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PERSPECTIVE

Better synoptic and subseasonal sea ice thickness predictions are urgently required: a lesson learned from the YOPP data validation

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1. Introduction

In the context of global warming, Arctic sea ice has declined substantially during the satellite era (Kwok 2018). The retreating and thinning of Arctic sea ice provide opportunities for human activities in the Arctic, such as tourism, fisheries, shipping, natural resource exploitation, and wildlife management; however, new risks emerge. To ensure the safety and emergency management of human activities in the Arctic, reliable Arctic sea ice prediction is essential.

As an essential variable, sea ice thickness (SIT) is particularly important for characterizing Arctic sea-ice properties and changes. For example, the thinning of SIT significantly increases upward heat fluxes, enhances near-surface temperature, and contributes to Arctic Amplification (Lang *et al* 2017). Besides the climatic significance, operational SIT prediction plays an important role in determining Arctic shipping routes and seasonal Arctic sea ice predictions (Bushuk *et al* 2017). This means that better predictions of Arctic SIT are urgently needed. However, knowledge regarding synoptic and subseasonal SIT prediction remains very limited. Xiu *et al* (2022) revealed a major challenge regarding dynamical subseasonal SIT prediction, which suffers from large initial errors and generally shows a limited skill for the future 46 days. As a result, improved predictions of Arctic SIT are urgently needed and additional research is required to enhance the understanding of dynamical synoptic SIT predictions.

In the past decade, significant efforts have been made toward skillful sea ice predictions and a series of milestones have been achieved. For example, the Polar Prediction Project (PPP) was initiated by the World Meteorological Organization's World Weather Research Programme in 2013, which aimed to improve weather and environmental prediction services in the Arctic regions on hourly to seasonal time scales. As the flagship activity of the PPP, the Year of Polar Prediction (YOPP) coordinated a series of intensive observations, modeling, verification, user-engagement, and education activities through its preparation, core, and consolidation phases, enabling significant improvement of predictive skills in the polar regions (Goessling *et al* 2016, Jung *et al* 2016). To showcase the achievements of YOPP, the YOPP final summit was held from 29 August to 1 September 2022 (https://yoppfinalsummit.com/; Wilson *et al* 2023), on which SIT predictions received great attention. Particularly, the YOPP dataset of the European Centre for Medium-Range Weather Forecasts provides SIT analysis and 15 day forecasts (referred to as EC-YOPP SIT) from June 2019 to December 2020, initialized from the Operational Sea Surface Temperature and Sea Ice Analysis in its sea ice component (Bauer *et al* 2020). The availability of coincident *in-situ* and satellite SIT observations provides a new opportunity for the evaluation of synoptic SIT predictions. On the one hand, an observational network consisting of 19 Snow and Ice Mass Balance Array (SIMBA) buoys were deployed (Lei *et al* 2021) during the largest Arctic expedition in history, i.e. the Multidisciplinary drifting Observatory for the Study of Arctic Climate (MOSAiC; Shupe *et al* 2020). These buoys provided *in-situ* SIT observations

