Response to comments by Reviewer #2

We would like to thank the reviewer for the helpful comments on the paper. Please find below our responses to the comments.

This paper documents the results from a deep learning effort at predicting maps of Antarctic sea ice from the NSIDC. The model is generally well-described, with well documented results that are effectively compared to simple linear trends and anomaly persistence. However, the paper focus is only on the performance of a single effort of sea ice prediction and contains no effort to use this tool to add any scientific knowledge or insight to Cryospheric science. There is only the briefest attempt to contextualise the importance of Antarctic Sea Ice prediction, and the reasoning behind the variable selection is not described at all. There is very little documentation on how the model was developed and any insight into what was learnt during the development process. The publishing criteria for the Cryosphere is that there needs to be a scientific aspect to the publications beyond model description and results, therefore this paper is not acceptable=and in opinion needs to be rejected.

Particular issues:
Throughout the paper there is a lack of knowledge of the system that is being investigated, and the study is only focused or representing the input data and the physical system. For example the title says it 'predicts' sea ice – there are many aspects of sea ice that are not considered here. This paper only looks at monthly sea ice concentration maps from the NSIDC – possibly the simplest representation of sea ice. There are many other datasets available – this needs to be documented. The introduction is very brief and contains no description of the system being investigated.

Thank you for your comments. Firstly, we modified the introduction to emphasize the importance of accurate predictions for Antarctic sea ice concentration. Compared to the Arctic, the prediction of Antarctic sea ice has received much less attention. Also, the demand for subseasonal to extended seasonal Antarctic sea ice predictions has been recognized due to the expanding range of activities in the Southern Ocean (Zampieri et al., 2019; Bushuk et al., 2021; Libera et al., 2022). Accurate sea ice concentration predictions can provide early warnings about sea ice changes and related hazards. This is particularly important for managing the risks of shipping activities in the Southern Ocean. For example, two polar vessels, Akademik Shokalskiy and Xuelong became trapped in rapidly formed sea ice in the Antarctic coastal region (Wang et al., 2014). Commercial fishing and tourism operations mostly use ice-strengthened vessels rather than icebreakers, which are vulnerable to sea ice hazards. It also supports ecosystem management and informs policy decisions, since the seasonal variations in Antarctic sea ice have a profound influence on marine productivity and fisheries (Libera et al., 2022).

Secondly, the deep learning model developed for Antarctic sea ice concentration predictions has been described in Figure R1. To further address your concerns, we have included more details about the model system being developed. A U-shaped architecture based on convolutional neural networks is widely used for many applications, i.e., remote sensing image segmentation tasks (Marmanis et al., 2016; Wang et al., 2023). Recently, Andersson et al. (2021) employed the U-Net for three-class predictions of Arctic sea ice concentration. For accurate forecasts of Antarctic sea ice concentration, we made necessary modifications to the original architecture of U-Net and turned it into single value regression rather than the classification. The ANTSIC-UNet's inputs are feature maps of high-resolution sea ice concentration, other multiple climate variables related to sea ice changes over different lead/lag months and a land mask. The outputs are high-resolution sea ice concentration maps for the future months. The inputs are processed into a large number of feature maps with decreased dimensionality by the encoder part of ANTSIC-UNet. Such deep layers and large-scale features allow the model to capture complex nonlinear relationships and provide an interpretation of the inputs. The decoder then upscales the feature maps extracted by the encoder into upsampled features and uses four skip connections to combine them with multi-scale features from different scale levels of the encoder. This process results in high-resolution output maps that align with the spatial dimensions of the input data. Sigmoid activation functions are used in the final six convolutional layers to generate regression predictions of Antarctic sea ice concentration maps for six months. There are also other attempts in the training algorithm for enhancing the predictive skill of the proposed model, for example, the hybrid loss function combining sea ice concentration mean square error (MSE) and integrated ice-edge error (IIEE) (see details in Section 4). The results presented evidence that models trained with this approach predict more accurately at the sea ice edge, thereby improving prediction performance.

