Ocean Modelling 93 (2015) 22–39

Contents lists available at ScienceDirect

Ocean Modelling

journal homepage: www.elsevier.com/locate/ocemod

Assimilation of sea surface temperature, sea ice concentration and sea ice drift in a model of the Southern Ocean

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ARTICLE INFO

Article history:
Received 17 December 2014
Revised 8 July 2015
Accepted 14 July 2015
Available online 29 July 2015

Keywords:
Ensemble Kalman filter
Data assimilation
Sea ice drift
Model output statistics
Southern ocean

ABSTRACT

Current ocean models have relatively large errors and biases in the Southern Ocean. The aim of this study is to provide a reanalysis from 1985 to 2006 assimilating sea surface temperature, sea ice concentration and sea ice drift. In the following it is also shown how surface winds in the Southern Ocean can be improved using sea ice drift estimated from infrared radiometers. Such satellite observations are available since the late seventies and have the potential to improve the wind forcing before more direct measurements of winds over the ocean are available using scatterometry in the late nineties. The model results are compared to the assimilated data and to independent measurements (the World Ocean Database 2009 and the mean dynamic topography based on observations). The overall improvement of the assimilation is quantified, in particular the impact of the assimilation on the representation of the polar front is discussed. Finally a method to identify model errors in the Antarctic sea ice area is proposed based on Model Output Statistics techniques using a series of potential predictors. This approach provides new directions for model improvements.

1. Introduction

Observations of the sea ice extent in the Southern Ocean derived from satellite data display a trend of 0.13 to 0.2 million km^2 per decade between November 1978 and December 2012 (Vaughan et al., 2013). Although the magnitude of this trend is subject to uncertainties (e.g., Eisenman et al., 2014), the behavior of the Antarctic sea ice cover is in sharp contrast with its Arctic counterpart which displays a decrease in sea ice extent over the last decades (e.g., Turner and Overland, 2009). Several explanations have been proposed to account for the slight increase in Antarctic sea ice extent but no consensus has been reached yet. Among the proposed mechanisms, a potential link with the stratospheric ozone depletion has been pointed out (Solomon, 1999) but this hypothesis is not compatible with recent analyses (e.g., Bitz and Polvani, 2012; Smith et al., 2012; Sigmond and Fyfe, 2013). Changes in the atmospheric circulation or in the ocean stratification may also have contributed to the observed expansion of the sea ice cover (e.g., Zhang, 2007; Stammerjohn et al., 2008; Goosse et al., 2009; Kirkman and Bitz, 2011; Landrum et al., 2012; Holland and Kwok, 2012; Bintanja et al., 2013; Goosse and Zunz, 2014; de Lavergne et al., 2014). The internal variability of the system, particularly strong in the Southern Ocean, may be responsible for the observed positive trend in Antarctic sea ice extent as well (e.g., Mahlstein et al., 2013; Zunz et al., 2013; Polvani and Smith, 2013; Swart and Fyfe, 2013).

Observations in the Southern Ocean are rather sparse in space and time. In particular, reliable observations of the sea ice concentration are available from the late 1970's only (e.g., Parkinson and Cavalieri, 2012). In this context, climate models constitute adequate tools to compensate for the lack of observations and investigate the processes that govern the behavior of the sea ice cover around Antarctica. Coupled climate models are particularly useful to analyze the interactions between the different components of the climate system. Present-day general circulation models involved in the 5th Coupled Model Intercomparison Project (Taylor et al., 2011) generally simulate a decrease in the Antarctic sea ice extent over the last 30 years but a positive trend such as the observed one remains compatible with the internal variability simulated by these models (e.g., Mahlstein et al., 2013; Zunz et al., 2013; Polvani and Smith, 2013; Swart and Fyfe, 2013).

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http://dx.doi.org/10.1016/j.ocemod.2015.07.011
1463-5003/

Nevertheless, these models often display systematic biases in their representation of the seasonal cycle or of the internal variability (or both) of the Antarctic sea ice (e.g., Turner et al., 2013; Zunz et al., 2013). The reconstruction of the sea ice cover in the Southern Ocean provided by these models have thus to be considered cautiously.

One way to more closely constrain the simulation of the ocean and the sea ice is to prescribe the atmospheric conditions at the atmosphere/ocean–sea ice interface. These so-called "forced" simulations resort generally to atmospheric reanalyses as boundary conditions, and have been used extensively to study the past variability of the ocean and sea ice states (Fichefet et al., 2003; Fichefet and Maqueda, 1999; Holland et al., 2014; Zhang, 2007). It is clear the quality of these forced simulations is strongly dependent on that of the atmospheric product utilized. Intercomparisons between different reanalysis products and assessments against in-situ measurements all suggest that the reanalyzed atmospheric data are subject to large uncertainties or systematic errors in the Southern Ocean (Bromwich et al., 2007; Hines et al., 2000; Vancoppenolle et al., 2011) translating inevitably to the ocean–sea ice system (Stössel et al., 2011; Timmerman et al., 2004).

An even tighter constraint on the oceanic and sea ice states can be realized if observations are used to update model estimates. Data assimilation has been an active area of research in climate science. A limited number of studies have, however, attempted to implement data assimilation in the Southern Ocean (Balmaseda et al., 2008; Carton and Giese, 2008; Ferry et al., 2012; Janjić et al., 2012; Massonnet et al., 2013; Stammer et al., 2002; Stössel, 2008) where pressing scientific questions remain, though.

