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CRSLR Research Group

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Wave downscaling using machine learning

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Goal & Motivation

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Problem

- Ensemble nearshore wave projections are required to assess uncertainties in **future wave climate**
- Ensemble wave projections are available offshore
- Wave downscaling from offshore to nearshore using numerical models requires high computational capacity -> **Wave propagation involves non-linear processes**

Solution?

- **Can machine learning models be an efficient tool for downscaling wave projections?**
  - Condition: A representative set of nearshore and offshore wave data is needed in order to train the model

Methods

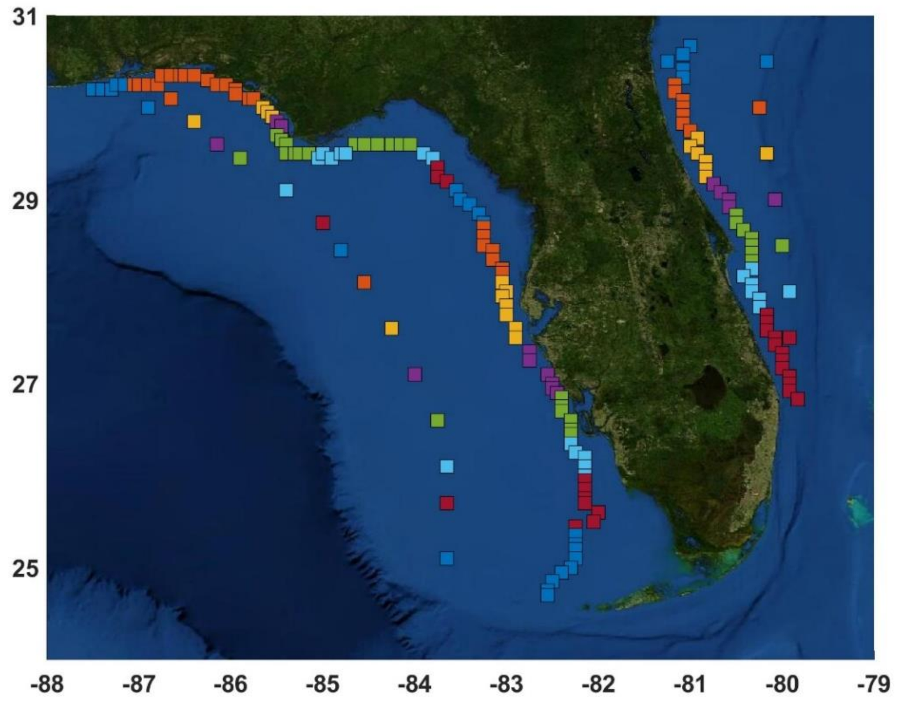
- We test the **performance** of 4 models on representing the links between offshore & nearshore waves:
  - **Multi Linear Regression** (MLR)
  - **Random Forest** (RF)
  - **Multivariate Adaptive Regression Splines** (MARS)
  - **Artificial Neural Networks** (ANN)

Machine Learning Models

- **Inputs & Outputs:** Offshore & Nearshore wave parameters

$$\mathbf{X}(Hs, Tm, Tp, Dir)_{OFFSHORE} \longrightarrow \mathbf{Y}(Hs, Tm, Tp, Dir)_{NEARSHORE}$$

- **Data**: Wave Information Studies Hindcast (WIS) of US Army Corps of Engineers
  - Hourly Sea States from 1980 to 2014



- **Input & Output stations**: Correlation between offshore and nearshore Stations

- **Performance**: 10-Fold cross validation
  - RMSE, R^2 (bias, scatter index,…)

