Estimating Landfalling Hurricane Wave Characteristics with Parametric Modelling

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Contents

Wave Downscaling & Its Significance

Wave Downscaling: From offshore wave data to localized nearshore insights.

- Tropical Cyclones:
  - Predict destructive wave patterns
  - Urgent due to rising damages
- Historical Data:
  - Guides marine design and risk analysis
  - Current sources are limited

Downscaling Methods & Research Aims

- **Current Strategies**: Numerical downscaling, Statistical Downscaling
- **The Hybrid Approach:** A surrogate model for the numeric model
- **Deep Learning**: Exploration of MLP and LSTM for wave downscaling.
- **Research Aims**: Innovative solutions, performance testing, and model generalization.

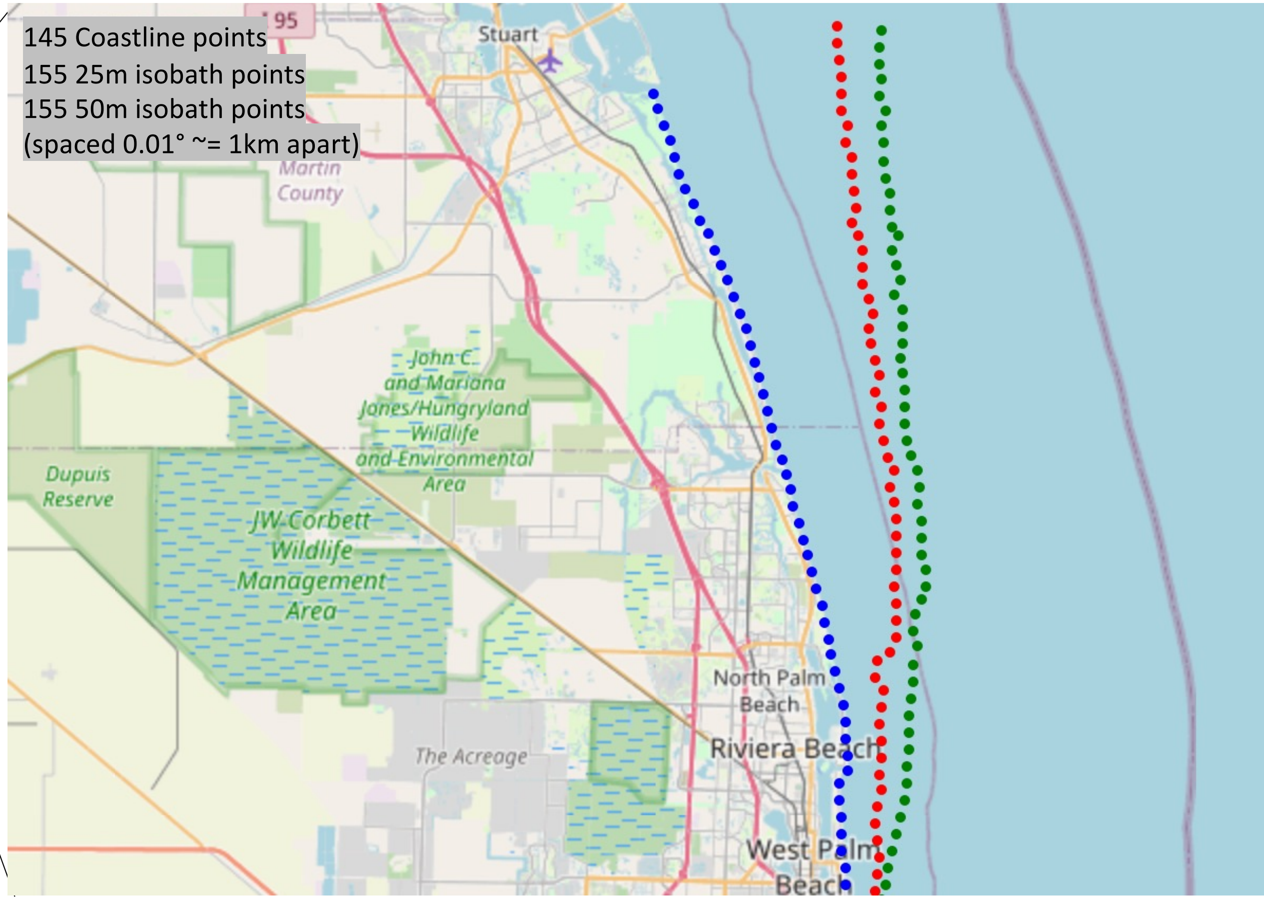
Data

Location: Coastline of Florida, USA
Source of data: RMS company

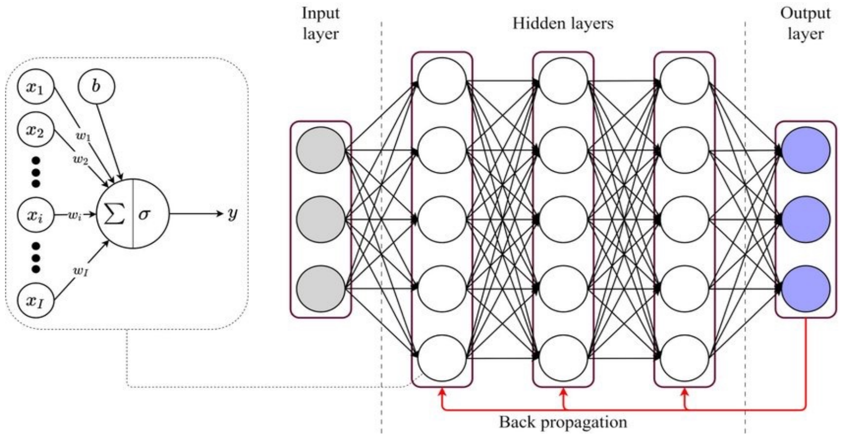
Predictor:
'MWD', 'PWP', 'SWH', 'TWD', 'WiD' and 'WiS' at 25m isobath (red points)

Predictand:
Significant Wave Height at coastline (blue points)

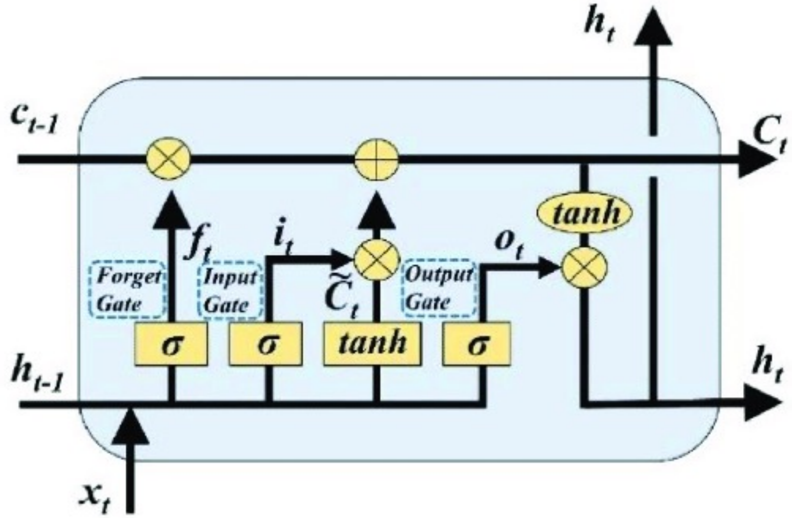
- Data derived from numerical simulation
- 50m data not used as it is highly similar to 25m
- Data pre-processing



Surrogate Models



Basic structure of MLP. (Wang & Wu, 2020)

