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Review

Assimilation of Oceanographic Data into Numerical Models over the Seas around Korea

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Abstract : This review provides a summary of data assimilation applied to the seas around Korea. Currently the worldwide efforts are devoted to applying advanced assimilation to realistic cases, thanks to improvements in mathematical foundations of assimilation methods and the computing capabilities, and also to the availability of extensive observational data such as from satellites. Over the seas around Korea, however, the latest developments in the advanced assimilation methods have yet to be applied. Thus it would be timely to review the progress in data assimilation over the seas. Firstly, the definition and necessity of data assimilation are described, continued by a brief summary of major assimilation methods. Then a review of past research on the ocean data assimilation in the regional seas around Korea is given and future trends are considered. Special consideration is given to the assimilation of remotely-sensed data.

Key Words : Data Assimilation, Prediction, Ocean Model, Remote Sensing.

1. Introduction

Data assimilation is a method to improve the utility of observation data, remotely-sensed and in situ alike, and the performance of a numerical model. The basic theory and mathematics of data assimilation have been developed in the areas of optimal estimation and automatic control (Gelb, 1974). One of the initial and popular applications was the tracking of combat aircrafts. In geophysics, meteorologists have been using data assimilation since 50s. They established an operational system as early as in 70s and are currently operating an advanced scheme like a 4-D variational method in the atmospheric model of European Centre for Medium-Range Forecast (ECMWF, Marecal *et al.*, 2001). In physical oceanography, the development was much delayed, for example, the direct insertion by Malanotte-Rizzoli and Holland (1986). Outside the above fields, data assimilation can be applied so long as numerical models and observational data are available: e.g., ion-layer modeling (Rosen *et al.*, 2001).

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The necessity of data assimilation lies in that via the assimilation the deficiency of a model and observation can be compensated by the merits of each other. The model deficiency can be classified as model equation error and model representation error (Fukumori, 2001). The former includes truncation error, errors due to griding scheme and so forth, while the latter arises due to lack of layers, ignored physics etc. Observations are incomplete because of noise, limitation in space-time coverage and the inability to measure certain parameters such as in-depth properties. From a remote sensing viewpoints, satellite observations are limited only to the surface. Although many efforts are paid to infer in-depth properties from surface observations (e.g., Imawaki *et al.*, 2001), generally it is difficult. Using satellite observations as initial/boundary conditions of a model can improve the model only at the moment of forcing, but cannot influence the model performance dynamically and consistently throughout the model's entire temporal and spatial domains. Data assimilation is required to extract physical signals from observations and extend the signals into unobservable variables or unobservable regions.

Despite the merits of the assimilation, only in the late 90s the ocean data assimilation became practical and accurate. The main reasons for the delay are the lack of need for forecasting and accurate modeling, comparative deficiency in observational data, and immaturity of numerical models. During 90s it was realized that ocean forecasting is not merely an academic issue any more, instead that the ocean is an integral and active part in the earth's climate system. The realization was triggered by observing the climate phenomena such as global warming, El Nino and North Atlantic Oscillation. Then it was confirmed by discovering the essential role of the ocean such as CO2 absorption, global transportation of heat, salt and freshwater. To meet the need for better understanding of the ocean, globally-concerted observation programs such as WOCE (World Ocean Circulation Experiment), TOGA (Tropical Ocean Global Atmosphere Experiment) and GOOS (Global Ocean Observing System) have been undertaken since 90s and provided unprecedented amount of observational data. So did remote sensing satellites such as TOPEX/Poseidon (T/P) and NOAA. In ocean modeling, models are now good enough to reproduce reality at fine scale, e.g., eddies. Following these progresses in observations and modeling, data assimilation has been developed to form an international activity such as the Global Ocean Data Assimilation Experiment (GODAE). Currently advanced assimilation schemes are run on global scales (e.g., Fukumori *et al.*, 1999).

By comparison, assimilation over the seas around Korea appears not as mature. Thus a review of the status of ocean data assimilation over the seas around Korea will help take part in the rapid advance in the research frontiers.

2. Overview of Methods

Data assimilation methods in oceanography are originally developed in meteorology fields. Ghil and Malanotte-Rizzoli (1991, GM91 hereafter) and Fukumori (2001) give a good summary of oceanographic implementation of data assimilation. The mathematical notations follow those in Fukumori (2001). The characters in a bold and gothic font represent matrixes.

