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An effective deep-learning prediction of Arctic sea-ice concentration based on the U-Net model

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A R T I C L E I N F O

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CFSv2
NorCPM

A B S T R A C T

Current shipping, tourism, and resource development requirements call for more accurate predictions of the Arctic sea-ice concentration (SIC). However, due to the complex physical processes involved, predicting the spatiotemporal distribution of Arctic SIC is more challenging than predicting its total extent. In this study, spatiotemporal prediction models for monthly Arctic SIC at 1- to 3-month leads are developed based on U-Net—an effective convolutional deep-learning approach. Based on explicit Arctic sea-ice–atmosphere interactions, 11 variables associated with Arctic sea-ice variations are selected as predictors, including observed Arctic SIC, atmospheric, oceanic, and heat flux variables at 1- to 3-month leads. The prediction skills for the monthly Arctic SIC of the test set (from January 2018 to December 2022) are evaluated by examining the mean absolute error (MAE) and binary accuracy (BA). Results showed that the U-Net model had lower MAE and higher BA for Arctic SIC compared to two dynamic climate prediction systems (CFSv2 and NorCPM). By analyzing the relative importance of each predictor, the prediction accuracy relies more on the SIC at the 1-month lead, but on the surface net solar radiation flux at 2- to 3-month leads. However, dynamic models show limited prediction skills for surface net solar radiation flux and other physical processes, especially in autumn. Therefore, the U-Net model can be used to capture the connections among these key physical processes associated with Arctic sea ice and thus offers a significant advantage in predicting Arctic SIC.

摘要

准确地预测北极海冰密集度 (SIC) 对北极航运, 旅游和资源开发等十分重要. 由于北极海冰的复杂多变, 预测北极SIC的时空分布比预测海冰范围更具有挑战性. 基于一个有效的卷积类机器学习模型—U-Net, 本文研制了可用于预测未来1至3个月北极SIC的模型. 基于北极海–冰–气物理过程, 本文选取了前期11个与北极海冰变化密切相联的变量作为预测因子, 包括北极SIC, 大气, 海洋和热通量等变量. 较CFSv2和NorCPM而言, 本文研制的U-Net模型具有更高的预测技巧. 此外, 诊断各预测因子的相对重要性显示, 提前1个月的预测模型更依赖于前期的SIC, 但提前2和3个月的预测模型则更依赖于前期的地表净短波辐射通量. 然而, 动力模式对地表净短波辐射和其相关物理过程的预测技能有限, 这可能是U-Net模型预测技巧较动力模式更高的原因之一. 本研究既有利于提升对北极SIC空间分布的预测能力, 也有助于进一步认识动力模式对海冰预测效能有限的原因.

1. Introduction

Arctic sea ice has experienced unprecedented rapid melting in the context of global warming (Cohen et al., 2014). The dramatic changes in Arctic sea ice have significantly impacted extreme climate events and mid-to-high latitude regions (Ding and Wu, 2021). In addition, the decline of Arctic sea ice has the potential to bring substantial economic benefits via effects on Arctic shipping routes, tourism, and resource development (Petrick et al., 2017). Thus, it is becoming more important to accurately predict Arctic sea ice.

The variability of Arctic sea ice is jointly influenced by radiative feedback, ocean heat transport, and atmospheric circulation (Liu, 2022; You et al., 2021). In the radiative feedback mechanism, the sea-ice-albedo feedback plays a dominant role: sea-ice melt reduces the ocean

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albedo, increases the absorption of solar radiation, and further accelerates the reduction in sea ice (Pistone et al., 2014). In the cloud/water vapor-radiation feedback, reduced sea ice leads to increased water vapor in the lower troposphere and more low clouds, which strengthens the absorption of longwave radiation, further promoting warming of the atmosphere and decreasing sea ice over Arctic (Philipp et al., 2020). Regarding ocean heat transport, the Bering Strait and Fram Strait, as major channels, directly influence changes in sea-ice melt and thickness through warm water and heat flux transport (Dmitrenko et al., 2015; Schauer et al., 2004). Since 2008, the dynamic processes in the Arctic have become more important in affecting the growth of sea ice (Yi et al., 2024; Zhang et al., 2024). In atmospheric circulation, the positive phase of the North Atlantic Oscillation/Arctic Oscillation, while the positive phase of the Arctic dipole promotes Arctic sea-ice export and heat transport (Liang et al., 2020; Zhang et al., 2008). Furthermore, the polar anticyclonic circulation plays an important role in regulating the distribution of sea ice, particularly in summer (Ding et al., 2017).

Current studies on Arctic sea-ice prediction focus mostly on the sea-ice extent (SIE), with predictions of the spatial distributions of sea-ice concentration (SIC) being relatively less common (Wei et al., 2021). The prediction skill of dynamic models for Arctic SIC, especially at seasonal scales, still needs further improvement (Blanchard-Wrigglesworth et al., 2023). This limited prediction skill of dynamic models could be due to the biases in assimilating initial sea-ice conditions and internal physical processes (Blanchard-Wrigglesworth et al., 2023; Luo et al., 2021). In addition, previous studies used methods such as linear regression and Markov chains for Arctic sea-ice prediction (Chen et al., 2021; Wang et al., 2022; Wang et al., 2023). Although some statistical prediction models can simplify calculations and explain clear relationships through linear assumptions, their predictions often show significant bias when the actual data exhibit nonlinear features or complex interactions (Doscher et al., 2014).

