Deep Learning Based Ocean Current Feature Detection for Prediction

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Presentation Agenda

Section I: Introduction

Section II: Data Reconstruction

Section III: Current Boundary Detection

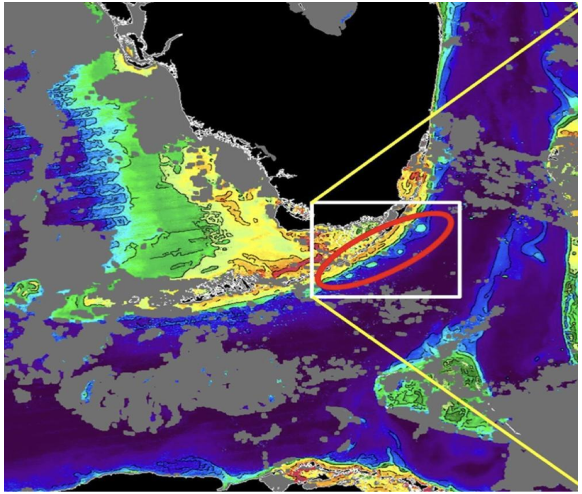
Section IV: Conclusions & Future Work

For the context of this presentation, reconstruction refers to the recovery of flow speeds and directions at missing data points.

I. Introduction

Research Background

- The Florida Current (FC) is one of the most energy-dense currents with power densities exceeding 1,500 W/m^2 [1].
- Surface currents contain features, such as eddies and meanders, that impact their flow speeds and directions.
- Sea surface temperature (SST), sea surface chlorophyll-a (SSCa), and high-frequency (HF) radar observations are utilized within this study to better detect submesoscale (small-scale) features.
- Ocean current features have characterized and predicted in [2-5] using deep learning tools, such as a convolutional neural network (CNN) along with a gated recurrent unit (GRU), temporal kNN model, U-net model, and long short-term memory (LSTM) recurrent neural network.



Chlorophyll Intermittencies within the FC [6]

[1] Sadoughipour, Mahsan et al. (2025). *Drifter-based global ocean current energy resource assessment*. Elsevier.
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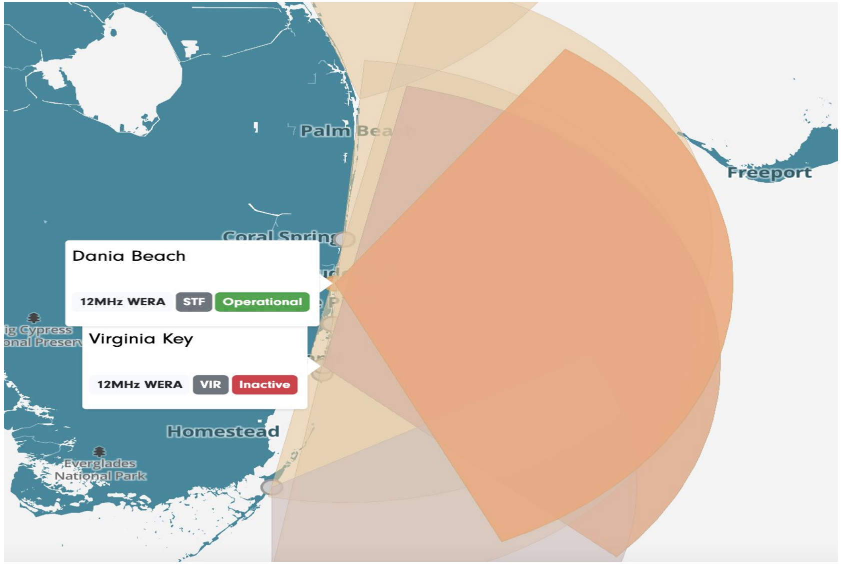
[4] Ali, Muhamed Ali et al. (2024). *Ocean Currents Velocity Hindcast and Forecast Bias Correction Using a Deep-Learning Approach*. JMSE.
[5] Kugusheva, Alisa et al. (2024). *Ocean Satellite Data Fusion for High-Resolution Surface Current Maps*. Remote Sensing.
[6] Zhang, Yingjun et al. (2019). *Submesoscale and Mesoscale Eddies in the Florida Straits: Observations from Satellite Ocean Color Measurements*. Geophysical Research Letters.