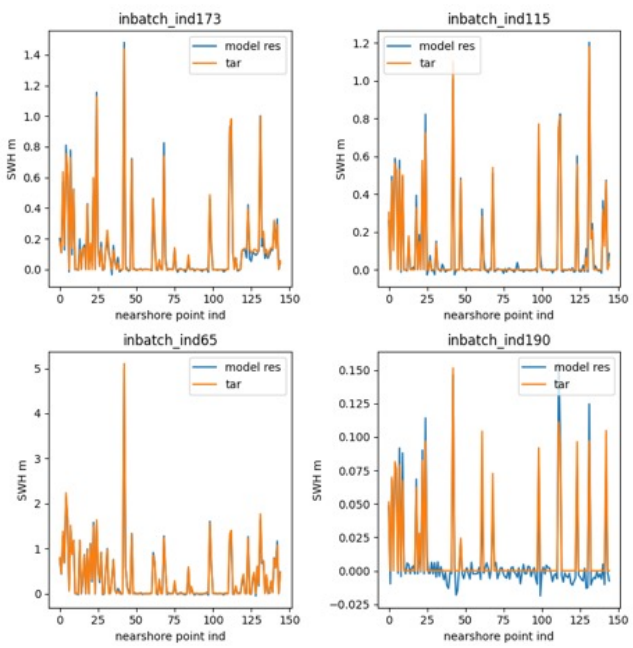


The structure of a LSTM cell. (Jiang et al., 2020)

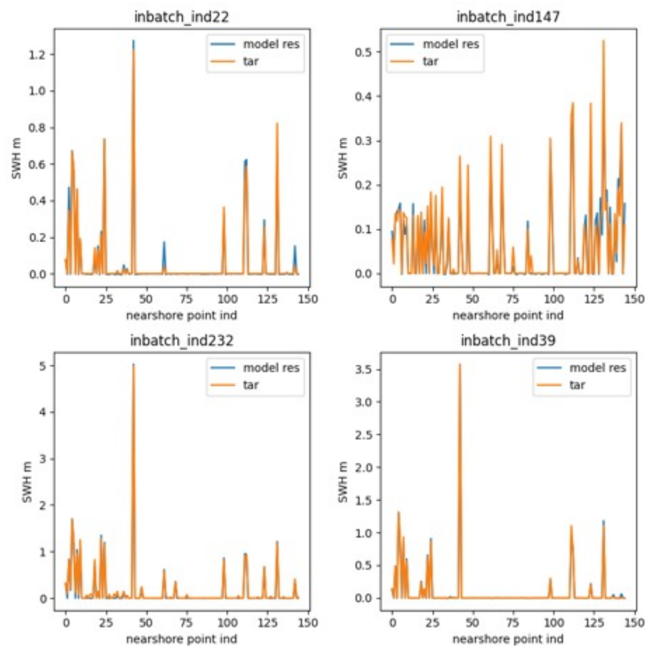
- Loss function: MSE Loss with L2 regularization
- Models are tested on unseen tracks, time and space respectively

Results&Discussion - Model Accuracy

LSTM Prediction



MLP Prediction



	Bias (10^{-3} m)	RMSE (10^{-2} m)	MAE (10^{-2} m)	SI	CC	CoE	IoA
LSTM	-2.25	3.68	1.98	0.22	0.996	0.992	0.998
MLP	-2.84	2.67	1.15	0.17	0.998	0.995	0.999

- Insight: Both models show commendable agreement
- Observation: A context sensitive model behaviour
- MLP slightly outperform the LSTM
- Comparative advantage over prior research (James et al., 2018 , Malde et al., 2016)

Results&Discussion - Model Generalization

Dimension to generalize: Time

	Bias (10^{-3} m)	RMSE (10^{-2} m)	MAE (10^{-2} m)	SI	CC	CoE	IoA
LSTM	390	59	39	5.27	0.648	-3.30	0.589
MLP	1.02	4.48	2.03	0.37	0.990	0.979	0.995

Dimension to generalize: Track

	Bias (10^{-3} m)	RMSE (10^{-2} m)	MAE (10^{-2} m)	SI	CC	CoE	IoA
LSTM	-3.33	3.18	1.78	0.18	0.997	0.994	0.999
MLP	-1.37	4.05	1.70	0.25	0.995	0.990	0.997

Table of performance metrices for estimation of SWH at coastline against numerical model output.