In recent years, deep-learning methods have been widely applied in Arctic sea-ice prediction, achieving remarkable results, such as CNN, ConvLSTM, etc. (Kim et al., 2021; Ali and Wang, 2022; Chi and Kim, 2017; Huan et al., 2023). Deep-learning models have many advantages over traditional prediction methods. For instance, the ability of deep-learning models to fit nonlinear relationships between data allows them to capture predictive sources that traditional prediction methods ignore (Reichstein et al., 2019). Additionally, most traditional statistical models can only build point-wise models, while some deep-learning models can consider the interaction between neighboring points through the convolutional operation. These advantages give deep-learning methods a promising future in Arctic SIC prediction.

The U-shaped convolutional network (U-Net) model proposed by Ronneberger et al. (2015) is a deep-learning model capable of extracting features at different scales from a relatively small number of samples and considering the spatial correlation between adjacent grid cells. The U-Net model has been effectively used in probabilistic prediction for Arctic sea ice (Andersson et al., 2021). Huan et al. (2023) developed a U-Net model for Arctic sea ice by using SIC as a single predictor. The question remains, however, as to how the U-Net method can be utilized to develop a prediction model that considers the combined impact of multiple physical processes of Arctic sea ice.

In this study, a quantitative prediction model of the spatial distribution of Arctic SIC was developed by employing the U-Net method and considering key influencing factors. To assess their prediction skills and gain insights into the relative importance of the predictors in the model, the prediction results were compared with predictions from dynamical models. In the future, we expect to combine the prediction results from multiple models and dynamical systems, to further improve the skills of operational predictions of monthly Arctic sea ice, which is also the motivation and purpose of this study.

The rest of this paper is organized as follows: The datasets and methods used in the study are described in Section 2. The prediction results are presented in Section 3. Finally, Section 4 provides a summary and discussion.

2. Data and methods

2.1. Data

The monthly average SIC observation data are from the National Snow and Ice Data Centre (NSIDC) (DiGirolamo et al., 2022). The data have a spatial resolution of 25 × 25 km. The atmospheric and heat flux variables are from the ERA5 reanalysis dataset on a $1^\circ \times 1^\circ$ grid (Hersbach et al., 2020), and the sea surface temperature (SST) data are from the Hadley Centre, on a $1^\circ \times 1^\circ$ grid (Rayner et al., 2003).

In addition, the prediction results of the National Centers for Environmental Prediction Climate Forecast System, version 2 (CFSv2) (Saha et al., 2014), and the Norwegian Climate Prediction Model (NorCPM) (Counillon et al., 2016)—two advanced dynamical climate prediction models known to be effective in predicting Arctic SIC on a monthly scale (Dai et al., 2020; Wang et al., 2013)—are applied as a comparative benchmark with our U-Net model. All observed and predicted data are interpolated using bilinear interpolation to the same grid as the observed SIC data from NSIDC.

2.2. U-Net model

The U-Net model has now been widely applied in semantic segmentation and image prediction (Siddique et al., 2021). The architecture of U-Net used in this study is shown in Fig. 1. The size of the input image

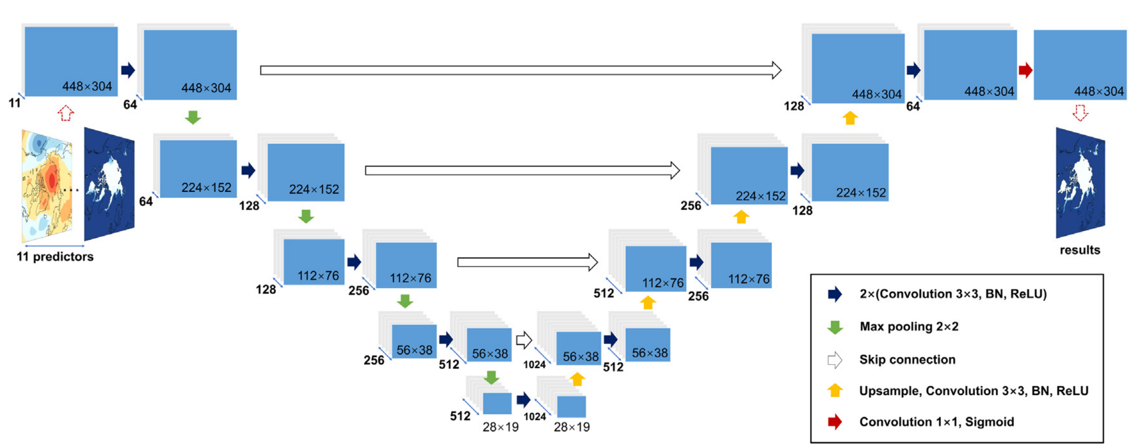

Fig. 1. Diagram illustrating the architecture of the U-Net model. The number of channels is indicated in bold in the bottom-left corner, and the horizontal dimensions are indicated in the bottom-right corner of each layer. The different colored arrows indicate the different operations applied to each layer. BN and ReLu stand for "batch normalization" and "rectified linear unit", respectively.

