Dear Editor and Reviewer:

Thank you very much for your careful reading, insightful comments and constructive suggestions concerning our manuscript "IceTFT v 1.0.0: Interpretable Long-Term Prediction of Arctic Sea Ice Extent with Deep Learning" (ID: gmd-2022-293), which would greatly help us improve both the content and the presentation of our work. We have carefully considered all comments and are revising the manuscript accordingly. Below all reviewer comments are produced in blue. Our comments are in black, and changes in the manuscript are provided in indented quotes with line numbers.

Reviewer 1:

1. Lines 3-4: In fact, sea-ice melting does not raise the sea level.

Thank you for assisting us in correcting this issue. We re-wrote these sentences(pg 1, line 2-4):

> Due to global warming, Arctic sea ice extent (SIE) is rapidly decreasing each year. According to the International Panel on Climate Change (IPCC) climate model projections, the summer Arctic will be nearly sea-ice free in the 50s of the 21st century, which will have a great impact on global climate change. As a result, accurate predictions of Arctic sea ice are of significant interest.

2. The authors used two words, forecasting/forecast and prediction/predict, in the manuscript. As the timescales are different between forecast and prediction, I recommend that authors use predict/prediction in the manuscript.

We have completed the revision of the entire manuscript and unified it as prediction/predict.

3. Line 13: The authors only gave the prediction results in advance 9 months for 2021, and they should clarify more accurately in the abstract in case of misleading readers. The authors can evaluate more cases for lead times as 9 months.

In the IceTFT, it can generate next 12 months predictions according to last 12 months. For the 12 steps of predictions, the lead time is different for each step. The output of the 1^{st} step is only one month ahead, while the output of the 12^{nd} step is twelve months ahead. To avoid misunderstandings, we re-wrote the abstract to emphasise that the model predicts 12-month SIE directly, and clarify the inputs and outputs of the model(pg 1, line 10):

> The IceTFT model can provide the 12-month SIE directly according to the inputs of the last 12 months.

What's more, we discuss the prediction results of IceTFT from 2019 to 2022. It contains both 3 cases for hind-cast experiments(2019-2021) and 1 case for actual predictions(2022). For the results of hind-cast experiments, it shown in Table 4 (pg 13) , Figure 7 (pg 14), Figure 8 (pg 16) and Figure 9 (pg 17). For the actual predictions experiment, we submitted to SIO the prediction of 2022 September SIE in

2022 June, and the results shown in Figure 10 (pg 19).

4. Line 15: has some physical interpretability -> has a physical interpretability
We have fixed it (pg 1,line 16):

> This confirms that the IceTFT model has a physical interpretability.

5. Line 37: Wei et al. (2021) -> (Wei et al., 2021)
We have fixed it (pg 2, line 34-35):

> And it represents the current predict level and community knowledge of the state and evolution of Arctic sea ice on the sub-seasonal-to-seasonal (S2S) timescale (Wei et al., 2021).

6. The introduction is too long and redundant. For example, in Lines 49-54, it seems that the data assimilation is not close to the manuscript's key point and can brief these to one sentence. Lines 37-38, what's the purpose of "For example, the average SIE…". The authors should reorganize the introduction structure.

We re-wrote the introduction to remove the content related to the dynamical models and data assimilation. The current content of the introduction has been revised to introduce the importance of sea ice and the difficulties of SIE prediction, followed by an introduction to the current state of development of SIE prediction models through SIO, and then an introduction to the current machine learning based prediction of SIE based on previous work, summarising the limits of the models are single step prediction, short-term prediction and interpretability of models. Finally, the work and contributions of this paper are presented (pg 1-4, line 19-84).

7. Lines 94-97: It seems there is a high overlap between contributions #1 and #2. It'd be better to merge them into one.
Thank you very much for your comment. We merged contributions #1 and #2, and merged #3 and #4 (pg 3-4, line 73-79):

> 1) The IceTFT model uses LSTM encoders to summarize past inputs and generate context vectors, so it can directly provide a long-term prediction of SIE for up to 12 months. And it can predict September SIE 9 months in advance, which is longer than other studies with lead time of 1-3 months. IceTFT has the lowest prediction errors for hind-cast experiments from 2019 to 2021 and actual prediction in 2022, which compared with SIO.
>
> 2) The IceTFT model is interpretable. It can automatically filter out spuriously correlated variables and adjust the weight of inputs through VSN, reducing noise interference in the input data. At the same time, it can also explore the contribution of different input variables to SIE predictions and reveal the physical mechanisms of sea

ice development.

8. There is a missing part about the description of the data used in the study. It could be added after section 2.

Thank you very much for your comment, although the "Selecting Predictors" section that after Section 2 describes the data used and the reasons for their selection.

9. Figure 2, it's better if authors list the variables used in the IceTFT framework and give the output clearly (similar to illustration input SIE).

We have modified the IceTFT framework(Figure 2, pg5):

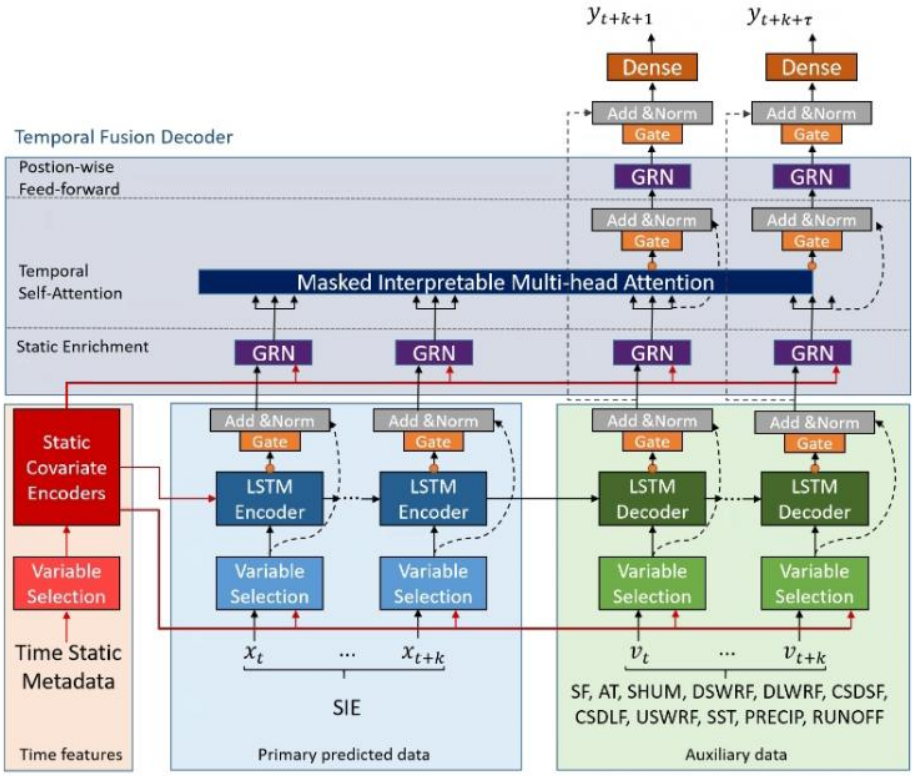


Figure 2. The IceTFT architecture is adapted on the basis of original TFT(Lim et al., 2021). The static time metadata, historical SIE data and other atmospheric and oceanographic variables are all inputs to the IceTFT. The auxiliary data include snowfall (SF), 2m air temperature (AT), 2m surface air specific humidity (SHUM), downward shortwave radiative flux (DSWRF), downward longwave radiation flux (DLWRF), clear sky downward longwave flux (CSDLF), clear sky downward solar flux (CSDSF), upward solar radiation flux (USWRF), sea surface temperature (SST), precipitation (PRECIP) and river runoff (RUNOFF).

