Consensus Among Climate Models via Synchronized Chaos

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Supported by:
DOE Grant# DE-SC0005238

SUMMARY

- Problem: IPCC-class climate models give widely divergent predictions in regard to:
  - a) magnitude of long-term climate change
  - b) detailed regional predictions
  - c) short-term climate change

  Can we do better than averaging model outputs?

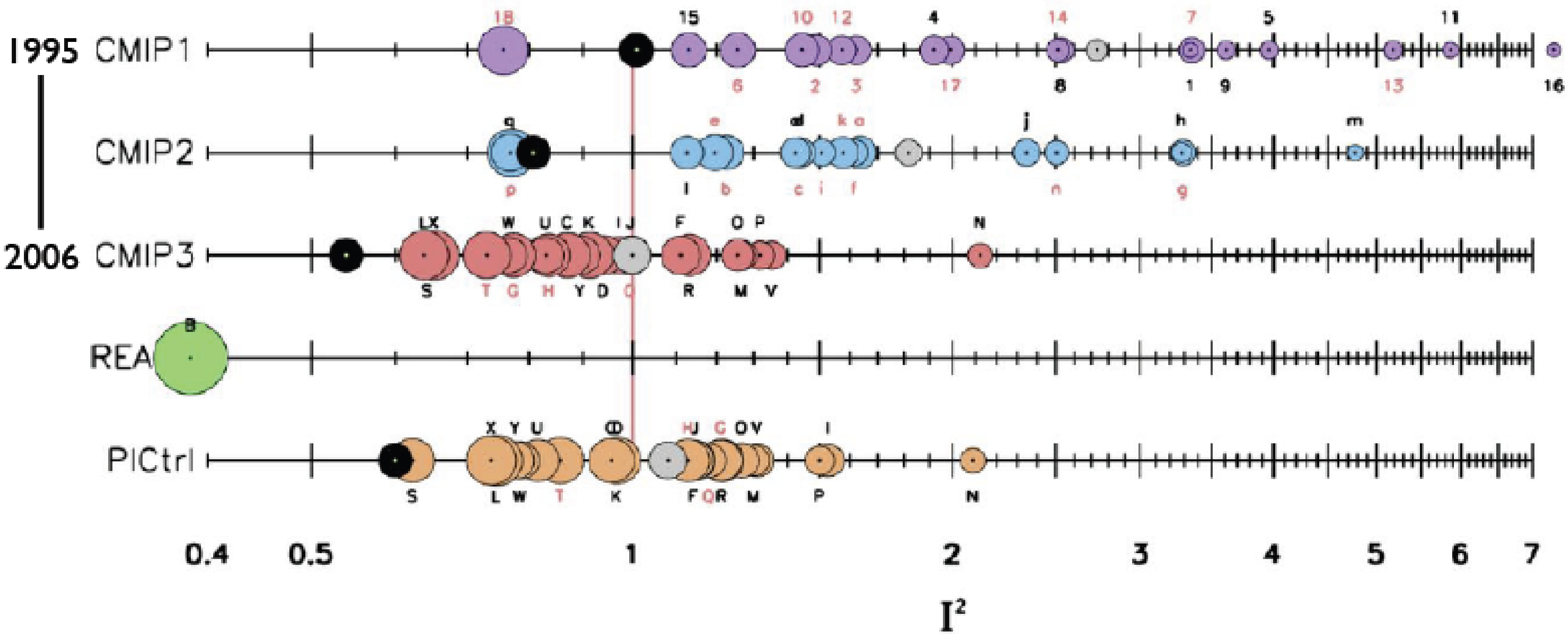
- Potential Solution: Take the synchronization view of data assimilation, and allow models to form a consensus (synchronize) by assimilating data from one another.
  - Sync extends the “nudging” approach to assimilation.
  - Parameters can be nudged as well as states *without ensembles*.
  - Choose the adaptable parameters to be connection coefficients linking corresponding variables in different models; adapt them using historical data.

Coupled Model Intercomparison Project

Reichler, T., and J. Kim (2008): How Well do Coupled Models Simulate Today's Climate? *Bull. Amer. Meteor. Soc.*, **89**, 303-311.

Performance metric

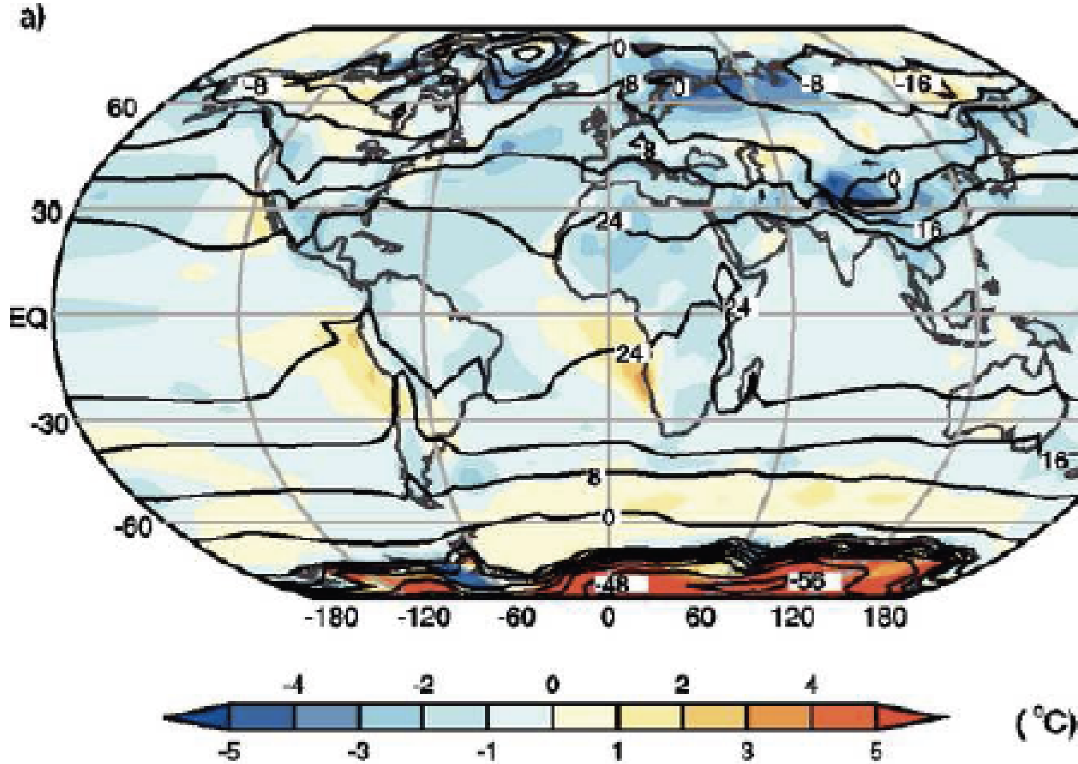
Based on mean squared errors in time mean global temperatures, winds, precipitation, ...



● = index value based on multi model mean fields: outperforms individual models: why ?

