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, 519082 Zhuhai, China.

Corresponding author: Qinghua Yang (yangqh25@mail.sysu.edu.cn)

Key Points:

- A convolutional long short-term memory (ConvLSTM) network is constructed to predict the Antarctic sea ice for the next 60 days
- The ConvLSTM network exhibited predictive skill of about 1 month in predicting daily spatial patterns of the Antarctic Sea ice concentration
- The ConvLSTM network can predict the sea ice extent maximum and minimum 1 month in advance

Abstract

Antarctic sea ice predictions are becoming increasingly important both scientifically and operationally due to climate change and increased human activities in the region. Conventional numerical models typically require extensive computational resources and exhibit limited predictive skill on the subseasonal-to-seasonal scale. In this study, a convolutional long short-term memory (ConvLSTM) deep neural network is constructed to predict the 60-day future Antarctic sea ice evolution using only satellite-derived sea ice concentration (SIC) from 1989 to 2016. The network is skillful for approximately one month in predicting the daily spatial distribution of Antarctic SIC between 2018 and 2022, with the best prediction skill found from June to September. ConvLSTM can also successfully predict extreme Antarctic sea ice extent (SIE) one month in advance, with the monthly mean SIE error mostly below 0.2 million km^2, suggesting substantial potential for the application of machine learning techniques for skillful Antarctic sea ice prediction.

Plain Language Summary

Predicting the Antarctic sea ice evolution tends to be difficult due to the complex interaction between the components of the climate system in the polar regions. Here we introduce a convolutional long short-term memory (ConvLSTM) deep neural network, which is capable of representing the non-linear relationships between the predictors and predictands to formulate actual predictions on the evolution of the Antarctic sea ice cover up to 60 days in the future. Such machine learning-based approaches are emerging as alternatives to traditional prediction systems, where the prediction is informed by fundamental physical principles and empirical parameterizations. Our retrospective forecast experiments reveal that the ConvLSTM exhibits predictive skill of about one month in predicting daily spatial patterns of the Antarctic SIC between 2018 and 2022, and yields satisfactory performances in capturing unusually low sea ice conditions. These encouraging results show the great potential of machine learning applications in the field of Antarctic sea ice prediction.

1 Introduction

Antarctic sea ice is a crucial component of the climate system. Its seasonal variability has a regulatory effect on the salinity structure of the Southern Ocean (Haumann et al., 2016; Goosse et al., 2018), CO_2 uptake and release (Delille et al., 2014; Gray et al., 2018), and the global ocean circulation (e.g., Pellichero et al., 2018). In recent years, with increased human activities (e.g., fishing, scientific research, tourism and associated logistics), skillful subseasonal-to-seasonal (S2S) predictions of the Antarctic sea ice are becoming important to ensure safety and efficiency for these operations (Jung et al., 2016; Tejedo et al., 2022; Liu et al., 2022). Motivated by these scientific and practical necessities, the investigation of S2S prediction skill and predictability increasingly became a priority of the scientific community (Holland et al., 2013; Alley et al., 2019; Steele et al., 2021) and community projects, such as the Sea Ice Prediction Network South (SIPN South) (Massonnet et al., 2023), have emerged.

Sea ice prediction, in particular on the S2S time scale, has traditionally been a challenge for polar researchers (e.g., Jung et al., 2016; Guemas et al., 2016; Zampieri et al., 2018; Zampieri et al., 2019; Xiu et al., 2022). To date, coupled numerical models are the main tool for S2S sea ice forecasting in polar regions (Holmes et al., 2022), and the output of these models is distributed, for example, by the Copernicus Climate Change Service (C3S) (https://climate.copernicus.eu/) or the World Weather Research Program and the World Climate Research Program

(WWRP/WCRP) S2S Project (http://www.s2sprediction.net). Although S2S Antarctic sea ice predictions are believed to have promising potential and skillful winter sea ice extent (SIE) predictions up to 11 months in advance have been achieved in some regions (Bushuk et al., 2021), only one model currently has the predictive skill in terms of sea ice edge better than a climatological prediction at a lead time of 30 days (Zampieri et al., 2019). Improving Antarctic sea ice forecasting with coupled models still requires substantial effort for better parameterizations, initialization, increased spatial resolution, etc. An alternative but valuable method is formulating sea ice prediction based on statistical models, which exploits recurrent predictor-predictand relationships in past data (e.g., Chen and Yuan, 2004; Wang et al., 2016; Pei, 2021). For the Antarctic SIE, statistical models exhibit better performance than dynamical models in practical prediction exercises (Massonnet et al., 2023). However, the predictive skill of these statistical models is largely constrained by their insufficient nonlinear fitting capability (Wang et al., 2013). Given the abovementioned limitations of climate and statistical models, there is an urgent need for a more efficient strategy to deal with the highly-nonlinear problem of S2S Antarctic sea ice prediction.

