Estimation of a GM Coefficient using Gaussian Process Emulation

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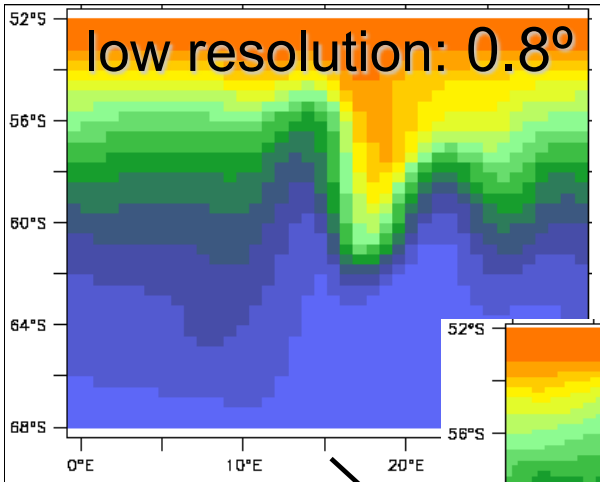
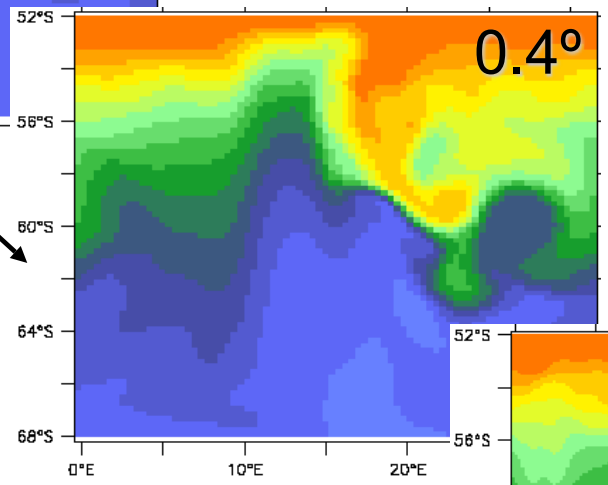
too many simulations, too little time...

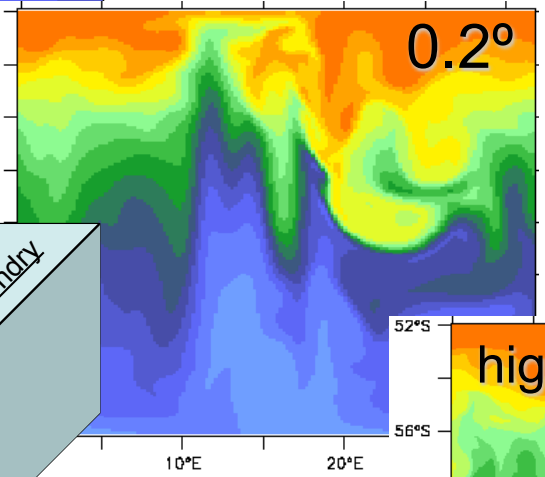
- when quantifying uncertainty in climate model results
  - ensembles are usually small
    - even before consideration of input parameter variation
- when selecting optimal input parameters
  - particular when number of related parameters > one

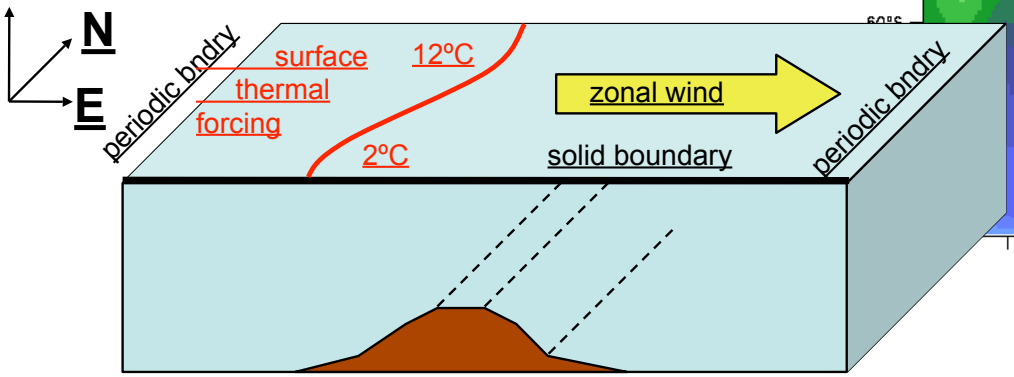
The test problem

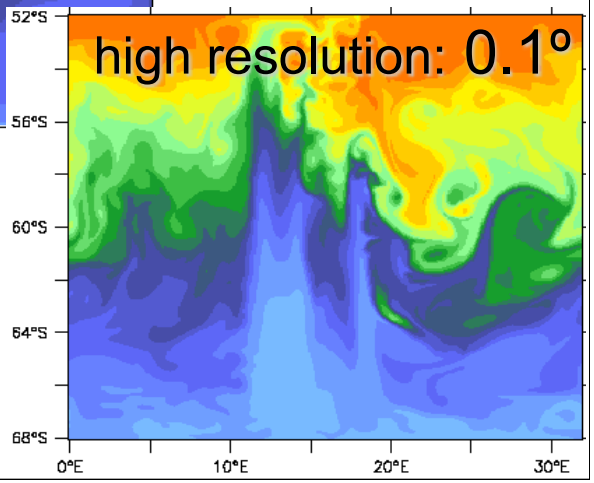




(cost of doubling horizontal grid is factor of 10)







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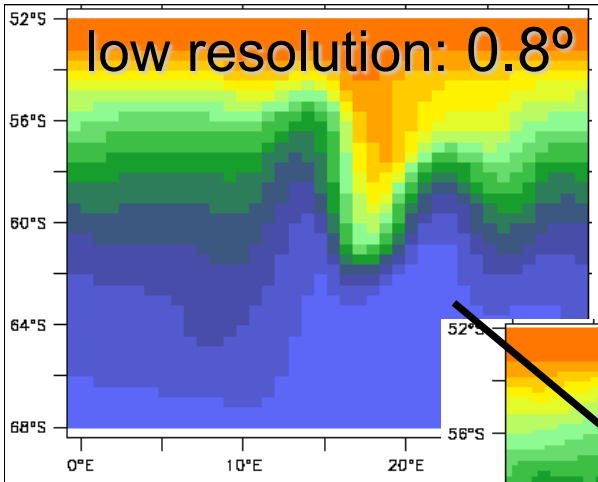

