Nonlinear Wave Ensemble Averaging using Neural Networks

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"Improving Global Wind-Wave Probabilistic Forecasts and Products Beyond Week 2"
Award Number: NA16NWS4680011
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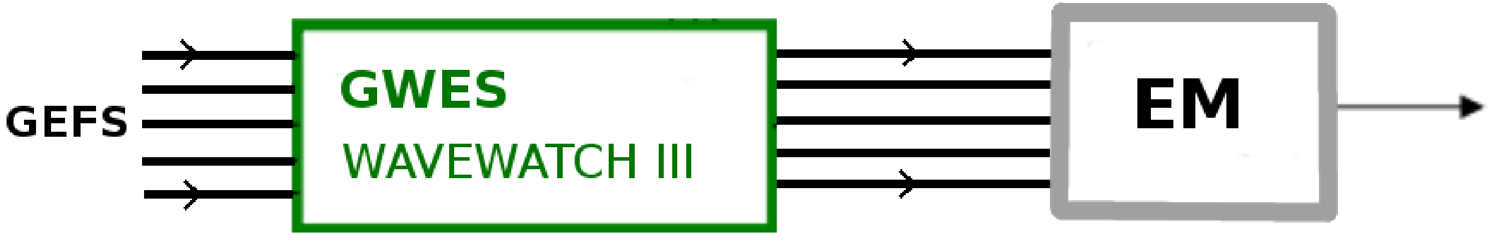
Outline

- Introduction to GWES
- MLP Neural Networks applied to non-linear ensemble averaging
- First tests at single locations
  - NN Architectures
  - Tests with number of neurons, normalization etc
  - Error in function of Forecast time
  - Error in function of Severity (Percentiles)
- **NN spatial approach - GOM**
  - **NN Training Strategy**
  - **Spatial Distribution of Wind and Wave Climates**
  - **Assessment of GWES using NDBC buoys**
  - **Large sensitivity test (105,600 NNs): number of neurons, initialization, filtering**
  - **Results for GOM**
- Conclusions and Next steps

Global Wave Ensemble System (GWES)

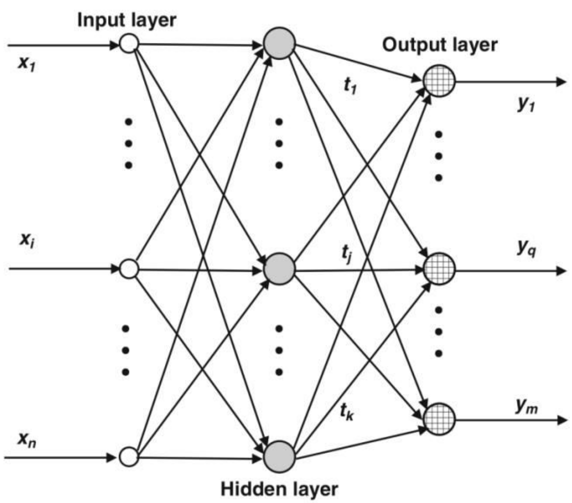
- The GWES was implemented in 2005 (Chen, 2006);
- 4 cycles per day;
- Resolution of 0.5 degree and 3 hours;
- Forecast range of 10 days;
- Total of 20 ensemble members plus a control member
- Forced by Global Ensemble Forecast System (GEFS) winds on WAVEWATCH III model (Tolman, 2016)
- Last major upgrade: 12/2015
- Arithmetic Ensemble Mean: $EM = \frac{1}{n}\sum_{i=1}^{n} x_i$



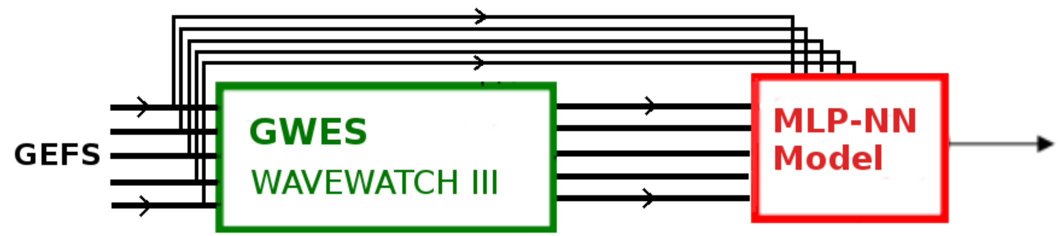
MLP Neural Networks

Multilayer perceptron model (MLP-NN) with hyperbolic tangent at the activation function. x_i is the input and y_q the output, a and b are the NN weights, n and m are the numbers of inputs and outputs respectively, and k is the number of nonlinear basis functions (hyperbolic tangents, or ¨neurons¨)

$$NN(x_1, x_2, \cdots, x_n; a, b) = y_q = a_{q0} + \sum_{j=1}^{k} a_{qj} \, . \, tanh\left(b_{j0} + \sum_{i=1}^{n} b_{ji} . x_i\right); \quad q = 1,2, \ldots, m$$



AI techniques provide a number of advantages, including easily generalizing spatially and temporally, handling large numbers of predictor variables, integrating physical understanding into the models, and discovering additional knowledge from the data (McGovern et al., 2017).



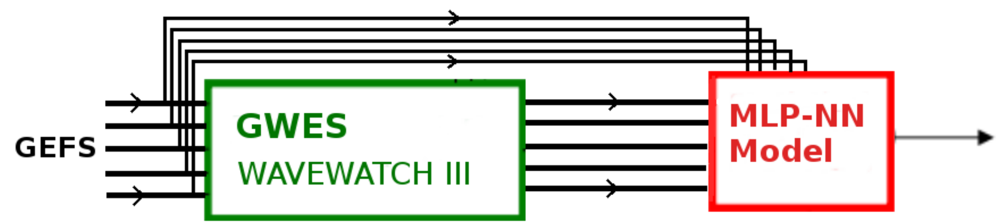
- Constructed based on Haykin (1999), Krasnopolsky (2013), and Krasnopolsky and Lin (2012)
- NNs have been used in a wide variety of meteorology applications since the late 1980s (Key et al. 1989), from cloud classification (Bankert 1994), tornado prediction and detection (Marzban and Stumpf 1996; Lakshmanan et al. 2005), damaging winds (Marzban and Stumpf 1998), hail size, precipitation classification, tracking storms (Lakshmanan et al. 2000), and radar quality control (Lakshmanan et al. 2007; Newman et al. 2013).

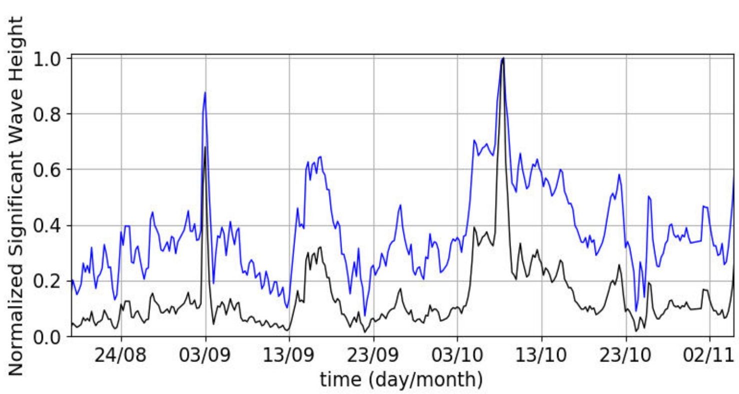
MLP Neural Networks

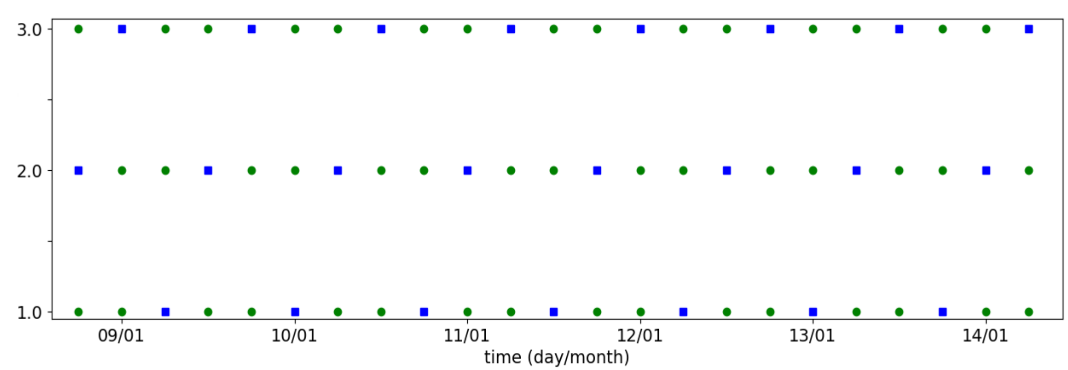
$$NN(x_1, x_2, \cdots, x_n; a, b) = y_q = a_{q0} + \sum_{j=1}^{k} a_{qj} \,.\, tanh\left(b_{j0} + \sum_{i=1}^{n} b_{ji} . x_i\right); \quad q = 1,2, \ldots, m$$

