Exploring Non-Gaussian Sea Ice Characteristics via Observing System Simulation Experiments

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Abstract. The Arctic is warming at a faster rate compared to the globe on average, commonly referred to as Arctic amplification. Sea ice has been linked to Arctic amplification and gathered attention recently due to the decline in summer sea ice extent. Data assimilation (DA) is the act of combining observations with prior forecasts to obtain a more accurate model state. Sea ice poses a unique challenge for DA because sea ice variables have bounded distributions, leading to non-Gaussian distributions. The non-Gaussian nature violates Gaussian assumptions built into DA algorithms. This study ~~configures~~ presents different observing system simulated experiments (OSSEs) to find the ~~optimal~~ best data assimilation configuration for assimilating sea ice and snow ~~observation subset for assimilation to~~ observations that produce the most accurate analyses and forecasts. Findings indicate that not assimilating sea ice concentration observations while assimilating snow depth ~~observation~~ observations produced the best sea ice and snow forecasts. A simplified DA experiment helped demonstrate that the DA solution is biased when assimilating sea ice concentration observations. The biased DA solution is related to the observation error distribution being a truncated normal distribution, and the assumed observation likelihood is normal for the DA method. Additional OSSEs show that using a ~~non-parametric~~ non-Gaussian DA method does not alleviate the non-Gaussian effects of ~~the~~ sea ice concentration observations, and assimilating sea ice surface temperatures ~~have~~ has a positive impact on snow updates. ~~Lastly~~Finally, it is shown that perturbed sea ice model parameters, used to create additional ensemble spread in the free forecasts, lead to a year-long negative snow volume bias.

1 Introduction

Warming over the Arctic region, a phenomenon commonly referred to as Arctic amplification (Serreze and Francis, 2006), has been identified in both observations (Serreze et al., 2009; England et al., 2021) and climate models (Holland and Bitz, 2003). Numerous studies have found this warming rate to be ~~around~~ approximately twice as fast as the global average (Walsh, 2014; Jansen et al., 2020; Yu et al., 2021). A recent study ~~has~~ found that Arctic amplification-related warming could be three-to-four times faster than the global average, more than double the warming rate previously estimated (Rantanen et al., 2022). Projections of Arctic amplification rely heavily on the ability of coupled numerical models to represent each Earth-system component. One important Earth-system component linked to Arctic amplification–the cryosphere–has gathered attention recently due to the declining summer sea ice extent over the recent decades (Screen and Simmonds, 2010; Jenkins and Dai, 2021). During

wintertime, sea ice can act as an insulator trapping ocean heat, created from the absorbed shortwave radiation during the summer sea-ice loss season, within the ocean allowing for cooler winter atmospheric temperatures (Chung et al., 2021). Additionally, snow cover on top of sea ice can impact seasonal sea ice evolution, growth, and melt (Holland et al., 2021). Providing more accurate sea ice and snow states via data assimilation in our coupled Earth-system modeling frameworks could help improve future projections of the climate and the processes related to Arctic amplification.

Data assimilation (DA) is the action of optimally combining information from prior forecasts with observations to improve the current estimate of the state of any Earth-system component. The statistical methods used to optimally combine this information often have Gaussianity assumptions, depending on the choice of the data assimilation method. One data assimilation method that has commonly been applied in Earth-system problems is the ensemble Kalman filter (EnKF; Evensen 2003; Houtekamer and Zhang 2016), which includes Gaussian assumptions in its original Kalman filter formulation (Kalman, 1960). These Gaussian assumptions can lead to biased solutions when prior forecast distributions are non-Gaussian or errors associated with the observations are also non-Gaussian. Common sea ice variables have both double and single bounded quantities (e.g., doubly-bounded: sea ice concentration; singly-bounded: sea ice thickness) that lead to non-Gaussian distributions, which would violate Gaussian assumptions. Studies have investigated the performance of different EnKF formulations (stochastic versus deterministic) under non-Gaussian conditions and found that while the stochastic formulation was more stable, both had biased solutions (Lawson and Hansen, 2004; Lei et al., 2010). Different ensemble data assimilation methods that remove the Gaussian assumption have been proposed, however, many have only been tested in low-order models and could be potentially expensive in high-dimensional geophysical models (Pham, 2001; Anderson, 2010; Sakov et al., 2012b; Metref et al., 2014). Here, instead of testing a new ensemble data assimilation method, we will conduct experiments to highlight the impacts of different non-Gaussian sea ice variables during data assimilation updates.

The application of data assimilation to sea ice problems is not a novel idea since this research topic has been investigated for more than two decades. Common observation descriptive quantities for sea ice are concentration (e.g., the fraction of a grid cell covered with sea ice) and thickness (e.g., the sea ice surface extending down into the ocean). Previous studies have highlighted the importance of initial conditions when trying to predict Arctic sea ice from local to seasonal time scales, especially regarding accurate initialization of sea ice thickness (Msadek et al., 2014; Day et al., 2014; Dirkson et al., 2017). Although different data assimilation techniques have been used to update sea ice state variables (Meier and Maslanik, 2003; Van Woert et al., 2004; Lindsay and Zhang, 2006; Stark et al., 2008), numerous studies have tested updating sea ice state variables using the EnKF data assimilation method (Lisæter et al., 2003; Barth et al., 2015). These EnKF studies were tested both in a synthetic observation framework referred to as observing system simulation experiments (OSSEs; Barth et al. 2015; Kimmritz et al. 2018; Zhang et al. 2018) and using real observations from remote sensing platforms (Sakov et al., 2012a; Massonnet et al., 2015). These studies found improvements in both sea ice analyses and their corresponding forecasts related to the spatial sea ice concentration field but little improvement in sea ice thickness. Massonnet et al. (2015) improved the initialization of sea ice cover when updating sea ice thickness via a multivariate framework when assimilating only sea ice concentration observations. More recent studies have tested the assimilation of other

60   sea ice observations (e.g., sea ice thickness) and found further improvements to sea ice states (Mathiot et al., 2012; Chen et al., 2017; Mu et al., 2018; Fiedler et al., 2022). While results from assimilating sea ice thickness observations are positive, they contain large observation uncertainties because satellite remote sensing retrieval algorithms contain large uncertainties due to input parameters and instrument errors (Kwok and Cunningham, 2008; Tilling et al., 2016; Ricker et al., 2017). Further research is needed to determine how to properly handle ~~the~~ these uncertainties when assimilating sea ice observations.

65   This study uses different OSSEs to investigate how the non-Gaussian nature of different sea ice fields impacts ~~the~~ data assimilation-generated sea ice analyses. This study ~~will expand~~ expands on previous research on sea ice data assimilation that was laid out by Zhang et al. (2018). The OSSEs presented in this study will test different experimental setups to investigate ~~if there is an optimal data assimilation setup for sea ice along with the associated snow cover on top~~their impacts on sea ice and snow states generated by data assimilation. These experiments will investigate the impacts of post-processing updates for

70   snow on top of sea ice, different assimilated observation combinations, and different data assimilation methods. This study ~~will highlight~~ highlights the impacts of the non-Gaussian nature of certain sea ice variables on the generation of sea ice analyses when using an EnKF data assimilation method. Section 2 describes the sea ice model and the data assimilation experimental setup along with the description of the different OSSEs that were completed. Section 3 presents the results ~~that were found~~ obtained from the different OSSEs. Section 4 discusses the conclusions and future work on this research.

75   2   Methods and Experimental Setup

2.1   DART-CICE data assimilation system

For this study, the Los Alamos Sea Ice Model version 5 (CICE5; Hunke et al. 2015) is used to integrate the analyses forward in time while using an ensemble Kalman filter (EnKF) data assimilation technique to generate analyses. The Data Assimilation Research Testbed (DART; Anderson et al. 2009) software was used to implement the EnKF. Hereafter, we refer to this modeling

80   configuration as CICE-DART. The ~~data assimilation settings follow closely to the optimal settings Zhang et al. (2018) found while the experimental setups~~ CICE5 model setup closely follows that in Zhang et al. (2018) while the data assimilation setting will be different in the experiments.

2.1.1   DART

The data assimilation technique used in this study is the ensemble adjustment Kalman filter (EAKF; Anderson 2001), which

85   is a modified version of the ~~Kalman filter (Kalman, 1960)~~ ensemble Kalman filter (Burgers et al., 1998) and a variation of the deterministic ensemble square-root filter (Tippett et al., 2003). The EAKF combines observations with an ensemble of short-term model forecasts over a specific observation window to produce an ensemble of ~~accurate~~ the best estimate of the sea ice state. One ~~unique~~ important aspect of the EAKF is ~~it allows for the use of~~ its ability to use the ensemble to estimate a flow-dependent background-error covariance, which differs from a static background-error covariance typically

90   employed by variational techniques. Additionally, a ~~non-parametric~~ non-Gaussian rank histogram filter (RHF, filter option

8 in DART; Anderson 2010) is tested to compare with EAKF results. ~~While the RHF can represent non-Gaussian priors and arbitrary likelihoods for observed variables. Additionally, the RHF can be modified to work with bounded quantities (Anderson, 2020, 2022), however, that application is not applied in this study.~~ To reduce sampling errors due to limited ensemble member size, ~~horizontal~~ covariance localization was applied only in the horizontal direction. A Gaspri-Cohn ~~fifth order~~ fifth-order polynomial was applied in the horizontal directions to limit observation updates within a specified cutoff radius of 0.05 (i.e., ~320 km; Gaspari and Cohn 1999). Adaptive prior covariance inflation was applied ~~to eliminate potential issues related to poor representation of model errors~~ by "inflating" the ensemble perturbations in prior background fields, increasing the variance by pushing ensemble members away from the ensemble mean (Anderson, 2007). Zhang et al. (2018) found a reduction in Arctic sea ice area and volume errors when prior inflation was applied in their study. Inflation damping is set to 0.9 to help control the growth of the inflation factor for the different state model variables. Any assimilated observation type is allowed to update all model state variables during the assimilation step unless otherwise noted. There was no cross-variable localization applied in this study.

2.1.2 CICE

CICE5 is the sea ice component within the Community Earth System Model (CESM; Danabasoglu et al. 2020) that is used to make ~~projections of the climate~~ climate projections. CICE5 simulates the evolution of sea ice and snow ~~as a result~~ through the representation of thermodynamic and dynamical processes using ~~a~~ an ice thickness distribution. The evolution of sea ice thickness, which is represented by the ~~product~~ quotient of sea ice volume and sea ice area, is accomplished by partitioning the sea ice pack distribution within a grid cell into multiple thickness categories (Lipscomb, 2001). For this study, there are five ~~categories~~ thickness categories for both sea ice and snow with lower bounds of 0, 0.64, 1.39, 2.47, 4.57 m. Respecting the category bounds ~~provides an unique~~ poses a challenge during the data assimilation step when updating sea ice area and sea ice volume. Snow depth is also partitioned into ~~the~~ five categories. Each thickness category is divided into multiple layers (both sea ice and snow if present) to represent the evolution of sea ice temperature, salinity, and enthalpys related to sea ice and snow. CICE was coupled to a slab ocean model (SOM) that provides the ocean forcing in the form of annually periodic, prescribed ocean forcing data (e.g., sea surface temperatures, ocean heat fluxes). The atmospheric forcing data comes from the Community Atmosphere Model version 6 (CAM6)/Data Assimilation Research Testbed ensemble reanalysis (Raeder et al., 2021) for the time period of interest. Default namelist settings were used in this study (Hunke et al., 2015) except for perturbing several input CICE parameters, which will be discussed ~~more~~ in the next section.

2.2 Perfect model OSSEs

Given the uncertainties and potential biases of ~~sea ice thickness and snow-depth~~ satellite-retrieved sea ice and snow observations, this study applies perfect model OSSEs to investigate non-Gaussian impacts that could be introduced while assimilating these observations. Each ensemble consists of 80 CICE5 members ~~since~~ because there are 80 different CAM6/DART reanalysis atmospheric forcing files. Each CICE5 ensemble member uses the same SOM forcing. To increase ~~CICE5~~ the ensemble spread, three different parameters were perturbed that impact albedo, heat transfer through snow, and the ability to move sea

ice within the ocean. ~~Perturbed parameters are the~~ The standard deviation of the dry snow grain radius (R_{snw}) ~~, the~~ controls the optical properties of snow and is one of the key parameters that determines snow albedo in the solar radiation parameterization (Briegleb and Light, 2007). The thermal conductivity of snow (k_{snw}) ~~and the~~ directly impacts the amount of heat that can be transferred through the snow pack, thereby affecting the evolution of sea ice (Sturm and Massom, 2017). The neutral ocean-ice drag coefficient (dragio) controls the horizontal momentum exchange at the ice-ocean interfaces, which determines the drag forces on the sea ice (Lu et al., 2011). These three parameters were chosen because they are among the top parameters ~~to~~ that drive variability within CICE5 in both summer and winter (Urrego-Blanco et al., 2016). ~~To reach a spun-up equilibrium~~ See the data availability statement for access to the perturbed parameter values used in this study. To achieve the climatological state of sea ice and snow~~state~~, a single member is run for 40 years using periodic atmospheric forcing for the year 2012. To build our 80 member ensemble, we first used only ~~the~~ 80 different atmospheric forcings to cycle over 2012 for 10 years to build in variability related to the atmosphere. ~~Then, each member is~~ Each ensemble member is then run for an additional 15 years, cycling over 2012, using the distinct atmospheric forcing and parameter set to generate free forecasts that can be used as a reference case (Fig. 1). One of the free forecast members is randomly chosen as the simulated "truth." For this study, the free forecast ensemble mean is negatively biased compared to the truth member for ~~the~~ different sea ice and snow characteristics. The free forecasts will provide a reference for comparison with the different data assimilation experiments.

