Kalman filter based data assimilation system to improve numerical sea ice predictions in the Arctic Ocean

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***Abstract*—With the recent changes in the Arctic climate, increased transportation can be observed in the Arctic Ocean. For safe navigation along the Arctic Sea routes, it is important to accurately predict the ice conditions. In this study the ice-ocean coupled Ice-POM model is improved by a Kalman filter based data assimilation system. This system incorporates sea ice observation data such as sea ice concentration, sea ice thickness and sea ice velocity to improve the numerical predictions. Ocean part of the model is based on the Princeton Ocean Model while the Ice model considers the discrete characteristics of ice along the ice edge. In an ice-ocean coupled model, atmospheric forcing directly affects the accuracy of predictions. However, different atmospheric data sets produced by different weather agencies show large differences in the Arctic region. Model errors largely depend upon the inaccuracies in forcing data. This study uses an ensemble of multiple atmospheric data sets collected from different weather agencies and the spread of the ensemble is taken as an indicator of the model error covariance. The Observation errors were varied according to the location and the season. Assimilation has improved the predictions of sea ice variables. It has also indirectly improved the ocean conditions. This Atmospheric forcing based Kalman filter (AFKF) method outperforms other assimilation methods such as direct assimilation and nudging methods.**

***Index Terms*—Data assimilation, Arctic Sea Routes, Sea ice prediction, Satellite sea ice observations**

I. Model Description

The ice dynamic model in Ice-POM considers the ice discrete characteristics along the ice edge area. The ice thermodynamic model is a zero-layer model with snow-cover effect taken into account [1]. The ocean part of Ice-POM is based on Princeton Ocean Model (POM) [2]. The model domain is a z-sigma-coordinate, three-dimensional model with spatial resolution of 25km for the whole Arctic domain and 2.5km for the regional models (Figure 1) . The atmospheric forcing data were obtained from ERA-interim six hourly products. Polar science center Hydrographic Climatology data is used to set the boundary conditions for ocean salinity and temperature. First, the model is spun up for 12 years by providing the year 1979 atmospheric data cyclically. Entire model domain reaches a steady state 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 extent minimums in 1996, 2007, and 2012 [3].

For data assimilation experiments, year 2013 is selected. The model behavior in the year 2013 shows that the overall sea ice extent in the year 2013 is overestimated [4]. One of the reasons for discrepancies between the model sea ice extent and the observation sea ice extent is the imperfections in ocean boundary conditions. PHC data set provides climatology data which is lower in temperature than the warming temperatures in the Atlantic Ocean. Sea ice thickness in the model is underestimated near the North Pole compared to observation due to the overestimation of sea ice velocity in the same area that advects sea ice away from the North Pole. Since ocean boundary conditions and initial data are set by the Polar science center Hydrographic Climatology data, the model underpredicts both sea surface salinity and sea surface temperature.

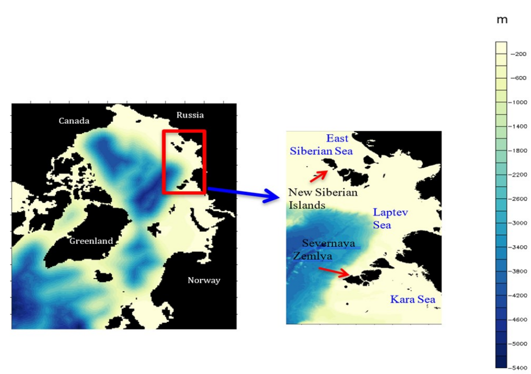

Fig. 1. (a)whole Arctic domain(left) and (b) regional model(right)

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II. Data Assimilation Technique

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. Daily sea ice thickness is calculated using an algorithm [5] based on AMSR-2 satellite data. Sea ice velocity data set is extracted from KIMURA Sea ice velocity data set [6]. 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.

The timespan of data assimilation experiment is set to year 2013. In an ice-ocean coupled model, atmospheric forcing directly affects the accuracy of predictions. Especially, precipitation data directly relates to the sea ice formulation process. However, different atmospheric data sets including reanalysis data sets show large differences in the Arctic region. In a study that evaluates seven atmospheric products over the Arctic, shows that there are large variations in atmospheric data sets in Arctic [7]. According to the study, different products show large variations in sea level pressure over Greenland. Wind speed shows variations in most parts of Arctic Ocean. Precipitation data also varies over North Atlantic and North Pacific Ocean. In this study an ensemble of multiple atmospheric data sets is considered, and the spread of the ensemble is proportional to the uncertainties in model prediction. Hence this spread is taken as an indicator of the model error variance.

