PolarWatch
A NOAA COASTWATCH NODE

From Historical Trends to Future Predictions: A Comprehensive Analysis of Arctic Sea Ice Concentration

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CSU Council on Ocean Affairs, Science, & Technology (COAST)

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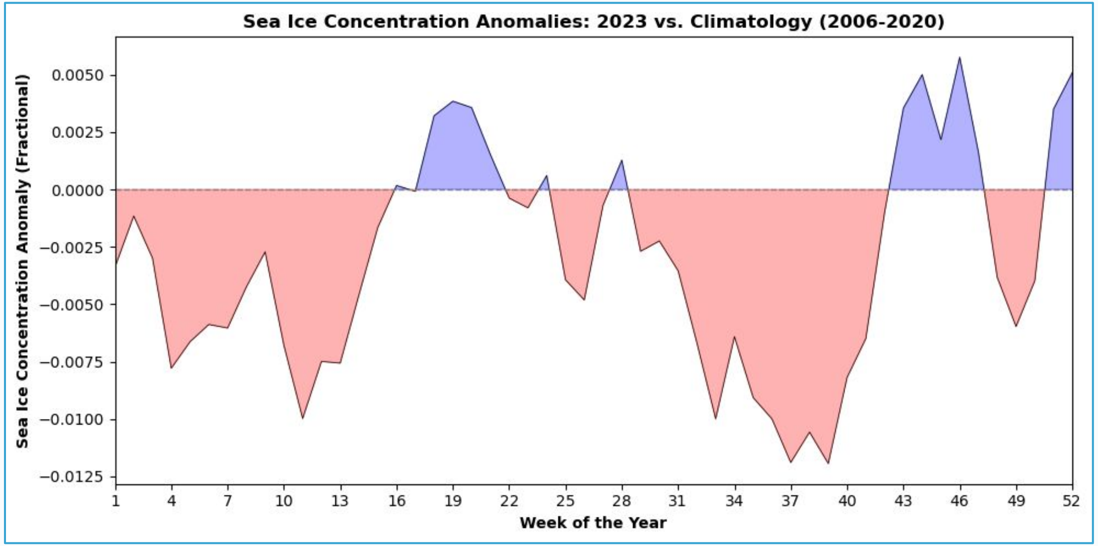
Summer 2024 Internship at NOAA PolarWatch (06/03 - 08/16)

Milestone 3: Statistical Analysis and Visualization

Mapping anomalies and sea ice concentration

Sea Ice Concentration, NOAA/NSIDC Climate Data Record V4, Northern Hemisphere, 25km, Science Quality, 1978-Present, Daily
https://polarwatch.noaa.gov/erddap/griddap/nsidcG02202v4nhlday.html



Milestone 3: Statistical Analysis and Visualization

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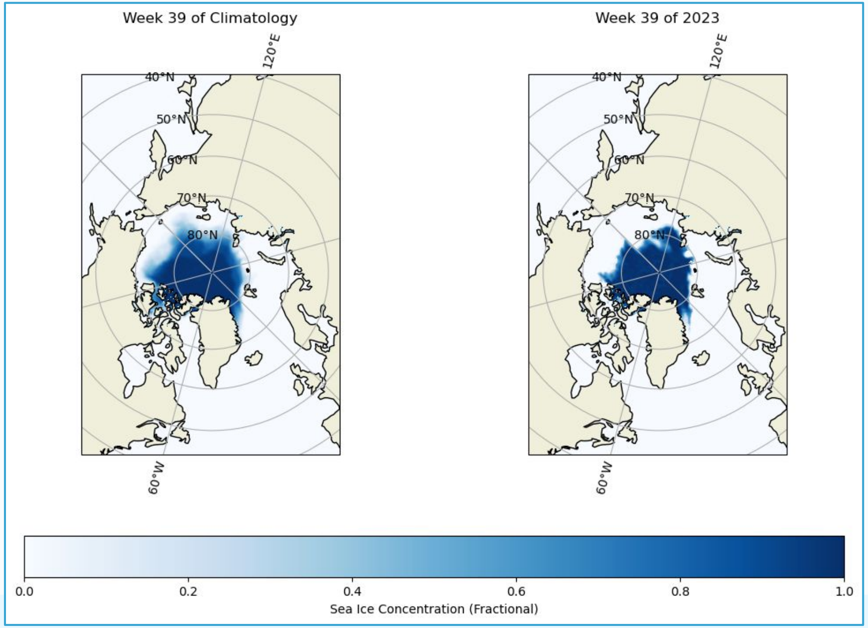


Background

Key Role of Sea Ice in Climate Change

- Sea ice decline: Arctic sea ice extent has halved since 1979, signaling rapid Arctic warming and occurring at nearly twice the global rate.

