Improving Seasonal Arctic Sea Ice Predictions with the Combination of Machine Learning and Earth System Model

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1. Introduction

Machine learning (ML) has recently emerged as a data-driven technique to mitigate dynamical prediction errors. Two prevalent approaches include constructing an ML-dynamical hybrid model (Gregory et al. 2024) and post-processing/calibrating model output (Palerme et al. 2024). The former is considered as online error correction, while the latter refers to offline error correction. In this study, we utilized the two ML-based error correction methods to the Norwegian Climate Prediction Model (NorCPM) for seasonal prediction of Arctic sea ice.

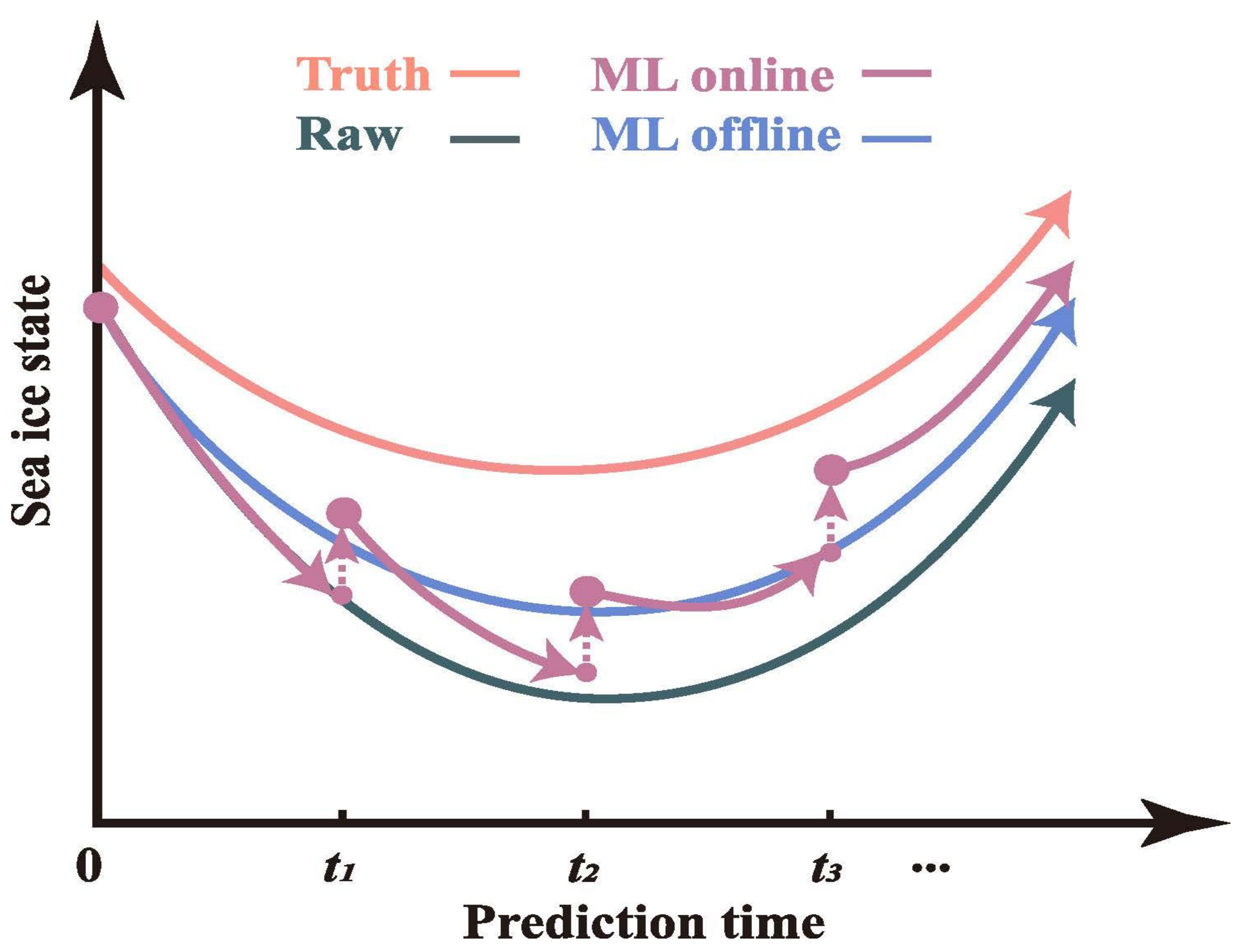
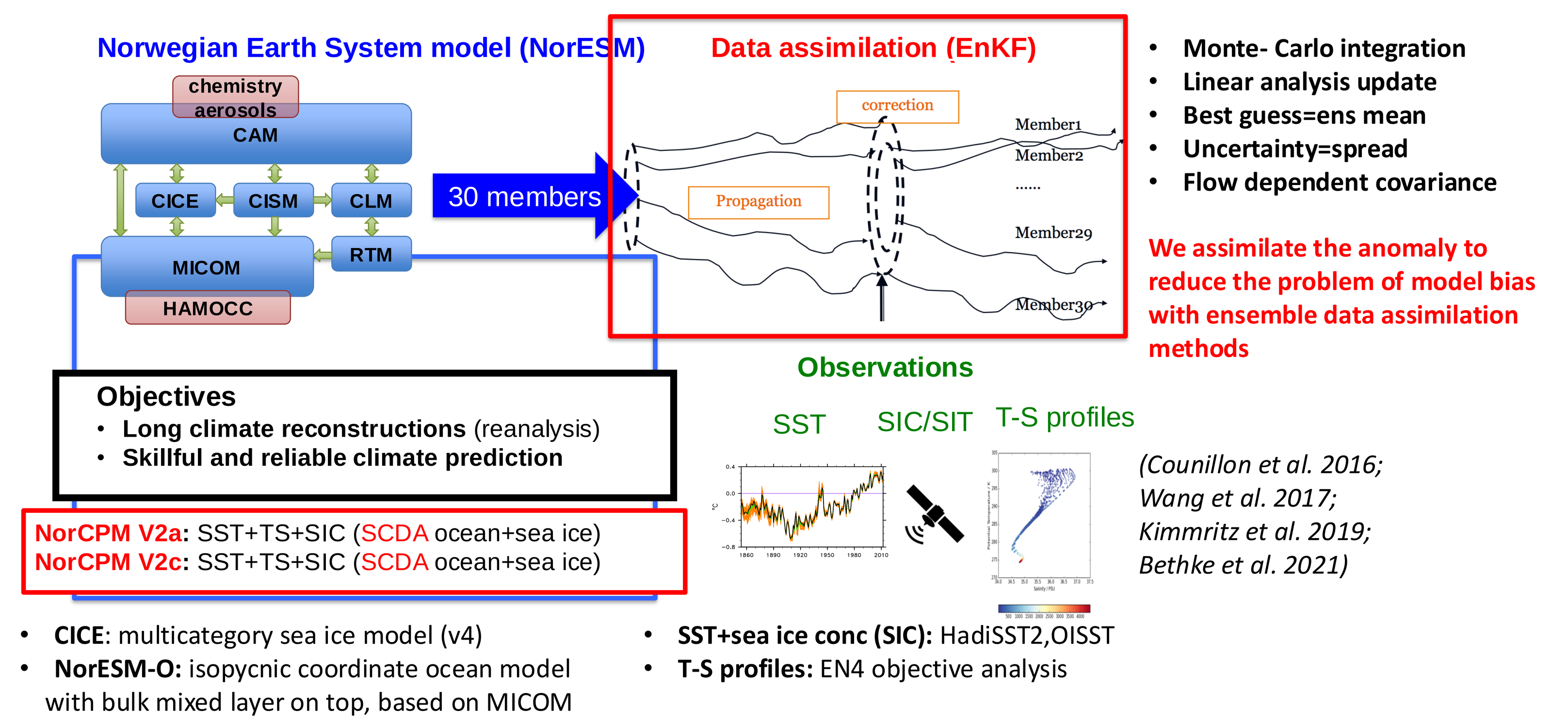


Figure 1. Schema for the online and offline ML-based error correction methods. The pink line represents the truth. The gray line represents dynamical prediction without error correction. The purple (blue) line represents prediction with online (offline) ML-based error correction. The purple dashed arrows indicate pauses during the prediction production, facilitating correction to the instantaneous model state.