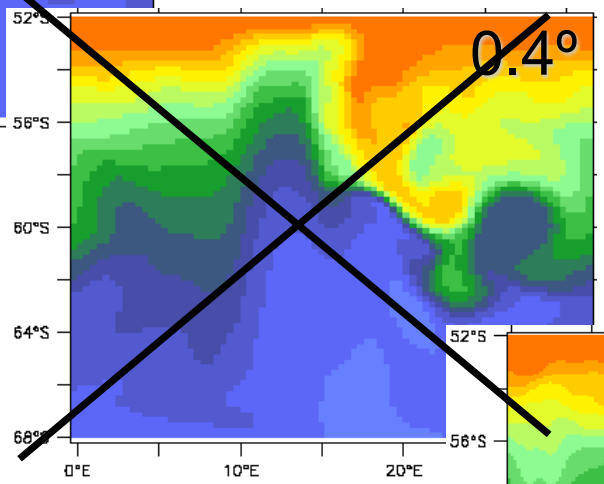

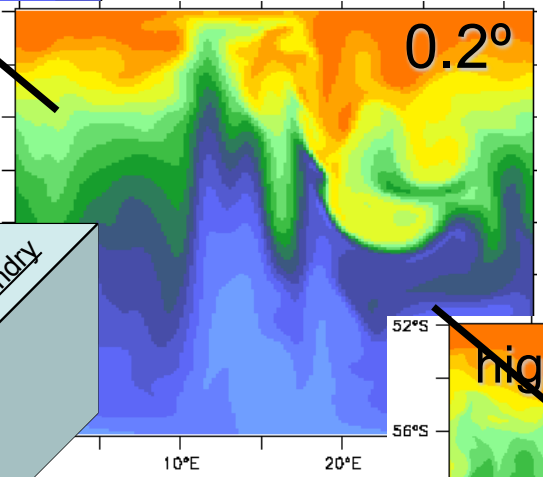

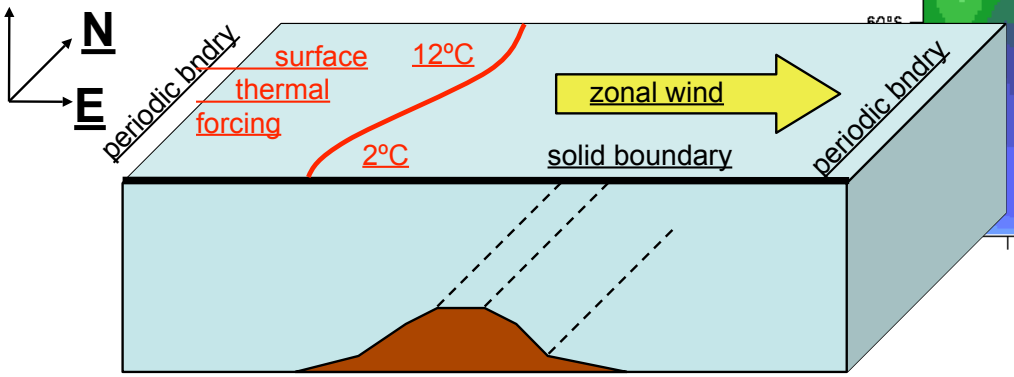

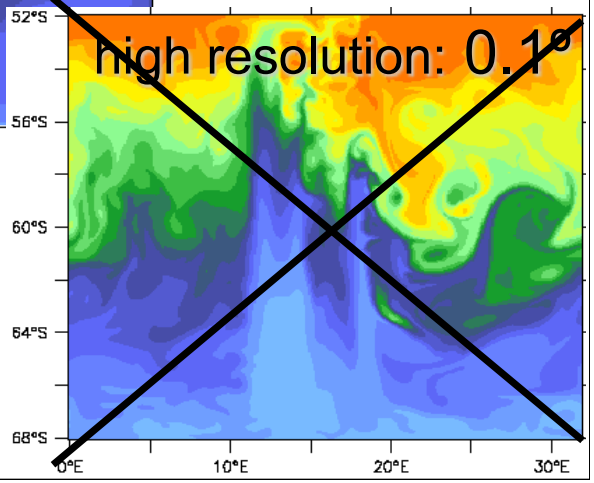

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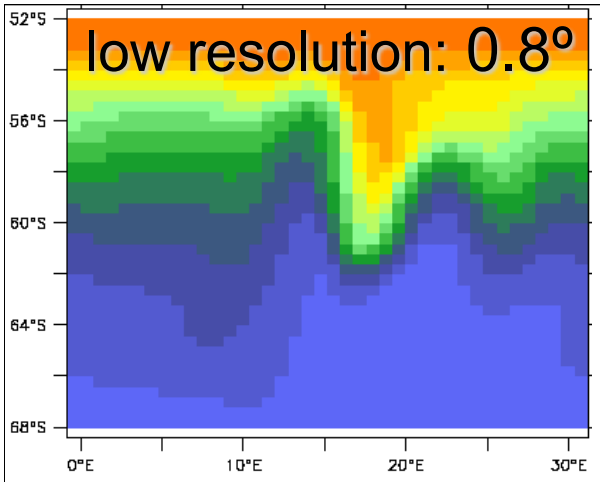
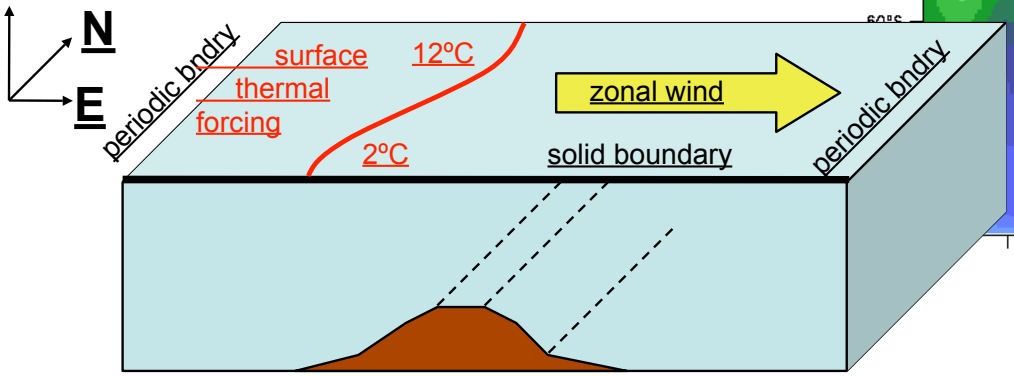
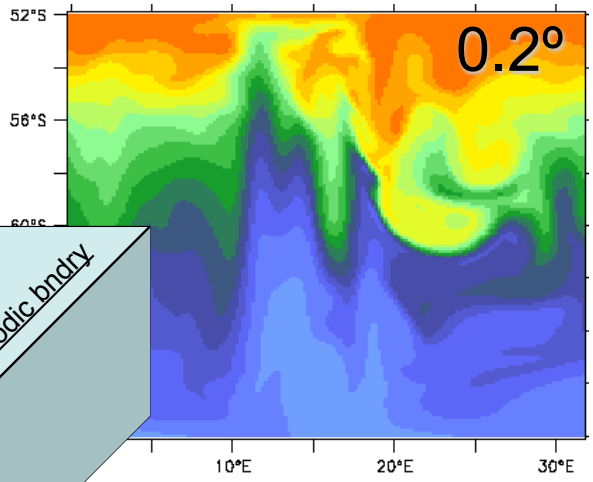


The test problem

At 0.8º, adjust GM coefficient to match 0.2º result





but in what convenient, simple metric?

