Development of a Four-Dimensional Variational Assimilation System for Coastal Data Assimilation around Japan

NORIHISA USUI, YOSUKE FUJII, KEI SAKAMOTO, AND MASAFUMI KAMACHI
Oceanography and Geochemistry Research Department, Meteorological Research Institute, Tsukuba, Japan

(Manuscript received 8 October 2014, in final form 15 June 2015)

ABSTRACT

The authors have developed an assimilation system toward coastal data assimilation around Japan, which consists of a four-dimensional variational (4DVAR) assimilation scheme with an eddy-resolving model in the western North Pacific (MOVE-4DVAR-WNP) and a fine-resolution coastal model covering the western part of the Japanese coastal region around the Seto Inland Sea (MOVE-Seto). The 4DVAR scheme is developed as a natural extension of the 3DVAR scheme used in the Meteorological Research Institute Multivariate Ocean Variational Estimation (MOVE) system. An initialization scheme of incremental analysis update (IAU) is incorporated into MOVE-4DVAR-WNP to filter out high-frequency noises. During the backward integration of the adjoint model, it works as an incremental digital filtering. MOVE-Seto, which is nested within MOVE-4DVAR-WNP, also employs IAU to initialize the interior of the coastal model using MOVE-4DVAR-WNP analysis fields. The authors conducted an assimilation experiment using MOVE-4DVAR-WNP, and results were compared with an additional experiment using the 3DVAR scheme. The comparison reveals that MOVE-4DVAR-WNP improves mesoscale variability. In particular, short-term variability such as small-scale Kuroshio fluctuations is much enhanced. Using MOVE-Seto and MOVE-4DVAR-WNP, the authors also performed a case study focused on an unusual tide event that occurred at the south coast of Japan in September 2011. MOVE-Seto succeeds in reproducing a significant sea level rise associated with this event, indicating the effectiveness of the newly developed system for coastal sea level variability.

1. Introduction

Ocean data assimilation, which synthesizes observations and numerical models to obtain the statistically best estimate of the ocean state, has been widely used for various purposes such as ocean monitoring, forecast, and reanalysis (e.g., Bennett 1992, 2002; Ghil and Malanotte-Rizzoli 1991; Wunsch 1996; Talagrand 1997; Lewis et al. 2006; Evensen 2007). The variational method is one of the major approaches in data assimilation. Based on the maximum likelihood estimation theory, it attempts to obtain ocean state estimates by minimizing a cost function defined as a sum of quadratic terms of errors in model background states and observations.

Three-dimensional variational (3DVAR) data assimilation identifies the best estimate at a specific analysis time using observations obtained around the time. In contrast, four-dimensional variational (4DVAR) data assimilation attempts to obtain the best estimate of the ocean state over a finite time interval (assimilation window) by using all available observations and a numerical model to dynamically interpolate information in space and time. That is, observation time is taken into account in 4DVAR, while 3DVAR assumes that all observations are obtained simultaneously at the analysis time. Besides, in contrast to use of prescribed background error covariances in 3DVAR, 4DVAR can implicitly consider time evolution of background error covariances within the assimilation window, resulting in dynamically balanced analysis fields. It should be here noted that there is a variant of 3DVAR method, in which observations are compared to the first guess at the appropriate time (FGAT), but FGAT also assumes analysis increments to be constant within the assimilation window as in the 3DVAR algorithm.

Because of the progress of numerical ocean models and enhancement of ocean observation data such as Argo floats and satellite-derived sea surface data in the
past decade, many research groups have developed realistic data assimilation systems (e.g., Cummings et al. 2009; Dombrowsky et al. 2009; Hurlburt et al. 2009), some of which adopt the variational assimilation scheme. Weaver et al. (2003) applied an incremental 3DVAR and 4DVAR approach to the Parallel Ocean model (Madec et al. 1998) in the tropical Pacific Ocean. Ishikawa et al. (2009) developed a 4DVAR assimilation system with an eddy-resolving ocean general circulation model (OGCM) in the western North Pacific to represent realistic mesoscale features in the seas around Japan. Recently, the variational data assimilation method has been applied to coastal data assimilation systems. Moore et al. (2011) developed a 4DVAR assimilation scheme for the Regional Ocean Modeling System (Shchepetkin and McWilliams 2005), which has been widely used in various regional assimilation systems including coastal areas such as the New York Bight (Zhang et al. 2010), the California Current system (Broquet et al. 2009), the Gulf of Mexico, and the Caribbean Sea (Powell et al. 2008). Kurapov et al. (2011) constructed a coastal data-assimilative model off Oregon based on the representer method (e.g., Bennett 1992, 2002; Chua and Bennett 2001), a kind of the 4DVAR scheme. State-of-the-art coastal systems are summarized in Kourafalou et al. (2015).

The Meteorological Research Institute (MRI) of the Japan Meteorological Agency (JMA) developed a 3DVAR assimilation system, namely the MRI Multivariate Ocean Variational Estimation (MOVE-3DVAR) system (Usui et al. 2006). The MOVE system is based on a multivariate 3DVAR analysis scheme with a vertically coupled temperature–salinity (T–S) empirical orthogonal function (EOF) modal decomposition of a background error covariance matrix (Fujii and Kamachi 2003b). The global version and the western North Pacific version of the MOVE system (MOVE-3DVAR-G and MOVE-3DVAR-WNP) have been used as operational systems at JMA since 2008. The main target of MOVE-3DVAR-G is El Niño–Southern Oscillation, while MOVE-3DVAR-WNP was developed for monitoring and forecasting of ocean state around Japan where energetic mesoscale features such as mesoscale eddies and fluctuations of the Kuroshio and Oyashio currents occur. We have been developing a next-generation data assimilation system with a fine-resolution model, which aims to improve the representation of coastal processes. As a first step toward this goal, we have now developed a prototype coastal system which will be introduced at JMA in 2015. The system consists of a 4DVAR version of the MOVE system (MOVE-4DVAR) with an eddy-resolving OGCM in the western North Pacific (MOVE-4DVAR-WNP) and a fine-resolution coastal model covering western part of Japan around the Seto Inland Sea (MOVE-Seto). The coastal model is nested into the western North Pacific model and is initialized by using MOVE-4DVAR-WNP results.