Since satellites can not retrieve ~~the~~ multi-category model quantities, aggregate synthetic observations are generated from the truth member to produce sea ice concentration (SIC), sea ice thickness (SIT), snow depth (~~SNWD~~D_{snow}), and sea ice surface temperature (SIST). The multi-category state model variables that are updated via data assimilation or post-processing are sea ice area ($A_{ice,n}$), sea ice volume ($V_{ice,n}$), and snow volume ($V_{snow,n}$). When those multi-category state model variables are summed over the different categories, they are referred to as A_{ice}, V_{ice}, and V_{snow}. To compute data assimilation updates, it is necessary to compute an observation's expected value from the model state, which is called the forward operator. SIC is just the sum of the ~~concentration~~ area values in the different thickness categories ~~. SIT~~ computed as

$$SIC = \sum_{n=1,5} A_{ice,n}. \tag{1}$$

The mean SIT of a grid cell is computed by summing the sea ice volumes in the different thickness categories ~~than~~ and then dividing by the aggregated sea ice ~~concentration. SNWD~~ area as follows

$$SIT = \frac{\sum_{n=1,5} V_{ice,n}}{\sum_{n=1,5} A_{ice,n}}. \tag{2}$$

The mean D_{snow} of a grid cell is computed in the same fashion as SIT except using summed snow volumes ~~. SIST is the concentration~~

$$D_{snow} = \frac{\sum_{n=1,5} V_{snow,n}}{\sum_{n=1,5} A_{ice,n}}. \tag{3}$$

The mean SIST of a grid cell is the area weighted mean temperature across the different thickness categories on the surface of the sea ice

$$\text{SIST} = \frac{\sum_{n=1,5} \text{SIST}_n * \text{A}_{\text{ice},n}}{\sum_{n=1,5} \text{A}_{\text{ice},n}} \tag{4}$$

where SIST_n is the sea ice surface temperature for the different thickness categories. Normally, synthetic observations are created by adding a draw from a normal distribution with ~~zero mean and~~ a mean of zero and a specified observation error standard deviation. This method can be used to create synthetic sea ice surface temperatures. However, sea ice and snow quantities have ~~both~~ single (SIT, ~~SNWD~~D_{snow}) and double (SIC) bounds in their ~~representation~~representations. Because of this, we will use a single (SIT,~~SNWD~~D_{snow}) and double (SIC) truncated normal distribution when generating the synthetic observations. The observation error standard deviation ~~, which follows those found in Zhang et al. (2018),~~ for SIC is 15% of the true values of SIC ($\text{SIC}_{\text{error}} = \text{SIC}_{\text{truth}}*0.15$; Zhang et al. 2018) and 0.1 m for SIT ~~.~~(approximation of future high precision data; Zhang et al. 2018). While studies that use real SIT observations have varied their uncertainties depending on the thickness value (Xie et al., 2018; Cheng et al., 2023), due to the complexity of computing SIT (Zygmuntowska et al., 2014) this study chose to use a single value for SIT uncertainty. The observation error standard deviation is 10% of the true values of ~~SNWD (Rostosky et al., 2020)~~D_{snow} (approximation of future high precision data; Rostosky et al. 2020) and 1.5°C for SIST (Hall et al., 2015). Due to the SIC observation error method, only SIC observations greater than 0.01 (approximately the precision found in passive microwave sea ice concentration observation files, Meier et al. 2021) are assimilated. Similarly, the observation error for D_{snow} has a lower bound of 0.005 m for observations close to zero. The locations for all synthetic observation types were based on ~~10-second~~ CryoSat-2 locations (locations measured every 10 seconds), which provides a realistic observational network for testing (Fig. 2). ~~The multi-category model variables that are updated via the data assimilation or post-processing are AICEN, VICEN, and VSNON, which represent sea ice concentration, sea ice volume, and snow volume. When those multi-category model variables are summed up over the different categories, they are referred to as SIC, VICE, and VSNO~~While sea ice observation networks in the real world usually do not match, the observation network was chosen for easy experimental setup and fair comparison between the observations that were assimilated in this study.

Six different experiments were completed to test different observation combinations, data assimilation techniques, and post-processing updates (Table 1). ~~Experiment 1~~EAKF-ConcThick is an extension of the work completed by Zhang et al. (2018) where they only allowed observation increments to update the sea ice area in the different categories while updating the sea ice and snow volume via post-processing. In ~~experiment 1~~EAKF-ConcThick, we allow ~~sea ice concentration~~ the category-based sea ice area and volume to be updated independently by SIC and SIT observations while updating snow volume via post-processing. The ~~equation~~ equations for post-processing snow volume ~~(VSNON)~~ updates in the different categories ~~is~~ are the following:

$$\text{VSNON}^{\text{posterior}} = \text{AICEN}^{\text{posterior}} \times \text{hsnon}^{\text{prior}}h^{\text{prior}}_{\text{snow},n} = \frac{V^{\text{prior}}_{\text{snow},n}}{A^{\text{prior}}_{\text{snow},n}}, \tag{5}$$

~~where AICEN is the sea ice concentration~~

$$V_{snow,n}^{posterior} = A_{ice,n}^{posterior} \times h_{snow,n}^{prior}, \tag{6}$$

where $A_{ice,n}^{prior}$ is the prior sea ice area in the different ~~categories~~ thickness categories, $V_{snow,n}^{prior}$ is the prior snow volume in the different thickness categories, $A_{ice,n}^{posterior}$ is data assimilation updated sea ice area in the different categories and $h_{snow,n}^{prior}$ are the prior snow thickness values in the different categories. In EAKF-ConcThickSnow, snow volume is no longer updated by post processing and ~~hsnon are the category-based snow thickness . In experiment 2, the post-processing snow volume updates are removed and~~ assimilation of ~~SNWD~~ D_{snow} is included in the observation subset. All assimilated observations (SIC,SIT,SNWD) update all category-based model state variables ($A_{ice,n}, V_{ice,n}, V_{snow,n}$). To test the non-Gaussian effects of SIC observations, ~~experiment 3~~ EAKF-ThickSnow only assimilates SIT and ~~SNWD~~ D_{snow} while allowing the ~~sea ice concentration~~ category-based sea ice area, sea ice volume, and snow volume state variables to be updated from the observation increments. ~~Experiment 4~~ RHF-ConcThickSnow investigates the impacts of using a ~~non-parametric~~ non-Gaussian data assimilation method, the rank histogram filter, when working with the non-Gaussian sea ice and snow variables in the CICE model. ~~Experiment 5~~ EAKF-ModifiedFO investigates the impacts of having sea ice thickness and snow depth output from CICE instead of having the forward operators within DART compute these quantities. This arises from the fact that prior inflation is applied, which can push either the sea ice ~~concentration or volume below the zerobound~~ area or sea ice volume below zero. Since computing sea ice thickness or snow depth is the division of either sea ice or snow volume by the sea ice area, this could lead to shuffling of the distribution if values become negative. ~~Lastly, experiment 6~~ Finally, EAKF-SIST tests the impacts of assimilating additional SIST observations to further improve the updates of sea ice ~~states along with~~ and snow states. While SIST observations are assimilated, sea ice surface temperatures in the different thickness categories are not updated from the data assimilation step.

Due to the bounds related to sea ice and snow state variables, there are different conditions ~~when~~ under which special treatment is needed to ensure that the respected bounds are met. SIC (summed sea ice ~~concentration~~ area across the categories) must remain between 0 and 1. Similarly, sea ice and snow volumes (summed across the categories) must remain above zero. If negative values occur for SIC or the volumes, all categories are set to zero. Additionally, category-based sea ice ~~concentration~~ area values are scaled if the SIC exceeds one after the assimilation updates. In the event SIC exceeds one, the scaling of the category-based sea ice ~~concentration~~ area is as follow:

$$squeeze = \frac{1.0}{SIC}, AICEN = AICEN * squeeze, A_{ice,n} = A_{ice,n} * \frac{1}{SIC}. \tag{7}$$

~~where squeeze is the factor by which the individual category-based AICEN values are adjusted.~~ In the case where SIC is within the bounds but individual categories become negative, those categories are set to zero and the remaining ~~non-zero~~ nonzero categories are reduced proportionally to compensate for the negative amount. Lastly, special care is taken to account for the cases where SIC is greater than zero but sea ice volume ~~become zerodue to the assimilation updates~~ in all categories is zero. This can occur during data assimilation updates to the category-based sea ice volume (updates removes all the sea ice volume) or if the data assimilation updates create some amount of sea ice area but the sea ice volume remains zero. A new sea ice

volume is computed ~~for the category~~by multiplying the average thickness value allowed in the associated category (0.32, 1.01, 1.93, ~~to replace the zero value, by multiplying the mid-point sea ice thickness by the sea ice concentration for the associated~~ 3.51, 6.95) by the sea ice area for the category.

The same initial conditions used to generate the free forecasts were used for the experiments listed in Table 1. The free forecasts provide a reference to the amount of variability that was generated during the spin-up process (Fig. 1). All experiments were initialized on 1 January 2013 and the cycling period was for the entire year 2013. In all experiments, observations ~~are~~ were assimilated at a daily interval.

2.3 Model Verification Metrics

~~Total~~ Time series of total sea ice area, sea ice volume, and snow volume will be ensemble mean forecast quantities used to evaluate CICE-DART performance over the cycling period. ~~Total~~ The equations for computing total sea ice area ~~was chosen as it provides the actual area covered by sea ice compared to the common Arctic sea ice extent is the total area where the sea ice concentration exceeds~~ and volume are as follows:

$$\text{Total-Sea-Ice-Area}(t) = \sum_{n=1,j} (\text{SIC}(t)_j * \text{grid-cell-area}_j), \tag{8}$$

$$\text{Total-Sea-Ice-Volume}(t) = \sum_{n=1,j} (\text{V}_{ice}(t)_j * \text{grid-cell-area}_j), \tag{9}$$

where t is time, j is the total number of grid points in the Northern Hemisphere and grid-cell-area is the area of the grid cell. Total snow volume is computed in the same way as total sea ice volume but instead using snow volume. Spatial Probability Score (SPS) is computed to investigate potential sea ice edge errors over the cycling period (Goessling and Jung, 2018). Following Goessling and Jung 2018, the ice edge is defined using the 15% ~~. Total sea ice area will allow for better evaluation of the actual sea ice concentration values since they are used in the calculation compared to sea ice extent~~sea ice concentration contour in this study. Due to data storage issues, SPS could not be calculated for EAKF-SIST. Additionally, ensemble mean spatial biases will be computed for SIC, sea ice volume, and snow volume over different cycling periods. Welch's t-test will be applied to test for significant biases (Welch, 1947). The ensemble mean was chosen because the statistics were nearly identical regardless of whether the ensemble mean or ensemble median was used.

Mean absolute bias (MAB) and mean square error (MSE) will be computed ~~for~~ over the time series of total sea ice area, sea ice volume, and snow volume for additional performance evaluation. The equations for MAB and MSE are as follows:

$$\text{MAB} = \sum_{t=1}^{N} |X_i^m - X_i^t|, \tag{10}$$

$$\text{MSE} = \sum_{t=1}^{N} (X_i^m - X_i^t)^2, \tag{11}$$

245 where i is the time index, N is the total number of times (i.e, number of days), X_i^m ensemble mean forecast quantity (e.g., total sea ice area), and X_i^m is the true value for the forecast quantity. The integrated ice-edge error (IIEE) is another forecast metric that ~~will be applied to evaluate sea ice coverage in this study~~ is applied to the ensemble mean, which is analogous to SPS when using a single, deterministic forecast (Goessling et al., 2016). IIEE ~~will evaluate~~ evaluates potential sea ice edge differences between the ensemble mean and the truth. IIEE is more suitable for user forecast evaluation of the sea ice edge compared to the traditional sea ice extent (Tietsche et al., 2014). The IIEE is the sum of the area grid boxes where the ensemble mean and the truth disagree on whether sea ice is present (over-prediction~~;~~ $SIC_{truth}=0$ and $SIC_{ensemble\ mean}>0$) or not (under-prediction~~). Like in ~~, $SIC_{truth}>0$ and $SIC_{ensemble\ mean}=0$). Similar to previous studies computing IIEE, a SIC threshold of 15% is used to determine whether a grid cell is identified as having sea ice (Goessling and Jung, 2018; Zampieri et al., 2018). An attractive feature of IIEE is that it can be decomposed into an absolute extent error (AEE) and a misplacement error (ME). AEE is the absolute difference (|over-prediction - under-prediction|) between predictions, which can help determine whether there is a bias for ~~over or under predicting~~ over- or under-predicting sea ice coverage. MEE is the misplacement error ($2 \times$ **min**(over-prediction,under-prediction)) reflecting whether there is too much sea ice in one location and too little in another. IIEE along with ~~its components~~ AEE and ME will be computed daily. ~~A~~ Welch's t-test was used to determine whether there were significant differences between MAB, MSE, and IIEE values between experiments. ~~Lastly~~Finally, Spearman correlations are computed between the perturbed parameters and different CICE model ~~output~~outputs.

