Data assimilation to improve sea ice predictability in the Arctic Ocean

（北極海の海氷予測改善のためのデータ同化）

ドゥリニ　ヤサーラー　ムドゥンコトゥウェ

Keywords: Data Assimilation, Ensemble Kalman filter, Nudging, Sea ice concentration, Sea ice thickness, Sea ice velocity

１．Introduction

Rapid retreat of summer sea ice away from the landmasses in the recent years has led to extending the navigation period of the Arctic sea routes (ASR). In order to safely navigate in the Arctic Ocean, it is important to predict sea ice distribution accurately. Ice-ocean coupled model (Ice-POM) is used to predict sea ice condition in the Arctic Ocean. However, the results of the simulations from the model alone are prone to produce several errors due to uncertainties in initial conditions, uncertainties in the forcing data and limitations of the temporal and spatial resolutions. Satellite observations of sea ice distributions are also available, yet satellite data are also subjected to instrument errors, conversion errors and limitations of temporal and special resolutions. Data assimilation is an effective tool to best combine satellite data and model predictions. The focus of this study is to introduce data assimilation into Ice-POM. The aim is to improve the initial conditions of the high-resolution models by including data assimilation to mid resolution model from which initial conditions are extracted for high-resolution models. An extensive literature survey was carried out and it was found that the accuracy of sea ice prediction is improved when more than one variables are assimilated. Several assimilation techniques were tested. Direct insertion method, Newtonian relaxation (nudging) method and ensemble Kalman filtering methods were used. Sea ice concentration, sea ice thickness and sea ice velocity were assimilated individually and in combination. Sea ice concentration assimilation time interval was varied in daily, weekly, monthly and yearly intervals.

2. Model Description

The ice dynamic model in Ice-POM takes into account the ice discrete characteristics along the ice edge area. The ice thermodynamic model is a zero-layer model (Semtner A.J., 1976) with snow-cover effect taken into account (Zhang X., 2001). The ocean part of Ice-POM is a primitive equation model based on Princeton Ocean Model (POM). The model domain (Fig.1) is a z-sigma-coordinate, three-dimensional model with spatial resolution of 25km in horizontal plane and 33 z-sigma layers in vertical direction. It contains the entire Arctic Ocean, the Greenland-Iceland-Norwegian (GIN) seas and the North Atlantic Ocean. The bottom topography is created from 1 arc minute data of ETOPO1 data set. The atmospheric forcing data were obtained from ERA-interim six hourly products. The radiation boundary condition is applied at the open lateral boundaries and no-slip boundary condition is used along the coastlines. First, the model was spun up for 12 years by providing the year 1979 atmospheric data cyclically. Entire model domain reached equilibrium after 12-year spin up. Then the model was integrated from year 1979 to 2013 with ERA-interim realistic atmospheric forcing. After simulating this 33-year experiment, the model could well reproduce the ice condition.

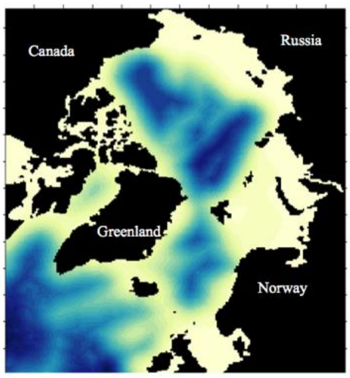

Fig. 1 : Model domain

3. Assimilation Method

Sea ice concentration is obtained from the advanced microwave scanning radiometer (AMSR2) onboard the GCOM-W satellite. Daily gridded sea ice concentration data set is extracted from Arctic Data archive System (ADS) from their website, https://ads.nipr.ac.jp/. Daily sea ice thickness is calculated using (Krishfield et. al, 2014) algorithm based on AMSR-2 satellite data. Sea ice velocity data set is extracted from KIMURA Sea ice velocity data set (Kimura et. al, 2013). Sea ice concentration data are available in a daily interval for the year 2013. Sea ice thickness and sea ice velocity data sets are only used from January to May of 2013 due to their unreliability in summer. Sea ice observation gridded data sets are available in 10km zonal and meridional resolution. The observation data sets are interpolated to the model grid using inverse distance interpolation considering the nearest four observation points in 7km radius around a model grid cell. In this study the timespan of data assimilation experiment is set to year 2013. The intermittent approach (Bloom, S.C., et al. 1996) is used to assimilate sea ice observations. They are assimilated daily and are integrated for 24 hours.