II. Data Reconstruction for HF Radar

Data Pre-Processing

- Raw HF radar measurements are interpolated on a 0.0275° grid.
- Quality-control procedures associated with the HF radar, which are discussed in [7] and [8], are implemented to retain reliable measurements.
    - **Range threshold:** Measurements exceeding 80 km from the HF radar instruments are removed.
    - **Accuracy threshold:** Radial velocity values over 8 cm/s are removed.
    - **Azimuthal span:** Retaining the regions where HF radar measurements from both instruments overlap.
    - **Radial velocity magnitude:** The magnitude of radial velocities cannot exceed 3 m/s.
    - **GDOP threshold:** The GDOP regarding measurements cannot be above 2.5.
- A weighted least squares approach is used to calculate surface-current velocities from radial velocities.

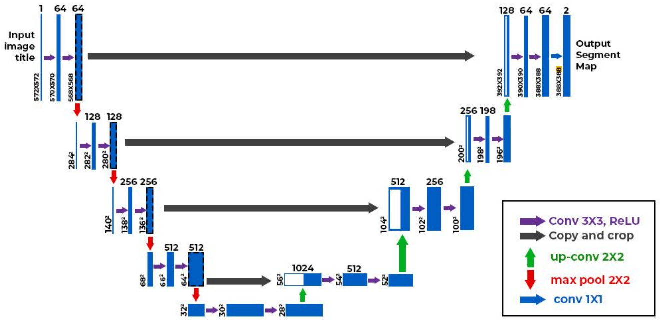


HF Radar Sites (SECOORA)

[7] Cosoli, Simone et al. (2019). *Estimating Ocean Surface Currents With Machine Learning*. Frontiers in Marine Science.
[8] Chapman, Rick et al. (1997). *Validation of HF Radar Measurements*. The Oceanography Society.

Reconstructing Missing Data

- A U-net deep learning model, known for its U-shaped encoder and decoder, is used to reconstruct the surface-current velocity field.
- The U-net model encoder uses 3x3 convolutions along with the ReLU activation followed by 2x2 max pooling layers to the data.
- The U-net model decoder upsamples the data through transposed convolutions, concatenated skip connections, two 3x3 convolutional layers, and one final 1x1 convolutional layer that linearly maps the zonal and meridional surface-current velocity components.
- Two test sets were used: 1) Hourly HF radar datasets with at least 30% data coverage; 2) Datasets with limited spatial data availability but partially valid fields.
- Data reconstruction accuracy is evaluated based on mean average error (MAE), mean squared error (MSE), root mean squared error (RMSE), and coefficient of determination (R^2). The table below shows the results for the first test set.



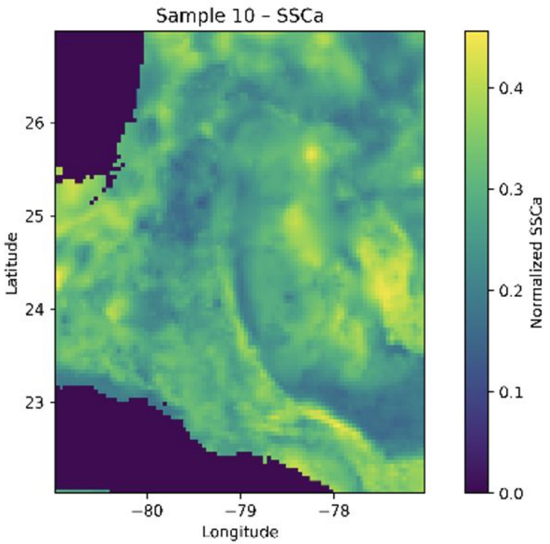
U-net Model Architecture (Medium)

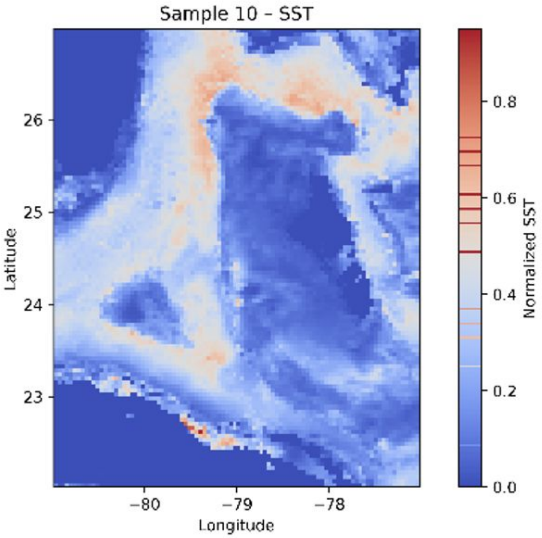
Component	MAE	MSE	RMSE	R^2
Zonal	0.0351 m/s	0.0025 m/s	0.0496 m/s	0.9703
Meridional	0.0276 m/s	0.0018 m/s	0.0419 m/s	0.9809

