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Response to Reviewer 2

General Comments:

The authors present a regional sea ice forecasting method using a linear Markov model. The methodology is variation of an established pan-Arctic version of this model. The novelty is a focus on the Bering Sea and the Sea of Okhotsk and using varying predictors by season. The method shows good prediction skill compared to the pan-Arctic version and to an anomaly persistence model.

Overall, this is a good study and is worthy of publication, but some additions would make this paper more compelling. I would like to see more discussion on the choice of predictors. There have been many studies on sea ice forecasting, only a couple of which are referenced here. A more in-depth literature review could be a good place to start when discussing the choice of predictors. The study area is also a bit confusing. It is stated that this method forecasts in the Bering Sea and the Sea of Okhotsk, but Figures 1, 2, 6, & 7 show forecasting in most of (if not all) of the Chukchi Sea as well. Maybe redefine your study area or clarify your delineation of sea ice regions more clearly.

Thanks for your interest in our research and positive comments. These comments will help us improve our manuscript, and provide important guidance for our future research. Following your suggestions, we will add more discussion on the choice of predictors.

Sorry for the confusion, our model is constructed in the entire sea ice cover in the Pacific-Arctic sector including the Bering Sea, the Sea of Okhotsk, and the Chukchi Sea. So Figures 1-8 and 10 show forecasting in the area including these three regions.

Concerning the current research status and problems that low prediction skill occurs in the Pacific sector of the Arctic, particularly in the Bering Sea and the Sea of Okhotsk, compared with other Arctic regions (Bushuk et al., 2017; Yuan et al., 2016). Here the regional Markov model is compared with previous models in these regions with low prediction skills to assess whether the prediction skill is improved. The results are presented in Figure 9 and Figure 11, respectively. We will clarify the delineation of sea ice regions more clearly in our revision.

Specific Comments:

Literature Review: You've listed a couple previous studies of sea ice forecasting methods, but I think you are missing out on a lot of work that has been done, even quite recent publications. I think lines 57-87 could benefit greatly from a more in-depth discussion of previous forecasting methods. Section 2.1 would also benefit from this when discussing your choice of predictors. See references below:

Many thanks for your recommendation. We have read those references and will discuss more on previous forecasting methods and choice of predictors.

Andersson, Tom R., J. Scott Hosking, María Pérez-Ortiz, Brooks Paige, Andrew Elliott, Chris Russell, Stephen Law, et al. "Seasonal Arctic Sea Ice Forecasting with Probabilistic Deep Learning." Nature Communications 12, no. 1 (August 26, 2021): 5124. https://doi.org/10.1038/s41467-021-25257-4.

Chi, Junhwa, and Hyun-choel Kim. "Prediction of Arctic Sea Ice Concentration Using a Fully Data Driven Deep Neural Network." Remote Sensing 9, no. 12 (December 2017): 1305. https://doi.org/10.3390/rs9121305.

Horvath, Sean, Julienne Stroeve, Balaji Rajagopalan, and William Kleiber. "A Bayesian Logistic Regression for Probabilistic Forecasts of the Minimum September Arctic Sea Ice Cover." Earth and Space Science 7, no. 10 (2020): e2020EA001176. https://doi.org/10.1029/2020EA001176.

Horvath, Sean, Julienne Stroeve, and Balaji Rajagopalan. "A Linear Mixed Effects Model for Seasonal Forecasts of Arctic Sea Ice Retreat." Polar Geography 0, no. 0 (October 15, 2021): 1–18. https://doi.org/10.1080/1088937X.2021.1987999.

Wang, Lei, Xiaojun Yuan, Mingfang Ting, and Cuihua Li. "Predicting Summer Arctic Sea Ice Concentration Intraseasonal Variability Using a Vector Autoregressive Model." Journal of Climate 29, no. 4 (December 8, 2015): 1529–43. https://doi.org/10.1175/JCLI-D-15-0313.1.

For instance, in lines 116-117, is there a reason 850 hPa geopotential height and winds were chosen over other pressure levels?

