RC2:

In this study, Zhao et al. present an operational Southern Ocean Ice Prediction System and exhibit its ability for Antarctic sea ice prediction on synoptic time scales. They developed the prediction system based on MITgcm and assimilated satellite-derived sea ice concentration data, making predictions for the future 7 days. The prediction system shows promising skill in predicting the sea ice concentration, sea ice thickness, sea ice drift, and sea ice convergence.

Considering the limited effort for the operational Antarctic sea ice prediction when compared to its Arctic counterpart, this study is valuable by providing evidence of the model's ability for skillful Southern Ocean and sea ice prediction. In addition, the manuscript is well-organized and easy to understand. However, I found some points to be further clarified, which are listed below. I suggest a major revision is needed.

Response:

Dear reviewer, thanks a lot for your time and valuable comments on this manuscript. In the revised manuscript, we rename the original experiment as DA_Forecast run, and involve two additional experiments in the analysis: a experiment without any data assimilation (NoDA_Forecast) and a experiment of persistence forecast (PE_Forecast). The setting of the NoDA_Forecast run is the same to the DA_Forecast run except that no observational data has been assimilated. The PE_Forecast run uses the initial condition of the DA_Forecast run as forecasts of the following 168 hours. Note that the PE_Forecast run includes the observational sea ice concentration information due to data assimilation. Our replies to your comments and suggestions are as follows.

Major comment:

1. Despite the main point of this work being to demonstrate the ability of the prediction system for the operational Antarctic sea ice prediction, the added scientific

discussions will improve the manuscript a lot. The following are a few examples, but not limited to these.

（1）Why is the RMSE of prediction in Fig. 3 smaller than the RMSE of observation February and March? Why does the RMSE of prediction peak in April?

Response:

The AMSR2 data was assimilated into the ensemble of model restart fields on a daily basis, and an analyzed (updated) ensemble of model restart fields was generated. The analyzed model restart fields combined the modeled sea ice states with the observational sea ice states. Initialized from the analyzed ensemble of model restart fields, each ensemble member was integrated for 168 hours driven by atmospheric forcing. So the forecasts included not only the observational information, but also sea ice changes generated by model physics, which caused the better performance of the DA_Forecast run in comparison with that of the AMSR2 data, especially at lead time of 24-hour and 72-hour in January–early March and May–September.

Figure 4 shows that large sea ice concentration RMSE appears in most areas of sea ice zone around the Antarctica in March–April, suggesting that the model has a relative low capacity in correctly simulating sea ice growth rate during this onset–to–fast freezing period. This partly originates from that the sea ice model in the SOIPS uses the zero-layer ice/snow thermodynamics (Semtner, 1976), which is a simple sea ice model compared to sophisticated multi-layer ice/snow thermodynamical models.

We added the statement of “The AMSR2 sea ice concentration data was assimilated into the ensemble of model restart fields on a daily basis, and an analyzed (updated) ensemble of model restart fields combining the modeled and observational sea ice states was generated, which were further integrated for 168 hours driven by atmospheric forcing. The forecasts included not only the observational information, but also sea ice changes generated by model physics. This causes the better performance of sea ice concentration forecasts in the DA_Forecast run in comparison with that of the AMSR2 data, especially at lead time of 24-hour and 72-hour in January–early March and May–September. On the other side, large sea ice concentration RMSE appears in most areas of sea ice zone around the Antarctica in March–April, suggesting that the model has a relative low capacity in correctly simulating sea ice growth rate during this onset–to–fast freezing period. This probably originates from that the sea ice model in the SOIPS uses the zero-layer ice/snow thermodynamics, which is a simple sea ice model compared to sophisticated multi-layer ice/snow thermodynamical models." into the revised manuscript.

（2）L180-190: it's interesting to know how many errors can be explained by the difference between OSISAF and AMSR2 and how many are caused by error growth during the model integration.

Response:

The monthly patterns of the RMSEs of sea ice concentration between the AMSR2 and OSISAF data (Figure R1) show large values in the northern marginal ice zone and the coast while small values in between, which sets the base for those between the forecasts and the OSISAF data. Due to the large spatial-temporal differences of the sea ice concentration RMSE, it is hard to quantitatively clarify how many errors are caused by error growth during the model integration. As a reference, with respect to the OSISAF data, the annual mean RMSEs of the AMSR2 data, the forecasts at lead times of 24-hour, 72-hour, 120-hour and 168-hour are 0.165, 0.15, 0.16, 0.17 and 0.19, respectively. The rates of the RMSE of the forecasts to the AMSR2 data are 91%, 97%, 103%, and 115%, respectively. We put Figure R1 into the supplementary material.