Because the 4DVAR scheme exploits tendency information in observations as described above, it is expected that MOVE-4DVAR improves short-term variations compared to the present 3DVAR system, which are considered to be important in coastal areas. Actually, Vialard et al. (2003) showed that 4DVAR significantly enhances short-term variability at a 30–40-day time scale related to tropical instability waves by comparing assimilated fields of their 3DVAR and 4DVAR assimilation systems in the tropical Pacific. Such an effect of 4DVAR would be expected in mid-latitude western boundary current regions, which exhibit energetic mesoscale eddy activity. Therefore, this paper intends to show preliminary results of the newly developed assimilation system with a particular focus on comparison with the present 3DVAR system as well as to give a detailed description of the system.

This paper is organized as follows. Section 2 describes the formulation of the MOVE-4DVAR scheme. Descriptions of the assimilation system and experimental conditions are given in section 3 and section 4. Assimilation results are shown in section 5 and section 6 with particular attention to mesoscale and coastal variability, respectively. Section 7 gives summary and discussion.

2. Formulation of the MOVE-4DVAR scheme

We first describe the 3DVAR method used in MOVE-3DVAR. The analysis scheme for MOVE-3DVAR is based on a multivariate 3DVAR using vertical coupled temperature and salinity (T–S) EOF modes for the background error covariance matrix, which was originally introduced by Fujii and Kamachi (2003a). The cost function for MOVE-3DVAR $J_3D$ is defined by

\[
J_{3D}(z) = \frac{1}{2} \sum_l z_l^T (B_l)^{-1} z_l + \frac{1}{2} (Hx - y^{TS})^T R^{-1} (Hx - y^{TS})
+ \frac{1}{2\sigma_h^2} [\hat{t}(x) - y^{SLA} - H_n \hat{h}]^T \times [\hat{t}(x) - y^{SLA} - H_n \hat{h}] + J_c,
\]

where $z$ is the control variable, consisting of amplitudes for the vertical coupled $T$–$S$ EOF modes, and $x$ is the state vector of temperature and salinity fields, which is a function of the control variable $z$. Matrices $(B_l)_l$ and $R$ are the horizontal correlation matrix for background errors and the observation error covariance matrix, $y^{TS}$ and $y^{SLA}$ are observation vectors for $T$–$S$ profile and...
altimeter-derived sea level anomaly (SLA), matrices $\mathbf{H}$ and $\mathbf{H}_b$ represent spatial interpolation from model grid to observation locations for $T$–$S$ and SLA data respectively, $\mathbf{h}$ is the vector consisting of sea surface dynamic height (SDH) at each horizontal grid point, and $\mathbf{h}$ is mean SDH. The last term on the right-hand side, $J'$, represents additional constraints, which are used for various purposes such as for avoiding density inversion (Fujii et al. 2005) and excessively low temperature colder than the freezing point (Usui et al. 2011). The model domain is divided into subregions and the $T$–$S$ EOF modes are calculated for each subregion using historical $T$–$S$ profile observations. The subscript $l$ denotes the $l$th subregion. To prevent discontinuities in the analysis fields, there are buffer zones around boundaries between the subregions, where the analysis fields are obtained by a weighted average of the estimates for the overlapping subregions.

The operator $\mathcal{H}$ calculates SDH at each observation point from the $T$–$S$ field of the state vector $\mathbf{x}$ as follows:

$$\mathcal{H}(\mathbf{x}) = \mathbf{H}_n \mathbf{h} \quad \text{and}$$

$$h_i = -\frac{1}{\rho_i} \int_0^{z_m} \rho_i'(T,S,p) dz, \quad (3)$$

where $h_i$ is the $i$th component of $\mathbf{h}$ (i.e., SDH at the $i$th horizontal grid point), $z$ denotes the vertical coordinate, $z_m$ is the reference depth (1500 m) for the SDH calculation, $p$ is the pressure, $\rho_i$ is the surface density, and $\rho_i'$ is the density deviation of the reference state ($T = 0^\circ$C and $S = 35$ psu). It should be noted that the operator $\mathcal{H}$ does not take into consideration ocean mass-related sea level changes. We have, however, confirmed that in many areas of the western North Pacific except for shallow coastal regions more than 80% of the total SLA variance is explained by variations in SDH. We also have a plan to improve the assimilation scheme for SLAs by removing mass-related signals from SLA observations (Kuragano et al. 2014).

The analysis increment, $\Delta \mathbf{x}$, is calculated by

$$\Delta \mathbf{x} = \mathbf{x}(z) - \mathbf{x}^b = \mathbf{S} \sum_l \mathbf{W}_l \Lambda_l \mathbf{z},$$

$$= \mathbf{Gz}, \quad (4)$$

where $\mathbf{x}^b$ is the first guess; $\mathbf{S}$ is a diagonal matrix whose diagonal elements are composed of standard deviation of the background field; $\mathbf{U}_l$ is a matrix composed of dominant $T$–$S$ EOF modes; $\Lambda_l$ is a diagonal matrix whose diagonal elements are the singular values of $T$–$S$ EOF modes; $\mathbf{W}_l$ is a diagonal weight matrix for the $l$th subregion whose $m$th diagonal element, $w_{lm}$, needs to satisfy $\sum_l w_{lm}^2 = 1$ (Fukumori 2002); and $\mathbf{G}$ is defined as a transform matrix from $\mathbf{z}$ to $\Delta \mathbf{x}$.

The background error covariance matrix $\mathbf{B}$ is expressed with the horizontal background correlation matrix $\mathbf{B}_h$ and the statistics in $(4)$ as follows:

$$\mathbf{B} = \mathbf{S} \left[ \sum_l \mathbf{W}_l \Lambda_l \mathbf{U}_l^T \mathbf{B}_h \mathbf{U}_l \Lambda_l \right] \mathbf{S}. \quad (5)$$

The vertical correlation matrix of the background errors is thus modeled by $\mathbf{U}_l \Lambda_l$. The horizontal correlation $\mathbf{B}_h$ is modeled by the Gaussian function with area-dependent decorrelation scales, which are assigned according to Kuragano and Kamachi (2000).