Deep Learning (DL) is a technique in the field of artificial intelligence (AI) that uses a deep neural network (DNN) to well capture the highly-nonlinear relationship between the features (i.e., predictors) and labels (i.e., predictands) (Schmidhuber, 2015). In recent years, DL has been applied to the sea ice prediction. Chi and Kim (2017) made the first attempt at using DL in the prediction of Arctic sea ice based on a fully-connected neural network and a long short-term memory (LSTM) network. Liu et al. (2021) predicted the weekly Arctic sea ice concentration (SIC) using a convolutional LSTM (ConvLSTM), which has predictive skills of up to 6 lead weeks in the operational forecast. Andersson et al. (2021) used an ensemble of U-Net to predict the binary sea ice probability for the next 6 months and showed that the U-Nets predict the sea ice edge position better than the SEAS5 model (Johnson et al., 2019) in extreme events. Ren et al. (2022) optimized the structure of the U-Net, and their DNN is skillful in predicting the daily Arctic SIC up to 28 days in the future. However, most of the attempts at integrating AI and sea ice prediction are still in their infancy. The DNNs still have limited skill in quantitative daily sea ice prediction, and a coherent two-dimensional model for the prediction of the whole polar domain, rather than a time series for each pixel or part of the region is strongly required. Kim et al. (2020) and Asadi et al. (2021) trained 12 individual monthly models respectively for 12 calendar months. However, in practical application, it is desirable to use a single model to consistently complete a task. Importantly, as often happens in sea ice research, the existing literature is strongly focused on the Arctic, while the application of machine learning (ML) techniques for the prediction of Antarctic sea ice is less common.

This paper aims to construct and test a ConvLSTM DNN to predict daily Antarctic sea ice concentration fields. ConvLSTM (Shi et al., 2015) is a neural network designed to deal with spatial and temporal information simultaneously and thus should have the ability to capture the spatial and temporal variation of sea ice. The scientific questions that we address in this study are the following:

1) Can we perform reasonable sea ice concentration predictions by relying only on past SIC observations?

2) How does the predictive skill of ConvLSTM vary regionally and seasonally?

To the best of our knowledge, this is the first application of ConvLSTM in Antarctic sea ice prediction. Once ConvLSTM DNN is successfully constructed, it can also be easily employed to make predictions of the annual SIE, thus contributing to established initiatives of the sea ice prediction community, such as the SIPN-South project.

2 Data and Methods

2.1 Model predictors and design of the training dataset

The daily Antarctic sea ice concentration is the NASA-Team (Comiso, 2017), from 1st January 1989 to 31st December 2021, released by the National Snow and Ice Data Center (NSIDC). In this paper, we regrid the SIC data from the original 25 km polar stereographic grid to the 100 km grid for the DL calculations. We divided the data into two groups. The data from January 1st, 1989 to December 31st, 2016 are assigned to the training set, and from January 1st, 2018 to December 31st, 2022 to the independent testing set. The daily climatology and standard deviation of SIC are calculated from the training set.

