· Article ·

Advances in Polar Science

doi: 10.3724/SP.J.1085.2013.00258

December 2013 Vol. 24 No. 4: 258-264

Ice concentration assimilation in a regional ice-ocean coupled model and its application in sea ice forecasting

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Received 6 August 2013； accepted 24 October 2013

Abstract A reasonable initial state of ice concentration is essential for accurate short-term forecasts of sea ice using ice-ocean coupled models. In this study, sea ice concentration data are assimilated into an operational ice forecast system based on a combined optimal interpolation and nudging scheme. The scheme produces a modeled sea ice concentration at every time step, based on the difference between observational and forecast data and on the ratio of observational error to modeled error. The impact and the effectiveness of data assimilation are investigated. Significant improvements to predictions of sea ice extent were obtained through the assimilation of ice concentration, and minor improvements through the adjustment of the upper ocean properties. The assimilation of ice thickness data did not significantly improve predictions. Forecast experiments show that the forecast accuracy is higher in summer, and that the errors on five-day forecasts occur mainly around the marginal ice zone.

Keywords **ice concentration assimilation, combined optimal interpolation and nudging, sea ice forecast, skills core**

Citation: Li Q, Zhang Z H, Sun L, et al. Ice concentration assimilation in a regional ice-ocean coupled model and its application in sea ice forecasting. Adv Polar Sci, 2013, 24:258-264, doi: 10.3724/SP.J.1085.2013.00258

1 Introduction

Satellite data regarding sea ice concentration have revealed the accelerated decline of the Arctic sea ice, especially in recent decades. The negative trend has reached a peak of ~10% per decade, which is about 4 times that of the period 1979–1996[1]. A decline in the multiyear ice extent and area has also been observed[2]. In addition to its indicative role in global climate change, the potential opening of the Arctic Route has spurred increasing interest in the forecasting and prediction of Arctic sea ice[3]. However, observational records of sea ice have a limited history, and cannot be used to reliably predict future sea ice extent. The application of numerical ice-ocean models enables the reconstruction of historical patterns of sea ice, and the ability to forecast and predict future change. However, forecasts of sea ice variation based solely on the coupled model can be limited[4]. A better option is to combine the ice-ocean model and observational data to improve sea ice state estimates and forecasts using data assimilation techniques. These methods can be used for process studies, or to obtain the best possible information on the initial sea ice state for sea ice forecasts[5].

Different assimilation methods have been applied in coupled ice-ocean models, assimilating ice concentration[6-8], and drift[9]. However, when data assimilation is used in an operational application, the efficiency of computation should be a priority. In this paper, we introduce the assimilation of ice concentration into an operational ice forecast system, based on a combined optimal interpolation and nudging method. The method was first introduced into the operational ice forecast system at the Norway Meteorological Institute by Wang et al.[8], and preliminary applications have shown positive results in terms of efficiency and accuracy.

In forecast systems, forecast skill scores have been widely used to evaluate system performance. Murphy introduced the use of the mean-square error as a measure of accuracy and discussed the nuances of using various defini-

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tions of the reference state[10]. He also showed that the critical element of forecast verification is the selection of the reference value. Here we choose the daily observation data of the corresponding time as a reference state for skill score calculation and conduct a preliminary evaluation of the forecast system's performance.

The model configuration is presented in Section 2 and followed by the introduction of the assimilation and evaluation method in Section 3. Section 4 outlines the analysis of the model results and forecast ability evaluation, and discussion and conclusions are presented in Section 5.

