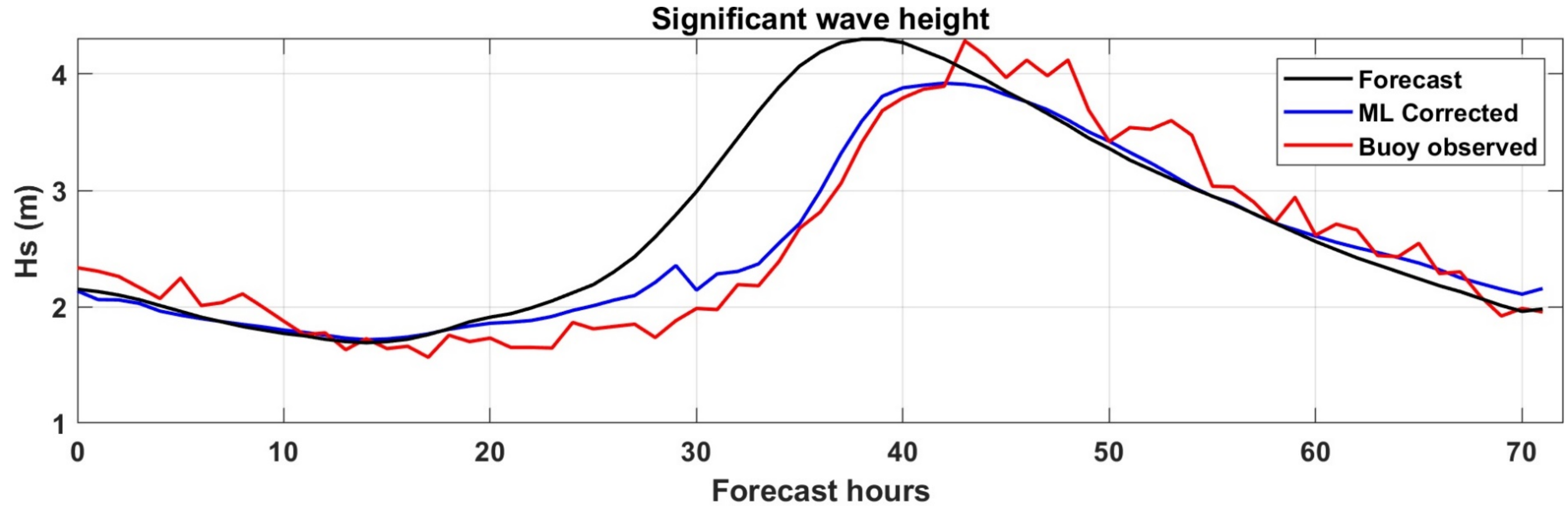
Results

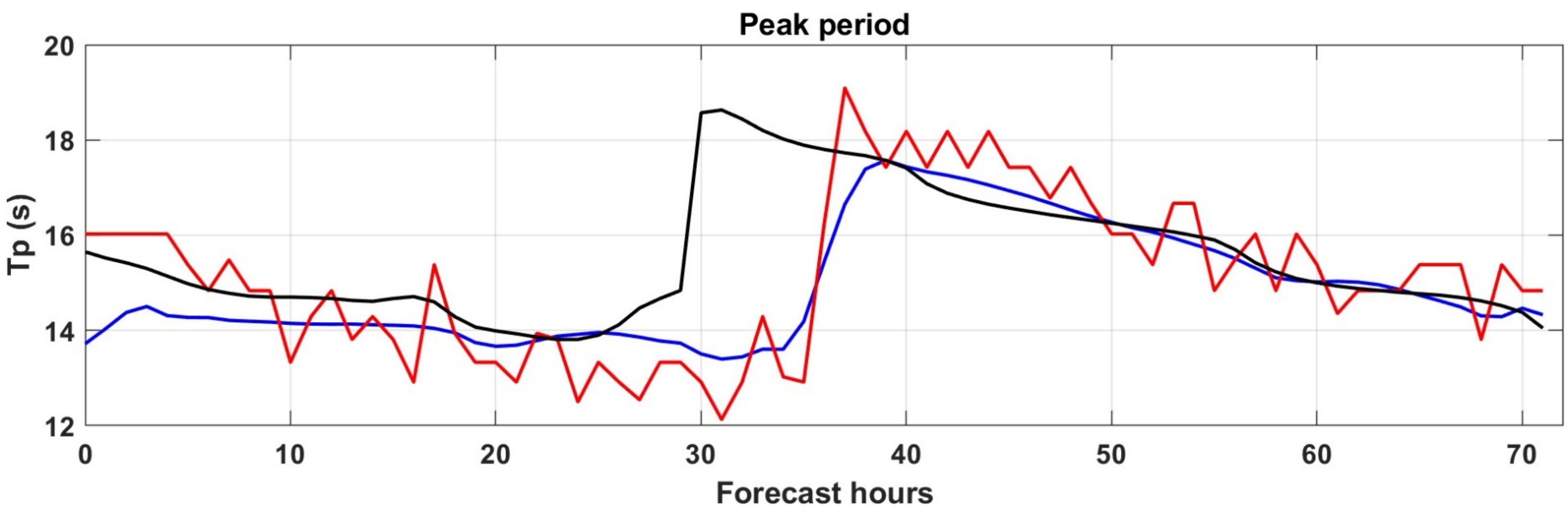
For the 150 randomly selected 72 hour forecast periods, the ML algorithm reduced the forecast RMSE by 19% for significant wave height and 38% for peak period.