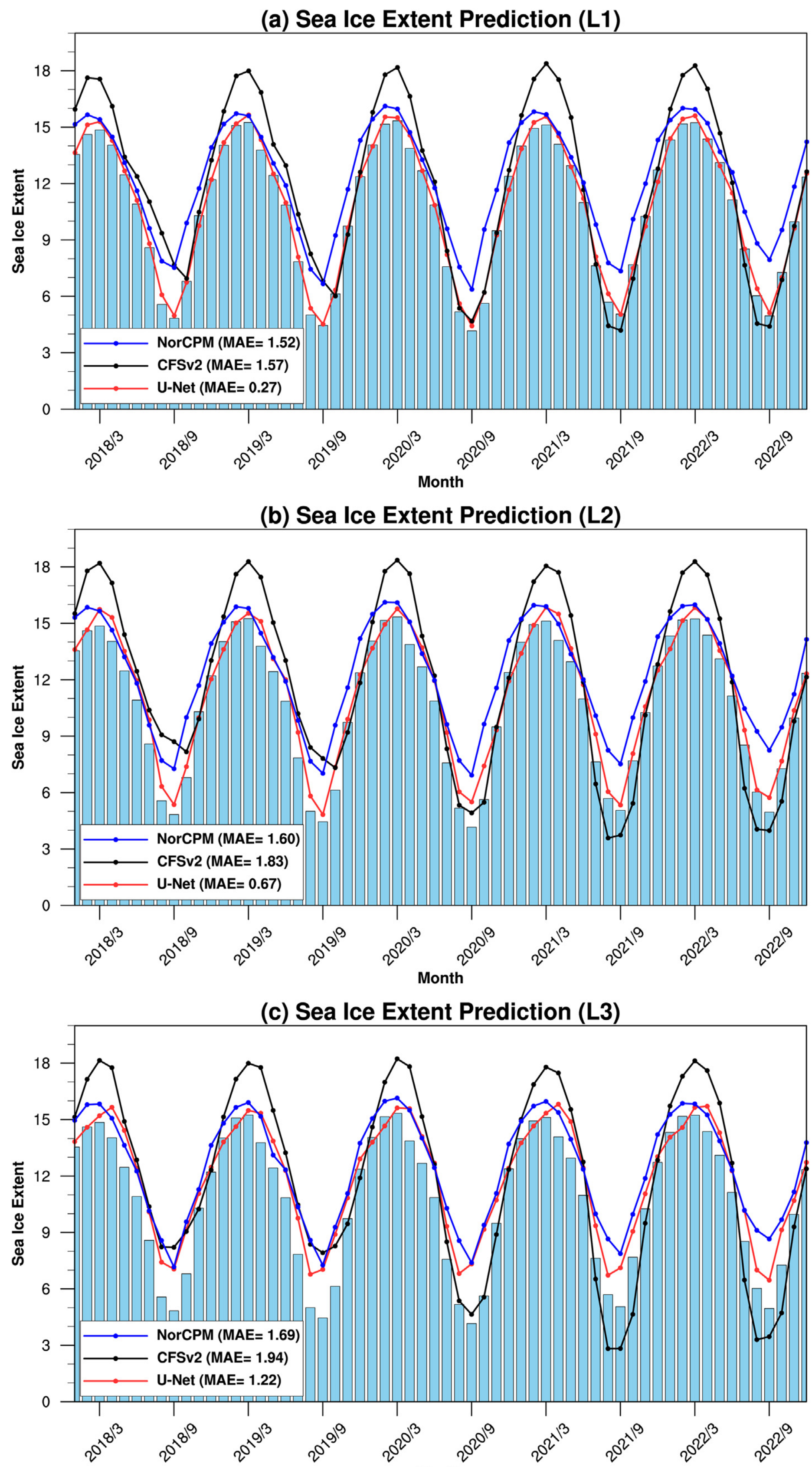

Fig. 2. Time series of the observed (blue bars), U-Net-predicted (red line), CFSv2-predicted (black line), and NorCPM-predicted (blue line) Arctic SIE (units: million km^2) at (a) 1-, (b) 2-, and (c) 3-month leads from January 2018 to December 2022. The MAE between the predicted and observed SIE is indicated in the bottom-left corner of each chart.

is (11, 448, 304), where 11 denotes the channels of predictors, and 448 and 304 are the width and height, respectively. The feature maps obtained at each downsampling step will be progressively restored to the same width and height as the input image during the upsampling process. The final output will be an image with a size of (448, 304). More details on the architecture of the U-Net model and training procedure can be found in Text S1.

In this study, the mean absolute error (MAE) and binary accuracy (BA) are used to evaluate the prediction skill of the models. The MAE represents the difference between the predicted and observed SIC, reflecting the prediction skill for the spatial distribution of SIC. The BA can measure the prediction skill for the sea-ice edge, and a higher value indicates higher accuracy. Additionally, the permutation importance method is employed to investigate the relative importance of each predictor in the U-Net model. The permutation importance method has been widely used to explain deep-learning models in previous studies (Andersson et al., 2021; Lyu et al., 2023). More details can be found in Text S2–4.

