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The impact of open boundary forcing on forecasting the East Australian Current using ensemble data assimilation

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ABSTRACT

We investigate the performance of an eddy resolving regional ocean forecasting system of the East Australian Current (EAC) for both ensemble optimal interpolation (EnOI) and ensemble Kalman filter (EnKF) with a focus on open boundary model nesting solutions. The performance of nesting into a global re-analysis; nesting into the system's own analysis; and nesting into a free model is quantified in terms of forecast innovation error. Nesting in the global reanalysis is found to yield the best results. This is closely followed by the system that nests inside its own analysis, which seems to represent a viable practical option in the absence of a suitable analysis to nest within. Nesting into a global reanalysis without data assimilation and nesting into an unconstrained model were both found to be unable to constrain the mesoscale circulation at all times. We also find that for a specific interior area of the domain where the EAC separation takes place, there is a mixture of results for all the systems investigated here and that, whilst the application of EnKF generates the best results overall, there are still times when not even this method is able to constrain the circulation in this region with the available observations.

1. Introduction

The East Australian Current (EAC) in the Tasman Sea plays a key role in Australia's weather, climate and marine ecosystems, delivering heat and nutrient-poor subtropical water, originating from the flow of the South Equatorial Current into the Coral Sea, to higher latitudes (Ridgway and Dunn, 2003; Ridgway, 2007). The EAC separates from coast between 32–33°S and typically retrogrades between 34–35°S (Everett et al., 2013) to form the eastward flowing Tasman Current and a southward flowing eddy field (Godfrey et al., 1980; Roughan and Middleton, 2002). The separation is sometimes referred to as the EAC extension. The separation of the EAC greatly influences coastal ecosystems and there are strong relationships between water mass characteristics in the separation zone with fish diversity and abundance (Suthers et al., 2011). At the separation zone the EAC is characterised by sharp oceanic fronts where sea surface temperature (SST) gradients can be up to 5 °C/50 km (Roughan and Middleton, 2002; Mata et al., 2000). These fronts delineate different water masses and the separation drives upwelling, which can result in cooler water emerging rapidly at the surface and persisting for days to weeks (Oke and Griffin, 2011).

The low nutrient levels of the EAC source water have a broad impact on primary productivity confining most of the drivers of chlorophyll-α concentration in surface waters to coastal and dynamic upwelling governed by local wind and ocean dynamics (Everett et al., 2013). Often clear fronts in chlorophyll-α concentrations can be seen in ocean colour imagery. These observations represent a combination of phytoplankton levels and other suspended and dissolved particulate and organic matter. The resulting image can be interpreted as a complex combination of physical and biological processes. Every so often, observations of ocean colour, such as those from the Moderate Resolution Imaging Spectro-radiometer (MODIS) on board the Aqua Satellite trace out the positions of the fronts and eddies to deliver a clear view of the boundary between the EAC source waters and the waters further south. This information provides a useful reference for the positions of fronts in assessing the performance of ocean prediction systems (Chassignet et al., 2005). Whilst this region is relatively under-observed and challenging to predict, previous efforts to constrain ocean models using remotely sensed altimetric sea-level, SST and in situ Argo temperature and salinity profiles have been relatively successful (see Oke et al. (2013b) and references therein).

Western boundary current systems, like the EAC, are typically where the largest forecast errors occur in ocean models due to the non-linear nature of the flow and the relatively fast growing dynamical instabilities, which are unable to be adequately cap-

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tured by observations (O'Kane et al., 2011). This places a strong emphasis on model, observations and data assimilation (DA) system performance making it an ideal case for developing and improving ocean prediction systems such as OceanMAPS (Brassington, 2013; Brassington et al., 2007) and the Bluelink ReAnalysis (BRAN) (Oke et al., 2013b). To make advances in system performance in these dynamical regimes, flow dependent errors, such as those provided by an EnKF system should be considered when assimilating observations.

In this study a regional eddy-resolving limited-area ocean model and an ensemble DA system are used to evaluate forecasts of the EAC separation. Error characteristics with respect to different nested open boundary conditions are assessed. The aim is to improve understanding of the influence of open boundary nesting data on predicting features of the circulation. We also compare the performance of a regional EnKF system using the best open boundary nesting data, as determined from the experiments, to both the regional and global EnOI systems for the same region and period. The EnKF system is presented purely as a reference as the focus of this study is on the open boundary nesting options rather than the difference between EnKF and EnOI systems.

From here on, a brief description of the model, observations and data assimilation system is presented followed by an outline of the cases and datasets used in the study. A section containing the results with an accompanying discussion is then given, which is followed by a section containing the conclusions.