Example forecasts

BOM=black **ML= blue** **Buoy=red**





Example forecasts

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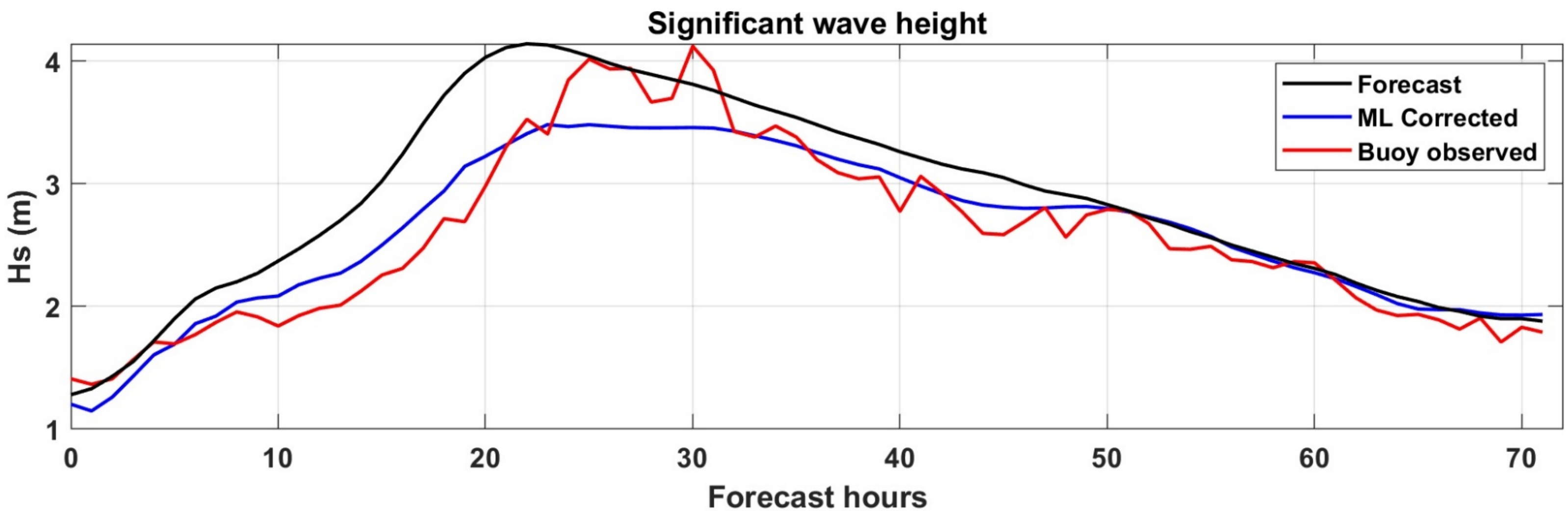