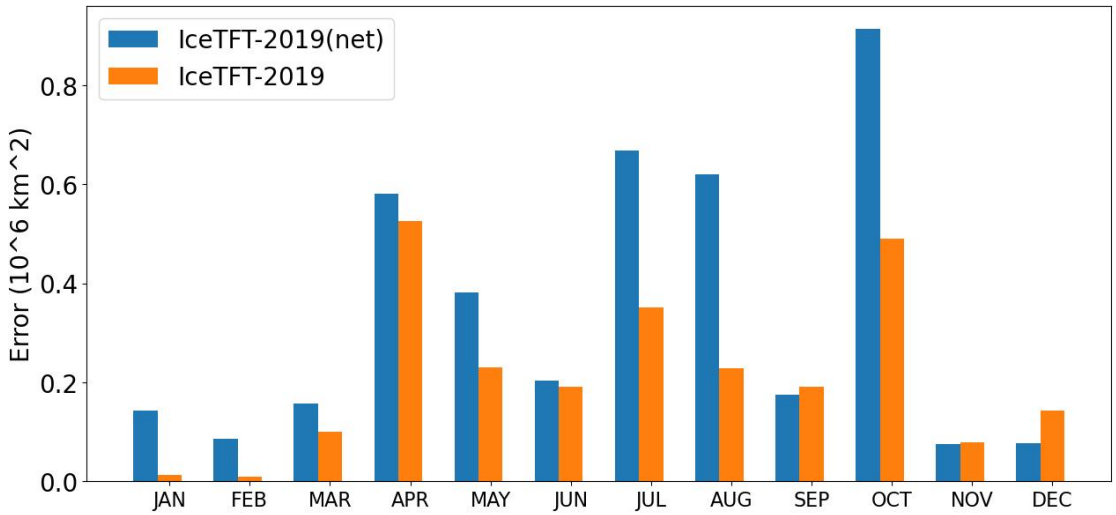
10.Line 158: 39.23°-90°N?

We revised it to '39.23°N-90°N' (pg7, line 135).

11.Figure 3: the variables in this figure do not match the variables in the IceTFT framework, such as SW, LW. Meanwhile, according to the authors discussed in section 5.7, I wonder if the results become better using the SW and LW instead of DSWRF, CSDSF, USWRF and DLWRF, CSDLF.

Your comments are very meaningful, and we have added new experiments according to your suggestions. Taking 2019 as an example, we conducted the experiment using

the SW, LW data instead of DSWRF, CSDSF, USWRF and DLWRF, CSDLF, and the experiment called IceTFT-2019(net). And we ran the experiments 20 times to get the average predictions for comparison. The results are shown below:



It can be seen that the new experiment IceTFT-2019(net) has a much higher error than the original experiment results in most of the months except December. Since SW/LW are the radiation of DSWRF/DLWRF minus USWRF/ULWRF. Although from the physical mechanism net retains the information characteristics associated with the radiation, for the model this means that DSWRF/DLWRF and USWRF/ULWRF are given fixed weights (1 and -1), and as seen in our experiments, their contributions are different. Thus using DSWRF, CSDSF, USWRF, DLWRF, and CSDLF data would give the model more options to adjust the weights of the input data to improve the predictive performance. Therefore, we still choose the original data (DSWRF, CSDSF, USWRF and DLWRF, CSDLF).

12. The NCEP-NCAR Reanalysis 1 was used in this work. I wonder if the results will change while changing the data to ERA5 or JRA-55. In other words, does the framework depend on the dataset?

Thank you! Indeed this is a good point. The influence of data from different sources on the model performance has be discussed with the JRA-55 data suggested in the comments. We have added new experiments with JRA-55 and addeds a new section of "6.2 Impacts of Datasets on Predictions" (pg17-18, line 301-315):

> To investigate whether the prediction results of IceTFT are affected by the source of input data, we replaced the data from the NCEP-NCAR Reanalysis 1 in Table.4 with JRA55. The same experiments were conducted. Different data sources may be associated with different observation errors, but the physical trends embedded in these data are similar. IceTFT model can automatically adjust the weights of the input data during the training process by adaptively learning the features according to the forecast errors. The label data with different errors can affect the prediction error calculated by the IceTFT model and thus have a large impact on the prediction skill. Theoretically speaking, the prediction skill of

the IceTFT model is limited by the source of the label data and does not depend on the source of the input data.

Table 5. The three metrics (MAE, RMSE, RMSD) among three models with reanalysis datasets of JRA-55 on SIE predictions during 2019-2021. Except for SST and SF, other inputs were replaced with JRA-55.

Predictive Year		2019			2020			2021		
Model Name		MAE	RMSE	RMSD	MAE	RMSE	RMSD	MAE	RMSE	RMSD
IceTFT-2018	best	**0.1681**	**0.2214**	**0.4936**	-	-	-	-	-	-
	mean	0.2891	0.3659	0.7165	0.3616	0.4858	0.8166	0.2255	0.2959	0.6131
IceTFT-2019	best	-	-	-	**0.2676**	**0.3360**	**0.6406**	-	-	-
	mean	-	-	-	0.4434	0.6585	1.0836	0.2130	0.2479	0.5458
IceTFT-2020	best	-	-	-	-	-	-	**0.1428**	**0.1801**	**0.4272**
	mean	-	-	-	-	-	-	0.1951	0.2203	0.4966

However, the results are shown in Table 4. It can be seen that the best results of the three models are relative to the original results which are from Table 3, but the mean predictions are higher. This indicates that the models can always get the optimal predictions after several training epochs in the hind-cast experiments and are not limited to the datasets. However, the existence of different observation errors in different datasets makes the bias trends of the predictions different, and therefore makes the mean predictions different. Since the prediction errors using NCEP-NCAR Reanalysis 1 are a little smaller, because in this paper we still use the original dataset for the experimental analysis.

13. Line 223: Evaluation -> Evaluation method

Thank you for your comment, we have modified it to “Evaluation metrics” (pg 9, line 180).

