Development of Ensemble Coupled Data Assimilation System for GFDL's SPEAR Prediction Models

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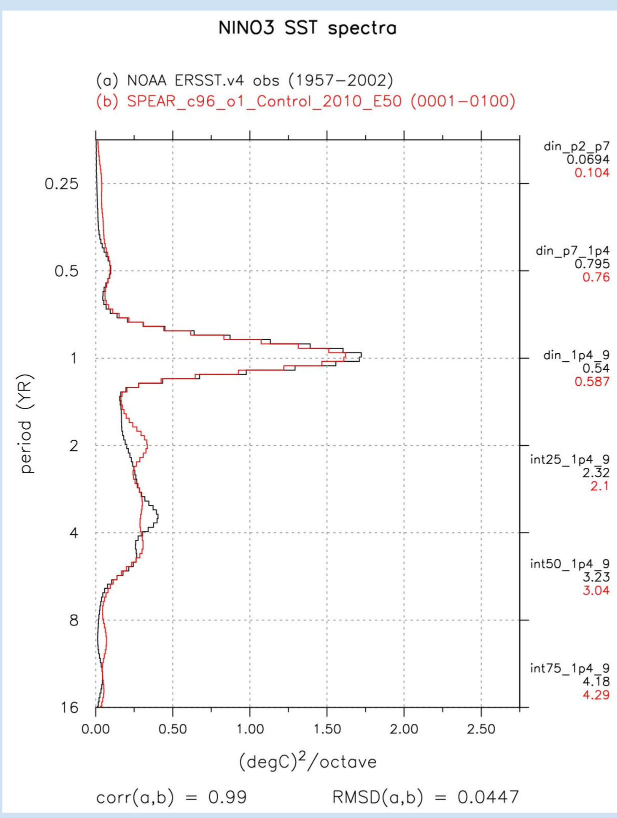
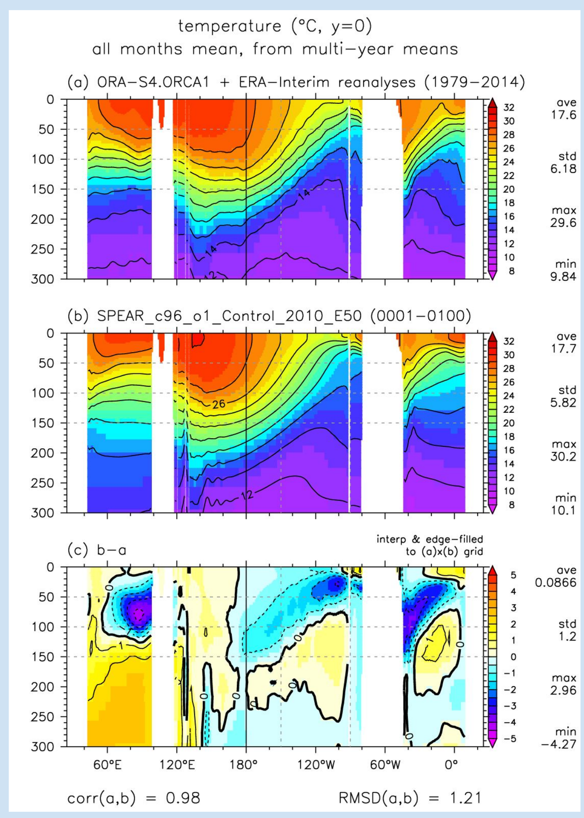
SPEAR Prediction Models

Seamless system for **P**rediction and **EA**rth system **R**esearch

- Leveraged off last 5 years of atmosphere, ocean, land, ice component model development (CMIP6) at GFDL
- Planned SPEAR versions:.
  - **SPEAR_LO** (C96 AM4 100km, 1 deg MOM6 ocean)
  - **SPEAR_MED** (C192 AM4 50km, 1 deg MOM6 ocean)
    - S2D Prediction, Large ensembles for near term projection
  - **SPEAR_HI** (C384 AM4 25km, 1 deg MOM6 ocean)
    - Tropical Cyclones, Regional Hydro-climate, extreme events