2 Model configuration

The coupled ice-ocean model developed for this study is under the framework of the Estimating the Circulation and Climate of the Ocean, Phase II (ECCO2) program[11]. The ocean component is based on the MIT ocean general circulation model (MITgcm), which employs fluid isomorphisms and can be used to simulate both atmospheric and oceanic flow[12]. A dynamic-thermodynamic sea ice model has been coupled into the MITgcm. The dynamic part is based on viscous-rheology[13], with the traditional zero-layer is adopted as the thermodynamic default[14]. However, Zhang and Rothroch revealed that the zero-layer model tends to exaggerate the seasonal variability of the sea ice thickness because there is no consideration of the sea ice heat capacity[15]. This shortcoming can be significantly reduced by employing the three-layer thermodynamic module from Semtner, which accounts for the storage of heat in the sea ice[16]. Winton reformulated this three-layer module and improved the model physics by representation of the brine content of the upper layer ice with a variable heat capacity[17]. We incorporated this reformulated thermodynamic module, with snow cover accounting for the flooding process, into the MITgcm. The sea ice-ocean model is dynamically coupled via exchange of momentum, heat, and buoyancy between models at set coupling time intervals[18]. This framework has been used as the operational Arctic sea ice forecast system at the National Marine Environmental Forecasting Center (NMEFC) in Beijing, China[19].

In our configuration, the ocean and sea ice models share the same grid, a curvilinear-orthogonal grid derived from the global cube-sphere grid, with a resolution of ~18 km. The model covers most regions north of 55°N and includes the entire Arctic Ocean. It has been used in a wide variety of studies including Arctic sea ice forecasts in China[19]. The forecast system was based on the direct insertion of the initial ice concentration, which has potential inconsistency and stability problems. In this study we implement ice concentration assimilation based on a combined optimal interpolation and nudging scheme, which can provide a more consistent initial state for short-term sea ice forecasts or seasonal predictions[8]. The model is forced by the JRA-25 reanalysis data, as outlined in Nguyen et al. [20]. The reanalysis data have been greatly improved for the Arctic region and have a higher spatial resolution, which further improves the performance of the ice-ocean coupled model used here. The model is integrated from 1992–2010, and the ice concentration is assimilated from 1 January 2006.

3 Assimilation scheme and evaluation method

3.1 Assimilation scheme

The assimilation method used here is the combined optimal interpolation and nudging scheme. At each time step, the model estimate C_{mod} is combined with a revised estimate $\hat{C}_{\mathrm{mod}}$ based on the relationship:

$$\hat{C}_{\mathrm{mod}} = C_{\mathrm{mod}} + G(G_{\mathrm{obs}} - C_{\mathrm{mod}}), \quad (1)$$

where G is the nudging coefficient and C_{obs} is the observed ice concentration. The nudging coefficient is expressed as:

$$G = \frac{K}{\tau}, \quad (2)$$

where K is the weighting coefficient of the optimal interpolation for combining two estimations of the same quantity[21]:

$$K = \frac{\sigma_{\mathrm{m}}^2}{\sigma_{\mathrm{m}}^2 + \sigma_{\mathrm{o}}^2}, \quad (3)$$

where σ_{m}^2 and σ_{o}^2 are the standard deviations for modeled and observational data, respectively. The standard deviation σ_{m}^2 is approximated by $\sigma_{\mathrm{m}}^2 = |C_{\mathrm{mod}} - C_{\mathrm{obs}}|^2$ and σ_{o}^2 is the error variance of the observational data. To improve the efficiency of the sea ice data assimilation, a better understanding of the errors in observational data is necessary[7-8]. Because of the practical difficulties in quantifying the errors in sea ice concentration measurements, a fixed value of $\sigma_{\mathrm{o}} = 0.05$ is used.

Finally, the nudging time scale τ is chosen to be:

$$\tau = \tau_0 \exp[2.5(C_{\mathrm{mod}} + C_{\mathrm{obs}})], \quad (4)$$

where τ_0 is the homogeneous time scale, and the exponential component denotes the temporal and spatial variation of the time scale. Eq. (4) indicates that τ changes temporally and spatially during the entire assimilation period. The exponential component is a parameterization of the temporal and spatial variation in the nudging time scale. Numerical experiments show that this time scale formulation behaves better than using a constant value[8].