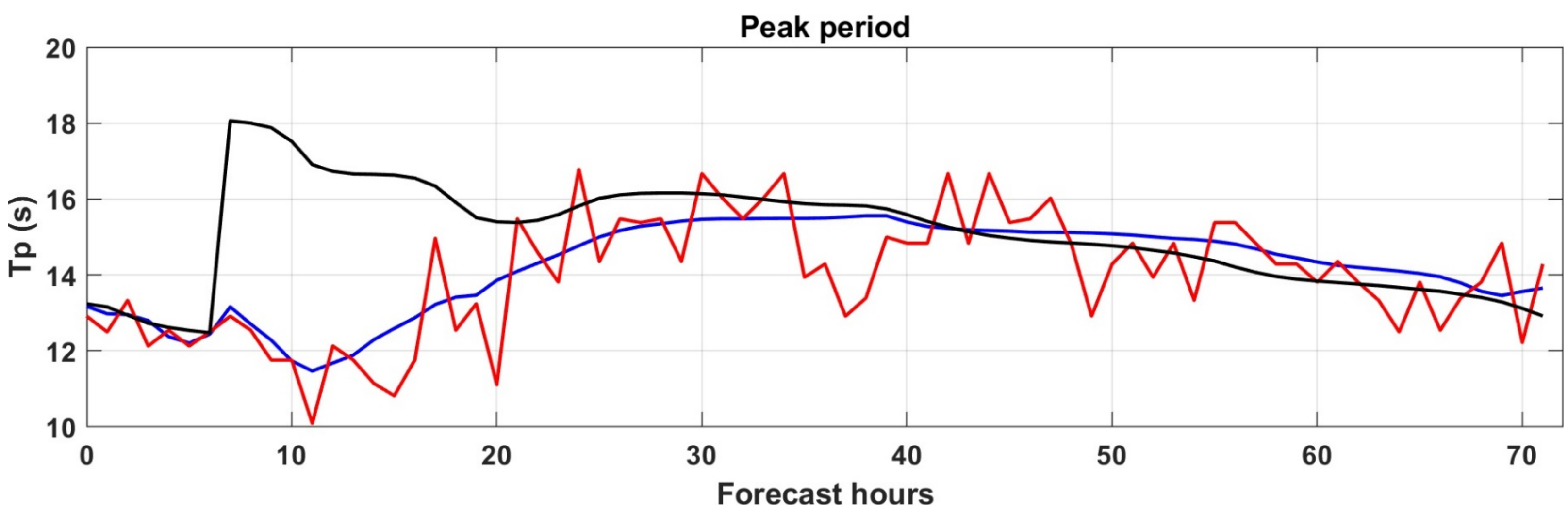

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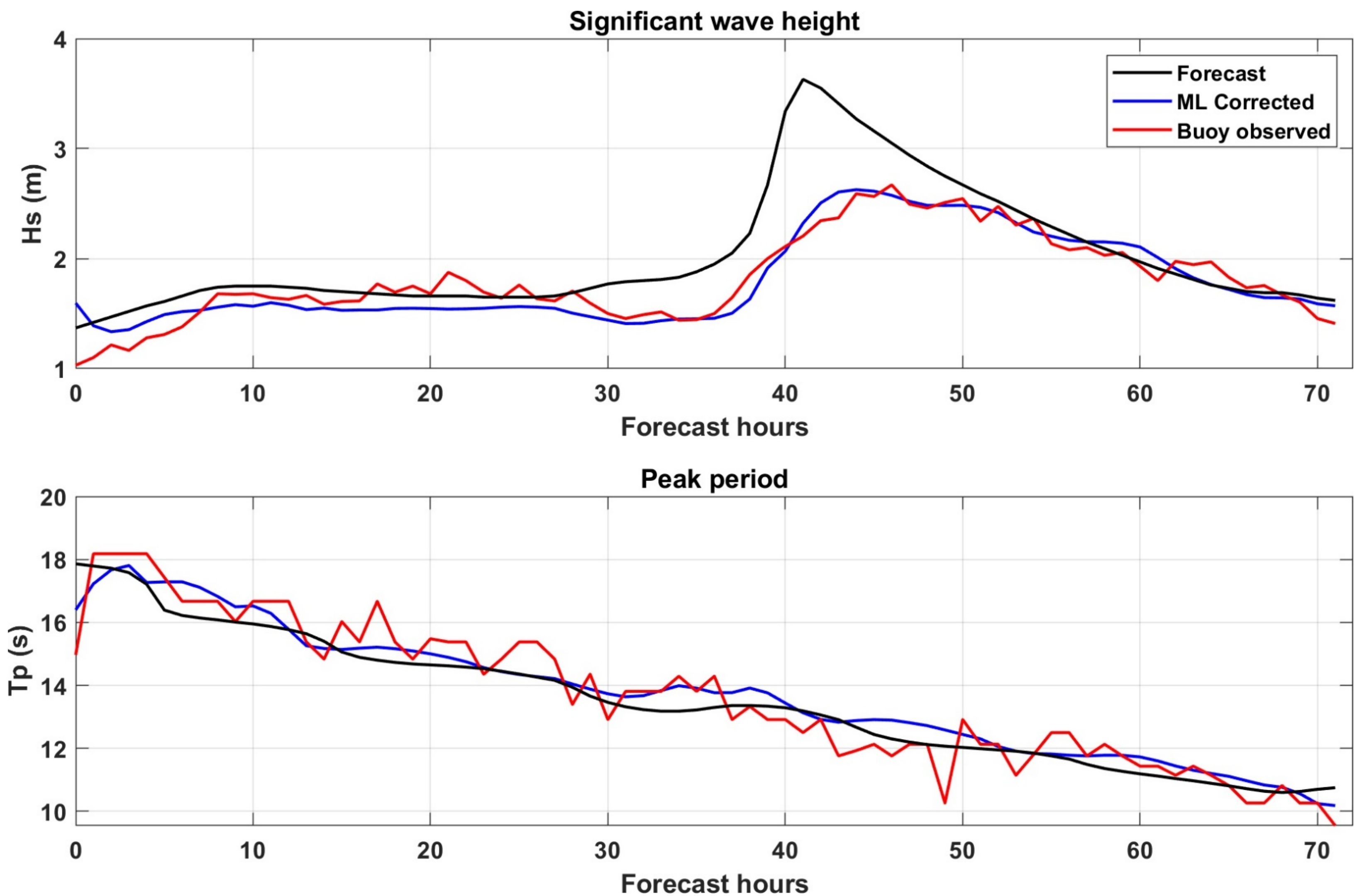