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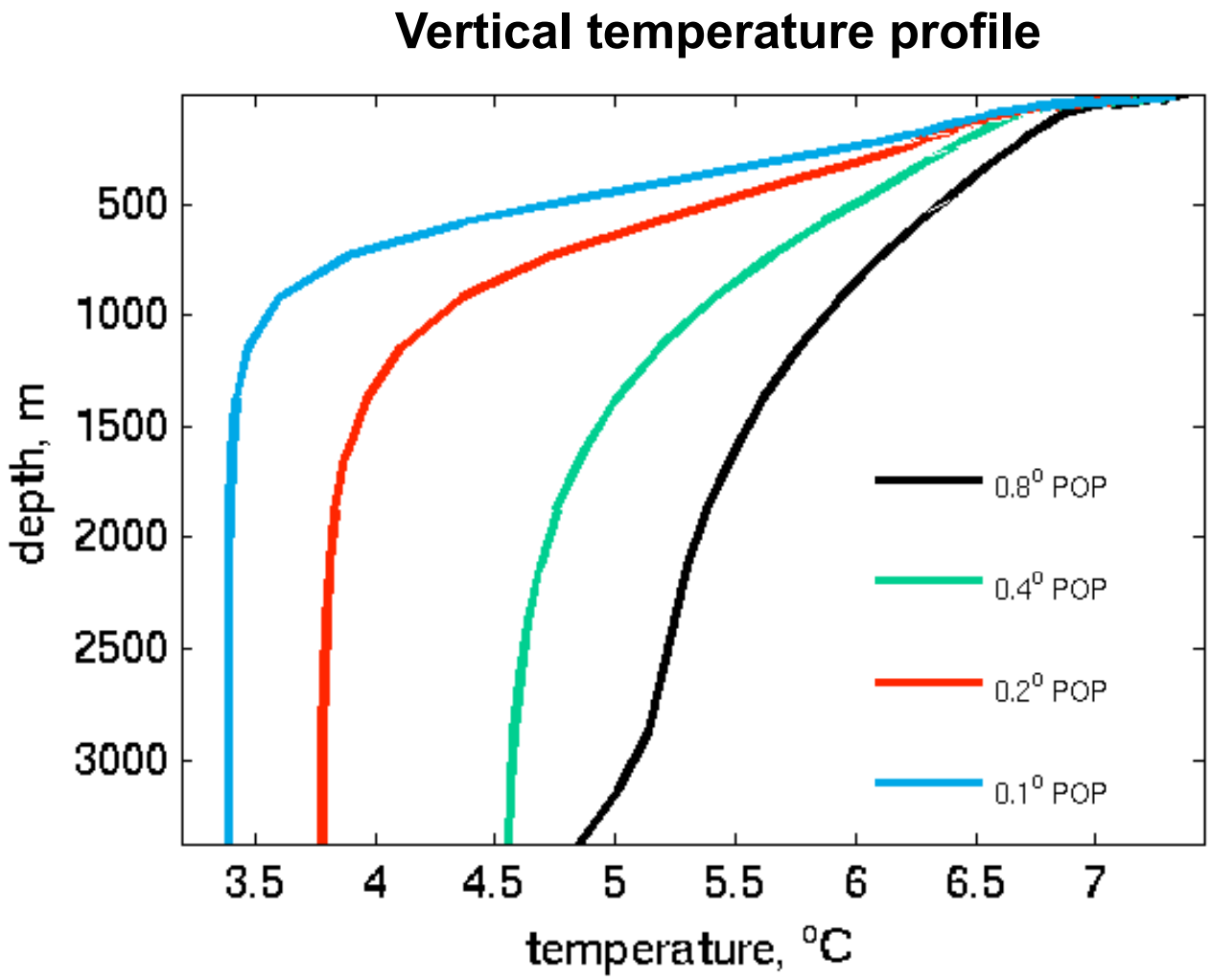
our simple metric

averaged
over
lat, lon



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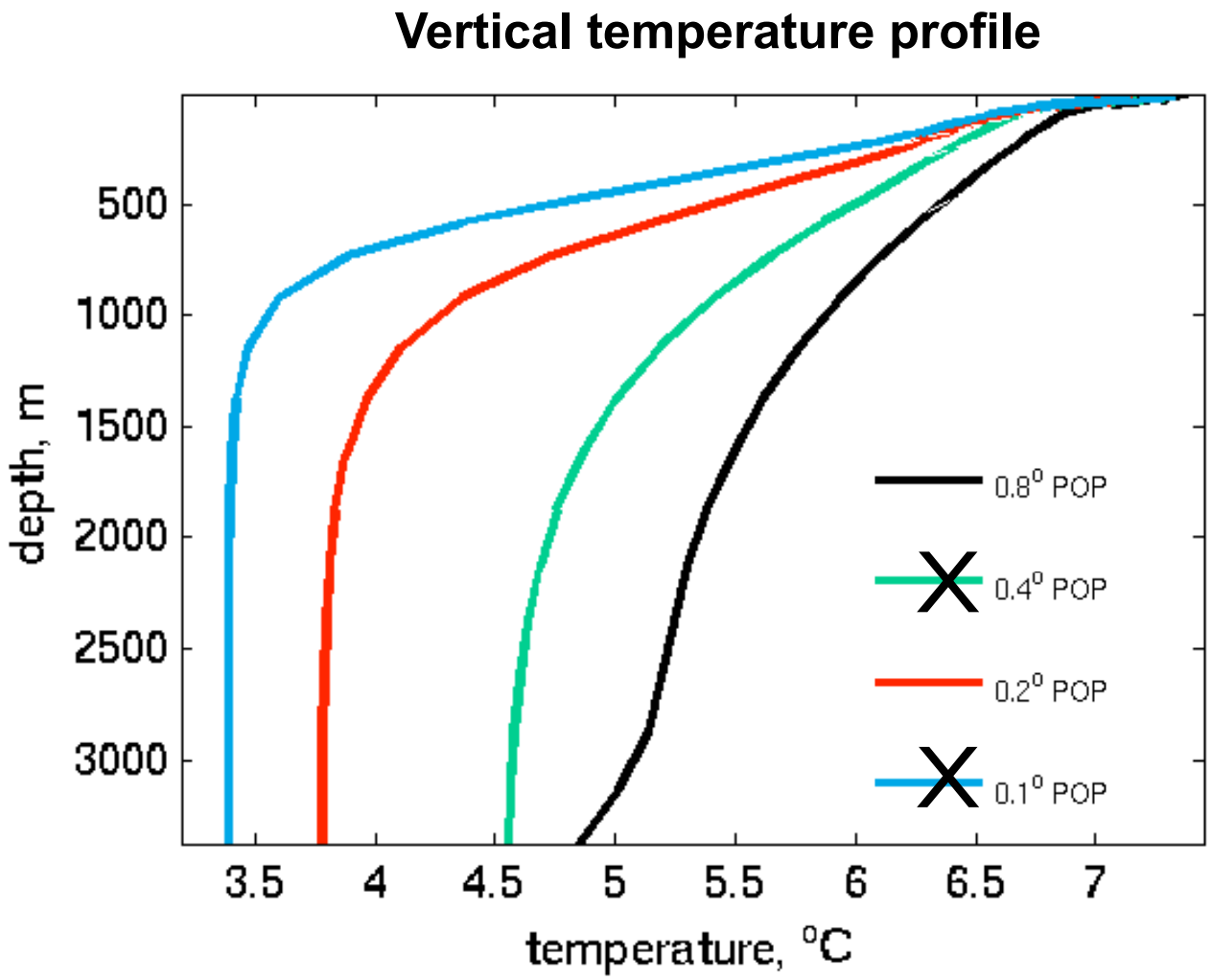
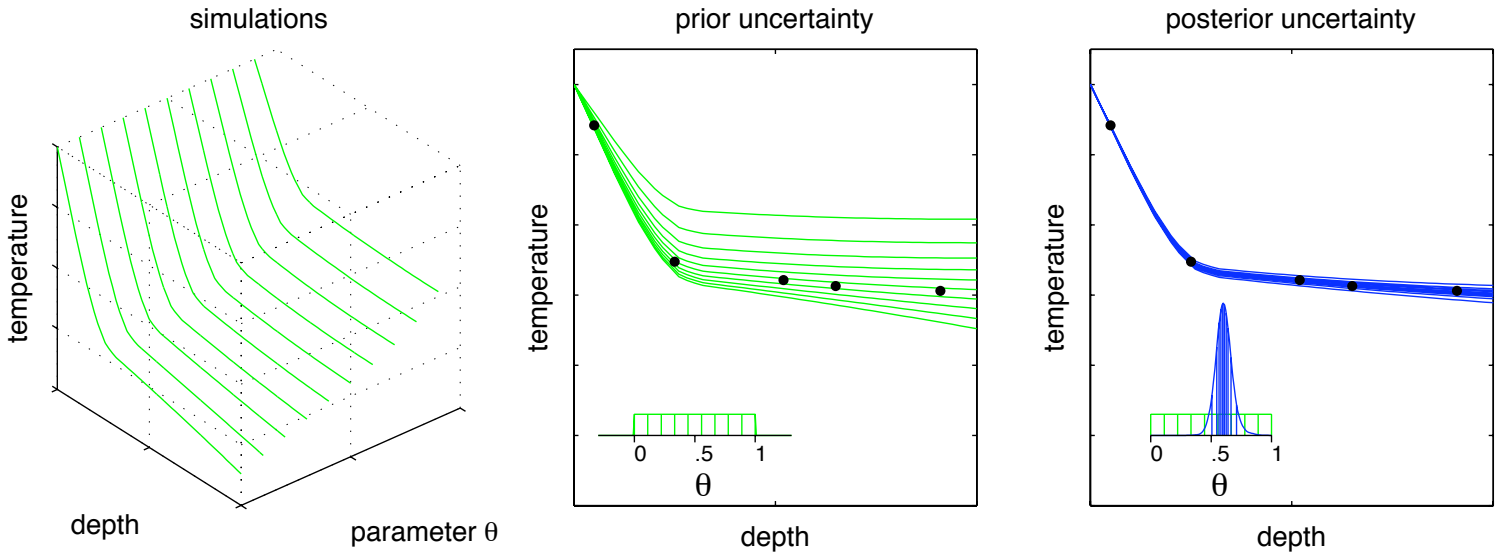


