# SEA ICE FORECASTING USING ATTENTION-BASED ENSEMBLE LSTM


Sahara Ali, Yiyi Huang, Xin Huang, Jianwu Wang

*University of Maryland Baltimore County*



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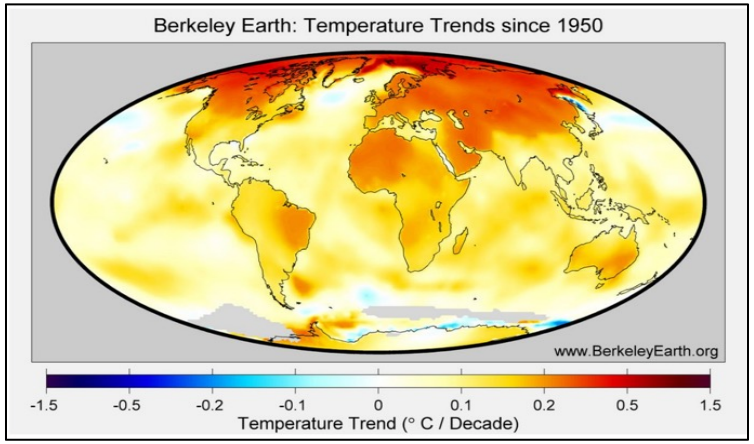
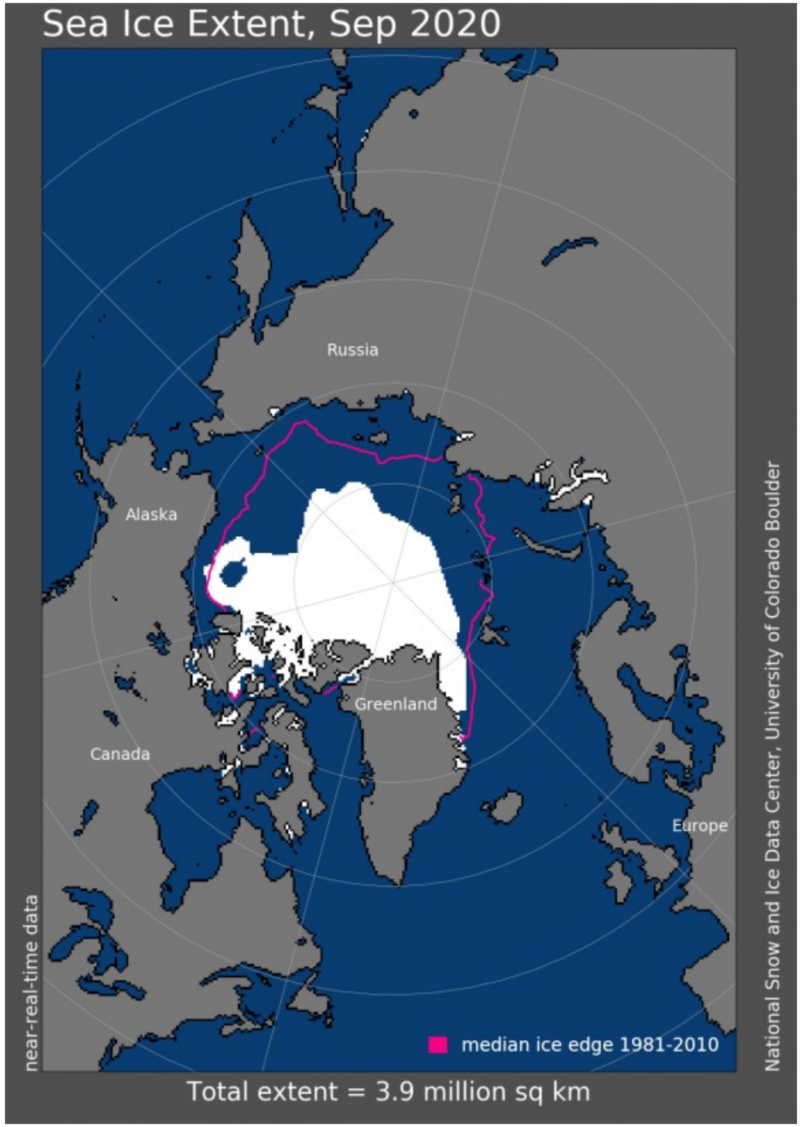
# MOTIVATION

- Warming of the sea ice in the Arctic has been almost twice faster than the rest of the world [1].
- Decline in sea ice exerts a large influence on the Earth's atmosphere, forecasting transporting routes, resource development, coastal erosion, threats to Arctic coastal communities and wildlife.
- 2021's historic cold snap in Texas and Oklahoma, resulted in at least 176 fatalities and $195 billion economic loss [2].