The modeled mean sea ice thickness and snow thickness are adjusted to be consistent with the sea ice concentration. For areas of non-zero modeled mean sea ice thickness, the effective sea ice thickness (mean sea ice thickness/sea ice concentration) and snow thickness (mean snow thickness/sea ice concentration) are assumed to remain unchanged.

3.2 Methods of forecast skill assessment

The forecast skill score is a scaled representation of forecast error that relates the forecast accuracy of a particular forecast model to a reference simulation[10], and can be written as:

$$\mathrm{SS} = 1 - \frac{\mathrm{MSE}_f}{\mathrm{MSE}_r}, \tag{5}$$

where the MSE_f (forecast mean square error) is defined as:

$$\mathrm{MSE}_f = \frac{1}{N}\sum_{i=1}^{N}(f_i - O_i)^2, \tag{6}$$

in which f_i and O_i are the i^{th} forecast and observation, respectively. Correspondingly, the forecast value f_i is replaced with the mean observation values for the corresponding times in the definition of MSE_r in Eq. (6), such that:

$$\mathrm{MSE}_r = \frac{1}{N}\sum_{i=1}^{N}(\bar{O} - O_i)^2. \tag{7}$$

The mean observation data at the corresponding time are defined as:

$$\bar{O} = \frac{1}{N}\sum_{i=1}^{N}O_i. \tag{8}$$

A forecast skill of 1 indicates a perfect forecast, with a negative score indicating the forecast is less accurate than the reference experiment.

4 Analysis of results

4.1 Sea ice area

A good understanding of the seasonal cycle of sea ice variation and sufficient remote sensing data regarding sea ice extent are important for accurate short-term sea ice forecasts. The most convenient parameter to validate the model performance is sea ice concentration.

The time series data for sea ice area presented in Figure 1 compares the performance of different model setups. Sea ice areas derived from observational and modeled results show similar behavior. In the free-run mode, the model is better at accurately capturing the freezing process than the melting process. For the melt season, the model overestimates the rate of sea ice melting from June, and underestimates the minimum sea ice area as compared to observations. Most of this bias is a result of the lower concentration of the entire ice pack in the numerical model. With the assimilation of sea ice concentration data, the modeled seasonal cycle of sea ice variation is more consistent with the observed cycle, especially in the summer. However, there is still a slight difference during the month of rapid melting. As pointed out by Lindsay and Zhang[7], the difference is not zero because the observational data are not heavily weighted. However, reasonable performance of the model-only simulation, without the benefit of assimilation, is a precondition for improved results from assimilation, since data assimilation is not appropriate for correcting very large model errors. For example, in the summer season, if the sea ice is melting rapidly, heat could be stored in the upper ocean inducing higher sea surface temperatures, and it could be difficult to maintain the accuracy of sea ice modeling using assimilation.

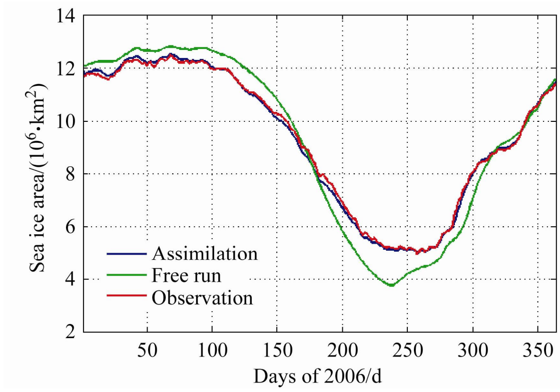

Figure 1 Daily sea ice area of the Arctic Ocean in 2006 (area is defined as the product of ice concentration and grid area).