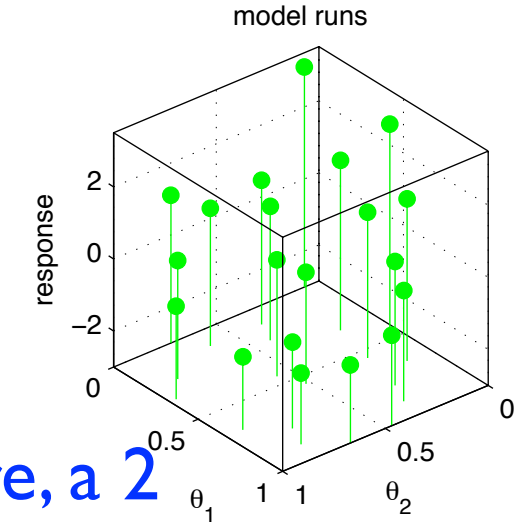
Parameter Estimation: in Concept

Use statistical approach to find input settings to match the target profile

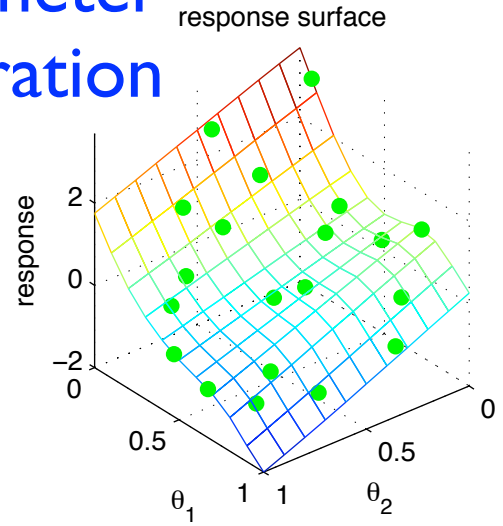


- Finds input parameter settings that best match the target temperature profile
- Requires that initial ranges for the parameters be specified

Construct a response surface of the simulation output to predict at untried settings

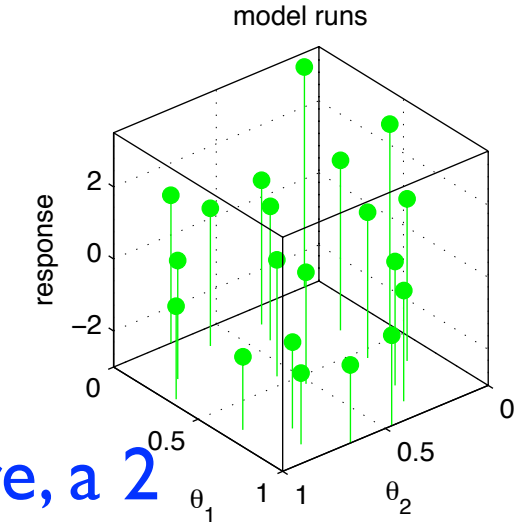


Here, a 2 parameter illustration



- Actual application requires a basis representation to predict temperature profiles
- Can use holdouts to assess accuracy of response surface
- Can carry out sensitivity analysis using response surface

Construct a response surface of the simulation output to predict at untried settings



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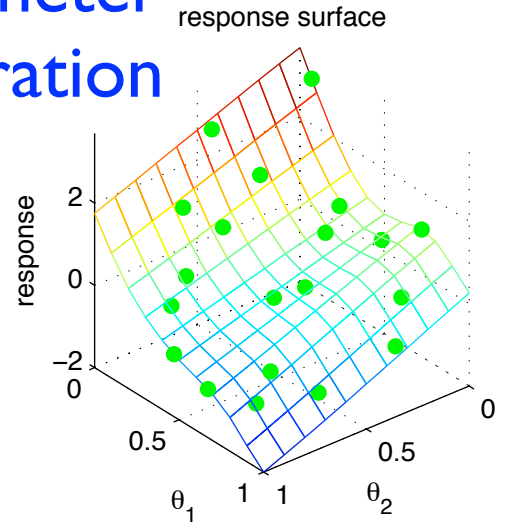

- Actual application requires a basis representation to predict temperature profiles
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Prediction at untried settings based on Gaussian process emulators (there's a literature on this)