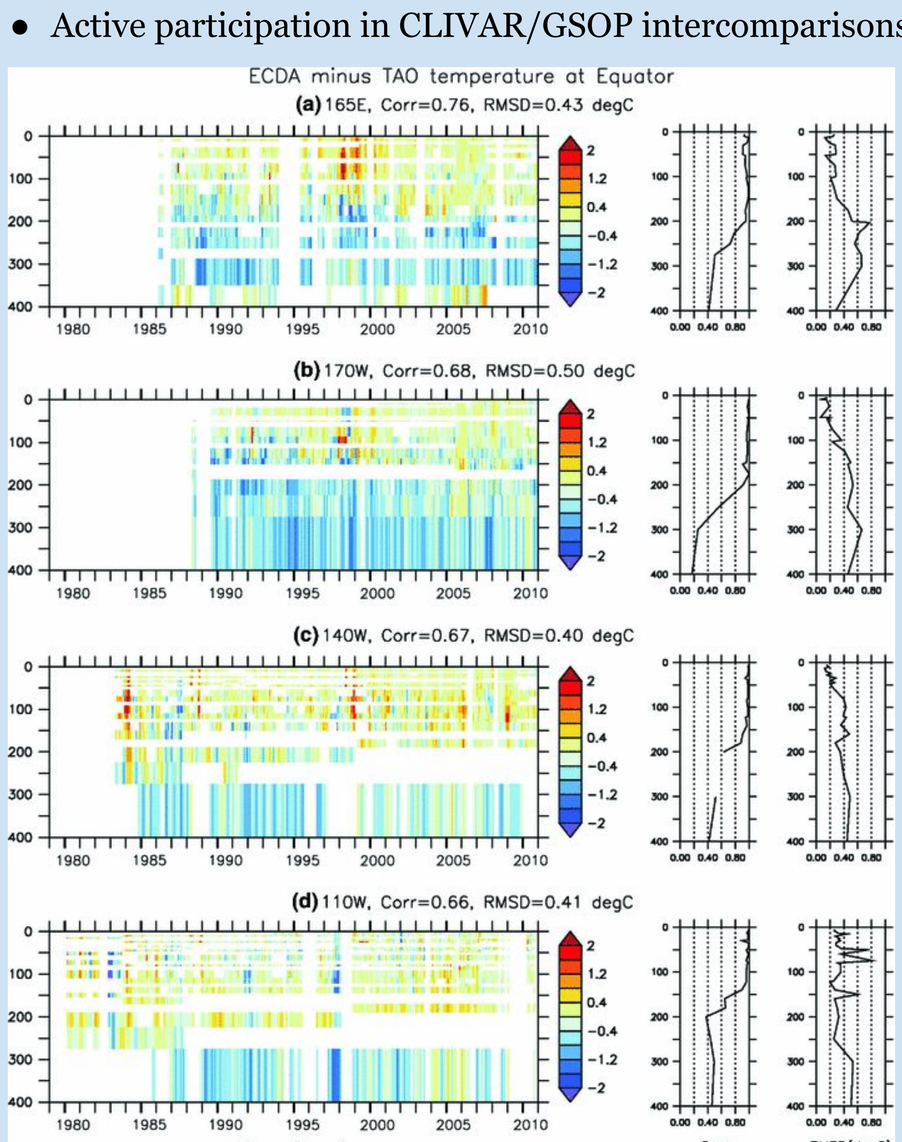


SPEAR_LO

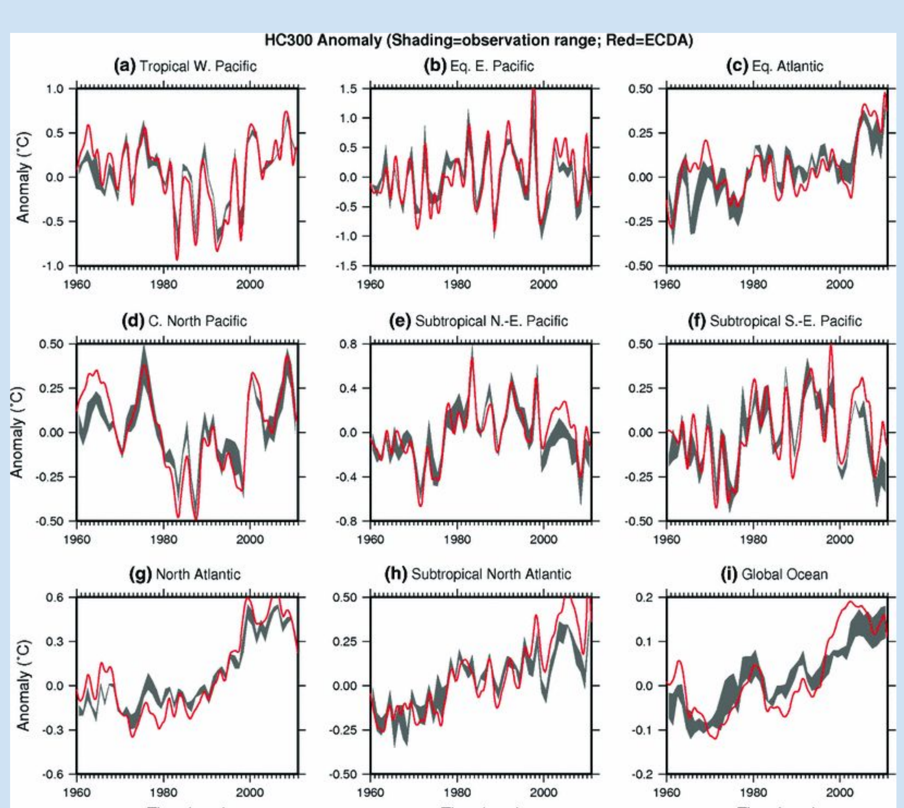


ECDA (Ensemble Coupled Data Assimilation) v3.1

- Ocean observations assimilated: XBT, CTD, SST analysis, Moorings, ARGO (WOD data => GTSPP data). Details in Zhang et al. (2007)
- Provides initial conditions for seasonal to decadal prediction (CM2.1, FLOR, FLOR_FA, HiFLOR)
- Provides validation for predictions and model development