3.1 Direct insertion and Newtonian relaxation (nudging)

In this study the timespan of data assimilation experiment is set to year 2013. The intermittent approach (Bloom, S.C., et al. 1996) is used to assimilate sea ice variables. During assimilation experiments the model estimates are nudged to new estimates with the following relationship.

$$C_{\mathrm{estimate}} = C_{\mathrm{model}} + K(C_{\mathrm{obs}} - C_{\mathrm{model}}) \quad (1)$$

K is the weighting. C is the prognostic variable; in this study variables are sea ice concentration, sea ice thickness or sea ice velocity. The optimal least square value of the weighting is formulated as in equation 2.

$$K = \frac{R^2_{\mathrm{model}}}{R^2_{\mathrm{model}} + R^2_{\mathrm{obs}}} \quad (2)$$

R^2_{model} and R^2_{obs} are the error variances of the model estimate and the observation, respectively. Errors are assumed to be unbiased and normally distributed. Very little is known about the model errors and observation errors. The error variance of the observation varies considerably with time and location. Therefore we have selected different values for the ice edge and the other areas. We have also selected different values for the summer since the observations are not so reliable in the summer. Observation errors are selected according to the instrumentation errors (Japan Aerospace Exploration Agency (JAXA)). ${R_{\mathrm{obs}}}^2 = 6.25 \times 10^{-4}$ is used where the ice concentration is 1. Along the ice edge ${R_{\mathrm{obs}}}^2 = 1.5625 \times 10^{-2}$ is used. In the summer ${R_{\mathrm{obs}}}^2 = 6.25 \times 10^{-2}$ is used. The weight K is formulated as,

$$K = \frac{|C_{\mathrm{obs}} - C_{\mathrm{model}}|^2}{|C_{\mathrm{obs}} - C_{\mathrm{model}}|^2 + R^2_{\mathrm{obs}}} \quad (3)$$

For direct assimilation computations K is set to be 1 ignoring the observation error. The impact of assimilation time interval is also studied. Yearly, monthly, weekly and daily assimilation intervals are examined. Some corrections are done to adjust the non-assimilated variables to avoid numerical instabilities.

3.2 Ensemble Kalman filter

The ensemble Kalman filter (EnKF) [Evensen, 1994] method estimates model error statistics using an ensemble of model states. Error statistics are calculated using different realizations of model states at the current time requiring more CPU time. In this study ψ_i^f is model forecast of the ensemble member $i \in \{1,2 \ldots N\}$. H is a linear operator that transfers the model state to the observation space. The analysis update (ψ_i^a) is given by equation 4, where d is observation. Due to the computational constraints in this study, we have limited our ensemble size to seven ensemble members. Since observation perturbation could lead to errors in a small ensemble, observations aren't perturbed in this study. To differentiate ensemble members, the model is forced using different atmospheric forecast data from seven atmospheric agencies. Observation error variance used to assimilate sea ice observations are selected based on the instrument error variance of AMSR-2. Different values are selected for ice edge and other areas as stated above in Newtonian relaxation method. Observation variance is also varied according to the season. Higher values are selected during summer due to the unreliability of satellite observations in summer. Observation errors and model errors are assumed to be uncorrelated, yielding a diagonal matrix, which is trivial to invert in equation 5.

$$\psi_i^a = \psi_i^f + K_e\,(d - H\psi_i^f) \quad (4)$$

Ke is the Kalman gain, which is given in equation 5.

$$K_e = P_e^f H^T (H P_e^f H^T + R)^{-1} \quad (5)$$

P_e^f is model state error covariance computed from equation 6. $\overline{\psi^T}$ is the ensemble average of the prognostic variable.

$$P_e^f = \overline{(\psi_i^f - \overline{\psi^f})\ (\psi_i^f - \overline{\psi^T}\ )^T} \quad (6)$$