Data assimilation is basically an inverse method and can be expressed as:

$$\mathbf{A}(\mathbf{x})=\mathbf{y}, \quad (1)$$

where **x** is unknown, **y** the observation and **A** represents the data and model equations. **x** includes model variables such as temperature and salinity over the entire temporal and spatial domains of a model. The data equation relates a model state variable to an observation (e.g., x_i = sea surface temperature from satellite). The model equation is an expression of model dynamics such as the continuity equation.

The theoretical difficulty of data assimilation arises because it is an ill-posed problem: practically the rank of **y** cannot be greater than that of **x**. For example, it is not possible to measure the absolute velocity accurately, nor can one obtain a complete coverage of temperature and salinity in time and space. Various assimilation methods are not more than the search of optimum solution for **x**.

Noting that there are quite a few assimilation methods, the classification of the methods would help to understand the nature of each method. Fukumori (2001) distinguishes advanced from simple methods depending on whether the inverse problem is solved throughout the entire time span (i.e., the index of **x** includes time), which is whether the dynamic consistency is maintained throughout the solution search. According to GM91, the advanced methods can be further grouped into statistical approaches where the variance between the model and the observation is minimized (the Kalman filter) and control approaches where the model-observation distance is minimized by least squares (variational methods such as the adjoint or the representer). Simple methods (OI, nudging and direct insertion) have been developed in meteorology to meet the need for operational forecast.

Below, a brief summary of major methods is given. Since a complete mathematical description can be found elsewhere, the focus is made on descriptive accounts. Each method is reviewed in the following aspects: optimization scheme, practical difficulties such as computation and liberalization and error specification.

1) Adjoint Method

In the adjoint method, the optimal solution of the inverse problem, Eq. 1, is obtained by minimizing the cost function J:

$$J(\mathbf{x})=(\mathbf{y}-\mathbf{A}(\mathbf{x}))^T\mathbf{W}(\mathbf{y}-\mathbf{A}(\mathbf{x})), \quad (2)$$

where **W** is the weighting or error covariance matrix. For the minimization the gradient $J(\mathbf{x})/d\mathbf{x}$ is computed using the model's adjoint equations. To transform Eq. 2 into a constrained minimization problem, it is useful to introduce a Lagrange function. Then the adjoint equations are the derivatives of the Lagrange function with respect to the model state variables. In this respect, the advantage of the adjoint method is the transformation into a constrained problem. As for disadvantages, firstly, one must construct the adjoint equations. Though it has been a difficult task, now their generators are available (Gierling and Kaminski, 1998). Secondly, the integration of the adjoint equations and the forward model has to be repeated tens of times, which requires significant computing power. As a solution, various approximations and reduction schemes have been developed (see Bennett, 1999). A posteriori error for the assimilation can be specified accurately (Thacker, 1989).

2) Representer Method

The representer method (Bennett, 1992) simplifies Eq. 1 into Euler-Lagrange equation by employing a representer. A representer is a linear combination of some model equations, e.g., $(du/dt+du/dx-F)$, where u is the velocity and F the forcing (Bennett, 1999). Then the assimilation becomes the determination of the coefficients of a representer. The coefficient determination is achieved by the minimization of a cost function as in Eq. 2. Simplification of Eq. 1 can be made by using other basis functions such as the model Green's function (Stammer and Wunsch, 1996).

3) Kalman Filter

The Kalman filter (Kalman, 1960) was developed for aircraft tracking and many applications are found in engineering field. Two integral parts of the Kalman filter are a sequential scheme and the optimal weight **K**. The sequential scheme is expressed as (Gelb, 1974, GM91):

$$\mathbf{x}_k^f = \mathbf{A}_{k-1}\mathbf{x}_{k-1}^f, \qquad \mathbf{x}_k^a = \mathbf{x}_k^f + \mathbf{K}_k(\mathbf{y}_k - \mathbf{H}_k\mathbf{x}_k^f) \tag{3}$$

where k denotes time, f forward prediction, a the analysis or the revision of the past through assimilation, and **H** is a matrix such that **Hx** is the model's theoretical estimate (i.e., the size of $\mathbf{y}_k$ is smaller than $\mathbf{x}_k$). Eq. 1 covers the entire time span while $\mathbf{x}_k$ covers only the unit time frame at k, thus $\mathbf{x} \supset \mathbf{X}_k$. An optimal **K** can be determined uniquely from an error covariance matrix **P**:

$$\mathbf{K}_k = \mathbf{P}_k^f\mathbf{H}_k^T(\mathbf{H}_k\mathbf{P}_k^f\mathbf{H}_k^T + \mathbf{R}_k)^{-1}, \qquad \mathbf{P} = (\mathbf{x}_k - \mathbf{x}_k^t)^T(\mathbf{x}_k - \mathbf{x}_k^t) \tag{4}$$

where **R** is the noise covariance matrix. $\mathbf{x}_k^t$ is such that $\mathbf{y}_k = \mathbf{H}_k\mathbf{x}_k^t + \mathbf{b}$, where t stands for truth and b the noise. **R** and **b** are assumed to be known. The optimality is obtained by minimizing the variance, $\langle\langle \mathbf{y}-\mathbf{A}(\mathbf{x})\rangle\langle \mathbf{y}-\mathbf{A}(\mathbf{x})\rangle\rangle$ with brackets being an average.

The Kalman filter is a statistical average of the model state prior to assimilation and data, weighted according to the uncertainties (error covariance). The Kalman filter assimilation is also called the Kalman smoother because it smoothes the future prediction using the past measurement.

Unlike the variational methods such as the adjoint, the Kalman filter runs sequentially in time (past observations are discarded after assimilation) and uses the minimum variance rather than the least square estimator (LSE). Essentially, however, both the adjoint and the Kalman filter cover the entire time span and, as discussed in Wunsch (1996), the minimum variance estimation and the LSE are the same.

The greatest obstacle in the Kalman filter utilization is the computation of **P**. If the order of computation required for the sequential equation or in Eq. 3 is O(N), that for **P** is $O(N^2)$. Note that N has the size of O(6) (see Section 2).

Finally, the Kalman filter is often used for satellite data assimilation because the method runs sequentially in time and satellite data are given periodically. An example of assimilating spaceborne sensing of temperature and sea surface elevation can be found in Kelly and Qiu (1995) and assimilation of various altimetric data are available in the works by I. Fukumori.

4) Optimal Interpolation (OI)

The optimal interpolation (Gandin, 1963) is one of the most frequently used methods for operational data assimilation. OI is a minimum variance sequential estimator and may be regarded as a simplified version of the Kalman filter. The key difference from the Kalman filter is that the error covariance (**P** in Eq. 4), is prescribed rather than optimally estimated. Commonly **P** is given as a Gaussian function with respect to the distance in time or space. Consideration of observational errors is possible as well during the prescription of **P**. **P** is determined only once while in the Kalman filter it is updated in each instance of time throughout the time domain of interest. In this regard, OI is in fact a suboptimal estimator. Naturally, OI does not provide the error during the assimilation unlike the Kalman filter. With OI, it is not possible to improve model parameters and to assimilate 4-dimensional observations dynamically. Despite the limitations, OI is widely used for an operational forecast because of light computing load, though still more expensive than nudging and direct insertion.

5) Direct Insertion (Blending) and Nudging

Direct insertion (Hurlburt, 1986) is expressed as:

$$\mathbf{x}_{k+1} = \alpha \mathbf{y}_k - (1-\alpha)\mathbf{x}_k. \tag{5}$$

α is an empirical weight constant. It may be regarded as a highly simplified version of OI, in that α is a scalar constant in the direct insertion but spatially varies in OI. An underlying assumption behind the fact that the observation $\mathbf{y}_k$ is used for the next estimation by only a constant multiplication is the infinite confidence on the accuracy of the observation. This method is similar to model initialization by observation data: when $\alpha = 1$, the two become identical. Direct insertion (e.g. Malanotte-Rizzoli and Holland 1986) is essentially the same as nudging.

6) Utility of Data Assimilation

In this section, the discussion is made on what benefits can be gained by data assimilation, especially data assimilation as a tool to improve a numerical model.

■ Data assimilation solves the following deficiencies in observations and models: limitation in time and space of in-situ observations, confinement limitation to the surface of remote sensing data, and improvement of inaccurate model state variables. For example, statistical interpolation of altimeter data does not provide realistic picture while dynamic interpolation (assimilation) does (White *et al.*, 1990).

