An EOF-based observing system design for a tropical Indian Ocean mooring array

Objective

Through a series of Observing System Simulation Experiments (OSSEs) we seek to design a mooring array for a tropical Indian Ocean mooring array that is suitable for resolving oceanic variability on interannual time scales, represented by the depth of the 20º isotherm (D20), and intraseasonal variability, represented by high-pass filtered mixed layer depth (MLD).

Model Configuration

The model is a global configuration of MOM2 with zonal resolution of 2º, meridional resolution of 0.5º near the equator and 1.5º near the poles; and with 25 vertical levels. Following a 20-year spin-up, the model is run for 12 years and is forced by 3-day-averaged wind stress from a blend of NCEP-NCAR fields and FSU climatology; and surface heat and freshwater fluxes derived from an atmospheric boundary layer model with a flux correction.

Analysis System and Array Design

A column vector of the analysed model state \( w \) is given by

\[
    w = w^{\text{true}} + M(c),
\]

where \( w^{\text{true}} \) is the temporal mean; \( M = (w_1^{\text{EOF}} w_2^{\text{EOF}} \ldots w_m^{\text{EOF}}) \) is a matrix of Empirical Orthogonal Functions (EOFs) and \( c \) is a column vector of weighting coefficients that are determined by calculating the least-squares solution to

\[
    (HM)^T(HM) = 1
\]

where \( H \) is an operator that interpolates from grid-space to observation-space, and \( d \) is a vector of observations. The ability of (1-2) to determine the correct weights \( c \) depends on how well the observations project onto the EOFs; and more specifically, how well they distinguish between the different EOFs.

We seek to define \( H \) (i.e., the observation locations) so that \( HM \) is orthonormal. To achieve this, we apply a procedure that attempts to define \( H \) so that \( \operatorname{cond}(HM)^{-1} \) is minimized (\( HM \) is orthogonal if \( \operatorname{cond}(HM)^{-1} = 1 \)). Starting with locations at every model grid point, we eliminate the location that, when withheld, gives the smallest \( \operatorname{cond}(HM)^{-1} \). We recursively repeat the procedure until the desired number of locations remain.

Results

We perform a series of OSSEs that produce analyses of D20 and MLD using simulated observations for model years 7-12, using EOFs derived from model years 1-6. For some OSSEs, where it is explicitly stated, we include Argo observations on a uniform 6x6º grid. We compare the true and analysed fields to determine the root-mean-squared error (RMSE) for each OSSE. The expected lower bound for the RMSE using an optimal array is given by the residuals of the reconstructed EOFs using 6 and 12 modes (Figure 1). The standard deviations of D20 and MLD are also shown in Figure 1.

We compare the RMSE using the proposed array (Figure 2) and the optimal array (Figure 3) for OSSEs using 6 and 12 EOFs for D20 and MLD. Clearly the optimal arrays outperform the proposed array. However we note that the details of the optimal arrays are quite different for each OSSE. To assess this sensitivity we perform a total of 24 OSSEs (using 3 times series; 6 and 12 EOFs; with and without Argo observations for D20 and MLD). Using observation locations from all OSSEs we construct a map of the relative frequency of optimal locations (Figure 4) and construct a consolidated array that represents the general features of the arrays identified by different OSSEs.

Conclusions

We find that in general, observations south of 8ºS and off the Indonesian coast are most important for resolving interannual variability; while observations a few degrees south of equator, west of 75ºE; and a few degrees north of the equator, east of 75ºE, are important for resolving intraseasonal variability.