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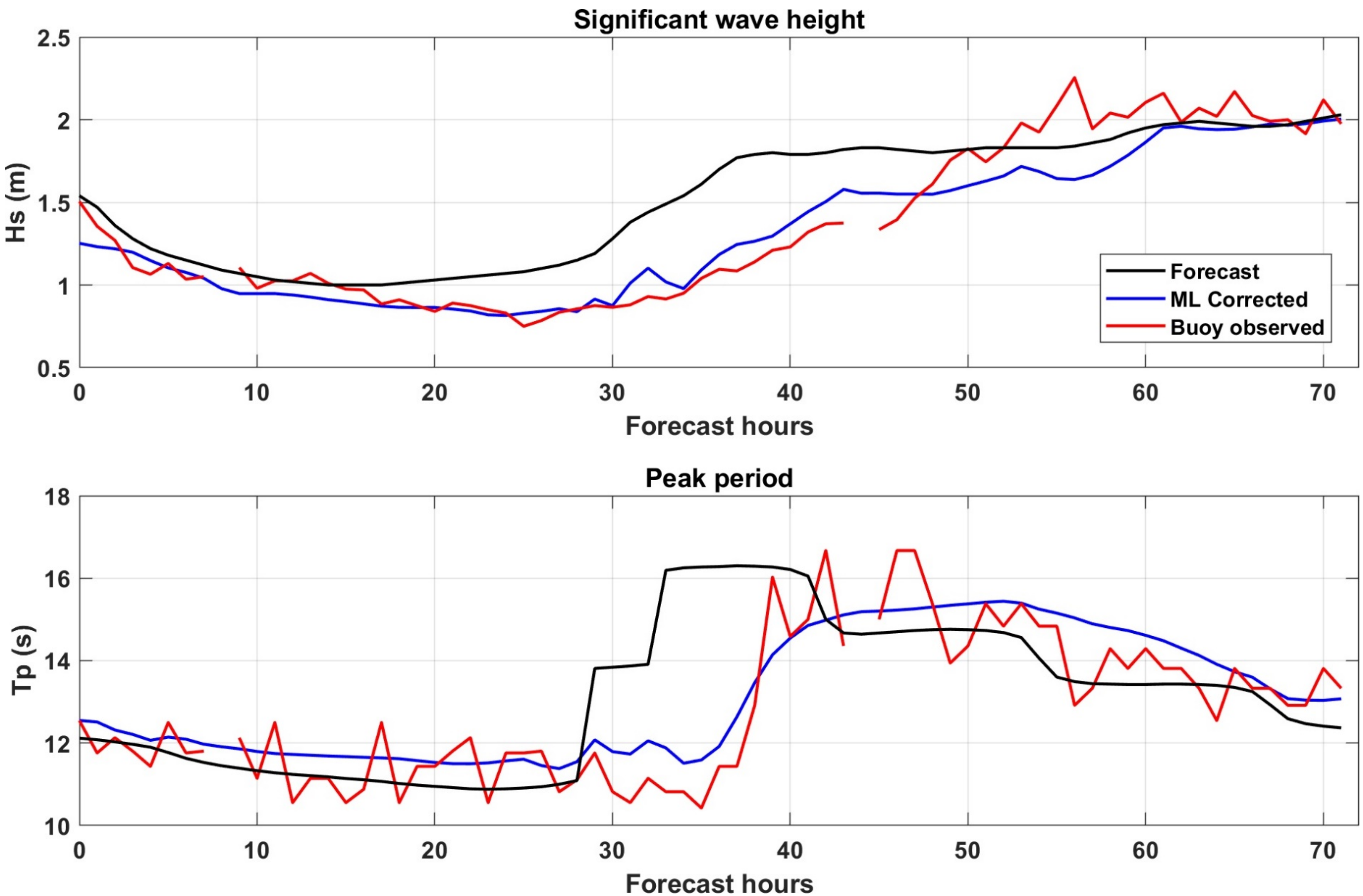