MOVE-4DVAR was developed as a natural extension of the above 3DVAR scheme and employs an initialization scheme. The cost function $J_{4D}$ is written by

$$J_{4D}(z) = \frac{1}{2} \sum_l \mathbf{z}_l^T (\mathbf{B}_h)^{-1} \mathbf{z}_l + \sum_{l=1}^{t_f} \left\{ \frac{1}{2} (\mathbf{H}_s - \mathbf{y}_t)^T \mathbf{R}_s^{-1} (\mathbf{H}_s - \mathbf{y}_t) + \frac{1}{2\sigma_h^2} [\mathcal{H}(\mathbf{x}_t) - \mathbf{y}_t^{\text{SLA}} - \mathbf{H}_s \bar{\mathbf{h}}]^T \right\}$$

$$+ \left[ \mathcal{H}(\mathbf{x}_t) - \mathbf{y}_t^{\text{SLA}} - \mathbf{H}_s \bar{\mathbf{h}} \right] + J^p + \sum_{l=1}^{t_f} J_{t_l}^p + J^c, \quad (6)$$

where the subscript $l$ denotes the time index and the time interval $(t_l - N, t_f)$ represents the assimilation window. $J^p$ is the background term, and $J^c$ is the observation term at time $t$. MOVE-4DVAR estimates the optimal temperature and salinity fields, and the control variable is amplitudes of the vertical coupled $T$–$S$ EOF modes as MOVE-3DVAR. Thus, the corrections to the first guess, $\Delta \mathbf{x}$, is represented by the same form as $(4)$.

In the conventional 4DVAR scheme, the analysis increment is added to the first-guess field at once at the initial time. In that case, the increment sometimes leads to high-frequency noises because the spatial structure of the increment at the initial time depends on the background error covariance matrix based on a statistical assumption. For that reason, MOVE-4DVAR adopts an initialization scheme of incremental analysis updates (IAU; Bloom et al. 1996) in order to filter
out high-frequency noises due to the analysis increment. A schematic of the initialization scheme employed in MOVE-4DVAR is shown in Fig. 1.

Thus, in MOVE-4DVAR the time evolution of the state vector during \((t-1, t)\) is expressed by a nonlinear operator \(L_{t-1,t}\) as follows:

\[
x_t = L_{t-1,t}(x_{t-1}, \Delta x_t). \tag{7}
\]

The operator \(L_{t-1,t}\) is further decomposed into two parts:

\[
x_t = M_{t-1,t}(x_{t-1}) + \Delta x_t^{\text{cor}}, \tag{8}
\]

where

\[
\Delta x_t^{\text{cor}} = g_t \Delta x_{t-1}, \quad g_t = \begin{cases} 1/N & (t_f - N < t \leq t_f) \\ 0 & (t_f < t \leq t_p). \end{cases} \tag{9}
\]

Operator \(M_{t-1,t}\) denotes a nonlinear model and \(\Delta x_t^{\text{cor}}\) represents the correction term, which works during the initialization period from \(t_f - N\) to \(t_f\). It should be noted that this initialization reduces to the conventional form when \(N \to 1\). Fujii et al. (2008) actually applied the same incremental correction technique to singular vector analysis for the formation of a Kuroshio large meander and pointed out that this correction method is effective to extract slowly varying modes related to Kuroshio path variations by filtering out high-frequency signals.

Taking the first variation of both sides in (8) yields

\[
\delta x_t = M_{t-1,t} \delta x_{t-1} + g_t \delta(\Delta x_t) = \sum_{k=t_f-N}^{t} g_k M_{k,t} \delta(\Delta x_t), \tag{10}
\]

where \(M_{t-1,t} = \partial M_{t-1,t}/\partial x_{t-1}\) is the tangent linear operator of the original nonlinear model, \(M_{k,t} = M_{t-1,k} \otimes M_{t-2,k} \otimes \ldots \otimes M_{t-k+1,t} \), and \(M_{0,t} = I\). It should be noted that \(\delta x_{t_f - N} = 0\) because the model state at the initial time step \(x_{t_f - N}\) is not corrected. This also means that the operator \(L_{t_f - N,t}\) can be understood as a function of \(\Delta x\) as follows:

\[
x_t = L_{t_f - N,t}(\Delta x). \tag{11}
\]

Comparing (10) and the first variation of (11), the tangent linear and the adjoint operators of \(L_{t_f - N,t}\) are written by

\[
L_{t_f - N,t} = \sum_{k=t_f-N}^{t} g_k M_{k,t} \quad \text{and} \quad L_{t_f - N,t}^* = \sum_{k=t_f-N}^{t} g_k M_{k,t}^*, \tag{12}
\]

where \(M_{k,t}^*\) is the adjoint operator of \(M_{k,t}\). Applying the above adjoint operator to \(\tilde{x}\), corresponding to adjoint variables of \(x_t\), we obtain its backward evolution in time as follows:

\[
\tilde{\Delta x} = L_{t_f - N,t}^* \tilde{x}_t = \sum_{k=t_f-N}^{t} g_k M_{k,t}^* \tilde{x}_t = \sum_{k=t_f-N}^{t} g_k \tilde{x}_k, \tag{14}
\]

where \(\tilde{\Delta x}\) is adjoint variables of \(\Delta x_t\). When \(t \equiv t_f\), (14) becomes

\[
\tilde{\Delta x} = \frac{1}{N} \sum_{k=1}^{N} \tilde{x}_{t_f-k}. \tag{15}
\]

That is, \(\tilde{\Delta x}\) is obtained as an average of \(\tilde{x}\) over the initialization period. It can be understood as a kind of an incremental digital filtering (IDF), which is also effective for suppressing high-frequency noises. Actually, Polavarapu et al. (2004) pointed out that IAU and IDF have the same filtering property.

The optimal temperature and salinity fields are obtained by minimizing the cost function. To implement the minimization procedure, it is necessary to calculate the gradient of the cost function with respect to the control variable \(z\), which is written by

\[
\nabla_x J_{4D} = \sum_{t} (B_t)^{-1} z_t + \sum_{t} \nabla_x J_{4D} + \nabla_x J_{r}. \tag{16}
\]

Using (4), (6), and (11), the gradient of the observation term \(\nabla_x J_{4D}\) at time \(t\) in the second term on the right-hand side is represented by

\[
\nabla_x J_{4D} = \frac{\Delta x}{\Delta z} \frac{\partial J_{4D}}{\partial x} = G^T L_{t_f - N,t} \left( H^T R_{t_{f-j}}^{-1} (H_{t_f-j} - y_{t_{f-j}}^{TS}) + \frac{1}{\sigma^2_n} H_{SDH}^{*} \left[ p(x_{t_{f-j}} - y_{t_{f-j}}^{SLA} - H_{t_{f-j}})^2 \right] \right), \tag{17}
\]
where $H^*_{3D}$ is the adjoint operator of $H$. Therefore, the gradient of the cost function with respect to the control variable, $V_x J_{3D}$, can be calculated by the following procedure:

$$
\tilde{x}_t = \frac{\partial J_{3D}}{\partial x_t},
$$
(18)

$$
\tilde{x}_{t-1} = L^*_{t-1} \tilde{x}_t + \partial J_{3D}/\partial \tilde{x}_t (t_j - N < t < t_F), \quad \text{and}
$$
(19)

$$
V_x J_{3D} = \sum_l (B_l^H)^{-1} x_l + G^T \Delta x + V_x J^c.
$$
(20)

Note that $\tilde{x}_t$ represents variables for the adjoint model $L^*$ forced by data misfits between the model and observations as shown in (19).