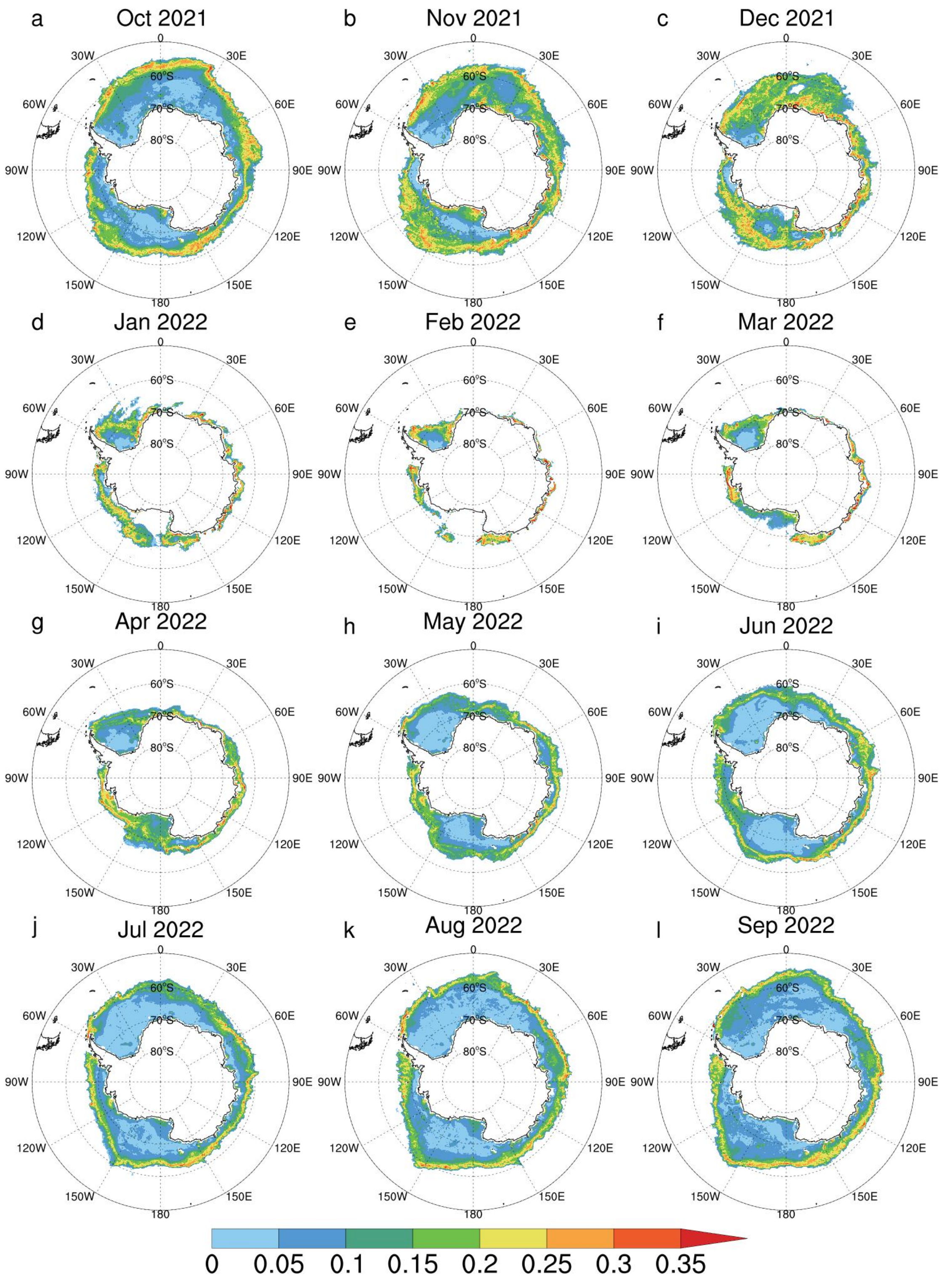

Figure R1. Monthly patterns of the RMSEs of sea ice concentration between the AMSR2 and OSISAF data. (a)–(l) denote October 2021–September 2022.

（3） What model deficiency in Fig. 5 leads to an increase in predicted IIEE in March-April and a decrease in April-May? Why is there little difference in IIEE for different lead times in January-June, but significant differences in other months?

Response:

As mentioned in the response to your major comment 1(1), the model has a relative low capacity in correctly simulating sea ice growth (expansion) rate during March–April (the onset–to–fast freezing period). This probably originates from that the sea ice model in the SOIPS uses a simple zero-layer ice/snow thermodynamics.

Figure R2 shows the monthly patterns of sea ice edge forecasts at lead time of 168-hour with respect to the OSISAF data. In comparison with July–December, the sea ice zone is smaller during January–June, so the integrated ice-edge error grows moderately in response to prolonged forecast lead time. Moreover, the sea ice edge locates more north during July–December, and the marginal ice zone is more close to the ACC-impacting areas where active oceanic and atmospheric dynamical processes promote the amplification of the integrated ice-edge error along with the prolong of forecast lead time.