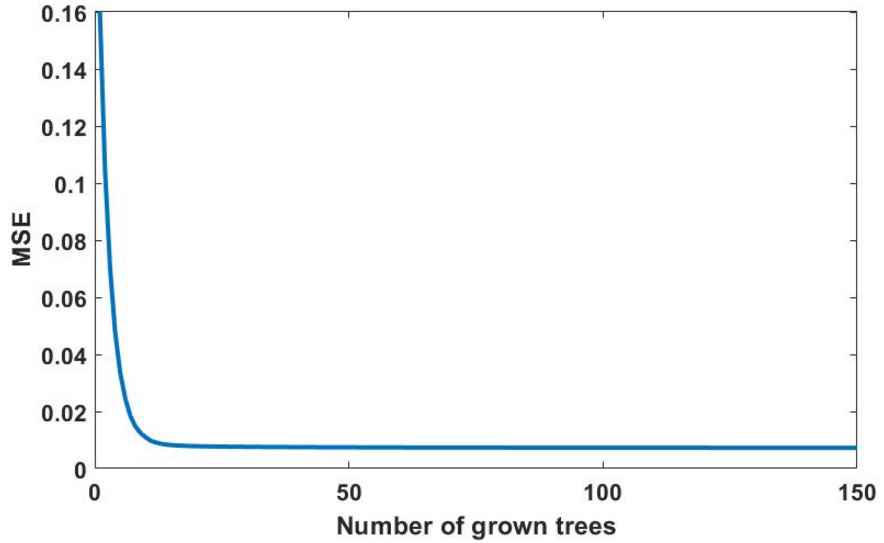
Machine Learning Models

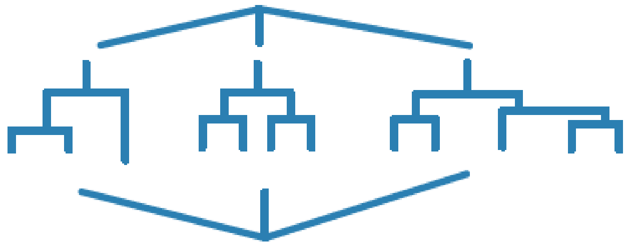
- **Multi Linear Regression**

$$\boxed{\mathbf{Y}(Hs,Tm,Tp,Dir)_{NEARSHORE} = \beta \cdot \mathbf{X}(Hs,Tm,Tp,Dir)_{OFFSHORE}}$$

  - Pros: Easy implementation and interpretation
  - Cons: Non-linear wave propagation processes

- **Random Forest**
  - A number of decision trees (*bagged*) are trained independently on bootstrapped data from the input dataset.
  - Pros: Fast algorithm, easy implementation, able to capture non-linearities and provides quantiles of the response variable
  - Cons: Difficult interpretation





Machine Learning Models

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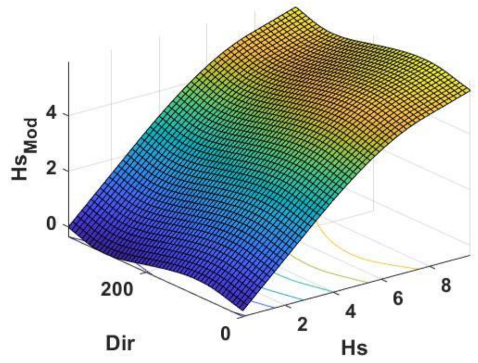
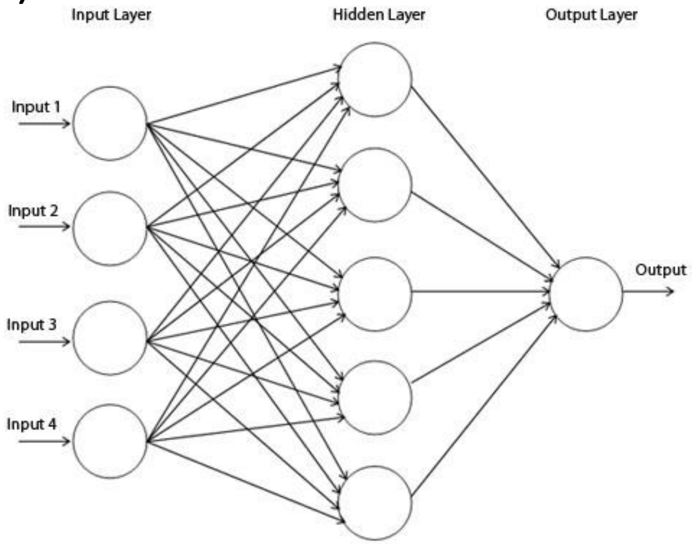
- **Multivariate Adaptive Regression Splines**
  - The algorithm automatically selects the cutpoints (*Knots*) of the predictors for fitting cubic regressions where the smallest error is achieved.
  - Pros: Automatically captures non-linear relationships and easy interpretation
  - Cons: Computational expensive compared to MLR and RF