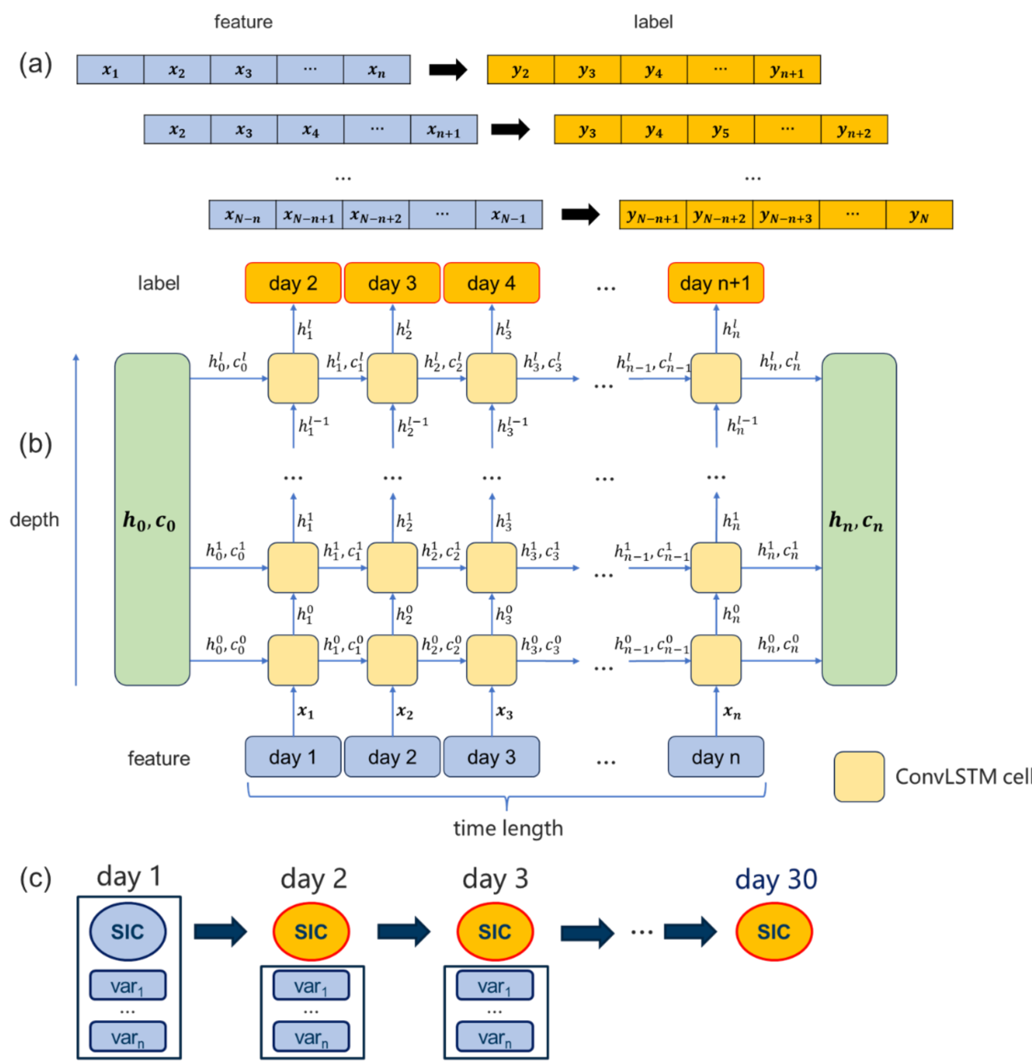

Figure 1. Schematic diagram of ConvLSTM network for Antarctic sea ice concentration (SIC) prediction. (a) The feature-label dataset created with a rolling strategy. (b) The data flow of one sample in ConvLSTM. The inputs of day(1) – day(n) are regarded as features (i.e., the vector input into the model $\boldsymbol{x_i}$), and the outputs of day(2) – day(n+1) are regarded as labels. The $\boldsymbol{h_i}$ represents the hidden variable, and the $\boldsymbol{c_i}$ represents the cell state. (c) The schematic diagram for constrained prediction schemes. The variables within the blue area refer to the given data, and the variables within the orange area refer to the predicted data. The dark blue arrow signals that the model is calculated once forward in time.

In this study, we select six variables as the predictors. Three predictors are variables that contain SIC information: (1) the daily SIC data, (2) the daily climatology of SIC, and (3) its corresponding standard deviation. Three predictors are metadata or constant: the (4) sine and (5) cosine of the yearly time index, and (6) a gridded land mask (0 for land, 1 for ocean). It is worth noting that the metadata and constants employed here follow the approach of Andersson et al., 2021, such that the sine and cosine of the time index is a periodic sequence of 1 year. The dataset is created using a rolling strategy as illustrated in Figure 1a. $\boldsymbol{x_i}$ represents the tensor containing six variables, and $\boldsymbol{y_i}$ represents the SIC for prediction. In this way, more than 10000 samples are obtained from the training set. All variables except the metadata and constants are Gaussian-normalized before the input into the model.

2.2 The ConvLSTM neural network

ConvLSTM is a neural network that combines the CNN (Lecun et al., 1998) and LSTM (Houchreiter and Schmidhuber, 1997), by embedding the convolutional cells into LSTM cells (i.e., ConvLSTM cell in Figure 1b). In this way, ConvLSTM can extract both spatial and temporal information and is a powerful tool for intricate 3D-spatiotemporal sequence prediction problems. Here we use a typical structure of the network and its hyperparameters: 5 hidden layers (the channel of which are [8,8,4,2,1]), kernel size of (5,5), a learning rate of 0.001, and weight decay of 0. The Mean Absolute Error (MAE) is used as the loss function, which is calculated for SICs across the entire Antarctic region between the ConvLSTM's output and the corresponding SICs from the reanalysis. The ConvLSTM is trained with 300 epochs by applying a batch size of 32. The data flow of ConvLSTM of one sample is illustrated in Figure 1b. The time length of one sample is set to 90 days, thus the data of feature-label correspondence is a 90-day to 90-day series with a 1-day lag. Correspondingly, the constructed ConvLSTM model is a 1-lead prediction model.

