Adaptive ensemble size reduction and preconditioning

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ABSTRACT

The ensemble size in sequential atmospheric data assimilation using the Heikes and Randles (1995a,b) global shallow-water model is reduced by projecting the ensemble on a subspace. Symmetries of the subspace of correlation matrices connected with ensemble algorithms are exploited to reduce the computational cost of the ensemble data assimilation implementation. The ensemble size is determined by retaining the most energetic modes of the flow. Regularization methods by filtering smaller singular values can also be employed. The efficiency of these approaches for adaptively updating the ensemble size in a Maximum Likelihood Ensemble Filter (MLEF) by Zupanski et al. (2005a, 2005b) used for ensemble data assimilation is finally assessed and compared. A reduction by a factor of four in the number of members of the ensemble was obtained, yielding comparable ensemble data assimilation (ENSDA) results. This novel approach results in sizable computational resource economy for general ensemble data assimilation methods.

1 Introduction

The basic idea of reduction methods is that of the condensation of large system (of algebraic and/or differential equations) to a similar (in some sense) much smaller substitute. Many of the reduction methods reported in the literature can be thought of as two-step hybrid analysis techniques combining a discretization method with a direct variational technique. In the first step a number of global approximation vectors (modes or basis vectors), for approximating the response of the system, are generated using a discretization method in conjunction with another approach and in the second step the amplitudes of the global approximation vectors are determined via a direct variational technique. One model reduction method which has been successfully used for dynamical systems analysis is a Proper Orthogonal Decomposition (POD) method Sirovich (1987). This method has become popular as a means of extracting dominant energy-containing structures from flow field data and by using these structures as basis functions, generating low order dynamical models for the associated systems. The method has been applied to fluid problems by Sirovich (1987) and other researchers Berkooz et al. (1993) to understand the important dynamical features or coherent structures seen in fluid flows.

With very few exceptions, data assimilation methods used for ocean and atmospheric models have been based on an assumption of linearity or near-linearity. The majority of these schemes have at their root some least-squares assumption. Direct application of least squares may not yield satisfactory results in cases in which the underlying probability distributions are significantly non-Gaussian. In many cases where the behavior of the system is governed by intrinsically nonlinear dynamics, distributions of solutions which are initially Gaussian will not remain so as the system evolves.

The presence of noise is an additional complicating factor. Besides the imperfections in the models which result from physical (Tremolet 2004) or computational simplifying assumptions, there is uncertainty in forcing fields such as wind stress and heat flux. The real world is a noisy place; this is an unavoidable fact, and the effects of noise upon highly nonlinear systems can be complex.

The data assimilation methods in use for numerical prediction in oceanographic or atmospheric model were gener-