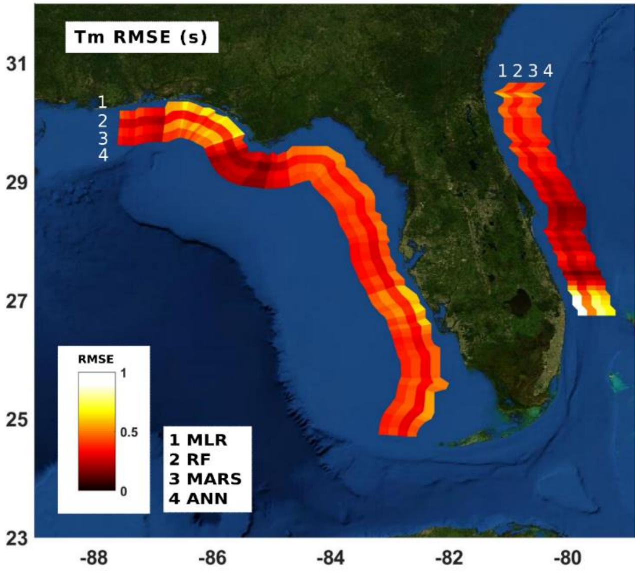


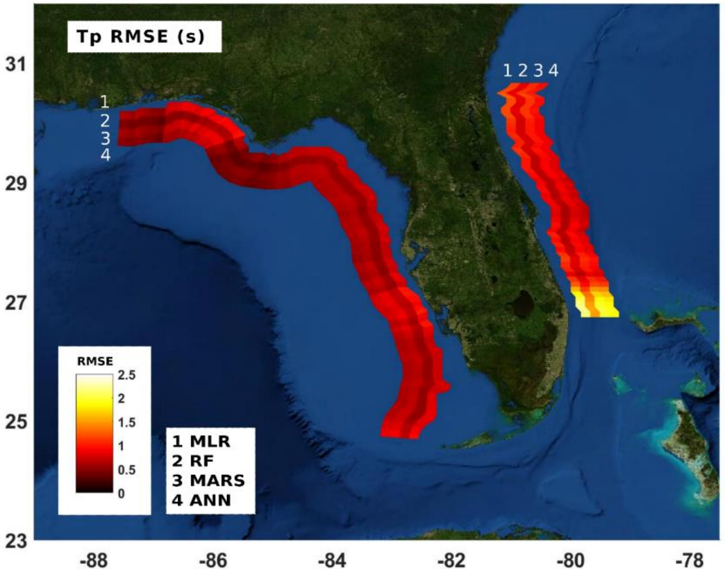
- **Artificial Neural Network**
  - Connected networks of neurons that are iteratively trained (by modifying the weights of the connections) to relate the inputs (*predictors*) to the output (*response*)
  - Network architecture:
    - 1 Hidden Layer with 10 neurons
    - Transfer function hidden layer: tan sigmoid
    - Transfer function output layer: purelin
  - Pros: Automatically captures non-linear relationships
  - Cons: Not computational efficient compared to MLR and RF, network architecture has to be defined in order to obtain good performance

