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Ocean Modelling 14 (2006) 102–121

Ocean Modelling

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Wave data assimilation using ensemble error covariances for operational wave forecast

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Received 30 September 2005; received in revised form 12 April 2006; accepted 13 April 2006
Available online 17 May 2006

Abstract

Most of the present operational data assimilation techniques provide an improved estimate of the *system state* up to the current time level based on measurements. From a forecasting viewpoint, this corresponds to an updating of the initial conditions of a numerical model. The standard forecasting procedure is then to run the model into the future, driven by predicted boundary and forcing conditions. In the wind–wave modelling context, the impact of the initial wave conditions quickly disappears within 6–12 h. Thus, after a certain forecast horizon, the model predictions are no better than from an initially uncorrected model. This paper considers a novel approach to wave data assimilation and demonstrates that through the measurement forecast (made using so-called local models), the entire model domain can be corrected over extended forecast horizons (i.e., long after the updated initial conditions have lost their influence), thus offering significant improvements over the conventional methodology. The proposed data assimilation scheme can be executed in the post-processor and is operationally viable with the requirement of insignificant execution time. This scheme produces an efficiency of 30–60% in reducing root mean square error wave height over a forecast period up to 24 h. The application of this proposed data assimilation procedure is demonstrated through a real-world wave data assimilation case study in the South East Asian Seas. The distribution of error forecasts over the entire model domain was estimated using a steady gain matrix derived from the ensemble of spatial error covariances. The improvements in the prediction of wave characteristics are highlighted.

Keywords: Wave forecasting; Wave model; Gain matrix; Local model; Error correction; Data assimilation

1. Introduction

Wave forecasting is of prime importance for safe navigation and offshore operations as well as to improve the prediction of ocean currents, transport and mixing characteristics. The present state-of-the art third generation wave models (The WAMDI group, 1988; Tolman, 1999) play an important role in simulating wind

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1463-5003/$ - see front matter
doi:10.1016/j.ocemod.2006.04.001

waves in regional seas. Accepting the limitations of the present state-of-the-art physics of wind–wave evolution, the accuracy of forecast is mainly based on the precision of the prescribed driving wind field. The erroneous wind field thus would be carried over to the predicted wave condition. To obtain a better wave climate, one has to improve the accuracy of wind estimates which can be derived either from an improved atmospheric model or by assimilating wave observations. Due to the complexity of various atmospheric processes, the precision of forecast wind over a period of time would deteriorate, and in turn errors accumulate in the wave prediction. Recent technology advancements have made high resolution wave observations available through in situ and remote sensing methods. This information propelled the data assimilation scheme to a prominent place in the wave forecasting studies.

The key advantage of data assimilation schemes is in the distribution of wave observations at discrete stations to the entire domain, so that the assimilated data approximate the actual sea condition more closely. Data assimilation can update the model predictions in different ways. These are designed to either improve the description of initial conditions at the time of forecast or provide correction of model predictions during a forecast period. In the earlier case, the assimilation scheme updates the wind fields using the observed wave parameters and hence improves the wave predictions. This is the classical method justified by the fact that input uncertainties may be the dominant error source in operational forecasting. This approach is referred to as inverse modelling and, it can be argued that the full effectiveness of this approach has not yet been utilised. Some authors (De Valk, 1994; De las Heras et al., 1994; Bauer et al., 1996) claimed to obtain significant improvements, but they failed to provide a systematic approach of updating past wind fields under operational conditions (Voorrips and de Valk, 1997).

The wave predictions can also be improved by the better definitions of the model parameters (Hersbach, 1998) during the assimilation process. However, continuous adaptation of model parameters is a matter of continuous debate that the model parameters cannot be changed recurrently. Thus having a wave model with non-trivial complexity, recalibration of the model parameters at every time step has no real advantages. The most widely used operational assimilation schemes, at present, are sequential schemes such as Optimal Interpolation (OI) (Lionello et al., 1995; Hasselmann et al., 1997; Voorrips and de Valk, 1997) and successive correction (Breivik et al., 1994). The optimal interpolation approach is time independent application and the initial conditions would be disappeared if the forecast wind is not corrected as well. In the dynamic approach, such as variational formulation and Kalman filter (Gelb, 1974), the control variables are minimized with the time interval. The control variables can be either model state variables or driving force. The latter is the common to choose. This approach however lacks the application of the model to operational forecasting due to its time expensive computations. Overall, the dynamical consistency of the model physics can be maintained only when the forcing variables or the state variables are updated. If the output of the model is updated directly, the corrections of the model will not be consistent with the model physics. In the wave modelling, the initial state of the system would not play a major role for more than 12 h period.

In the present study, the possible errors in the model (WAM, The WAMDI group, 1988) physics are not considered and, only the source of error in the prediction of wind waves is in the specification of driving force, wind. Naturally, while WAM was driven by forecast winds (polluted by errors), the resultant wave characteristics deviate from the real sea state which calls for correction. The model output variables are updated. The deviations between the simulation model prediction and the observed variables such as wave height are model errors. This paper illustrates a wave data assimilation scheme by combining an error forecasting algorithm based on 'local model' and a spatial distribution scheme using ensemble error covariances. In the forecast horizon, the model predictions at observation stations are corrected using the error forecasts based on the stochastic model. The essential prerequisite is the availability of historical wave records at the observation station. Then, forecast errors at discrete observation stations are carried to the entire model domain using the gain matrix based on the propagation of model error covariances. In this study, the output variables such as significant wave height and mean wave period are corrected. The improvements in the assimilated wave characteristics are discussed in detail. All the corrections are carried out to the output variables of the model and hence, the proposed data assimilation scheme can be executed offline to the wave model.

The following sections have clearly been demarcated to demonstrate the efficiency of the assimilation algorithm. Section 2 explains the deterministic wave model, WAM used in this study. Conversely, Section 3 presents an entirely new concept of wave forecasting using chaos theory, called the local model. This stochastic model is