Error in annual mean surface air temperatures

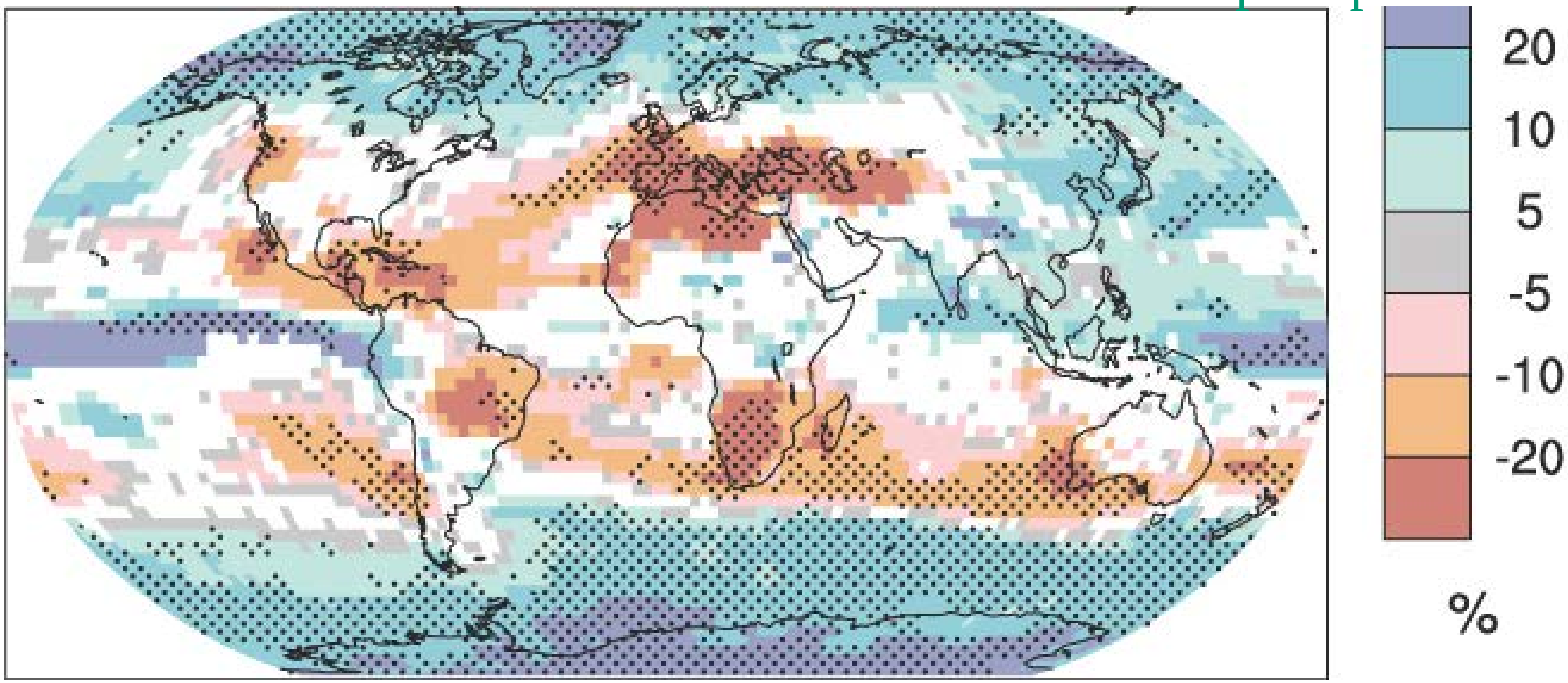
multi model mean over all CMIP3 simulations



IPCC 2007

EXAMPLE: DIVERGENT MODEL PROJECTIONS OF REGIONAL PRECIPITATION CHANGE

increased or decreased precipitation

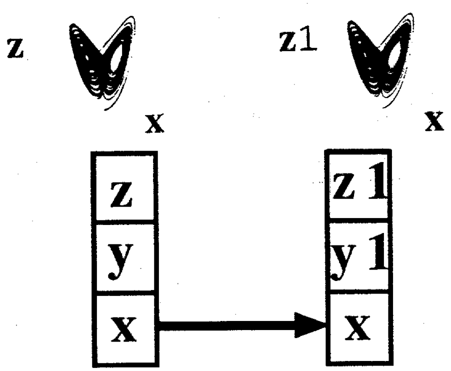


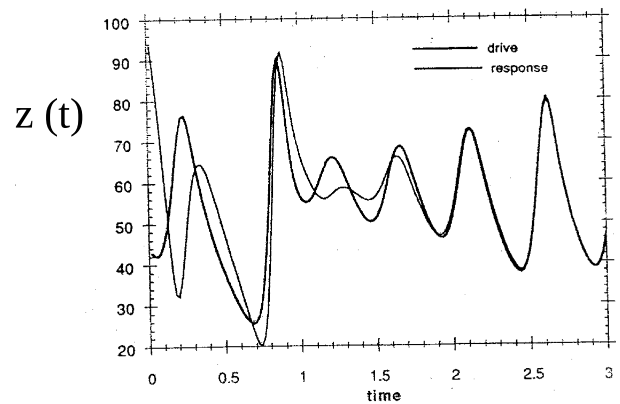
White areas: less than 2/3 of models agree on the sign of precipitation change

Stippled areas: more than 90% of models agree on the sign

SUPPOSE THE WORLD IS A LORENZ SYSTEM AND ONLY *X* IS OBSERVED

- two coupled chaotic systems can fall into synchronized motion along their strange attractors when linked through only one variable



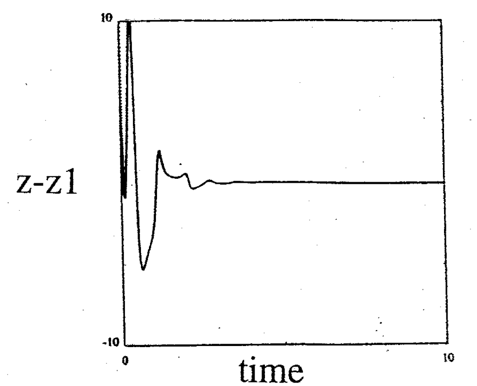


$$x' = \sigma(y-x)$$

$$y' = \rho x - y - xz \qquad y_1' = \rho x - y_1 - x(z_1)$$

$$z' = -\beta z + xy \qquad z_1' = -\beta(z_1) + x(y_1)$$

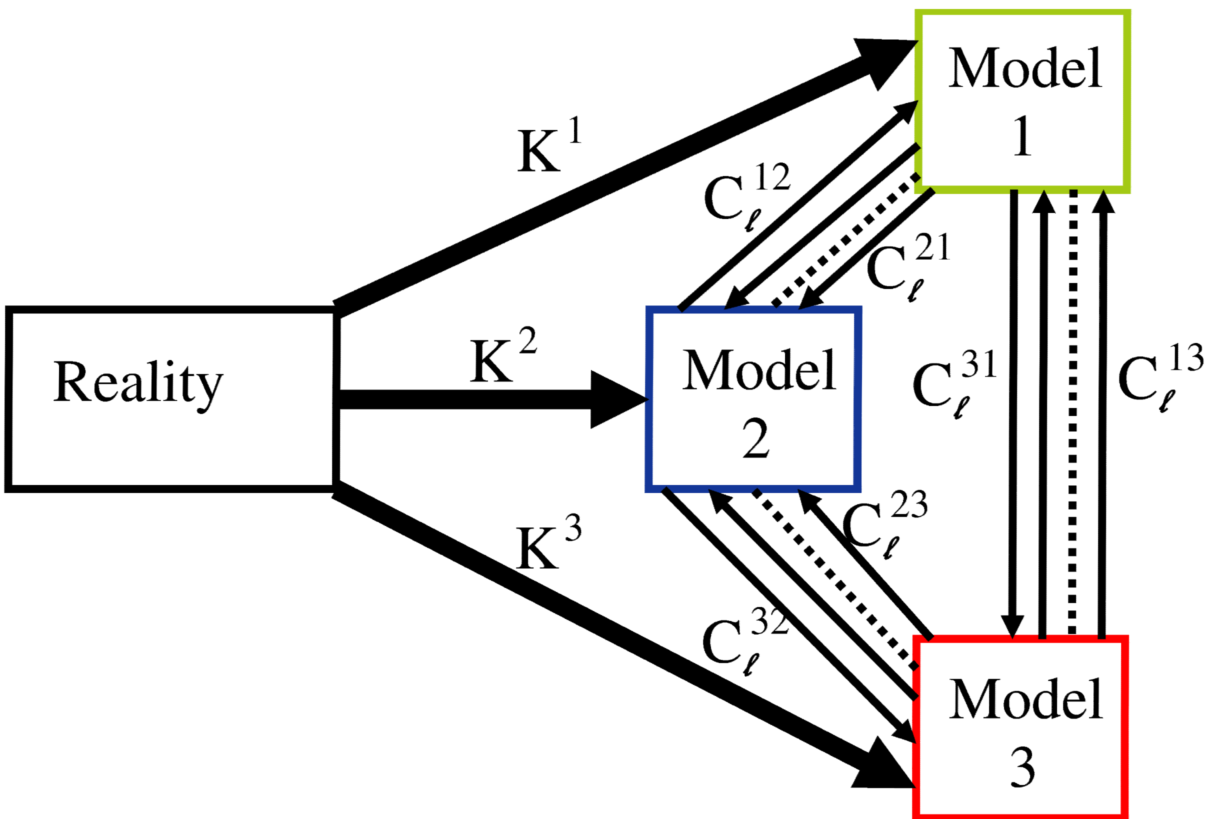
(also works for y-coupling, but not for z-coupling)