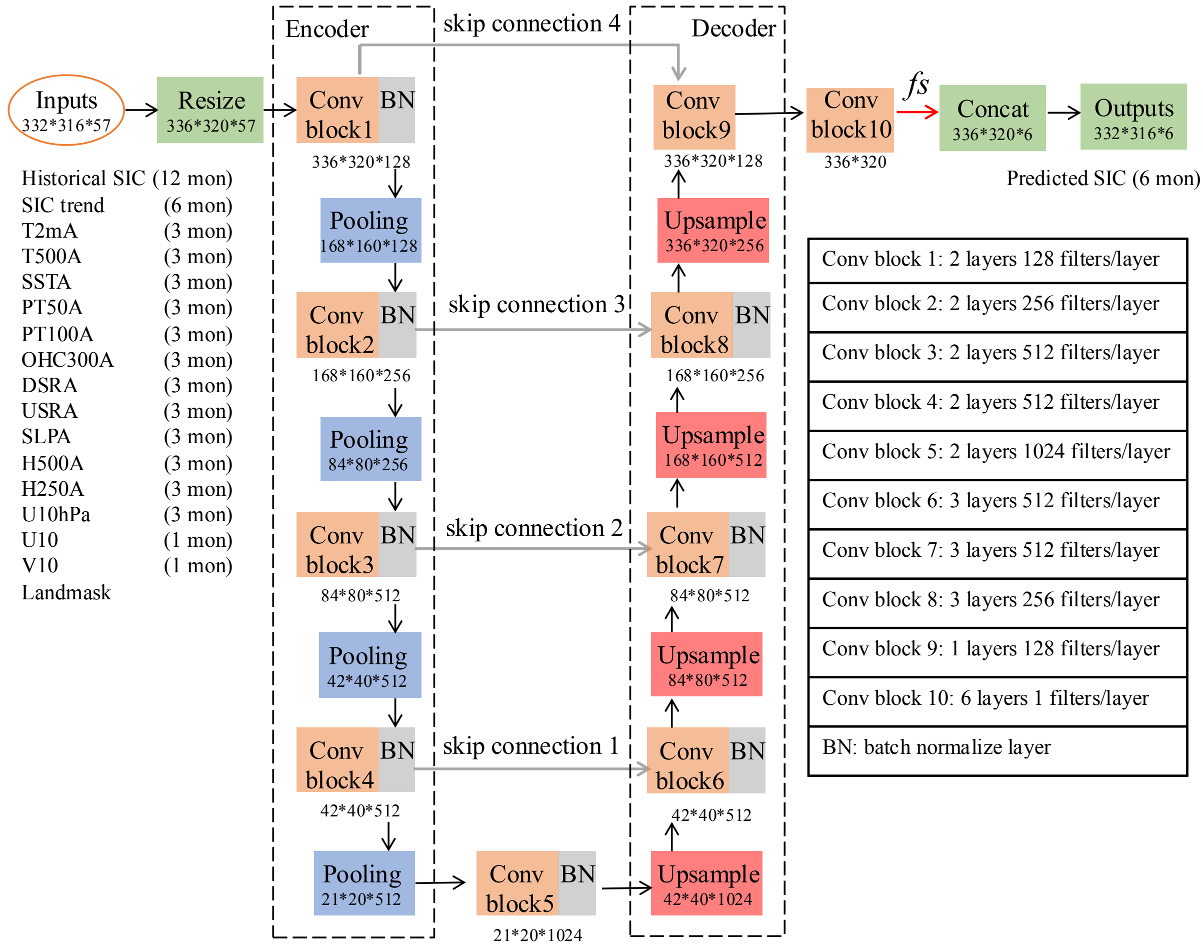

Figure R1. Configuration of ANTSIC-UNet model used for extended seasonal Antarctic sea ice prediction. Inputs are sea ice concentration, other climate variables related to sea ice changes over different lead/lag months and a land mask. The U-shaped architecture includes the encoder, decoder and four skip connections. Sigmoid activation functions (*fs*) are used in the final six convolutional layers to generate regression predictions of Antarctic sea ice concentration maps for six months.

Thirdly, this work is motivated by the fact that the Antarctic sea ice extent exhibits significant variability driven by the complex air-ice-sea interactions that are not yet fully understood. In this study, we clarified how each climate variable contributes to sea ice variation selected for the training of ANTSIC-UNet and explored which specific variable plays more important roles in the different months of sea ice prediction. Our results show evidence that ANTSIC-UNet can successfully extract key information from the complex ocean-ice-atmosphere interactions to predict sea ice concentration and capture seasonal variations through the different important climate variables. This approach could be effectively extended to other sea ice variables once the relevant long-term data becomes available (i.e., sea ice thickness). This potential for broader applicability underscores the significance of our work and its contribution to advancing Antarctic sea ice predictions.

Finally, sea ice concentration is the essential variable for investigating the variation of sea ice (i.e., extent) and the satellite observation provides long-term records of the data. Thus, our study focused on sea ice concentration, and used monthly maps from the NSIDC which provides long-term records of data for the training of deep learning models since the late 1970s. Following the reviewer's suggestion, in the discussion, we further documented other available datasets and discussed the potential for extending our research by integrating these additional datasets into future studies. These include Antarctic sea ice thickness data from satellite altimetry missions including the ICESat data (from 2003-2008), ICESat-2 data (from late 2018 onward) and CryoSat-2 data (from 2010 onward) which remains limited in terms of confidence and temporal coverage which are not yet suitable for deep learning applications (Hendricks et al., 2018; Kacimi and Kwok, 2020; Fons et al., 2023). The Polar Pathfinder product (Tschudi et al. 2019) provides daily sea ice motion vectors at a spatial resolution of 25 km which is valuable for investigating sea ice movement patterns under the influence of wind and ocean currents. In future research, we will explore whether incorporating ice drift can enhance the accuracy of sea ice predictions.