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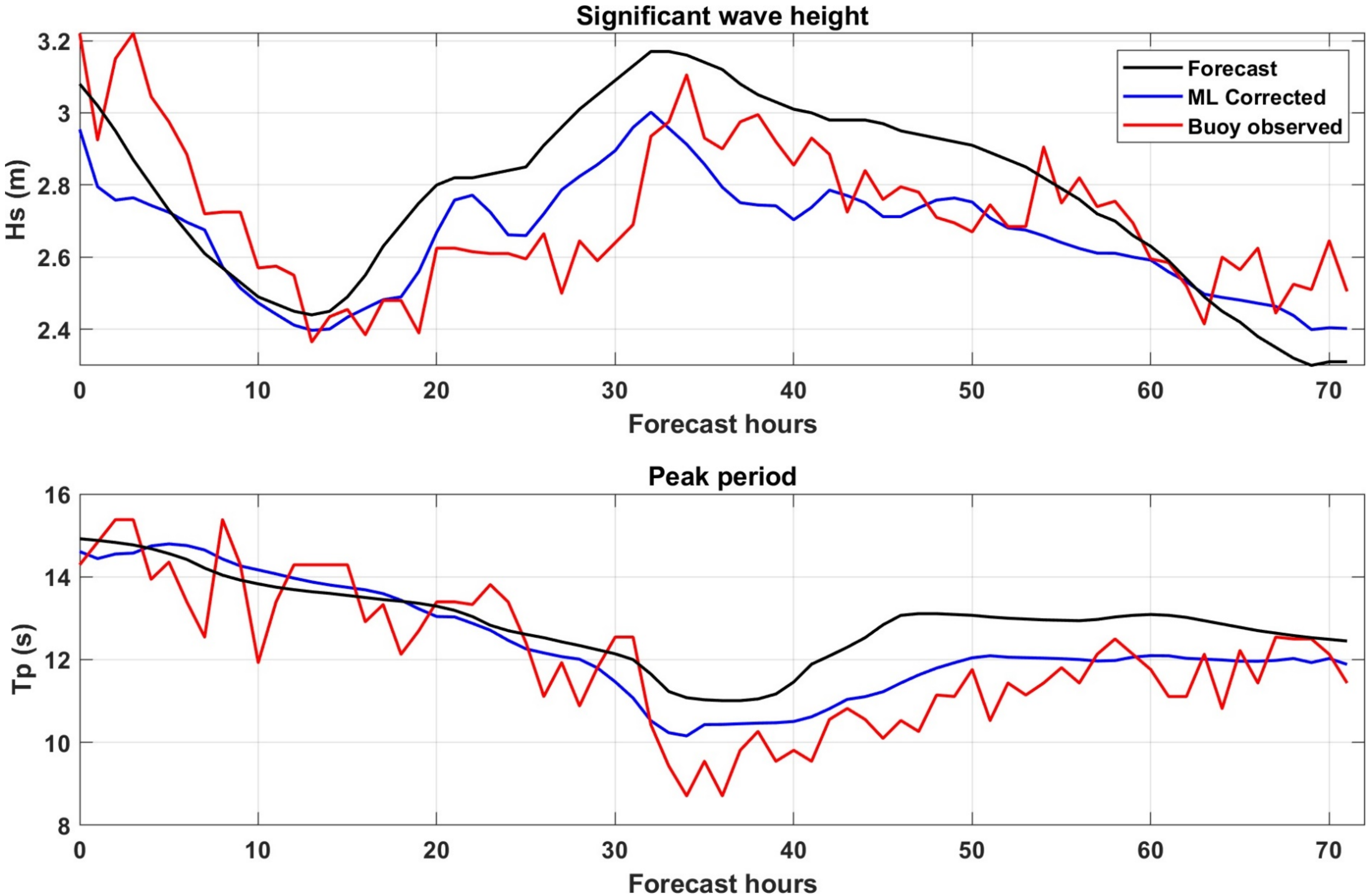