4.2 Sea ice thickness

Sea ice thickness is an important parameter to characterize sea ice properties. Submarine data were widely used before the application of remote sensing techniques, though most of the observations were carried out in the late spring[22-23]. In recent years, it has been proved that the retrieval of sea ice freeboard and thickness data from the laser altimeter on the Ice, Cloud and land Elevation Satellite (ICEsat) is feasible. Basin-wide ice thickness estimates from ten ICEsat campaigns have been produced and the comparison with the submarine and moored profiling data showed these data to be consistent and of good quality[24]. The advantage of the ICESat data is that they capture the large-scale pattern of sea ice thickness distribution, which provides the opportunity to assess the ability of the model to reproduce the spatial pattern of Arctic ice thickness. Difference maps are also computed for each ICESat campaign in 2006. The overall pattern of the observed and modeled basin-wide sea ice thickness distribution is very consistent. Pattern correlations are high, with R^2 values of 0.79 (FM06, Figures 2a–2b), 0.88 (MJ06, Figures 2c–2d), and 0.85 (ON06, Figures 2e–2f), and the general pattern seen is similar to previous studies[7,24-25]. The thickest ice is mainly situated along the northern coast of Greenland and in the Canadian Archipelago (Figures 2a, 2c and 2e). However, compared with the ICESat observational data, the modeled ice thicknesses are smaller, and the meridional gradients are smoother. The difference maps show that the model overestimates the sea ice thickness in most of the Pacific sector of the Arctic Ocean and in regions close to the Siberian coast, but underestimates thickness in the multiyear ice region along the northern coast of Greenland and the west coast of Greenland in winter. Lindsay and Zhang[7] and Mathiot et al.[5] reported similar findings. Even when the ice velocity field is also assimilated[7], the spatial pattern of the model bias still exists. Lindsay and Zhang[7] proposed that there might be some large-scale error in either the thermodynamic or dynamic process components of current sea ice models. It should be noted that there was successful capture of the large polynya around the Northwind Ridge, present in the summer of 2006, in the ice thickness field (Figure 2), which implies that the prediction of ice thickness using ice concentration data assimilation is feasible.

