Seamless Diagnosis of Predictability on Multiple Time Scales

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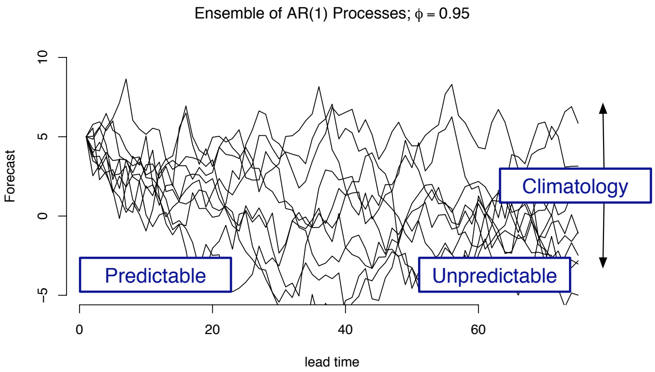
Definition of Predictability



$$\text{Predictability Measure } = P = \frac{\sigma^2_{clim} - \sigma^2_{forecast}(\tau)}{\sigma^2_{clim}}$$

Average Predictability Time (APT) Analysis

Determine linear combination of variables that maximize integral of P.

$$APT = 2\int_0^\infty \left(\frac{\sigma^2_{clim} - \sigma^2_{forecast}(\tau)}{\sigma^2_{clim}} \right) d\tau$$

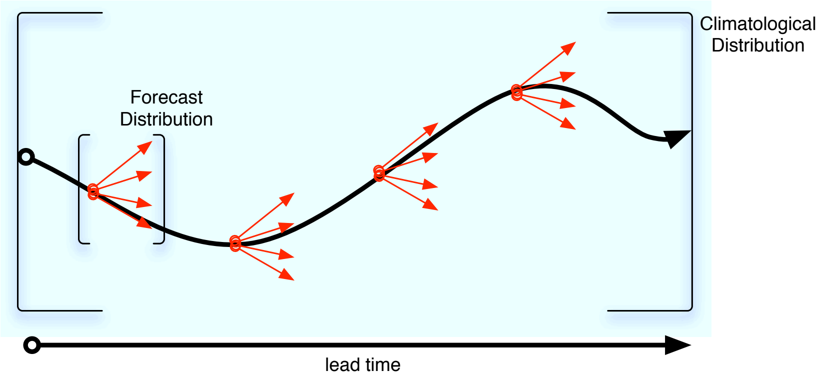
The desired weights **w** are found by solving eigenvalue problem

$$\int_0^\infty (\Sigma_c - \Sigma_f(\tau))\,\mathbf{w} = \lambda \Sigma_c \mathbf{w}$$

where Σ_f and Σ_c are covariance matrices for the forecast and climatological distribution.

- Related to Predictable Component Analysis
- Schneider and Griffies (1999), DelSole and Tippett (2007)
- DelSole and Tippett (2009a, b)

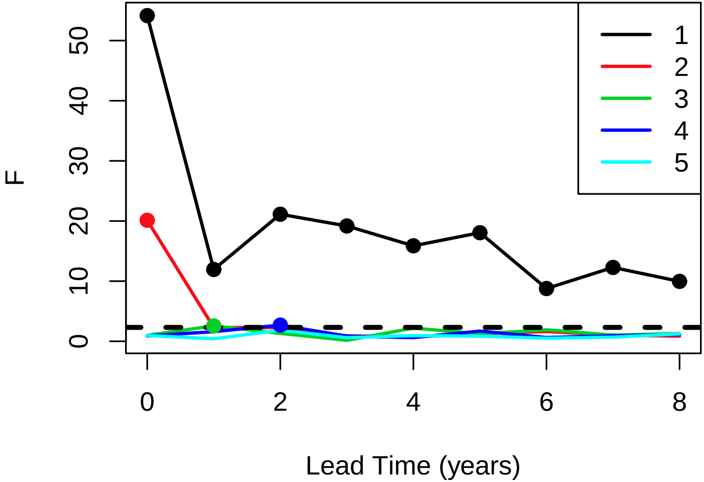
Estimating Predictability From Ensemble Forecasts



Decadal Hindcasts with Climate Forecast System (CFSv2)