14. Tables 3 and 4, what does the percentage mean? The authors should describe the new statistics variable clearly in the manuscript.

The percentages have no special meaning, they are just to show the data more aesthetically. To avoid any misunderstanding, we have reworked it (pg 13).

Table 4. The three metrics (MAE, RMSE, RMSD) among three models on SIE predictions during 2019-2021.

Predictive Year		2019			2020			2021		
Model Name		MAE	RMSE	RMSD	MAE	RMSE	RMSD	MAE	RMSE	RMSD
IceTFT-2018	best	**0.1649**	**0.1942**	**0.4554**	-	-	-	-	-	-
	mean	0.2126	0.2668	0.4756	0.3016	0.3808	0.6182	0.1990	**0.2475**	0.5782
IceTFT-2019	best	-	-	-	**0.2007**	**0.2478**	**0.4890**	-	-	-
	mean	-	-	-	0.2847	0.3747	0.5894	0.2545	0.3345	0.7759
IceTFT-2020	best	-	-	-	-	-	-	**0.1684**	0.2677	**0.6689**
	mean	-	-	-	-	-	-	0.2577	0.3018	0.7071

15.Line 246: By using the short input length (6 months) leads to worse results. So, what if the input length increases to 18 or 24 months?

Thank you very much for your comment. Considering the difficulty of the 12-step prediction and the fact that the cycle of sea ice includes both melting and freezing processes, we decided to divide the 12-step prediction into two segments of 6 steps each to improve the prediction accuracy. However, actual results show that this assumption is not feasible.

At your suggestion, we conducted experiments with different input steps to discuss the model prediction techniques in terms of the input steps of the model. We re-wrote the section 5.2 “The Input Length” (pg10-11, line209-219):

> To investigate the effect of input length on the prediction skill, we chose to set up four sets of comparison experiments with input length of 6,12,18 and 24. Using 2019 prediction as an example, the results of the monthly errors are shown in Fig.6. The results of 2022-2021 are similar and we omit to show them. As a whole, the prediction errors for the models with the input lengths of 6 and 24 are significantly higher than the results for models with other lengths. Probably because the time window of 6 is too short to include both the March maximum and the September minimum in each epoch. This may affect the model learning for the features of the extremes, increasing the inaccuracy of the extremes. However, if the input lengths are too long, the correlation between the recent historical SIE sequence and the future SIE sequence is weakened, increasing the prediction error. In addition, the errors of a model with 18-month are comparable to that with the 12-month, but for the difficult prediction of 2019, i.e., October, which has a large slope, the error of a model with 18-month is significantly higher than that with the 12-month. Therefore, for the monthly prediction of SIE, a reasonable choice for the input length is 12-month, it probably is because the period of SIE is 12-month.

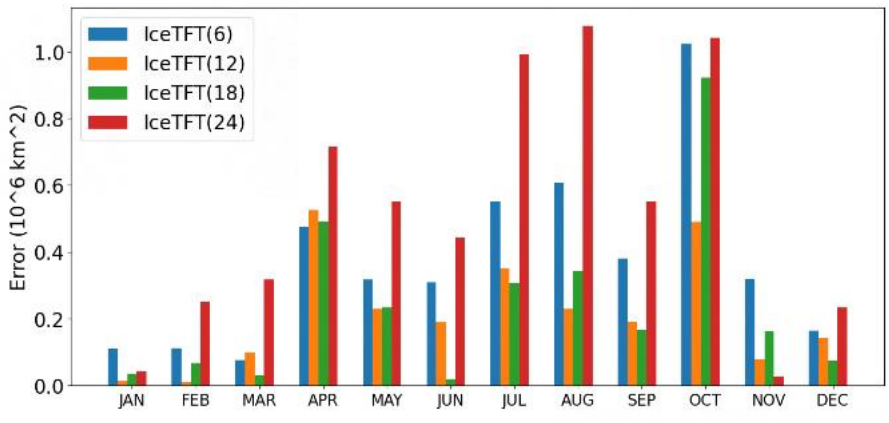


Figure 6. The errors of the IceTFT with different input length for 2019

16.From figure 6, it can be seen that the biases are much larger in Sep than in winter or other seasons.

Figure. 6 (now it is Figure. 7) contains two vertical coordinates, but we do not explain them in detail. Now we added in the title of the Figure. 7 (pg 14).

> The SIE predictions, observations, and the monthly errors during 2019-2021. The line graph represents the observations and SIE predictions, corresponding to the y-axis on the right; the bar graph represents the errors, corresponding to the y-axis on the left.

We have discussed the biases, and the September errors are relatively small. The predictive months with large prediction errors are mainly in July, October and November(pg 15, line 251-260):

> From the bar graphs in Fig.7, there is a clear trend of predictions for different years, and it also shows the monthly errors. As can be seen, the predictions of multiple training form a predict period in which the vast majority of observations fall within the range. Except for September 2020, the mean predicted results have the same trend as the observations. In terms of the monthly error of the model with different settings, all the experiment runs had high errors in October or November. In addition, they had another high error in July, except for 2019. Due to global warming, it is a challenge to predict SIE in summer. In the melt seasons, which is from June to September, the SIE continued to decline with steep slope. The line passing through the observed value of SIE in June and July has the steepest slope. It demonstrates that the SIE reduced significantly from June to July. Thus, it is difficult to predict the downturn. And as a result, the July prediction is higher than observation with higher error. The SIE archive minimum in September, and sea ice becomes frozen after that time. Similarly, as temperature anomaly or other climate effect, the October or November prediction is on the high side.

So, it's better that the authors can evaluate the IceTFT model's ability in different seasons, which may be more helpful for using the IceTFT model and understanding the sea-ice prediction ability. In fact, the prediction ability in summer (JJAS) is also more important than in other seasons.

We analyzed the predictive limits of IceTFT in SIE prediction in different months.The SIE has strongly cyclical, the IceTFT with large model errors when the SIE trend is more volatile, i.e. when the slope is larger. These predictive limits are described in (pg 15, line 255-260):

> Due to global warming, it is a challenge to predict SIE in summer. In the melt seasons, which is from June to September, the SIE continued to decline with steep slope. The line passing through the observed value of SIE in June and July has the steepest slope. It demonstrates that the SIE reduced significantly from June to July. Thus, it is difficult to predict the downturn. And as a result, the July

prediction is higher than observation with higher error. The SIE archive minimum in September, and sea ice becomes frozen after that time. Similarly, as temperature anomaly or other climate effect, the October or November prediction is on the high side.