We added the statement of "In comparison with July–December, the sea ice zone is smaller during January–June, so the IIEE grows moderately in response to prolonged forecast lead time. Moreover, the sea ice edge locates more north during July–December, and the marginal ice zone is more close to the ACC-impacting areas where active oceanic and atmospheric dynamical processes promote the amplification of the IIEE along with the prolong of forecast lead time." into the revised manuscript.

We put Figure R2 into the supplementary material.

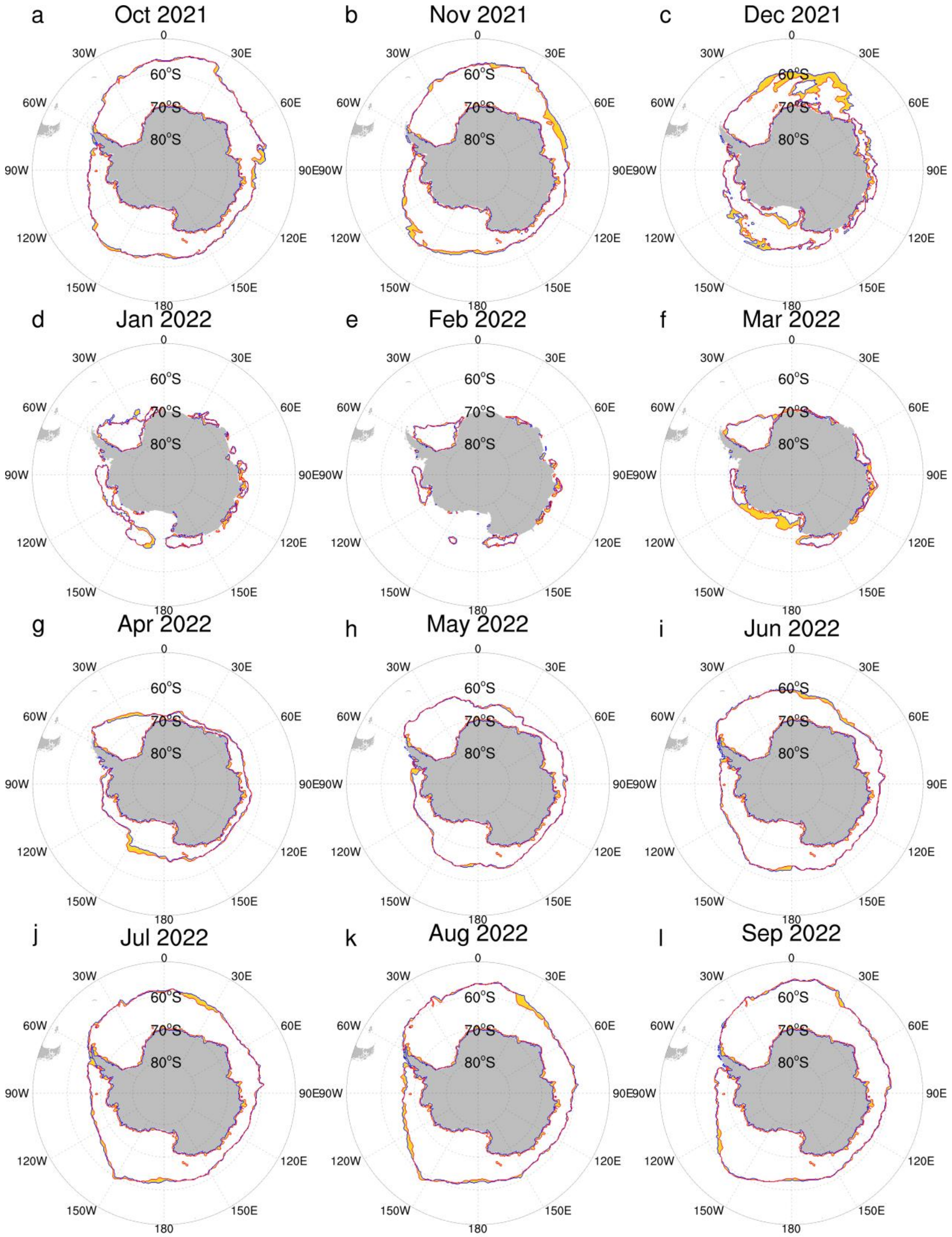

Figure R2. Monthly patterns of sea ice edge forecasts at lead time of 168-hour with respect to the OSISAF data. (a)-(l) denote October 2021–September 2022. The blue lines denote the DA_Forecast run. The red lines denote the OSISAF data. The gold contours denote the IIEE.

（4）In Fig. 9, why the evolution of forecast errors in magnitude of sea ice drift is different from that in direction? Additionally, due to the complexity of the South Pacific Ocean current system, it is recommended to showcase the drift forecast capability in more ways, such as its spatial distribution.

