Electronic Supplementary Material to: Contrasting the Skills and Biases of Deterministic Predictions for the Two Types of El Niño

ZHENG Fei[1,2] and YU Jin-Yi[3]

[1] *International Center for Climate and Environment Science, Institute of Atmospheric Physics, Chinese Academy of Sciences, Beijing* 100029, *China*

[2] *Collaborative Innovation Center on Forecast and Evaluation of Meteorological Disasters, Nanjing University of Information Science & Technology, Nanjing* 210044, *China*

[3] *Department of Earth System Science, University of California, Irvine, CA* 92697-3100, *USA*

Citation: Zheng, F., and J.-Y. Yu, 2017: Contrasting the skills and biases of deterministic predictions for the two types of El Niño. *Adv. Atmos. Sci.*, **34**(12), 1395–1403, https://doi.org/10.1007/s00376-017-6324-y.

Introduction

The supporting contents provide additional information to (1) describe the details in constructing the EnKF data assimilation system for the model; (2) explain the reasons for choosing the ECHAM4.5 simulated wind stress products; and (3) illustrate the model's spin-up and data assimilation cycle.

Text S1. The EnKF data assimilation system

The EnKF data assimilation system for initializing the ICM was first developed by Zheng et al. (2006, 2007). In the system, the EnKF is implemented by using an ensemble square-root filter algorithm with no perturbation of observations (e.g., Evensen, 2004). This EnKF data assimilation scheme was further improved by using a balanced, multivariate model-error approach (Zheng and Zhu, 2008) and was upgraded to use mean preserving transformations in the square-root scheme (Sakov and Oke, 2008; Evensen, 2009). During the assimilation cycle, the state vector contains both atmosphere and ocean states, and the innovation vector is defined as the departure between the observed and modeled ensemble mean wind stress and SST anomalies. Since the background error covariance is constructed from the coupled state ensemble member and contains error correlations between atmosphere and ocean states, all the coupled model variables are updated by multiplying the Kalman gain matrix by the innovation vector. The wind stress and SST anomaly data can then be consistently assimilated into the coupled model to provide a dynamically consistent and accurate initial condition for real-time SST prediction (Zheng and Zhu, 2010, 2015).

Text S2. The choice of ECHAM4.5 simulated wind stress products

Since the ECHAM4.5 simulated wind stress products (1963–96) were used to construct the statistical atmosphere model (Zhang et al., 2005), it is more favorable to use the ECHAM4.5 simulation output as the observations to initialize the model to produce dynamically consistent initial conditions. Also, the use of the ensemble mean data for assimilation enables us to enhance the SST-forced signals by reducing the atmospheric noise (Zhang et al., 2005). The ensemble spread of the 24 ensemble members was calculated as the standard deviation of (wind stress) observation error to be used in the ensemble Kalman filter (EnKF; Zheng and Zhu, 2010).

Text S3. The model's spin-up and data assimilation cycle

For the hindcast experiments, the model's spin-up and data assimilation cycle were carried out by the following steps: (1) Starting from January 1880, the model restores the SST anomaly data through a nudging approach for 30 years to get a reasonable model starting state; (2) From January 1900 to December 1949, the SST anomaly data are assimilated into the ICM through the EnKF to generate the ensemble initial condition for the subsequent initialization and prediction; and (3) Starting from January 1950, available wind stress and SST observations from 1950 to 2012 are assimilated into the EPS once per month through the coupled data assimilation scheme (Zheng and Zhu, 2010) to update all model variables and to generate the initial condition for ENSO prediction. The same SST dataset was also used to validate the model predictions.

REFERENCES

Evensen, G., 2004: Sampling strategies and square root analysis schemes for the EnKF. *Ocean Dynamics*, **54**, 539–560, doi: 10.1007/s10236-004-0099-2.

Evensen, G., 2009: *Data Assimilation*: *The Ensemble Kalman Filter*. 2nd ed., Springer, Berlin Heidelberg, 307 pp.

Sakov, P., and P. R. Oke, 2008: Implications of the form of the ensemble transformation in the ensemble square root filters. *Mon. Wea. Rev.*, **136**, 1042–1053, doi: 10.1175/2007MWR2021.1.

Zhang, R.-H., S. E. Zebiak, R. Kleeman, and N. Keenlyside, 2005: Retrospective El Niño forecasts using an improved intermediate coupled model. *Mon. Wea. Rev.*, **133**, 2777–2802, doi: 10.1175/MWR3000.1

Zheng, F., and J. Zhu, 2008: Balanced multivariate model errors of an intermediate coupled model for ensemble Kalman filter data assimilation. *J. Geophys. Res.*, **113**, C07002, doi: 10.1029/2007JC004621.

Zheng, F., and J. Zhu, 2010: Coupled assimilation for an intermediated coupled ENSO prediction model. *Ocean Dynamics*, **60**, 1061–1073, doi: 10.1007/s10236-010-0307-1.

Zheng, F., and J. Zhu, 2015: Roles of initial ocean surface and subsurface states on successfully predicting 2006-2007 El Niño with an intermediate coupled model. *Ocean Science*, **11**, 187–194, doi: 10.5194/os-11-187-2015.

Zheng, F., J. Zhu, R.-H. Zhang, and G.-Q. Zhou, 2006: Ensemble hindcasts of SST anomalies in the tropical Pacific using an intermediate coupled model. *Geophys. Res. Lett.*, **33**, L19604, doi: 10.1029/2006GL026994.

Zheng, F., J. Zhu, and R.-H. Zhang, 2007: The impact of altimetry data on ENSO ensemble initializations and predictions. *Geophys. Res. Lett.*, **34**, L13611, doi: 10.1029/2007GL030451.