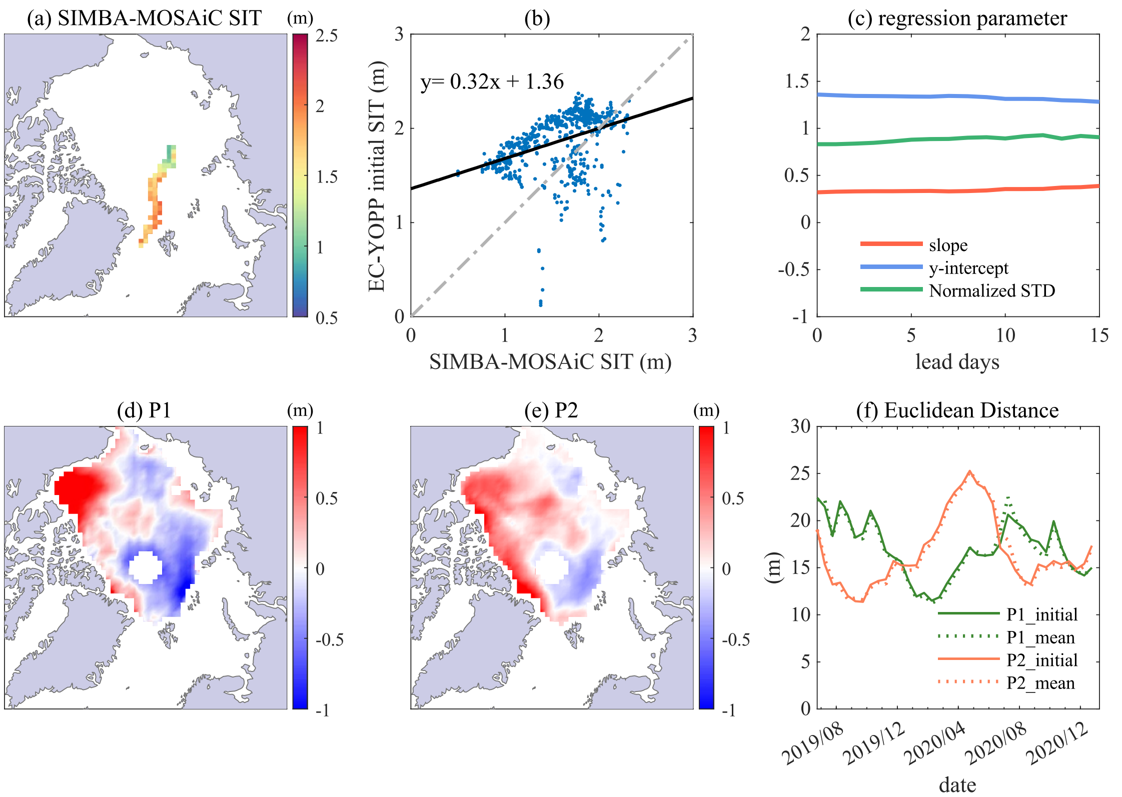

Figure 1. (a) Spatial distribution of SIMBA-MOSAiC SIT. (b) Scatter plot of the EC-YOPP initial SIT and SIMBA-MOSAiC SIT. Linear regression is indicated in the black solid line with the equation listed above. (c) The linear regression parameters (the slope in orange line and the y-intercept in cyan line), and the normalized standard deviation (normalized_STD, light green line) as a function of lead days for the EC-YOPP forecasts. The Normalized STD is defined as the EC-YOPP SIT divided by the STD of SIMBA-MOSAiC SIT. (d) The mean spatial pattern of the first cluster of EC-YOPP SIT initial errors with respect to CS2 SIT. (e) Same as (d) but for the second cluster. (f) Temporal evolution of the Euclidean distance between EC-YOPP SIT errors with P1 (green lines) and P2 (orange lines). The solid lines represent the distance between EC-YOPP initial errors with P1/P2 while the dotted lines represent the mean distances averaged over different lead days.

(abbreviated as SIMBA-MOSAiC SIT) from October 2019 to August 2020 from the Central Arctic to the Fram Strait (figure 1(a)). On the other hand, Landy *et al* (2022) overcome the challenges for retrieval algorithms posed by summer melt ponds and provide a year-round pan-Arctic SIT biweekly record from the CryoSat-2 radar altimeter with a resolution of 80 km from 2011 to 2020 (denoted as CS2 SIT hereafter).

2. Comparison with SIMBA-MOSAiC and CS2 SIT

Here we evaluate the EC-YOPP SIT predictions based on SIMBA-MOSAiC SIT and CS2 SIT, with all the SIT datasets remapped to the coarsest 80 km CS2 grid to allow them to be fairly intercompared. The SIMBA-MOSAiC SIT shows ice thinner than 1.5 m in the Central Arctic and ice thicker than 2 m north of the Fram Strait (figure 1(a)). It appears that the EC-YOPP SIT initial conditions overestimate ice thinner than ∼1–1.5 m and underestimate ice thicker than ∼2 m (figure 1(b)), indicating an underestimation of the geographic SIT variability. The relationship between the EC-YOPP SIT initial conditions and the SIMBA-MOSAiC SIT is quantified using linear regression. The regression parameters (the slope and the y-intercept), and the normalized standard deviation of EC-YOPP forecast SIT remain stable with increasing lead days (figure 1(c)), which means the relationship between the EC-YOPP SIT predictions and SIMBA-MOSAiC SIT remains almost unchanged as the forecast lead time increases.

The wide spatial-temporal coverage of CS2 SIT enables us to distinguish the spatial characteristics of EC-YOPP SIT prediction errors and document their temporal evolutions. To achieve this, the fuzzy c-means (Bezdek 2013) clustering method is applied to group the EC-YOPP SIT initial errors at different target dates into several clusters, with the EC-YOPP initial errors at a certain date belonging to every cluster to a certain degree. The results display two main spatial patterns (figures 1(d) and (e)). The mean pattern of the first cluster (denoted as P1) shows the EC-YOPP SIT analysis overestimates SIT in the Beaufort Sea and the adjacent Central Arctic and underestimates SIT elsewhere (figure 1(d)). The mean pattern of the second cluster (denoted as P2) underestimates SIT in seas northeast of Svalbard and overestimates elsewhere (figure 1(e)). The Euclidean distance quantifies the degree of similarity between

