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Erratum

Erratum to "A simple method for reducing seasonal bias and drift in eddy resolving ocean models" [Ocean Modelling 13 (2006) 109–125]

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The Publisher regrets that in the above article all figures were printed incorrectly in black and white. The article is now reproduced correctly, below.

Abstract

An effective and computationally efficient method is described for reducing bias and drift in eddy resolving ocean models. The basic idea is to nudge the model towards gridded climatologies of observed temperature and salinity in prescribed frequency-wavenumber bands; outside of these bands the model's dynamics are not directly affected by the nudging and the model state can evolve prognostically. Given the restriction of the nudging to certain frequency-wavenumber bands, the method is termed spectral nudging. The frequency-wavenumber bands are chosen to capture the information in the climatology and thus are centered on the climatological frequencies of 0, 1 cycle per year and its harmonics, and also low wavenumbers (consistent with the smooth nature of gridded climatologies). The method is first tested using a linear, barotropic ocean model forced by a time-varying wind stress curl. For this example it is possible to give explicit expressions for the effect of spectral nudging on the model's response to wind forcing. The method is then applied to an eddy permitting model of the North Atlantic driven by realistic surface fluxes. It is shown that the model maintains a statistical steady state over the several decades of integration with no evidence of bias or drift. Further the seasonal cycle of coastal sea level, and the spatial distribution of sea level variance, are shown to agree well with independent sea level measurements made by tide gauges and altimeters, respectively. The application of spectral nudging to shelf and coupled atmosphere–ocean modelling is discussed.

Keywords: Ocean models; Bias; Drift; North Atlantic; Sea level

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1. Introduction

Bias and drift are common problems with ocean models (e.g. Bleck, 2002; Halliwell, 2004; Huddleston et al., 2004). Many factors can contribute to bias and drift including inadequate model resolution, poor parameterizations of sub-grid scale processes and inaccurate surface and lateral boundary conditions. Given the range and complexity of potential contributors, it is hardly surprising that a general solution to these problems is not available. The objective of this study is to develop a simple method for suppressing bias and drift in eddy resolving models when the variability of interest has periods of days to seasons. The method proposed here may be used in the reconstruction of historical changes of the ocean state and also making forecasts with lead times of days to seasons.

The method is based on the simple idea of nudging the model toward seasonal climatologies of ocean observations in specified frequency and wavenumber bands; outside of these bands the model is unconstrained. The Bayesian framework (e.g. Lorenc, 1986) is arguably the most useful in terms of motivating the new method, and relating it to other assimilation approaches. Let $x_{t+1} = \phi_t(x_t, w_t)$ represent a nonlinear dynamic model that describes how the discretized ocean state vector, x_t, is advanced forward one time step. In one of our applications the nonlinear dynamic operator ϕ_t corresponds to a fully nonlinear, eddy permitting model of the North Atlantic. Uncertainty in the forecast is reflected by the inclusion of the model error vector w_t. The relationship between x_t and the contemporaneous vector of observations, y_t, is modelled by $y_t = h_t(x_t, v_t)$ where h_t is the observation operator and v_t defines the observation error (e.g. Daley, 1994). It is well known (e.g. Jazwinski, 1970) that if the error terms are mutually independent, and Y_t denotes all available observations up to and including time t, then routine application of Bayes' Rule allows the probability distribution of x_t given Y_t to be updated sequentially using $p(x_t|Y_t) \propto p(y_t|x_t) \int p(x_t|x_{t-1})p(x_{t-1}|Y_{t-1})\,\mathrm{d}x_{t-1}$. This conditional density contains all the information on x_t given Y_t; quantities like the conditional mean of x_t, its covariance and higher order moments can all be obtained from this probability density function.

Unfortunately the updating equation given in the previous paragraph can only be solved by direct integration for low dimensional problems (e.g. Kitagawa, 1998); approximate numerical schemes must be developed for use with high-dimensional ocean models. If ϕ_t and h_t are linear operators, and w_t and v_t are normally distributed with zero mean, the celebrated linear Kalman Filter (e.g. Jazwinski, 1970) provides an elegant way of sequentially updating the conditional mean and variance of x_t given Y_t. For nonlinear problems the situation is less clear cut and a number of sub-optimal schemes have been proposed including the extended Kalman Filter, the singular evolutive extended Kalman Filter (Pham et al., 1998) and the ensemble Kalman Filter (Evensen, 1994).

All forms of Kalman Filter correspond to 'nudging' the ocean state toward the observations using an equation of the form $x_t = x_t^{\mathrm{f}} + K_t(y_t - h_t(x_t^{\mathrm{f}}))$ where $x_t^{\mathrm{f}} = \phi_t(x_t)$ is the one-step-ahead-forecast, and K_t are the nudging coefficients organized in the so-called Kalman gain matrix. The differences in the various Kalman Filters affect only the calculation of K_t. A major simplification is to prescribe K_t based on an assumed covariance structure of the forecast errors (e.g. Daley, 1994). If K_t is assumed to be diagonal then the nudging terms take the conventional form $\gamma(y_t - x_t^{\mathrm{f}})$ at observation points where γ^{-1} corresponds to a relaxation time in model time steps. Sarmiento and Bryan (1982) used this form of nudging to assimilate observations of temperature and salinity into a realistic ocean model. Their technique has proved very useful over the years and is usually referred to as the robust diagnostic method. If $\gamma = 1$ the nudged ocean state is replaced by directly observed values, a procedure known as direct insertion. It corresponds to the standard diagnostic method of Sarkisyan (1977) if temperature and salinity data are assimilated. The main advantages of the standard and robust diagnostic forms of nudging are that they are easy to implement, robust and can keep the model arbitrarily close to the observations. Unfortunately there are serious limitations including the suppression of eddies when nudging toward climatological observations, and the introduction of artificial phase lags in the model response (e.g. Woodgate and Killworth, 1997).

An important assumption underlying the Kalman Filter is that the model's predictions are unbiased. Direct comparison of time-averaged model predictions and observations suggests that this is often not the case. It is true that sequential schemes like the Kalman Filter, which are based on estimates of forecast error variability about the mean, can still be used to nudge a biased model toward observations but this will be achieved in a suboptimal way; it is highly unlikely that the covariance structure of the forecast errors will match the spatial