Reference:

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Bushuk, M., Winton, M., Haumann, F. A., Delworth, T., Lu, F., Zhang, Y., Jia, L., Zhang, L., Cooke, W., Harrison, M., Hurlin, B., Johnson, N. C., Kapnick, S. B., McHugh, C., Murakami, H., Rosati, A., Tseng, K.-C., Wittenberg, A. T., Yang, X., and Zeng, F.: Seasonal Prediction and Predictability of Regional Antarctic Sea Ice, Journal of Climate, 34, 6207–6233, https://doi.org/10.1175/JCLI-D-20-0965.1, 2021.

Libera, S., Hobbs, W., Klocker, A., Meyer, A., and Matear, R.: Ocean-Sea Ice Processes and Their Role in Multi-Month Predictability of Antarctic Sea Ice, Geophysical Research Letters, 49, e2021GL097047, https://doi.org/10.1029/2021GL097047, 2022.

Marmanis, D., Datcu, M., Esch, T., and Stilla, U.: Deep Learning Earth Observation Classification Using ImageNet Pretrained Networks, IEEE Geoscience and Remote Sensing Letters, 13, 105–109, https://doi.org/10.1109/LGRS.2015.2499239, 2016.

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Wang, X., Hu, Z., Shi, S., Hou, M., Xu, L., and Zhang, X.: A deep learning method for optimizing semantic segmentation accuracy of remote sensing images based on improved UNet, Sci Rep, 13, 7600, https://doi.org/10.1038/s41598-023-34379-2, 2023.

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Zampieri, L., Goessling, H. F., and Jung, T.: Predictability of Antarctic Sea Ice Edge on Subseasonal Time Scales, Geophysical Research Letters, 46, 9719–9727, https://doi.org/10.1029/2019GL084096, 2019.

The most useful aspect of the study can be to inform of what variables from the chosen reanalysis are the strongest predictors. This is attempted in section 3.4 – but it has no contextualization. Key aspects that need including: Why physically may each variable be useful in prediction? How accurate are each variable within the reanalysis product? The lack of predictive importance for Downward solar for example may be due to this variable being poorly represented within the reanalysis. What other scientific analysis has been performed using this reanalysis? How has it been used outside of Deep learning to investigate sea ice?

Thank you for your comments. In this revision, we have made several improvements to address your concerns.

Firstly, we provided an overview of how reanalysis products have been applied to sea ice investigations outside of deep learning and summarized the representation accuracy within the chosen reanalysis products. Reanalysis products are vital tools for studying climate variability in the Antarctic due to the sparse observations. They are widely used as inputs of dynamical models, serving as initial and boundary conditions, and are also crucial for validating model simulations and predictions (Hobbs et al., 2020; Goosse et al., 2023; Mezzina et al., 2024). The ECWMF Reanalysis v5 (ERA5) data is generally considered the best-performing atmospheric reanalysis dataset for polar regions. Previous studies have extensively evaluated the performance of ERA5, which accurately represents near-surface wind, temperature, and sea level pressure in the Antarctic (Gossart et al., 2019; Tetzner et al., 2019; Andres-Martin et al., 2024). However, deficiencies in cloud cover and water content have resulted in significant surface radiation biases during the austral summer, particularly due to the underestimation of cloud cover (Wang et al., 2020; Mallet et al., 2023). The limited observational data in the mid-to-upper troposphere and the stratospheric leads to certain uncertainty in mid- and high-level pressure and temperature, and the representation of the stratospheric polar vortex (Orr et al., 2021). In addition to atmospheric reanalysis, oceanic reanalysis products like Ocean Reanalysis System 5 (ORAS5) are crucial for understanding the principal mechanism of the Southern Ocean. ORAS5 has been shown to effectively capture sea surface temperatures in the Antarctic, with the vertical temperature structure also aligning closely with observations (Cai et al., 2023).

Secondly, we elaborated on the physical relevance of each variable for predicting sea ice concentration. In our study, 14 atmospheric and oceanic variables from ERA5 and ORAS5 are selected to capture the key physical mechanisms influencing sea ice variations. Variables such as sea surface temperature, 2m air temperature, and radiation impact heat flux exchanges at the air-ice-sea interface (Bourassa et al., 2013). Near surface winds drive sea ice movement and large-scale tropospheric circulation impacts sea ice through its effects on winds, temperature, precipitation, and cloud cover (Raphael and Hobbs, 2014). The 10-hPa zonal wind represents stratospheric zonal circulation, which impacts surface circulation through downward propagation, influencing sea ice dynamics (Cordero et al., 2023). Sea temperature anomalies and the upper-ocean heat content anomaly for the upper 300 m taken from ORAS5 play a crucial role in the heat energy exchange at the ocean–ice interface (Purich and Doddridge, 2023; Bianco et al., 2024). The upwelling of warmer subsurface water can further influence sea ice formation and melting in the high latitude of the Southern Ocean (Cai et al., 2023).