Southern Ocean Testbed GM Calibration

LA-UR-11-11969

Jim Gattiker, Matthew Hecht

November 10, 2011

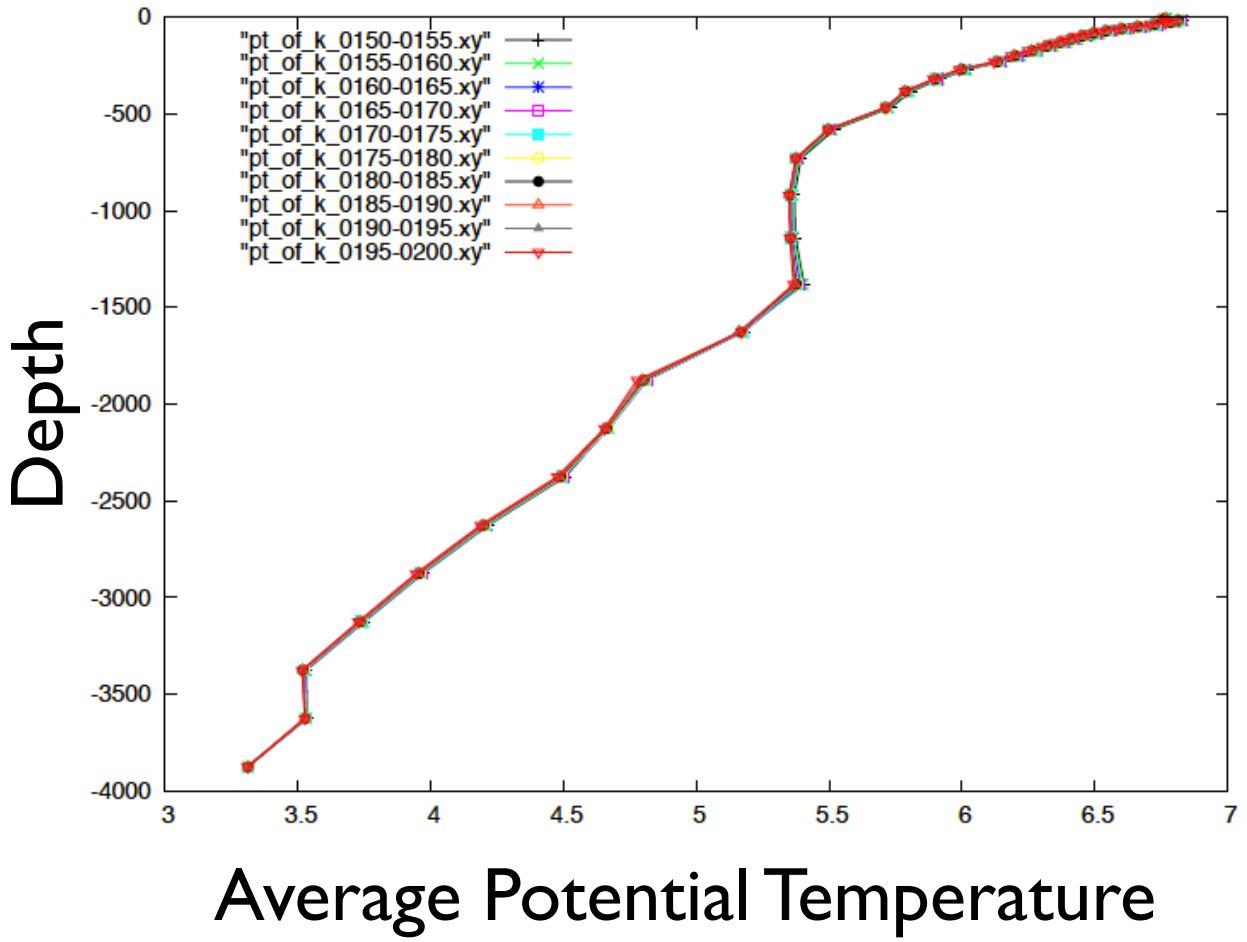
Simple, readily evaluated demonstration of the methodology on constant-coefficient GM.

Based on 11 evenly spaced values of the GM parameter, from 0.15 to 1.0 x 10^3 m^2/s

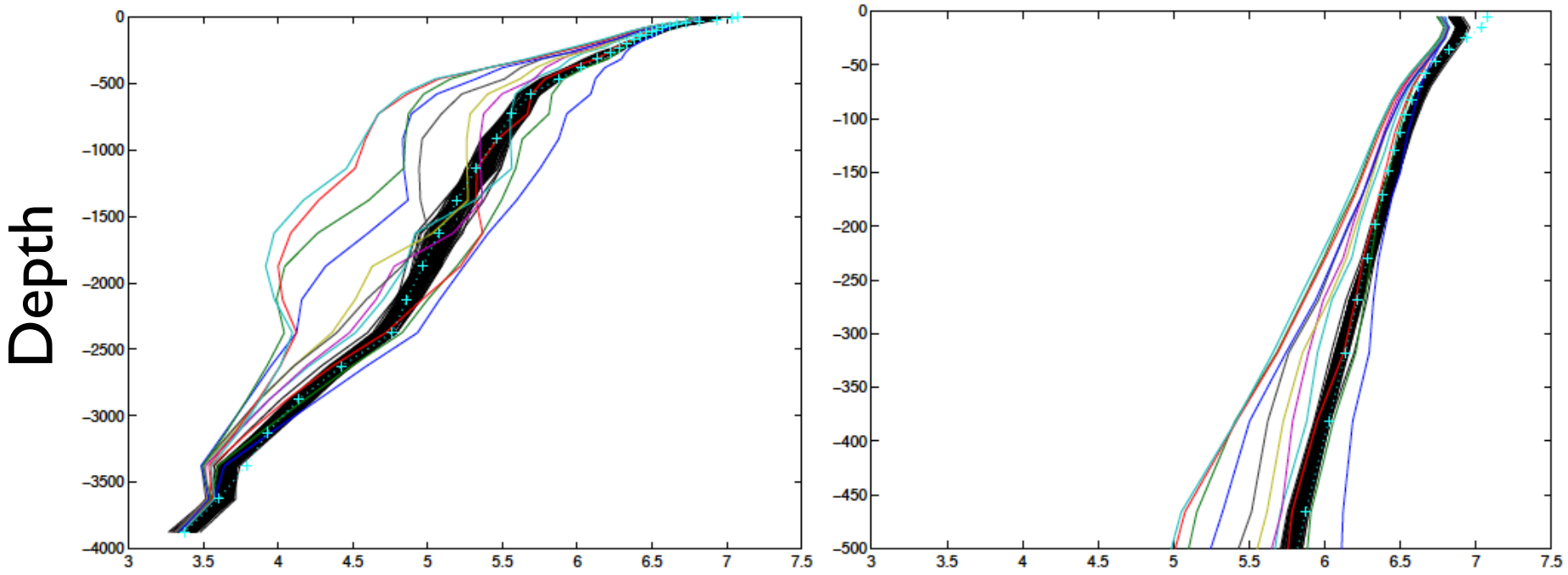
Experimental procedure

0.2° case run for several years. Then, upscaled to provide 0.8° initial condition.