- Target variables: significant wave height (Hs), peak wave period (Tp) and 10-meter wind speed (U10m) from measurements;
- Evaluated against buoy measurements during the training process;
- 21 ensemble members (20 plus the control member) per variable (total of 63), plus the sin and cosine of time;
- Latitude and Longitude are included as inputs during the regional analyses;
- For now: one NN per forecast time.

- Training (2/3) and test set (1/3);
- Cross-validation with 3 cycles;
- Normalization using log function:





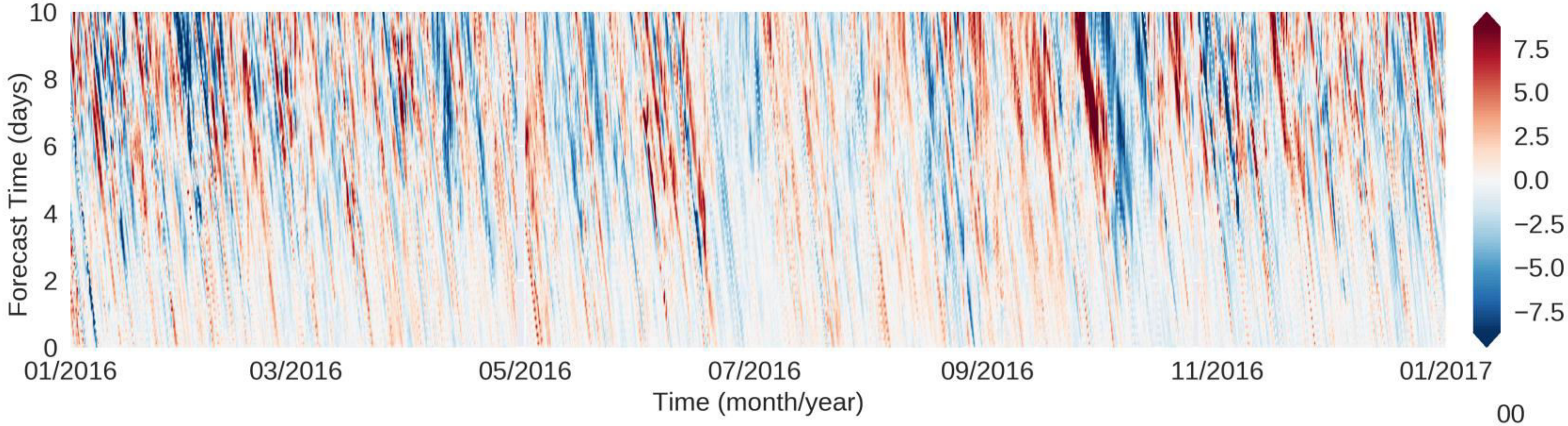


First tests at single locations

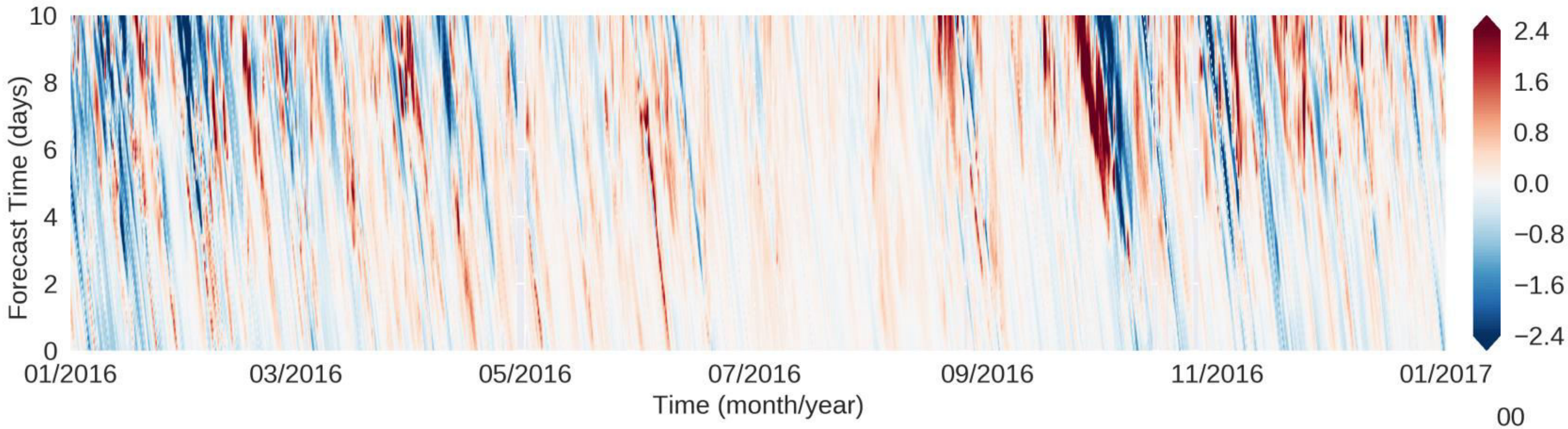
$$Bias = \frac{\sum_{i=1}^{n}(M_i - B_i)}{n}$$

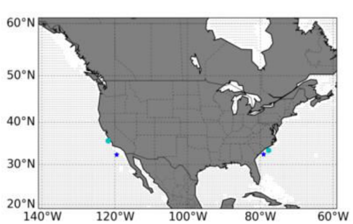
Evolution of the GWES error with forecast time (up to 10 days)

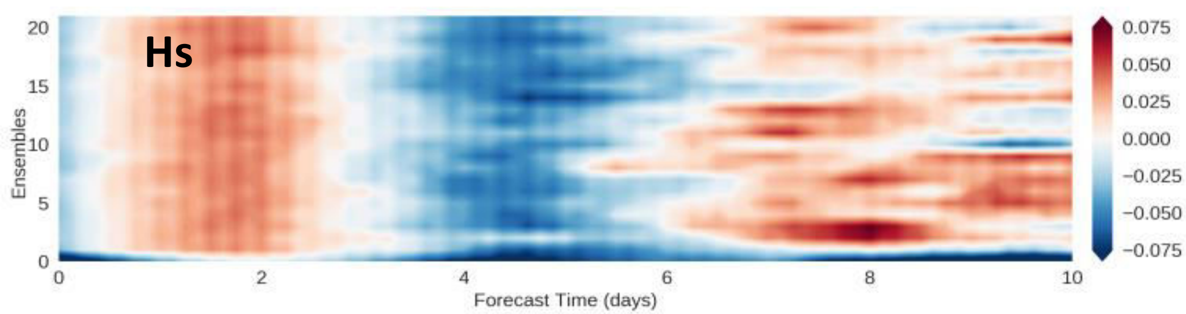
U10m



Hs

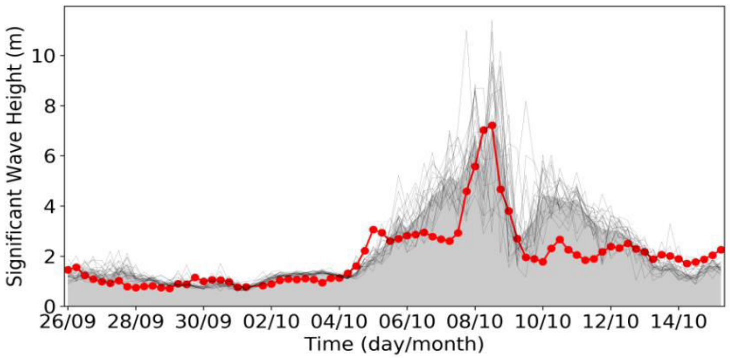






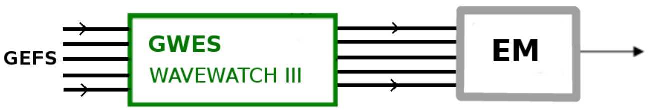
First tests at single locations

¨*NNs are never used (or should never be used) for problems that can be solved using linear models*¨ (Krasnopolsky, 2014) .