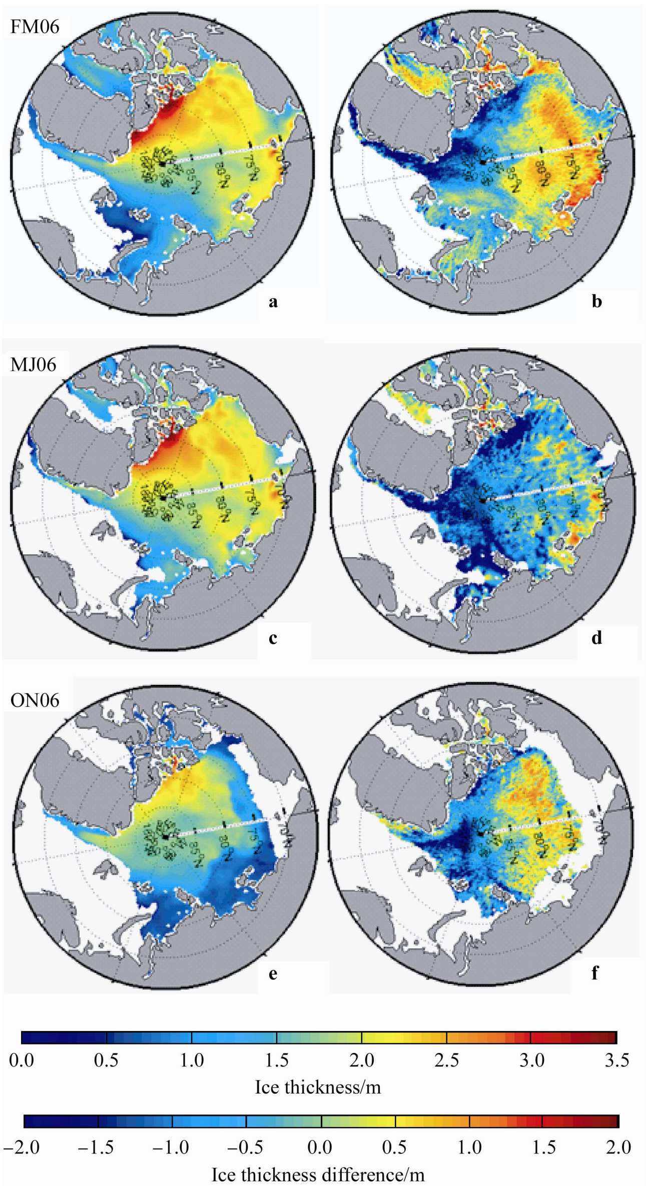

Figure 2 Modeled ice thickness distribution (Figures 2**a**, 2**c** and 2**e**) for three data periods corresponding to the data campaign in 2006, and the differences between modeled and observational data (Figures 2**b**, 2**d** and 2**f**). FM06:22 Feb to 27 Mar; MJ06:24 May to 26 Jun; and ON06:25 Oct to 27 Nov. The model data are averaged for the same period and interpolated onto the observational grid.

It is important to stress that there are also uncertainties in the observational data on sea ice thickness. Uncertainty for the Arctic Ocean average sea ice thickness from observations is estimated by Kwok and Rothrock[24] to be ~30 cm. Other ice thickness data sets also contain uncertainties and bias[23, 25]. At present we cannot determine whether this is a result of deficiencies in the model or deficiencies in the observations. A thorough evaluation of modeled thickness with respect to observations is not possible at this time because of the sparseness and uncertainty of sea ice thickness observations.

4.3 Impact of sea ice concentration assimilation on the ocean state

Because the ice and ocean properties are physically coupled in the model, the adjustment of sea ice concentration during the assimilation step will have a great impact on the ocean state directly below and adjacent to the ice. To ensure the validity of the numerical forecast model and the assimilation method, consistent adjustment of related variables during the analysis updates should be guaranteed. In the current implementation, no artificial adjustment is applied to the ocean variables, but dynamic adaptation is allowed, and the results show that the simulated field is reasonable.

An example from the model results showing the difference in sea surface temperature (SST) (Figures 3c–3d) and sea surface salinity (SSS) (Figures 3e–3f), along with the ice concentration difference (Figures 3a–3b), is shown in Figure 3 for two different dates, one in summer (15 Sept, left column) and one in winter (15 Mar, right column). It should be noted that the ice concentration difference is the daily average, while the SST and SSS difference fields reflect cumulative effects of the assimilation.

From the difference field, it can be seen that the assimilation of ice concentration has a visible effect on the upper ocean variables. The assimilation of ice concentration mainly affects the ice edge region, and in the winter, most of the difference is seen in the Atlantic sector. Sea ice concentration along the west coast of Greenland is too wide in the model-only simulation, but its southward extension is less than the observations and assimilation results. This could further influence deep convection for long-term integration in the Labrador Sea. Sea ice concentration in the northern Barents Sea and the Labrador Sea are also overestimated in the model-only run. This difference is also reflected in the SST and SSS fields, more ice induces lower surface temperatures around the sea ice edge region in the Atlantic sector. Around Iceland, too much ice induces lower SSS, which also implies that the ice here is mainly advected from the north, not locally generated by thermodynamic growth.

Compared with the winter, the differences in summer are more significant and the assimilation of ice concentration also mainly affects the results regarding the marginal ice zone (Figure 3a). The model-only simulation underestimates the sea ice concentration in most of the marginal ice zone, except around the Svalbard coast. Of interest is the presence of a large polynya around the Northwind Ridge region of the Beaufort Sea in 2006, which is not captured by the model-only run. This could be because of the low resolution of the atmospheric reanalysis forcing field. However, in the assimilation experiment, the polynya is captured, not only in the ice concentration field, but also in the ice thickness field. The SST difference field is negatively correlated because the slowed sea ice melting in the summer season (Figure 1) delays and reduces the absorption of heat input from the atmosphere. The SSS difference also reflects the slowed sea ice melting out of the marginal ice zone. The sea ice melting is stronger in the previous day compared to the model-only run, which reduces the SSS. This pattern is positively correlated with the SST change. However, inside the ice pack in the summer, the SSS difference is also significant. This is a result of the overestimation of the sea ice melting in the model-only run, in which sea ice concentration is lower than the observational and assimilation simulations, and which induces more ice melting inside the ice pack and lower surface salinity.