(*Pecora and Carroll '90*)

- SYNCHRONIZATION ⟶ DATA ASSIMILATION

LET A COLLECTION OF MODELS ASSIMILATE DATA FROM (SYNCHRONIZE WITH) ONE ANOTHER; ADAPT THE COUPLING COEFFICIENTS



K^i constant:
data assimilation

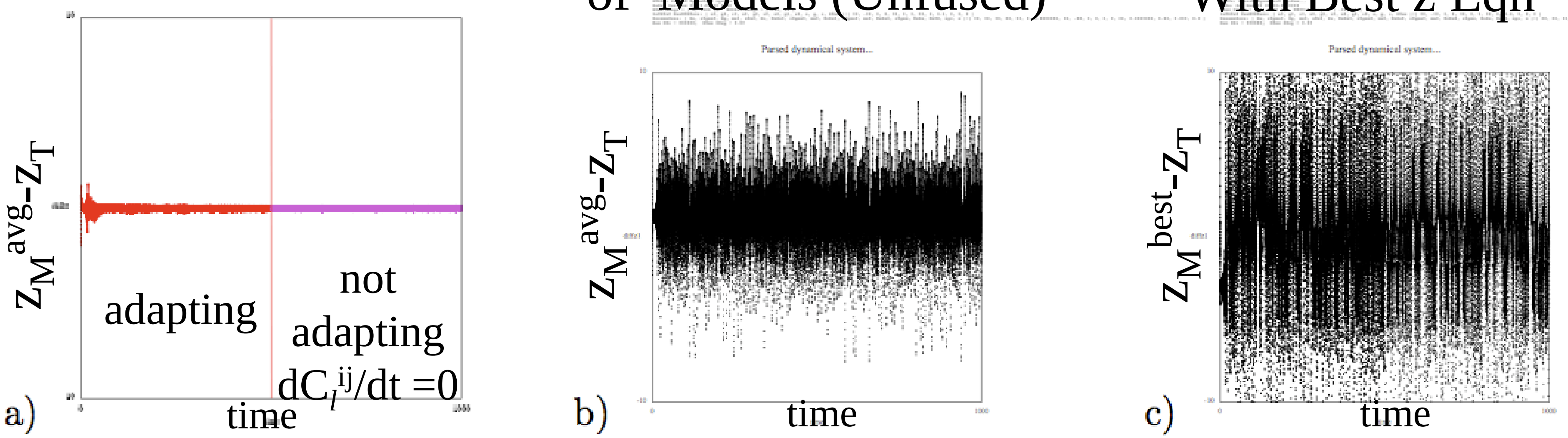
adapt C_l^{ij}:
learning

CONSENSUS

-couple corresponding “model elements” l

Test Case: Fusing 3 Lorenz Systems With Different Parameters

Fused Models | Average Output of Models (Unfused) | z from Model With Best z Eqn



$$
\begin{aligned}
\dot{x} &= \sigma(y-z)\\
\dot{y} &= \rho x - y - xz\\
\dot{z} &= -\beta z + xy\\
\dot{x}_i &= \sigma_i(y_i - z_i) + \sum_{j\neq i} C^x_{ij}(x_j - x_i) + K_x(x - x_i)\\
\dot{y}_i &= \rho x_i - y_i - x_i z_i + \mu_i + \sum_{j\neq i} C^y_{ij}(y_j - y_i) + K_y(y - y_i) \qquad i = 1,2,3\\
\dot{z}_i &= -\beta_i z_i + x_i y_i + \sum_{j\neq i} C^z_{ij}(z_j - z_i) + K_z(z - z_i)
\end{aligned}
$$