Here, we see that 200 years of 0.8° simulation is sufficient to equilibrate



matching the 0.2° profile

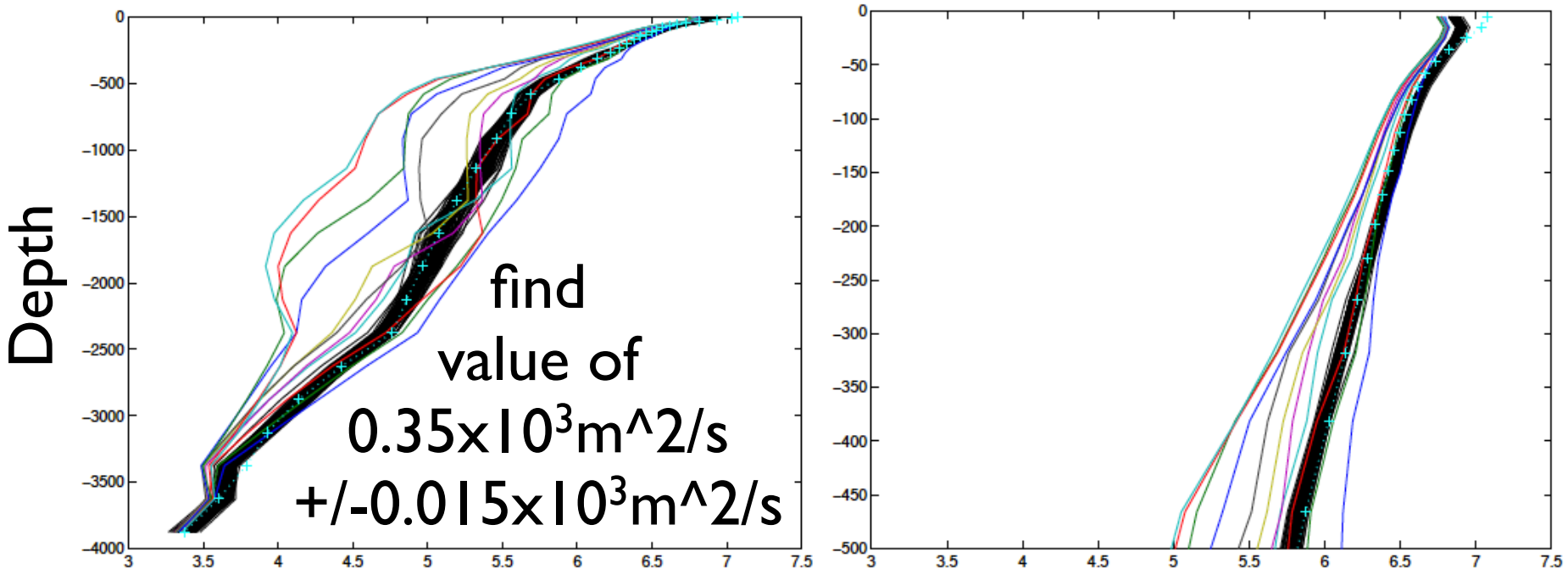


Average Potential Temperature

0.2° target are the +'s (cyan).

The 11 calibration cases are the colored lines, calibrated predictions in black

matching the 0.2° profile



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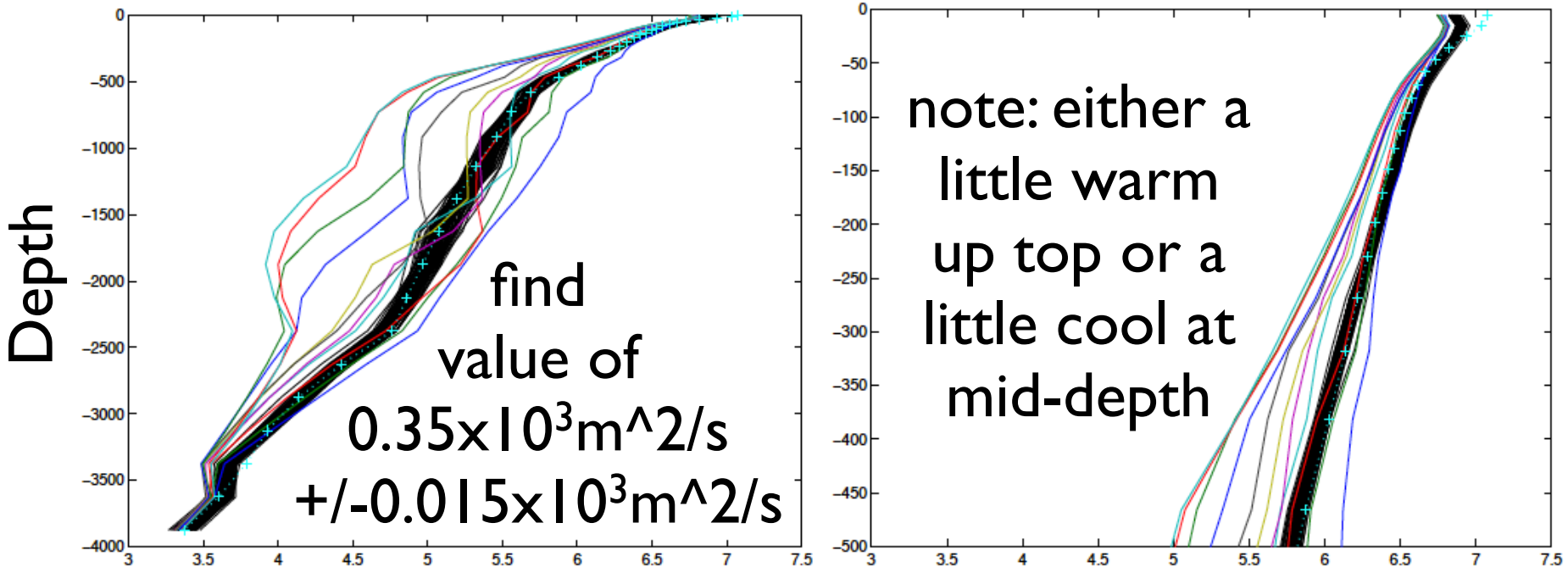

Average Potential Temperature

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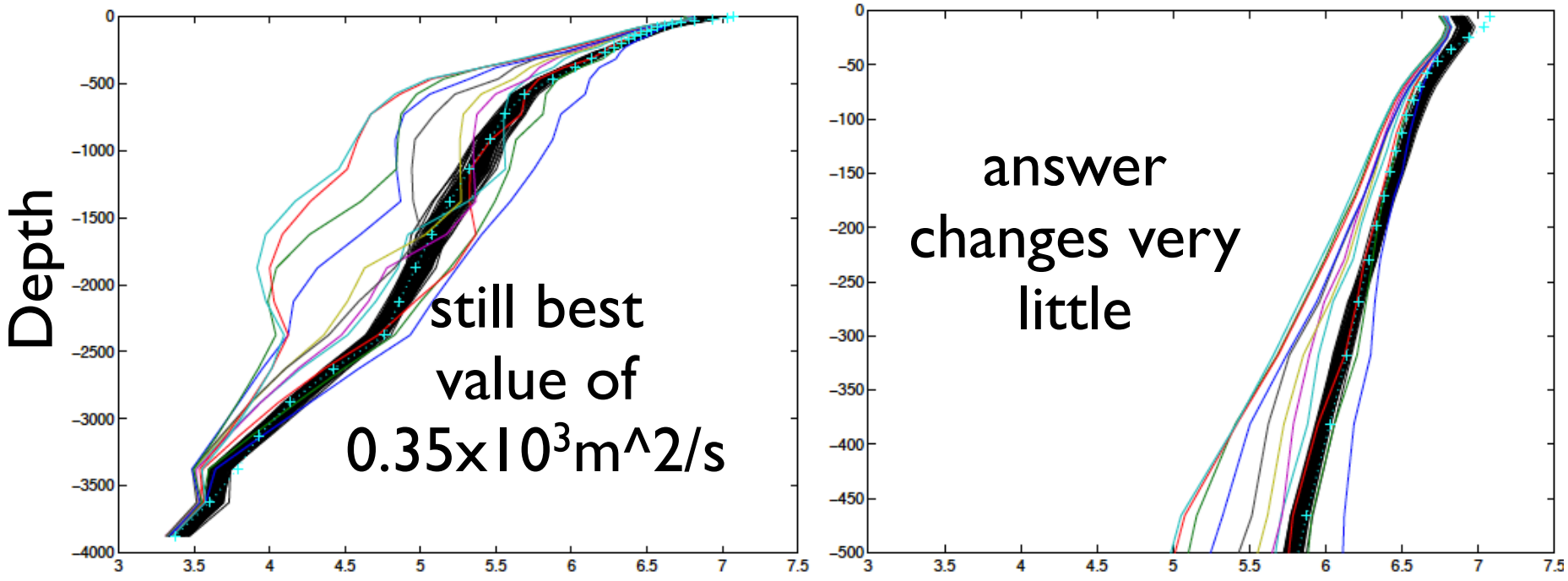
include discrepancy model