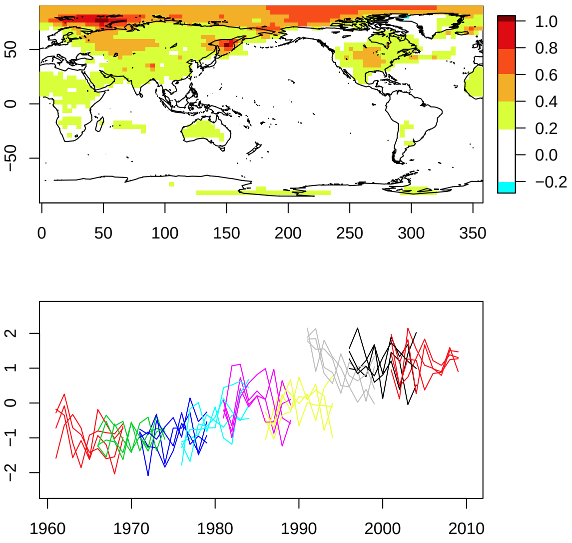
- CFS version 2 by NCEP (identical to I-S prediction model)
  - Atmosphere is T126L64
  - Ocean has 40 levels, 0.25 degree horizontal resolution in tropics
  - Sea-ice model is 3-layers and interactive
  - Land model has 4 soil levels and interactive
- Initial Atmosphere, land, sea ice: CFSR reanalysis
- Initial Ocean: NEMOVAR (ECMWF) interpolated to CFS
- Initialized Nov. 1960, 1965, 1970, 1975, ... 2000, 2005
- 10-year hindcasts of 4 member ensembles
- includes anthropogenic and natural forcing
- run on NASA Pleiades

APT Components 1-5 of CFSv2 JFM 2m-Temperature

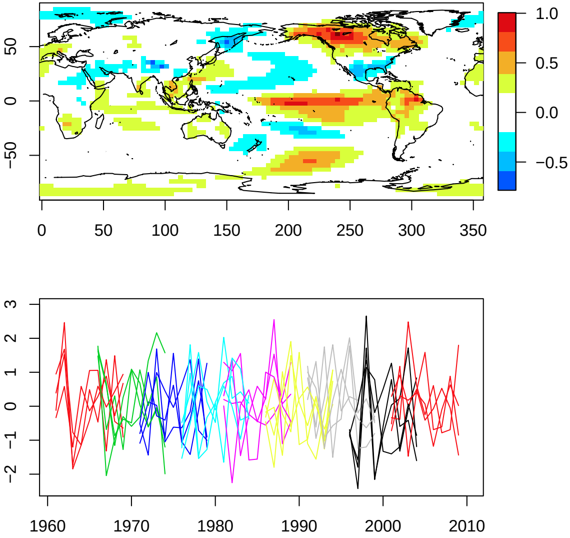


"0" lead means the first JFM after the Nov. initial condition

Leading APT Component of CFSv2 JFM 2m-Temperature

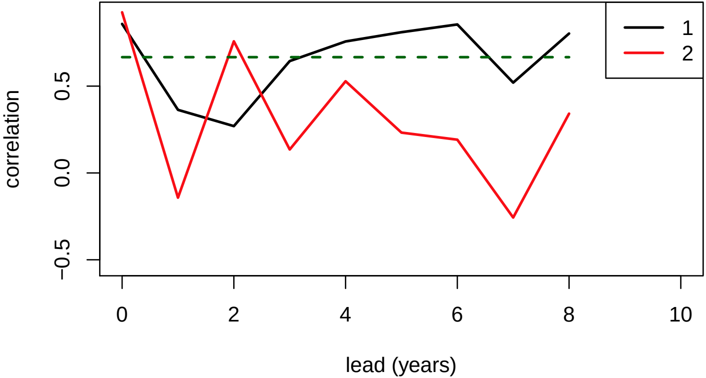


Second APT Component of CFSv2 JFM 2m-Temperature



Skill of APT Components of CFSv2 JFM 2m-Temperature

Correlation between observed and forecasted predictable components



Verification: JFM 2m Temperature from NCEP/NCAR Reanalysis

Decadal Predictability Estimated from CMIP3

Forced Run:
Simulation with natural and anthropogenic forcing (includes volcanic and solar forcing).

Control Run:
Simulation without natural and anthropogenic forcing (simulates variability due only to the internal dynamics of the coupled atmosphere-ocean-biosphere-cryosphere system).

Optimize APT in Control Runs

- Use IPCC AR4 data set (also called CMIP3).
- Last 300 years of PICNTRL are used.
- Model grids interpolated onto HadSST2 grid.
- Only "well-observed" grid points in the model are analyzed.
- Annual averaged sea surface temperature.
- Each model's climatology subtracted out.
- All runs pooled to compute "total EOF" and "total APT."
- The "outliers" IAP, GISS-EH, GISS-ER were omitted.
- 14 models, effective time series length = 4200 years.
- 40 EOF truncation, 20-year maximum lag for APT.
- No Detrending
- Null hypothesis: white noise when sampled every 2 years.

