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On improving storm surge forecasting using an adjoint optimal technique

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ABSTRACT

A three-dimensional ocean model and its adjoint model are used to simultaneously optimize the initial conditions (IC) and the wind stress drag coefficient (C_d) for improving storm surge forecasting. To demonstrate the effect of this proposed method, a number of identical twin experiments (ITEs) with a prescription of different error sources and two real data assimilation experiments are performed. Results from both the idealized and real data assimilation experiments show that adjusting IC and C_d simultaneously can achieve much more improvements in storm surge forecasting than adjusting IC or C_d only. A diagnosis on the dynamical balance indicates that adjusting IC only may introduce unrealistic oscillations out of the assimilation window, which can be suppressed by the adjustment of the wind stress when simultaneously adjusting IC and C_d. Therefore, it is recommended to simultaneously adjust IC and C_d to improve storm surge forecasting using an adjoint technique.

1. Introduction

With the potentially increasing intensity of tropical cyclones (TCs) under the background of the global warming (Webster et al., 2005; Emanuel, 2005; Emanuel et al., 2008; Elsner et al., 2008; Knutson et al., 2010), the TC-induced storm surges become a severe threat to the coastal regions with dense population and large economic community. For instance, the storm surges accompanied with TCs in the western Pacific and the South China Sea (SCS) cause huge damage of property and loss of lives each year in the East Asian countries such as Philippines, Vietnam and China (Wu and Kuo, 1999).

In the last several decades, considerable improvements have been made in the real-time prediction skill of storm surges with the use of high resolution 3-D model and advanced data assimilation methods (e.g., Griffith and Nichols, 2000; Zhang et al., 2003; Lionello et al., 2006; Peng and Xie, 2006; Butler et al., 2012). However, large errors still exist due to the uncertainties in the sea surface wind forecasting which is largely dependent on the accuracy of the TC track and intensity forecasts. Although continuous improvements in the TC track forecasting skill have been made during the last several decades, no significant improvements are seen in the TC intensity forecasting skill (Lowag and Black, 2008; Evans and Falvey, 2013). In addition, with the potential increase of TC destructive power in the future (Webster et al., 2005; Emanuel, 2005; Emanuel et al., 2008; Elsner et al., 2008; Knutson et al., 2010), it will be more difficult to make an accurate sea surface wind forecasting, resulting in larger bias in storm surge forecasting.

Many previous studies have indicated that the accuracy of storm surge forecasting is mainly dependent on that of sea surface wind stress calculation (Doyle, 2002; Moon, 2005; Xie et al., 2008). The most common formula employed to calculate wind stress is the quadratic one with respect to the wind speed, i.e.,

$$\boldsymbol{\tau} = \rho_a C_d |\mathbf{v}|\mathbf{v}, \tag{1}$$

$$\mathbf{v} = \mathbf{v_a} - \mathbf{v_o}, \tag{2}$$

where ρ_a is the air density, C_d the drag coefficient $\mathbf{v_a}$ the wind velocity at 10 m height above the surface, and $\mathbf{v_o}$ the velocity of ocean surface currents. It is obvious that the values of wind stress depend on both the wind speed and the drag coefficient C_d. In storm surge models, $\mathbf{v_a}$ is usually obtained from a simple wind model such as the Holland model (Holland, 1980) based on the TC track and intensity forecasting or from a complex weather forecasting model such as the Weather and Research Forecast (WRF) model, and the large uncertainties in the TC track and intensity forecasts may lead to large bias in $\mathbf{v_a}$. On the other hand, C_d has often been set either as a constant (Jones and Davies, 1998; Konishi et al., 1985, 1986) or

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using an empirical formula which is a linear function of wind speed (Sheppard, 1958; Smith, 1980; Large and Pond, 1981; Wu, 1980, 1982) in practice:

$$C_d = \frac{\rho_a}{\rho_w}(a + b|\mathbf{v}|), \quad (3)$$

where ρ_a and ρ_w are the air density and water density, respectively, and a and b are the empirical parameters. Under the intermediate wind speed range (approximately from 7 to 20 m s^{-1}), the ocean surface is hydrodynamically rough and the corresponding drag coefficient C_d displays a general tendency of increasing with wind speed (Garratt, 1977; Wu, 1980). For lower wind speeds, the ocean surface is either in hydrodynamically smooth or transitional regime and the wave influence is competing with the viscous effects (Donelan, 1990). For very high wind speeds (over 25 m s^{-1}), extensive wave-breaking occurs. The resulting spume, flying spray, and broad regions with flow separation act like a shroud shielding the fine-scale wave roughness from the airflow. Field measurements indicate that C_d reaches a maximum near 32 or 33 m s^{-1} and then decreases with increasing wind speed (Powell et al., 2003; Jarosz et al., 2007). Jarosz's results also show that when using a linear increasing empirical formula C_d is underestimated in the intermediate wind and overestimated in the high wind, inevitably resulting to bias in the wind stress calculation. Therefore, to reduce the errors in the wind stress calculation, we have to reduce the bias in $\mathbf{v_a}$ and/or C_d.