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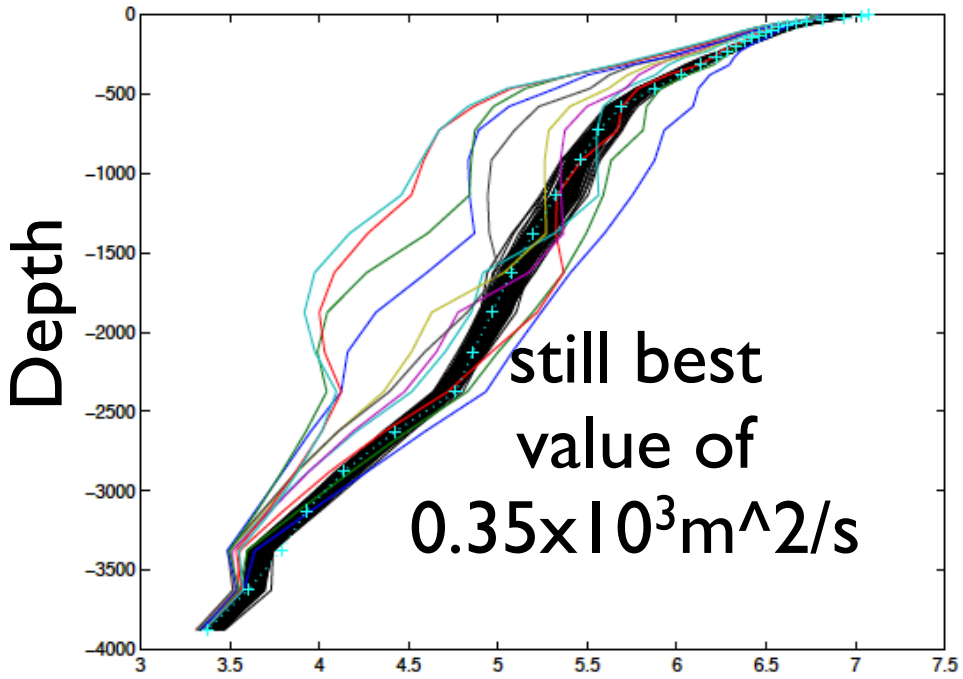
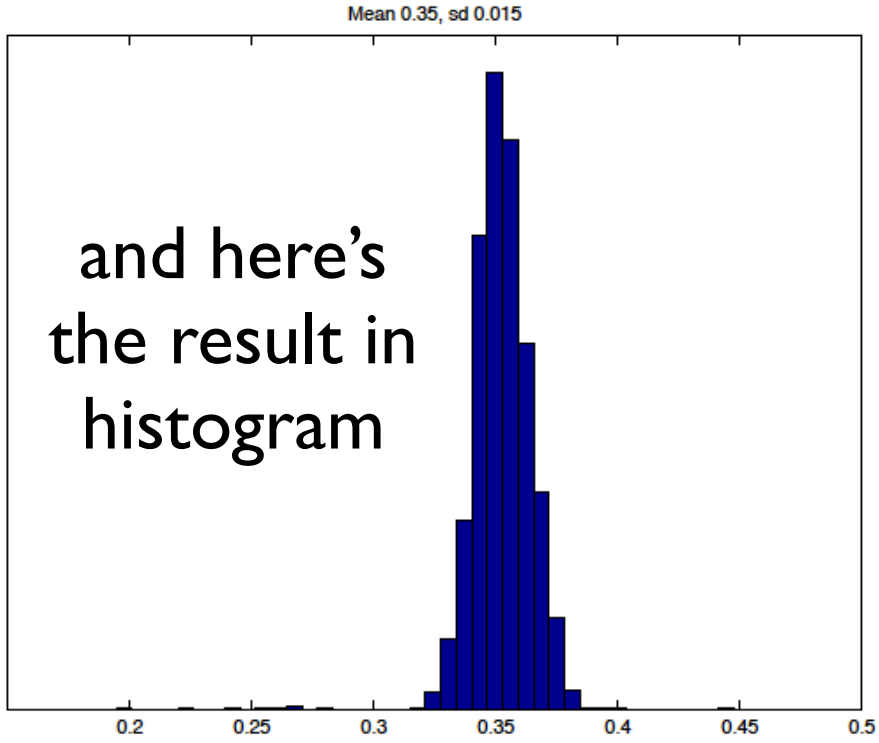
calibrated result





demonstration and beyond

- in this case, could have gotten a similar answer just from the usual inspection of the eleven cases
  - not so if two or three related parameters must be considered, all of them bounded apriori only within some range
- now, apply this to current CESM GM
  - Is this a good enough testbed?

UQ example

Quantile Estimation in a Climate Model

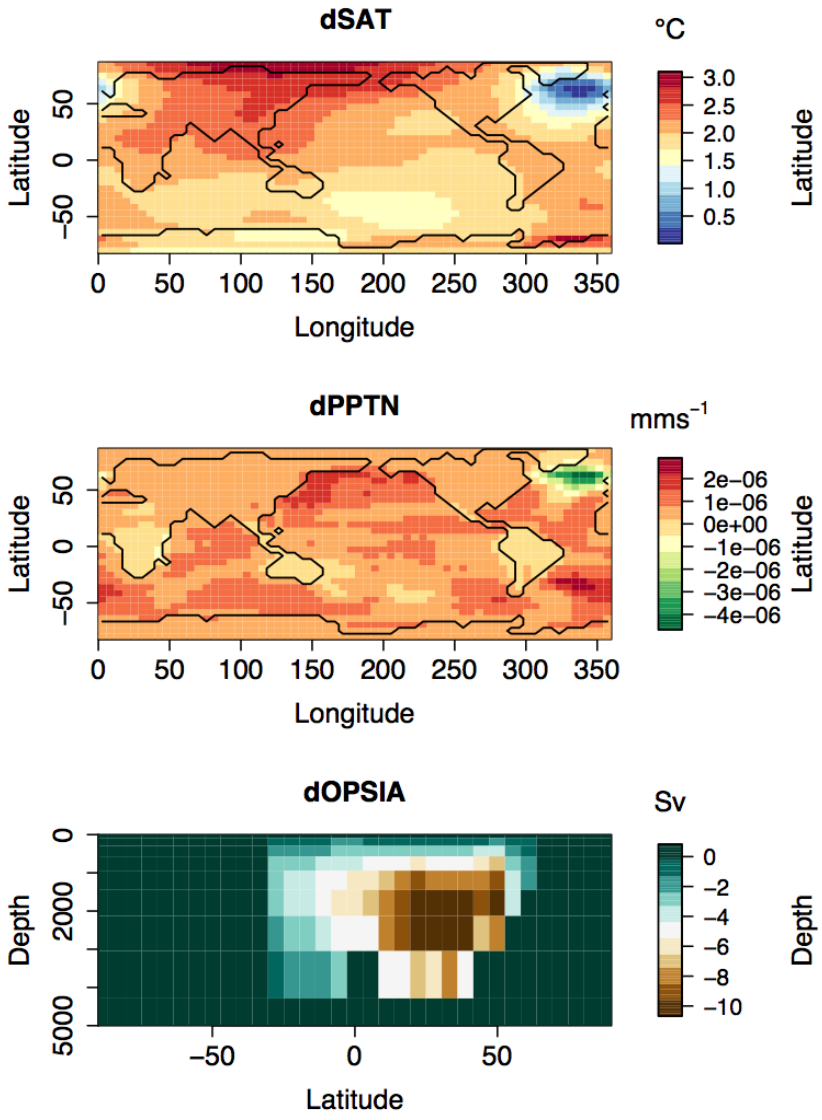
LA-UR 09-03674

James R. Gattiker, Scott Vander Wiel [1]
Doug McNeall[2], Peter Challenor [3]