Because the polar troposphere has barotropic nature (Ting 1994; Chen 2005) and the correlation between sea level pressure and SIC is small relative to that in other levels (Yuan et al, 2016). We chose geopotential height and wind vector at 850 hPa to define the low-level atmospheric circulation, whose interaction with sea ice is strongest relative to that in higher levels. We will add more discussion on the choice of this level in the revision based on your recommended literature.

Methodology:

Lines 94-99: Here you differentiate the Bering Sea and the Chukchi Sea, but as mentioned above it looks like you are indeed forecasting in both areas. More clarification here is needed.

We are sorry for the unclear content. Here we tried to elucidate that sea ice in the Bering Sea is driven by more complex physical processes than that in other regions. Although the sea ice variability in the Bering Sea is different from the Chukchi Sea in different seasons, our regional Markov model has the ability to capture sea ice anomaly signals in each region, which benefits from that the SIC predictions were performed at each grid cell and each season. Our regional model is indeed constructed in the entire sea ice cover in the Pacific-Arctic sector including the Bering Sea, the Sea of Okhotsk, and the Chukchi Sea. We will modify this part and make it more clear.

How are you detrending the model in Section 3.4? Removing the trend from the data prior to running the model? Detrending the predictions with the observed trend? With the predicted trend? It is difficult to assess how well the detrended model is actually doing without knowing this.

Sorry for the unclear content, we conducted postprediction analysis. Monthly trends were removed from the predictions and observations respectively. Figure 10b in the original manuscript shows the correlation between detrended predictions and detrended observations. We will make those content clear in our revision.

Other:

Lines 324-328: Similar results were found in Horvath et al., 2020, namely that forecasts made in March showed worse skill than those made in January and February. Perhaps this warrants further analysis.

For this model weakness, we improved the model construction by adding sub-surface ocean heat content (OHC; using Ocean Reanalysis System 5 (ORAS5)) and sea ice thickness (SIT; from PIOMAS), and the weakness that forecasts made in March showed worse skill was improved by the updated model.

The details of improving model construction are as follows. The new variable-combinations was shown in Table 1. The updated predictive skill measured by PGS and mean RMSE for each lead time in each season are calculated and shown in Figure 1. Based on the PGS and RMSE, we primarily chose three superior model configurations marked by black boxes in Figure 1. we spatially average the SIC prediction skill from these superior models with 1- to 12-month leads (Figures 2 and 3). Based on the construction principle same to the original manuscript, we finally chose V9M16, V11M20, V5M10, and V5M7 in winter, spring, summer, and autumn respectively. We will update all relevant contents throughout the manuscript.

Table 1. Variable combinations in cross-validated experiments. V1 represents the No. 1 variable-combination. √ represents the variable included in the corresponding combination.

	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12
SIC	√	√	√	√	√	√	√	√	√	√	√	√
OHC		√		√	√	√	√	√	√	√	√	√
SST			√	√						√	√	√

SIT					√							√
SAT						√						√
Surface net turbulent heat flux								√			√	√
Surface net radiative flux							√			√		√
850hPa GPH, U, V									√			√