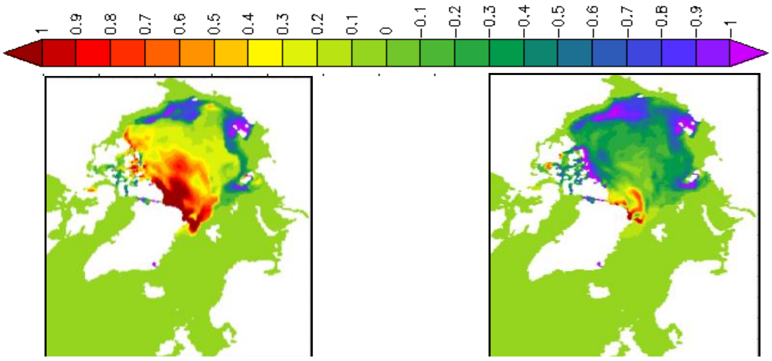

Fig 1. a (left) Difference between sea ice thickness of ensemble average and model in meter in September. (EnKF sea ice thickness - model sea ice thickness) b (right) Difference between sea ice thickness of nudging method and model in September.

Analyzed model state (P_e^a) is given in equation 7.

$$P_e^a = (I - K_e\ H)P_e^f \tag{7}$$

Corrections were done to non-assimilated variables as explained above in the Newtonian relaxation method to avoid numerical instabilities.

4. Results and Discussions

It could be observed that sea ice thickness has increased near the pole and decreased near the ice edge in Newtonian relaxation experiments as well as in EnKF experiments (Fig. 2) compared to the model prediction. In the year 2013 the model had over predicted sea ice extent. Therefore decreased sea ice thickness along the ice edge is an improvement in sea ice predictions. One of the issues mentioned by (De Silva et. al, 2013) in the model prediction is that sea ice is thinning near the North Pole. One of the reasons for this is an over prediction in sea ice velocity that leads to advection of sea ice away from the North Pole. Improved sea ice thickness in assimilation experiments is a result of improved velocity predictions as well as corrections we did to sea ice thickness during assimilating experiments.

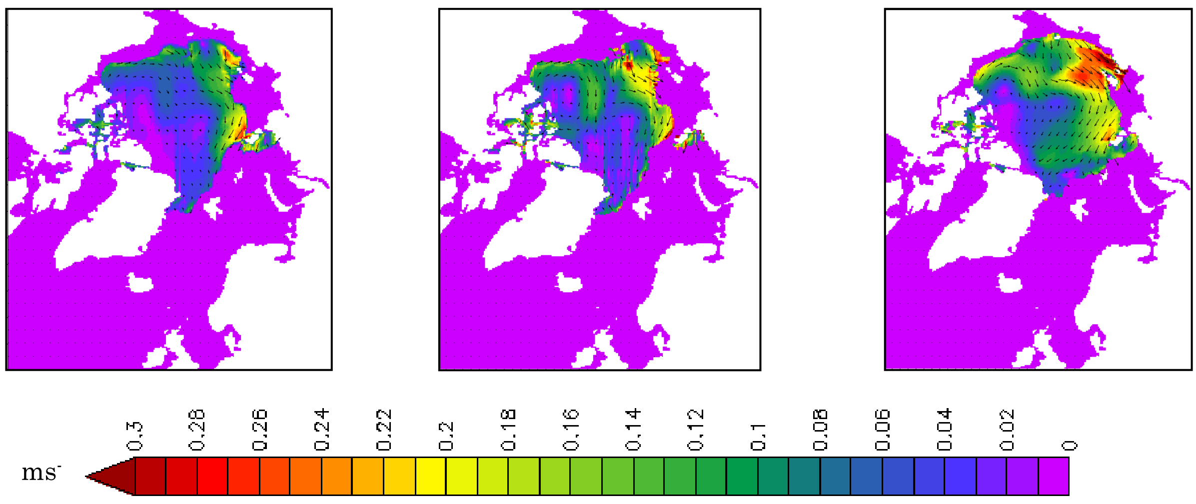

Fig 2. Sea ice velocity in September 2013 in ms^{-1} (a) left sea ice velocity from EnKF experiment, (b) center sea ice velocity from nudging experiment (c) right sea ice velocity from the model.