- Ocean analysis kept current and available on GFDL website
- Active participation in CLIVAR/GSOP intercomparisons, IRI/CPC, NMME



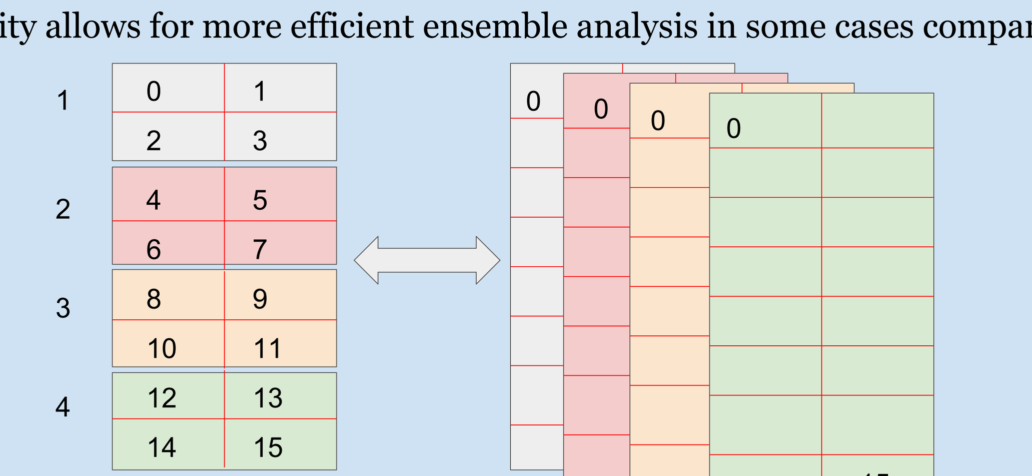
Difference between the ECDA and TAO temperature (°C) at four equatorial TAO mooring sites at a 165°E, b 170°W, c 140°W, and d 110°W. Right two panels show the vertical structure of the correlation coefficient and Root Mean Square Difference (RMSD) between the ECDA and TAO averaged for the analyzed periods