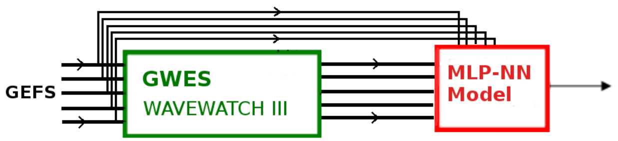


1. NN models are indicated primarily to nonlinear problems;
2. NN cannot deteriorate the EM!

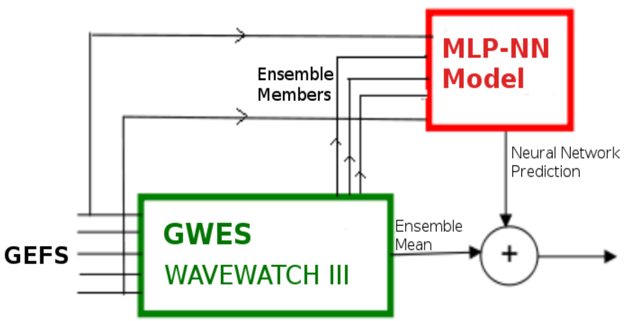
Residue (measurements - model**) as the target variable**



$$EM = \frac{1}{n}\sum_{i=1}^{n} p_i \quad (1)$$



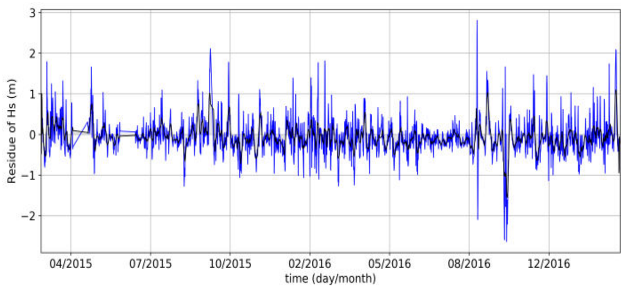
$$NEM = NN(p_1, p_2, \cdots, p_n) \quad (2)$$



$$NEM = EM + NN_r(p_1, p_2, \cdots, p_n) \quad (3)$$

First tests at single locations

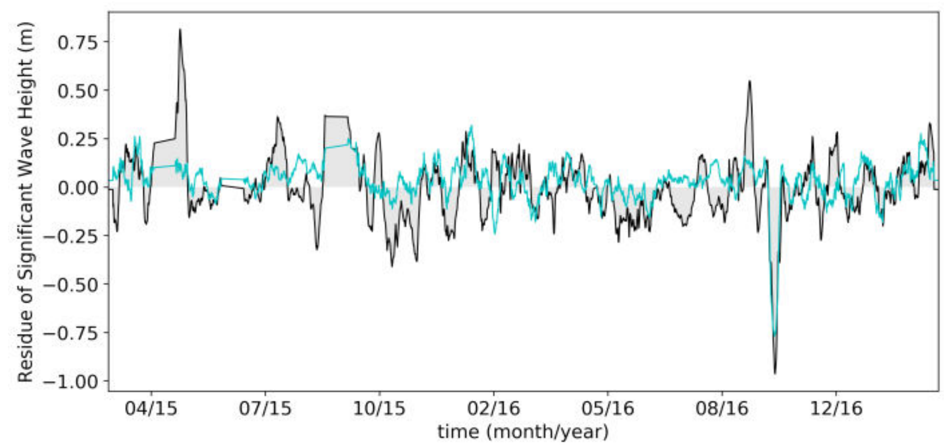
Initial problems with noise



The best NN model: 11 neurons at the intermediate layer

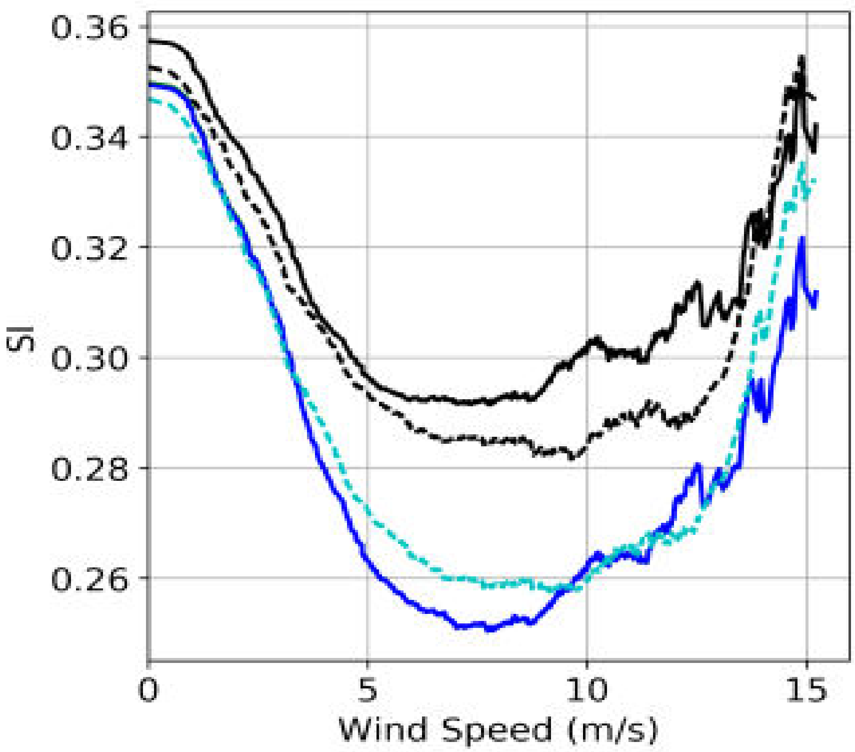
41004	bias	RMSE	SI	CC
Best Member GWES	-0.101	0.526	0.427	0.724
EM GWES	-0.115	0.457	0.371	0.755
Linear Regression model	0.094	0.433	0.352	0.739
NN ensemble (5 members)	0.041	0.373	0.303	0.807

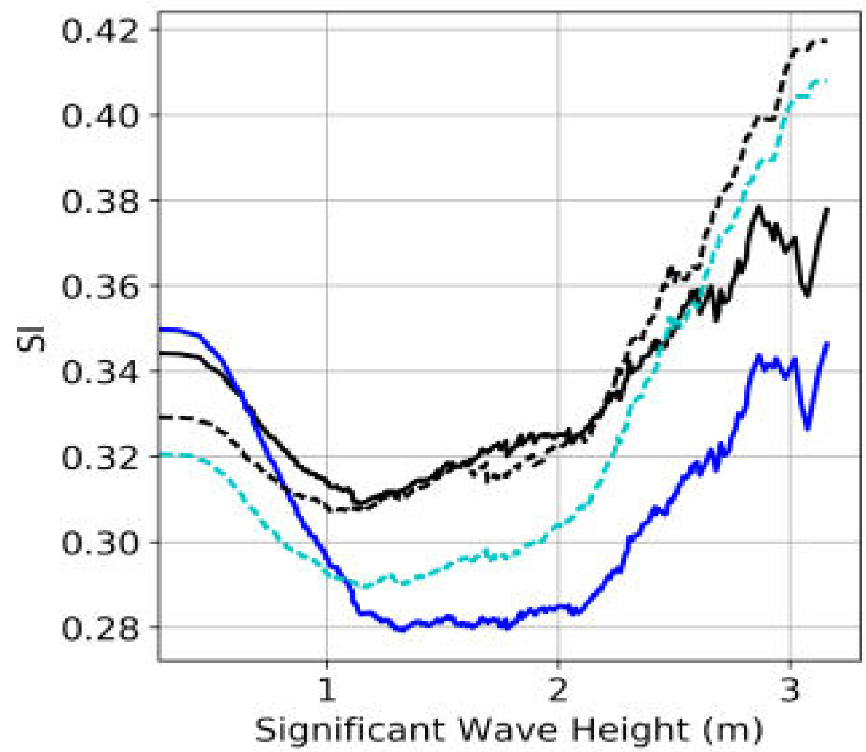
Time series of filtered residue of Hs (meters) in black (buoy measurement minus the GWES arithmetic mean of ensemble members) and the predicted residue in cyan, for the independent validation set at buoy 41013



First tests at single locations

Reduction of the error with increasing quantiles.
Results of the NN simulation at the two Atlantic Ocean buoys. Curves of scatter indexes in function of quantiles; black: arithmetic mean of ensembles (EM); blue: NN-training set (buoy 41004), cyan: NN-validation set (buoy 41013). Solid lines indicate buoy 41004, and dashed lines buoy 41013.



