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Article

Improving numerical sea ice predictions in the Arctic Ocean by data assimilation using satellite observations

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Abstract

This study focuses on improving sea ice predictions in the Arctic Ocean by introducing data assimilation into an ice-ocean coupled Ice-POM model that is used to predict sea ice conditions in the Arctic sea routes. Ocean part of the model used in this study is based on the Princeton Ocean Model (POM). The ice model considers discrete characteristics of ice along the ice edge. The model domain consists of the Arctic Ocean, Greenland-Iceland-Norwegian (GIN) seas and the Northern Atlantic Ocean. The model grid is with 25km horizontal resolution. An improved nudging method that takes the observation errors into account is used in this study. Observation errors are varied in accordance with the season and the location. Sea ice concentration, sea ice thickness and sea ice velocity are assimilated simultaneously. Assimilation improved ocean and ice conditions significantly. This is evident from the changes in sea ice extent, sea ice thickness and ocean salinity.

Key words: Arctic sea ice, data assimilation, sea ice concentration, sea ice thickness, sea ice velocity, nudging

1. INTRODUCTION

With increased use of Arctic Sea Routes, accurately predicting sea ice conditions in the Arctic Ocean is vital. Numerical simulations are considered to produce accurate predictions economically. However, the results of the simulations from the model alone are prone to several errors such as uncertainties in initial conditions, boundary condition and forcing data. Temporal and spatial resolutions are also limiting factors. Therefore, it is necessary to introduce satellite observations based correction method to model predictions. There are various data assimilation methods that are widely used in ocean modeling. Direct insertion, nudging, optimal interpolation, 3DVAR, 4DVAR and ensemble Kalman filter (EnKF) are commonly used methods. Methods such as 3DVAR, 4DVAR, EnKF methods comes with a high computational cost. Therefore, in this study an improved nudging method based on Lindsay (2006) is used. Sea ice concentration, sea ice thickness and sea ice velocity are assimilated simultaneously

2. MODEL DESCRIPTION

The ice-ocean coupled model, ice-POM that is used in this study is the model used by Fujisaki *et al*. (2010) and De Silva *et al*. (2015) for ice-ocean coupled computations. The ocean model of the ice-POM is based on generalized coordinates, the Message Passing Interface (MPI) version of the Princeton Ocean Model (POM) (Mellor *et al*. 2003). Zero-layer thermodynamic model by Parkinson *et al*. (1979) is used as the ice thermodynamic model.

Model domain contains the entire Arctic Ocean, Greenland-Iceland-Norwegian (GIN) seas and the Northern Atlantic Ocean as shown in fig. 1 The resolution of zonal and meridional grid are set to about 25km x 25km. The vertical grid is composed of z-sigma coordinates system with 33 levels. A z-coordinate system is used for top three layers with 1m depth in each layer. Remaining 30 layers are composed of sigma coordinate system. The bottom topography is created from Earth Topography 1 Arc-minute Gridded Elevation (ETOPO1) dataset.

Radiation boundary condition is applied at the open lateral boundaries and no-slip boundary condition is used along the coastlines. Singularity at the North Pole is avoided by rotating the whole Arctic model grid to place its North Pole over the equator. The atmospheric forcing data are obtained from The European Centre for Medium-Range Weather Forecasts Re-Analysis Interim (ERA-interim) six hourly data. Precipitation is obtained by National Center for Environmental Prediction (NCEP) 6 hourly reanalysis data. First, the model is spun up for 10 years by providing the year 1979 atmospheric data cyclically. Then the model is integrated from year 1979 to 2013 with ERA-interim and NCEP realistic atmospheric forcing (Mudunkotuwa *et al*. 2015). The ice model and ocean model time steps are set to 4 minutes. The ocean and ice conditions resulting from this 33-year integration are used to initialize data assimilation experiments.

