



## Regional influences of ocean-atmosphere interaction on climate variability using partial coupling

### R. S. Ajayamohan and William J Merryfield Canadian Center for Climate Modelling and Analysis, Victoria, Canada

## Introduction

- Sources of climate variability include
  - intrinsic atmospheric variability
  - atmospheric response to ocean variability
  - coupled ocean/atmosphere interactions
- Attribution difficult in fully coupled simulations
- Objective: distinguish regional contributions of air-sea coupling to climate variability and predictability through model runs using *partial coupling* in specified regions
- Preliminary results presented here

## Model and partial coupling methodology

- Coupled climate model: CCCma CGCM3.7
  - AGCM3, T63L31, filtered physics
  - OGCM 1.4° lon  $\times$  0.94° lat  $\times$  40 levels ( $\Delta z = 10$  m in upper ocean), anisotropic viscosity, KPP mixed layer, penetrative solar radiation
- Partial Coupling: atmosphere sees specified SSTs instead of interactive SSTs in specific regions
- In these experiments the specified SSTs consist of model climatological SSTs obtained from a fully coupled control run  $(\rightarrow SSTA = 0)$
- Results presented here are based on 300 years of model output following 70-year spin-up period (runs are ongoing)
- Examine effects on climate variability and potential predictability

## Partial Coupling Masks



## Analysis

- 300 year model simulations for each of the 6 masked runs.
- Monthly mean data is used to evaluate
- Potential predictability of seasonal means
- Results presented for December-January-February (DJF)
- Variables considered:
  500hPa height,
  850hPa temperature
  Mean sea level pressure

#### Impact of masking on interannual variability of DJF seasonal means



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#### Calculation of Potential Predictability

Statistical model based on 1-way ANOVA (Zwiers 96, Zhengetal 2000)

$$X_{yt} = \mu + \beta_y + \mathcal{E}_{yt}$$

 $\mu$  represents long term seasonal mean

 $\beta_y$ 's represents year-to-year variations in the levels of X that are potentially predictable

 $\mathcal{E}_{yt}$ 's represent within season variations that are presumably not predictable on seasonal and longer time scales.

The total interannual variance of the seasonal mean of  $X_{yt}$  is

$$\sigma^2 x_{yo} = \frac{1}{(Y-1)} \sum_{y=1}^{Y} (X_{yo} - X_{oo})^2$$

 $X_{yo}$  denotes the year y seasonal mean and  $X_{oo}$  mean of seasonal means

$$\sigma^{2} X_{yo} = \frac{1}{(Y-1)} \sum_{y=1}^{Y} (\beta_{y} + \varepsilon_{yo} - (\beta_{o} + \varepsilon_{oo}))^{2}$$
$$\sigma^{2} X_{yo} = \sigma^{2} \beta + \sigma^{2} \varepsilon_{yo}$$

Total interannual variance of seasonal mean in the model contains Climate signal and weather noise components.

Whether the observed process is potentially predictable is determined by testing the null hypothesis that the seasonal means of X vary only because of weather noise.

$$H_o: \sigma^2{}_\beta = 0$$

 $\Box$ 

We require an unbiased estimate of variance of the weather Noise that is statistically independent of the total variance. When only monthly means are available, an unbiased estimate of weather noise can be estimated by

$$\sigma^{2}_{\varepsilon_{yo}} = SSE \frac{(3+4\rho_{1}+2\rho_{2})}{6Y(3-2\rho_{1}-\rho_{2})}$$
  
where  $SSE = \sum_{y} \sum_{t=1}^{3} (X_{yt} - X_{yo})^{2}$  and  $\rho_{1}, \rho_{2}$   
are lag-1 month and lag-2 month auto-correlations.

 $F = \frac{\sigma^2 X_{yo}}{\sigma^2_{\varepsilon_{yo}}}$ 

measure of potential predictability

 $\rightarrow$  F-1 measures potentially predictable signal (valance exceeds noise)

#### Comparison of potential predictability of DJF seasonal means Model vs Observations





300-year control simulations Monthly means used



28-years, 1979-2007 Monthly means used

500mb



E tropical Pacific masked

1208

9ÔM

1500

North Pacific masked



120E

nort pac z500 F-Ratio dji

80N

4 OK

20N

EQ

205

40S -

80S

3ÔF

6ÔF

9ĥF

equatorial Pacific masked





tropical Pacific masked



500mb height





 $\rightarrow$  Masked IO run



#### mean sea level pressure

North Pacific masked

**E** tropical Pacific masked



ation dif equatorial Pacific masked





## Summary

- Partial coupling procedure enables effects of local and remote air-sea interactions to be distinguished from intrinsic atmospheric variability
- Initial results presented here
- ENSO SSTA are responsible for much (but not all) of climate variability (wrt to z500, t850 and mslp) both locally (in tropical Pacific) and remotely.
- Ongoing work includes
  - longer time series
  - other seasons
  - more detailed analysis on climate variability wrt to larger modes of climate variability like ENSO, IOD etc
  - comparison with CGCM3.8 which has a stronger ENSO

## Assumptions

- We assume that the random variables  $\{\hat{a}_{y}, y=1,...Y\}$  to be independently distributed random variables with mean zero and variance  $\sigma^{2}_{\hat{a}}$ .
- Weather noise time series {å<sub>yt</sub>, t=1,..T} are assumed to be independent realizations of the same Gaussian stochastic process.
- The weather noise process is assumed to be independent of the potential predictable process  $\{\hat{a}_v^{},y{=}1,{\dots}Y\}$
- Each weather noise time series {å<sub>yt</sub>, t=1,..T} is assumed to behave as red noise.
- Clearly there are limitations to the utility of this model.
- Nonetheless departures from this assumptions would appear mild enough that the model remains as a useful device for partitioning variance into potentially predictable and non-predictable components.

850mb temperature







# Example: Effect of SSTA on standard deviation of monthly surface temperature anomalies