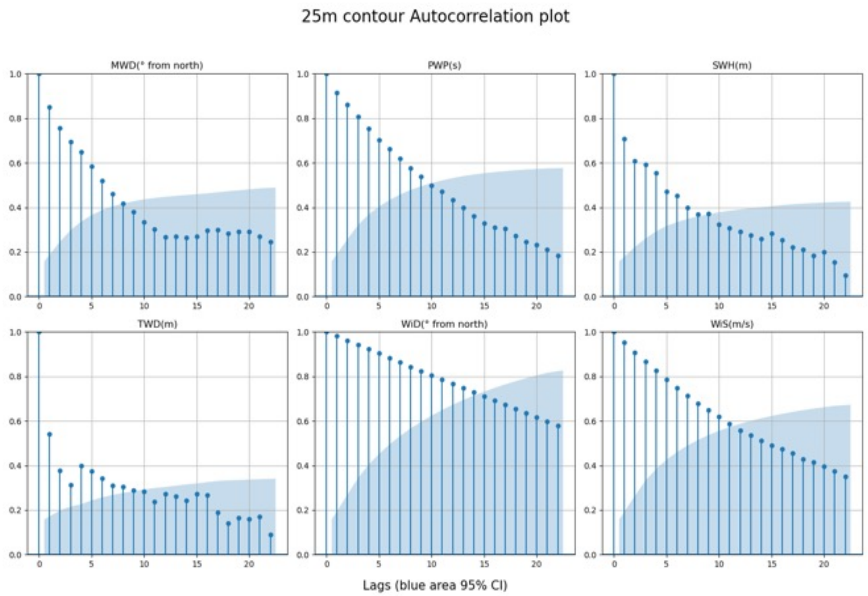
Observation:

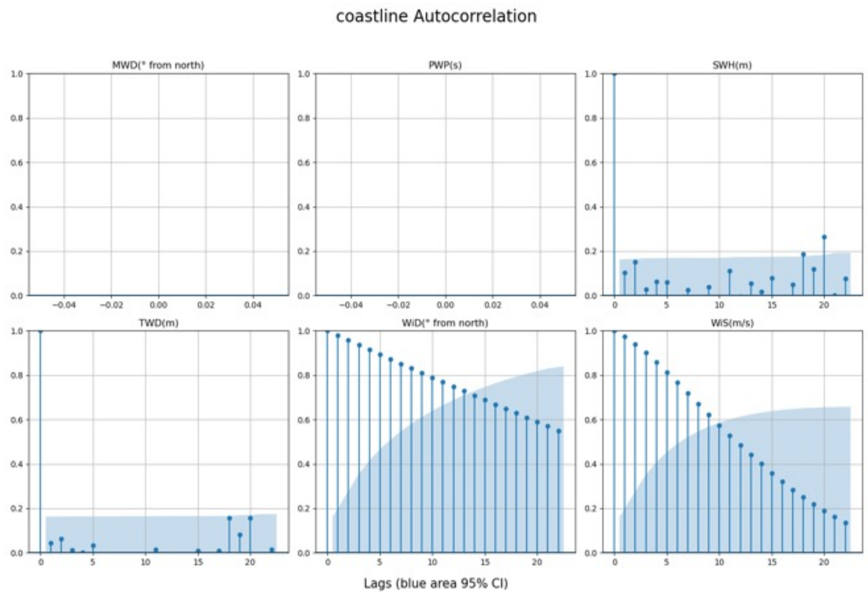
- Both models predict well on unseen tracks. The LSTM slightly outperforms MLP.
- The LSTM fails on unseen time (the last 20% of time). MLP acts more consistently.