[1]Statistical Sciences, Los Alamos Nat'l Lab
[2] UK Met Office
[3] UK National Oceanography Center

June 11, 2009

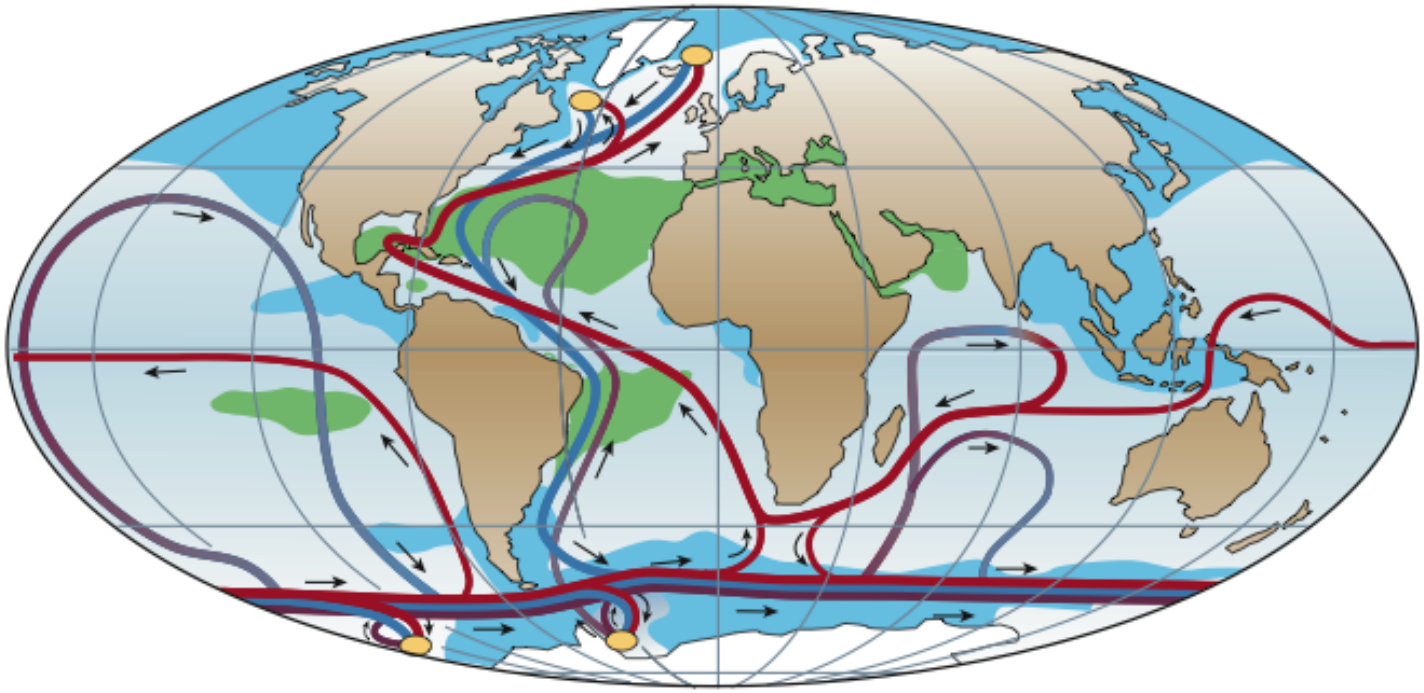
The Problem



We have the climate model GENIE-1:

- Intermediate complexity model.
- 64 long. $\times$ 30 lat. $\times$ 8 depth.
- Deterministic simulation.
- Derive a scalar measure of MOC strength.
- Limited runs available.

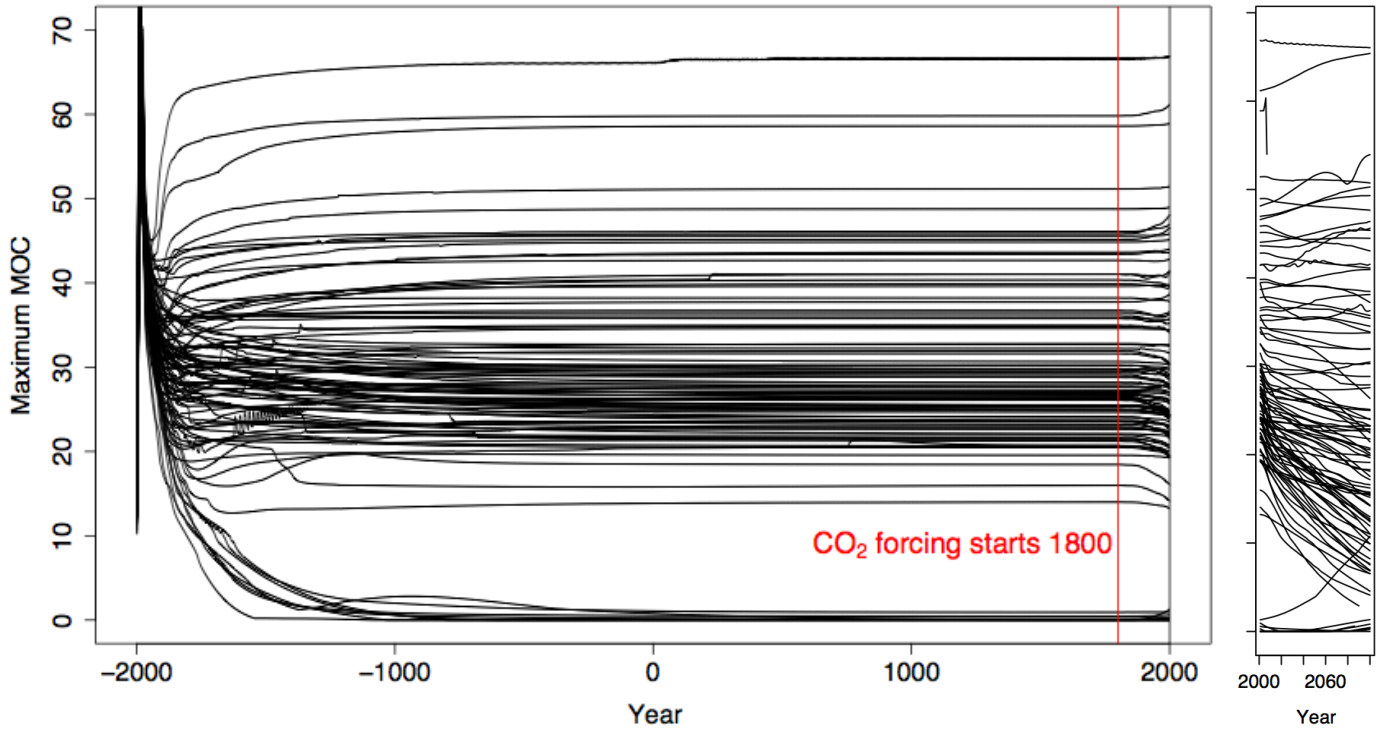
The Problem



From that model, we would like to estimate the likely decrease in MOC circulation by 2100.

The Approach

Design an ensemble of model runs, systematically varying uncertain inputs in a designed experiment (Latin Hypercube).



(forced by IPCC Scenario A1B)

Final MOC Distribution

According to GENIE-1 and expert estimates of input distributions over uncertain parameters, the change in MOC from 2000 to 2100 is very uncertain. The 33rd percentile is ~14 +/- 3.5 Sv, or a 90% confident interval of [8,20]Sv