3. Description of the assimilation system

The newly developed assimilation system includes two models (Fig. 2). One is MOVE-4DVAR-WNP, which consists of an eddy-resolving OGCM in the western North Pacific and the 4DVAR assimilation scheme. The other is a fine-resolution coastal model, MOVE-Seto, which covers western part of the Japanese coastal region including the Seto Inland Sea. MOVE-Seto is nested into the western North Pacific model and is initialized with MOVE-4DVAR-WNP results (Fig. 3).

In the following subsections, descriptions of both MOVE-4DVAR-WNP and MOVE-Seto will be given.

a. MOVE-4DVAR-WNP

The OGCM used in MOVE-4DVAR-WNP is based on the western North Pacific version of the MRI Community Ocean Model version 2.4 (MRI.COM-WNP; Tsujino et al. 2006). MRI.COM is a free-surface, depth-coordinate model that solves the primitive equations under the hydrostatic and Boussinesq approximations. The barotropic part of the equations is solved based on a one-way nesting algorithm (Killworth et al. 1991). The vertical coordinate near the surface follows the surface topography like $\sigma$ coordinates. A biharmonic operator with a coefficient $1.0 \times 10^8 \text{m}^4 \text{s}^{-1}$ is used for the horizontal mixing of tracers. For the horizontal momentum mixing a biharmonic Smagorinsky viscosity (Griffies and Hallberg 2000) is applied. The vertical viscosity and diffusivity are determined by the turbulent closure scheme of Noh and Kim (1999). The bottom friction is calculated according to the formula proposed by Weatherly (1972).

The configuration of this model is basically the same as that used in Tsujino et al. (2006) except for vertical grid spacing near the bottom and for discarding a sea ice model. The model domain spans from 117$^\circ$E to 160$^\circ$W zonally and from 15$^\circ$ to 65$^\circ$N meridionally (Fig. 2). Horizontal resolution is variable. It is $1/10^\circ$ from 117$^\circ$ to 160$^\circ$E and $1/6^\circ$ from 160$^\circ$E to 160$^\circ$W zonally, and it is $1/4^\circ$ from 15$^\circ$ to 50$^\circ$N and $1/8^\circ$ from 50$^\circ$ to 65$^\circ$N meridionally. There are 54 vertical levels with thickness increasing from 1 m at the surface to 600 m at 6300-m depth. Oceanic states at the open boundaries are obtained from a North Pacific data assimilative model with a resolution of $1/5^\circ$ using the one-way nesting method. The 3DVAR scheme is adopted to the North Pacific model and daily outputs from the North Pacific model are linearly interpolated both in time and space to update open boundaries of the high-resolution western North Pacific every time step.

The tangent linear and adjoint codes of MRI.COM were developed manually. We made the following approximations for the linear codes. In the turbulent closure scheme, the vertical mixing coefficients are calculated from the background state and the dependency of the coefficients on the deviation from the background state is ignored. We also apply the same approximation to the bottom friction. This approximation avoids the instability of tangent linear models (Zhu and Kamachi 2000). In addition, we modified the code in order to avoid singularities. The adjoint code was written as the exact transpose of the tangent linear code. We have confirmed that $(L^a)^T(L^a) = a^2 L^a(L^a)$ for any vector $a$. The tangent linear and adjoint codes have been already applied to various analyses. Fujii et al. (2008) performed singular vector analysis in order to estimate optimal perturbations for the Kuroshio large meander. In addition, using the tangent linear and adjoint codes, Fujii et al. (2013) identified the pathway of the North Pacific Intermediate Water from its origin in the subarctic North Pacific to the subtropical region.

The model domain is divided into 13 subregions and the vertical $T$–$S$ EOF modes from the surface to 1500 m, which model the vertical correlation matrix of background errors, are calculated using historical $T$–$S$ profile data in each subregion and monthly climatological $T$–$S$ fields from the World Ocean Atlas (WOA) 2001. It should be noted here that the vertical correlation matrix is constructed using $T$–$S$ anomalies from the WOA monthly climatology and thus the obtained $T$–$S$ EOF modes do not include seasonal changes. In each subregion, we utilize the dominant 12 modes for the assimilation procedure that explain more than 90% of the total variance. That is, the vertical profile of the analysis temperature and salinity is represented by a linear combination of the 12 modes. The mean SDH, $\bar{H}$, in (6) was calculated by the following procedure. First, we produce monthly mean temperature and salinity fields during 1993–99, which is the same as the reference period for the altimeter-derived SLA. The monthly fields
are obtained by the 3DVAR analysis using in situ $T$–$S$ profiles and the monthly mean climatology as a first guess. Second, monthly SDHs during 1993–99 are calculated from the monthly mean temperature and salinity obtained by the above analysis. By taking the average, we finally obtain the mean SDH.

In the MOVE system, the preconditioned optimizing utility for large-dimensional analyses (POpULar; Fujii 2005) is adopted to minimize the cost function. POpULar is based on a nonlinear preconditioned quasi-Newton method and can minimize a nonlinear cost function without inversion of a nondiagonal background error covariance matrix.

b. MOVE-Seto

MOVE-Seto consists of the fine-resolution coastal model (MRI.COM-Seto) based on MRI.COM version 3.2 (Tsujino et al. 2010) and an initialization scheme using the IAU method. The model covers western part of the Japanese coastal region including the Seto Inland
Sea, which is a semiclosed sea and has complicated coastal topography. The model domain extends from 129° to 138°E longitude and from 28° to 35.2°N latitude. The horizontal resolution is about 2 km: 1/33° in the zonal and 1/50° in the meridional directions. The model has 50 vertical levels, with the layer thickness increasing from 4 m at the surface to 600 m at 6300-m depth. It should be noted that the vertical grid spacing for MRI.COM-Seto near the surface is somewhat coarse compared to that for MRI.COM-WNP. The higher vertical resolution leads to better representation of bathymetry in shallow water. In the next step of the development such an improvement will be made.