Discussion:

- High feature dimensions (track * time) and much shorter timeseries length. (Sutskever et al., 2014, Pascanu et al., 2013)
- And (next slice)

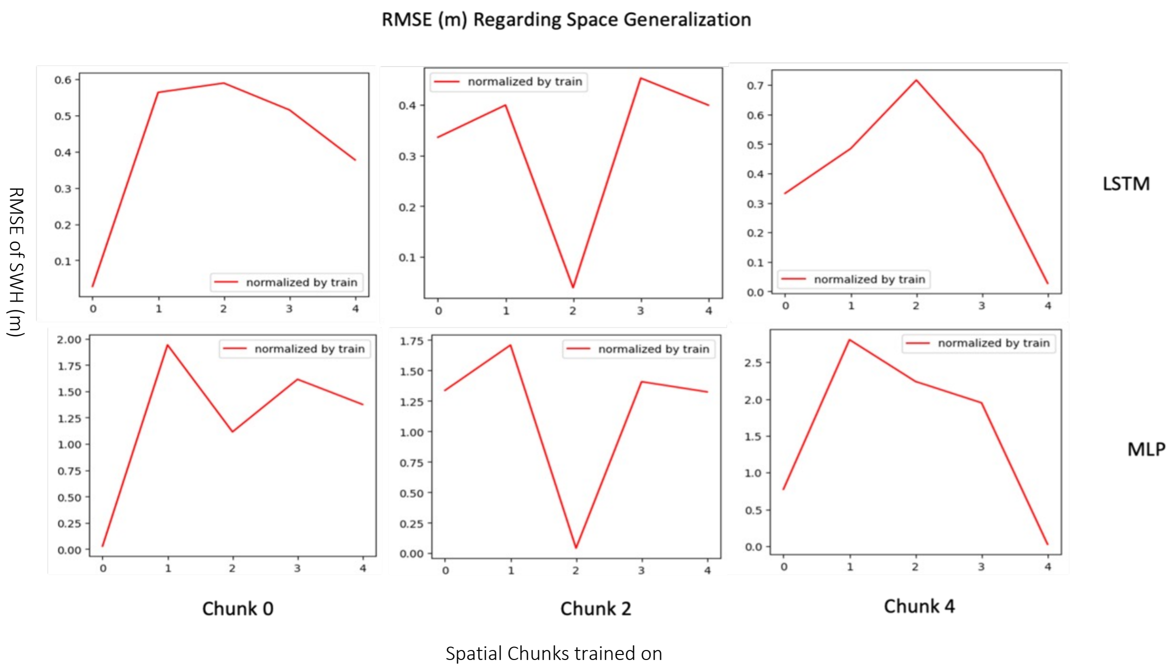
Results&Discussion - Model Generalization





- A lack of time structure in model target (SWH at coastline)

Results&Discussion - Model Generalization



RMSE of models tested on neighbor space chunks

Observation:

- The error is 3-6 times larger than the mean value. Both model failed, even in the closest chunk.

Discussion:

- Spatial Generalization Challenges. A lack of bathymetry
- Attempts at Incorporating Spatial Characteristics
  - Despite adding elevation levels and distance metrics, no improvement in model generalization

Conclusions & Future Directions

1.Conclusion

1. Recap: Aim to use MLP & LSTM as surrogates to enhance computational efficiency in wave downscaling.
2. Discoveries: Models tend to slightly over/underestimate SWH; In generalization, LSTM struggles with high feature dimensions and short sequences; Generalization to neighboring locations remains a challenge.

2.Future Work

1. Incorporate bathymetry data.
2. Revise model structures to predict different spaces.
3. Contrast traditional ML surrogate models with DL surrogates concerning extreme wave conditions.
4. Investigate the impact of feature dimension and time series length on LSTM performance.

Thanks for Listening

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