3 Results and discussion

3.1 Optimization of sea ice and snow data assimilation

~~In experiments 1–3~~ The first three experiments investigate which assimilated observation subset produces the most accurate forecasts for both sea ice and snow. All the experiments have similar skill in predicting the sea ice edge and are better than the free forecast (Fig. 3A). However, there is a period during August and September when experiments assimilating SIC, EAKF-ConcThick, and EAKF-ConcThickSnow, have smaller errors in predicting the sea ice edge. Daily biases of total sea ice area, sea ice volume, and snow volume are computed throughout the cycling period to compare the performance of the experiments with the truth and free forecasts (Fig. 3~~). For experiment 1,SIC and SIT observations are assimilated which provides updates to the prognostic sea ice state variables (AICEN and VICEN)while the prognostic snow state variable (VSNON) is updated via post-processing. Compared to ~~B,C,D). Compared with the free forecast, ~~experiment 1~~EAKF-ConcThick performs better for both total sea ice area and sea ice volume. However, total sea ice area and sea ice volume were negatively biased from the start of the melt season in May until the re-freeze in September. Total snow volume for ~~experiment 1~~EAKF-ConcThick is comparable to the free forecasts. This means that the post-processing updates for the snow state variable are not as accurate compared to the sea ice state variables, which are updated directly from the multivariate data assimilation step. ~~Experiment 2 assimilates snow depth observations so no post-processing is performed for snow. While ~~For EAKF-ConcThickSnow, there is little impact on biases associated with ~~the ~~sea ice quantities~~, the biases are reduced for ~~. The biases associated with total snow volume ~~throughout the cycling period with smaller bias than the free forecast. Experiment 3 removed SIC as an~~

~~assimilated observation, which leaves only SIT and SNWD observations that are assimilated. For sea ice area~~ are reduced in the EAKF-ConcThickSnow compared to EAKF-ConcThick and the free forecasts. The negative biases found for total sea ice

280 and sea ice volume ~~, the negative biases~~ during the summer ~~are near zero~~ for the first two experiments are now near zero for EAKF-ThickSnow. Improvements in total snow volume for ~~experiment 3~~ EAKF-ThickSnow are isolated to the start of the melt season, however, the biases are similar to the ~~other~~ first two experiments after this period. Regardless of these improvements, total snow volume is negatively biased throughout the ~~entire~~ cycling period for experiments where ~~SNWD~~ D_{snow} observations are assimilated. Additionally, the biases for total snow volume are larger during the winter seasons leading up to June and

285 then approach zero thereafter for experiments where D_{snow} observations are assimilated. This result could mean that it takes a seasonal cycle to pull ensemble snow values closer to the truth. Removing SIC observations from the assimilated observation subset eliminates ~~a non-Gaussian component during the assimilation step, which~~ an observation that is doubly-bounded and whose values approach both of the bounds. Since SIC observations are more likely to be affected by their associated bounds (bulk of SIC observations near 1 unless near marginal ice zone) this could be the driving factor for the poor forecasts in

290 ~~experiments 1 and 2.~~ the first two experiments.

Temporal forecast metrics are computed over the cycling period to pin-point which experiment is more accurate (Fig. 4). ~~Experiments 1 and 2~~ EAKF-ConcThick and EAKF-ConcThickSnow have the lowest total IIEE and are significantly different from the free forecast and ~~experiment 3.~~ EAKF-ThickSnow. This means that ~~experiments 1 and 2 provide~~ both EAKF-ConcThick and EAKF-ConcThickSnow produce a more accurate forecast of sea ice coverage over the cycling period.

295 This might seem inconsistent since ~~experiment 3~~ the EAKF-ThickSnow daily biases were smaller. ~~Sea~~ EAKF-ThickSnow has sea ice area MSE and MAB ~~for experiment 3 are~~ that is lower and significantly different ~~than~~ from the other experiments and the free forecast. This means that removing the SIC observations provided a more accurate forecast of the sea ice area, however, this did have a negative impact on predicting the sea ice edge in ~~experiment 3.~~ EAKF-ThickSnow. This indicates that ~~the~~ SIC observations play an important role in maintaining the sea ice edge close to the truth. Additionally, all experiments ~~perform~~

300 performed better for sea ice volume compared ~~to~~ with the free forecast, with ~~experiment 3~~ EAKF-ThickSnow being the most accurate. For snow volume, ~~experiment 1~~ EAKF-ConcThick is not statistically better than the free forecast, ~~meaning~~ indicating that post-processing snow updates is not ~~an optimal~~ a favorable method. Once again, ~~experiment 3~~ EAKF-ThickSnow performs the best for snow volume even though SIC observations are not assimilated. While not assimilating SIC observations improves most forecast metrics, ~~it is obvious that these observations should be crucial for~~ these observations are crucial for accurately

305 representing the sea ice edge~~accurately.~~

While ~~experiment 3~~ EAKF-ThickSnow provided the most accurate forecasts for ~~the~~ aggregated quantities, ~~like~~ such as total sea ice area, it is unclear where those improvements occurred spatially over the Arctic at the start of the melt season. To gain more insight ~~on~~ into the improved results~~from experiment 3~~, May-through-June averaged spatial biases of SIC, ~~VICE and VSNO~~ V_{ice} and V_{snow} are computed for the free forecast and each ~~experiment~~ of the first three experiments (Fig. 5). For

310 SIC, there are significant biases for the free forecast where the SIC values are too large over the central Arctic and too small near the ~~sea ice marginal zone. Experiments 1 and 2~~ marginal ice zone. EAKF-ConcThick and EAKF-ConcThickSnow show predominantly significant negative biases over the sea ice for SIC~~while experiment 3 has reduced~~, whereas EAKF-ThickSnow

reduces the spatial biases to near zero. The negative SIC spatial bias over the central Arctic explains why the total sea ice area for EAKF-ConcThick and EAKF-ConcThickSnow performed poorly compared to EAKF-ThickSnow. However, there are areas of larger bias value near the marginal ice zone for EAKF-ThickSnow, meaning it was less accurate in representing the sea ice edge. While all experiments reduced the magnitude of the V_{ice} spatial bias, there is still an overall significant negative bias for EAKF-ConcThick and EAKF-ConcThickSnow. The spatial biases for EAKF-ThickSnow are near zero, and there are essentially no areas of significant bias. For V_{snow}, there are differences between the spatial biases for EAKF-ConcThick and EAKF-ConcThickSnow, highlighting the benefits of assimilating D_{snow} observation over post-processing V_{snow} updates. In EAKF-ThickSnow, there is an overall reduction in the significant negative biases over the central Arctic compared with EAKF-ConcThickSnow. In EAKF-ConcThick and EAKF-ConcThickSnow, the SIC observations have a negative impact on both the observed and non-observed model state variables. Removing SIC observations from the assimilated observation subset reduced the spatial coverage of significant biases for all state model variables.

An analysis increment indicates how the observations are pushing or pulling state model variables. Evaluating analysis increments will help determine how SIC observations impact the different data assimilation experiments. For EAKF-ThickSnow, there is a reduction in the magnitude of the spatial analysis increments at the start of the melt season compared with EAKF-ConcThick and EAKF-ConcThickSnow (Fig. 6A). The analysis increment reduction is mainly located over the central part of the Arctic, where SIC values for all ensemble members are close to 1. This implies that the assimilation of SIC observations leads to low biased SIC analyses. The SIC analysis increments become more similar across the experiments as one moves away from the central Arctic toward the marginal ice zone. The analysis increment patterns and magnitudes near the marginal ice zone for EAKF-ConcThick are less different than one might expect because of the increase in IIEE. However, these analysis increments are averaged from May through June; therefore, the IIEE might be picking up on sea ice edge errors at different times throughout the cycling period. This is similar for the V_{ice}, where there is a reduction in the analysis increment magnitude over the central Arctic for EAKF-ThickSnow compared with EAKF-ConcThick and EAKF-ConcThickSnow (Fig. 6B). For V_{snow} analysis increments, there is a flip in the sign between EAKF-ConcThick and EAKF-ConcThickSnow (Fig. 6). The negative V_{snow} analysis increments in EAKF-ConcThick are connected to the SIC analysis increments due to the equation for post-processing (Equations 5 and 6). Since SIC analysis increments are mainly negative over the central Arctic, this would also lead to negative V_{snow} analysis increments over this region due to the post-processing method. The differences in V_{snow} analysis increments between EAKF-ConcThickSnow and EAKF-ThickSnow are small, indicating that the removal of SIC observations from the assimilated subset does not have a negative impact on the adjustments. Overall, EAKF-ThickSnow provides the best setup for sea ice and snow data assimilation. Even with a slightly higher IIEE,

the removal of the SIC observations from the assimilate observation subset did provide better results. Further investigation is needed to understand the reason behind the persistent negatively biased total snow volume compared to the truth.

3.2 ~~Simplified Data Assimilation Experiment~~

350 ~~To further investigate the poor results when assimilating SIC observations, a simplified data assimilation experiment is setup. This simplified DA experiment will mimic SIC during the wintertime over the pole, meaning the truth SIC does not change over time. With a constant truth value that does not change, observations are created that will be assimilated over the cycling period. The truth SIC value is 0.99 and it's corresponding observation error uses the same method as the OSSE experiments. Two different initial ensemble distributions are created; small ensemble spread (standard deviation: 0.0007) and large ensemble~~

355 ~~spread (standard deviation: 0.0142). When prior inflation is tested, it will be set to a constant inflation factor set of 2. All other data assimilation settings (e.g., filter type EAKF) are the same as those in the experiments. Four mini experiments are completed using a combination of the different initial ensemble spreads and prior inflation either turned off or on. The experiments are cycled 5,000 times, assimilating the observations generated from the truth using a truncated normal distribution. These experiments will work with SIC directly, meaning there are no thickness categories as in CICE. This means that the mapping~~

360 ~~between observation space to state space is linear, further simplifying this data assimilation experiment.~~

~~For all experiments, the prior ensemble mean drifts away from the true value and moves toward the average observation value over the cycling period (Fig. 7). The rate at which the prior ensemble mean moves toward the average observation value depends on both the initial ensemble spread and if prior inflation is applied. For small initial ensemble spread, the prior ensemble mean drifts away from the true value faster with prior inflation compared to when prior inflation is turned off (Fig.~~

365 ~~7A, B). While it takes many cycling times, the prior ensemble mean is pulled below the true value without prior inflation for a small initial ensemble spread. When the initial ensemble spread is increased, the prior ensemble mean moves away from the truth at an increased rate with and without prior inflation (Fig. 7C, D). This effect is similar to the results in experiment 2 related to total sea ice area. During the wintertime, SIC ensemble variance is small over most of the ice pack, which is why data assimilation has little impact (similar to results in Fig. 7A). However, once the melt season starts, there is an increase~~

370 ~~in the SIC variance. Combining the increased SIC variance with prior inflation likely leads to a negatively biased solution in experiment 2 (Fig. 3A).~~

~~The fact that the prior ensemble mean moves away from the true value regardless of the initial ensemble variance demonstrates that our data assimilation solution is biased. This is due to the fact that our observation error distribution is a truncated normal while the observation likelihood for the EAKF is assumed to be normal. Applying a non-Gaussian distribution for observation~~

375 ~~errors while using a Gaussian observation likelihood can lead to erroneous observation impacts, biasing analysis estimates (Pires et al., 2010; Fowler and Jan Van Leeuwen, 2013). The effects of prior inflation exacerbate the bias by increasing prior variance, which weights the observations even more. A better choice might be an optimal combination of distributions representing the prior state and the observation errors more appropriately, as laid out in Anderson (2022).~~

3.2 Further discussion on sea ice data assimilation

380 The removal of SIC as an assimilated observation improved forecasts of total sea ice, however, forecasts of the sea ice edge were less accurate according to the total IIEE ~~. This suggests that , near the sea ice margin,~~ and SPS. This result indicatess that near the marginal ice zone there are benefits to assimilating SIC observations and that SIT observations provide poor multivariate updates for ~~AICEN~~ $A_{ice,n}$. Three additional experiments were completed to investigate the ~~sea ice impacts~~ impacts on sea ice when using a ~~non-parametric~~ non-Gaussian RHF, modified forward operators for thickness observations, and the assimilation

385 of SISTs. Each additional experiment is compared with ~~experiment 3. Experiment 4~~ EAKF-ThickSnow. Sea ice edge errors are lower in RHF-ConcThickSnow, and the errors are larger in EAKF-ModifiedFO compared with EAKF-ThickSnow (Fig. 7A). Once again, this result highlights improvements when assimilating SIC observations near the sea ice edge. RHF-ConcThickSNow performs worse than ~~experiment 3~~ EAKF-ThickSnow during the summer according to daily biases of total sea ice area, sea ice volume, and snow volume (Fig. ~~8~~7B,C,D). The use of the ~~non-parametric RHF in experiment 4~~ non-Gaussian RHF did not han-

390 dle the SIC observations better. Compared to ~~experiment 3, experiments 5 and 6~~ EAKF-ThickSnow, EAKF-ModifiedFO and EAKF-SIST have similar daily biases for total sea ice ~~volume~~ and snow volume, however, not for total sea ice area. ~~Experiments 5 and 6~~ EAKF-ModifiedFO and EAKF-SIST have persistent, larger daily biases during ~~the~~ summer compared to ~~experiment 3.~~ EAKF-ThickSnow. There does appear to be a slight improvement in total snow volume for ~~experiment 6 compared to compared experiment 3~~ EAKF-SIST compared with EAKF-ThickSnow during May, however, there are still negative biases throughout

395 the cycling period.