■ Data assimilation also improves model parameters, external forcing and boundary conditions: e.g., the phase speed of a model in Smedstad and O'Brien (1991).

■ Data assimilation provides the error in the model estimation, for example, the error covariance matrix **P** of the Kalman filter. This is one significant advantage over simple application of observations to a model via initial conditions.

■ Through data assimilation the accuracy in forecast would improve (e.g., El Nino index prediction of Lee *et al.*, 2000). Without data assimilation, not all the model state variables and parameters are improved by even the most accurate observations. Thus the prediction would not be as accurate as one after assimilation.

■ Even when data assimilation were infinitely powerful, the assimilated result would still contain errors. The errors would arise from observation errors and incompleteness in models such as concepts (e.g., reduced gravity assumption), approximations (e.g., of nonlinear physics), or implementation (griding scheme). Then a posteriori error of data assimilation can provide a basis for necessary improvements of the models incompleteness.

■ Data assimilation can also be used to determine the configuration of an observation system such as the temporal and spatial sampling interval (White, 1995 for XBT; Verron *et al.*, 1996 for T/P).

Last, it should be addressed that data

assimilation not always improve the model performance. Because data assimilation fits the model into the observation, if errors exist in the observations, data assimilation may degrade the model performance. The greatest danger of this kind exists in the direct insertion method where the observations are treated as if they have no errors. On the other hand, other methods reflect the observation errors: **P** of Eq. 4 for OI and the Kalman filter and **W** of the variational methods.

3. Assimilation of Remotely-sensed Ocean Data

The most prominent difference in assimilation between satellite data and other data is the size of dimensions. Let us consider a model with the horizontal grid of 200 by 100 and 20 vertical layers, where there are four model state variables (temperature, salinity and *u*- & *v*- velocities). If the time span is 5 years and an observation interval is a week as in T/P observation, the dimension of **x** is ~300 million. For **y**, its dimension becomes 3.5 million. Then inversion of **A** is not a trivial task. Thus Hirose and Ostrovskii (2000) have to use a supercomputer for the East Sea assimilation at 1/6° grid spacing. For these reasons, handling such a large amount of data is a key issue in assimilation of satellite data. Various physical and computational approximations are made such as reducing the model state (Fukumori and Malanotte-Rizzoli, 1995) and the model itself (Menemenlis and Wunsch, 1997). To reduce the dimension of data, only major modes of EOFs are used (Verron *et al.*, 1999). To simplify the inversion of the Kalman gain matrix, the correlation terms can be assumed zero under certain physical conditions (Annan and Hargreaves, 1999). To cope with fully nonlinear models, an extended Kalman filter can be used (Fukumori and Malanotte-Rizzoli, 1995). Lermusiaux and Robinson (1999) estimate that by using reduction schemes the computation time may be reduced from an order of years for the full Kalman filter to an order of hours.

Spatial coverage is also an important factor determining the performance of an assimilation system. Masina *et al.* (2001) find that assimilation of sparse data, 1° by 1° Reynolds sea surface temperature (SST) that is the combination of in situ and satellite observations, introduces unrealistic spatial variability in the temperature field. This deficiency is partially overcome when they also assimilate altimeter observations since the coverage is complete and uniform.

Table 1 summarizes the merits and drawbacks of the assimilation methods reviewed above especially from the viewpoint of satellite data assimilation.

Table 1. Qualitative summary of merits and drawbacks of assimilation methods. Computation refers to computation cost. Model improve refers the possibility to modify model parameters.

Method	Acc-uracy	Error specify	Model improve	Compu-tation	Assimilation of satellite data
Adjoint	O	O	O	Δ	O
Representer	O	O	O	Δ	O
Kalman	O	O	O	Δ	O
OI	×	×	×	O	O
Blending & Nudging	×	×	×	O	O

4. Data Assimilation Applied to the Seas around Korea

In this section, data assimilation work on the seas around Korea is surveyed. Numerous examples on global and other regional seas are available, for which one may refer to GM91, Malanotte-Rizzoli (1996) and Fukumori (2001).

1) East Sea

Hirose and Ostrovskii (2000) employ the approximate Kalman filter of Fukumori and Malanotte-Rizzoli (1995) for assimilation of the T/P altimeter data into a 1/6° resolution 1.5 layer reduced gravity model. The assimilation is indented to remove the noise and undesired signals and to dynamically interpolate the altimetric observations. Compared with no-assimilation case, assimilation correctly described the evolution of the quasi-biennial variability in sea surface elevation (Fig. 1).