Estimating APT With Only One Ensemble Member

- Project data onto M principal components $\mathbf{r}(t)$.
- Construct multivariate linear regression model

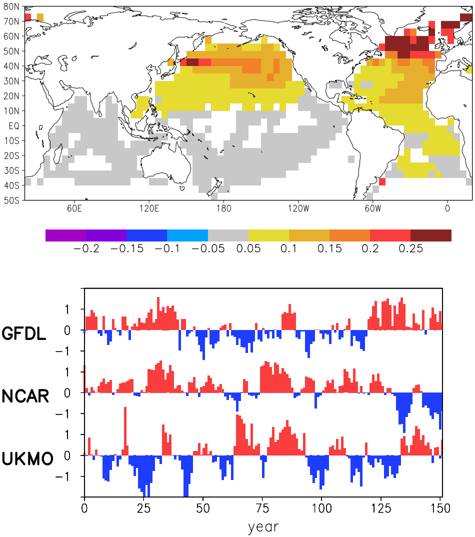
$$\mathbf{r}(t+\tau) = \mathbf{L}_\tau \mathbf{r}(t) + \epsilon(t).$$

- Determine forecast variance from standard regression formula

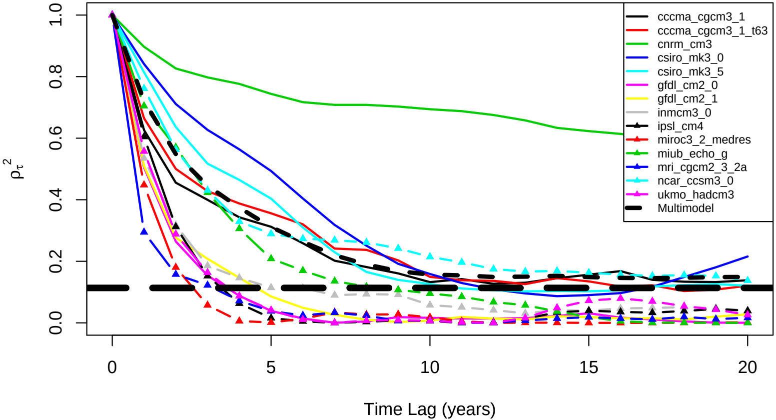
$$\Sigma_f = \Sigma_r - \mathbf{L}_\tau \Sigma_r \mathbf{L}_\tau^T.$$

  where Σ_r is the covariance matrix of $\mathbf{r}$.
- Optimize APT using Σ_f defined above and $\Sigma_c = \Sigma_r$.
- **Limitations:** May miss non-linear predictability.

Leading Predictable Component of CMIP3 Controls



Scientific Basis for Decadal Predictability of Internal Variability



Why No Decadal Predictability Was Detected in CFS2?

- CFS2 used “realistic” initial conditions based on observations.
- CFS2 involves a relatively small sample size (9 initial start dates)
- AMOC (source of decadal predictability) is problematic in CFS2.

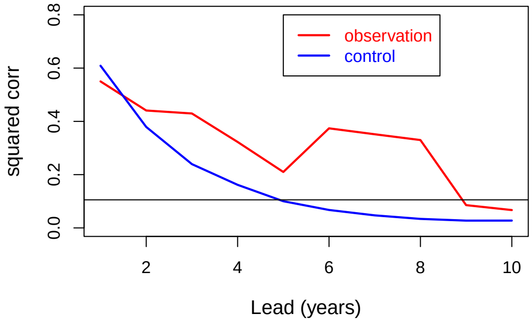
Empirical Model for Decadal Prediction

Linear prediction equation for M principal components

$$\underbrace{\mathbf{p}(t+\tau)}_{\textit{predictand}} = \underbrace{\mathbf{L}_\tau}_{\textit{propagator}} \underbrace{\mathbf{p}(t)}_{\textit{predictor}} + \underbrace{\epsilon(t)}_{\textit{noise}}$$

Propagator $\mathbf{L}_\tau$ determined from CMIP3 control runs, then applied to independent observations, minus forced response.

Skill of Empirical Predictions of the Leading APT Component of Annual Mean 2m Temperature



observation: empirical prediction of observation minus forced response 1975-2010

control: empirical prediction of control simulations (300 years).

Decadal Prediction

Empirical models provide a “baseline” for comparison.

Today’s dynamical model probably cannot beat “baseline” because

1. Subsurface initial condition is not well observed.
2. Difficult to initialize models with the observed state.
3. Models may not evolve climate state correctly (climate drift).

Similar to ENSO prediction two decades ago– only in the last decade have dynamical models been able to beat statistical models.

Summary

1. APT analysis provides a way to diagnose predictability over a wide range of time scales (seasonal to decadal).
2. Preliminary analysis of CFSv2 initialized decadal experiments reveal just two predictable components: climate change and ENSO.
3. CMIP3 models contain a component that is predictable as long as 10 years in many models.
4. An empirical model trained on CMIP3 data shows skill on decadal time scales.

Current dynamical models are unlikely to beat empirical models because subsurface initial condition is not well observed, dynamical models are difficult to initialize with observations, and model error, all of which can be mitigated by empirical models.