Finally, we discussed the reasons for the lack of predictive importance of variables such as downward solar radiation in ANTSIC-UNet. When a variable shows minimal or even negative importance, it suggests that the ANTSIC-UNet might be overlooking that feature or has not yet fully captured the intrinsic relationships involving that variable. It may also be related to the accuracy of the reanalysis data used as input. For example, the lack of predictive importance for downward solar radiation could be due to this variable being poorly represented in the Southern Ocean within the reanalysis as discussed above. Thus, it is crucial to consider the accuracy of input variables chosen from reanalysis data for Antarctic sea ice predictions.

Reference:

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Bianco, E., Iovino, D., Masina, S., Materia, S., and Ruggieri, P.: The role of upper-ocean heat content in the regional variability of Arctic sea ice at sub-seasonal timescales, The Cryosphere, 18, 2357–2379, https://doi.org/10.5194/tc-18-2357-2024, 2024.

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Goosse, H., Allende Contador, S., Bitz, C. M., Blanchard-Wrigglesworth, E., Eayrs, C., Fichefet, T., Himmich, K., Huot, P.-V., Klein, F., Marchi, S., Massonnet, F., Mezzina, B., Pelletier, C., Roach, L., Vancoppenolle, M., and van Lipzig, N. P. M.: Modulation of the seasonal cycle of the Antarctic sea ice extent by sea ice processes and feedbacks with the ocean and the atmosphere, The Cryosphere, 17, 407–425, https://doi.org/10.5194/tc-17-407-2023, 2023.

Gossart, A., Helsen, S., Lenaerts, J. T. M., Broucke, S. V., Lipzig, N. P. M. van, and Souverijns, N.: An Evaluation of Surface Climatology in State-of-the-Art Reanalyses over the Antarctic Ice Sheet, https://doi.org/10.1175/JCLI-D-19-0030.1, 2019.

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Mallet, M. D., Alexander, S. P., Protat, A., and Fiddes, S. L.: Reducing Southern Ocean Shortwave Radiation Errors in the ERA5 Reanalysis with Machine Learning and 25 Years of Surface Observations, https://doi.org/10.1175/AIES-D-22-0044.1, 2023.

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Orr, A., Lu, H., Martineau, P., Gerber, E. P., Marshall, G. J., and Bracegirdle, T. J.: Is our dynamical understanding of the circulation changes associated with the Antarctic ozone hole sensitive to the choice of reanalysis dataset?, Atmospheric Chemistry and Physics, 21, 7451–7472, https://doi.org/10.5194/acp-21-7451-2021, 2021.

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Raphael, M. N. and Hobbs, W.: The influence of the large-scale atmospheric circulation on Antarctic sea ice during ice advance and retreat seasons, Geophysical Research Letters, 41, 5037–5045, https://doi.org/10.1002/2014GL060365, 2014.

Tetzner, D., Thomas, E., and Allen, C.: A Validation of ERA5 Reanalysis Data in the Southern Antarctic Peninsula—Ellsworth Land Region, and Its Implications for Ice Core Studies, Geosciences, 9, 289, https://doi.org/10.3390/geosciences9070289, 2019.

Wang, H., Klekociuk, A. R., French, W. J. R., Alexander, S. P., and Warner, T. A.: Measurements of Cloud Radiative Effect across the Southern Ocean (43° S–79° S, 63° E–158° W), Atmosphere, 11, 949, https://doi.org/10.3390/atmos11090949, 2020.

Finally there is little to no contextualization of results amongst contemporary literature and other prediction efforts. Section 4 contains only a handful of citations when it is essential to contrast the results here with other efforts at sea ice predictions. How do the reported skills in forecasting compare to other efforts, Andersson et al. (2021) is an important bench mark here. How are the extreme years (2017, 2022, 2023) described in literature? What other hypothesis exist about what affected sea ice in these years?

Thank you for your comments. Andersson et al. (2021) focused on Arctic sea ice prediction, comparing deep learning model performance at sea ice edge with the dynamic model and linear trend predictions, including extreme September sea ice events. Antarctic sea ice prediction has received less attention compared to the Arctic. To further assess the Antarctic sea ice predictive skill of ANTSIC-UNet against other prediction efforts, we included the dynamic model's monthly mean Antarctic sea ice concentration predictions calculated by the ensemble mean of 51 members of SEAS5, provided by the Copernicus Climate Change Service (C3S) Prediction project (Thépaut et al., 2018). SEAS5, ECMWF's fifth-generation seasonal forecast system, is recognized for its state-of-art predictive skill among the dynamical models which provides Antarctic sea ice concentration prediction for up to six months (Johnson et al., 2019). As shown in Figure R2, ANTSIC-UNet has small root-mean-square errors (RMSE) for Antarctic sea ice concentration, and outperforms the anomaly persistence predictions at all lead times. Compared to RMSE of SEAS5, ANTSIC-UNet shows slightly larger errors at 1-3 month lead, and smaller errors as lead time exceeds 4 months, which remains highly competitive. In terms of IIEE, ANTSIC-UNet shows significantly superior performance relative to all other models. The improvement in sea ice edge predictions of ANTSIC-UNet becomes more pronounced as the lead time increases.