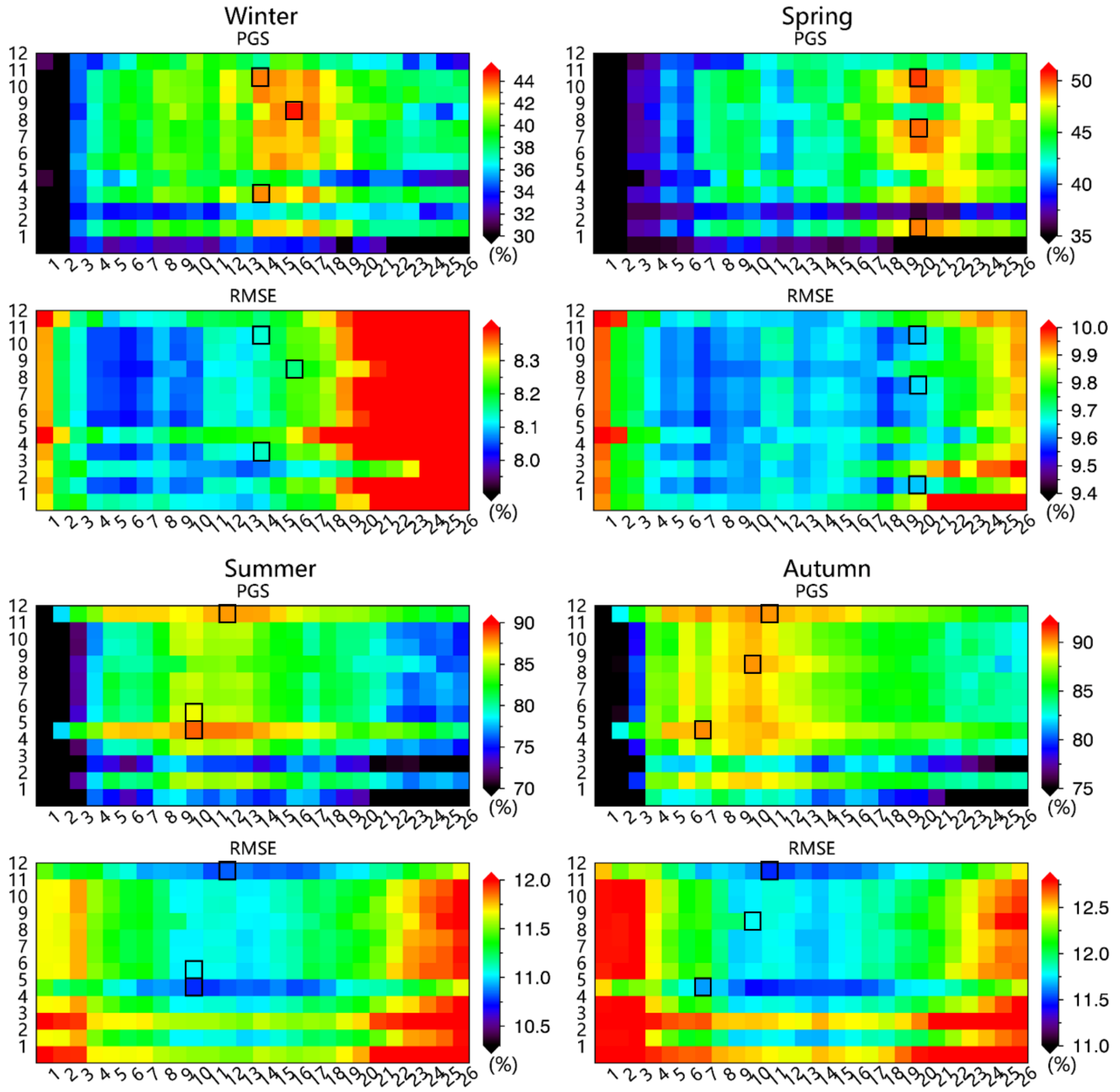

Figure 1. Mean PGS and mean RMSE between the observations and predictions in four seasons. (a) Mean PGS is obtained by averaging all lead months for winter predictions. The x-axis represents the number of MEOF modes, and the y-axis represents the combination of the variables corresponding to Table 1. (b, e, and f) are the same as (a) except for spring, summer, and autumn respectively. (c, d, g, and h) are the same as (a, b, e, and f) except for

RMSE.