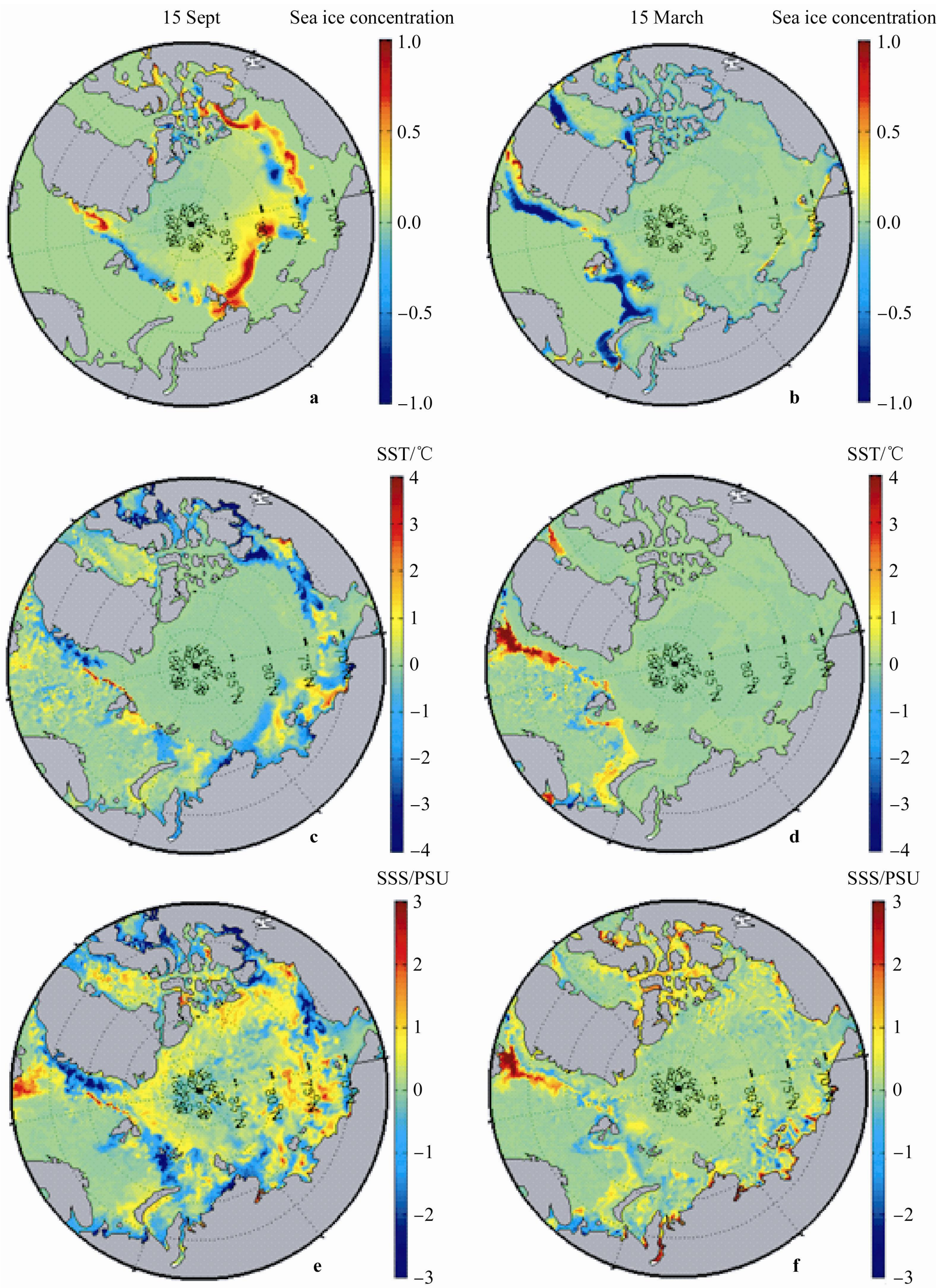

Figure 3 Effect of the assimilation on sea ice concentration (**a**–**b**), sea surface temperature (**c**–**d**, SST, Units: ℃), and sea surface salinity (**e**–**f**, SSS, Units: PSU).

4.4 Forecast experiment

Short-term sea ice forecasts mainly focus on short time scales of 5–7 d. For example, the U.S. Navy Global Atmospheric Prediction System (NOGAPS) offers a 120-hour forecast of sea ice concentration, drift, and thickness[26]. In this experiment, the assimilation scheme is applied at the initialization of the sea ice forecast system. The forcing fields are the same as in the previous experiment but the difference is that the ice concentration assimilation is closed when the forecast starts. Four groups of forecast experiments were carried out and each ran for 20 d.

The development of skill as defined in Eq. (5) is depicted in Figure 4 for the 20 d of the forecast runs. Different markers distinguish the different forecast experiments at four times of the year in 2010. The higher skill values of the assimilation experiment relative to