Model error covariance matrix P_e^f in ensemble Kalman filter is defined in terms of the true state as

$$P_e^f = \overline{(\psi^f - \psi^t)(\psi^f - \psi^t)^T} \tag{1}$$

where ψ^f is model forecast and ψ^t is the true state [8]. Ensemble numerical predictions are widely used recently due to their better predictability skills compared to single computations. These ensemble predictions are performed using different atmospheric forcing data sets or by differentiating initial conditions [9]. Model errors largely depend upon the inaccuracies in forcing data. In a computation that uses ensemble of multiple atmospheric data sets, the spread of the ensemble is proportional to the uncertainties in model prediction. Hence this spread could be an indicator of the model error variance. In atmospheric forcing Kalman filter(AFKF) method an ensemble of multiple atmospheric data is used. Since there are significant differences in the atmospheric data sets, the true state is assumed to be the mean of the ensemble prediction. Therefore, the true state is considered to be $\overline{\psi^f}$, the ensemble mean of the prognostic variable. In each ensemble member, the model is forced using different atmospheric forecast data from seven atmospheric agencies. The equation 1 is revised as below to use ensemble mean as the truth.

$$P_e^f = \overline{(\psi^f - \overline{\psi^f})(\psi^f - \overline{\psi^f})^T} \tag{2}$$

$$K_e = P_e^f H^T (H P_e^f H^T + R)^{-1} \tag{3}$$

$$\psi_i^a = \psi_i^f + K_e(d - H\psi_i^f) \tag{4}$$

$$P_e^a = (I - K_e H) P_e^f \tag{5}$$

Observation variance is varied according to the season and the location where the values in the sea ice edge are different from that of the ice pack. 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 3. In this study ψ_i^f is model forecast of the ensemble member i ϵ {1,2...N}. H is a linear operator that transfers the model state to the observation space. K_e is the Kalman gain, which is given in equation 3. The updated state estimate (ψ_i^a) is given in equation 4, where d is observation. Analyzed model state covariance (P_e^a) is given in equation 5. The method used is inspired by the Ensemble Kalman filter method [8]. However, the key difference between the two methods is that in this study the ensemble is formulated by using different atmospheric data sets, instead of observation perturbation that is often used in ensemble Kalman filter method. Even though the error variance is assumed to be non-correlated the impact of non-correlated variables are considered through corrections. It prevents the discrepancies between assimilated and non-assimilated variables.

The whole Arctic model with 25km resolution cannot be used to investigate the fine details of sea ice dynamics such as ice edge positions and extents accurately for applications such as navigation in ASRs. Therefore, regional models are required for those applications. Figure 1(b) consists of the area with 50E:165E longitude and 68N:85.5N latitudes. The region consists of Laptev Sea, part of Kara and East Siberian Seas.

The basic mechanisms of the model used in these high-resolution computations are same as those used in whole Arctic computation. The resolution of zonal and meridional directions are set to be 2.5km2.5km in horizontal plane and 33 sigma layers in the vertical direction. Initial ice, ocean conditions and boundary conditions are given by the output of the whole Arctic AFKF assimilation run. Regional model run

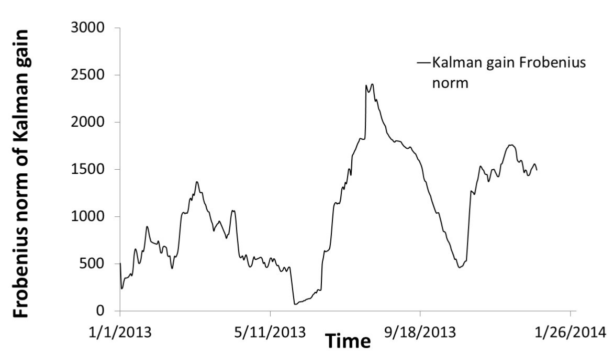

Fig. 2. Time series of Frobenius norm of the Kalman gain matrix for AFKF experiment sea ice concentration