3. Results

Based on the understanding of the main mechanisms influencing Arctic sea-ice variation revealed by previous research, such as radiative feedback, ocean-to-pole heat transport, and atmospheric circulation (Liu, 2022; You et al., 2021), 11 variables representing the radiative, thermal, and dynamic processes are selected as predictors (summarized in Table S1). U-Net prediction models for Arctic SIC at 1- to 3-month leads are developed. We divide the data into three parts: 1979–2012 as the training set, 2013–2017 as the validation set, and 2018–2022 as the test set. The monthly prediction results of the test set from January 2018 to December 2022 are shown in Figs. S1–S3. Data from different lead times are used to train three separate models—specifically, models for 1-, 2-, and 3-month leads. For example, in the 1-month lead model, data from December 2021 to November 2022 are used to predict the SIC from January to December 2022.

3.1. Prediction skill of the U-Net model

Firstly, the skill of the U-Net model in predicting the Arctic SIE is evaluated during 2018–2022 (Fig. 2). At 1-, 2-, and 3-month leads, the average MAE for the monthly Arctic SIE from January 2018 to December 2022 predicted by the U-Net model is 0.27, 0.67, and 1.22 million km^2, respectively. These results are generally better than those of CFSv2 (1.57, 1.83, and 1.94 million km^2) and NorCPM (1.52, 1.60, and 1.69 million km^2). At the 1-month lead, the U-Net model shows better prediction skill for SIE compared to both CFSv2 and NorCPM in all months (Fig. 2(a)); and at 2- and 3-month leads, it shows significant improvement over CFSv2 in winter and over NorCPM in summer (Fig. 2 (b, c)).

The U-Net model shows relatively lower MAE from August to October, indicating better prediction skill of the magnitude of late summer–autumn sea ice (Table S2). Meanwhile, compared to CFSv2 and NorCPM, the U-Net model has lower MAEs in all months at 1- to 3-month leads, with seasonal variations in the extent of improvement (Fig. 3 (a, b)). Also, U-Net exhibits greater enhancement compared to CFSv2 in January–April, and compared to NorCPM in August–October.

Regarding prediction of the sea-ice edge, the U-Net model demonstrates relatively high prediction skill in terms of BA from January to May (Table S3). The U-Net model has higher accuracy at 1- to 3-month leads than CFSv2 and NorCPM (Table S4). The greatest improvement is in August–September, compared to both CFSv2 and NorCPM (Fig. 3 (c, d)).

To further compare the prediction skill of the established U-Net model with other convolutional deep-learning models, another model should be trained. Ali and Wang (2022) indicated that the CNN model—a convolutional deep-learning model—can be used to predict the Arctic sea ice. Therefore, a replica CNN model was trained using our dataset and the same time period. As shown in Table S4, the MAE (BA) of our U-Net model at 1- to 3-month leads is lower (higher) than that of the CNN model. Thus, our U-Net model can more accurately predict the sea-ice edge and spatial distributions over the Arctic compared to the CNN model at 1- to 3-month leads.

3.2. Relative importance of each predictor in the U-Net model

The above analysis indicates that our U-Net model can make skillful predictions of Arctic SIC on a monthly scale. To quantify the importance of each factor, the permutation importance method is applied to identify which factors play significant roles in our U-Net model.

Fig. 4 displays the relative importance of the predictors in the U-Net model at different monthly leads. Overall, the Arctic SIC at the 1-month lead plays an important role in the prediction model, but its