We evaluate the IceTFT model's ability in different seasons and explore the potential causes for the inaccuracy between the SIE observations and the predictions according to the RMSD between the detrended quarterly SIE observations and the predictions for the 2019−2021 period (pg 15-16, line 268-283):

To further explore the potential causes for the inaccuracy between the SIE observations and the predictions, we calculated the RMSD between the detrended quarterly SIE observations and the predictions for the 2019−2021 period. The results are shown in Fig. 8. The RMSD ranges from 0.076 to 0.918 million km2 in Fig.8 (a), and the findings from the three years show a wide spread in RMSD on quarter. Figure 8 (b) displays a histogram of the temporal variation of squared RMSD, consisting of “bias” and “variance” according to Eq. (4). It can be seen that there is a very large variance in the spring (JFM) of 2020 and 2021, which is responsible for the high RMSD in this season. The correlation coefficients in Fig.8 (c) also display an obvious reduction in spring 2020, which is consistent with the variance variations in Fig.8 (b). This result indicates that the significant lower correlation coefficients are partially responsible for the RMSD peak. Moreover, except for a few months, the magnitude of the bias is substantially larger than the variation in Fig.8 (b), indicating that the change in bias is the main factor for the increase in RMSD. Figure 8 (d) shows the standard deviations of the predictions of IceTFT model and observations, and the annual standard deviation represents the amplitude of the seasonal cycle of SIE. The results show that the difference between these two standard deviations is obviously increasing, which contributes to the lager increase in bias over the same period. Furthermore, this is consistent with the finding in Fig. 7. The IceTFT with large model errors when the SIE trend is more volatile, i.e. when the slope is larger, such as in July and October. The biases between predictions and observations are larger for the season containing these two months. This suggests that IceTFT does not fully capture the signals from the historical data and does not reflect the seasonal variability in the SIE. Thus, we can improve the predictive model by focusing on the seasonal variability in the predictions to reduce the RMSD.

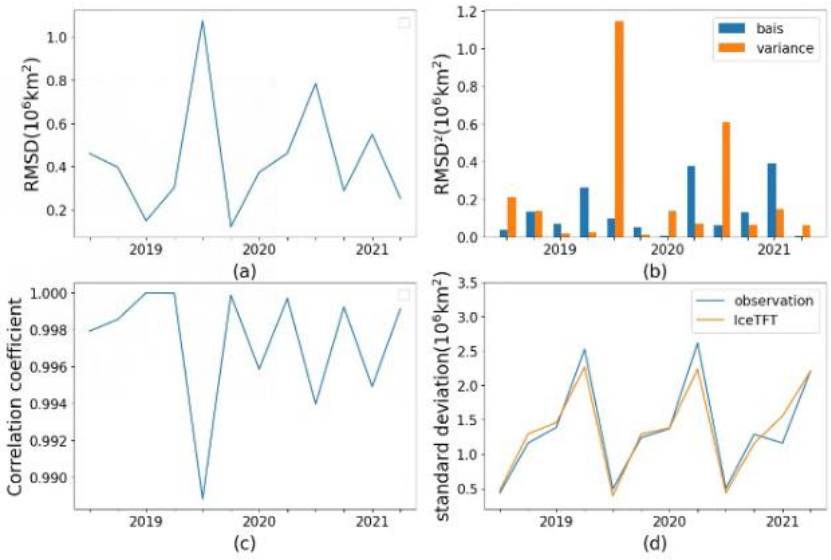


Figure 8. Time series of the RMSD between the detrended quarterly SIE on the IceTFT-model over the period 2019-2021: (a) RMSD; (b) squared RMSD (histogram), consisting of "bias" and "variance"; (c) correlation coefficient between predictions and observations; (d) standard deviation of predictions (orange line) and observations (blue line).

In addition, We have done interpretable analysis for seasonal predictions in Sect.8.3 "Analysis of the physical mechanisms on the seasons", mainly for summer(JJAS) and winter(JFM). Some of the conclusions are as follows (pg 22-23,line 389-433):

> Consequently, during the melting season, a relatively small area of sea ice cover exposes a large area of sea surface, and warming seawater affects sea ice melt. Since our model cannot simulate the process of radiation absorption by the ocean, SST can provide the IceTFT model with a direct factor affecting sea ice melt. However, for the freezing season, when the sea ice cover is large and the exposed sea surface area is small, the effect of SST on sea ice melt is relatively small. Rather, heat fluxes and warming air temperatures from water vapor, cloud cover and radiation mechanisms have a greater effect on sea ice melt (Kapsch et al., 2013; Boisvert and Stroeve, 2015). Thus validating the conclusions of our experiments that SST is an important factor influencing prediction from August to October, while radiation-related variables and AT are from January to May.

17.Figure 8: as we know, SIO is the prediction results from June, July, and August. The authors should clarify what kind of prediction data of SIO used in this figure.

There are more models in the SIO, and we have collected all the models which in the manuscript, recording the types of models and the data they use, listed in Appendix A (pg 25-27):

Appendix A: The Data used in SIO Models

Model	Type	Data
NSIDC (Meier)	Statistical	SIE
IceNet1(not include 2019)	Machine Learning	climate simulations (CMIP6), OSI-SAF SIC and ERA5
Sun, Nico	Statistical	SIC, CryoSat-2 SIT
RASM@NPS (Maslowski et al.)	Dynamic Mode	NOAA/NCEP CFSv2, CORE2 reanalysis
NASA GSFC	Statistical	SIE, SIC
UTokyo (Kimura et al.)	Statistical	SIC
Lamont (Yuan and Li)	Statistical	SIC, sea surface temperature (ERSST), surface air temperature,GH300, vector winds at GH300 (NCEP/NCAR reanalysis)
ANSO IAP-LASG	Dynamic Model	wind components (U and V), Temperature (T) in atmosphere and potential temperatur
Climate Prediction Center	Dynamic Model	SIC, Climate Forecast System Reanalysis (CFSR)
CPOM UCL (Gregory et al)	Statistical	SST(ERA5 reanalysis)
CPOM	Statistical	ice area covered by melt-ponds
University of Washington/APL	Dynamic Model	SIC, CryoSat-2 SIT, SST
FIO-ESM (Shu et al.)	Dynamic Model	SST, sea level anomaly(SLA)
Met Office (Blockley et al.)	Dynamic Model	FOAM/NEMOVAR, MO-NWP/4DVar, SIC