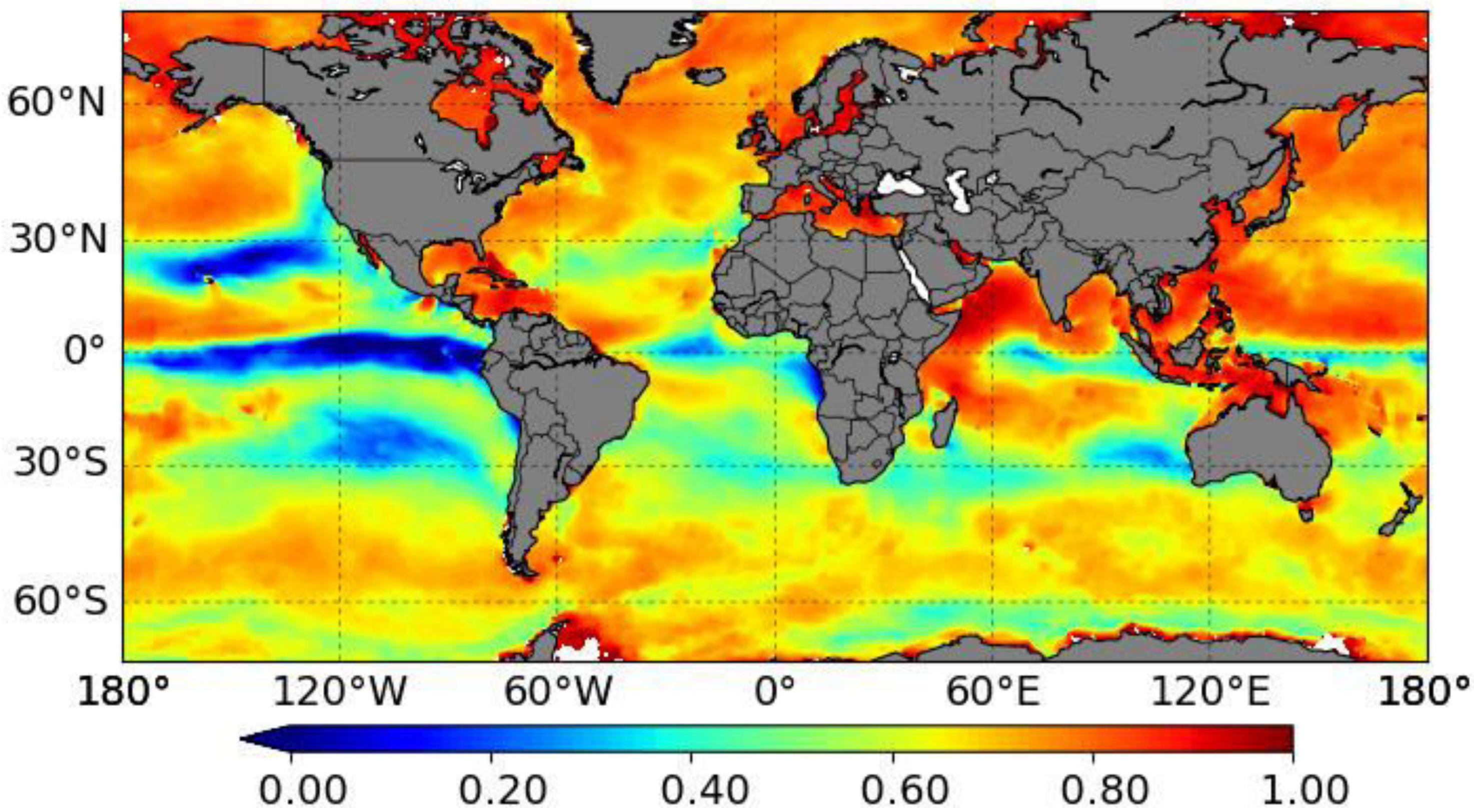


NN spatial approach

- Introduction of Lat/Lon as input variables instead of building one NN per grid point;
- Increase of NN complexity, Krasnopolsky (2013):

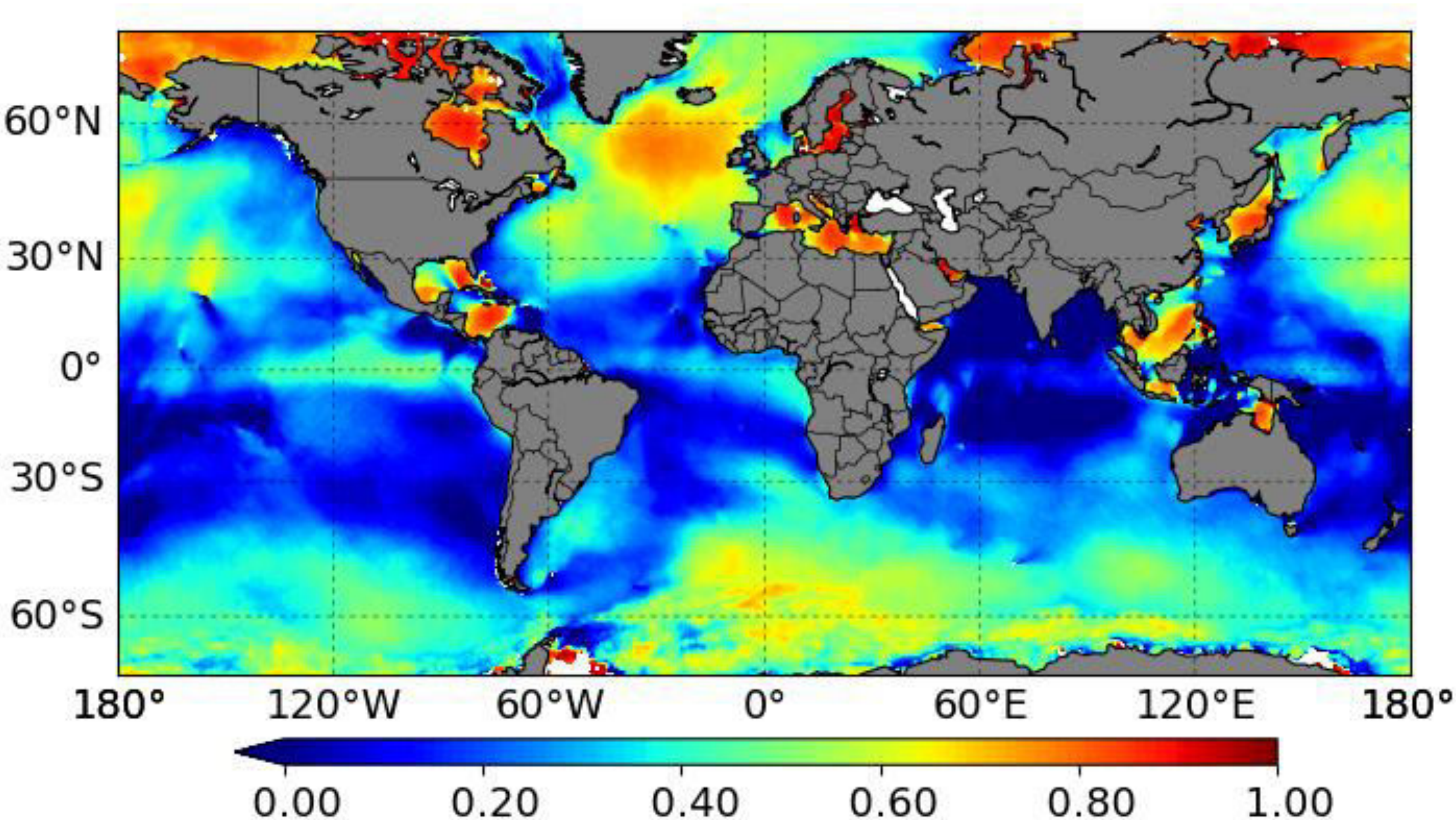
$$N_c = k.(n + m + 1) + m$$

Different wind and wave climates. Correlation Coefficient Map of U10m and Hs



NN spatial approach

Different wind and wave climates. Correlation Coefficient Map of Hs and Tp



NN spatial approach - GOM

Simulation at the Gulf of Mexico. Sensitivity test:

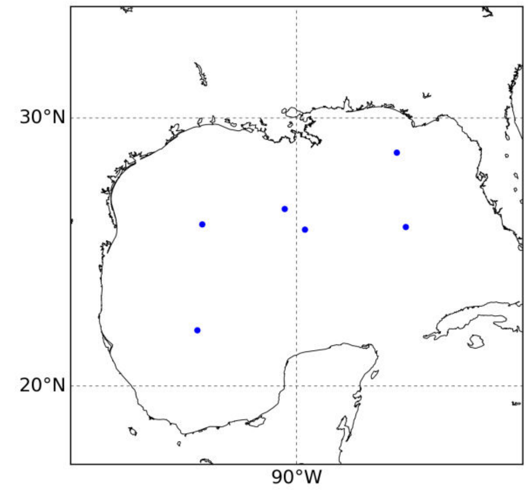
- Total of 12 different numbers of neurons

N [2, 5, 10, 15, 20, 25, 30, 35, 40, 50, 80, 200]

- 8 different filtering windows

FiltW [0, 24, 48, 96, 144, 192, 288, 480] hours

- 100 seeds for the random initialization

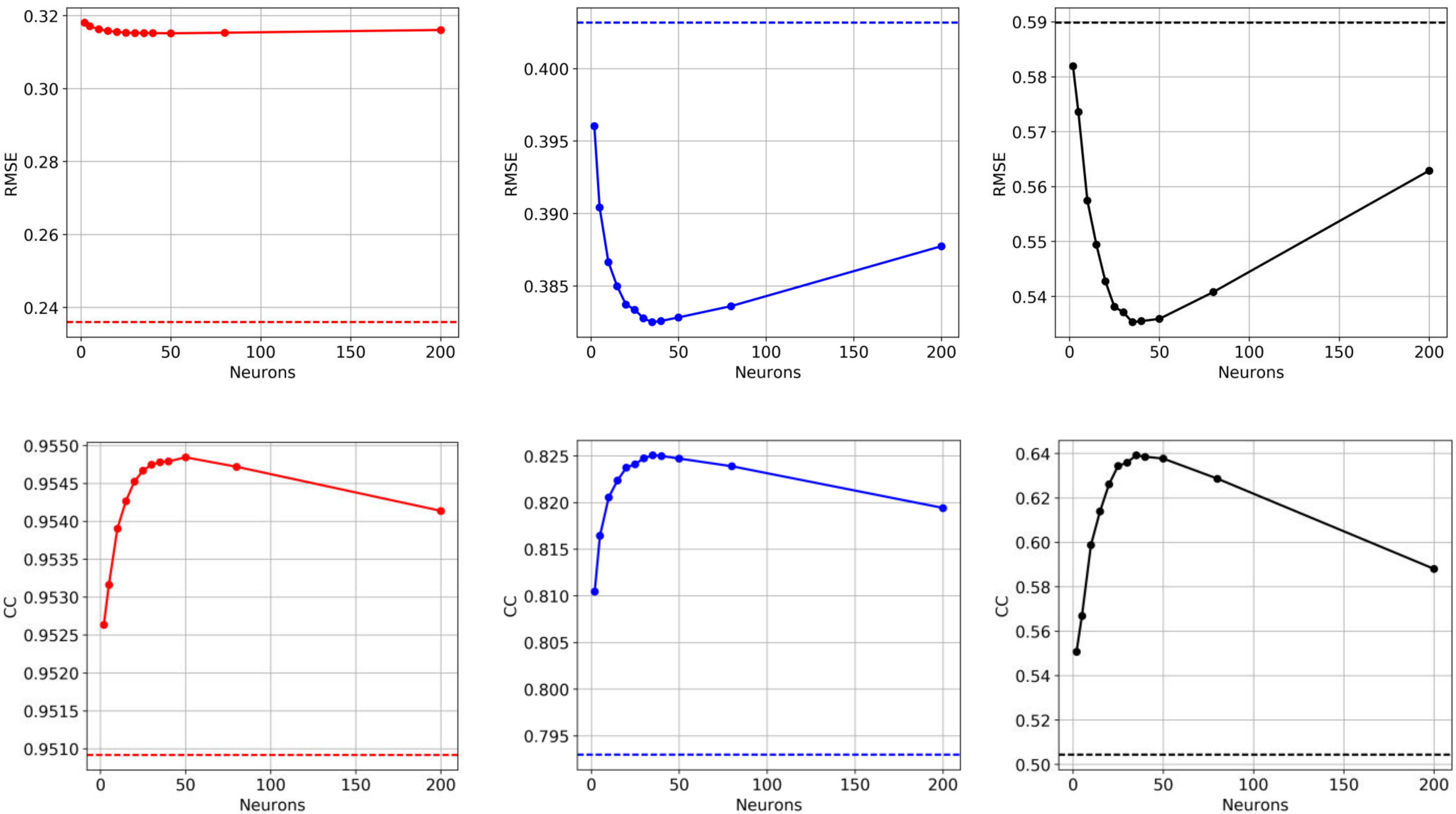


- Separated NNs for specific forecast days, from Day 0 to Day 10
- Total of 105,600 NNs
- NN training, 2/3 of inputs were selected for training and 1/3 for the test set, using a cross-validation scheme with 3 cycles
- *scikit-learn* (python) to reduce computational cost
- Six buoys appended to build the array with size 7913. NN is using sequential training