In Yoshikawa *et al.* (1999) the nudging method is applied to the assimilation of in-situ temperature and salinity to a 1/4° resolution 20 layer model. After the assimilation, the errors in the surface heat flux are reduced by 20% (Fig. 2).

Hirose *et al.* (1999) use the Kalman filter for assimilation of T/P altimeter. They run a hindcast scheme from 1993 to 1994 to a 1.5 layer reduced-gravity shallow water model. Through assimilation, the strong variability of 20-cm^2 variance is reconstructed at the subpolar front.

Bang *et al.* (1996) apply the direct insertion to the circulation model of the East Sea. In-situ

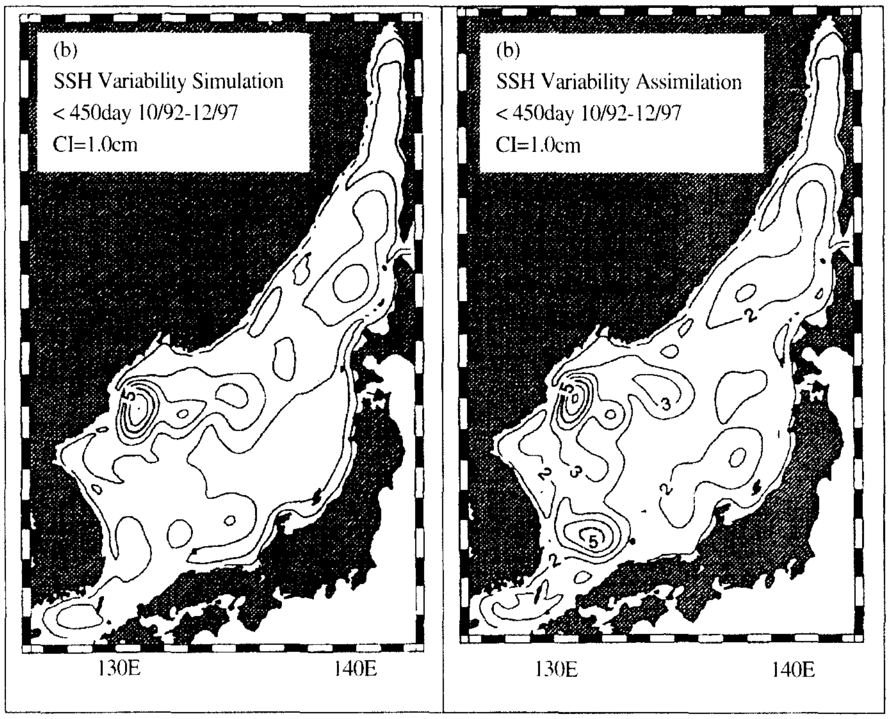

Fig. 1. Assimilation of T/P sea surface height (SSH) assimilation: before (left) and after (right). The contour of ~ 5 cm^2 is correctly present after assimilation and it moves eastward temporally. From Figs. 8 and 12 of Hirose and Ostrovskii (2000).

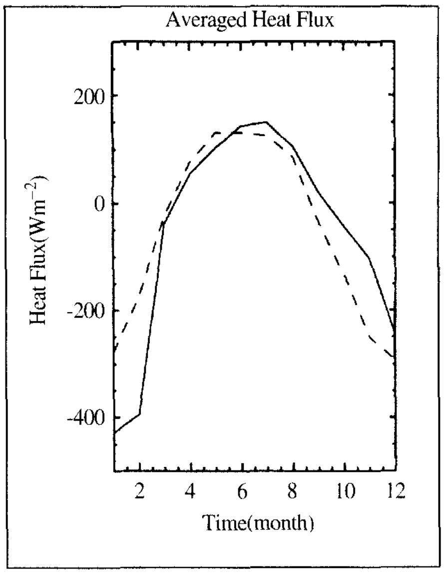

Fig. 2. Monthly mean surface heat flux after assimilation (solid) and bulk-formulae estimation (broken). From Yoshikawa *et al.* (1999).

temperature data collected from Korea, Japan and US data centers are assimilated and they experiment by empirically varying the gain α in Eq. 5 and the temporal frequency of the insertion. They find that nudging affects the model performance significantly: measured in terms of the stream function, the changes caused by assimilation reach 100%.