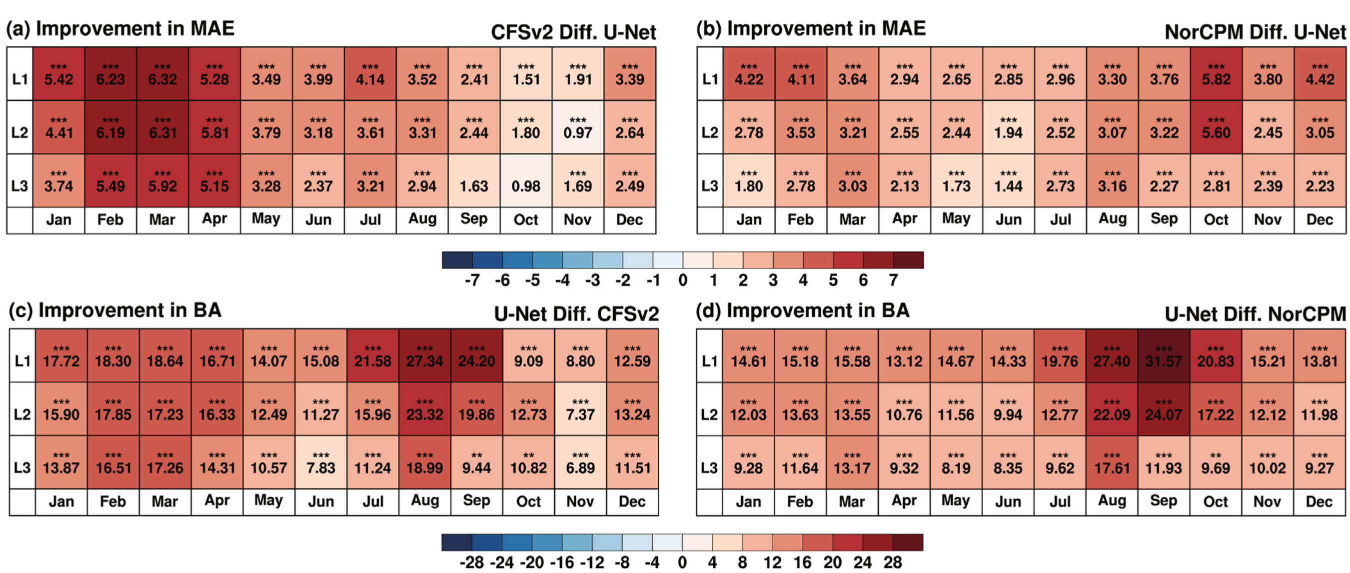

Fig. 3. Improvement of U-Net compared to (a, c) CFSv2 and (b, d) NorCPM in terms of (a, b) MAE (%) and (c, d) BA (%) at 1-, 2-, and 3-month leads from January 2018 to December 2022. *, **, and *** indicate statistical significance at the 90 %, 95 %, and 99 % confidence levels, respectively, through the Monte Carlo permutation test (details provided in Text S2).

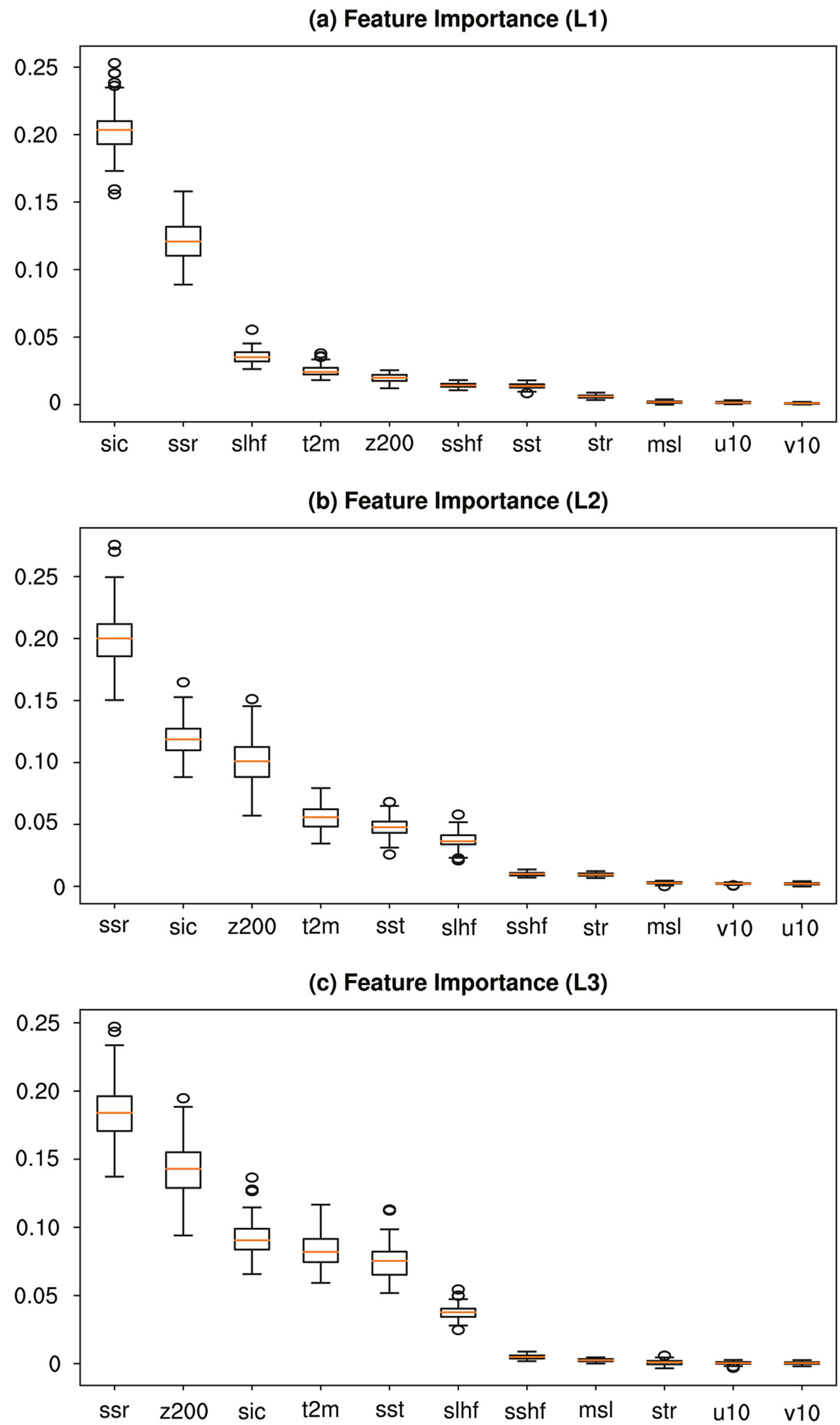

Fig. 4. The importance metric distributions of the predictors in the U-Net model for (a) 1-, (b) 2-, and (c) 3-month leads during 2018–2022. The orange line across each box and the upper and lower boundaries of the box refer to the median and upper and lower quartiles, respectively. The black circles represent the outliers.