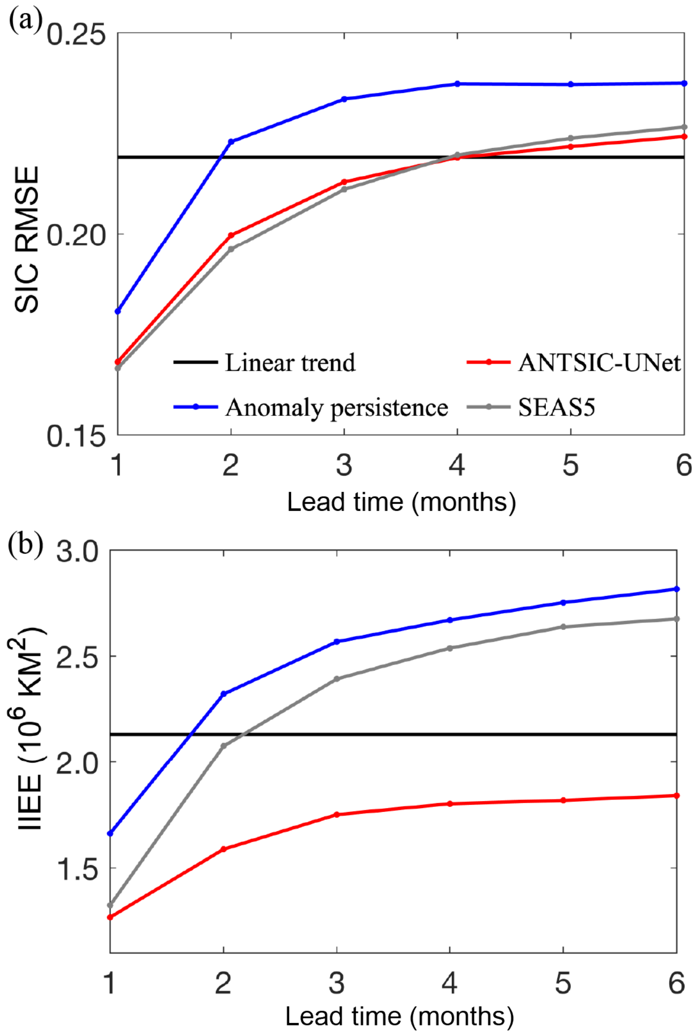

Figure R2. The average predictive skill of Pan-Antarctic sea ice for ANTSIC-UNet, linear trend, anomaly persistence and SEAS5 predictions during the testing years. (a) SIC RMSE: root-mean-square error and (b) IIEE: integrated ice-edge error.

To our knowledge, little research has focused on the predictability of Antarctic sea ice extent in extreme years. We further compared the ANTSIC-UNet's accuracy performance on sea ice edge predictions for the extreme summer years, relative to linear trend predictions and SEAS5. As shown in Figure R3, both ANTSIC-UNet and SEAS5 have increasing sea ice edge errors as lead time increases. The linear trend predictions are independent of lead time. ANTSIC-UNet outperforms SEAS5 and linear trend predictions at sea ice edge error in all extreme summer years. At short lead times, ANTSIC-UNet has substantial improvement over the linear trend predictions and moderate improvement over SEAS5. At long lead times, ANTSIC-UNet's improvements over SEAS5 become more significant. These results suggest that ANTSIC-UNet has high predictive skills for extended seasonal predictions of Antarctic sea ice concentration, especially for extreme events, compared to other statistical and dynamic models.

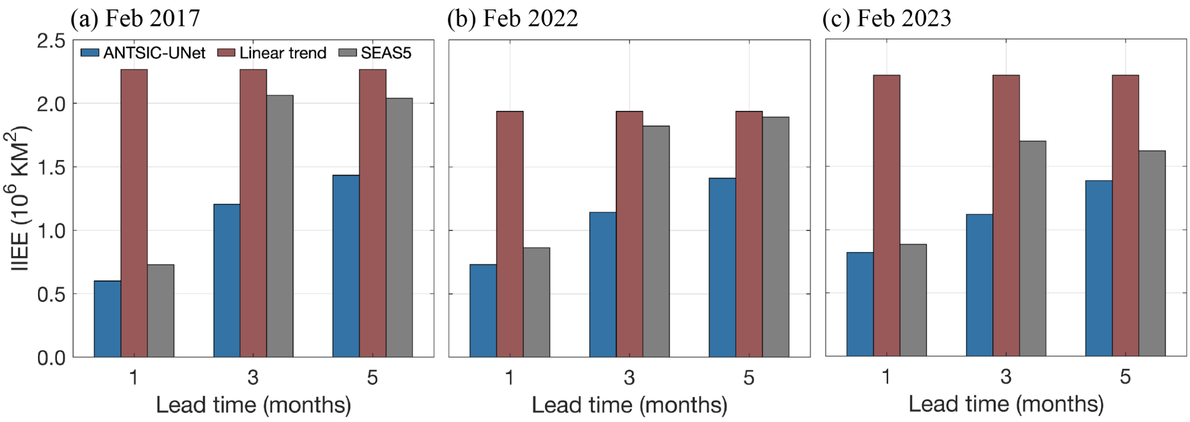

Figure R3. Integrated ice-edge error (IIEE) of ANTSIC-UNet, the linear trend forecast and SEAS5 for February forecasts at lead time of 1, 3, and 5 months for the extreme summer years. (a) 2017, (b) 2022 and (c) 2023.