NN spatial approach - GOM

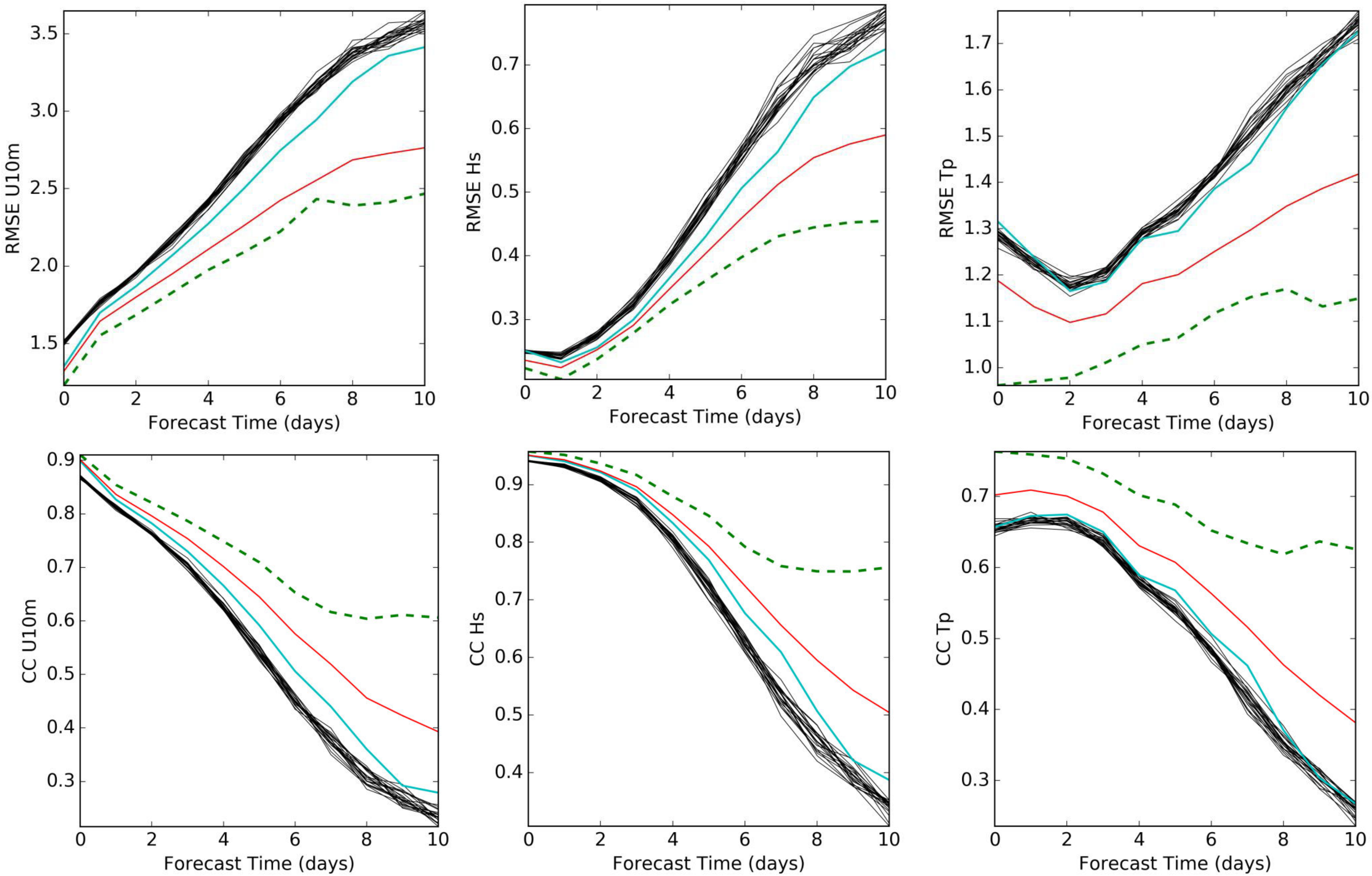
Hs

Day 0 | Day 5 | Day 10



Results: NN spatial approach - GOM

-Black: ensemble members
-Red: ensemble mean
-Cyan: control run
--Green: NN



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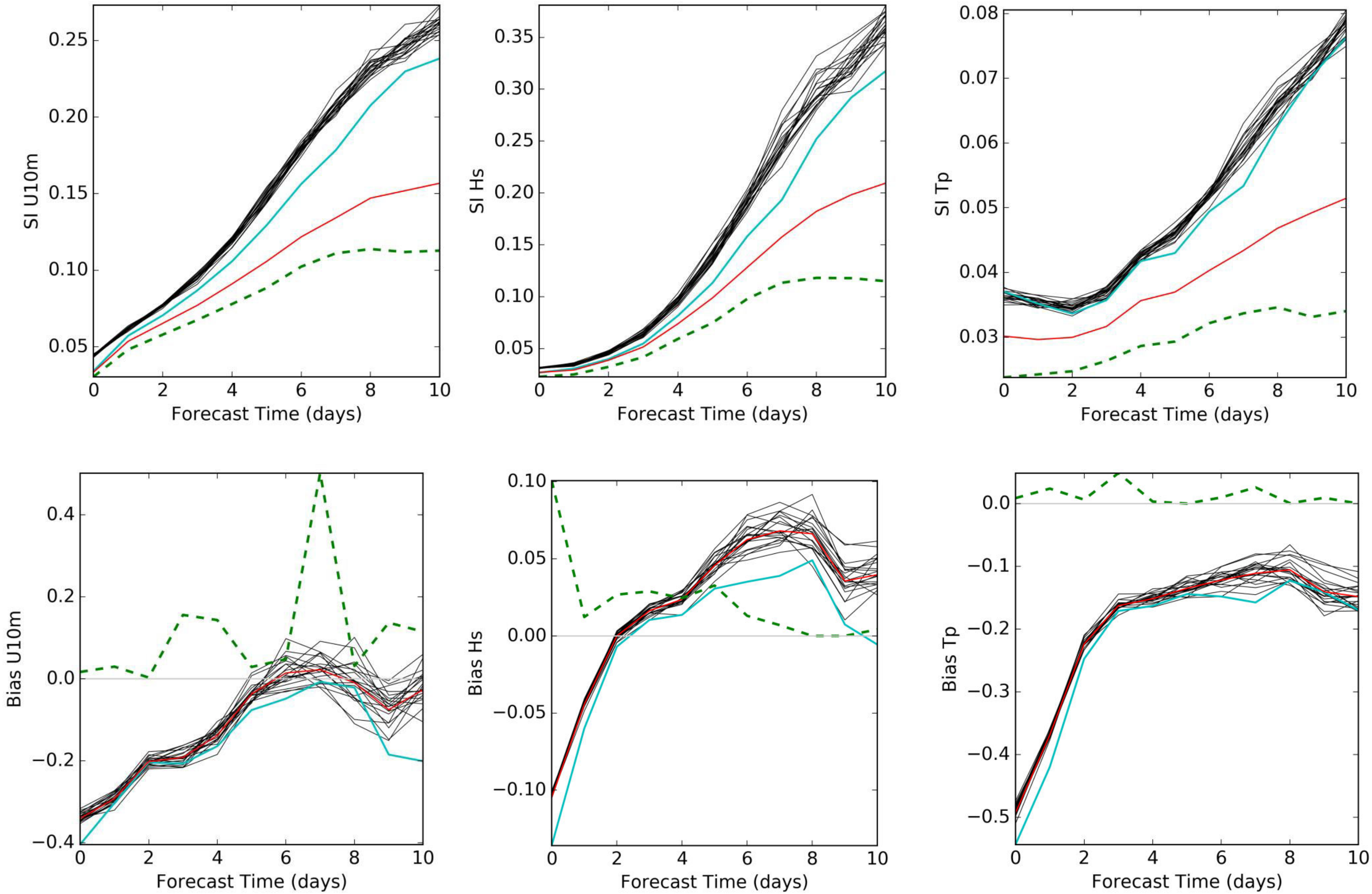


NN spatial approach - GOM

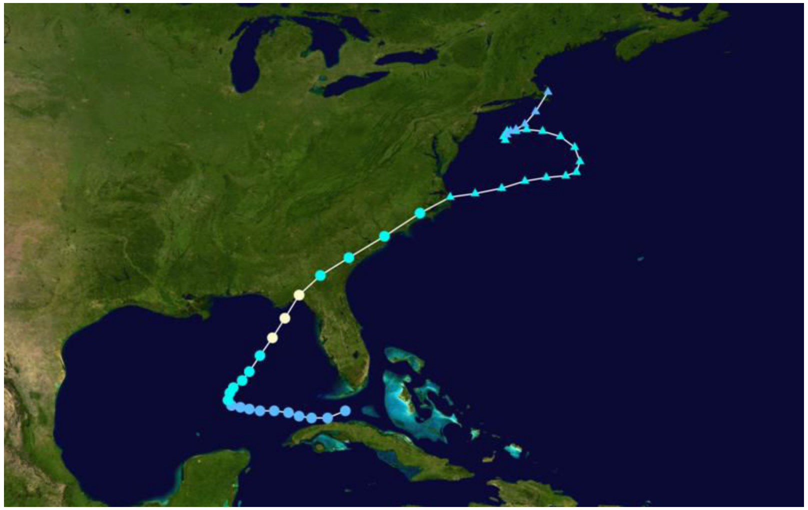
Hurricane Hermine

- August 28, 2016 to September 8, 2016
- Highest winds (1-minute sustained): 80 mph (130 km/h)
- Lowest pressure: 981 mbar (hPa)