Response:

Similar to the patterns of sea ice concentration RMSE (Figure 4 in the original manuscript), the monthly patterns of the magnitude bias between the sea ice drift forecasts at lead time of 24-hour and the NSIDC data (Figure R3) show large values in the northern marginal ice zone and the coast, while small values in between. During January–March, the Antarctic sea ice zone shrinks to its annual minima, large biases in magnitude of sea ice drift occur in most sea ice areas, and thus the mean absolute error in magnitude of sea ice drift forecasts is large during January–March (Figure 9 in the original manuscript). In other months, large biases in sea ice drift direction forecasts also occur in the densely packed sea ice zone, especially the Bellingshausen-Amundsen-Ross Seas and the southeastern Antarctic Ocean sector (Figure R4), thus the mean absolute error in direction of sea ice drift forecasts is large in other months. We added Figure R3, R4 into the revised manuscript.

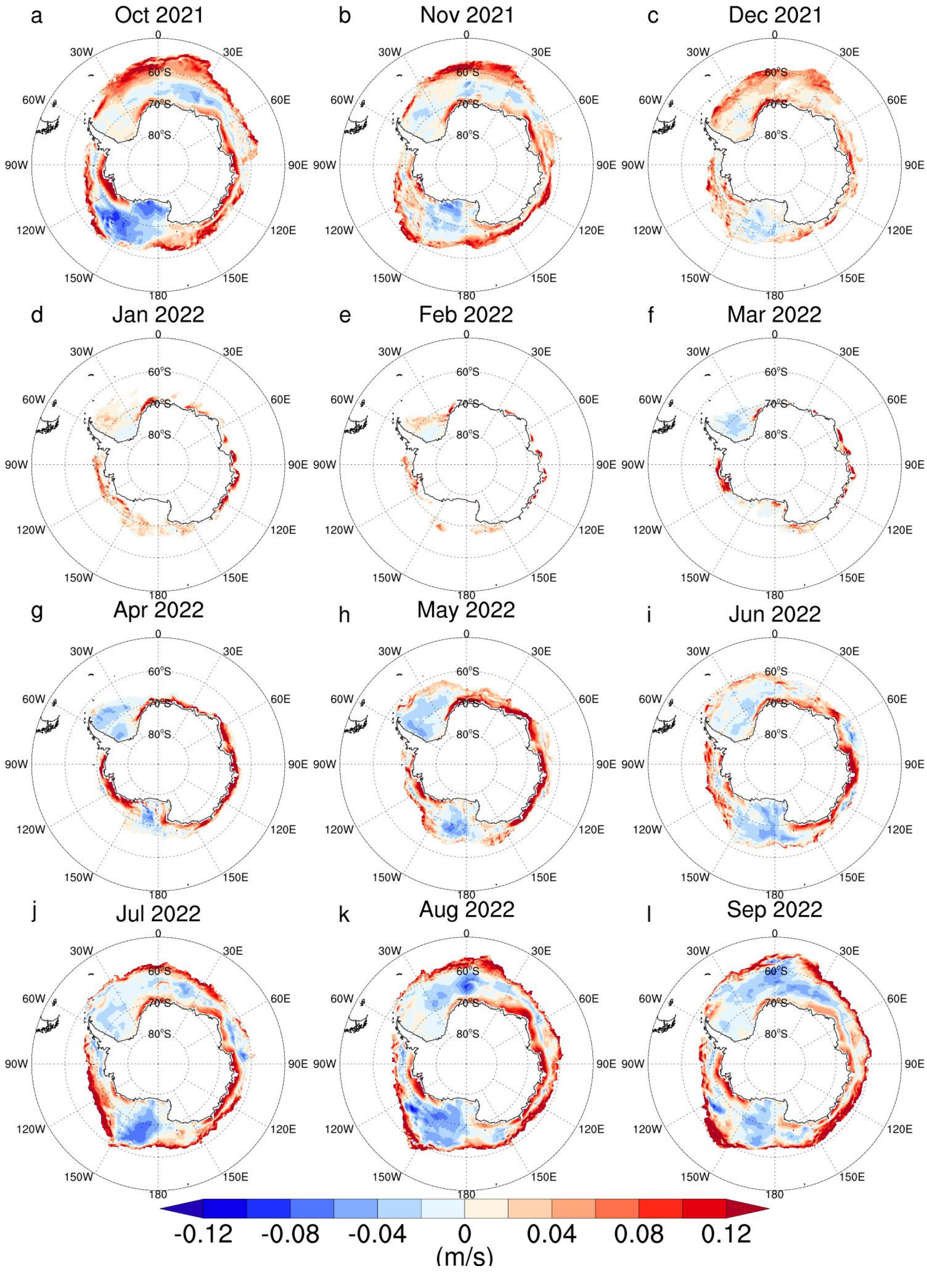

Figure R3. Monthly patterns of the magnitude bias between the sea ice drift forecasts at lead time of 24-hour and the NSIDC data. (a)-(l) denote October 2021–September 2022.