In practical predictions, the model iterates the prediction result recurrently, with a self-constrained strategy (to be described in Sect. 2.3). We give the model the data from 90 days before the initialization date, including the initialization date, to initialize the model (i.e., the data from day[-89] to day[0]). The model will output the data for 90 days with a 1-day lag from the initialization (i.e., the predicted data is from day[-88] to day[1]). The last date (day[1]) is the predicted result for day[1] that we keep, while the first 89 days of prediction are discarded. Then, the data from day[-88] to day[1]–the features of day[1] are those just predicted–will be inputted into the model, and the model can output the predicted data of day[2]. Iteratively, we can get the predicted result for all the target days. The process of prediction can be summarized by Eq. 1:

$$label_{pred[t_0+\delta t]} = ConvLSTM\left(feature_{obs[t_0+\delta t-n,t_0+\delta t-n+1,\dots,t_0]+pred\&real[t_0+1,t_0+2,\dots,t_0+\delta t-1]}\right)[-1] \quad (1)$$

where t_0 is the day of initialization, δt is the lead time, n is the time length (here 90 days), and $[-1]$ means the last of the 90 outputs of ConvLSTM.

2.3 Self-constrained prediction strategy

Figure 1c shows the constrained prediction strategy. The constrained scheme is similar to Liu et al. (2021), i.e., the real feature data are input into the model as features in long-time prediction. It is a scheme that is usually used to test the maximum expected predictability given by the chosen forecast methods and input fields. In this paper, the selected predictors are themselves information on the sea ice, or alternatively metadata and constant. In this way, the predictors that are used to constrain the predictands are known at the initialization, thus the model can make an operational prediction using a constrained prediction strategy, which we call "self-constrained prediction strategy".

3 Results

3.1 Predictive skill of ConvLSTM

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). 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 skill metrics and benchmark predictions are described in detail in the supporting information (Text S1). Figure 2 shows the hemispheric-averaged metrics of ConvLSTM and the three benchmark predictions. Of the three benchmark predictions, the damped anomaly persistence is the most skillful at short lead times, while the climatology is superior after about 30 forecast days. Based on the climatological benchmark, the SIC prediction skill is best in the austral winter (JJA) (Figures 2j to 2l), while it is worst in the summer (Figures 2d to 2f). When compared to the damped anomaly persistence, the memory of spCorr is more skillful in terms of the RMSSS and IIEE metrics, and its performance steadily approaches that of the two benchmark forecasts as the lead time increases.

In terms of RMSSS metrics, ConvLSTM remains skillful for over 40 days compared to the anomaly persistence throughout the year (the first column of Figure 2) and holds predictive skill for 20 days compared to the damped anomaly persistence (Figure 2a). During the austral winter and spring (SON), the ConvLSTM beats simple anomaly persistence for up to 60 lead days and shows the highest skill in JJA, when ConvLSTM beats all three benchmarks up to 40 days. As shown by the spCorr metric, the ConvLSTM-predicted SIC does not have a higher spatial correlation with the observations compared to that of the (damped) anomaly persistence benchmark, and this correlation decreases rapidly with time (Figure 2b). In austral summer (DJF) and winter (JJA), the ConvLSTM shows only an overall skill of 20 days compared to the climatological benchmark (Figure 2b) and a modest skill of 40 days compared to the anomaly persistence (Figures 2e, 2k).

In contrast to the moderate performance on the point-to-point SIC comparison metrics (i.e., RMSSS and spCorr), the ConvLSTM shows better skill in predicting the Antarctic sea ice edge, which is relevant information for potential forecast users. Specifically, ConvLSTM has better predictive skills than the damped anomaly persistence up to 30 forecast days (Figure 2c), a signal significant in all seasons except spring (Figures 2f, 2i, and 2o). From the above comparison, although the ConvLSTM is relatively unskilled in providing detailed spatial information of sea ice within the pack ice compared to the persistence benchmark, it performs better in predicting the distribution of sea ice edge. This is a general characteristic of AI predictions: they may be skillful enough for binary problems (e.g., the presence or not of sea ice in a grid cell), but less meaningful when examining the spatial variations of a continuous field in detail.