$dC_x^{ij}/dt = a(x_j - x_i)(x - \tfrac{1}{3}\sum x_k)$

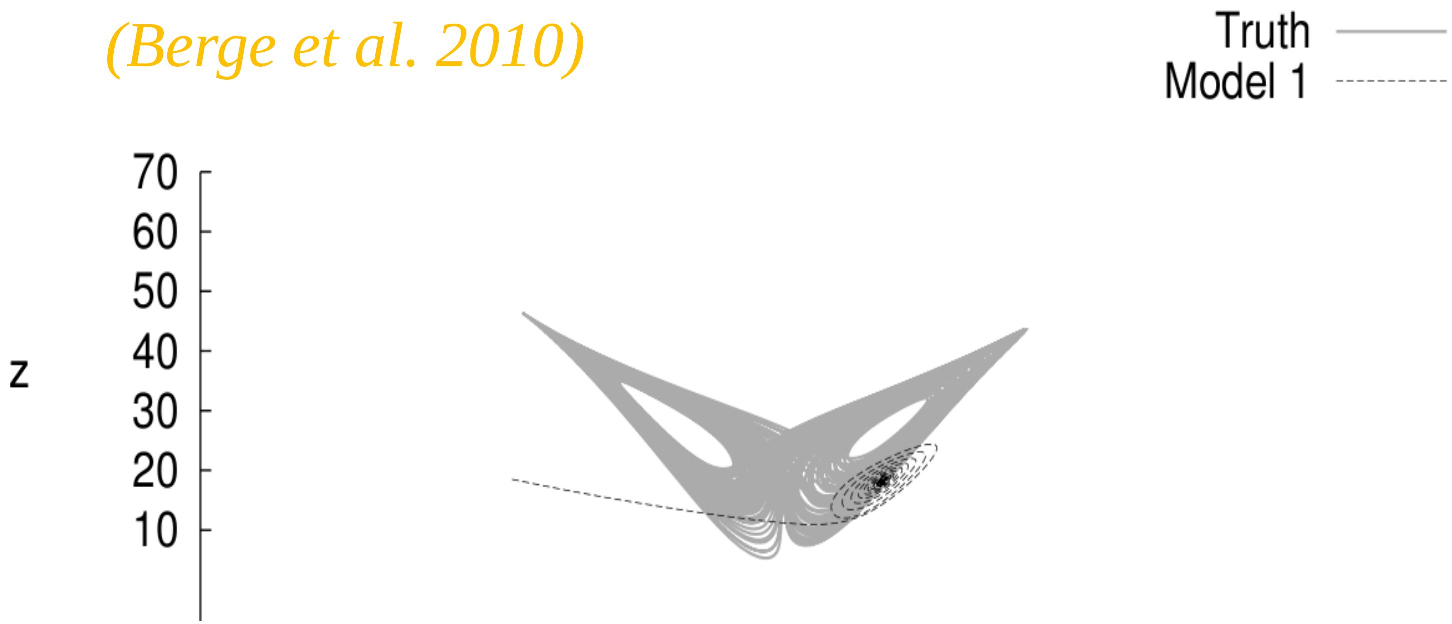
$dC_y^{ij}/dt = \ldots\ldots$

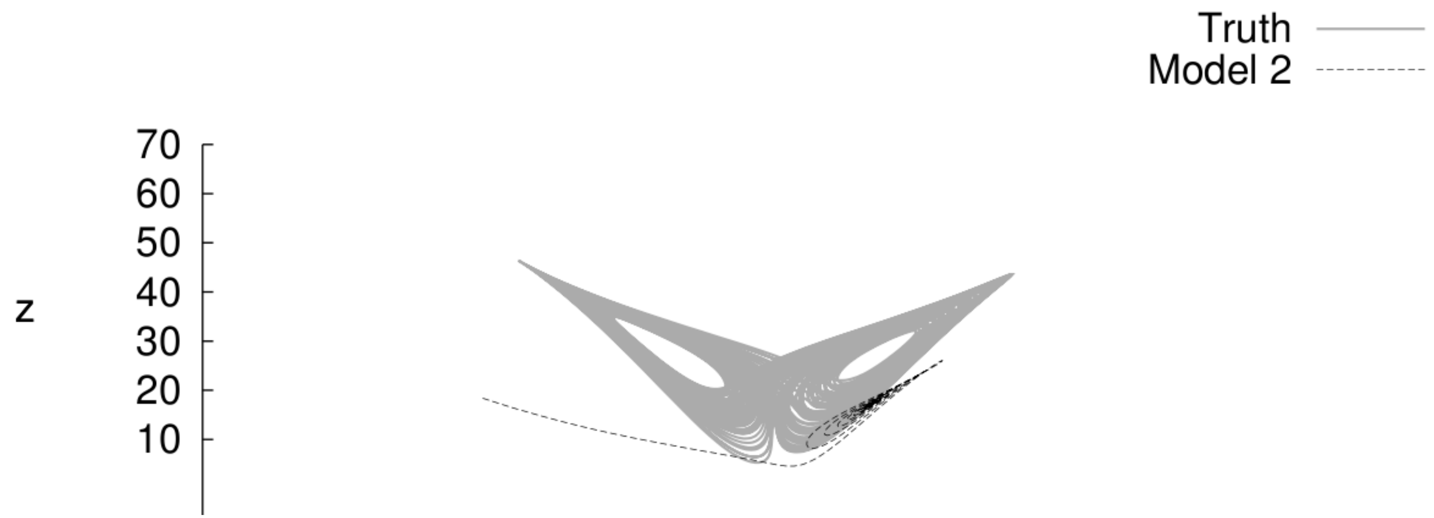
$dC_z^{ij}/dt = \ldots\ldots$

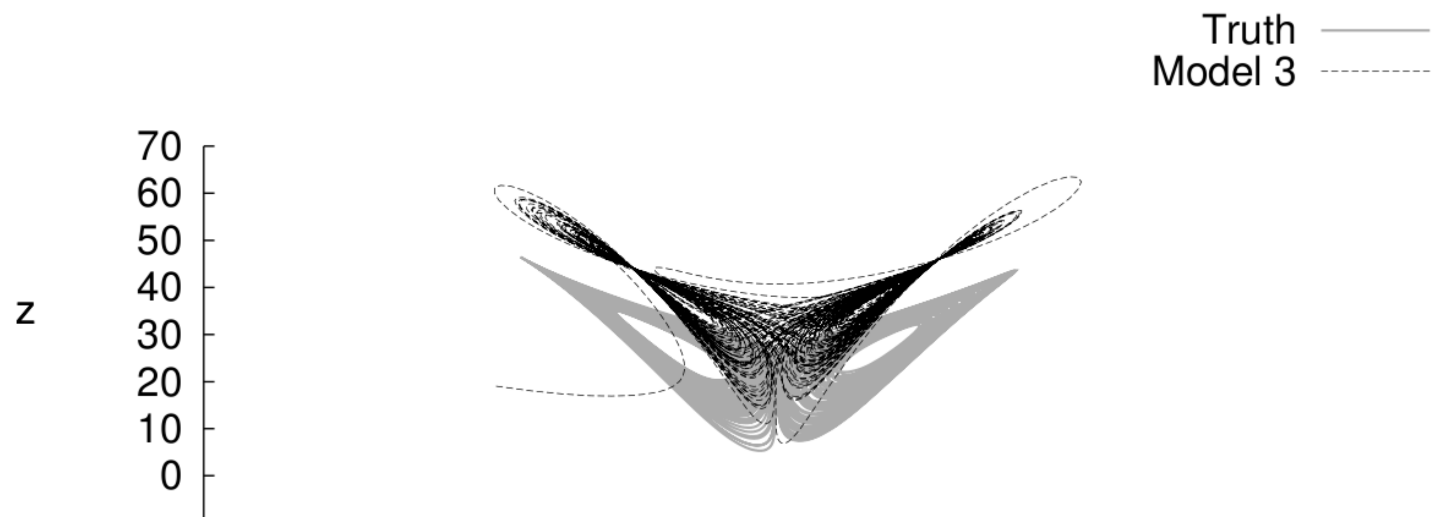
- Model fusion is superior to any weighted averaging of outputs