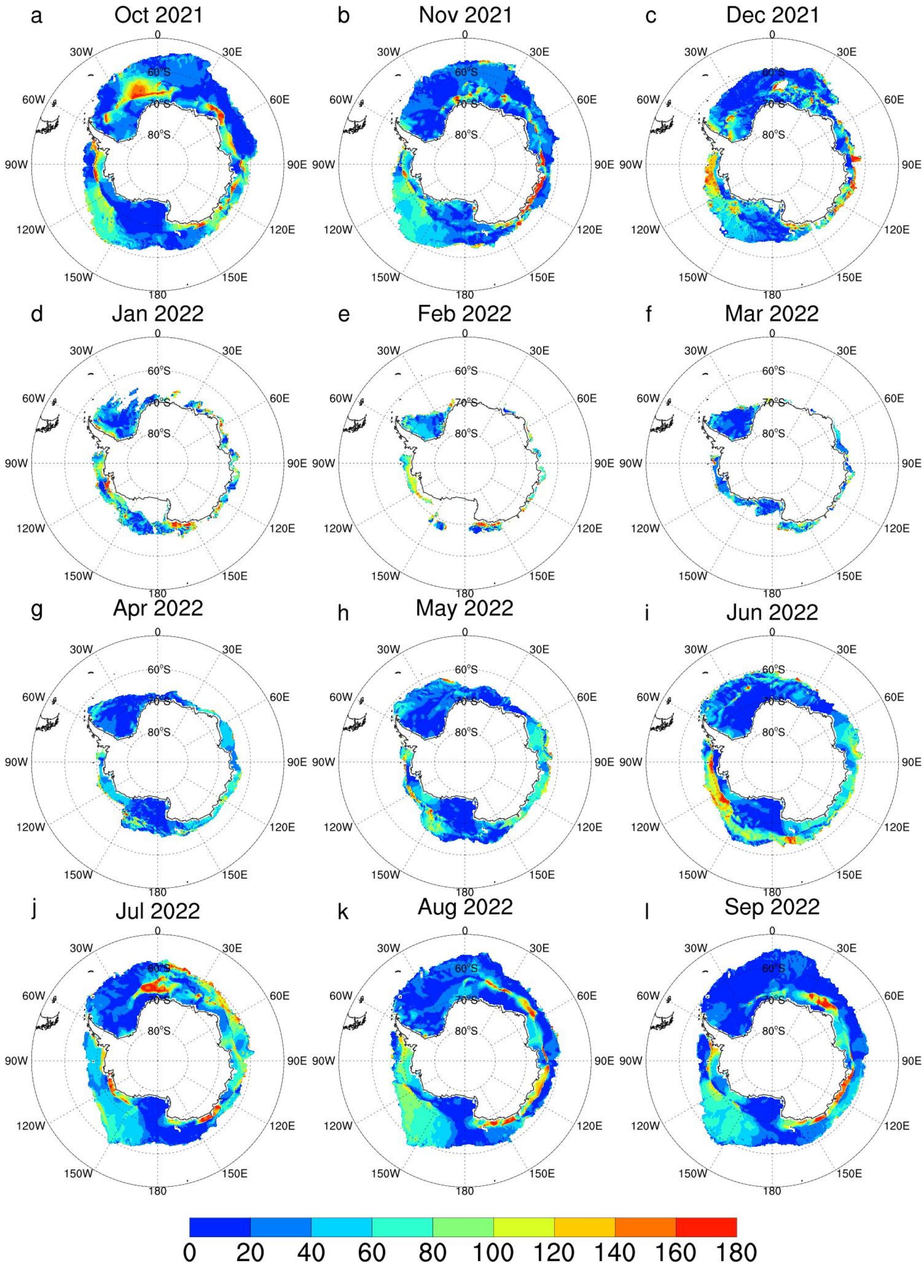

Figure R4. Monthly patterns of the absolute bias between the direction of sea ice drift forecasts at lead time of 24-hour and the NSIDC data. (a)-(l) denote October 2021–September 2022.

2. Compared to other studies, an important feature of this research is the incorporation of ice-shelf model. Thus,

(1) Please provide more details on the ice-shelf model and coupling method. According to Line 98-99, it's hard to realize the differences between the ice-shelf model used here and boundary conditions used in previous studies.

Response:

We apologize for the misleading statement. At the current stage, the ice-shelf modular in the MITgcm is not a sophisticated ice-shelf model, yet this ice-shelf model can still function as an effective static boundary condition. This ice-shelf model was developed by Losch (2008). Since Losch (2008) has provided a description of this ice-shelf model in detail, we have not repeated the documentation of this model in this study. We agree with the reviewer that we should describe the ice-shelf model more clearly.

The ice-shelf model affects the coupled model system through dynamics and thermodynamics. Dynamically, the ice shelf draft on the top of the water column has a similar role as the surface orography. Underneath an ice shelf, the pressure at the top of the water column is the sum of the atmospheric pressure and the weight of the ice shelf column. Thermodynamically, the freezing and melting at the basal surface of the ice shelf can induce effective heat flux and virtual salt flux at the ice–ocean interface, with an additional tendency term of temperature and salinity to the ocean at the depth of the ice-shelf draft. Then, a boundary layer between the ice shelf and the ocean is formed. In addition, the application of partial cells has also been introduced in the ice-shelf model, and thereby it can properly represent the geometry of the sub-ice-shelf cavity and allow for an accurate and smooth solution at the ocean–ice-shelf interface.