~~Experiment 4~~ RHF-ConcThickSnow does the best job representing sea ice coverage since its total IIEE is the lowest and it is significantly different from the other experiments (Fig. ~~9). Experiment 4~~ 8). RHF-ConcThickSnow assimilates SIC observations, which is likely why it is similar to our previous result from ~~experiment 2~~ EAKF-ConcThickSnow (compare Fig. 4A with Fig. ~~9~~8A). ~~Experiments 5 and 6~~ EAKF-ModifiedFO and EAKF-SIST essentially have the same total IIEE, which ~~are~~ is

400 statistically worse than ~~experiment 3. The modification to~~ EAKF-ThickSnow. The modification of the forward operator along with assimilating SIST observations ~~poorly represents~~ does not improve the representation of sea ice coverage. For total sea ice area and sea ice volume, ~~experiment 4~~ RHF-ConcThickSnow has the largest aggregated errors that are significantly different from the other experiments (Fig ~~9~~8B, C). This result is similar to ~~experiment 2~~ EAKF-ConcThickSnow, where SIC observations were assimilated. ~~Experiment 3~~ While EAKF-ThickSnow does the best job representing the total sea ice area and sea ice

405 volume~~. However~~, one thing that needs to be mentioned is that ~~experiment 6 uses the~~ EAKF-SIST uses a modified forward operator. Since the sea ice statistics appear very similar between ~~experiments 5 and 6~~ EAKF-ModifiedFO and EAKF-SIST, the modified forward operator could ~~be the reason~~ explain why the results for ~~experiment 6~~ EAKF-SIST are worse than those for ~~experiment 3.~~ EAKF-ThickSnow.

Evaluating SIC over the start of the melt season (May-through-June) reveals that ~~experiment 4 has mostly~~ RHF-ConcThickSnow

410 mostly has significant negative biases compared to the truth (Fig. ~~10~~9A). This result is similar to ~~experiment 2~~ EAKF-ConcThickSnow, where the EAKF is used instead of the RHF. Compared to ~~experiment 3~~ EAKF-ThickSnow, there are larger, positive SIC biases for ~~experiments 5 and 6 near the sea ice margin~~ EAKF-ModifiedFO and EAKF-SIST near the marginal ice zone. These biased

areas are mainly located in the Baffin Bay, Greenland Sea, and Barents Sea. The poor representation of the ~~sea ice margin zone for experiments 5 and 6~~ marginal ice zone for EAKF-ModifiedFO and EAKF-SIST could explain the larger total IIEE com-

pared to ~~experiment 3. Experiment 4~~ EAKF-ThickSnow. RHF-ConcThickSnow has significant negative sea ice volume biases over most of the sea ice pack (Fig. ~~10~~9B). Again, this agrees with the spatial biases for ~~experiment 2~~ EAKF-ConcThickSnow over this period, further showing that switching to the RHF over the EAKF did not help alleviate the impacts of the SIC observations. The spatial biases of sea ice volume for ~~experiments 5 and 6~~ EAKF-ModifiedFO and EAKF-SIST closely resemble those found in ~~experiment 3~~ EAKF-ThickSnow, except near the ~~sea ice margin~~ marginal ice zone. The modified forward opera-

tor might introduce poor ~~sea ice margin~~ marginal ice zone updates without the constraint of ~~the~~ SIC observations in this region. Overall, switching the data assimilation filter type did not ~~fix~~ resolve the issues related to assimilating SIC observations, and there are potential issues with using the modified forward operator near the ~~sea ice margin~~ marginal ice zone. However, the spatial biases are similar over most of the central Arctic~~meaning more investigating~~, indicating that further investigation is needed to determine the negative impacts of the modified forward operator.

3.3   ~~Further discussion on snow data assimilation~~Simplified Data Assimilation Experiment

~~Regardless of the experiment~~To further investigate the poor results obtained when assimilating SIC observations, a simplified data assimilation experiment was setup. This simplified DA experiment mimics SIC during wintertime over the pole, meaning that the true SIC does not change over time. With a constant truth value that does not change, observations are created that will be assimilated over the cycling period. The true SIC value is set to 0.99, and its corresponding observation error will vary from 0.1485 (value if using the same method as the OSSE experiments), 0.07425, and 0.037125. Two different filters, EAKF and RHF, will be tested using different observation specifications. The initial ensemble spread has a standard deviation of 0.0142. No prior inflation was applied in these experiments. Six mini experiments were completed using a combination of different filter types (EAKF or RHF) and different specified observation errors. The experiments were cycled 5,~~the daily biases for snow volume are negative throughout much of the entire cycling period~~compared to the truth (Figs. 3C) . ~~Even the daily biases for the additional experiments are mainly negative throughout the~~ 000 times, assimilating the observations generated from the truth using a truncated normal distribution. These experiments will work with SIC directly, meaning that there are no thickness categories as in CICE. This means that the mapping between observation space to state space is linear, further simplifying this data assimilation experiment.

For all experiments, the prior ensemble mean drifts away from the true value and moves toward the average observation value over the cycling period (Fig. ~~8C~~10). The ~~use of the RHF in experiment 4 does not improve the representation of snow volume, while experiments 5 and 6 are similar to experiment 3. For snow volume, experiment 6 is performing better than experiment 3 throughout May. Experiment 6 has smaller MSE and MAB values for snow volume and is significantly different from experiment 3~~ average observation value depends on the observation error specification; a smaller error leads to an average observation closer to the truth. For the largest observation error, the EAKF drifts toward the average observation value at a quicker rate compared with the RHF (Fig. 10A,D). The slower rate exhibited by the RHF could mean that the filter weights the observations less compared with the EAKF. Even as the observation errors decrease, both the EAKF and the RHF move away

from the truth and drift toward the average observation value (Fig. ~~9C~~10B,C,E,F). These experiments highlight that a reduction in the observation error still results in the prior ensemble being negatively biased when using distributions and observations near a bound.

450   The fact that the prior ensemble mean moves away from the true value regardless of filter type and observation error value demonstrates that our data assimilation solution is biased. This is because our observation error distribution is a truncated normal, whereas the observation likelihood for EAKF and RHF is assumed to be normal. Applying a non-Gaussian distribution for observation errors while using a Gaussian observation likelihood can lead to erroneous observation impacts, biasing analysis estimates (Pires et al., 2010; Fowler and Jan Van Leeuwen, 2013). This negative bias is exacerbated by the effects of prior

455   inflation in our OSSEs by increasing prior variance, which further weights the observations even more. A better choice might be a combination of distributions representing the prior state and the observation errors more appropriately, as laid out in Anderson (2022).

3.4   Further discussion on snow data assimilation

Regardless of the first three experiments, the daily biases for snow volume are negative throughout much of the entire cycling

460   period compared to the truth (Figs. 3D). ~~This means assimilating additional SIST observations provided a more accurate update to snow volume. While mainly negative ,~~ Even the ~~magnitude of~~ daily biases for the ~~spatial biases are larger with more areas with significant biases for experiment 4 (Fig. 10C). Even though experiment 6 had the lowest MSE and MAB for snow volume, it is hard to identify any particular spatial region over the sea ice where the biases are closer to zero compared to the other experiments~~ additional experiments are mainly negative throughout the cycling period (Fig. ~~10C).~~

465   7D). Further investigation is needed to fully understand why the snow volume is negatively biased regardless of the experimental setup. ~~Experiment 3~~ EAKF-ThickSnow will be further evaluated to investigate the reason for the low bias in snow volume. Since the ocean forcing is the same across ensemble members, the atmospheric forcing is evaluated for the ensemble mean. Breaking down the individual atmospheric heat fluxes, the shortwave radiation has the largest bias compared to the truth (Fig. 11A). The other atmospheric heat fluxes have smaller and near zero biases for most of the cycling period. The

470   positive shortwave heat flux bias occurs during sunrise over the Arctic, which also corresponds to the period in ~~experiment 3~~ EAKF-ThickSnow where the daily biases for snow volume are the largest (Fig. 3C). The spread in the absorbed shortwave heat flux grows during the onset into summer, which is during the start of the ~~melt season for snow~~ snow melt season (Fig. 11B). ~~The ensemble on average~~On average, the ensemble has absorbed too much incoming shortwave radiation compared to the truth. Interestingly, the spread of the absorbed shortwave heat flux collapses at the start of July, when the snow on top of

475   the sea ice ~~would be at it's~~ is at its minimum (Fig. 3C). One feature that can impact the absorbed shortwave radiation and is connected to snow ~~would be~~ cover is surface albedo (Fig. 11C). During the same period, the spread in the absorbed shortwave heat flux increases and ~~there is an increase~~ the spread in the surface albedo spread increases. The spread in the surface albedo then collapses, ~~like~~ similar to the incoming shortwave radiation heat flux, near the ~~start~~ beginning of July. The surface albedo is~~on average~~, on average, too small compared to the truth, which could be the reason for the positive bias in the absorbed

480 shortwave radiation. Lastly, the ensemble members almost appear ~~sorted,~~ to be sorted for both absorbed shortwave radiation and mean surface albedo, hinting that ~~there is something systematic driving~~ something systematic drives these quantities.

One potential reason that could be driving the negative biases found for the ensemble mean snow volume is that the snowfall originating from the atmospheric forcing file for the truth member is an outlier. This does not appear to be the case when comparing daily biases of snowfall ~~for~~ with the ensemble mean (Fig. 11D). The snowfall biases for the ensemble mean are

485 near zero and fluctuate about the zero line, ~~meaning~~ indicating that there is no clear systematic difference from the truth. One issue that has not been discussed is the role that the CICE perturbed parameters could ~~be playing in the~~ play in snow evolution. Perturbed parameters have been used over the years to create more spread in atmospheric models (Murphy et al., 2004; Stainforth et al., 2005; Christensen et al., 2015; Orth et al., 2016), where the system is more chaotic. However, the impact the perturbed parameters would have on a less-chaotic system ~~like~~ such as the cryosphere is unclear. Concerning total snow

490 volume, there are larger and more significant correlations between the R_{snw} parameter compared ~~to~~ with the other perturbed parameters throughout the cycling period (Fig. 12A). The positive correlations ~~mean~~ indicate that larger standard deviations of the dry snow grain radius lead to ~~more~~ greater total snow volume. This connection is a result of the larger standard deviations of dry snow grain radius resulting in a higher albedo, reflecting more incoming shortwave radiation (Hunke et al., 2015). Looking at snow melt, there are negative and significant correlations during the melt season for the R_{snw} parameter, while the other

495 parameters have little significant correlations (Fig. 12B). This means there is more snow melt for lower standard deviations of dry snow grain radius, resulting in more absorbed shortwave radiation due to a lower surface albedo. The R_{snw} parameter for the truth member is located above the 75th percentile compared with the rest of the perturbed R_{snw} parameters (Fig. 12C). Even with snow assimilation updates, the impact ~~from~~ of the perturbed R_{snw} parameter might play a larger role in snow evolution. Due to this fact, it is not surprising to find that the ensemble mean is negatively biased compared to the truth for total snow

500 volume.

4   Conclusions

To advance our understanding of the global climate, it is critical to improve our representation of the different underlying Earth-system components within our coupled numerical climate models. One important Earth-system component–the cryosphere–has gathered recent attention due to declining Arctic summer sea ice and ~~the~~ its link back to Arctic amplification. Data assimilation

505 methods, ~~like~~ such as the ensemble Kalman filter (EnKF), are one way to improve the representation of sea ice states by exploiting information from observations taken from satellites. However, the formulation of the EnKF has Gaussian assumptions and most state variables representing sea ice have some form of boundedness, which can lead to non-Gaussian distributions near those bounds. This study investigates the data assimilation impacts of the non-Gaussian nature of sea ice and snow variables on the generation of analyses within different observing system simulation experiments (OSSEs). The different OSSEs

510 presented in this study will ~~test for the optimal setup for~~ investigate which data assimilation setup provides the most accurate representation of sea ice and snow ~~data assimilation~~ when dealing with non-Gaussian ~~states~~ observations and state variables.

In this study, a sea ice model called CICE is coupled to the ensemble data assimilation software provided by DART to obtain a sea ice modeling system called CICE-DART. CICE-DART is used to conduct OSSEs to test different data assimilation configurations. Six different experiments were completed to test different observation combinations, data assimilation techniques, and post-processing updates (Table 1).

The first three experiments explore the impacts different assimilated observation subsets have on generating the most accurate forecasts for both sea ice and snow states. According to the daily biases and aggregated statistics, EAKF-ThickSnow is more accurate, when compared to the truth, for sea ice area, sea ice volume, and snow volume. This highlights the negative impacts that SIC observations have on forecasts when they are assimilated in EAKF-ConcThick and EAKF-ConcThickSnow. Doubly-bounded SIC observations can impose non-Gaussian effects both during the summer and winter. Early springtime SIC truth values are still close to one, maximizing their observation error (15% of the truth value), which leads to observations being drawn further below the truth due to the bound at one. Additionally, prior spread increases due to both the start of springtime melt and prior inflation. Combining the low-bias observations with the increase in the prior spread leads to an enhancement of the non-Gaussian effects during early springtime. Interestingly, SIC observations do provide positive updates in the marginal ice zone, as shown by SPS and total IIEE being lower in EAKF-ConcThick and EAKF-ConcThickSnow. Due to positive updates in the marginal ice zone, it would be optimal to assimilate SIC observations within the data assimilation system.

To better understand the assimilation impacts due to the SIC observations, a simplified data assimilation experiment is completed. This simplified experiment mimics central Arctic SIC during the winter time, meaning the truth does not change. The generation and assimilation of SIC observations followed the same setup as the CICE-DART experiments. In each simplified experiment, the prior ensemble mean moves away from the truth and closer to the average observation value during the cycling period. The rate at which the prior ensemble mean moved away from the truth depended on the initial ensemble size and whether prior inflation was used. These experiments verified that near a bound, the performance of the EAKF is suboptimal. We believe the suboptimal performance is linked back to using a truncated normal distribution as the observation error distribution while the observation likelihood for the EAKF is assumed to be normal. Future projects focusing on sea ice data assimilation might want to consider a different choice for the observation likelihood specification, similar to those laid out in Anderson (2022).

