High-performance Computing of Ocean Models for Japan Coastal Ocean Predictability Experiment: Utilization of ensemble simulations for forecast skill improvements

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1. Introduction

To improve skills in predicting the Kuroshio path variations south of Japan, we have developed a four-dimensional (4D) ensemble-based data assimilation (DA) system on ES4. We have been repeatedly conducting the forecast experiments using an eddy resolving ocean circulation model initialized by a three-dimensional (3D) DA method, which basically ignores time dependence of assimilated data within an assumed time window [1]. For a period from March to December 2020, the Kuroshio path states were quite unstable and the forecast skills in some cases deteriorated with failing to represent such extremely variable phenomena. For this period, cold eddies were frequently ejected from the tip of the Kuroshio Large Meander (KLM). In October, the KLM disappeared after the shedding of a large-size cold eddy, but KLM again appeared in December through evolution of a trigger meander.

We investigated possible skill improvements of representing the Kuroshio path variations in such interesting period by applying the newly developed 4D ensemble-based DA method. In this fiscal year, we continued the implementation of the ensemble background error covariance (BEC) as we did in the last fiscal year [2]. We further examined the feasibility of utilizing ensemble information for diagnosing the predictability of the targeted phenomena.

2. Adjoint-free 4dVar DA system

Based on the JCOPE-T Northwestern Pacific model optimized on ES4 [3], we have constructed an ensemble DA system using the adjoint-free 4d variational (Var) method [4] (JCOPE-a4dVar). JCOPE-a4dVar creates 22 ensemble members from the first guess initial condition produced by the multi-scale 3dVar DA method (ms3dVar) [1].

Both a4dVar and ms3dVar assimilate the along-track SSHA and the synthetic merged sea surface temperature data (MGDSST). In addition, ms3dVar assimilates high-resolution satellite sea surface temperature (Himawari-8) and in-situ temperature-salinity profile data (GTSPP). The a4dVar algorithm is designed for mainly extracting time-dependent observed information on the oceanic variability from SSHA during the time window [4]. The length of the time window is 10-day, which is a repeated period of a typical Jason-series satellite altimeter, and all SSHA data within the time window are assimilated daily. MGDSST is assimilated only at the time of the initialization. The observation errors in assimilating SSHA and MGDSST are fixed as 0.1m and 2 °C, respectively.

The ensemble members are generated at each iteration step of the a4dVar cost function minimization based on the combined information of model dynamics and model-data misfit during the time window [4]. The correction to the first guess initial condition is iteratively made as the weighted sum of the ensemble member perturbations at each iteration step. The iteration counts are fixed as 10 times for a time window, because the reduction of the cost function is generally slowed down after10 iterations.

The DA skills are validated against independent observations such as SSHA measured after the time window, sea surface drifters, temperature/salinity profiles, and the tide gauge sea level anomaly. The Kuroshio path locations evaluated by the Japan Coast Guard on a daily basis are also used for the validation. Some critical parameters in the a4dVar system are iteratively tuned through the validation using the independent data.

The most critical parameters of the a4dVar system are included in BEC prescribing the simulation errors in the DA process. BEC in the a4dVar system [4] is represented as,

$$\mathrm{BEC} = C_B L V_T C_d (S) V_T L^t \qquad (1)$$

, where C_B denotes a non-dimensional scalar constant (same for the all variables) that defines the ratio of the simulation errors to the observation errors, L denotes an operator describing geostrophic and hydrostatic balance, V_T denotes a diagonal matrix representing a three-dimensional distribution of the simulation error magnitude for each control variable (temperature, salinity, horizontal velocities, and sea level), and $C_d(S)$ denotes a non-dimensional horizontal diffusion operator, which represents horizontal correlation characterized by an exponential function with a scale parameter S, and a superscript 't' means a transpose of a matrix.

V_T is represented as $V_T = \min(STD_T, MAX_T)$, where STD_T is standard deviation of a target variable calculated from an ocean reanalysis product JCOPE2M, and MAX_T is a maximum limit. After conducting a number of preliminary experiments, we have determined $MAX_{temperature}$, $MAX_{salinity}$, $MAX_{velocities}$, and $MAX_{sea\ level}$ are 0.5 (°C), 0.05 (psu), 0.1 (m/s), 0.05 (m), respectively. A horizontal scale parameter S, and a constant C_B have been determined as 4 grid size (approximately 36 km), which approximately corresponds to 36 km, and 0.2, respectively.

3. Utilization of the ensemble information

We investigated feasibility of utilizing the created ensemble information in terms of representation of BEC and sensitivity analysis of the forecast results.

