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Supporting Information for

Antarctic Sea Ice Prediction with A Convolutional Long Short-Term Memory Network

Xiaoran Dong[1], Yafei Nie[1], Qinghua Yang[1*], Lorenzo Zampieri[2], Jiuke Wang[3], Jiping Liu[1], Dake Chen[1]

[1]School of Atmospheric Sciences, Sun Yat-sen University, and Southern Marine Science and Engineering Guangdong Laboratory (Zhuhai), 519082 Zhuhai, China

[2]Ocean Modeling and Data Assimilation Division, Fondazione Centro Euro-Mediterraneo sui Cambiamenti Climatici - CMCC, Bologna, Italy

[3]School of Artificial Intelligence, Sun Yat-sen University, and Southern Marine Science and Engineering Guangdong Laboratory (Zhuhai), 519082 Zhuhai, China

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Introduction

Text S1 describes the skill metrics and benchmark predictions. Text S2 describes and analyzes the empirical orthogonal function (EOF) result of sea ice concentration anomaly (SICA) (Figure S2). Figure S1 shows the ConvLSTM's seasonal prediction skill for regional Antarctic SIC compared to damped anomaly persistence. Figure S2 shows the EOF result of SICA.

Text S1. Skill Metrics and benchmark predictions

To assess the predictive skill, we use the Root-Mean-Square Skill Score (RMSSS, Barnston et al., 2015), Spatial Correlation (spCorr), and Integrated Ice Edge Error (IIEE, Goessling, et al., 2016, Goessling, 2018). RMSSS measures the amount of information captured by the model as a percentage of that contained in the real label and is calculated as

$$RMSSS(\hat{y},\, y) = 1 - \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}}{\sigma_y} \quad (1)$$

where y_i is the observed data, $\hat{y}_i$ is the predicted value, σ_y is the standard deviation of y_i. We define an active grid cell region as Andersson et al. (2021) in the calculation of the spatial averaged RMSSS, to offset the seasonal variation of SIE. The region shrinks in summer and expands in winter based on the SIC, and the threshold was set as the mean observed SIC>1% in a given calendar month for the examination of SIC.

The spCorr, measuring the predictive skill of spatial variation, is calculated as:

$$spCorr(\hat{y},\, y) = \frac{\sum_{i=1}^{n}\left(\hat{y}_i - \bar{\hat{y}}\right)(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}\left(\hat{y}_i - \bar{\hat{y}}\right)^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}} \quad (2)$$

where the bar means the average.

The IIEE is the sum of the area where the forecast and the truth disagree on the ice concentration being above or below 15%, thus measures the symmetric difference between the areas enclosed by the predicted and the true ice edge, and is calculated as

$$IIEE = \int_A max\left(c_p - c_o, 0\right) dA + \int_A max\left(c_o - c_p, 0\right) dA \quad (3)$$

where A is the grid-cell area, $c = 1$ where the SIC>15%, and $c = 0$ elsewhere. The subscripts p and o denote the prediction and the observation.

Following Wang et al., (2018), we use three benchmark predictions, namely climatology, anomaly persistence, and damped anomaly persistence, to further evaluate the predictive skill of ConvLSTM. The climatology predicts zero anomalies and the future state of SIC follows the climatological annual cycle. The anomaly persistence assumes the anomaly constant in time after the initialization, while the damped anomaly persistence assumes the anomaly dissipative in time after the initialization following the local autocorrelation (r_{Auto}). At long lead times, the anomaly persistence prediction gradually approaches the climatology prediction as the r_{Auto} vanishes.

Text S2. The description of EOF of SICA

Figure S2 shows the first three EOF analyses of SICA. The spatial pattern of the first mode is dominated by a dipole pattern of SICA, which is called Antarctic Dipole (ADP, Yuan and Martinson, 2001), with one pole centered in the central polar Pacific and the other opposite pole in the central polar Atlantic. The spatial pattern of the second mode looks like the first one being rotated eastward by a quarter of a wavelength. The spatial pattern of the third mode is a seasonal mode, which is evident in the significant meridional gradient. The first three modes account for about 7.82%, 4.56%, and 4.15% of the total variance respectively, which are all below 10%. The Fourier spectrum decompositions of PC show that the energy spectrums of PCs' period are all concentrated in the low frequency. Those features let the information about SICA seem like white noise. It reveals that predicting the SIC by capturing only the sea ice statistics without other oceanic or atmospheric parameters is not an easy task.