Antarctic sea ice has decreased in recent years, with summer sea ice coverage frequently reaching historic lows, including three extreme summer events. Some research have been carried out to investigate the key climate drivers and potential mechanisms behind these extreme conditions. The anomalous sea ice melting during the summer of 2017 might be associated with early spring atmospheric conditions over the Southern Ocean were primarily influenced by a positive phase of the zonal wave 3 (ZW3) pattern, followed by a near-record negative Southern Annular Mode (SAM) (Turner et al., 2017; Schlosser et al., 2018). The significant weakening of the polar stratospheric vortex was identified as a key driver of the SAM changes (Wang et al., 2019). The extremely low sea ice events in the summer of 2022 and 2023 occurred with the deepening of the Amundsen Sea Low (ASL), triggering feedbacks that played a crucial role in the reduction of summer sea ice (Turner et al., 2022; Wang et al., 2022). A few studies have emphasized that the influence of a warm subsurface ocean is a contributor to the recent record-low summer sea ice events (Liu et al., 2023; Purich and Doddridge, 2023). Different large-scale atmospheric circulation patterns may also lead to similar regional prevailing winds, driving the negative Antarctic sea ice extent anomalies (Mezzina et al., 2024).

Reference:

Mezzina, B., Goosse, H., Klein, F., Barthélemy, A., and Massonnet, F.: The role of atmospheric conditions in the Antarctic sea ice extent summer minima, The Cryosphere, 18, 3825–3839, https://doi.org/10.5194/tc-18-3825-2024, 2024.

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“sea ice concentration” or area or extent needs mentioning in the title.

As suggested by the reviewer, we modified the title to “Extended seasonal prediction of Antarctic sea ice concentration using ANTSIC-UNet”.

L 9 the changes to Antarctic Sea Ice a subtle and require more than this introductory sentence – after a period of increasing summer minima there have then been reductions.

The Abstract needs more description on why Antarctic sea ice needs predicting. L 15 – 20 can be removed as this is too much detail for an abstract. The final 5 lines are ok as a summary. Some contextualization amongst previous publications is needed for the abstract too.

Thank you for your comments. We modified the abstract to emphasize the subtle change of Antarctic sea ice and the importance of accuracy prediction.

Antarctic sea ice has experienced rapid change in recent years, with the total sea ice extent abruptly decreasing after a period of gradual increase from the late 1970s until 2014. Accurate long-term predictions of Antarctic sea ice concentration are crucial to support expanding activities in the Southern Ocean, such as scientific research, tourism and fisheries management. However, dynamic models often face difficulties in accurately predicting Antarctic sea ice due to limited representations of air-ice-sea interactions, especially on seasonal timescales and during the summer months. In response to these challenges, we develop a deep learning model (named ANTSIC-UNet) trained by physically enriched climate variables and evaluate its skill for extended seasonal prediction of Antarctic sea ice concentration (up to 6 months in advance). We compare the predictive skill of ANTSIC-UNet in the Pan- and regional Antarctic with two benchmark models (linear trend and anomaly persistence models). In terms of root-mean-square error (RMSE) for sea ice concentration and integrated ice-edge error (IIEE), ANTSIC-UNet shows much better skills for the extended seasonal prediction, especially for the extreme events in recent years, relative to the two benchmark models. The predictive skill of ANTSIC-UNet is season and region dependent. Sea ice prediction errors increase as lead times increase, with smaller errors observed during autumn and winter, and larger errors in summer. The Pacific and Indian Ocean regions show accurate prediction performance at the sea ice edge during summer. ANTSIC-UNet also shows high predictive skill in capturing the interannual variability of Pan-Antarctic and regional sea ice extent anomalies. We also quantify variable importance through a post-hoc interpretation method. It suggests in addition to sea ice conditions, the ANTSIC-UNet prediction at short lead times shows sensitivity to sea surface temperature, radiative flux, and atmospheric circulation. At longer lead times, zonal wind in the stratosphere appears to be an important influencing factor for the prediction.

L 25 a first general sentence on the nature of sea ice will help here.

As suggested by the reviewer, we added the sentence "Sea ice, which formed entirely in the ocean, affects the climate system through modulating the exchange of heat, momentum, moisture and gases between the atmosphere and ocean."

L 27 this is only true for the summer minimum.