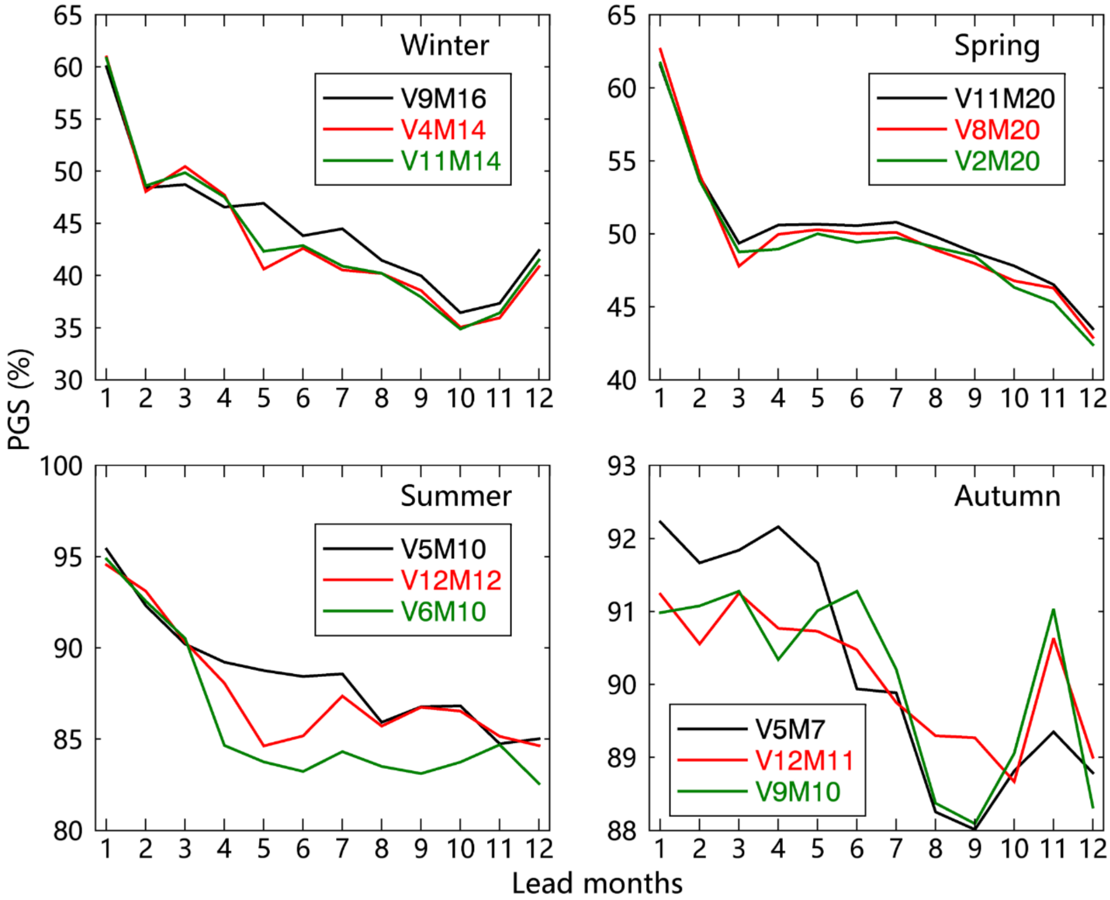

Figure 2. PGS for the preliminary selection of superior models in each season.