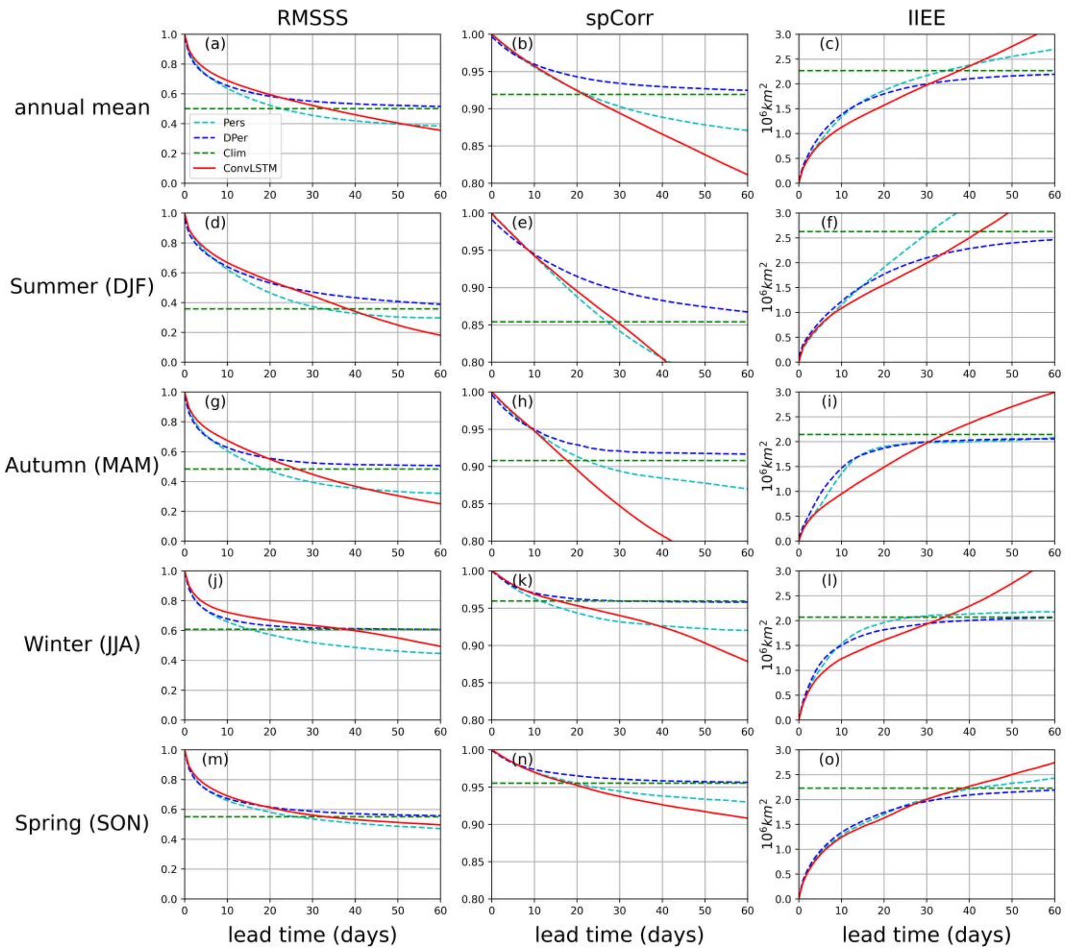

Figure 2. 2018 to 2022 pan-Antarctic annual mean prediction skill quantified by RMSSS (a), spCorr (b), and the IIEE (c). (d-e-f), (g-h-i), (j-k-l), and (m-n-o) are the same as (a-b-c) but for December to February (DJF), March to May (MAM), June to August (JJA), and September to November (SON), respectively. RMSSS = Root-Mean-Square Skill Score; spCorr = Spatial Correlation; IIEE = Integrated Ice Edge Error.

3.2 The spatial and temporal dependency of predictive skill of ConvLSTM

Since different sources of predictability characterize the sea ice in each sector of the Southern Ocean (Bushuk et al., 2021), the forecast predictive skill also significantly varies regionally and temporally (Zampieri et al., 2019). In this section, we present the predictive skill of ConvLSTM in each sector of the Southern Ocean, namely: the Ross Sea (RS, 160° E–130° W), the

Amundsen/Bellingshausen seas (ABS, 130–60° W), the Weddell Sea (WS, 60° W–20° E), the Indian Ocean (IO, 20–90° E), and the Western Pacific Ocean (WPO, 90–160° E). Figure 3 shows the RMSSS and spCorr for regional SIC predictions of ConvLSTM. The skills vary by region and season. It is found that the regional SIC skill is comparable to or exceeds that of the anomaly persistence (refer to dot markers in Figure 3). For some target months and some regions, the predictive skill outperforms the anomaly persistence up to 60 lead days, indicating that ConvLSTM successfully captured some aspects of the sea ice variability at the S2S timescale.