Model	Type	Data
PolArctic	Machine Learning	SIE
AWI Consortium (Kauker et al.)	Dynamic Model	SIC,CryoSat-2 SIT, NCEP-CFSR, NCEP-CFSv2
NMEFC of China (Li and Li)	Statistical	SIE, SIC
Wu, Tallapragada and Grumbine	Dynamic Model	NCEP SIC Analysis for the CFSv2, NCEP GFS, GFDL MOM4,Modified GFDL SIS
McGill Team (Brunette et al.)	Statistical	sea level pressure(SLP), area of ice exported through Fram Strait
ARCUS Team (Wiggins et al.)	Dynamic Model	CryoSat-2 SIT, SIC and SST (MERRA-2 atmospheric reanalysis)
ASIC, NIPR	Statistical	SIC, ice thickness, ice age, mean ice divergence
ArCS II Kids	Heuristic	SIC
Cawley, Gavin	Statistical	SIE
CSU-REU21	Statistical	ERA5, Pan-Arctic Ice Ocean Modeling and Assimilation System(PIOMAS)
EMC/NCEP (UFS)	Dynamic Model	NSIDC NASA Team Analysis
GFDL/NOAA (Bushuk et al.)	Dynamic Model	towards 3-D temperature, wind, and humidity data (CFSR), OISST
HEU Group (Zhao, et al.)	Statistical	SIC
Horvath, et al.	Statistical	SIE, ERA5
Kondrashov, Dmitri (UCLA)	Statistical	SIE
KOPRI (Chi et al.)	Machine Learning	SIC
LPHYS2268 - CDDF	Statistical	sea ice volume(SIV), SIT
METNO-SPARSE-ST (Wang et al.)	Statistical	SIE
MetService (Yizhe Zhan)	Statistical	SIE, top-of-atmosphere(TOA), reflected solar radiation (RSR)
NCEP-EMC (Wu et al.)	Dynamic Model	NCEP SIC Analysis for the CFSv2
NCAR/CU (Kay/Bailey/Holland)	Heuristic	Mitch Bushuk GFDL for a synthesis project)
NSIDC Hivemind	Heuristic	SIE
Simmons, Charles	Statistical	Moana Loa monthly CO2 concentrations, Northern Hemisphere snow area, SIC
Slater-Barrett (NSIDC)	Statistical	SIC
SYSU/SML-KNN	Machine Learning	SIE, SIC
SYSU/SML-MLM	Statistical	SIC, SST, surface air temperature (SAT), surface net radiation flux (NR)
UPenn-UQAM Group	Statistical	SIE, SIC
UKMO-OIT	Heuristic	-
UQAM (VARCTIC)	Statistical	SIC, SIV

Reviewer 2:

General comments:

However, the overall structure of the ms is not very reasonable and rigorous. For example, the introduction should not overly emphasize the present study and main point, but focus on reviewing the methods and shortcomings of SIE predictions in the previous studies, then gradually introduce one's own work and emphasize the advantages of the current work.

Thank you for your assistance in improving the manuscript. We re-wrote the introduction to remove the content related to the dynamical models and data assimilation. The current content of the introduction has been revised to introduce the importance of sea ice and the difficulties of SIE prediction, followed by an introduction to the current state of development of SIE prediction models through SIO, and then an introduction to the current machine learning based prediction of SIE based on previous work, summarising the limits of the models are single step prediction, short-term prediction and interpretability of models. Finally, the work and contributions of this paper are presented (pg 1-4, line 19-84).

1. Line 95, the contributions of this paper are not concise enough. For example, (1) is repeated with (2), (3) is a part of (4).

Thank you very much for your comment. We merged contributions #1 and #2, and merged #3 and #4 (pg 3-4, line 73-79):

1) The IceTFT model uses LSTM encoders to summarize past inputs and generate context vectors, so it can directly provide a long-term prediction of SIE for up to 12 months. And it can predict September SIE 9 months in advance, which is longer than other studies with lead time of 1-3 months. IceTFT has the lowest prediction errors for hind-cast experiments from 2019 to 2021 and actual prediction in 2022, which compared with SIO.

3) The IceTFT model is interpretable. It can automatically filter out spuriously correlated variables and adjust the weight of inputs through VSN, reducing noise interference in the input data. At the same time, it can also explore the contribution of different input variables to SIE predictions and reveal the physical mechanisms of sea ice development.

2. Add the reference about the definition of SIE in Line 150

We have added the reference about the definition of SIE (pg 7, line 132-134):

SIE is defined as the total area covered by grid cells with SIC > 15%, which is a common metric used in sea ice analysis (Parkinson et al., 1999).

3. The contemporaneous correlation in Table 1 is calculated between the global mean monthly one of eleven variables (e.g., SST) and SIE? And what's the lag-correlation since we are more concerned about the prediction not simulation?

Yes. The contemporaneous correlation is only a preliminary indicator that we use to expand on more input data and is not an important indicator for analysing predictions of SIE. We calculated the autocorrelation of SIE, as shown below:

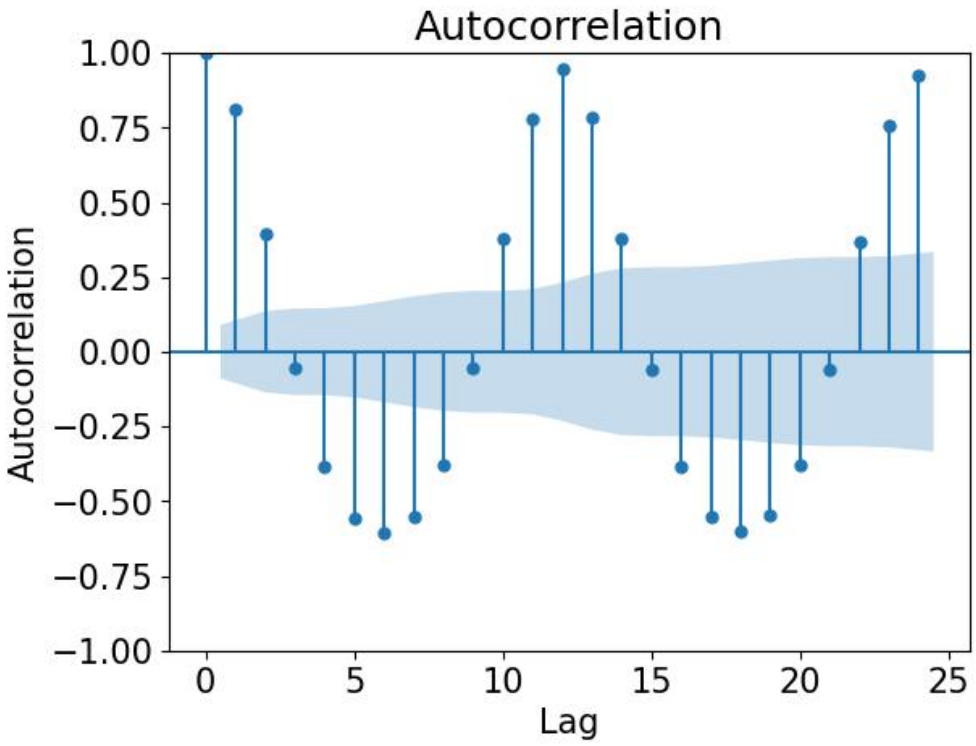


Figure 1. The Autocorrelation of SIE

The x-axis represents the time lag, the y-axis represents the autocorrelation of SIE, and the shaded area is the 95% confidence interval; if the data lies outside the confidence interval, it is autocorrelated. As can be seen from the Fig. 1, the data are all outside the confidence interval, which means that they are all autocorrelated, so that historical data of SIE can be used to predict the SIE. The SIE is highly cyclical, with a 12-month period. It can also be seen from the Fig. 1 that its self-correlation varies with a period of 12. Therefore, with the predicted variable SIE as the primary predictor, we consider the model with an input step of 12 and do not concern ourselves with the lag-correlation of the other auxiliary predicted data. For the other works with using multivariate to predict sea ice which are presented in the introduction, they also only focus on sea ice when considering the input length.