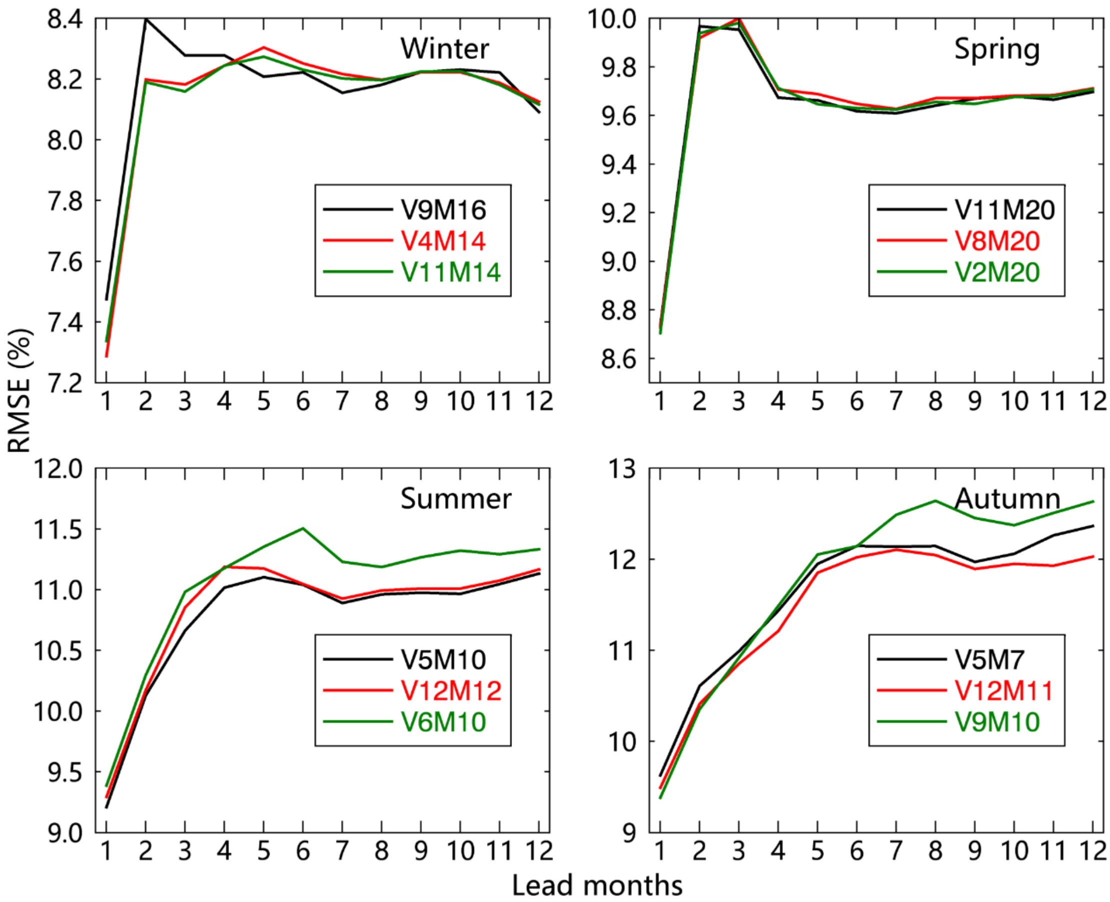

Figure 3. Same as Figure 2 but for RMSE.

Technical Comments:

LN 303-305: The fact that more modes are needed during the cold season is repeated. I suggest combining these sentences to clarify.

Thanks for the suggestions. We have changed 'more modes are needed in the cold season to capture the predictable signal of SIC. This indicates that sea ice in the cold season has requires more modes to capture its variability, likely due to the weaker trends in these months.' to 'more modes are needed in the cold season to capture the predictable signal of SIC, which is likely due to the weaker trends in these months. '

LN 505: remove 'the'. "In other words,…"

We have changed it.

References

Ting, M. F.: Maintenance of northern summer stationary waves in a GCM. J. Atmos. Sci., 51, 3286–3308, doi:10.1175/1520-0469(1994)051,3286:MONSSW.2.0.CO;2, 1994.

Chen, T. C.: The structure and maintenance of stationary waves in the winter Northern Hemisphere. J. Atmos. Sci., 62, 3637–3660, doi:10.1175/JAS3566.1, 2005.

Yuan, X., Chen, D., Li, C., Wang, L., and Wang, W.: Arctic sea ice seasonal prediction by a linear Markov model, J. Clim., 29, 8151-8173, https://doi.org/10.1175/JCLI-D-15-0858.1, 2016.

Bushuk, M., Msadek, R., Winton, M., Vecchi, G. A., Gudgel, R., Rosati, A., and Yang, X.: Skillful regional prediction of Arctic sea ice on seasonal timescales, Geophys. Res. Lett., 44, 4953-4964, https://doi.org/10.1002/2017GL073155, 2017.