- Global impact: Affects transportation routes, resource development, coastal erosion, Arctic communities, and wildlife

- Climate indicator: Rapid sea ice loss is a clear marker of human-caused climate change.

(Ali et al., 2021)

Why It Matters

Importance of Accurate Sea Ice Predictions

- Vital for climate science: Crucial for understanding Arctic amplification and its influence on global climate patterns

- Policy and decision-making: Improved forecasts guide shipping, resource extraction, and infrastructure planning

- Need for advanced models: Current forecasting models face limitations, underscoring the need for techniques like the attention-based LSTM for enhanced accuracy.

(Ali et al., 2021)

Research Question and Objective

Research Question

How can we predict future sea ice extent using historical data and machine learning techniques?

Objective

Replicate and develop an attention-based Long Short-Term Memory (LSTM) model for predicting monthly sea ice extent with a 1-month lead time, based on the model presented in the paper *Sea Ice Forecasting using Attention-based Ensemble LSTM*

(Ali et al., 2021)

LSTM and Attention Mechanisms

Long Short-Term Memory (LSTM)

- Handle sequential data and capture long-term dependencies
- Consist of memory cells, input gates, output gates, and forget gates
- Applications
  - Time series forecasting, natural language processing, etc.

Attention Mechanisms

- Enhance model performance by focusing on important parts of the input sequence

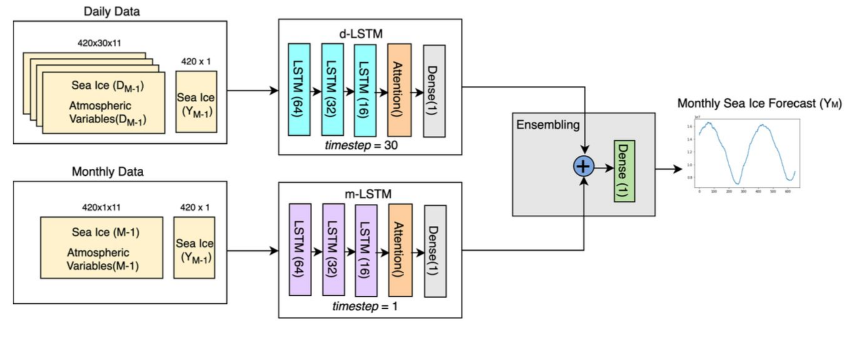


Figure 1. Overall Architecture of Attention-based LSTM Ensemble (EA-LSTM).

Milestone 4: Machine Learning Modeling

Dataset

- Variables: 10 atmospheric/ocean variables and sea ice extent (derived from sea ice concentration)
- Sources: ERA-5 global reanalysis product and National Snow and Ice Data Center
- Time span: 39 years (1979-2018)

Added variable: Sea Ice Thickness (SIT), [0, 10], m

Sea Ice Thickness and Multi-variable Extended AVHRR Polar Pathfinder APP-X NCEI Climate Data Record V2, Arctic, 1982-Present, Twice Daily

https://polarwatch.noaa.gov/erddap/griddap/ncei_polarAPPX20_nhem.html

Table 1. Variables included in the Dataset

VARIABLE	RANGE	UNIT
SURFACE PRESSURE	[400,1100]	HPA
WIND VELOCITY	[0,40]	M/S
SPECIFIC HUMIDITY	[0,0.1]	KG/KG
AIR TEMPERATURE	[200,350]	K
SHORTWAVE RADIATION	[0,1500]	W/m^2
LONGWAVE RADIATION	[0,700]	W/m^2
RAIN RATE	[0,800]	MM/DAY
SNOWFALL RATE	[0,200]	MM/DAY
SEA SURFACE TEMPERATURE	[200,350]	K
SEA SURFACE SALINITY	[0,50]	PSU
SEA ICE CONCENTRATION	[0, 100]	%

Data Preparation

- Load the SIT data
  - Import twice-daily sea ice thickness data from 1982 to 2018 using xarray

- Compute the monthly means
  - For each month, compute the mean SIT over the spatial dimensions

- Read the CSV file (the original dataset) in the DataFrame using pandas

- Data alignment
  - Merge the SIT mean as a new column in the original dataset, aligning by month and year to maintain temporal consistency across all features

- Handling missing data
  - Fill missing SIT values by replacing them with the mean of the column

Data Preparation

- Lag target values
  - Correctly lag the target variable to align with the features
- Sequential split
  - Divide data into training and validation sets (80:20)
- Normalization
  - Use StandardScaler to standardize features and target values for effective model training

Building the Model

LSTM with attention mechanism

- Implemented an LSTM model to handle sequential monthly data
- Added attention layers to focus on the most relevant time steps and features.