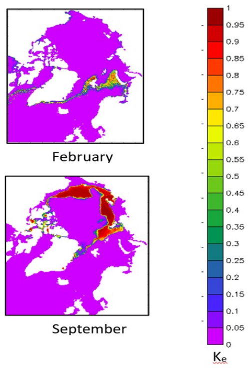

Fig. 3. Diagonal components of Kalman gain matrix of AFKF experiment sea ice concentration. (a)02/2013(top) (b)09/2013 (bottom)

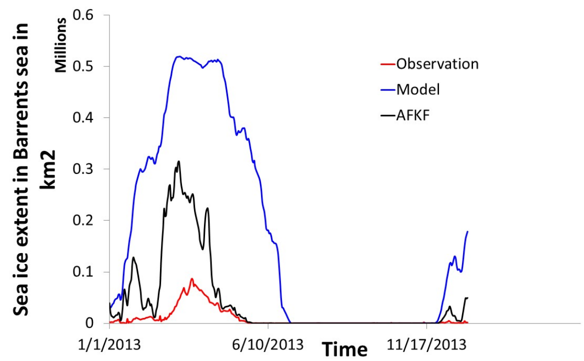

Fig. 4. Time series of sea ice extent in Barents sea from AMSR2 observations, model run and AFKF assimilation run

starts at the end of August (28th August 2013) and runs until the end of freezing season (November 2013).

III. Results and Discussion

Figure 2 presents the magnitude of the Kalman gain matrix when sea ice concentration is assimilated. It is presented as the Frobenius norm. Frobenius norm is calculated to be the trace of the squared of the diagonal components of the Kalman gain matrix. It is an indication of the model error. Model error grows gradually in winter and the freezing season. Model error is a maximum in summer where the uncertainty of the forcing data is high.

Figure 3 presents the structure of the Kalman gain matrix. The Kalman gain is an indication of how model error and the observation error are reflected in the assimilation. In winter, assimilation has the strongest impact on sea ice edge. Due to similarity between observation and model in ice pack, in winter, assimilation has very little impact on sea ice concentration in the ice pack.

In summer uncertainty of forcing data is high, especially along the sea ice edge, increasing the model error along the sea ice edge. This is reflected in the Kalman gain in figure 3 (b) where observations are weighted along the sea ice edge. Due to similarities in model and observations in the ice pack, assimilation has little impact on sea ice concentration of the ice pack.

Figure 4 compares sea ice extent in the Barents sea where there is marginal sea ice. It can be observed that the sea ice extent has improved compared to that of the model. It should be noted that the AMSR2 observations also contains errors. This is reflected in atmospheric forcing Kalman filter method where sea ice extent is not too close and not too far from the observation.

Model under estimates sea ice thickness in the polar area compared to the Cryosat data set. This is improved with the assimilation run. Figure 5 presents the root mean squared difference(RMSD) between the assimilation and the cryostat data from October 2013 to December 2013 in the same area. While nudging methods show a growth in RMSD, atmospheric forcing Kalman filter method shows a decline. It can be seen that the sea ice thickness hasnt grown abnormally in atmospheric forcing Kalman filter method. The reason for this sea ice thickness rise is the improved sea ice velocity in the Polar area as presented in figure 6. Sea ice velocity has decreased in the area increasing sea ice thickness. Changes in salinity are observed as a result of assimilation experiments. This is specifically highlighted in the areas where there is a significant sea ice extent difference between the model and the assimilation

There are two possible reasons for the rise in sea surface salinity(SSS). When the sea ice is removed as a correction done by assimilation, freshwater is being removed as a result. This is the reason where the salinity difference is highlighted in areas like Barents Sea where there are disparities between model sea ice extent and AMSR2 sea ice extent.

For the same reason the SSS bias becomes a maximum in summer according to figure 7. In the model with no assimilation, sea ice melts in summer and therefore sea surface salinity is low in summer but in the assimilation there is no ice to melt hence the bias is larger in summer. Another reason for the rise in SSS is evaporation. When there is open ocean, surface albedo is about 0.06 where in sea ice the value can vary between 0.5-07. Therefore, more heat is absorbed by the ocean

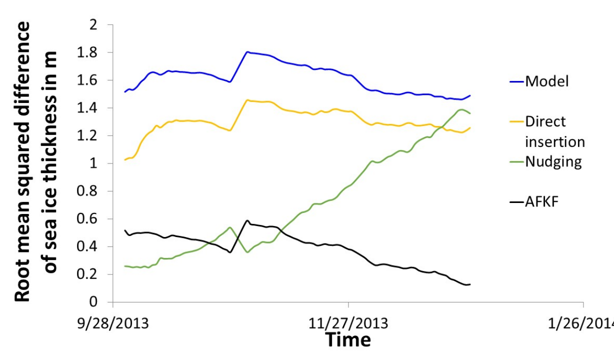

Fig. 5. Time series of the root mean squared difference(RMSD) between different methods and independent cryostat data