2. Data and Methods



Reanalysis (30 members) and retrospective forecasts (9/10 members)

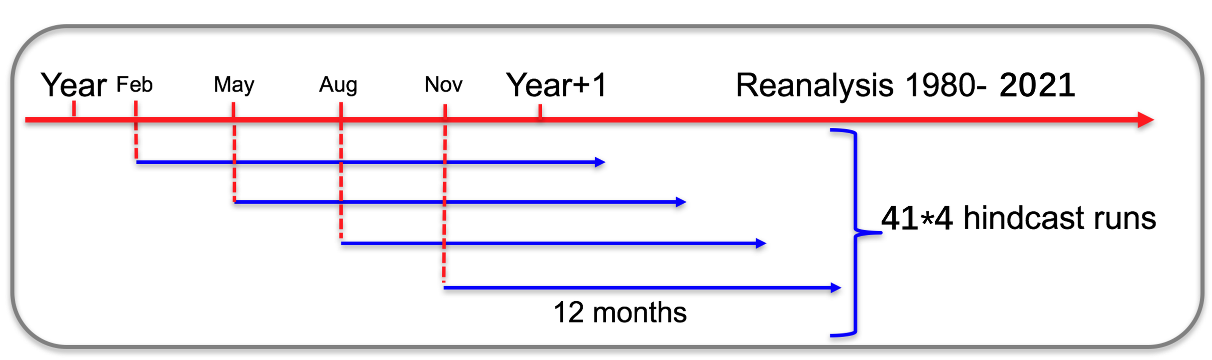


Table 1. Information about OnlineML and OfflineML models

	OnlineML	OfflineML
Input features	Instantaneous SST, SSS, latitude, 5 categories SIC and sea ice volume	Monthly SST, SSS, latitude, SIC and sea ice volume
Output features	Instantaneous SST, SSS and 5 categories SIC errors	Monthly SIC prediction error
Data	The most recent eleven years data (ten years for training and one year for validation)	
Remark	Only apply to sea-ice covered grids in the Arctic with SIC values greater than 1%.	

- **Running training**:

We employed a running training set approach using data from the most recent 11 years. For example, to build an error correction model for January 2019, data from January 2009 to January 2017 is used for training, and data from January 2018 for validation.

