Remote Sensing for Ocean Acidification:

Estimation of Dissolved Inorganic Carbon using a Neural Network Approach

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BACKGROUND:

- ↑ Atmospheric CO_2 → ↑ Ocean Acidification
- Impacts calcifying organisms
- Carbonate system controlled by balance of DIC
  - Aqueous CO_2
  - Carbonic acid
  - Bicarbonate
  - Carbonate

Neural Network (NN): machine deep learning structure that learns a set of undefined rules to transform input data into expected results. Once rules are learned (NN training), new input data can be fed into the NN to generate predictions.

IMPORTANCE:

Maine's economy is heavily dependent on the fisheries industry. In 2020, 80-85% of landings were comprised of calcium carbonate shelled organisms.

OBJECTIVE:

Quantify the DIC carbon pool in the Gulf of Maine via ocean color satellite reflectance data.

METHOD:

Train a neural network on field DIC measurements matched to corresponding satellite pixels.

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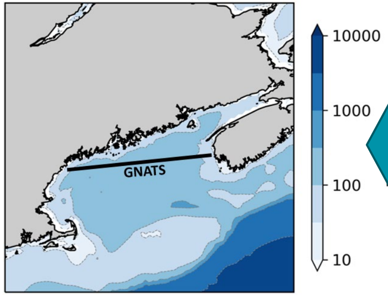
DATASET:

Field Data:

Gulf of Maine North Atlantic Time Series (GNATS)



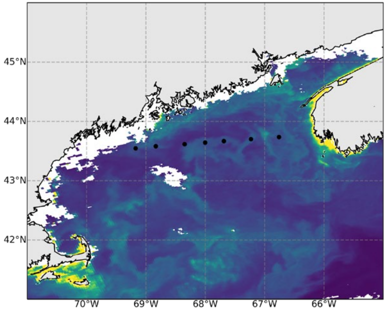
- Data spans 1998-present
- Physical biological, optical, and biogeochemical parameters measured including:
  - DIC
  - Temperature, Salinity
  - Radiometry

Matchup
3 hr, 1 km

271 Field RRS:DIC
325 Satellite RRS:DIC

Satellite Data:

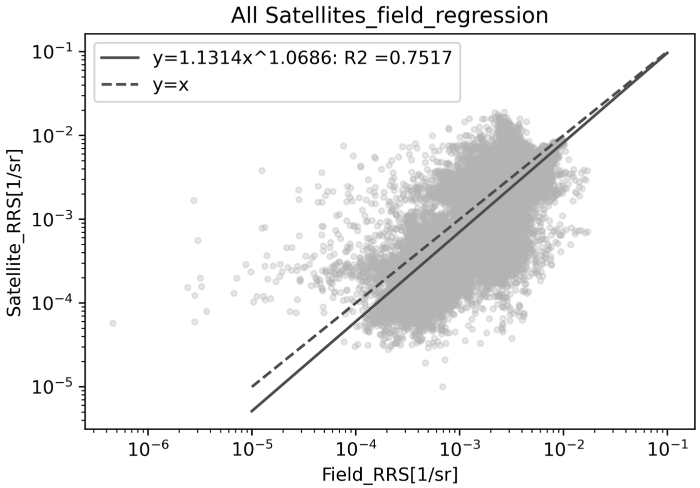
VIIRS, Terra, Aqua



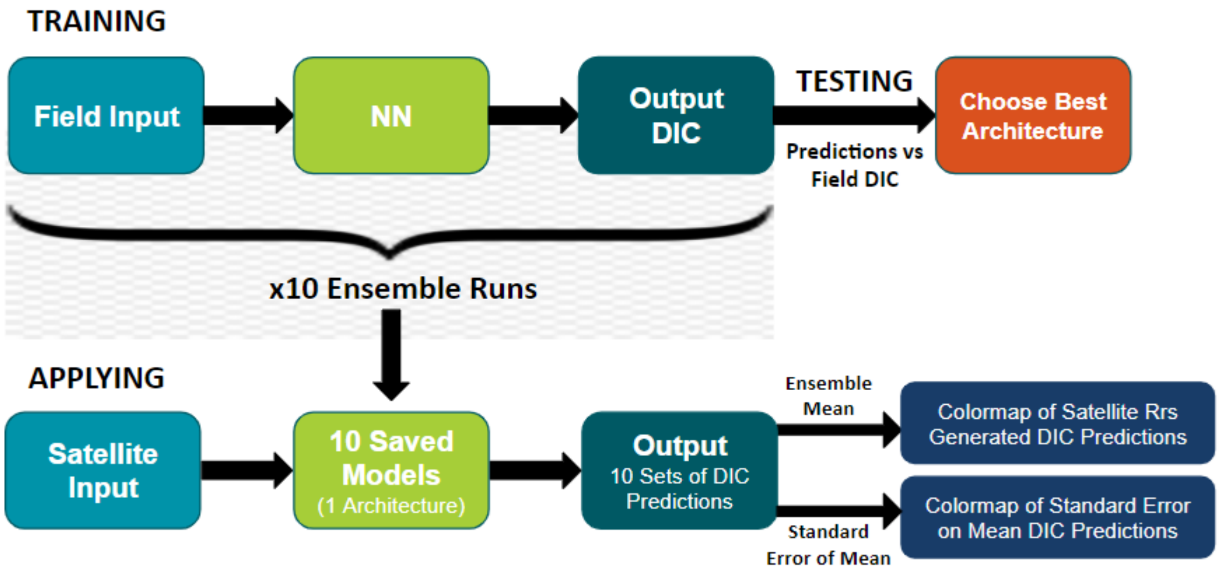
- $R_{rs}(412)$
- $R_{rs}(441)$
- $R_{rs}(490)$
- $R_{rs}(555)$
- $R_{rs}(671)$
- $R_{rs}(684)$
- Temperature

Rrs Regressions:

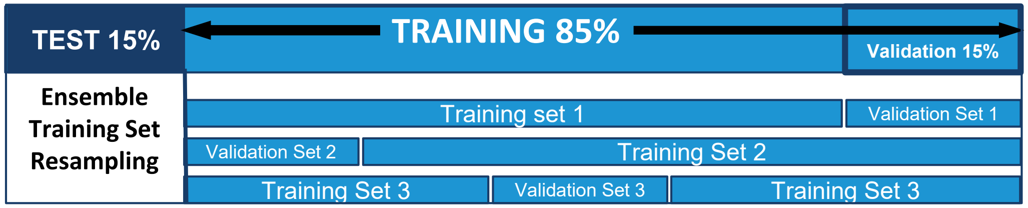
Question: Do the field R_{rs} data and satellite R_{rs} data agree, so that a Neural Network (NN) can be trained on the field R_{rs} values and be applied to the satellite R_{rs} values?



NEURAL NETWORK:



DATA SPLIT:



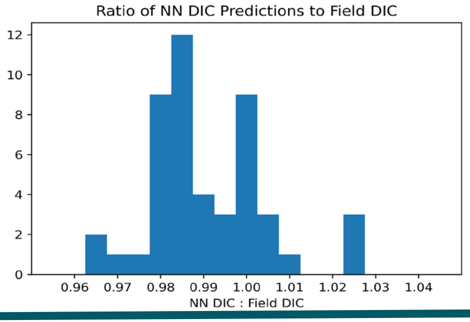
INPUT DATA:

- Field or Satellite
- SST
- $R_{rs}(412)$
- $R_{rs}(441)$
- $R_{rs}(490)$
- $R_{rs}(555)$
- $R_{rs}(671)$
- $R_{rs}(684)$

WORKFLOW:

1) Trained on field R_{rs}
2) Tested on field DIC
3) Applied to satellite Rrs
4) 10x Ensemble model trained on randomly resampled data
   a) increased robustness for small data set
   b) provides pixel by pixel ensemble mean with standard error of mean