We added the statement of "The ice-shelf, serving as as a static surface boundary condition, exerts dynamic and thermodynamic influences on the underlying ocean and thus affects ocean circulation and sea ice (Losch, 2008). Dynamically, the ice shelf draft on the top of the water column has a similar role as the surface orography. Underneath an ice shelf, the pressure at the top of the water column is the sum of the atmospheric pressure and the weight of the ice shelf column. Thermodynamically, the freezing and melting at the basal surface of the ice shelf can induce effective heat flux and virtual salt flux at the ice–ocean interface, with an additional tendency term of temperature and salinity to the ocean at the depth of the ice-shelf draft. Then, a boundary layer between the ice shelf and the ocean is formed. In addition, the application of partial cells has also been introduced in the ice-shelf model, and thereby it can properly represent the geometry of the sub-ice-shelf cavity and allow for an accurate and smooth solution at the ocean–ice-shelf interface.” into the revised manuscript.

(2) More analyses should be conducted to highlight the advantages of this feature. For example, the Larsen-B ice shelf collapsed in January 2022 (doi: 10.5194/tc-2023-88), which occurred during the experimental period, so it is advisable to investigate the impact of this event on sea ice assimilation and prediction.

Response:

Since the ice-shelf model functions as a static surface boundary condition, the ice-shelf model does not simulate collapse of ice-shelf, and the ice-shelf topography remains unchanged during the experimental period.

We added the statement of “On the eastern side of the Antarctic Peninsula, the multi-year landfast ice in the northern Larsen B embayment breakout and disentangled from the Larsen B ice shelf in January 2022 (Ochwat et al., 2024). Since the involved ice-shelf model does not simulate collapse of ice-shelf and the ice-shelf topography remains unchanged in the SOIPS, replacing the simple static ice-shelf modular by a sophisticated thermodynamic–dynamic ice-shelf model may further improve the performance of the SOIPS on sea ice forecasts.” into the revised manuscript.

Minor comment:

Line 66-71: Because the preceding paragraph mentioned the advantages of regional models, it might be better to illustrate data assimilation studies based on regional models, such as SOSE.

Response:

We added the statement of “The Southern Ocean State Estimate (Mazloff et al., 2010) constrains model state using in situ and satellite measurements through 4D-Var data assimilation.” into the revised manuscript.

Line 82: Considering the submission is in 2024 and an operational forecasting system is involved, the experiment should be extended to include 2023 when the Antarctic sea ice reaches its minimum extent.

Response:

Thanks for the suggestion. We prefer to keep the original study period in the revised manuscript. Meanwhile, we have validated the sea ice extent forecasts before September 2023 in the operational record and put Figure R5 into the supplementary material. The minimum sea ice extent forecasts of the DA_Forecast run at lead time of 24-hour are 1.73×10^6 km^2 in 2022 and 1.49×10^6 km^2 in 2023. The minimum sea ice extent derived from the AMSR2 data are 1.76×10^6 km^2 in 2022 and 1.63×10^6 km^2 in 2023. The SOIPS predicted a lower sea ice extent minimum in 2023 than in 2022.

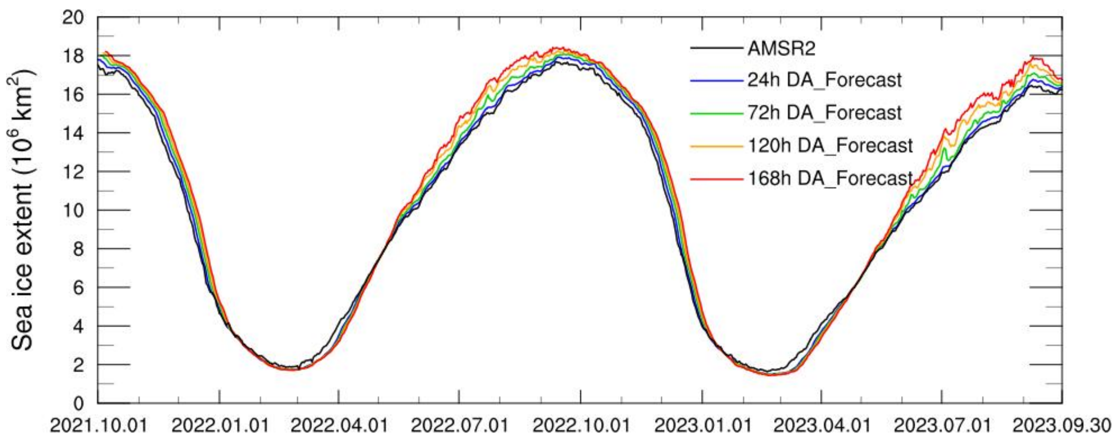

Figure R5. Sea ice extent evolution of the AMSR2 data (black line) and the DA_Forecast run at lead time of 24-hour (blue line), 72-hour (green line), 120-hour (yellow line), and 168-hour (red line).