Additional OSSEs are performed to further investigate potential data assimilation improvements for sea ice (Table 1). A non-Gaussian RHF was tested since it was developed for non-Gaussian situations. The results showed little improvement over the EAKF when assimilating SIC observations. This is likely linked back to the RHF making some non-Gaussian assumptions on the tails and assumed normal likelihood when the distribution is not bounded. The modification to the forward operators did not improve sea ice data assimilation, especially regarding sea ice edge errors. This could mean that there are few instances of shuffling the sea ice thickness distribution due to prior inflation. Additionally, the multivariate update between sea ice thickness observations and sea ice area might be the reason for the increase in sea ice edge errors. Lastly, assimilating SISTs did not lead to increased skill for sea ice variables. The correction between the SISTs and sea ice model variables might not be significant, leading to little improvement.

Evaluation of the additional OSSEs are To better understand the assimilation impacts due to the SIC observations, a simplified data assimilation experiment is completed. This simplified experiment mimics central Arctic SIC during the winter time, meaning the truth does not change. Regardless of the filter type or observation error value, the prior ensemble mean moves away from the truth and closer to the average observation value during the cycling period. These experiments verified that near a bound, the performance of the EAKF and the RHF is suboptimal. We believe the suboptimal performance is linked back to using a truncated normal distribution as the observation error distribution while the observation likelihood for the EAKF and RHF is assumed to be normal. Future projects focusing on sea ice data assimilation might want to consider a different choice for the observation likelihood specification, similar to those laid out in Anderson (2022). This would include using distributions for the prior PDF and the observation likelihood that are similar to the observation error distribution and consider the bounds more appropriately (e.g., a truncated Gaussian distribution).

The evaluation of the additional OSSEs is performed to investigate their impact on snow updates. The improvements associated with using the non-parametric non-Gaussian RHF over the EAKF were small for snow volume. This means that the non-Gaussian impacts from the SIC observations were negative on for snow volume updates. Additionally, the modified forward operators have little impact on snow volume updates. However, there is a slight improvement in the snow volume when SISTs are assimilated. This improvement occurred during May and not over a specific area of the sea ice. This could mean that the connections between SISTs and snow are more significant than compared to those between sea ice, where the impacts were less impactful. Regardless, all additional experiments still experienced a negative bias throughout the entire cycling period. Further investigation revealed that one of the perturbed parameters could be driving the negative bias for snow volume. Correlations were larger and significant between snow variables and the representation of the dry snow grain radius size (R_{snw}) within our ensemble. Due to the random choice of the R_{snw} parameter for the truth member, it is likely the reason the that the ensemble mean is negatively biased for snow volume.

Future work will further investigate how to properly assimilate SIC observations. Due to Because of their positive impact on the sea ice margin marginal ice zone, an experiment could be proposed where in which only SIC observations are assimilated in that remote location. Additionally, further investigation is needed to test the use of more sophisticated data assimilation methods that accurately handle non-Gaussian distributions. The RHF can represent non-Gaussian priors and arbitrary likelihoods for the observed variables. The RHF can be modified to work with bounded quantities (Anderson, 2020, 2022), which should be investigated in future studies. Lastly, supplementary OSSE experiments could be completed with a different ensemble member chosen as the truth to further understand the impacts of the perturbed parameters have on representing snow volume. These additional experiments would will further help us understand the optimal correct data assimilation setup for representing sea ice and snow in climate analyses.

Code availability. CICE version 5 used for the experiments described here is part of the CESM2 framework which is publicly available for download from https://www.cesm.ucar.edu/models/cesm2/download.html (accessed in August of 2020). The data assimilation software used here can be downloaded from https://github.com/NCAR/DART (accessed in August of 2020).

580 *Data availability.* The perturbed CICE parameters used in this study is publicly available for download from https://doi.org/10.5281/zenodo.8164431. Post-processed and raw data from the experiments described here are stored on NCAR's campaign storage.

Author contributions. The development of the CICE-DART framework was completed by both CR and JA. CR prepared and performed the experiments under the supervision of JA. The manuscript was composed by CR with contributions and feedback from JA.

Competing interests. The contact author has declared that neither they nor their co-author have any competing interests.

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Table 1. List of CICE-DART OSSEs with the different configurations.

Experiments	Assimilated Observations	Modified Forward Operator	Postprocessed States	Assimilation Algorithm	Data Assimilation Updated State Vector
EAKF-ConcThick	SIC SIT	No	Category Snow Volume	EAKF	Category Sea Ice Area Category Sea Ice Volume
EAKF-ConcThickSnow	SIC SIT D_{snow}	No	No	EAKF	Category Sea Ice Area Category Sea Ice Volume Category Snow Volume
EAKF-ThickSnow	SIT D_{snow}	No	No	EAKF	Category Sea Ice Area Category Sea Ice Volume Category Snow Volume
RHF-ConcThickSnow	SIC SIT D_{snow}	No	No	RHF	Category Sea Ice Area Category Sea Ice Volume Category Snow Volume
EAKF-ModifiedFO	SIT D_{snow}	Yes	No	EAKF	Category Sea Ice Area Category Sea Ice Volume Category Snow Volume
EAKF-SIST	SIT D_{snow} SIST	No	No	EAKF	Category Sea Ice Area Category Sea Ice Volume Category Snow Volume
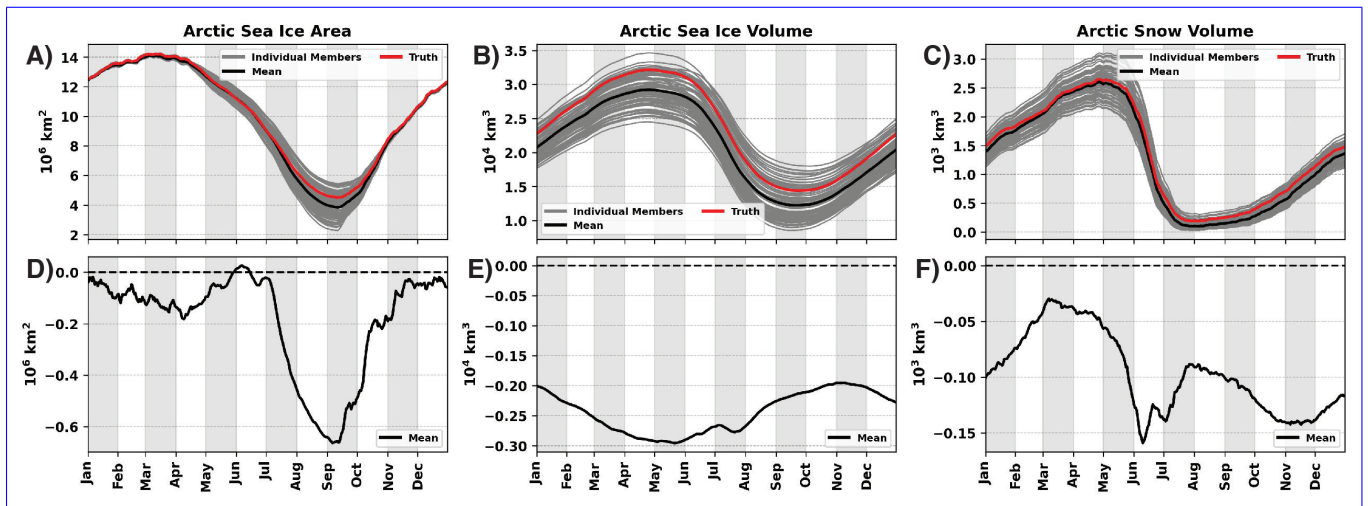
Figure 1. Daily total Arctic (A) sea ice area, (B) sea ice volume, and (C) snow volume from CICE5 free forecast simulations. Each gray line represents an individual ensemble member, black line represents the ensemble mean, and the red line represents the truth member. The truth member is a randomly selected ensemble member. Daily biases of the total Arctic (A) sea ice area, (B) sea ice volume, and (C) snow volume where the black line represents the ensemble mean difference compared to the truth. The black dashed line is the zero reference line. The free forecast period is for the year 2013.

~~List of CICE-DART OSSEs with the different configurations. >X >X >X >X >X >XExperiments Assimilated Observations Modified Forward Operator Postprocessed States Assimilation Algorithm State Vector Exp. 1 SIC,SIT No VSNON EAKF AICEN,VICEN Exp. 2 SIC,SIT,SNWD No —EAKF AICEN,VICEN,VSNON Exp. 3 SIT,SNWD No —EAKF AICEN,VICEN,VSNON Exp. 4 SIC,SIT,SNWD No —RHF AICEN,VICEN,VSNON Exp. 5 SIT,SNWD Yes —EAKF AICEN,VICEN,VSNON Exp. 6 SIT,SNWD,SIST Yes —EAKF AICEN,VICEN,VSNON~~