Source: *(Land + Ocean Data - Berkeley Earth, 2021)*




*September 2020 sea–ice extent map.*
*Image courtesy of the National Snow and Ice Data Center*

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# INTRODUCTION

- Recent shift from physics-based earth system models to statistical and machine learning models for sea ice forecasting.
- LSTM [3], CNN [4] and Convolutional LSTM [5] based models have been able to predict Sea Ice Concentration (SIC) with 9 – 22% RMSE loss.
- We propose a sea ice forecasting system with Attention-based Ensemble Long Short-Term Memory (LSTM) networks to predict monthly sea-ice extent with a lead time of 1 month.
- Our contribution:
  - An ensembling method for multi-temporal Deep Learning model.
  - Forecasting sea ice concentrations with a lead time of 1 month with RMSE ~ 4%.
  - Incorporating attention-mechanism to assign importance score to the features.

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# DATASET

- Time Series Data 1979 – 2018
  - Daily data: 14,160 temporal records
  - Monthly data: 480 temporal records
- Geolocation: >30N in Northern Hemisphere
- Sources of data:
  - Nimbus-7 SSMR and DMSP SSM/I-SSMIS passive microwave data version: Sea-ice concentrations [6].
  - ERA-5 global reanalysis product: Atmospheric and Ocean variables.

| Sr No. | Variable | Range | Unit |
|---|---|---|---|
| 1 | surface pressure | [40000,110000] | Pa |
| 2 | wind velocity | [0,40] | m/s |
| 3 | specific humidity | [0,0.1] | kg/kg |
| 4 | air temperature | [200,350] | K |
| 5 | shortwave radiation | [0,1500] | W/m2 |
| 6 | longwave radiation | [0,700] | W/m2 |
| 7 | rain rate | [0,800] | mm/day |
| 8 | snowfall rate | [0,200] | mm/day |
| 9 | sea surface temperature | [200,350] | K |
| 10 | sea surface salinity | [0,50] | PSU |
| 11 | sea ice concentration | [40000,110000] | % |

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# OVERALL ARCHITECTURE : ATTENTION-BASED LSTM ENSEMBLE (EA-LSTM)