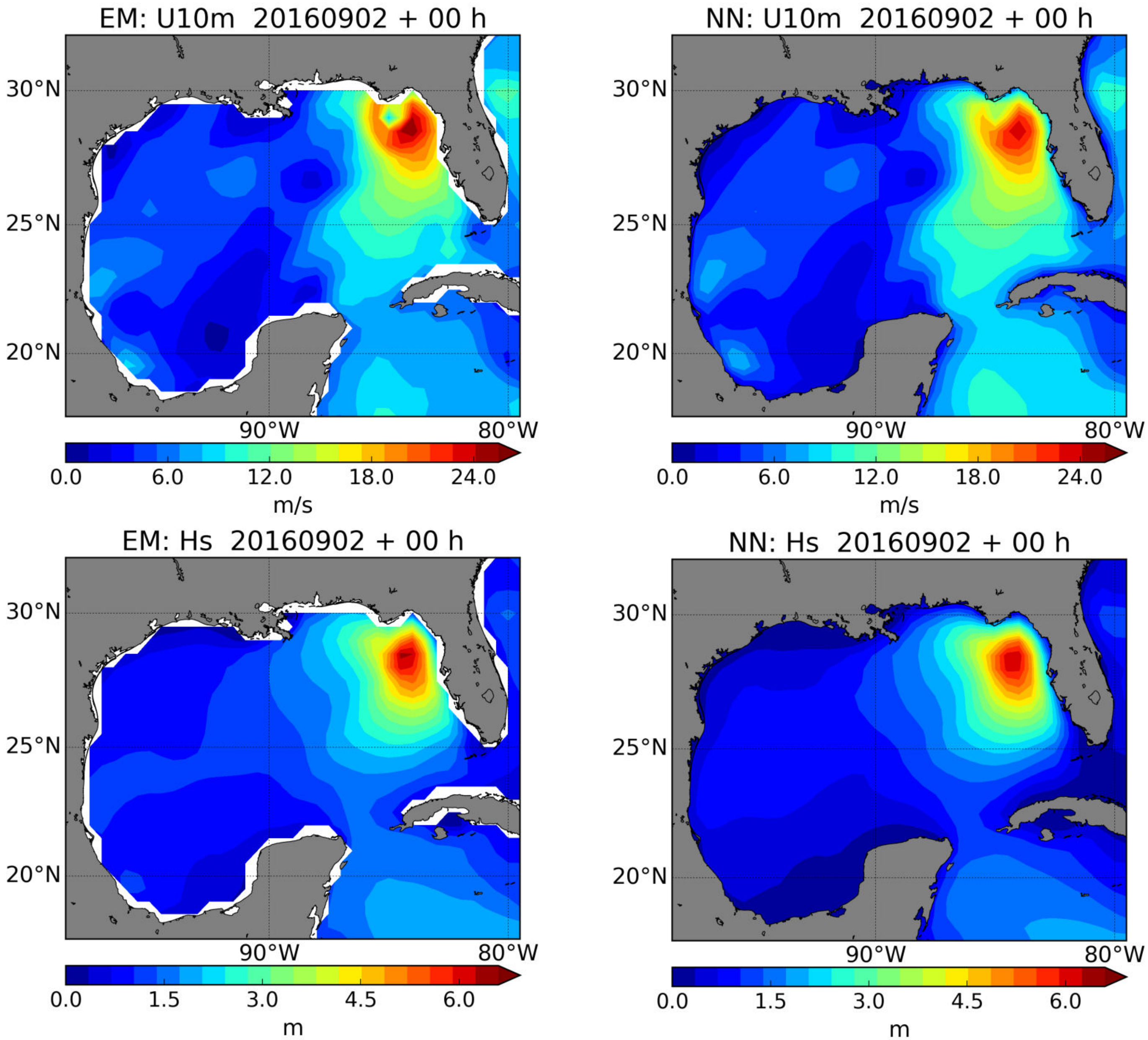
Example:

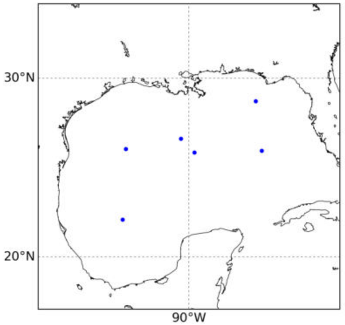
<u>Plots for the same day/time **September 02, 2016 – 00Z**</u>.

0, 5, and 10 days before.