725
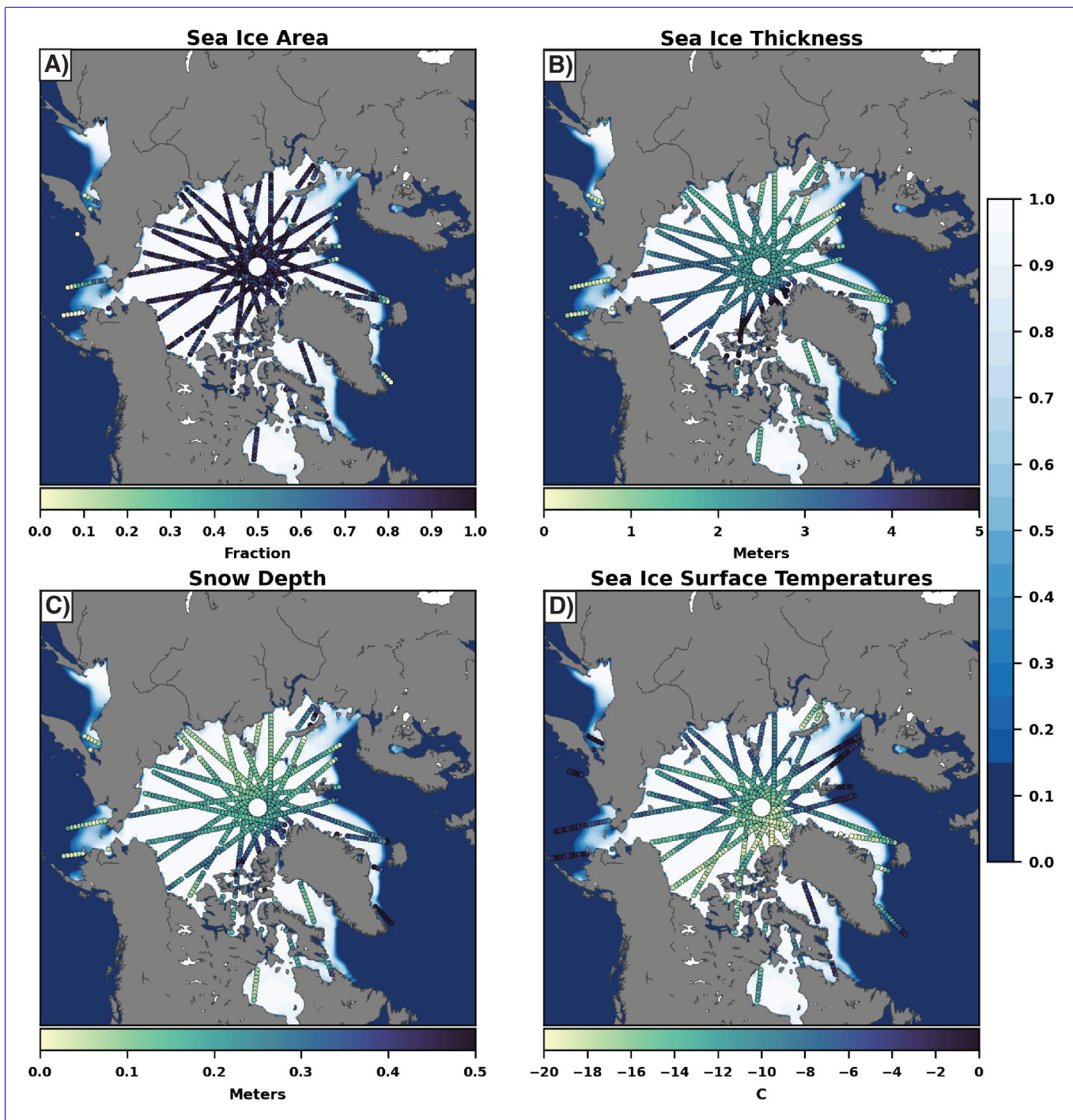
Figure 2. An example of the spatial locations of assimilated (A) sea ice area, (B) sea ice thickness,(C) snow depth and (D) sea ice surface temperature observations. Colorfill is the ensemble mean of the sea ice area and the dots are the observation locations along with their associated value.
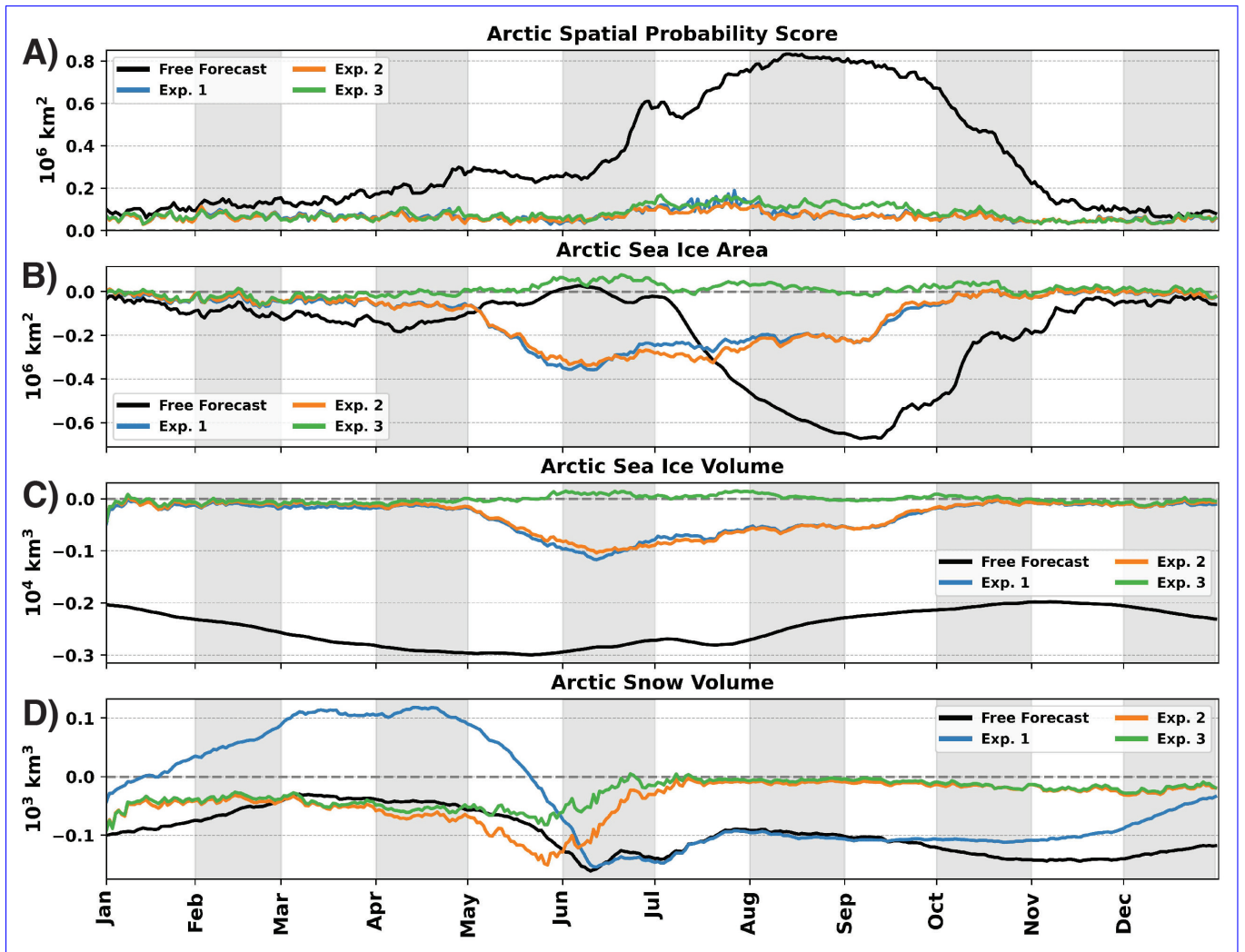
Figure 3. Daily biases of the Arctic total (A) sea ice area, (B) sea ice volume, and (C) snow volume from the free forecasts, ~~Control-EAKF,~~ ~~Add-SnowD,~~ and ~~experiments 1–3~~ EAKF-ConcThick. Gray dashed lines are the zero reference line.
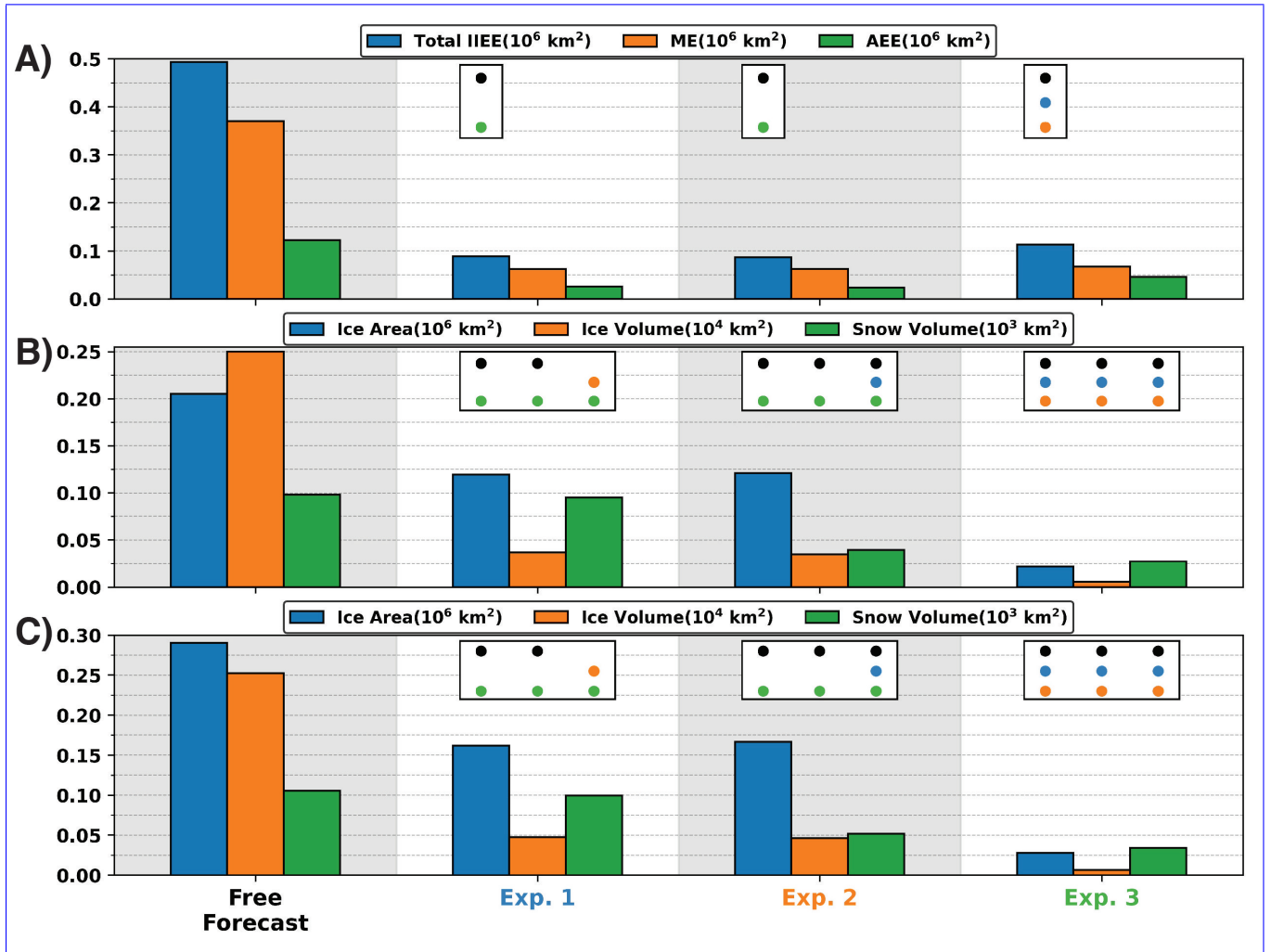
Figure 4. The (A) IIEE, (B) MAB, and (C) RMSE of sea ice area, sea ice volume and snow volume from the free forecast, ~~Control-EAKF,~~ ~~Add-SnowD,~~ and ~~experiments 1–3~~ EAKF-ConcThick. Each index is computed using the ensemble mean and over the entire cycling period. Dots represents ~~an~~ any pairs of experiments that are significantly different from a different experiment using a student t-test. Dot colors correspond to the different experiments.
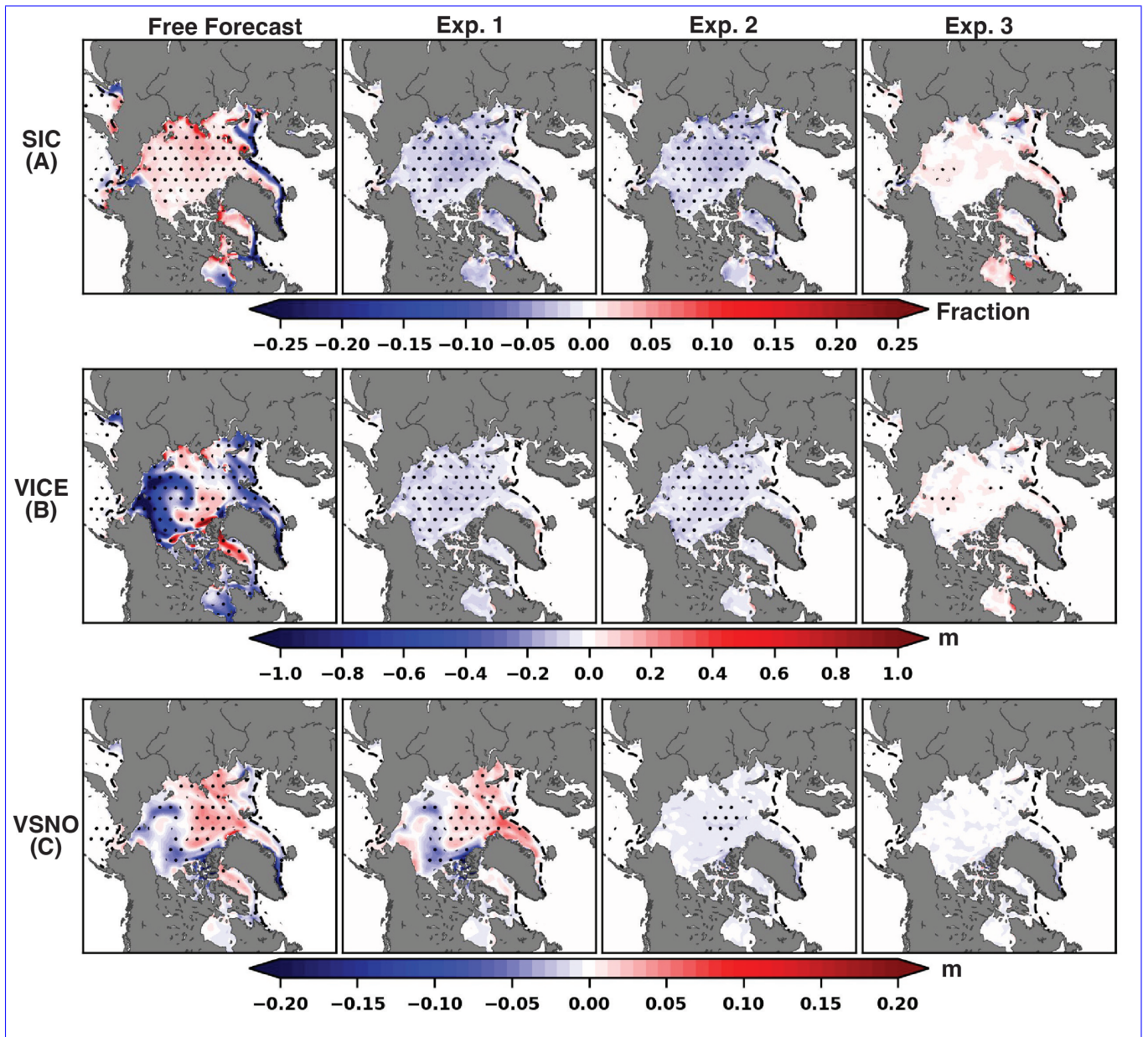
Figure 5. Ensemble mean spatial biases of (A) SIC, (B) ~~VICE~~V_{ice}, and (C) ~~VSNO~~ V_{snow} averaged over May–June for the free forecast, Control-EAKF, Add-SnowD, and ~~experiments 1–3~~EAKF-ConcThick. Stippling represents significant biases at the 95% confidence interval using a Welch's t-test. The black dashed line is the sea ice edge (0.15 SIC).