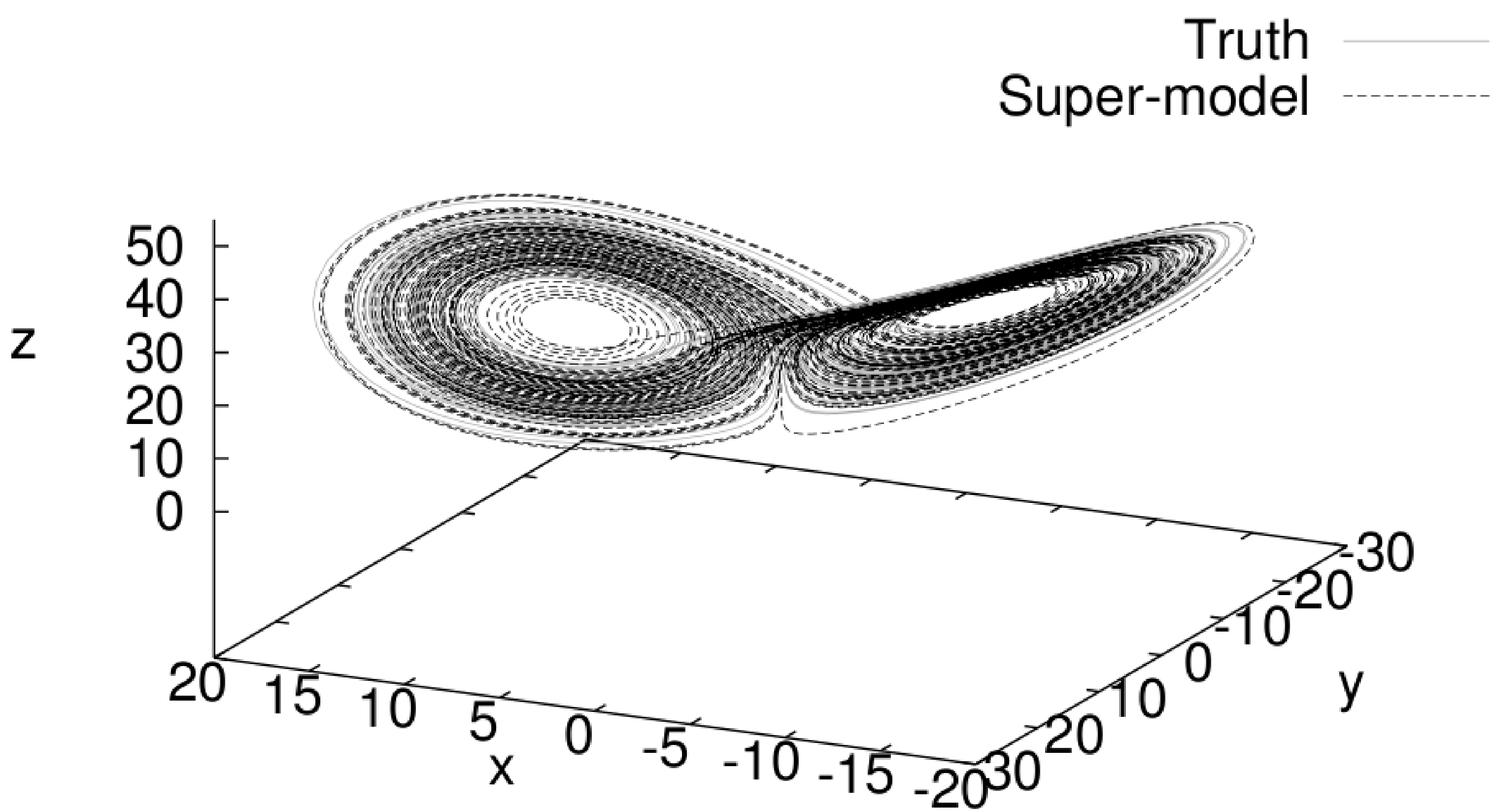
…..OR CAN USE STANDARD MACHINE LEARNING METHODS TO ADAPT INTER-MODEL CONNECTIONS

(Berge et al. 2010)






Truth
Model 3
z
70
60
50
40
30
20
10
0


Truth
Super-model
z
50
40
30
20
10
0
x
20
15
10
5
0
-5
-10
-15
-20
y
30
20
10
0
-10
-20
-30

PROJECT PLAN

- address theoretical issues using simple ODEs
  - negative connections if all models are biased in same direction
  - multiple time scales (ocean/atmosphere) in models
  - globally vs. locally optimal connection schemes

  ……….

- specialize to climate application using QG models
  - determine minimal spatial density of connections
  - choose variables to couple
  - test robustness of trained “supermodel” against increases in N-S temperature gradient

- apply to suite of 3 full climate models: 2 versions of CCSM and NOAA CFS

Supermodeling Works With Multi-time-scale Models

Lorenz ‘84 coupled to ocean box model:

$$x' = -(y^2) - (z^2) - a\,x + a\,(F_0 + F_1\,T) \qquad f = \omega\,T - \xi\,S$$

$$y' = x\,y - b\,x\,z - y + G_0 + G_1\,(T_{av} - T)$$

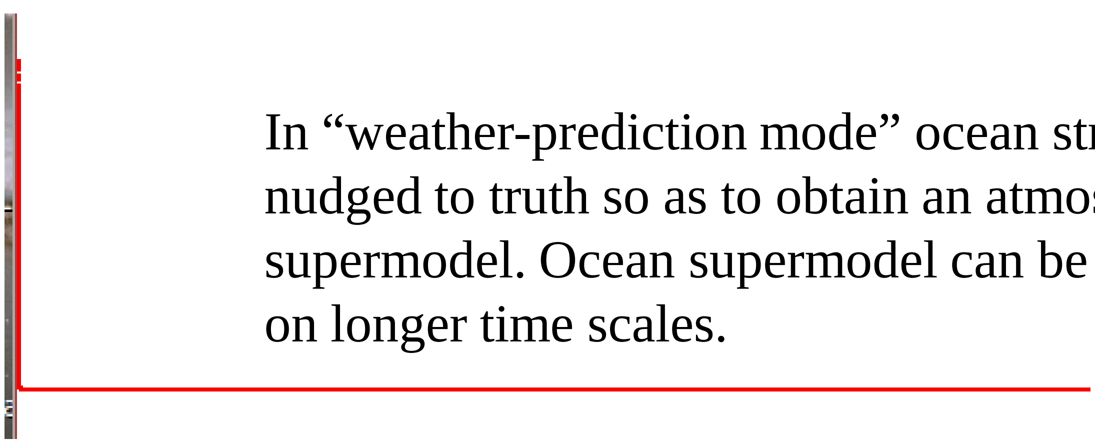
$$z' = b\,x\,y + x\,z - z$$

$$T' = k_a\,(\gamma\,x - T) - |f|\,T - k_w\,T$$

$$S' = \delta_0 + \delta_1\,(y^2 + z^2) - |f|\,S - k_w\,S$$

$X_{supermodel} - X_{truth}$

$T_{supermodel} - T_{truth}$

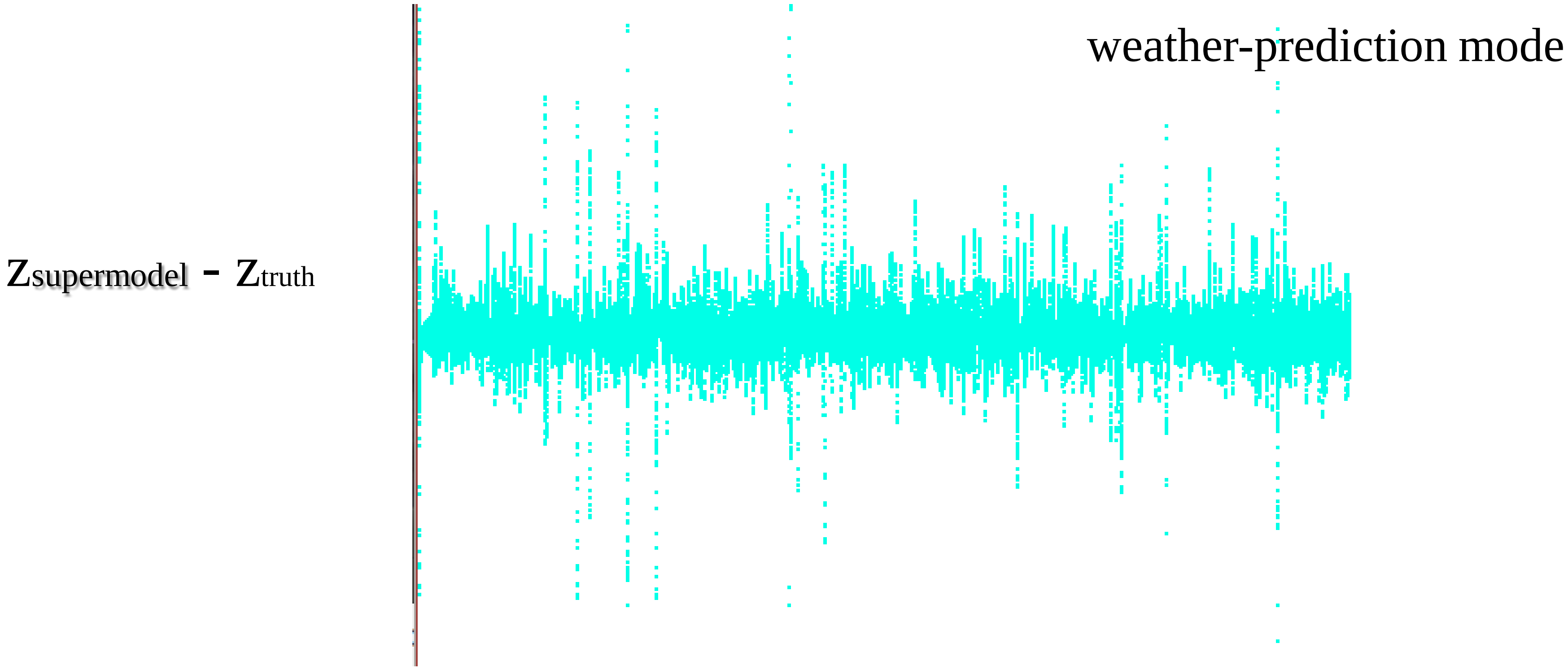


In “weather-prediction mode” ocean strongly nudged to truth so as to obtain an atmospheric supermodel. Ocean supermodel can be trained on longer time scales.

What if all models are biased in same direction?

Lorenz supermodel with $\sigma_{truth} < \sigma_1, \sigma_2, \sigma_3$

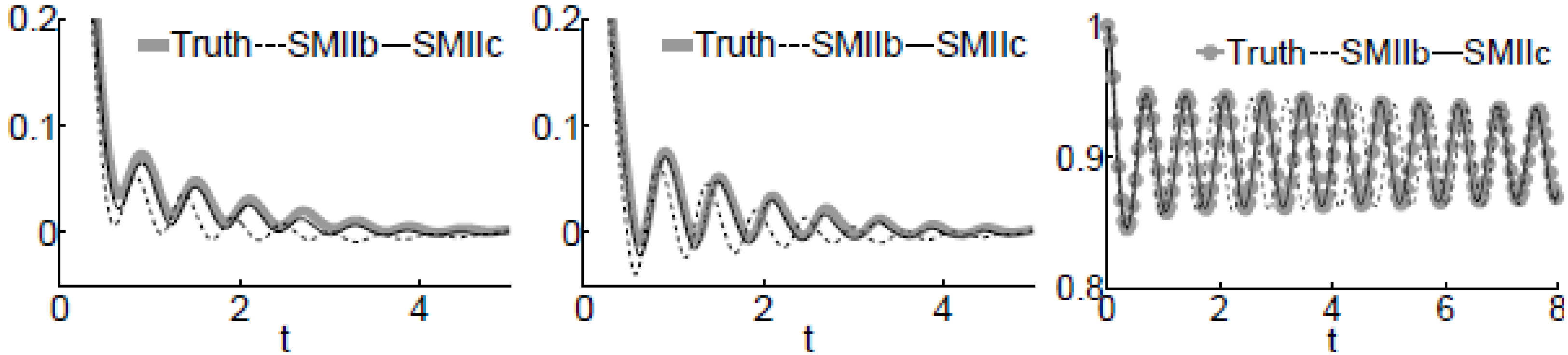
$\Rightarrow$ Some connections become negative



Not as effective as positive connections, but better than averaging.

Stochastic Learning Methods Can Help Optimize Supermodel

Autocorrelations for Truth and Two Supermodels



(a) x (b) y (c) z

SMIIb is formed using a deterministic learning method

SMIIc is formed using a stochastic learning method

Extension to PDE's: What is the required spatial density of inter-model coupling?

Synchronization of two 1D Kuramoto-Sivishinsky systems:

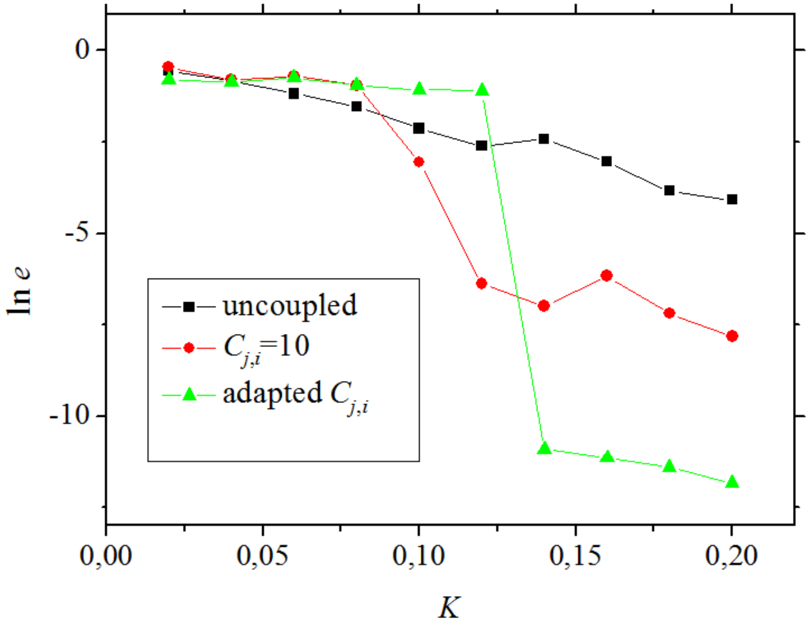
$$u_t = -u_{xxxx} - \alpha_u u_{xxx} - u_{xx} - 2uu_x$$

$$v_t = -v_{xxxx} - \alpha_v v_{xxx} - v_{xx} - 2vv_x + K[u(x) - v(x)]\, f(x)$$

$f(x)$ non-vanishing only at discrete points

Maximum coupling distance is length scale of coherent structures:

Can form supermodel from 3 KS's:



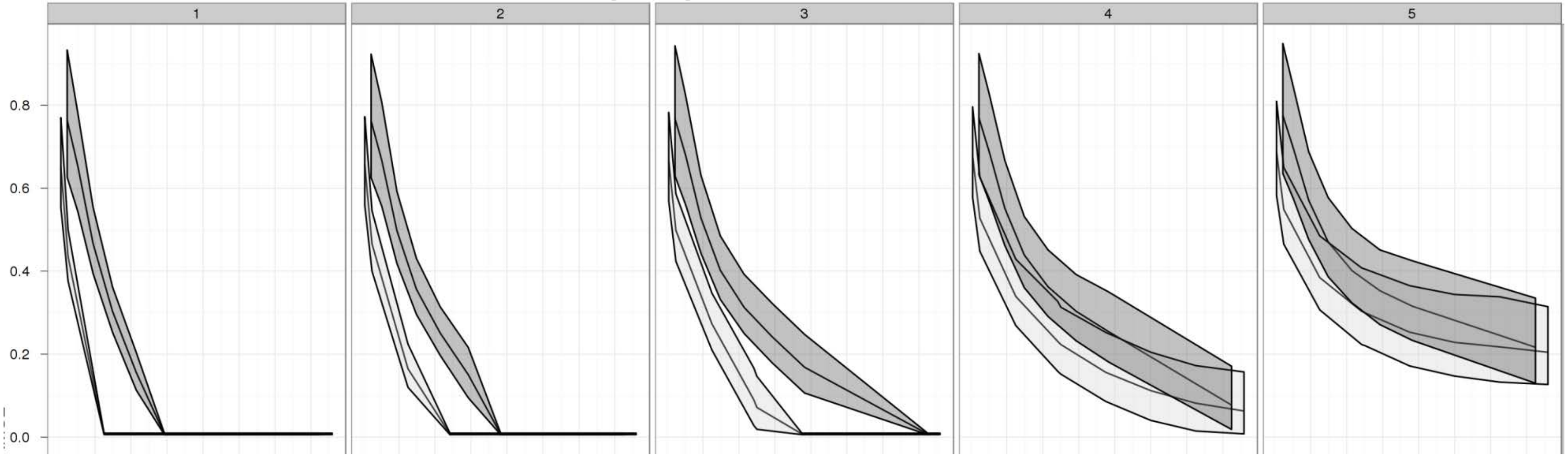
What variables should be coupled?