the forecast without data assimilation clearly show the improvement that results from the data assimilation procedure. The numerical model with data assimilation reproduces sea ice conditions in very close agreement with remote sensing data. The experiment without data assimilation shows consistently lower skill values throughout the forecast period. However, the skill values for the assimilated model run decrease with time because the positive influence of the assimilated observation decreases with time. In addition, the modeled sea ice forecast is also dependent on the atmospheric forecast conditions, which are also subject to increasing errors with time.

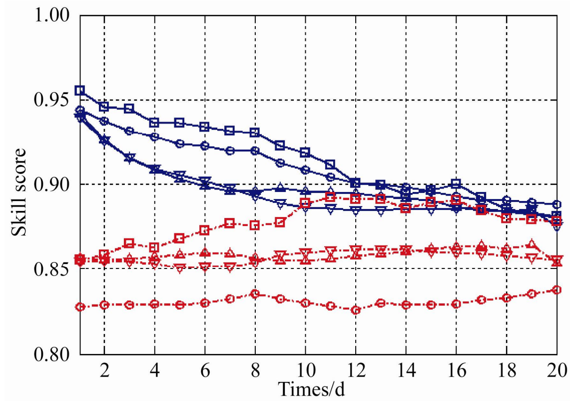

Figure 4 Skill scores relative to the reference simulation for the forecast experiment (blue) and the free run (red). The bold solid and dashed lines with squares denote the 15 Aug forecast and free-run skill scores, respectively. The solid and dashed lines with circles denote the 15 Sept forecast and free-run skill scores, respectively. The lines with triangles are the winter experiments.