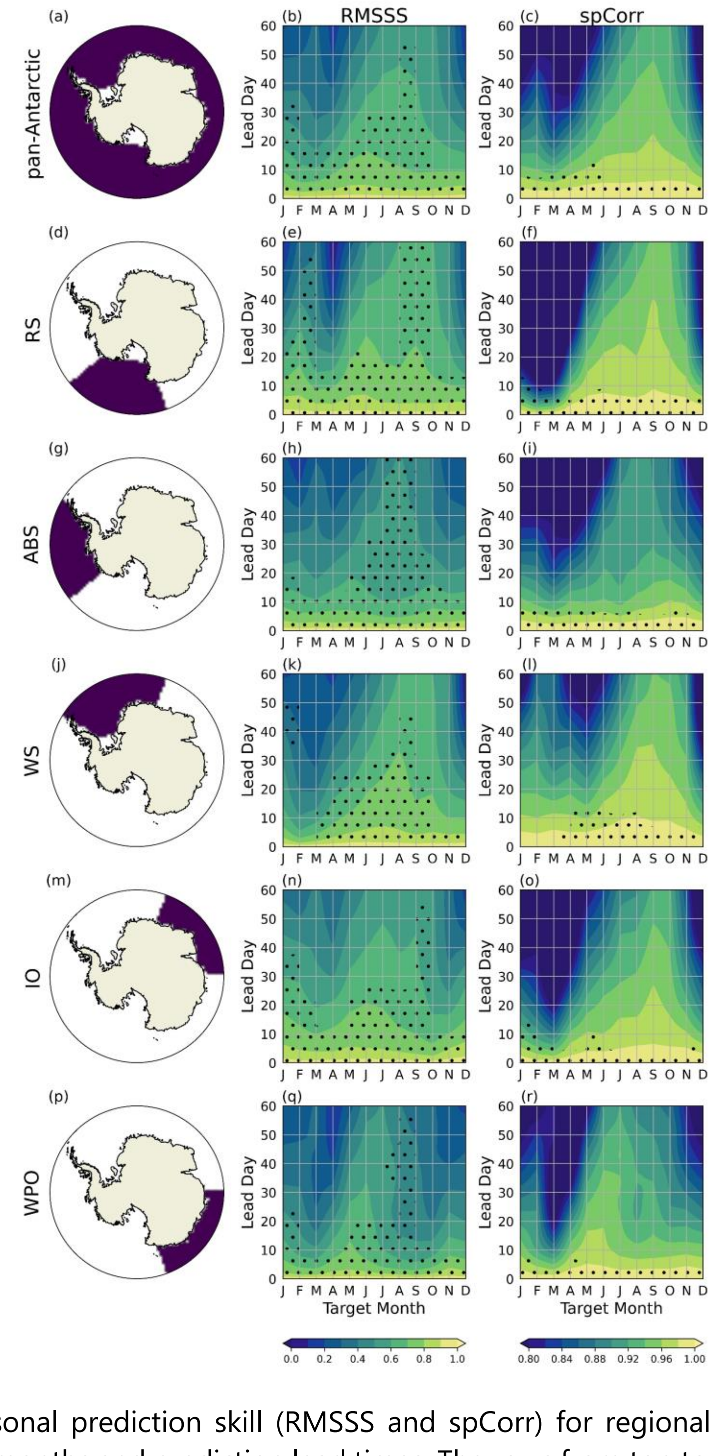

Figure S1. Seasonal prediction skill (RMSSS and spCorr) for regional Antarctic SIC for different target months and prediction lead times. The rows from top to bottom represent pan-Antarctic, Ross Sea (RS), Amundsen and Bellingshausen Sea (ABS), Weddell Sea (WS), Indian Ocean (IO), and West Pacific Ocean (WPO), respectively. The dot markers indicate months where the skill of ConvLSTM beats the damped anomaly persistence forecast.

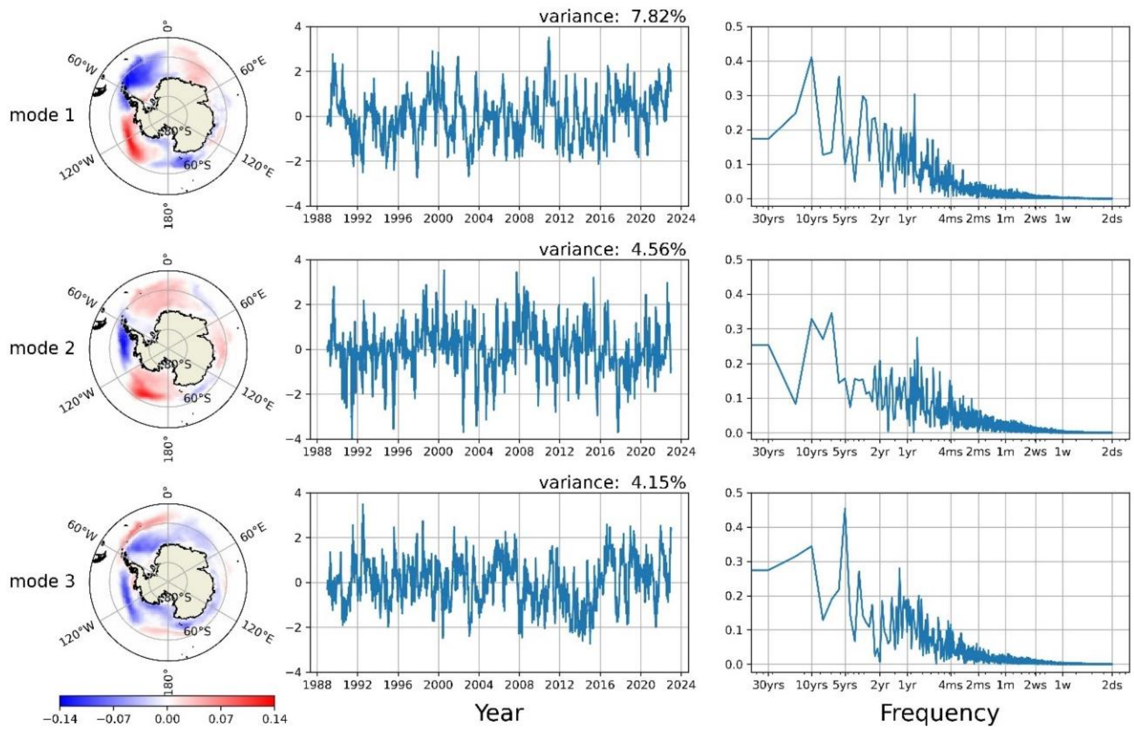

Figure S2. The empirical orthogonal function (EOF) result of sea ice concentration anomaly (SICA) from 1st January 1989 to 31st December 2021. The row from the top to the bottom represents mode 1, mode 2, and mode 3, respectively and the column from the left to the right represents the spatial pattern, the principal components (PC) (the corresponding explained variance was listed), and the Fourier spectrum decomposition of PC respectively.

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