- **Reanalysis as the truth**

3. Results

3.1 Error correction model performance

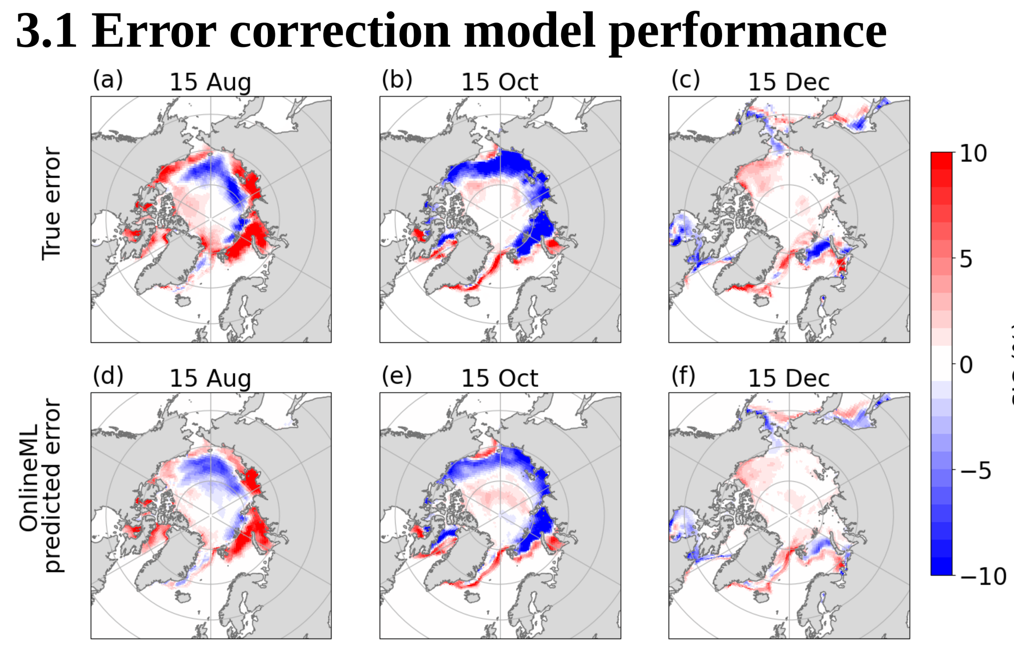


Figure 2. Top row: true errors of SIC in the middle of the month based on analysis increment. Bottom row: the predicted errors of OnlineML. The errors are averaged over the period 2003--2021.

- Machine learning can learn the model error.

3.2 Pan-Arctic SIE prediction skill

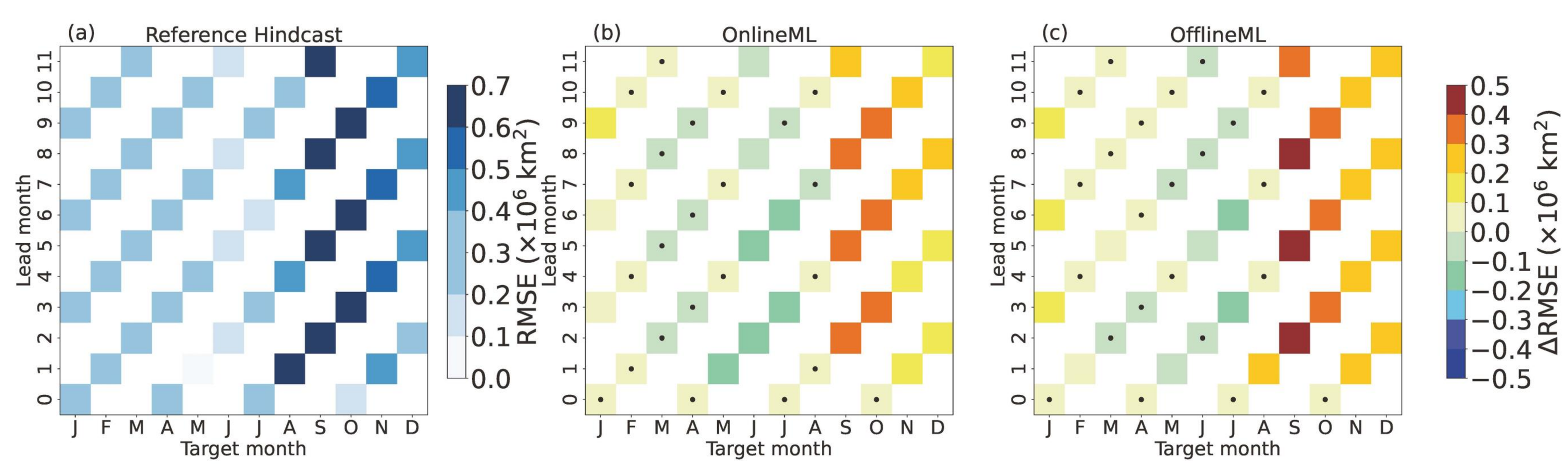


Figure 3. (a) RMSE of the Reference hindcast, and ΔRMSE of SIE between (b) Reference and OnlineML hindcasts, (c) Reference and OfflineML hindcasts. Warm colors (red/yellow) indicate areas where error-corrected hindcasts perform better than the Reference, while cold colors (blue/green) indicate areas where they perform worse. The black dots represent regions where the ΔRMSE does not pass the 95% significance test.