Physical schemes adapted to MRI.COM-Seto are basically the same as those of MRI.COM-WNP used in MOVE-4DVAR-WNP except for a high accuracy tracer advection scheme (Prather 1986). MRI.COM-Seto is nested into MRI.COM-WNP using the one-way nesting; that is, prognostic variables at the open boundaries are given from MRI.COM-WNP. We utilize daily outputs of MRI.COM-WNP, which are linearly interpolated both in time and space to replace the oceanic states of MRI.COM-Seto at every time step. Note that the linear spatial interpolation is performed not only in the horizontal direction but also in the vertical direction, because the vertical grid spacing is different between MRI.COM-Seto and MRI.COM-WNP.

To initialize the fine-resolution model, MOVE-Seto employs the IAU initialization scheme. Temperature and salinity in the whole region of the fine-resolution model are initialized every assimilation window using MOVE-4DVAR-WNP temperature and salinity analysis fields as schematically shown in Fig. 3. Specifically, the following procedures are conducted every assimilation window. First, MRI.COM-Seto is integrated until the center of the initialization period without any correction, and temperature and salinity fields in the final state are linearly interpolated to the MOVE-4DVAR-WNP grid in the horizontal and vertical directions. Second, the interpolated model field is compared to analysis temperature and salinity fields of MOVE-4DVAR-WNP on the same day in order to make correction fields in the MOVE-4DVAR-WNP grid. Then the corrections are interpolated to the MRI.COM-Seto grid and are divided by the number of time steps in the IAU period. Finally, MRI.COM-Seto is integrated during the period from the initial time of the IAU period to the end of the assimilation window. The divided corrections are added to the model fields at every time step during the IAU period.

In this nested coastal system, MOVE-Seto and MOVE-4DVAR-WNP can be regarded as a fine-resolution forecast model and a low-resolution analysis model, respectively, like the so-called incremental method (Courtier et al. 1994). The present system is however different from the incremental 4DVAR because results of the fine-resolution model are not taken into account as the background state in MOVE-4DVAR-WNP. Such improvement will be subject of future study.

4. Experimental setup

We conducted two sets of assimilation experiments, which are summarized in Table 1. The first set is WNP-3DVAR and WNP-4DVAR, which aim to evaluate mesoscale variability. WNP-3DVAR was carried out using MOVE-3DVAR-WNP, in which the 3DVAR...
scheme was applied to MRI.COM-WNP. It should be noted that MOVE-3DVAR-WNP includes a sea ice model consisting of the thermodynamic model (Mellor and Kantha 1989) and the dynamics model based on the Los Alamos sea ice model (Hunke and Dukowicz 1997, 2002), while MOVE-4DVAR-WNP does not include the sea ice model as mentioned above. The experiment WNP-4DVAR was performed by MOVE-4DVAR-WNP. The second one is Seto-3DVAR and Seto-4DVAR, which were done by MOVE-Seto to evaluate coastal sea level variability. Experimental conditions for each assimilation experiment are described below.

First, we conducted two assimilation experiments, WNP-3DVAR and WNP-4DVAR, during the period from 2000 to 2003. The common observation data including in situ temperature and salinity profiles, gridded SST, and altimeter-derived SLA were used. The in situ temperature and salinity profiles are collected from the World Ocean Database 2001 (WOD01; Conkright et al. 2002) and the Global Temperature Salinity Profile Program (GTSP; Hamilton 1994). The gridded SST is Merged satellite and in situ data Global Daily Sea Surface Temperatures (MGDSST; Kurihara et al. 2000), which is produced by JMA and has a horizontal resolution of \(\frac{1}{4}\) \(\times \frac{1}{4}\). The satellite SLA observations are the along-track data of TOPEX/Poseidon, Jason-1, ERS-2, and Envisat, which are obtained from the SSALTO/Data Unification and Altimeter Combination System (DUACS) delayed time multisatellite products (CLS 2004).

The assimilation window is 10 days for both experiments. Because the main target of MOVE-4DVAR-WNP is mesoscale phenomena such as Kuroshio meanders and mesoscale eddies, the IAU period for initialising the forward model in MOVE-4DVAR-WNP is set to 3 days in order to filter out high-frequency signals such as gravity waves and near-inertial oscillations. It should be noted that MOVE-3DVAR-WNP also adopts the IAU scheme for the initialization and its period is 10 days (i.e., the same as the assimilation window), while it is 3 days for WNP-4DVAR. Thus, we would need to take into consideration the difference in the IAU period when we compare results of the two experiments. Both experiments start from the same initial state on 1 January 2000, which is obtained from a reanalysis experiment using MOVE-3DVAR-WNP (Usui et al. 2006). The model is driven by daily wind stress and heat fluxes from the Japanese 25-yr Reanalysis and JMA climate data assimilation system (Onogi et al. 2007). Latent and sensible heat fluxes are calculated by the bulk formula of Kondo (1975) using model sea surface temperature (SST). The freshwater flux is corrected by restoring sea surface salinity toward the monthly mean climatology with a restoring time scale of 1 day to prevent a model drift.

Experiments named Seto-3DVAR and Seto-4DVAR were carried out by using MOVE-Seto. In the experiment Seto-3DVAR (Seto-4DVAR), the 2-km coastal model is initialized by MOVE-3DVAR-WNP (MOVE-4DVAR-WNP) analysis fields. The initialization period is set to be 3 days, which is the same as the IAU period used in MOVE-4DVAR-WNP, and it is performed on the 4–6th day in each assimilation window of MOVE-3DVAR-WNP or MOVE-4DVAR-WNP. Here we focus on a specific event in September 2011, and hence the experiments were conducted during the period from 1 August to 31 October 2011. The atmospheric forcing is JRA-25, which is the same as that used for the experiments WNP-3DVAR and WNP-4DVAR.

In the following sections, we will evaluate model results using daily outputs in all of the four experiments. The outputs were sampled during the model integration, which is represented by a similar form as (8). The correction term \(\Delta x^c\) works only during the 1st–3rd day (4–6th day) in each assimilation window for WNP-4DVAR (Seto-3DVAR and Seto-4DVAR), while it works throughout the assimilation window of 10 days for WNP-3DVAR.

5. Mesoscale variability

In this section we focus on mesoscale variability. Figure 4 compares mean and root-mean-square variability of the sea surface height (SSH) fields over four years in 2000–03 among altimeter-derived observation, WNP-3DVAR, and WNP-4DVAR. The observation used here is the gridded SSH dataset obtained from Archiving, Validation and Interpretation of Satellite Oceanographic data (AVISO; http://www.aviso.oceanobs.com/duacs). The dataset merges along-track SSH measurements from all altimeter missions and has a 7-day temporal resolution and a \(\frac{1}{4}\) \(\times \frac{1}{4}\) spatial resolution. The mean and standard deviation of SSH for MOVE-3DVAR-WNP and MOVE-4DVAR-WNP are calculated from daily outputs over 4 yr from 2000 to 2003. Those for AVISO SSH data are calculated from the weekly data in 2000–03.