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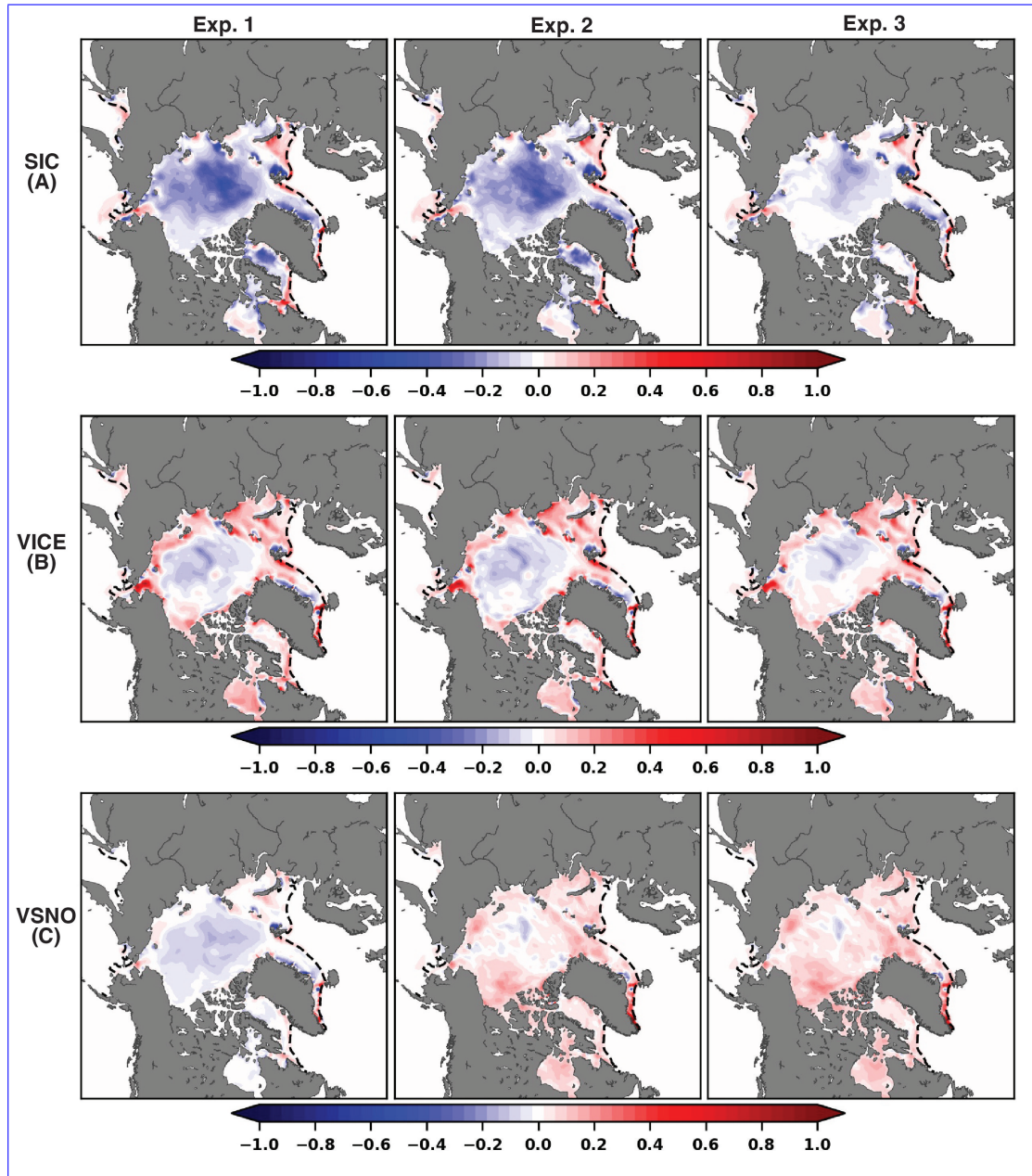
Figure 6. Normalized spatial analysis increments of (A) SIC, (B) ~~VICE~~V_{ice}, and (C) ~~VSNO~~ V_{snow} averaged over May–June for ~~experiments 1–3~~Control-EAKF, Add-SnowD, and EAKF-ConcThick. Analysis increments of SIC, ~~VICE~~V_{ice}, and ~~VSNO~~ V_{snow} were normalized using the largest absolute value from across the three experiments. The black dashed line is the sea ice edge (0.15 SIC).
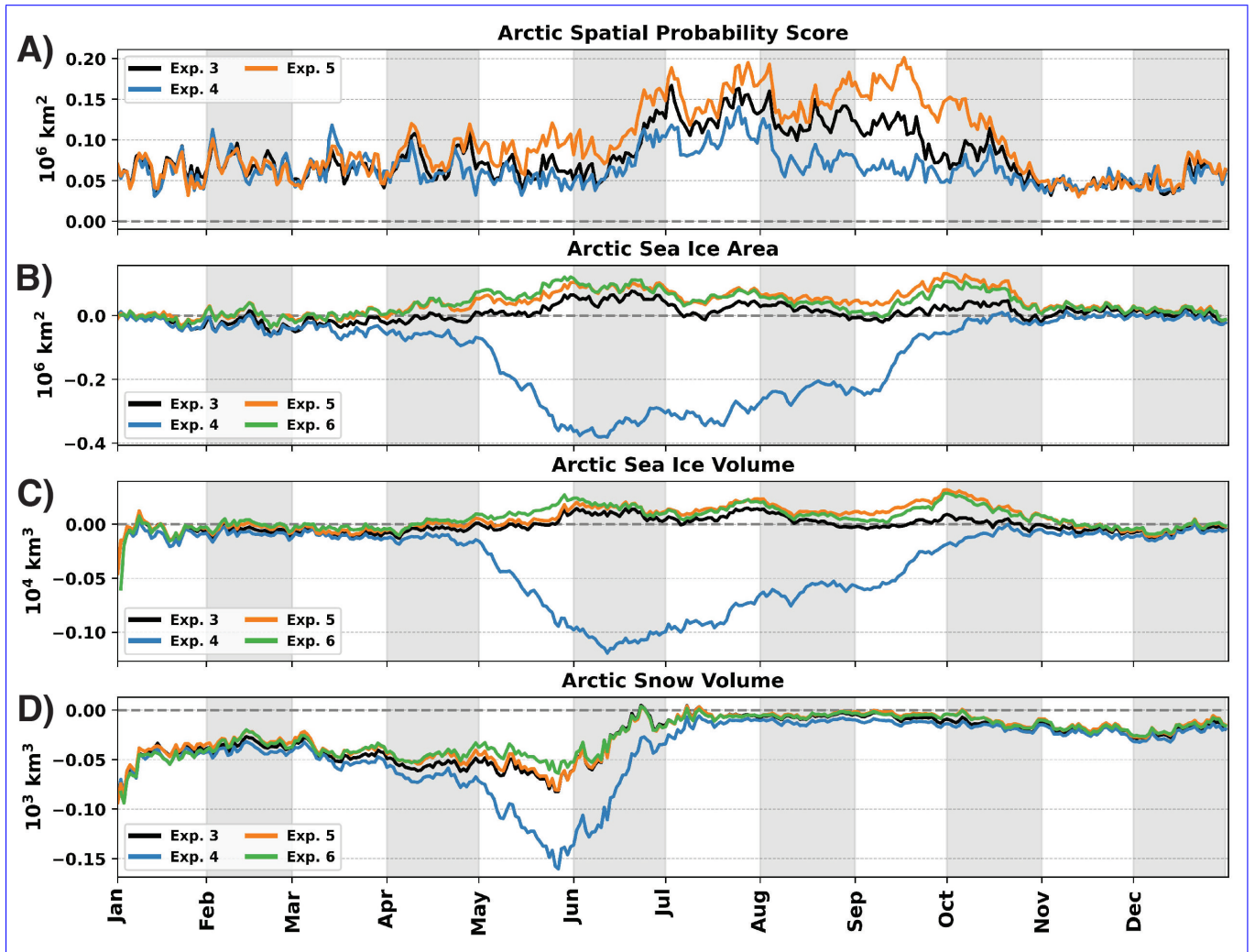
Figure 7. Same as Figure 3 but for EAKF-ConcThick, RHF-ConcThickSnow, Modified-FO and EAKF-SIST.
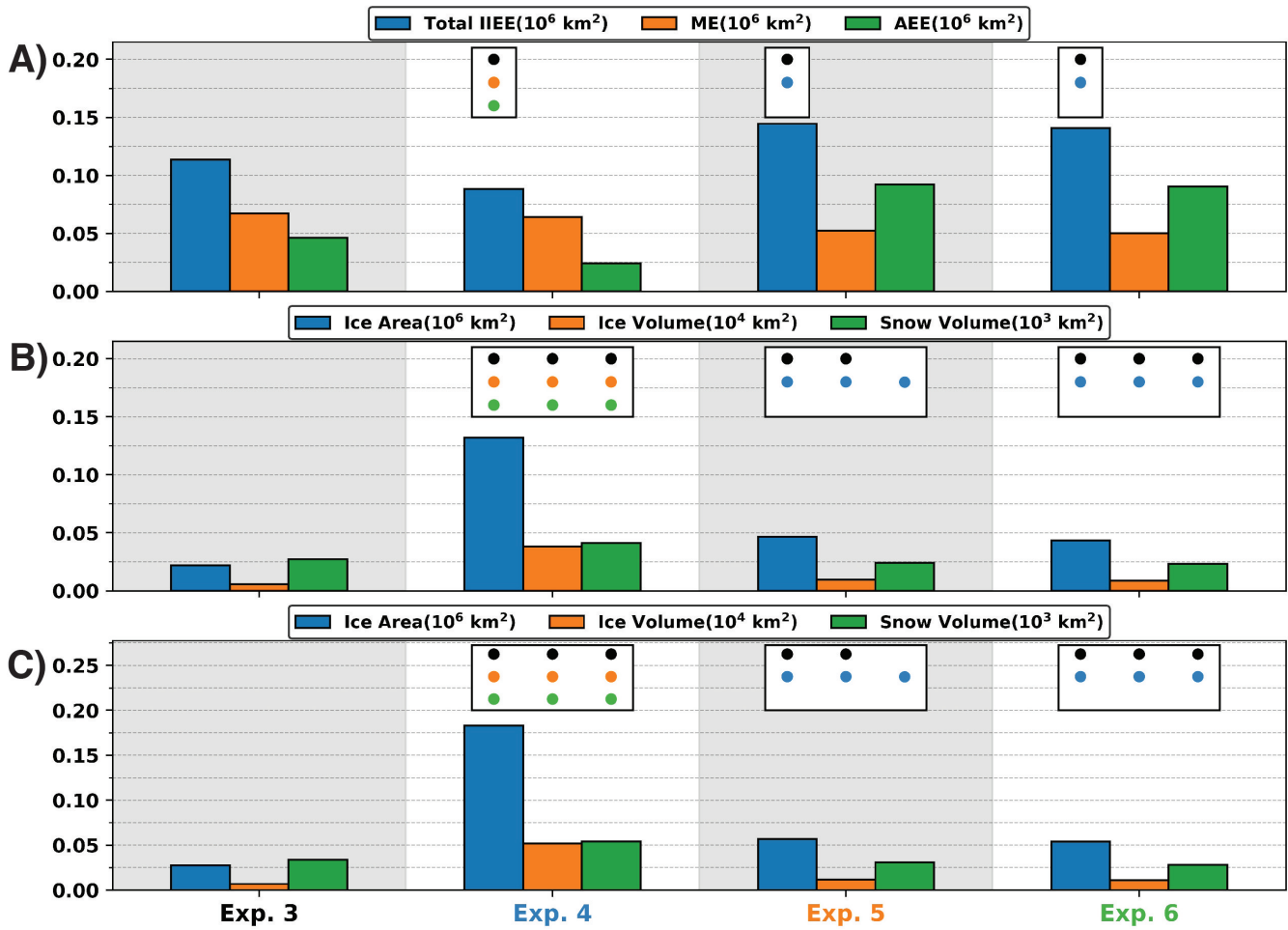
Figure 8. Same as Figure 4 but for EAKF-ConcThick, RHF-ConcThickSnow, Modified-FO and EAKF-SIST
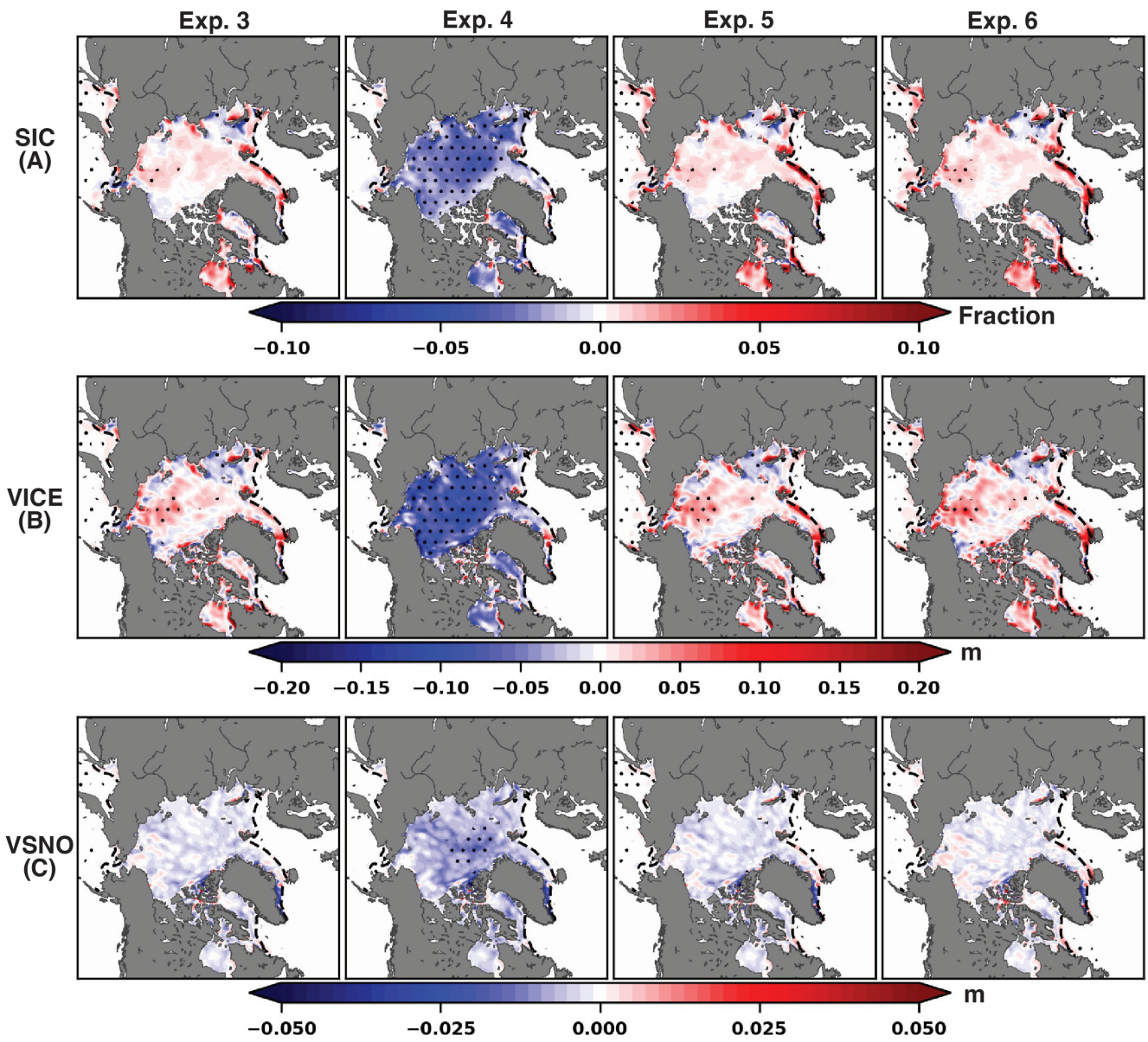
Figure 9. Same as Figure 5 but for EAKF-ConcThick, RHF-ConcThickSnow, Modified-FO and EAKF-SIST.
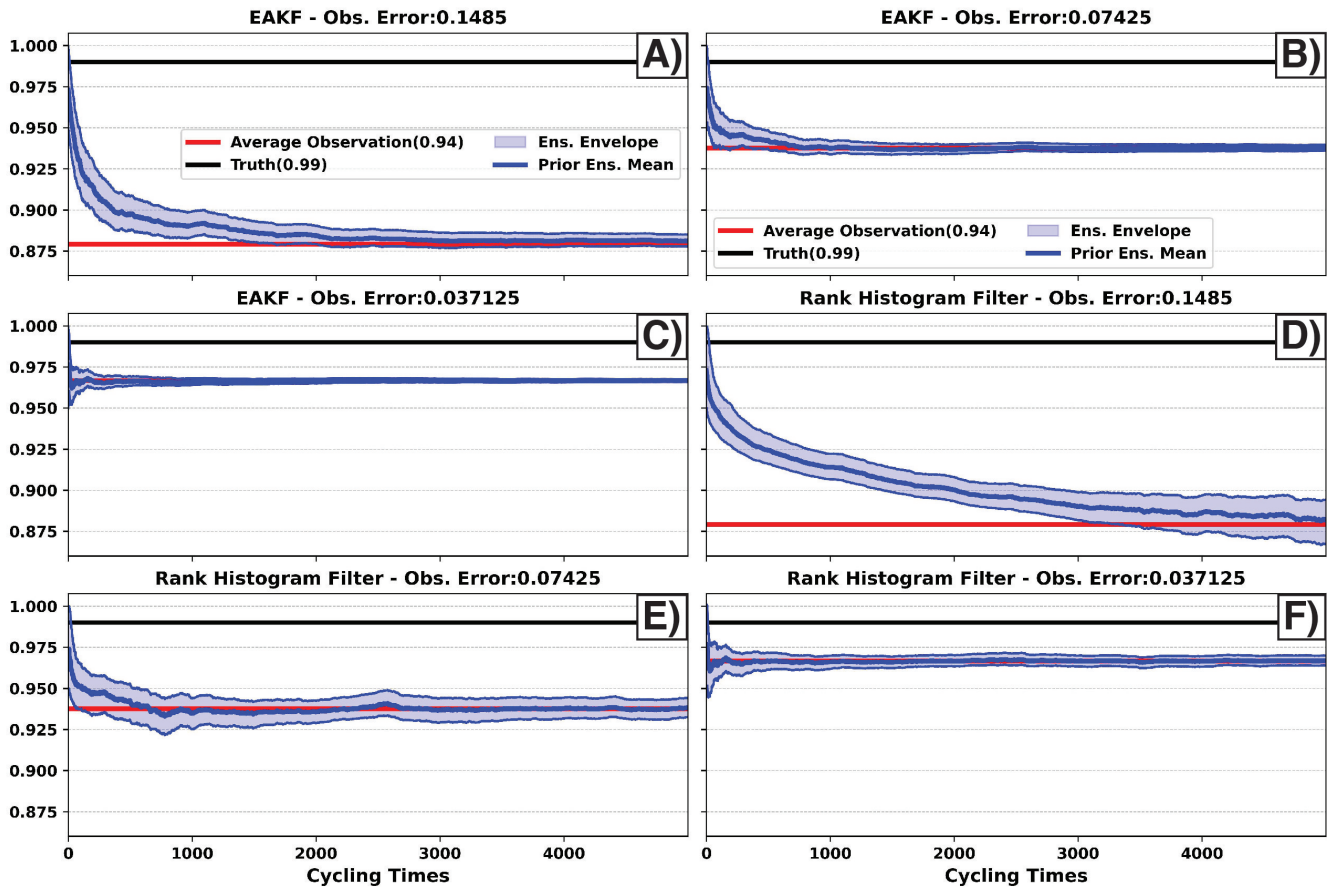
Figure 10. Prior ensemble mean (blue line) time series of SIC for experiments using (A,B) small initial ensemble spread and (C,D) large initial ensemble spread. Each experiment was completed with prior inflation (A,C) turned off and (B,D) turned on. The red line represents the average observation value over the cycling period. The black line represents the true value over the cycling period.