We modified the sentence "The summer total Antarctic sea ice extent (SIE) has gradually increased until 2014 since the late 1970s and then abruptly decreased."

L 29, variability in what? I guess extent?

Yes, we modified the sentence "Antarctic sea ice extent shows large seasonal and interannual variability, and its trend is spatially heterogeneous."

L 32 everything here after "like" is very vague and needs rewriting.

Thanks for your comment. We rewrote the sentence "Compared to the Arctic, the prediction of Antarctic sea ice has received much less attention. Also, the demand for subseasonal to extended seasonal Antarctic sea ice predictions has been recognized due to the expanding range of activities in the Southern Ocean (Zampieri et al., 2019; Bushuk et al., 2021; Libera et al., 2022). Accurate sea ice concentration predictions can provide early warnings about sea ice changes and related hazards. This is particularly important for managing the risks of shipping activities in the Southern Ocean. For example, two polar vessels, Akademik Shokalskiy and Xuelong became trapped in rapidly formed sea ice in the Antarctic coastal region (Wang et al., 2014). Commercial fishing and tourism operations mostly use ice-strengthened vessels rather than icebreakers, which are vulnerable to sea ice hazards. It also supports ecosystem management and informs policy decisions, since the seasonal variations in Antarctic sea ice have a profound influence on marine productivity and fisheries (Libera et al., 2022).”

L 37 these air-ice-sea interaction processes need further description.

Thanks for your comment. We added further elaboration of air-ice-sea interaction processes. “Dynamically, sea ice movement and deformation are driven by wind and ocean currents. Thermodynamically, sea ice melting and formation are influenced by convection associated with ocean vertical mixing, heat exchange driven by surface radiation budget and turbulence, and heat advection through horizontal transport of air and water masses”

L 64 this sentence is difficult to follow. Are linear monthly trends extrapolated to future dates used as a model input?

Thanks for your comment. The linear monthly trends are extrapolated to future dates and are also used as input to the model. We agree that this sentence was not very clear, therefore we modified this sentence “A linear least-squares trend was fit to observed SIC over the past 30 years at each grid cell for each calendar month and used to predict SIC values for the corresponding month in the following year. These SIC predictions from the linear trend model are also used as the input of ANTSIC-UNet.”

L 66 a description of why reanalysis data is sought is required either here or in an earlier description of the project incentives. What do each data represent and why are they needed for predictions?

Thanks for your comments. We added the text at the beginning of L66 to clarify the reason for using reanalysis data. “Long-term observations are scarce in the Antarctic, which cannot provide the comprehensive and consistent three-dimensional and time-evolving gridded field of atmosphere and ocean parameters necessary to understand sea ice changes. Reanalysis datasets, which assimilate observations and satellite data, are valuable tools for investigating climate changes in polar regions, offering complete and multivariate descriptions of atmospheric and oceanic conditions.”

We added a more detailed description of ERA5 and ORAS5 to explicitly state what each dataset represents and why they are essential for Antarctic sea ice predictions. “ECWMF Reanalysis v5 (ERA5, Hersbach et al., 2020) provides high-resolution and three-dimensional gridded data of comprehensive atmospheric variables from 1940 to the present. ERA5 and its predecessor ERA-Interim are widely regarded as the best-performing reanalysis datasets in polar regions, with particularly reliable analyses over the Southern Ocean compared with surface and upper-level observations (Bracegirdle & Marshall, 2012; Bromwich et al., 2011). Ocean Reanalysis System 5 (ORAS5, Zuo et al., 2019) is a global eddy-permitting ocean and sea-ice ensemble reanalysis which provides historical ocean and sea-ice conditions from 1979 to the present, which adopts the same sea surface temperature as ERA5 taken from observations. Sea ice changes are strongly influenced by the atmosphere above and the ocean below through dynamic and thermodynamic processes. Therefore, the relevant atmospheric variables selected from ERA5 and oceanic variables obtained from ORAS5 are also used as inputs by ANTSIC-UNet to investigate the key factors contributing to sea ice predictions in the complex interaction between sea ice, ocean and atmosphere.”

L 76 Is the input data volume held static throughout all development? The data lag is often an option that requires testing and investigation.

Yes, the input data volume was static throughout all development. The variable importance analysis helped identify the most effective combination of relevant variables at different time lags to enhance prediction accuracy. In future research, we plan to investigate the impact of the time length of individual climate variables by retraining the deep learning model. This will allow us to assess how such changes in data lags affect the model's predictive performance, though it will require significant computational resources.

L 72 why is v10hPa not included also?

Thank you for your query regarding the exclusion of v10hPa. Other studies have already clarified that the changes in stratospheric zonal circulation predominantly affect the circumpolar westerly winds in the troposphere through downward propagation, which in turn affects the sea ice distribution and variability (Wang et al., 2019; Cordero et al., 2023). Therefore, we only include 10-hPa zonal wind.