A possible alternative representation of the correlation matrix in the BEC formula (1) using the ensemble simulation results is

$$C_e = \mathrm{Diag}(C_l \circ XX^t)^{-1/2} \ (C_l \circ XX^t)\ \mathrm{Diag}(C_l \circ XX^t)^{-1/2} \quad (2)$$

, where X denotes the ensemble anomaly vector which includes temperature, salinity, horizontal velocities, and sea level. C_l denotes the horizontal localization operator depending on the localization scale L_e [5]. We applied $L_e = 4$ (grids) as the same as the scale parameter used in the diffusion operator. We examined sensitivity in the skills by use of the ensemble BEC

$$BEC_e = C_B L V_T C_e\ (L_e) V_T\ L^t \quad (3)$$

We also developed a diagnosis method of the ensemble simulations using derivation of an ensemble regression to a target quantity [6]. The ensemble regression (ER) of ensemble anomaly vectors X(t) at time t to an ensemble target quantity vector Y(t0) at a targeted time t0 (t0 > t) is represented as,

$$ER(t) = X(t)(X(t)^t X(t))^{-1} Y(t0) \quad (4)$$

The ensemble anomaly vectors X and target quantity Y could be temperature, salinity, horizontal velocities, sea level, or any others.

4. The a4dVar experiments on ES4

We produced first guess data by applying ms3dVar for a period from March to December 2020. The a4dVar was applied for two 10-day window periods: 9 to 19 April (the April period) and 10 to 20 October (the October period). KLM was maintained throughout the former and its succeeding 60-day periods. In contrast, KLM disappeared owing to shedding of a large cold core ring from the tip of KLM in the latter period. But a trigger meander formed southeast of the Kyushu Island propagated eastward for a period from October to December, and KLM again appeared through amplification of the trigger meander.

It was found that a hindcast simulation starting from the first guess produced by ms3dVar failed to maintain KLM owing to unrealistic shedding of a cold core ring from the tip of KLM for the April period. Also, for the October period, the simulation starting from the first guess failed to represent the eastward propagation of the trigger meander. The newly developed JCOPE-a4dVar improved the first guess initial conditions to prevent the unrealistic eddy shedding for the April period and to reasonably represent the eastward propagation of the trigger meander for the October period (not shown) in cases of the diffusion type BEC (1) with suitable choices of C_B (0.3-0.5). The skill changes in case of BEC_e (3) will be eventually reported in a journal paper together with detailed analyses of the all experiments.

5. Ensemble regression for sensitivity analysis

Here we demonstrate an example of the ensemble regression analysis using the JCOPE-a4dVar product. Figure 1 shows an extremely strong current on 21 May 2020 (See a blue square region in a left panel of Fig. 1) represented by the hindcast simulation. The eastern part of KLM significantly approached near the coast and caused the extreme current. The ensemble regression to the coastal extreme at that time of the thermocline temperature distribution suggests the sensitive regions that are closely related to the targeted extreme current. In this case both a bent area of the Kuroshio path and a warm eddy east of the Kuroshio path before 2 weeks of the occurrence on 7 May (See a blue colored ellipse in a right panel of Fig. 1) would affect the coastal extreme on 21 May.

We expect how the forecast skills would be improved if the sensitive areas are observed prior to occurrence of the targeted event. Hopefully, on-going rapid development of advanced observation technology such as Automatic Unmanned Vehicles (AUVs) will open the door of such targeted observation in ocean state forecasting.

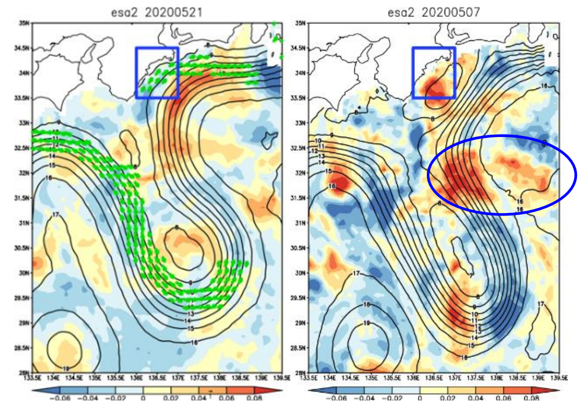

Fig. 1: Ensemble regression (4) of temperature at 400m X(t) to number of grids Y(t0) with velocity magnitude at 1m depth greater than 1m/s (denoted by green colored vectors) in a blue colored square on 21 May 2020 (t0). Left: 21 May 2020 (t). Right: May 2020 (t0). A blue colored ellipse region in right indicates possible sensitive regions.

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