~~Same as Figure 3 but for experiments 3–6.Same as Figure 4 but for experiments 3–6.Same as Figure 5 but for experiments 3–6.~~
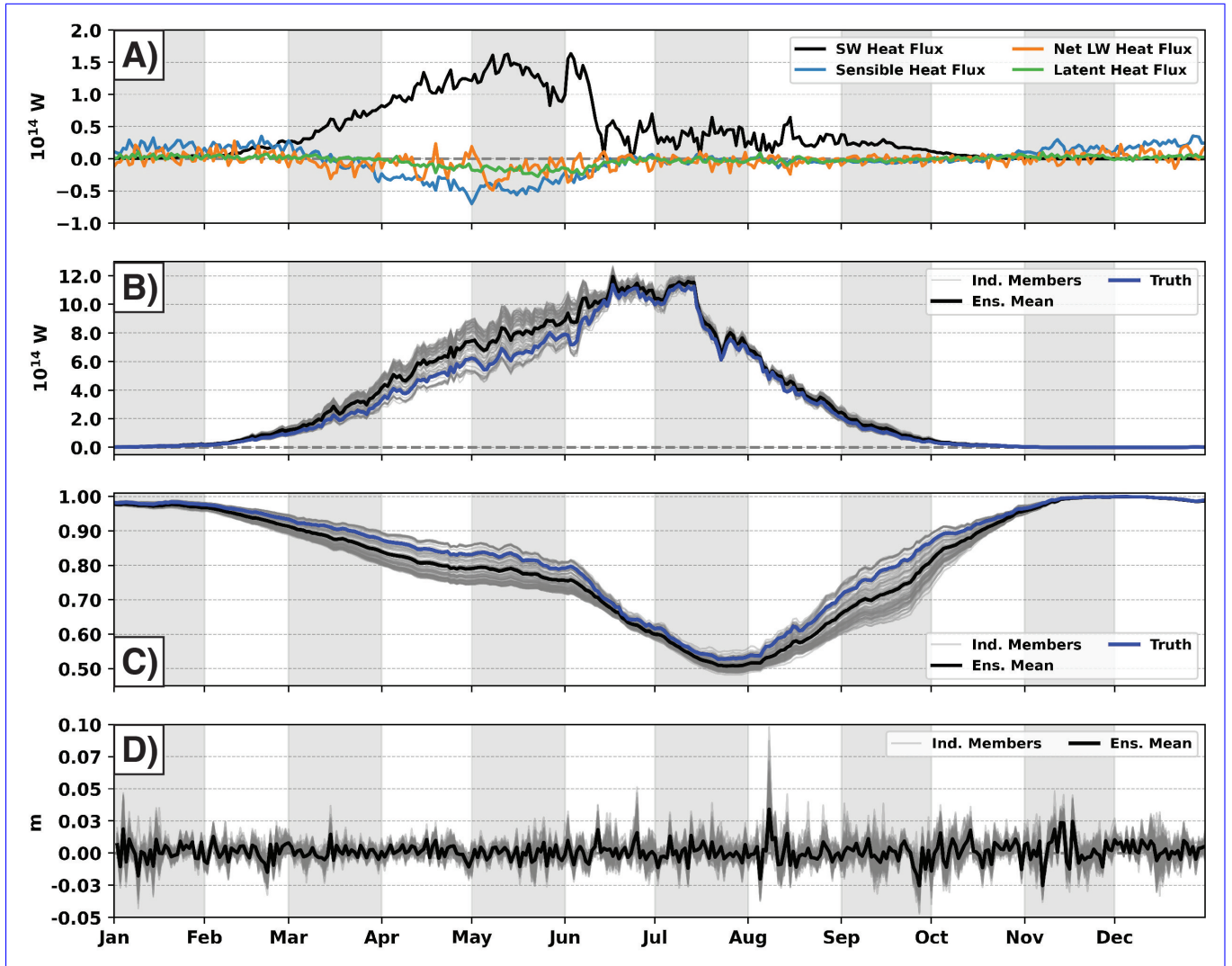
Figure 11. Panel (A): Ensemble mean daily biases of sea ice accumulated atmospheric heat fluxes for ~~experiment 3~~ EAKF-ConcThick compared to the truth. The plotted atmospheric heat flux components include: shortwave heat flux (black line), sensible heat flux (blue line), net longwave heat flux (orange line), and latent heat flux (green line). Gray dashed line represents the zero reference line. **Panel (B):** Time series of sea ice accumulated shortwave heat flux for ~~experiment 3.~~ EAKF-ConcThick. The gray lines are the individual ensemble members, the black line is the ensemble mean, and the blue line is the truth. Gray dashed line represents the zero reference line. **Panel (C):** Same as Panel (B) but for mean surface albedo over sea ice. **Panel (D):** Daily biases of sea ice accumulated snowfall for ~~experiment 3~~ EAKF-ConcThick compared to the truth. The gray lines are the individual ensemble members, and the black line is the ensemble mean.
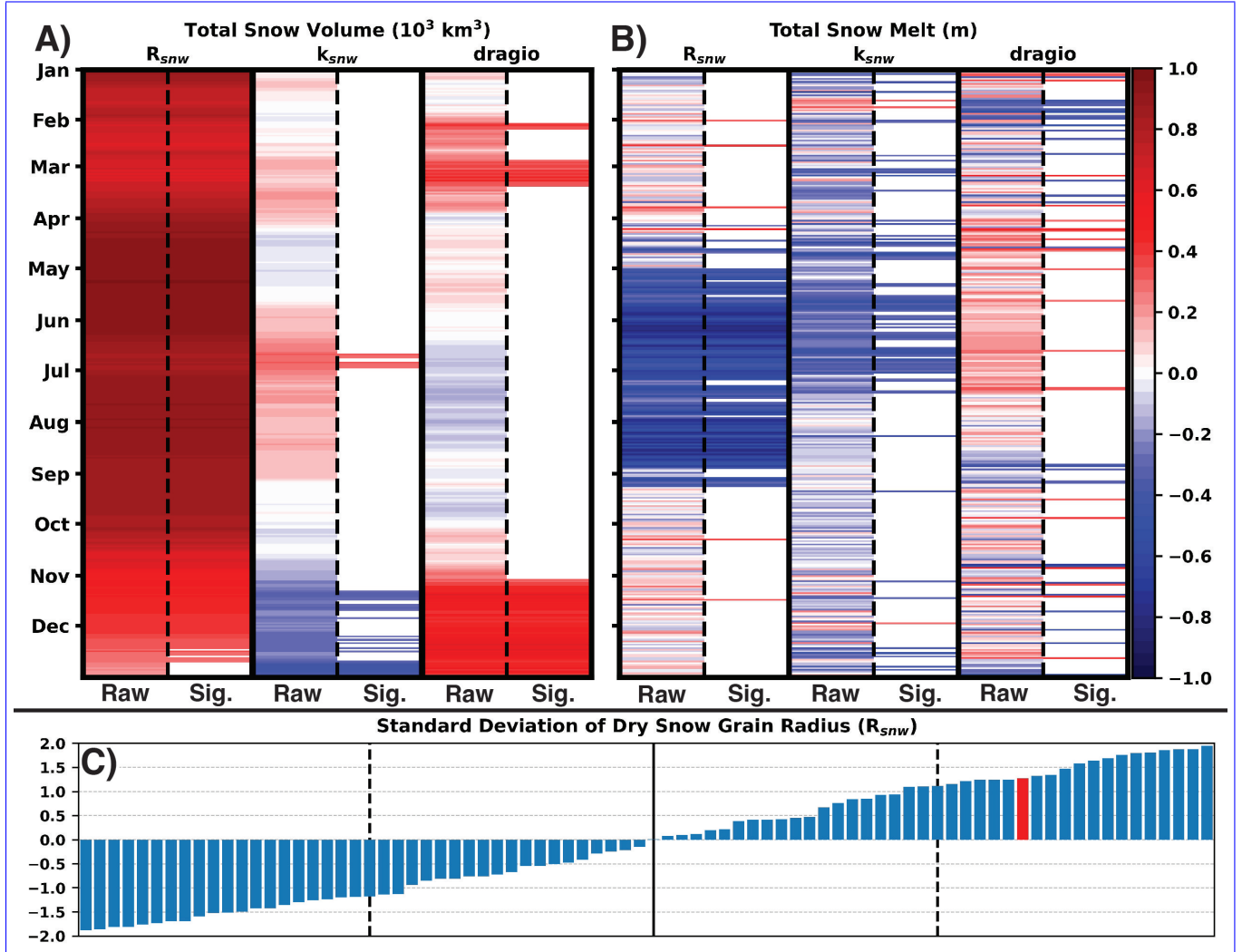
Figure 12. Panel (A): Daily correlations between perturbed CICE parameters and total snow volume over the Arctic. Correlations are computed using a Spearman's rank correlation method where both the raw correlations (**Raw**) and significant correlations with confidence at 99% (**Sig.**) are shown. **Panel (B):** Same as Panel (A) but for total snow melt over the sea ice in the Arctic. **Panel (C):** Sorted perturbed R_{snw} parameter values for each ensemble member. Red bar indicates the truth member. Black line is the median and the two dash lines represent the interquartile range.