3.3 Regional SIE prediction skill

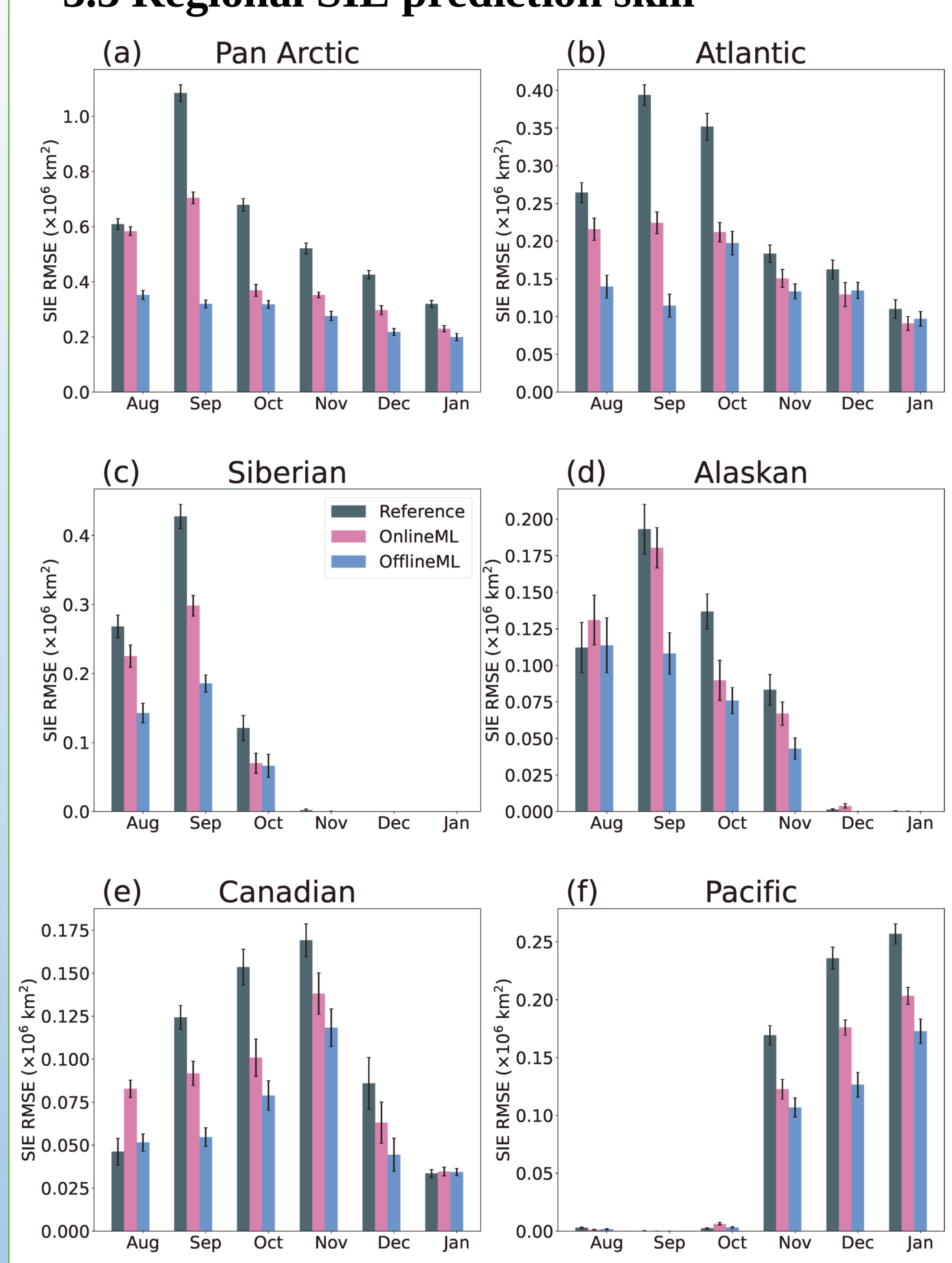


Figure 5. RMSE of the Pan-Arctic and five subregions SIE for Reference (gray bar), OfflineML (blue bar), OnlineML (purple bar) hindcasts.