The mean SSH fields for both WNP-3DVAR and WNP-4DVAR well capture observed features of the mean flow pattern of the Kuroshio such as a sharp front and a separation off the Boso Peninsula (35°N, 141°E). The SSH variability for the assimilated fields also compares well with the observation. The Kuroshio Extension (KE) region has the largest SSH variability as a result of energetic mesoscale eddy activity. The subtropical counter current region also exhibits relatively
large variability, which is also related to mesoscale eddies. It is worth noting that the WNP-4DVAR result shows slightly larger variability compared to the WNP-3DVAR result and is in good agreement with the observed variability.

Next we compare vertical temperature distributions along 144°E across the KE path with an observation. Figure 5a displays a temperature section observed during 25–29 June 2000 by an observation vessel, Kofu Maru, operated by Hakodate Marine Observatory in JMA. Because this observed temperature was used in the assimilation experiments for both WNP-3DVAR and WNP-4DVAR, first-guess temperature fields just before assimilating the Kofu Maru data, which are obtained by forecast runs starting from the final states in the previous assimilation window, are compared with the observation. To be specific, Fig. 5b shows a snapshot temperature field on 26 June 2000 that is the center of the assimilation window in 21–30 June 2000 and was used as the first-guess field in WNP-3DVAR. Although the first guess in WNP-4DVAR is not a snapshot field but a time-varying field, daily mean temperature section of the WNP-4DVAR first-guess field on 26 June 2000 is plotted in Fig. 5c for comparison.

In this period, the Kuroshio main current was located between 36° and 37°N. It is recognizable as a tilted thermocline in Fig. 5a. Another feature in the observed temperature section is the existence of a warm-core eddy located at 38.5°N. The WNP-4DVAR first-guess field succeeds in reproducing the above observed features even though there exist some mismatches; for example, surface water to the south of the Kuroshio is warmer and vertical structures of the Kuroshio and the warm-core eddy are somewhat deeper. In contrast, discrepancies between the WNP-3DVAR first-guess field and the observation are more visible. The Kuroshio axis and the warm-core eddy are located to the south compared to the observation. Comparison of analysis fields on 26 June 2000 for WNP-3DVAR and WNP-4DVAR (i.e., assimilation results using the Kofu Maru observation together with other observations) also indicates that the WNP-4DVAR result shows a better representation of the observed features (Fig. 6). For example, subsurface cold water to the north of the Kuroshio front (37.5°N) that is somewhat warmer in the WNP-4DVAR first-guess field compared to the observation (see Fig. 5a) is much improved in the analysis. It is also noticeable that an subsurface temperature minimum in
40.5°–42°N, which is known as the dichothermal water (Ueno and Yasuda 2000) and is not represented in the WNP-4DVAR first-guess field, is well captured in the WNP-4DVAR assimilated field (Fig. 6c). In the WNP-3DVAR first-guess field the subsurface temperature minimum is partly captured although the spatial structure is an eddylike and discontinuous unlike the observed one. The eddylike structure is improved in the analysis field. The cold water corresponding to the subsurface minimum is considered to be originated from the Bering Sea or the Sea of Okhotsk and is brought to the south of Hokkaido by the Oyashio Current. Because many areas in the Bering Sea and the Sea of Okhotsk are capped by sea ice in winter, incorporating a sea ice model might be important for realistic representation of the subsurface temperature minimum. In fact, MOVE-3DVAR-WNP includes the sea ice model as described in section 4, while MOVE-4DVAR-WNP does not incorporate it.

On the other hand, the assimilation result of WNP-3DVAR fails to reproduce the observed mesoscale features (Fig. 6a). It should be noted that analysis increments from 3DVAR are not sufficiently reflected to the model field at the time of 26 June 2000 since in the IAU scheme adopted to WNP-3DVAR the increments are divided by the number of time steps corresponding to the assimilation window and the divided increments are added as a forcing term at every time step during the assimilation window. Nevertheless, the large errors in the first-guess field would be the primary reason for the poor performance of the WNP-3DVAR.
For more quantitative evaluation, we calculate SDH innovation standard deviations, which is written by
\[
\sqrt{\langle [\mathcal{H}(\mathbf{x}^b) - \mathbf{y}^{\text{SLA}} - \mathbf{H}_n \mathbf{h}]^T [\mathcal{H}(\mathbf{x}^b) - \mathbf{y}^{\text{SLA}} - \mathbf{H}_n \mathbf{h}] \rangle},
\]  
(21)

where the angle brackets \(\langle \cdot \rangle\) denotes the expectation. We calculate the SDH innovation for both WNP-3DVAR and WNP-4DVAR. The first guess for WNP-3DVAR is obtained from a model output at the center of each assimilation window as described above. To compare WNP-3DVAR and WNP-4DVAR under the same condition, innovations for WNP-4DVAR (shown by the red line in Fig. 7) are calculated by using the first-guess field at the center of the assimilation window. Figure 7 compares time series of SDH innovations for WNP-3DVAR (blue line) and WNP-4DVAR (red line) around the KE region (30°–42°N, 142°–165°E), which exhibits strong mesoscale eddy activity. The SDH innovation for WNP-4DVAR exhibits high-frequency oscillations and its period corresponds to the assimilation cycle. The oscillations are probably due to differences in time between observations and the first guess used for the calculation. In fact, the high-frequency signals vanish in another SDH innovations for WNP-4DVAR depicted with the black line and open circles, which were calculated using the first guess at the appropriate time. The SDH innovation for WNP-4DVAR is obviously lower than that for WNP-3DVAR. Mean values of the SDH innovations for WNP-3DVAR and WNP-4DVAR are 18.5 and 16.5 cm, respectively. Another SDH innovation of WNP-4DVAR calculated using the first guess at the appropriate time is further reduced to 14.5 cm. Both time series show a clear seasonal variation—that is, the innovation is high (low) in summer (winter). The relatively large errors in summer
are probably due to strong density stratification in the surface layers, which is not considered in the background error covariance because the vertical $T-S$ EOF modes we used do not change seasonally. Thus, further improvement might be expected by taking account of the summertime strong stratification in the background error covariance, which should be the subject of future studies.