NN Ensemble Test Predictions vs Test Field DIC Matchups:



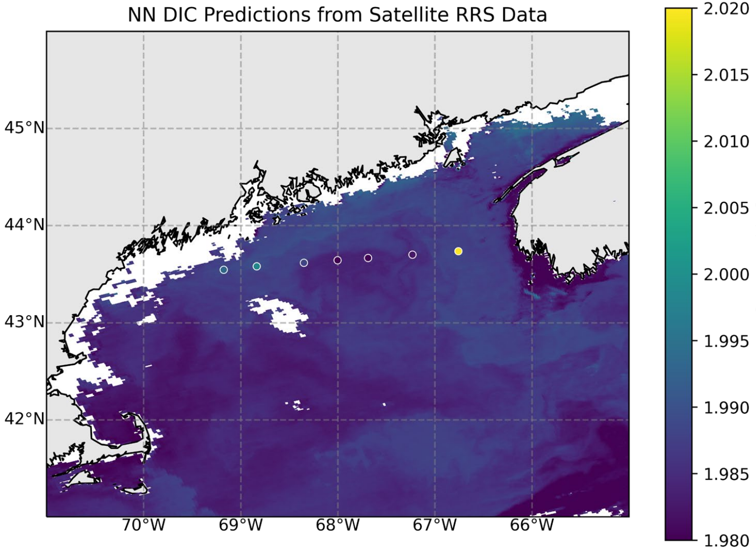
RESULTS:

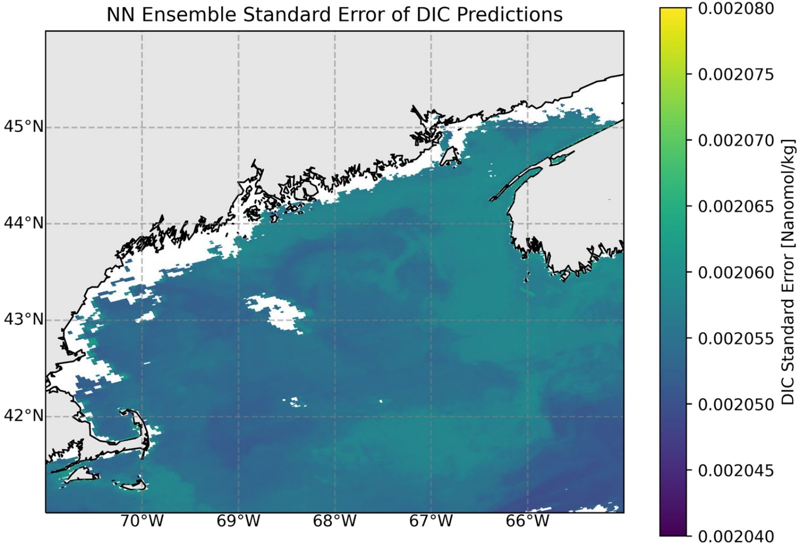
Median Absolute Error:
1.01376 (1.4%)

Bias:
0.99070 (-1%)

NN Satellite Generated Predictions:

Note:
The circles and their colors represent 7 GNATS field DIC measurement locations and values taken within the 3hr/1km matchup window of the satellite file used to generate the map via the NN.





CONCLUSIONS:

- Using a NN approach, we can predict DIC from satellite Rrs and SST data with a MAE of 1.4% and a bias of -1%.
- When applied to satellite imagery, the spatial patterns correspond to our field observations.
- The variability observed between different NN architectures and between ensemble runs of one architecture is likely an effect of the limited size of our training data set.

NEXT STEPS:

- PCA transformation of the input data
- Train the neural network on satellite Rrs values:
  - This will yield more matchups.
  - We expect increased generalization due to randomness provided by multiple satellite files mapped to one field DIC value.
- Include satellite SSS with input data
  - Preliminary tests showed an average 18% decrease in test MAE scores when field salinity was included as input.
- Increase training data set size:
  - Expand satellite matchup window.
  - Gather more field DIC data .