4. The metrics (MAE, RMSE, RMSD) have units. What's the meaning of the percentages and those in parentheses in Table 3 and Table 4? Please describe the calculation.

The percentages have no special meaning, they are just to show the data more aesthetically. To avoid any misunderstanding, we have reworked it (pg 13).

Table 4. The three metrics (MAE, RMSE, RMSD) among three models on SIE predictions during 2019-2021.

Predictive Year		2019			2020			2021		
Model Name		MAE	RMSE	RMSD	MAE	RMSE	RMSD	MAE	RMSE	RMSD
IceTFT-2018	best	**0.1649**	**0.1942**	**0.4554**	-	-	-	-	-	-
	mean	0.2126	0.2668	0.4756	0.3016	0.3808	0.6182	0.1990	**0.2475**	0.5782
IceTFT-2019	best	-	-	-	**0.2007**	**0.2478**	**0.4890**	-	-	-
	mean	-	-	-	0.2847	0.3747	0.5894	0.2545	0.3345	0.7759
IceTFT-2020	best	-	-	-	-	-	-	**0.1684**	0.2677	**0.6689**
	mean	-	-	-	-	-	-	0.2577	0.3018	0.7071

5. Please give the detailed meaning of the x-axis in Figures 5,6. Time along the x-axis means the started month or target month? How to obtain Error and SIE along the y-axis?

The x-axis is the target month in these two figures.

The line graph represents the observations and SIE predictions, corresponding to the y-axis on the right; the bar graph represents the errors of the observations and the SIE predictions, corresponding to the y-axis on the left.

Now we added in the title of the Figure. 7 (Figure 6. from the previous version of the ms has now become Figure. 7) (pg 14).

> The SIE predictions, observations, and the monthly errors during 2019-2021. The line graph represents the observations and SIE predictions, corresponding to the y-axis on the right; the bar graph represents the errors, corresponding to the y-axis on the left.

6. Many figures and tables are not cited in ms, such as table 4, figure 5 and figure 6.

Thank you for your assistance in improving the manuscript. Although all the figures and tables are cited in the manuscript.

Table 4 shows the three metrics (MAE, RMSE, RMSD) among three models (IceTFT-2018, IceTFT-2019,IceTFT-2020) on SIE predictions during 2019-2021, and it is cited in (pg 13, line 234).

Figure. 6 (Figure 5. from the previous version of the ms has now become Figure. 6) shows the prediction errors of the IceTFT with different input length (6,12,18,24) for 2019, and it is cited in (pg 10, line 210).

Figure.7 (Figure 6. from the previous version of the ms has now become Figure. 7) shows the SIE predictions, observations, and the monthly errors during 2019-2021, and it is cited in (pg 15, line 251).

7. What's the INITIAL experiment in Table 5? The INITIAL experiment seems to be described near Line 388 but the table 5 is first cited in Line 368. Similar issues exist in other figures.

The INITIAL experiment is the sensitivity experiments with 11 variables. (It has been renamed 11var in the new ms.)

We have restructured the entire article to ensure that the abbreviation is always preceded by the full name of the abbreviation.

8. What's PRATE?

PRATE is precipitation(PRECIP).

We have completed the revision to standardise the abbreviations for precipitation throughout the manuscript to PRECIP.

9. The authors mentioned that VSN in IceTFT can filter the spurious correlations (Line 137). In Section 5.7, the authors only analyze the variable sensitivity. Results in Tables 5 and 6 reflect some common key variables (such as SST and DSWRF), and also demonstrate some individual high-correlated variables (such as PRATE in 2019). From the perspective of statistics, can I consider that the individual high-correlated variables are belong to spurious correlations? Please add some explanations on such phenomenon under different ice cases from the perspective of dynamics.

If a variable makes a large contribution to the forecast, it should have a high sensitivity and can be considered to be highly causal. However, if the variable is highly correlated in Table 1 but has a low sensitivity value in Tables 5 and 6, it can be considered a spuriously correlated variable (such as DLWRF). For PRATE (PRECIP) , it is not considered highly correlated and not very sensitive in 2019-2021. PRATE (PRECIP) can be considered less causal for SIE. In our analysis, we found that latent heat exchange alters the cloud, allowing for an increase in DLWRF and PRATE (PRECIP), so that PRATE (PRECIP) is the result of other physical factors. We added some explanations (pg 21-22, line 366-377):

> While DLWRF is highly correlated in Table. 1 but has a low sensitivity value in Table. 5, it indicates that this variable is not the cause of the sea ice change, but may be the effect due to other variables. Other studies have shown that latent heat exchange causes more water vapor and clouds to be present in the atmosphere. This enhances the atmospheric greenhouse effect and results in an increased emission of DLWRF. In addition, the increase in water vapor and clouds will lead

to more PRECIP. Therefore, there is a correlation between DLWRF and PRECIP, and their sensitivity values change in agreement which both have a higher sensitivity in 2019 and are lower in other years.The positive feedback effect, along with the DLWRF, affects the development of sea ice (Kapsch et al., 2016). Since the machine learning model lacks the partial differential equations of the dynamical model, it cannot simulate the variation of clouds in positive feedback. Therefore, it is difficult to assist in SIE prediction based only on the data trends in DLWRF.

10.From figure 8, the authors compare IceTFT with other models in SIPN. I focus that the others mainly belong to dynamical numerical models and there are no deep learning models. This also means the authors have not compared IceTFT with ordinary deep (machine) learning models. I don't have a clear quantification on how much improvement of TFT and others (such as MLP, LSTM). It is quite a consensus that a deeper (more complex) network is better, but I still want to know if this improvement matches the time and computation comsumption.

We constructed the LSTM model and tuned the model to optimality. And we trained the LSTM model 20 times, taking the best and the mean prediction results for comparison. The results are shown in the table below:

Table 1. The mean results of IceTFT and LSTM model

RMSE	IceTFT	LSTM
2019	0.2668	0.5813
2020	0.3747	0.5715
2021	0.3018	0.6866

Table 2. The best results of IceTFT and LSTM model

RMSE	IceTFT	LSTM
2019	0.1947	0.3864
2020	0.2478	0.4964
2021	0.2677	0.5738

As can be seen from the table, LSTM has a much higher prediction error than IceTFT. By our calculations, the LSTM takes 5 minutes to train 20 times, while the IceTFT takes 5 minutes to train once. But they both take less than 1 minute to test. Although IceTFT takes more time to train, the training time is only in the order of minutes, and small prediction errors can be obtained. Therefore the benefit is worthwhile.