As described in the introduction, it is expected that the 4DVAR scheme improves oceanic variations on a short time scale because 4DVAR extracts information about the time evolution of observed phenomena. To see this, we look into variability in the Kuroshio south of Japan. Figure 8 presents the time series of sea level anomalies at Hachijo-jima Island (HJ) that is located very close to the Kuroshio path (see Fig. 10b). The sea level at HJ is thus strongly influenced by variations in the Kuroshio path. Assimilation results for both WNP-3DVAR and WNP-4DVAR largely follow the observed sea level variations at HJ. Comparison of the time series of the two assimilated fields indicates that short-term variations on a time scale of a few 10 days are more enhanced in WNP-4DVAR as expected. The enhancement of the short-term variations for WNP-4DVAR can also be seen in Fig. 9, which displays power spectra of the sea level anomalies at HJ for WNP-3DVAR, WNP-4DAR, and tide-gauge observation. The SLA spectrum for WNP-4DVAR has larger power than that for WNP-3DVAR at a time scale shorter than about one month, while the power spectra have similar magnitude at longer time scales. It should be noted that amplitude of the SLA variability for WNP-4DVAR is still low compared to the observation. This is probably because the spatiotemporal resolution of the model and its atmospheric forcing is still insufficient to resolve such short-term variability.

In addition to the enhancement of the SLA short-term variability, another advantage for WNP-4DVAR relative to WNP-3DVAR can be found in Fig. 8. Taking a close look at several specific events in, for example, August 2001 and May 2002 that exhibit rapid sea level rise or drop, we find that WNP-4DVAR is more accurate than WNP-3DVAR although in some cases WNP-4DVAR fails to reproduce observed sea level changes. The root-mean-square error (RMSE) between the observation and assimilation results in 2000–03 for WNP-4DVAR (11.1 cm) is smaller than that for WNP-3DVAR (13.2 cm).

A typical example of Kuroshio path fluctuations causing the short-term variabilities is shown in Fig. 10, which compares assimilated SST snapshot fields for WNP-3DVAR and WNP-4DVAR with satellite SST images from 10 January to 5 February 2000. In the satellite SST image on 10 January 2000, two meanders of the Kuroshio (A and B) can be found. WNP-4DVAR captures well features of the shape of the Kuroshio path.
in the satellite SST image including the two meanders. In contrast, the Kuroshio path in WNP-3DVAR is somewhat smoothed, resulting in poor representation of the smaller-scale meander B. The satellite SST image indicates that the two meanders move while changing their amplitude. It is noticeable that as a result of development of the meander B warm Kuroshio water intrudes into the coastal regions (136°–138°E) in the end of January. WNP-4DVAR succeeds in reproducing this warm-water intrusion event, and the steep shape of the meander A at that time is also well represented. On the other hand, the warm-water intrusion is unclear in WNP-3DVAR, and the shape of the meander A in the end of January is less seaward compared with the observation. Looking at the sea level variations associated with this Kuroshio path fluctuation at HJ in Fig. 8, we can see that WNP-4DVAR actually shows better representation compared to WNP-3DVAR.

6. Coastal sea level variability

In the previous section we found that MOVE-4DVAR-WNP is effective for short-term mesoscale variability such as short-term and small-scale Kuroshio path fluctuations. Because the Kuroshio path has a large impact on sea level variability at the south coast of Japan (e.g., Kawabe 1980), it is expected that MOVE-4DVAR-WNP leads to better representation of the coastal sea level variability. Thus, in this section we perform a case study in order to explore the validity of the 4DVAR scheme for coastal sea level variability. For
Figure 11 shows time series of SLAs in September to October 2011 at four tide-gauge stations along the south coast of Japan: Aburatsu (AB), Uwajima (UW), Sumoto (SM), and Miyake-jima (MJ) (see Fig. 12 for geographical locations). Here we define the model SLAs as deviations from mean SSH field in 1993–2007, which is obtained from an ocean reanalysis experiment with MOVE-3DVAR-WNP (Usui et al. 2006). In addition, correction factors are added to the model SLAs in Fig. 11.
so that average SLAs over the period (1 September–10 October) are the same as those for the tide-gauge observations. Model results in Figs. 11a–c are obtained from Seto-3DVAR and Seto-4DVAR, and those in Fig. 11d are from WNP-3DVAR and WNP-4DVAR. The SLAs for tide-gauge data were obtained as anomalies from astronomical tide including seasonal change provided by JMA and the inverted barometer correction was also applied to the anomalies using JRA-25 sea level pressure. The SLAs of the model results are defined as anomalies from 1993–2007 daily climatological SSH fields obtained from a reanalysis experiment with MOVE-3DVAR-WNP (Usui et al. 2006). In addition, correction factors are added to the model SLAs so that average values are the same as those for tide-gauge observations. The correction factors are shown by blue and red numbers for 3DVAR and 4DVAR, respectively. Arrows with black dotted lines in (a)–(c) denote the period of the unusual tide event focused on in this study.

Comparison of the assimilated SLAs for Seto-3DVAR and Seto-4DVAR with tide-gauge observations in Figs. 11a–c indicates that Seto-4DVAR succeeds in quantitatively reproducing the observed sea level rise associated with the unusual tide, while the sea level rise in Seto-3DVAR is unclear. Figure 11 displays time evolution of Seto-4DVAR (Seto-3DVAR) SLA fields superimposed on WNP-4DVAR (WNP-3DVAR) SLAs. Note that the correction factors added to the SLAs in Fig. 11 are not considered for SLAs in Fig. 12. It is worth noting that the two SLA maps for Seto-4DVAR and WNP-4DVAR (Seto-3DVAR and WNP-3DVAR) in Fig. 12 are smoothly connected each other, indicating that the nesting procedure between the two models and initialization of MRI.COM-Seto works well. Positive SLAs can be found at the south coast of Japan, and the SLA signals associated with this event are confined along the coastal area. SLA amplitude for Seto-4DVAR is more enhanced compared to that for Seto-3DVAR even though the atmospheric forcings used in both experiments were the same. This implies that the model sea level rise associated with this event arises from oceanic circulation features such as fluctuations of the Kuroshio, produced by their respective data assimilation systems.

Although SLA maps for Seto-3DVAR (WNP-3DVAR) and Seto-4DVAR (WNP-4DVAR) exhibit similar patterns, there is a slight difference in the shape of the Kuroshio path on 23 September 2011, when it takes a meandering path as depicted by arrows in Fig. 12. In the 4DVAR case, the Kuroshio meander is steeper than that
in the 3DVAR case. As a result, a sharp crest of the Kuroshio path (see arrow B in Fig. 12b) located around MJ on 23 September is formed in the 4DVAR case and its accompanied positive SLA approaches to the southern tip of the Boso Peninsula. Then the sea level along the south coast of Japan rises and part of the positive SLAs go into the Japan Sea.