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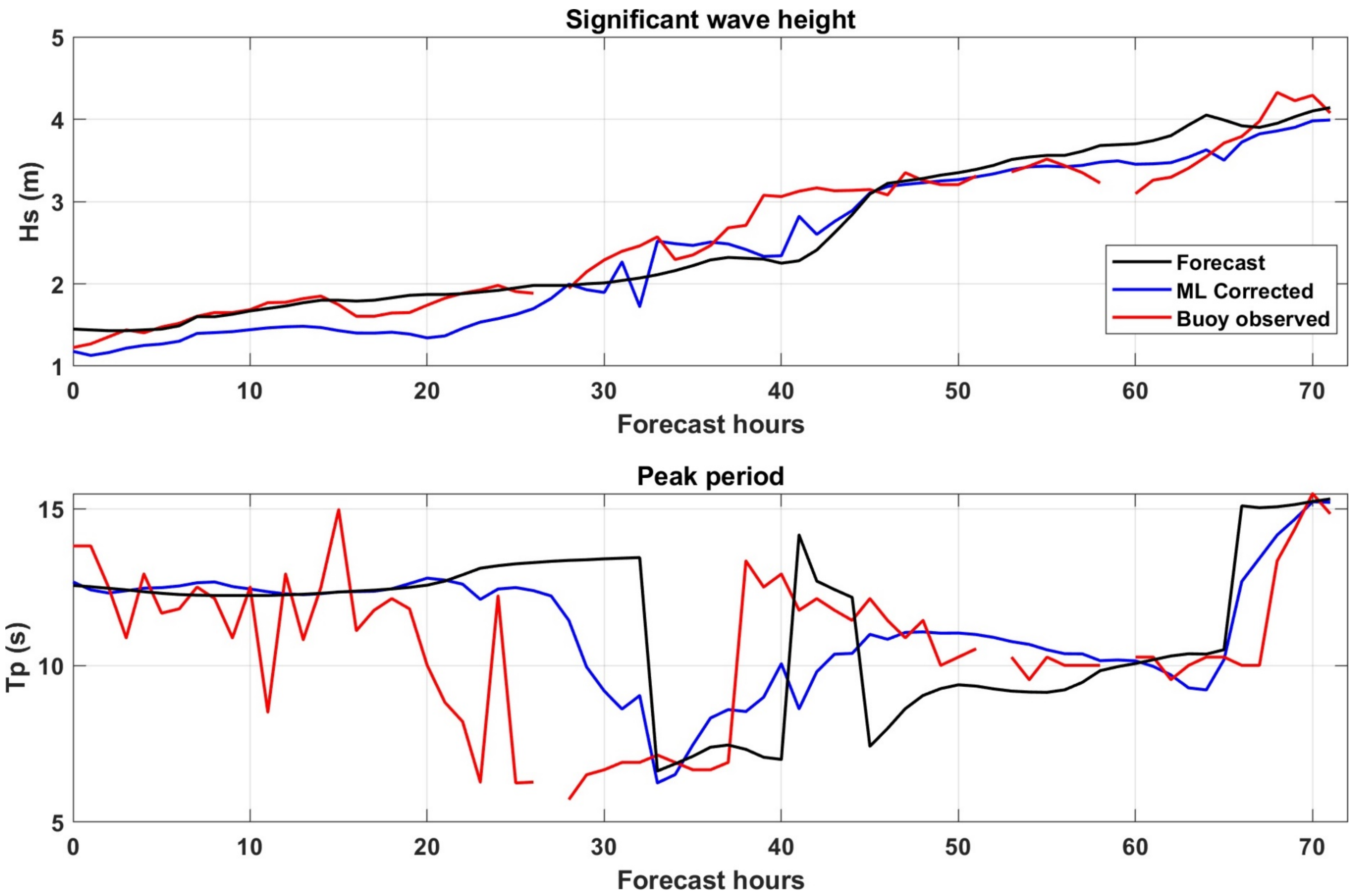