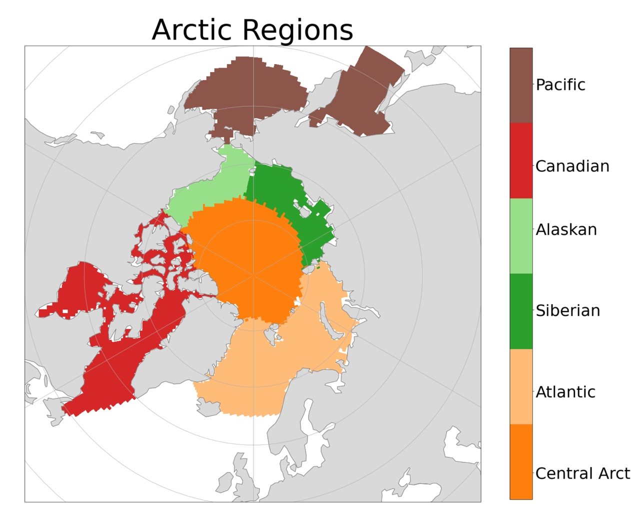
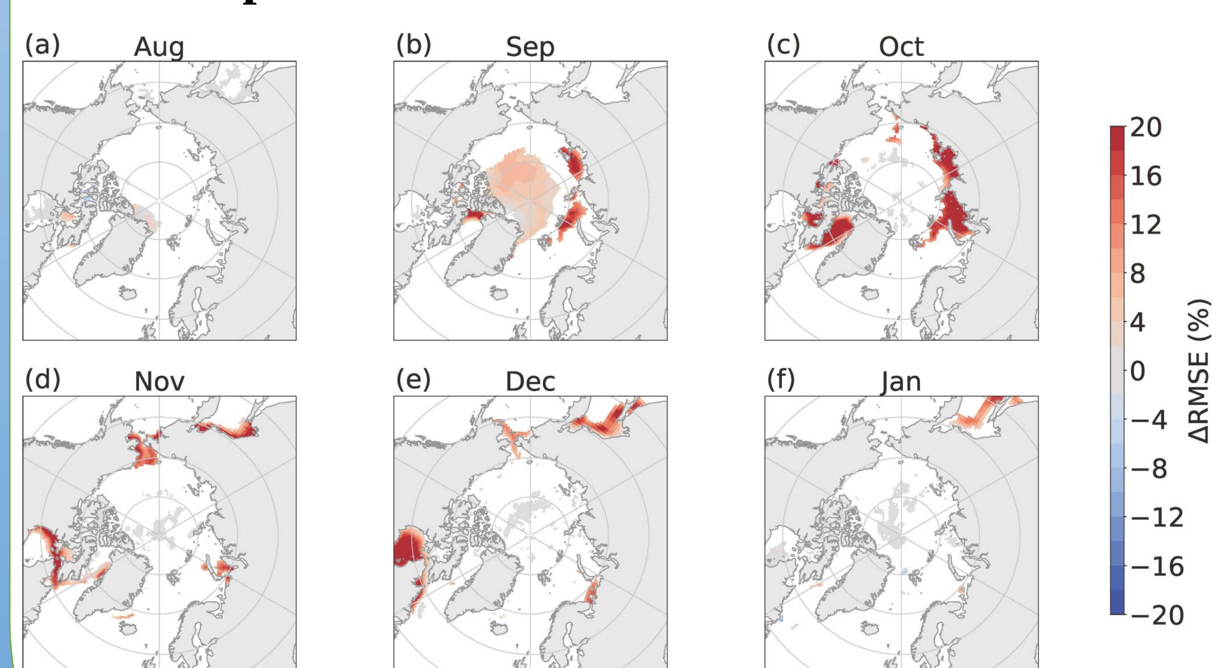


Figure 4. Regional domain definitions for Central Arctic, Atlantic, Siberian, Alaskan, Canadian, and Pacific.

- Improvements vary by target months and regions;
- The improvement mainly in margin regions.

3.4 SIC prediction skill



- Improvements vary by target months and regions;
- The improvement mainly in margin regions;
- OfflineML has more noise in the Central Arctic.

Figure 6. Differences between SIC RMSE of Reference and OfflineML initialized from July. Warmer (colder) colors indicate that the OfflineML prediction performs better (worse). The white color indicates the differences don't exceed significant test.

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