Input features

- 10 atmospheric/ocean variables + sea ice thickness
- Monthly input data from 1979-2018

Output

- Predict monthly sea ice extent with a 1-month lead time

Model: "functional"

Layer (type)	Output Shape	Param #	Connected to
input_layer (InputLayer)	(None, 1, 12)	0	-
lstm (LSTM)	(None, 1, 64)	19,712	input_layer[0][0]
dropout (Dropout)	(None, 1, 64)	0	lstm[0][0]
lstm_1 (LSTM)	(None, 1, 32)	12,416	dropout[0][0]
lstm_2 (LSTM)	(None, 1, 16)	3,136	lstm_1[0][0]
lstm_3 (LSTM)	(None, 1, 16)	2,112	lstm_2[0][0]
attention (Attention)	(None, 1, 16)	0	lstm_3[0][0], lstm_3[0][0]
concatenate (Concatenate)	(None, 1, 32)	0	lstm_3[0][0], attention[0][0]
dropout_1 (Dropout)	(None, 1, 32)	0	concatenate[0][0]
flatten (Flatten)	(None, 32)	0	dropout_1[0][0]
dense (Dense)	(None, 32)	1,056	flatten[0][0]
dense_1 (Dense)	(None, 16)	528	dense[0][0]
dense_2 (Dense)	(None, 1)	17	dense_1[0][0]

Total params: 38,977 (152.25 KB)
Trainable params: 38,977 (152.25 KB)
Non-trainable params: 0 (0.00 B)
None

Training the Model

Callbacks

- Utilize EarlyStopping and ModelCheckpoint to prevent overfitting and save the best model

Fitting

- Train the model with proper settings for epochs and batch size

```
history = model.fit(
    x_train,
    y_train,
    epochs=500,
    batch_size=12,
    verbose=2,
    validation_split=0.3,
    shuffle=True,
    callbacks=keras_callbacks
)
```

```
  warnings.warn(
27/27 - 10s - 365ms/step - loss: 0.9081 - val_loss: 1.1251
Epoch 2/500
27/27 - 0s - 11ms/step - loss: 0.7053 - val_loss: 0.3867
Epoch 3/500
27/27 - 0s - 11ms/step - loss: 0.2530 - val_loss: 0.1768
Epoch 4/500
27/27 - 1s - 20ms/step - loss: 0.0923 - val_loss: 0.1275
Epoch 5/500
27/27 - 0s - 17ms/step - loss: 0.0607 - val_loss: 0.1370
Epoch 6/500
27/27 - 0s - 18ms/step - loss: 0.0496 - val_loss: 0.0779
Epoch 7/500
27/27 - 0s - 18ms/step - loss: 0.0438 - val_loss: 0.0711
Epoch 8/500
27/27 - 1s - 22ms/step - loss: 0.0352 - val_loss: 0.0624
Epoch 9/500
27/27 - 0s - 12ms/step - loss: 0.0307 - val_loss: 0.0453
Epoch 10/500
27/27 - 0s - 10ms/step - loss: 0.0291 - val_loss: 0.0654
```

```
Epoch 126/500
27/27 - 0s - 10ms/step - loss: 0.0145 - val_loss: 0.0378
Epoch 127/500
27/27 - 0s - 9ms/step - loss: 0.0141 - val_loss: 0.0638
Epoch 128/500
27/27 - 0s - 11ms/step - loss: 0.0136 - val_loss: 0.0634
Epoch 129/500
27/27 - 0s - 9ms/step - loss: 0.0124 - val_loss: 0.0540
Epoch 130/500
27/27 - 0s - 9ms/step - loss: 0.0121 - val_loss: 0.0462
Epoch 131/500
27/27 - 0s - 11ms/step - loss: 0.0133 - val_loss: 0.0621
Epoch 132/500
27/27 - 0s - 12ms/step - loss: 0.0147 - val_loss: 0.0519
```