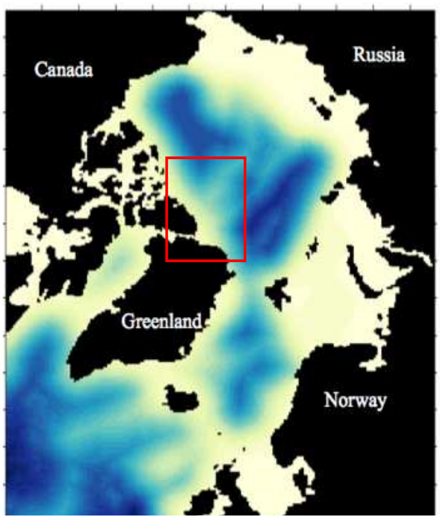

Fig. 1 Model domain. (The area enclosed by red square represents the polar area compared in the study.)

3. DATA USED

The 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. The gridded daily sea ice thickness data set is also obtained from ADS. 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 assimilated during first four months since the two data sets aren't reliable in summer. To validate the study two independent data sets are used that are not used in assimilation experiments. Monthly averaged Cryosat sea ice thickness data and NSIDC Aquarius weekly sea surface salinity data sets are used for validation.

4. DATA ASSIMILATION METHOD

In this study the timespan of data assimilation experiment is set to year 2013. The Incremental analysis update (Bloom, S.C., *et al.* 1996) is used to assimilate sea ice concentration, sea ice velocity and sea ice thickness. In this experiment model is nudged towards the observation with the following relationship.

$$C_{estimate} = C_{model} + \frac{K}{\tau}(C_{obs} - C_{model}) \qquad (1)$$

Where, C is the prognostic variable and τ is the time relaxation coefficient. τ is set to be 12 hours in this study. *K* is the nudging weight. Optimal least square value of the weighting is formulated as in the following equation according to Lindsay (2006).

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

Where R^2_{model} and R^2_{obs} are the error variance of model and the observations respectively. Lindsay (2006) method uses $|C_{obs} - C_{model}|^2$ to be the model error. One of the issues with this method is that it assumes observation to be the truth by assuming the model error to be $|C_{obs} - C_{model}|^2$. Therefore as an improvement to the formulation the model error is assumed to be $|(C_{obs} \pm R_{obs}) - C_{model}|^2$.

With this method, truth is assumed to be,

$$C_{truth} = C_{obs} \pm R_{obs} \qquad (3)$$

This method yields *K* as below,

$$K = \frac{|(C_{obs}+R_{obs})-C_{model}|^2}{|(C_{obs}+R_{obs})-C_{model}|^2 + R^2_{obs}} \qquad (4)$$

$$K = \frac{|(C_{obs}-R_{obs})-C_{model}|^2}{|(C_{obs}-R_{obs})-C_{model}|^2 + R^2_{obs}} \qquad (5)$$

As a result, two sets of values are used for *K* yielding a range as a forecast.

R_{obs} is calculated as,

$$\sigma^2_{observation} = \sigma^2_{instrument} + \sigma^2_{algorithm} \qquad (6)$$

Unlike Mudunkotuwa *et al.* (2016) algorithm errors are also considered in this study. The values used for instrument errors and algorithm errors are presented in table 1. The values are obtained from Ludovic *et al.* (2014), Kimura *et al.* (2016), Ono *et al.* (2016), and JAXA (2014). An experiment is performed assimilating sea ice concentration, sea ice thickness and sea ice velocity simultaneously. Sea ice concentration is assimilated for the entire year 2013. Sea ice thickness and sea ice velocity are assimilated only during first four months.

To avoid disparities between observation data sets and to improve the ocean conditions, some corrections are done to sea ice variables and ocean variables as described in detail in Mudunkotuwa (2016).

5. RESULTS AND DISCUSSION

According to Mudunkotuwa *et al.* (2016) Ice-POM model over predicts sea ice extent in the Barents Sea in the winter. This has been improved by the assimilation. Figure 2 presents the sea ice extent from the two experiments. An average is calculated from the upper and lower limits. It can be seen that both nudging weights produce similar sea ice extent values that are close to the observation. One of the criticisms of the Ice-POM model is that sea ice thickness near the North Pole and the Canadian basin is under predicted (Mudunkotuwa *et al*. 2016), however sea ice thickness shows improvement according to fig. 3.

