EGU2020-2683
https://doi.org/10.5194/egusphere-egu2020-2683
EGU General Assembly 2020

An improved variational Data Assimilation method for ocean models with limited number of observations.

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Data assimilation (DA) is a critical component for most state-of-the-art ocean prediction systems, which optimally combines model data and observational measurements to obtain an improved estimate of the modelled variables, by minimizing a cost function. The calculation requires the knowledge of the background error covariance matrix (BECM) as a weight for the quality of the model results, and an observational error covariance matrix (OECM) which weights the observational data.

Computing the BECM would require knowing the true values of the physical variables, which is not feasible. Instead, the BECM is estimated from model results and observations by using methods like National Meteorological Centre (NMC) or the Hollingsworth and Lönnberg (1984) (H-L). These methods have some shortcomings which make them unfit in some situations, which includes being fundamentally one-dimensional and making a suboptimal use of observations.

We have produced a novel method for error estimation, using an analysis of observations minus background data (innovations), which attempts to improve on some of these shortcomings. In particular, our method better infers information from observations, requiring less data to produce statistically robust results. We do this by minimizing a linear combination of functions to fit the data using a specifically tailored inner product, referred to as an inner product analysis (IPA).

We are able to produce quality BECM estimations even in data sparse domains, with notably better results in conditions of scarce observational data. By using a sample of observations, with decreasing sample size, we show that the stability and efficiency of our method, when compared to that of the H-L approach, does not deteriorate nearly as much as the number of data points decrease. We have found that we are able to continually produce error estimates with a reduced set of data, whereas the H-L method will begin to produce spurious values for smaller samples.

Our method works very well in combination with standard tools like NEMOVar by providing the required standard deviations and length-scales ratios. We have successfully ran this in the Arabian Sea for multiple seasons and compared the results with the H-L (in optimal conditions, when plenty of data is available), spatially the methods perform equally well. When we look at the root

mean square error (RMSE) we see very similar performances, with each method giving better results for some seasons and worse for others.