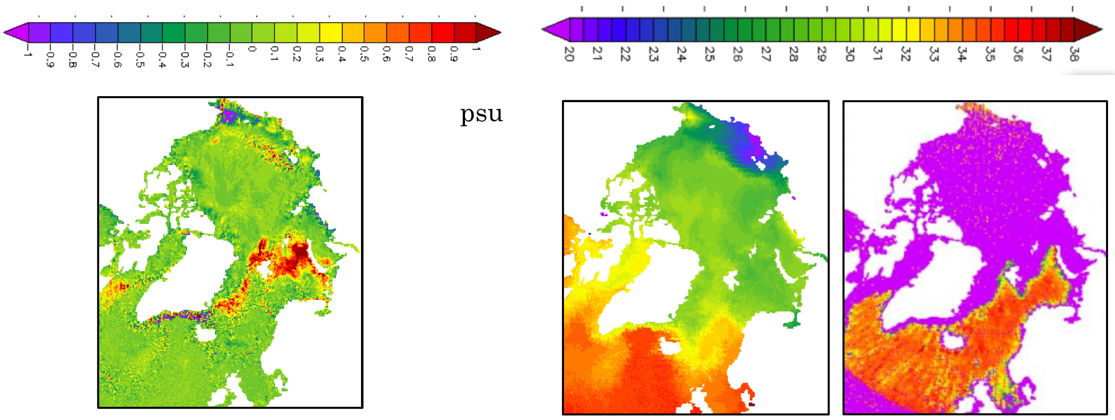

Fig 3. a (left) Difference between SSS (in psu) of ensemble average and model in winter (EnKF SSS - model SSS), b (center) SSS (in psu) of the model, c(right) SSS (in psu) of NSIDC satellite observation

It is evident in the figure.3 that sea ice velocity in assimilation experiments are lower than that of the velocity in the model prediction. This is specifically evident near the pole where increased sea ice thickness can be observed in assimilation experiments. EnKF method experiment outperforms the nudging method with regards to velocity. Resulting in better sea ice thickness distribution.
To validate assimilation effectiveness, resulting sea surface salinity (SSS) was compared with an independent data set (NSIDC) that was not used in our assimilation experiments. It was noted that the model under predicts salinity in the Barents Sea compared to the NSIDC data set (Figure 4b and 4c). EnKF assimilation experiment produce better salinity results in the Barents Sea compared to the model (Figure 4a). The reason behind increased salinity is the reduced sea ice extent in assimilation experiments. In both assimilation methods presence of sea ice in the Barents Sea is not as significant as in the model prediction. When sea ice cover is absent, salinity is affected by the inflow from the Atlantic Ocean. Another reason for this increased salinity could be the model response to create ice when the ice cover is removed by the assimilation.

The impact of assimilation time interval on the results has also been investigated. Sea ice concentration is assimilated in daily, weekly, monthly and yearly intervals. Ice extent from daily assimilation is comparable to the observed sea ice extent. It is also evident that the predicted sea ice extent from weekly and monthly assimilations could produce comparable sea ice extent to that of the observation after about 5 months in to the assimilation experiment. This is advantageous in predicting sea ice extent for the Arctic sea routes since the routes are operating only during the summer. It is also advantageous because weekly and monthly observation data are available more widely than that of daily observations. We can also see that yearly-assimilated experiment's ice extent has moved back to the model ice extent after three weeks. This is occurring because it takes several weeks to adjust the ocean conditions according to the changes in observed concentration.
Compared to sea ice thickness and sea ice velocity assimilations, sea ice concentration assimilations produce results that are more comparable with the observations.

5. Conclusions

Assimilating sea ice variables improved the ocean and ice conditions as expected. It is evident from the changes in sea ice extent, sea ice velocity, sea ice thickness and ocean salinity. Non-assimilated sea ice variables have also been indirectly improved by assimilation. Both direct insertion method and nudging method that considered error covariance have produced similar results due to the significant difference between the model and the satellite observations. EnKF method produced better sea ice and ocean conditions. The ice and ocean conditions in the Barents Sea are significantly improved after assimilation. The salinity is affected by the assimilation. There are two reasons behind this increased salinity. One is the Atlantic water flow and the other is the model responding to the removal of ice by the assimilation with creating more ice. The impact of assimilation time interval is also studied. Daily assimilation produces results that are closer to observations through out the year, while weekly and monthly-assimilation experiments produce results with adequate accuracy during the summer. This is favorable in real-time computations where observation data is not immediately available