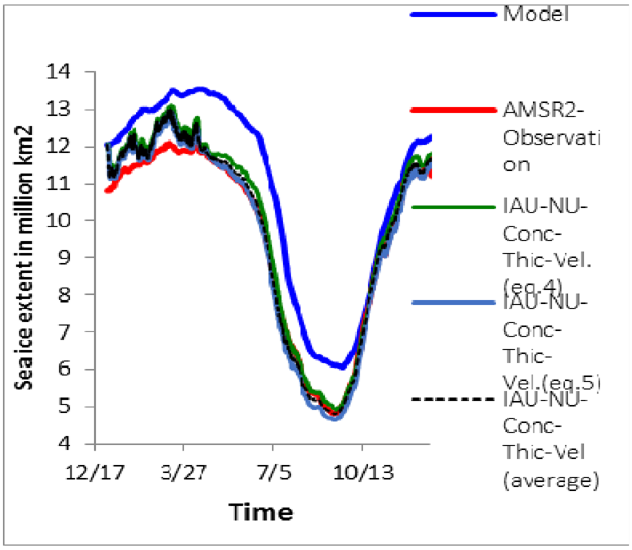

Fig. 2: Time series of sea ice extent for the whole domain from nudging experiments using Eq. 4 and 5, their average, model and AMSR2 observation

There's a considerable difference in sea ice thickness produced by Eq. 4 and 5 after sea ice thickness assimilation is seized in 4 months. The reason for this difference is that with K formulated as in Eq. 4, observation is considered to be underestimated (Observation error is added to the observation) making the model error larger than that of Eq. 5 formulation. Therefore, observation is weighted heavily with Eq. 4.

Sea ice thickness has increased near the pole and the Canadian basin compared to the model (fig. 3). The average sea ice thickness calculated from these two methods is closer to the independent sea ice thickness data set cryostat's values (fig. 3). Rise in sea ice thickness can be explained by the changes in sea ice velocity in the area. One of the reasons for ice-POM model to under predict sea ice thickness in the polar area is the over estimation in sea ice velocity in the area. However, with the introduction of satellite observations sea ice velocity in the Polar area has decreased (fig. 4), thereby it prevents advecting of sea ice away from the pole. This results in increased sea ice thickness in the Polar area.

Improved sea ice extent in the Barents Sea has led to improve ocean salinity in the area. Ice-POM model under predicts sea surface salinity in the Barents Sea, however assimilation removes sea ice in the Barents Sea in the winter (fig. 5). As a result freshwater in the Barents Sea is removed along with that. This increases sea surface salinity in the Barents Sea and along the marginal areas (fig. 6).

6. CONCLUSIONS

The nudging experiments have improved sea ice extent predictability of the model. Sea ice thickness is also improved in Polar area due to the improved sea ice velocity in the area. Sea ice extent is specifically improved in the Barents Sea resulting in improved sea surface salinity in the area.

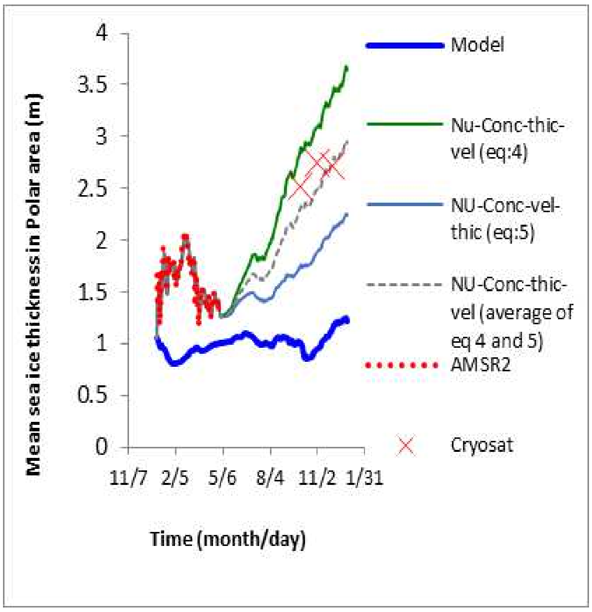

Fig. 3: Time series of mean sea ice thickness in polar area from nudging experiments using eq. 4 and 5, their average, model and AMSR2 observation

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Table 1: Satellite observation error data