importance decreases as the lead time increases (Fig. 4). This indicates that sea-ice persistence is an important prediction source at monthly scales (Guemas et al., 2016), and the U-Net model can effectively capture this characteristic. The role of thermal and dynamic processes becomes more important as the lead time increases. Specifically, the most important predictor in the models at 2- and 3-month leads is surface net solar radiation flux (Fig. 4(b, c)). Additionally, 200-hPa geopotential height is the third-most important predictor at the 2-month lead, and the second-most important predictor at a 3-month lead (Fig. 4(b, c)). Indeed, these high-latitude atmospheric circulation variations and radiation feedback have a significant impact on Arctic sea ice at both monthly and seasonal scales with explicit physical processes (Ding et al., 2017).

In terms of why the U-Net model shows better skill than CFSv2 and NorCPM in predicting the Arctic SIC, recent studies have pointed out that dynamic models have certain limitations in reproducing the interactions between summertime high-latitude circulation, clouds, and radiation (Luo et al., 2021). For instance, when CFSv2 and NorCPM make predictions in June, the surface net solar radiation flux over most of the Arctic Ocean for July–September is predicted with limitedskill (Fig. S4). Due to the persistence of sea ice, the errors in sea-ice predictions for July–September, caused by the low prediction skill for radiation, accumulate in the final prediction for September. The U-Net model can directly capture the connections between the surface net solar radiation flux in June and the SIC in September, which may result in a higher prediction skill compared to CFSv2 and NorCPM at the 3-month lead. If dynamical models can improve their prediction skills for surface net solar radiation flux and related physical processes in the future, this may promote their prediction skills for Arctic SIC at 2- and 3-month leads.

4. Summary and discussion

In this study, an efficient Arctic SIC prediction model at 1- to 3-month leads was developed based on the U-Net model and 11 predictors. The 11 predictors included the persistence of the Arctic SIC and 10 other atmospheric, oceanic, and heat flux variables closely related to the thermal and dynamic characteristics of Arctic sea ice. Results show that our U-Net model exhibits higher prediction skills at all lead times compared to two current advanced dynamic climate prediction systems (CFSv2 and NorCPM). The permutation importance method was used to quantify the relative importance of each predictor at 1- to 3-month leads. In the model at the 1-month lead, the Arctic SIC is the most important predictor. As the lead time increases, however, the surface net solar radiation flux and 200-hPa geopotential height become more important than the sea-ice persistence. These variations indicate that our U-Net model relies on the sea-ice persistence at the 1-month lead, whereas atmospheric circulation variations and radiation feedback are greater considerations at the 2- and 3-month lead times. In addition, the surface net solar radiation flux in autumn is predicted with limited skill in dynamic models, which affects the prediction skill for Arctic sea ice at the 2- and 3-month lead times.

Nevertheless, it is important to recognize that while deep-learning models have demonstrated substantial advantages over traditional prediction methods, there is no one-size-fits-all deep-learning model that can address every prediction challenge. In this study, the prediction skill of the sea-ice deep-learning model based on the U-Net method and previous predictors shows that as the prediction lead time increases (from 1 to 3 months), the model's prediction skill decreases. Other recent studies have also shown that the U-Net method can effectively improve the dynamical model's predictive skill for subseasonal precipitation in China by capturing the relationship between atmospheric circulation anomalies and precipitation patterns (Fan et al., 2024; Nie and Sun, 2024). In the future, the results of simultaneous sea ice, temperatures, and polar outer atmospheric circulation anomalies predicted by dynamical models should be added to the existing predictors, and a deep-learning prediction model combining dynamical and statistical factors should be developed to more accurately predict Arctic sea ice and achieve longer-term predictions (≥ 3 months).

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.aosl.2025.100691.

References

Ali, S., Wang, J., 2022. Mt-icenet-a spatial and multi-temporal deep learning model for arctic sea ice forecasting, Proceedings of 2022 IEEE/ACM International Conference on Big Data Computing, Applications and Technologies (BDCAT), pp. 1–10.

Andersson, T.R., Hosking, J.S., Perez-Ortiz, M., Paige, B., Elliott, A., Russell, C., Law, S., et al., 2021. Seasonal Arctic sea ice forecasting with probabilistic deep learning. Nat. Commun. 12. doi:10.1038/s41467-021-25257-4.

Blanchard-Wrigglesworth, E., Bushuk, M., Massonnet, F., Hamilton, L.C., Bitz, C.M., Meier, W.N., Bhatt, U.S., 2023. Forecast skill of the Arctic sea ice outlook 2008–2022. Geophys. Res. Lett. 50, e2022GL102531. doi:10.1029/2022gl102531.

Chi, J., Kim, H.-c., 2017. Prediction of Arctic sea ice concentration using a fully data driven deep neural network. Remote Sens. 9, 1305. doi:10.3390/rs9121305.

Chen, R., Dai, G., Liu, R., Wang, L., 2021. Seasonal influence of the atmosphere and ocean on the fall sea ice extent in the barents-kara seas. J. Geophys. Res.: Atmos. 126 (19), e2021JD035144. doi:10.1029/2021JD035144.