Reference:

Cordero, R. R., Feron, S., Damiani, A., Llanillo, P. J., Carrasco, J., Khan, A. L., Bintanja, R., Ouyang, Z., and Casassa, G.: Signature of the stratosphere–troposphere coupling on recent record-breaking Antarctic sea-ice anomalies, The Cryosphere, 17, 4995–5006, https://doi.org/10.5194/tc-17-4995-2023, 2023.

Wang, G., Hendon, H. H., Arblaster, J. M., Lim, E.-P., Abhik, S., and van Rensch, P.: Compounding tropical and stratospheric forcing of the record low Antarctic sea-ice in 2016, Nat Commun, 10, 13, https://doi.org/10.1038/s41467-018-07689-7, 2019.

L 108 The linear trend prediction is not described well in section 2.1

Thanks for your comment. We agree that this statement was not very clear. We rewrote the description of the linear trend prediction as "A linear least-squares trend was fit to observed SIC over the past 30 years at each grid cell for each calendar month and used to predict SIC values for the corresponding month in the following year. These SIC predictions from the linear trend model are also used as the input of ANTSIC-UNet."

L 112 This implies that the RHS of equation 1 is just the observed ice concentration field. What benefit is this? Further description of how anomaly persistence works as a prediction is needed here.

The benefit of the anomaly persistence model lies in its straightforward application to give a continuous prediction of the variable by carrying forward the initial state of anomalies. This statistical method has been widely used as a benchmark for predicting sea ice concentration on seasonal timescales since sea ice conditions often change gradually rather than abruptly (Wayand et al., 2019; Bushuk et al., 2021; Niraula and Goessling, 2021). The effectiveness of the anomaly persistence decreases with increasing lead time as the influence of initial anomalies diminishes.

We updated the explanation in the text “The anomaly persistence works by preserving the deviations from the climatological anomalies and assuming these anomalies will persist into the future. For example, if a particular region currently has more sea ice than average, this positive anomaly will continue as time increases. This statistical method has been widely used as a benchmark for predicting sea ice concentration on seasonal timescales since sea ice conditions often change gradually rather than abruptly (Wayand et al., 2019; Bushuk et al., 2021; Niraula and Goessling, 2021). While this method is effective for short-term forecasts, its accuracy declines over longer lead times as the influence of initial anomalies weakens.”

Reference:

Bushuk, M., Winton, M., Haumann, F. A., Delworth, T., Lu, F., Zhang, Y., Jia, L., Zhang, L., Cooke, W., Harrison, M., Hurlin, B., Johnson, N. C., Kapnick, S. B., McHugh, C., Murakami, H., Rosati, A., Tseng, K.-C., Wittenberg, A. T., Yang, X., and Zeng, F.: Seasonal Prediction and Predictability of Regional Antarctic Sea Ice, Journal of Climate, 34, 6207–6233, https://doi.org/10.1175/JCLI-D-20-0965.1, 2021.

Niraula, B. and Goessling, H. F.: Spatial Damped Anomaly Persistence of the Sea Ice Edge as a Benchmark for Dynamical Forecast Systems, Journal of Geophysical Research: Oceans, 126, e2021JC017784, https://doi.org/10.1029/2021JC017784, 2021.

Wayand, N. E., Bitz, C. M., and Blanchard-Wrigglesworth, E.: A Year-Round Subseasonal-to-Seasonal Sea Ice Prediction Portal, Geophysical Research Letters, 46, 3298–3307, https://doi.org/10.1029/2018GL081565, 2019.

L 165 key acronyms need defining in each figure caption. (and all others too)

Thank you for your comment. We updated all relevant figure and table captions to include definitions for acronyms such as RMSE (root-mean-square error) and IIEE (integrated ice-edge error), ensuring that readers can easily understand the terms used without needing to look back to the main text. For example, we modified the caption for Table. 2 as follows:

“Table 2. The averaged predictive skill of Antarctic sea ice for ANTSIC-UNet, linear trend and anomaly persistence models for all testing years (RMSE: root-mean-square error; IIEE: integrated ice-edge error)”

L 253 “extremely low” rephrase with better accuracy.

L 253 this table needs extra columns to show what was extreme about these years – SIE/SIC anomalies perhaps.

Thank you for your comments. We modified the title of the table and added the extra columns.

Table 3. The averaged predictive skill of ANTSIC-UNet, linear trend and anomaly persistence models for the extreme summer years of Antarctic sea ice extent. Here, Observed SIEA represents February monthly anomalies of sea ice extent from NSIDC observations for these extreme years, calculated by subtracting the February average sea ice extent for the period 1981-2011 (units: million square kilometers). RMSE: root-mean-square error; IIEE: integrated ice-edge error.

	Observed SIEA	Metrics	ANTSIC-UNet	Linear trend	Anomaly persistence
2017	-0.76	RMSE	0.21	0.25	0.24
		IIEE	1.80	2.56	2.52
2022	-0.84	RMSE	0.21	0.22	0.23
		IIEE	1.68	2.24	2.45
2023	-1.14	RMSE	0.24	0.27	0.31
		IIEE	2.00	3.05	3.11