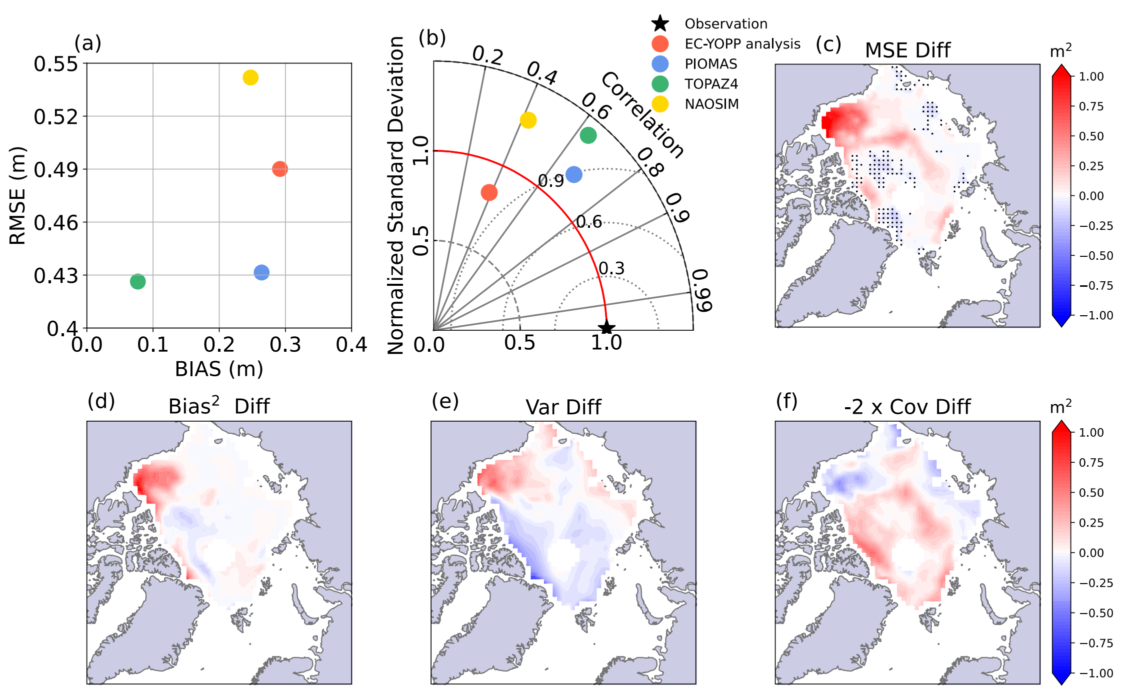

Figure 2. (a) RMSE vs bias of SIT in EC-YOPP analysis, PIOMAS, TOPAZ4, and NAOSIM and (b) Taylor diagram for these four SIT fields when compared to SIMBA-MOSAiC SIT observation. SIMBA-MOSAiC SIT observation is marked as a black pentagram in (b). (c) Differences of MSEs between EC-YOPP analysis SIT and ensemble mean when compared to CS2 observations (shading), with the red (blue) color indicating EC-YOPP analysis SIT has a larger (smaller) MSE than the ensemble mean. The areas covered by the dots indicate EC-YOPP SIT forecasts 15 d ahead have a smaller MSE than the ensemble mean. (d)–(f) Same as (c) but for the MSE decomposition terms, i.e. bias^2, variance, and negative two times the covariance.

EC-YOPP SIT initial errors on different dates with P1/P2 (figure 1(f)), with a shorter distance indicating a higher degree of similarity. It is shown that EC-YOPP SIT initial errors have shorter distances to P1 from December 2019 to June 2020 and from November 2020 to December 2020 (solid green line in figure 1(f)), and have a shorter distance to P2 during the other times (solid orange line in figure 1(f)). This means that the overestimation in the Beaufort Sea and the underestimation north of Svalbard in EC-YOPP SIT initial condition can be seen year-round while the errors in other regions evolve with the seasons. The situation remains unchanged with the increasing lead days, because the distances averaged over different lead days are very similar to the initial distance (compare dotted lines and solid lines in figure 1(f)). This means the EC-YOPP SIT initial errors remain stable on synoptic time scales and emphasizes the leading importance of the SIT initial conditions on the synoptic SIT forecast.