III. Current Boundary Detection Using Satellite Data

Data Pre-processing & Labeling

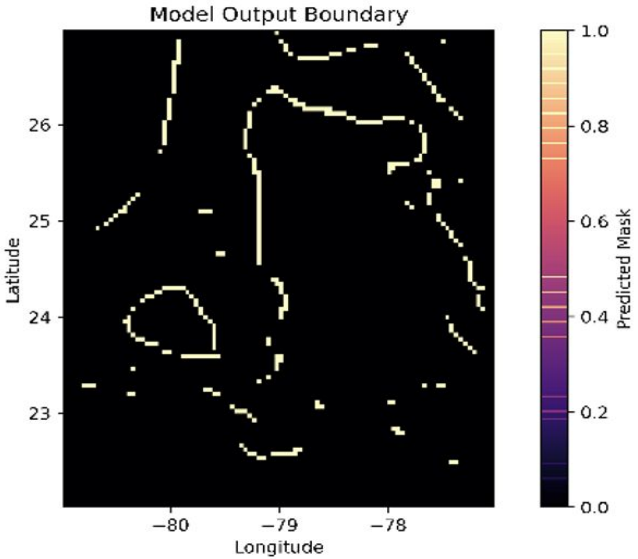
- SST and SSCa data are normalized, and then the SST data are downsampled so that the spatial resolution of both datasets match.
- The aligned fields combined channel-wise, resulting in an input tensor shape of (H, W, C), where H signifies the image height, W represents the image width, and C indicates the number of channels.
- To label the boundaries associated with both SST and SSCa intermittencies, four steps are taken.
  - **Step 1:** A Sobel filter is applied to both channels.
  - **Step 2:** The Sobel outputs were combined through a pixel-wise maximum.
  - **Step 3:** A Gaussian blur filter was applied to the output.
  - **Step 4:** Morphological skeletonization was implemented.

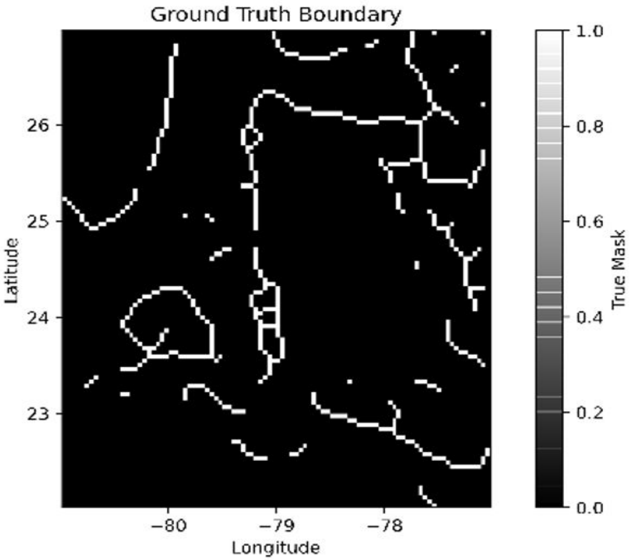




Attention U-net Edge Detection

- An attention U-net model is incorporated into this analysis because it builds upon the foundational U-net model by adding attention gates within the skip connections.
- The attention U-net model was associated with a **test loss of 0.0871** and an **accuracy of 97.17%**, but had an **intersection over union (IoU) of 0.2208**.





IV. Conclusions & Future Work

Conclusions & Future Tasks

Conclusions:

- Reconstructions of zonal and meridional currents within the FC provided a low RMSE and high R^2 when a test set of hourly HF radar data had at least 30% data coverage.
- However, surface-current reconstructions involving the hourly HF radar test set with sparse data coverage contained much lower accuracies, with a zonal RMSE of 0.0920 m/s and a meridional RMSE of 0.8686 m/s.
- Ocean current boundary detection utilizing a Sobel gradient extraction method resulted in an accuracy of 97.17%.

Future Work:

- Characterized flow features from satellite data will be validated using HF radar and ADCP measurements.
- The impact of flow features identified using satellite data on the ocean current velocity field will be quantified using HF radar and ADCP measurements.
- Existing methods will be refined to better detect and predict ocean current features within the FC, such as incorporating temporal-sequence models.
- Expand literature reviews on other models to comparatively analyze their effectiveness at ocean current detection and prediction, such as YOLO and U-transformer models.

Acknowledgements

This research was supported by the U.S. Department of Energy (DOE) under grant number DE-EE0011382. It was also supported by Florida Power & Light (FPL) through Florida Atlantic University's Center of Intelligent Energy Technologies (InETech).

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Thank you!
Any questions?