Model Evaluation

Performance Metrics

- Root mean square error (RMSE): Provide an absolute measure of prediction error

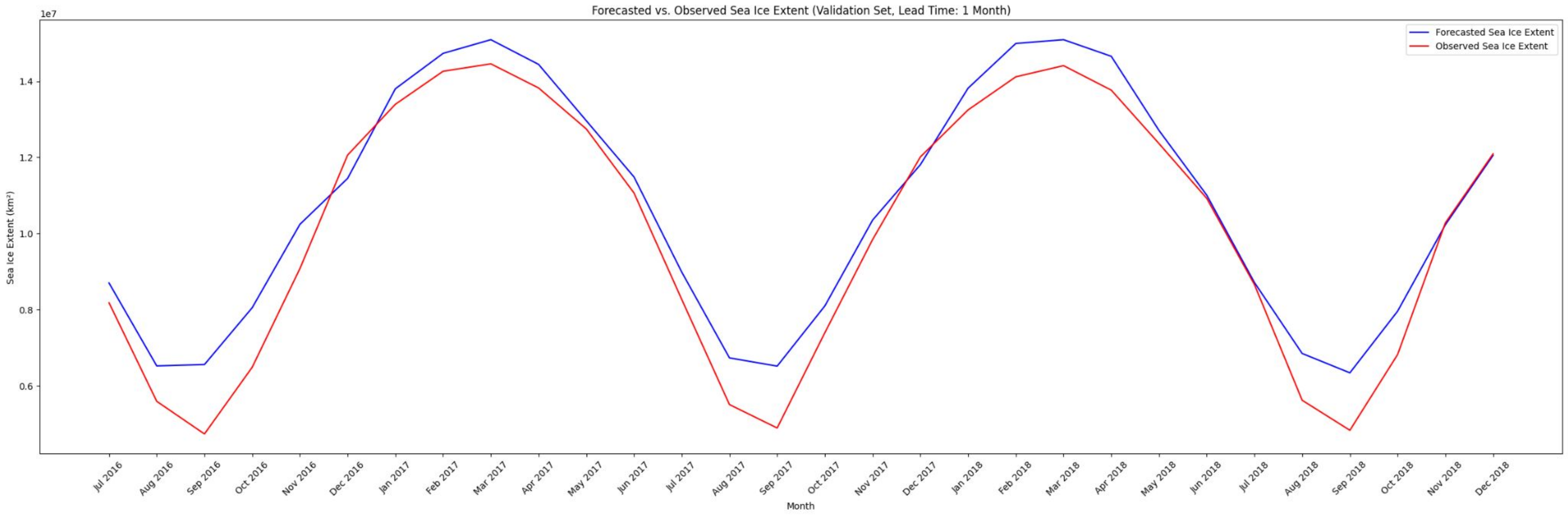
- Normalized root mean square error (NRMSE): Normalize RMSE to give a relative error measure

- R-squared: Measures how well your model's predictions match the actual data
  - 1: Perfect model with no error
  - 0: Model performs no better than the mean of the actual data.
  - Negative values: Model performs worse than simply predicting the mean of the target values.

Model Evaluation

Model	RMSE	NRMSE	R-Squared
Original Model with Original Dataset	2,126,871.173	0.203	0.645
Updated Model with Original Dataset	854,825.939	0.085	0.934
Updated Model with Updated Dataset	876,238.346	0.087	0.930

Model Evaluation



Conclusion

Improved Model Performance

- Updating the model with the new architecture significantly enhanced performance.
  - The RMSE decreased from 2.1 M to 854,825.939, a considerable improvement
  - The NRMSE dropped from 0.203 to around 0.085, showing better accuracy.
  - R-Squared improved from 0.645 to 0.934, indicating a stronger correlation between predicted and observed values.
- Adding sea ice thickness as a feature did not affect the performance of the model.

Predicted vs. Observed Trends

- The forecasted sea ice extent closely follows the observed values.

Next Steps

- Further refine model architecture and hyperparameters
- Investigate additional features or external data sources to enhance accuracy.
- Apply the model for longer-term sea ice prediction

References

Ali, S., Huang, Y., Huang, X., & Wang, J. (2021). *Sea ice forecasting using attention-based ensemble LSTM*. Tackling Climate Change with Machine Learning Workshop at ICML 2021. https://s3.us-east-1.amazonaws.com/climate-change-ai/papers/icml2021/50/paper.pdf

Key Takeaways from My Internship

Satellite Data Mastery

- Gained proficiency in accessing, analyzing, and visualizing satellite data, particularly sea ice concentration data using Python and ERDDAP
- Learned advanced data manipulation techniques with xarray and pandas, including computing climatology, filling missing values, and preparing data for machine learning models
- Performed anomaly detection, trend analysis using the Mann-Kendall test, t-tests for significance, and created polar maps for sea ice anomalies

Climate Modeling & Predictions

- Developed machine learning skills, including building attention-based LSTM models for sea ice prediction

These core skills have strengthened my ability to work on climate-related projects and enhance my data science skill set.

Acknowledgements

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