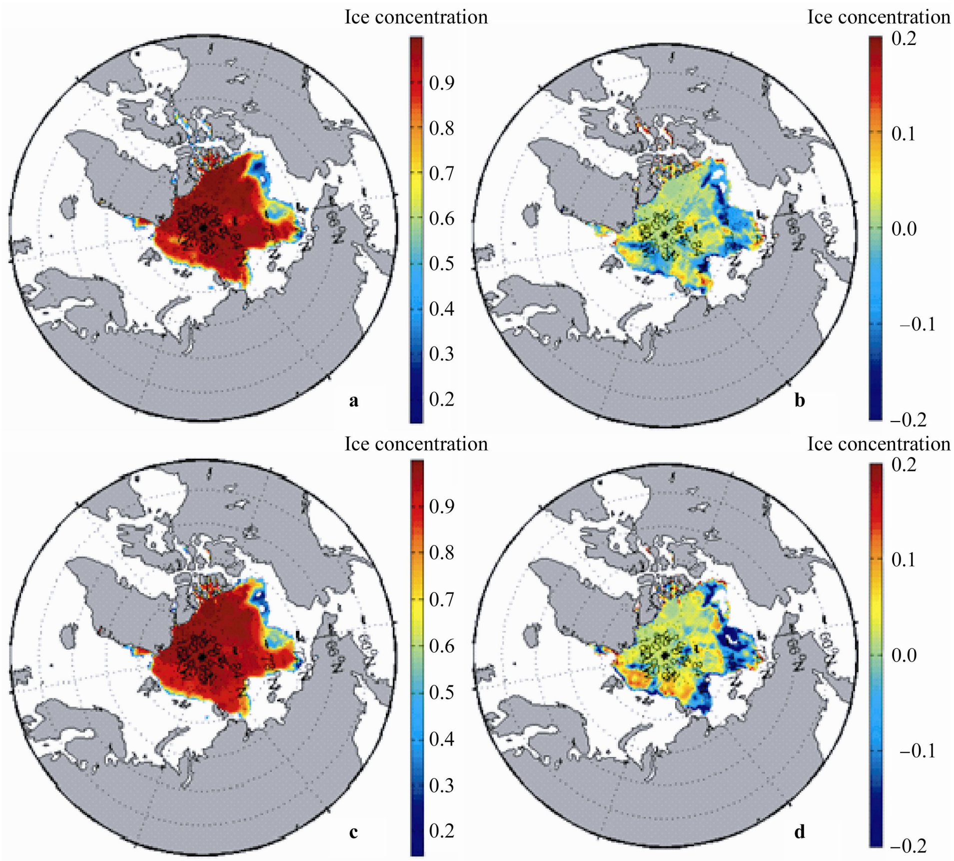

Figure 5 Spatial characteristics of the forecast ice concentration from 15 Sept, and the difference between modeled and observational data. Day 1 forecast result (**a**) and the difference field (**b**), Day 5 forecast result (**c**) and the difference field (**d**).

The model performance has been improved significantly through the optimization of the parameters related ice-ocean processes in the Arctic region, and so can give a more reasonable simulation/forecast field even without assimilation. Improved reference data gives a higher skill score than the climatology reference.

The sea ice concentrations predicted by the model and the difference between modeled and observational data for Days 1 and 5 of the forecast experiment are shown in Figure 5. It can be seen that the model captures most of the characteristics of the sea ice distribution and variation. Most of the variance occurs at the marginal ice zone, where sea ice variations occur rapidly, especially in the western Arctic Ocean. Overall, the sea ice concentration field becomes smoother with forecast time, which could be a result of the low resolution of the forcing field.

5 Summary and conclusions

A reliable and consistent analysis of the initial sea ice state is essential for short-term forecasts of sea ice conditions. Using a combined optimal interpolation and nudging technique, satellite sea ice concentration data were assimilated into a regional ice-ocean coupled model. This improved the explained variance between model prediction and observation. During the assimilation process, only ice thickness is tuned corresponding to the ice concentration updates. Other prognostic variables can only be changed through dynamical coupling of the model system. Results revealed that the response of the main upper ocean properties is acceptable.

With application of the best possible analysis of sea ice concentration and the optimal forcing conditions in the numerical model, a forecast of sea ice conditions for 5–10 d produces realistic results. This study shows that the model simulates sea ice conditions with reasonable accuracy. However, data assimilation techniques require careful consideration of physically coupled variables. At present, ice concentration is the most accessible sea ice parameter, since it can be monitored from satellites, and improved algorithms allow for a realistic estimation of sea ice concentration from these remote sensing data.

Acknowledgements This work was supported by the National Natural Science Foundation of China (Grant nos. 40906099, 40930848), the National Science and Technology Supporting Program of China (Grant no. 2011BAC 03B02-03-02); and the Ocean Public Welfare Scientific Research Project of China (Grant no. 2012418007).

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