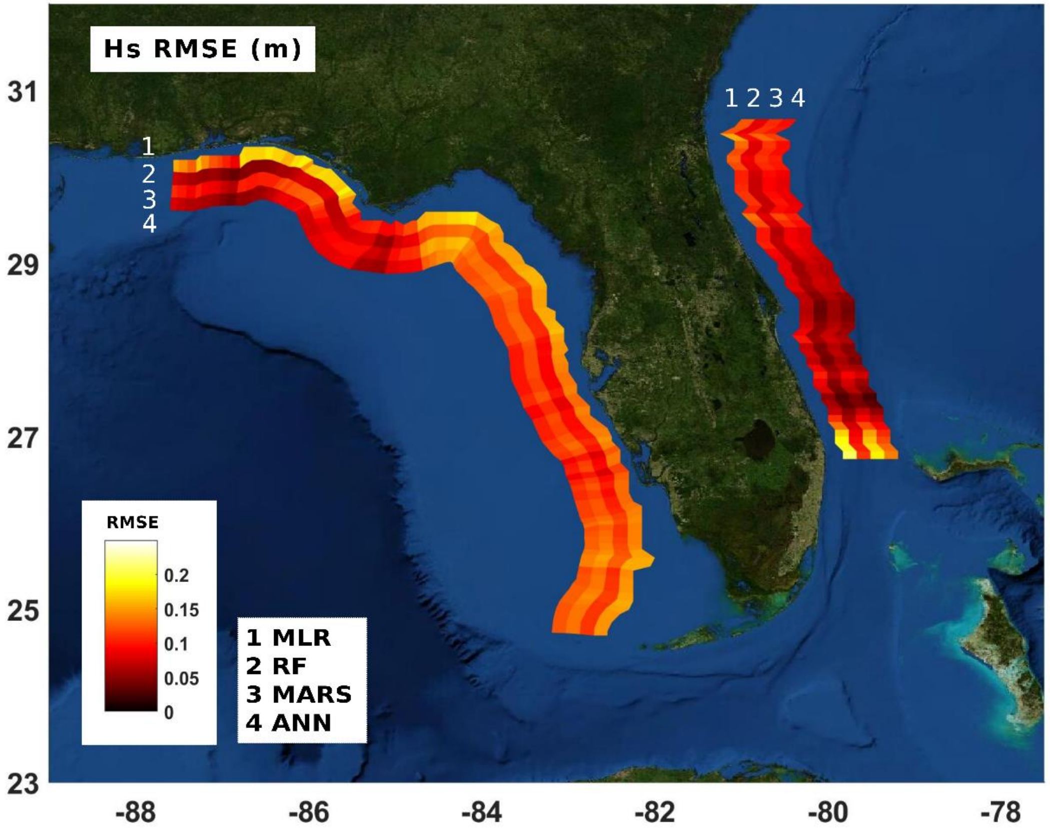


Models' Performance

- **RF outperforms** the other models, it is easy to implement and computational efficient
  - Hs is simulated with average error of 11% along the entire coast of Florida and 6% in the extremes
  - Similarly, Tp and Tm are simulated with errors between 5% to 6%