	Sea ice concentration	Sea ice thickness	Sea ice velocity
summer $\sigma_{algorithm}$	0.1~0.2	Not used in summer	Not used in summer
winter $\sigma_{algorithm}$	0.01~0.08	15cm	Zonal = 1.46 cm/s Meridional=1.35cm/s
sea ice edge $\sigma_{algorithm}$	0.05~0.15	42cm	Zonal = 1.46 cm/s Meridional=1.35cm/s
summer $\sigma_{instrument}$	0.1	Not used in summer	Not used in summer
winter $\sigma_{instrument}$	0.025	3.75cm	Zonal and meridional =0.05cm/s
sea Ice edge $\sigma_{instrument}$	0.125	12.5cm	Zonal and meridional =1.875cm/s

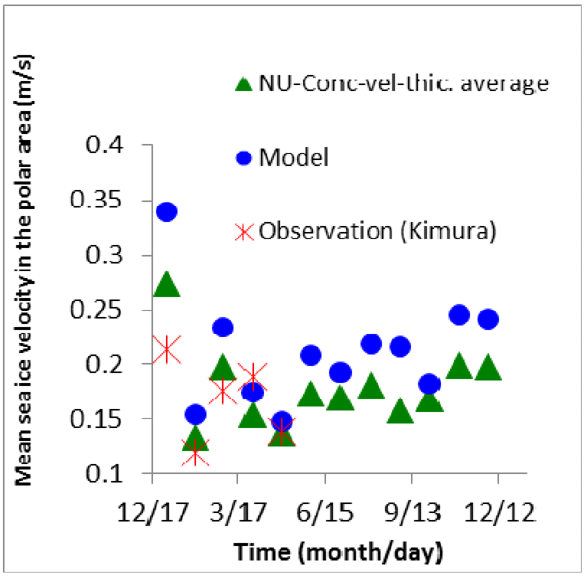

Fig. 4: Monthly averaged sea ice velocity in the polar area in (m/s) from the nudging assimilation average, model and observation

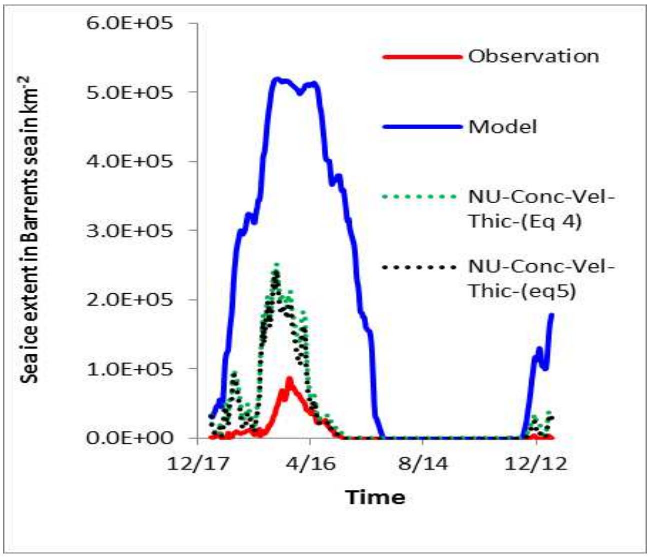

Fig. 5: Sea ice extent in Barents Sea from different methods, Eq. 4 and 5 methods, model and AMSR2 observations in 2013

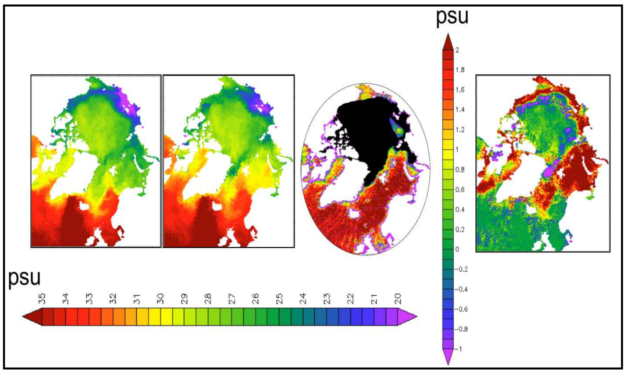

Fig. 6: from left sea surface salinity in psu of model, assimilation avg, Observation NSIDC(area in black is where there is no data), salinity difference (assimilation avg-model) respectively in September

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