Cohen, J., Screen, J.A., Furtado, J.C., Barlow, M., Whittleston, D., Coumou, D., Francis, J., et al., 2014. Recent Arctic amplification and extreme mid-latitude weather. Nat. Geosci. 7, 627–637. doi:10.1038/ngeo2234.

Counillon, F., Keenlyside, N., Bethke, I., Wang, Y., Billeau, S., Shen, M.L., Bentsen, M., 2016. Flow-dependent assimilation of sea surface temperature in isopycnal coordinates with the Norwegian Climate Prediction Model. Tellus A: Dyn. Meteorol. Ocean. 68, 32437. doi:10.3402/tellusa.v68.32437.

Dai, P., Gao, Y., Counillon, F., Wang, Y., Kimmritz, M., Langehaug, H.R., 2020. Seasonal to decadal predictions of regional Arctic sea ice by assimilating sea surface temperature in the Norwegian Climate Prediction Model. Clim. Dyn. 54, 3863–3878. doi:10.1007/s00382-020-05196-4.

DiGirolamo, N., C.L. Parkinson, D.J. Cavalieri, P. Gloersen, and H.J. Zwally, 2022. Sea ice concentrations from Nimbus-7 SMMR and DMSP SSM/I-SSMIS passive microwave data, version 2 [Data Set] Boulder, Colorado USA. NASA national snow and ice data center distributed active archive center. https://nsidc.org/data/nsidc-0051/versions/2. Date Accessed 07-01-2024.

Ding, Q., Schweiger, A., L'Heureux, M., Battisti, D.S., Po-Chedley, S., Johnson, N.C., Blanchard-Wrigglesworth, E., et al., 2017. Influence of high-latitude atmospheric circulation changes on summertime Arctic sea ice. Nat. Clim. Chang. 7, 289–295. doi:10.1038/nclimate3241.

Ding, S., Wu, B., 2021. Linkage between autumn sea ice loss and ensuing spring Eurasian temperature. Clim. Dyn. 57, 2793–2810. doi:10.1007/s00382-021-05839-0.

Dmitrenko, I.A., Rudels, B., Kirillov, S.A., Aksenov, Y.O., Lien, V.S., Ivanov, V.V., Schauer, U., et al., 2015. Atlantic water flow into the arctic ocean through the st. Anna trough in the northern kara sea. J. Geophys. Res.: Oceans 120 (7), 5158–5178. doi:10.1002/2015JC010804.

Doscher, R., Vihma, T., Maksimovich, E., 2014. Recent advances in understanding the Arctic climate system state and change from a sea ice perspective: A review. Atmos. Chem. Phys. 14, 13571–13600. doi:10.5194/acp-14-13571-2014.

Fan, Y., Lyu, Y., Zhu, S., Yin, Z., Duan, M., Zhi, X., Zhou, B., 2024. Monthly prediction on summer extreme precipitation with a deep learning approach: Experiments over the mid-to-lower reaches of the yangtze river. Earth Space Sci. 11 (11), e2024EA003926. doi:10.1029/2024EA003926.

Guemas, V., Blanchard-Wrigglesworth, E., Chevallier, M., Day, J.J., Deque, M., Doblas-Reyes, F.J., Fuckar, N.S., et al., 2016. A review on Arctic sea-ice predictability and prediction on seasonal to decadal time-scales. Q. J. R. Meteorol. Soc. 142, 546–561. doi:10.1002/qj.2401.

Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horanyi, A., Munoz-Sabater, J., Nicolas, J., et al., 2020. The ERA5 global reanalysis. Q. J. R. Meteorol. Soc. 146, 1999–2049. doi:10.1002/qj.3803.

Huan, X., Wang, J., Liu, Z., 2023. Monthly Arctic sea ice prediction based on a data-driven deep learning model. Environ. Res. Commun. 5, 101003. doi:10.1088/2515-7620/acffb2.

Kim, E., Kruse, P., Lama, S., Bourne, J., Hu, M., Ali, S., Huang, Y., Wang, J., 2021. Multi-task deep learning based spatiotemporal arctic sea ice forecasting. In: Proceedings of 2021 IEEE International Conference on Big Data (Big Data), pp. 1847–1857. doi:10.1109/BigData52589.2021.9671491.

Liang, Y., Bi, H., Wang, Y., Zhang, Z., Huang, H., 2020. Role of atmospheric factors in forcing arctic sea ice variability. Acta. Oceanol. Sin. 39 (9), 60–72. doi:10.1007/s13131-020-1629-6.

Luo, R., Ding, Q., Wu, Z., Baxter, I., Bushuk, M., Huang, Y., Dong, X., 2021. Summertime atmosphere-sea ice coupling in the Arctic simulated by CMIP5/6 models: Importance of large-scale circulation. Clim. Dyn. 56, 1467–1485. doi:10.1007/s00382-020-05543-5.

Lyu, Y., Zhu, S., Zhi, X., Ji, Y., Fan, Y., Dong, F., 2023. Improving subseasonal-to-seasonal prediction of Summer extreme precipitation over Southern China based on a deep learning method. Geophys. Res. Lett. 50, e2023GL106245. doi:10.1029/2023gl106245.