To further characterize the relative quality of the EC-YOPP SIT analysis, three popular SIT datasets are included for intercomparison, namely the Pan-Arctic Ice Ocean Modeling and Assimilation System (PIOMAS; Zhang and Rothrock 2003), the Towards an Operational Prediction system for the North Atlantic European coastal Zones (TOPAZ4; Xie *et al* 2018) and the North Atlantic/Arctic Ocean Sea Ice Model (NAOSIM; Sumata *et al* 2019). Compared to SIMBA-MOSAiC SIT, TOPAZ4 has the smallest bias and root mean squared error (RMSE) among all the SIT datasets. NAOSIM, EC-YOPP analysis, and PIOMAS have a similar bias but their RMSEs are in decreasing order (figure 2(a)), implying other factors (such as variability or correlation) rather than mean bias are responsible for the difference in RMSEs. Thus, the Taylor diagram is presented to give detailed comparisons between EC-YOPP SIT analysis and three popular SIT datasets (figure 2(b)). Results reveal the gap between EC-YOPP SIT analysis and other SIT datasets, as EC-YOPP SIT analysis has the weakest correlation with the reference among these four SIT datasets. Compared to the CS2 SIT, EC-YOPP SIT analysis is found to have a larger mean squared error (MSE) than the ensemble mean MSE of these three SIT datasets (denoted as ensemble mean hereafter) in the Beaufort Sea and part of the Central Arctic, while in certain regions (such as north of Greenland, part of the Central Arctic, and part regions of the Pacific Sector), EC-YOPP SIT analysis has a smaller MSE (figure 2(c)). The MSEs of EC-YOPP SIT analysis and the ensemble mean are decomposed respectively using the method in Murphy (1988), which reveals that larger MSE of EC-YOPP SIT analysis in the Beaufort Sea results from a larger bias (figure 2(d)) and variance (figure 2(e)), while larger MSE of EC-YOPP SIT analysis in the Central Arctic is dominated by an inferior covariance (figure 2(f)). The further analysis reveals the relationship between SIT climatology and SIT variance estimation error, i.e. the thicker

SIT climatology is, the more underestimation of SIT variance EC-YOPP SIT has (not shown). To sum up, evaluations based on SIMBA-MOSAiC SIT and the CS2 SIT both identify the existing gaps between the EC-YOPP analysis SIT and the three commonly used SIT datasets, particularly for the Beaufort Sea and the Central Arctic. It is suggested that besides advancing the development of the sea ice model physics (e.g. Massonnet *et al* 2011), improving the SIT initialization of the European Centre for Medium-Range Weather Forecasts system should bring large first-order improvements of operational synoptic SIT prediction.

3. Conclusion

EC-YOPP SIT prediction is compared with the latest SIMBA-MOSAiC SIT observations and CS2 SIT, highlighting that initial SIT tends to persist on synoptical time scales. The additional comparison with three popular SIT datasets reveals the gap between EC-YOPP SIT analysis and widely-used SIT datasets and calls for better SIT initialization.

During the YOPP campaign, numerous atmospheric observations have been collected through three special observing periods and two targeted observing periods, and several studies have been conducted to improve the operational weather forecast (Jung *et al* 2020). However, sea ice assimilation, especially SIT assimilation is still in an early stage. Due to the lack of SIT data assimilation, the large SIT initial errors persist and thus deteriorate the performance of the EC-YOPP synoptic SIT predictions. Consequently, there is an urgent need to include SIT assimilation in the operational prediction system.

Satellite-derived SIT has been successfully assimilated into the forecast system in several experiments, which leads to a significant improvement in sea ice and atmospheric field prediction (Day *et al* 2022). Conventionally, meltwater ponds accumulating at the sea ice surface are difficult to separate from open water by satellite altimeters, which limited satellite-derived SIT to only the cold season (October–April). In addition, inadequate knowledge of snow depth accumulated above the sea ice results in large uncertainty of satellite-derived SIT. As a result, the assimilation of new summertime SIT (Landy *et al* 2022) and snow depth products (Kwok *et al* 2020) offers the potential for improving sea ice forecasting on different timescales.

Despite substantial future work remaining, EC-YOPP SIT forecasts have already shown some advantages over the ensemble mean SIT in certain regions (i.e. the areas with dots in figure 2(c)), indicating the effectiveness of current operational synoptic SIT forecasts and their potential benefit. With the increasing observations in the Arctic and the associated advancements in sea-ice data-assimilation, the community and society will benefit more from improved SIT forecasts.

Data availability statements

EC-YOPP SIT is accessed from ECMWF YOPP data portal (https://apps.ecmwf.int/datasets/data/yopp/levtype=sfc/type=cf/, last access: December 2021). The SIMBA-MOSAiC SIT is accessed from https://doi.pangaea.de/10.1594/PANGAEA.938244, last access: June 2022. The CS2 SIT is available from https://data.bas.ac.uk/full-record.php?id=GB/NERC/BAS/PDC/01613, last access: October 2022. TOPAZ4 SIT is available from the CMEMS (http://marine.copernicus.eu, last access: April 2022), with a product ID of ARCTIC_MULTIYEAR_PHY_002_003. The PIOMAS SIT is downloaded from https://pscfiles.apl.washington.edu/zhang/PIOMAS/data/v2.1/hiday/. The NAOSIM SIT is available from https://doi.org/10.1175/MWR-D-18-0360.1.

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