Line 93: Considering that one important application of this system is for shipping services, the higher model resolution would indeed be preferable. Therefore, why not use a higher-resolution model such as MITgcm with 1/6° (doi: 10.1002/2016jc012650)?

Response:

We agree with your comment. At current stage, the use of low-resolution MITgcm model in the SOIPS is determined by the limitation of computational resource in the operational implementation. We have cited Verdy and Mazloff (2017) in the revised manuscript.

Line 130-132: Please provide more details on the initial field perturbation process, such as which variables are perturbed? What is the explained variance of the first 11 EOF modes?

Response:

We revised the sentence to “The initial ensemble of SOIPS is generated by disturbing the latest state of the model free run including sea ice concentration and thickness.”.

We have cited Pham (2001) in the revised manuscript, which introduces the method of applying an order-2 sampling scheme to leading EOF modes to generate perturbation.

The explained variances of the first and the 11th EOF modes are 47.48% and 0.66%, respectively. The first 11 EOF modes account in total for 69.34% of total variance.

Line 135-136: Please provide more information about the observational errors used in the assimilation. For example, is 0.15 the representative error of observations? If so, how are instrument errors identified?

Response:

We used a uniform value of 15% as the representative error of the AMSR2 sea ice concentration observations for simplicity in the SOIPS. We don't know how the instruction errors are identified, but according to the manual of the AMSR2 sea ice concentration product, the AMSR2 observations have different errors in different sea ice concentration ranges. In densely packed sea ice zone, the instrument error should be lower than 15%.

Line 138-140: The author's previous study used JRA55 as the atmospheric forcing, while this study uses GFS. Given the importance of atmospheric forcing for Antarctic sea ice simulation, did the author optimize the model parameters after changing the atmospheric forcing, as in doi: 10.1016/j.ocemod.2023.102183? If optimization has been conducted, are there significant changes in the model parameters? If not, could some of the subsequent results be attributed to the mismatch between the atmospheric forcing and the model, such as Line 213-214?

Response:

The JRA55 data is reanalysis data which can not be used to drive operational sea ice forecasts. The GFS product is an operational weather forecasting product.

We did not optimize the model parameters. According to our experience of polar sea ice modeling, the zero-layer ice/snow thermodynamics have low capacity in correctly simulating sea ice extent expand/shrink rate during melt/freeze transition period. We suspect that the mismatch between forecasts and observations in March–April originates from use of the zero-layer ice/snow thermodynamics, rather than from the change of atmospheric forcing.

We have cited Pascual-Ahuir and Wang (2023) in the revised manuscript.

Line 155: is it OSI-401-d?

Response:

The data ID is OSI-401-b before 24 April 2023, thereafter changed to OSI-401-d.

We have updated the data statement in Code and data availability.

Line 163-165: I would argue that the RMSE increases to the end of March, followed by a decrease starting from April.

Response:

We revised the sentence to "Basically the RMSEs between the SOIPS forecasts and OSISAF data gradually increase during October–March (hereafter the latter month in such expressions that the latter month is earlier than the former month denotes the month of the next year) followed by a decrease starting from April.".

Line 208-209: It's hard to follow and please rewrite this sentence.

Response:

We revised the sentence to "With respect to the OSISAF data, the curves of IIEEs of the DA_Forecast run at different lead times have similar shapes to that of the assimilated AMSR2 data.".

Line 219-221: It’s very interesting and It would be more valuable if the author could present the correction method and the corrected IIEE.

Response:

Thanks for the comment. We will perform the IIEE correction in future work.

Line 252-253: It's recommended to add the uncertainty of ICESat-2 to Fig. 8. From Fig. 7, the uncertainty appears to be around 0.5m, while in Fig. 8, the prediction error in the southern Weddell Sea and the western Ross Sea seem to reach up to 0.6m. Are these errors beyond the uncertainties of the observation? Why are the prediction errors of SIT larger in these areas?

Response:

We have added the ICESat-2 uncertainty into the figure and replaced the original Figure 8 by Figure R6 in the revised manuscript. The prediction errors in the southern Weddell Sea are in the range of the ICESat-2 uncertainty, but the prediction errors in the western Ross Sea are out of the range of the ICESat-2 uncertainty. We suspect that the larger SIT bias in these areas are caused by the poor simulation of growth rate of sea ice thickness during the freezing seasons, partly originating from the biases in the simulated ocean temperature or air temperature in the GFS data.