Liu, Z., 2022. Arctic sea ice decline and its driving mechanisms. Chin. J. Nat. 44 (1), 39–46. doi:10.3969/j.issn.0253-9608.2022.01.004.

Nie, Y., Sun, J., 2024. Improving dynamical-statistical subseasonal precipitation forecasts using deep learning: a case study in southwest China. Environ. Res. Lett. 19 (7), 074013. doi:10.1088/1748-9326/ad5370.

Pistone, K., Eisenman, I., Ramanathan, V., 2014. Observational determination of albedo decrease caused by vanishing arctic sea ice. Proc. Natl. Acad. Sci. 111 (9), 3322–3326. doi:10.1073/pnas.1318201111.

Philipp, D., Stengel, M., Ahrens, B., 2020. Analyzing the arctic feedback mechanism between sea ice and low-level clouds using 34 years of satellite observations. J. Clim. 33 (17), 7479–7501. doi:10.1175/JCLI-D-19-0895.1.

Petrick, S., Riemann-Campe, K., Hoog, S., Growitsch, C., Schwind, H., Gerdes, R., Rehdanz, K., 2017. Climate change, future Arctic Sea ice, and the competitiveness of European Arctic offshore oil and gas production on world markets. Ambio 46, 410–422. doi:10.1007/s13280-017-0957-z.

Rayner, N.A., Parker, D.E., Horton, E.B., Folland, C.K., Alexander, L.V., Rowell, D.P., Kent, E.C., Kaplan, A., 2003. Global analyses of sea surface temperature, sea ice, and night marine air temperature since the late nineteenth century. J. Geophys. Res: Atmos. 108, 4407. doi:10.1029/2002jd002670.

Reichstein, M., Camps-Valls, G., Stevens, B., Jung, M., Denzler, J., Carvalhais, N., Prabhat, 2019. Deep learning and process understanding for data-driven Earth system science. Nature 566, 195–204. doi:10.1038/s41586-019-0912-1.

Ronneberger, O., P. Fischer, and T. Brox, 2015. U-Net: convolutional networks for biomedical image segmentation, proceedings of 18th international conference on medical image computing and computer-assisted intervention (MICCAI), munich, GERMANY, Oct 05-09, 234–241.

Schauer, U., Fahrbach, E., Osterhus, S., Rohardt, G., 2004. Arctic warming through the fram strait: oceanic heat transport from 3 years of measurements. J. Geophys. Res.: Oceans 109 (C6), C06026. doi:10.1029/2003JC001823.

Saha, S., Moorthi, S., Wu, X., Wang, J., Nadiga, S., Tripp, P., Behringer, D., et al., 2014. The NCEP climate forecast system version 2. J. Clim. 27, 2185–2208. doi:10.1175/jcli-D-12-00823.1.

Siddique, N., Paheding, S., Elkin, C.P., Devabhaktuni, V., 2021. U-Net and its variants for medical image segmentation: A review of theory and applications. IEEE Access 9, 82031–82057. doi:10.1109/access.2021.3086020.

Wang, Y., Yuan, X., Bi, H., Bushuk, M., Liang, Y., Li, C., Huang, H., 2022. Reassessing seasonal sea ice predictability of the pacific-arctic sector using a markov model. Cryosphere 16 (3), 1141–1156. doi:10.5194/tc-16-1141-2022.

Wang, Y., Yuan, X., Bi, H., Ren, Y., Liang, Y., Li, C., Li, X., 2023. Understanding arctic sea ice thickness predictability by a markov model. J. Clim. 36 (15), 4879–4897. doi:10.1175/JCLI-D-22-0525.1.

Wang, W., Chen, M., Kumar, A., 2013. Seasonal prediction of Arctic sea ice extent from a coupled dynamical forecast system. Mon. Wea. Rev. 141, 1375–1394. doi:10.1175/mwr-D-12-00057.1.

Wei, K., Liu, J., Bao, Q., He, B., Ma, J., Li, M., Song, M., Zhu, Z., 2021. Subseasonal to seasonal Arctic sea-ice prediction: a grand challenge of climate science. Atmos. Ocean. Sci. Lett. 14. doi:10.1016/j.aosl.2021.100052.

Yi, D.L., Fan, K., He, S., 2024. Thermodynamic and dynamic contributions to the abrupt increased winter arctic sea ice growth since 2008. Environ. Res. Lett. 19 (1), 014048. doi:10.1088/1748-9326/ad13b7.

You, Q., Cai, Z., Pepin, N., Chen, D., Ahrens, B., Jiang, Z., Wu, F., et al., 2021. Warming amplification over the arctic pole and third pole: Trends, mechanisms and consequences. Earth-Sci. Rev. 217, 103625. doi:10.1016/j.earscirev.2021.103625.

Zhang, A., Yi, D.L., Fan, K., 2024. Nonstationary thermodynamic and dynamic contributions to the interannual variability of winter sea ice growth in the kara–laptev seas. Environ. Res. Lett. 19 (6), 064067. doi:10.1088/1748-9326/ad4fa4.

Zhang, X., Sorteberg, A., Zhang, J., Gerdes, R., Comiso, J.C., 2008. Recent radical shifts of atmospheric circulations and rapid changes in arctic climate system. Geophys. Res. Lett. 35 (22), L22701. doi:10.1029/2008GL035607.