Consider 3-layer QG model on sphere with realistic topography and a forcing chosen to reproduce the observed winter mean state.

Compare coupling in a basis of spherical harmonics to a basis of EOF’s:

nudging time scale

sync error



Number of components that are coupled

dark grey: spherical harmonics   light grey: EOF’s

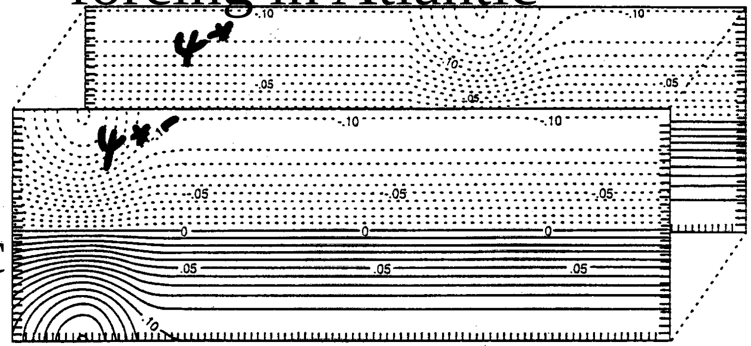
Immediate Plans

- Understand role of stochasticity in choosing among highly constrained connection schemes
- Study robustness of QG supermodel against changes in forcing
- Establish inter-model coupling within DART at NCAR

Proposed Adaptive Fusion of Two QG Channel Models

forcing in Atlantic $Dq/Dt = F + D$

forcing in Pacific



$Dq'/Dt = F' + D'$

$F = f_o\,(q - q^*) + c\,J(\psi, q - q')$

$F' = f_o\,(q' - q^{*\prime}) + c\,J(\psi', q' - q)$

c=1/2 $\Downarrow$

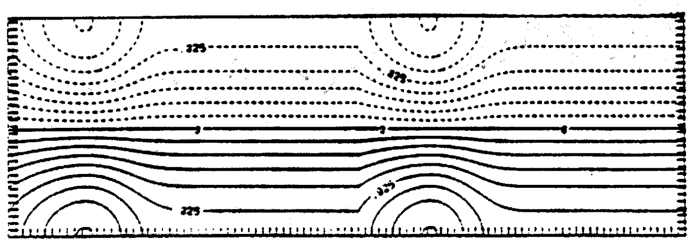
(k-dependence suppressed)

$F_o = f_o(q - q^*)$

$F_o' = f_o(q' - q^{*\prime})$

$D/Dt\,(q+q')/2 = (F_o + F_o')/2 + (D + D')/2$

- If the parallel channels synchronize, their common solution also solves the single-channel model with the average forcing



$$\frac{\Psi^* + \Psi^{*\prime}}{2}$$

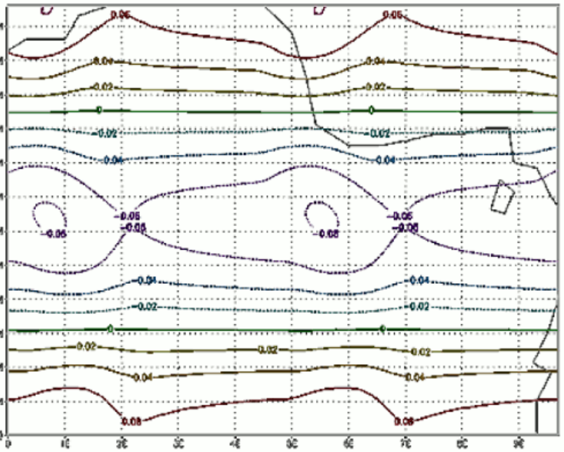
To find c adaptively:

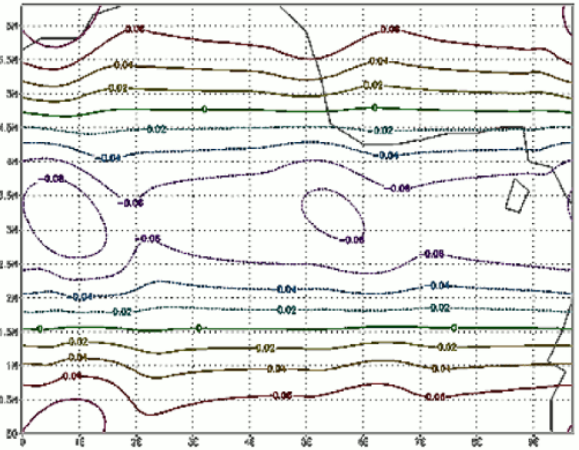
$$dc/dt = \int d^2\mathbf{x}\; J(\psi, q' - q)(q - q_{obs}) + \int d^2\mathbf{x}\; J(\psi', q - q')(q' - q_{obs})$$

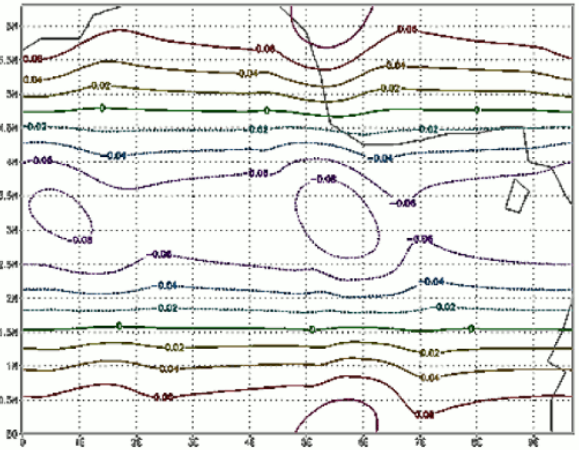
Models Synchronize With Each Other and With "Truth"

"truth"	model with Atlantic forcing	model with Pacific forcing

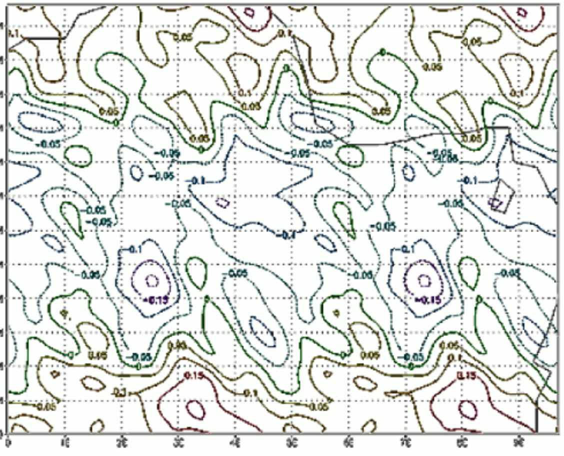
n = 1000:

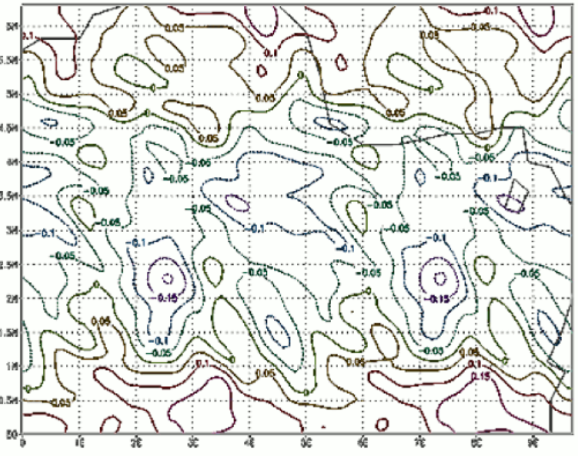


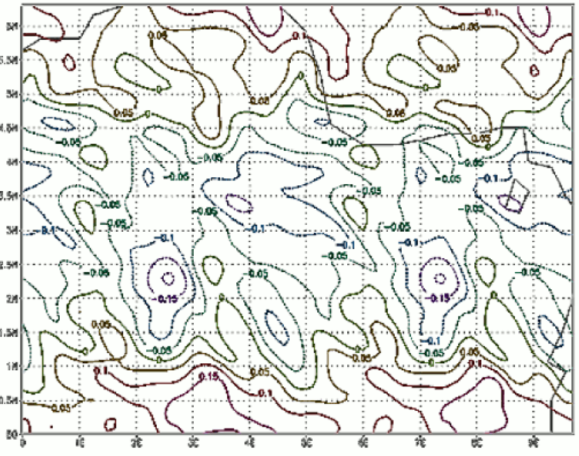




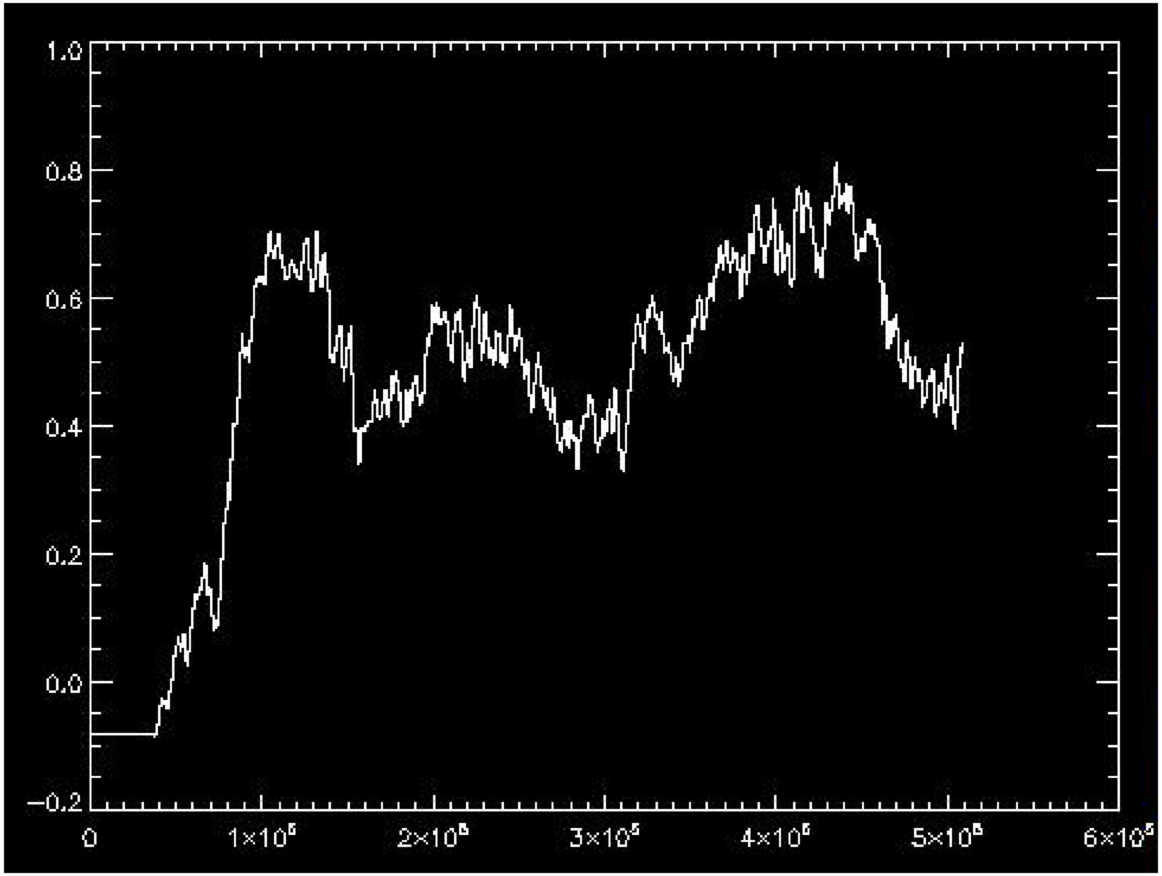
n = 30000:





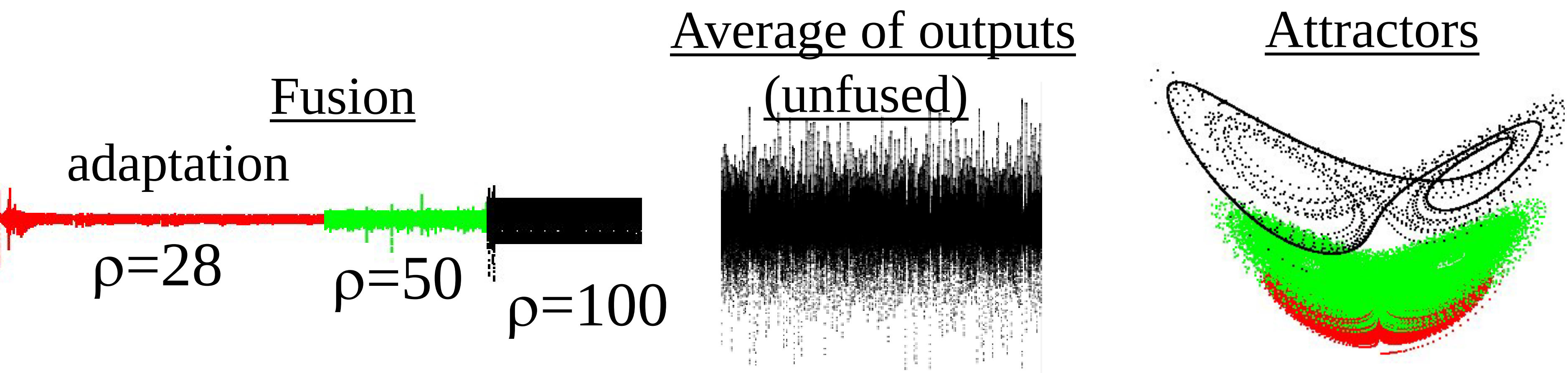


…..As the Adaptation Procedure Estimates the Intermodel Connection Coefficient $c \to 1/2$



Possible Issue 1: What if the dynamical parameters change drastically in the 21st century as compared to the training period?

Train with Lorenz ρ=28 and then reset ρ in "reality" and in 3 "models"



-fusion still better than averaging even when training and test systems differ by a large number of dynamical bifurcations

Possible Issue 2: Do the results apply to climate projection (vs. weather prediction)?

-It is actually easier to achieve *non-isochronic* synchronization (a.k.a. *measure synchronization*), where the attractors of two coupled systems become the same, without any agreement between concurrent states.