Japan Meteorological Agency also runs a nowcast system using OI of altimetric surface elevation and the temperatures from in-situ and satellites (Yoshioka, 2000). Also, Princeton Ocean Model has been used for hindcast using climatorological and satellite data with the nudging and OI (Ro, 2000; Suk *et al.*, 2000).

2) Yellow Sea

In the Yellow Sea, much of assimilation work is devoted to tidal modeling because of the large amplitude of tidal variations and energy dissipation (8% of such energy dissipation globally). One of the latest in assimilation by the tidal model is by Lefevre *et al.* (2000) where the representer method is applied for T/P data assimilation to improve the modeling of tidal variations and the tidal energy dissipation.

Yuan and Hsueh (1998) apply the adjoint method to the vertically-integrated constant-density Florida State Univ. model for assimilation of in-situ sea surface temperature. By assimilating for 1 month in 1986, they find the error in the temperature prediction is accurate to 50% (Fig. 3).

Chu *et al.* (1997) determine the decorrelation scales in time and space of the thermal variability in the Yellow Sea with a view to applying them to OI, and also to designing the optimum observational network as in White (1995). They find the scales are 4 - 6 days and 50 - 80 km in time and space, respectively.

Shulman *et al.* (1998) optimize the boundary condition by assimilation of tide gauge data and transect data with application to the M2 tide modeling in the Yellow Sea. They found 75% reduction in the tidal errors when compared with non-optimized case.

Blain (1997) assimilate the data from 114 tidal gauge stations into a shallow water model to determine sampling strategies for the best assimilation performance. They find that the tidal information from deep water is much less useful for accurate tidal modeling than those from shallow intermediate depths on the continental shelf.

In Lee and Jung (1996), the direct insertion is used for assimilation of tidal observations to a shallow water model. The best weight for the direct insertion, α in Eq. 5, is determined empirically. With the best α, the differences from the in-situ reference data are 5 cm and 8° in amplitude and phase, as opposed to 10 cm and 10°

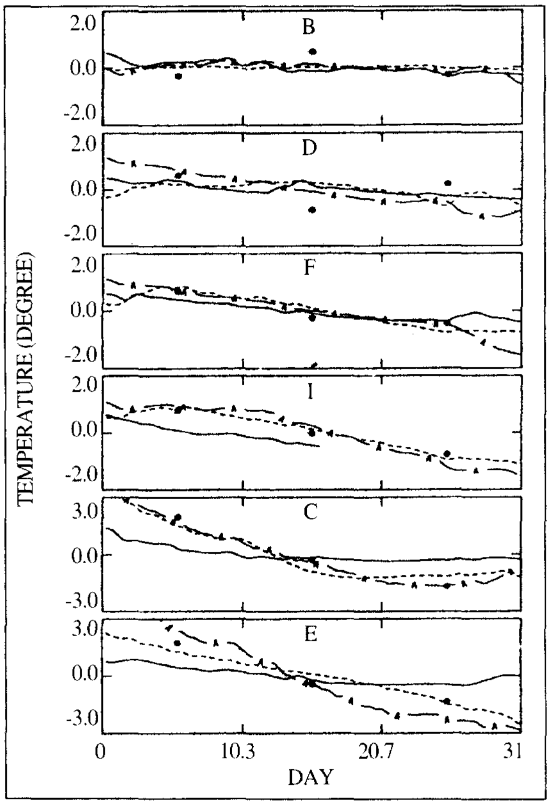

Fig. 3. Effect of assimilation: temperature residuals at six mooring stations. Mooring (solid), after (short-dash) and before (long-dash) assimilation. From Yuan and Hsueh (1998).

before assimilation.