Efforts have been made in reducing the bias in $\mathbf{v_a}$ (Hoteit et al., 2009; Broquet et al., 2011). Hoteit et al. (2009), Broquet et al. (2011) tried to correct the wind bias through data assimilation, but their method is only valid within the data assimilation window. Hoteit et al. (2009), Peng et al. (2007) used the 3-D Princeton Ocean model (POM) and its adjoint model to adjust the maximum wind radius in the wind stress calculation based on the empirical Holland model. However, their method is only applicable in the case of using an empirical formula for the wind speed calculation which is the function of the maximum wind radius; it is invalid when wind fields are obtained from numerical weather model output which does not contain the parameter of the maximum wind radius. On the other hand, the errors in wind stress calculation due to the bias in $\mathbf{v_a}$ can be reduced partially through adjusting the value of C_d which may have large uncertainty using the traditional formula (Peng et al., 2013). In addition, the systematic bias caused by many known or unknown sources such as insufficient resolution for an imperfect storm surge model can be also reduced by adjusting C_d (Peng et al., 2013). Therefore, adjusting C_d to an "optimal" value could be an effective way to improve the accuracy of the wind stress calculation and thus the storm surge forecasting.

To estimate the wind stress drag coefficient, one of the efficient ways is through fitting the model output to the observations using adjoint technique (Derber, 1987; Le Dimet and Talagrand, 1986; Yu and O'Brien, 1991; Zhang et al., 2002, 2003; Chen et al., 2008; Peng and Xie, 2006). Most studies used 1-D or 2-D model and its adjoint model with simplified physics to optimize C_d (Yu and O'Brien, 1991; Zhang et al., 2002, 2003; Chen et al., 2008; Peng and Xie, 2006). However, previous studies have shown that 3-D storm surge models can improve the storm surge forecasting considerably, compared to 1-D or 2-D models (Xie et al., 2004; Peng et al., 2005; Weisberg and Zheng, 2008), since the 3-D models can take into account the nonlinear processes such as the bottom friction and tide-current-wave interactions. Although a 3-D ocean model and its adjoint model require more computational resource, it is affordable with the rapid development of the computer technology. Therefore, it is worth to explore the effects of optimizing C_d in storm surge simulation in the framework of 3-D ocean models. A recent study of Zedler et al. (2013) indicates that a small number of measurements of upper ocean temperature and currents can be used to make estimates of C_d assuming a small range of uncertainty in C_d using adjoint technique. Their results also show that the initial state of the ocean, especially the field of background currents, is important for the estimation of C_d. The study of Peng et al. (2013) further indicates that adjusting C_d through adjoint technique based on 3-D POM and its adjoint model can lead to a significant improvement in storm surge forecasting up to 48 h.

Although the influence of the initial conditions (IC) on storm surge simulation is relatively small compared to the wind forcing or model physics (Flowerdew et al., 2010; Peng et al., 2013), previous studies have shown that the positive effect of optimizing IC on storm surge simulation is significant during the first several hours of the simulation (Peng and Xie, 2006; Li et al., 2011). Moreover, it is found that the errors of IC can affect the adjustment of boundary conditions or model parameters in the process of data assimilation (Zedler et al., 2013). In practice, since both the IC and the wind stress may contain uncertainties, we speculate that simultaneously adjusting both C_d and IC may be a more reasonable and effective way that may achieve more improvements than adjusting only IC or C_d for storm surge forecasting. To test this hypothesis, we perform both Identical Twin Experiments (ITEs) and the real case experiments of simultaneously adjusting IC and C_d in the frame of 3-D POM and its adjoint model in this study.

In Section 2, the POM and its adjoint model are briefly introduced. Section 3 describes the experimental setup, including the ITEs and the real data assimilation experiments. The experimental results and corresponding analysis are presented in Section 4. Conclusion and discussion are given in Section 5.

2. The data assimilation method and the POM-4DVAR system

The four dimensional variational data assimilation (4DVAR) approach is employed in this study. It aims to find an "optimal" initial model state or model parameters which minimizes the distance between the model output and the observations. In general, the distance is expressed as a so-called cost function J:

$$J(\mathbf{x}_0, p) = \int_0^T \left(H(M(\mathbf{x}_0, p)) - y^{obs}\right)^2 \mathrm{d}t, \quad (4)$$

where $\mathbf{x}_0$ and p represent the initial model state variables and model parameters to be adjusted, M nonlinear ocean model, H the observation operator, y^{obs} the observation variables, and T the assimilation time window. In this paper, $\mathbf{x}_0$ is the water level at every point of the domain and p is the empirical parameters (a, b) of C_d. It should be noted that we neglect a background term in Eq. (4) which measures the difference between the background fields and the adjusted fields of the control variables. It is well known that the background term in the cost-function has a function of limiting the adjustment of control variables to a reasonable range, and the background error covariance in the background term can play a role in expanding the local observational information to an area within the correlation scale and making multi-variable adjustment under the dynamic constrain of the model. For storm surge simulation, however, the role of the background term may be less important because the surges are mainly driven by the wind forcing and only water level is taken as the control variable of the IC in this study. On the other hand, neglecting the background term can allow the adjustment of C_d to have more freedom so that such an adjustment can compensate the wind errors and other unknown model errors, though the adjusted values of C_d could be out of the range of the physical meaning. Our goal is to determine an "optimal" value of C_d which minimizes the errors of the storm surge forecasts for a specific case, regardless of the physical meaning of the C_d value. Therefore, we ignore the background term in the calculation of cost function in this study.