The forecast skill shows a strong seasonal dependency. In terms of RMSSS, although the skill of ConvLSTM is similar in each season for one-week predictions, it is lower in the austral autumn (MAM) than in other seasons at the S2S timescale. The skills show diagonal features in all regions in MAM and JJA, which means that the predictive skill is low when initialized in the Austral summer. The high skill that emerged at the pan-Antarctic scale from winter to early spring (JJAS), with the RMSSS exceeding 0.6 for up to 1 forecast month, also holds in the Ross Sea (RS), Weddell Sea (WS), and Indian Ocean sector (IO), where ConvLSTM still outperforms the damped anomaly persistence (supporting information Figure S1). On the contrary, in summer and autumn, ConvLSTM shows relatively low skill at the S2S timescale, especially in April in the RS and the WPO. As for the February prediction at 1 lead month, ConvLSTM performs better than the anomaly persistence in the RS and IO but shows lower skill than anomaly persistence in ABS, WS, WPO, and pan-Antarctic.

The diagonal feature is still evident in the spCorr plots(the second column of Figure 2). Here, the diagonal feature peaks around September, revealing that the ConvLSTM has the highest skill for SIC spatial variation in this month. Similar to the RMSSS, the skill peaks in May in the WPO, suggesting that the season of the highest skill in this region is different from the others. The spCorr is evidently low in DJF and MAM when the SIE is low (corresponding to Figures 2e and 2h).

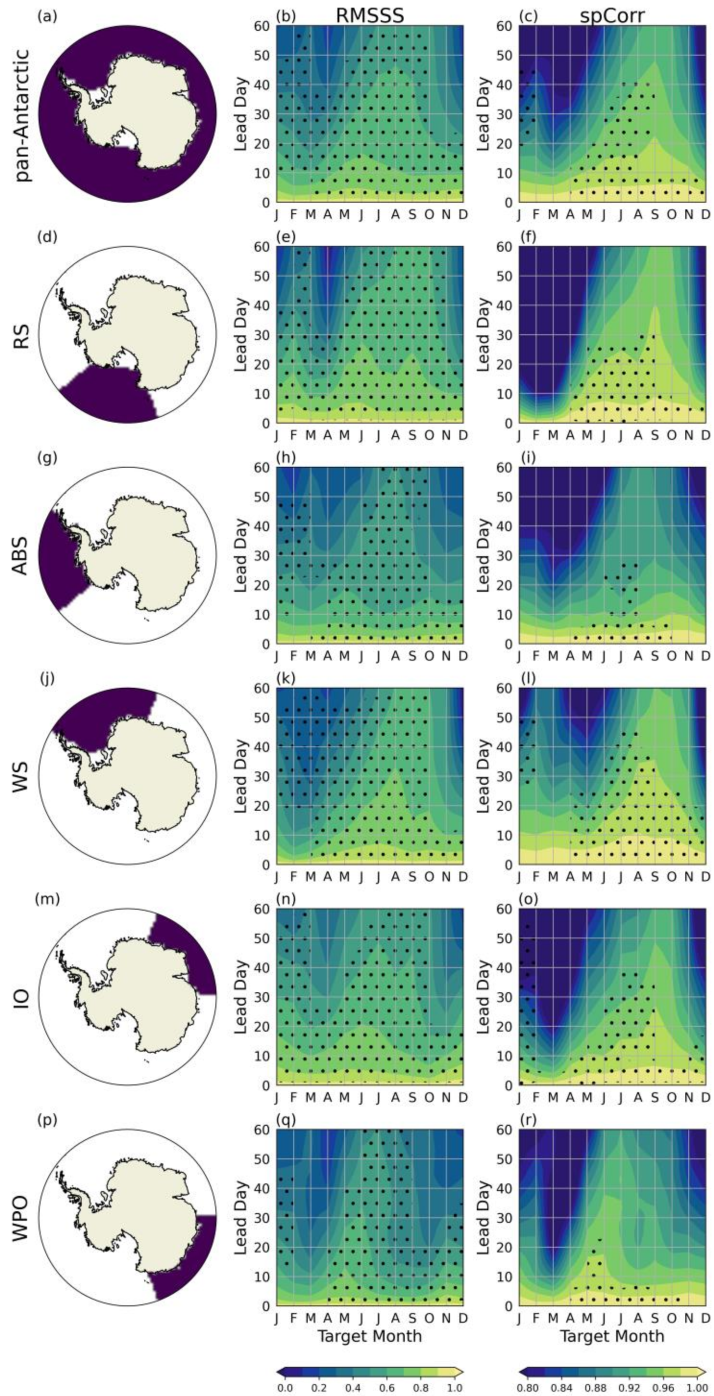

Figure 3. Seasonal predictive skill (RMSSS and spCorr) for the regional Antarctic SIC for different target months and prediction lead times. The six rows from top to bottom refer to pan-Antarctic, Ross Sea (RS), Amundsen and Bellingshausen Sea (ABS), Weddell Sea (WS), Indian Ocean (IO), and West Pacific Ocean (WPO), respectively. The dot markers indicate months where the skill of ConvLSTM beats the anomaly persistence forecast.

