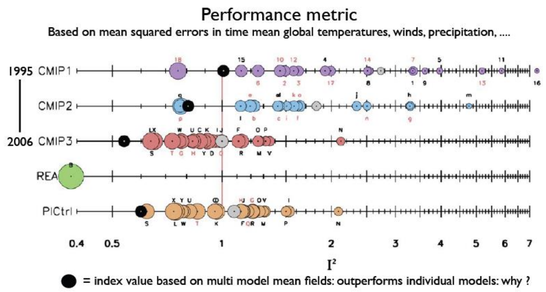
Fusion of Alternative Climate Models by Synchronization: Results With Realistic Models

Gregory S. Duane Geophysical Institute, University of Bergen, Norway, *and* Dept. of Atmospheric and Oceanic Sciences, University of Colorado, Boulder, USA
Mao-Lin Shen and Noel Keenlyside Geophysical Institute, University of Bergen, Norway
Frank Selten KNMI, The Netherlands

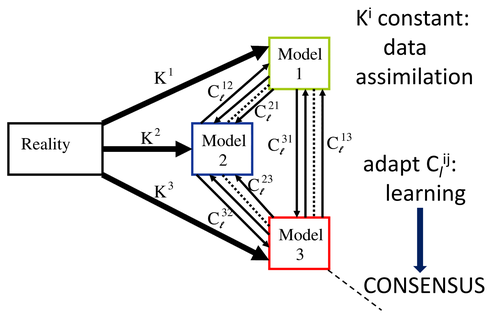
1. Introduction

- **Climate models differ widely in their detailed projections.**



- Can we do better than averaging model outputs?

- **Supermodel (interactive ensemble):**



K^i constant: data assimilation

adapt C_I^{ij}: learning

CONSENSUS

-couple corresponding "model elements" *I*

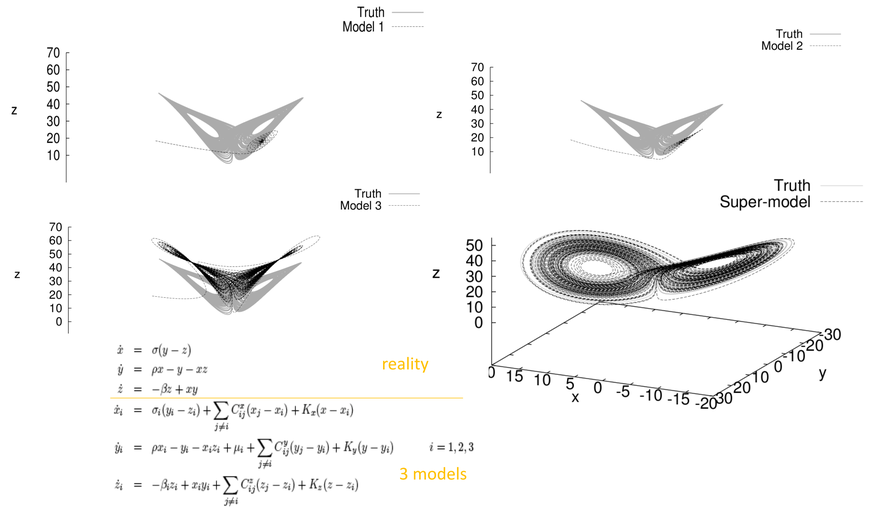
- **Connections or weights for corresponding dynamical variables are adapted by training on historical data.**

- **Models synchronize so as to form a consensus.**

- **For climate projection, use the same configuration of connected models but change the forcing.**

2. A Supermodel Formed From Lorenz '63 Models

Models Synchronize With Each Other and With "Truth"