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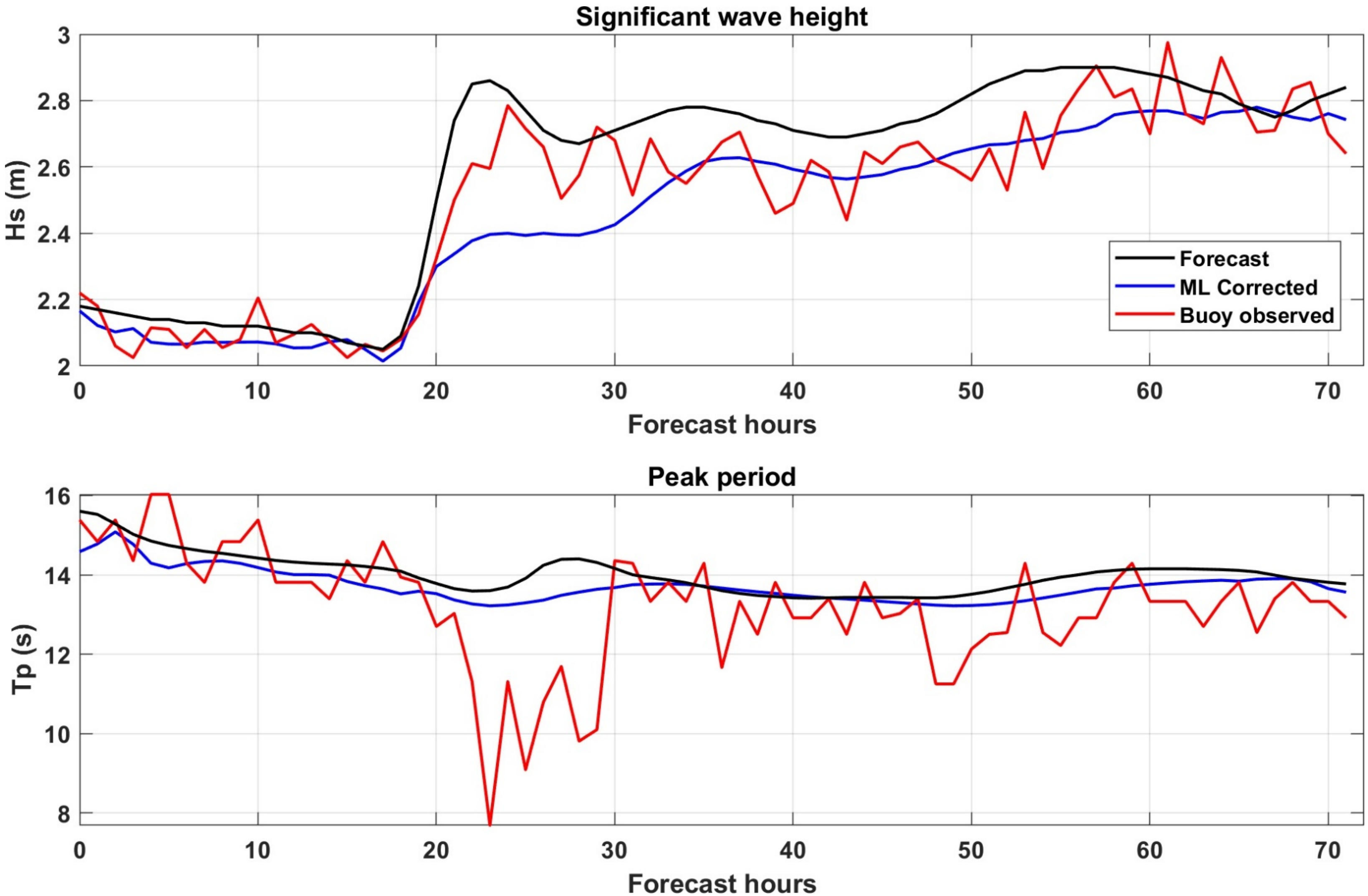
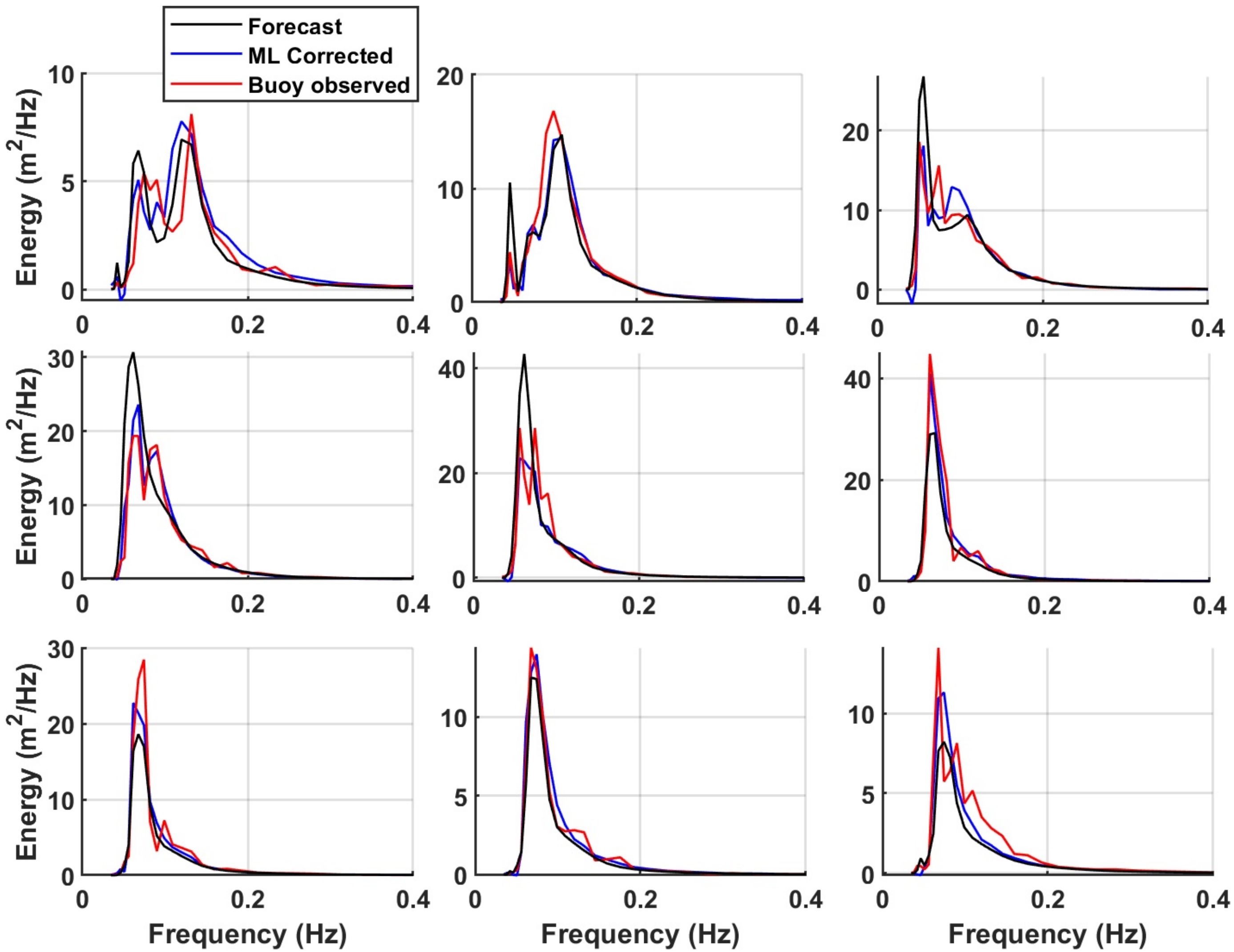