3.3 The prediction for February and September

To further examine the ConvLSTM's capability to predict the sea ice minimum and maximum, we predict the SIE for February (sea ice minimum month) and September (sea ice maximum month) from 2017 to 2022 at 1 month lead time. The results are shown in Figure 4. The ConvLSTM generally gives a satisfactory prediction of the extent extremes. The difference between the predicted and observed SIC is mostly below 20%. In February, the sea ice mainly concentrates in the WS, and the prediction error in this sector varies by year. In February, ConvLSTM tends to slightly overestimate the SIC in RS and WPO. In September, the SIC in the IO is overestimated every year. However, the effects of overestimation and underestimation of SIC on the prediction of sea ice edges are small, and the predicted position of the sea ice edge is in good agreement with the observation (second and fourth columns of Figure 4).

In terms of the SIE (Figure 4), ConvLSTM's predictions are mostly in the range of one observed standard deviation and generally more reliable than that of benchmark predictions (e.g., the damped anomaly persistence). The SIE forecast error in September is generally larger than in February and this could be explained by the annual variation of the sea ice edge length, which is shorter in summer than in winter. It should be noted that in the February of 2017 and 2022, when SIE hit record low values, the ConvLSTM made reliable predictions. The ConvLSTM prediction shows a slight overestimation in February 2020 (Figure 4m) and an underestimation in September 2019 and 2020 (Figures 4k, 4o). The minimum SIE event of February 2022 is characterized by a SIE decrease since September 2021 (Figure 4s), which the ConvLSTM fails to capture.