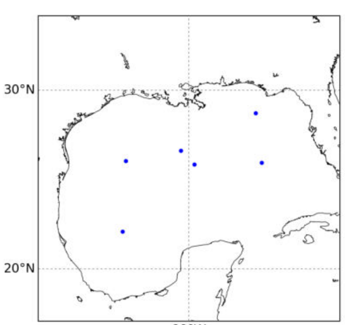


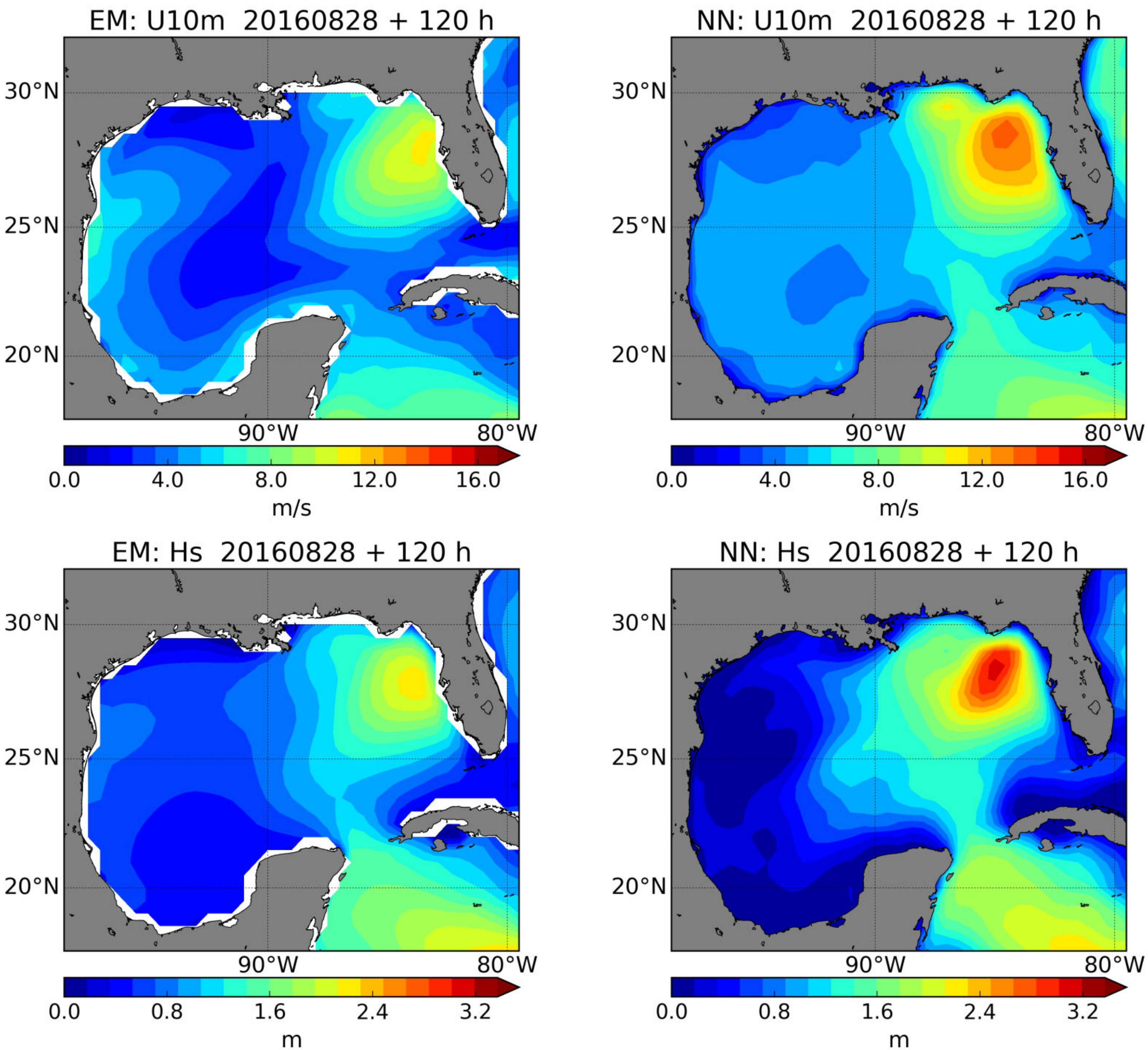
NN spatial approach - GOM



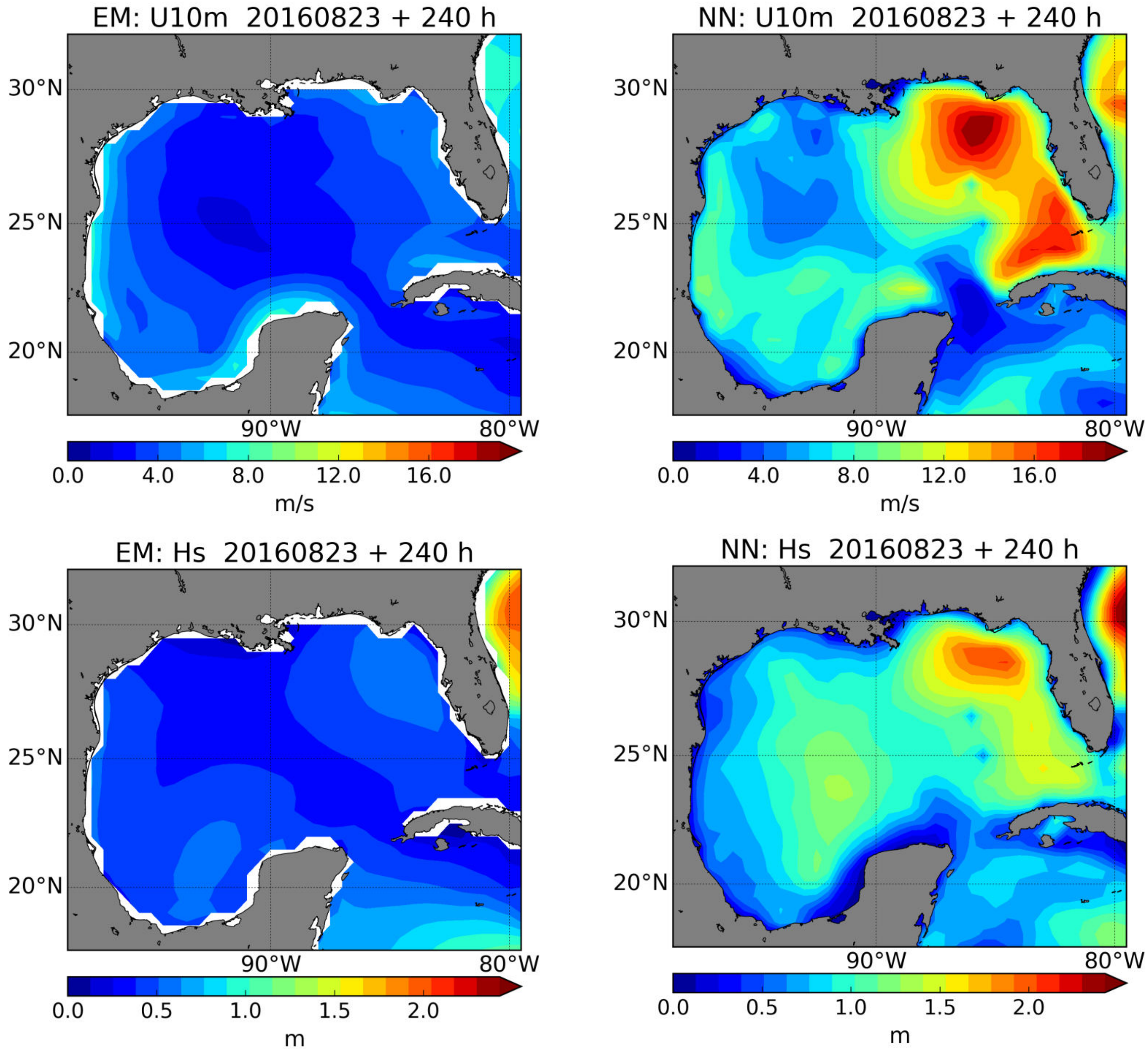


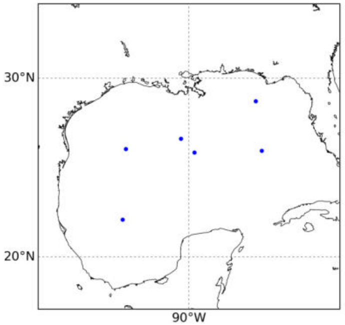
NN spatial approach - GOM





NN spatial approach - GOM



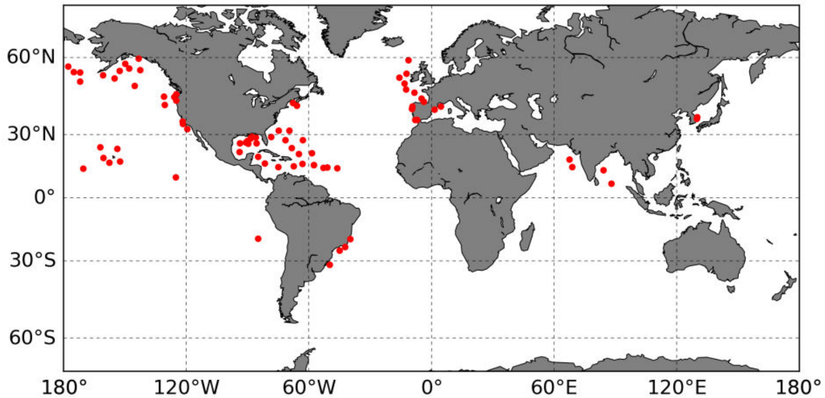


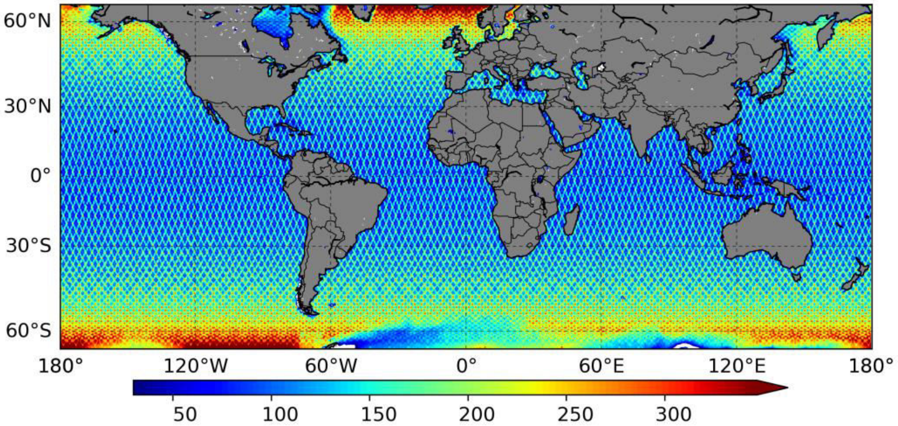
Conclusions

- **The largest errors in GWES, beyond forecast day 3, are found to be associated with winds above 14 m/s and waves above 5 m;**
- **Extreme percentiles after the 8th-day forecast reach 30% of underestimation for both U10 and Hs;**
- **Ensemble Approach: Critical systematic and scatter errors are identified beyond the 6th- and 3rd- day forecasts, respectively;**
- **The main advantage of the methodology using NNs at longer forecast ranges beyond four days.** NNs was able to improve the correlation coefficient on forecast day 10 from 0.39 to 0.61 for U10, from 0.50 to 0.76 for Hs, and from 0.38 to 0.63 for Tp.
- **Small number of neurons are sufficient to reduce the bias, while 35 to 50 neurons produce the greatest reduction in both the scatter and systematic errors.**

Next steps

- ❑ Currently expanding the NN modeling to the whole globe, using altimeter data, and joining all forecast times into the training (new degree-of-freedom);





- 07/2017 – 07/2018
- 84 buoys: 687,119 measurements of Hs, Tp and U10 (converted to 10-meter high)
- 4 satellite missions: 15,993,200 measurements between 60°S and 60°N

- ❑ Test different NN architectures and run more sensitivity tests;
- ❑ Analyze the error in function of location, forecast time, and percentiles;

Suggestions? Questions?

Obrigado!

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