2. Methods

2.1. Model

The three-dimensional primitive equation volume conserving ocean model MOM4p1 (Griffies et al., 2009) is used. The model is forced using 3 hourly surface fluxes of momentum, heat and salt from the ERA-Interim atmospheric reanalysis dataset (Dee et al., 2011). The grid is based on a Tasman Sea regional cut out of BRAN3.5, which uses bathymetric data from Smith and Sandwell (1997). Further details are provided in Oke et al. (2013b) and references therein. The grid has approximately 10 km horizontal resolution with 51 vertical levels. The top cell approximates quantities at 2.5 m depth and the average resolution in the upper 200 m is approximately 10 m. The region is within 146.05°E to 165.95°E and 44.95°S to 23.05°S and is shown in Fig. 1. By choosing the same grid as the parent global system, we optimise the configuration for assessing the impact of the regional open boundary forcing data on the model forecasts. The regional system is initialised and nested in either BRAN3 or the Ocean Forecasting Australian Model version 3 (OFAM3) (Oke et al., 2013a), except for the nesting in own analysis experiment, which is described separately in a later section.

The system uses the adaptive relaxation scheme of Sandery et al. (2011) for initialisation and open boundary conditions. These are applied to the horizontal components of currents at all depths, sea-level, temperature and salinity in the open boundary zones shown in Fig. 1. The open boundary zones represent the outer 0.5° or approximately 55 km of the domain. These are where the model is forced through tendency terms in the model equations to either the nested data or the regional analysis. The model employs a 4th-order Sweby advection method and a scale dependent isotropic Smagorinksy horizontal mixing scheme as described in Griffies and Halberg (2000). Vertical mixing is parameterized using the General Ocean Turbulence Model (GOTM) κ-ϵ scheme. Note that explicit tides are not modelled in this system, rather an implicit representation of tidal mixing is parameterised using the scheme of Lee et al. (2006). Simulations over a three-year period from 2006–2008 are carried out.

2.2. Data assimilation

Two sequential methods for ensemble DA are used, EnOI and EnKF (Evensen, 2003). The study uses a recently developed DA code EnKF-C (Sakov, 2014) designed for off-line DA with large-scale layered geophysical models and available from https://code.google.com/p/enkf-c. Whilst the results of this study are centred around the EnOI based systems, we also include the regional EnKF system as a reference. EnOI is an effective, relatively inexpensive multivariate assimilation technique that has been employed successfully for a number of years in ocean forecasting (see Oke et al. (2013b) and references therein). It uses a static ensemble, so that only one instance of the model needs to be integrated. The EnKF system uses a dynamic ensemble and requires integrating $O(100)$ instances of the model. It is theoretically more optimal, but requires significantly greater resources to run. The EnKF system presented in this study uses the so called deterministic EnKF scheme of Sakov and Oke (2008). It assimilates SST and SLA asynchronously using the method described in Sakov et al. (2010). A 144 member ensemble of intra-seasonal model state anomalies based on the difference between 3 day means and monthly means from OFAM is used with EnOI, which is the same ensemble used in Oke et al. (2013b). Also, a 250 km localisation radius is used in the EnOI system. In order to calculate sea-level anomalies in the analysis, the mean dynamic topography from OFAM3 is used.

We assess the system performance using innovation statistics where innovation is the difference between the forecast and observations in observation space. The EnOI system is run with a 3 day forecast cycle using a 3 day observation window (Fig. 2). With this setting all observations are assimilated only once. This means that the observations used for innovation statistics can be regarded as independent in order to assess the quality of the forecast.

The analysis is calculated at 12:00 UTC and the observation window is centred about the analysis time. The background fields used for the analysis are instantaneous rather than time-averaged, which are the most dynamically balanced for the model. The analysis time-of-day corresponds to 22:00 EST (at 150°E), which means the background fields are at night-time to avoid SST diurnal warming effects. After each forecast an analysis increment is calculated. The model is then stepped back 1 day and the increment is initialised for 1 day to minimise shock and so that it is incorporated at the analysis time, which is also the forecast base time. Whilst many of the details of the EnOI and EnKF systems are similar, such as in the assimilated observations, the model and open boundary configuration and surface forcing, the EnKF system uses a 5 day analysis-forecast cycle and a 100 member dynamic ensemble with a 150 km localisation radius. The reason for these differences is based on experiments (not shown) that showed these systems performed better with these settings.

2.3. Observations

The assimilated observations are the same for all systems. Both satellite derived and in situ observations are used. These include altimetric sea level data from the Radar Altimeter Database System (RADS) (Schrama et al., 2000), sea surface temperature retrievals from the NAVOCEANO (May et al., 1998) and WindSat (Gaiser et al., 2004) databases and subsurface temperature and salinity from Argo (Roemmich et al., 2009). The altimeters available during the study period were Jason-1, Jason-2, GEOSAT and Envisat. Altimeter observations in waters shallower than 200 m, which typically have a low signal to noise ratio, were not assimilated. Also, only night-time foundation SST observations were assimilated. The observations of each type within each model grid cell were merged into super-observations where the positions and values were weighted by the inverse error variance of the observations.