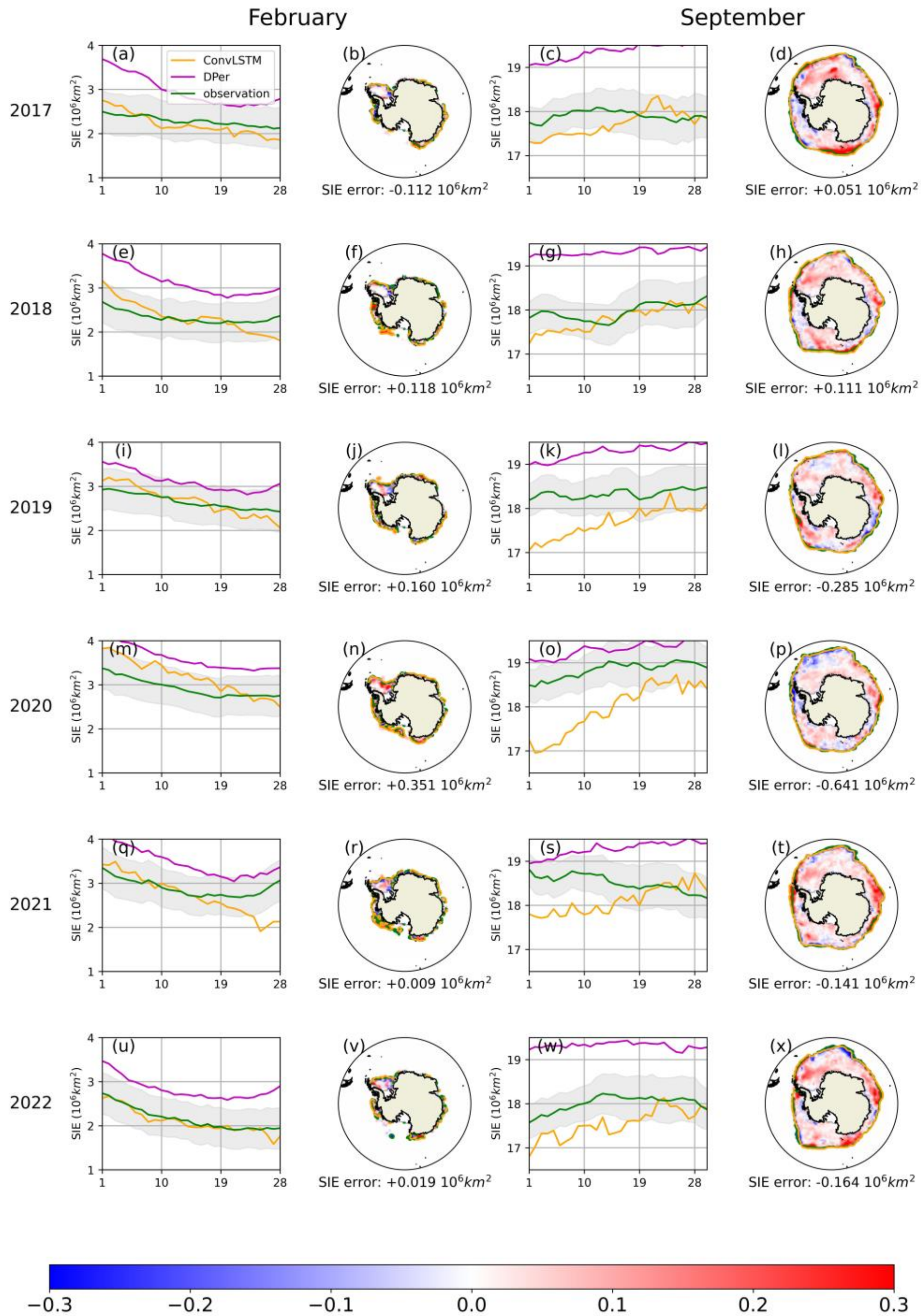

Figure 4. Comparison between the ConvLSTM 30-days predictions (orange lines), observations (green lines), and damped anomaly persistence (magenta lines) for February and September for the years 2017 to 2022. One standard deviation of the observations is displayed in gray shading. The maps show the difference between the predicted and observed monthly mean SIC in February 2017, with the two ice edges indicated by the orange and green contours, respectively. The sea ice edge is the 15% contour of SIC.

4 Summary and Outlook

We constructed a ConvLSTM DNN model to predict the daily Antarctic SIC based solely on information from the SIC observations. The model learns the information of one-step variation in the training set from 1st January 1989 to 31st December 2016 and then is used for SIC reforecasting from 2018 to 2022 through a self-constrained prediction strategy. By comparing the skills of the ConvLSTM with three benchmarks, our results indicate that the ConvLSTM model can maintain predictive skill for daily pan-Antarctic SIC for up to 1 lead month. The predictive skill of ConvLSTM has significant seasonality, with better performance from June to September. ConvLSTM also has good performances in predicting the SIE extremes 1 month in advance, with monthly mean SIE error below 0.2 million km^2, and makes skillful predictions of the SIE record low in 2017 and 2022.

Here, the design of the prediction method uses a self-constrained prediction strategy. Unlike the sequence-to-sequence method, the length of the period of prediction can be changed flexibly, which is preferred for practical applications of the prediction system. Indeed, operational predictions can be achieved independently by using the data from the statistics of SIC, metadata, and constant. As for the source of the predictive skill, we hypothesize that the SIC in the starting day provides the model with the initialization state of SIC, and the region where the SIC is more likely to change is provided by the standard deviation of SIC. The climatology, and sine/cosine of time index provide the model with information on the day of the year and the potential tendency of SIC. Finally, the land mask makes it possible for the model to distinguish between sea and land. In this way, the model is expected to outperform both the (damped) anomaly persistence and climatology prediction. The polar climate system is highly non-linear because of the ocean-ice-atmosphere interactions. Thus, in the future, it might be necessary to introduce further oceanic or atmospheric variables to improve the skills of ConvLSTM. For example, information on the oceanic and atmospheric state could be provided from a dynamic numerical model, which would require an evolution of the current self-constrained model to a constrained model that interacts with a dynamical model.

Future work is still needed to improve the skills of the model. The ConvLSTM employed here is based on a standard network structure, and it might benefit from customizations specific to the sea ice prediction problem. The quality and uncertainty of data capability the capability of the model. The amount of training samples is still small due to the limited observation record for SIC. This could be improved by pre-training using extra data, for example from the Coupled Model Intercomparison Project (CMIP, Eyring et al., 2016) database, which however provides only limited skill for historic simulations of the Southern Ocean sea ice (Roach et al., 2020). Finally, the computing power applied in this work is limited, and larger models could be tried in the future.

Nevertheless, this work reveals that by capturing only the sea ice statistics, without other oceanic or atmospheric parameters, the DNN can formulate meaningful sea ice predictions and perform better than typical benchmark predictions. Based on an analysis of the empirical orthogonal functions for the sea ice concentration anomaly, which is included in the supplementary material (Figure S2), we argue that this is not an easy task. According to this, the initial success of ConvLSTM already shows that DNN can capture the tenuous non-linear relationships driving the sea ice evolution in the Antarctic region. These encouraging results suggest the considerable potential of applying this type of ML infrastructure to formulate reliable Antarctic sea ice prediction.

Acknowledgments

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Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

All data used here have open access. The daily sea ice concentration data are downloaded from National Snow & Ice Data Center, https://nsidc.org/data/NSIDC-0051/versions/2, https://nsidc.org/data/NSIDC-0081/versions/2 (last access: May 2023). The network weights and design and the test dataset can be acquired from https://doi.org/10.5281/zenodo.8137291.

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