Time series of 1-year running mean of HC300 anomaly averaged in various boxes for the (red line) ECDA. Shading line indicates the different range among the NODC2009, NODC2005, and EN3 objectively analysis datasets based on only in situ data. Reference period for the anomaly is 1960–2003.

Design of Ocean Data Assimilation (ODA) Interface in MOM6

- Method independent interface for data assimilation implementation
  - Best suited for ensemble-based filters
  - No tangent linear model or adjoint model
- User-specified vertical coordinate for ODA
  - Remapping to a common (static) DA vertical grid
  - Using the ALE (Arbitrary-Lagrangian-Eulerian) algorithm
- Fully online implementation of the ODA interface and filtering
  - Efficiency: minimal I/O costs, use of FMS/MOM6 ensemble management and communication,
  - Daily assimilation of GTSPP data from profiling floaters costs 1% of MOM6 simulation time (8/12 ensemble members)
  - Offline ODA drivers available
- Fully parallel (FMS/mpp) ODA interface for ensemble gathering/scattering and observation localization
  - For ensemble methods using a suitable driver, model instances can be run in parallel - then gathered at analysis time using all PEs or some subset. After the analysis, the updated state or state increments are redistributed back to the original model decomposition.
  - Observations are read and stored locally on each PE, saving computational time and memory
  - This capability allows for more efficient ensemble analysis in some cases compared to offline methods.



4 parallel realizations on 16 cores

Redistribute for ensemble analysis - each core has copies of all ensemble members

- Diagnostic output of ODA
  - Increments from DA algorithm in the model space
  - Prior and posterior values in the observation space
- Multi-model potential: ensemble parameters can be independently specified in MOM6 at runtime

Next: ECDA for SPEAR Models

Development of ODA in MOM6: the ODA interface has been merged into the dev/gfdl branch of MOM6 on Github (PR#755).

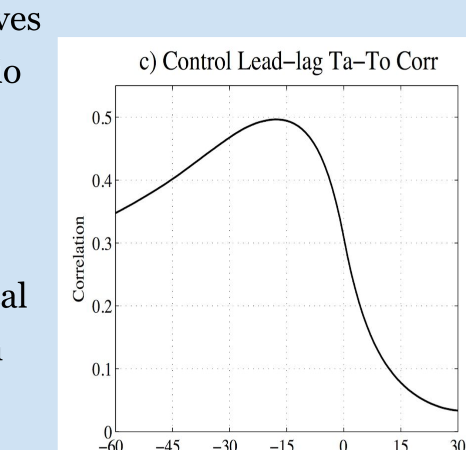
- Observation types
  - Already implemented: GTSPP data types, including profiles of temperature and salinity
  - Short-term plan: SST (analysis vs. satellite)
  - Long-term plan: SSH, surface fluxes, ocean currents
- ODA configuration
  - Ensemble Adjustment Kalman Filter (EAKF) with 30 members (tentatively)
  - Horizontal, vertial and temporal localization of covariances
- Planned applications
  - Ocean analysis for the ARGO era (2003-) and modern era (1960s-)
  - OSSEs for research and operational tests
  - Ensemble initialial conditions for seasonal to decadal prediction using SPEAR models