The observed SLA at MJ in Fig. 11d supports the above model results in the 4DVAR case. That is, SLA at MJ actually rises in advance of the sea level rise at the south coast of Japan, and then drops from the end of September to the beginning of October because of eastward movement of the crest (Fig. 12). These features of the observed SLA at MJ are well reproduced in WNP-4DVAR, although there is a few days’ difference in timing of the sea level rise and drop. The above results suggest a possible mechanism responsible for this event that the sea level rise was brought about by propagation of coastal trapped waves (CTWs), which were induced by a short-term fluctuation of the Kuroshio path. We however need further analyses to clarify the mechanism responsible for this event. It is beyond the scope of this study and therefore remains for the future study.

In the 3DVAR case, on the other hand, the crest of the Kuroshio path around MJ is somewhat smoothed and the positive SLA signals hardly get close to the coastal area (Fig. 12a). This weak fluctuation of the Kuroshio path can also be found in the time series of SLA at MJ in Fig. 11. That is probably why Seto-3DVAR underestimates the sea level rise at the south coast of Japan associated with the unusual tide.

To summarize the above results, we conclude that 4DVAR is effective for improving coastal sea level variability as well as short-term mesoscale variability. In this section we however focused on only one specific event. Hence, further evaluation in terms of the effectiveness of the 4DVAR scheme for coastal data assimilation is needed, which should be subject for future studies.

7. Summary and future work

We have developed an assimilation system toward coastal data assimilation around Japan, which consists
of a 4DVAR version of the MOVE system with an eddy-resolving western North Pacific OGCM (MOVE-4DVAR-WNP) and a fine-resolution coastal model for the Seto Inland Sea with an initialization scheme (MOVE-Seto). The 4DVAR scheme of MOVE-4DVAR-WNP was developed as a natural extension of the present operational 3DVAR scheme at JMA. That is, the background error covariance matrix is modeled by vertical coupled temperature and salinity EOF modes and amplitudes of the vertical EOF modes are employed as control variables. In addition, the incremental analysis update (IAU) initialization scheme is incorporated into the 4DVAR scheme in order to suppress high-frequency noises in the analysis increment. During the backward integration of the adjoint model, IAU acts to take a weighted mean of adjoint variables over the initialization period, which can be regarded as a kind of an incremental digital filtering. MOVE-Seto, which is nested within the eddy-resolving MOVE-4DVAR-WNP, also employs the IAU scheme in order to initialize temperature and salinity fields in the interior of MOVE-Seto using MOVE-4DVAR-WNP analysis fields.

First we conducted 4-yr assimilation experiments, WNP-3DVAR and WNP-4DVAR, in 2000–03 using MOVE-3DVAR-WNP and MOVE-4DVAR-WNP, and compared two results with particular attention to mesoscale variability. The comparison indicates that mesoscale features such as the position of mesoscale eddies and their vertical structures are much improved in WNP-4DVAR. Besides, close investigation of sea level variations at Hachijo-jima reveals that MOVE-4DVAR-WNP reasonably enhances short-term variability along with the improvement of mesoscale features associated with Kuroshio path fluctuations. To evaluate mesoscale variability in MOVE-4DVAR-WNP, we focused on the Kuroshio path variations south of Japan and mesoscale eddies off the east of Japan, which are somewhat limited compared to the model domain. We will therefore need further evaluation of MOVE-4DVAR-WNP targeting various areas, which should be subject for future study.

To confirm the effectiveness of the 4DVAR scheme for the coastal sea level variability, we then carried out two cases of assimilation experiments (Seto-3DVAR and Seto-4DVAR) using the MOVE-Seto system targeting an unusual tide event that occurred in September 2011. The Seto-4DVAR (Seto-3DVAR) experiment was done using the fine-resolution coastal model initialized with MOVE-4DVAR (MOVE-3DVAR) results. Seto-4DVAR succeeds in reproducing significant sea level rise at the south coast of Japan in the end of September 2011 associated with the unusual tide event. In addition, the Seto-4DVAR and MOVE-4DVAR results suggest that the sea level rise of this event was originated from a short-term Kuroshio path fluctuation. In contrast, Seto-3DVAR fails to represent the sea level rise, probably as a result of underestimation of the Kuroshio path fluctuation in MOVE-3DVAR. Therefore, the results of this case study strongly suggest the effectiveness of the 4DVAR scheme for coastal data assimilation.

Although there are a number of previous studies addressing the relationship between coastal sea level in Japan and Kuroshio path variations (e.g., Kawabe 1980; Senjyu et al. 1999), the mechanism responsible for it is still controversial. The Seto-4DVAR result in this study indicates that the newly developed MOVE-Seto system is effective for such kind of process study. As the next step of the case study, we are now performing a comprehensive analysis in order to elucidate the mechanism responsible for the unusual tide in 2011, which will be reported in the next paper.

As described in section 2, the present assimilation scheme in MOVE-4DVAR-WNP controls only temperature and salinity fields because the main target of MOVE-4DVAR-WNP is mesoscale phenomena such as mesoscale eddies and Kuroshio meanders, which are largely governed by geostrophic dynamics. The ageostrophic component is however considered to be important for coastal phenomena. Therefore, extension of the control variables to include velocity fields would be effective for further improvement of coastal phenomena.

Since the present MOVE-Seto system is a simple nested coastal model forced by MOVE-4DVAR-WNP with the IAU initialization, upgrade of MOVE-Seto would also lead to further improvement of assimilated fields in the coastal region. One possible upgrade is to introduce the incremental 4DVAR scheme (Courtier et al. 1994), in which results of the fine-resolution coastal model are used as the background field in the 4DVAR calculation. Construction of a 4DVAR assimilation system using the coastal model would also be effective for further improvement. In addition, use of new type of observations—for example, sea surface velocity measured using high-frequency radars and high-resolution SLAs by wide-swath altimeters—is also important, and such upgrade can be naturally introduced in the assimilation system by using the 4DVAR scheme. These upgrades should be subject for future studies.

Acknowledgments. The authors thank the members of the ocean modeling and assimilation group at the Meteorological Research Institute for fruitful discussions. Comments from anonymous reviewers greatly improved the earlier version of the manuscript. This work was funded by the Meteorological Research Institute, and
was partly supported by JSPS KAKENHI Grants 22106006 and 26400472 and by Research Program on Climate Change Adaptation (RECCA) of MEXT.

REFERENCES