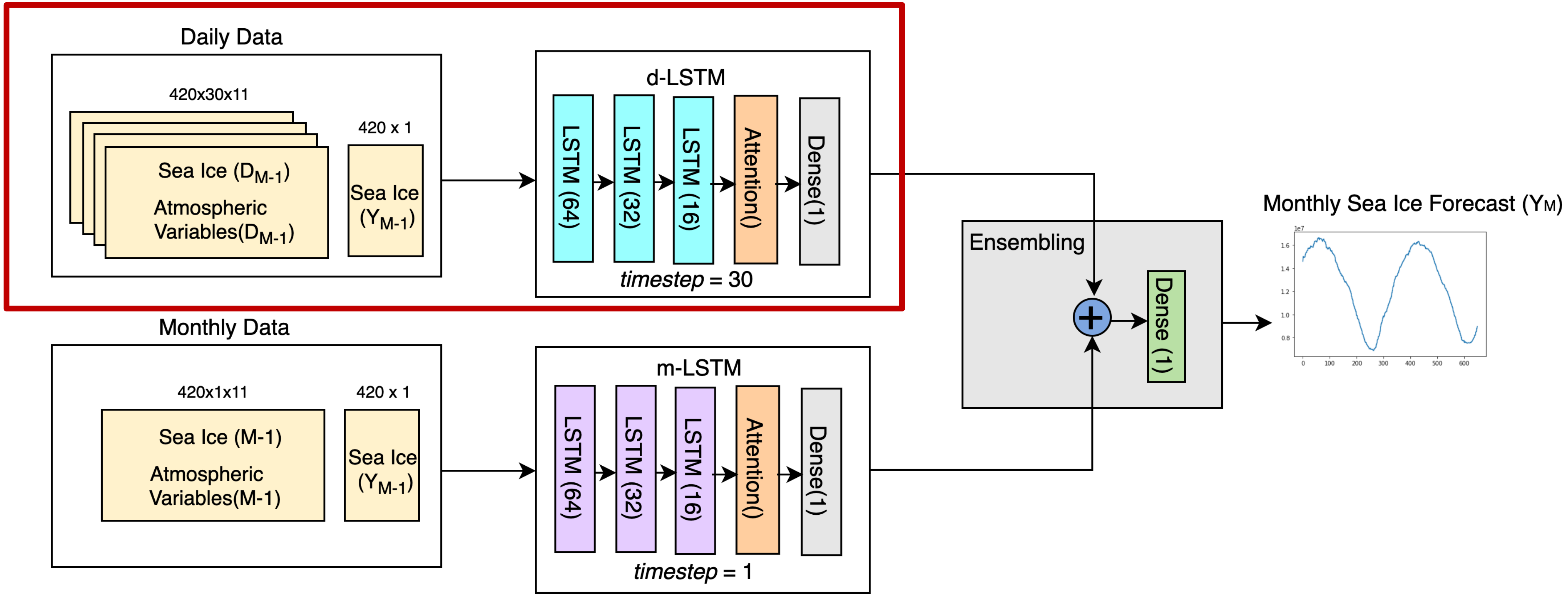


Figure: Overall architecture of the Attention-based LSTM Ensemble (EA-LSTM). Here, $D_{M-1}$ and $M-1$corresponds to daily and monthly records from preceding month and $Y_{M-1}$ represent sea-ice values from preceding month, whereas, $Y_M$ represents predictions for the next month.

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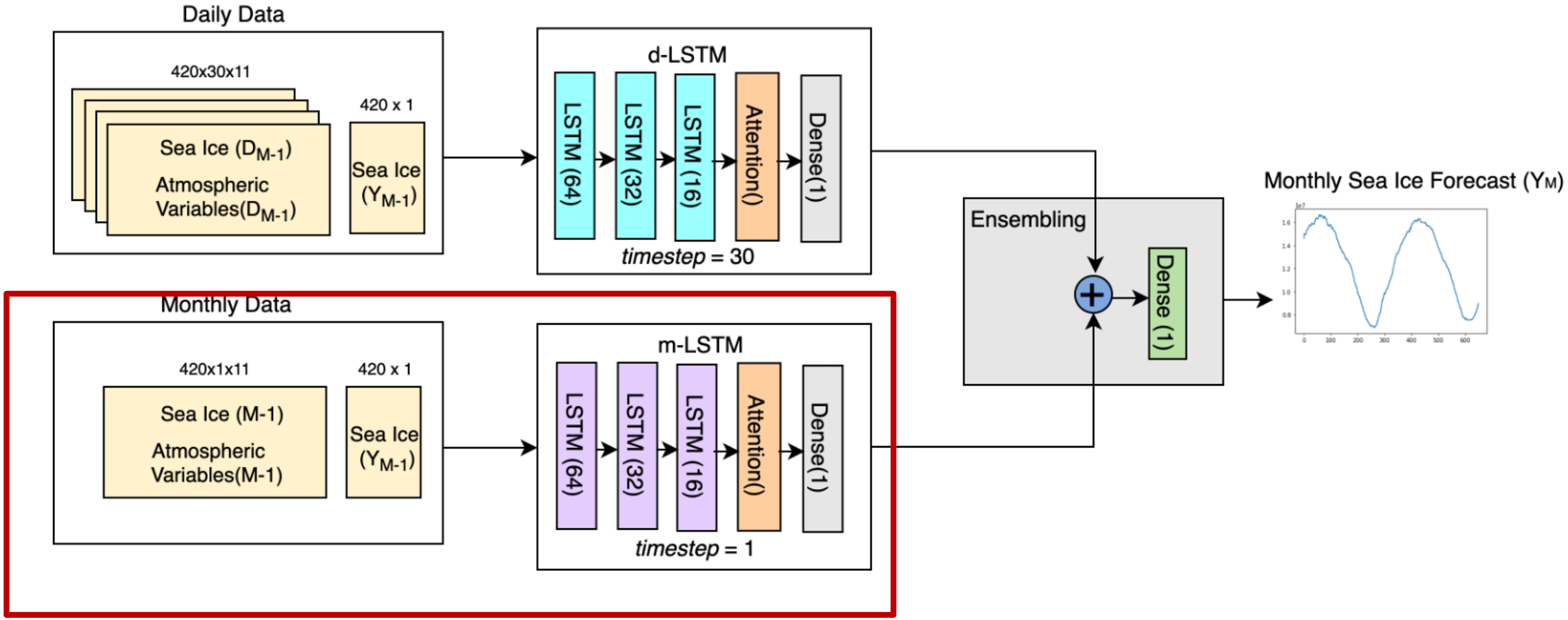