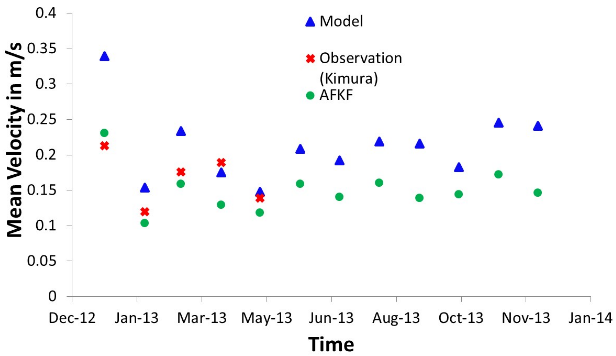

Fig. 6. Time series of mean sea ice velocity in polar area

and freshwater is evaporated increasing the salinity in those areas. Effect of salinity extends beyond the surface vertically due to the corrections that are done to inner ocean

To validate the assimilation experiment, the regional model was run in summer extracting the initial and boundary conditions from the AFKF whole Arctic model assimilation. One of the issues mentioned in [1] is that the regional model is not creating adequate ice in the freezing season. However According to figure 8 its clear that the regional model initialized by whole Arctic AFKF assimilation can reproduce sea ice extent that is in line with observations both in melting and freezing seasons. According to [1], the maximum bias between regional model and AMSR-2 observation is about 0.4 million square kms however, the maximum bias from the regional model figure 8 is about 0.13 million square kms in the freezing season

IV. Conclusions

Sea ice concentration, sea ice thickness and sea ice velocity are assimilated in the study. Assimilating sea ice variables improved ocean and ice conditions as expected. It is evident from the changes in sea ice extent, sea ice thickness, ocean temperature and ocean salinity. Non-assimilated sea ice variables have also been indirectly improved by assimilation. Improvements in sea ice variables are emphasized in the Barents Sea and near the pole. Sea ice thickness is improved near the pole as a result of decreased sea ice velocity near the pole. Sea ice extent is improved in the whole domain with assimilation

It can be observed that sea surface salinity is altered in the places where sea ice concentration is improved. This is a result of correcting sea ice extent in over predicted areas where freshwater is being removed from the model and increased evaporation in open ocean areas. Sea surface temperature has also improved as a result of improved sea ice extent.

The whole Arctic assimilation run is used to initialize regional model with 2.5km resolution. Regional model initialized by the whole Arctic AFKF assimilation can reproduce sea ice extent that is in line with observations. Specifically, accuracy has been improved in the freezing season. Regional model assimilation has further improved the prediction of the ice extent.

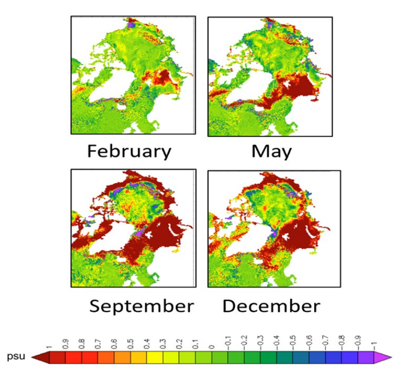

Fig. 7. Sea surface salinity bias(AFKF assimilation SSS-model SSS) in different months

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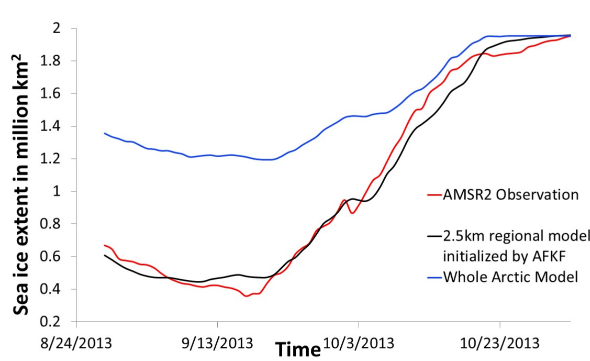

Fig. 8. Time series of sea ice extent in regional model run

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