In the study of original TFT (Lim et al. 2019) , TFT has been shown to be applied to time-series prediction of data in various domains, and it can captures long-term features through LSTM encoder and multi-headed attention mechanism. So TFT

outperforms other traditional models (such as Recurrent Neural Networks (RNN), Convolutional Transformer (ConvTrans) etc).

In addition, the models in SIPN include not only dynamical models, but also statistical methods, machine learning, etc. The types and the used data of models which are compared in the ms are listed in the Appendix A. Therefore, IceTFT also outperforms other machine learning models in SIPN.

Appendix A: The Data used in SIO Models

Model	Type	Data
NSIDC (Meier)	Statistical	SIE
IceNet1(not include 2019)	Machine Learning	climate simulations (CMIP6), OSI-SAF SIC and ERA5
Sun, Nico	Statistical	SIC, CryoSat-2 SIT
RASM@NPS (Maslowski et al.)	Dynamic Mode	NOAA/NCEP CFSv2, CORE2 reanalysis
NASA GSFC	Statistical	SIE, SIC
UTokyo (Kimura et al.)	Statistical	SIC
Lamont (Yuan and Li)	Statistical	SIC, sea surface temperature (ERSST), surface air temperature,GH300, vector winds at GH300 (NCEP/NCAR reanalysis)
ANSO IAP-LASG	Dynamic Model	wind components (U and V), Temperature (T) in atmosphere and potential temperatur
Climate Prediction Center	Dynamic Model	SIC, Climate Forecast System Reanalysis (CFSR)
CPOM UCL (Gregory et al)	Statistical	SST(ERA5 reanalysis)
CPOM	Statistical	ice area covered by melt-ponds
University of Washington/APL	Dynamic Model	SIC, CryoSat-2 SIT, SST
FIO-ESM (Shu et al.)	Dynamic Model	SST, sea level anomaly(SLA)
Met Office (Blockley et al.)	Dynamic Model	FOAM/NEMOVAR, MO-NWP/4DVar, SIC

Model	Type	Data
PolArctic	Machine Learning	SIE
AWI Consortium (Kauker et al.)	Dynamic Model	SIC,CryoSat-2 SIT, NCEP-CFSR, NCEP-CFSv2
NMEFC of China (Li and Li)	Statistical	SIE, SIC
Wu, Tallapragada and Grumbine	Dynamic Model	NCEP SIC Analysis for the CFSv2, NCEP GFS, GFDL MOM4,Modified GFDL SIS
McGill Team (Brunette et al.)	Statistical	sea level pressure(SLP), area of ice exported through Fram Strait
ARCUS Team (Wiggins et al.)	Dynamic Model	CryoSat-2 SIT, SIC and SST (MERRA-2 atmospheric reanalysis)
ASIC, NIPR	Statistical	SIC, ice thickness, ice age, mean ice divergence
ArCS II Kids	Heuristic	SIC
Cawley, Gavin	Statistical	SIE
CSU-REU21	Statistical	ERA5, Pan-Arctic Ice Ocean Modeling and Assimilation System(PIOMAS)
EMC/NCEP (UFS)	Dynamic Model	NSIDC NASA Team Analysis
GFDL/NOAA (Bushuk et al.)	Dynamic Model	towards 3-D temperature, wind, and humidity data (CFSR), OISST
HEU Group (Zhao, et al.)	Statistical	SIC
Horvath, et al.	Statistical	SIE, ERA5
Kondrashov, Dmitri (UCLA)	Statistical	SIE
KOPRI (Chi et al.)	Machine Learning	SIC
LPHYS2268 - CDDF	Statistical	sea ice volume(SIV), SIT
METNO-SPARSE-ST (Wang et al.)	Statistical	SIE
MetService (Yizhe Zhan)	Statistical	SIE, top-of-atmosphere(TOA), reflected solar radiation (RSR)

11. The authors construct the model based on the original TFT (Lim et al. 2019), please give a detailed parameter configuration, including the hidden layer number and hidden dimensions. Is the current configuration the best?

It is the best configuration. The script code for the call reference is submitted in zenodo.

We add the detailed parameter configuration in (pg 6, line 116-118):

> We have experimentally determined the optimal hyperparameters, the size of hidden layers is 160, the bach size is 128, the number of multi-head self-attentive is 4, the dropout rate is 0.1, the max gradient norm is 0.01 and the learning rate is 0.001.

Please give some discussions on the upper limit of IceTFT's forecasting skill and why it surpasses other models.

The IceTFT model has difficulty predicting those extreme years, such as 2020. This predictive limit is described in (pg 13, line 237-242):

> Compared to the results of these two years, the errors of the mean predicted results increased in 2020. This is because there is a second record-low SIE in September 2020. Moreover, due to the predicted period being too long relatively, evaluating the prediction skill of the IceTFT model using MAE as the loss function is difficult. A low MAE does not mean that the model can predict all 12-step with low errors. The IceTFT model focuses on different physical factors during some training, and generates predictions with different trends. The model is hard to predict this minimum value accurately in each training, so the errors of mean prediction are much higher than the best one.

In addition, the SIE has strongly cyclical, the IceTFT with large model errors when the SIE trend is more volatile, i.e. when the slope is larger. In addition, the model has difficulty predicting those extreme years, such as 2020. These predictive limits are described in (pg 15, line 251-260):

> As can be seen, the predictions of multiple training form a predict period in which the vast majority of observations fall within the range. Except for September 2020, the mean predicted results have the same trend as the observations. In terms of the monthly error of the model with different settings, all the experiment runs had high errors in October or November. In addition, they had another high error in July, except for 2019. Due to global warming, it is a challenge to predict SIE in summer. In the melt seasons, which is from June to September, the SIE continued to decline with steep slope. The line passing through the observed value of SIE in June and July has the steepest slope. It demonstrates that the SIE reduced significantly from June to July. Thus, it is difficult to predict the downturn. And as a result, the July prediction is higher than observation with higher error. The SIE archive minimum in September, and sea ice becomes frozen after that time. Similarly, as temperature anomaly or other climate effect, the October or November prediction is on the high side.

The reasons for IceTFT surpassing other models are described in (pg 4, line 86-92):

> Deep learning has good performance in time series prediction, but previous research mostly used CNN, ConvLSTM, which still have high prediction errors. The transformer model makes the attention mechanism fully capture the temporal dependence, and it performs better than the traditional Recurrent Neural Network (RNN) models. Based on the transformer model, temporal fusion transformer (TFT) was proposed for multi-step prediction. TFT not only uses a sequence-to-sequence layer to learn both short-term and long-term temporal

relationships at the local level, but also uses a multi-head attention block to capture long-term dependencies. The TFT has been verified that it has small prediction errors in several areas.The sea ice dataset is a time series with pronounced periodicity, which has a peak and a trough in a yearly cycle, these two peaks are usually critical to the prediction. Therefore, TFT, which can capture long-term temporal features, is suitable for sea ice prediction.