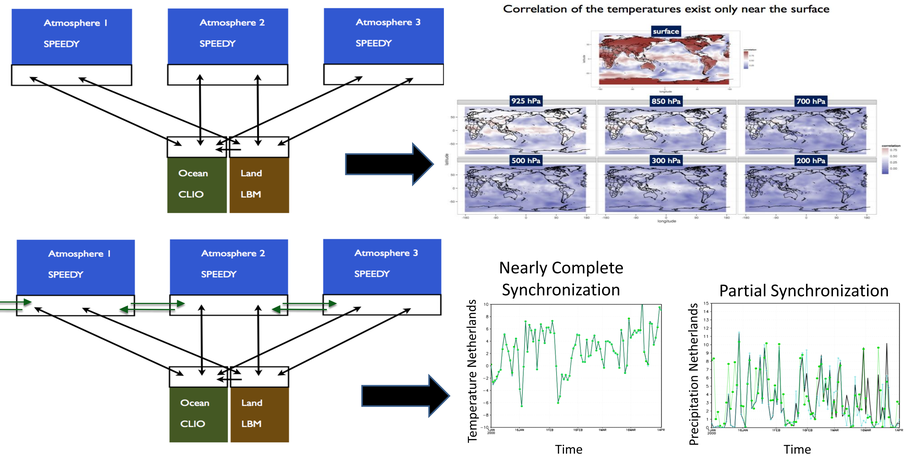


$$\dot{x} = \sigma(y-z)$$
$$\dot{y} = \rho x - y - xz \qquad \text{reality}$$
$$\dot{z} = -\beta z + xy$$
$$\dot{x}_i = \sigma_i(y_i - z_i) + \sum_{j\neq i} C_{ij}^x (x_j - x_i) + K_x(x - x_i)$$
$$\dot{y}_i = \rho x_i - y_i - x_i z_i + \mu_i + \sum_{j\neq i} C_{ij}^y (y_j - y_i) + K_y(y - y_i) \qquad i = 1,2,3$$
$$\dot{z}_i = -\beta_i z_i + x_i y_i + \sum_{j\neq i} C_{ij}^z (z_j - z_i) + K_z(z - z_i) \qquad \text{3 models}$$

- Use standard machine learning to fix C_{ij}
- If "forcing" ρ is varied in truth and all models, the supermodel still tracks truth

3. A Supermodel Formed From SPEEDO Models

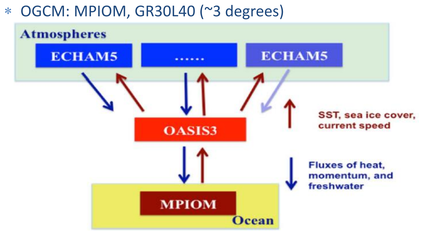
SPEEDO – a primitive equation atmosphere model (SPEEDY) coupled to land and ocean models



- **Synchronization implies that the unphysical inter-model nudging terms vanish**

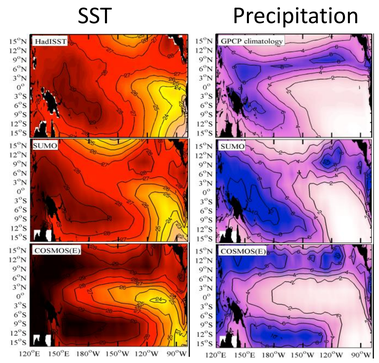
4. A Supermodel Formed From Two ECHAM Models With Different Convection Schemes (Nordeng and Tiedtke)

- COSMOS model (MPI, Germany)
  - AGCM: ECHAM5, T31L19 (~3.75 degrees horizontally)
  - OGCM: MPIOM, GR30L40 (~3 degrees)



3 independent inter-model weights for heat flux, momentum flux, and water flux, respectively; optimize using monthly mean SST's

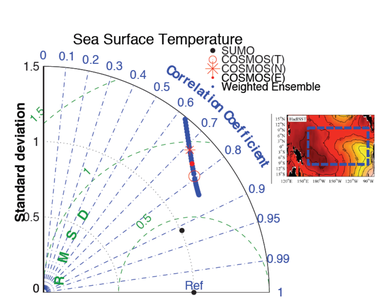
After learning: Weight for momentum flux: α=0.43 $H = \alpha H_{Nordeng} + (1-\alpha) H_{Tiedtke}$
Weight for heat flux: β=1.21 $Q = \beta Q_{Nordeng} + (1-\beta) Q_{Tiedtke}$



Observations:
-cold tongue only to dateline
-single ITCZ

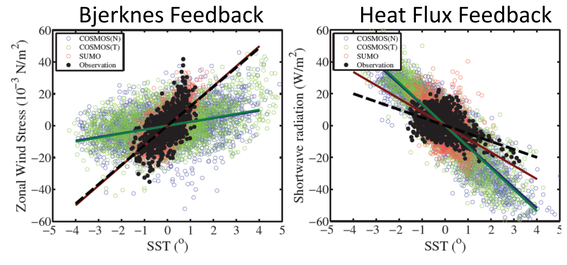
Supermodel (SUMO):
- cold tongue only to dateline
-single ITCZ
-extra precip in SPCZ

Multi-model mean:
-cold tongue to WP
-double ITCZ
- extra precip in SPCZ



- Supermodel is better than any weighted average of model outputs

- The advantage of supermodeling is especially in higher-order quantities like feedbacks



5. Future Work

- **Optimize connections in SPEEDO supermodel via machine learning.**
- **Introduce direct atmospheric connections in ECHAM supermodel, for increased synchronization, especially needed in midlatitudes.**
- **Apply to a regional climate phenomenon where there are large differences among models, e.g. AMOC.**

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