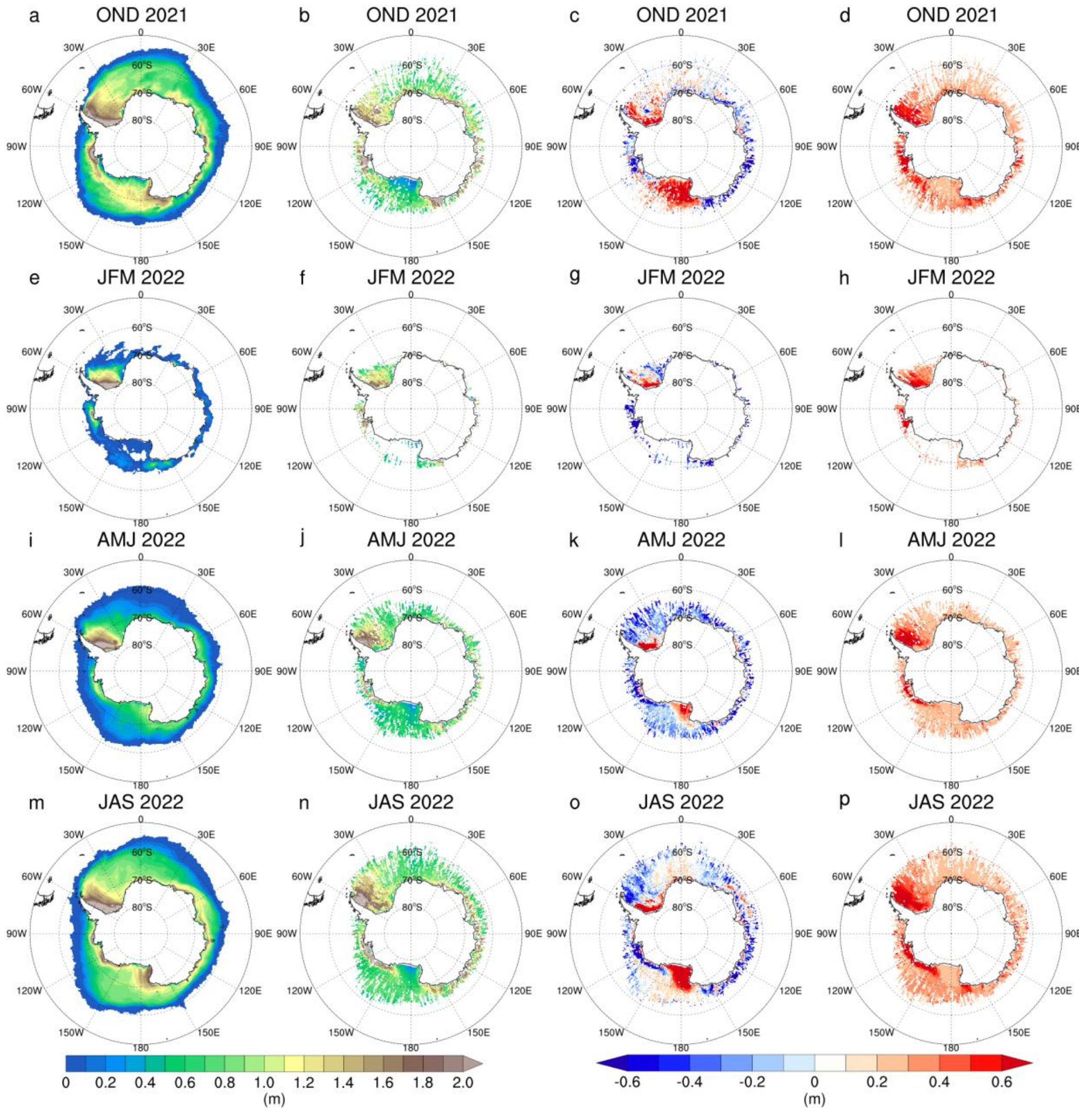

Figure R6. Seasonal patterns of the Antarctic sea ice thickness. The columns from left to right denote the DA_Forecast run at lead time of 24-hour, the ICESat2 observations, their deviations, and the uncertainties of the ICESat2 observations, respectively. The panels from top to bottom denote October–December, January–March, April–June, and July–September, respectively.

Line 295: Please provide the specific definition of Sea ice convergence rate. What are the similarities and differences between the sea ice convergence rate and the divergence of sea ice drift?

Response:

We defined sea ice convergence rate (SICR) as $SICR = -(\partial u_m / \partial x + \partial v_m / \partial y)$ (negative value represents sea ice dispersion, positive value represents sea ice accumulation). (u_m, v_m) are the ice drift components on the model coordinates. Sea ice convergence rate is the opposite of the divergence of sea ice drift.

We revised the sentence to "Sea ice convergence rate (SICR), defined as $SICR = -(\partial u_m / \partial x + \partial v_m / \partial y)$ (negative value represents sea ice dispersion, positive value represents sea ice accumulation), is a useful metric in guiding ship navigation in sea ice zone.".

There are quite a few typos. For instance, an extra hyphen of "synoptic-scale" in Line 332 and an extra left parenthesis in Line 359.

Response:

All revised.