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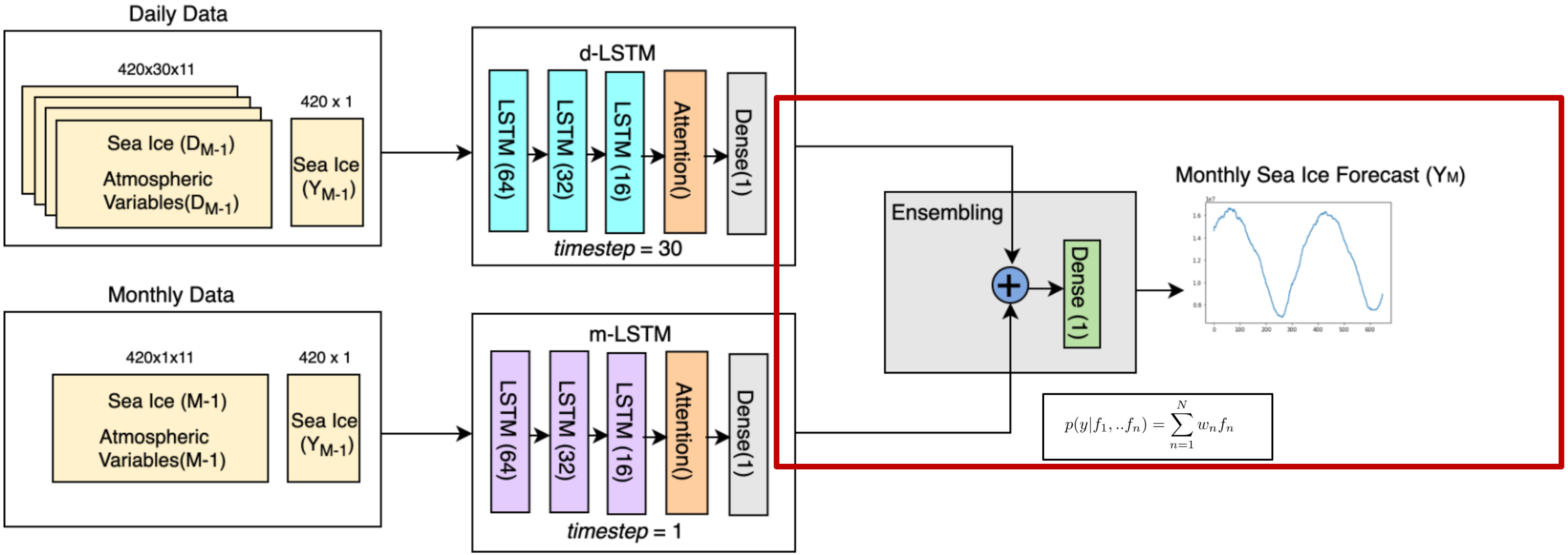


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# EXPERIMENTAL RESULTS

| **Model Type: proposed / baseline** | **Model** | $R^2$ SCORE | % RMSE |
|---|---|---|---|
| Baseline Model | Linear Regression | 0.974 | 5.05 |
| Baseline Model | Decision Tree | 0.963 | 6.00 |
| Baseline Model | Random Forest | 0.978 | 4.63 |
| Baseline Model | XGBoost | 0.976 | 4.83 |
| Baseline Model | Polynomial Regression | 0.966 | 5.76 |
| Proposed Model | d—LSTM | 0.980 | 4.45 |
| Proposed Model | m—LSTM | 0.981 | 4.21 |
| Proposed Model | E-LSTM | 0.977 | 4.60 |
| Proposed Model | **EA-LSTM** | **0.982** | **4.11** |