Preliminary spectral results

The RNN model was also trained with the forecasted and observed 1D spectra



Summary

- This pilot study has demonstrated that machine learning can identify and correct errors in spectral wave model forecasts using a limited (18 month) training data set.

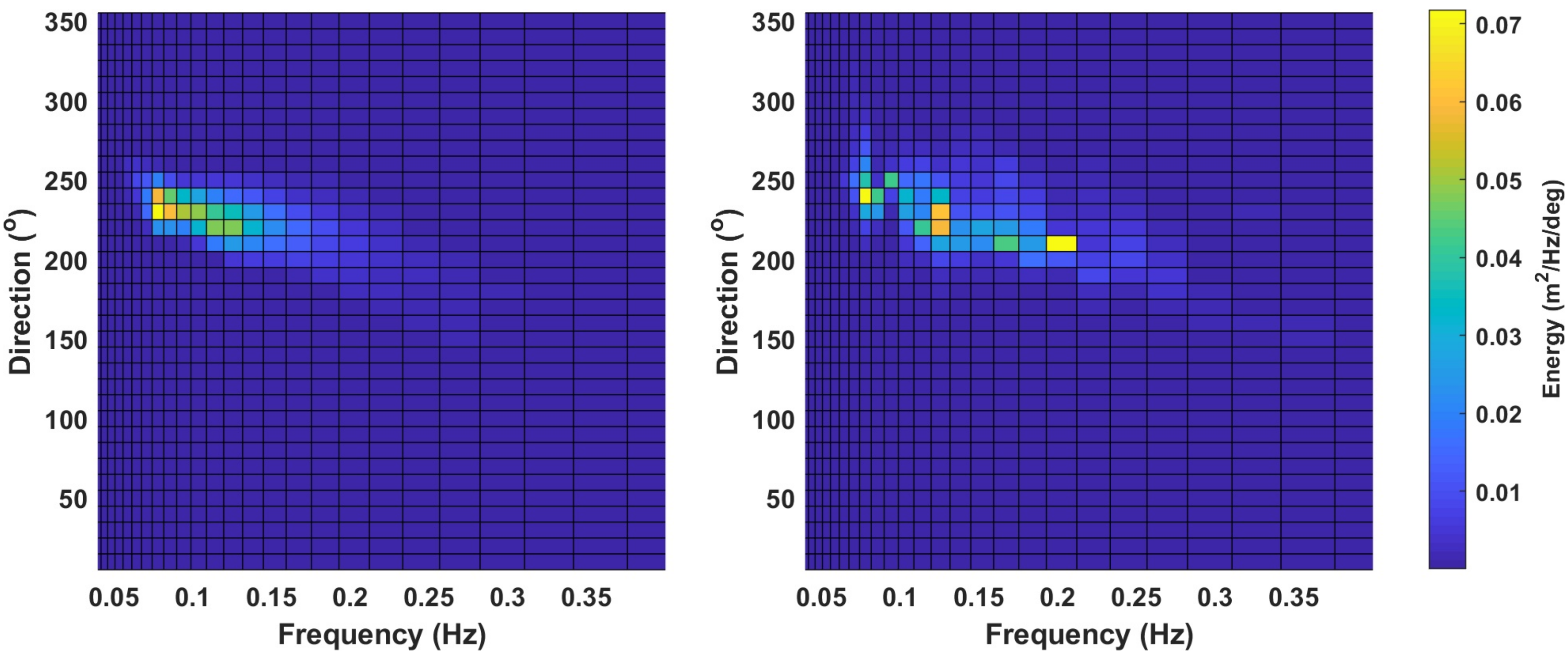
- For this study all locations were combined to increase the training data set, the forecast improvements suggest:
  - Errors in the forecast are regionally coherent (not so surprising given dominance of Southern Ocean swell) and ML forecast corrections may be useful over a broader region.

- The drawback of the ML approach is that you don’t really know what the ML model is doing!

Ongoing work

Ongoing/future work:

- Extending results to 2D spectra
- Investigating sensitivity to BOM model updates.
- Putting confidence intervals on ML forecast



Thanks