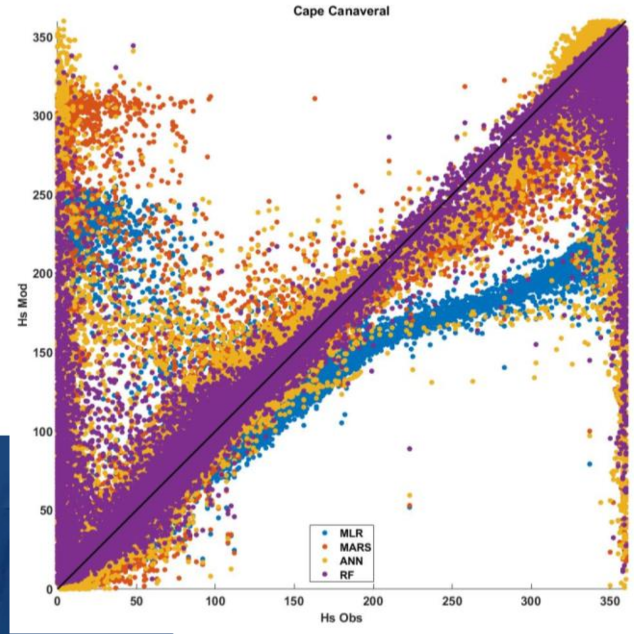




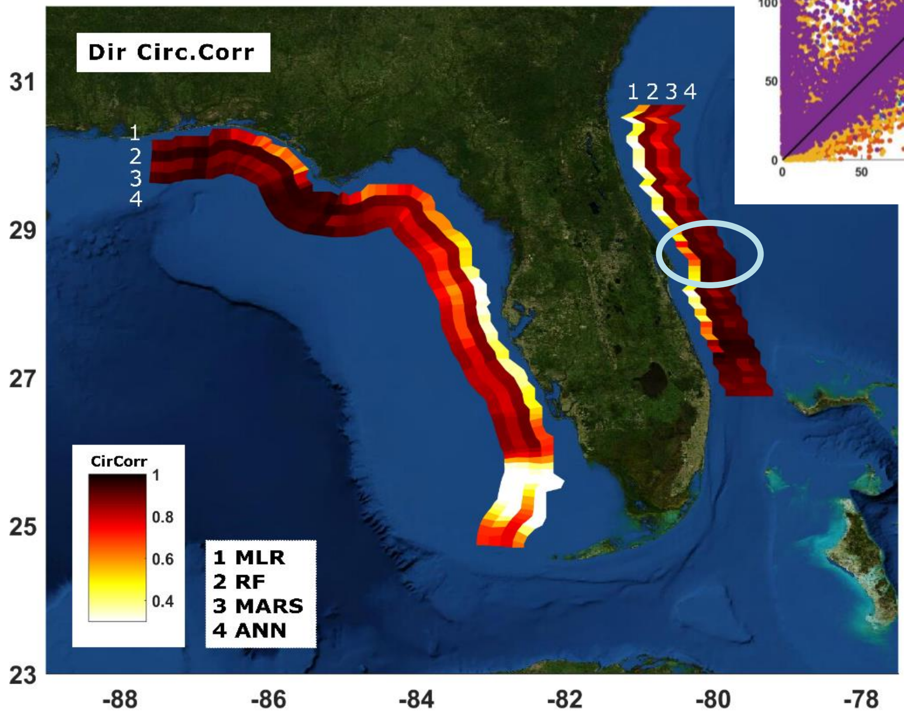


Models’ Performance Dir

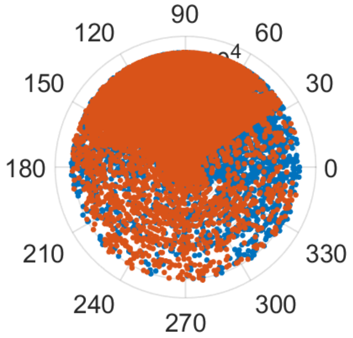
- Poor performance modelling the Dir by all models
- Models are not able to capture the behavior of directions within the North sector



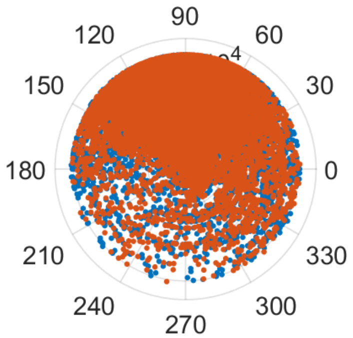
- <u>**Dir is a Circular Variable**</u>
- **Transformation of Dir** into 2 variables: **Sine & cosine** improves model performance



No Transformation



Transformation sin & cos



Take-Home Message

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Machine learning models are an efficient tool for downscaling wave projections, which are still omitted in the majority of coastal flood assessments

- **RF outperforms the other models and requires lower computational time**
- **Circular variables such as the Dir require a transformation into two variables in order to accurately model the North sector**