12. Why a higher sensitivity value indicates that the variable makes significant contributions to predictions? I don't understand why the sensitivity can be estimated by adding random noises. To investigate the contribution of different variables to SIE prediction in the model, one can artificially weaken the signal of the concerned variable and investigate the changes in prediction skills.

The basic idea of weakening or enhancing the signals of the variables to investigate the changes in prediction skills is similar. If the variable has a significant effect on prediction, then the prediction error changes as the signal of the variable changes.

$$y' = F(w_1x_1, \cdots, w_ix_i, \cdots, w_nx_n) \qquad (1)$$

$$y' + \Delta y_i = F(w_1x_1, \cdots, w_i(x_i + \Delta x_i), \cdots, w_nx_n) \qquad (2)$$

$$\text{Sensitivity}(x_i) = \frac{\text{RMSE}(y, y' + \Delta y_i)}{\text{RMSE}(y, y')} \qquad (3)$$

As in Eq.1. F() represents the deep learning model, x_i represents the input variables, w_i is the weight of the corresponding variable, and y' is the prediction result. For the IceTFT model, VSN automatically adjusts the weights of the input variables during training. If the variable x_i has a significant effect on the prediction, the weight w_i of this variable in the model will be larger. If random noise Δx_i is added to this variable, the change of the prediction result Δy_i will also be larger (Eq.2), increasing the change of RMSE , and therefore the sensitivity (x_i) obtained will be large (Eq.3). However, if the variable x_i has little effect on the prediction, the weight w_i of this variable in the model will be close to 0. When random noise Δx_i is added to x_i, the change of Δy_i is also close to 0. The change in RMSE is not significant, so the obtained sensitivity value is close to 1. Therefore, the higher sensitivity value indicates that the variable makes a significant contribution to predictions.

Kim et al. (2020) added random Gaussian noises to inputs and calculated the change in RMSE to evaluate variable sensitivity. Zhou, L.and Zhang, R (2023) perform sensitivity analysis by assigning a zero value to the temperature anomaly. So

artificially changing the signals of the variables of interest can be used to study changes in predictive skills.

Kim, Y. J. , Kim, H. C. , Han, D. , Lee, S. , & Im, J. . (2020). Prediction of monthly arctic sea ice concentrations using satellite and reanalysis data based on convolutional neural networks. The Cryosphere(3).

Zhou, L., & Zhang, R. (2023). A self-attention–based neural network for three-dimensional multivariate modeling and its skillful ENSO predictions. Science Advances, 9.

Other suggestion:

13. Line 35: “showed” => “shown, “… the errors were …” => “… that the errors were …”

Thanks to your suggestion, the sentence has been amended after our quote rewrite as follows (pg 2, line 32):

> Figure 1 a (b, c) shows that the September SIE prediction errors with a lead time of 3 (2,1) months during 2019 to 2021, which are published in the Sea Ice Outlook (SIO) by Sea Ice Prediction Network (SIPN).

14. Line 40: changed as “there is still a certain gap between these forecasts and observations”

We have fixed it (pg 2, line 36):

> From Fig.1, it can be seen that there is still a certain gap between these predictions and observations.

15. Line 71: “recursive” => “a recursive”

We have fixed it (pg 3, line 44-45):

> Then they used a recursive approach to make the prediction model provide 12-month predictions.

16. Line 80: “lack” => “the lack”

We have fixed it (pg 3, line 58-59):

> Compared to dynamic models, deep learning models are considered a "black box" due to the lack of physical mechanisms.

17. Line 88: “that increases” => “which increases”

Thank you for your suggestion, this sentence no longer exists after we rewrote the introduction.

18. Line 141: “encorder” => “encoder”, this misspelled is also seen elsewhere

We have corrected all spellings of the word in the ms.

19. Line 141: delete “from that”

We have fixed it (pg 6, line 120):

> The IceTFT model is designed to use static covariate encoder to integrate static features, and use GRN to generate different context vectors that are linked to the different locations.

20. Line 149: “input” => “inputs”

We have fixed it (pg 7, line 128):

Each head can learn different temporal features and attend to a common set of inputs.

21. Line 150: “in original TFT” => “in the original TFT”

Thank you for your suggestion, this sentence no longer exists after we rewrote the introduction.

22. Line 160: “in order to” => “to”

We have fixed it (pg 7, line 137):

> we select a number of variables to support the proposed model for SIE prediction to help it learn more physical mechanisms and improve its prediction skills.

23. Line 177: “ SHUM” => ”and SHUM”

We have fixed it (pg 7, line 153):

> we select these variables: 2m air temperature (AT), DSWRF, DLWRF, and SHUM these variables.

24. Line 285: “the SIE continued decline with steep slope” => “the SIE continued to decline with a steep slope”

We have fixed it (pg 15, line 256):

> In the melt seasons, which is from June to September, the SIE continued to decline with steep slope.

25. Line 295: “As a results” => “As a result”

We have fixed it (pg 15, line 258):

> And as a result, the July prediction is higher than observation with higher error.

26. Line 332: “lead time” => “lead times”

We have fixed it (pg 18, line 319):

> Figure 10 shows the 2022 SIE predictions of different models of SIO in different lead times.

27. Line 395: delete “has”

We have fixed it (pg 22, line 388):

> From Table.6 and Table.7, it can be seen that all six variables had a high sensitivity in the 11var experiment, but the sensitivity changed in the 6var experiment.

28. Line 396: “the more errors” => “more errors”

We have fixed it (pg 22, line 390):

> These changes cause more errors in summer(JJAS), autumn(OND), but fewer errors in winter(JFM), as can be seen from the first row of Table.8 (a).

29. Line 403: “on 2021 than 2019” => “on 2021 than on 2019”

We have fixed it (pg 22, line 397):

> It demonstrates that the factors affecting the 2019 predictions are similar to those for 2021, and SST and AT have a greater impact on 2021 than on 2019.

30. Line 450: “predict the next year SIE” => “predict the SIE in the next year”

Thank you for your suggestion, this sentence no longer exists after we rewrote the introduction. The similar sentence is as follows (pg 23, line 435):

The IceTFT model can provide the 12-month SIE directly according to the inputs of the last 12 months.

31. Line 451: “the previous year data” => “the previous year’s data”

Thank you for your suggestion, this sentence no longer exists after we rewrote the introduction. The similar sentence is as follows (pg 23, line 435):

The IceTFT model can provide the 12-month SIE directly according to the inputs of the last 12 months.

32. Line 456: “IceTFT model” => “the IceTFT model”. Missing “the” in many places of the ms.

Thank you for your assistance in improving the manuscript. We checked the grammar of the ms and corrected all the errors.