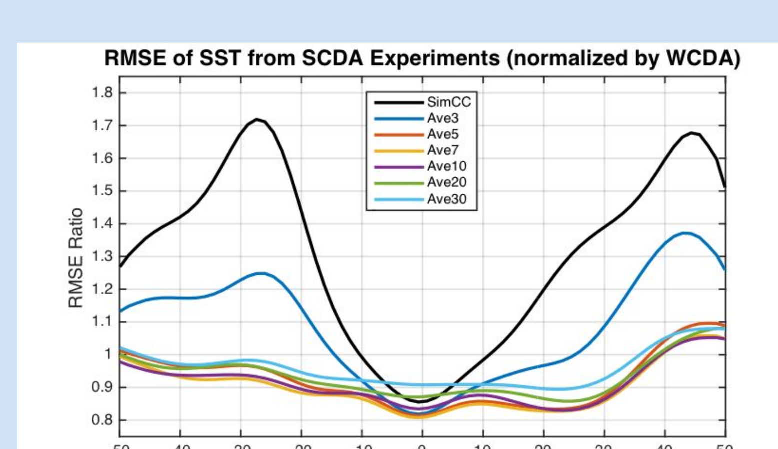
Atmosphere data assimilation

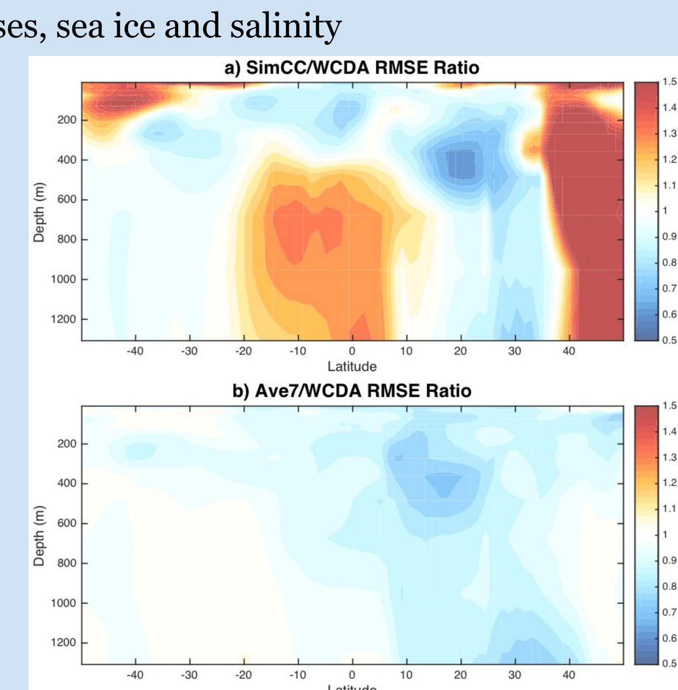
Sea ice data assimilation

Strongly Coupled Data Assimilation (SCDA)

- SCDA utilizes the covariance across model components for state estimation, in addition to running data assimilation in one or more model components of a coupled GCM.
- Direct implementation of SCDA could lead to worse filter performance due to the large signal-to-noise ratio when estimating the cross-component covariances.
- The LACC (Leading Averaged Coupled Covariance) method improves SST (slow component) analysis by boosting the signal-to-noise ratio in cross-component update
  - Increase cross correlation (leading and averaging)
  - Reduce atmosphere noise (averaging)
- LACC makes use of the principles of climate dynamics (extratropical ocean driven by atmosphere) to improve coupled data assimilation
- Potential applications of SCDA with LACC
  - Atmosphere temperature/wind => subsurface ocean
  - Atmosphere <=> hydrological cycle, land processes, sea ice and salinity
  - Carbon cycle data assimilation
  - Paleoclimate assimilation







References

Zhang, S. et al. 2007: System design and evaluation of coupled ensemble data assimilation for global oceanic climate studies. Mon. Wea. Rev. 135, 3541-3564.

Chang, YS. et al. 2013: An assessment of oceanic variability for 1960–2010 from the GFDL ensemble coupled data assimilation. Clim. Dyn., 40, 775

Lu, F. et al. 2015: Strongly coupled data assimilation using leading averaged coupled covariance (LACC). Part II: CGCM experiments. Mon. Wea. Rev., 143, 4645–4659

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