3) Pilot Study

Since advanced methods require difficulties in implementation and management of computer memories, the domestic progress is limited to pilot studies rather than operational research. Song *et al.* (2000) implement the adjoint method for a

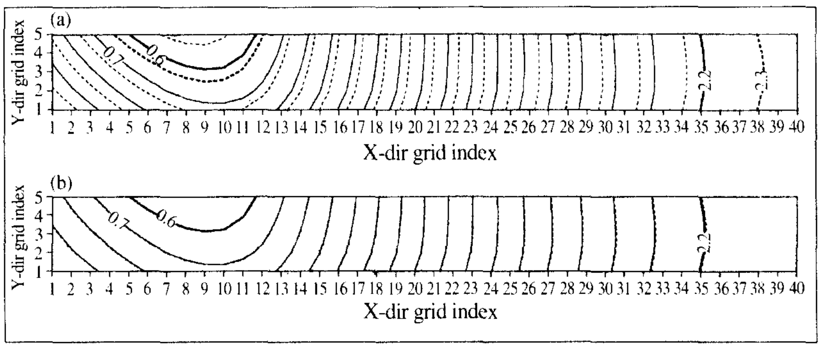

Fig. 4. Effect of assimilation: comparison of tidal amplitude between the mode (dots) and the truth (solid). Before (a) and after (b) assimilation. From Song *et al.* (2000).

linear tidal model in an idealized domain. By assimilating tide gauge data, the assimilation reproduces the observation with little error (Fig. 4). Lee *et al.* (2000) implement the Kalman filter and assimilate a time-series of surface elevation data into an idealized model domain. They confirm that the assimilation improves the model estimation and find that introduction of random noise deteriorate the assimilation results.

4) Other Adjacent Seas

Numerous assimilation studies are available over the South China Sea, the Kuroshio and its Extension region. To list just a few of them, Chu *et al.* (1997) assimilate CTD data into Princeton Ocean Model over the South China Sea using OI, noting that POM with surface flux forcing only is weak in salinity prediction. By assimilation the salinity is correctly estimated with r.m.s.e. for temperature being around 0.6℃, and for salinity being around 0.06 ppt.

In Wu *et al.* (1999), T/P data are assimilated into a 0.4° resolution 21-layer primitive equation model by the direct insertion. After the assimilation, the discrepancy between the model results and independent observations is reduced by a factor of more than two (Fig. 5).

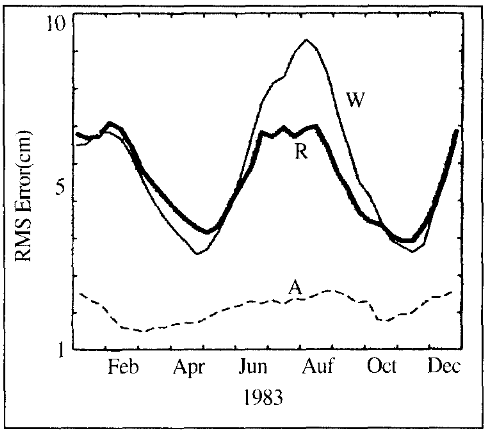

Fig. 5. Effect of assimilation: RMS error between T/P SSH and model SSH. Before (W,R) and after (A) assimilation. From Wu *et al.* (1999).

Ishikawa *et al.* (1996) assimilate drifting buoy and altimetry data over the Northwest Pacific into a 1.5 layer 1/12° primitive equation model using OI. After 1 year assimilation they observe that the error in the surface elevation has decreased by 40%.

Finally it would be useful for interdisciplinary cooperation to pay attention to the results of data assimilation in engineering fields in Korea. Shin *et al.* (1998) implement an extended Kalman filter for modeling of satellite orbit parameters such as the velocity and attitude. In their work, the observation data are ground measurements of the absolute coordinates of control points, which improve the state of the satellite orbit model. Assessed by independent measurements, the assimilation obtains 1 – 2 pixel accuracy. Kim and Lee (2000) apply OI for generation of a digital elevation model (DEM) from a set of scattered elevation data. Their work is focused on the determination of the special decorrelation: >100 km in the coastline direction and 50 km perpendicular to the coastline. In their work, the decorrelation scale has also been used for the design of the spatial configuration of the independent check points.

5. Future

Leading institutions around the world use the advanced methods for global scale experiments (e.g., Fukumori *et al.*, 1999) or operational forecasts (such as the adjoint assimilation for ECMWF, Marecal *et al.*, 2001). By comparison, domestic research is focusing on experimental studies of the advanced methods with operational application of assimilation being accomplished with simple methods. Also, on the seas around Korea though many of the simple methods exhibit good performances (Section 4), they are mainly for diagnostic studies. For prediction, the advanced methods would have to be used. In these regards, the future activities will likely be on implementing the advanced methods to realistic and nonlinear models and on minimizing the computing load, as discussed in Section 3.

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