Implementing a data assimilation method in a large-scale ocean–sea ice model presents a number of challenges as several methodological, statistical and physical questions are raised. In theory, the background error statistics should be perfectly known in order for the data assimilation to produce an optimal analysis. This is not feasible in practice, due to the very high dimensionality of the state vector. For this reason, the true covariance matrix of background errors is projected onto a space of much lower dimensionality and specified either a priori (Ferry et al., 2012) or estimated on-the-fly (Mathiot et al., 2012; Sakov et al., 2012) using a finite-size ensemble. For computational reasons, it is also common to assume a diagonal structure for the observational error covariance matrix (i.e., uncorrelated errors) while this is not necessarily the case in reality.

Most data assimilation methods also rely on statistical hypotheses. The Gaussianity of background and observational errors is often assumed, but rarely fulfilled. Not only can this lead to sub-optimal updates, this can also lead to physical inconsistencies. Resorting to the transformation of variables (e.g. Bertino et al., 2003; Simon and Bertino, 2009; Béal et al., 2010) can be a first step, but it only acts on the marginal, and not multivariate probability distribution functions. Likewise, since the background statistics are boiled down to the covariance matrix, the update of non-assimilated fields follows their linear relationship with the observable; this may result in an unphysical or imbalanced state after the update in regions where strong nonlinearities are present, e.g. between sea surface temperature and sea ice concentration (Lisæter et al., 2003).

Last but not least, a central and non-trivial issue concerns the decision on what should be estimated. While the state itself is commonly estimated for reanalysis purposes, the methods can be extended to the estimation of model bias to identify systematic errors (Sakov et al., 2012), to the estimation of model parameters to partly reduce such systematic errors (Massonnet et al., 2014) and ultimately to surface forcing estimation (Barth et al., 2011; Marmain et al., 2014; Ngodock and Carrier, 2014). The estimation of atmospheric forcing in the Southern Ocean has, to our knowledge, not been explored. Because Antarctic sea ice trends are largely controlled by the wind forcing (Holland and Kwok, 2012; Kimura, 2004), it seems natural to improve the representation of ice drift in the model. We propose to correct the wind forcing using satellite sea ice drift data, taking advantage of the strong relationship between sea ice drift and the wind field.

A first set of preliminary experiments have shown the difficulty to assimilate ice drift in a coupled ocean-sea ice model. Sea ice drift is strongly related to the wind forcings (Holland and Kwok, 2012; Kimura, 2004) with a temporal scale of the order of days (about 4 days based on the autocorrelation). The memory of the sea ice drift is thus relatively short. The corresponding time scale is in fact more similar to the temporal scale of the atmospheric variability than the temporal scale of ocean mesoscale circulation (order of weeks). This short scale would require in principle a very frequent assimilation of sea ice drift data to adequately resolve its underlying time-scale. However, a too frequent assimilation can deteriorate the model results (*e.g.* Malanotte-Rizzoli et al., 1989; Barth et al., 2007; Yan et al., 2014). To improve sea ice drift in the model, we therefore propose to correct the wind forcing. This is possible due to the strong relationship between wind field and sea ice drift (Holland and Kwok, 2012).

The objective of the study is to propose a methodology to use surface drift observations to constrain an ocean-sea ice large-scale circulation model. We also aim to test this approach in combination with sea surface temperature and sea ice concentration assimilation in a decadal simulation and to assess the quality of the results with independent data. This study also outlines an approach to evaluate the presence of model errors at the forecast step of the data assimilation and to identify their potential sources

The ocean model is introduced in Section 2 and then the used observations along with their error covariance are discussed (Section 3). The procedure adopted to correct the wind field is detailed and validated in Section 4. The data assimilation implementation is discussed in Section 5 and the results of the reanalysis are then presented and validated (Section 6). In the last section, post-processing techniques are used to relate forecast errors in sea ice coverage with model errors associated with the dynamics of sea surface temperature.

2. Model

The primitive-equations model used in this study is NEMO (Nucleus for European Modelling of the Ocean, Madec (2008)), coupled to the LIM2 (Louvain-la-Neuve Sea Ice Model) sea ice model (Bouillon and Maqueda, 2009; Fichefet and Maqueda, 1997; Timmermann et al., 2005). The global ORCA2 implementation is used, which is based on an orthogonal grid with a horizontal resolution of the order of 2° and 31 z-levels (Massonnet et al., 2013; Mathiot et al., 2011). The hydrodynamic model is configured to filter free surface gravity waves by including a damping term. The leap-frog scheme uses a time step of 1.6 h for dynamics and tracers. The model is forced using air temperature and wind from the NCEP/NCAR reanalysis (Kalnay et al., 1996). Relative humidity, cloud cover and precipitation are based on a monthly climatological mean. The sea surface salinity is relaxed towards climatology with a fresh water flux of −27.7 mm/day times the salinity difference in psu.

As in the following the link between sea ice drift and wind stress is studied, only the equation for sea ice drift is given here. The sea ice drift $\mathbf{u}$ is governed by the momentum equation where the advection of momentum is neglected by scale analysis (Fichefet and Maqueda, 1997):

$$m\frac{\partial \mathbf{u}}{\partial t} = -mf\mathbf{e_z} \wedge \mathbf{u} + \boldsymbol{\tau}_{ai} + \boldsymbol{\tau}_{wi} - mg\nabla\zeta + \mathbf{F} \quad (1)$$

where m is the mass of the snow-ice system, f is the Coriolis parameter, $\mathbf{e}_z$ is a unit vector pointing upward, $\boldsymbol{\tau}_{ai}$ (resp. $\boldsymbol{\tau}_{wi}$) denotes the drag with air (resp. water), g is the acceleration due to gravity, ζ is the surface elevation and $\mathbf{F}$ the force due to the variation of internal stresses. For the complete model equations, the interested reader is