Ocean Data Assimilation and Seasonal-Decadal Climate Prediction at GFDL

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1. The initialization problem is different from the state estimation problem
   - The best analysis may not be the best initialization
   - Overspecification as in the close fit to the ocean data can introduce a lot of noise. Balance constraints between variables
   - Particularly for the decadal initialization their may be an argument not to correct the mean state - but perhaps only correct the slowly varying component of the system eg. Large scale water mass properties
   - Spurious inter-annual variability due to non-stationary nature of observing system
2. Need good coupled models to assess the quality of initial conditions

- Model errors rather than initial errors dominate SF performance
- For teleconnections, circulation changes, the performance of the model is even more critical
- Improvements in coupled models also translate on the ability of using SF as evaluation of ocean initial conditions.
S/I Prediction Lessons

3. Initializing from the assimilation analysis

- To the extent that things are linear, the climatology of the forecasts may be subtracted thus removing the drift. Can this method be used for decadal predictions?

- Non-linearities could hurt- but starting close to reality lessens the problem.

- With the current generation of ocean data assimilation systems and coupled models it is possible to demonstrate the benefits of assimilating ocean data for the seasonal forecast skill.
3D-variational method – used in operational S/I prediction for over a decade. A minimum variance estimate using a constant prior covariance matrix, unchanged in time. Stationary filter.

4D-variational - A minimum variance estimate by minimizing a distance between model trajectory and observations using an adjoint to derive the gradient under model’s constraint. Linear filter. (ECCO, JPL, Harvard)

Ensemble filtering – accounts for the nonlinear time evolution of covariance matrix. Low maintenance. Ensembles are efficient way to scale parallelism.
Better Balanced Initialization

Coupled Data Assimilation
  “Assimilation of ocean data with a coupled model”
  Coupled 4D-var: JAMSTEC
  EnKF: GMAO, GFDL

Coupled Breeding Vectors and Stochastic Optimals:
  generation of the ensemble by projecting the uncertainty of
  the initial conditions on the fastest error-growth modes of
  the coupled system

Anomaly Initialization:
  Depresys (Met Office)
  GECCO
Ensemble Coupled Data Assimilation (ECDA) is at the core of GFDL prediction efforts

- Provides initial conditions for Seasonal-Decadal Prediction
- Provides validation for predictions and model development
- Ocean Analysis kept current and available on GFDL website
- Active participation in CLIVAR/GSOP intercomparisons
Pioneering development of coupled data assimilation system

Ensemble Coupled Data Assimilation estimates the *temporally-evolving probability distribution* of climate states under observational data constraint:

- Multi-variate analysis maintains physical balances between state variables such as T-S relationship – primarily geostrophic balance
- Ensemble filter maintains the nonlinearity of climate evolution
- All coupled components adjusted by observed data through instantaneously-exchanged fluxes
- Optimal ensemble initialization of coupled model with minimum initialization shocks

S. Zhang, M. J. Harrison, A. Rosati, and A. Wittenberg
MWR 2007
Tav300 Anomaly Correlation with EN3

(a) NODC
(b) GODAS
(c) ECMWF
(d) JMA
(e) CFSR
(f) GFDL
(g) GMAO
(h) MERCATOR
(i) BOM
(j) Mean
(k) Spread

YAN XUE 2012
HC300 Anomaly (Shading=observation range; Red=ECDA)

(a) Tropical W. Pacific
(b) Eq. E. Pacific
(c) Eq. Atlantic
(d) C. North Pacific
(e) Subtropical N.-E. Pacific
(f) Subtropical S.-E. Pacific
(g) North Atlantic
(h) Subtropical North Atlantic
(i) Global Ocean
ECDA research activities to improve Initialization

- Multi-model ECDA to help mitigate bias
- Fully coupled model parameter estimation within ECDA
- ECDA in high resolution CGCM
- Assess additional predictability from full depth ARGO profilers
Seasonal / Interannual Predictions - NMME

Mid-Nov 2012 Plume of Model ENSO Predictions

IRI/CPC

Dynamical Models:
- NCEP CFSv2
- NASA GMAO
- JMA
- SCRIPPS
- LDEO
- AUS/POAMA
- ECMWF
- UKMO
- KMA SNU
- ESSC ICM
- COLA ANOM
- MetFRANCE
- COLA CCSM3
- CSIR/MM
- GFDL CME:1
- CMC CANSIP

Statistical Models:
- CPC MKOV
- CDC UM
- CPC CA
- CPC CCA
- CSU CLPR
- UBC NINET
- FSU REGR
- UCLA-TCD

NMME Forecast for Nino 3.4 IC= 201211

OBS
CFSv2
CMC1
CMC2
GFDL
NASA
NCAR
NMME
DECADAL PREDICTION EXPERIMENTAL DESIGN

• Initialization- from Ensemble Coupled Data Assimilation (ECDA) Reanalysis
  • Atmosphere - NCEP Reanalysis2 (T,u,v,ps)
  • Ocean - xbt,mbt,ctd,sst,ssh,ARGO
  • Radiative Forcing - GHG, Solar, Volcano, Aerosol
• Hindcasts - 10 member ensembles, starting Jan every year from 1960-2012 for 10 years (total of >5k years)
• Predictions - RCP4.5 scenario
• Historic (uninitialized)- 10 member ensembles, 1860-2040, RCP4.5
• CM2.1 coupled model used for all experiments
NA SPG SST

(a) North Atlantic SST

(b) 35°N–65°N

(c) Global mean SST

Heat transport (PW)

SSTA (°C)

Year


Hindcast
Fixed-forcing
Summary

1. A series of initialized decadal hindcasts and forecasts as well as uninitialized historical runs were made in support of CMIP5 and IPCC AR5
2. Most of the decadal predictability is realized by the response to external radiative forcing
3. The initialization enhances prediction skill for internal decadal variability in the region of the AMO
Caveats

1. Shortness of observational record leads to sampling uncertainty
2. Inhomogeneity of climate observing systems-quality of initial states
3. Climate not stationary - natural and anthropogenic radiative forcings
4. Predictability may be state dependent
5. Expectations are quite high and likely over-optimistic