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# COMPARATIVE ANALYSIS

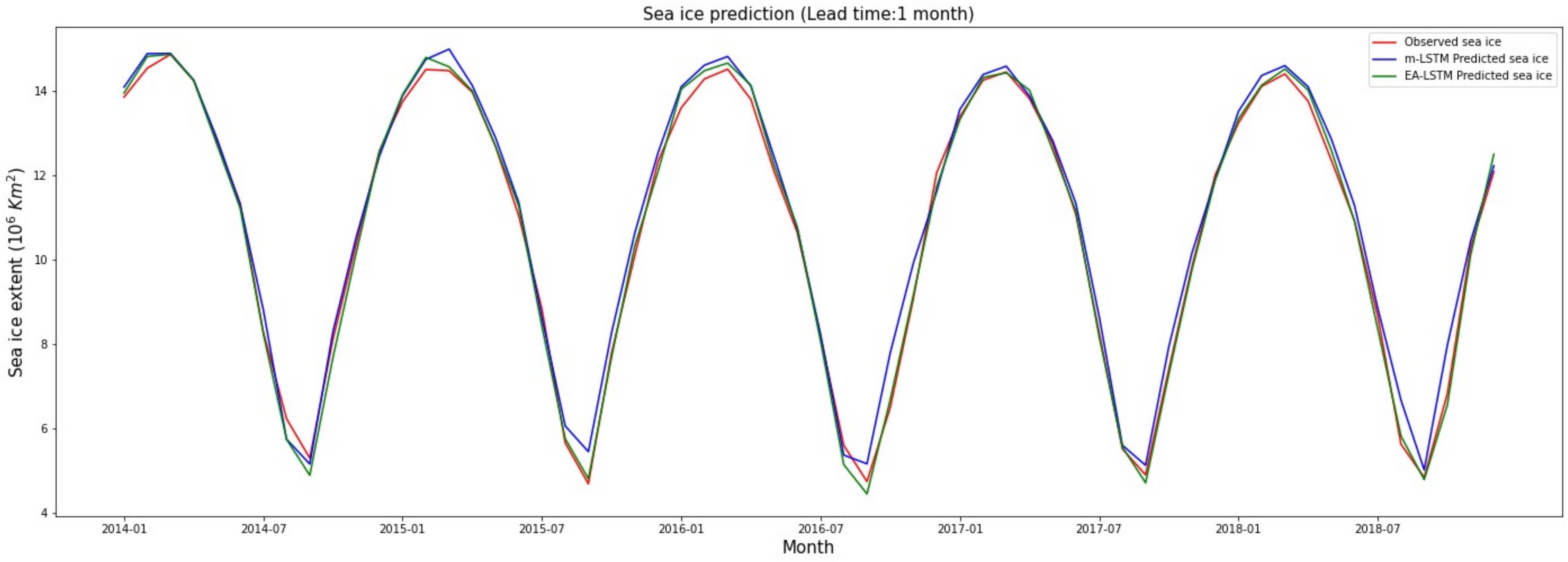


Figure: Time-Series Plot of Sea Ice observational data, m-LSTM predictions and EA-LSTM predictions for January 2014 - December 2018.

- Both m-LSTM and EA-LSTM perform well in predicting Sea Ice values for Oct – Jan, Apr-Aug.
- EA-LSTM performs better than m-LSTM in predicting maximum and minimum Sea Ice values i-e Feb-Mar, Sept.

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# CONCLUSION & FUTURE WORK

- Conclusion:
  - We present an attention-based LSTM ensemble method to predict monthly sea-ice values with a lead time of 1 month.
  - Our proposed model can be extended to include more models having different temporal resolutions and learn their weighted average using the ensembling technique.
- Future Work:
  - Extend our proposed ensemble method to combine spatiotemporal models with different spatial and temporal resolutions.
  - We also plan to visualize the attention weights learned from these intermediary attention layers to better interpret the underlying working of deep learning models.

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# THANK YOU!